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From Individual Fuzzy Cognitive Maps to Agent Based Models: Modelling Multi-Factorial and Multi-stakeholder Decision-Making for Water Scarcity

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Abstract: Policy making for complex Social-Ecological Systems (SESs) is a multi-factorial and multi-stakeholder decision making process. Therefore, proper policy simulation in a SES should consider both the complex behavior of the system and the multi-stakeholders' interventions into the system, which requires integrated methodological approaches. In this study, we simulate impacts of policy options on a farming community facing water scarcity in Rafsanjan, Iran, using an integrated modeling methodology combining an Agent Based Model (ABM) with Fuzzy Cognitive Mapping (FCM). First, the behavioral rules of farmers and the causal relations among environmental variables are captured with FCMs that are developed with both qualitative and quantitative data, i.e. farmers' knowledge and empirical data from studies. Then, an ABM is developed to model decisions and actions of farmers and simulate their impacts on overall groundwater use and emigration of farmers in this case study. Finally, the impacts of different policy options are simulated and compared with a baseline scenario. The results suggest that a policy of facilitating farmers' participation in management and control of their groundwater use leads to the highest reduction of groundwater use and would help to secure farmers' activities in Rafsanjan. Our approach covers four main aspects that are crucial for policy simulation in SESs: 1) causal relationships, 2) feedback mechanisms, 3) social-spatial heterogeneity and 4) temporal dynamics. This approach is particularly useful for ex-ante policy options analysis.

Keywords: Social-ecological systems; Fuzzy cognitive mapping; Agent-based modelling; Policy option analysis; Water scarcity.

1. Introduction

Environmental management and policy making for complex Social-Ecological Systems (SESs) are *multi-factorial* and *multi-stakeholder* decision-making processes. This has two important implications. First, SESs include multiple, interacting social and ecological factors (variables), e.g. natural resources, climate change, human interventions, emigration and social vulnerability. Interactions between these factors influence the behavior of the whole system. Therefore, policy analysis methods for SESs should be able to simulate the ex-ante impact of policies by considering the dynamic behavior and interactions of all important factors. Second, SESs involve many different stakeholders, from resource consumers to policy makers and managers, all of whom have different interests, which sometimes leads to conflicting decisions and actions. This heterogeneity may change the impact of policy options in different contexts (Levin et al., 2013, Mease et al., 2018).

This study aims to support policy making in an SES of a farming community in Rafsanjan, Iran, which is facing severe water scarcity. Rafsanjan is among the top producers and exporters of pistachios in the world. Being in an arid and semi-arid region, pistachio farmers in Rafsanjan depend entirely on groundwater to irrigate their orchards, however, their production has been severely threatened by water scarcity in recent years (Mehryar et al., 2015, Mehryar et al., 2016). Water scarcity in Rafsanjan is clearly a multi-factorial and multi-stakeholder problem. Many social and ecological variables are influencing or being influenced by water scarcity in this region e.g. precipitation, groundwater use, pistachio production, land cover change, farmers' social-economic vulnerability, land subsidence, etc., dynamics of which should be considered in water scarcity policy making. Also, different groups of farmers (based on their social-spatial situations) take various and sometimes conflicting adaptive actions to satisfy their water demand for water scarcity. The buying-out of small farmers by large-farmers, water marketing between small and large farmers, integrated farming, installing desalination system, deepening well and reducing orchard extents are among the famers' adaptive actions to water scarcity. For water scarcity policy making in Rafsanjan, such actions and interactions between multiple stakeholders should also be considered (Mehryar et al., 2016, Mehryar et al., 2017). The objective of this study is to develop a model to *compare* the impacts of water scarcity policy options on overall groundwater use (i.e. *rank* policy options) in Rafsanjan, Iran, through multi-factorial and multi-stakeholder approach.

This paper is organized as follows. Section 2 provides a literature review of the modelling techniques used in this study. Section 3 introduces an overview of our model development and implementation of the model in the case study. Section 4 represents and discusses the results of the policy simulation in the case study. Sections 5 and 6 reflect on the final results and the model, and conclude.

2. Literature review

To consider the two aspects of multi-factorial and multi-stakeholder decision-making, two approaches have been developed in simulating the impacts of policy options in SES: A *factor-based (system-level) approach* that represents changes in factors (variables) of a system and their interactions (Macy and Willer, 2002), e.g., Fuzzy Cognitive Mapping (FCM) (Kosko, 1986) and an *actor-based (individual-level) approach* that represents decisions, behaviors and interactions of stakeholders, e.g., Agent-Based Modelling (ABM) (Gilbert, 2008).

2.1. Fuzzy Cognitive Mapping

FCM, a combination of fuzzy logic and cognitive mapping, is widely used in environmental management and SES studies to represent knowledge of systems under conditions of data scarcity and data uncertainty (Özesmi and Özesmi, 2004, Papageorgiou and Kontogianni, 2012, Reckien, 2014). Structurally, it consists of a set of nodes[1] (representing various variables) and fuzzy signed directed edges (representing the strength of the causal relationships between variables) (Kosko, 1986). Thus, it encodes multiple causal relationships between variables of a system. FCM models are usually developed with a participatory approach. Stakeholders who are familiar with the operation and behavior of a system

[1] Known as "Concept" in FCM literature. In this paper we refer to FCM's s/concepts by using the general term of "variable".

or specific problem of a system are asked to mention the most important variables (e.g. environmental, social, ecological or economic variables), their causal relations, and the weights of the connections (i.e., how much a change of one variable causes a change in another variable) (Özesmi and Özesmi, 2004). A range of individual mental models of stakeholders is developed and aggregated into a semi-quantitative and standardized FCM model for simulation (Mehryar et al., 2017, Vasslides and Jensen, 2016). Thus, the connections in participatory FCMs represent causality perceived by participants.

FCM uses individuals as the units of data collection and analysis but aggregates their knowledge to provide a macro-level view of an entire system's behavior. Thus, FCM does not represent individuals' dynamic interactions with their environment. Besides, FCM provides semi-quantitative output data from qualitative stakeholders' knowledge, which may be used in combination with mathematical models. Therefore, FCMs are potentially useful in modelling aggregate human behavior and decisions (An, 2012). However, their lack of stakeholders' interactions, as well as temporal and spatial explicitness are their main limitations.

2.2. Agent Based Modelling

ABM provides a micro-level view of a system since each agent is explicitly represented and interacts with other agents as well as with the environment (Giabbanelli et al., 2017). Typically, ABMs are spatially explicit and simulate dynamics over time, which makes them appealing to model SESs. However, ABMs face the challenge of acquiring data for describing: 1) agents' behavioral options, 2) decision-making processes (the way an agent makes decisions), and 3) decision outcomes (impacts of their actions on others and on the environment). Due to the complexity of human decisions and actions, ABM studies regularly rely on rational choice theory to describe agents' behavior (Schlüter et al., 2017, Groeneveld et al., 2017). However, actual human behavior is subjective and has *bounded rationality* due to limitations of information access, time, personal beliefs and perceptions (Elsawah et al., 2015). This is particularly important in models for policy support (Schlüter et al., 2017). As a result, many modelers using ABMs try to replicate actual human behaviors and decision-making as closely as possible (Filatova et al., 2013) via participatory methods (An, 2012) such as role-playing games (Bousquet et al., 2002, Castella et al., 2005), Bayesian belief networks (Sun and Müller, 2013), cognitive mapping (Elsawah et al., 2015) or ethnographic methods (Ghorbani et al., 2015). Yet, the formulation and parametrization of qualitative knowledge gained through such approaches, their combination with quantitative data, and the identification and calibration of causal feedback mechanisms of a SES remain key challenges (Robinson et al., 2007, Sun and Müller, 2013, Ghorbani et al., 2015, Venkatramanan et al., 2017).

2.3. Techniques used in the present study

FCM and ABM are complementary in supporting SES policy making. Surprisingly, there have been only a few attempts to combine these two methods for SES modelling. Two studies have suggested distinct approaches to combine FCM and ABM. Elsawah et al. (2015) proposed a methodology that developed cognitive maps for use in ABM development. More specifically, they used *cognitive maps* to translate the subjective qualitative description of decision-making into formal rules in the ABM. In contrast, Giabbanelli et al. (2017) proposed two options for creating *hybrid* models, in which FCM and ABM are coupled and co-exist over a model run. In one option, an ABM represents the mental model of each agent as an FCM that can change through interactions with other agents. In another option, selected parts of an FCM are informed by an ABM. To our knowledge, no study has yet reported on implementing a combination of an FCM and an ABM such that the FCM informs both the agents' behavioral rules at the micro-level and the human-environment interaction rules at the macro-level. This is where our study steps in. For our case of water management in Rafsanjan we used FCMs to conceptualize an actor-based ABM. This ABM allows for testing the effects of different policy options and thus enables us to investigate dynamic processes and interactions among agents; a process which an FCM alone cannot do.

Similar to Elsawah et al. (2015), our focus is on structuring and using the collected qualitative data from a set of FCMs to develop an ABM. Yet, our approach significantly differs in two ways from theirs. First, we use FCMs instead of cognitive maps. Second, we use FCMs to model the whole system, including and not limited to stakeholders' actions. Thus, the FCM provides a macro-level view of the system i.e., the perceived interactions between social, ecological, environmental and economic variables, and also provides information for micro-level decision-making of agents i.e., type of actions and impacts of actions on the environment. The same variables collected in FCMs are used in ABM as environmental parameters and behavioral rules of agents. The outcome of our proposed modelling framework is useful for ex-ante policy options analysis.

3. Model building

3.1. Overview of model development

Our methodology consists of three main steps (Figure 1): 1. FCM modelling, 2. Translating FCM to ABM, and 3. ABM implementation and assessment. In step 1, the individual maps are first collected by interviewing stakeholders (step 1.1). Then, the individual maps are merged to create one FCM for each specific group of stakeholders (step 1.2). Finally, the time-series data is added to these subjective group FCMs to create the subjective-objective FCMs (step 1.3). In step 2, first the Overview, Design concepts, and Details (ODD) protocol is used to define the main elements required for ABM development in this study. Then, a Condition-Action-Impact (CAI) diagram is introduced and developed to translate and categorize the FCMs' variables into the set of available actions, and conditions-impacts for each action. Finally, a UML activity diagram is used to represent the sequential steps of actions and spatial-temporal aspects of decision-making processes by using the outcome of the CAI diagrams. In step 3, the ABM model is simulated and the results are validated with the historical data. The validated ABM is used to simulate the possible impacts of policy options via "what-if" analysis and compare their results with those of the baseline scenario. Finally, a sensitivity analysis is applied to the parameters of the model.

In the following sub-sections, each of these steps is discussed in more detail.

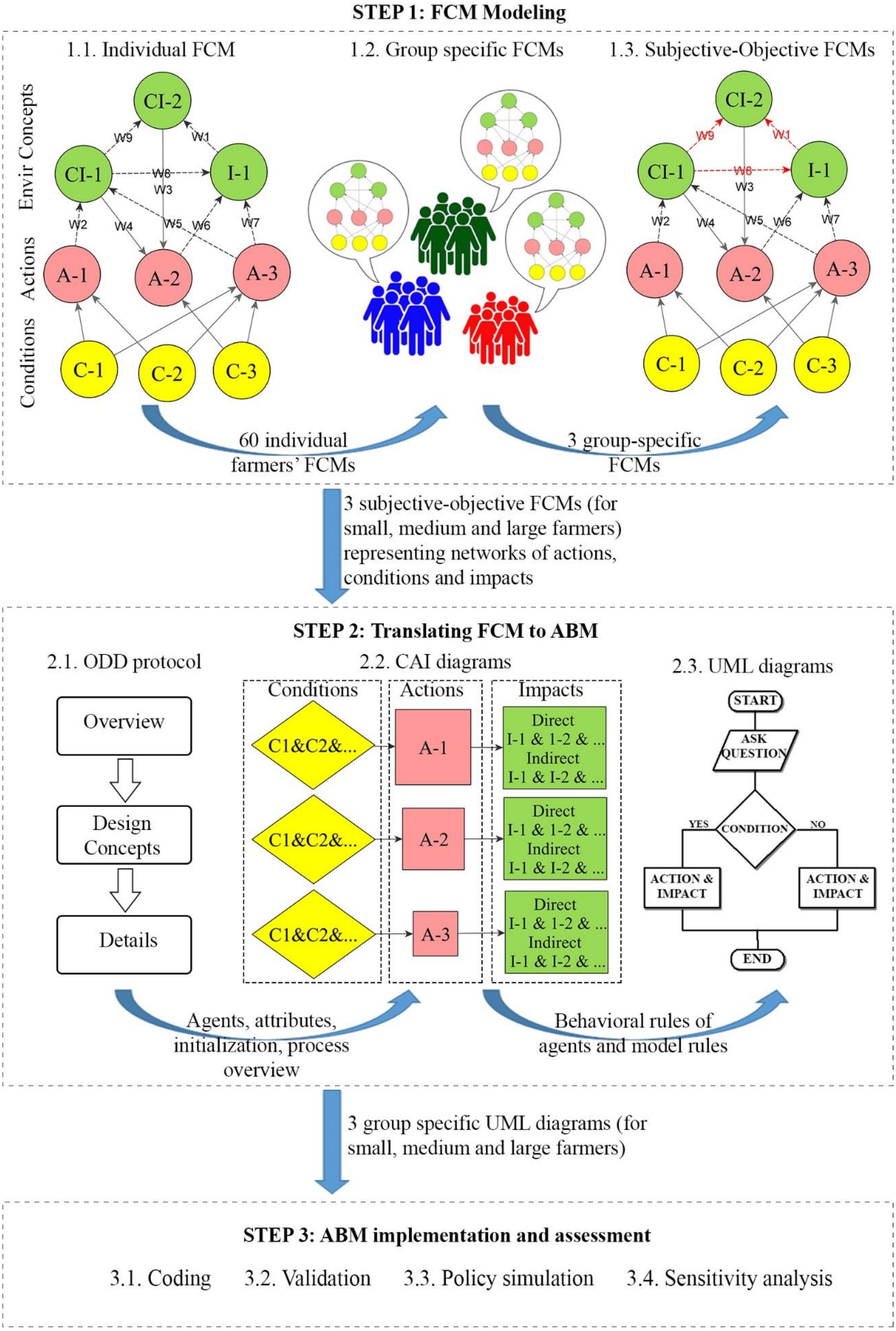

Figure 1: Main steps and sub-steps of methodology. Coding scheme - A: Action, C: Condition, I: Impact, CAI: Condition-Action-Impact, UML: Unified Modeling Language. In FCMs: red connections: weighted based on objective data, black connections: weighted based on subjective data, dashed lines: impact connections, solid lines: driving connections.

3.2. Step 1: FCM modeling

3.2.1. Collecting individual maps

There are different methods for individual FCMs' data collection, e.g. extracting data from transcripts of interviews, remotely online mapping with stakeholders, and face-to-face semi-structured interviews that can be done via either individual or group discussions with stakeholders (Özesmi and Özesmi, 2004, Gray et al., 2014, Jetter and Kok, 2014). While all of these methods can be valid, different contexts may require specific methods. In this case study, due to 1) the multi-variable and multi-aspect environment of water scarcity, and 2) the farmers' mistrust to share their information and perceptions, we chose to collect data with face-to-face interviews. These were useful in building a trustful relationship with interviewees, making the interview purpose explicit, and repeatedly offering explanations to the interviewees (Rahimi et al., 2018). Furthermore, due to the diversity of farmers in the area, and the heterogeneous impacts of water scarcity on different farmers, we chose individual interviews. In this way, we could capture the diverse, individual perceptions and local knowledge of farmers without them being influenced by larger, more powerful farmers (which could be the case in focus group discussions). Thus, we conducted individual interviews with 60 farmers (20 in each category of small, medium and large farmers) in August-September 2015—for demographic description of the interviewees see supplementary E. All the interviews were done with in-depth, open-ended questions. Interviewees were selected to represent different farm sizes (large, medium and small), from different sub-regions of Rafsanjan. A sample of the oral consent script alongside the interview questions can be seen in supplementary D.

The interviews were led by two main questions and two sub-questions:

1. What have been the main causes and impacts of water scarcity in your region/farm?

   1.1. How much has each of these variables caused an increase or decrease of other variables?

2. What have been your adaptive actions to combat water scarcity in your farm, and what have been the conditions to implement each action?

