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An agent-based-nash modeling framework for sustainable groundwater management: A case study

Saber Farhadi [a], Mohammad Reza Nikoo [a,*], Gholam Reza Rakhshandehroo [a], Masih Akhbari [b,c], Mohammad Reza Alizadeh [a]

[a] School of Engineering, Department of Civil and Environmental Engineering, Shiraz University, Shiraz, Iran
[b] Colorado Water Institute, Colorado State University, Fort Collins, CO 80523-1033, USA
[c] Riverside Technology Inc., Fort Collins, CO 80528, USA

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ABSTRACT

An agent-based-Nash modeling framework has been developed to find a sustainable solution for groundwater management in Daryan Aquifer, Fars Province, Iran. This framework also includes a MODFLOW simulation model, an Artificial Neural Network (ANN), and a Non-dominated Sorting Genetic Algorithm-II (NSGA-II) optimization model. Groundwater state was simulated using MODFLOW and it was calibrated based on the measured data provided by Regional Water Organization (RWO) of Fars Province. In order to reduce the computational time, an ANN was trained and validated based on the input-output data of the MODFLOW model to estimate groundwater level. The validated ANN was linked to a nonhomogeneous elitist NSGA-II multi-objective optimization model to find a Pareto optimal front among the three objectives of reducing irrigation water deficit, increasing equity in water allocation, and reducing groundwater drawdown, as the objectives of the three main groundwater resource stakeholders; farmers, the government executive sector, and the environmental protection institutes. The Nash bargaining model was applied to the optimal solutions in order to find a compromise among the stakeholders. Social influential factors in the study environment, and policy mechanisms to encourage agents to cooperate with the management decisions were implemented in the agent-based model. These factors include training, incentives, penalties, and social norming (neighbors' impacts), as well as considering the executive and judicial systems. After application of the agent-based model, computed optimum solutions were modified according to social conditions. Finally, the Nash bargaining model was used again to find a compromise among modified optimal objectives of the stakeholders. Implementation of this solution led to 58.3% less water extraction and approximately 3 m water level uplift.

1. Introduction

Growing human population, consumption, and using advanced technologies have led to a rising groundwater overuse (Dietz et al., 2003; Grimble, 1999) which should be controlled by appropriate groundwater management. Numerous groundwater management methods have already been proposed. Their evaluation has proven that sustainable groundwater withdrawals are achievable provided that the social behavior, preferences, dislikes of water users and their interactions with the environment are implemented in the method (Akhbari and Grigg, 2014; Berglund, 2015; Gleick, 2000; Liu et al., 2007; Pahl-Wostl, 2002, 2007).

Recently, different approaches have been developed for incorporation of the interaction of humans and the groundwater extractions. Pahl-Wostl (2002) showed that social factors are more influential than deterministic physical parameters in adaptive groundwater management. Schreinemachers and Berger (2011) introduced an agent-based software package, Mathematical Programming-based Multi-Agent Systems (MP-MAS), which builds on constrained optimization to simulate the decision-making of farmers in agricultural systems. Agricultural technologies, market dynamics, environmental changes, and policy interventions were incorporated in this model. However, the conflicting interests of the non-farmers, such as policy mechanisms and social normings, were excluded in this decision-making process. The influence of farmers' characteristics on land-use change and the corresponding groundwater overuse was studied also by Holtz and Pahl-Wostl (2012). They employed an agent-based model to investigate the history of irrigated agriculture in the Upper Guadiana Basin, Spain. The effects

* Corresponding author.
E-mail address: nikoo@shirazu.ac.ir (M.R. Nikoo).

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of gross margin, risk, labor (work) load, and illegal behavior of the farmers were considered as Cobb-Douglas function to compute the utility of land-use pattern. This study also lacked investigating the impacts of policy mechanisms to reduce water exploitation. Kelly et al. (2013) investigated five common approaches for integrated environmental assessment and management that have the capacity to accommodate multiple issues, values, scales, uncertainties, and stakeholder engagements. These approaches were system dynamics, Bayesian networks, coupled component, agent-based, and knowledge-based models. They corroborated that the agent-based models are of high utility for implementing social conditions in management of complex systems. Nikolic et al. (2013) integrated geographic information system, system dynamics, agent-based model, and hydrologic simulation tools to manage groundwater abstractions in Thames River Basin, Southern Ontario, Canada. The spatial and temporal variability of agricultural, industrial, and municipal water demands, harvest yield, and population growth were considered in the integrated decision-making framework, but the effects of social norming were not included. In order to discover the water users' roles in the management process, Zhao et al. (2013) compared their behavior under administered and market-based water allocation systems through an agent-based modeling framework. A penalty-based decentralized optimization framework provided by Inalhan et al. (2002) was used in this study to formulate the agents' behavior.

For social structures, the whole set of economic, social and environmental institutions, rules and social arrangements regulate individual and collective behavior of the water users (Pahl-Wostl, 2007). In complex systems, stakeholders' behavior and their interactions could be incorporated into decision-making procedures using agent-based models (Bandini et al., 2009; Reeves and Zelner, 2010), which requires close collaboration between researchers and stakeholders involved in the arenas of collective choice (Mazzega et al., 2014). Akhbari and Grigg (2013) developed a framework for a conflict management tool to simulate institutional interactions among competing parties in California's San Joaquin River watershed. They developed this framework using an agent-based modeling approach to find practical ways to increase agents' cooperation. Mulligan et al. (2014) used a multi-agent system simulation to evaluate the efficiency of different policy mechanisms, such as caps and tax, in the Republican River Basin, central United States. The comparison of the results with their proposed optimization model represented that more water would be consumed when more realistic, heterogeneous, myopic, and self-interested agents were considered in the multi-agent model. The individual benefits of each agent were maximized subject to some policy mechanisms, but the social interactions among water users were not involved in the decision-making process.

In the present study, a decentralized non-homogeneous groundwater management approach is proposed. This approach integrates groundwater simulation, Artificial Neural Network (ANN), Non-dominated Sorting Genetic Algorithm-II (NSGA-II) multi-objective optimization, the Nash bargaining, and agent-based models to find a practical optimal groundwater management decision which is respected by the stakeholders. Social factors and policy mechanisms such as training, incentives, penalties, and social norming (neighbors' impacts), as well as the executive and judicial systems are considered in the proposed framework and it was applied to Daryan aquifer in southwest Iran that is prone to severe depletion due to agricultural overuse of groundwater.

2. Methods

In the modeling of low-water management, the agents' rationality progressively leads to the adoption of a sociological position in which the agents' strategies could be far from rules and norms (Mazzega et al., 2014). In order to consider social properties in groundwater management, an integrated model is proposed, which implements the preferences of stakeholders. In the proposed framework, whose step-by-step flowchart is presented in Fig. 1, first, necessary data regarding hydrological and hydrogeological characteristics of the study area, social properties of the agents and the study environment, the agents' water demands, and the governmental regulations and plans were gathered. Then, a groundwater simulation model was developed and calibrated, using MODFLOW. To allocate the optimum amount of groundwater to water users, a multi-objective optimization model was employed and the calibrated groundwater simulation model was iteratively run to reach the optimum solution. But the large number of water users caused a long computational time. Therefore, to reduce the computational time and also to implement management mechanisms of the government, the study area was divided into managerial subregions, occupied by agents. Therefore, in this study, an agent is defined as farmers within a subregion. The calibrated MODFLOW groundwater simulation model was iteratively run for different possible groundwater allocation scenarios to the agents in order to reach an appropriate database for training an ANN metamodel. This metamodel was trained and validated based on the provided input-output database to substitute the MODFLOW groundwater simulation model and decrease computational time.

