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

Sara Mehryar[a,b*], Richard Sliuzas[a], Nina Schwarz[a], Ali Sharifi[a], Martin van Maarseveen[a]

[a] ITC-Faculty of Geo-Information Science & Earth Observation, University of Twente, P.O. Box 217, 7500AE, Enschede,The Netherlands

[b] Grantham Research Institute on Climate Change and the Environment, London School of Economics and Social Science, Houghton Street, London WC2A 2AE, United Kingdom

[*] s.mehryar@lse.ac.uk

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.

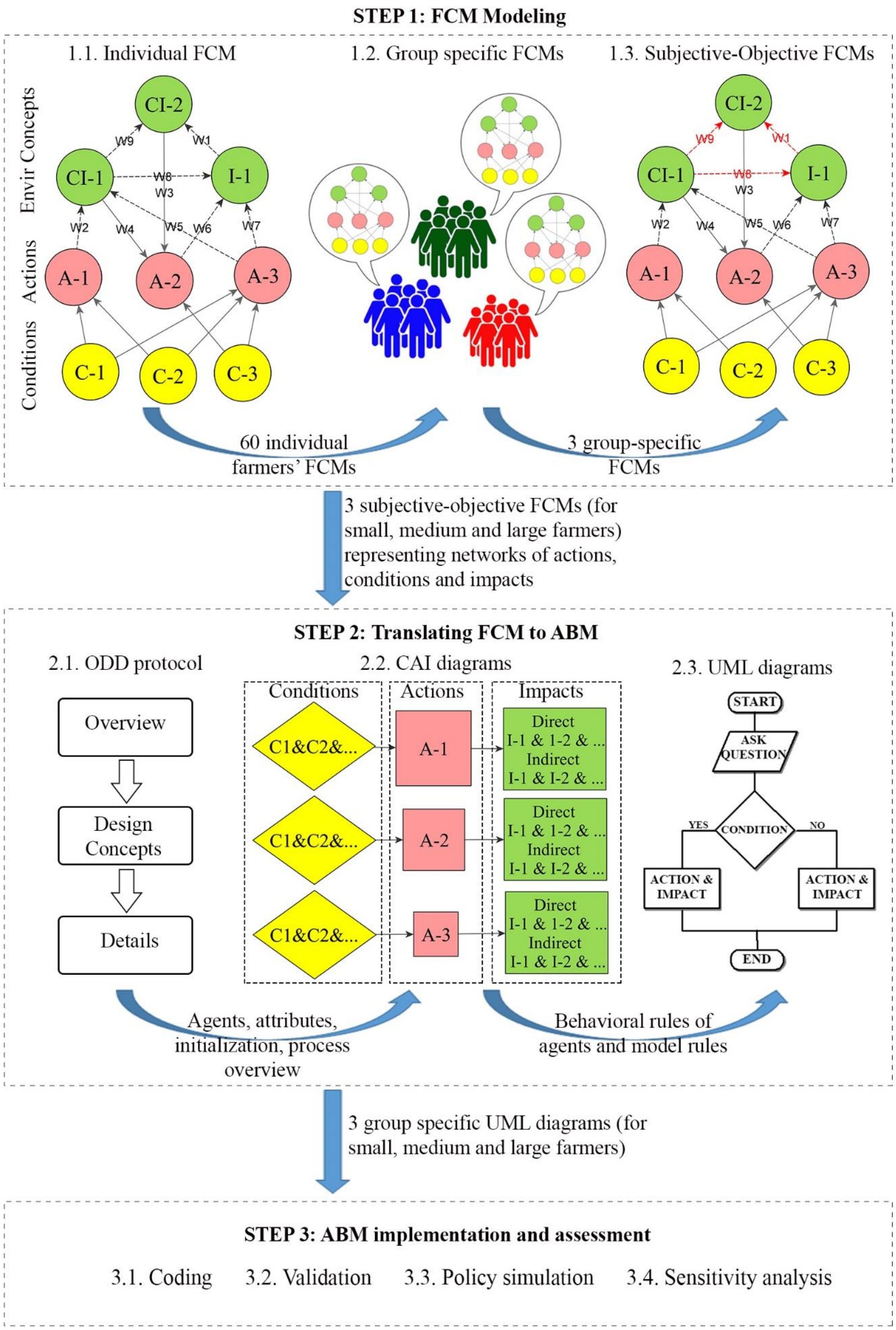

Figure 1: Main steps and sub-steps of methodology. Coding scheme - A: Action, C: Condition, I: Impact, CAI: Condition-Action-Impact, UML: Unified Modeling Language. In FCMs: red connections: weighted based on objective data, black connections: weighted based on subjective data, dashed lines: impact connections,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

