ASSESSING THE ROLE OF HUMAN BEHAVIORS IN THE MANAGEMENT OF EXTREME HYDROLOGICAL EVENTS: AN AGENT-BASED MODELING APPROACH

BY

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DISSERTATION

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Abstract

This thesis aims to assess the role of human behaviors in the management of extreme hydrological events. Using an agent-based modeling (ABM) approach, three specific issues associated with modeling human behaviors are addressed: (1) behavioral heterogeneity, (2) social interaction, and (3) the interplay of multiple behaviors. The modeling approach is applied to two types of extreme hydrological events: floods and droughts.

In the case of flood events, an ABM is developed to simulate heterogeneous responses to flood warnings and evacuation decisions. The ABM is coupled with a traffic model to simulate evacuation processes on a transportation network in an impending flood event. Based on this coupled framework, the model further takes account of social interactions, in the form of communication through social media, and evaluates how social interactions affect flood risk awareness and evacuation processes.

The case of drought events considers a hypothetical agricultural water market based on double auction. Farmers' multiple behaviors (irrigation and bidding behaviors) are modeled in an ABM framework. The impacts of the interplay of these behaviors on water market performance are evaluated under various hydrological conditions.

The results from the ABMs show that the three aforementioned aspects of human behaviors can significantly affect the effectiveness of the management policies in extreme hydrological events. The thesis highlights the importance of including human behaviors for policy design in flood and drought management. Further, the thesis emphasizes the efforts in collecting empirical data to better represent and simulate human behaviors in coupled human and hydrological systems.

To My Family

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Chapter I. Introduction

1.1 Problem Overview

Management and planning policies in water resource systems require a comprehensive understanding of both natural systems and human behaviors in response to the natural systems. In light of this, coupled human and natural systems (CHNS) have been recognized as an important modeling concept for simulating the interaction and coevolution between natural systems and humans [*Liu et al.*, 2007a], and understanding human decision making is important for effective policy designs in water resource planning and management [*Liu et al.*, 2007b; *O'Connell and O'Donnell*, 2014].

Although human behaviors play an important role in water resource systems, modeling human decisions is challenging, especially when data related to human cognitive processes that drive their decision-making are lacking. Two approaches for simulating human behaviors have been used: (1) optimization-based approaches and (2) rule-based approaches [*Hu*, 2015]. Optimization-based approaches simulate humans as *utility optimizers*, whose decisions are optimal ones based on the current available information for decision making [*Yang et al.*, 2012; *Hu et al.*, 2015]. Given that the information available for decision making are often not sufficient, optimization-based approaches typically can only represent ideal decisions and might not completely capture the empirical decision making process. On the other hand, rule-based approaches assume human behaviors follow some intuitive *if-then* decision rules [*An*, 2012]. Rule-based approaches are generally intuitive and easy to understand. However, derivation of such rules requires large amount of empirical data and comprehensive understanding of human cognitive processes, which are often not available to modelers [*Elsawah et al.*, 2015].

To address the challenges associated with modeling human behaviors in water resource systems, agent-based modeling (ABM) has been widely applied in various disciplines [*Heath et al.*, 2009; *Villamor et al.*, 2012; *Buchmann et al.*, 2016]. Unlike top-down approaches, such as optimization, which assume centralized control of decision-making processes, ABM takes a bottom-up approach in which each component in the system is simulated as an autonomous, interdependent, and adaptive agent with heterogeneous attributes and decision rules [*Bonabeau*, 2002; *Macy and Willer*, 2002]. This feature makes ABMs suitable for simulating autonomous and adaptive decision-units in complex systems [*Farmer and Foley*, 2009]. However, simulating such complex systems can be quite computationally expensive, which has been a constraint to the application of ABM in complex systems during the past decade. Recently, with more advanced high-performance computing technologies (e.g., parallel and cloud computing), ABM has been more widely applied to simulating human behaviors in many research domains, including water resource systems. Studies include, but are not limited to, irrigation behaviors in agricultural systems [*Ng et al.*, 2011; *Miro*, 2012; *Hu et al.*, 2015], social response to flood warning and evacuation during flood events [*Chen and Zhan*, 2008; *Dawson et al.*, 2011], and economic behaviors in water resource markets [*Zhang et al.*, 2010; *Nguyen et al.*, 2013; *Zhao et al.*, 2013]. These studies have demonstrated the usefulness of ABM in simulating human behaviors and have provided insights to guide planning and management policies in water resource systems.

Despite the efforts to take account of the role of human behaviors in water resource systems, issues remain in simulating human behaviors. Among them, the following three issues have been recognized as important ones. First, given that agents' decision rules might vary, it is important to represent heterogeneity in human behaviors, and evaluate whether and how behavioral heterogeneity affects modeling results in water resources systems [*Pennings and*

Leuthold, 2000; *Huang et al.*, 2013]. Second, agents' decisions in the face of uncertainty rely on available information. Since social communication can greatly affect information exchange and thus agents' decision-makings, it is important to evaluate how social communication affects human behaviors [*Baumann et al.*, 1997]. Third, for a complex system in which multiple factors affect system outcomes, simulating multiple behaviors is needed. Thus, it is important to investigate how the interplay of multiple behaviors affect the modeling results [*An*, 2012; *Ye and Mansury*, 2016].

Driven by these research needs, this thesis specifically investigates the aforementioned three issues in modeling human behaviors: (1) behavioral heterogeneity, (2) social interaction, and (3) interplay of multiple behavioral parameters. We will demonstrate the importance of taking account of these issues during extreme hydrological events, namely flood and drought.

1.2 Research Objectives and Thesis Outline

The goal of this thesis is to evaluate how behavioral heterogeneity, social interaction, and the interplay of multiple behaviors affect modeling results in water resource systems. We use the flood warning-response system as a case study for simulating human behavioral heterogeneity and social interaction during flooding events. The agricultural water market, an example for drought events, is used for simulating the interplay of multiple behaviors. Specific objectives and outlines of the thesis are summarized as follows.

(1) In Chapter II, an ABM framework is developed to simulate human behavioral heterogeneity in response to flood warnings. The framework is coupled with a traffic model to simulate agents' evacuation processes within a road network under various flood-warning scenarios. The coupled model is used to evaluate the impacts of human behavioral heterogeneity on the benefits of flood warnings.

(2) Based on the ABM framework developed in Chapter II, Chapter III evaluates how

social communication affects agents' flood risk awareness and evacuation behaviors. In particular, social communication through social media and the influence of neighbor's actions are evaluated in this section.

(3) Chapter IV addresses the issues of simulating multiple behaviors, using drought as a case study. The ABM developed in this chapter explicitly incorporates farmers' multiple behaviors, namely irrigation behavior (represented by farmers' sensitivity to soil water deficit) and bidding behavior (represented by farmers' rent seeking and learning rate), in a hypothetical water market based on a double auction. The joint impacts of the behavioral parameters on the water market are evaluated under different hydrological conditions.

(4) Chapter V summarizes the major findings and insights from present work, discusses the limitations, and proposes some future work.

Chapter II. Impacts of Human Behavioral Heterogeneity on the Benefits of Flood Warnings

This chapter proposes an ABM framework to evaluate the impacts of human behavioral heterogeneity on the benefits of flood warnings. Section 2.1 introduces the objective of this study and some background information, followed with a detailed literature review in Section 2.2. Section 2.3 provides a detailed description of the methodology of this study, including how the agent-based modeling framework is set up and how it is coupled with the traffic model. The coupled model is tested by a hypothetical case study in Section 2.3 and the preliminary results are presented in Section 2.4. Section 2.5 summarizes the main findings of this study and proposes some future work.

2.1 Introduction

Flooding is a common weather disaster in the United States (U.S.) that has caused significant social and economic loss [*Smith and Matthews*, 2015]. Flood warnings have been shown to be effective in reducing flood-related deaths and economic loss from flood damages [*Estrela et al.*, 2001]. Some studies suggest that as little as one hour of lead time can reduce flood damages by 10-20%, with potential savings of $1.62 billion annually in the U.S. [*National Hydrologic Warning Council*, 2002]. Additionally, many case studies around the world have reported the impact of early flood warning systems on saving human lives [*Golnaraghi et al.*, 2008].

Flood warning systems, which have often been described as a combination of tools and processes embedded in different institutional, organizational, and infrastructure systems, are composed of (1) knowledge-based modeling and forecasting of flooding, (2) a monitoring and warning system, (3) an information dissemination system, and (4) public preparedness and response. It is argued that the effectiveness of these systems is often rooted in the accuracy of the forecast, the lead time of the warning, and stakeholder's understanding of how the risk is translated and interpreted by the public, which ultimately will translate into direct actions. Naturally, a considerable amount of research and development has focused on providing flood warnings that have both high prediction accuracy and sufficient warning lead time [*Krzysztofowicz*, 1996; *Siccardi et al.*, 2005; *Verkade and Werner*, 2011]. Recent advances in predictions have allowed the public to obtain more reliable information in a timely manner, and longer time for planning and strategizing by emergency responders [*Cloke and Pappenberger*, 2009; *Golding*, 2009; *Arheimer et al.*, 2011].

Nevertheless, improvements in these areas do not reduce risk in disaster situations as reliable and timely warnings do little good if not followed by (early) actions. Research has demonstrated that people's behavior during disaster events can have major impacts on the effectiveness of emergency response and evacuation plans [*Starcke and Brand*, 2012; *Durage et al.*, 2014]. These studies have had limited consideration of how human's heterogeneous response to flood warnings affect the evacuation processes (i.e., considering how people respond differently to flood warnings). There is a need for a more comprehensive understanding of how human evacuation processes are affected by interpretations of flood warning information and, ultimately, how these translate into actions [*Dash and Gladwin*, 2007].

Evacuation decision-making processes are complex and uncertain. This is especially true when one tries to understand human cognition processes under disaster situations, which are affected by risk aversion, interpretation of warning systems, preparedness and education on evacuation procedures, etc. [*Dash and Gladwin*, 2007]. Moreover, to understand how human behavior systemically affects evacuation processes, one must consider the socio-economic aspects of households (e.g., residential location, access to evacuation transportation, previous experiences with floods, etc.) that affect all stages of evacuation processes. Considering all of these human behavioral and social-economic factors and their heterogeneities has often been identified as one of the primary challenges for effective flood-warning systems [*Pan et al.*, 2007; *Dawson et al.*, 2011].

Considerations such as what level of warning and/or with how much lead time the warning should be issued are critical to the effectiveness of flood warning systems. Earlier lead times have not proven to necessarily reduce the level of flood damages or loss of life, as the uncertainty with the forecast at those times is often quite high [Schröter et al., 2008]. At the same time, people have different risk aversion aptitudes that create difficulty in understanding what level of warning should be issued. High-risk warnings with high uncertainty could result in loss of trust in the flood warning system, while a low risk warning can result in catastrophic consequences if people's risk aversion levels are above it. Thus, there is a need for a framework that allows for a better understanding of how the heterogeneity of response to flood warnings influences the effectiveness of flood warning systems

This study proposes an agent-based modeling framework to incorporate human behavioral heterogeneity in flood warning-response systems. The objective is to test the hypothesis that the benefits of flood warnings will vary depending on heterogeneous responses to flood warnings. Furthermore, this study also explores the relationships between the benefits of flood warnings and residential density of flood zones. This will improve the understanding of priorities in developing evacuation plans for a specific community, and provide insights that will allow for more effective flood warning systems.

2.2 Literature Review

Previous studies that explored the effects of human behaviors on the benefits of flood warnings mainly focused on gathering empirical data, often through surveys [*Zhang et al.*, 2007; *Lazo et al.*, 2010; *Starcke and Brand*, 2012], or simulated the evacuation process using a complex mathematical model representing human rationale [*Ferrell*, 1983]. These studies have mostly concentrated on exploring the effectiveness of different evacuation plans under different flooding and traffic scenarios. These studies allow the inclusion of traffic dynamics on different road networks, and explicit modeling of rules that mimic human rationale and adaptability during emergencies, and they have enabled a better understanding of which factors influence the effectiveness of evacuation procedures. For example, *Dawson et al.* [2011] integrated a dynamic agent-based model with a hydrodynamic model and a traffic model, with the objective of understanding the probability of an individual being exposed to flood under different storm surge conditions and warning lead times. The results of the study demonstrated that the number of people exposed to dangerous water depths increases monotonically as the storm surge height increases and as the warning time becomes shorter. For a case study in the United Kingdom, there was almost a fourfold reduction in the number of agents exposed to flood when an effective flood warning system is used that considers the dynamics of the decision-making processes and consequential behaviors within the transportation system.

Among the studies that have explored the value of the warning information as a function of its own attributes is the analysis presented by [*Schröter et al.*, 2008]. This study analyzed the effectiveness and efficiency of an early warning system for flash floods. By using historical data in two river basins, the authors analyzed the relationship between the reliability of information and the potential damage reduction as a function of the warning lead time. Additionally, the authors compared the benefits and costs associated with using an early warning system as a function of the warning lead time. The authors found that longer lead times did not necessarily result in larger benefits as the reliability of the information at these times was often low. Finally, the study concluded that among the main factor that affects the effectiveness of the warning systems was stakeholder awareness, and that perhaps this was as important as improvements in flood forecast accuracy.

Similarly, *Verkade and Werner* [2011] assessed the cost-benefit ratio of providing flood warning information. Using a case study in White Cart Water in Glasgow, UK, the authors presented a framework to estimate the flood risk reduction when using flood forecasting, warning, and response systems. Using a hydro-economic model of expected annual damage due to flooding, combined with the concept of Relative Economic Value (REV), the method was able to estimate the benefits associated with reduction in flood losses while considering the cost of providing the warnings and the cost associated with forecast uncertainty. The study demonstrated that the use of a probabilistic forecast had the potential to gain higher benefits for any given lead time. It also demonstrated that the lead time of the warning information should be a function of the forecast uncertainty and the cost-loss ratio of the people receiving and responding to the warning, as longer lead times do not necessarily lead to a larger reduction in flood risk.

These previous studies have provided information on how the effectiveness of using flood warning information is affected by the accuracy of the prediction and the warning lead time, and/or have provided models of human decision-making processes and their effects on evacuation processes. Nevertheless, none of the previous studies has integrated the heterogeneity in people's behaviors with the effectiveness of flood warning information. Moreover, these studies have relied mostly on historical data to draw conclusions about the cost-benefit of using flood-warning systems. There is still a need for a framework that bridges the gap between these elements, where the empirical data gathered in previous studies would inform human decision-making rules and their interactions, while at the same time consider uncertainties in the flood warning information. The central premise of this study is to explore how interpretation and response to flood warnings affect the benefits of the information provided by the flood warning systems. In other words, the study aims to understand the marginal benefit of providing a more accurate forecast and/or longer lead times given the heterogeneity in risk aversion aptitudes and their socio-economic environments.

2.3 Methodology

Responses to flood warnings are very diverse as they are often influenced by many socio-economic aspects (e.g., social class, age, gender, past experience with floods, flood insurance, etc.,) and by the values and beliefs of family and neighbors [*Parker et al.*, 2009a]. The interactions among people with such diverse behaviors will eventually form a complex and dynamic system (human community) in which all its sub-system components (individuals) are interconnected with and affected by each other [*Liu et al.*, 2007b; *An*, 2012]. This property of the complex system imposes challenges to the use of traditional, top-down, centralized simulation approaches (e.g., optimization). Agent-based modeling has often been suggested as an appropriate solution to this kind of problem for capturing the dynamic feedback of sub-system components and their inherent complexities [*Heath et al.*, 2009]. Unlike top-down approaches, which assume centralized control of decision-making processes, agent-based modeling takes a bottom-up approach in which each system component is simulated as an autonomous, interdependent, and adaptive agent with heterogeneous attributes and decision rules [*Bonabeau*, 2002; *Macy and Willer*, 2002].

However, simulating such complex systematic interactions can be quite computationally expensive, which has constrained the application of agent-based models in simulating complex systems. With more advanced high-performance computing technologies developed in recent years, agent-based modeling has been more widely applied to simulating human behaviors in many areas, such as river basin management [*Cai et al.*, 2011a; *Hu et al.*, 2015], land use and land cover change [*Kelley and Evans*, 2011; *Ralha et al.*, 2013], agriculture and ecosystems [*Ng et al.*, 2011], economic and financial markets [*Raberto et al.*, 2001; *Zhao et al.*, 2013], and simulation of flood and other natural disaster events [*Shi et al.*, 2009; *Zhang et al.*, 2009; *Aschwanden et al.*, 2012]. These studies have shown that an agent-based modeling approach can potentially better represent empirical systems and improve understanding of the relationships among different system components. Therefore, this study adopts an agent-based modeling approach to simulate flood warning-response systems. The model simulates (1) a geographical system that consists of a group of residents (defined as agents) and a transportation network, (2) probabilistic flood warnings that indicate the probability of flood within a specified lead time (e.g., 80% chance of having a flood within 5 hours), and (3) decision-making processes that describe how the agents make evacuation decisions after receiving the flood warnings and how they evacuate to the safe area through the transportation network following certain evacuation rules (Figure 2.1a). The architecture of the proposed agent-based model is shown in Figure 2.1b. The upper level of the model describes the geographical environment and flood warning information that all of the agents receive. The lower level of the model describes how an agent is defined by its attributes and behaviors.

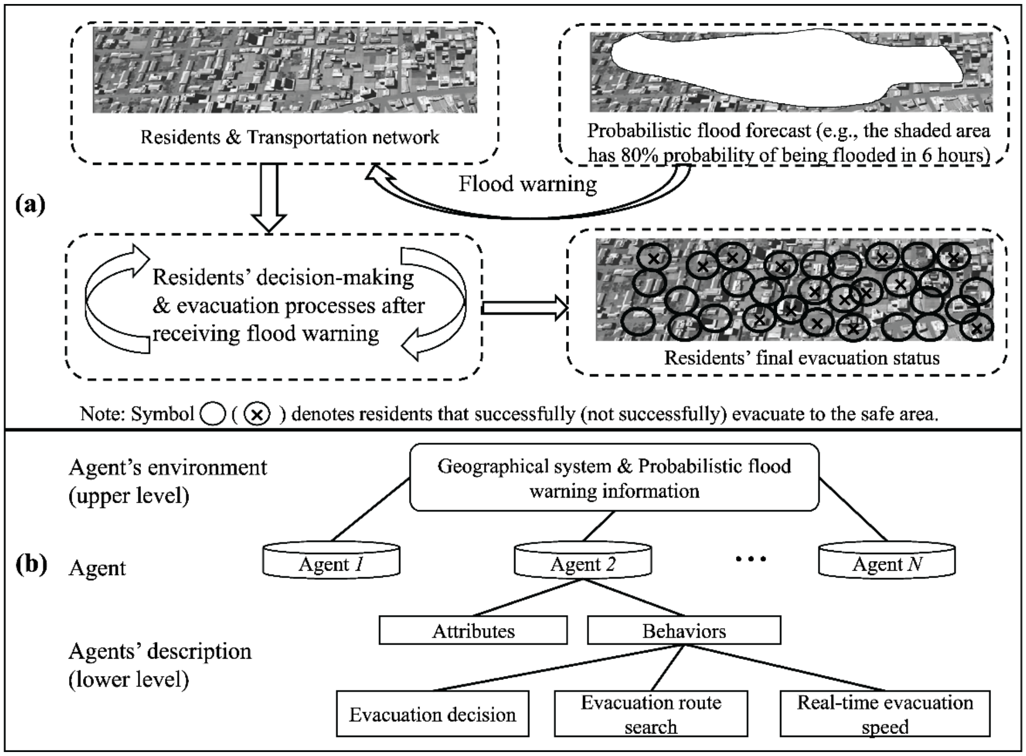


Figure 2.1 Illustration of (a) the main components of the flood warning-response system and (b) the architecture of the agent-based model. The four figures in Figure 2.1a are: (1) flood warning managers issue a flood warning to residents, (2) residents receive the flood warning and make evacuation decisions (stay or evacuate), (3) residents evacuate through the transportation network, and (4) agents' final evacuation status, respectively. Figure 2.1b illustrates the structure of the model. The upper level of the structure represents agents' environment (i.e., geographical system and flood warning information). The lower level represents the attributes and behaviors that are used to define agents.

Responses to flood warnings result from integration of a set of decision-making processes that includes reception of flood warning information, social psychological processes for understanding this information, and actions to reduce flood damage (e.g., moving valuables to flood-free places, evacuating to safe areas) [Mileti, 1995]. Transportation networks are important factors that affect both people's evacuation strategies and the total time needed for evacuation during emergencies [*Chen and Zhan*, 2008]. Thus, the proposed agent-based model takes both human components (people and their decision-making processes after receiving flood warnings) and evacuation transportation networks into consideration.

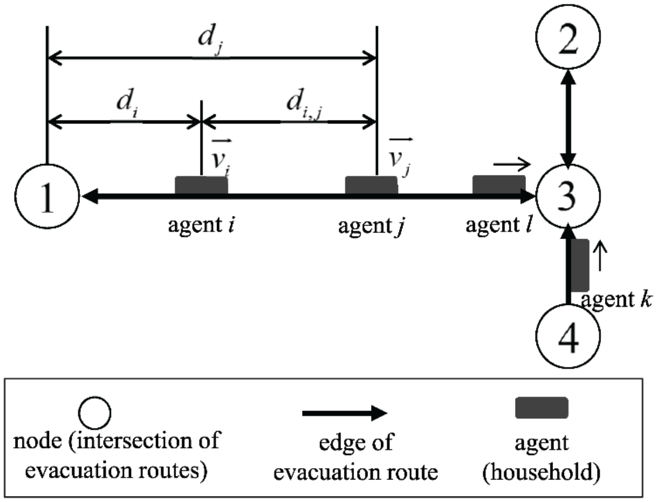
2.3.1 Transportation Network and Traffic Rules

The transportation system plays a pivotal role in evacuation planning and management and is framed in the National Response Framework as a critical infrastructure during natural disasters and other emergencies [*Department of Homaland Security*, 2013; *Murray-Tuite and Wolshon*, 2013]. The transportation system is an integrated system including transportation networks, vehicles in the networks, and traffic rules that regulate the movements and interactions of the vehicles. Thus, modeling a transportation system includes simulating two components: (1) the transportation network itself and (2) the traffic rules of the transportation network that all vehicles should follow. Regarding the first component, the complexities associated with transportation networks make it challenging to include all of their features in simulation model. In order to manage this complexity, many studies have suggested the use of simplified representations of transportation networks, such as a directed graph [*Sheffi et al.*, 1982; *Cova and Johnson*, 2003], which contains a set of nodes, edges and weights associated with edges.

Edges and nodes in a directed graph represent a transportation networks' routes and route intersections. The weight of an edge represents the cost of using the route it represents (e.g., distance of the route, speed limit, route capacity, etc.). Mathematically, a graph can be represented as a matrix. For example, the row and column of a matrix element can represent the starting and ending nodes of an edge, respectively, while the value of the element represents the cost (i.e., length) of the edge. Edges associated with nodes that are not directly connected are assigned an infinite cost to represent that no direct evacuation route exists between them. Figure 2.2 is an example representation of a transportation network as a graph. The transportation network in Figure 2.2a consists of 4 nodes (node 1, 2, 3 and 4); the directed edges among these nodes represent connections among them. The matrix in Figure 2.2b is the mathematical representation of the directed graph. Note that no direct edge connects node 3 to node 4; in the matrix, the length from 3 to 4 is therefore set to be infinite.

Traffic rules, as mentioned above, are also important components in transportation system simulation. Traffic rules regulate the movements and interactions of each individual vehicle in the network. Among a variety of traffic simulation methods developed in recent decades, individual-oriented methods have been suggested as powerful simulation tools for representing individual interactions and systematic traffic flow pattern in a transportation system [*Chen and Zhan*, 2008]. The Nagel-Schereckenberg model (N-S model), first proposed in 1992 by *Nagel and Schreckenberg* [1992], is a widely-used, individual-oriented method in both theoretical and empirical studies. The N-S model divides a road into cells and categorizes a vehicle's actions on the road into four groups in a time unit: acceleration, deceleration, randomization, and movement.

Because the N-S model can capture empirical traffic phenomena and allow for parallel computing, it has been widely applied in many studies and has been developed as the Transportation Analysis and Simulation System (TRANSIMS) for regional transportation system analysis [*Smith et al.*, 1995]. In our study, we use the N-S model to simulate evacuation processes on transportation networks, assuming that they will follow the rules defined in the N-S model. We assume that individuals follow the all-way stop rule when multiple vehicles arrive at a road intersection at the same time: a vehicle that arrives first has precedence over vehicles that arrive later.



(a) Example of a geographical system consists of a transportation network and four agents

$$
\begin{array}{c c}
 & \begin{array}{cccc} \mathbf{1} & \mathbf{2} & \mathbf{3} & \mathbf{4} \end{array} \\
\begin{array}{c} \mathbf{1} \\ \mathbf{2} \\ \mathbf{3} \\ \mathbf{4} \end{array} &
\begin{bmatrix}
0 & \infty & 100 & \infty \\
\infty & 0 & 100 & \infty \\
100 & 100 & 0 & \infty \\
\infty & \infty & 100 & 0
\end{bmatrix}
\end{array}
$$

(b) Matrix representation of the network

(Note: the row and column number of the matrix represent the starting and ending node of an edge, respectively. The value in the matrix represents the length of the edge.

Figure 2.2 Illustration of (a) a transportation network represented by a directed graph and (b) matrix representation of the network. In Figure 2.2(a), numbers inside nodes denote node numbers. Arrows of edges denote connections between nodes. Single arrow denotes one-way edge (e.g., agents can only move from node 4 to node 3, not in the other direction).

2.3.2 Household Agents

In the face of flood risk, we assume that all family members in a household will affect each other in arriving at final evacuation decisions. Both empirical and theoretical flood warning studies are typically conducted at the household level . Household demographics (e.g., location, education, income, etc.) are therefore assumed to provide sufficient information regarding socio-economic aspects of each agent. Therefore, each household is simulated as an agent in this study. An agent is defined by the attributes and decision rules that relate it to flood warning responses and actions (Figure 2.1b). We assume that all agents share a transportation network for evacuation during emergencies and will receive a flood warning at the same time. The agents will need to make decisions regarding whether to evacuate to a flood-free area outside of the neighborhood. The decision-making processes depend on each agent's attributes and decision rules. The following sections introduce how we define the agent's attributes and decision rules in this study.

Agent attributes are defined as a set of parameters that describe the characteristics of an agent. In this particular study, in which each household is defined as an agent, agent attributes refer to the characteristics of each household that relate to flood warning responses and evacuation processes. Previous studies have shown that flood warning responses and evacuation processes are affected by many physical, psychological and socioeconomic factors [*Drabek*, 1999; *Gladwin et al.*, 2009]. However, representing all of these factors in a model is challenging when lacking empirical data. Therefore, in this study, we simplify the representation of these factors and classify an agent's attributes as physical attributes that are related to its evacuation process, and psychological attributes that are related to its response to flood warnings (Table 2.1).

Physical attributes describe an agent's physical characteristics related to flood warning responses and evacuation actions (e.g., location of a house, house type, construction material of the house, etc.). To capture the attributes that are essential for simulating the agents' evacuation processes and evaluating the benefits of flood warnings, three types of physical attributes are included: agent's geographical location (*G*), maximum evacuation speed ($V_{\max}$) in the transportation network, and evacuation status (*ES*) at the end of the simulation period. An agent's geographical location in the transportation network is represented by three variables (i.e, N_s, N_e, d) that indicate the agent's movement from starting node (N_s) to ending node (N_e) and the distance between its current location and $N_s (d)$. For example, the geographical location of agent i in Figure 2.2a can be denoted by $[1, 3, d_i]$. An agent's maximum evacuation speed defines its maximum moving speed on a route in a transportation network, which is assumed to be the maximum speed limit of the evacuation route in this study. Evacuation status (*ES*) represents an agent's evacuation status at the end of the simulation period. *ES* is a categorical variable for which there are only three values: 1 (denotes that an agent stays at its initial location without considering evacuation), 2 (denotes that the agent is currently evacuating but has not arrived at the safe area, and 3 (denotes that the agent has arrived at the safe area).

Table 2.1 List of agents' attributes

Factors	Variables	Description of the variable [unit]
Physical	i	Agent's unique identification number [-]1
	ES	Agent's evacuation status at the end of simulation [-]
	G	Agent's geographical location in neighborhood [-]
	Vmax	Maximum evacuation speed in transportation network [L/T]
Psychological	RT	Risk threshold to flood risk [-]

1 [-] denotes dimensionless parameter.

Psychological attributes measure an agent's risk tolerance to flood risk in flood warning systems. Many studies have shown that responses to flood warnings are affected by socio-psychological factors such as understanding of flood warnings, interpretation of risk, rationality in decision-making, past experiences with floods [*Weinstein and Klein*, 1995; *Brewer et al.*, 2004]. When a flood warning is issued, an agent will consider all of these factors in making evacuation decisions. Lacking empirical data to represent the complex interconnected relationships among these factors, in this study we summarize all of these factors into a single parameter, risk tolerance threshold (RT), to measure an agent's maximum tolerance level for flood risk, where flood risk is represented by the probability of floods in the neighborhood. The agent will decide to evacuate to a safe area if the flood risk exceeds his or her tolerance threshold. We introduce quantification of RT in the case study section of this paper.

