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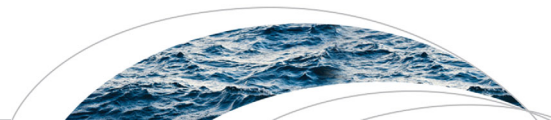
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RESEARCH ARTICLE

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Evaluating the impacts of farmers' behaviors on a hypothetical agricultural water market based on double auction

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Key Points:

- Farmers' behavioral parameters are incorporated in an agent-based model to evaluate their impacts on an agricultural water market
- Farmers' irrigation behavior determines the water market's potential Farmers' bidding behavior determines the actual transaction
- The water market can result in high crop yield when farmers are sensitive to soil dryness, rent seeking is low, and learning rate is high

Supporting Information:

- Supporting Information S1

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Abstract Agricultural water markets are considered effective instruments to mitigate the impacts of water scarcity and to increase crop production. However, previous studies have limited understanding of how farmers' behaviors affect the performance of water markets. This study develops an agent-based model to explicitly incorporate farmers' behaviors, namely irrigation behavior (represented by farmers' sensitivity to soil water deficit λ) and bidding behavior (represented by farmers' rent seeking μ and learning rate β), in a hypothetical water market based on a double auction. The model is applied to the Guadalupe River Basin in Texas to simulate a hypothetical agricultural water market under various hydrological conditions. It is found that the joint impacts of the behavioral parameters on the water market are strong and complex. In particular, among the three behavioral parameters, λ affects the water market potential and its impacts on the performance of the water market are significant under most scenarios. The impacts of μ or β on the performance of the water market depend on the other two parameters. 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, and the second requires well-developed water market institutions that provide incentives to bid true valuation of water permits.

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 [Iftekhhar 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; Turrall 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; Iftekhhar *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; Iftekhhar *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 timescale [Yang *et al.*, 2012; Iftekhhar *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 remainder of this paper is structured as follows. Section 2 introduces the methodology, focusing on water market mechanisms, agents' behaviors, and model construction. Section 3 gives an overview of the

case study area and the experimental design. Section 4 presents modeling results, followed by discussions in section 5 and conclusions in section 6.

2. Methodology

This section introduces the mechanisms of the agricultural water market (section 2.1), the agent-based model used to simulate farmers' behaviors (section 2.2), and model construction and execution process (section 2.3).

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 [Turrall *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 timescale.

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 López-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 López-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

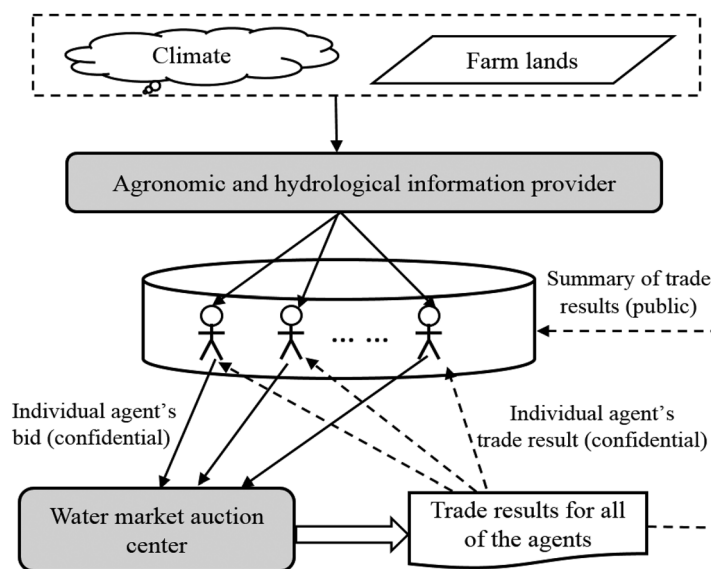


Figure 1. Information flow in the agricultural water market.

not result in transactions, are able to obtain some information about the market prices, which supports the learning processes (as illustrated in Figure 1).

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.

2.2.1. 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 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 nonnegative, 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).

$$\text{Irrigation} = \begin{cases} \text{No,} & \text{if } D_c < \lambda \times d_{MAD} \\ \text{Yes,} & \text{if } D_c \geq \lambda \times d_{MAD} \end{cases} \quad (1)$$

2.2.2. 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-foot); 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).

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

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. Additional equations for the derivation of an agent's reservation price are provided in the supporting information.

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 $\mu \geq 1$ 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).

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

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 [2003] proposes two model validation methods for ABMs: (1) structural validation that measures if the model structure agrees with theoretical mechanisms and expert opinions and (2) outcome validation that evaluates the fitness between the model outputs and empirical data. This study mainly focuses on understanding 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.

2.3. Model Implementation

We construct the agent-based model in the object-oriented programming language Java. Table 1 lists the key environmental, economic, institutional, and behavioral parameters for model input. Figure 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.

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 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.

3. Case Study and Experimental Design

To assess the effects of farmers' behaviors using the model developed in section 2, we develop a hypothetical water market as a case study, described in section 3.1, based on a range of precipitation experienced recently in a Texas watershed, including the severe drought of 2011, the normal year of 2010, and the wet year of 2007. Using this case study, experiments are designed to evaluate the impacts of the behavioral parameters and hydrologic conditions on market performance (section 3.2).