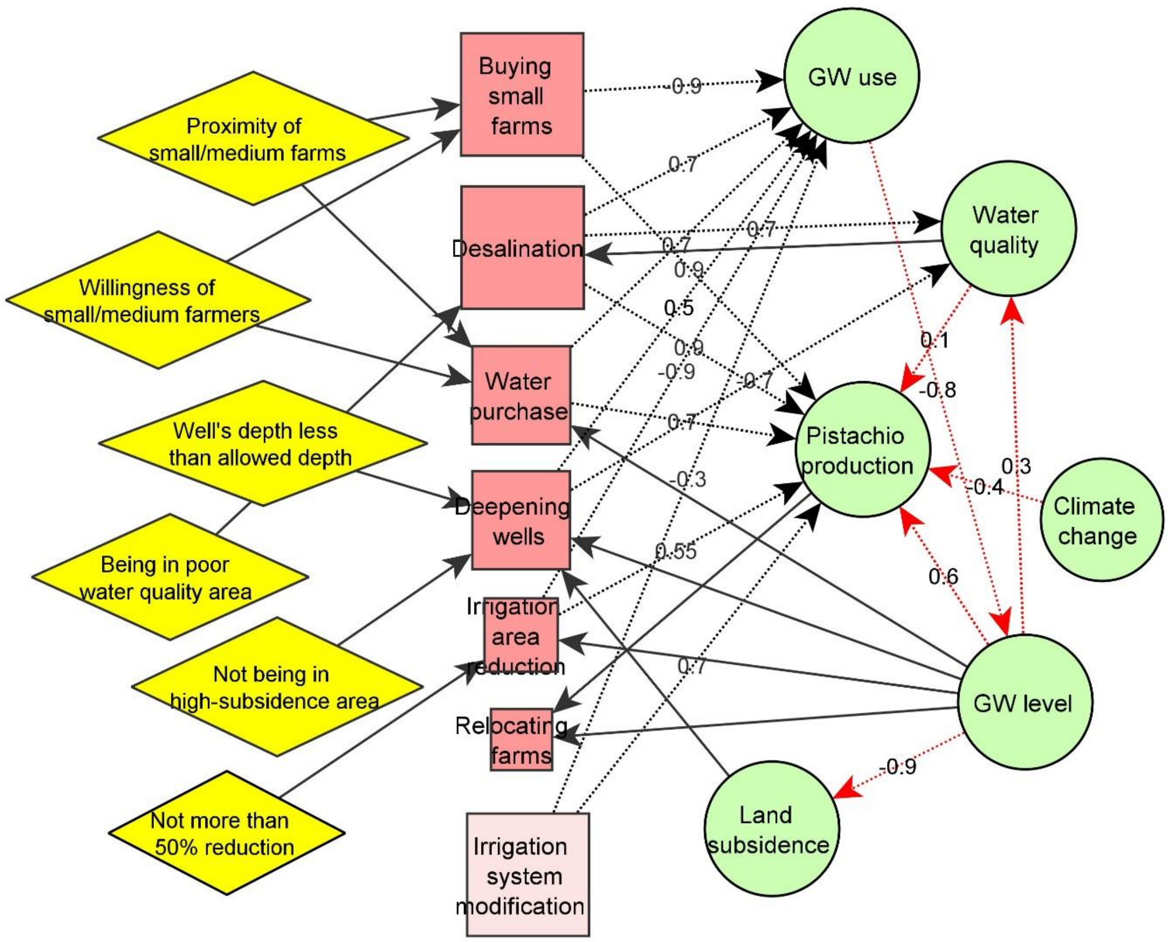

Figure 2. Large-farmers' FCM combined with objective data. The red squares show farmers' actions and their size shows the number of farmers who took this action i.e. level of preference or priority of actions. Yellow diamonds are conditions and green circles are either impacts or condition for some variables 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.

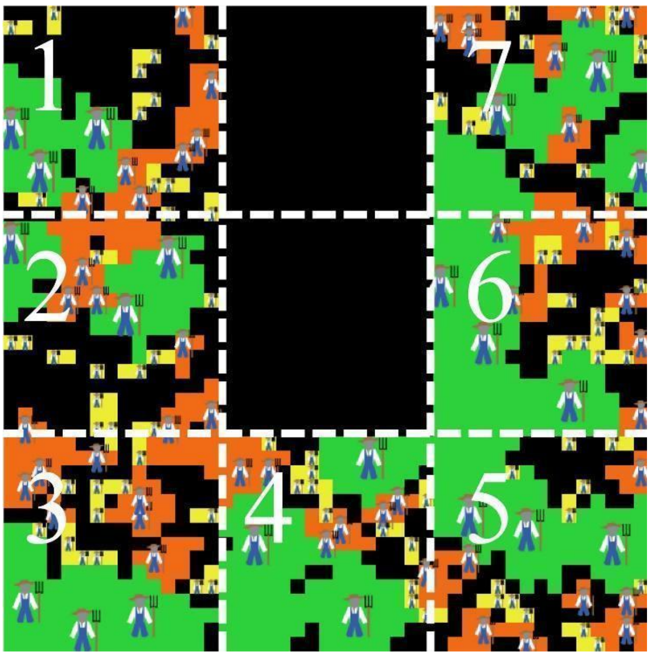

Figure 3. Set-up and allocation of farmers and farms in Netlogo. Green, orange and yellow cells represent large, medium and small farms, respectively. The two black regions in the middle are not farming regions (to represent the real U-shape landscape of Rafsanjan).

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).