Naturally, the agents will behave differently in addressing these flood risks. Risk-tolerant agents do not respond as actively as risk-averse agents do. Two common methods have been proposed for representing the heterogeneity of an agent's decision. The first method is to classify agents into several categories (e.g., *Li and Liu* [2007] divided household agents in a city into six groups based on the agents' income and household size; *Ng et al.* [2011] divided farmer agents into bold and cautious groups based on the agents' adaptation of biofuel crops. The second method is to continuously vary agent's behavioral parameters (e.g., *Benenson* [1999] continuously varied agents' income to study residential distribution in a community; *Huang et al.* [2013] varied agent's purchasing budgets and preference for location parameters to study the spatial patterns of urban land markets). This study applies the second method, continuously varying agents' behavioral parameters, with the aim of evaluating how these decision parameters affect model output across a broad range of parameter settings.

Understanding flood warning information and making evacuation decisions are very complex processes [Mileti, 1995]. Simplified decision-making processes have been applied by many studies to simulate evacuation behaviors during natural disasters [Shi et al., 2009]. In our work, an agent's response to flood warnings is simplified into three steps: (1) decide if evacuation action should be taken based on the flood risk, (2) choose an evacuation path if the agent decides to evacuate, and (3) evacuate through the selected path following traffic rules.

Based on these three decision-making processes, three types of behaviors are simulated in this work: evacuation decision, evacuation path search, and real-time evacuation speed (Figure 2.1). Evacuation decision describes the process of an agent receiving flood warnings and deciding if the agent wants to evacuate to a safe area or not. An agent's evacuation decision depends on the probability of flooding and the agent's risk tolerance threshold. An agent will decide to evacuate if the probability of flooding exceeds its risk tolerance threshold. Otherwise, agents will choose not to evacuate even if there is a flood warning. The second type of behavior describes how an agent selects its evacuation path to the safe area. In this study, it is assumed that all of the agents have good knowledge about the transportation network and they will choose the shortest path from their current locations to the safe area as their evacuation path.

Besides evacuation route selection, the third important behavior is deciding on the evacuation speed at each time step. As an agent evacuates on a route, its speed is contained by (1) its own maximum evacuation speed, (2) maximum speed limits on the route, and (3) the location and evacuation speed of other agents on the same route. In this study, the agents' real-time evacuation speed is regulated by the N-S traffic model; for more details of how the moving speed of an agent is determined, see [*Nagel and Schreckenberg*, 1992].

2.3.3 Model Implementation

We implement the agent-based model using an object-oriented programming language, Java. The model execution process can be summarized in three steps (Figure 2.3): (1) prepare input data to construct agents, (2) execute agent-based model, and (3) analyze and output model execution results. The following sections introduce more details on the implementation of each of these steps.

Step 1. Prepare Input Data to Construct Agents.

Two types of input data are needed to initialize the model: input data for agents and input data for evacuation transportation network. Input data for agents define each individual agent's attributes and behavior parameters, which are listed in Table 2.1. One of this study's main objectives is to understand how the agent's risk threshold will affect the benefits of flood warnings. Without empirical knowledge about the distribution of human behavior parameters, it is often assumed that people's behavioral parameters (i.e., risk threshold in this study) follow probability distributions. Uniform and normal distribution are two commonly applied assumptions for modeling agents' behavior through parameter distributions. Because the coefficient of variation is a standard measurement of the dispersion of a distribution, this study applies the normal distribution to generate agents' risk threshold. The mean value of the normal distribution measures the agents' overall risk threshold for floods (μ_{RT}), while the coefficient of variation (CV_{RT}) measures agents' behavioral heterogeneity. Coefficient of variation is set to be zero to simulate agents with homogeneous risk threshold.

Input data for the evacuation transportation network defines the number of nodes and how the nodes connect with one another in the network. One of these nodes is set as the evacuation destination to represent the safe area without flood risk. To improve computational speed, the shortest path from any given location to this evacuation destination is calculated before model execution and is stored in a Java hashtable with keys and values. The hashtable key is the location of an agent in the transportation network. The hashtable value is the shortest path from any given location to the evacuation destination. The hashfunction of the hashtable will return the shortest evacuation path from the agent's current location to the evacuation destination.

Step 2. Execute Model.

The model execution process starts with a probabilistic flood warning that indicates the probability of flooding within a specified lead time. All of the agents will receive this flood warning and make evacuation decisions based on the decision rules described in the previous sections. For the agents who decide to evacuate through the transportation network, their evacuation processes are simulated by the N-S traffic model at discrete time steps within the flood warning lead time.

Step 3. Analyze the Benefits of Flood Warnings.

At the end of the model execution process, the model will return the evacuation status of each agent. The benefits of flood warnings can be measured by multiple criteria such as total flood damage reduction or saving of human life. In this study, we measure the benefits of flood warning by the percentage of agents that have evacuated to the safe area at the end of the model simulation.

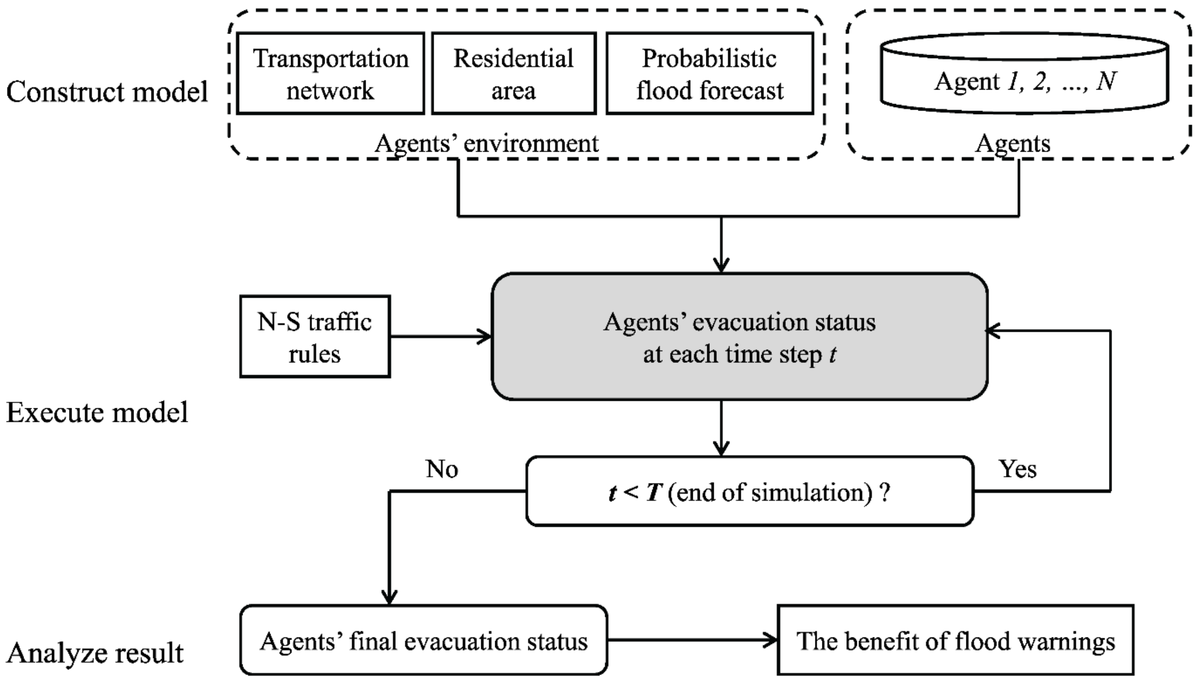


Figure 2.3 Flowchart of the agent-based model. The items along the left hand are the three model execution steps. In the final step, the benefits of flood warnings are measured by the percentage of agents that have evacuated to safe area.

2.3.4 Model Validation

Model validation is an essential step in the model development process. The main objective of model validation is to demonstrate that the model simulation results can reasonably represent or approximate the behaviors observed in the real systems [*Heath et al.*, 2009]. A variety of model validation methods and techniques have been proposed for agent-based models [*Ngo and See*, 2011]. Among them, structure validation and output validation are two of the most important and common methods. The objective of structural validation is to demonstrate that the agent-based models can correctly represent the behaviors and the operation rules of the real systems. Outcome validation compares the model output with observations from real systems when empirical data are available.

When empirical data are not available to show the interactions among the autonomous agents in the system, model validation becomes challenging. To address this challenge, many studies have used expert's knowledge for a qualitative assessment of the model performance [*Heath et al.*, 2009]. In this theoretical study, with no empirical data about the model outputs, the model validation is conducted from a qualitative perspective with empirical findings from previous studies [*Mileti*, 1995; *Parker et al.*, 2007a; *Paul*, 2012]. The output validation was done by comparing the model output with the expert's knowledge about flood warning-response systems. The next section gives more details about the model validation.

2.4 Case Study

2.4.1 Transportation Network

A hypothetical geographical system is designed as the case study. The geographical system consists of a transportation network and a number of household agents (Figure 2.4). To consider flood warning-response systems with different spatiotemporal scales, we use general units to measure length and time, following the approach adopted by *Zhang et al.* [2009]. The length and time units are represented by L and T, respectively. The evacuation transportation network has 16 nodes, with one node selected as the evacuation destination, and 16 routes. Each evacuation route is assumed to be a two-way road with one lane for each traveling direction [*Chen and Zhan*, 2008]. The total length of the transportation network is 2210 L. We assume that all lanes in this network have the same speed limit (10 L/T in this study) and all route intersections have an all-way stop sign to regulate traffic, which means that an agent arriving at the intersection first will take precedence over agents arriving later. More complex transportation networks could be used to generate more complex evacuation phenomena, which are discussed further in the conclusion section.

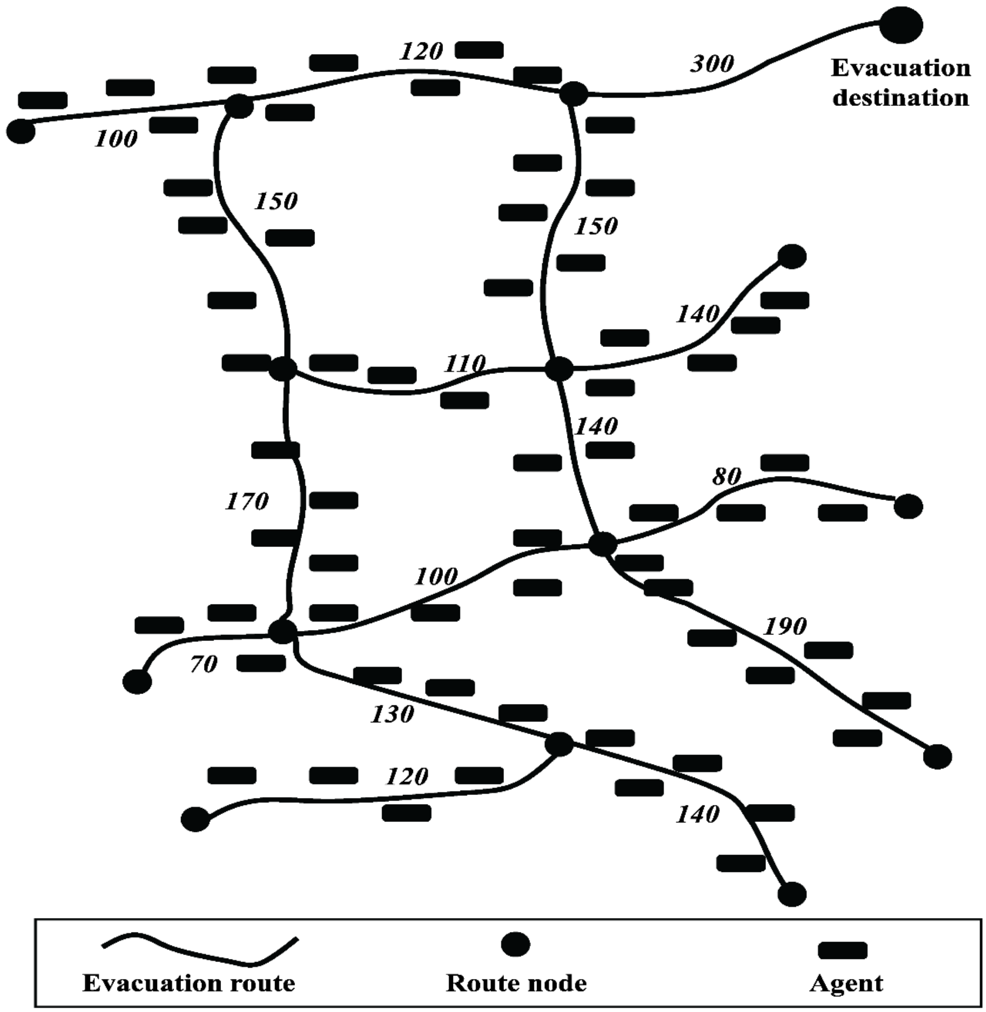


Figure 2.4 The transportation network and household agents for the hypothetical case study area. (Numbers along routes denote the length of routes. The number of agents in the network ranges from 320 to 640. Agents are uniformly distributed along the routes.)

The household agents are uniformly distributed along the transportation routes. The residential density of the neighborhood (*RD*) is defined as the total number of agents in the transportation system divided by the number of nodes in the network. In this study, the total number of agents in the transportation network ranges from 320 to 640 (i.e., *RD* ranges from 20 agents/node to 40 agents/node) to explore how residential density affect agents' evacuation processes.

2.4.2 Scenario Design

With the aforementioned transportation network as a case study area, this study aims to investigate how human's heterogeneous behaviors (i.e., risk tolerance threshold) and residential density could affect the benefits of flood warnings. We design three scenarios. The first scenario is for model validation, which we conduct by comparing the results of a set of experiments with empirical knowledge about flood warning systems. The second scenario explores how agent's heterogeneous behaviors affect the benefits of flood warnings. The third scenario investigates the potential interplay between residential density and flood forecast accuracy and its effect on the benefits of flood warnings. Table 2.2 shows the parameters of these three scenarios.

This study focuses on simulating agents' evacuation processes during flood events, without considerations of false alarms (i.e., the agents receive flood warnings, but eventually there is no flood). Therefore, we consider flood forecast accuracy only in terms of the predicted flood probability. For example, for a flood forecast indicating 85% probability of having a flood in 3 hours, the associated forecast accuracy and lead time will be 0.85 and 3 hours, respectively. We also assume that the agents will receive a flood warning at the beginning of model execution, and will not receive any other flood warning information during the following simulation periods. In other words, the agents only receive one piece of flood warning information during the entire simulation.

Table 2.2 Parameters for the three simulated scenarios in the case study area

Parameter [unit]	Scenario 1	Scenario 2	Scenario 3
Mean value of agents' risk threshold [-]1	0.75	0.6:0.05:0.92	0.75
Coefficient of variation of risk threshold [-]	0.1	0:0.05:0.3	0.1
Predicted flood probability [-]	0.6:0.05:0.9	0.75	0.6:0.05:0.9
Flood forecast lead time [T]	100:100:700	200:200:600	400
Residential density [number of agents/node]	30	30	20:10:40

1 [-] denotes dimensionless parameter.

2 X:d:Y denotes a numeric vector from X to Y with increment of d. For example, vector [1, 3, 5, 7] can be represented by 1:2:7.

2.5 Results and Discussion

2.5.1 Model Validation

In this section, we test whether our model can capture the following findings of previous empirical studies: (1) that the benefits of flood warnings have a positive relationship with flood forecast accuracy and (2) that the benefits of flood warnings have a positive relationship with flood warning lead time [*Estrela et al.*, 2001; *National Hydrologic Warning Council*, 2002; *Golnaraghi et al.*, 2008]. The results of model validation are shown in Figures 2.5a-c.

Figure 2.5a shows that the benefits of flood warnings increase as flood warning lead time increases. Figure 2.5b shows that the benefits of flood warnings increase as predicted flood probability increases. Figure 2.5c further suggests that the benefits of flood warnings are constrained by both predicted flood probability and flood warning lead time. The benefits of flood warnings are always low if predicted flood probability or lead time reaches its lower limit (0.7 for predicted flood probability and 200 T for flood warning lead time). In addition to the lower limits for flood warnings, upper limits also exist beyond which the benefits of flood warnings will not increase significantly (0.75 for predicted flood probability and 500 T for flood warning lead time in the case study). The results from Figure 2.5a-c demonstrate that the model is able to capture the empirical findings from experts' domain knowledge of flood warning information.

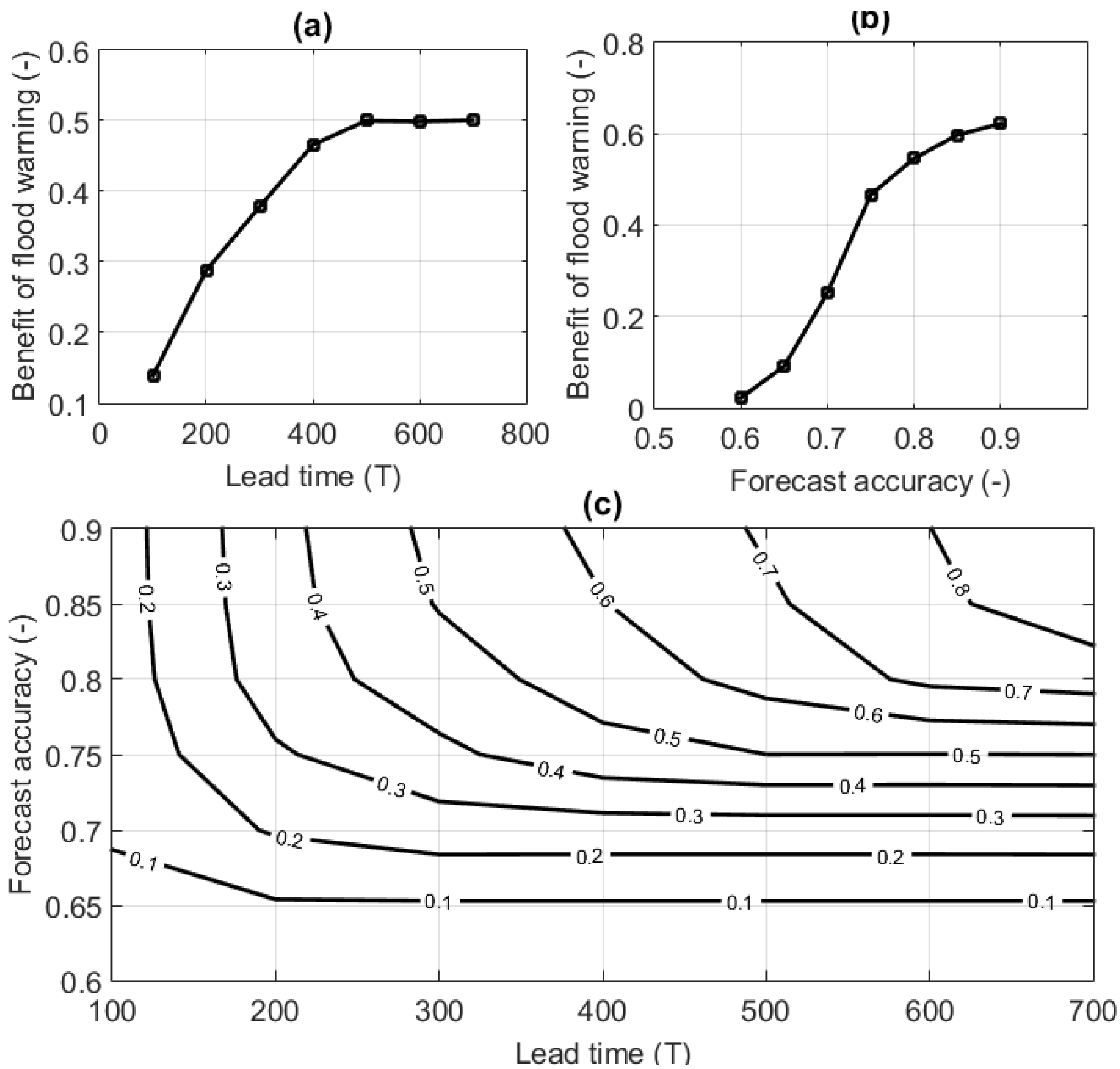


Figure 2.5 (a) The relationship between the benefits of flood warnings and flood warning lead time when predicted flood probability is 80%; (b) The relationship between the benefits of flood warnings and predicted flood probability when flood warning lead time is 400 T; and (c) Contour

Figure 2.5 (cont.) plot of the benefits of flood warnings associated with predicted flood probability (Y-axis) and flood warning lead time (X-axis)

2.5.2 Impacts of Behavioral Heterogeneity on Modeling Results

This scenario aims to explore the relationships between the benefits of flood warnings and agents' flood warning response behaviors. To be specific, this scenario addresses two questions: (1) Will agents' flood-warning response behaviors (i.e., agents' risk-tolerance threshold) affect the benefits of flood warnings? (2) How will agents' behavioral heterogeneity (i.e., variation of agents' risk-tolerance threshold) affect the benefits of flood warnings? The first question aims to demonstrate that the benefits of flood warnings can be affected by agents' behaviors; the second question is intended to evaluate the importance of considering the characteristic of behavioral heterogeneity in simulating agents' behaviors.

Agents' behavioral heterogeneity implies that different agents will behave differently under identical environment conditions (i.e., flood warnings). In this study, we measure behavioral heterogeneity by the coefficient of variation of the agents' risk threshold. Four groups of agents are investigated: two groups of risk-tolerant agents with average risk threshold higher than predicted flood risk, and two groups of risk-averse agents with average risk threshold lower than the predicted flood risk. We set seven levels of behavioral heterogeneity, with coefficient of variation of risk threshold varying from 0 to 0.3. Agents are homogeneous when the coefficient of variation is 0.

Figure 2.6 shows the simulation results for a scenario in which the predicted flood probability (p_f) is 0.75 and flood warning lead time is 400 T. The results show that the benefits of flood warnings increase as agent heterogeneity increases for risk-tolerant agents ($\mu_{RT} > p_f$). The opposite phenomena hold true for risk-averse agents ($\mu_{RT} < p_f$). Given that the residents' risk tolerance (*RT*) follows normal distribution with mean value (μ_{RT}) and coefficient of variation CV_{RT} , $(RT \sim N(\mu_{RT}, \mu_{RT}\,\mathrm{CV}_{RT}) \mid \mathrm{RT} \in [0,1])$, the percentage of residents (p_e) who decide to evacuate after receiving flood warning can be represented by:

$$p_e = \int_0^{p_f} p_{RT} dRT = \Phi(\frac{p_f - \mu_{RT}}{\mu_{RT} CV_{RT}})$$

where p_f is the predicted flood probability of the issued flood warnings, p_{RT} is the probability distribution function of *RT*, and $\Phi(\bullet)$ is the cumulative distribution function of a standard normal distribution. For risk-tolerant agents ($\mu_{RT} > p_f$), p_e increases as CV_{RT} increases, indicating that more agents decide to evacuate as behavioral heterogeneity indicator CV_{RT} increases. Therefore, the benefits of flood warnings increase as agent behavioral heterogeneity increases. The opposite holds true for risk-averse agents. This finding agrees with previous studies that the relationship between agent heterogeneity and model output is not uniformly monotonic [*Huang et al.*, 2013]. This finding suggests that, when providing the public with flood warning information, flood-warning managers should not expect that all of the public interpret and respond to the information in the same way. Instead, special information and consideration should be given for certain groups of people. For example, people who have no experience with floods are less likely to respond to flood warnings compared with people who have past experience. This experience includes not only experiences of evacuation during actual flood events with different flood warning systems, but also experiences in practicing evacuation as part of emergency preparedness. It has been shown that practicing evacuation drills is effective to enhance the awareness of flood risk and mitigate flood damages [*Yamada et al.*, 2011]. Social class, gender, and level of education might also affect people's understanding of flood warnings and evacuation actions [*Parker et al.*, 2007a]. These findings show that flood-warning managers should take the heterogeneity of human attributes into consideration when issuing flood warnings. For example, the model results suggest that risk-tolerant agents will not take actions to evacuate unless they are provided with warnings of high flood probability. Thus, it is important for flood warning managers to identify risk-tolerant agents in the community and provide additional information or resources to aid their decision-making.

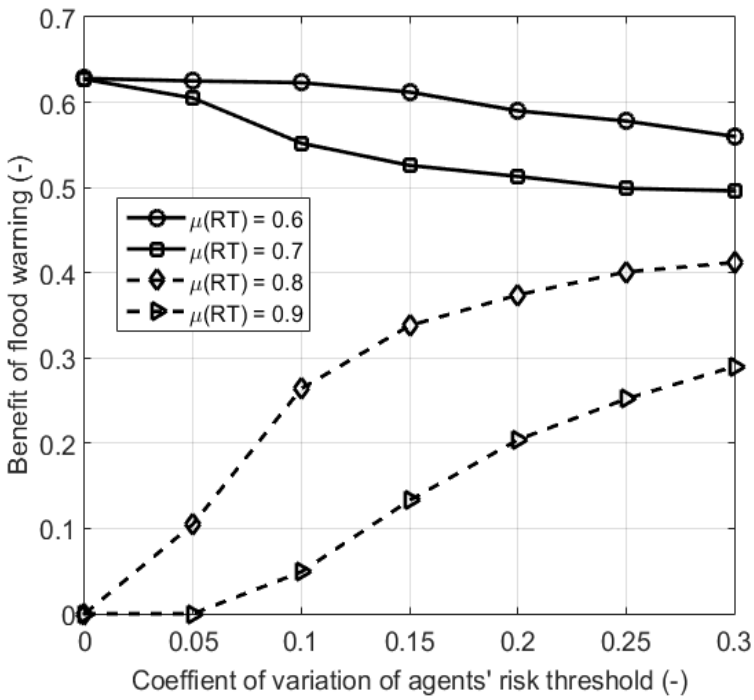


Figure 2.6 The relationship between the benefits of flood warnings and agent's behavioral heterogeneity when predicted flood probability (p_f) is 75% and flood warning lead time is 400 T. Results for risk-tolerant agents ($\mu_{RT} > p_f$) are shown by dotted lines. Results for risk-averse agents ($\mu_{RT} < p_f$) are shown by solid lines.

Besides risk threshold heterogeneity, agents' average risk threshold is also an important factor affecting the benefits of flood warnings. To understand the relationship between flood warning benefits and agents' average risk threshold levels, we investigate three different flood warnings with the same predicted flood probability but different lead times (Figure 2.7). The results provide at least two insights. First, as expected, modeled flood warnings with longer lead times outperform those with relatively shorter lead times, since longer lead times allow the agents more time to respond to flood warnings and evacuate to safe areas. However, the results also show that the marginal benefit from the improvement in lead time depends, to a great extent, on the agents' risk threshold. More benefits could be achieved by increasing warning lead times for risk-averse agents than for risk-tolerant agents. However, even a longer warning lead time yields no additional benefits if the agents' risk threshold exceeds a limit (0.85 in this case). This suggests that risk-tolerant agents will not benefit from flood warnings with longer lead times if their risk thresholds do not change. This finding leads to the second insight of the results: in addition to providing the public with better flood warning information, informing them about how to respond to flood warnings could be an effective way to reduce flood-related damage. For example, the model results here show that there are almost no additional benefits if the flood warning lead time is increased from 200 T to 400 T when the agents' average risk threshold is 0.80. However, a benefit increase of 0.22 is achieved if the agents become more risk averse, with the risk threshold reduced from 0.8 to 0.75 (from A to B in Figure 2.7). Empirical studies have shown that people's understanding of flood risk is often not necessarily logical, leading to misjudgment of flood risk [*Tversky and Kahneman*, 1973; *Weinstein and Klein*, 1995]; educating them how to respond appropriately could be beneficial. Thus, combining appropriate flood warning response with reliable information can make flood warnings more valuable.

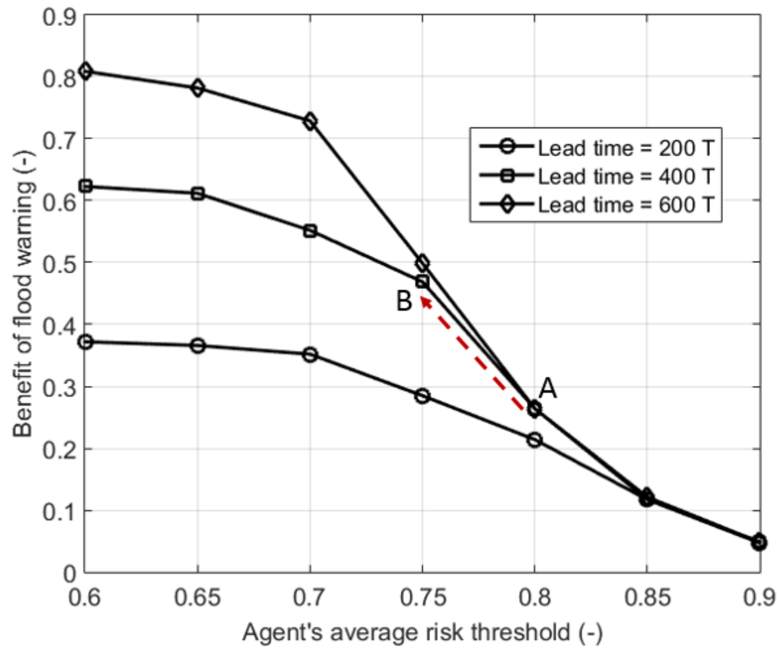


Figure 2.7 The relationship between the benefits of flood warnings and agents' average risk threshold under three flood-warning scenarios in which predicted flood probability is 75% and lead times are 200 T, 400 T, and 600 T, respectively.

2.5.3 Impacts of Residential Density on Modeling Results

This scenario aims to understand how the attributes of residential properties affect agent's evacuation process and ultimately affect the benefits of flood warnings. The attributes of residential properties can be measured by multiple matrices, such as distribution, density, educational level and social class of residents, etc. In this particular study, we only focus on residential density (*RD*), which may significantly affect traffic load during an emergency evacuation process.

