Role of Heterogeneous Behavioral Factors in an Agent-Based Model of Crop Choice and Groundwater Irrigation

Yao Hu[1] and Steve Beattie[2]

Abstract: Unsustainable groundwater use has led to the lowering of groundwater levels and the degradation of groundwater-dependent ecosystems worldwide. Integrated hydrologic-ecological-economic models have been developed to simulate and optimize the coupled human and groundwater systems, and address the issue of unsustainable groundwater use. However, a lack of understanding of the heterogeneity of groundwater users undermines the performance of the integrated models. In this paper, an agent-based model is developed using a two-stage optimization strategy with the goal of optimizing the decision making of heterogeneous farmers on crop choice and groundwater irrigation. The performance of the optimization strategy is evaluated under the influence of four behavioral factors. The results illustrate that the optimization strategy can lead to higher crop profits or a slower rate of groundwater depletion in comparison with the observations, but does not necessarily guarantee the optimal solution in balancing these two objectives. In order to achieve sustainable groundwater use, the roles that behavioral factors play in farmers' decision making need to be better understood, and better accounted for in groundwater policy.
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Introduction

Groundwater sustainability refers to the development and use of groundwater resources to meet current needs without causing unacceptable environmental and socioeconomic consequences (Alley et al. 1999; Brown 2017). However, many unacceptable consequences are occurring from unsustainable groundwater use, such as groundwater overdraft. Overdraft occurs when the rate of withdrawal from the aquifer exceeds its recharge rate. When this happens, the water table declines, pumping costs increase as the energy required for pumping increases, and land subsidence can take place. Furthermore, overdraft can cause groundwater contamination, and the ecosystems that depend on the health and stability of the aquifer can be significantly impacted (Gorelick and Zheng 2015).

Understanding the interplay between heterogeneous groundwater users and hydrologic responses is essential to addressing the issues related to unsustainable groundwater use (Gorelick and Zheng 2015). From this perspective, integrated hydroeconomic models have been developed and applied for water resource allocation and management (Harou et al. 2009). However, these models commonly lack the capability to describe the heterogeneity of water users and their impact, resulting in uniform water management policies. For example, the same tax and quota are often uniformly applied to groundwater users without explicit consideration of the heterogeneity of basins and groundwater users, undercutting the expected benefits of these policies (Mulligan et al. 2014).

[1]Postdoctoral Fellow, Dept. of Civil and Environmental Engineering, Univ. of Michigan, 2350 Hayward St., Ann Arbor, MI 48109 (corresponding author). ORCID: https://orcid.org/0000-0002-0199-6044. Email: huya@umich.edu; tomhuyao@gmail.com

[2]Undergraduate, Dept. of Statistics, Univ. of Michigan, Ann Arbor, MI 48109.

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The heterogeneity of water users is often rooted in behavioral factors affecting their decision making (Gregory and Leo 2003). For example, in the face of uncertain future weather and crop prices, some groundwater users rely on their past experiences to decide which types of crops to grow and the amount irrigation to apply, while others prefer to base their decisions on more recent observations (Ng et al. 2011; Hu et al. 2015). As such, these differing behaviors may lead to different crop profits and groundwater levels. Agent-based models (ABMs) are increasingly being used to incorporate behavioral factors and evaluate their impact on water policies and beyond (Ng et al. 2011; Du et al. 2017).

Agent-based modeling is a bottom-up simulation framework based on autonomous, interdependent, and adaptive decision-making entities called agents. These agents interact with each other and/or their surrounding environment based on certain behavioral rules. These behavioral rules are subject to change, enabling agents to learn and adapt to the environment (North and Macal 2007). Although ABMs are used frequently in social science, they are well suited to simulating systems where the emerging and intricate system dynamics are the result of simple but heterogeneous behaviors of the interacting components within the system. Both the behaviors and interactions can be well described using an ABM. Thus, when compared with conventional simulation models (based on the top-down approach), ABMs are usually better suited to representing system dynamics and capturing emergent phenomena (Hu 2016).

In coupled human and natural systems, agent-based models can describe the feedback between human and environmental systems and incorporate the effects of institutional and physical constraints at various levels (Gilbert 2008). This ability allows for the mapping of complex system dynamics at different spatiotemporal scales, and makes ABMs an ideal candidate for sociohydrological issues such as development of sustainable groundwater resource management practices (Mitchell 2009; Miller and Page 2009; Foster and Perry 2010; Foster and Garduño 2013). By using an ABM to model coupled human and groundwater systems, we can gain better understanding of the factors that affect stakeholders' decision-making processes and test new groundwater management policies and regulations (Zellner 2008; Wise and Crooks 2012; Mulligan et al. 2014; Farhadi et al. 2016).

The application of optimization methods within an agent-based model offers a promising approach for achieving sustainable groundwater use, while accounting for groundwater users' real-world irrigation practices (Oremland and Laubenbacher 2014; Farhadi et al. 2016). For example, irrigation planning generally involves a trade-off between maximizing crop profits and prioritizing the goal of sustainable groundwater use (Kennedy et al. 2016), or involves identifying the optimal way to achieve both to the greatest extent possible (Berglund 2015). In addition, through the incorporation of these optimization principles into agent-based modeling (Ding et al. 2016; Erfani and Erfani 2015), we can evaluate the influence of behavioral factors on the behavioral rules derived from optimization strategies for heterogeneous agents.

In this paper, we present a new agent-based model with a two-stage optimization strategy that builds upon the previous work by Hu et al. (2015), which optimized farmers' decision making on an annual scale. The new ABM aims to optimize farmers' crop profits under the constraints for groundwater irrigation on a daily scale, while taking farmers' behavioral factors into account. We also provide a case study to illustrate the application of the ABM in the context of coupled human and groundwater systems.

Methodology

In this section, we adopt the overview, design concepts, and details (ODD) principles (Grimm et al. 2006, 2010) to describe the agent-based model with the two-stage optimization.

Purpose

Because water is a limited resource, maximizing crop profits while not overexploiting groundwater is critical. With this in mind, we developed an agent-based model that prescribes farmers' behaviors in crop choice and groundwater irrigation. To make the model more effective, we developed a two-stage optimization strategy to optimize farmers' behaviors. Our goal was to evaluate the performance of the optimization strategy compared with actual crop profits and groundwater usage.

Entities, State Variables, and Scales

The two-stage optimization strategy finds optimal behaviors while simultaneously accounting for the traits of individual farmers. A farmer is characterized by the following state variables: types of crops they want to plant; their prior knowledge of crop harvesting prices in November; total precipitation during the crop growing season from May to October; their confidence with respect to their prior knowledge when predicting the crop prices and precipitation; their tolerance level with the fluctuation of crop profits; and their sensitivity to crop water stress as shown by Table 1.