3.1. Overview of the Case Study Area

We apply the water market model to the Guadalupe River Basin (GRB) in

Table 1. List of Variables Associated With Agricultural System and Agent's Behaviors

Factors	Variable	Meaning [Unit]
Environmental and agronomic	<i>Loc</i>	Geographical location (i.e., latitude and longitude) (-) ^a
	<i>ET</i>	Crop evapotranspiration (inch/d)
	<i>P</i>	Precipitation (inch/d)
	<i>ST</i>	Soil type (e.g., clay, sand, and loam) (-)
	<i>CA</i>	Crop area (acre)
	<i>CY</i>	Crop yield (bushel/acre)
	<i>IC</i>	Irrigation cost (\$/acre-feet)
	<i>IE</i>	Irrigation efficiency (-)
	<i>LF</i>	Leaching fraction for salinity control (-)
Institutional	<i>WP</i>	Water permit (acre-feet)
	ω	Coefficient of transaction cost for water trading (-)
Economic	<i>PC</i>	Price of crop (\$/bushel)
	<i>PW</i>	Price of water permit (\$/acre-feet)
Behavioral	λ	Sensitivity to soil water deficit (-)
	μ	Rent seeking (-)
	β	Learning rate (-)

^a(-) denotes dimensionless variable.

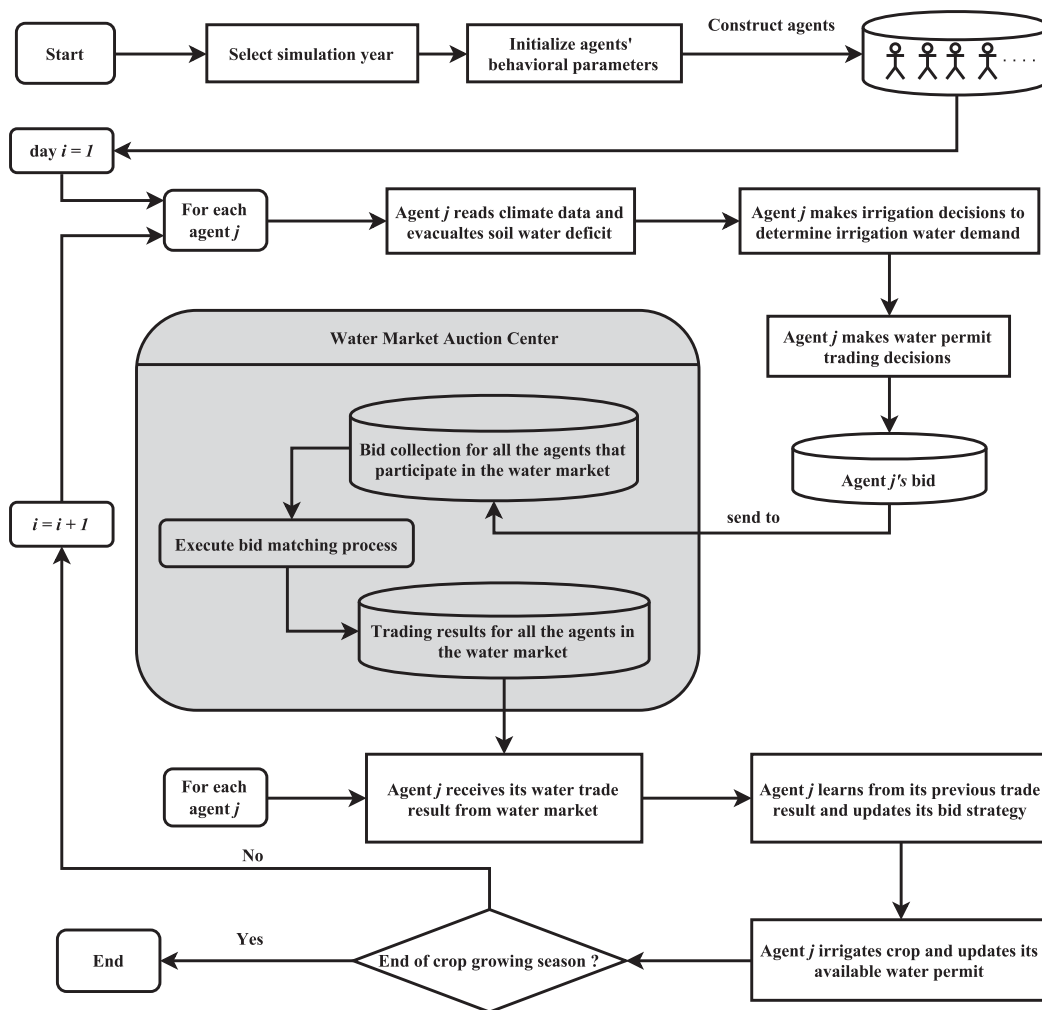


Figure 2. Flowchart of agent-based water market model.

south Texas, a southwestern state within the United States. The GRB encompasses an area of 3256 km² (~800,000 acres) (Figure 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 3b), which provides potential for water permits to be traded during drought events.