   2.1. How much has each action impacted other variables mentioned earlier?

The interviewees were free to mention any variables related to the questions 1 and 2: causes and impacts of water scarcity (e.g. precipitation, irrigation efficiency, agricultural productivity, economic situation, etc.), their adaptive actions (irrigation system change, deepening wells, integrated farming, etc.), and conditions of actions which could be a word or a phrase (e.g. having government loan for irrigation change, having permission for well's deepening, willingness of neighbor farmers for integrated farming, etc.). The variables related to question 1 and 2 provided *environmental variables*, and condition/action/impact variables, respectively (figure 1, step 1.1).

The interviewees were also asked about the degree of influence of each variable (i.e. actions or environmental variables) on other variables (questions 1.1 and 1.2). They were asked to identify causal weights of relations based on the linguistic values of "very low", "low", "average", "high" and "very high". Later on, such values were equated with a five point numerical scale: very low = 0.1, low = 0.3, average = 0.5, high = 0.7, very high = 0.9—While the transformation from a linguistic variable into a crisp number often uses fuzzy membership function, our study applied a simpler process but acknowledging that approaches examining uncertainty in answers are an important objective for future work (section 5.2). A positive value indicated that an increase in one variable caused an increase in another. A negative value indicated that an increase in one variable caused a decrease in another variable (Mehryar et al., 2017).

Regarding the second question, farmers were also asked to specify the frequency of each action, i.e., if the action is repeated every month, every year, etc. or taken only once (e.g. desalination). Moreover, farmers were asked about the situation that leads them to take each specific action, which could be constant variables. Therefore, the interviewer wrote down the fixed, i.e. true/false, conditions as input variables into the actions e.g. having documents or legal permission. For such variables, we used the structure of cognitive maps, i.e. including connections without weights where connection arrows represent implication and are interpreted as "may lead to" (Elsawah et al., 2015).

Important variables and causal connections were drawn on paper during the interviews by the researcher who constantly validated these with interviewees (an example from one of the interview maps can be seen in supplementary F). The result of this step is many individual maps including the environmental network and actions of farmers. Each map is then stored as an adjacency matrix.

3.2.2. Generating group specific FCMs

To develop an FCM model, all of the individual maps are aggregated to a single unified model that encompasses all of the individual's knowledge. The individual maps are merged through matrix algebra, whereby each entry of the merged model is the average of the connection weights assigned by individuals (Vasslides and Jensen, 2017)—other approaches for group-level aggregation of FCMs are proposed in Gray et al. (2014) and Lavin et al. (2018). However, stakeholders may differ in their preferences, decisions and rules of behavior. By aggregating all individual maps, the heterogeneity of stakeholders is lost. To preserve the diversity of decision makers' mental models, the individual cognitive maps can be aggregated into different groups of FCMs. Categorizing FCMs can be based on the structure of the maps' outputs (e.g. centrality, number of inputs and outputs, etc.) or content of the outputs (e.g. specific variables that are important for different research objectives).

In our case, the action variables mentioned by farmers (in their FCMs) were significantly different among three groups of small, medium and large farmers mainly due to the size of their lands and their economic situation. For instance, large farmers (> 80 ha) can buy-out small and medium farms that have little access to irrigation water, or set up a water desalination system which is a very expensive option for providing good quality irrigation water, or purchase surplus water from small and medium farmers who are no longer harvesting their orchards. Whereas medium farmers (15 to 80 ha) tend to integrate their farms and irrigation systems amongst themselves to increase the efficiency of their lands' irrigation water use and productivity, or modify their irrigation systems from flood irrigation into drip irrigation, something that most large farmers have already done. Small farmers (< 15 ha) have fewer options to adapt to water scarcity: these are basically changing the irrigation system or turning off their well pumps during the night or over the winter. There are also some common adaptive actions among all groups of farmers, e.g. *deepening wells* or *shrinking the orchard size.* The extent of shrinking differs based on the location and size of the farms. Because of such differences in behavior, we aggregated the individual maps in three groups of large, medium and small farmers (figure 2 and supplementary A)[2]. In the ABM, we used the numerical values for the group-specific weights for the agents' decision-making.

[2] The initial FCM model that we developed in the field work included a much larger number of variables indicating causes and impacts of water scarcity than what we used in this study. Since the aim of this study was to investigate the impact of farmers' actions on groundwater use and emigration, we only kept the variables relevant to this objective. However, considering the objective of policy makers and researchers, the size of FCMs can be larger or smaller, by using different simplification methods in FCM (Hatwagner et al., 2018, Lavin and Giabbanelli, 2017)

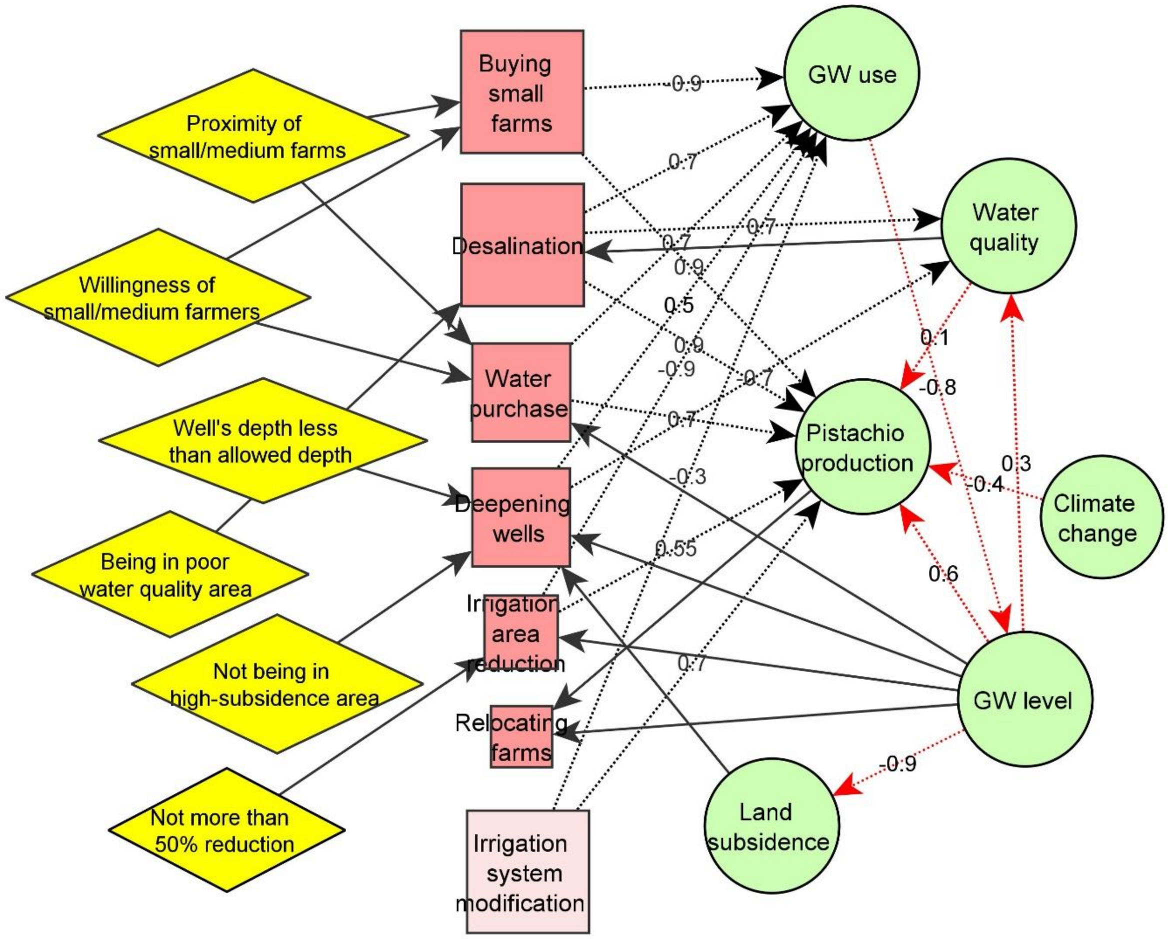

Figure 2. Large-farmers' FCM combined with objective data. The red squares show farmers' actions and their size shows the number of farmers who took this action i.e. level of preference or priority of actions. Yellow diamonds are conditions and green circles are either impacts or condition for some variables and impacts for other. Dashed and solid lines represent impact and driving connections, respectively. Black and red lines represent perceived connections and data-driven connections, respectively. FCMs of medium and small farmers are given in supplementary A.

3.2.3. Combining subjective and objective data in FCM

In modeling SESs, many social and ecological variables interact with each other. For some of these variables, we may lack accurate objective data but have information about stakeholders' knowledge and perceptions, e.g. individual land productivity and farmers' vulnerability. For other variables, we may have access to objective data measured by formal scientific methods, e.g. precipitation and groundwater levels. Therefore, both subjective and objective data are crucial and complementary to enable a full understanding of the system (Gosselin et al., 2018), particularly for building an ABM. In this step, we combined both subjective knowledge derived from farmers and the objective knowledge derived from formal scientific studies. First, among all available connections between variables in farmers' FCMs, we identified the connections that can be measured more accurately with available empirical data, e.g. hydrological and ecological variables. Then, such connections received a data-driven value based on correlation coefficients between two variables' time-series data (supplementary C). Since the correlation coefficient alone does not imply causation, we only applied the correlation values to the connections for which the causality has already been determined by farmers[3]. The results of this step are group specific FCMs containing two groups of connections: 1) those perceived by farmers (black connections in figure 1, step 1.3), and 2) those for which the causality is perceived by farmers and the correlation values are derived from time-series data (red connections in figure 1, step 1.3). Therefore, such group specific

[3] Another recommended approach is using statistical techniques such as Granger causality test to test whether there is a causal impact among the time-series data.

FCMs are combinations of farmers' perceptions and data-driven knowledge covering different aspects of an SES.

All data-driven connection values developed by available time-series data and validated by farmers' perceived FCM are listed in supplementary C. These data-driven values were used instead of perceived values in all three group-specific FCMs, to cover the ecological and data-abundant part of the system (red connections in figure 2). Yet all other connections, including those representing the impacts of actions, remained with their perceived values obtained from farmers (black connections in figure 2).

3.3. Step 2: Translating FCM to ABM

3.3.1. ODD protocol

We used the ODD protocol for describing the ABM (Grimm et al., 2010). The ODD protocol is a standard framework of elements that need to be covered when developing and describing an ABM. It requires descriptions of *entities* in the model, their characterized attributes and *behavioral rules* (which entity does what, in what order, what rules do entities have for making decisions or changing their behavior in response to environmental changes), and *model rules* (what are the direct interactions among entities and indirect interactions via environmental variables) (Grimm et al., 2017). The behavioral rules of agent, and model rules were extracted from FCM models developed in step 1. The agents, their characterized attributes, initial values for environmental parameters and process overview (model updates and activities in each time step) are the new ABM elements.

A full ODD description is given in supplementary A. Below, we provide a summary of the ODD.

Agents represent a total of 154 farmers in three groups: 21 large-farmers, 49 medium-farmers, and 84 small-farmers (section 3.2.2). These farmers are distributed across a stylized representation of the Rafsanjan landscape, distinguished by nine sub-regions in the ABM, out of which two represent non-vegetated areas (i.e., arid land). Each sub-region consists of 15 by 15 cells, leading to a total of 45*45 cells (figure 3, details on initialization based on empirical data are given in supplementary A). Each cell can be owned by one farmer; each farmer may own 1 or more cells. Agents are distributed equally in the seven sub-regions (mainly because there is no significant difference in the number of farmers in these 7 sub-regions) and randomly within each region (figure 3). Each cell represents 5ha of pistachio land. Cells are characterized by: 1) Depth of groundwater level, 2) Groundwater quality, 3) Land subsidence level, 4) Groundwater use 5) Well depth, and 6) Allowed well depth.

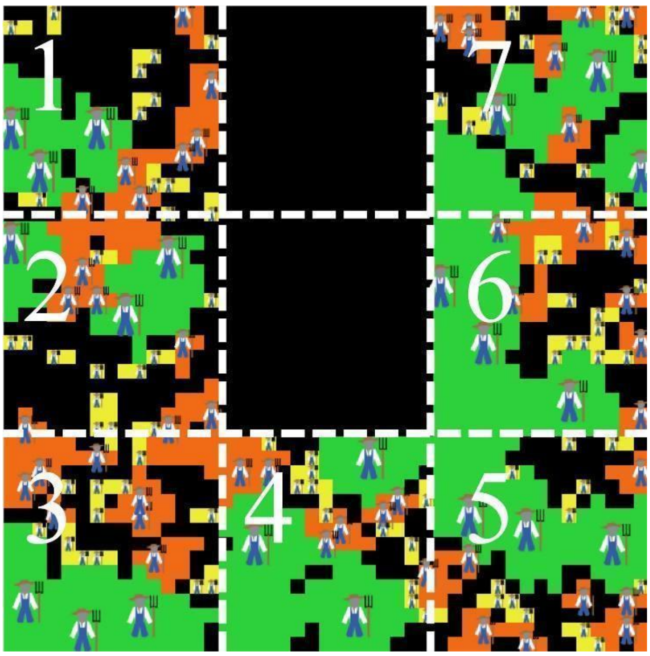

Figure 3. Set-up and allocation of farmers and farms in Netlogo. Green, orange and yellow cells represent large, medium and small farms, respectively. The two black regions in the middle are not farming regions (to represent the real U-shape landscape of Rafsanjan).

Temporal resolution: The time step is 1 month. Actions in reality can be repeated at different time intervals, therefore, we took the smallest time interval (i.e. 1 month) for the temporal resolution. The time horizon of the model is 15 years, i.e. 180 time steps. This time horizon is chosen to be able to see some effect, but not go too far into the future since new technologies we cannot foresee now might emerge as well as other political and economic uncertainties which would make these simulations useless.

Process overview: Within each time step two main activities take place in the following order:

1) Cells' update: There are two types of updates for each cells' properties: 1) based on variables' dynamic changes collected from empirical data, e.g. groundwater level change and land subsidence level change, 2) based on impacts of actions from the previous step on environment variables.

2) Agents' decision-making: First, each agent checks its groundwater access. If the agent is not satisfied with the groundwater access, it enters a decision making process to adapt its groundwater access. Otherwise, it exits this time step.

Agents' decision-making: At each time step, agents observe the environmental situation of their cells and make a decision. Therefore, all agents have full knowledge about the state of their groundwater access, groundwater quality, land subsidence, their neighbors' willingness to sell their water/lands, and the execution of different policies. The possible actions that each group of agents can take are listed in table 1. Their decision-making is described using CAI diagrams (section 3.3.2) and formalized in UML activity diagrams (section 3.3.3).

Table 1. The set of possible actions that can be taken by large, medium and small farmers.

Action	**Description**	**Farmers who take this action**
Buying small/medium farms	Buying farms from medium or small farmers who are not willing to continue pistachio production	Large farmers
Desalination	Set up desalination system on farms with saline groundwater to remove salt and minerals	Large farmers
Water purchase	Buying water from medium or small farmers who are not using their well's water for irrigation	Large farmers
Deepening wells	Digging water wells to get access to groundwater	Large/Medium farmers
Irrigation area reduction	Shrinking (dry-off) small part of the farm to increase the efficiency of water use for rest of the farm	Large/Medium/Small farmers
Integrating farms	Integrate irrigation systems of several farms to increase their efficiency	Medium farmers
Irrigation system modification	Changing traditional flood irrigation to drip irrigation	Medium/Small farmers

Well's turn-off	Increasing the wells' off-time (overnight or during winter)	Small/farmers
Relocating farms	Leave the region and buy a farm in another area with a better water situation	Large farmers

3.3.2. CAI diagrams

At an abstract level, the *behavior rules* in an ABM constitute the set of actions that agents might take, the conditions under which these activities take place, and actions' outcomes (impacts). The s*et of actions* and *order of actions* stemming from the FCMs can be used in constructing the behavioral rules, and *conditions* and *impacts of actions* can be defined by inputs and outputs of those actions in FCM. Therefore, a set of Conditions-Action-Impacts (CAI) for each group-specific FCM is produced in this step, covering three main components of decision making:

- *Set of actions:* represent different actions taken by each group of farmers. The priority of actions is represented by the number of times they have been mentioned by farmers as their chosen adaptive action (shown by the size of action variables in FCM, figure 2). Therefore, higher priority actions have a higher preference for farmers/agents to be implemented. However, the preference order may not be the actual order of decisions taken by farmers, since some actions cannot be performed in some locations or during some months of the year). These two aspects are added later in the ABM implementation.
- *Conditions of actions:* are input variables of each action representing driving forces or situations that should be satisfied to make that action available. Condition of actions can be either dynamic e.g. groundwater level in figure 2 (accompanied with weighted connections to actions), or fixed (true/false) variables, e.g. proximity of farm in figure 2 (accompanied with connections without weight).
- *Impact variables:* are output variables of each action along with their causal network, i.e. direct and indirect impacts of that action. Impact variables are dynamic variables (with changing states)[4].