Process Overview and Scheduling

Each year of the simulation proceeds in two stages. First, before the crop planting and growing season (i.e., the first stage; Fig. 1), farmers make predictions of the future crop harvesting prices for the coming November and total precipitation during the entire growing season from May to October. Given the predicted precipitation, farmers estimate crop total water demand during the crop growing season. Then, estimations of crop water demand and prices for different crops are fed to an objective function, which is used to define farmers' utility. Through maximization of their individual utility, farmers decide the types of crops to plant, the upper bound of the irrigated area, and the lower bound of the dryland area for the crops. During the crop growing season (i.e., the second stage), farmers make daily decisions on actual water use for irrigated crop areas given the observations of daily precipitation. As such, they maximize their crop profits at harvest. These processes are repeated for each year of simulation.

Table 1. List of farmer state variables

Variable	Description (unit)
J	Types of crops to plant: corn, sorghum, wheat, and soybean
$A^*_{d,j}$	Planted dryland area for crop j (acre)
$A^*_{i,j}$	Planted irrigated area for crop j (acre)
$A_{d,j}$	Actual dryland area for crop j (acre)
$A_{i,j}$	Actual irrigated area for crop j (acre)
CP_j	Prior knowledge of the harvesting price of crop j (e.g., in November)
P	Prior knowledge of total precipitation during the crop growing season (e.g., from May to October)
$CP_{j,obs}$	Observations of the harvesting price of crop j of last year
P_{obs}	Observations of total precipitation during the crop growing season of last year
κ_o	Level of confidence farmers have on CP_j and P
ν_o	Level of confidence farmers have on the variance of CP_j and P
λ	Tolerance level with the variation of crop profits
D_{gw}	Depth to groundwater level (ft)
SC	Sensitivity to crop deficit
MAD	Management allowed depletion
I_j	Daily crop irrigation for crop j (in.)

Initialization

We initialized two types of farmers defined by four behavioral factors, including κ_o, ν_o, λ, and SC (definitions given in Table 1). As shown by Table 2, with larger κ_o and smaller ν_o, Type I farmers place greater importance on prior knowledge of the historical mean values of crop prices and precipitation and are less affected by the variation of the recent observations when predicting the future crop prices and precipitation. In other words, Type I farmers place more value on their past average experiences. In contrast, Type II farmers, with smaller κ_o and larger ν_o, are more willing to make predictions of the future crop prices and precipitation based on recent observations, and make irrigation decisions accordingly. Larger λ indicates greater intolerance of variations in crop profits arising from the uncertainty of the predicted precipitation and crop prices. In addition, SC is equal to 1 for Types I and II farmers, showing their compliance with the guideline of crop management allowed depletion (MAD) (Noël and Cai 2017).

Input

For the first stage, the input data include (1) four candidate crops to plant (i.e., corn, sorghum, wheat, and soybean) and their initial dryland and irrigated areas; (2) prior knowledge of crop harvesting prices and total precipitation during the crop growing season; (3) water permits for groundwater irrigation; (4) initial depth to groundwater level; and (5) labor and transportation costs;

For the second stage, the input data are four stages of crop growth (i.e., initial, development, midseason, and late stage) and crop parameters at different stages as shown by Table 3 and farmers' sensitivity level to daily crop water demand.

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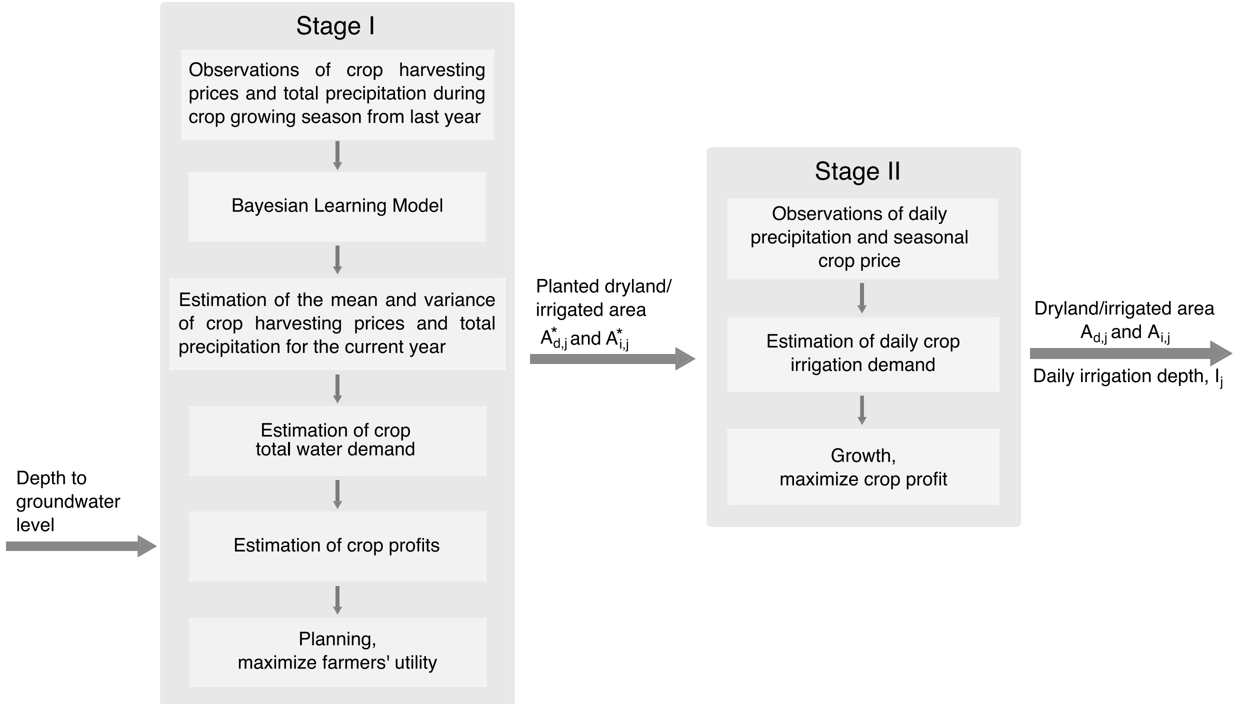

Fig. 1. Two-stage irrigation strategy.

Table 2. Farmer type

Farmer type	κ_o	ν_o	λ	SC
I	Large	Small	Large	1
II	Small	Large	Small	1

Table 3. Data input for the second stage

Variable	Definition	Unit	Temporal
Drz	Root depth	in.	Stage[a]
%MAD	Managed allowed water deficit fraction	—	Stage[a]
Kc	Crop coefficient	—	Stage[a]
Ks	Crop stress coefficient	—	Stage[a]
P	Precipitation	in.	Daily
ET_d	Crop reference evapotranspiration	in.	Daily

[a]Four stages (i.e., initial, development, midseason, and late stage) are used to describe crop growth from planting to harvest.

Design Concept

Emergence

Dynamics of groundwater level emerge from daily irrigation decisions made by the individual farmers. To maximize crop profits while balancing groundwater use, crop patterns emerge as the result of decisions on crop types and their irrigated areas made in the face of uncertainties in crop harvesting prices and total precipitation during the crop growing season.