The ANN model was linked to an NSGA-II multi-objective optimization model in order to compute the optimized groundwater allocation to each agent while the objectives of the main stakeholders of the groundwater resource were addressed in the model. The stakeholders were considered as the society of farmers, i.e., the agents, with the objective of a maximum profit, the executive government sector with the objective of maximum groundwater distribution equity, and environmental protection institutions with the goal of having a sustainable groundwater abstraction, i.e. a minimum groundwater drawdown. The multi-objective optimization model resulted in many sets of optimal solutions that comprise an optimal Pareto front among the objectives. For any optimal set of solutions, which implies certain water allocations to the agents, different levels of each objective were satisfied. Choosing any of these optimal allocation scenarios could raise conflicts among the principal stakeholders who have different preferences. A Nash bargaining conflict-resolution model was therefore applied to the optimal Pareto front to find a theoretical compromised solution among all stakeholders. This solution is derived from the results of the NSGA-II multi-objective optimization model. Although, this model has been developed based on stakeholder's preferences to find the optimal solution, it does not consider social properties of the study area and especially the agents, as the groundwater extractors. Therefore, the resulted solutions might not be accepted by the agents, resulting in their non-cooperation.

To incorporate the human-environment interactions into the proposed framework for groundwater resource management with a sustainable approach, an agent-based model was developed and the social properties of agents and also the study environment were considered to test the agent's reactions to all optimal solutions. A modified optimal Pareto front was then derived. Each point on this modified optimal set of solutions specifies the water demand of each agent influenced by societal conditions.

To reach a consensus and find a compromise solution that is acceptable by the agents while it addresses all principal objectives, i.e. sustainability of groundwater, equity in water withdrawals and economic benefits of stakeholders, once again the Nash bargaining model was employed. Indeed, Nash model seeks a solution based on each stakeholder's individual preferences, while the agent-based model provides an opportunity to consider the societal impacts on the agents' reactions to governmental policy mechanisms, and

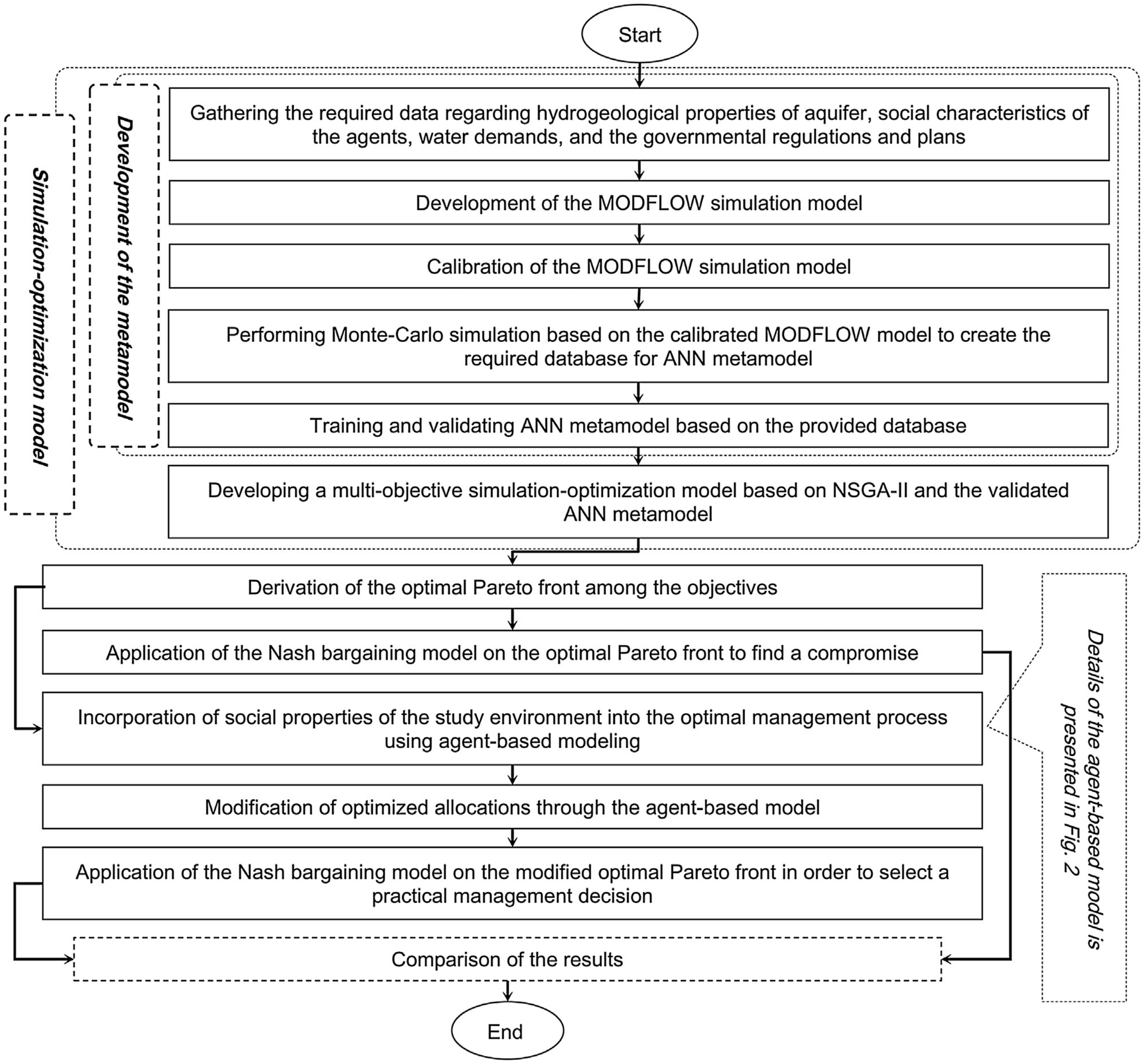

Fig. 1. The algorithm of the proposed method for groundwater management.

helps identify the ones that encourage agents to cooperate. It may be claimed that this integrated model leads to a practical optimal solution since it embeds social behaviors of agents and satisfies their new maximum water demands, which is a modified demand, considering social properties. Therefore, the Nash bargaining model was used twice after the application of the optimization model. First, it was used without considering social characteristics of the study area, and then it was used once again after considering these characteristics in the agent-based model. Changes in water allocation rates will impact sustainability of groundwater, as a shared resource that may be depleted. The impacts caused by modified water allocation rates derived from NSGA-II optimization were compared with those resulted from the proposed agent-based model. In fact, this comparison represents the effect of social behaviors incorporation in groundwater management, in contrast to merely optimizing groundwater allocations neglecting social conditions.