At the daily timescale, 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

Table 2. Baseline and Benchmark Models

Model	Model Description	Agents' Behavioral Parameters in the Model	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

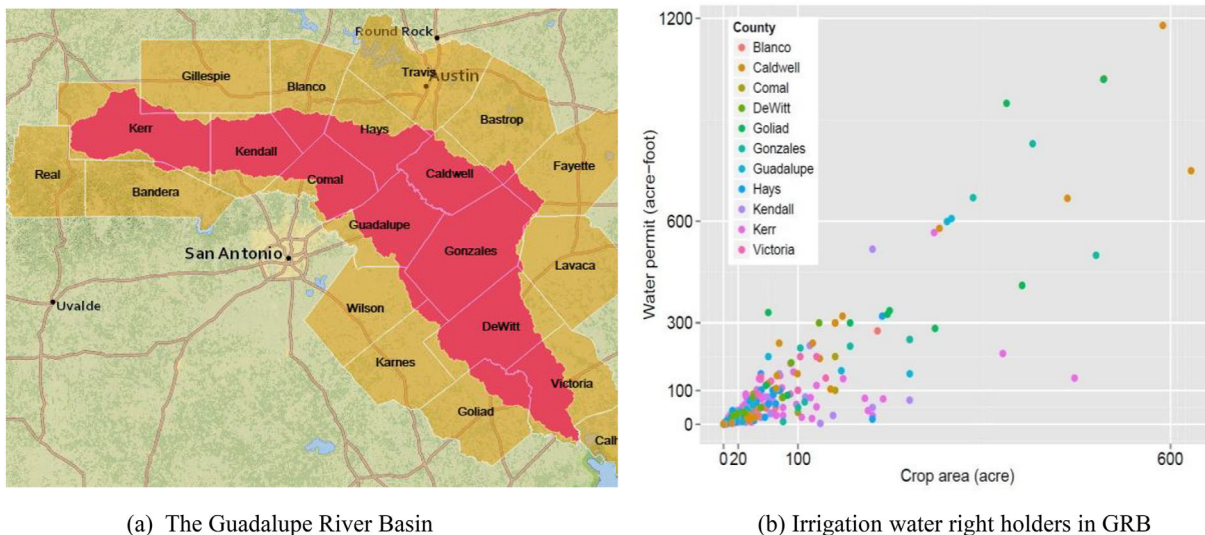


Figure 3. (a) Guadalupe River Basin and (b) water permits versus crop area for irrigation water right holders in the watershed.

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 sold 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 16 March and harvest on 2 August (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>).

In this study, we simulate a hypothetical water market that operates at the daily timescale, 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., 2011; 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.

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 2: (1) a baseline model that represents the scenario without water markets (model B1) and

Table 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	

(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 those from 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.

Scenario-based analysis is applied to evaluate the impacts of farmers' behaviors on the water market. Two experiments are designed as shown in Table 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 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 gives an example of parameterizing agents' behavioral parameters for one particular scenario.

4. Results

This section presents the model results and discussion. First, we execute experiment 1 to give an overview of the model results (section 4.1) and evaluate the impacts of the bidding parameters on the water market

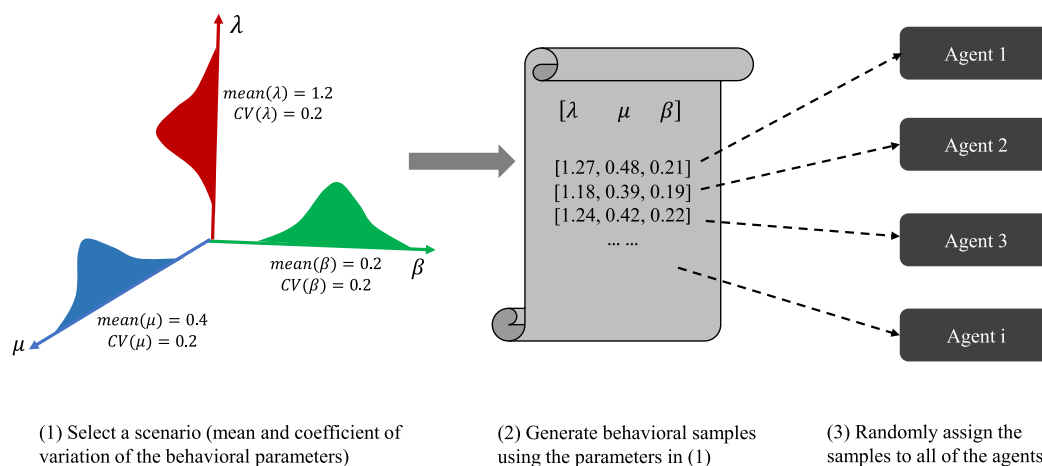


Figure 4. Illustration of the procedure for sampling the agents' behavioral parameters for one run in the Monte-Carlo simulation (i.e., the mean value for λ , μ , and β is 1.2, 0.4, and 0.2, respectively; coefficient of variation (CV) is 0.2 for λ , μ , and β).