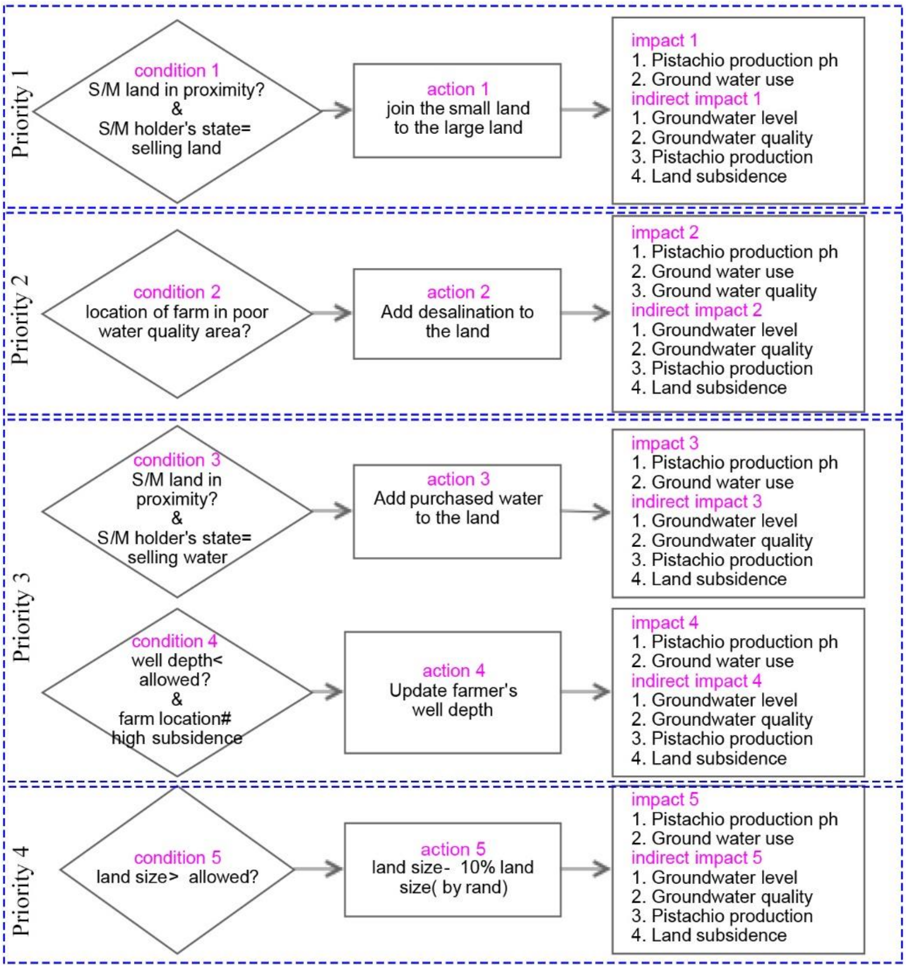

Figure 4: CAI of large farmers that represents set of conditions and impacts for each specific action. S/M: Small/Medium, ph: per hectare.

To implement the direct impact of actions X onto variables A of the FCM model (represented as $X \xrightarrow{w} A$), 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* $\xrightarrow{0.7}$ *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). 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 $A \xrightarrow{w} B$) the value of *Variable B* in the new time step is calculated as:

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

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 2011 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 2004-2011, 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 2011, thus 84 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 via running (1) Feasible Generalized Least Square (FGLS) and (2) FGLS with linear time trend specifications (details in supplementary G).

3.4.2. Baseline scenario and policy options

First, the baseline scenario was simulated. In this scenario, 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 FGLS estimation procedure to compare simulation run and historical data of groundwater use per each time step (considering the run time autocorrelations). Results show that our simulation model explains around 81% of variation in historical data, though the relationship is not one to one and the simulation does not explain all the temporal trend in data (details of the FGLS can be seen 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.

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.

