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Agent-Based Modeling for Evaluation of Crop Pattern and Water Management Policies

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Abstract

The objective of the present paper is to propose a framework for development of an optimal cropping pattern aimed at ground water recovery using an agent based approach. In the proposed agent-based model (ABM), the agents' learning from each other as well as their self-learning from their own behavioral feedback was studied through simulation of the behavior of agricultural agents using fuzzy inference system (FIS). Moreover, the agents' behavior were determined using linear programming in order to maximize the farmers' income. The governmental agent regulated the interactions between agricultural and environmental agents by imposing its policies in the form of scenarios. The efficiency of the presented methodology was evaluated using hydrological data of Najaf Abad region, located in Iran's central plain, on the basis of three hydrological scenarios (wet, normal, and dry) subject to governmental policy of aquifer recovery. The results showed that in a normal scenario with current groundwater withdrawal, the water level reduced by an average of 0.18 m per year. In contrast, the water level increased by an average of 0.48 m under aquifer recovery scenario. Furthermore, despite 17% reduction in water rights of agricultural agents in the study area, the total long-term agricultural income declined only by less than 4%, and in the planning horizon, their average annual income associated with these two management scenarios were estimated at 123.5 and 119 million US dollars, respectively.

Keywords Agent Based Model · Fuzzy Inference System · Behavioral Constraints · Ground Water Recovery · Non-Dominated Sorting Genetic Algorithm

1 Introduction

Conjunctive surface water and groundwater management is inevitable in semi-arid water scarce regions. Numerous studies have been conducted on conjunctive surface-ground water

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exploitation in order to determine agricultural water allocation with economic objectives. Linear optimization (e.g. Khare et al., 2007; Das et al., 2015), non-linear optimization (e.g. Aljanabi et al. 2018) and simulation-optimization approaches (e.g. Singh 2014 and Peralta et al., 2014) are among the approaches adopted in conjunctive use. Heydari et al., 2016 developed a simulation-optimization model through quantitative-qualitative simulation of Najaf Abad aquifer using MODFLOW and MT3DMS, and their surrogate Artificial Neural Network (ANN) and genetic programming models, respectively. They used Non-dominated Sorting Genetic Algorithm (NSGA-II) to determine cropping pattern and crops' water allocation in order to minimize water shortage, drawdown, as well as changes in the quality of groundwater.

Many of such studies proposed a cropping pattern for improving the overall function of the hydrologic system. However, the results may not be implementable because they fail to comply with the farmers' behavioral norms. Agent-based simulation is a powerful tool for simulation of players' action-reaction as it considers the behaviors of the agents involved in a system (Voinov and Bousquet, 2010; Levin, et al., 2013). ABM attempts to simulate the system's dominant rules in the form of mathematical relationships through considering the interactions between agents, such as the environment and agriculture. ABM applications in complex water resource systems has been growing in recent years (Berglund 2015).

Among various applications of ABM, one may refer to its use in water quality management (Berglund 2015 and Ng et al. 2011), urban water management (Galán et al., 2009, Ni et al., 2013, Kanta and Zechman, 2013, Koutiva and Makropoulos 2016 and Darbandsari et al. 2017), land use change modeling (Giacomoni and Zechman, 2010), and agricultural land and water management (Murray-Rust et al., 2014). ABM extensive applications may be rooted in it's natural and transparent interpretation of the simulated system (Galán et al., 2009). The ABM is focused on the local relationships between decision makers (Gunkel 2005), different levels of decision making (Berglund 2015), and different economic, social, regional and technical dimensions (Akhbari and Grigg 2013).

- Nikolic et al. (2013) examined the existing decision support tools for integrated water resources management and proposed a combined, multi-method modeling structure in which all structural complexities and interactions of water resource systems were considered. They were able to examine the relationships between water resource systems and the socio-economic environment. The proposed structure adopted spatially explicit ABMs to simulate consumers' use of common natural resources. The efficiency of the structure was investigated by creating a functional model for the Upper Thames river basin in south-eastern Ontario, Canada, examining three climate and two socio-economic scenarios.
- Farhadi et al. (2016) found a sustainable solution for managing groundwater resources through a framework based on agent-based modeling. They conducted aquifer simulation using MODFLOW, and its surrogate ANN, with the help of NSGA-II in order to reduce water shortage and groundwater pollution and improve water allocation equality. Nash bargaining model was adopted to reach an optimize solution among stockholders. Training, penalty and the effects of neighbors were among the factors incorporated in the agent-based simulations.

The present study aims to, by providing an agent based modeling framework, study the effects of different land and water management approaches on the agricultural sector and present a sustainable solution for conjunctive management of surface water and groundwater resources.

Furthermore, according to the behavioral principles of the decision-making agents, a novel method based on FIS, linear programming, and a groundwater conceptual model was developed to simulate the hydrogeological, agricultural and economic system.