Figure 2.8 explores the impacts of residential density on the benefits of flood warnings under different flood warning scenarios. In general, flood warnings with higher predicted flood probability are associated with greater benefits, especially in low-density residential areas. However, the benefits associated with more accurate flood warnings is constrained in high residential areas because a large fraction of the agents that take evacuation actions may not successfully evacuate to a safe area as a result of traffic congestion caused by high traffic loads. In other words, the marginal benefit of providing higher predicted flood probability is higher in low residential areas than in high residential areas. Therefore, the model results show that it is more effective to increase predicted flood probability in low residential areas. In contrast, in high residential areas, increase in predicted flood probability does not yield a significant increase in the benefits of flood warnings. Instead of working on increasing predicted flood probability, increasing flood warning lead time or improving evacuation routes may be more beneficial.

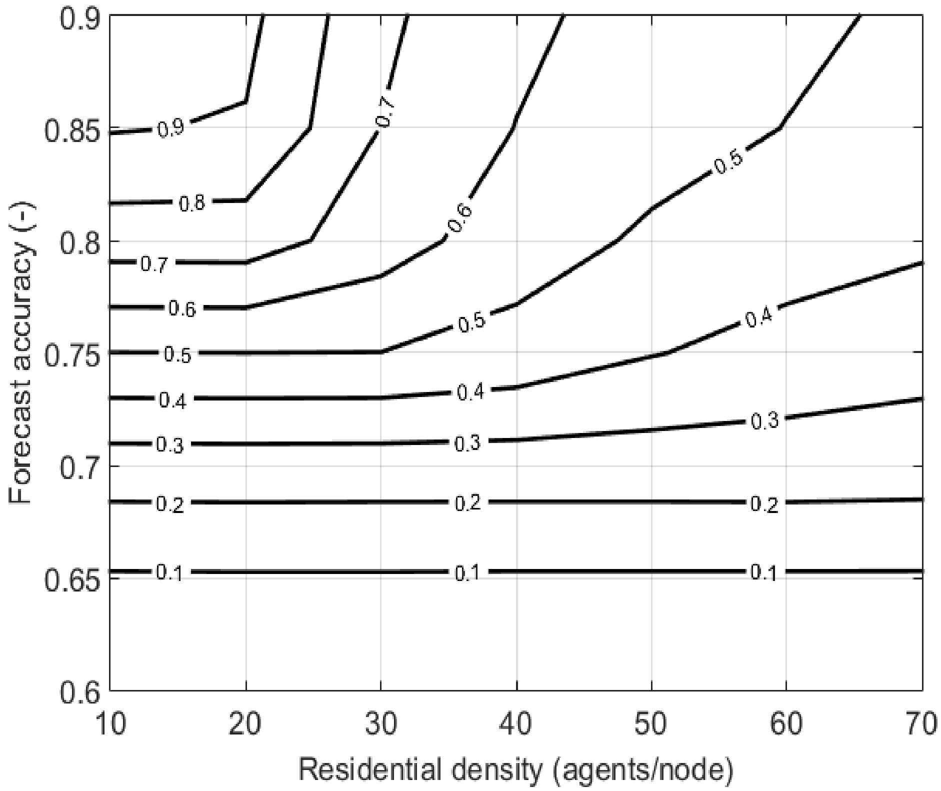


Figure 2.8 Contour plot of the benefits of flood warnings, residential density, and predicted flood probability when agents' average risk threshold is 0.75 and coefficient of variation of risk threshold is 0.1

Figure 2.9 summarizes agents' evacuation status and evacuation times under different residential densities. As residential density increases, the number of agents that decide to evacuate through the transportation network increases. This results in two phenomena as shown in Figure 2.9. First, the percentage of agents that successfully evacuate to the safe area decreases as residential density increases. For example, 100% of the agents that decide to evacuate can successfully evacuate to the safe area when the residential density is 20 agents/node. However, this value decreases to 81% and 68% when the residential density is 30 agents/node and 40 agents/node, respectively (Figure 2.9a). Second, the average evacuation time for all of the agents increases as residential density increases, which is 150.2 T, 162.3 T and 169.6 T when residential density is 20 agents/node, 30 agents/node, and 40 agents/node, respectively (Figure 2.9 b-d). The model results suggest that residential density is an important factor that affects the agents' evacuation process in the transportation network. Flood warning managers need to pre-estimate the total time needed for the people to evacuate to the safe area when issuing flood warnings, especially in high residential areas where traffic load can be high when all people decide to evacuate.

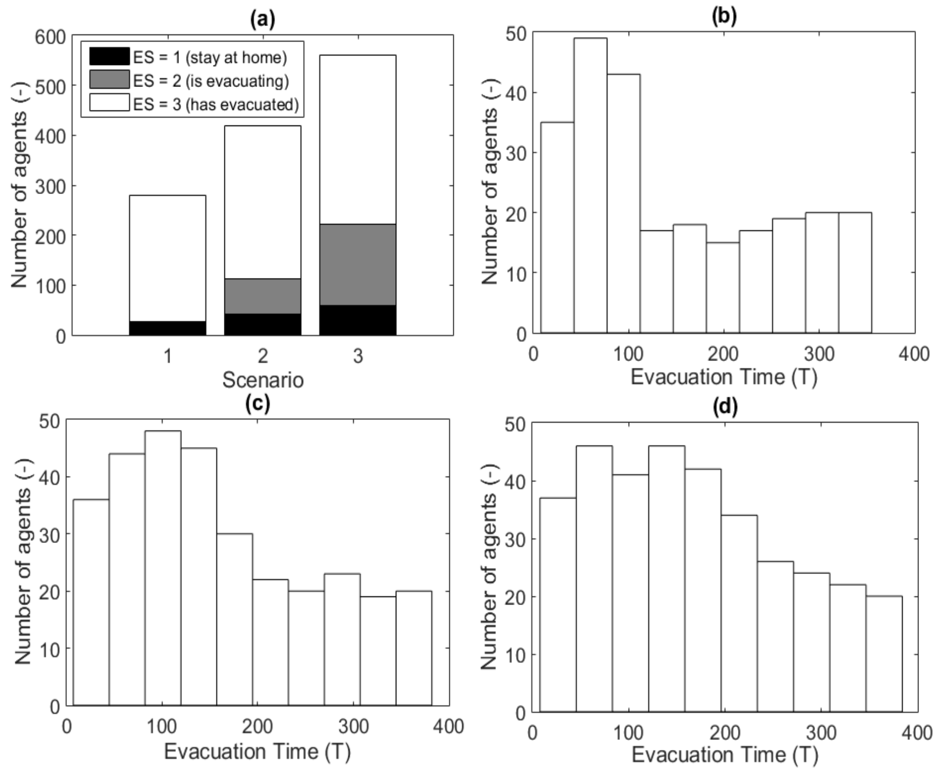


Figure 2.9 Agents' evacuation statistics when predicted flood probability is 80% with flood warning lead time of 400 T. (a) Summary of the agents' evacuation status when residential density is 20 agents/node (scenario b), 30 agents/node (scenario c), and 40 agents/node (scenario d), respectively; (b-d) Distribution of agents' evacuation time (i.e., the time that an agent takes to evacuate to safe area) for scenario b, c, and d.

To further investigate how residential density affects agents' evacuation processes, we simulate the evacuation process when residential density is 20 agents/node, 30 agents/node, and 40 agents/node, respectively. The simulation results are shown in Figure 2.10. The time needed for 50% (100%) of the agents to evacuate to the safe area is approximately 200 T (580 T) when residential density is 30 agents/node. This time is approximately 150 T (430 T) and 250 T (785 T) when the residential density is 20 agents/node and 40 agents/node, respectively. The results suggest that more evacuation time is needed to achieve high flood warning benefits when residential density increases. For example, when residential density increases by 33% (from 30 agents/node to 40 agents/node), the time needed for 50% of the agents to evacuate to the safe area increases by 25% (from 200 T to 250 T). However, the time for 100% of the agents to evacuate to the safe area increases by 35% (from 580 T to 785 T). Similar conclusion can be drawn when residential density increases from 20 agents/node to 30 agents/node. This implies that achieving high benefits from flood warnings is much more challenging in high residential areas than in low residential areas, because the increase in evacuation time is larger than the increase in agent population.

It is also noticed that, for all three cases of residential density, evacuation rates increase slower after a certain time when more agents are evacuating through the transportation network. This is caused by traffic jams when the number of agents that are evacuating through the transportation network exceeds transportation capacity. Furthermore, evacuation rates increase faster in cases with lower residential density than those with higher residential density. We expect that residential density will have less impact on evacuation rates if the transportation network's capacity is higher (e.g., with multiple evacuation destinations instead of only one).

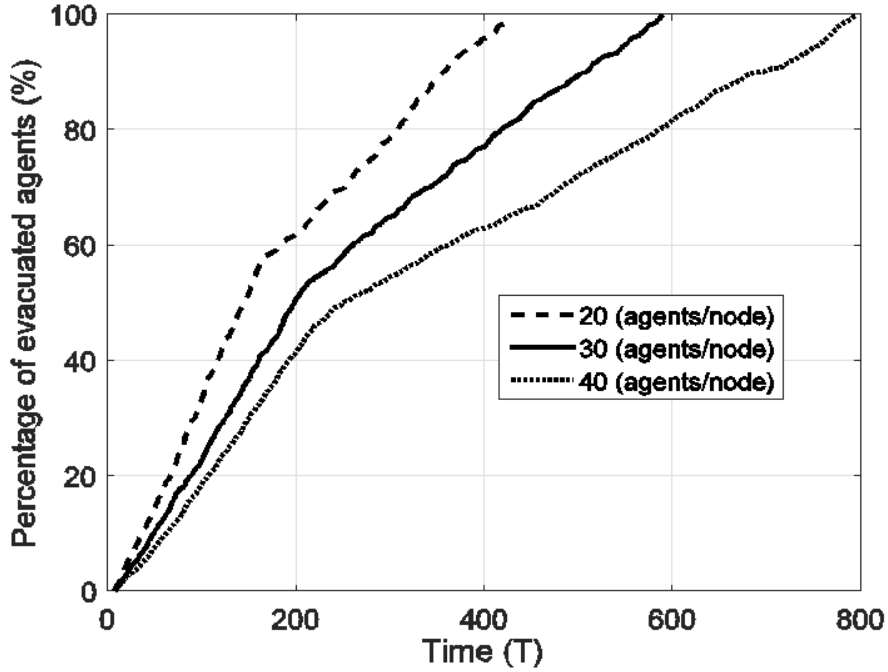


Figure 2.10 Simulation of agents' evacuation processes when residential density is 20 agents/node (dashed line), 30 agents/node (solid line), and 40 agents/node (dotted line), respectively.

2.6 Conclusions

This study proposes an agent-based modeling framework for incorporating the quality of flood warnings (i.e., predicted flood probability and lead time), the heterogeneous nature of response to flood warnings (i.e., the mean and coefficient of variation of agents' risk threshold), and residential density in flood warning-response systems. The framework is coupled with a traffic model to evaluate how these components interplay with each other to affect agents' evacuation processes in the face of flood warnings. There are three important findings from this study: (1) the benefits of flood warnings are affected not only by the quality of flood warning information, but also by responses to such information; (2) the marginal benefit associated with providing better flood warnings is significantly constrained if people behave in a more risk-tolerant manner; and (3) residential density plays an important role in evacuation effectiveness and ultimately the benefits of flood warnings. This highlights the need for different flood warnings depending on the specific residential density of flood zones.

While tremendous efforts have focused on providing better flood warning information to the public, this study suggests that collecting and using information on human behaviors and residential characteristics of flood-threatened areas will make flood warnings more beneficial. Such information can help flood-warning managers increase warning efficiency by enabling them to determine when and how to release flood warnings to the public. With advanced information delivery technologies such as social media, it is not beyond the realm of reality that all of this information could be available and accessible in real-time. Twitter, Facebook, and cell phone location services could provide real-time information about flood situations and recommended actions in floods. Flood warning managers could also collect and use information from social media to update the current flood forecast with increased detail and accuracy. Such information may also assist emergency managers to rescue people during floods. For example, in the 2011 Thai flood, Twitter was used by local citizens to collect and disseminate up-to-the-minute flood information and requests for assistance. It was quite beneficial for emergency managers to analyze and use this Twitter information to provide assistance in a timely manner according to specific needs [*Kongthon et al.*, 2012].

This study is a theoretical modeling framework to investigate the complexities of flood warning response and evacuation systems and inevitably has some limitations. First, we simulate a single flooding event without considering the public's behavioral changes resulting from experiences of flood events. In reality, people might change their flood risk tolerance based on their experiences. For example, after experiencing several flooding events and high flood-related costs, risk-tolerant agents might become risk-averse agents. Future work can obtain residents' socioeconomic and demographic data and their responses to flood warnings to understand the decision-making processes during flood events. Second, in this paper, we assume that all of the agents remaining in the area at the end of model execution will be flooded, and the agents that have evacuated to the safe area before the end of model execution will not be flooded. Thus, we did not specify the direction, speed, or timing of the flood inundation processes. In future work, we will simulate the gradual inundation processes to better model flood behaviors in the real world. Third, some assumptions of the theoretical model may not apply to real-world situations. For example, we assume that all of the households are knowledgeable about evacuation paths and will choose the shortest one. However, in reality the agents might dynamically change evacuation paths based on real-time traffic conditions and warning information. Further exploration of the impact of individual's route choice behaviors on transportation conditions during evacuations has been previously suggested [*Pel et al.*, 2011] and our study concurs with this need. Finally, this study assumes that agents make independent evacuation decisions without communicating with each other. In the real world, relatives, neighbors, and friends greatly affect evacuation decisions [*Parker et al.*, 2009a, 2009b]. In general, interactions among agents affect not only individual behaviors but also the emergence of the overall system. Future work may explore how an agent's decisions are related to the agent's geographical location in the residential area (e.g., agents that are more close to safe areas may be more likely to behave in a risk-tolerant manner). Other socioeconomic household characteristics (e.g., size of household, economic value of the home, pet ownership) might also affect agents' behaviors. This study can be expanded by incorporating additional socio-economic heterogeneities into the model. These improvements can better capture the complex behaviors of flood warning-response systems and help emergency managers with more informed decision-making during flood events.

Chapter III. Impacts of Social Interactions: Do Social Media Make Us More Resilient or Vulnerable to Flood Risk?

Based on the modeling framework presented in Chapter II, this chapter focuses on evaluating how social interactions affect agents' flood risk awareness and evacuation behaviors. Section 3.1 overviews previous studies on social interaction through social media and introduces the objective of this study. Section 3.2 presents the methodology, focusing on individuals' opinion dynamics when exposed to multiple information sources and the traffic model that simulates individuals' evacuation process in transportation network. Section 3.3 presents the case study and modeling results, followed by conclusions in section 3.4.

3.1 Introduction

With the rapid development of computer-mediated technologies and more universal internet accessibility, social media, such as Twitter, Facebook and other information sharing platforms, have become important tools for individuals to obtain and share information with each other [*Asur and Huberman*, 2010; *Kwak et al.*, 2010; *Gil de Zúñiga and Diehl*, 2017]. Unlike conventional media such as radio and television that are typically developed for one-to-many information dissemination, social media allow both one-to-many and many-to-many information dissemination and message exchange [*Bassett et al.*, 2012; *Houston et al.*, 2015]. Individuals can easily share their daily activities, news, opinions, ideas, etc., with their neighbors, families and friends, interest groups, and the public through social networks that transcend territorial boundaries, which makes communication between individuals faster and more efficient [*Zhu*, 2017]. Due to the many advantages in information dissemination and social networking, social media have been used in a variety of domains. These include political activities (e.g., presidential elections [*Gil de Zúñiga et al.*, 2012], protests such as Arab Spring [*Hussain and Howard*, 2013]), economic behaviors such as business and marketing [*Asur and Huberman*, 2010; *Marshall et al.*, 2012], and coordination and management during natural disasters [*Palen et al.*, 2010; *Kongthon et al.*, 2012; *Alexander*, 2014; *Houston et al.*, 2015; *Smith et al.*, 2015]. This study focuses on the role of social media in evacuation processes during flood events.

Floods are common natural disasters in the U.S. and many other countries and have caused significant economic damage and loss of life [*Heaney et al.*, 2000; *Smith and Matthews*, 2015]. Flood warning systems have been recognized as efficient tools for flood damage mitigation and crisis management [*Cloke and Pappenberger*, 2009; *Parker et al.*, 2009a; *Pappenberger et al.*, 2015; *Parker*, 2017]. However, studies have shown that the benefits of flood warnings can be significantly affected by (1) the delivery of flood warnings that determines if communities in flood zones can receive accurate and timely flood warnings, and (2) some socioeconomic factors (e.g., education and income of the members in household, economic value of the home) that could affect households' responses and reactions to flood warnings [*Parker and Handmer*, 1998; *Kongsomsaksakul et al.*, 2005; *Parker et al.*, 2007b, 2009a]. Therefore, it is important to evaluate the benefits of flood warnings in the context of a coupled social, economic and hydrologic framework [*Sivapalan et al.*, 2012; *Di Baldassarre et al.*, 2013, 2014; *Girons Lopez et al.*, 2017], with consideration of the heterogeneity in households' responses to flood warnings.

In recent years, social media have been used to spread warnings of natural disasters, including floods, to increase awareness of the danger and to provide efficient communications between affected individuals, emergency managers, and first responders [*Palen et al.*, 2010; *Kongthon et al.*, 2012; *Alexander*, 2014; *Houston et al.*, 2015]. For example, during the 2009 Red River flood, over four million Tweets were posted that are related to sandbagging, evacuation, damage reports, and other flood-related subjects [*Palen et al.*, 2010; *Vieweg et al.*, 2010]. Similarly, significant numbers of Twitter messages were generated and shared by citizens in flood zones during the 2011 Thai flood. These messages provided up-to-the-minute information about location-based flood conditions, available resources, and needed rescues. Emergency responders can use the information to create instant flood situation maps and to better coordinate available resources for rescues and evacuations [*Russell*, 2011; *Kongthon et al.*, 2012].

Despite these advantages, social media could also pose potential threats to crisis management when outdated, false, or misleading information is spread through social media [*Acemoglu et al.*, 2010; *Nguyen et al.*, 2012; *Alexander*, 2014]. This concern is partially the result of individuals having limited time to verify the accuracy of information on social media during emergencies. For example, during Japan's Fukushima nuclear crisis in 2011, rumors claiming that iodized salt can prevent radiation-related illness and that all importing of sea salt would be exposed to nuclear pollution after the nuclear meltdown were rapidly and widely spread on China's social media. Many people rushed into supermarkets and grocery stores to buy and hoard salt, which resulted in market swarms and unprecedented salt shortage in many regions of China [*Brenhouse*, 2011]. In the case of Hurricane Sandy in 2012, altered images and false news were spread and shared by many social media users, and were even picked up by mainstream media in New York City until they were corrected by field checking [*Alexander*, 2014]. The impact of such misinformation from social media in natural disaster management requires timely attention.

Motivated by this need, this study examines how social media affects individuals' flood risk awareness and consequent evacuation processes. We consider a residential area with an impending flood event, where emergency managers obtain and broadcast flood warnings to the residents. The residents receive the flood warnings from emergency managers and communicate with each other through social media (e.g., Twitter or Facebook) to share their opinions about their perceived flood risk. A resident will choose to evacuate to a safe area if he thinks that the flood is sufficiently likely to occur.

Some studies have modeled individuals' evacuation behaviors as responses to flood warnings [*Chen and Zhan*, 2008; *Zhang et al.*, 2009; *Dawson et al.*, 2011; *Du et al.*, 2016]. For example, *Dawson et al.* [2011] integrated a hydrodynamic model and a traffic model to estimate the number of people exposed to floods under varying storm surge conditions. Furthermore, *Du et al.* [2016] investigated how individuals' evacuation behaviors are affected by their heterogeneous responses to flood warnings, as well as flood prediction accuracy and lead time. The results show that residents' evacuation behaviors can be significantly affected by various individuals' flood risk-tolerance thresholds.

Studies have also modeled how individuals form their opinions through social interactions. Among them, *Hegselmann and Krause* [2002] proposed various models for simulating individuals' opinion formation within interacting groups. *Watts* [2002] developed a binary-decision model in which individuals' decisions are explicitly dependent on the actions of their neighbors. The model was shown to be capable of capturing some important features of global cascades in social and economic systems. *Bassett et al.* [2012] developed an opinion dynamics model to simulate individual's opinion formation when exposed to multiple information sources (e.g., communication on social media and observations of the neighbors' actions) in natural disasters. Similarly, *McCullen et al.* [2013] developed an innovation diffusion model in which households form opinions through pairwise social interactions and choose to adopt innovations when their motivations exceed a certain threshold. Moreover, *Yildiz et al.* [2011] investigated the role of stubborn individuals, who can influence others but do not change their own opinions, in a group's opinion dynamics.

Although existing studies have shown how individuals' opinions can be shaped by social networking, few studies have taken into account information from multiple sources in a consistent framework to analyze the impact of social media on opinion dynamics. Real-world information sources includue global broadcast, social media, and observations of other individuals' actions [*Acemoglu and Ozdaglar*, 2011; *Crokidakis and Anteneodo*, 2012; *Ghaderi and Srikant*, 2013; *Jia et al.*, 2015], as illustrated in Figure 3.1. Global broadcast is information that emergency managers spread to all of the agents in the system [*Bassett et al.*, 2012]. Examples of global broadcast include radio and television emergency alerts, as well as some other public notices. Social media (e.g., Twitter and Facebook) allow for pairwise information transmission between the agents in a group. When two agents interact on social media, they will exchange each other's opinion on flood risk [*Acemoglu and Ozdaglar*, 2011]. Neighbor observation takes account of how an agent's opinion is affected by the actions of other agents in a group [*Watts*, 2002]. In this study, we integrate social media with global broadcast and neighbor observations into a general quantitative framework with consideration of individual heterogeneity in beliefs about different sources of information and learning attitudes (i.e., the extent to which individuals adopt new information).

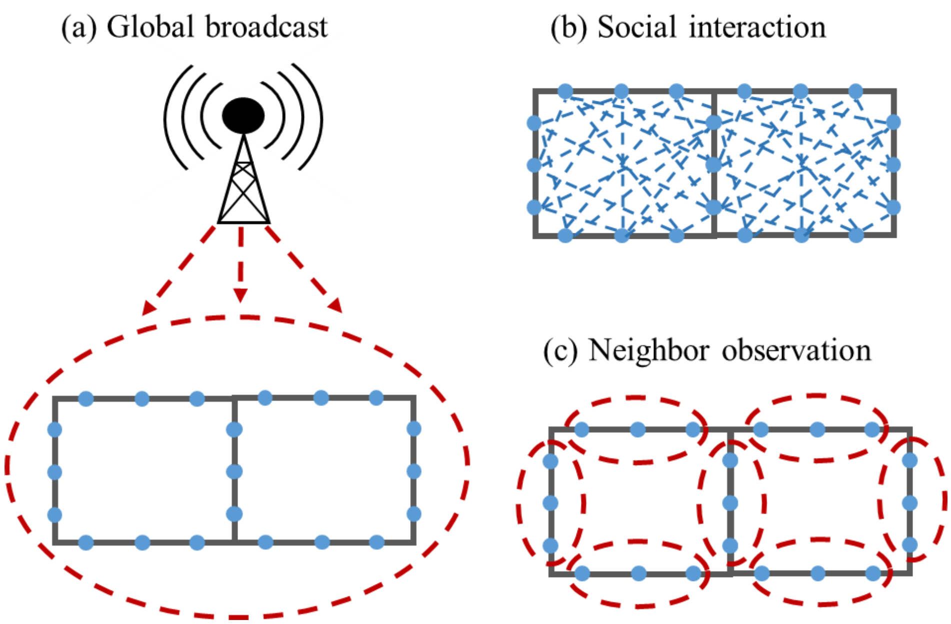


Figure 3.1 Illustration of three types of information sources related to flood warning dissemination: (a) global broadcast that spreads flood warnings from the global source to all of the individuals, (b) social media that allow pairwise information exchange (illustrated by blue dashed lines), and (c) neighbor observations that consider the influence of each individual's neighbors (illustrated by the red circles).

Moreover, according to our knowledge, there is still a need to bridge the gap between opinion dynamics and evacuation processes that are influenced by individuals' opinions on flood risk, evacuation decisions, and transportation networks. Thus, we propose a modeling tool to couple the simulation of opinion dynamics and the evacuation processes. An agent-based model (ABM) is developed to simulate opinion dynamics. A traffic model is used to simulate the evacuation process. The coupled ABM and traffic model simulates how individuals update their awareness of flood risk and how individuals' opinion dynamics affect their evacuation processes in the transportation network. Using the modeling tool, we address the following research questions: (1) Will social media increase the level of people's flood risk awareness in an impending flood event? (2) Do social media help increase the evacuation rate of a community? (3) How do stubborn individuals (i.e., those who do not change their opinions on flood risk) affect the opinion dynamics and evacuation processes of the community?

The remainder of this paper is structured as follows. Section 3.2 introduces the methodology, focusing on modeling individuals' opinion dynamics when exposed to multiple information sources and their evacuation processes in a transportation network. Section 3.3 presents an example of a hypothetical residential area, the modeling results, and discussions. Finally, conclusions are presented in section 3.4.

3.2 Methodology

We consider a residential area consisting of households and a transportation network. Following the approach of our prior work [*Du et al.*, 2016] (Chapter II of this document), the transportation network in this paper is represented by a directed graph consisting of a number of links (i.e., roads) and nodes (i.e., road intersections). Each household is represented by an agent with a set of attributes and rules that describe the agent's geographical location, risk-tolerance threshold for flooding, priorities to the various information sources, and learning attitudes, etc.

3.2.1 Modeling Opinion Dynamics

In this study, an agent's opinion (denoted by a continuous variable S, $S \in [0,\ 1]$), refers to his perception of how likely there will be a flood in the residential area [*Lorenz*, 2005]. Each agent has a flood risk-tolerance threshold (denoted by a continuous variable τ, $\tau \in [0,\ 1]$) [*Schelling*, 1973; *Watts*, 2002]. At each time step, the agent will make a binary decision (denoted by a binary variable X, $X \in \{0,\ 1\}$) to evacuate ($X = 1$) or not ($X = 0$) in the face of the flood risk. In this study, we use a simple decision rule to describe agents' evacuation decisions: at any time step *t*, an agent *j* will choose to evacuate if his opinion of flood risk exceeds his risk-tolerance threshold:

$$X_{j,t} = \begin{cases} 0 & \text{if} \quad S_{j,t} < \tau_{j,t} \\ 1 & \text{if} \quad S_{j,t} \geq \tau_{j,t} \text{ or } X_{j,t-1} = 1 \end{cases} \tag{1}$$

Opinion dynamics refers to the process in which agents form and update their opinions over time. Given that agents might not always collect information to update their opinions at each time step, we simulate agents' opinion dynamics as a stochastic process: At each time step, an agent will either choose to collect new information and update his opinion or not. Let a binary variable $\mu_{j,t}$ ($\mu_{j,t} \in \{0, 1\}$) denote whether agent *j* updates his opinion at time *t*. When choosing not to update his opinion ($\mu_{j,t} = 0$), the agent will keep his opinion of time step *t*-1 (i.e., $S_{j,t} = S_{j,t-1}$). Otherwise, the agent will use new information on flood risk to update his opinion.

For agent *j* at time step *t*, we use $I_{j,t}^G$, $I_{j,t}^S$, and $I_{j,t}^N$ to denote the information about flood risk obtained from global forecast, social media, and neighbor observations, respectively. Each of these information sources is described in turn below.

Let G_t denote the value of flood risk broadcast from a global source at time *t* (i.e., $G_t \in [0, 1]$, a higher value of G_t indicates a higher flood risk). Since global broadcast is a one-to-many information broadcast process, all of the agents will obtain the same global information at each time step (i.e., $I_{j,t}^G = G_t$).

Following previous studies, an agent's information obtained from social networking is modeled as a linear combination of the opinions of all of the agents that are connected to the agent [*DeGroot*, 1974; *Hegselmann and Krause*, 2002; *Ghaderi and Srikant*, 2014]. Denoting $\omega_{ij,t}$ as the weighting factor that measures how much agent *j* weights agent *i*'s opinion at time *t*, agent *j*'s information obtained from social networking ($I^S_{j,t}$) can be modeled as a weighted average of information from all agents with whom agent *j* communicates, as shown in equation (2):

$$I^S_{j,t} = \sum_{i=1}^{n} \omega_{ij,t} S_{i,t-1} \tag{2}$$

We model agents' social networking as a binary stochastic process: at each time step t, agent *j* either exchanges information with agent *i* (i.e., agent *j* reads agent *i*'s post on social media at time *t*, denoted by $a_{ij,t} = 1$) or not (i.e., $a_{ij,t} = 0$). Taking account of all of the *n* agents that could be socially connected with agent *j*, weighting factor $\omega_{ij,t}$ can be represented by equation (3).

$$\omega_{ij,t} = \frac{a_{ij,t}}{\sum_{i=1}^{n} a_{ij,t}} \tag{3}$$

In a social network with *n* agents, agents with stronger social connections have larger probabilities to read each other's posts. In this study, we assume that agents who are physically closer to each other have stronger social connections and thus have larger probabilities to share their opinions [*Bassett et al.*, 2012]. Denoting the distance between agents *i* and *j* as d_{ij} and the maximum distance between any of the two agents in the system as $d_{\max}$, we use a simple model to represent the relationship between the probability that they exchange information at time *t* and their distance: $p(a_{ij,t} = 1) = 1 - d_{ij} / (d_{\max} + 1)$.