Adaptation

For the two-stage optimization, at the first stage farmers are equipped with one of two alternative behavior rules to make estimations of the crop prices and precipitation. They can either place more value on their past long-term experiences of crop prices and precipitation, or more on their most recent observations (e.g., last year). In addition, farmers can adopt different levels of tolerance (i.e., λ) for the variance of the annual crop profits, and different levels of sensitivity (i.e., SC) to daily crop water demand.

Objective

The agent-based model with two-stage optimization strategy aims to maximize crop profits under the water permit constraint for groundwater irrigation.

Sensing

Farmers sense the depth of the groundwater level at the first stage. At the second stage, farmers sense daily crop water demand given the MAD and soil water deficit (SWD).

Interaction

The interactions of the agents are modeled implicitly via groundwater usage. All farmers pump groundwater for irrigation from the same aquifer. Their individual pumping behavior affects groundwater level; the more they pump, the lower the groundwater level. As a result, it becomes more expensive to pump for all farmers.

Prediction

Every year, farmers make predictions of the crop harvesting prices in November and total precipitation during the entire growing season from May to October based on a Bayesian learning model, which incorporates farmers' long-term experience of crop prices and precipitation acting as the prior knowledge and the observations from last year.

Stochasticity

Crop harvesting prices and total precipitation are simulated as random processes via the Bayesian learning model. Importance sampling is used to calculate their mean and variance, which are fed to the planning model for farmers to decide the types of crops to plant and their irrigated area.

Collective

All of the farmers in the same county are assumed to be homogeneous and thus aggregated to be considered as a single superfarmer. This aggregation is mainly due to the fact that most of the relevant data are only available at county level, e.g., types of planted crops and their irrigated area.

Output

To test and analyze our agent-based model, we output the data of crop irrigation depth for different crops and their dryland and irrigated areas on a daily scale. On an annual scale, we output crop profits, total groundwater use for crop irrigation, and the groundwater level.

Submodels

Bayesian Learning Model

Crop harvesting prices and total amount of precipitation during the crop growing season are important to farmers' behaviors in crop choice and groundwater irrigation (Ng et al. 2011). In this model, we use a Bayesian learning approach to simulate farmers' predictions of crop prices and precipitation. A normal distribution was chosen for the likelihood function of both predictions as shown by Eq. (1)

$$p(\mathbf{D}|\mu,\sigma^2) = \frac{1}{(2\pi\sigma^2)^{-n/2}} \exp\left\{-\frac{n}{2\sigma^2}\left[\sum_{i=1}^{n}(x_i - \bar{x}) + (\bar{x}-\mu)^2\right]\right\} \tag{1}$$

where $\mathbf{D} = (x_1, \ldots, x_i, \ldots, x_n)$ is the sequence of observations and each x_i in $\mathbf{D}$ is independent and identically distributed (IID); $\bar{x}$ = mean of the sequence; and μ and σ^2 = mean and variance of the likelihood function.

A conjugate prior [a normal-inverse-chi-squared($NI\chi^2$) prior] is used to simulate agents' prior knowledge of historical crop harvesting prices and precipitation as shown by Eq. (2) (Murphy 2007)

$$\begin{aligned} p(\mu,\sigma^2) &= NI\chi^2(\mu_o, \kappa_o, \nu_o, \sigma_o^2) \\ &= N(\mu|\mu_o, \sigma^2/\kappa_o)\cdot\chi^{-2}(\sigma^2|\nu_o,\sigma_o^2) \end{aligned} \tag{2}$$

where μ_o and σ_o^2 = prior mean and variance. As described in Table 1, κ_o and ν_o indicate the level of confidence on μ_o and σ_o^2, respectively. Based on Bayes' theorem, the posterior distributions of crop prices and precipitation are obtained (Lee 2004, p. 67)

$$\begin{aligned} p(\mu,\sigma^2|\mathbf{D}) &= NI\chi^2(\mu_n,\kappa_n,\nu_n,\sigma_n^2) \propto p(\mu,\sigma^2)p(\mathbf{D}|\mu,\sigma^2) \\ \mu_n &= \frac{k_o\mu_o + n\bar{x}}{k_o} \\ \kappa_n &= \kappa_o + n \\ \nu_n &= \nu_o + n \\ \sigma_n^2 &= \frac{1}{\nu_n}\left(\nu_o\sigma_o^2 + \sum(x_i-\bar{x})^2 + \frac{n\kappa_o}{n+\kappa_o}(\mu_o-\bar{x})^2\right) \end{aligned} \tag{3}$$

where μ_n and σ_n^2 = posterior mean and variance; and κ_n and ν_n indicate the level of confidence on μ_n and σ_n^2, respectively. As a result, agents update their annual predictions of the posterior mean and variance of crop prices and precipitation accordingly.

Crop Total Water Demand

The predicted precipitation from the Bayesian learning model is used to calculate the potential water availability during the crop growing season. To estimate water availability, the expected amount of rainfall used for crop growth (i.e., effective rainfall) during the crop growing season, P_e, is first calculated using the USDA Soil Conservation Service (SCS) method (USDA 1967)

$$P_e^* = \max\left(0, \left[1.253\cdot\left(\frac{\tilde{P}}{nm}\right)^{0.824} - 2.935\right]\cdot 10.0^{[(0.001ET_c)/nm]}\right)$$

$$P_e = \begin{cases} nm\cdot\min\left(P_e^*, \dfrac{\tilde{P}}{nm}, \dfrac{\tilde{E}T_c}{nm}\right), & \dfrac{\tilde{P}}{nm} > 12\text{ mm} \\ \tilde{P}, & \text{otherwise} \end{cases} \tag{4}$$

where P_e^* = average monthly effective rainfall (mm); nm = number of months accounted for in the crop growing season; $\tilde{P}$ = expected amount of rainfall during the period estimated using the Bayesian approach (mm); and ET_c = expected potential crop evapotranspiration (ET) equal to $\bar{K}_c\cdot ET_m$, with $\bar{K}_c$ and ET_m being the crop coefficient and the reference crop evapotranspiration during the growing season (mm). Daily reference crop evapotranspiration ET_d (mm/day) is first calculated using the 1985 Hargreaves equation (Hargreaves and Samani 1985) and summed over the growing season to obtain ET_m

$$\begin{aligned} ET_d = a + b\cdot\frac{0.0023}{\lambda_d}\cdot\left(\frac{T_{\min}+T_{\max}}{2} + 17.8\right) \\ \cdot\sqrt{T_{\max}-T_{\min}}\cdot R_a \end{aligned} \tag{5}$$

where the coefficient $a = 0$, $b = 1$, and $\lambda_d = 1$; $T_{\min}$ and $T_{\max}$ = minimum and maximum daily air temperature obtained from Daily Global Historical Climatology Network (GHCN-DAILY) (Menne et al. 2012) (°C); and R_a = extraterrestrial solar radiation ($\text{MJ}\times\text{m}^{-2}\times\text{day}^{-1}$), which is calculated based on the method by Dingman (2015). Once the effective rainfall is determined, we then estimate the expected water demand I_e (mm) during the crop growing season by Eq. (6)

