From Individual Fuzzy Cognitive Maps to Agent Based Models: Modeling 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

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

93 or specific problem of a system are asked to mention the most important variables (e.g. environmental,
94 social, ecological or economic variables), their causal relations, and the weights of the connections (i.e.,
95 how much a change of one variable causes a change in another variable) (Özesmi and Özesmi, 2004).
96 A range of individual mental models of stakeholders is developed and aggregated into a semi-
97 quantitative and standardized FCM model for simulation (Mehryar et al., 2017, Vasslides and Jensen,
98 2016). Thus, the connections in participatory FCMs represent causality perceived by participants.

99 FCM uses individuals as the units of data collection and analysis but aggregates their knowledge to
100 provide a macro-level view of an entire system's behavior. Thus, FCM does not represent individuals'
101 dynamic interactions with their environment. Besides, FCM provides semi-quantitative output data from
102 qualitative stakeholders' knowledge, which may be used in combination with mathematical models.
103 Therefore, FCMs are potentially useful in modelling aggregate human behavior and decisions (An,
104 2012). However, their lack of stakeholders' interactions, as well as temporal and spatial explicitness are
105 their main limitations.

2.2. Agent Based Modelling

107 ABM provides a micro-level view of a system since each agent is explicitly represented and interacts
108 with other agents as well as with the environment (Giabbanelli et al., 2017). Typically, ABMs are
109 spatially explicit and simulate dynamics over time, which makes them appealing to model SESs.
110 However, ABMs face the challenge of acquiring data for describing: 1) agents' behavioral options, 2)
111 decision-making processes (the way an agent makes decisions), and 3) decision outcomes (impacts of
112 their actions on others and on the environment). Due to the complexity of human decisions and actions,
113 ABM studies regularly rely on rational choice theory to describe agents' behavior (Schlüter et al., 2017,
114 Groeneveld et al., 2017). However, actual human behavior is subjective and has *bounded rationality* due
115 to limitations of information access, time, personal beliefs and perceptions (Elsawah et al., 2015). This
116 is particularly important in models for policy support (Schlüter et al., 2017). As a result, many modelers
117 using ABMs try to replicate actual human behaviors and decision-making as closely as possible
118 (Filatova et al., 2013) via participatory methods (An, 2012) such as role-playing games (Bousquet et al.,
119 2002, Castella et al., 2005), Bayesian belief networks (Sun and Müller, 2013), cognitive mapping
120 (Elsawah et al., 2015) or ethnographic methods (Ghorbani et al., 2015). Yet, the formulation and
121 parametrization of qualitative knowledge gained through such approaches, their combination with
122 quantitative data, and the identification and calibration of causal feedback mechanisms of a SES remain
123 key challenges (Robinson et al., 2007, Sun and Müller, 2013, Ghorbani et al., 2015, Venkatramanan et
124 al., 2017).

2.3. Techniques used in the present study

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

141 Similar to Elsawah et al. (2015), our focus is on structuring and using the collected qualitative data from
142 a set of FCMs to develop an ABM. Yet, our approach significantly differs in two ways from theirs. First,
143 we use FCMs instead of cognitive maps. Second, we use FCMs to model the whole system, including

144 and not limited to stakeholders' actions. Thus, the FCM provides a macro-level view of the system i.e.,
145 the perceived interactions between social, ecological, environmental and economic variables, and also
146 provides information for micro-level decision-making of agents i.e., type of actions and impacts of
147 actions on the environment. The same variables collected in FCMs are used in ABM as environmental
148 parameters and behavioral rules of agents. The outcome of our proposed modelling framework is useful
149 for ex-ante policy options analysis.