2 Methodology

This research presents an agent-based modeling framework with the purpose of aquifer recovery. The framework takes into account the social behavior of farmers and their interaction with other influential agents. In this regard, the conceptual model in Fig. 1 is proposed where agriculture, regulator, and environment are considered as three major agents. Each agent has its own behavioral principles and all descriptions associated with the regulator agent, including executive and political power as well as financial, technical, and human resources may be highlighted. Characteristics of the agricultural agents include geographical location, crop type and its associated indicators such as water demand, support components, planting/growing/harvesting technology, and available harvest area. Characteristics of the environmental agent are described by its hydrological response to agricultural agent behaviors as groundwater reservoir volume changes.

Each agent, according to its active and passive nature, wishes to reach a target that is rooted in its behavioral principles. In this research, the behavior of agricultural agents was made focused on maximization of income reached through selling agricultural products, while the behavior of the regulator agent was aimed at aquifer recovery. The environmental agent, focusing on groundwater, was considered as a passive agent.

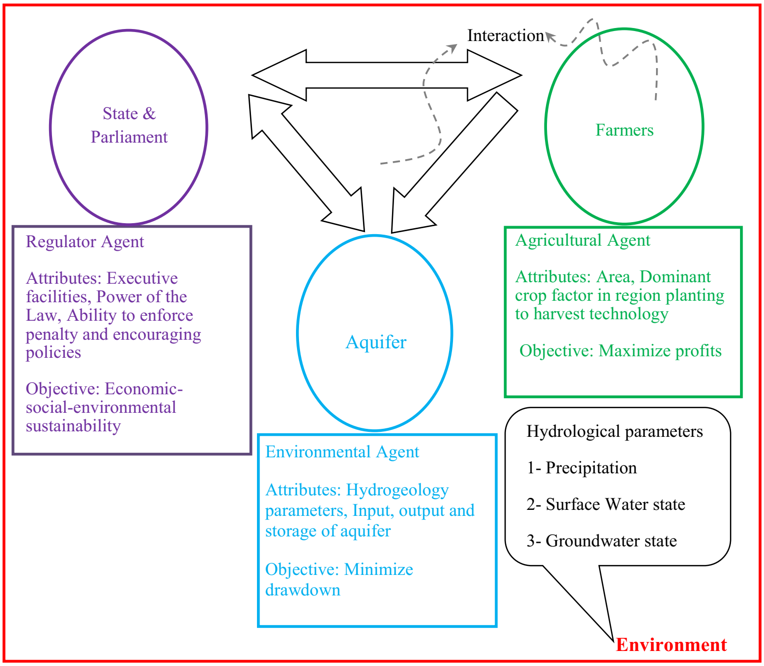

Fig. 1 The conceptual ABM of the study

This agent is generally influenced by the environment (precipitation and other inputs), two other agents (water rights of the agricultural agent as determined by the regulator agent), and water withdrawal for other uses. The environment is influenced by various hydrological and hydrogeological characteristics such as precipitation, evapotranspiration, vegetation, hydraulic conductivity of the aquifer, inputs from the river, and return flow from different water uses.

Each agent interacts with itself and with the environment (its system status). The regulator agent affects agricultural agents as well as the aquifer status (as an indicator of the environmental agent) by enforcing regulations and policies on aquifer recovery via alteration in water rights of agricultural agents and in crop pattern. Agricultural agents affect the environmental agent via withdrawals from surface water and groundwater.

Another issue is the internal interaction among agricultural agents. Selection of cultivation area for each crop by each agricultural agent is not solely determined on the basis of a simple relationship between water demand and available water/land. The cultivation area and constraints of each agricultural agent are determined based on the behavior of the agent to maintain a given crop pattern and on learning of the agent according to its past experience with the crop profit as well as the cultivated area operated by other agricultural agents in the preceding periods. In this study, behavioral principles and interactions among agricultural agents were determined using a simulation-optimization modeling framework. Moreover, in order to determine the best policy for the regulator agent where both status of aquifer recovery and livelihood of agricultural agents are taken into account, a number of hydrological scenarios were laid out. In what follows, different components of the proposed agent-based model are described.

2.1 Groundwater System Simulation

In this study, groundwater is the focus of the environmental agent representing a passive agent. The aquifer is influenced by the existing environmental conditions as well as water withdrawal for various uses. Hence, the aquifer behavior is impacted by various water consuming agents.

The groundwater flow in a transitional state may be expressed by the following form (Bear, 1979):

$$\nabla.(K\nabla h) = S\frac{\partial h}{\partial t} \pm Q \tag{1}$$

where ∇ represents gradient vector, K is the hydraulic conductivity tensor, h is the piezometric head, Q represents discharge/pumping rate per unit area, and S is the storage coefficient.