Figure 4 indicates the series of CAI diagram transferred from large farmers FCM. The CAI diagrams for medium and small farmers are shown in supplementary A. For example, for the first action of large farmers i.e. *buying small/medium farms* the conditions are *proximity of small/medium farms* to the large farm and *willingness of their owners to sell-off their farms*. Thus, this action is possible for large farmers when there is at least one small or medium farm in their proximity whose owner is no longer willing to harvest pistachio and who is also willing to sell the land. This action affects *pistachio production* and *groundwater use* with different levels of influence, based upon the large-farmers' FCM. Likewise, these two variables affect *groundwater level*, *groundwater quality*, *pistachio production* and *land subsidence*, which are the indirect impacts of action 1. Moreover, actions are prioritized based in their variable size for each group separately, and the variables with the same or similar variable size have the same priority.

[4] One variable in FCM can be a condition for some actions and impact for others. The function of each variable is defined in relation to its connection (input or output) with action variables (figure 1, steps 1.1 and 1.3).

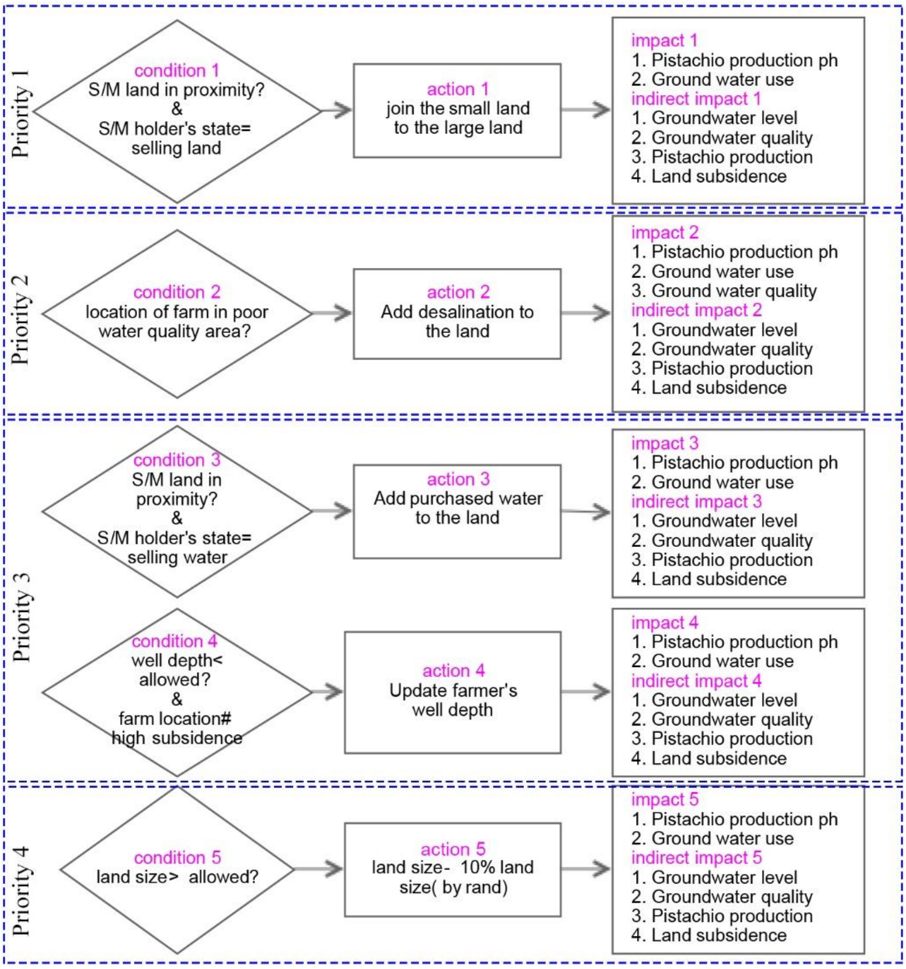

Figure 4: CAI of large farmers that represents set of conditions and impacts for each specific action. S/M: Small/Medium, ph: per hectare.

To implement the direct impact of actions X onto variables A of the FCM model (represented as $X \overset{w}{\rightarrow} A$), in each time step that action X has executed the value of *Variable A* in that time step is calculated as:

$$\textit{Equation 1:}\ A_{t+1} = A_t + (A_t \times w)$$

For example, when we have *desalination* $\overset{0.7}{\rightarrow}$ *groundwater use* (in figure 2), whenever that action *desalination* is executed, it impacts *groundwater use* by 0.7 of its current value. So *Groundwater use* $_{t+1}$ = *Groundwater use* $_t$ + (*Groundwater use* $_{t}$ $*$ 0.7). Please note that this equation may cause the variables to get infinitely large or negative in a large number of runs (time steps). However, the result of our model did not reach infinite or negative values in 180 time steps. Moreover, due to the objective of this study, i.e. ranking policy options, we are not looking at the exact values of groundwater use, rather, we are exploring the order of policies by comparing their impacts on groundwater use. Thus, the results required for this objective are not affected by unbounded values. Yet, in other studies, to calculate the *accurate values of variables* over time one may need a clipping function that maps the infinite values into an operating range (which is missed in this equation).

All indirect impacts of actions are calculated at the beginning of the next step (in the *cell's update* step in section 3.3.1). Indirect impacts of actions are the impacts of variables affected by actions on other variables in FCM. To implement the impact of *Variable A* onto the *Variable B* (represented as $A \overset{w}{\rightarrow} B$) the value of *Variable B* in the new time step is calculated as:

$$B_{t+1} = B_t + B_t \times \frac{A_t - A_{t-1}}{A_{t-1}} \times w$$

Equation 2:

The direct and indirect impact of actions may also take the role of condition for the same or other actions in the next time step, which represent feedback loops in FCM (e.g. loop of *water purchase* → *groundwater use* → *groundwater level* → *water purchase, in figure* 2).

3.3.3. UML diagram

Unified Modeling Language (UML) was used to develop the ABM structure. UML proposes a set of well-defined and standardized diagrams to design and describe a system before coding it (Bersini, 2012). One of the most commonly used UML diagrams with ABM is the activity diagram, which represents the sequential steps of actions and timing of processes (Bersini, 2012, Elsawah et al., 2015). To transfer CAI diagrams into UML diagrams, there are some crucial aspects that cannot be collected and represented in FCM, i.e., *randomness*, *temporal* and *spatial dimensions*. We know from FCMs what are available actions, the conditions that make those actions available and the possible impact of those actions. However, human decision-making is not based on a linear and simple "what-if" relationship. In addition to conditions, decision making of farmers depends on their locations, what type of actions they have taken in previous steps, their relations with their neighbor farmers, etc. We captured part of such decision-making process by adding randomness, temporal and spatial dimensions. Such aspects have been added to each actions' *priorities*, *conditions* and *initial values of parameters* by using quantitative data from studies and government reports, and estimates based upon local knowledge collected during interviews.

- **Time scale**: Actions may be taken by farmers every month, every six months or every year. Moreover, some actions can be taken by farmers only once (e.g. desalination or irrigation system change), whereas other actions can be taken several times until their limits are reached (e.g. well deepening or land shrinking). Therefore, the time scale (i.e. frequency and one-time or repetitive) are added to the condition of each action. Thus, if an action is executed annually, the condition for this action is *to be in time step multiples of 12*.
- **Randomness:** Randomness is added to the priority set of actions in the behavioral rules of agents as well as in the initialization of parameters' values. In the priority set of actions, some actions have the same or very similar priority[5]. In these cases, one action is randomly chosen to have priority over the other. Applying randomness in the agent's behavior also helps to include the outliers' behavior who may not follow the same behavior rules as other agents. Randomness is also used in the distribution of agents over the seven sub-regions, as well as their farm sizes within the ranges of small, medium and large farms' area mentioned in section 3.2.2. For the initialization of parameters' values, an interval of initial values was collected for each parameter in each sub-region and randomly distributed over the farm patches (supplementary A, section 3.1).
- **Spatial dimension:** Some environmental properties have significantly different values in different regions of Rafsanjan. For example, groundwater quality and land subsidence level are different in each of the seven sub-regions and thus have a different impact on farmers' decisions. This spatial heterogeneity is represented in the cells' properties and added to the conditions of each action.

In supplementary A, the UML activity diagram of large farmers (i.e. the sequence diagram of farmers' decisions and actions) is shown as an example. This UML diagram shows that at each step, agents first check their actions' conditions through their priority order of actions. If the conditions are confirmed they execute the action, giving rise to associated impacts. If the conditions are not met, they go to the next action. If a small or medium farmer reaches the end of the action list the final action is to sell the farm to a large-farmer and leave the region. For large farmers, their final action is to leave the region.

[5] When the number of times two actions mentioned as preferred action by stakeholders differs by less than 3, i.e. 0.05 of the total population, we consider them as similar priority actions.

3.4. Step 3: ABM implementation and assessment

In this step, the ODD and UML activity diagram from the previous section was used to build the pseudo-code and then translate it into an actual code implementation. We used the Netlogo 6.0.1 platform to implement the ABM (Wilensky, 1999). The source code of this model can be found online in "CoMSES Computational Model Library" (https://doi.org/10.25937/rxqn-4g38).

For building the model, we followed the stepwise-design approach suggested by Sun et al. (2016) i.e. starting with a simple model version that captures basic processes and then, adding more detailed processes and components to the model structure such that the relative importance of each component could be quantified and assessed along the way. For example, we started first with the same initial well's depth and groundwater level for all cells of each region. This resulted to a staircase-like groundwater use for each region since all agents would lose groundwater access and start taking action at the same time. Therefore, we added variety of wells' depth and groundwater level in different cells (and applied randomness) to model the heterogeneous reactions of farmers at each time step. When adding more details in a stepwise process, a point was reached eventually at which further additions had no impact on groundwater use or farmers migration (which are the main outcomes of our model). That is where we stopped adding more details to the model—other approaches are proposed in Edmonds and Moss (2004) and Sun et al. (2016).

3.4.1. Validation

Historical data on groundwater use for 2004 to 2012 were used to validate the simulation model since no other time series data (e.g. about farmers leaving the region, or groundwater use per each sub-region) was available. The idea was to see how well this model replicates the historical reality. To align with reality, the validation model only simulates the implementation of actions that were available in the past, but with the same level of impact, conditions, etc. as the present. First, the four environmental parameters (groundwater level, well's depth, groundwater quality, and land subsidence) were initialized with their values in the year 2003. Second, *desalination*, *water marketing*, and *land integration* were removed from the validation model, since such actions are recent adaptation actions taken by farmers. Moreover, irrigation system change was still an option for large farmers over the period 2004-2012, so this action is included in the action set of large farmers for the validation.

The setup of the simulation experiments is as follows. The validation covers the period from 2004 to 2012, thus 96 time steps. 100 simulations were run, and confidence intervals for the acquired mean values of overall groundwater use suggest that this amount of simulation runs led to satisfactorily precision for this output variable (Figure 5A). The values of both simulation and reality data-sets were normalized to show the percentage of changes. We then compared the results of groundwater use in the simulation and reality with an ANOVA test.

3.4.2. Baseline scenario and policy options

First, the baseline scenario was simulated. In this, agents decide and act based on their current situation and without any policy interference. Besides simulating the current situation, we also need a set of simulations to compare the impact of different policies that influence farmers' decisions and actions. Among current government policies toward water scarcity (Kerman Provincial Government, 2014, Mehryar et al., 2015), we chose three that aim to reduce groundwater use by changing behavior and actions of farmers:

Policy of shrinking lands: This policy focuses on decreasing the irrigation water use by reducing the areas used for pistachio production. To implement this policy, the government buys-off parts of the farms and changes their land use to non-agriculture activities. Based on our field work experience and due to the severity of water scarcity in Rafsanjan, many farmers agree to sell-off some of their lands, but only to an extent that still enables them to profit from production.

We implemented this policy by removing actions of *land marketing* and *water marketing* between large and small farmers, since as a result of this policy, small and medium farmers sell their lands to the government instead of large farmers.

Policy of irrigation system change: This policy focuses on replacing current flood irrigation systems with a drip irrigation system. To encourage farmers, the government provides an irrigation modification subsidy for farmers with land tenure documents. Currently, about 50% of the small farmers and 30% of the medium farmers do not have land documents due to the informal exchange of lands during the 1978 revolution. Therefore, the lack of land documents is the main obstacle for farmers who cannot afford to independently finance expensive drip irrigation systems. In this policy, the government aims to remove the land document problem and provide a subsidy to all farmers.

We implemented this policy by removing the condition of land documents for small and medium farmers. Therefore, all medium and small farmers who reach this action in their priority list execute irrigation system change.

Policy of farmer participation: This policy focuses on encouraging and involving farmers to reduce their water use by decreasing the priority of actions that increase their groundwater use like desalination and well deepening, as well as increasing the priority of actions that reduce their water use like integrated farming.

Implementation of this policy was done by removing desalination, water purchase and well-deepening, and adding farm integration to large farmers.

These new policies were simulated for the time period of 2015 to 2030 (i.e., 180-time steps), and the environmental parameters were initialized with their values in 2015. Similar to the validation runs, 100 simulation runs were analyzed for each scenario, leading to large standard deviation for groundwater use in some regions (Figures 5B and 6). The reason for the large standard deviation in those regions is the randomness used in choice of actions (with similar priority but different impacts) in these regions (more details in section 4.4). To identify the adequate number of simulation replications, we tested the model with larger number of simulation runs (i.e. 200, 300 and 500) and compared their results with the result of 100 simulation runs (the results are shown in supplementary H). The result of our experiments showed that while the confidence intervals of the mean values decreased with increasing simulation runs, the **order** of policies (exploring which is the main objective of this study) would stay the same. Therefore, we concluded that this number of simulation suffices for the purpose of this study, i.e. the qualitative comparison of different policies.

3.4.3. Sensitivity analysis

We applied one-factor-at-a-time (OFAT) sensitivity analysis to explore the relationships between the model output and input parameters. OFAT consists of varying one parameter at each time over a wide range of its possible values while keeping all other variables fixed (Ten Broeke et al., 2016) and thereby, monitoring changes of the simulation model output. OFAT helps to identify those parameters that have a strong influence on model output, and are therefore most important (Thiele et al., 2014). However, OFAT does not take into account the simultaneous variation of input variables, thus does not detect the presence of interactions between input variables. To show the form of relationship between the interacting variables and the output other methods such as Regression-based analysis, and Sobol model (Ten Broeke et al., 2016) can be used.

We used OFAT to evaluate the influence of: 1) parameters' changes on groundwater use including impact values derived from FCM model and thresholds derived from hard data and estimated data, 2) stochasticity in our model results (i.e. random processes used in the initial distribution of farm sizes, initial well depths and choosing between actions with the same priority). A full list of parameters with their range of values used for sensitivity analysis is shown in supplementary B.

4. Results

4.1. Validation

We used the one-way ANOVA test to compare simulation run and historical data of groundwater use per each time step (time step as independent factor). The result of the test shows that we do not have enough evidence to conclude that there is a significant difference between the simulated and the real data—$F = 0.86$, F crit$= 3.89$, P-value$= 0.35$, and $\alpha = 0.05$ (detail of ANOVA test is presented in supplementary G). There are two specific peaks of groundwater use, both in the simulation and in the real data (Figure 5A). Such peaks, in reality, are because of significant well deepening in different regions (i.e. first in sub-regions 1 and 2 and later in sub-regions 6 and 7), where around 2015 most of the wells have already reached their maximum depth. The difference between simulated and real groundwater use after 2011 (Figure 5A) is because of the introduction of new actions by farmers, i.e. desalination and water marketing. In reality, they already appeared around the year 2011 and influenced overall groundwater use. However, since we had not included them in the model version for the validation (section 3.4.1), groundwater use at the end of the validation run is overestimated by our model.

4.2. Baseline scenario

The result of the baseline scenario (i.e. the impact of aggregated farmer's decisions and actions on overall groundwater use), is shown in figure 5B. Due to a lack of space, we do not report on actions taken by individual farmers. We explain these results in pairs of regions that show similar results.

Regions 4 and 5: Farmers in these two regions still can deepen their wells at the beginning of the simulation, while other regions have either very poor water quality or very high land subsidence that prohibit more *well deepening* (supplementary A). *Well deepening* and *water marketing* in regions 4 and 5 results in a rapid rise in their aggregated groundwater use. The peaks of groundwater use in these two regions occur when farmers reach their permitted well depth, at which time further deepening stops. Hereafter, trends of groundwater use are followed by a slight decrease due to actions like *shrinking lands* and *buying/integrating farms*. Since region 5 has better access to groundwater than region 4 (supplementary A), farmers in region 5 start taking adaptive actions later than those in region 4. Therefore, the groundwater use in region 5 lags slightly behind that of region 4.