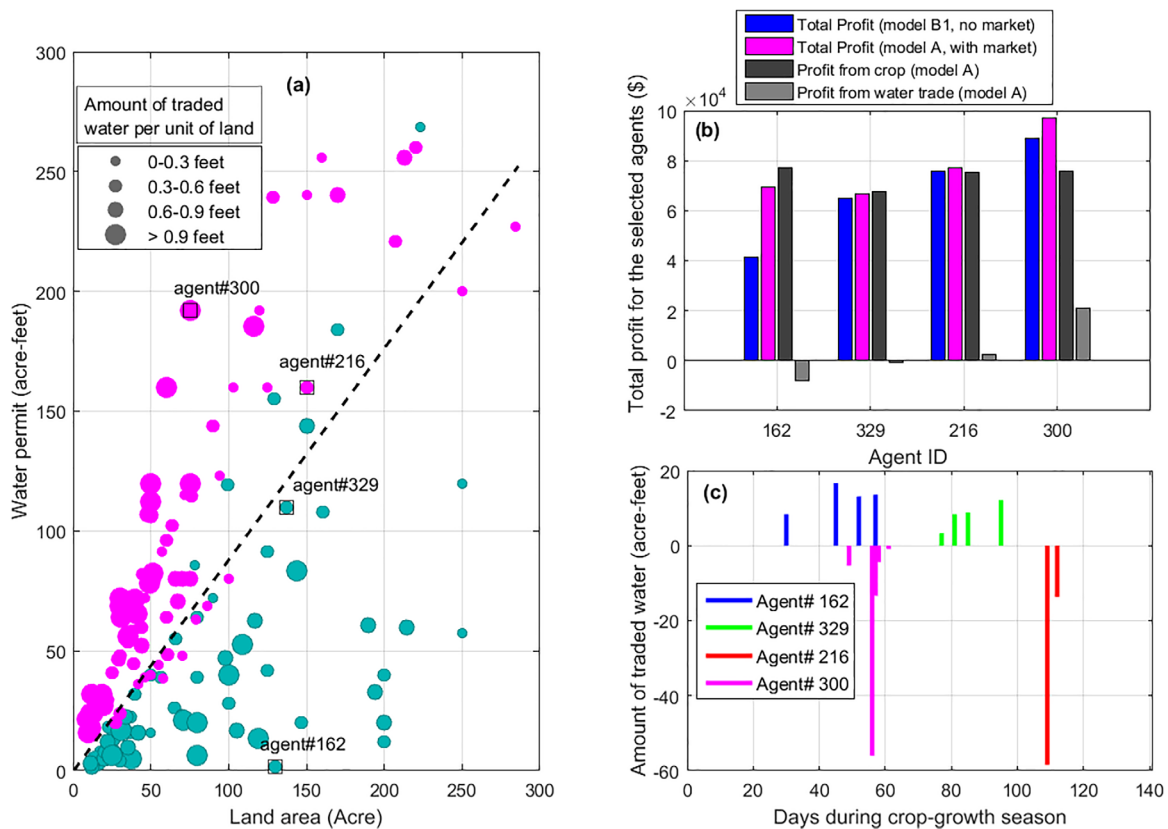


Figure 5. Results of (a) total traded water permits for all of the agents (pink dots represent sellers, green dots represent buyers; the size of the dots represents the traded water amount divided by the agent’s land area); (b) profits of the four selected agents with and without water market; and (c) 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.

(section 4.2). Then, we execute experiment 2 to evaluate the impacts of the irrigation parameter (section 4.3) and evaluate how the three parameters jointly affect the water market (section 4.4).

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 5 shows the simulation results for a particular scenario. Figure 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 5a) are selected to compare their profit with and without the water market (Figure 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).

4.2. Impacts of Bidding Behaviors

This section explores the impact of agents’ bidding behaviors on the performance of the water market. Figure 6 shows the summary of the system-level total crop production (TCP) from the three models (i.e., models A, B1, and B2, defined in Table 2) for all of the scenarios.

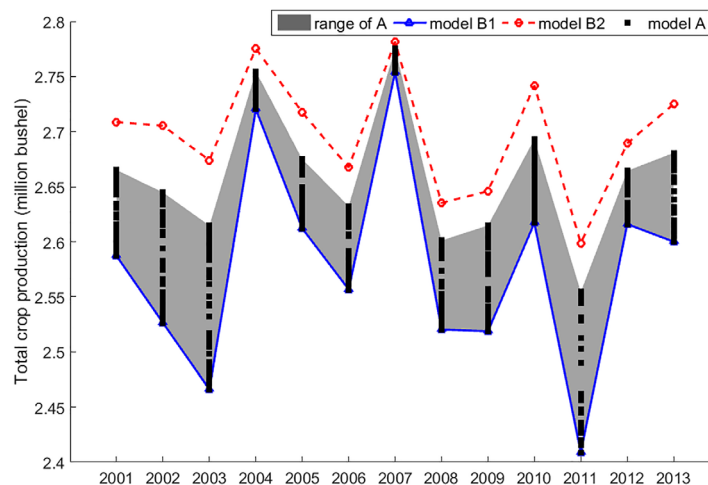


Figure 6. Summary of total crop production for all of the agents under model A (black square), model B1 (blue triangle), and model B2 (red circle). Note that the shaded grey area represents the range of model A's possible simulation results.