In this study, quantitative simulation of the aquifer was performed using MODFLOW model (McDonald and Harbaugh, 1988) as was calibrated by Heydari et al. (2016).

2.2 Simulation of Agricultural Agent Behavior

Simulation of behavioral principles of the agents may be performed based on the constraint thresholds, if-then rules, optimization models, and the behavioral functions surveyed by informed sources (Berglund, 2015). One of the attractive models to be used in agent based modeling is socio- economic optimization models to maximize profit of the agents (Plummer et al., 1998). In this regard, the objective function to maximize the income gained by selling agricultural products under physical and behavioral constraints is as follows:

$$max\ Z_{t,i} = Income_{t,i} = \sum_{j=1}^{n} \mathrm{Pro}_{t,i,j} * P_{t-1,j} \quad \forall i \tag{2}$$

$$\mathrm{Pro}_{i,j} = f_{i,j}\left(Area_{i,j}, Water_{i,j}\right) \tag{3}$$

where $Z_{t,\,i}$ is the objective function value of agricultural agent i during period t, $Income_{t,\,i}$ is the expected income of agricultural agent i during period t (in US million dollars), $\mathrm{Pro}_{t,\,i,\,j}$ is the production value of agent i from product j during period t (ton), $P_{t,\,j}$ is the cost to produce j during period t (in US million dollars per ton), $f_{i,\,j}$ is the performance function of agent i for product j, $Area_{i,\,j}$ is the cultivated area of agent i from product j (in hectare), $Water_{i,\,j}$ is the volume of water agent i uses to produce j (in thousand cubic meters per hectare), and n represents the total number of crops.

Due to various market variables, such as change in production, the cost of products varies between the time that farmers decide on the cultivation area of each product and the time that production is distributed in the market. The cost of product may be predicted using a simple regression model (Kim and Kaluarachchi, 2016) as follows:

$$P_t = AQ_t + B \tag{4}$$

Where P_t is the cost, and Q_t is the volume of production during period t.

In this study, the optimization constraints may be divided into two categories: physical and behavioral. The physical constraints indicate the equilibrium constraints of the cultivation area and water available to each agent:

$$\sum_{j=1}^{n} \left(Area_{i,j} * Water_{i,j}\right) \le Water_i^G + Water_i^S \tag{5}$$

$$\sum_{j=1}^{n} Area_{i,j} \le Area_i^{Ave} \tag{6}$$

Where $Water_i^S$ represents the surface water right of agent i (in thousand cubic meters), $Water_i^G$ is the groundwater right of agent i (in thousand cubic meters), and $Area_i^{Ave}$ is the total available cultivation area of agent i.

Behavioral constraints represent psychological and cognitive constraints which induce optimization model to move out of normal condition so that farmers set another boundary, beyond physical constraints, for minimum and maximum cultivation area. In fact, each agricultural agent optimizes its cognitive optimization function based on feedback of selected crops in the preceding periods, training, social pressure from other agricultural agents, advertising, belief and interest in a special crop, and other psychological constraints.

In this study, the learning factor was impacted by self-learning and learning from other agricultural agents. Learning of each agricultural agent for each crop results from the feedback of that agent from the his/her own produced crop as well as those produced by other agents in the region. However, self-learning is mainly based on the agent's experience. According to cognitive differences of the agricultural agents, this type of learning could vary for each agent/crop. This constraint could be expressed as follows.

$$\mathrm{Pro}_{t,i,j} \leq \left(\alpha_1 learning_{i,j}^{\beta_1}\right)_{\max} \forall i,j \tag{7}$$

$$\mathrm{Pro}_{t,i,j} \geq \left(\alpha_2 Sotiolearning_{i,j}^{\beta 2}\right)_{\min} \forall i,j \tag{8}$$

Where $(learning_{i,j})_{\max}$ is the learning function of agent i for the upper threshold associated with production of product j, $(learning_{i,\ j})_{\min}$ is the learning function of agent i for the lower threshold associated with production of product j, and α, β represent the coefficients related to crops and different agents.

Since the learning function is a result of human's inference, it could be simulated based on the if-then rules. The FIS is a suitable model to simulate self-learning factor. FIS mathematical inference is based on fuzzy logic and is similar to that of the human being.