2.1. Optimization formulation

In its decision-making process, the government considers preferences of involved stakeholders, while they might be in conflict. Also, it is assumed that the government allocates optimum volume of water to the agents. In the present study, an NSGA-II multi-objective optimization model proposed by Alizadeh (2014) was utilized to reach an optimum water allocation defined by the government. The preferences of farmers, the executive sector of government, and the environmental protection institutions were included in the optimization model as te objective functions presented below:

$$\text{Irrigation water deficit}: \ Min\, Z_1 = \sum_{r=1}^{nr} (A_{ind} + A_{domest}) \quad (1)$$

$$\text{Equity in water allocation}: \ Max\, Z_2 = Min \left(\frac{A_{agr,\ r}}{D_{agr,\ r}} \right) \quad (2)$$

Groundwater level drawdown :

$$Min\,Z_3 = f(A_{agr},\ A_{ind},\ A_{domest},\ H_{init},\ \mathrm{Re},\ K) \leq dr_{all} \tag{3}$$

Subject to:

$$A_{agr} + A_{ind} + A_{domest} = A \tag{4}$$

$$A_{ind} + L_{ind} = D_{ind} \tag{5}$$

$$A_{domest} + L_{domest} = D_{domest} \tag{6}$$

$$A_{agr} + L_{agr} = D_{agr} \tag{7}$$

$$A_{agr} + A_{domest} + A_{agr} < W_{all} \tag{8}$$

where, Z_1, Z_2, and Z_3 are te principal objective functions, which represent irrigation water deficit, equity in water allocations to $r = 1,2,\ldots,nr$ agents, and groundwater level drawdown, respectively. A is the allocated amount of water, D is the demand, L is the lack of water allocation, dr is the groundwater drawdown, H_{init} is the initial water level, Re is the groundwater recharge, K is the average hydraulic conductivity, and W_{all} is the total allowable withdrawal. Subscripts *agr*, *ind*, and *domest* represent agricultural, industrial and domestic purposes, respectively, and subscript *all* stands for *allowable*. Eq. (3) is computed through the developed metamodel.

Agricultural, industrial, and municipal sectors are the main water users in the study area. Hence, the total water demand, D, equals summation of their demands, $D = D_{agr} + D_{ind} + D_{domest}$. Regarding the groundwater sustainability, in order to maximize the agents' groundwater allocation, A_{agr}, assumed to be equivalent to the agents' profit, summation of other allocations, i.e. A_{ind} and A_{domest}, should be minimized for all agents, Eq. (1). The highest portion of groundwater is usually consumed by farmers (World Water Assessment Program, 2009). Therefore, it was assumed that the agricultural sector, i.e. the agents, would gain the maximum economical profit if irrigation water deficit is minimized. As presented in the constraints, since the agents' water demand, D_{agr}, is usually higher than the manager's water allocations, A_{agr}, it is assumed that their demands equal summation of allocation, A_{agr}, and lack of allocated water, L_{agr}, or mathematically, $D_{agr} = A_{agr} + L_{agr}$. Similar assumptions are considered for industrial and domestic purposes, i.e. $D_{ind} = A_{ind} + L_{ind}$ and $D_{domest} = A_{domest} + L_{domest}$. The optimization model also maximizes the equity in water allocation to agents, Eq. (2), and minimizes the groundwater level drawdown, Eq. (3). Actually, NSGA-II uses initial population of potential solutions and modifies them according to the objective functions to find the optimum. In this problem, any potential solution meant a different possible groundwater allocation to the agents. To find the maximum equity in water allocation to agents, at first, for any potential solution, NSGA-II calculated A_{agr}/D_{agr} ratio for every agent, and then, the minimum was specified. A small quantity for A_{agr}/D_{agr} means that allocated water to the agent is too much smaller than its water demand. After finding these minimums for all potential solutions, the maximum (of all minimums) was selected by NSGA-II model and this process was repeated till the final solution was derived. It might be interpreted that in this process, the worst case of groundwater allocation to an agent, i.e. the most unfortunate agent with minimum A_{agr}/D_{agr}, has been iteratively improved, i.e. maximizing the minimum A_{agr}/D_{agr}, till the maximum equity in groundwater allocations has been attained. As the third objective function, water level drawdown was minimized through NSGA-II by means of the linked ANN metamodel, Eq. (3).

2.2. Nash bargaining model

Nash (1953) suggested the following non-linear optimization model to ensure a fair allocation of a resource through bargaining:

$$\Omega = \max \prod_{j=1}^{n} \left(x_j - d_j\right) \tag{9}$$

Subject to:

$$\text{Resource availability constraint}: \sum_{j=1}^{n} x_j \leq S \tag{10}$$

$$\text{Individual rationality constraint}: x_j \geq d_j \tag{11}$$

$$\text{Non-negativity constraint}: x_j,\ d_j \geq 0 \tag{12}$$

where, Ω is the optimum solution, S, x_j and d_j are, respectively, the total available resources, the stakeholder's share from the resource under cooperation, and the stakeholder's share from the resource when acting individually (non-cooperatively). Subscript j denotes the stakeholders, and $(x_j\text{-}d_j)$ is the gain to stakeholder j from cooperation (Kerachian and Karamouz, 2007; Madani and Lund, 2012).

In order to select a fair scheme of water allocations to the agents, from the Pareto optimal set obtained from the optimization model, the Nash bargaining model was used, which helped find a compromise among the conflicting objectives of stakeholders. This model simulated a three-player bargaining process among the stakeholders; agents, executive sector of the government, and environmental protection institutions. Although, solutions obtained from this model considered the stakeholders' preferences, they ignored interactions among agents and their reactions to the management. For more information on the Nash bargaining model refer to Madani (2011).

2.3. Agent-based approach

To find feasible and practical management strategies that address the competing interests of water resources users, agent-based modeling can be considered as a promising tool (Akhbari and Grigg, 2014). Incorporating human decision-making characteristics into an agent-based model and its implication is a complex and controversial task (Pahl-Wostl, 2002). Numerous factors make prediction of agents' reactions difficult and usually impossible. Akhbari and Grigg (2015) proposed an agent-based framework to incorporate the agents' interests and environmental factors in a decision-making support tool for water resources management. The present study builds on Akhbari and Grigg's framework to implement it for a groundwater management problem.

Incentives, penalties, education (training), filing a lawsuit by environmental stakeholders, and social norming were considered as the social parameters and managerial policies. The incentives and penalties impacts on the agents' behaviors were assumed as power functions, which could be precisely defined by the government for any study area. The proposed agent-based model was comprised of the following phases, illustrated in details in Fig. 2:

a. Identifying agents' behavior as Cooperative (C) or Non-Cooperative (NC).
b. Controlling whether any specific plan is proposed by the government to limit groundwater extractions or not. It is assumed that for some agents, the government might plan some strategies to restrict groundwater withdrawals by an optimum water allocation.
c. Incorporating social characteristics of agents as well as the environment, and application of policy mechanisms to encourage agents to cooperate.