Regions 1 and 2: These two regions have very poor water quality in the lower layer of their aquifer, thus *deepening wells* is not a useful option for their farmers. Facing low water access, large farmers install a *desalination* system which has a very high, though short duration, impact in increasing their groundwater use. Thus, after a short term peak in groundwater use, region 1 shows a steady decrease of groundwater use due to *buying/integrating farms*, *land shrinking* and *irrigation system change*. In region 2, after the initial peak, there is another slight increase in groundwater use because of *water marketing* between small and large farmers which is feasible in the southern part of this region.

Regions 3 and 6: Parts of regions 3 and 6 do not allow for more well deepening due to poor water quality and land subsidence, respectively. Farmers in both regions start with *buying/integrating land* and *irrigation system change* at the beginning (when the water scarcity is less). With these two actions, they reduce their water use and increase their water access, both at a relatively low level. After about 5-6 years, farmers who can, *deepen their wells* and *purchase water*, which increases groundwater use. After meeting their allowed well depth and the buy-out and emigration of small/medium farmers, they continue mostly by *shrinking lands* in order to steadily reduce their groundwater use.

Region 7 has the best water situation, in terms of both access and quality, but faces high land-subsidence which prohibits more well deepening. When farmers face water scarcity, their available actions are *buying/integrating lands*, *shrinking lands* and *irrigation system change*, all of which reduce groundwater use to some extent. Therefore, region 7 shows a constant decrease of groundwater use.

Overall, all regions face a slight and constant decline of groundwater use after meeting their peaks—either at the beginning or in the middle of simulation process, at which time the farmers have no other options than *shrinking farms* or *selling their farms* to the farmers who still have access to groundwater. This only happens after farmers meet limitations of other actions e.g. *well deepening* and *well termination* and/or accomplish all one time actions e.g. *desalination*, *irrigation change* and *farms' integration*. Therefore, such groundwater use reduction only happens after a large increase of groundwater consumption by farmers which is followed by emigration of farmers.

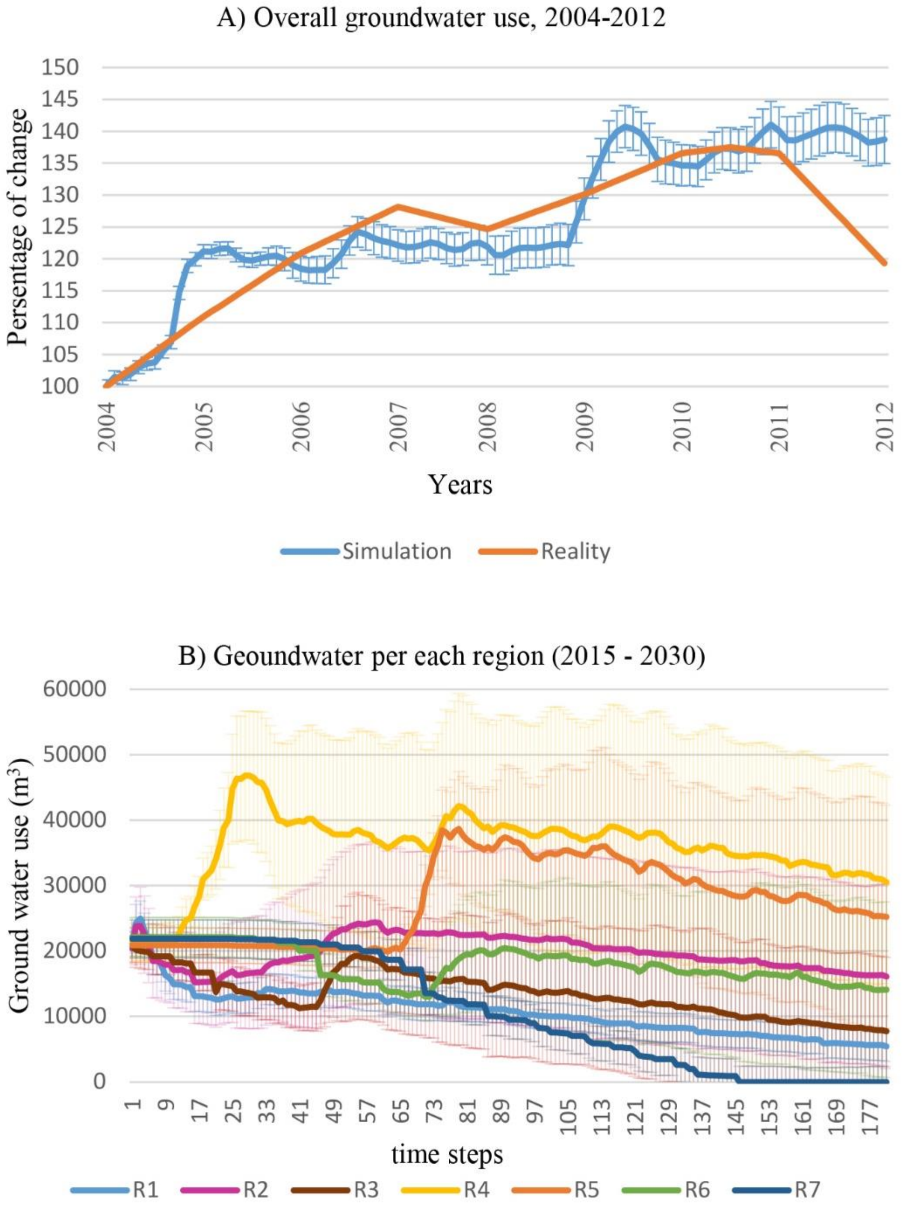

Figure 5. A) Validation using groundwater use of whole Rafsanjan in simulation and reality over the period 2004-2012. Due to difference in initial values of simulation and reality, their data-sets are normalized to show the *percentage* of changes. The bars depict confidence intervals (with confidence level of 95%) of the mean estimate over 100 replicated simulations. B) Groundwater use per region (for all groups of farmers) in the baseline scenario (2015 - 2030). The shaded areas depict standard deviation for each region over 100 time simulations. R: region.

4.3. Policy options simulations

Simulating the impact of different policy options revealed striking impacts on groundwater use overall and in the different regions (Figure 6):

The policy of shrinking lands has a strong impact on reducing groundwater use because it also implies that water and land marketing are no longer feasible in the region. Yet, it results in higher emigration of farmers than in the other policy scenarios (Figure 7).

The policy of irrigation system change is very similar to the baseline scenario. This is due to the past experience of irrigation system change among large farmers. According to large farmers' perceptions (Figure 2), changing the irrigation system to drip irrigation has not changed their water consumption, but has been used by farmers to expand their pistachio area and/or increase the productivity of their lands. Therefore, this policy has a positive impact in encouraging medium-farmers and small-farmers to stay in the region, since it helps to improve their production quantity and quality.

The participation policy has the highest impact on reducing groundwater use and keeping farmers in the region. Stopping the high water consumption actions e.g. well deepening and desalination, besides focusing on reducing water demand by farm integration and reducing farm areas shows the largest reduction on overall groundwater use compared with other scenarios. Moreover, it has the least impact on emigration of large farmers and after the *irrigation change* the least impact of emigration of medium and small farmers.

The results of baseline and irrigation change scenarios in regions 2-6 have a large standard deviation range (Figure 6). The sensitivity analysis of all parameters for such policies indicates *well deepening* as the most sensitive parameter. Regions 1 and 7 are the only regions that do not have the action of *well deepening,* and thus simulation of all policies in these two regions shows a small standard deviation range. Similarly, policy options of *land shrinking* and *farmer participation* are the only scenarios that do not change the execution or impact of well deepening, thus they also show a small standard deviation range in all regions (orange and yellow lines in figure 6).

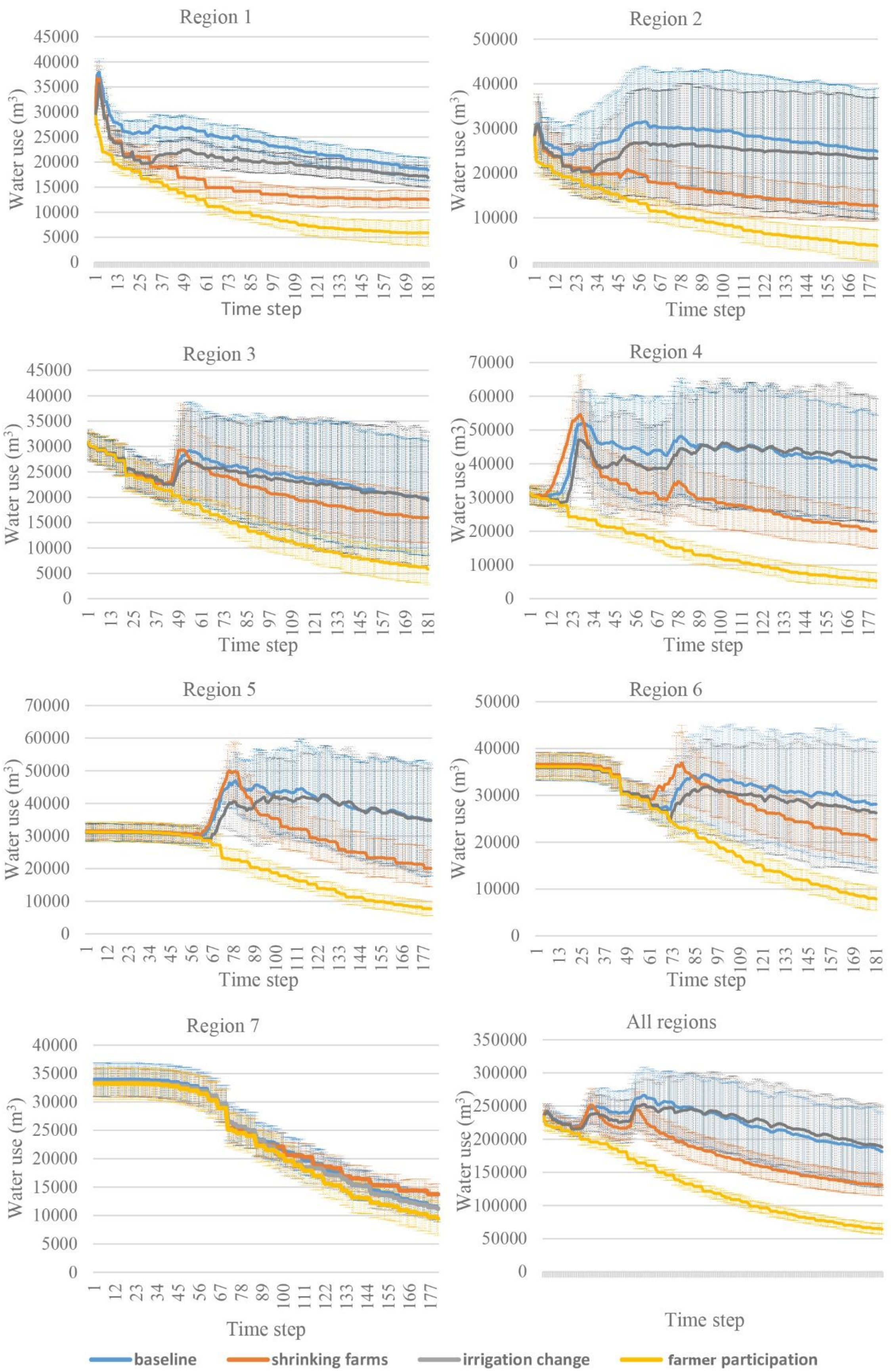

Figure 6: Groundwater use per region and overall groundwater use in three policy options scenarios compared to the baseline. The shaded areas depict standard deviation for each scenario over 100 replicated simulations.

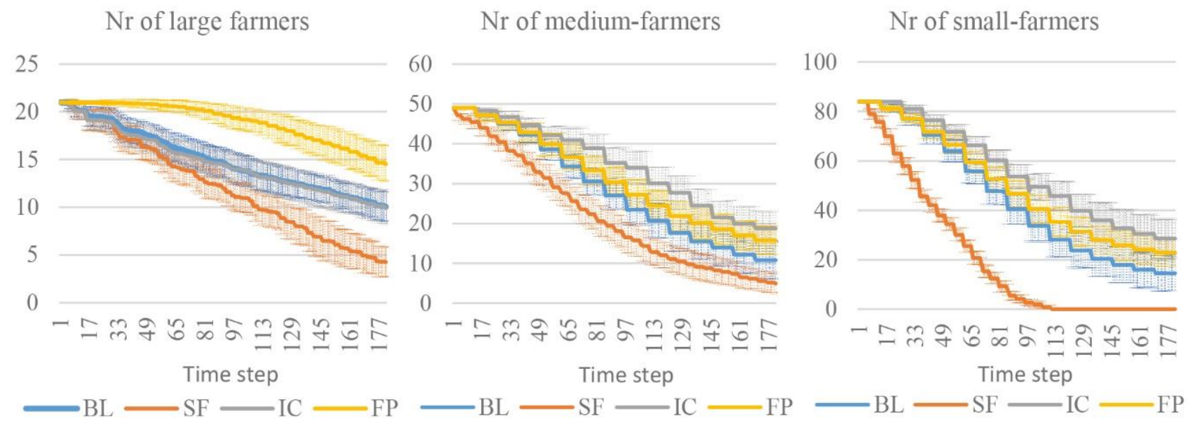

Figure 7: Number of large, medium and small farmers as a function of time in three policy scenarios compared to baseline. BL: baseline, SF: shrinking farms, IC: irrigation change, FP: farmer participation. The shaded areas depict standard deviation for each scenario over 100 replicated simulations.

4.4. Sensitivity analysis

The results of the sensitivity analysis (shown in supplementary B) indicate that *well deepening* and *land shrinking* on groundwater use have the largest influence on the overall groundwater use in Rafsanjan. By contrast, *desalination* has the least impact on groundwater use, though it has a high impact value in the FCM. This is because very few farmers actually execute this action either because of their farms' location (i.e. being in good groundwater quality regions), or because of their economic situation (i.e. not being able to afford to install and operate desalination systems).

Sensitivity analysis of random processes shows that changes in the spatial distribution of farm cells during initialization and initial values of well depths per cell do not lead to distinctly different outcomes, meaning that the model is not sensitive to these two random processes. However, the results show high sensitivity to the random choice between actions 3 and 4 of large farmers (i.e. *water purchasing* and *well deepening)*. Specifically, if the model always executes action 3, *water purchasing*, the results show little sensitivity (standard deviation), whereas, if the model executes either always action 4, *well deepening*, or a random choice between these two, the results show high sensitivity (standard deviation). This highlights again the important role of the *well deepening* action on the overall groundwater use.

5. Discussion

To support effective policy making in SESs, a policy simulation has to consider the multi-factorial behavior of the system as well as multi-stakeholders' decision making and the impact of these decisions on the physical system. This paper shows how a combination of FCM and ABM methods for simulating impacts of policy options in the case of water scarcity in Rafsanjan, Iran could be useful. In this section, we reflect on our approach in developing the model by presenting its strengths, limitations and suggesting possible future improvements.

5.1. Strengths

Our study showed that FCM and ABM are complementary and together can cover the four main features of an SES for policy making purposes: 1) *Causal relationships* between human actions and their surrounding social and ecological factors. FCM represents the decision making process of stakeholders and their impact on the environment in a causal directed graph. Therefore, it shows how each action causes direct and indirect changes in environmental variables. 2) *Feedback mechanism*: FCM's outcomes explicitly incorporate feedback in human-environment interactions (e.g. the positive and negative impact of an action on environment reinforce a subsequent action). 3) *Social-spatial heterogeneity*: ABM incorporates various stakeholders' preferences, available actions and long-term goals (i.e. part of individual heterogeneity) and it involves various environmental properties in different locations (i.e. spatial heterogeneity). 4) *Temporal dynamics*: ABM can represent time scale in agents' actions and environment variables, (e.g. slowly changing variables such as population change) vs. fastchanging variables (e.g. annual agriculture production) or high-frequency actions (e.g. farm irrigation) and low-frequency actions (e.g. buying lands).

In addition, the combined use of FCM and ABM in a modeling process is useful to formulate and parametrize the qualitative knowledge gained by stakeholders, combine it with quantitative knowledge from “hard” data and use both data types in simulating human-environment interactions. Our proposed modelling framework is particularly useful for policymakers to incorporate human perceptions, preferences, decisions and actions in the process of ex-ante policy options analysis. Moreover, it provides the macro level observation of the system’s elements, (i.e. multi-variables interactions), as well as the micro level view of the individual interventions and decision-making, which supports comprehensive policy analysis.