A FIS is a system that determines the degree of accuracy of each inference principle after fuzzification of input sets (Eqs. 9 and 10). Then it defuzzifies the outputs by aggregation of the degree of accuracy of all principles (Eq. 11) (Perera and Lahat, 2015).

$$\begin{array}{l} if\ \ x_1\ \ is\ A_{1,k}\ \ (and/or)\ \ x_2\ \ is\ A_{2,k}\ \ (and/or)...(and/or)x_n\ \ is\ A_{n,k} \\ then\ \ y_k\ \ is\ B_k\ \ \forall k \end{array} \tag{9}$$

$$\begin{array}{l} if\ \ \mu_{A_{1,k}}\ (x_1)\ \ (and/or)\ \ \mu_{A_{2,k}}(x_2)\ \ (and/or)...(and/or)\ \ \mu_{A_{n,k}}\ (x_n) \\ then\ \ \mu_{B_k}\ (y_k)\ \ \forall k \end{array} \tag{10}$$

$$learning_{t,i,j} = Defuzzify\left[\mu_{B_1}(y_1) + \mu_{B_2}(y_2) + \ldots + \mu_{B_k}(y_k)\right] \tag{11}$$

For instance, a simple learning rule for the agricultural agent i, who makes a decision on crop j during time t, could be stated as follows:

$$\begin{array}{c} \text{If Price of Crop}_{\mathrm{j,t-1}}\ \text{is}\ High_{i,j}\ \text{and Area of Crop}_{\mathrm{i,j,t-1}}\ \text{is}\ Low_{i,j} \\ \text{then Area of Crop}_{\mathrm{i,j,t}}\ \text{is}\ High_{i,j} \end{array} \tag{12}$$

The number/inputs of the rules as well as the fuzzy value of descriptive statements used in the rules could be determined by questionnaires and/or historic observations of the products' costs and cultivated area. The questionnaire determines what factors for each agricultural agent are effective in decision making for each crop. For instance, the rule in Eq. 12 indicates that the cost and cultivation area in the preceding period is a decision making factor for cultivation area in the current period. In addition, the descriptive statements, such as *low*, *medium*, and *high*, differ for each agent and crop. For example, 1000 ha of a given crop may be considered "*high*" for an agent, but "*medium*" for another. Similarly, this is true for a distinct agent and different crops.

2.3 Calibration of Agricultural Agents' Behavioral Model

The behavioral constraints of Eqs. 7 and 8, described in Section 2.1, contain coefficients that must be determined for each agricultural agent based on behavioral and psychological characteristics. Some of the coefficients are determined by the questionnaire and some by means of the historic data associated with the cultivation area by each agents.

The calibration process was performed using genetic algorithm as shown in Fig. 2. The decision variables were the coefficients while the root mean square error (RMSE) between observed and simulated area of the cropping pattern is minimized through the proposed simulation-optimization model. In order to avoid over fitting, 15% of the time series were used for validation.

3 Study Area

Najaf Abad plain is part of the Zayanderud river basin in central Iran. The plain with an area of 1742.21 km^2 lies between 50º-57′ to 51º-44′ E longitude and 32º-19′ to 32º-49’ N latitude. This plain contains an alluvial aquifer with an area of 1065 km^2, which, along with a surface irrigation network, is responsible for supplying agricultural, industrial, and drinking water. Precipitation, stream network, and irrigation return water are the most important recharge sources (inputs) of the Najaf Abad Aquifer. In the past decade, the aquifer has received considerable attention in conjunctive management of surface and groundwater, since its water level has dropped by an annual average of 80 cm.

More than 95% of the water is consumed in agricultural sector in the study area. Hence, agricultural agent plays the most significant positive/negative role in aquifer recovery. The total consumed groundwater and surface water are approximately 661 and 294 million cubic meters,

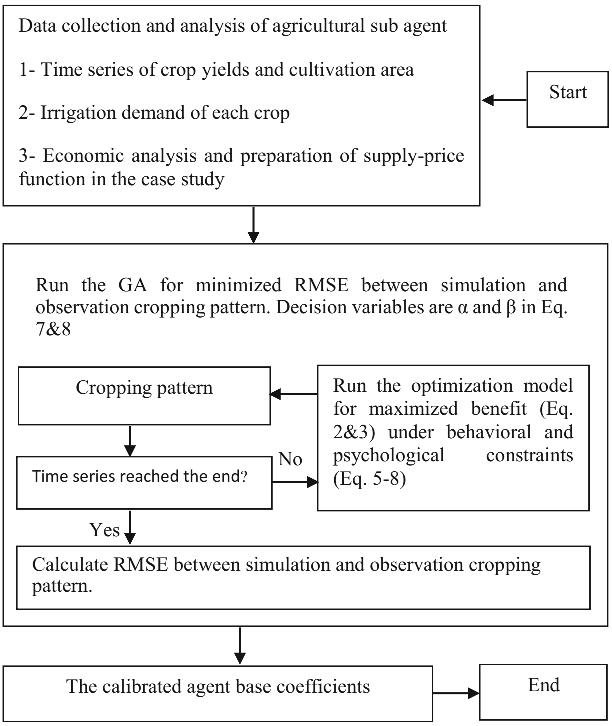

Fig. 2 Model calibration flowchart

respectively. According to a field research, five main agricultural agents are identifiable that are differentiated via political divisions. The geographic location of these agents are presented in Fig. 3, while their characteristics, including area and dominant crop, are listed in Table 1. Comparison of second and third columns in Table 1 indicates that a significant reduction in the total area of arable land for different agents is detected due to growing water scarcity.