The assumption of agents' social interaction (i.e., the likelihood of social interaction decreases with proximity) employed in this study is based on intuitive reasoning that individuals living closer to each other will have more chance to meet each other to exchange information on social media. However, we admit that this assumption does not necessarily hold true in some real-world case studies, but the validation of the assumption goes beyond the scope of this work. Future work can validate or refine this assumption by mapping individuals' social connections using data mining tools when detailed social communication data become available [*Sobkowicz et al.*, 2012; *Gil de Zúñiga and Diehl*, 2017; *Zhu*, 2017].

Combining equations (2) and (3), agent *j*'s information obtained from social media can be represented by equation (4):

$$I_{j,t}^{S} = \sum_{i=1}^{n} \frac{a_{ij,t}}{\sum_{i=1}^{n} a_{ij,t}} S_{i,t-1} \tag{4}$$

In contrast to sharing opinions over social media, neighbor observations are observed *actions*. Many studies have shown that an agent's opinion is often affected by the actions of other agents in the group, due to the fact that individuals might not have sufficient information to make decisions, or their ability to process information is limited during emergency situations [*Schelling*, 1973; *Watts*, 2002; *Kearns et al.*, 2009; *Centola*, 2010]. We use the weighted average of the actions of an agent's neighbors to represent the information obtained from neighbor observations. Agent *j*'s neighbors can be defined by a group of agents that are close to *j* in their residential area. In this study, we define agent *j*'s neighbors as the set of agents that live on the same road as *j* (e.g., the red circles in Figure 3.1c) based on the assumption that agents who live on the same street can directly observe the actions of each other. Let b_{ij} denote if agents *i* and *j* are neighbors ($b_{ij} = 1$) or not ($b_{ij} = 0$), agent *j*'s information obtained from neighbor observations can be represented by equation (5):

$$I_{j,t}^{N} = \sum_{i=1}^{n} \frac{b_{ij,t}}{\sum_{i=1}^{n} b_{ij,t}} X_{i,t-1} \tag{5}$$

So far, we have modeled how agents obtain information from multiple separate sources. When all of these information sources are available, agents might have different degrees of trust in, and are influenced differently by, these information sources, depending on a variety of factors. For example, if global broadcast information has proven to be unreliable in the past, people might rely less on global broadcast. Similarly, rumors and misleading information on social media might reduce the influence of social media on agents' opinion formation. *McCullen et al.* [2013] proposed using a set of weighting factors to formulate agents' opinion dynamics driven by multiple information sources. In this study, we follow this approach and introduce three information influence parameters, α_j, β_j, and γ_j to represent the influence of global broadcast, social media, and neighbor observation on agent *j*'s opinion adoption, respectively, and $\alpha_j + \beta_j + \gamma_j = 1$. Thus, the information obtained from multiple sources can be represented by equation (6).

$$I_{j,t} = \alpha_j I_{j,t}^G + \beta_j I_{j,t}^S + \gamma_j I_{j,t}^N \quad (6)$$

When new information on flood risk is obtained, the agent *j* will update his opinion on flood risk. We adopt the Widrow-Hoff learning rule to simulate the agent's opinion dynamics [*Sutton*, 1988; *Widrow and Hoff*, 1988; *Widrow and Lehr*, 1993], as shown in equation (7).

$$S_{j,t} = S_{j,t-1} + \theta_j \times \Delta I_{j,t} \quad (7)$$

where $\Delta I_{j,t}$ is the difference between the flood risk obtained from multiple sources at time *t* and the agent's original opinion on flood risk at time *t*-1 ($\Delta I_{j,t} = I_{j,t} - S_{j,t-1}$). θ_j is the agent's learning rate, which is a behavioral parameter measuring how much the agent adheres to his past opinion when new information is available. This parameter considers that an agent might not completely abandon his past opinion to accept new information ($\theta_j = 1$), nor completely disregard new information to keep his past opinion ($\theta_j = 0$) [*Friedkin and Johnsen*, 1999]. The concept of opinion adherences is based on observations that individuals' beliefs typically display some amount of inertia [*Watts*, 2002; *Dash and Gladwin*, 2007]. Combining equations (6) and (7), agent *j*'s opinion dynamics can be represented by equation (8).

$$S_{j,t} = (1-\theta_j)S_{j,t-1} + \theta_j(\alpha_j I_{j,t}^G + \beta_j I_{j,t}^S + \gamma_j I_{j,t}^N) \tag{8}$$

The opinion dynamics model (i.e., Equation (8)) presented in this study is a more general form compared with those used in previous models [e.g., *Bassett et al.*, 2012; *McCullen et al.*, 2013]. For example, by setting $(\alpha_j,\ \beta_j,\ \gamma_j,\ \theta_j) = (1,\ 0,\ 0,\ 0.5)$ (i.e., the agent only uses global information and treats prior opinion and new information equally), Equation (8) becomes equivalent to the opinion dynamics model driven by global information proposed by *Bassett et al.* [2012]. Similarly, the model is made equivalent to that given by *McCullen et al.* [2013] by setting $\theta_j = 1$ (i.e., the agent only uses new information to update his opinion).

In addition, Equation (8) considers differences in people's behaviors through the agents' behavioral parameters α_j, β_j, γ_j, and θ_j. This takes advantage of the strength of agent-based models in representing the heterogeneity in agents' behaviors [*Huang et al.*, 2013], and relaxes the assumption that all agents in a community behave in the same manner (e.g., as handled in the opinion dynamics model by *Bassett et al.* [2012]). In this hypothetical study without behavioral data, we use a coefficient of variation (C_v) for each of the behavioral parameters (α, β, γ, and θ) to measure the level of agents' behavioral heterogeneity. Following previous studies [*Marino et al.*, 2008; *Bertella et al.*, 2014], we use a normal distribution to sample the behavioral parameters for each agent.

In an impending flood event, the predicted flood probability will increase over time before the flood. Furthermore, forecasting with better prediction capability will give a higher flood probability and/or a longer lead time. Considering these two factors, we use a simple model, for illustrative purpose, to represent the predicted flood risk as a function of time *t* during the flood forecast horizon (*FH*) ($t = 1, 2, ..., FH$), shown in Equation (9):

$$G(t) = \frac{1}{FH} t + \delta;\ G(t) \in [0,\ 1] \tag{9}$$

where $\delta \in [-1, 1]$ is a parameter that measures the quality of flood warnings. A larger δ is associated with flood warnings that can predict higher flood risk in flood events. Predicted flood risk *G*(*t*) is closer to 1 (actual flood risk) when δ is larger.

3.2.2 Modeling the Evacuation Process

Agents that decide to evacuate will move from their current location to the evacuation destination in the transportation network. We assume all agents have good knowledge of the transportation network and will choose the shortest route to evacuate. We use a categorical parameter K_j to represent agent *j*'s evacuation status. $K_j = 0$ denotes that agent *j* decides not to evacuate; K_j =1 when agent *j* decides to evacuate but does not arrive at the destination; K_j =2 when the agent arrives at the destination, which represents a successful evacuation case.

In this study, as in the previous chapter, we adopt the Nagel-Schreckenberg traffic model (N-S model) to simulate agents' evacuation behaviors via a transportation network [*Nagel and Schreckenberg*, 1992]. For details of the N-S model, see Chapter 2 and the Appendix of this thesis.

3.2.3 Model Outputs at the System Level

We use multiple indicators to measure behaviors at the system level (i.e., a community), which result from the evacuation of individual agents, including: (1) agents' opinion trajectory S

($S=[S_{t=1},\ S_{t=2},\ ...,\ S_{t=T}]$, where $S_{t=k}$ is the average opinion over all agents at time step *k*), (2) agents' decision trajectory X ($X=[X_{t=1},\ X_{t=2},\ ...,\ X_{t=T}]$, where $X_{t=k}$ is the average decision over all agents at time step *k*), and (3) agents' evacuation rate Φ (i.e., $\Phi=[\Phi_{t=1},\ \Phi_{t=2},\ ...,\ \Phi_{t=T}]$, where $\Phi_{t=k}$ is the percentage of agents that successfully evacuate to the destination at time step *k*).

Given the fact that not everyone opens social media channels at all times for social interaction, information transmission and social communication are assumed to occur in a stochastic manner. The Monte Carlo method (i.e., execution of the model multiple times with model inputs that are randomly and repeatedly sampled from the sampling space) is applied in this study to address the stochastic characteristics of the study problem [*Decker*, 1991]. We executed the model 1000 times (the number of simulations that ensures output stabilization for this study) to obtain the ensemble opinion trajectory $<S>$, ensemble decision trajectory $<X>$, and ensemble evacuation rate $<\Phi>$.

3.3 A Demonstration Example

We apply the model described above in a synthetic residential area, which consists of a transportation network and a group of agents (Figure 3.2). Following previous studies, we use *L* and *T* to represent the units of length and time, respectively [*Zhang et al.*, 2009; *Du et al.*, 2016]. In this transportation network, all of the roads are assumed to have length of 100 *L*, indicating that each road can be divided into 100 cells. Among the 16 nodes in the transportation network, the one on the bottom right is set as the evacuation destination.

Agents are uniformly distributed along the roads in the transportation network. Residential density (denoted by d) is represented by the number of agents on a road in the transportation network, and is set as 10 in this study (i.e., corresponding to 240 agents in the transportation network). The sensitivity of residential density is examined in section 3.3.5.

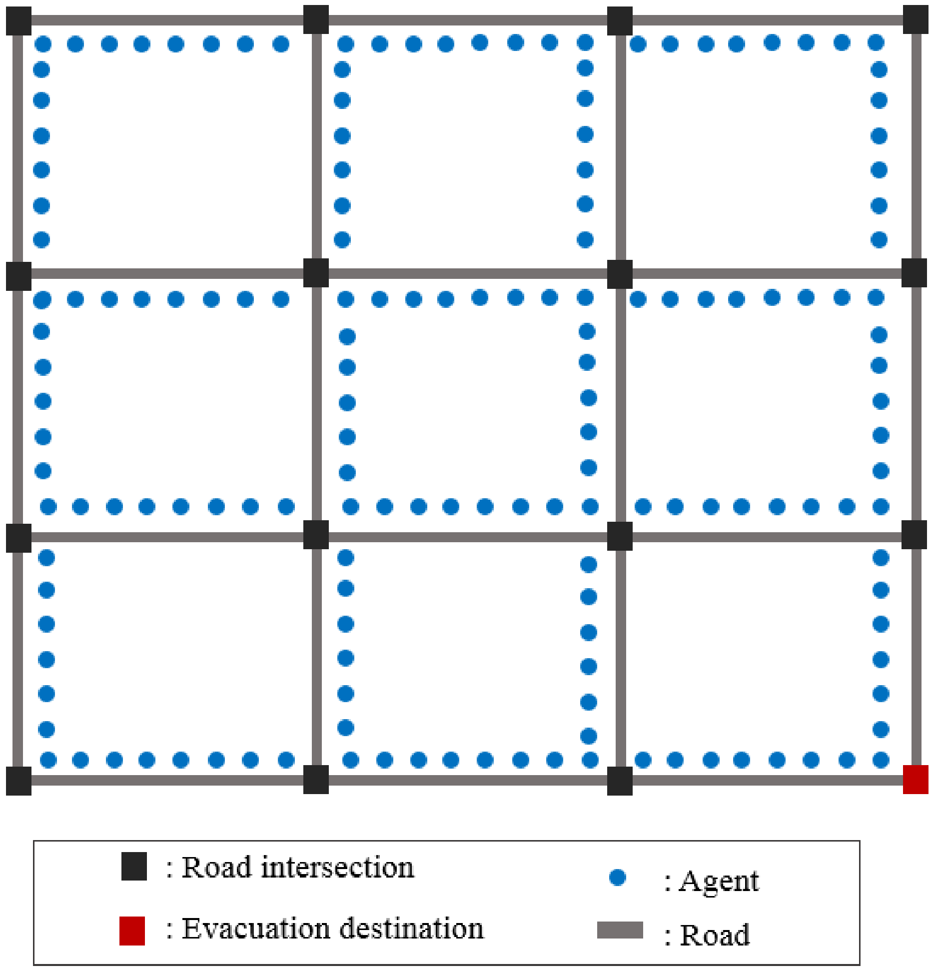


Figure 3.2 Illustration of the synthetic case study area that consists of a transportation network and a number of agents. The transportation network is a regular lattice network with 24 roads and 16 nodes (the node on the bottom right is set as the designated evacuation destination for all of the agents). The agents are uniformly distributed along the roads.

The following sections present the modeling results. Sections 3.3.1 and 3.3.2 present scenario-based analysis and sensitivity analysis, respectively. Next, sections 3.3.3 and 3.3.4 evaluate the impacts of social media and stubborn agents on evacuation processes, respectively.

Finally, section 3.3.5 shows how evacuation rates are jointly affected by sources of information, transportation capacity, and flood warnings with various forecast capabilities.

3.3.1. Scenario-Based Analysis

To assess the impact of model parameters on the results, a scenario-based analysis is conducted. We design three scenarios, each of which represents a special combination of information sources. The first scenario considers the case in which only global broadcast information is available. The second case considers the case with only global broadcast and social media, without neighbor observations. The third case considers the scenario with only global broadcast and neighbor observations, without social media. Table 3.1 lists the values of the key parameters in the model.

Table 3.1. The Values of Model Parameters

Scenario	α_j	β_j	γ_j	θ_j	$p_{j,t}$ [a]	τ_j	δ
Case 1	1(0) [b]	0	0				
Case 2	0.5(0.1)	0.5(0.1)	0	0.5(0.1)	0.1(0.1)	U(0.1, 0.9) [c]	1
Case 3	0.5(0.1)	0	0.5(0.1)				

[a] $p_{j,t}$ is the probability that agent *j* receives information from multiple sources to update his opinion at time step *t*.

[b] $x_1(x_2)$ indicates the mean value of the variable is x_1, and the coefficient of variation C_V of the variable is x_2.

[c] $U(x_1,\ x_2)$ means the value of the parameter is sampled from a uniform distribution in which the lower and upper bound of sample space is set as x_1 and x_2, respectively.

Figure 3.3 provides an overview of a randomly selected agent's opinion trajectory S under the three model parameter cases, as well as overall statistics on all agents. By comparing Cases 1 and 2, it can be noticed that, with the presence of social media, agents' opinions update in a smoother manner as a function of time (comparing Figure 3.3a and Figure 3.3d). There is also less variance among agents' opinions in Case 2, which results in a cascade-like pattern for opinion update (Figure 3.3e). However, the speed of agents' opinion update is slower in Case 2 compared with Case 1, implying that social media could slow down the speed of agents' opinion update. This result is consistent with the findings by *Bassett et al.* [2012].

In Case 3, when agents' opinion exchange only occurs through neighbor observation, the individual agent's opinion trajectory is smoother than that in Case 1. This indicates that information exchange, either by social media or by neighbor observation, can make agents' opinion trajectory smoother and reduce the variance in agents' opinions (red lines in Figures 3.3f and 3.3i). However, agents do not reach opinion consensus in Case 3. A few agents' opinions are less than 1 at the end of the simulation (e.g., agent 145 in Figure 3.3g). As illustrated by the blue line in Figure 3.3i, agents' average opinion is less than, although very close to, 1 in the end.

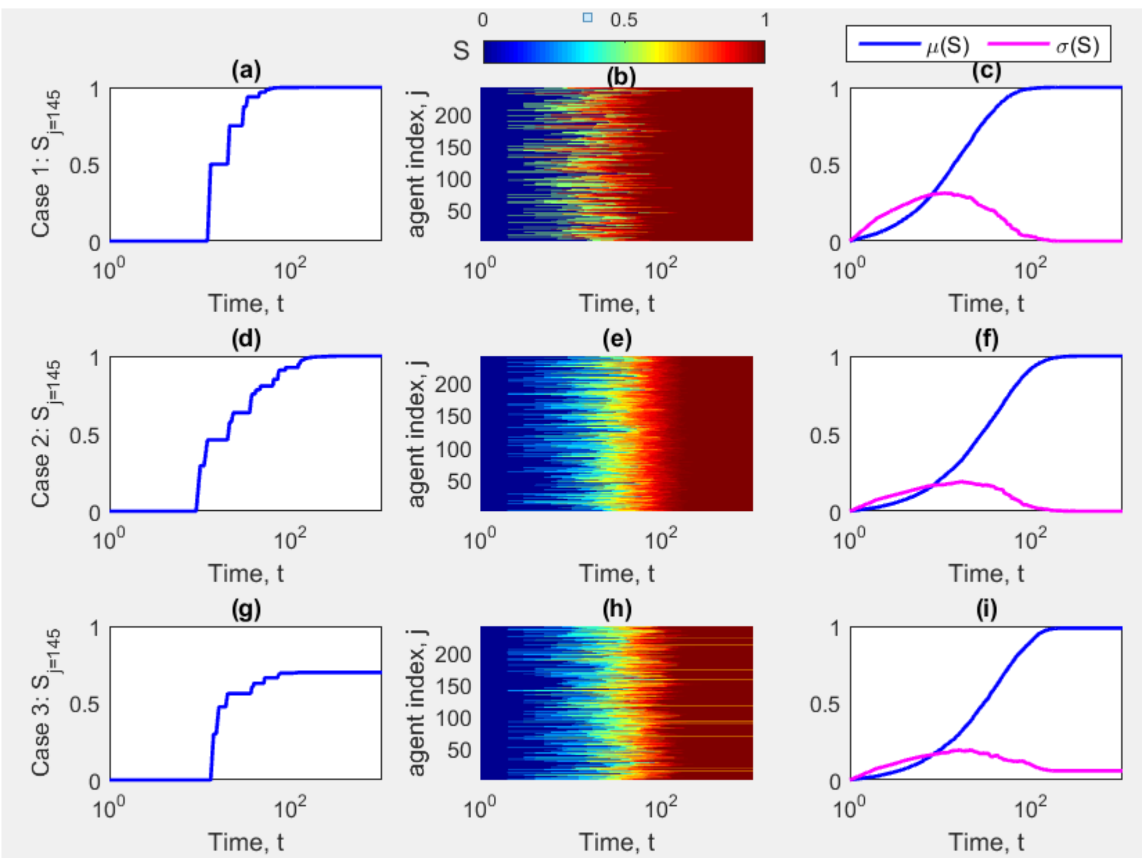


Figure 3.3 (a) The opinion trajectory for a randomly selected agent in Case 1. (b) The opinion trajectory for all of the agents in Case 1. (c) The mean (blue line) and standard deviation (red line)

Figure 3.3 (cont.) of all the agents' opinions in Case 1. Figures 3.3d-3.3f and 3.3g-3.3i present the corresponding results for Cases 2 and 3, respectively.

We further investigate how the agents' opinion dynamics affect their evacuation processes under these three cases (Figure 3.4). Notice that the agents in Case 1 start to take evacuation actions earlier than Cases 2 or 3 (the green lines in Figures 3.4c, 3.4f and 3.4i). This is consistent with the results presented in Figure 3.3, which shows that information exchange through either social media or neighbor observations will slow down the speed of agents' opinion update. However, there is no noticeable difference in the percentage of agents at status 2 over time (i.e., agents that successfully evacuate to the destination, corresponding to the red lines in Figures 3.4c, 3.4f and 3.4i). We also notice that all the agents in Cases 1 and 2 eventually choose to evacuate. In comparison, some agents in Case 3 do not evacuate (e.g., Figures 3.4g-3.4h). This suggests that the decision-making rule based on neighbors' actions sometimes will keep some agents from updating their opinions, especially when no one takes initial evacuation actions.

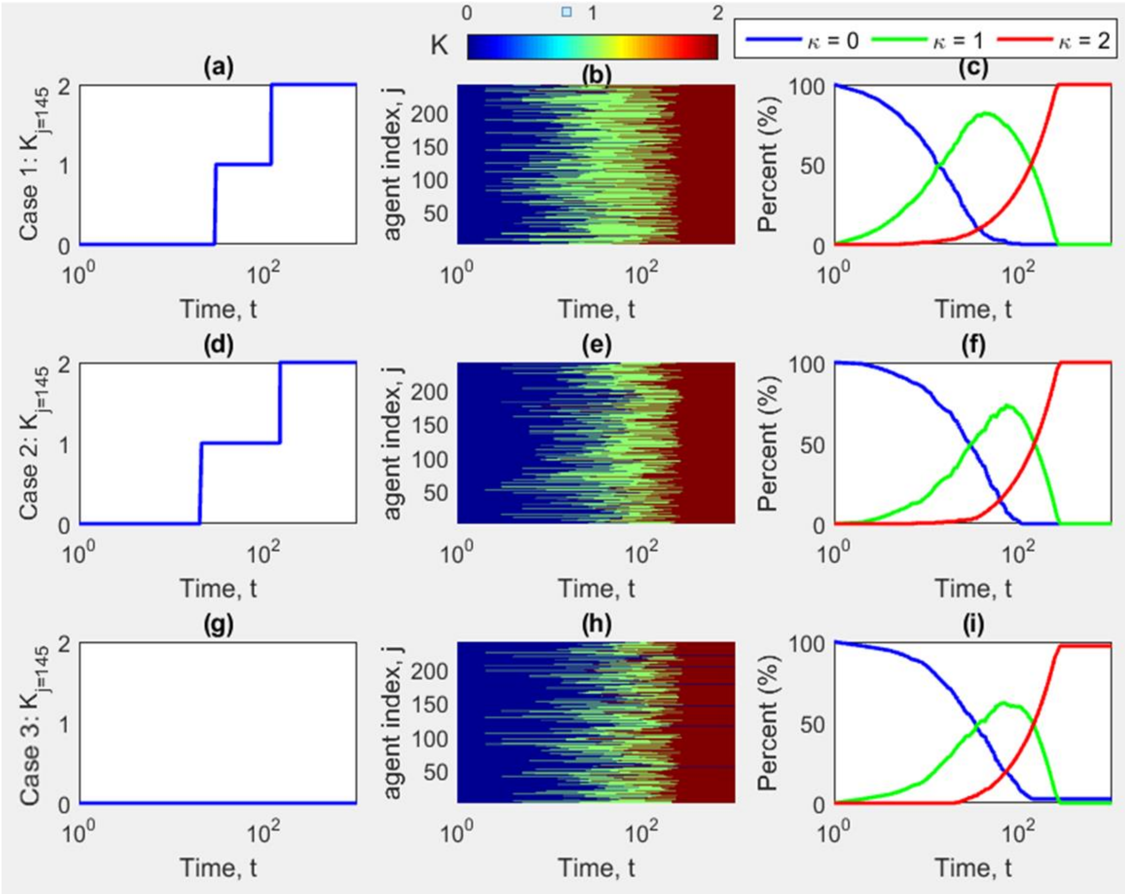


Figure 3.4 (a) The evacuation status of a randomly selected agent in Case 1. (b) All agents' evacuation status in Case 1. (c) The percentage of each type of agents as a function of time in Case 1. Figures d-f and g-i present the corresponding results for Cases 2 and 3, respectively.

3.3.2. Sensitivity Analysis

Next, a sensitivity analysis is conducted to understand the influence of agents' opinion adherence parameter (θ) and weighting parameters (α, β, γ) on agents' ensemble opinion trajectory $< S >$, decision trajectory $< X >$, and evacuation rate $< \Phi >$.

Figures 3.5a-3.5c show the impacts of opinion adherence parameter θ on the model results. The figures indicate that a smaller θ (i.e., agents adhere more to their past opinions) will slow down the speed of the agents' opinion update $< S >$, evacuation actions $< X >$ and evacuation rates $<\Phi>$. However, the influence of θ on agents' evacuation rate $<\Phi>$ is not as significant compared with opinion update $<S>$ and evacuation actions $<X>$. This is due to the constraint of traffic capacity as implied by Figure 3.4. We expect that θ will have a stronger impact on $<\Phi>$ with less traffic bottlenecking.

Figures 3.5d-3.5i show the influences of α, β and γ on the modeling results. It is observed that, in both Cases 2 and 3, a decrease in α (i.e., the global broadcast has less impact on agents' opinion update) will slow down the speed of agents' opinion update $<S>$, evacuation actions $<X>$ and evacuation rates $<\Phi>$. There are no opinion updates and evacuation actions when α is small enough (e.g., $\alpha \leq 0.1$ in Figures 3.5g-3.5i) in Case 3. Under these conditions, agents' opinions remain unchanged because their opinions are mainly affected by their neighbors' actions. For each member in the group, an agent will not update his opinion if his neighbors do not take evacuation actions. This in turn results in no opinion updates and no agent will evacuate in the end.

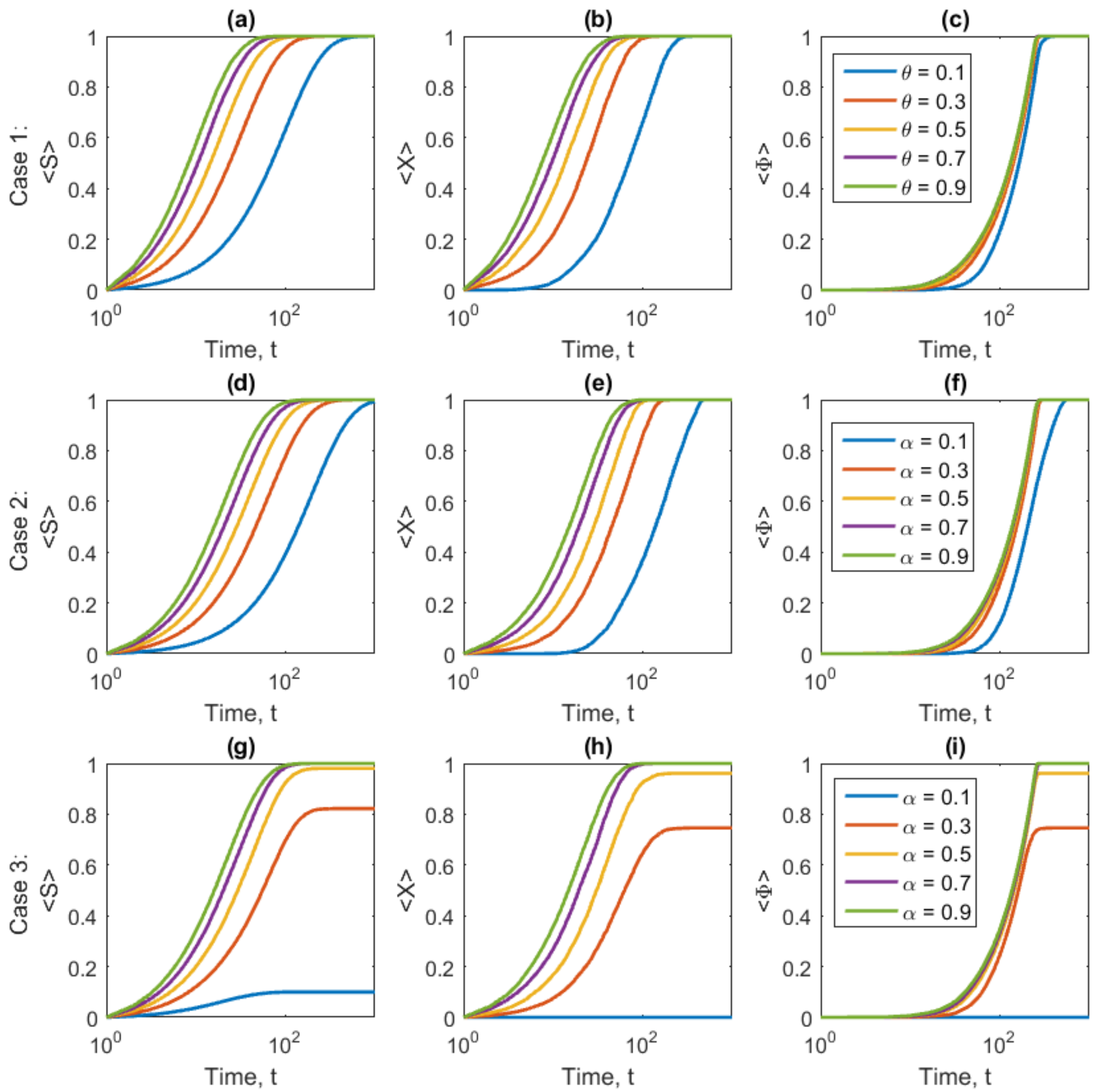


Figure 3.5 The impact of the opinion adherence parameter θ on (a) agents' opinion trajectory $< S >$, (b) decision trajectory $< X >$, and (c) evacuation rate $< \Phi >$ for Case 1. The impact of α on agents' (d) opinion trajectory $< S >$, (e) decision trajectory $< X >$, and (f) evacuation rate $< \Phi >$ for Case 2. The corresponding results for Case 3 are presented in Figures g-i. Note that $\theta = 0.5$ for the analysis in Cases 2 and 3.

3.3.3 Impacts of Social Media on Agents' Evacuation Processes

The sensitivity analysis of the previous section considers at most two information sources simultaneously. In this section, we consider all three information sources (i.e., global broadcast, social media, and neighbor observation as illustrated in Figure 3.6a) and evaluate how they jointly affect agents' opinion dynamics and evacuation processes. In particular, we analyze the impacts of social media on the modeling results.

Figure 3.6b shows the agents' evacuation rates under different settings of influence parameters $\alpha,\ \beta,$ and γ. The modeling results provide several implications. First, we observe that the system can achieve a high evacuation rate when global broadcast has a large influence on agents' opinion dynamics (i.e., α is large, corresponding to zone B in Figure 3.6b). In contrast, agents' evacuation rate is low when neighbor observation has large influence (i.e., γ is large, corresponding to zone A in Figure 3.6b).