5.2. Limitations and future studies

One limitation of the FCM method is its limitation in defining the *nonlinear* relationships between variables (Voinov et al., 2018). For example, using FCM gave us the immediate and fixed impact of actions on variables, which resulted in presenting the linear relations among variables. However, some actions’ impacts may be nonlinear (i.e., adapt dynamically and increase or decrease over time). In this study, we used the traditional FCM method since the focus of our study was on translating FCM causal relationships and feedback loops into behavioral rules of ABM. However, there are some extensions to the FCM methodology to capture nonlinearities. Rule-Based Fuzzy Cognitive Map (RBFCM) (Mourhir and Papageorgiou, 2017, Carvalho and Tomè, 2000) is an approach that captures and represents non-monotonic relations between variables, thus can better show the dynamic impact of actions on variables. Replacing FCM with RBFCM in this method is proposed for future studies involving the dynamic impact of actions. Additionally, fuzzy numbers could be used to incorporate sensitivity to the linguistic weights (i.e. how fuzzy participants’ perceptions may be) in the ABM; the impacts can be tested by using the fuzzy membership function (Papageorgiou et al., 2009, Papageorgiou et al., 2011, Giabbanelli et al., 2012). In our model, the uncertainty that participants have about the weights has not been considered.

Second, an aggregated FCM represents the average of all individual FCMs. In our study, the variability of farmers’ preferences, decisions and actions are represented by grouping FCM models for large, medium and small farmers. In some applications, it is necessary to take into account the distribution of stakeholders’ perceptions even within each group. Therefore, another interesting approach or extension to this work would be to use interval (or standard deviation) instead of a fixed average value for the FCM connections’ weights and apply randomness within the range of values in each time step. In this way, the variation of collected data from stakeholders can be used in describing the impact of agents’ actions in ABM. However, we need larger sample sizes for each group of stakeholders to estimate the standard deviations and variances of their FCM connections’ weights (Harrell Jr, 2015).

Third, building an ABM on FCMs means that connections between variables are largely based on farmers’ perceptions and not calibrated to fit past time series data. Therefore, they are proper for qualitatively comparing potential impact of different policy options but not for quantitatively predicting the future of the system.

Fourth, learning and prediction are two important properties of many ABMs. In this study, we did not integrate these two aspects as agents’ properties. However, for future studies, farmers’ abilities to learn from their experiences, adapt their actions and estimate future consequences of their decisions could also be added to the simulation model.

Fifth, validation of the model has been done for the whole region due to the availability of historical groundwater use data only for the whole region but not for each specific sub-regions. However, in the case of data availability, validation of simulation for each sub-region separately would provide more confidence in the model.

Last, ODD+D protocol (Müller et al., 2013) can also be used in this methodology instead of standard ODD. This protocol rearranges the design concepts to better capture human *decision-making*.

6. Conclusion

This study introduces a step-wise methodology to integrate a factor-based modeling approach (i.e. FCM), with an actor-based modeling approach (i.e. ABM), to support policy option analysis in SESs. In this methodology: 1) FCM aggregates the qualitative stakeholders' knowledge and perception to model the SES function and stakeholders' adaptive reactions to the system, 2) the output of FCM is translated to be used as ABM input data 3) ABM is developed to simulate and compare the impacts of different policy alternatives considering human-environment dynamic interactions. We applied this methodology for the case of a farming community facing water scarcity in Rafsanjan, Iran. The results show that this integrated methodology takes into account aspects of complex SESs that cannot be fully covered by either modelling approach if used individually.

Moreover, our case study indicates that among three policies of *shrinking farms*, *irrigation change* and *farmers' participation*, the policy of shrinking farms is a high incentive policy for farmers to reduce their irrigation areas and thus decrease pressures on aquifer and groundwater use. However, due to the high emigration of farmers in this scenario, it is not a satisfactory policy from a socio-economic perspective. Rather a policy to facilitate farmers' participation in the management and control of their groundwater use has the highest impact in reducing overall groundwater use, and it reduces emigration. Surprisingly, adopting new irrigation technologies does not have any significant impact on reducing overall groundwater use in the region.

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Supplementary for the article "From Aggregated Knowledge to Interactive Agents: an Agent Based Approach to Support Policy Making in Social-Ecological Systems"

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Overview, Design concepts and Details

1. Overview

1.1. Purpose

This model simulates different farmers' decisions and actions to adapt to the water scarce situation in Rafsanjan, Iran. This simulation helps to investigate how stakeholders' strategies may impact on macro-behavior of the system i.e. overall groundwater use change and emigration of farmers.

1.2. Entities, state variables, and scales

Agents: In this model, agents represent the total number of 154 farmers in three types of 21 large, 49 medium, and 84 small farmers. Their attributes are 1) their land size: 250ha > large farms > 80 ha > medium farms > 15 ha > small farms, 2) their sub-region, and 3) the actions they take.

Environment: Farmers are distributed across a stylized representation of the Rafsanjan landscape. As Rafsanjan is spatially heterogeneous, we distinguish nine sub-regions in the ABM, out of which two are representing non-vegetated area. Each sub-region consists of 15 by 15 cells, leading to a total of 45*45 cells. Each cell can have one farmer owning the cell; each farmer may have 1 or more cells. Agents are distributed equally across the seven regions and randomly within each region. Each cell represents 5ha of pistachio land. Cells are characterized by 1. Depth of groundwater level 2. Groundwater quality, 3. Productivity, 4. Land subsidence level, 5. Groundwater use 6. Well's depth, and 7. Allowed well's depth.

Temporal resolution: Time step is 1 month, and variables' changes are monthly or yearly. The temporal extend of the model is 15 years, i.e. 180 time steps.

1.3. Process overview and scheduling

Basically this model considers two main process in each time step:

1) Cells' update: There are two types of updates for cells' properties, 1) based on variables' dynamic changes collected from empirical data, e.g. groundwater level change and land subsidence level change, 2) based on impacts of actions –from previous step- on environment variables.

2) Agents' decision-making: First, all agents check their groundwater access. If an agent is not satisfied with the groundwater access, it enters the decision making process to adapt its groundwater access. Otherwise, it exits this time step.

2. Design concepts

2.1. Basic principles

The model is informed by Fuzzy Cognitive Mapping (FCM) models developed from time-series data (where formal data is available) and stakeholders' perception via interviews and mind mapping (for variables without formal data). From FCM models, we learn how macro level variables of a system, i.e. groundwater, regional economy, production, land use change, water management, human interventions etc., are influencing each other. Therefore, we know what are the causes and effects of different possible adaptive actions from farmers. Causes are the conditions of each action and effects are the impacts of each action on properties of agents or environment in the ABM. From FCM, we also have the weight or level of impacts of each action on other variables. Notice that in FCM we have the level of causal relations, but not the absolute value of each variables. Therefore, this models is meant to compare the impact of different adaptive strategies on specific variables rather than calculate or forecast the absolute value of each variables.

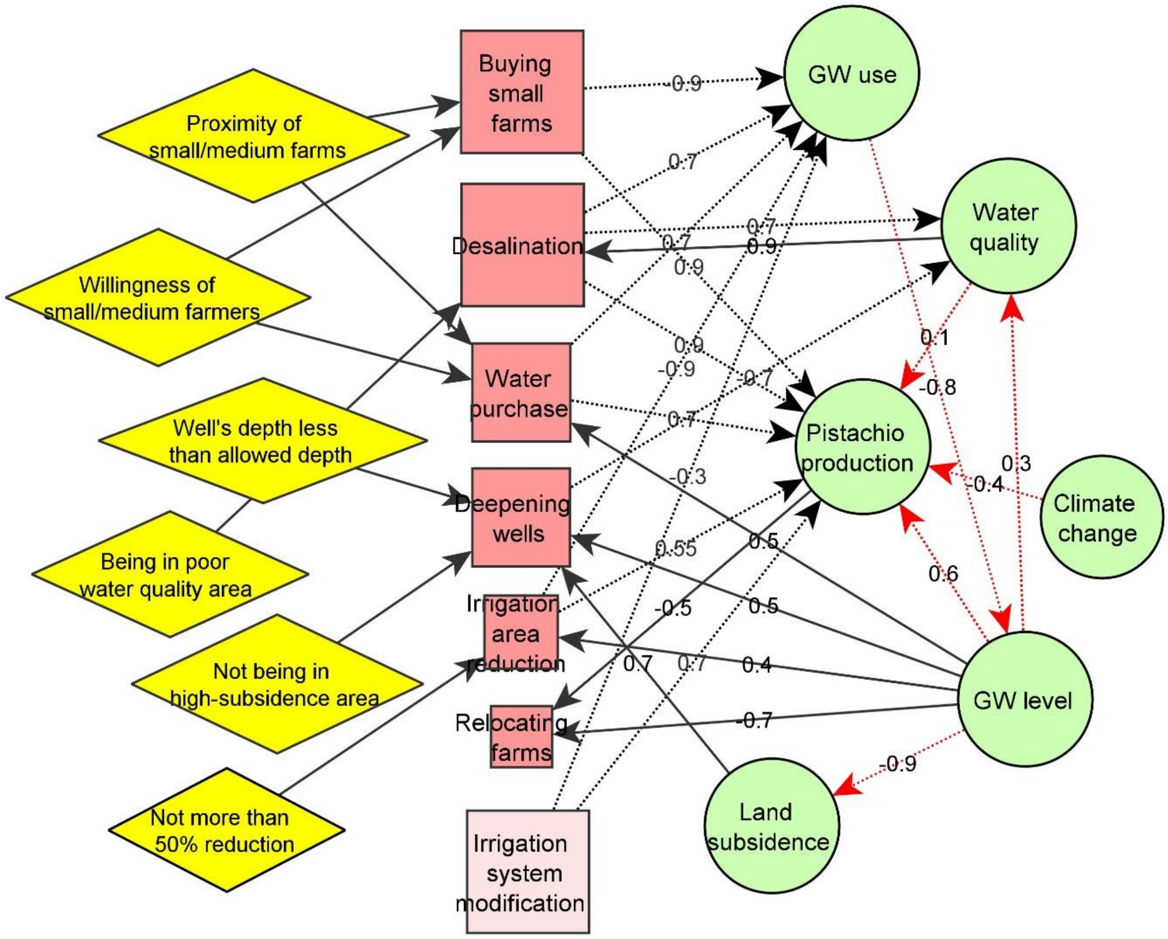

Figure1. Large-farmers' FCM combined with objective data. The red squares show farmers' actions and their size shows the number of farmers who took this action i.e. level of preference or priority of actions. Nodes with input to (yellow diamonds) and output from (green circles) actions represent conditions and impacts of those actions, respectively. Black and red lines represent perceived connections and data-driven connections, respectively. Solid and dashed lines show positive and negative causal connections, respectively.

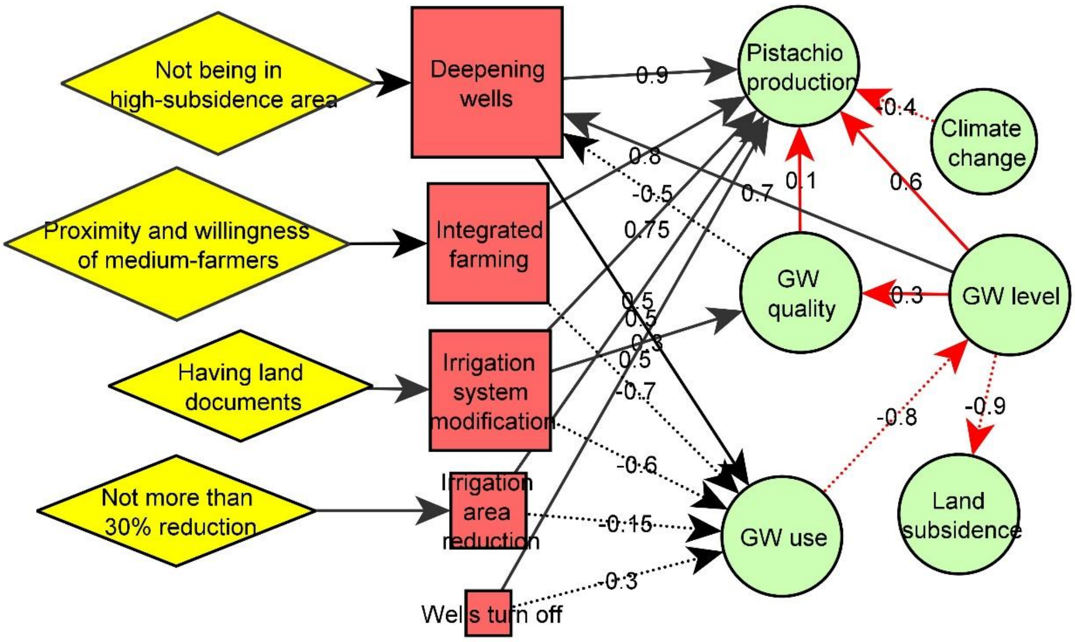

Figure2. Medium farmers’ FCM combined with objective data

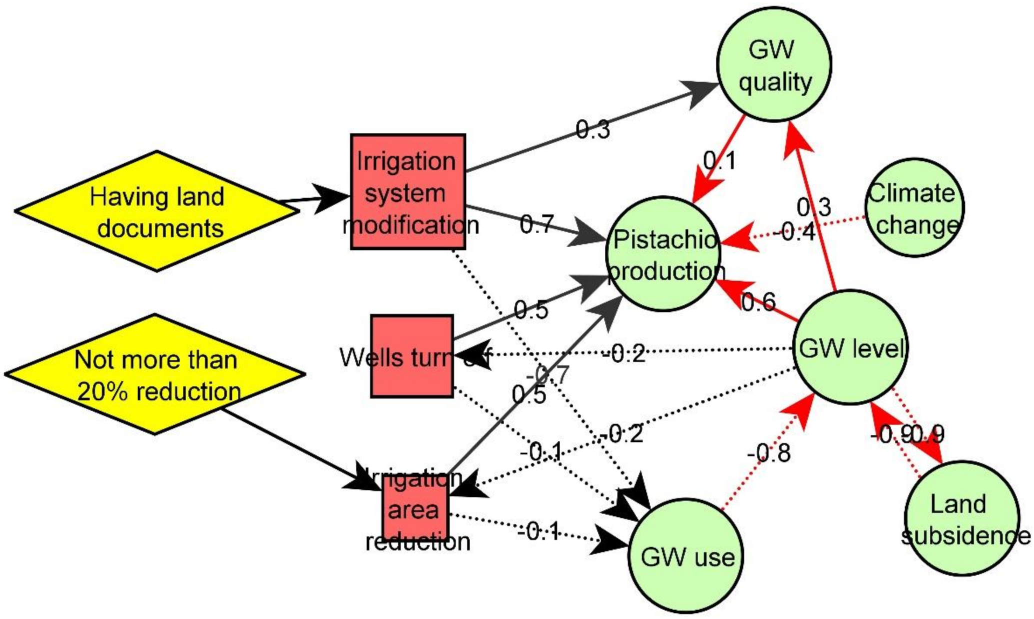

Figure3. Small-farmers’ FCM combined with Objective data

2.2. Emergence

This model is designed to explore the relationship between farmers’ adaptive actions towards water scarcity and two related emergent phenomena: overall groundwater use change and emigration of farmers. Overall groundwater use results from aggregated individual farmers’ water use that may change over time due to their dynamic adaptive actions towards water scarcity and interactions with other farmers. Emigration of farmers results from their both groundwater access and interactions with other farmers.

2.3. Adaptation

All individual farmers do these adaptive actions to increase their ground water access or control their water use, and eventually increase their farms' production.

2.4. Objectives

Farmers want to keep their pistachio production and keep their access to groundwater for irrigation. If they are unsatisfied they leave and relocate their farms to the other regions.

2.5. Learning and Prediction

Individuals do not learn from their own experiences, i.e. positive or negative impacts of previous actions. Also, individuals do not predict or estimate future consequences of their decisions.

2.6. Sensing

Farmers have the full knowledge about the state of their groundwater access, their available options, their neighbors' willing to sell/buy land/water or integrate their lands, and their lands' groundwater quality, land subsidence, and allowed wells' depth. They do not have knowledge about the state of the overall groundwater level change in their region—which can help them in predicting future groundwater situation.

2.7. Interaction

Large farmers buy land and water from small and medium farmers. Medium farmers share their farms for efficient irrigation and farming. The structure of their social network for selling and buying land and water is emergent during the simulation. When the vulnerability of small or medium farmers becomes high, they will be willing to sell off their water and lands to the large farmers.