$$I_e = ET_c - P_e \tag{6}$$

Crop Profit

Based on the estimated crop prices from the Bayesian learning model and crop total water demand from the crop total water demand, we obtain crop profit by Eq. (7)

$$\begin{aligned} \pi &= \sum_{j=1}^{n}\pi_j \\ &= \sum_{j=1}^{n}A_{i,j}[(\widetilde{CP}_j - tc_{i,j})\cdot Y_j - cw_{i,j}\cdot I_{i,j} - F_{i,j}] \\ &\quad + \sum_{j=1}^{n}A_{d,j}[(\widetilde{CP}_j - tc_{i,j})\cdot Y_{d,j} - F_{d,j}] \end{aligned} \tag{7}$$

where $\widetilde{CP}_j$ = predicted harvesting price for crop j; $tc_{i,j}$ = corresponding transportation cost (\$/bushel); $I_{i,j}$ = total irrigation depth during the crop growing season (in.); $F_{i,j}$ and $F_{d,j}$ = fixed production cost for irrigated and dryland cropland (\$/acre); and the unit energy/labor cost associated with pivot irrigation is denoted by $cw_{i,j}$ (\$/acre-in.), which is proportional to the depth to groundwater level: the lower the groundwater level, the higher the $cw_{i,j}$; and Y_j = crop yield in the following

$$Y_j = Y_{d,j} + (Y_{m,j} - Y_{d,j})[1-(1-I_{r,j})^{1/\beta}] \tag{8}$$

where $Y_{m,j}$ and $Y_{d,j}$ = maximum crop yield without water stress and dryland crop yield (bushel/acre) (Palazzo 2009); β = irrigation

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efficiency ($\beta \in [0,1]$); and $I_{r,j}$ = ratio of $I_{i,j}$ to the expected total water demand $I_{e,j}$ for crop j from Eq. (6).

Planning

Farmers' utility is defined as the difference between the expected value of crop profits, π, and the product of λ and the variance of crop profits [Eq. (9)]. At the planning stage, through maximization of their individual utility, farmers decide which crops to grow, and the corresponding irrigated and dryland area (acre) ($A_{i,j}$ and $A_{d,j}$) as follows:

$$U(\pi) = E(\pi) - \lambda \cdot \mathrm{var}(\pi) \tag{9}$$

where $E(\pi)$ and $\mathrm{var}(\pi)$ are the expected value and variance of the crop profits; and λ is used to characterize farmers' tolerance level with respect to the fluctuation of crop profits: the larger the value of λ, the less tolerant the farmers are, leading to lower utility. As a result, the planning stage is formulated as follows:

$$\begin{aligned}
&\text{maximize}\, U(\pi) \\
&\text{subject to} \sum_{j=1}^{n} (A_{i,j}^{\text{planted}} + A_{d,j}^{\text{planted}}) \leq \bar{A} \\
&\qquad\qquad \sum_{j=1}^{n} A_{i,j}^{\text{planted}} I_{e,j} \leq \text{TWA} \\
&\qquad\qquad 0 \leq I_{i,j} \leq I_{e,j} \\
&\qquad\qquad A_{i,j}^{\text{planted}} \geq 0, \qquad A_{d,j}^{\text{planted}} \geq 0
\end{aligned} \tag{10}$$

where $\bar{A}$ = total cropland area (acre); total water availability TWA (acre-in.) is estimated as the product of water permits I_p (in.) and initial irrigated area A_i (acre) for individual farmers; and n = number of crop types taken into account. Solving this optimization problem at the planning stage provides the upper bound of irrigated cropland area, $A_{i,j}^{\text{planted}}$, for the second stage.

Daily Crop Irrigation Demand

When farmers start planting crops at the second stage (i.e., the growth stage, Fig. 1), the daily crop irrigation demand (ID) is solely dependent on farmers' perception of crop water demand, not water availability. The latter has already been taken into account at the planning stage to determine the planted cropland acreage. The daily perception of crop water demand is parsed into two parts: (1) the MAD, maximum amount of plant available water allowed to be removed from the soil without impairing crop growth (in.); and (2) the SWD, which is a water accounting variable. SWD describes the amount of water that a crop is perceived to be in need of at a given time (in.). The daily crop ID is calculated at the beginning of each day t during the crop growing season, which depends on the value of SWD and MAD at day of $t-1$ as shown by Eq. (11)

$$\mathrm{ID}_t = \begin{cases} \mathrm{SWD}_{t-1} - \mathrm{MAD}_{t-1}, & \mathrm{SWD}_{t-1} \geq \mathrm{MAD}_{t-1} \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

In the following, we will discuss how these two variables are calculated on a daily scale, which will lead to the calculation of daily ID (in.).

Crops absorb water through the roots, and the maximum amount of water available to the plant at a given time [i.e., maximum available water (MAW)] is thus proportional to the depth of the root zone, Drz (in.) as described by Eq. (12)

$$\mathrm{MAW}_{t-1} = \mathrm{AWC} \cdot Drz_s \tag{12}$$

where t = current day during the crop growing season (days). The entire growing season is divided into different growth stages denoted by s, including initial, development, midseason, and late stage (Steduto et al. 2012). Available water capacity (AWC) is the coefficient that describes the fraction of the root zone that can hold water, and varies between soil types due to factors such as soil texture and organic matter (Hudson 1994). Thus, daily MAD can be derived from the following equation:

$$\mathrm{MAD}_{t-1} = \mathrm{SC} \cdot \%\mathrm{MAD}_s \cdot \mathrm{MAW}_{t-1} \tag{13}$$

where $\%\mathrm{MAD}_s$ = management allowed water depletion fraction at the growth stage s recommended by the United Nations' Food and Agriculture Organization (Brouwer and Heibloem 1986); the sensitivity coefficient, SC, represents farmers' comfort level with crop water stress. An SC of 1 indicates farmers' unconditional compliance with the guidelines of %MAD.

To calculate SWD at day $t-1$, daily crop evapotranspiration ET_{t-1} is estimated first using Eq. (14)

$$ET_{t-1} = Kc_s \cdot Ks_{t-1} \cdot ET_{d,t-1} \tag{14}$$

where $ET_{d,t-1}$ = daily reference evapotranspiration obtained at the day $t-1$ from Eq. (5); and Kc_s = crop-specific coefficient and varies between crop growth stages. Crop stress coefficient Ks_{t-1} is the transpiration-reduction factor ($Ks_{t-1} \in [0,1]$), which depends on the maximum daily available water, MAW, as shown in Eq. (15). As the depth of the water in the root zone approaches 0, Ks_{t-1} approaches 0 as well

$$Ks_{t-1} = \frac{\mathrm{MAW}_{t-2} - \mathrm{SWD}_{t-2}}{(1 - 0.01 \cdot \mathrm{MAD}_s) \cdot \mathrm{MAW}_{t-2}} \tag{15}$$

As a result, daily SWD is obtained based on the water balance in the soil

$$\mathrm{SWD}_{t-1} = \mathrm{SWD}_{t-2} + ET_{t-1} - P_{t-1} - I_{t-1} \tag{16}$$

where SWD_{t-2} = soil water deficit 2 days before; P_{t-1} = daily precipitation at $t-1$; and I_{t-1} = daily irrigation supply at $t-1$, which itself is defined as the portion of ID_{t-1} provided to crops.