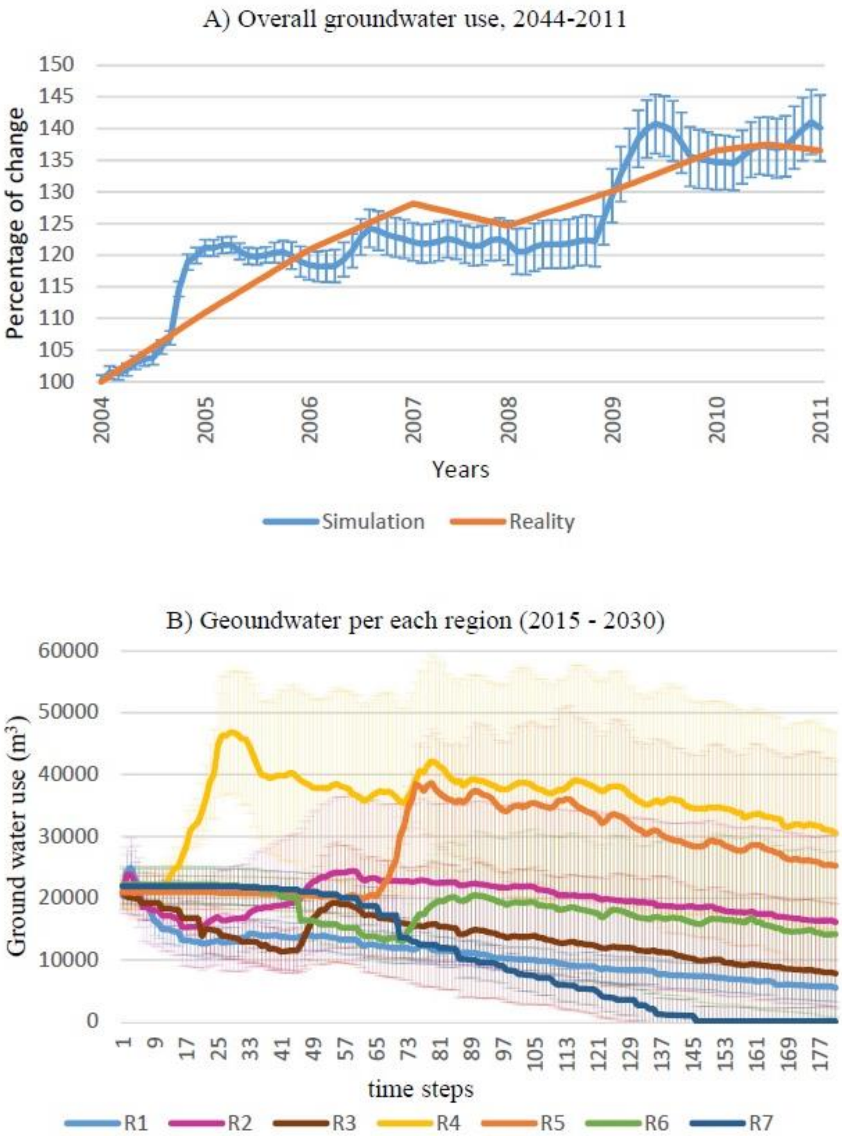

Figure 5. A) Validation using groundwater use of whole Rafsanjan in simulation and reality over the period 2004-2011. Due to difference in initial values of simulation and reality, their data-sets are normalized to show the *percentage* of changes. The bars depict confidence intervals (with confidence 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).