2.8. Stochasticity

Randomness is used in two processes: 1) executing of actions with the same priority, e.g. action number 3&4 in priority 2 of large farmers' actions list, and 2) the initial distribution of agents (farmers), farm sizes and initial values of parameters.

2.9. Collectives

There are no collectiveness among agents.

3. Details:

The model is implemented in NetLogo 6.0.1 (Wilensky, 1999) and available at ….

3.1. Initialization and input data

Initial patch properties (i.e. groundwater use, groundwater quality, land subsidence, ground water level, and well's depth) are extracted from GIS attribute data of 1369 wells in Rafsanjan collected in 2015 by Iran Water Resource Management Company (http://wrbs.wrm.ir/). In each sub-region an interval of initial values are calculated as explained below and them randomly distributed over the patches.

Initial groundwater use: groundwater use per hectare per month is calculated by:

$$\boldsymbol{Groundwater\ use}\ (\frac{\boldsymbol{mm^3}}{\boldsymbol{ha.mo}}) = \frac{\boldsymbol{Discharge} \times \boldsymbol{360} \times \boldsymbol{H} \times \boldsymbol{30}}{\boldsymbol{ha} \times \boldsymbol{10^6}}$$

Discharge (of wells' pumps) = volume of extracted water per second (m^3/s) for each well

H = Number of hours per day with wells' pump on (taken from GIS data for each well)

Ha = Pistachio land area covered with each well (taken from GIS data)

Initial wells' depth, groundwater level are calculated by their mean ± standard deviation

Initial land subsidence and groundwater quality are distributed in five levels of very low, low, medium, high and very high

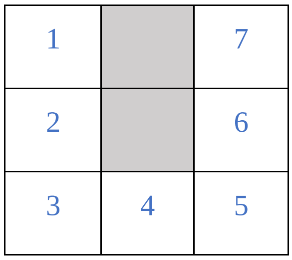

Figure 1. spatial representation of 7 regions

Table 1. Initial values of environment parameters.

	Location 1	**Location 2**	**Location3**	**Location4**	**Location 5**	**Location 6**	**Location7**
GW use (m^3/ha)	120	121	122	122	122	124	124
Well's depth (m)	95 - 100	105 - 110	130 - 140	130 - 140	135-145	140-150	125-135
GW level (m)	90	100	120	115	120	120	110
GW quality	Very low	Very low	high	Very high	Very high	medium	medium
Land subsidence	Low	low	Very high	Low	high	High-Very high	Very high

3.2. Sub models

Step 1) Update patches:

Indirect impacts of actions from previous time step are calculated at the beginning of the next step as follow:

Indirect impacts of actions are the impacts of variables affected by actions on other variables in FCM. To implement the impact of *Variable A* onto the *Variable B* (represented as $A \xrightarrow{w} B$) the value of *Variable B* in the new time step is calculated as:

$$B_{t+1} = B_t + B_t \times \frac{A_t - A_{t-1}}{A_{t-1}} \times w$$

Step 2) Agents' decision making:

2.1) each agent checks its groundwater access, based on:

GW access = depth of GW - Well’s depth

If the agent is not satisfied it continues its decision making, otherwise it ends this time step.

The available actions that agents can take from are as follows:

- *Buying small/medium farms:* Buying farms from medium or small farmers who are not willing to continue pistachio production in their farms
- *Desalination*: set up desalination system on farms with poor water quality to remove salt and mineral from saline groundwater.
- *Water purchase*: Buying water from other farmers
- *Deepening wells:* Digging water wells to get access to groundwater
- *Irrigation area reduction*: shrinking (dry-off) small part of the farm to increase efficiency of water use for rest of the farm.
- *Integrating farms:* integrate irrigation system of some farms together to increase their efficiency.
- *Irrigation system modification*: changing traditional flood irrigation to drip irrigation.
- *Well’s turn-off:* Increasing the wells’ off-time over nights or winters
- *Relocating farms:* leave the region and buy farm in other areas with better water situation

2.2) Checks conditions of available actions: In this step, each agent check the actions’ conditions through their priority order of actions. If the conditions are confirmed, it executes the action and if not it goes to the next action.

2.3) Action execution: Each agent execute possible actions. These executions depends on type of actions.

2.4) Implement impact of actions: execution of each action has specific level of impacts on other variables of the environment. This level of impact comes from the FCM model. Therefore, the state of influenced variables (affected variables in FCM) gets updated after execution of each action. Here we only implement the direct impact of actions on other variables. To implement the direct impact of actions X onto variables A of the FCM model (represented as $X \xrightarrow{w} A$), in each time step that action X is executed the value of *Variable A* in that time step is calculated as:

$$A_{t+1} = A_t + (A_t \times w)$$

For example, when we have *desalination* $\xrightarrow{0.7}$ *groundwater use* (in figure 2), whenever that action *desalination* is executed, it impacts *groundwater use* by 0.7 of its current value. So *Groundwater use* $_{t+1}$ = *Groundwater use* $_t$ + (*Groundwater use* $_t$ * 0.7).

2.5) At the end of each action list, if agent has no other actions left, it has to sell off its farms to large-farmers and leave if it belongs to small or medium holders. Large farmers have to relocate their farms to out of the region at the end of their action list.

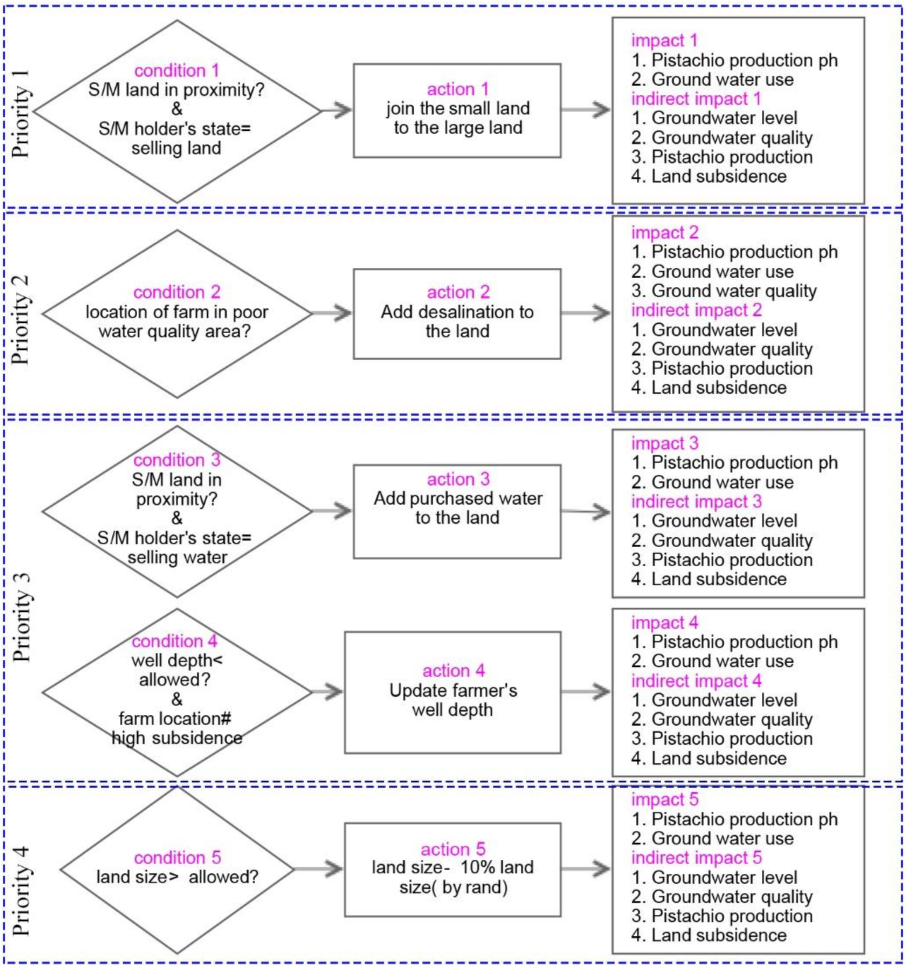

Figure 5. Conditions, actions and impacts for large-holders' set of actions

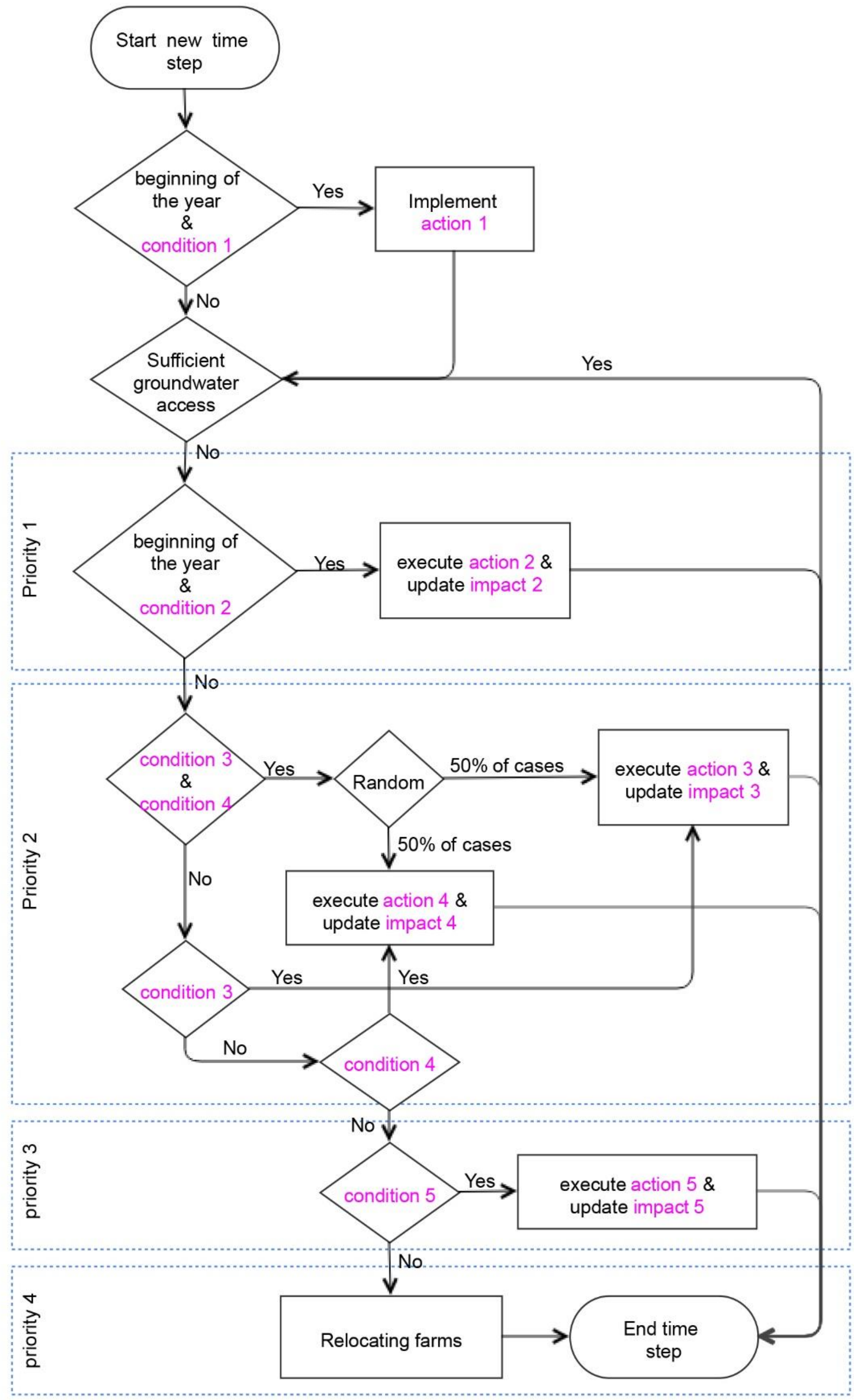

Figure 6. UML activity diagram of large farmers' behavioral rules in each time step

Table 2. Conditions, actions and impacts for large-farmers' set of actions

Action name	Conditions	Execution	impacts
1.Buying small/medium farms	Small land in neighborhood &	Change owner of small farm from small-farmer to the	On small-farm patches 1. GW-use= GW-use * 0.1

	Small-farmer is willing to sell-off land	large-farmer in neighbor	2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.9
2. Desalination (one-time action)	Action 2 is available (has not been executed before) & Location of farm in poor GW quality area	Set action 2 not available for next steps	1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * 0.7 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.9
3. Water purchase	Small land in neighborhood? & Small-farmer is willing to sell-off water	Add purchased water to the properties of farm-cluster	On small/medium farm: 1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * 0.7 2. Productivity = 0 On large farm: Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.2
4. Deepening wells	Well depth < allowed well depth & Farm location is not in high subsidence areas	Update the depth of the well	1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * 0.5 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.7
5. Irrigation area reduction	Land size >= 50% initial land size (large farmers accept to shrink up to 50% of their lands)	Change 10% of farm patches to no-farm	On dried patches: 1.GW-use = 0 2. Productivity = 0 On farm patches: 1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.1) 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.5
6. Relocating farms	No other available actions	Change all farm-patches to no-farm	1.GW-use = 0 2. Productivity = 0

Table 3. Conditions, actions and impacts for medium-farmers' set of actions

Action name	Conditions	Execution	Impacts
1.Deepening wells	Well depth < allowed well depth & Farm location is not in high subsidence areas	Update the depth of the well	1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * 0.5 2. Productivity $_{t+1}$ = Productivity $_n$ + Productivity $_{(t)}$* 0.9
2.Integrating farming (By rand: change farmer’s	Medium land in neighbor? &		On both medium farms: 1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.7)

state = integrating farm)	Neighbor medium-farmer is willing to land integration		2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.80
3. Irrigation system modification	Act 3 = 1 (available) & Farmer's land doc = 1 (available)	Add irrigation-modification to the properties of farm-cluster Set act 3 = 0	1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.6) 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.75
4. Irrigation area reduction	Land size >= 60% initial land size	Change 10% of farm clusters to no-farm	On dried patches: 1.GW-use = 0 2. Productivity = 0 On farm patches: 1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.15) 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.5
5. Sell land and relocation	Farmer's vulnerability = very high	Change all farm-cluster to no-farm	1.GW-use = 0 2. Productivity = 0

Table 4. Conditions, actions and impacts for small-holders' set of actions

Action name	Conditions	Execution	impacts
1.Irrigation system modification	Act 3 = 1 (available) & Farmer's land doc = 1 (available) & Random > 33%	Add irrigation-modification to the properties of farm-cluster Set act 3 = 0	1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.7) 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.7
2.well's turn off			1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.3) 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.7
4. Irrigation area reduction	Land size >= 70% initial land size	Change 10% of farm clusters to no-farm	On dried patches: 1.GW-use = 0 2. Productivity = 0 On farm patches: 1. GW-use $_{t+1}$ = GW-use $_t$ + GW-use $_{(t)}$ * (-0.1) 2. Productivity $_{t+1}$ = Productivity $_t$ + Productivity $_{(t)}$* 0.5
5. Sell land and relocation	Farmer's vulnerability = very high	Change all farm-cluster to no-farm	1.GW-use = 0 2. Productivity = 0

Example: Large farmers have six possible adaptive action.

Action 1) is "*buying small/medium farms*" for which there are two conditions: there should be at least one small/medium land in the neighborhood of that agent's patch and that small farmer's state of "selling land" should be "on" that shows small farmer is willing to sell his/her land. When both of these conditions are confirmed, the small patch will be added to the large patch. By executing of this action 1. Ground water use of the small farms decreases by 90%, and 2. Pistachio production of small land increases by 90%.

Action 2) Desalination, for which there are two conditions: 1. this action should have not been implemented before, so, "desalination" property of farm should be equal to 0, and 2. the farm should be located in poor quality area. When both of these conditions are confirmed, the desalination is added to the land (desalination = 1), meaning not available for next time steps. By executing of this action 1. Pistachio production increases by 90%, and 2. Ground water use increases by 70%.

Action 3) Purchasing water, for which there are two conditions: there should be at least one small land in the neighborhood and that small farmer's state of "selling water" should be "on" that shows small-farmer is willing to sell his/her water. This property is related to the small farmer's level of vulnerability. When both of these conditions are confirmed, the "purchased water" gets added to the property of land. By executing of this action 1. Small/medium farm get no pistachio production, 2. Ground water use of small farms increases by 70%, and 3. Pistachio production of large farmers increases by 20%.