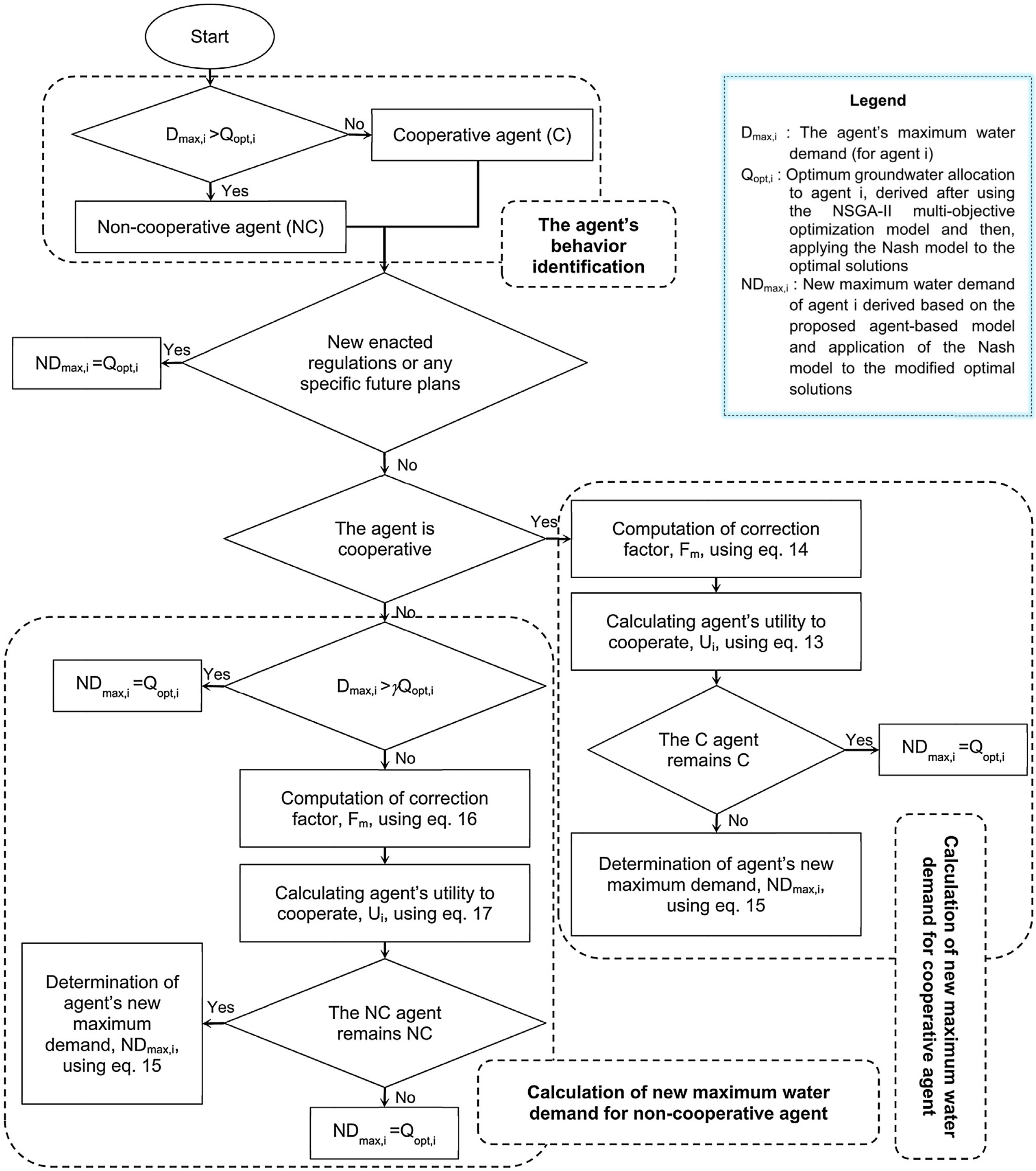

Fig. 2. The algorithm of the proposed agent-based model to implement social characteristics of agents.

d. Determining new water demands for each agent after incorporation of policy mechanisms.

In the first step, cooperative or non-cooperative behavior of agent i was specified according to their maximum water demand, $D_{max,i}$, to identify whether they accepted the optimized groundwater allocation, $Q_{opt,i}$, or not. If the agent's maximum water demand was lower than the allocated water, they abided by the decision (cooperative behavior) and withdrew their allocated share, i.e. $Q_{opt,i}$. If the agent's behavior was non-cooperative, i.e. they did not abide by the decisions, certain policy mechanisms could be applied to encourage/force them towards cooperation. It was checked whether new enacted regulations or specific future plans were effective for agent i in order to restrict its water consumption to $Q_{opt,i}$.

If agent i was cooperative and no specific groundwater extraction restricting plan was designed, their utility to cooperate, U_i, was computed as (Akhbari and Grigg, 2013):

$$U_i = \max \begin{cases} U_{i,C\to C} = a \times V_{i,C} + F_m \\ U_{i,C\to NC} = b \times V_{i,NC} \end{cases} \quad (13)$$

where, $a = 0.7$, $b = 0.3$ (suggested by Edwards et al., 2005), $V_{i,C}$ and $V_{i,NC}$ are respectively the fraction of cooperative and non-cooperative neighbors of agent i. In Eq. (13), if $U_{i,C\rightarrow C} > U_{i,C\rightarrow NC}$, the behavior of the agent will remain cooperative; otherwise, it will shift to a non-cooperative behavior. If the agent's behavior is cooperative, the government may provide incentives and training facilities to encourage these agents keep their cooperative behavior in the future. The influences of these two encouraging mechanisms on the agents' behavior are embedded in the correction factor, F_m, as:

$$F_m = (1-a) \times \langle \underbrace{\{\alpha \times i_{train}\}}_{education\ impact} + \underbrace{\left\{(1-\alpha) \times \left[\frac{Q_{opt,i} - D_{\max,i}}{Q_{opt,i}}\right]^2\right\}}_{incentives\ impact} \rangle \tag{14}$$

where, i_{train} is the training impact on agent i, which represents the effect of agents education and knowledge level on utility of the agent to cooperate. It is assumed that the government trains the agents to consume less water. α is a local coefficient that defines the fraction of training and incentives impact on a cooperative agent, defined based on sociological studies. A power function was proposed for the incentives impact term in the equation; assumed to be a second-order function in this study. By means of this function, cooperative agents who demanded less amount of water were thanked by a higher level of incentive. However, the societal investigations and managers' attitude might modify this function. In the proposed approach, more groundwater allocation was endowed to the agent as the incentive, but in reality it could be f any kind of subsidy.

Next, the agents' new maximum water demand, $ND_{max,i}$, is calculated using their utility to cooperate:

$$ND_{\max,i} = Q_{opt,i} + \left[\left(D_{\max,i} - Q_{opt,i}\right) \times (1 - U_i)\right] \tag{15}$$

The non-cooperative agents who consume more than $\gamma \times Q_{opt,i}$ will be obliged by the judicial system to cooperate, i.e. $ND_{max,i} = Q_{opt,i}$. The quantity of γ could be defined based on the hydrologic conditions in the study area and the $D_{max,i}/Q_{opt,i}$ ratio for different agents. But, if their maximum water demand is between $Q_{opt,i}$ and $\gamma \times Q_{opt,i}$, a type of penalty, such as paying more tax, will be imposed to them and its encouraging impact would be considered in the utility of non-cooperative agents to cooperate. However, they could extract their maximum demand, $D_{max,i}$. The formulation shows that more groundwater was allocated to them, but indeed, this was a figurative amount of water which is equivalent to the penalty imposed on these non-cooperative agents. The motivating impacts of training and penalty on non-cooperative agents were incorporated into the model through a correction factor, F_m, computed as:

$$F_m = (1-b) \times \langle \underbrace{\{\beta \times i_{train}\}}_{training\ impact} + \underbrace{\left\{(1-\beta) \times \left[\frac{D_{\max,i} - Q_{opt,i}}{\gamma \times Q_{opt,i}}\right]^2\right\}}_{penalty\ impact} \rangle \tag{16}$$

where, β is a local coefficient which determines the fraction of training and penalty impacts on decision-making of agents, and social studies on agents' behavior may quantify it.