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 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].

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 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

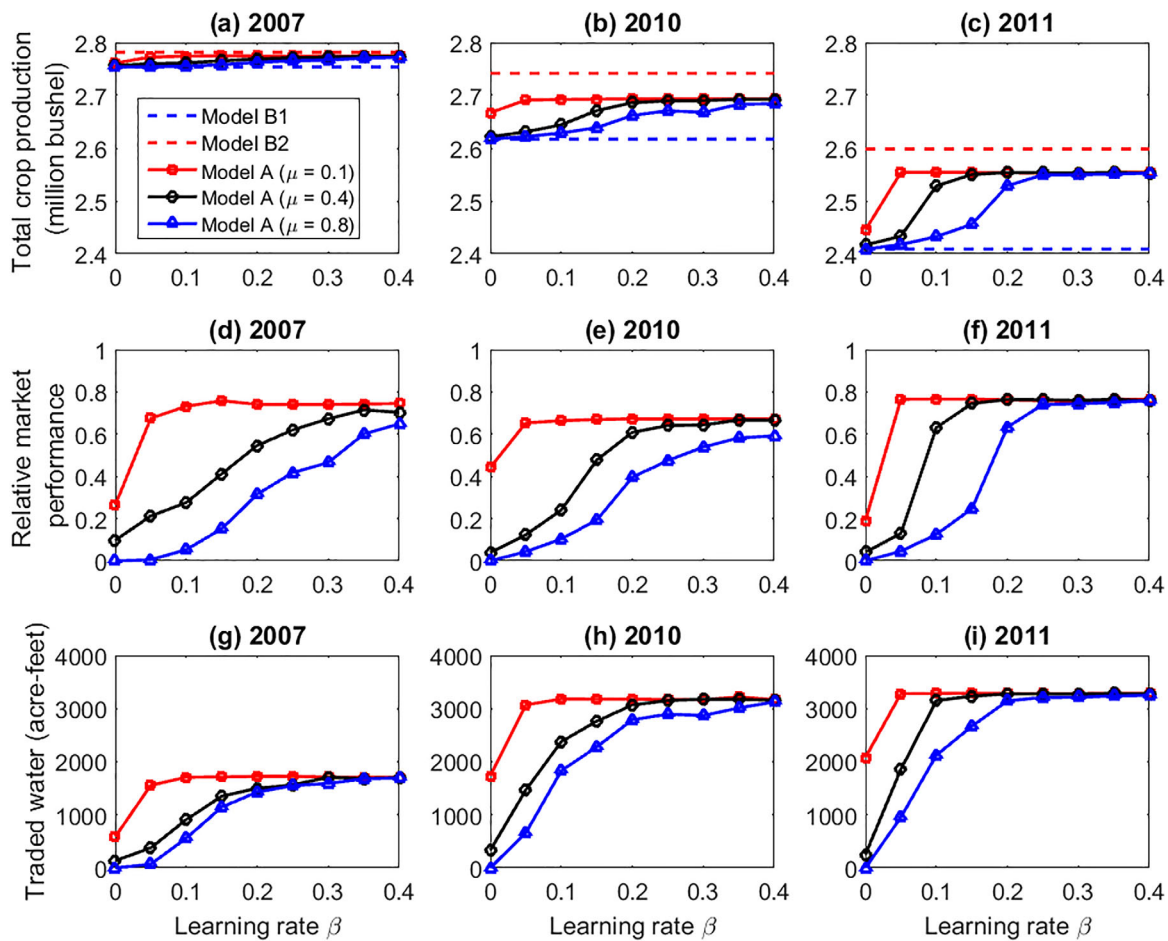


Figure 7. The impacts of learning rate on: total crop production in (a) 2007, (b) 2010, and (c) 2011; relative market performance in (d) 2007, (e) 2010, and (f) 2011; and total traded water permit in the water market in (g) 2007, (h) 2010, and (i) 2011.

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.

Figures 8a–8c 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 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 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–8f) show that the agents' bidding prices between 50 and 70 days (i.e., flowering stage for corn) are higher than on the rest of the days. This is consistent with the trend