4 Scenario Planning

The proposed framework may become exposed to various hydrological and management scenarios. As mentioned before, decline in groundwater level has been significant in the past decade. Therefore, aquifer recovery is one of the goals of regulator agent in study area. So the management scenarios in this research are determined based on regional land and water management policies. In scenario zero, known as business-as-usual, the current practice in water allocation/consumption continues in the future. The first management scenario, put forth by the regulator agent, aims to reduce 17% of Najaf Abad Aquifer withdrawals for agricultural purposes in a 20-year plan. Another scenario is to prohibit rice crop which, despite continued expert insistence on its restriction, is cultivated in over 10,000 ha annually by all agents due to long history of economic dependence in this region. Since rice water consumption is quite high, its prohibition would increase water available to planting of other products. Yet in third management scenario, the government can provide subsidies allocated to increased water efficiency. According to field studies, the average water efficiency in the study area is about 40%, which may be upgraded to about 70% via improved irrigation in a 20-year plan.

Furthermore, hydrological scenarios must be considered in conjunction with management scenarios in order to determine aquifer condition in the future. Based on analysis of long-term precipitation and runoff series, three hydrological scenarios including wet, normal, and dry may be enforced. Table 2 summarizes the studied scenarios.

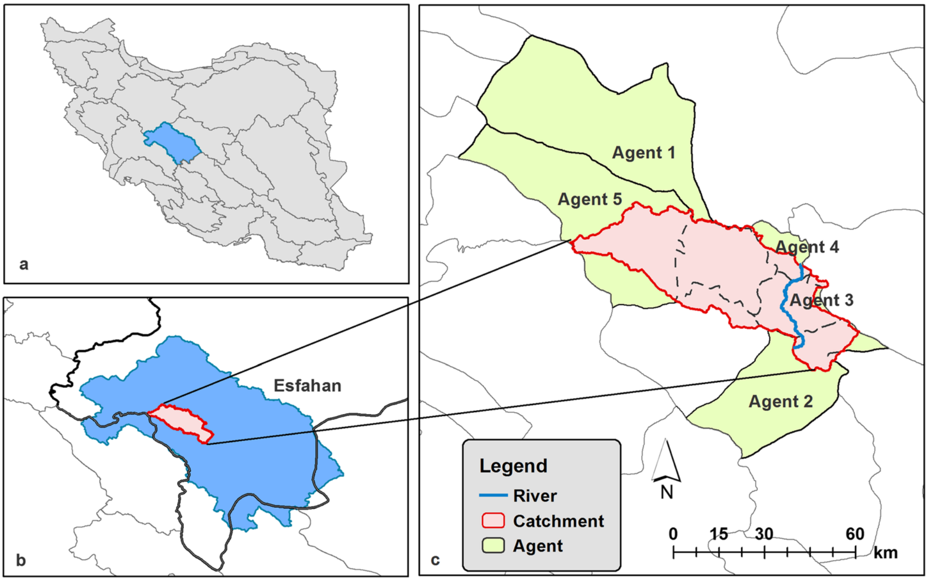

Fig. 3 Study area and agents' status

Table 1 General information related to agricultural agents

Agents No.	Maximum Area in last decade (ha)	Area in 2014(ha)	Dominant Crop *
1	10113	4485	1, 2, 4, 7, 9, 10
2	17286	11580	1, 2, 3, 7, 9 10
3	15638	12810	1, 2, 4, 5, 6, 7, 8, 9, 10
4	4544	2341	1, 2, 4, 6, 7, 8, 9, 10
5	8192	4990	1, 2, 4, 6, 7, 9, 10

*1-Wheat, 2-Barley, 3-Millet, 4-potato, 5-onion, 6-vegetables, 7-alfalfa, 8-Clover, 9-Corn, 10-Rice

5 Results

5.1 Calibration of Agent Based Model

As discussed in Section 2.1, the behavior of agricultural agents was simulated through optimization model subject to physical and behavioral constraints that involve the learning of agricultural agents. The objective function was to maximize the income of each agricultural agent, according to Eq. 2. The price of products were estimated based on Eq. 4. As the performance of agricultural production varies with available water, it was estimated with a fixed-demand approach for each product based on available data in the study area.