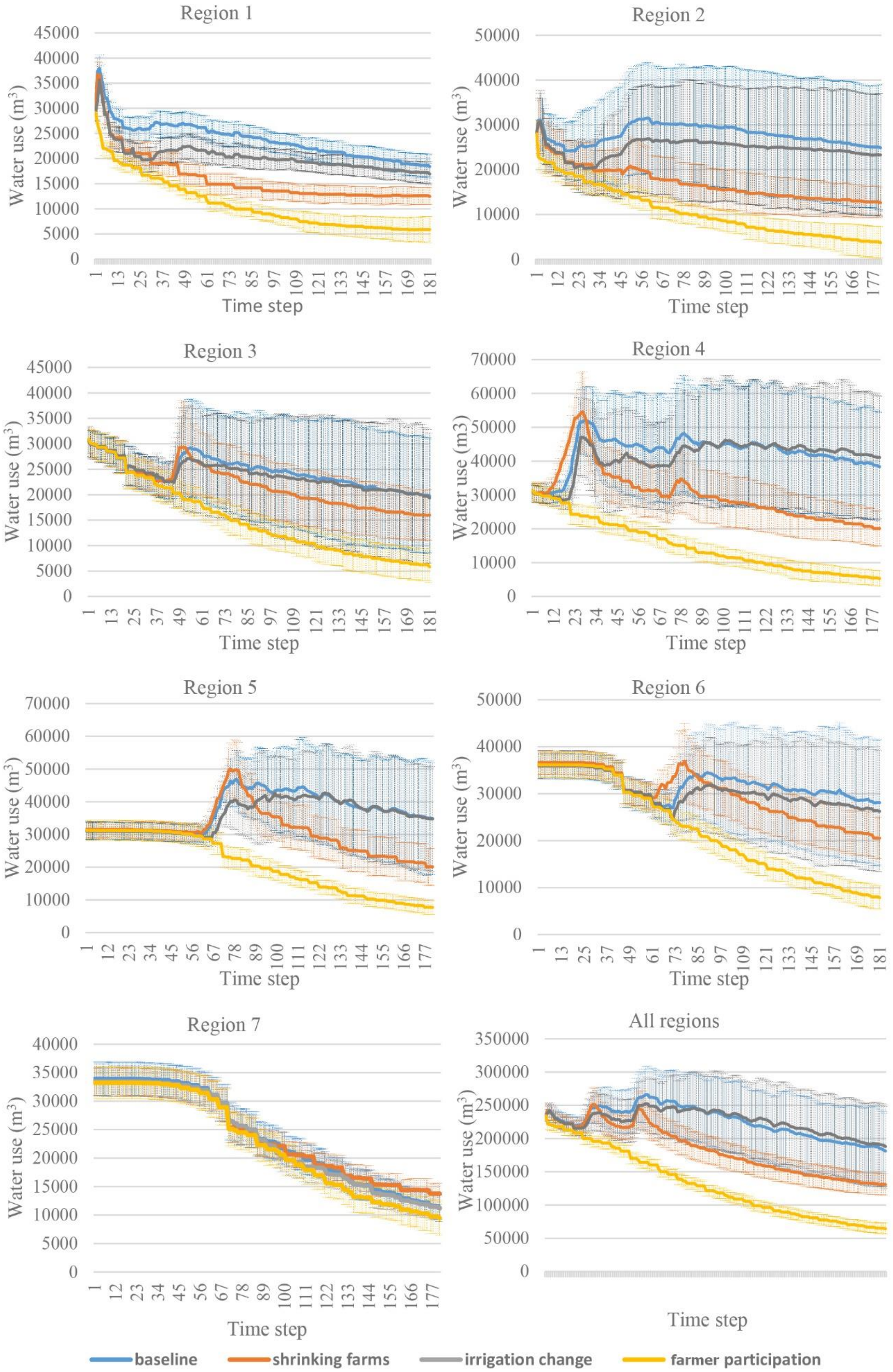

Figure 6: Groundwater use per region and overall groundwater use in three policy options scenarios compared to the baseline. The shaded areas depict standard deviation for each scenario over 100 replicated simulations.

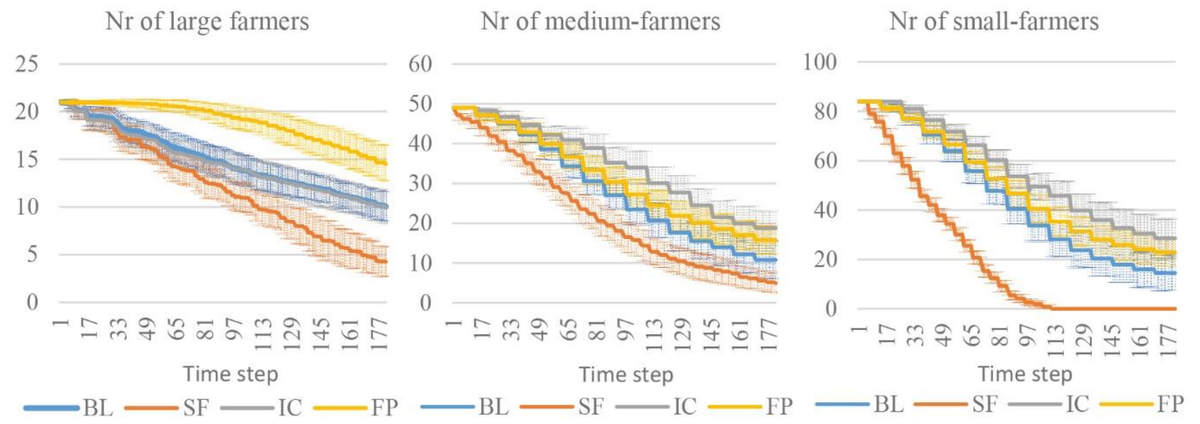

Figure 7: Number of large, medium and small farmers as a function of time in three policy scenarios compared to baseline. BL: baseline, SF: shrinking farms, IC: irrigation change, FP: farmer participation. The shaded areas depict standard deviation for each scenario over 100 replicated simulations.

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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