Growth

For the growth stage, farmers make decisions on the daily irrigation supply for crop j, I_j, and the irrigated crop area, $A_{i,j}$, given the observations of daily precipitation during the crop growing season. Potential crop yield, $Y_{j,p}$, is calculated by Eq. (8) on a daily scale, where the ratio, $I_{r,j}$, is I_j divided by the daily crop ID, ID_j from the daily crop irrigation demand for crop j. In addition, farmers can switch from irrigated to dryland cropland when irrigation costs are likely to outweigh the crop profits. However, the switch is irreversible, i.e., farmers cannot switch back to irrigated cropland once they terminate irrigation at a specific day when it is needed. As a result, through maximization of daily crop profits, π_p, as the result of $Y_{j,p}$ as shown by Eq. (17), farmers decide the optimal daily water use, I_j, and actual irrigated and dryland crop area, $A_{i,j}$ and $A_{d,j}$, for different crops

$$\begin{aligned}
&\text{maximize}\, \pi_p \\
&\text{subject to}\, 0 \leq A_{i,j} \leq A_{i,j}^{\text{planted}} \\
&\qquad\qquad 0 \leq A_{d,j} \leq A_{i,j}^{\text{planted}} + A_{d,j}^{\text{planted}} \\
&\qquad\qquad 0 \leq I_j \leq \mathrm{ID}_j
\end{aligned} \tag{17}$$

At the end of the crop growing season, the total amount of irrigation applied to the crop during the growing season is taken into consideration when calculating the actual crop yield, which is calculated by Eq. (8), where $I_{r,j}$ is the sum of I_j divided by the sum

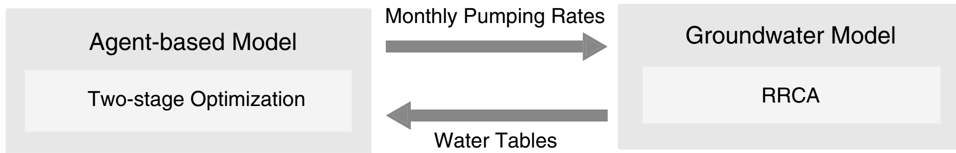

Fig. 2. Exchange of pumping rates and water tables between the agent-based model and the groundwater model.

of ID_j over the crop growing season. Thus, actual crop profits are calculated by Eq. (7) accordingly.

Coupling

To understand the impact of farmers' daily decisions on the groundwater system, the ABM is coupled with a groundwater model. Through the growth module, the optimal irrigation depth and irrigated and dryland cropland area are obtained on a daily scale. This information is then used to derive the monthly pumping rates that drive the groundwater model. The feedback from the groundwater model includes groundwater level, which is translated into the depth to groundwater level used to calculate energy cost (Palazzo 2009). For the sake of the computational cost, the groundwater level at the end of last year is used to calculate the total pumping cost at the first stage and daily pumping cost at the second stage of the current year. This assumption is justified by the analysis that the pumping cost is not sensitive to the small difference in groundwater drawdown between the end of last year and the crop growing season of the current year. Fig. 2 shows the coupling of the ABM and the groundwater model.

Case Study

Study Area

A case study of the High Plains Aquifer Hydrologic Observatory Area (HPAHOA) is used to illustrate the application of the agent-based model with the two-stage optimization strategy. Intensive agricultural development in this area since the 1970s has led to a significant increase in groundwater use. Due to this increase, water conflicts and lawsuits have arisen among three states, Colorado, Kansas, and Nebraska, that share groundwater resources as shown in Fig. 3. A comprehensive groundwater model, the Republican River Compact Administration (RRCA) groundwater model, was developed using MODFLOW-2000 to understand the groundwater movement through the collaboration of the three affected states, the US Geological Survey, and the US Bureau of Reclamation (McKusick 2003). Based on the principle of water balance, the RRCA model allows for the heterogeneity in model parameters, such as hydraulic conductivity (K), ET, and recharge. The model is calibrated to simulate groundwater level and determine the amount, location, and timing of stream depletion as the result of well pumping to a reasonable degree (RRCA 2003; Mulligan et al. 2014).

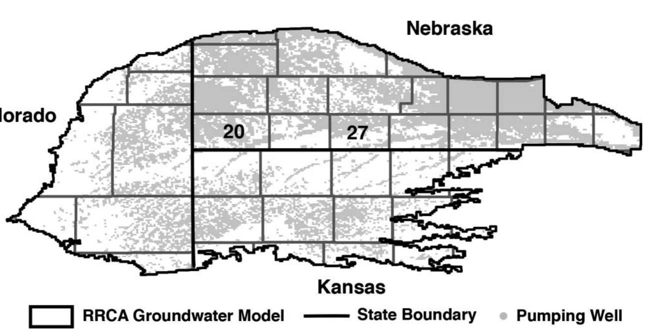

Fig. 3. Aerial view of the HPAHOA in MODFLOW-2,000 with pumping wells. Blocks within HPAHOA represent different counties in Colorado, Nebraska, and Kansas. Each county is treated as a super-farm agent and the numbers are selected agents for our analysis.

Implementation

In this case study, the physically based RRCA model was coupled with the ABM to investigate the impact of behavioral factors on farmers' decisions derived from the two-stage optimization. Each county within the area was defined as a super-farm agent with 46 agents in total (Fig. 3). Two types of farmer agent (i.e., Types I and II in Table 2) were tested separately using the coupled ABM and RRCA model: one scenario being set up with all agents as Type I (i.e., Type I scenario), and the other scenario with all Type II agents (i.e., Type II scenario). The results of farmers' behaviors from the two optimization scenarios were then compared with the results from the baseline scenario in which only the RRCA model is executed with the observations of irrigated and dryland crop areas and irrigation depth. For each of the three scenarios, along with the entire HPAHOA, two representative agents (i.e., Agents 20 and 27) were selected for the comparison as shown in Fig. 3.

Results

When farmers were Type I, their predicted mean values of precipitation (μ_p) and crop prices (e.g., soybean price, μ_{cp}) were less affected by the observations from last year in comparison with the Type II agent, whose prediction showed large variation from year to year (Fig. 4). Conversely, the predicted variance of precipitation (σ_p) and crop prices (e.g., soybean price, σ_{cp}) of the Type I agent were more sensitive to small variations in the predicted mean values (Fig. 4). In addition, the change of σ_{cp} was much smaller than the change of σ_p due to the smaller change of μ_{cp}.