Second, increasing influence of social media will make the system more sensitive to the influence of other information sources (i.e., from zone C to D and E in Figure 3.6b). For example, a small change in α or γ leads to a significant change in agents' evacuation rates in zone E. Social media result in lower evacuation rates when the influence of global information decreases (indicated by the solid arrow in Figure 3.6b). On the other hand, social media will increase evacuation rates when the influence of global broadcast increases (indicated by the dashed arrow in Figure 3.6b).

The results suggest that the influence of the global forecast α is crucially important to agents' evacuation behaviors. No agents will evacuate if the influence of global information is very weak. This is similar to a real world case of a 2016 flash flood in Xingtai, a city in China.

The local government's flood warning was not on time, many local residents did not take evacuation actions, and more than 150 people lost their lives in the flood [*Makinen*, 2016].

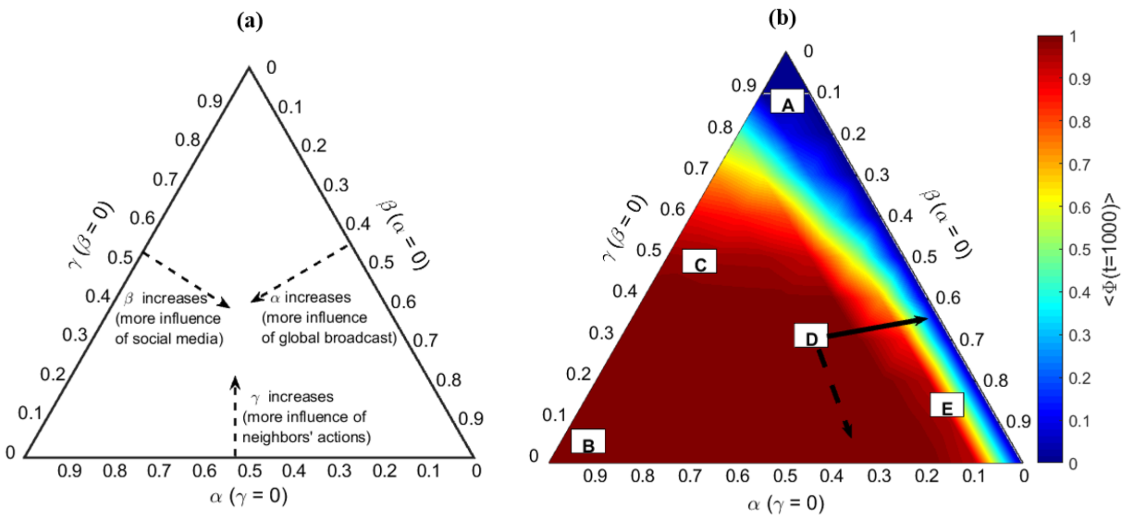


Figure 3.6 (a) Illustration of the scenarios that consider influences of the three information sources. (b) Ternary plot of agents' evacuation rates $<\Phi>(t=1000)$ under different settings of influence parameters α, β, and γ.

The results here also show that communication through social media decreases the variation among individuals' opinions and causes them to take actions at a similar pace. This is in line with empirical observations of herd-like behaviors during emergency situations, in which some people simply follow others' actions [*Schelling*, 1973; *Haque*, 1995; *Watts*, 2002]. Social media ease sharing of individual opinions and enhance influence on others' decision making, and thus could cause unexpected collective behaviors or even chaos (e.g., the "salt-rush" in China after the 2011 Japan nuclear crisis [*Brenhouse*, 2011]).

3.3.4 Impacts of Stubborn Agents Escalated by Social Media

Many previous studies have indicated that some agents insist on their own opinions and ignore any new information [*Galam and Jacobs*, 2007; *Yildiz et al.*, 2013]. These agents are typically referred to as *stubborn agents* in the study of opinion dynamics [*Ghaderi and Srikant*, 2014]. For example, in the case of the 2007 Cyclone Sidr in Bangladesh, thousands of individuals remained in their homes despite receiving early warnings and evacuation orders from emergency managers [*Paul and Dutt*, 2010]. This section investigates how the behaviors of stubborn agents affect the opinion dynamics and evacuation processes of the entire community.

In this study, stubborn agents' opinions are set as 0 over the entire simulation time. Figure 3.7 presents the entire population's average opinions and evacuation rates corresponding with various percentages of stubborn agents in the group. The results show that stubborn agents can prevent the entire group from updating their opinions to high levels and therefore reduce agents' evacuation rates, especially when there are many stubborn agents or social media weighting is higher (β is larger). For example, the agents' evacuation rates decrease from 80% to 58% when the percentage of stubborn agents increases from 10% to 20% (the red line in Figure 3.7b). With a fixed 5% of stubborn agents in the group, the agents' evacuation rates are reduced to 94%, 91%, and 73% when β is 0.3, 0.5 and 0.7, respectively (Figure 3.7b). In particular, as can be seen, evacuation rates respond to the percentage of stubborn agents in a non-linear manner when social media become more influential. When the percentage of stubborn agents exceeds a threshold (e.g., 5% in Figure 3.7b for the red line), the impact of stubborn agents on evacuation rates will be intensified by sources of information. Stronger social media can significantly reduce evacuation rates (e.g., in the case of 10% stubborn agents, evacuation rates decrease from 90% to 80% when β increases from 0.5 to 0.7).

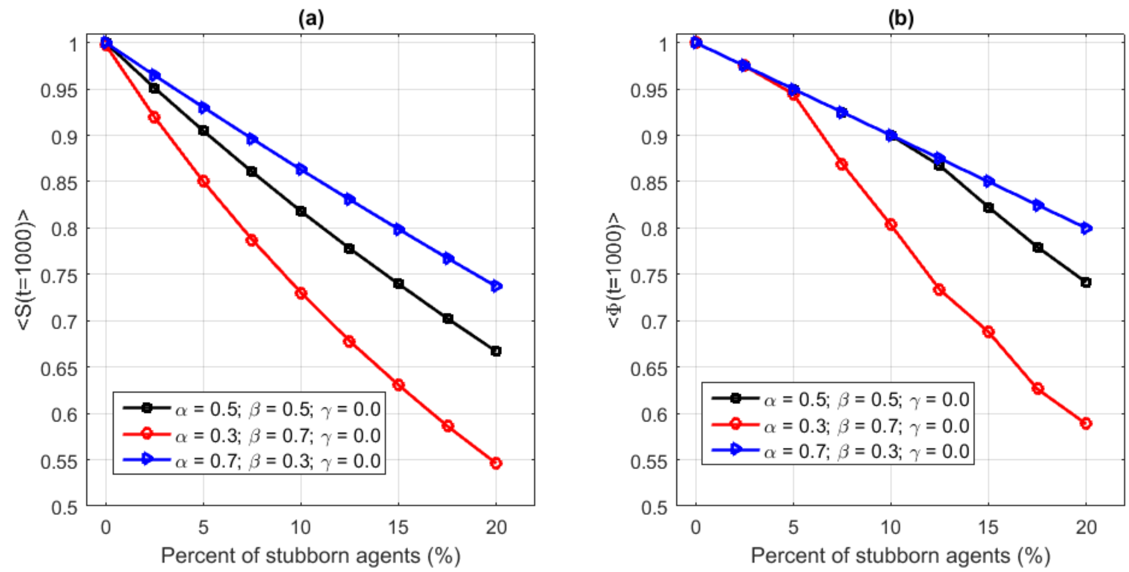


Figure 3.7 The impacts of stubborn agents on agents' (a) average opinion $< S > (\mathrm{t} = 1000)$ and (b) evacuation rates $< \Phi > (\mathrm{t} = 1000)$.

Figure 3.8 illustrates how the impacts of stubborn agents on the evacuation rate are affected by the weights of multiple information sources. Figure 3.8a displays agents' evacuation rates with 5% stubborn agents in the group. It is noticed that the patterns of the agents' evacuation rates are consistent with those shown in Figure 3.6b (e.g., zone A has a low evacuation rate due to limited influence of global flood warnings). However, the evacuation rate in Figure 3.8a changes in a smoother manner. Figure 3.8b compares the differences between the cases with (Figure 3.8a, 5% stubborn agents) and without stubborn agents (Figure 3.6b). It is noticed that the impact of stubborn agents increases from regions C to D and E. This implies that social media, as they become more influential, make the evacuation process more vulnerable to stubborn agents. This is shown in some real world incidences of inaccurate and misleading information from social media, e.g., altered images and false news about the flood conditions during the days of Hurricane Sandy in 2012 [*Alexander*, 2014]. Thus, it is important for emergency managers to identify stubborn agents in the community and correct the misinformation that they broadcast through social media in a timely manner during a crisis.

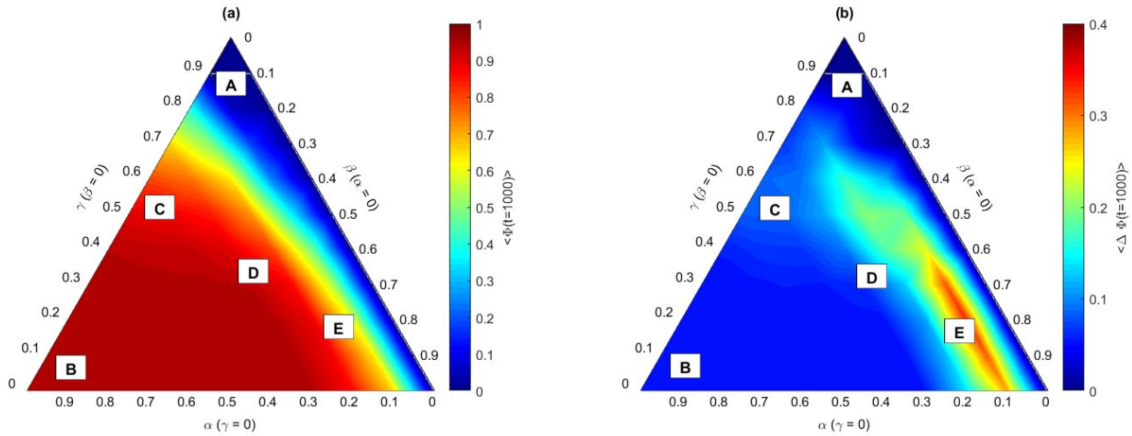


Figure 3.8 (a) Ternary plot of agents' evacuation rates $<\Phi>(\mathrm{t}=1000)$ with 5% of stubborn agents in the group, and (b) the differences in $<\Phi>(\mathrm{t}=1000)$ between the scenario with 5% of stubborn agents (Figure 3.8a) and the scenario without stubborn agents (Figure 3.6b).

3.3.5 Impacts of Flood Forecast Quality and Transportation Capacity

Lastly, we investigate the impacts of two other key factors on agents' opinion dynamics and evacuation processes: flood forecast quality and transportation capacity.

Figures 3.9a-3.9c show that the quality of the flood forecast can significantly affect agents' opinions on flood risk and evacuation rates. Poor quality of flood warnings (i.e., with smaller δ) results in slower update of flood risk awareness (Figure 3.9b) and fewer agents choosing to evacuate (Figure 3.9c). This concurs with the need for improving the reliability of flood warnings for crisis management, as evidenced by the case of 2016 Xingtai flood in China [*Makinen*, 2016].

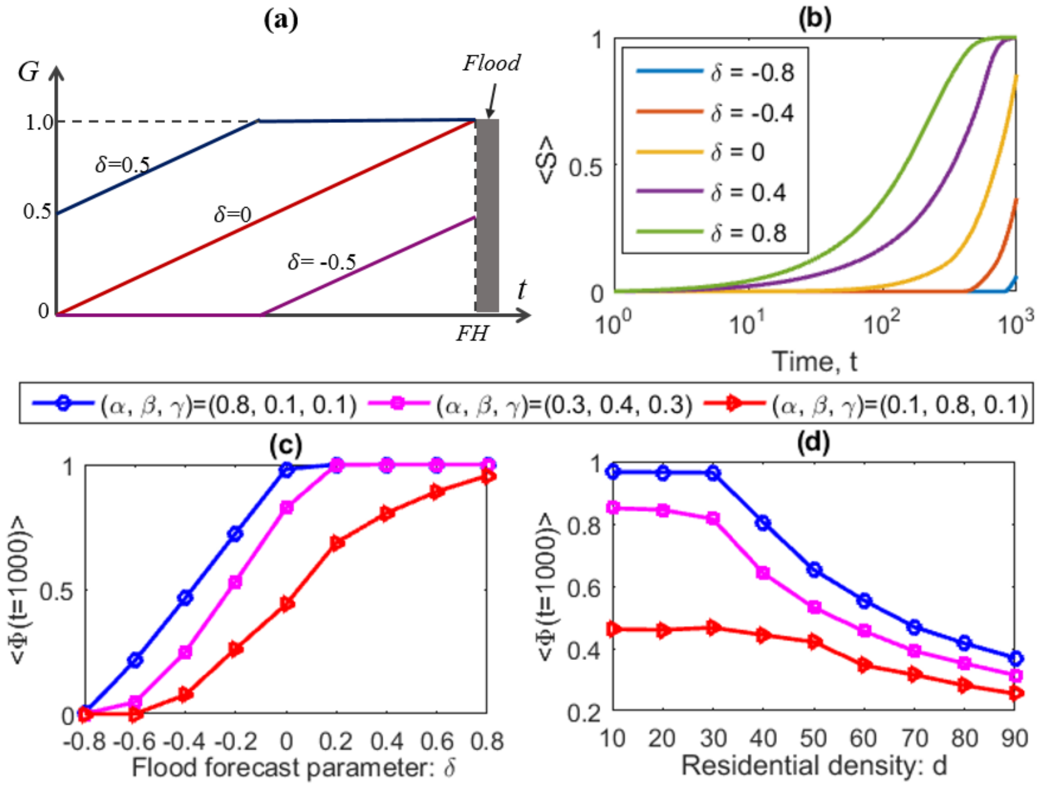


Figure 3.9 (a) A simple model of flood forecast quality with smaller δ for poorer forecast. (b) Agents' opinion trajectories under scenarios of different flood risk forecast qualities when $(\alpha,\beta,\gamma)=(0.3,0.4,0.3)$. (c) The joint impacts of weighting parameters for information sources ($\alpha,\ \beta,$ and γ) and forecast quality (δ) on agents' evacuation rate (when the residential density is set as $d=20$). (d) The joint impacts of weighting parameters and residential density on agents' evacuation rate (when $\delta=0$).

Furthermore, we assess the joint impacts of multiple modeling parameters, i.e., flood forecast uncertainty, residential density (a substitute for network capacity), and weights of information sources, on agents' evacuation rates (Figures 3.9c-3.9d). In general, the figures show that evacuation rates are higher when global flood warnings are more influential (α is larger), flood forecast quality is higher (δ is larger), and residential density is lower (d is smaller).

However, the impacts of each individual parameter on the modeling results also depend on other parameters. The complex interplay of these parameters is summarized as follows.

First, under a poor flood forecast scenario (e.g., $\delta < 0$) , the quality of flood warnings becomes a dominant factor that affects the modeling results. When flood forecast improves (δ becomes larger), the weighting parameters for information sources (α, β, and γ) become more important factors. It is also noticed that more influential social media can slow down the increase of agents' evacuation rates with improved flood forecast (Figure 3.9c). Second, when the residential density is low (e.g., $d = 10$), the weighting parameters for information sources are the dominant factors on agents' evacuation rates. In contrast, when residential density is high (e.g., $d = 90$), the weighting parameters have little impact on the modeling results (Figure 3.9d). These findings suggest that the quality of flood warnings and residential density determine the range of agents' evacuation rates. In comparison, the weighting parameters of the information sources determine the actual evacuation rates based on the influence of the various information sources. When flood warning and residential density are not hard constraints (e.g., $\delta \geq 0; d \leq 30$ in Figures 3.9c-3.9d), the weighting parameters of the information sources become the dominant factors that affect agents' evacuation processes. This highlights that crisis management in flood events requires (1) satisfactory flood forecasts, (2) efficient flood warning dissemination systems, and (3) well-planned evacuation procedures in a community with low residential density and high transportation capacity [*Litman*, 2006; *Murray-Tuite and Wolshon*, 2013].

3.4 Conclusions

In this study, we develop an agent-based modeling framework that couples a general opinion dynamics model and a traffic model to investigate the influence of opinion dynamics on flood evacuation processes. The coupled model simulates agents' opinion dynamics and evacuation processes under the influence of multiple information sources, flood forecast quality, and transportation systems. The results show that stronger social media can make evacuation processes more sensitive to the change of global flood warnings and/or neighbor observations, and thus, impose larger uncertainty on evacuation processes (i.e., a large range of evacuation rates corresponding to the change of global information and/or neighbor observation). We also find that evacuation rates respond to the percentage of stubborn agents in a non-linear manner. After the percentage of stubborn agents exceeds a threshold, the impact of stubborn agents on evacuation rates will be intensified by sources of information, and stronger social media can significantly reduce evacuation rates under this condition. Therefore, social media impose uncertainties to the flood evacuation processes and complicate evacuation planning and coordination during flood events.

Our results highlight the importance of mapping inaccurate or misleading information in social media and identifying stubborn individuals to allow first responders and emergency managers to mitigate any undesirable influences. In addition, flood warnings with low quality and high residential density can result in low evacuation rates, which highlights the need for improving the quality flood warnings and transportation infrastructure during flooding events.

Opinion formation, flood risk perception, and evacuation decision are complex processes that need both empirical and theoretical investigation from interdisciplinary fields [*Haque*, 1995; *Parker et al.*, 2007b; *Gladwin et al.*, 2009]. Social media not only provide efficient communication platforms for individuals to exchange information, but also create large amounts of data that describe people's behaviors. These data can be collected and analyzed by advanced data query and machine learning technologies [*Bellomo et al.*, 2016; *Granell et al.*, 2016; *Gil de Zúñiga and Diehl*, 2017]. Synthetic models, such as the one presented in this study, can benefit from these data and technologies for model verification and calibration. Recommended future studies include the use of empirical data to measure the various behavioral parameters, validating or modifying assumptions in the opinion dynamics simulation, extending the model to more realistic and complex transportation networks, and incorporating uncertainties in spatial and temporal variability in flood warnings.

Chapter IV. Impacts of the Interplay of Farmers' Behaviors on an Agricultural Water Market

This chapter addresses the issue of simulating multiple behaviors, using drought as a case study. Farmers' multiple behaviors, namely irrigation behavior and bidding behavior, are incorporated in a hypothetical water market based on a double auction. The joint impacts of the behavioral parameters on the water market are evaluated under different hydrological conditions.

4.1 Introduction

Irrigation is the primary water consumer in many regions around the world [*Donohew*, 2009; *Wang*, 2012]. Satisfying agricultural water demand has become more challenging due to population growth and competing water demands from municipal and industrial sectors, especially during drought events. Under conditions of water scarcity, water markets are considered efficient instruments to reallocate water and increase crop production because they can enable water to be transferred from low-value uses to high-value uses [*Hearne and Easter*, 1997; *Easter et al.*, 1999; *Yoskowitz*, 1999; *Adler*, 2009; *Palazzo and Brozović*, 2014].

In the past decades, many regions have proposed and/or implemented a variety of water-trading programs for both surface water and groundwater resources management [*Saliba*, 1987; *Dragun and Gleeson*, 1989; *Hamilton et al.*, 1989; *Chang and Griffin*, 1992; *Griffin and Boadu*, 1992; *Murphy et al.*, 2000; *Raffensperger and Milke*, 2005; *Brennan*, 2006; *Raffensperger et al.*, 2009; *Bauer*, 2010; *Grafton and Horne*, 2014]. Some studies also propose to address environmental issues in the context of water markets [*Iftekhar et al.*, 2013; *Kuwayama and Brozović*, 2013]. However, it is widely recognized that water markets do not function as well as expected in the real world [*Easter et al.*, 1998; *Hadjigeorgalis*, 2008; *Kaufman*, 2012]. The potential benefits of water markets are influenced by a variety of institutional, environmental and economic factors, including but not limited to (1) water rights legislation and institutional developments that clearly define water rights and facilitate water trading among water right holders [*Griffin*, 1998; *Bjornlund*, 2003; *Howe and Goemans*, 2003; *Turral et al.*, 2005; *Brozović and Young*, 2014], (2) transaction costs (e.g., the cost of finding trading partners and trading water) and third-party effects (e.g., downstream stakeholders might be affected by water trading in upstream) [*Colby*, 1990; *Pujol et al.*, 2006; *Luo et al.*, 2007; *Donohew*, 2009; *Wang*, 2012; *Erfani et al.*, 2014], (3) hydrological conditions [*Pujol et al.*, 2006; *Luo et al.*, 2007; *Kuwayama and Brozović*, 2013; *Palazzo and Brozović*, 2014], and (4) the behaviors of water users (i.e., water sellers and buyers in a water market) [*Easter et al.*, 1998; *Bjornlund*, 2003; *Nguyen et al.*, 2013]. In this paper, we will analyze the impacts of water users' behaviors on the performance of agricultural water markets.

In agricultural systems and water markets, farmers' decision making for irrigation and water trading are complex and may vary from farmer to farmer, from region to region, and from year to year. Many studies simulate farmers' water use behaviors and/or evaluating the potential benefits of water markets under a variety of hydrological and institutional conditions [*Garrido*, 2000; *Tisdell*, 2001; *Iftekhar et al.*, 2013; *Foster et al.*, 2014; *Zeng et al.*, 2015]. However, these studies in general have two limitations. First, farmers are typically simulated as homogeneous decision makers [*Tisdell*, 2001; *van Heerden et al.*, 2008], but the heterogeneity in farmers' individual irrigation decision-making (e.g., risk aversion to crop water deficit) is not explicitly captured in these models. However, studies have shown that farmers' decision-making can be affected by their own perceptions, experiences and social networks [*Mertz et al.*, 2009; *Deressa et al.*, 2011; *van Duinen et al.*, 2015].

Second, to simulate farmers' trading decisions, previous studies typically use optimization methods to represent farmers' water-trading behaviors in order to evaluate the performance of water markets [*Characklis et al.*, 1999; *Garrido*, 2000; *Pujol et al.*, 2006; *Luo et al.*, 2007; *Erfani et al.*, 2014; *Zeng et al.*, 2015]. However, the assumptions behind the optimization methods (e.g., symmetric and sufficient information available for all farmers to find trading partners, efficient bargaining process for farmers to determine water price, etc.) can rarely be satisfied in the real world [*Nguyen et al.*, 2013]. Studies have shown that the performance of markets can be greatly affected by market participants' individual trading strategies, which are not necessarily fully rational and can prevent water markets from being perfectly competitive [*David and Wen*, 2000; *Hao*, 2000; *Rodriguez and Anders*, 2004; *Vytelingum et al.*, 2008; *Wang et al.*, 2011; Nguyen et al 2013]. Thus, following the argument of *Nguyen et al.* [2013], it can be more practical to simulate water markets based on a set of trading rules and market structures.

To represent and simulate individuals' heterogeneous behaviors, agent-based modeling (ABM) has been used in many studies in a variety of domains, including decision making in social and economic sciences [*Bonabeau*, 2002; *Farmer and Foley*, 2009; *Berglund*, 2015; *van Duinen et al.*, 2016]. Unlike the centralized top-down approach, ABM follows a bottom-up approach to simulate systems with a group of autonomous, interdependent, and adaptive decision makers (defined as agents) [*Macy and Willer*, 2002; *Kirman and Tuinstra*, 2005; *An*, 2012]. ABM can explicitly represent the heterogeneous attributes and behaviors of each agent at the bottom level, and then aggregates the behaviors of all individual agents to explore the complex emergent phenomena at the system level [*Rand and Rust*, 2011].

In recent years, there have been several studies applying ABM to simulate farmers' irrigation behaviors in agricultural systems [*Ng et al.*, 2011; *Miro*, 2012; *Noël and Cai*, 2017].

Miro [2012] incorporates a behavioral parameter in an ABM to represent farmers' sensitivity to soil water deficit. *Ng et al.* [2011] develop an ABM to simulate farmers' land use decisions in the context of biofuels development. They explicitly incorporate multiple behavioral parameters in the model to simulate farmers' responses to the variability of weather and crop prices. *Noël and Cai* [2017] demonstrate that model outputs can be influenced by including individual heterogeneities. Other studies have focused on applying ABM to simulating markets for water resources and emission credits [*Zhang et al.*, 2010; *Yang et al.*, 2012; *Iftekhar et al.*, 2013; *Nguyen et al.*, 2013]. In particular, *Zhang et al.* [2010] and *Nguyen et al.* [2013] simulate auction markets for sulfur dioxide and wastewater pollution credits, respectively, in which agents' trading behaviors are represented by a set of behavioral parameters that describe agents' degree of rent seeking when making bids and learning rate for updating bidding strategies.

According to our knowledge, this study is the first to combine farmers' irrigation behaviors [*Miro*, 2012; *Noël and Cai*, 2017] and bidding behaviors [*Zhang et al.*, 2010; *Nguyen et al.*, 2013] in an ABM to simulate their joint impacts on an agricultural water market. The model allows us to explore the interplay of these factors and their joint impacts on water market performance under different hydrological conditions. This extends the models developed by *Miro* [2012], *Zhang et al.* [2010] or *Nguyen et al.* [2013] by evaluating how multiple behavioral parameters jointly affect the model outputs and how the impacts and interplay of the parameters vary under different hydrological conditions. In addition, unlike previous water market simulations that operate at annual or seasonal time scale [*Yang et al.*, 2012; *Iftekhar et al.*, 2013], we simulate a daily water market that allows exploration of the impacts of agents' behavioral parameters on daily price dynamics [*Bjornlund*, 2003; *National Water Commission*, 2009; *Broadbent et al.*, 2010].

The rest of this chapter is structured as follows. Section 4.2 and 4.3 introduce the methodology and case study, respectively. The modeling results are presented in Section 4.4, followed by discussions in Section 4.5 and conclusions in Section 4.6.

4.2 Methodology

This section introduces the mechanisms of the agricultural water market, the agent-based model used to simulate farmers' behaviors, and model construction and execution process.

4.2.1 Mechanisms of the Water Market

Empirically, water rights are typically traded in two ways in water markets: permanent sale and short-term lease [*Brennan*, 2006; *Hansen et al.*, 2015]. The former refers to trade of water entitlement while the latter refers to lease of water use rights without transfers of water right entitlement [*Easter et al.*, 1999]. Short-term lease does not change water entitlements and provides flexibilities for water right holders to make decisions in the face of uncertainties about future water availability. Studies have shown that water right holders traded much more water through short-term leasing than permanent sale [*Turral et al.*, 2005; *Donohew*, 2009]. In this study, we simulate short-term leasing water markets. Farmers can buy water permits from, or sell them to, other farmers without changing the ownership of their water right entitlements. Furthermore, following *Broadbent et al.* [2010], which describes the institutional framework for the operation of real-time water markets, this study simulates a water market that operates at a daily time scale.

This study adopts auction as a trading mechanism that has been promoted by experimental economists and applied to numerous market studies [*Nicolaisen et al.*, 2001; *Posada and Lóoez-Paredes*, 2008; *Zhang et al.*, 2010; *Bai*, 2013; *Nguyen et al.*, 2013]. An auction is a typical trading mechanism for people to trade goods. Among various types of auction mechanisms, the double auction is considered to have great potential to increase the efficiency of water markets and has been implemented in the real world (e.g., Australia, U.S.) [*Howe*, 1997; *Bjornlund*, 2003; *Brozović and Young*, 2014] and many other studies [*Nicolaisen et al.*, 2001; *Posada and Lóoez-Paredes*, 2008; *Bai*, 2013; *Nguyen et al.*, 2013]. The double auction can function as either uniform-price auction (i.e., all units in the market are traded at the same price) or discriminatory-price auction (i.e., units are traded at different prices) [*Nicolaisen et al.*, 2001; *Jackson and Kremer*, 2006]. As shown by *Jackson and Kremer* [2006], if the supply is fixed, then either a uniform price auction or discriminatory price auction leads to efficient allocations. For the market designed for this study, the total amount of water permits to trade is fixed. Thus, either of two market mechanisms satisfies the efficient condition. We simulate the discriminatory-price double auction, in which each agent's transaction price depends on his own bid price. This takes the advantage of an ABM that simulates the heterogeneous behaviors of bidding decisions.

The procedures of the market operations are described as follows. At the beginning of each day, the water market opens to receive farmers' bids. Each bid will specify the name of the bidder, the bid price, and the amount of permitted water allocations to trade (Note that the term "amount of permitted water allocations" is abbreviated to "water permits" in the following sections). Then the market will collect all of the bids and match them to result in transactions in the following way. Sellers' (buyers') bids are sorted in ascending (descending) order according to their bid prices. The buyer with the highest bid price will be matched with the seller with the lowest bid price. A transaction will occur if the bid price of the buyer is higher than the bid price of the seller. The transaction price is set as the average of the two bid prices and the transaction amount is set as the smaller of the two bid amounts. If the buyer's and seller's bid amounts are not equal, the bid with a remaining trade amount will be matched with the second best bid in the market. This process continues until the highest bid price of buyers is lower than the lowest bid price of sellers. For detailed descriptions of the matching process, see *Nguyen et al.* [2013].

After the matching process, the water market informs each market participant of the transaction results. The transaction results include the following information: (1) whether the previous bid has resulted in transactions, (2) the trade price, and (3) the trade amount. In the proposed sealed-bid auction market, agents present their own individual bids, but they do not necessarily share their bids to and/or deduce the bids of their transaction partners. Such complex processes are not simulated in our model. Instead, we assume that the market authority will release the average trade price of implemented transactions to the public [*Bjornlund*, 2003]. In this way, agents, including those who do not participate in the market and/or whose bids do not result in transactions, are able to obtain some information about the market prices, which supports the learning processes (as illustrated in Figure 4.1).