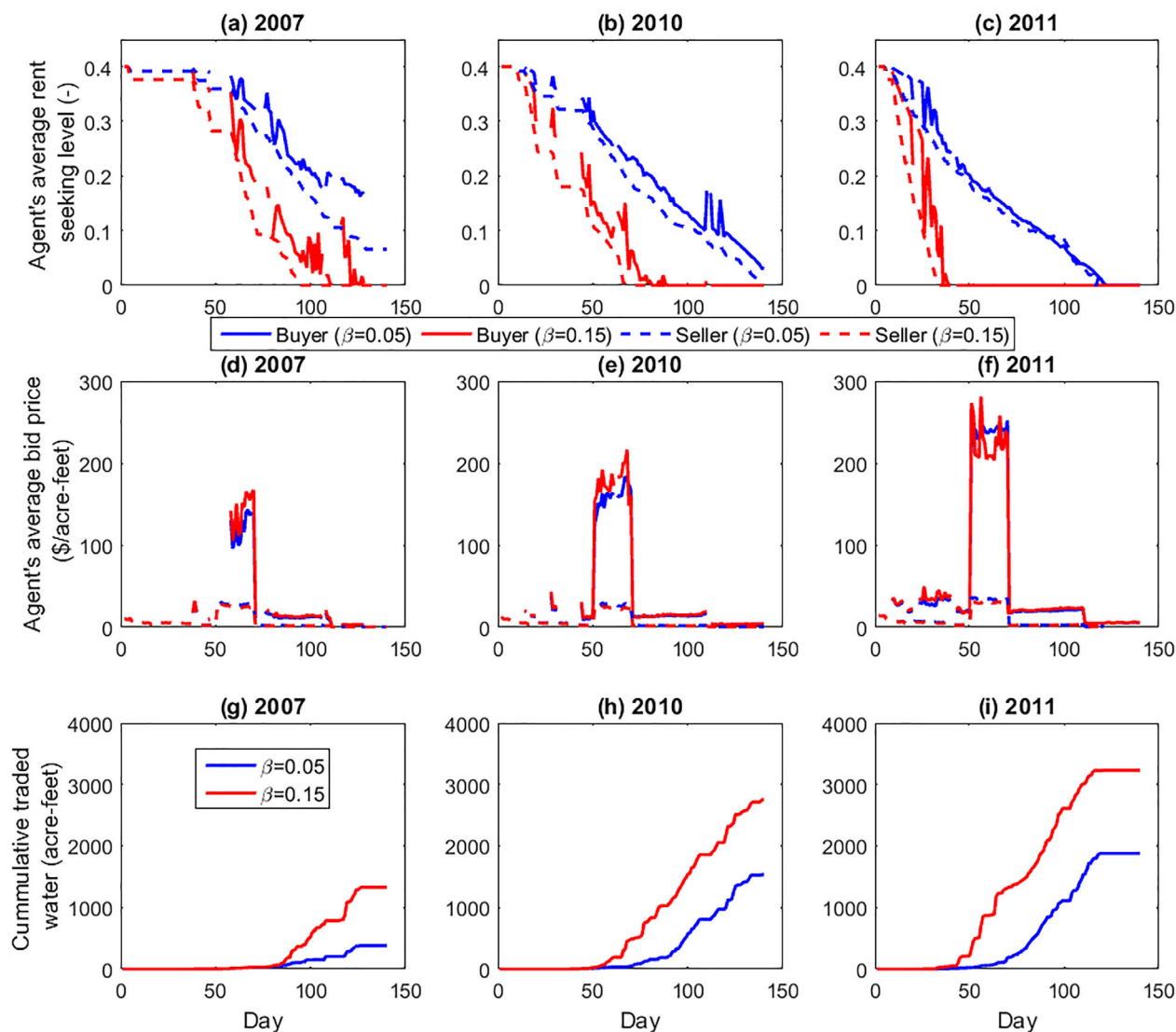


Figure 8. The impacts of learning rate on: agents' average rent seeking in (a) 2007, (b) 2010, and (c) 2011; agents' average bidding price in (d) 2007, (e) 2010, and (f) 2011; and cumulative total traded water in the market in (g) 2007, (h) 2010, and (i) 2011.

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.

4.3. 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 9 summarizes all of the simulation scenarios in experiment 2 (shown in Table 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 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

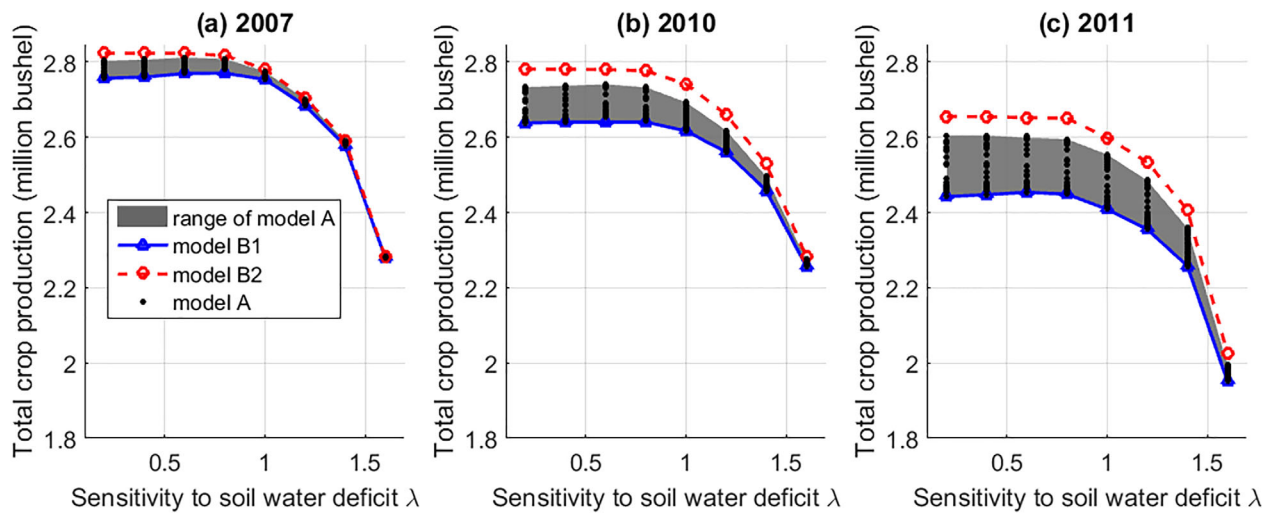


Figure 9. Total crop production of models A, B1, and B2 in (a) 2007, (b) 2010, and (c) 2011.