Through the two-stage optimization, agents decided the irrigated and total crop area for different crops. For the entire HPAHOA, we found that agents in the Type II scenario (e.g., Agents 20 and 27) are more likely to plant crops in both irrigated and total crop area in comparison with agents in the Type I scenario (Fig. 5). As such, Type II agents used more groundwater for irrigation (Fig. 6). The total crop area in the baseline scenario was set as the cap for total available land to grow crops in this study. Agents in the Type II scenario usually chose to grow crops on all available land, while Type I agents grew crops on all available land only when the total arable area was small [e.g., 1.0×10^5 ha (2.5×10^5 acre) for Agent 27 in Fig. 5].

The crop choice depends on a variety of factors, including crop water demand, prices, and precipitation. The choices made by agents in the optimization scenarios differ from the choices of the same agents in the baseline scenario (Fig. 5). For example, for the entire HPAHOA, agents from the optimization scenarios chose to grow more sorghum and soybean (along with corn) on the irrigated

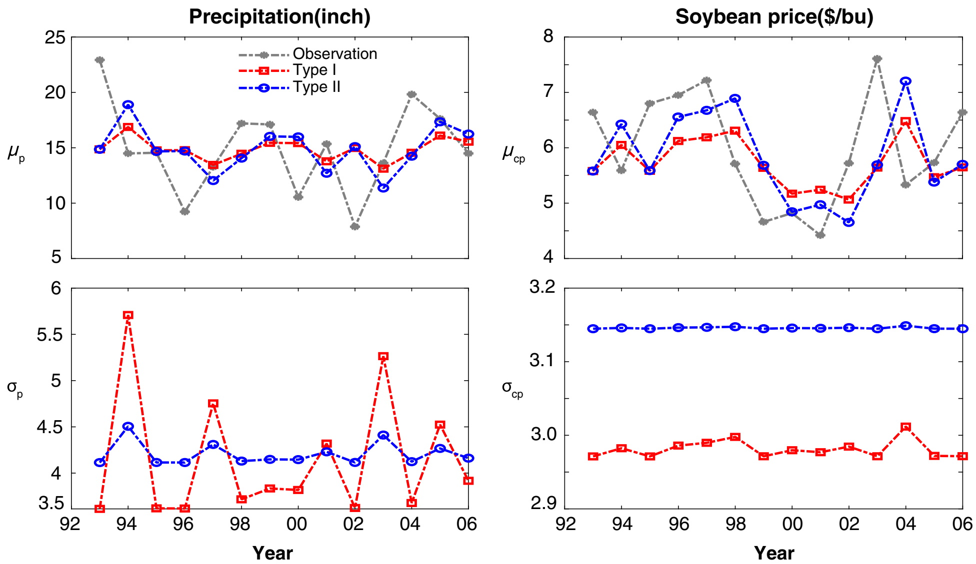

Fig. 4. Observations of precipitation and soybean price and predictions of their mean (μ) and variance (σ) made by Types I and II agents.

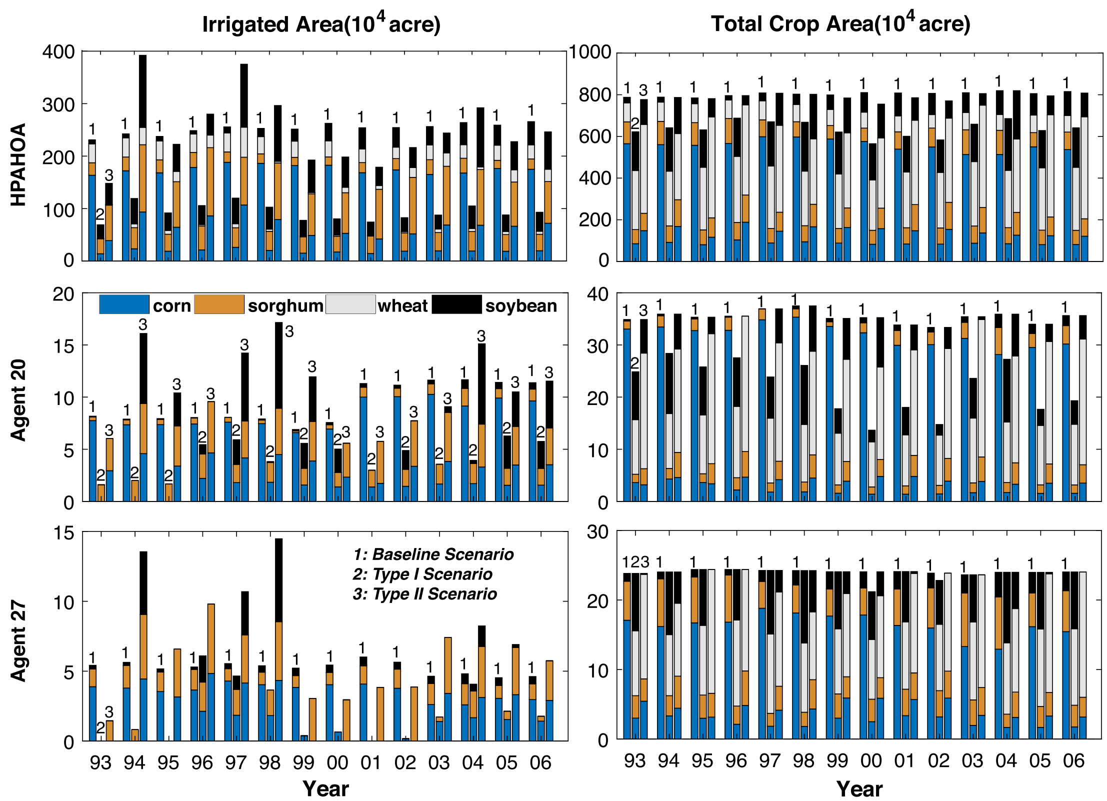

Fig. 5. Comparison of irrigated and total crop area under three scenarios between 1993 and 2006. Each year, three stacked bars are grouped together for three scenarios: (1) Baseline scenario, (2) Type I scenario, and (3) Type II scenario. The entire HPAHOA and two individual agents were chosen for the comparison.

cropland, while the same agents from the baseline scenario chose to grow corn as the dominant crop. Moreover, agents grew diverse crops (i.e., corn, sorghum, wheat, and soybean) for both the baseline and the optimization scenarios, which is also reflected by individual agents from the optimization scenarios (e.g., Agents 20 and 27). They chose to grow more diverse crops on both the irrigated and total crop area than the corresponding agents in the baseline scenario (Fig. 5).