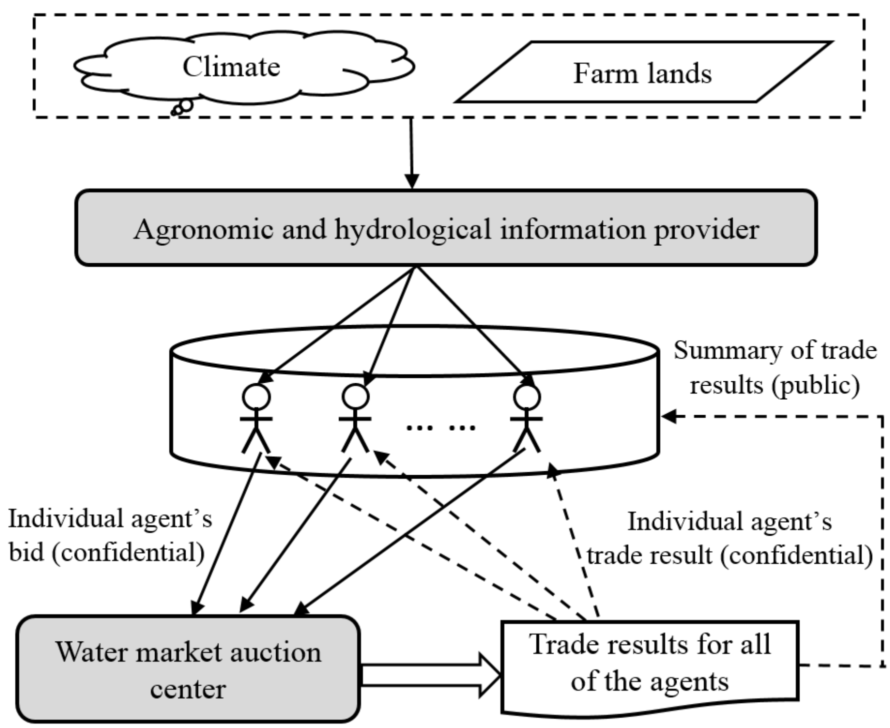


Figure 4.1 Information flow in the agricultural water market based on double auction

4.2.2 Agents and Behaviors

In this study, each farmer is simulated as a computer agent, which is described by a set of parameters representing the agent's attributes and behavioral rules. We primarily focus on two types of behaviors in this work, namely irrigation behavior and bidding behavior.

(1) Irrigation Behavior

Farmers' irrigation decisions (e.g., when and with how much water to irrigate crops) can depend on many factors, including their observations of soil dryness, plants' response to water deficit, water availability, observation of other farmers' actions especially those nearby, and suggestions from technicians such as crop advisors [*Jones*, 2004; *USDA*, 2008; *Andales et al.*, 2011; *van Duinen et al.,* 2016]. In this study, we follow previous studies and assume that farmers' irrigation decisions are driven by maintaining a certain level of soil moisture to reduce crop yield losses or increase profits [*Jones,* 2004; *Foster et al.*, 2014]. Following this concept that has been adopted in previous studies on farmers' decision making [*Steduto et al.*, 2009; *Andales et al.*, 2011], we use the water balance approach to simulate farmers' irrigation decisions. In this approach, farmers compare water deficit in soil (D_c) and management allowed water deficit (d_{MAD}) for the crop and apply irrigation practices when D_c exceeds d_{MAD} [*Allen et al.*, 1998]. It is assumed that information about soil moisture, crop growth, and climate are available to all of the farmers through an information provider (Figure 4.1), thus farmers can follow this standard rule to guide their irrigation practices.

As mentioned above, farmers' irrigation decisions can be affected by many factors and their irrigation decisions may vary, leading to behavioral heterogeneity [*Andriyas and McKee*, 2014; *van Duinen et al.*, 2015]. To represent this heterogeneity, we include a behavioral parameter λ in farmers' irrigation decisions, following the approach of *Miro* [2012] and *Noël and Cai*,

[2017]. λ is a non-negative, dimensionless parameter that measures the degree of a farmer's sensitivity to soil water deficit (i.e., a larger λ represents a farmer that is less sensitive to water deficit). The irrigation decision of a farmer is represented by equation (1).

$$\text{Irrigation} = \begin{cases} No, & \text{if } Dc < \lambda \times d_{MAD} \\ Yes, & \text{if } Dc \geq \lambda \times d_{MAD} \end{cases} \tag{1}$$

(2) Bidding Behavior and Learning

Bidding behavior describes how an agent makes strategic bidding decisions to trade water permits in the market and how the agent updates its bidding strategy by learning from its trade experiences. In this study, each agent has a water permit, which constrains the maximum amount of water the agent can withdraw from river. Agents can enter the market to make a bid to buy or sell their water permits. The bid consists of three variables: (1) the agent's role in the market, denoted by a categorical variable *r* (-1 for selling a water permit, 1 for buying water permits, and 0 for not participating in the market); (2) bid price (p , \$/acre-feet); and (3) bid amount (q, acre-feet). Agents who have used their entire water permits have to buy permits from other agents to satisfy their irrigation demands (r = 1). Agents who have leftover water permits can sell part of their permits to the agents who need them (r = -1). Agents that do not have leftover water permits will not participate in the water market (r = 0) if they do not need to irrigate crops.

It is assumed that agents' decision-making on bid price is affected by two factors: (1) reservation price (η) that presents an upper bound (for water buyers) or lower bound (for water sellers) of the bid price, and (2) rent seeking (μ) that measures the degree of the agent's greediness to pursue profit from trade [*Cliff and Bruten*, 1997]. By denoting agent *i*'s reservation price and rent seeking at time *t* as $\eta_{i,t}$ and $\mu_{i,t}$, respectively, the agent's bid price $p_{i,t}$ can be represented by equation (2).

$$p_{i,t} = \begin{cases} (1-\mu_{i,t}) \times \eta_{i,t}, & \text{(for buyer, } 0 \le \mu_{i,t} \le 1) \\ (1+\mu_{i,t}) \times \eta_{i,t}, & \text{(for seller, } 0 \le \mu_{i,t}) \end{cases} \quad (2)$$

In this study, agents' reservation prices depend on the marginal benefit of irrigation water use and transaction cost for water trade. The marginal benefit of irrigation depends on crop price, crop-growing stage, soil properties, irrigation cost, and other agronomic parameters; therefore, agents' reservation prices will vary over time for an individual farmer and vary across farmers. We assume there is a transaction cost for each unit of traded water permit. Transaction cost can be set as a constant cost (e.g., registration cost for participating in the market) plus a trading cost for each transaction (e.g., tax for trading) [*Luo et al.*, 2007; *Zhang et al.*, 2010]. In this study, we assume there is no registration cost for market participation, and the transaction cost is dependent on the amount of transacted water use permits and trading price. Coefficient of transaction cost (ω) is used to measure the ratio of trading cost relative to the trading price for water permit (e.g., for a transaction with trading price *p* and trade amount *Q*, transaction cost can be represented by ωpQ). A larger ω is associated with a higher transaction cost.

As mentioned above, when making a bid in the market, a buyer (seller) will always bid a price lower (higher) than his reservation price in order to gain profit. The larger the value of rent seeking (μ) is, the more profit the agent aims to gain from trade ($\mu \in [0,\ 1]$ for buyers, and $\mu \ge 1$ for sellers). In this context, whether the two bids from a buyer and a seller can result in a transaction depends on: (1) if the buyer's reservation price is higher than the seller's (i.e., a transaction can happen only when the buyer's reservation price is higher than the seller's), (2) agents' degree of rent seeking, and (3) transaction cost for water trade. If buyers and sellers both have a high degree of rent seeking, or transaction cost for water trade is high, their bid prices will diverge more from their reservation prices and trade will be less likely to occur in the market.

After receiving the transaction results from the auction center, an agent will learn from the results and adapt its bid strategies for the next round. The adaptation process requires agents to have some level of intelligence. Some studies have explored the level of intelligence that could make agents achieve human-level performance in markets. *Gode and Sunder* [1993] proposed Zero-Intelligence (ZI) agents and found that the ZI agents could achieve market equilibrium as long as the bids do not result in loss-making transactions. Based upon this work, *Cliff and Bruten* [1997] proposed Zero-Intelligence-Plus (ZIP) agents that incorporate a machine-learning algorithm to update agents' degree of rent seeking based on previous transaction results. They showed that the performance of ZIP agents is more robust than that of ZI agents. A series of laboratory experiments conducted by *Das et al.*, [2001] further demonstrated that ZIP agents could obtain larger gains from trade than ZI agents in the auction experiments because of behavioral improvements via machine learning. A number of studies have adopted ZIP agents' learning strategies in simulating different types of markets such as emission allowance markets [*Zhang et al.*, 2010; *Liu et al.*, 2012; *Zhou et al.*, 2013], energy markets [*Nicolaisen et al.*, 2001; *Pourebrahimi et al.*, 2008; *Fagiani and Hakvoort*, 2014] and financial markets [*Vytelingum et al.*, 2008].

In this study, we apply the learning strategies of the ZIP agent to simulate farmers' learning process. ZIP agents' learning process is represented by a behavioral parameter, learning rate (β), as shown in equation (3).

$$\mu_{i,t+1} = \mu_{i,t} + \beta_i(\tau_t - p_{i,t}) / \eta_{i,t} \tag{3}$$

where τ_t is the target price at *t*, which is set as the transaction price if agent *i*'s bid at time *t* results in transactions, or the average market price for water released by the market if the agent's bid does not result in a transaction or if the agent does not participate in the market at time *t*. β_i is the agent i 's learning rate, which is a dimensionless number ($\beta \in [0, 1]$). An agent with a larger β changes its degree of rent seeking by a greater value than those with a smaller β (the agent will not change its degree of rent seeking when $\beta = 0$). A momentum coefficient is typically introduced in ZIP bidding strategies to consider the randomness in agents' degree of rent seeking. For a more detailed description of the ZIP agent, see *Cliff and Bruten* [1997].

Quantification of agents' behavioral parameters is challenging if empirical knowledge of the distribution of agents' behaviors is lacking. Previous studies often address this challenge by assuming agents' behavioral parameters follow certain distributions (e.g., uniform or normal distributions) [*An*, 2012; *Bruch and Atwell*, 2015]. The normal distribution has been widely used in previous studies to introduce heterogeneity in agents' behaviors for sensitivity analysis [*Marino et al.*, 2008; *Huang et al.*, 2013; *Bertella et al.*, 2014]. In this study, due to the lack of available data, we use normal distributions to sample the behavioral parameters (i.e., λ, μ, and β) for sensitivity analysis for each scenario. Note that it is also feasible to use other distributions (e.g., uniform distribution). The next section provides details on how these behavioral parameters are assigned in each scenario.

ABMs typically face difficulty in model validation when empirical data are not sufficient [*Manson*, 2003; *Ngo and See*, 2011; *Huang et al.*, 2013]. To address this issue, *Manson* [2013] proposes two model validation methods for ABMs: (1) structure validation that measures how well the model represents theoretical mechanisms and expert opinions, and (2) outcome validation that measures how well the model outputs fit empirical data. This study mainly focuses on understand some theoretical questions regarding human behaviors in a hypothetical water market, rather than on comparing our model results with observed trading data. Therefore, in the current study we focus on "structural validation" – ensuring that the model follows some validated theories of farmers' irrigation decisions (e.g., [*Steduto et al.*, 2009; *Noël and Cai*, 2017]) and agents' behaviors in markets (e.g., [*Smith*, 1982; *Cliff and Bruten*, 1997; *Nguyen et al.*, 2013]). In future if the water market is implemented in the real world, we can perform "outcome validation" when observed water trading data become available.

4.2.3 Model Implementation

We construct the agent-based model in the object-oriented programming language Java. Table lists the key environmental, economic, institutional, and behavioral parameters for model input. Figure 4.2 depicts the flowchart of the model execution process. The model starts with the selection of a simulation year and agents' behavioral parameters for model construction. Then the model will simulate each agent's irrigation and bidding behaviors during the crop-growing season. At the end of each simulation year, the model will calculate crop production and evaluate the performance of the agricultural water market.

Table 4.1 List of variables associated with agricultural system and agent's behaviors

Factors	Variable	Meaning[unit]
Environmental and agronomic	*Loc*	Geographical location (i.e., latitude and longitude) [-]
	ET	Crop evapotranspiration [inch/day]
	P	Precipitation [inch/day]
	ST	Soil type (e.g., clay, sand, loam) [-]
	CA	Crop area [acre]
	CY	Crop yield [bushel/acre]
	IC	Irrigation cost [$/acre-feet]
	IE	Irrigation efficiency [-]
	LF	Leaching fraction for salinity control [-]
Institutional	*WP*	Water permit [acre-feet]
	ω	Coefficient of transaction cost for water trading [-]
Economic	*PC*	Price of crop [$/bushel]
	PW	Price of water permit [$/acre-feet]

Table 4.1 (cont.)

Behavioral	λ	Sensitivity to soil water deficit [-]
	μ	Rent seeking [-]
	β	Learning rate [-]

Note: [-] denotes dimensionless variable.

In this study, the performance of the water market is mainly measured by a matrix with two indicators at the system (watershed) level: (1) increased crop production (*ICP*, bushel), which is the difference of the total crop production (*TCP*) between the scenario with and without the water market, and (2) total traded water permit (*TTW*, acre-feet) in the water market. We also evaluate the relative water market performance (*RMP*) that compares the *ICP* of the agent-based water market and the optimization-based water market (i.e., model B2 in Table 4.2). Note that there are other indicators to measure the performance of water markets (e.g., equity of water permit distribution through markets), which are beyond the scope of this study.

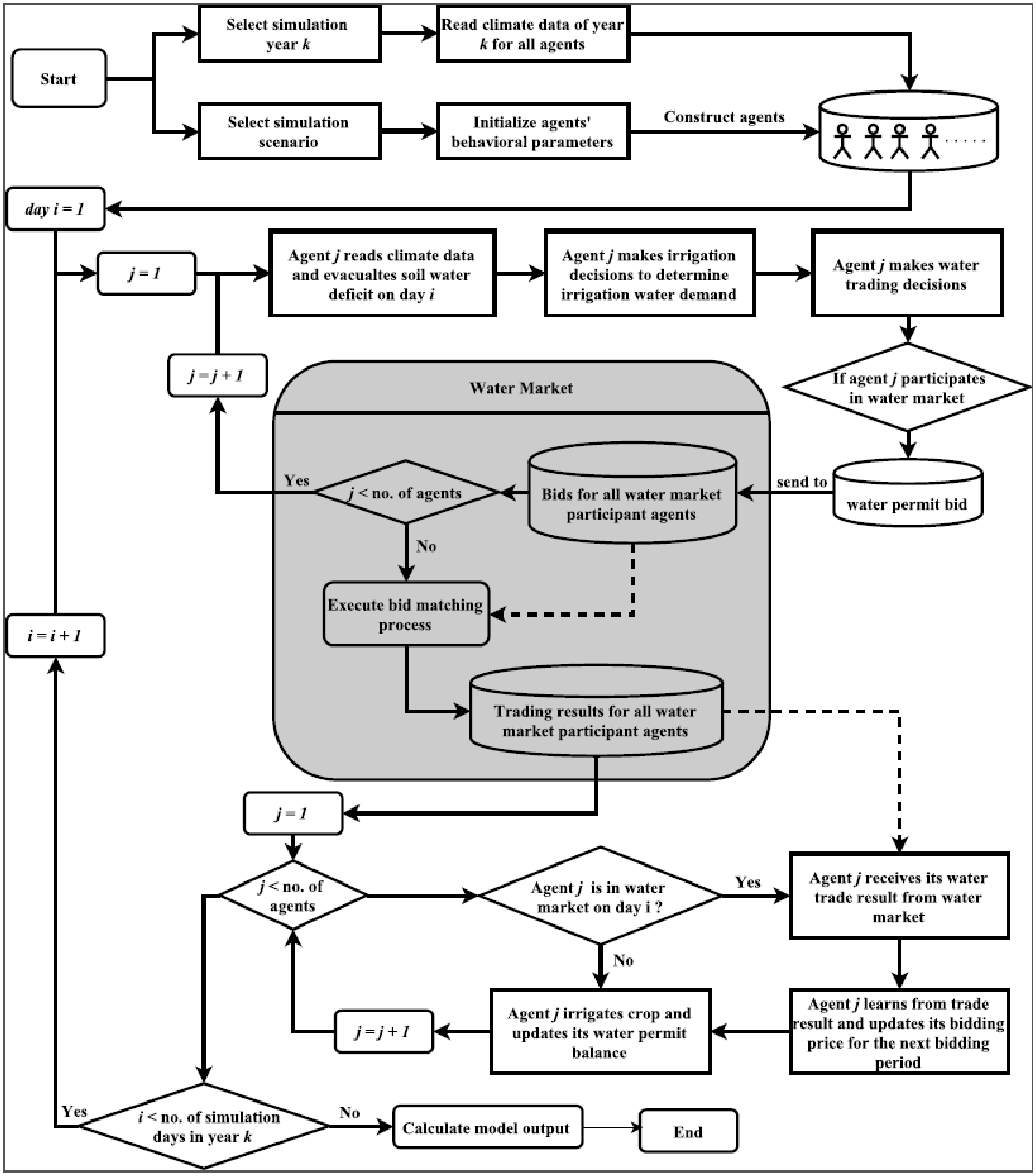


Figure 4.2 Flowchart of the agent-based model for agricultural water markets

4.3 Case Study and Experimental Design

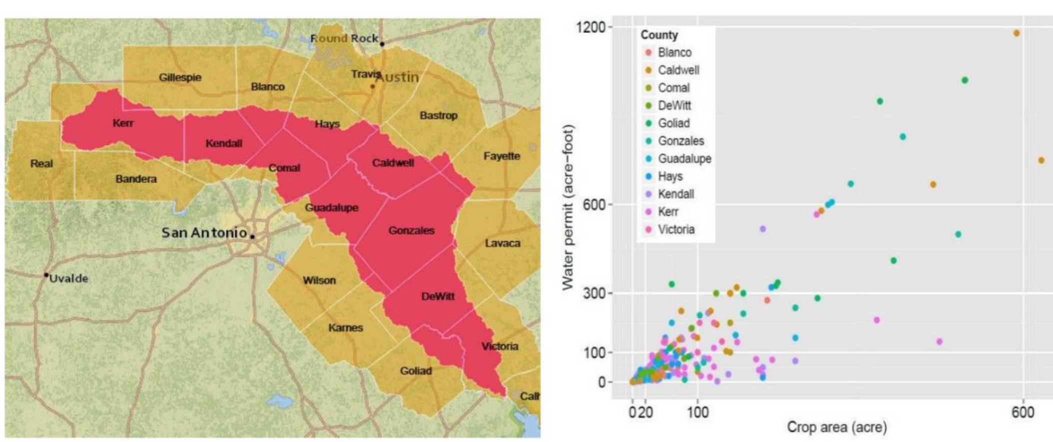
To assess the effects of farmers' behaviors using the model developed in section 4.2, we develop a hypothetical water market as a case study, based on a range of precipitation experienced recently in a Texas watershed, including the severe drought of 2011, the normal year of 2010, and wet year of 2007. Using this case study, experiments are designed to evaluate impacts of the behavioral parameters and hydrologic conditions on market performance.

4.3.1 Overview of the Case Study Area

We apply the water market model to the Guadalupe River Basin (GRB) in south Texas, a southwestern state within the United States. The GRB encompasses an area of 3,256 km^2 (~800,000 acres) (Figure 4.3a), with irrigation as one of the largest water consumers. The Texas Commission on Environmental Quality (TCEQ) regulates surface water resources. The water right holders' water permits, which we obtained from a TCEQ database, have been defined by the water law and their water uses are monitored by water masters employed by TCEQ [*Garcia et al.*, 2009]. There are in total 334 irrigation water right holders (corresponding to 334 agents in the model) distributed in 11 counties in the GRB. Water permits are not equally allocated among farmers. Some farmers' water permits allow much less water withdrawals than other farmers' (Figure 4.3b), which provides potential for water permits to be traded during drought events.

At the daily time scale, for rivers with a certain length (such as the study site, ~300 km), it is reasonable to assume that all farmers, upstream or downstream, can withdrawal some amount of water that satisfies their normal daily water demand. We assume the river is a common "lake" and upstream-downstream issues and streamflow hydrology do not affect the trade transaction. Since total water sought is equal to total water bought under the double auction, the daily streamflow at the outlet of the basin may remain the same as that without any trade. Streamflow at different segments of the river may be more or less affected depending on the locations of water sellers and buyers.

In order to simplify the agricultural system without addressing the complex decisions on crop choice, we assume the agents plant corn (i.e., the major crop planted in this area) on their croplands following the same crop planting and harvesting schedule. In this study, the agents are assumed to plant corn on March 16th and harvest on August 2nd (140 days in total), following the recommended date for corn's growing season in central Texas (http://www.texascorn.org). In irrigation practices, irrigation efficiency, leaching fraction for soil salinity control, and irrigation cost in the study area are set as 90%, 0.15, and 2.47$/acre-inch, respectively [*Letey et al.*, 2011; *Wagner*, 2012; *Foster et al.*, 2014]. Coefficient of transaction cost for water trade is set as 10%. Other data used in the model include soil properties (obtained from USDA soil survey, http://websoilsurvey.sc.egov.usda.gov), meteorology data (obtained from Weather Underground, http://www.wunderground.com), crop yield and crop price (obtained from USDA statistics services, http://quickstats.nass.usda.gov), and water permits and land area for each water user (obtained from TCEQ database, http://www.tceq.texas.gov/agency/data).



(a) The Guadalupe River Basin (b) Irrigation water right holders in GRB

Figure 4.3 (a) The geographical location of the Guadalupe River Basin; (b) Water permits versus crop area for irrigation water right holders in the watershed

In this study, we simulate a hypothetical water market that operates at the daily time scale, assuming that the infrastructure and institutional developments needed for the daily market is in place [*National Water Commission*, 2009; *Broadbent et al.*, 2010, 2011]. As mentioned in the previous section, an agent's water permit reflects the average weather condition and does not change with weather. Agents with limited water permits will face water shortages in dry years. We assume that agents will buy water permits only when the water remaining in their permits (i.e., total water permits minus total water withdrawals) cannot satisfy irrigation demand. This assumption is reasonable because speculative investments in water permits by those who are not in need of water to meet valid uses might impose threat to society [*Kaufman*, 2012]. Furthermore, we assume that agents do not have accurate weather forecast capabilities, and their irrigation decisions are only based on current irrigation demand. Previous work show that weather forecast has a limited role in farmers' irrigation scheduling [*Wang and Cai*, 2009; *Cai et al.*, 2011b; *Hejazi et al.*, 2014; *Shafiee-Jood et al.*, 2014]. However, to make the model more realistic, future work will be conducted to consider farmers' different responses to forecasts and forecast uncertainties.

4.3.2 Experimental Design

In this study, two other models are designed for comparison with the agent-based water market model, as shown in Table 4.2: (1) a baseline model that represents the scenario without water markets (model B1) and (2) a benchmark model that represents the market that would yield maximum crop production at the system level (model B2). Specifically, model B2 adopts an optimization approach that simulates a water market in which the cropland with highest crop productivity uses water first, followed by the lands with relatively lower productivity.

It is expected that system-level total crop production and total traded water permits from model A will be higher than those from model B1 and lower than model B2. The performance of model A water market will be highly dependent on agents' behavioral parameters. Similar to the findings of previous studies (e.g., [*Rosegrant et al.*, 2000; *Luo et al.*, 2007]), we expect that the water market will yield more increase in crop production in dry years than wet years.

Table 4.2 Baseline and benchmark models

Model	Model description	Behavioral parameters	Note
A	Agent-based water market model	λ, μ, and β	
B1	No water trading among agents	λ	Baseline model
B2	The water market that yields maximum crop production	λ	Benchmark model

Scenario-based analysis is applied to evaluate the impacts of farmers' behaviors on the water market. Two experiments are designed as shown in Table 4.3. The first experiment aims at exploring the impacts of the agents' two bidding parameters (i.e., rent seeking μ and learning rate β) on the water market. The second experiment then introduces multiple scenarios for the irrigation parameter (i.e., sensitivity to soil water deficit λ) in order to evaluate the joint impacts of the three behavioral parameters on the water market.

Monte-Carlo simulation method is used to obtain the average modeling results for each scenario. The procedure consists of three steps. The first step is selecting a particular scenario with the mean and coefficient of variation of each set of behavioral parameters in Table 4.3. The second step is generating random samples using the behavioral parameters in step one. The number of samples is equal to the number of agents (i.e., 334 in this study). The third step is assigning the behavioral parameters generated in step two to all of the agents without replacement. The model is executed 100 times to obtain the average modeling results for each scenario. Figure 4.4 gives an example of parameterizing agents' behavioral parameters for one particular scenario.

Table 4.3 Experiments to explore the impacts of agents' behaviors on the water market

Parameters	Experiment 1		Experiment 2	
	Mean	CV	Mean	CV
Sensitivity to soil water deficit λ	1		0.4~1.6	
Rent seeking μ	0~0.8	0.2	0~0.8	0.2
Learning rate β	0~0.4		0~0.4	

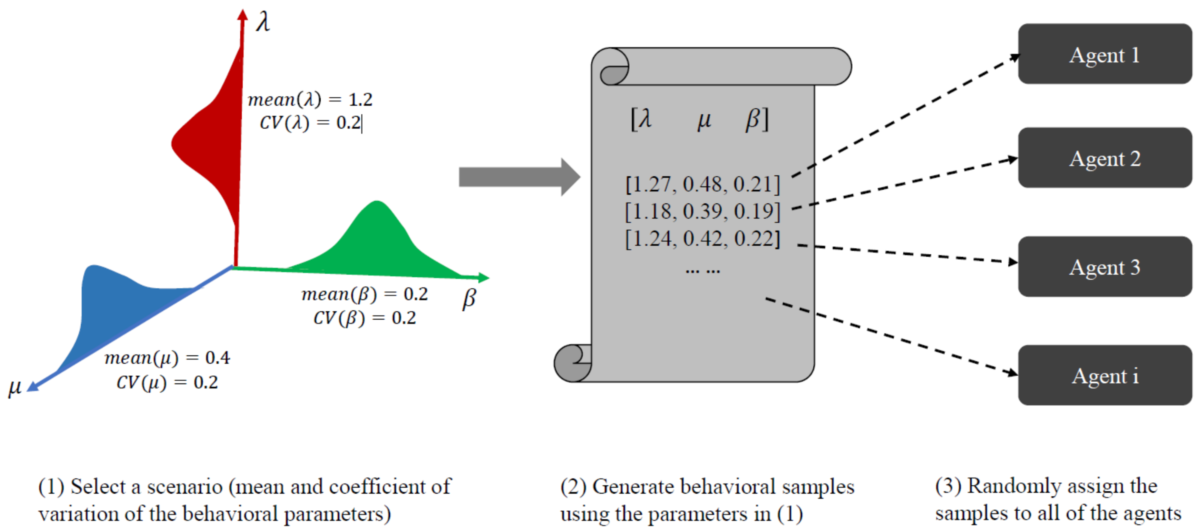


Figure 4.4 Illustration of the procedure for sampling the agents' behavioral parameters for one run in the Monte-Carlo simulation (i.e., the mean value for λ, μ, and β is 1.2, 0.4, and 0.2, respectively; coefficient of variation is 0.2 for λ, μ, and β).

4.4 Results

This section presents the model results and discussion. First, we execute experiment 1 to give an overview of the model results and evaluate the impacts of the bidding parameters on the water market. Then, we execute experiment 2 to evaluate the impacts of the irrigation parameter and evaluate how the three parameters jointly affect the water market.

4.4.1 Overview of Model Results for One Set of Parameters

The model is executed from 2001 to 2013 to evaluate the performance of the water market under different hydrological conditions. Figure 4.5 shows the simulation results for a particular scenario. Figure 4.5a shows the water-trading results for all of the agents, which indicate a clear pattern in agents' roles in the market. As expected, the agents with more water permits typically sell water to the ones with less water permits.

Four agents (identified from Figure 4.5a) are selected to compare their profit with and without the water market (Figure 4.5b), showing different impacts of the water market for different agents. With a water market, the total profit increases for all of the agents, especially for those with fewer water permits (e.g., agent 162 has a greater increase in total profit than agent 329). Agents with more water permits (e.g., agent 300 and agent 216) have reduced crop production because they sell a portion of their water permits to other agents, leaving less water to satisfy their own irrigation demand. However, the total profit of these agents increases because of the increased income from selling water. In addition, buyers with few water permits become active in the market earlier and buy more permits through the market than those with more permits (e.g., compare agent 162 and agent 329), which is in line with intuitive reasoning (i.e., during a drought event, agents with fewer water permits will experience water shortages earlier than those with more water permits).