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.

4.4. Joint Impact and Interplay of the Three 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 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–10c). (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 do not change significantly (Figures 10g–10i). 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–10f). 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).

Lastly, we evaluate how hydrological conditions affect the interplay of the behavioral parameters (Figure 11) and the impact of transaction cost on the modeling results (Figure 12). Compared with the results in Figure 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

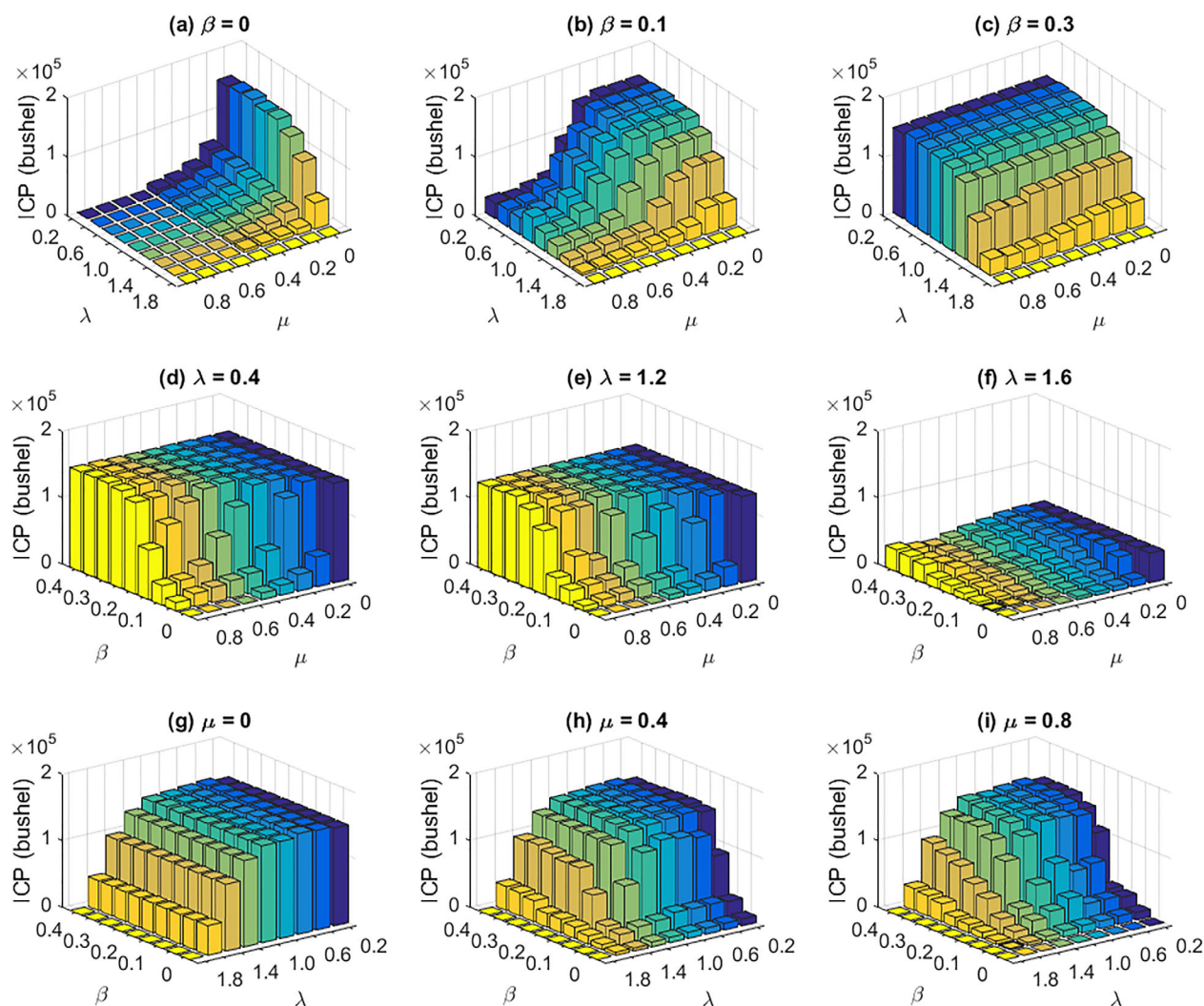


Figure 10. The interplay of the three behavioral parameters in 2011.

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 12).

5. Discussion

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.