150 **3. Model building**

151 **3.1. Overview of model development**

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

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

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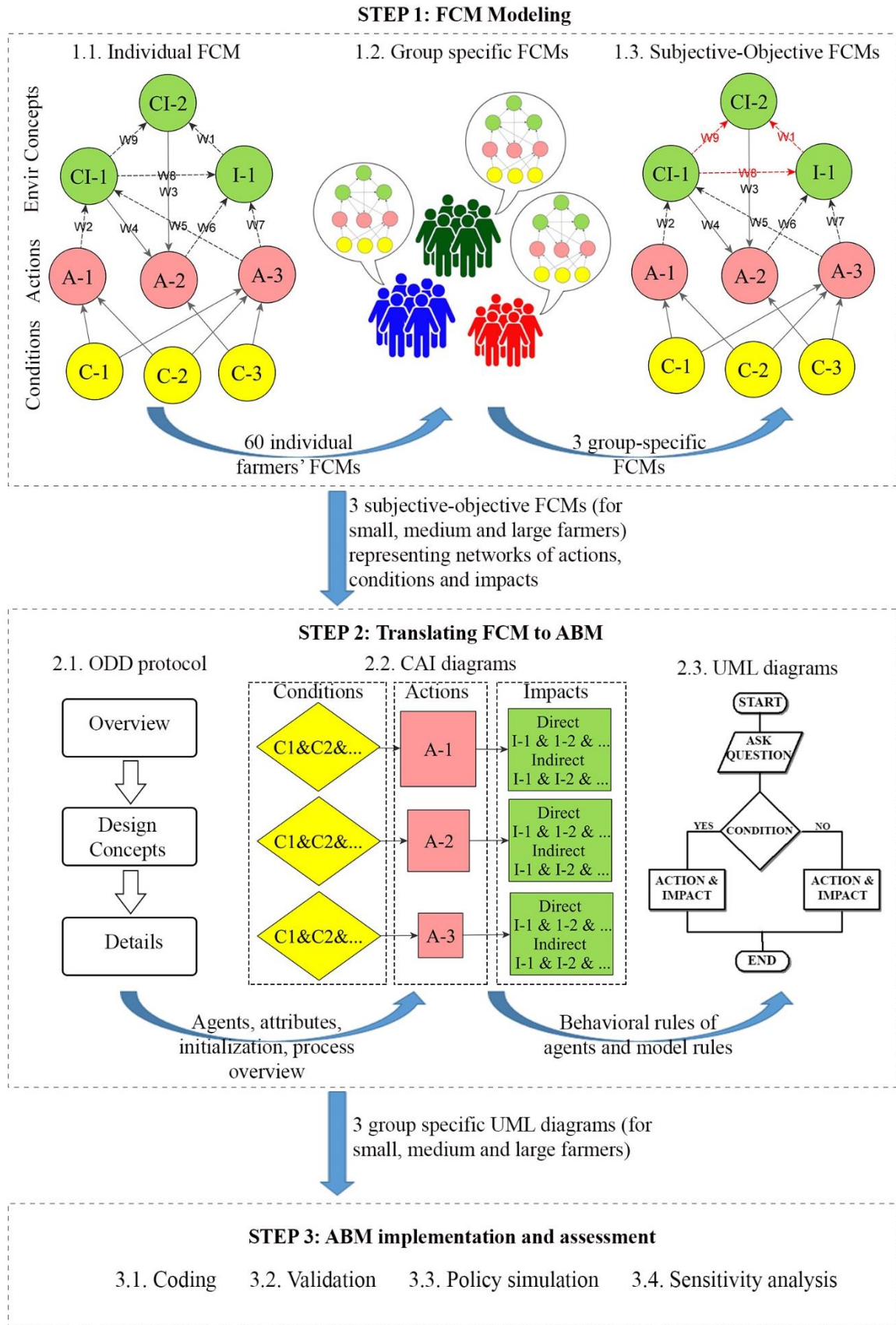
Figure 1: Main steps and sub-steps of methodology. Coding scheme - A: Action, C: Condition, I: Impact, CAI: Condition-Action-Impact, UML: Unified Modeling Language. In FCMs: red connections: weighted based on objective data, black connections: weighted based on subjective data, dashed lines: impact connections,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