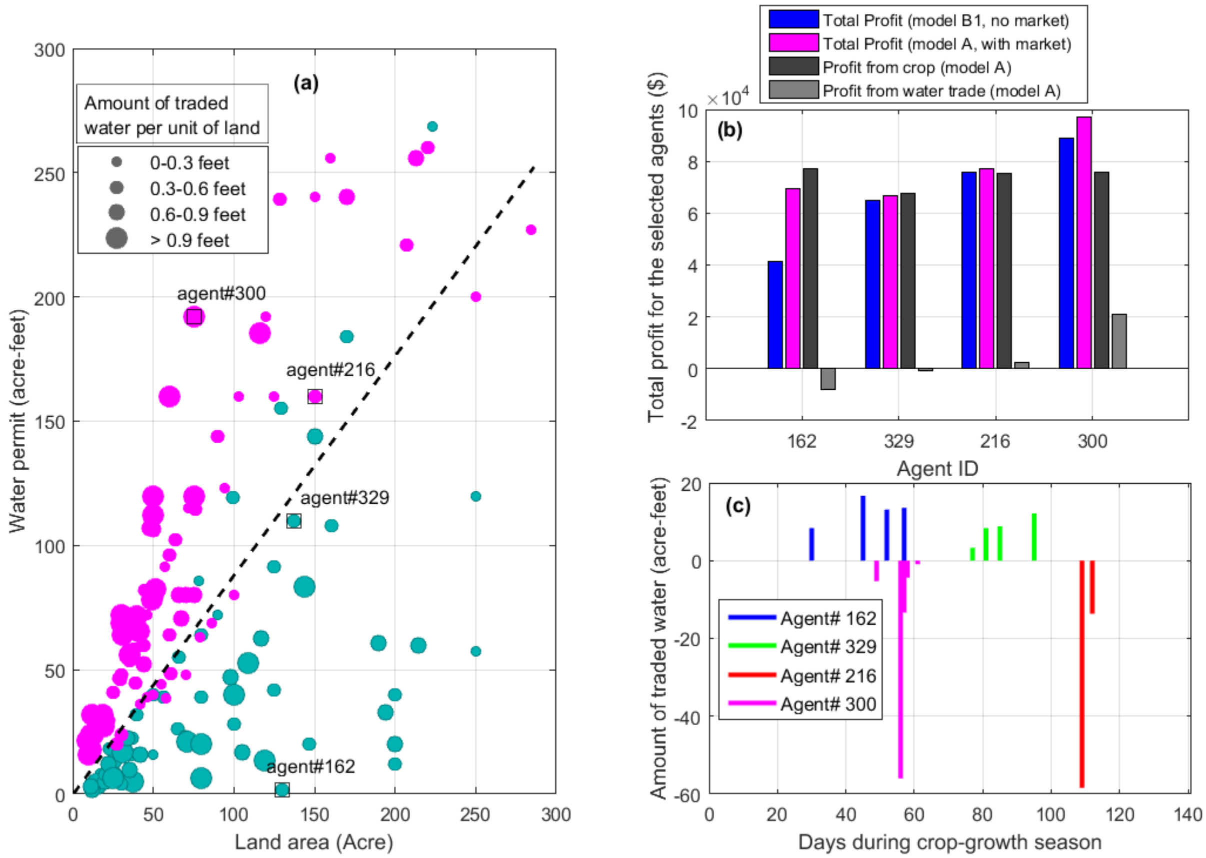


Figure 4.5 Results of (a) total traded water permits for all of the agents (pink dots represent sellers, green dots represent buyers; the size of the dots represents the traded water amount divided by the agent's land area); (b) profits of the four selected agents with and without water market; and (c) daily water trade of the four selected agents. Note: Simulation year is 2011; mean values for λ, μ, and β are 1.0, 0.2, and 0.15, respectively.

4.4.2 Impacts of Bidding Behaviors

This section explores the impact of agents' bidding behaviors on the performance of the water market. Figure 4.6 shows the summary of the system-level total crop production (*TCP*) from the three models (i.e., model A, B1, and B2, defined in Table 4.2) for all of the scenarios.

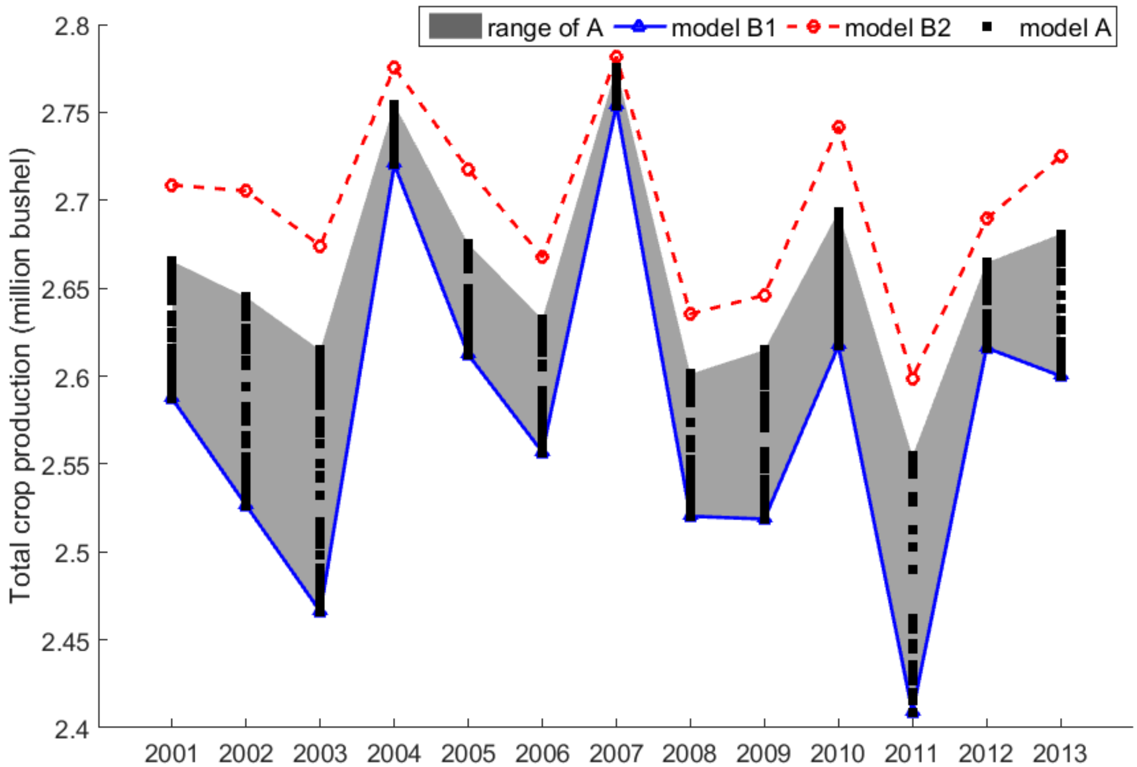


Figure 4.6 Summary of total crop production for all of the agents under model A (black square), model B1 (blue triangle), and model B2 (red circle). Note that the shaded grey area represents the range of model A's possible simulation results.

First, as expected, *TCP* with the water market (model A) is always higher than that without the water market (model B1), especially under normal (e.g., 2010) and dry conditions (e.g., 2011). *TCP* in wet years (e.g., 2007) is maintained at a relatively high level even without the water market, thus the benefit of the water market in wet years is not as significant as that in dry years. This result is consistent with *Luo et al.* [2007].

Second, *TCP* of model A varies significantly between the results of model B1 and B2 for the drier simulation years. The performance of the water market (model A) highly depends on the setting of the agents' bidding behaviors. The *TCP* of model A can be the same as model B1 under some particular conditions (e.g., when $\mu = 0.8$ and $\beta = 0$), implying that the water market will yield no increase in crop production when the agents behave inefficiently in the market.

On the other hand, model A does not yield the same results as model B2, which means that the maximum benefit of the market (i.e., reflected by the optimization model B2) cannot be reached in reality if we consider the factors that may constrain the agents' decision-makings. For example, the optimization approach typically assumes that the agents have sufficient information for decision-making and are able to make optimal bidding decisions that could yield efficient water reallocations. However, this assumption may not be realistic when we consider that agents, in reality, typically have limited information from the market to make bidding decisions and the bargaining processes between agents are not always efficient, which constrains the performance of the market.

Figure 4.7 specifically shows how the bidding parameters affect performance of the water market for three representative hydrological conditions: wet year (2007), normal year (2010) and severe dry year (2011). First, from a qualitative perspective, the relationships between agents' bidding behaviors and the performance of the water market show similar patterns for all of the hydrological conditions. In general, *TCP*, *RMP*, and *TTW* increase when μ decreases and/or when β increases. This implies that agents with smaller rent seeking and/or larger learning rates will make the agents bid prices that are closer to their reservation prices, and, as a result, cause the water market to yield more benefits overall (e.g., trade more water and increase more crop production). The results concur with the need to design effective auction mechanisms that could give market participants incentives to bid their true value [*Vickrey*, 1961; *Hailu and Thoyer*, 2006; *Jackson and Kremer*, 2006].

Second, from a quantitative perspective, changes in bidding behaviors (μ and β) will result in different rates of changes in the performance of the water market. When μ is large and/or β is small, the modeling results are more sensitive to the changes in β . For example, the relative market performance is 20% when $\mu = 0.1$ and $\beta = 0$. With a small increase in β from 0 to 0.05, the relative market performance can increase from 20% to 80%. In contrast, when $\mu = 0.8$, the relative market performance will reach 80% when β exceeds 0.3. These results highlight that the market performance depends on hydrological conditions (i.e., dry and wet years), market institutions (i.e., model A and model B2), as well as human behaviors (i.e., μ and β) in markets [*Smith*, 1982; *Gode and Sunder*, 1993].

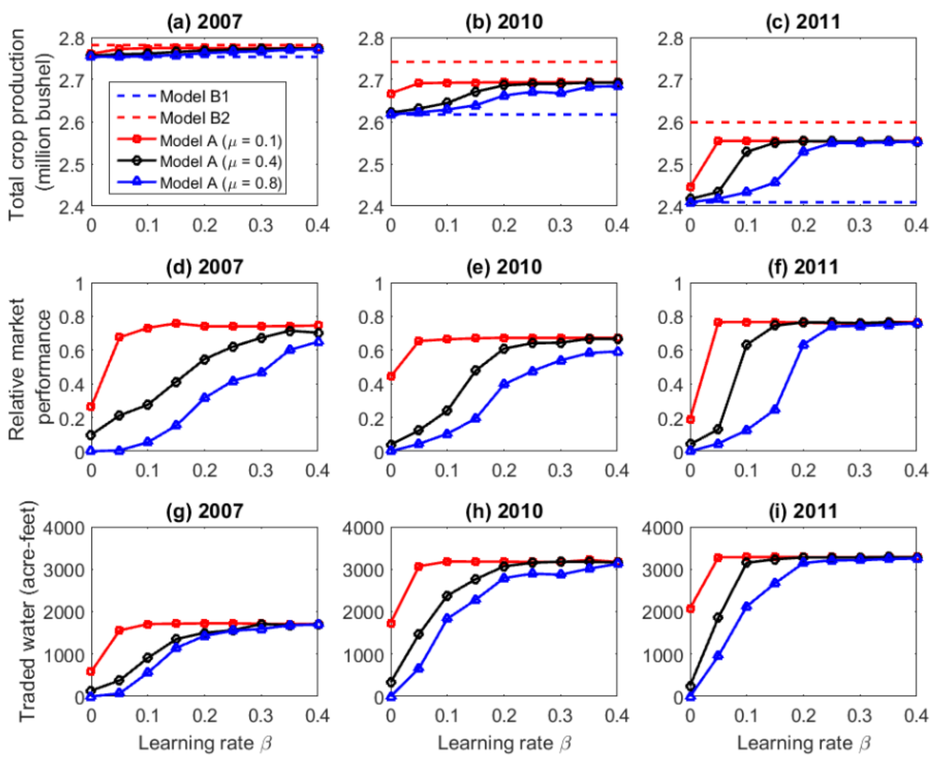


Figure 4.7 The impacts of learning rate on: total crop production in 2007 (a), 2010 (b), and 2011 (c); relative market performance in 2007 (d), 2010 (e), and 2011 (f); and total traded water permit in the water market in 2007 (g), 2010 (h), and 2011(i).

In the proposed water market, agents are able to make bid decisions and update their bid strategies each day. This allows for simulating daily dynamics in the market and evaluating how the market dynamics are affected by agents' behaviors. Figure 4.8 shows the impacts of agents' learning rate on the dynamics of agents' rent seeking, bidding price, and cumulative traded water in the market under different hydrological conditions. The results show that the agents' daily rent seeking, bidding price, and traded water permit allocations are all affected by β . In general, the market dynamics are more noticeable when β increases, resulting in more rapid changes in agents' rent seeking and bidding prices, as well as more traded water in the market. In addition, the impacts of β on the market dynamics become more significant in drier conditions (e.g., 2011), when more agents participate in the market to trade water permits.

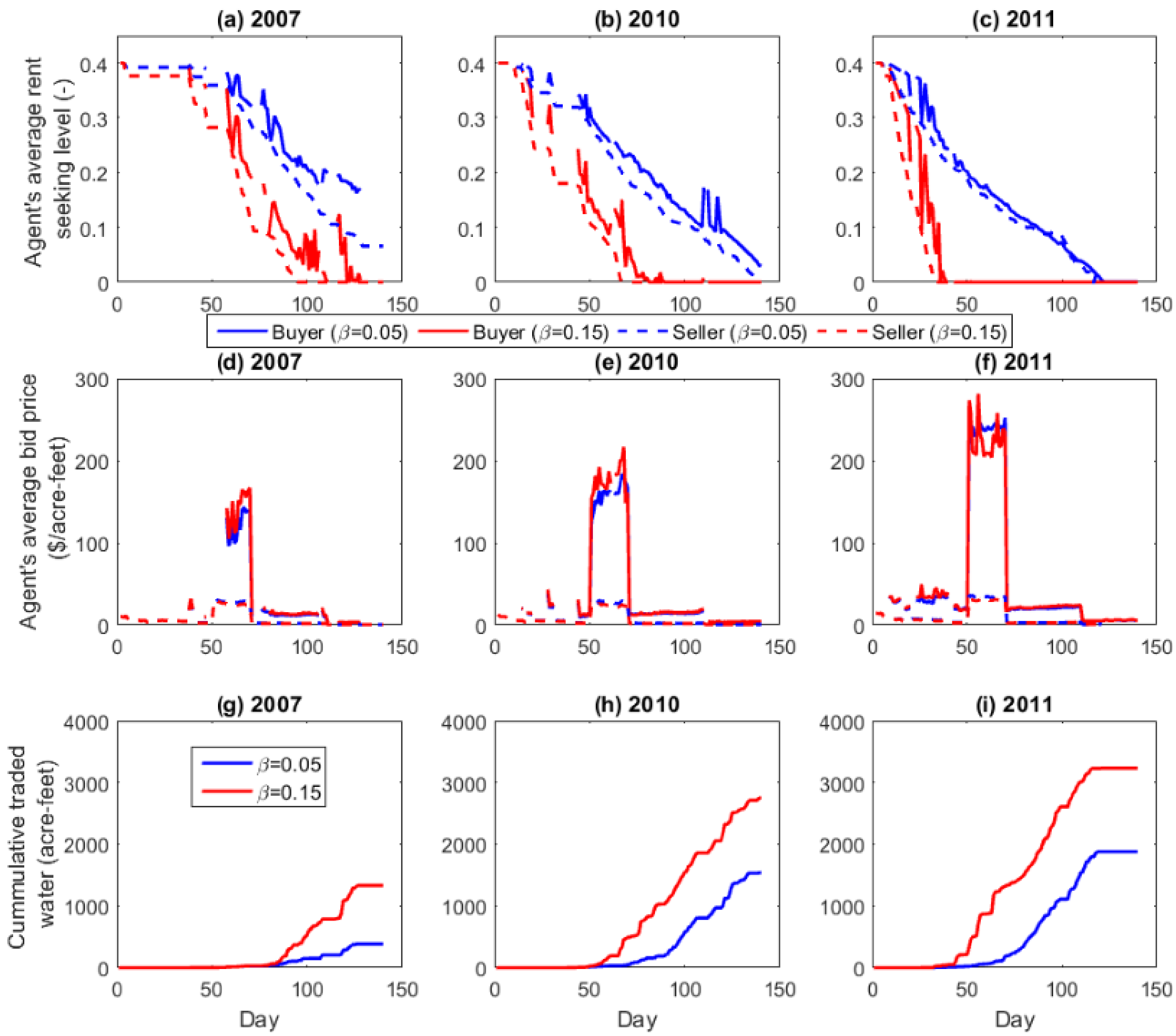


Figure 4.8 The impacts of learning rate on: agents' average rent seeking in 2007 (a), 2010 (b), and 2011 (c); agents' average bidding price in 2007 (d), 2010 (e), and 2011 (f); and cumulative total traded water in the market in 2007 (g), 2010 (h), and 2011 (i).

Figures 8a-c show that the buyers' and sellers' degrees of rent seeking are constant in the early days of the simulation and then have a declining trend in later periods. The sellers' rent seeking decreases faster than that of the buyers. This result can be explained by the following analysis.

On the first several days, no agents enter the market to buy water permits because all of them have sufficient water permits. Thus, the agents are not able to update their rent seeking without transaction information from the market. After a certain number of days (e.g., 10 days in Figure 4.8b), some agents with limited water permits will enter the market to buy water permits after they have used all of their permits, and the agents' will update rent seeking as transactions occur. At the beginning, sellers outnumber buyers in the market. Under this relatively disadvantageous situation, the sellers will decrease rent seeking greatly in order to make their bids more competitive in the market. This is more noticeable in drier hydrological conditions (Figure 4.8c). However, the sellers are in a more advantageous situation under drier hydrological conditions when more agents need to buy water permits. Therefore, the sellers' rent seeking will be closer to that of the buyers.

The daily dynamics of water price (Figures 8d-f) show that the agents' bidding prices between 50 to 70 days (i.e., flowering stage for corn) are higher than on the rest of the days. This is consistent with the trend of yield response factor for corn. Corn's yield response factor during the flowering stage is much higher than in other stages, implying that soil water deficit will cause larger yield loss during the flowering stage, thus making the marginal benefits of water higher. The agents will bid higher prices in response to the high marginal benefits of water at this stage. In addition, it is noticed that the agents with large β bid prices more conservatively (i.e., buyers bid higher prices and sellers bid lower prices) for all of the scenarios.

4.4.3 Impacts of Irrigation Behavior

This section evaluates the impact of the agents' irrigation behavior, which is modeled using the parameter λ (sensitivity to soil water deficit). Figure 4.9 summarizes all of the simulation scenarios in experiment 2 (shown in Table 4.3). For both model B1 (baseline) and B2 (benchmark), *TCP* increases as λ decreases. Agents with smaller λ are more sensitive to soil water deficit D_c and tend to irrigate crops even before D_c reaches its critical level. Therefore, agents with small λ will take more risk-averse irrigation schedules that reduce the chance of crops experiencing water deficit, leading to higher crop production.

Comparing model B1 (baseline) with model A (or model B2), it is noticed that the potential performance of the water market increases when λ decreases and/or the weather is drier. For example, Figure 4.9 shows that in 2010 the water market has the potential to increase crop production by 0.1 million bushels (i.e., from 2.64 to 2.74 million bushels) when λ is 0.6. However, the water market can only increase crop production by 0.05 million bushels (i.e., from 2.45 to 2.50 million bushels) when λ is 1.4. In 2011, the impacts of λ on the potential performance of the water market become more significant (e.g., the water market has the potential to increase crop production by 0.15 and 0.09 million bushels when λ is 1.4 and 0.6, respectively). In contrast, in wet years such as 2007, the potential benefit of the water market is quite limited because the crop production can be maintained at a relatively high level with sufficient precipitation.

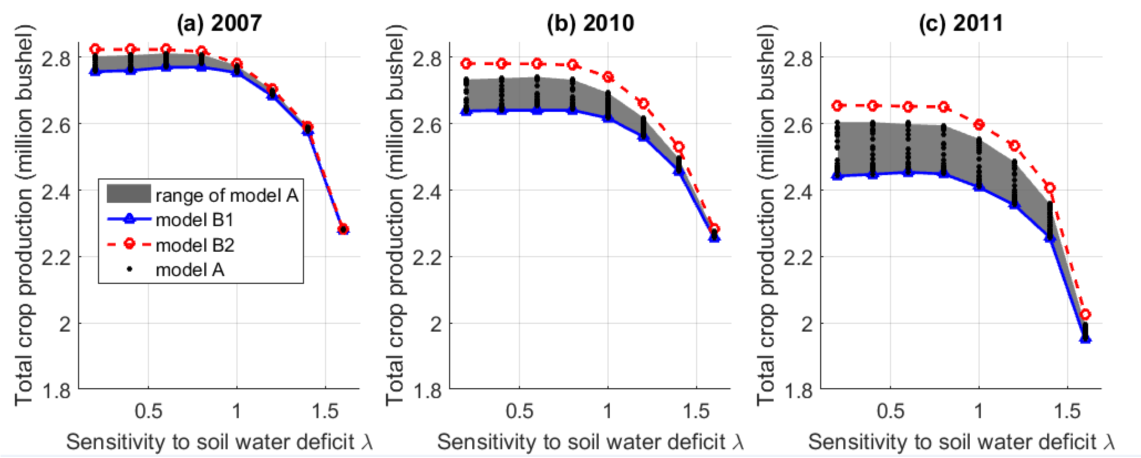


Figure 4.9 Total crop production of models A, B1, and B2 in 2007 (a), 2010 (b), and 2011 (c).

4.4.4 Interplay of Multiple Behavioral Parameters

While agents' bidding and irrigation behaviors are investigated separately in the previous sections, this section examines how the three behavioral parameters jointly affect the water market (Figure 4.10). The results show that the impact of one particular behavioral parameter on the water market highly depends on the settings of the other parameters, which can be categorized into three patterns.

The first pattern is that changing the value of one parameter will alter the active parameter of the model, without changing the potential impacts of the parameters on the water market (Figures 10a-c). (Here we define a parameter as an active parameter if the model results change dramatically when the value of this parameter changes. In other words, model results are sensitive to this parameter.) This pattern applies for the relationship between β and the interplay of μ and λ. When β is small, the *ICP* is sensitive to the change of μ ; while the change of λ does not have much impact. However, when β is large, λ becomes an active parameter while μ becomes inactive.

The second pattern is that changing the value of one parameter makes one of the other two parameters more active. The potential joint impacts of these two parameters does not change significantly (Figure 4.10g-i). This pattern applies for the relationship between μ and the interplay of β and λ. When μ is small, λ is an important model parameter that affects *ICP*; while β is not as important compared with λ. However, when μ is large, β also becomes an important parameter in affecting *ICP*.

The third pattern is that changing the value of one parameter does not qualitatively change the interplay of the other two parameters. Instead, the magnitude of the potential impacts of the two parameters changes (Figures 10d-f). This pattern applies for the relationship between λ and the interplay of μ and β. The trend of the interplay between μ and β is consistent for different values for λ, and only the magnitude of the interplay changes. When λ is small (large), the potential joint impacts of μ and β on *ICP* is large (small).

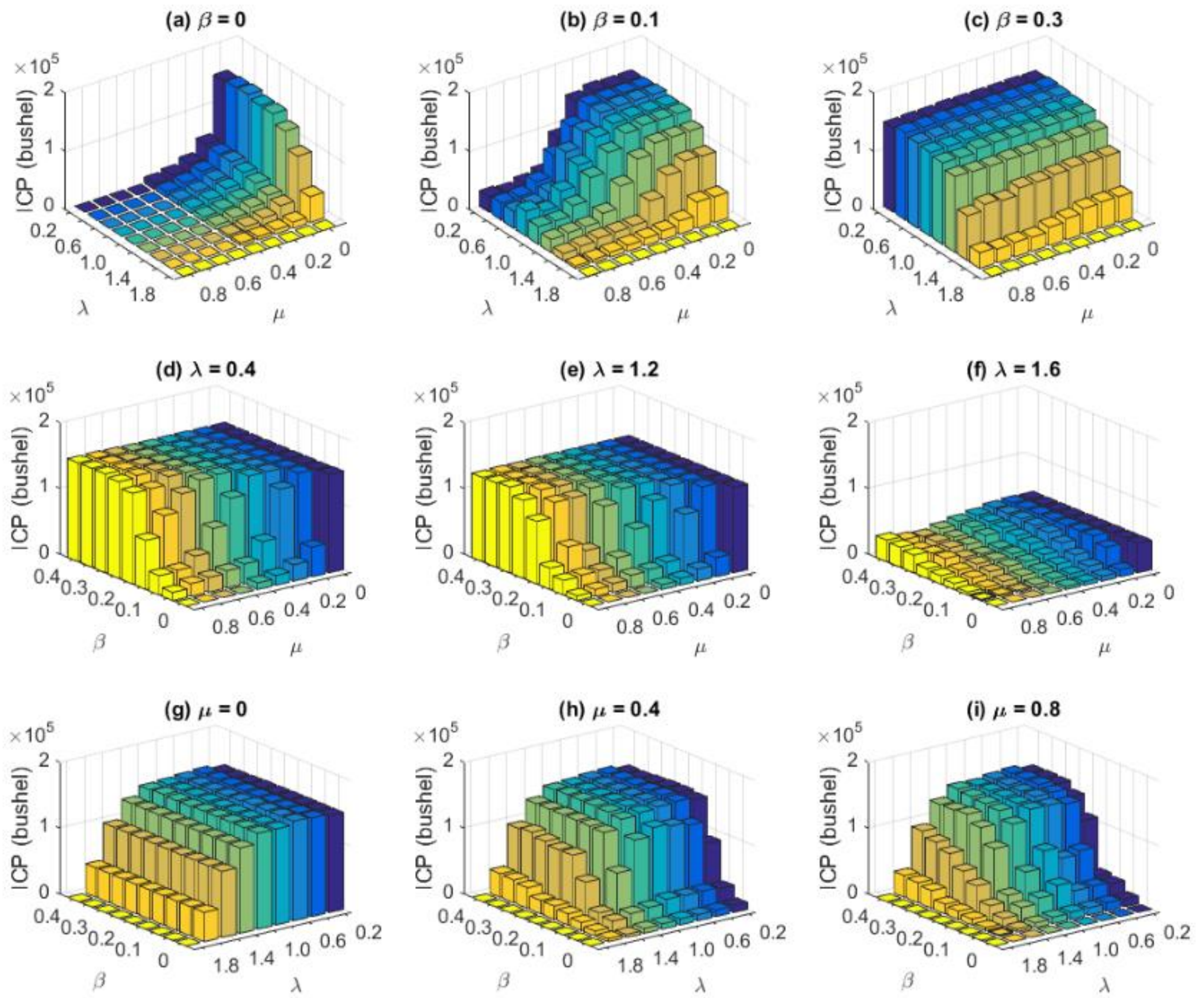


Figure 4.10 The interplay of the three behavioral parameters in 2011

Lastly, we evaluate how hydrological conditions affect the interplay of the behavioral parameters (Figure 4.11) and the impact of transaction cost on the modeling results (Figure 4.12). Compared with the results in Figure 4.10, notice that the three patterns discussed above are consistent under different hydrological conditions, implying that hydrological conditions do not qualitatively change interactions among the behavioral parameters. However, the magnitude of the interplay among the parameters depends largely on hydrological conditions. Typically, the interplay of the behavioral parameters is more significant in dry conditions than that in wet conditions. The sensitivity analysis of the transaction cost shows that, as expected, total crop production is lower (i.e., fewer water permits are traded in the market) when transaction cost increases. In particular, high degree of rent seeking and high transaction cost cause the trade transactions to be low (Figure 4.12).

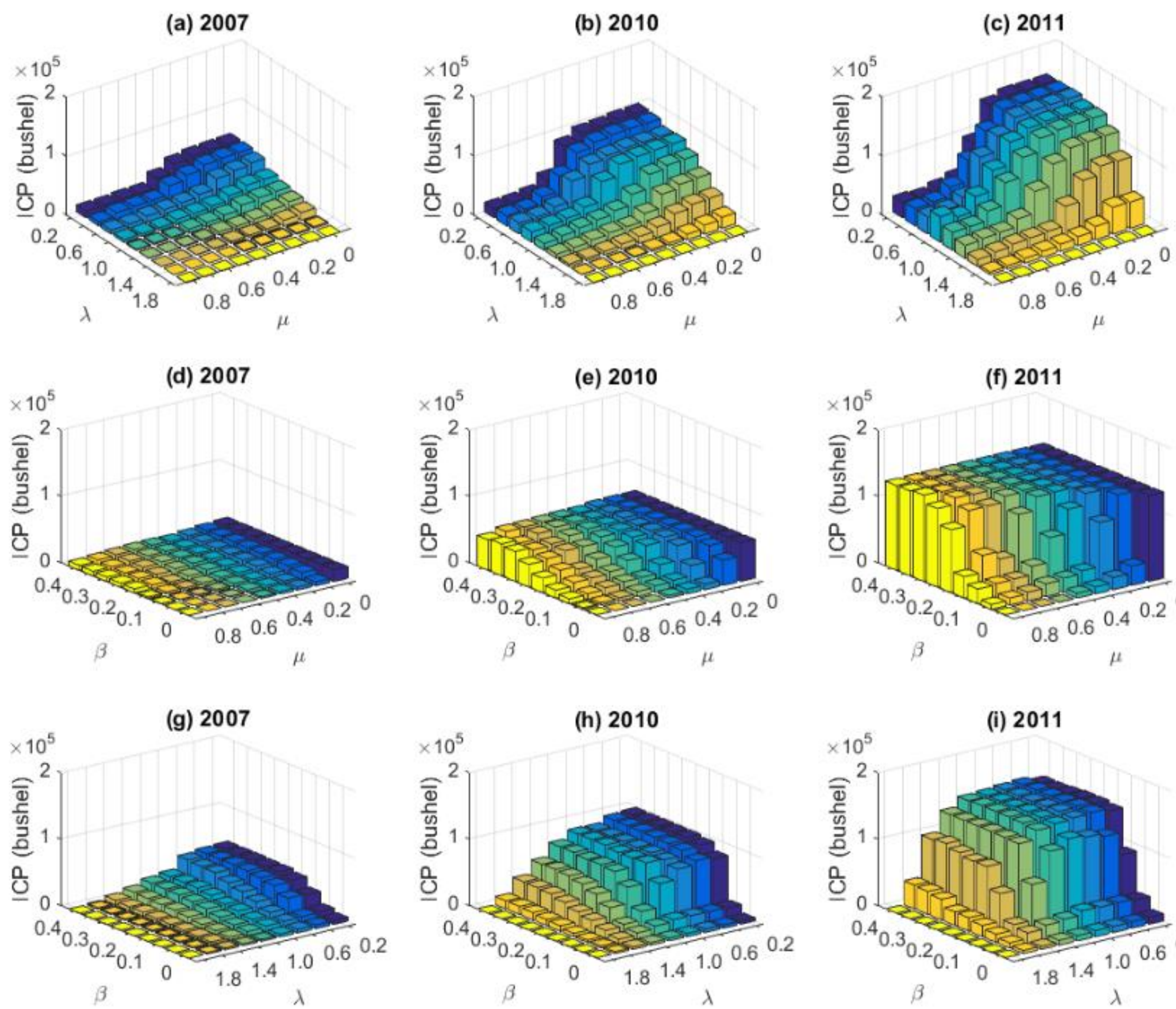


Figure 4.11 The interplay of the behavioral parameters under different hydrological conditions. (Note: β is 0.1 for Figures a-c; λ is 1.2 for Figures d-f; μ is 0.4 for Figures g-i.)