Action 4) deepening wells, for which there are two conditions: wells depth should not be equal or lower than the permitted depth and farm's location should not be in very high land subsidence areas. When both of these conditions are confirmed the wells depth gets update. By execution of this action 1) Ground water use increases by 50%, and 2) pistachio production increases by 70%.

Action 5: for which there is only one condition. As the last action before selling or relocating the lands, farmers start to shrink their farming area to increase efficiency of their production per hectare. However the land area reduction keeps happening till farmers still have some benefit of their lands. Otherwise they prefer to sell off land/water or relocate their land which can be more beneficial than shrinking and farming in the smaller lands. The threshold of shrinking lands is approximately 30% for small-holders, 40% for medium-holders and 50% for large-holders from FCM models. Therefore, if the agent's patches is bigger than minimum possible land ($p> 70\%/60\%/50\% * p_1$) then the agent's patches reduces by 10% ($p_{n+1}=90\% * p_1$). By execution of this action 1) groundwater use and pistachio production of dried patches get equal to zero, 2) groundwater use of not dried patches decreases by 10%, and pistachio production of not dried patches increases by 50%.

Reference

WILENSKY, U. 1999. NetLogo. http://ccl.northwestern.edu/netlogo/. Center for Connected Learning and Computer-Based Modeling: Northwestern University, Evanston, IL.

Supplementary B – Sensitivity Analysis

Parameter	Description	Source of data	Nominal value (L/M/S)
Actions → GW use	Impact of different actions on groundwater use for three groups of large, medium and small farmers	FCM	
1. Buying land → GW use (L)			-0.9
2. Desalination → GW use (L)			0.7
3. Water purchasing → GW use (L)			0.7
4. Deepening wells → GW use (L,M)			0.5 / 0.4
5. Shrinking lands → GW use (L,M,S)			-0.1/ -0.15/ -0.1
6. Irrigation change → GW use (M,S)			-0.6 / -0.7
7. Farm integration → GW use (M)			-0.7
8. Well's turn off → GW use (M,S)			-0.3 / -0.1
9. GW access → GW use (L,M,S)	Impact of changing groundwater access limitation (GW level – Well's depth) on groundwater use	Stakeholders' Estimation	