During the crop growing season, agents' daily pumping behavior is determined by the second stage of the two-stage optimization. The comparison of daily irrigation behavior (for Agents 20 and 27) with respect to each of the four candidate crops during the crop

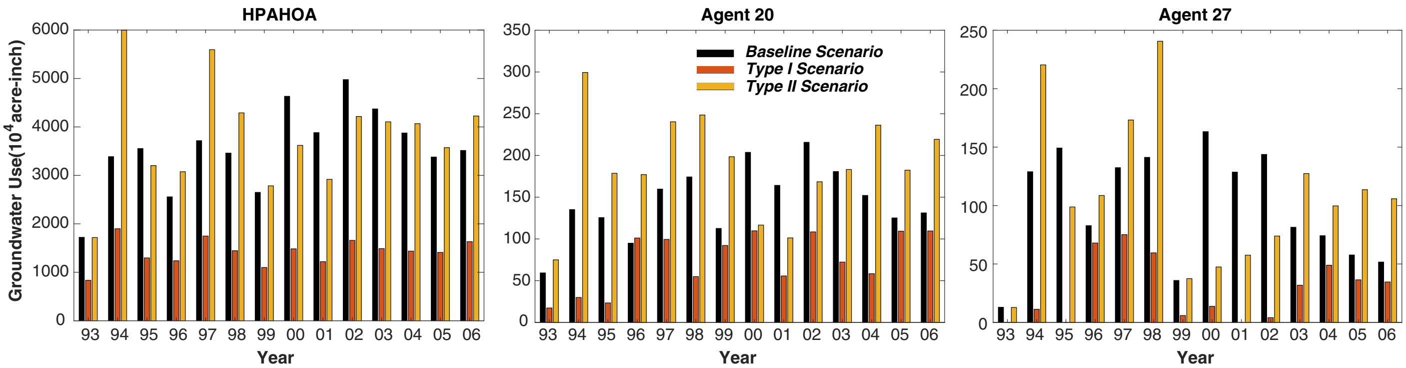

Fig. 6. Comparison of groundwater use under three scenarios between 1993 and 2006 for the entire HPAHOA and two individual agents.

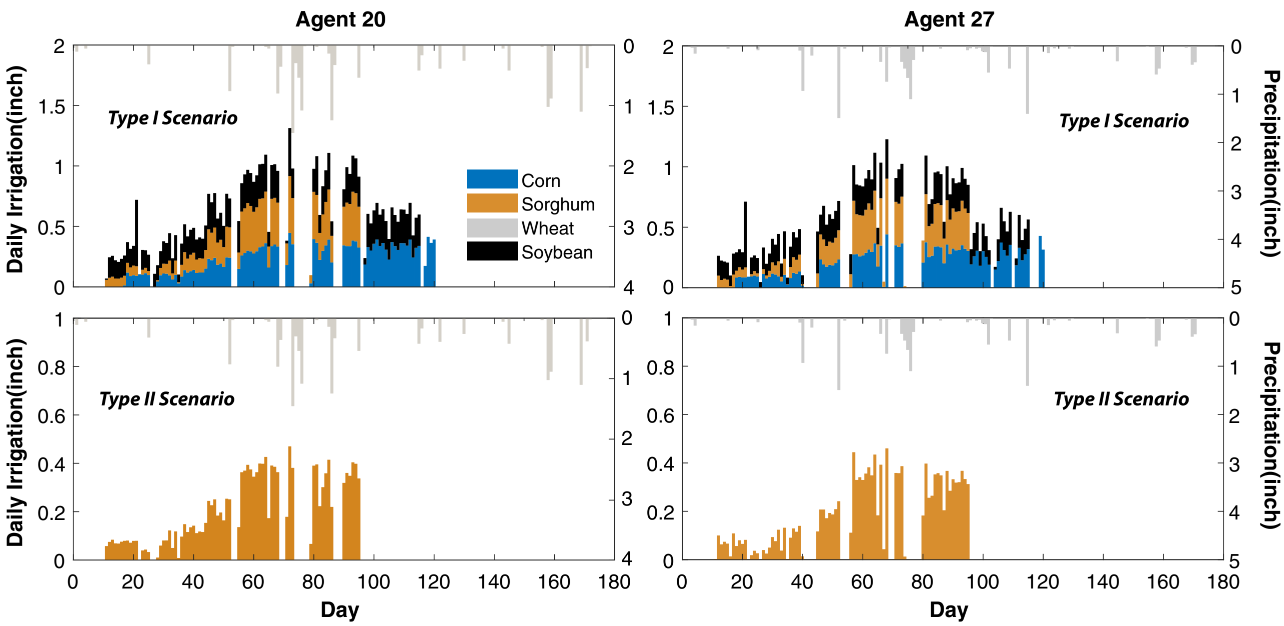

Fig. 7. Comparison of daily irrigation and precipitation during the crop growing season in 1994 under Types I and II scenarios.

growing season in 1994 under the optimization scenarios is illustrated by Fig. 7. This figure reflects the fact that agents in the Type II scenario used more groundwater for irrigation. In addition, for the individual agents, Fig. 7 shows identical daily irrigation behavior irrespective of the scenarios when the corresponding irrigated crop area is positive. For example, Agent 20 had the same daily irrigation to grow sorghum for both the Types I and II scenarios.

The difference in groundwater use affects groundwater level to various degrees; the more groundwater used for irrigation, the lower the water table. Type II agents planted more crops on the irrigated area, which led to more groundwater use and a higher rate of decline in groundwater level (Fig. 8). In contrast, Type I agents used less groundwater for irrigation by growing crops mostly on dryland area, and had the lowest rate of decline in the water table among the scenarios. In some cases, the water table for some agents in the Type I scenario (e.g., Agent 27) was increasing rather than declining over the years (Fig. 8).

Crop profits are the differences between crop revenue and the associated costs, the largest portion of which is pumping cost. Compared with the baseline scenario, as shown in Fig. 8, agents in the Type I scenario often have larger crop profits with larger variation, while agents in the Type II scenario have lower but relatively stable crop profits.

Discussion

Farmers' behaviors in crop choice and irrigation were driven by behavioral factors (e.g., κ, ν, and λ) affecting their perception of future crop prices, profits, precipitation, and the variation of these. On the one hand, Type I agents placed more value on their historical experience of crop prices and precipitation and thus were less affected by the recent observations (e.g., last year) when making predictions. However, they were more likely to experience large variations in the predicted variance of the future values when their predictions were different from their prior knowledge, which could lead to the large variation of the predicted crop profits (Fig. 4). As such, the utility of Type I agents, associated with large λ [Eq. (9)], was penalized more as the predicted variance increased. On the other hand, Type II agents valued more recent observations when making predictions, resulting in larger variation in the predicted mean values but smaller variation in the predicted variance (Fig. 4). Associated with smaller λ [Eq. (9)], their utility was