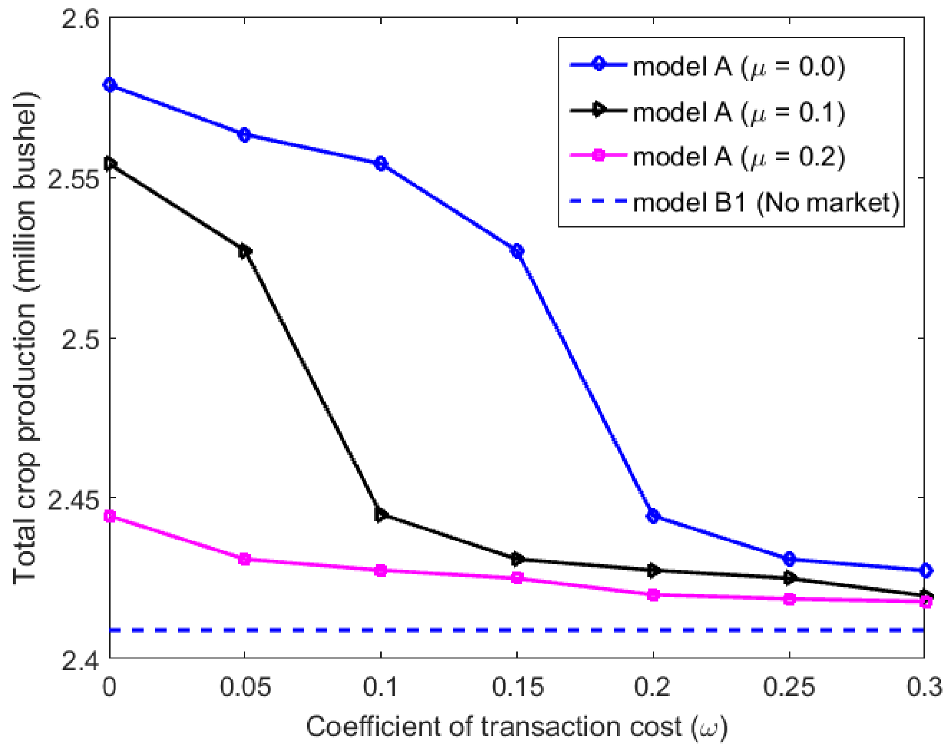


Figure 4.12 Total crop production under different levels of transaction costs

4.5 Discussion

4.5.1 Policy Implications

Some insights on implementing and improving the water market can be obtained from the results. The previous analysis shows that farmers' irrigation and bidding behaviors can significantly affect the performance of the water market. Thus, it is important for policy makers to consider these factors when implementing water markets. Some studies have shown that farmers' irrigation decisions are complex and can be affected by their perceptions, experiences, and social network [*van Duinen et al.*, 2015]. Appropriate educational and information dissemination programs, as well as effective social networking, can support farmers in making better irrigation and water trading decisions. These programs could educate farmers to use timely information (e.g., real-time soil moisture status) to guide their irrigation decisions before the water deficit reaches critical levels. The programs could also educate farmers to be more realistic (i.e., considering lower degree of rent seeking) and more adaptive in learning when making bids in the market. Rewards from transactions can also provide incentives to use moderate rent seeking when making bids.

The results of this study may also provide insights for policy makers to identify appropriate education programs towards behavior changes. For example, the irrigation parameter λ has greater impact on *ICP* than the learning rate coefficient β when μ is small and λ is large (e.g., $\mu = 0$, $\lambda \geq 1.4$ in Figure 4.10g). This implies that an education program for crop science and irrigation engineering might be more beneficial than a water-trading education program for farmers with low sensitivity to soil water deficits and low rent seeking. However, the opposite conclusion will hold true when μ is large (e.g., $\mu = 0.8$, β=0.2 in Figure 4.10i). These behavior parameter thresholds are obtained from a hypothetical case study, and need to be tested with real world water markets. Moreover, the sensitivity analysis with different hydrological conditions suggests that timely education programs during dry years will be more beneficial given that farmers' behaviors can have greater impacts on the water market in dry years than in normal or wet years.

4.5.2 Limitations and Future Directions

The ABM presented in this study is subject to many assumptions and simplifications due to data incompleteness and the scope of this work. This study is not intended to provide a tool ready for real-world use at this stage, but focuses on exploring the impacts of multiple behaviors on the performance of a particular form of water market based on double auction. Several future directions can lead to improvement of this work. First, due to the lack of empirical data on farmers' behaviors, the agents' behavioral parameters are assumed to be normally distributed, and are independent from hydrological, institutional, and socioeconomic factors. This assumption might not hold true because farmers' behaviors, in reality, might be affected by factors such as limits in water availability [*Foster et al.*, 2014] and social interactions with other farmers[*Ng et al.*, 2011; *van Duinen et al.*, 2016]. Further studies are therefore needed to refine the distributions of behavioral parameters and to explore the relationships among farmers' behavioral parameters and the associated hydrological, institutional, and socioeconomic conditions. This can be achieved by surveys, interviews, and expert knowledge [*Smajgl et al.*, 2011].

Second, the agricultural system in this study is a simplified system, in which we assume, for illustrative purposes, the most widely planted crop (i.e., corn) is planted in all of the agents' croplands. In future work, a crop choice model could be used to simulate agricultural systems consisting of multiple crops and to simulate farmers' crop choice decisions at the beginning of each crop-planting season. Third, in this study we only incorporate three behavioral parameters in farmers' decision-making processes in the water market. Some other factors, such as weather forecast, crop price and externalities (e.g., water quality), can also affect farmers' choice of crops and irrigation decisions. Incorporating these additional components into the model could better mimic the performance of agricultural water markets. However, it is not expected that these additional components would qualitatively alter the findings and implications of this study.

Finally, this study only simulates agricultural water use in the river basin, without taking account of other water users (e.g., municipal and industrial water uses). Thus, we assume that farmers are allowed to use water as long as their water use is less than their water permits. However, during extreme drought conditions, some farmers might not be able to use water if they have lower water right priority compared with other water users such as municipal water users [*Garcia et al.*, 2009]. In addition, because groundwater rights are not well defined and monitored in the case study area, we only consider trade of surface water permits in the current study. Future work could couple the presented model with a hydrological river flow model to simulate the impacts of groundwater use and other types of water uses on the water market. This will allow for better understanding of the impacts of farmers' behaviors on agricultural water markets. In addition, the current study only considers a specific type of water market (i.e., sealed-bid double auction). Under this market mechanism, agents' bidding price and bidding strategies are confidential. In other words, agents do not share their bidding information with other agents. Future work can extend the scope of the current study and simulate other types of water markets (e.g., open-cry auction market) in which agents can observe others' behaviors and interact with each other.

4.6 Conclusions

An agent-based model of farmers' irrigation and bidding decisions under the influence of farmers' behavioral factors is developed to simulate an agricultural water market based on double auction. The model is applied to a hypothetical water market designed for the agricultural system of the Guadalupe River Basin in Texas. The results demonstrate that farmers' behaviors can significantly affect the performance of the water market, as summarized below:

1. Among multiple behavioral parameters (i.e., sensitivity to soil water deficit λ, rent seeking μ, and learning rate β), the water market's potential is only significantly affected by λ.

2. The impact of λ on the performance of the water market is significant under most cases. However, the impact of μ or β depends on the other two parameters. When μ is larger, β has greater impacts on the performance of the water market; in contrast, when β is larger, μ has lower impacts.

3. The water market could significantly increase crop production only when the following conditions are satisfied: (1) λ is small, and (2) μ is small and/or β is large. The first condition requires efficient irrigation scheduling. The second condition requires well-developed water market institutions that provide incentives to bid true valuations of water permits.

Thus, farmers' sensitivity to soil water deficit and hydrological conditions constrain the potential performance of the water market. Farmers who are more sensitive to soil dryness, especially under drier hydrological conditions, will enhance the market potential. However, farmers' bidding behaviors will eventually determine how much of the market potential can be obtained. Water markets will perform better when farmers are willing to accept smaller rent seeking in making bids, and when they are able to learn and update their bidding strategies quickly. The latter highlights the importance of sharing market information with agents in timely manner, as well as designing effective auction mechanisms so that agents are more willing to bid their true valuations of water permits [*Krishna*, 2010]. Although these findings are derived from a hypothetical case study, they provide meaningful hypotheses for further research on the impacts of individual behaviors on water markets.

It is important to note that, this study simulates a hypothetical water market. In order to implement water markets in the real world, there are many institutional, regulatory, and technical issues to concern. These include strong legal systems to define water rights and to address the conflicts in water trading, engineering infrastructure for water transfer and storage, stakeholders' participation, and third-party effects. Incorporating these factors into the proposed model would make the model more realistic. We envision that the proposed water market framework can be useful for future development of water markets and for testing the findings when water market observations become available.

Chapter V. Conclusions and Future Work

The previous three chapters address three issues associated with modeling human behaviors in the management of floods and droughts. This chapter summarizes the main findings obtained from the modeling results (Section 5.1) and discusses the limitations and future directions of the thesis (Section 5.2).

5.1 Conclusions

This thesis assesses the impacts of human behaviors on the performance of water resource systems during extreme hydrological events. Using an agent-based (ABM) modeling approach, three issues associated with modeling human behaviors are addressed: (1) agents' behavioral heterogeneity, (2) social interaction, and (3) interplay of multiple behaviors. Two types of extreme hydrological events, drought and flooding, are used as case studies.

In Chapter II, an ABM framework is developed to simulate human behavioral heterogeneity in response to flood warnings. The framework is coupled with a traffic model to simulate agents' evacuation processes within a road network under various flood-warning scenarios. The results show that the marginal benefit associated with providing better flood warnings (i.e., flood warnings with high prediction accuracies and/or longer lead times) is significantly constrained if people behave in a more risk-tolerant manner, especially in high-density residential areas. The results also show significant impacts of human behavioral heterogeneity on the benefits of flood warnings, and thus highlight the importance of considering human behavioral heterogeneity in simulating flood warning-response systems. The results reveal the importance of modeling human behavioral heterogeneity, as well as including more attributes of residential areas to estimate and improve the benefits of flood warnings.

Chapter III extends the framework developed in Chapter II, and evaluates how social communication affects agents' flood risk awareness and evacuation behaviors. The results show that agents' social communication can make the evacuation process more sensitive to the influence of global flood warnings and/or neighbor observations, and thus impose uncertainties in the benefit of flood warnings. In particular, when social media become more influential, and individuals have less trust in global flood warnings, the evacuation process can be more vulnerable (i.e., evacuation rate is lower). Stubborn individuals on social media are shown to significantly hinder the speed and level of opinion adoption of the entire group. These results highlight the role of social media in flood evacuation and the need to monitor social media so that misinformation can be corrected in a timely manner during a disaster evacuation process.

Chapter IV addresses the issues of simulating multiple behaviors, using drought as a case study. The ABM explicitly incorporates farmers' multiple behaviors, namely irrigation behavior (represented by farmers' sensitivity to soil water deficit) and bidding behavior (represented by farmers' rent seeking and learning rate), in a hypothetical water market based on a double auction. It is found that the joint impacts of the behavioral parameters on the water market are strong and complex. In particular, irrigation behavior affects the water market potential and its impacts on the performance of the water market are significant under most scenarios. The water market could significantly increase crop production only when the following conditions are satisfied: (1) farmers are sensitive to soil water deficit, and (2) rent seeking is small and/or learning rate is large. The first condition requires efficient irrigation scheduling, and the second requires well-developed water market institutions that provide incentives to bid true valuation of water permits.

Overall, the results from the three case studies show that ABM is a useful modeling approach for simulating human behaviors in coupled human and natural systems. Applying ABM in the management of floods and droughts, this thesis investigates some specific issues associated with modeling human behaviors. However, ABM typically faces difficulty in model validation due to lack of data, which imposes challenges in implementing ABM for planning and management of water resource systems. In the big data era, with advanced data collection technologies and data mining tools, more data on human behaviors in water resource systems can be collected and analyzed. These will provide great opportunities for implementing ABM in the management of real-world extreme hydrological events. The following section specifically introduces other limitations of this thesis and recommended future work.

5.2 Limitations and Future Work

The major challenge for simulating human behaviors with an ABM is the lack of empirical data. Thus, more data are needed to verify the modeling results presented in the above three chapters. More specific limitations and future research related to this work are discussed as follows.

In the case of human behaviors in flood warning-evacuation systems (the ABM in Chapter II), relationships between agents' risk tolerance thresholds and their socioeconomic and demographic conditions are not represented. In fact, agents' response to flood warnings could be affected by these factors, such as the size of household, economic value of the home, pet ownership, etc. Future work should consider connections among these factors, and build models that could better simulate agents' evacuation decisions. Second, in the present work, we assume that all of the agents remaining in the area at the end of model execution will be flooded, and the agents that have evacuated to the safe area before the end of model execution will not be flooded. Thus, we did not specify the direction, speed, or timing of the flood inundation processes. In future work, considering the impacts of more gradual inundation processes may be needed to better model flood behaviors in the real world. In particular, we can consider the heterogeneity of flood damages at different locations within a residential area, and evaluate how the spatial distribution of flood inundation affects the modeling results. Finally, in the current study, the benefit of flood warnings is measured by the percentage of agents that successfully evacuate to safe area. Future work can introduce more criteria to measure the benefit of flood warnings, such as the economic value of flood-damage mitigation.

In Chapter III, due to lack of agents' social interaction data, we assume agents who are closer to each other have stronger social connections and tend to have more communications. This might agree with intuitive reasoning that individuals living closer to each other will have more chance to meet each other and exchange information. However, this assumption does not necessarily hold true in some real-world case studies. Future work could refine this assumption by mapping individuals' social connections using advanced data mining tools when social communication data become available. Second, this present work considers a special case of regular lattice transportation network with only one evacuation destination at a specific location (i.e., on the corner of the transportation network). Future work could consider other types of traffic network structures and more evacuation destinations in the transportation system. The problem of shelter allocation during natural disasters has been investigated in many previous studies. It would be interesting to investigate the role of social media in shelter-allocation optimization to extend the scope of this work. Third, in the current work, we only simulate the process in which agents share their opinions on flood risk, without considering that agents could also share their risk-tolerance thresholds. Future work can investigate how agents' risk-tolerance thresholds are affected by social interactions.

Both chapter II and chapter III use synthetic residential areas as case studies. Future work can extend the scope of the current study and use real-world residential areas as example [*Dawson et al.*, 2011]. This requires a variety of field data, including (1) census data that provide information on the population in the community, their risk-tolerance thresholds to flood risk, responses to different types of information sources, access to transport during floods, etc., (2) transportation network that connects households to evacuation destinations in the residential area, and (3) information on flood warning systems during flood events. Implementing the current model in a real-world case study can provide more realistic simulation of households' evacuation processes during floods.

In the case of the agricultural water market (Chapter IV), the ABM is also subject to many assumptions and simplifications due to data incompleteness. First, due to the lack of empirical data on farmers' behaviors, the agents' behavioral parameters are assumed to be normally distributed, and are independent from hydrological, institutional, and socioeconomic factors. This assumption might not hold true because farmers' behaviors, in reality, might be affected by factors such as limits in water availability and social interactions with other farmers. Further studies are therefore needed to refine the distributions of behavioral parameters and to explore the relationships among farmers' behavioral parameters and the associated hydrological, institutional, and socioeconomic conditions. Second, the agricultural system in this study is a simplified system, in which we assume, for illustrative purposes, the most widely planted crop (i.e., corn) is planted in all of the agents' croplands. In future work, a crop choice model could be used to simulate agricultural systems consisting of multiple crops and to simulate farmers' crop choice decisions at the beginning of each crop-planting season. Third, the present work simulates a hypothetical water market, without considering many institutional, regulatory, and technical issues. These include strong legal systems to define water rights and to address the conflicts in water trading, engineering infrastructure for water transfer and storage, stakeholders' participation, and third-party effects. Incorporating these factors into the proposed model would make the model more realistic.

Finally for either of the extreme hydrological events (i.e., droughts and floods), future work can couple a more realistic hydro-climatic model that provide forecast of an extreme event to an ABM. Furthermore, economic experiments and surveys can be conducted to obtain data on agents' behaviors, and build more realistic models to simulate the role of human behaviors in the management of floods and droughts.

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Appendix A

This section introduces the N-S traffic model. In the N-S model, space and time are both discrete variables and each traffic road in the transportation network is divided into cells, each of which can be occupied by one vehicle. At each time step, the moving speed and the location of a vehicle is constrained by: (1) the moving speed of the vehicle, (2) the acceleration and deceleration rate, (3) the number of empty cells in front of the vehicle to avoid collusion, and (4) maximum moving speed allowed in the transportation network.

For vehicle *i* and vehicle *j* (the vehicle that is ahead of vehicle *i*) with traveling speed v_i and v_j, respectively, the speed of vehicle *i* is determined by the following rules for each time step:

- If the distance between vehicle *i* and vehicle *j* is greater than a safe distance, the vehicle will accelerate, increasing moving speed by a unit. Since there is a speed limit on each edge, the vehicle's moving speed would not exceed the road's maximum limit speed.
- If the distance between vehicle *i* and vehicle *j* is less than a safe distance, the vehicle will decrease its moving speed by a unit.
- A vehicle will randomly change its speed by one unit with a certain probability.
- At the end of each time step, a vehicle will move one time step and update its location on its current route.

We apply the all-way stop rule in road intersections. Vehicles must stop when arriving at road intersections and proceed only when the way ahead is clear. When multiple vehicles approach at the same road intersection, vehicles' right-of-way to proceed follows the order of their arriving times (Figure A1). For details of the N-S model and how it is implemented to simulate agents' evacuation process, see *Nagel and Schreckenberg*, [1992], *Nagel and Rickert*, [2001], and *Du et al.*, [2016].

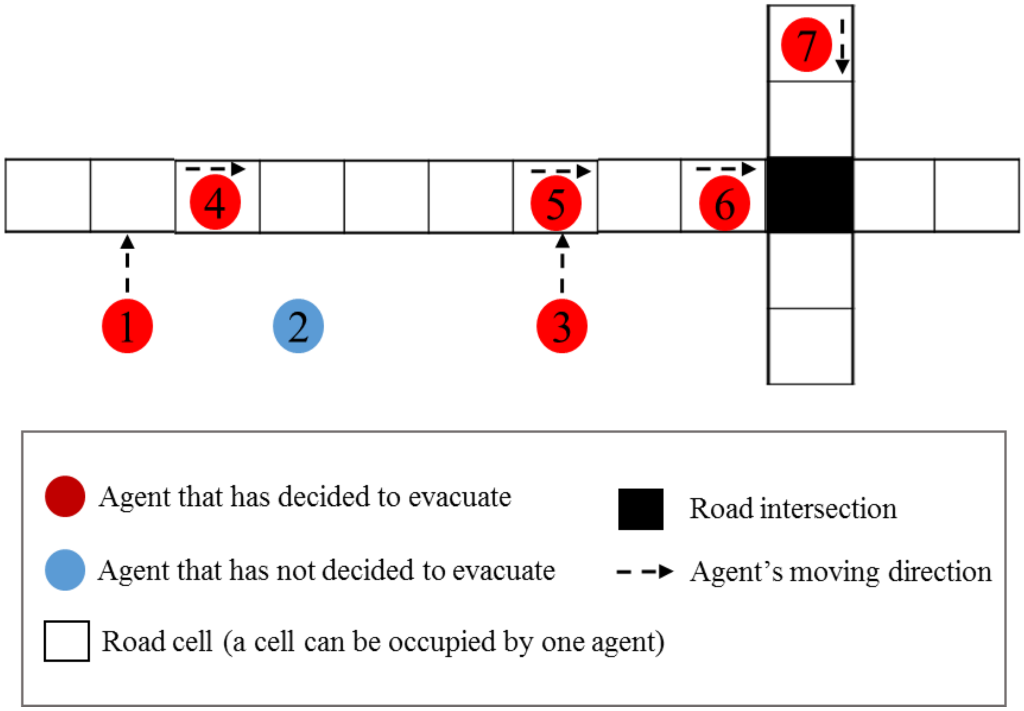

Figure A1 Illustration of traffic road in the N-S model. The road are divided into a number of cells. Each cell can be occupied by one agent at a time. Each agent has a designated cell to start evacuation (the closest one to the agent). An agent will start its evacuate process when (1) it decides to evacuate (illustrated by red color such as agent 1 and agent 3), and (2) its designated cell is currently not occupied by other agents (agent 1 will start evacuation immediately; while agent 3 has to wait until agent 5 move out of its designated cell).

Appendix B

This section briefly introduces the water balance approach and derivation of the marginal benefit for irrigation used in the agent-based model. Following previous studies, we use a simple, linear water-crop production function to calculate the reduction in crop yield when crop yield reduction is caused by water stress, as shown in equation B1[*Allen et al.*, 1998; *Steduto et al.*, 2009; *Wang and Cai*, 2009; *Andales et al.*, 2011]..

$$1-\frac{Y_a}{Y_m}=k_y(1-\frac{ET_{c,adj}}{ET_c}) \tag{B1}$$

where Y_a and Y_m are crop yield (bushel/acre) with and without water stress, respectively. k_y is crop's yield response factor, which is a dimensionless parameter that measures the effect of evapotranspiration reduction on crop yield loss. ET_c is evapotranspiration for the crop (i.e., corn in this study) under standard management conditions without water shortage ($ET_c = ET_0 \times k_c$). ET_0 is the reference evapotranspiration calculated by Hargreaves equation [*Hargreaves and Samani*, 1985]. ET_{adj} is adjusted evapotranspiration as a result of water stresses ($ET_{adj} = ET_c \times k_s$). k_c is crop coefficient factor and k_s is a dimensionless evapotranspiration reduction factor dependent on available soil water ($k_s \in [0,1]$). k_s is calculated by equation B2 [*Allen et al.*, 1998, 2005]:

$$k_s=\frac{AWC\times Drz-D_c}{(1-MAD)\times AWC\times Drz} \tag{B2}$$

where *AWC* is the capacity of available water in crop root zone (inch of water/inch of soil), which is the difference between field capacity and wilting point. The value of *AWC* corresponding to different soil types can be obtained from *Allen et al.* [1998]. *MAD* is crop depletion factor, a dimensionless parameter measuring the faction of total available water that a crop can extract from soil without suffering water stress. *MAD* is set as 0.6 for corn [*Allen et al.*, 1998]. *Drz* is the depth of the root zone (inch). D_c is soil water deficit (inch) that needs to be satisfied from irrigation. We adopt the water balance approach to simulate the hydrological process in crop root zone [*Allen et al.*, 1998; *Andales et al.*, 2011]. In the water balance approach, soil water deficit D_c can be estimated by equation B3:

$$D_c = D_{c,p} + ET_{adj} - P - \frac{I}{CA} \quad \text{(B3)}$$

where $D_{c,p}$ is soil water deficit of the previous day (inch). *P* is precipitation amount (inch). *I* is farmers' effective irrigation amount after taking account of water loss due to irrigation efficiency and leaching fraction for salinity control (acre-inch). *CA* is crop area (acre).

We assume crop yield of the entire crop-growing season is a linear combination of the hypothetical crop yield on each individual day *t* [$Y_{m,t} = (k_{y,t} / \sum_t k_{y,t}) Y_m$]. Denote irrigation cost ($/acre-inch), crop planting cost ($/acre), and crop price as *IC*, *C* and *PC*, respectively. Crop profit (π) of the entire season is represented by equation B4:

$$\pi = Y_a \times CA \times PC - IC \times I - C \times CA \quad \text{(B4)}$$

Combining equations B1-4, the marginal benefit (MB_t) for irrigating crop on day *t* ($/acre-inch) is calculated by equation B5:

$$MB_t = \frac{\partial \pi_t}{\partial I_t} = \frac{PC \times Y_{m,t} \times k_{y,t}}{ET_{c,t} + (1 - MAD) AWC \times Drz_t} - IC \quad \text{(B5)}$$

In the auction market, we assume transaction between each individual pair of buyer and seller is associated with a transaction cost. In this study, we use coefficient of transaction cost (ω) to measure the ratio of transaction cost per unit of water permit relative to the trading price (e.g., for a transaction with trading price *p* and trade amount *Q*, transaction cost can be represented by $\omega p \times Q$). A larger ω is associated with a higher transaction cost ($\omega \in (0, 1)$).

With transaction cost, buyers (sellers) will need to decrease (increase) their reservation prices in order to avoid profit-losing transactions. The reservation price ($\eta_{i,t}$) for agent *i* on day *t* is then set as $MB_{i,t} / (1+\omega)$ for buying water permits or $MB_{i,t} / (1-\omega)$ for selling water permits, which could ensure the agent will not lose profit if its bid results in transactions. Note that high transaction cost will increase sellers' reservation prices (decreases buyers' reservation prices) and therefore reduce the number of transactions in the market.

The development for corn consists of five stages, which are establishment, vegetative, flowering, yield formation, and ripening. Yield response factor k_y for these stages are 0.2, 0.4, 1.15, 0.5, and 0.2, respectively. The duration for these stages are 20, 30, 20, 40, and 23 days, respectively (133 days in total) [*Doorenbos and Kassam*, 1979; *Wang and Cai*, 2009]. In order to adjust it to 140 days (from March 16th to August 2nd) in this study, the numbers of days for the five development stages are proportionally increased to be 21, 32, 21, 42, and 24 days, respectively.

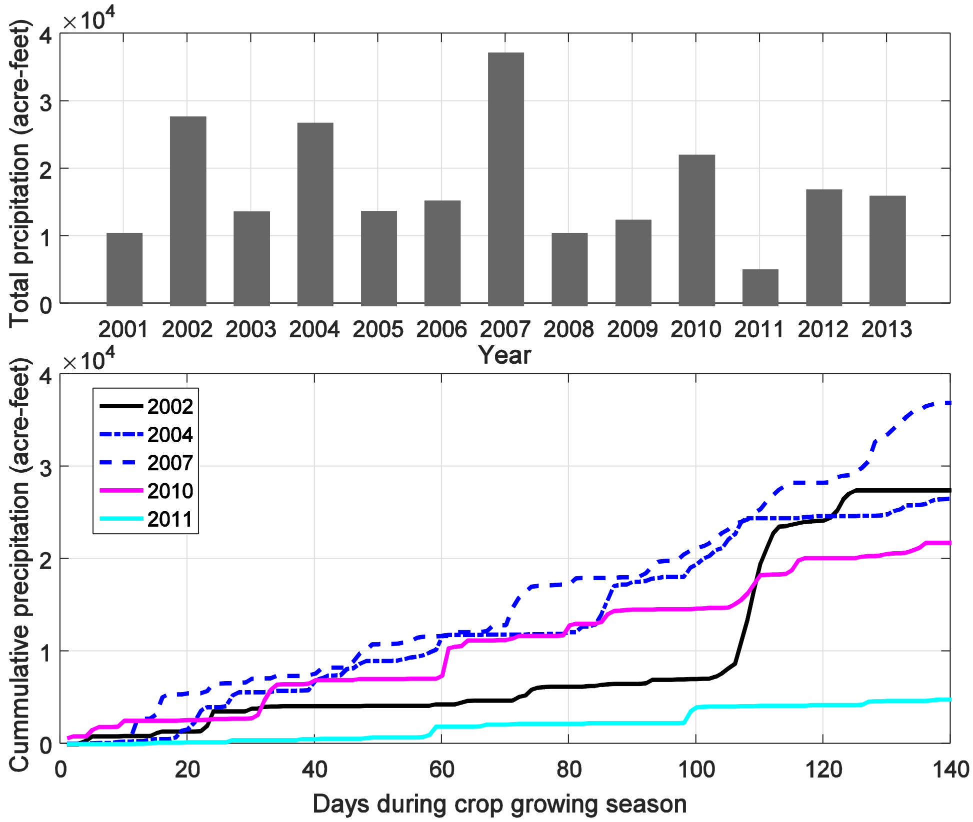

Figure B1 The total amount of precipitation from 2001 to 2013 in the Guadalupe river basin (GRB). Year 2007 is a wet year for GRB, with 3.7×10^4 acre-feet (20.4 inches) of rainfall during the crop-growing season for all of the agents. In comparison, year 2011 is a severe dry year and the total precipitation is only 4.8×10^3 acre-feet (2.64 inches). The total precipitation in year 2010 falls in the middle of years 2007 and 2011. Therefore, these three years are selected as representative wet, severe dry and normal years in the case study.