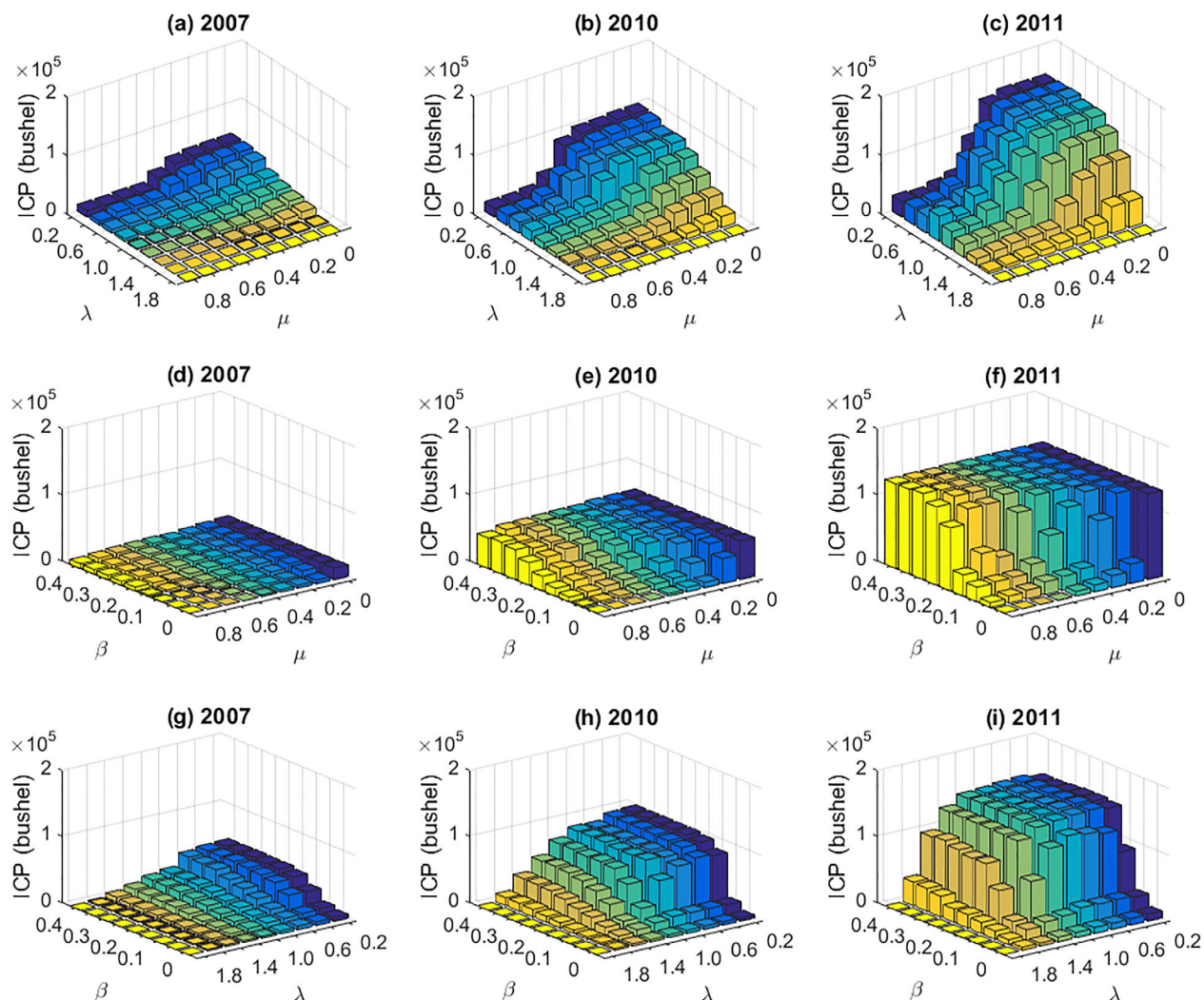


Figure 11. The interplay of the behavioral parameters under different hydrological conditions. (Note: β is 0.1 for Figures 11a–11c; λ is 1.2 for Figures 11d–11f; μ is 0.4 for Figures 11g–11i).

The results of this study may also provide insights for policy makers to identify appropriate education programs toward 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 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., $\mu=0.8$, $\beta=0.2$ in Figure 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.

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

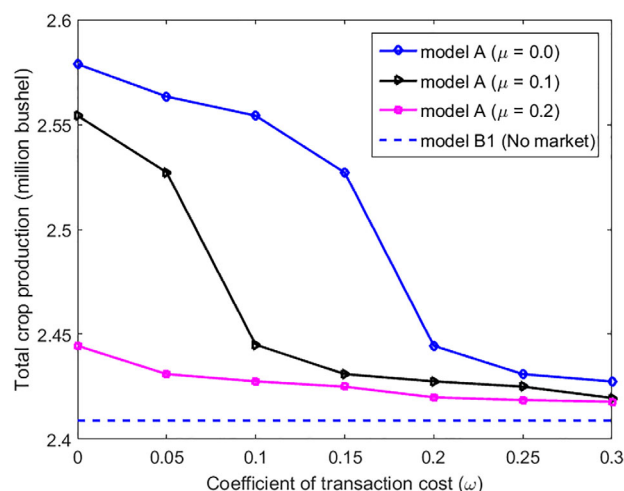


Figure 12. Total crop production under different levels of transaction costs.

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.

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.

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