The utility of non-cooperative agents, U_i, to follow the management decisions or not was calculated through the following equation:

$$U_i = \max \begin{cases} U_{i,NC\rightarrow C} = b \times V_{i,C} + F_m \\ U_{i,NC\rightarrow NC} = a \times V_{i,NC} \end{cases} \tag{17}$$

If $U_{i,NC\rightarrow C}$ was the maximum, agent's behavior changed to cooperative and their new demand was equal to the optimized allocated volume of water, $Q_{opt,i}$, but if $U_{i,NC\rightarrow NC}$ was the maximum, the agent's behavior remained non-cooperative and their new maximum water demand was calculated using Eq. (15).

The basics of the adapted agent-based model could be found in Young (1999), Edwards et al. (2005), Akhbari (2012), and Akhbari and Grigg (2013, 2015).

3. Study area

The proposed approach was applied to Daryan Aquifer, Fars Province, Iran, where water scarcity has been crucial for a sustainable groundwater management. This area is one of the 27 study zones specified by Regional Water Organization (RWO) within the watershed of lakes Maharloo, Tashk, and Bakhtegan. The watershed's total area is approximately 31,492 km^2 and Daryan Aquifer covers approximately 334 km^2 (Fig. 3). Generally, three entities are key stakeholders in groundwater extractions in this area; farmers, the executive sector of government, and the environmental protection institutions. Farmers use approximately 97 percent of the extracted groundwater (Regional Water Organization report, 2010).

About 92.26 million cubic meters per year of groundwater is extracted through 814 wells, two springs, and three qanats; gently sloped horizontal wells with a series of vertical access wells that extract water from an aquifer. During the past 14 years (2001–2014), water level observations in 11 piezometric wells have demonstrated 3.57 m drawdown, and accordingly, RWO has reported that the aquifer's status is beyond the sustainable condition (Regional Water Organization report, 2010). Daryan aquifer's watershed was divided into thirteen management subregions, considered as agents, to evaluate the influence of different management strategies and policy mechanisms in the study area (Fig. 4).

The MODFLOW simulation model was developed and calibrated using annual hydraulic and hydrological records of precipitation, water level in piezometric wells, pumping rates, stream flows, and recharge. The calibration period was from 2001 through 2006 and the model was verified from 2007 to 2008. The optimum number of neurons in the ANN metamodel was specified through sensitivity analysis and the trained model was validated using 15% of the data.

Based on field observations, statistical study, and physical properties of the study area, parameters of the agent-based model, α, β, γ, and i_{train}, for the 13 agents were determined. Based on the experts' viewpoints, it was assumed that in comparison with the incentives impact on cooperative agents, the penalties would have greater impacts on non-cooperative agents, and their encouraging impacts were considered to be less than training and educational level influence to encourage agents act cooperatively. Therefore, the local coefficients α and β were, respectively, considered equal to 0.7 and 0.6. As this study aims to show the functionality of the proposed framework rather than finding actual solutions, and also considering the fact that it was not supported by required social studies, training impact coefficients, i_{train}, for agents were assumed randomly (Table 1). As another model parameter, the local coefficient γ was assumed equal to a small value of 1.2 in Daryan zone to put pressure on non-cooperative agents to cooperate. Model parameters for each agent in the agent-based model are presented in Table 1.

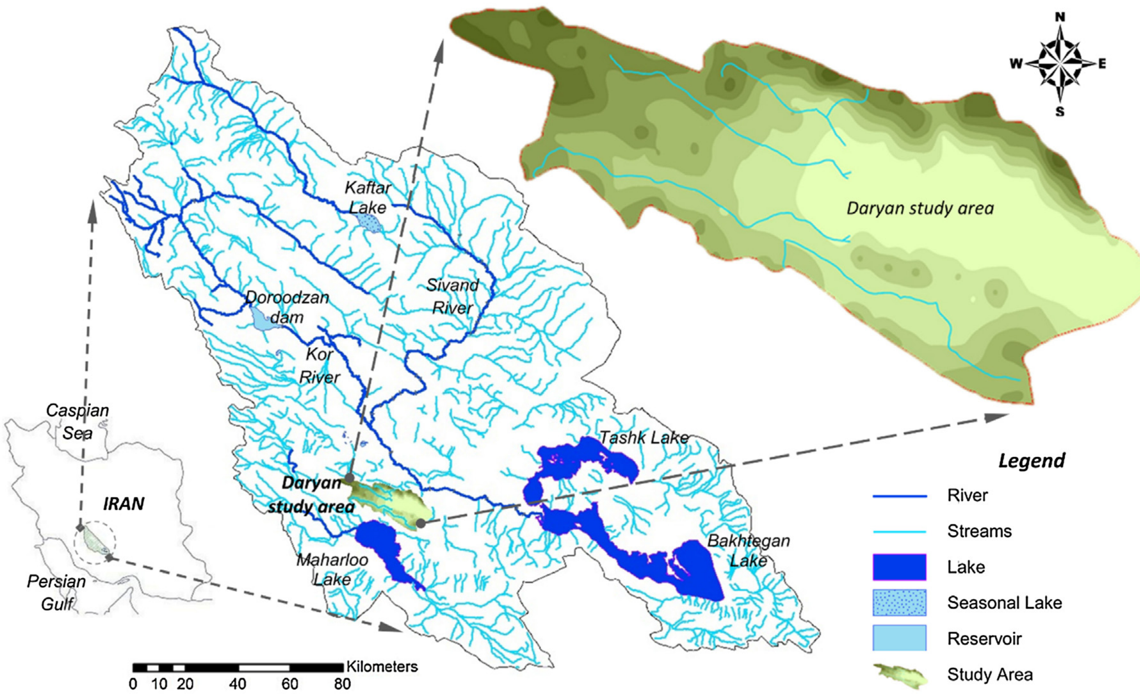

Fig. 3. Geographical map of Daryan Aquifer located in the Maharloo, Tashk and Bakhtegan Lakes watershed, Fars province, Iran.

4. Results and discussion

The optimized trade-off among groundwater drawdown, equity in water allocations to the agents, and irrigation water deficit (Fig. 5) shows that increasing groundwater extraction and the consequent water drawdown results in lower water deficit, which can be translated into higher profits, but equity in water distribution might not be guaranteed. Although critical water shortage in Daryan aquifer would not allow the decision-makers to overexploit this resource, in the current uncontrolled system, the agents strongly prefer to withdraw as much water as possible to increase their profit. This has brought the area's groundwater resources into a critical position. In order to prevent this complex system from disruption, the conflict between the objectives of the conflicting parties, who may be the farmers and the government or any other stakeholder, has to be resolved.