The upper and lower bounds of behavioral constraint were determined by the FIS. The input and rules of the FIS were determined by means of questionnaires. Coefficients of if-then rules were calibrated according to Fig. 2 and based on Eqs. 8 and 9 using genetic algorithm using Najaf Abad agricultural data corresponding to 2002–2013 period. The characteristics of FIS and produced error, as reported in Table 3, indicate that calibration is generally favorable. However, error was detected in some crops because in some years the government and farmers followed a certain policy.

5.2 Evaluation of Management Scenarios

Different management scenarios, as presented in Section 3.3, were studied individually and conjunctively in a 20-year horizon. The output associated with the ABM agricultural sector were crop pattern and the income for each of the five sub-agents while the environmental agent output was annual groundwater level. The crop pattern corresponding to each agricultural sub-agent in each management scenario is shown in Fig. 4. In order to compare management scenarios in economic terms, the total income of each agricultural sub-agent are reported in Fig. 5 over the 20-year horizon. In each management scenario, the aquifer was simulated in

Table 2 Evaluated management scenarios in the study

Description	Scenario
Business as usual	RSc0
Decrease of 17% of the water rights of agents in the 20 year plan	RSc1
RSc1+ Reduce and ban rice cultivation on 10 year plan	RSc2
RSc1 + Increases efficiency from 40% to 70% in the 20 year plan	RSc3

Table 3 FIS characteristics and error report for each crop and agent

Agents	Dominant Crop	Input of FIS's	R^2	Nash	PRMSE	RMSE (ha)	GC *
1	1	1, 2, $P_{1,t-1}$**	0.98	0.98	0.075	106	1
	2	1, 2, $P_{2,t-1}$	0.82	0.77	0.147	132	
	10	10, $P_{10,t-1}$	1.00	1.00	0.003	2	
	4	1, 2, 4, $P_{4,t-1}$	0.87	0.83	0.187	53	2
	7	7, 9, $P_{7,t-1}$	0.85	0.81	0.088	81	3
	9	7, 9, $P_{9,t-1}$	0.92	0.89	0.087	53	
2	1	1, 2, 3, $P_{1,t-1}$	0.94	0.91	0.073	175	1
	2	1, 2, 3, $P_{2,t-1}$	0.92	0.88	0.035	135	
	3	1, 2, 3, $P_{3,t-1}$	0.82	0.78	0.119	66	
	10	10, $P_{10,t-1}$	1.00	1.00	0.000	2	
	7	7, 9, $P_{7,t-1}$	0.91	0.88	0.051	43	3
	9	7, 9, $P_{9,t-1}$	0.83	0.83	0.175	70	
3	1	1, 2, $P_{1,t-1}$	0.95	0.95	0.031	49	1
	2	1, 2, $P_{2,t-1}$	0.67	0.57	0.080	63	
	10	10, $P_{10,t-1}$	0.99	0.99	0.001	3	
	4	4, 5, $P_{4,t-1}$	0.93	0.92	0.083	114	2
	5	4, 5, $P_{5,t-1}$	0.91	0.76	0.065	53	
	6	6, 7, 8, 9, $P_{6,t-1}$	0.91	0.89	0.141	134	
	7	6, 7, 8, 9, $P_{7,t-1}$	0.89	0.87	0.101	79	3
	8	6, 7, 8, 9, $P_{8,t-1}$	0.95	0.94	0.113	122	
	9	6, 7, 8, 9, $P_{9,t-1}$	0.97	0.96	0.078	27	
4	1	1, 2, $P_{1,t-1}$	0.85	0.85	0.065	38	1
	2	1, 2, $P_{2,t-1}$	0.94	0.89	0.097	28	
	10	10, $P_{10,t-1}$	0.99	0.99	0.002	1	
	4	4, 8, 9, $P_{4,t-1}$	0.91	0.88	0.056	32	2
	6	6, 7, 8, 9, $P_{6,t-1}$	0.94	0.92	0.176	84	
	7	6, 7, 8, 9, $P_{7,t-1}$	0.78	0.59	0.117	59	3
	8	6, 7, 8, 9, $P_{8,t-1}$	0.94	0.92	0.125	21	
	9	6, 7, 8, 9, $P_{9,t-1}$	0.61	0.30	0.263	31	
5	1	1, 2, $P_{1,t-1}$	0.95	0.94	0.028	61	1
	2	1, 2, $P_{2,t-1}$	0.91	0.86	0.095	83	
	10	10, $P_{10,t-1}$	1.00	1.00	0.000	0	
	4	1, 2, 4, $P_{4,t-1}$	0.86	0.81	0.203	79	2
	6	6, 7, 9, $P_{6,t-1}$	0.95	0.95	0.181	62	
	7	6, 7, 9, $P_{7,t-1}$	0.86	0.85	0.116	85	3
	9	6, 7, 9, $P_{9,t-1}$	0.90	0.90	0.110	42	

* The 1st GC is cereals containing wheat, barley, rice and millet, 2nd GC is vegetables containing potatoes, onions and other vegetables and 3th GC is fodder containing alfalfa, clover and corn. ** $P_{t,j}$ is the cost to produce j during period t

three hydrological conditions; that is: dry, wet, and normal. Hydrological conditions were determined based on the standardized precipitation index (SPI) meteorological drought index. The simulated aquifer levels corresponding to 5th, 10th, 15th, and 20th year in each management scenario are presented in Table 4.