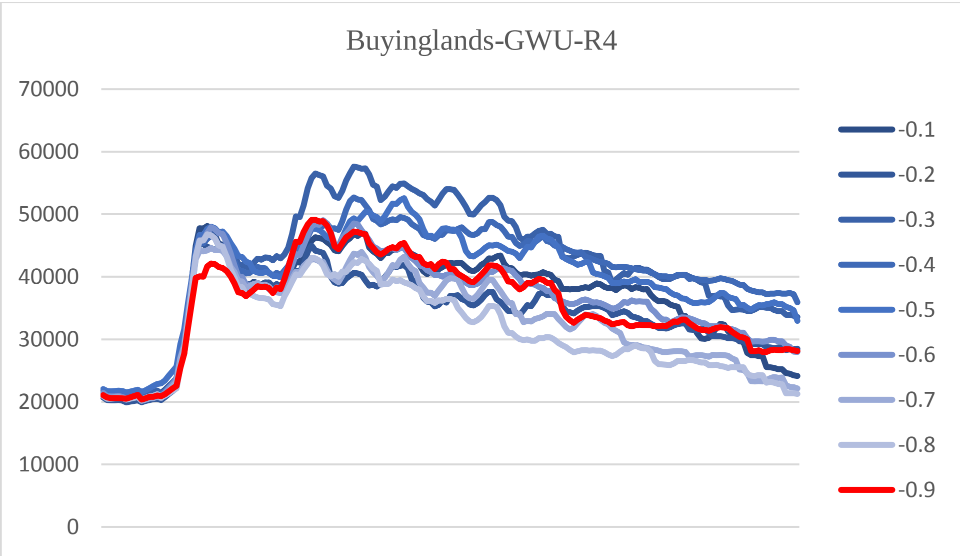

Figure 1: Changing impact of buying lands on groundwater use – Region 4

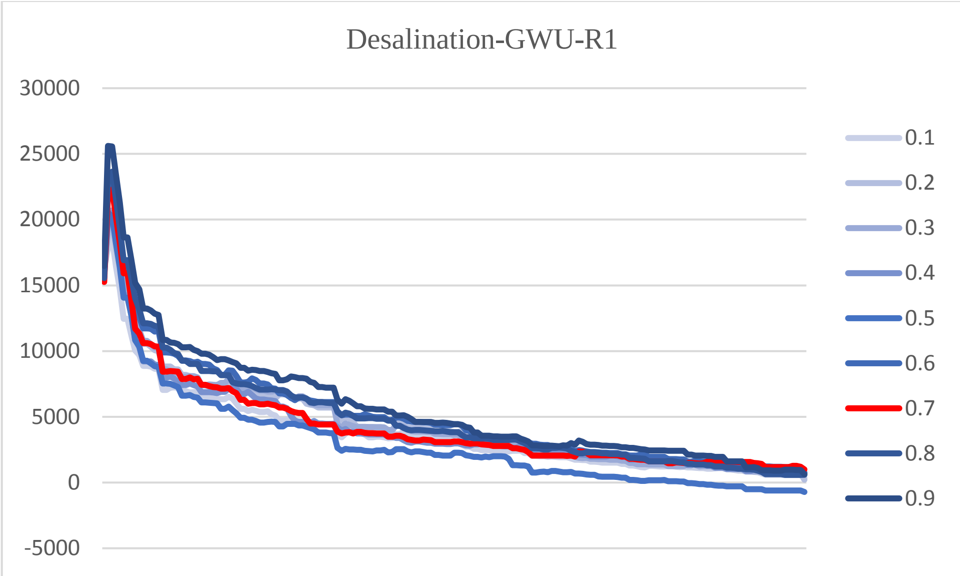

Figure 2: Changing impact of desalination on groundwater use – Region 1

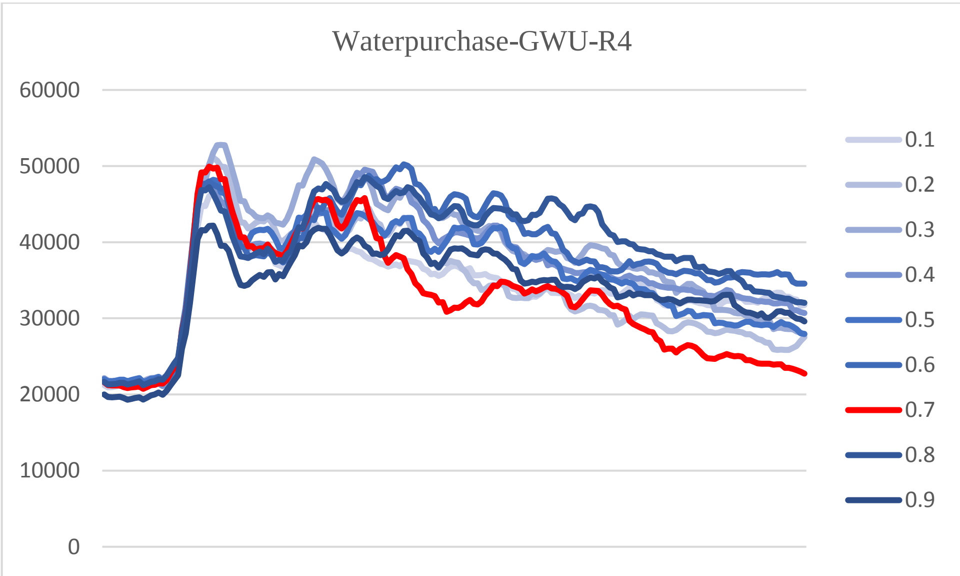

Figure 3: Changing impact of water purchase on groundwater use – Region 4

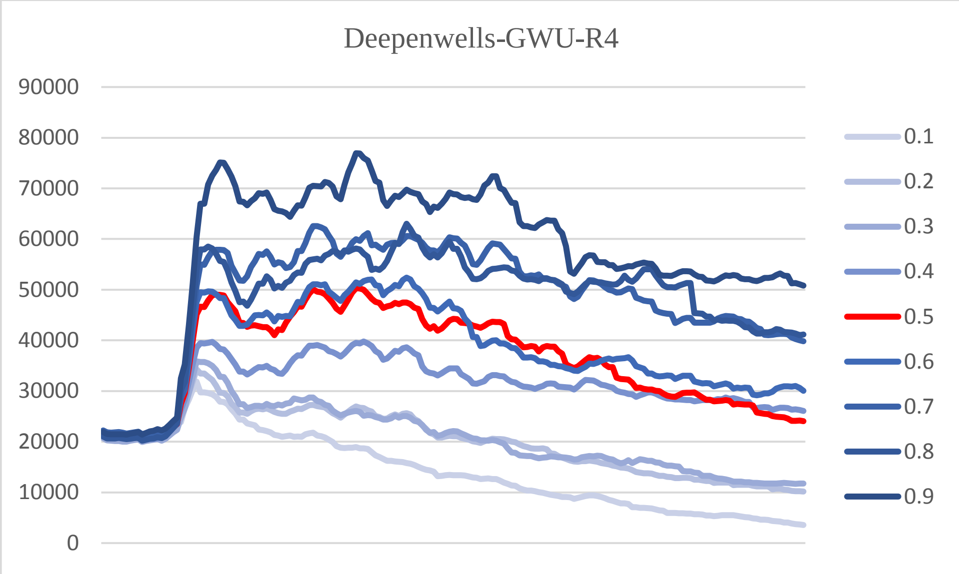

Figure 4: Changing impact of deepening wells on groundwater use – Region 4

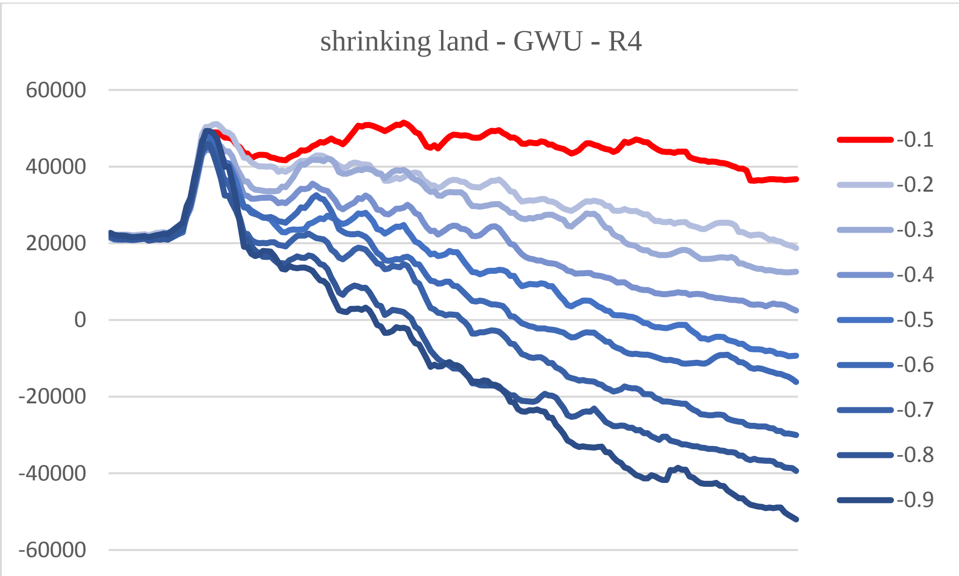

Figure 5: Changing impact of shrinking lands on groundwater use – Region 4

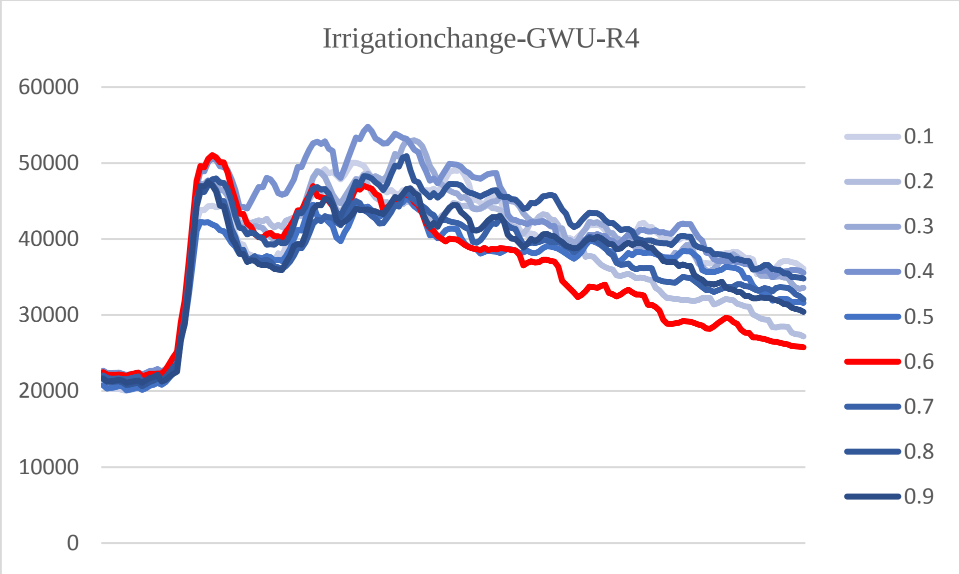

Figure 6: Changing impact of irrigation change on groundwater use – Region 4

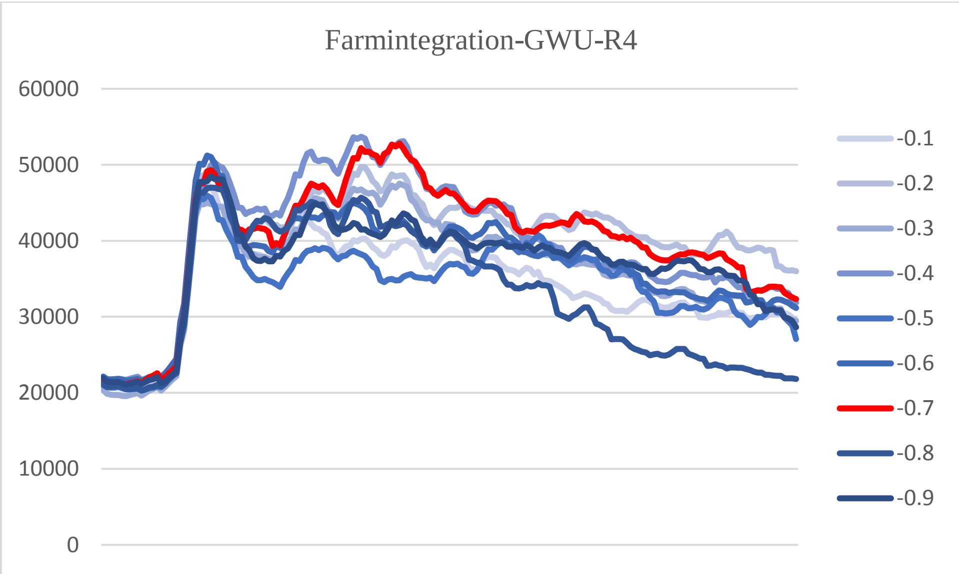

Figure 7: Changing impact of farm integration on groundwater use – Region 4

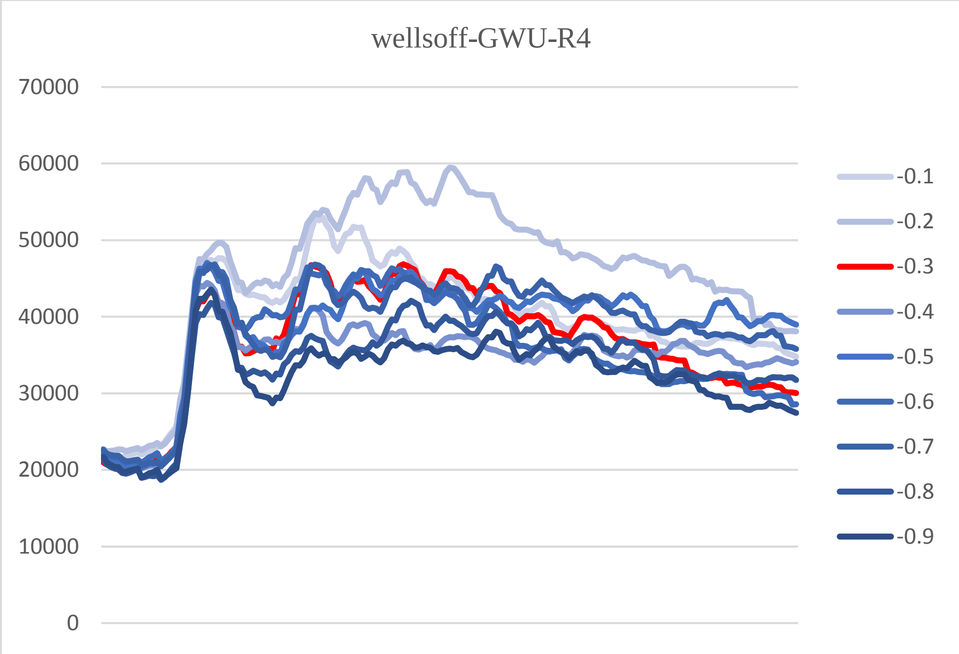

Figure 8: Changing impact of wells-off on groundwater use – Region 4

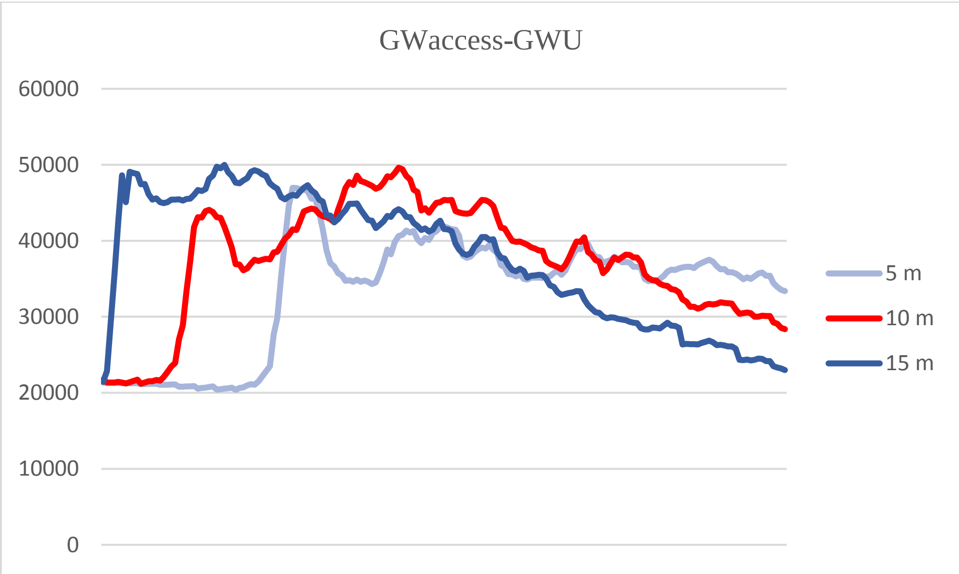

Figure 9: Changing groundwater access limitation – Region 4

Supplementary C

Data-driven connections, their correlated connections and perceived connections by large farmers

Table 1: Connections with data-driven weights and perceived weights in large farmers' FCM

Connections	Measured data correlation	Perceived by farmers
Climate change → Pistachio production	**-0.4**	
Groundwater exploitation → Groundwater level	**-0.8**	
Groundwater level → Groundwater quality	**0.3**	
Groundwater level → Land subsidence	**-0.9**	
Groundwater level → Pistachio production	**0.6**	
Groundwater quality → Pistachio production	**0.1**	
Buying land → GW use		**-0.9**
Desalination → GW use		**0.7**
Water purchasing → GW use		**0.7**
Deepening wells → GW use		**0.5**
Irrigation area reduction → GW use		**-0.9**
Buying land → Pistachio production		**0.9**
Desalination → pistachio production		**0.9**
Water purchasing → Pistachio production		**0.7**
Irrigation area reduction → Pistachio production		**0.55**
Desalination → water quality		**0.7**
Deepening well → water quality		**-0.7**
Irrigation system change → GW use		**-0.3**
Irrigation system change → pistachio production		**0.7**

Table 2. Description of variables with available time-series data

Variable name	**Description**	**Years of data**	**Source**
Climate change (precipitation and heat)	Annual precipitation (mm) and average monthly maximum temperature	1982 to 2016 annually	Iran Meteorological Organization (IRIMO)
Groundwater exploitation	Sum of the annual groundwater exploitation by total wells (mm^3)	1971- 1973- 1974- 1975- 1976- 1981- 1983- 1986- 1989- 1993- 1997- 2005- 2006	Official reports, Water research institute, Ministry of Energy
Groundwater level	Average of the annual groundwater level of the whole Rafsanjan	1983 to 2013 annually	Official reports, Iran water resources Management Company http://wrbs.wrm.ir/
Groundwater quality	Average of the annual Electrical Conductivity (EC) of groundwater in Rafsanjan	1998 to 2015 annually	Official reports, Iran water resources Management Company http://wrbs.wrm.ir/
Pistachio production	Sum of production in the whole Rafsanjan	1982 to 2015 annually	Iran Pistachio Association iranpistachio.org/fa/sample/before
Land subsidence		2004 to 2016 annually	Scientific studies (Motagh et al., 2017)

Appendix D

At the beginning of each interview, the interviewees were informed about the purposes of the study, confidentiality of their information, and outcome of the interview. Their oral informed consents were obtained and recorded using a digital recorder (alongside the whole interview). Below is the (translated) oral consent script of our interviews and the main questions for discussions.

Oral Consent Script

This interview is designed to collect data for the PhD project of me, [*name of researcher*] in [*name of university and country*] about the problem of water scarcity in Rafsanjan. The outputs of this interview will be exclusively used for academic purposes. In any report on the results of this research, your identity will remain anonymous and details of your interview will be aggregated with others for presentation in the reports.

During the interview, you will be asked questions and based on your answers I draw a mind map like this one (an FCM irrelevant to the topic of research is shown to the interviewee) on the paper, which you can view and comment on. I would like to record this interview if you do not mind. I may also contact you for follow-up questions or clarification. No-one other than me (the first author) will have access to raw data i.e. your mind maps and detail information.

You don't have to agree to take part; you can ask me any questions you want before or throughout; you can also withdraw at any stage without giving a reason.

Do you give your permission for me to interview and audio record you, and re-contact you to clarify information?

Guiding Questions

Name, age, gender:
Location and size of the farm:
Other source of income:
Nr of wells and depth of each well:

1. What have been the main causes of water scarcity in your region/farm?
2. What have been the main impacts of water scarcity in your region/farm?
3. How much has each of these variables caused an increase or decrease in other variables?
4. What have been your adaptive actions to combat water scarcity in your farm
5. What have been the conditions to implement each action?
6. How much has each action impacted other variables mentioned earlier?

Ending Questions

Would you please provide me with your phone number for follow-up questions?

If you like to see the aggregated mind-map of all farmers please give me your email address (or send me the email address of a person you know).

Appendix E: Demographic characteristics of interviewees

Demographic Variable	**Large Farmers**	**Medium Farmers**	**Small Farmers**
Number	20	20	20
Age	M=65.7, SD=10.6, Range= 32-93		
Gender	M=18, F=2	M=20, F=0	M=20, F=0
Location of farms	Sub-region 1 = 3 Sub-region 2 = 3 Sub-region 3 = 2 Sub-region 4 = 3 Sub-region 5 = 3 Sub-region 6 = 3 Sub-region 7 = 3	Sub-region 1 = 3 Sub-region 2 = 3 Sub-region 3 = 2 Sub-region 4 = 3 Sub-region 5 = 3 Sub-region 6 = 3 Sub-region 7 = 3	Sub-region 1 = 3 Sub-region 2 = 3 Sub-region 3 = 2 Sub-region 4 = 3 Sub-region 5 = 3 Sub-region 6 = 3 Sub-region 7 = 3
Farm Size	Range= 80-250 ha M= 112	Range= 15-80 ha M= 47	Range= 0.5-15 ha M= 5
Other source of income	Yes= 18, No= 2	Yes= 11, No= 9	Yes= 7, No= 13

year	Simulation	Reality	Diferrence
2004	100	100	0
	101.4662	100.9104	0.555835
	101.2744	101.8207	-0.5463
	101.9205	102.7311	-0.81064
	103.0114	103.6415	-0.63007
	103.5621	104.5518	-0.98973
	103.7683	105.4622	-1.69386
	105.4825	106.3725	-0.89003
	106.9412	107.2829	-0.34174
	114.6597	108.1933	6.466378
	118.9013	109.1036	9.797661
	119.9531	110.014	9.939136
2005	121.1566	110.9244	10.23223
	121.1273	111.753	9.374288
	121.5772	112.5817	8.995529
	121.6426	113.4104	8.232236
	120.6051	114.239	6.366033
	119.8669	115.0677	4.79925
	119.7545	115.8964	3.858191
	120.0375	116.725	3.312525
	120.387	117.5537	2.833305
	120.503	118.3824	2.120693
	119.933	119.211	0.721942
	118.9985	120.0397	-1.04123
2006	118.4529	120.8683	-2.41549
	118.1979	121.4753	-3.27738
	118.2527	122.0822	-3.8295
	118.2838	122.6891	-4.40526
	119.3101	123.296	-3.98584
	120.7329	123.9029	-3.17001
	122.8817	124.5098	-1.62806
	124.2286	125.1167	-0.88816
	123.8556	125.7236	-1.86806
	123.2409	126.3305	-3.08962
	122.809	126.9374	-4.12842
	122.5502	127.5444	-4.99413
2007	122.0976	128.1513	-6.05364
	121.7924	127.833	-6.04057
	121.8725	127.5146	-5.64211
	122.1988	127.1963	-4.99755
	122.5714	126.878	-4.30659
	122.3073	126.5597	-4.25238
	121.7034	126.2414	-4.53804
	121.365	125.9231	-4.5581
	121.5508	125.6048	-4.054
	122.3721	125.2865	-2.91442
	122.5273	124.9682	-2.44089

Root Mean Square Errc
6.386515

Anova: Single Factor

SUMMARY

Groups	*Count*
Simulation	97
Reality	97

ANOVA

Source of Varia	*SS*
Between G	94.22494
Within Gro	20996.71
Total	21090.94

2008	121.9176	124.6499	-2.7323
	120.5737	125.105	-4.53136
	120.5945	125.5602	-4.96576
	121.2508	126.0154	-4.76456
	121.6747	126.4706	-4.79584
	121.739	126.9258	-5.1868
	121.7231	127.381	-5.65784
	121.8321	127.8361	-6.00403
	122.1868	128.2913	-6.10456
	122.3588	128.7465	-6.38768
	122.1583	129.2017	-7.04341
	125.7709	129.6569	-3.88598
2009	129.3978	130.112	-0.71425
	132.8005	130.6489	2.151579
	135.5941	131.1858	4.408339
	138.3885	131.7227	6.665846
	139.9538	132.2596	7.694214
	140.7321	132.7965	7.935677
	140.3739	133.3333	7.040537
	139.6375	133.8702	5.767298
	137.7637	134.4071	3.356556
	135.5946	134.944	0.650595
	135.18	135.4809	-0.30086
	134.9754	136.0177	-1.04232
2010	134.6639	136.5546	-1.89073
	134.6657	136.7122	-2.04645
	134.4807	136.8697	-2.38906
	135.5182	137.0273	-1.50908
	136.6757	137.1849	-0.50922
	137.3008	137.3424	-0.04162
	137.2138	137.5	-0.28617
	136.8889	137.3424	-0.45356
	137.2124	137.1849	0.027523
	138.5804	137.0273	1.553044
	139.9039	136.8697	3.034144
	141.0296	136.7122	4.317448
2011	140.0934	136.5546	3.538824
	138.5935	135.2295	3.363986
	138.5767	133.9043	4.672393
	139.0629	132.5792	6.48369
	139.5548	131.254	8.300796
	140.0964	129.9289	10.16752
	140.5467	128.6037	11.94295
	140.6169	127.2786	13.33827
	140.4264	125.9535	14.4729
	139.8483	124.6283	15.21996
	139.1242	123.3032	15.82104
	138.2145	121.978	16.23644
	138.3794	120.6529	17.72656
2012	138.7018	119.3277	19.37408

or (RMSE)

Sum	Average	Variance
12221.83	125.9982	121.3426
12086.62	124.6044	97.37315

df	MS	F	P-value	F crit
1	94.22494	0.86162	0.354451	3.890348
192	109.3579			
193				

F < F crit
P-value > 0.05

Comparing the results of different number of simulation replications:

We checked whether the model results change with increasing number of simulations runs. As an example, we provide here the result of policy simulation in sub-region 4 with results from four sets of simulation runs: 100 runs, 200 runs, 300 runs and 500 runs. Figure H.1 shows small changes in mean values and slightly decreasing confidence intervals around these means for increasing numbers of simulation runs. However, the **order** of policies (exploring which is the main objective of this study) stays the same as for 100 simulation runs. So, the simulation analysis convinced us that 100 simulation suffices for the aim of this study.

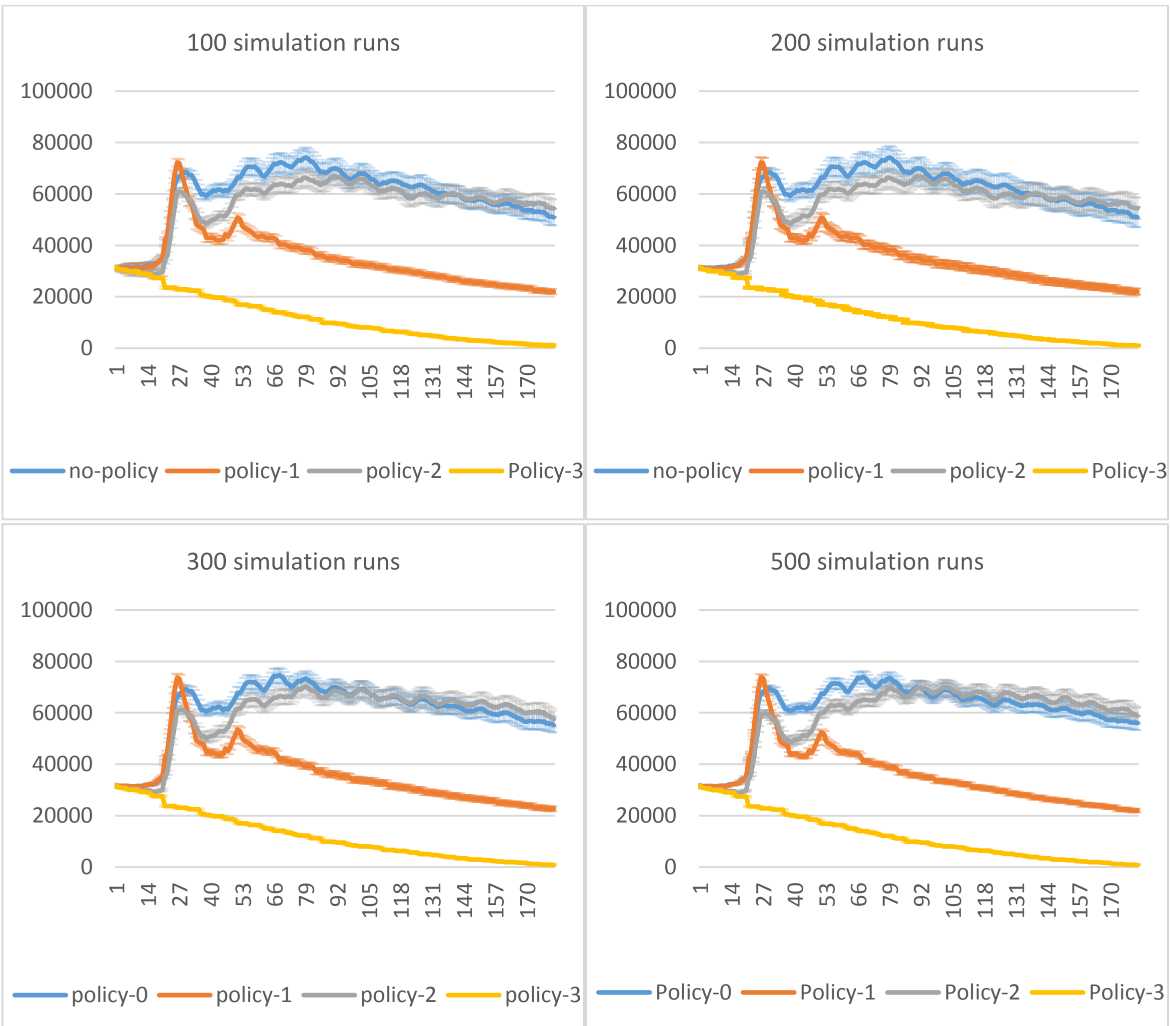

Figure H.1: Comparing policy simulations in sub-region 4 for 200, 300 and 500 simulation runs over time. The shaded areas depict confidence intervals (with confidence level of 95%) around the mean values for groundwater use for each policy scenario in sub-region 4.