The Nash bargaining model was used as a conflict-resolution procedure to find an appropriate decision in which the interests of the conflicting parties could be met. All optimized water allocations, specified by the Pareto optimal front, were analyzed and negotiations between the conflicting parties were simulated to find an optimal compromise. This optimal compromise, which implies optimized groundwater allocations, $Q_{opt,i}$, for the 13 agents is presented in Table 2. Comparison of agents' maximum water demands, $D_{max,i}$, with $Q_{opt,i}$ shows that about 70% of the agents demand water more than twice as the optimized allocation, $Q_{opt,i}$. For the rest

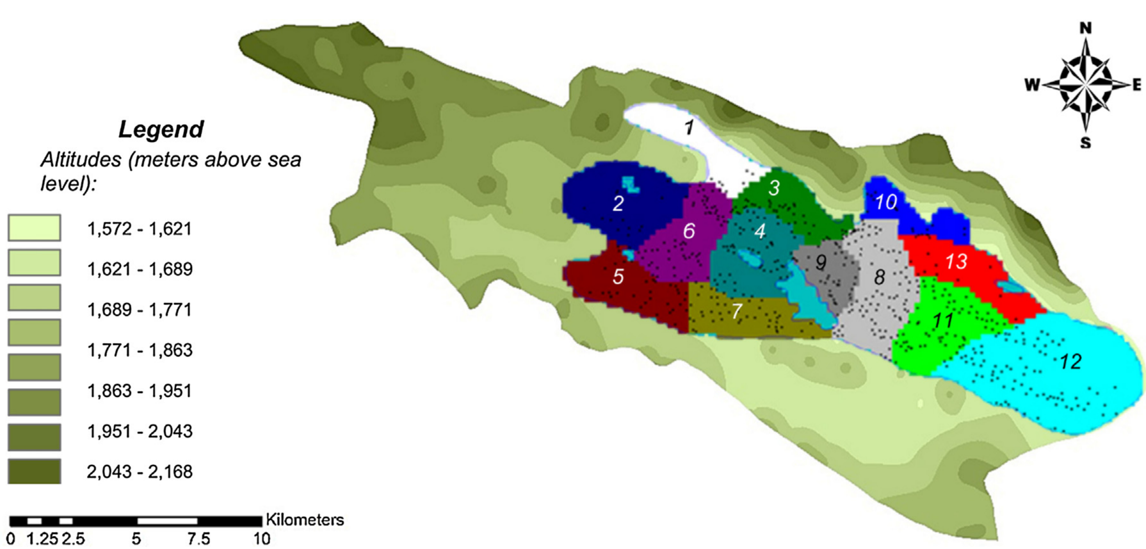

Fig. 4. Management subregions (agents) in the Daryan aquifer.

Table 1
Model parameters of the agent-based model specified for the agents.

Agent number	$D_{max,i}$[a] (m^3/day)	i_{train}[b]	specific plan
1	855.74	0.3	–
2	4104.34	0.35	–
3	10138.89	0.4	–
4	23913.51	0.25	yes
5	15914.21	0.6	–
6	20464.34	0.7	–
7	15259.06	0.9	–
8	21511.45	0.5	–
9	8941.66	0.4	–
10	4868.98	0.45	yes
11	13291.11	0.3	–
12	15317.51	0.55	–
13	2616.83	0.65	–
$\sum$	157197.6		

[a] $D_{max,i}$: maximum water demand of agent i which is their current water demand.
[b] i_{train}: the training impact on agent i.

of them, $D_{max,i}$ is at least three times greater than $Q_{opt,i}$. It indicates that the agricultural water use in the study area is far away from sustainability. This unbalanced water demand and supply has resulted in catastrophic environmental and societal consequences in Daryan area.

The $D_{max,i}/Q_{opt,i}$ ratio in Table 2 also shows that all agents except 9 and 13 act non-cooperatively and overwhelmingly exploit groundwater resources. Due to uncontrolled groundwater extractions over the past 14 years (2001–2014) and severe groundwater drawdown, extreme restrictions were considered in groundwater exploitations in the proposed management approach to push these agents towards cooperation. Therefore, γ was considered equal to 1.2 in the agent-based model, which allows 20% more water extraction than the optimized values as opposed to the current 300% over extractions. It should be noted that $D_{max,i}/Q_{max,i}$ for almost all agents in this zone is larger than 1.2. The agent-based model incorporates social characteristics of the agents and recalculates the optimal solutions for the three objectives of irrigation water deficit, water allocation equity, and groundwater drawdown (Fig. 6). Then, the Nash model was employed to find a modified optimal compromise among these groundwater allocations scenarios. The new maximum water demands, $ND_{max,i}$, obtained from the Nash model, are presented in Table 2. Comparison of the optimal compromise and the modified optimal compromise shows that water extractions for the two cases could be 54.3 and 58.3% less than the current state, respectively.

Fig. 7 illustrates water level contours for three states; current state, optimized groundwater allocations, and after incorporating social features of the study environment using the agent-based model. Comparing Figs. 7b (optimized allocations) with 7c (current state) shows that the optimized model has considerably increased water levels. It is revealed that the optimized water allocations would result into an average of three-meter water level uplift. However, not considerable changes were observed in water levels after incorporating the agent-based model in comparison with the optimized results (Fig. 7a and b). Groundwater depletion risks in the area has forced the managers to select a small γ and it has resulted in almost the same quantities of optimal allocations, $Q_{opt,i}$, and new maximum demands of agents, $ND_{max,i}$ (Table 2). However, social norming, training, and incentives/penalties have had positive effects to reduce water abstractions. The policy mechanisms to reduce groundwater abstractions caused agent 9 to demand 448 m^3/day less than $D_{max,i}$, but 1699.11 m^3/day more than $D_{max,i}$ will be allocated to agent 13. These agents' incentives are computed as the equivalent more allowable water abstractions. Indeed, this amount of water is not allocated to them, but, depending on the manager's decision, they might receive it as a loan, subsidy or any other kind of incentive. It can encourage the non-cooperative agents to cooperate in future. High rates of incentives and penalties are applied to encourage or push non-cooperative water users to change their behavior and cooperate with the managerial decisions. Application of the agent-based model reduced water demands of agents 4 and 10 down to less than $1.2Q_{opt,i}$. But the other agents still tend to consume more than $1.2Q_{opt,i}$. Since water use situation