As shown in Fig. 4, if there is no change in water rights of the agricultural agents (RSc0 scenario), crops cultivation area steadies with no meaningful change. The aquifer simulation in this scenario showed that, in normal hydrological conditions, the annual average aquifer water level drops by about 0.18 m. This reduction in water level is 0.75 m in dry conditions while in wet conditions, the level increases by an average annual of 0.33 m.

The RSc1 management scenario involves 17% linear (with time) reduction in groundwater rights of agricultural agents over the next 20 years. In general, the reduction in water rights of agricultural agents led to reduction in the cultivation area, and consequently, their income

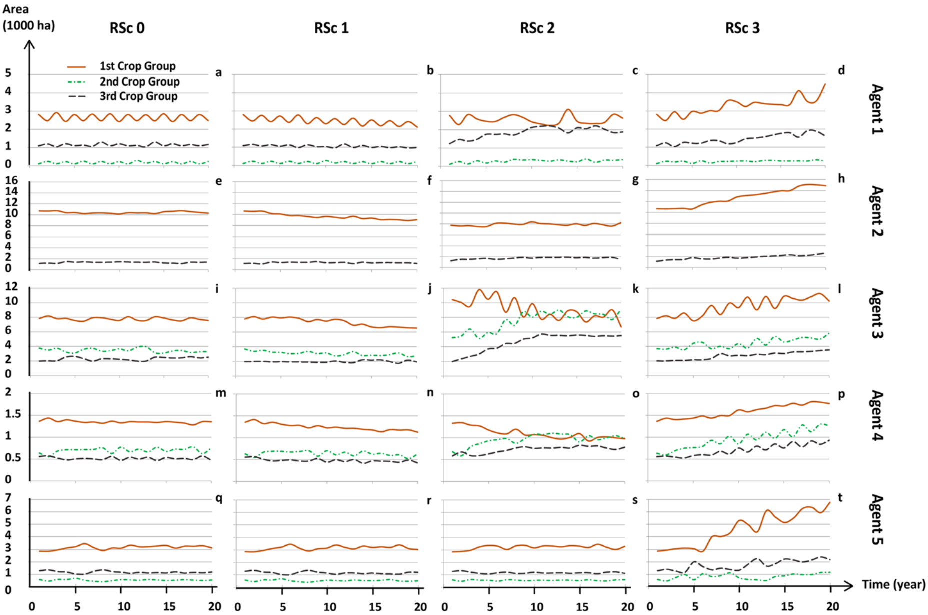

Fig. 4 Status and pattern of area under cultivation for agricultural agents in different scenarios

decreased. However, the response of the agricultural agents was different to this change. According to column 2 in Fig. 4, 1–4 agents had to significantly reduce the cultivation area of the first GC. However, there was no trend in their cultivation area due to dependence on the third GC. In the first few years of RSc1, the third agricultural agent tried to keep the cultivation area of group product 1 by reducing the cultivation area of the second group. However, after a number of years passed, it changed its policy and kept the second group cultivation area constant and reduced the first group cultivation area. Hence, it may be concluded that the third agricultural agent was more dependent on the first crop. No trend was observed in the cultivation area of the fifth agent due to its low dependence on groundwater. Nevertheless,

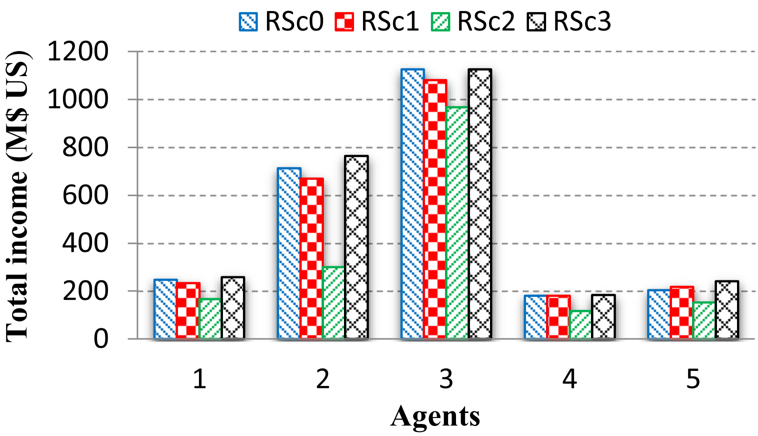

Fig. 5 The income of agricultural sub-agents for each scenario (million US dollars)