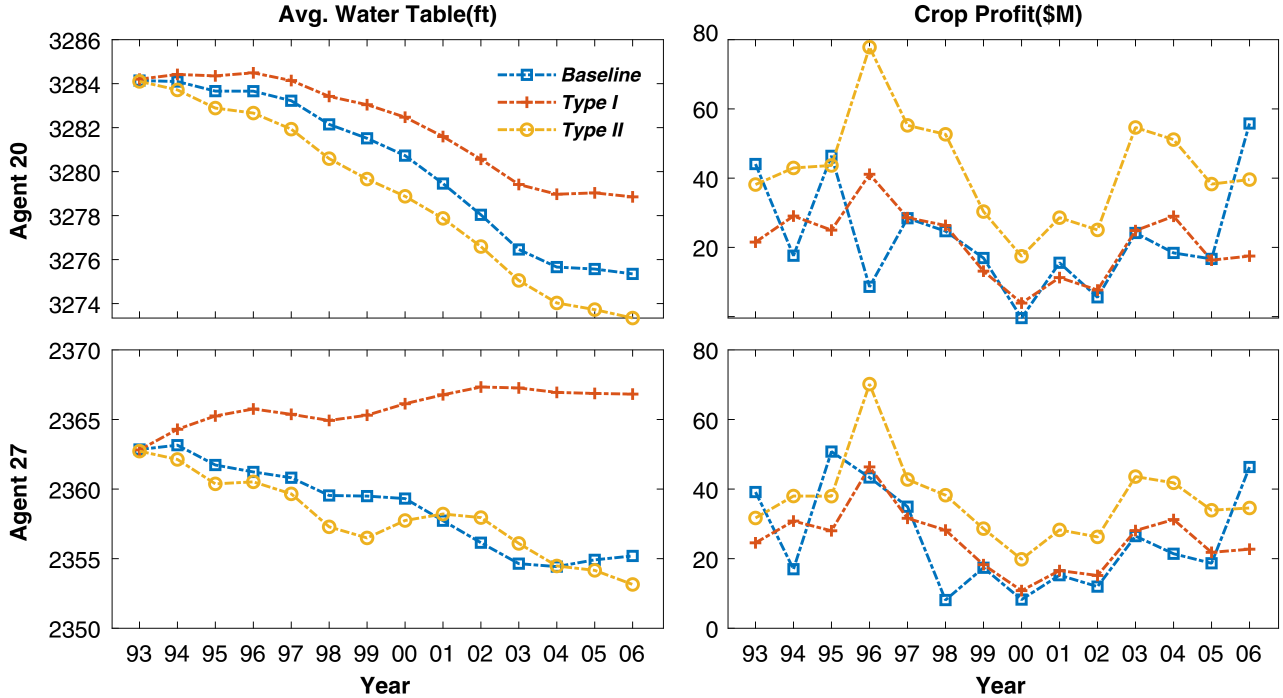

Fig. 8. Comparison of average water tables and crop profits under three scenarios between 1993 and 2006.

less affected by the variation of the predicted crop profits. The relative impact of these factors on the utility is not discussed in this work, but further investigation may be useful.

Farmers' planted irrigated crop areas were determined via the optimization of their utility (Fig. 1). In the second stage, no irrigated crop area would switch to dryland crop area under the assumption of no water stress. As such, planted irrigated crop areas were equal to actual irrigated crop areas. To maximize the utility, Type I agents chose to have less total crop area and plant more crops in the dryland area to reduce the pumping costs. In this way, they attempted to minimize the variance of crop profits arising from the predicted variance. On the contrary, Type II agents were less affected by the variation of the predictions. When the predicted values of the current year were larger than the predicted values of last year (e.g., higher crop prices and larger precipitation), Type II agents were more likely to plant crops in the irrigated area, leading to more groundwater use and higher crop profits.

Unlike the simulation model used to reflect farmers' actual behaviors in crop choice and irrigation, these behaviors are prescribed when the two-stage optimization strategy is used. The differences in crop choice and irrigated areas reflect the discrepancy between how decisions are actually made (reflected by the baseline scenario) versus how decisions are made according to the optimization. Under the optimization scenarios, individual farmers chose to plant diverse crops (Fig. 5) at the first stage, which can reduce the variation of crop profits (in particular for the Type I agent) (Fig. 8). At the second stage, farmers maximized their crop profits as the result of the daily pumping behavior, which was only affected by physical factors such as daily precipitation, soil water content, and crop growth stage. Thus, their pumping behaviors were identical and independent of the types of the agents (Fig. 7).

The two-stage optimization aims to help farmers maximize their crop profits under the water permit constraint for groundwater irrigation. However, neither Type I nor Type II agents are good examples of sustainable groundwater use: Type I agents tended to have less groundwater use but lower crop profits. By contrast, Type II agents often had higher crop profits but more groundwater use. To balance crop profits and groundwater use under the optimization, different approaches needed to be taken. For example, Type I agents' behaviors were mostly affected by the variation of crop profits. Lowering its influence, for example, by decreasing λ, can encourage Type I agents to plant more crops on the irrigated area, which will result in higher crop profits. Type II agents planted more crops on the irrigated area given the current water permit. A more stringent water permit will cause Type II agents to plant fewer crops on the irrigated area and decrease groundwater depletion.

The two-stage optimization strategy could provide a viable basis for the development of a successful strategy for crop cultivation that uses groundwater in a sustainable manner. To achieve this goal, this work demonstrates that there is a need to understand the behavioral factors affecting farmers' behaviors in crop choice and irrigation. Because farmers are heterogeneous in their decision making, different actions for different types of farmers need to be taken in the pursuit of groundwater sustainability. Some farmers (e.g., Type I agents) would benefit from better education about managing uncertainties. For other farmers (e.g., Type II agents), more stringent water permits may be needed. While the optimization strategy does not consider some factors (e.g., crop rotation and crop insurance) that could influence farmers' decisions, further investigation into these factors will be meaningful to expand and assess the strategy.

Conclusion

This paper introduced a two-stage optimization strategy to maximize farmers' crop profits by optimizing their behaviors in crop choice and irrigation using an agent-based modeling framework. The performance of the two-stage optimization was evaluated under various behavioral factors (i.e., κ, ν, λ, and SC).

In comparison with farmers' actual behaviors, the behavior rules derived from the optimization strategy can lead to either higher crop profits or a slower rate of groundwater depletion, but do not necessarily guarantee a good balance of these two objectives. To achieve sustainable groundwater irrigation, we have shown the need exists to better understand the roles that behavioral factors play in farmers' decision making. Moreover, new groundwater policy should be crafted with these behavioral factors in mind.

Data Availability Statement

The following data, models, and code generated or used during the study are available from the corresponding author by request:

- Models: The coupled agent-based model and RRCA model. The agent-based model is written in Java and coupled with the RRCA model, which is available at http://www.republicanrivercompact.org/.
- Data: The input data to run the coupled agent-based model and RRCA model from 1993–2006, including but not limited to the data for variables in Tables 1 and 3, as well as the output data as the result of running different scenarios as described in the paper.
- Code: The SQL and MATLAB scripts to process the outputs to generate the figures in the paper.

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