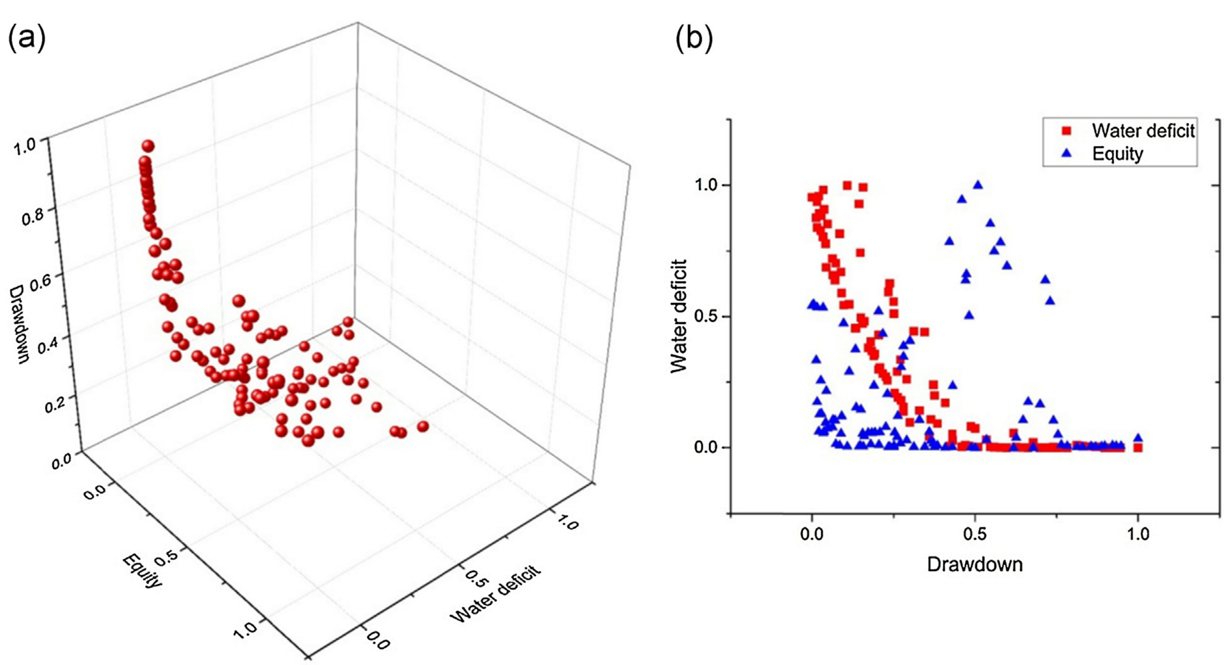

Fig. 5. Optimal Pareto front between the normalized objectives quantities computed based on the developed NSGA-II multi-objective simulation-optimization: (a) three-dimensional scheme, and (b) two-dimensional scheme.

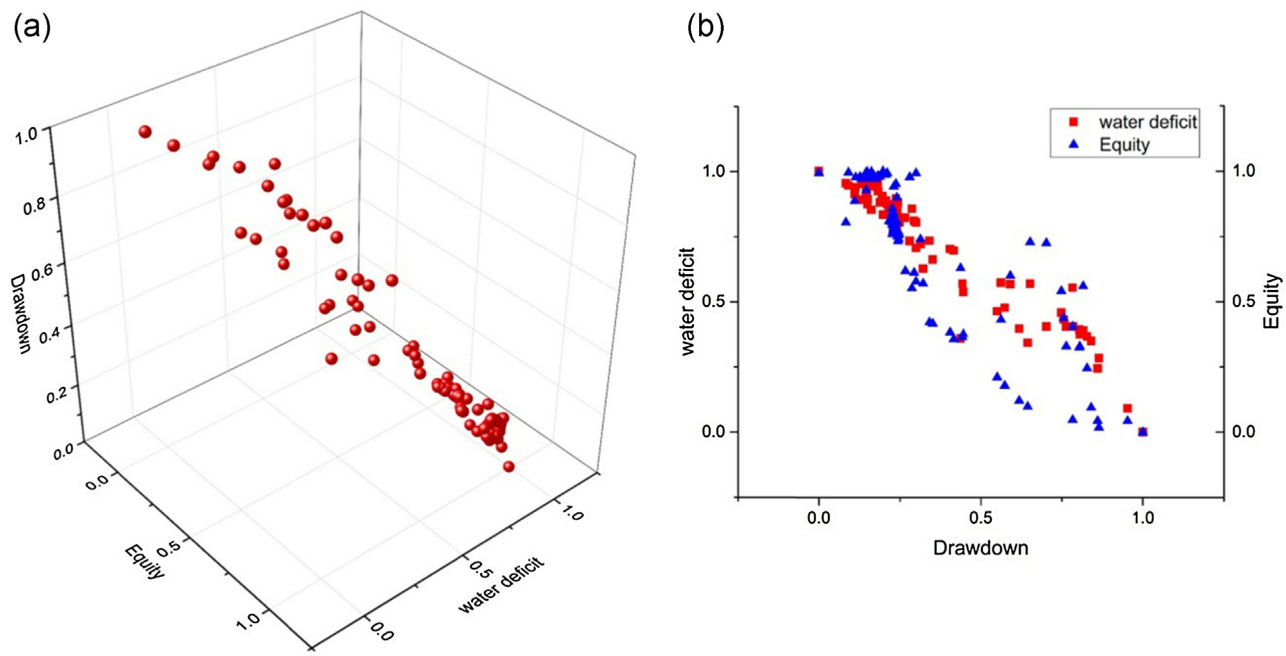

Fig. 6. (a) Three-dimensional, and (b) Two-dimensional, illustrations of the modified Pareto front between the normalized objectives quantities computed based on the developed agent-based model.

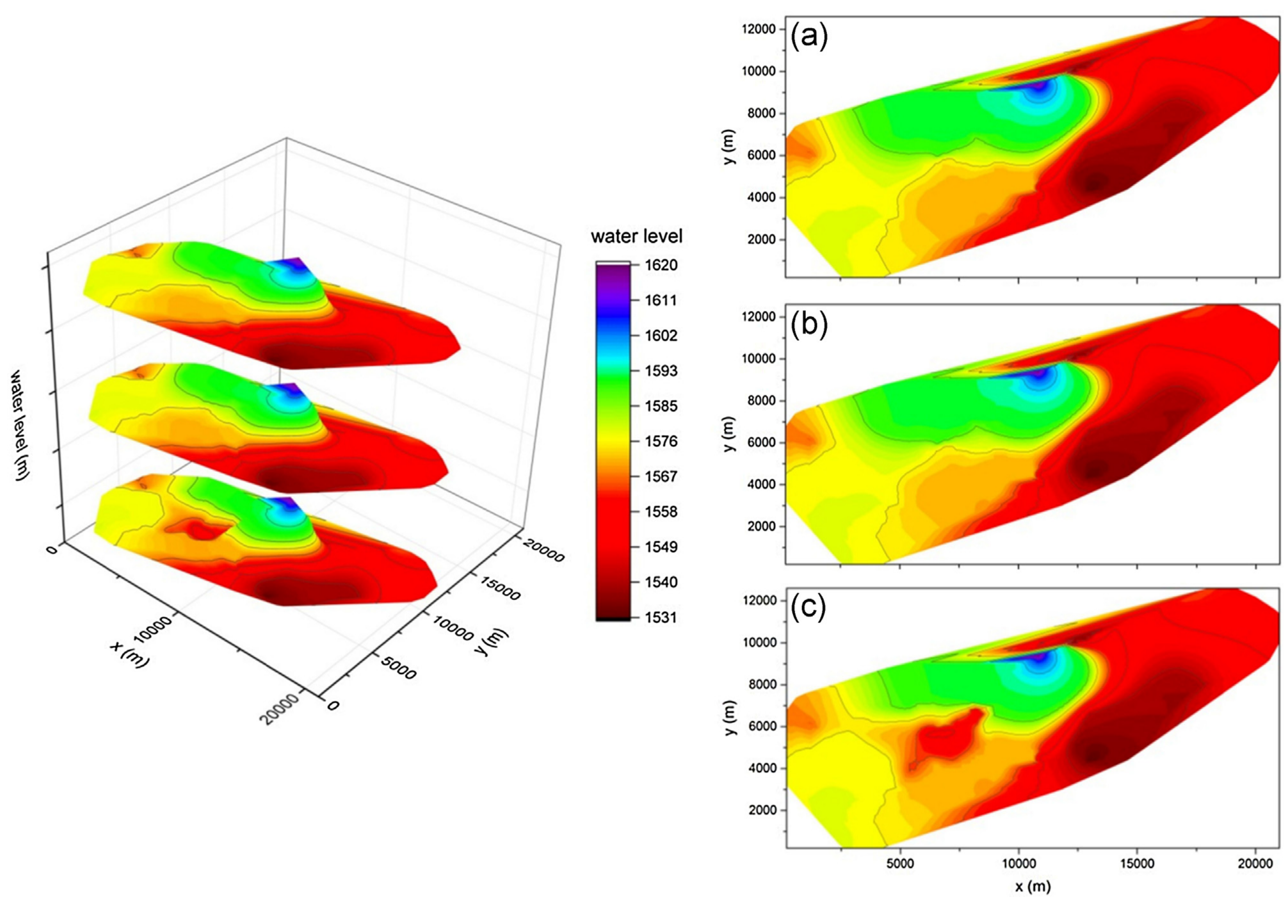

Fig. 7. Three- and two-dimensional illustrations of groundwater level for: (a) modified optimal allocations derived from agent-based model, (b) optimal management scenario derived from NSGA-II model, and (c) current state with the maximum demands (it shoud be noted that in the 3-dimensional figure the depth between water level states is shown schematically and is not scaled correctly.).