Table 4 Groundwater level changes in each management scenario (meter)

Year	RSc0			RSc1 & RSc2			RSc3		
	Dry	Normal	wet	Dry	Normal	Wet	Dry	Normal	Wet
present	0	0	0	0	0	0	0	0	0
5	−4.23	0.91	1.29	−3.31	1.84	2.23	−4.46	0.66	1.06
10	−8.89	−1.74	2.74	−5.44	1.69	6.16	−11.69	−4.51	−0.01
15	−13.7	−0.85	4.32	−6.21	6.6	11.75	−20.84	−7.98	−2.78
20	−18.25	−3.49	6.56	−5.12	9.54	19.53	−31.4	−16.62	−6.44

as presented in Table 4, the income of this agent increased compared to that of the RSc0 due to decline in cultivation area and increase in price of the products.

RSc2 scenario is a combination of the first scenario plus enforcing rice crop prohibition. The rate of prohibition was applied linearly over a period of 10 years. Based on this scenario, the cultivation area of the first group reduced due to decrease in rice, while the overall area increased because of the conserved water previously consumed by rice. Hence, the crop pattern of the first GC did not change for the first and second agricultural agents. Nonetheless, there was a significant decrease in the first group of the third agent, due to high rice cultivation area. The third agent increased the cultivation area of the first and second groups using the saved water made available through reduction in rice planting. Since the fifth agricultural agent had a very low rice cultivation area, there was no change in its crop pattern. In this scenario, since rice yields high income for agricultural agents compared with other crops, the total income of the first to fourth agents was reduced. However, due to increase in the total volume of crops in the study region and thus decline in the overall prices, the fifth agent income also declined.

Since the groundwater withdrawn by agricultural agents was similar in RSc1 and RSc2, the aquifer status was identical in these management scenarios. For instance, in normal and wet conditions, the average annual aquifer water level would increase by 0. 48 and 0.98 m, respectively. Compared to RSc0 scenario, RSc1 and RSc2 scenarios improve the current aquifer condition in the recovery phase. However, under dry hydrological condition, the aquifer is still in negative territory such that its water level would decline by 0.1 m annually.

The increase in water use efficiency from 40% to 70% was investigated in Scenario 3 in which more water could be available for crops, resulting in agricultural development and increased cultivation area. Therefore, all agricultural agents, based on their behavioral pattern, could increase their income through expansion of cultivation area.

6 Conclusion

In this paper, a simulation-optimization ABM framework was proposed in order to assess various management strategies involving coupled agricultural and ground water systems. The ABM included the regulator agent, the environmental agent, and the agricultural agents. In this study, groundwater system was considered as an environmental agent and its behavior was simulated as a passive agent. Moreover, the behavior of the agricultural agent(s) was simulated by a mathematical programing model aimed to maximize the income of the agricultural sector based on its behavioral constraints. Furthermore, the behavior of the regulator agent was analyzed through different management scenarios. The research findings highlights the importance of agricultural agents behaviors as well as land-water management policies.

Different statistical evaluation criteria in calibration of the agricultural agent sub-model showed that FIS is a powerful tool for simulating behavioral rules and cognitive characteristics of agricultural agents. Such ability is due to the similarity of human decision making process to the fuzzy logic rules. Furthermore, the learning rules of each agricultural agents, as simulated by FIS, were not similar. This difference for a given crop pattern is due to the agent's personal interest in given crops, as well as its experience and technical knowledge, risk taking and risk aversion to select and/or vary cultivation area. Fluctuations in area for each GC rooted in the price variation and the response of the agents to such variation, which affected the ABM objective function and behavioral constraints. However, the fluctuation of cultivation area was not uniform among agents, being more severe in some agents and weaker in others, in all studied scenarios. Furthermore, fluctuation of cultivation area directly affected the agents' income.

The simulation of the future aquifer status in three scenarios showed that reduction in groundwater rights associated with agricultural agents is necessary for aquifer recovery. Implementation of the first aquifer recovery scenario would result in lesser income relative to that of the present for majority of agricultural agents. The simulation of the scenario associated with gradual prohibition of rice planting indicated that the agents would instead allocate more water to other groups. However, the income of the agricultural agents decreased significantly relative to the present situation. Therefore, the sole application of this policy benefited neither the aquifer nor the agricultural economy.

The scenario associated with the improvement of irrigation system water use and efficiency led to allocation of conserved water to expand cultivation area. On the other hand, increased efficiency and reduced return water to the aquifer caused the aquifer to move towards a more critical condition relative to the present situation. Overall, it is recommended that the water rights of the agricultural agents be reduced in a such way that loss in the income of agricultural agents stay minimized through improved efficiency and government subsidizes while the aquifer may recover gradually.

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