Table 2
Social characteristics, demands and groundwater allocations specified for the agents.

Agent number	$V_{i,C}$[a]	$V_{i,NC}$[b]	$D_{max,i}$[c] (m^3/day)	$Q_{opt,i}$[d] (m^3/day)	$D_{max,i}/Q_{opt,i}$	$ND_{max,i}$[e] (m^3/day)	$100 \times (ND_{max,i}/Q_{opt,i}$[f]
1	0	1	855.74	437.63	1.95	436.31	99.70
2	0	1	4104.34	1412.62	2.91	1409.83	99.80
3	0	1	10138.89	3040.06	3.14	2987.92	98.28
4	0.25	0.75	23913.51	6880.61	3.31	7331.15	106.55
5	0	1	15914.21	4862.69	3.26	4861.39	99.97
6	0	1	20464.34	6158.41	3.33	6155.51	99.95
7	0	1	15259.06	5339.57	2.85	5341.31	100.03
8	0.17	0.83	21511.45	8947.76	2.40	8991.36	100.49
9	0	1	8941.66	13166.24	0.68	8493.66	64.51
10	0.5	0.5	4868.98	2209.86	2.17	2142.53	96.95
11	0.33	0.67	13291.11	7400.58	1.74	6206.60	83.87
12	0.5	0.5	15317.51	6887.18	2.21	6804.51	98.80
13	0	1	2616.83	5036.47	0.52	4315.94	85.69
$\sum$			157197.6	71779.68		65478.02	

[a] $V_{i,C}$: the fraction of cooperative neighbors of agent *i*.
[b] $V_{i,NC}$: the fraction of non-cooperative neighbors of agent *i*.
[c] $D_{max,i}$: maximum water demand of agent *i* which is their current water demand.
[d] $Q_{opt,i}$: the optimized groundwater allocation, computed through the application of the Nash model to the optimal Pareto front.
[e] $ND_{max,i}$: the modified optimized groundwater allocation, computed through the application of the Nash model on the modified optimal Pareto front obtained from the agent-based model.
[f] This ratio represents that considering social situations in the study area has led to whether increase (the ratio larger than 100) or decrease (the ratio smaller than 100) of groundwater extraction with regard to the optimized groundwater allocation, $Q_{opt,i}$.

is in a critical state, the judicial system ought to strictly limit pumping rates of these agents. It is estimated that water use would be approximately 4% less than the optimized use.

5. Summary and conclusions

It is necessary to include social influential parameters, such as training, incentives, penalties, and social norming (neighbors' impacts), as well as considering executive and judicial systems, in water management decisions-making process. In the present study, social characteristics of the agents in Daryan area were incorporated into optimized groundwater allocations through an agent-based model to find a sustainable solution for groundwater management. The Nash bargaining model was also used for conflict resolution to increase the chance of practicality for the optimum decision. Due to the critical conditions of Daryan Aquifer, strict policy mechanisms were considered to force the agents to cooperate with the governmental sector's decisions. Implementing these strategies in the study area requires a powerful integrated supervision and executive sector? Community-based social studies are also required to specify relevant parameters for the agent-based model to accurately simulate behaviors of agents and governmental authorities in Daryan aquifer. Here, to show how the proposed framework may be applied, values of these parameters were assumed for one temporal step. Future studies should consider temporal societal changes and dynamic interactions between managerial mechanisms and their resulting socio-physical changes.

The Pareto optimal front among the objectives was computed for the optimized and agent-based models. The conflict-resolution Nash bargaining model was utilized to find the compromise for both of these Pareto fronts. Incorporating social norming, training agents, incentives, and penalties in the agent-based model led to a 9% reduction in total water demand in the region compared with the solution derived based on the NSGA-II optimization model. Final volume of extracted water was decreased by 58.3%, compared to the current state, resulting in a 3-m uplift in groundwater level. The difference between groundwater uplift obtained from the optimization and the agent-based models was negligible. However, the agent-based model provides decision-makers with the opportunity to evaluate functionality of different management scenarios and make more practical decisions.

Appendix A.

Nomenclature

A	The allocated amount of water (m^3/day)
C	Cooperative agent
D	The agent's groundwater demand (m^3/day)
d_j	The stakeholder's share from the resource when acting individually (non-cooperatively)
$D_{max,i}$	Maximum water demand of agent *i* which is their current water demand? (m^3/day)
dr	Groundwater drawdown (m)
F_m	Correction factor to incorporate some social conditions in the agent-based model
H_{init}	Initial water level (m)
i_{train}	The training impact on agent *i*
K	Average hydraulic conductivity (m/day)
L	The lack of water allocation (m^3/day)
NC	Non-Cooperative agent
$ND_{max,i}$	The modified optimized groundwater allocation, computed through the application of nash model on the modified optimal pareto front obtained from the agent-based model (m^3/day)
$Q_{opt,i}$	Optimized groundwater allocation, computed through the application of nash model to the optimal pareto front (m^3/day)
Re	Groundwater recharge (dimension?)
S	Total available resources
U_i	Utility of agent *i* to cooperate
$U_{i,C\rightarrow C}$	Utility of cooperative agent *i* to have cooperative behavior in the next managerial period
$U_{i,C\rightarrow NC}$	Utility of cooperative agent *i* to have non-cooperative behavior in the next managerial period
$V_{i,C}$	Fraction of cooperative neighbors for agent *i*
$V_{i,NC}$	Fraction of non-cooperative neighbors for agent *i*
W_{all}	Total allowable withdrawal (m^3/day)
w_i	Normalizing weights, where *i=1,2,. . .,5*, are normalizing coefficients
x_j	Stakeholder's share from the resource under cooperation
$(x_j - d_j)$	j^{th} stakeholder's gain from cooperation

Z_1 The first objective function for NSGA-II optimization model: minimizing irrigation water deficit
Z_2 The second objective function for NSGA-II optimization model: maximizing water allocations equity
Z_3 The third objective function for NSGA-II optimization model: minimizing groundwater level drawdown
α A local coefficient that defines the fraction of training and incentives impacts
β A local coefficient that defines the fraction of training and penalty impacts
γ A regional coefficient that specifies the agents who should be obliged to follow the groundwater allocations
Ω The optimized solution for nash bargaining model

Subscripts
agr Agricultural purpose
all Allowable (amount of water)
domest Domestic purpose
ind Industrial purpose

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