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

226   ### 3.2.2.   Generating group specific FCMs

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

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

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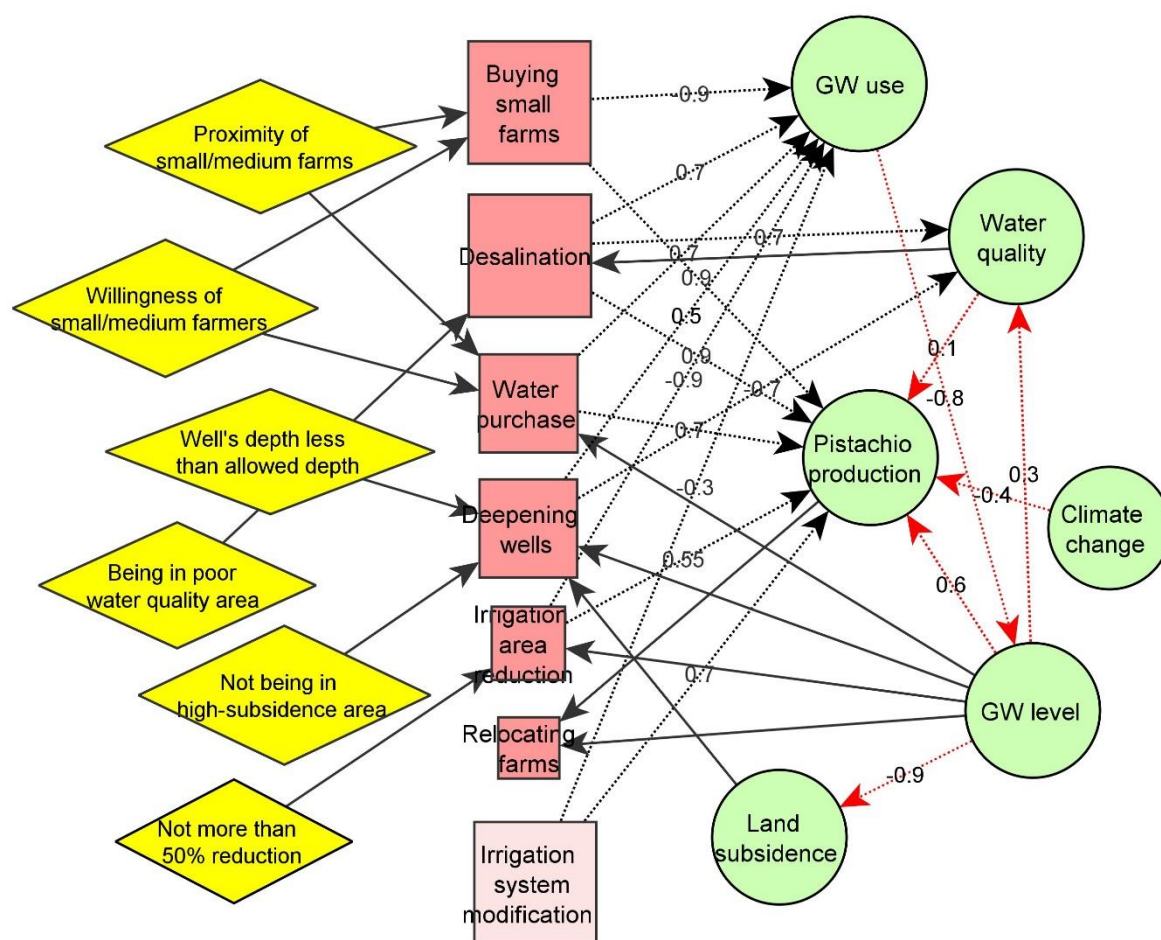
Figure 2. Large-farmers' FCM combined with objective data. The red squares show farmers' actions and their size shows the number of farmers who took this action i.e. level of preference or priority of actions. Yellow diamonds are conditions and green circles are either impacts or condition for some variables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

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[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.

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

279 All data-driven connection values developed by available time-series data and validated by farmers'
280 perceived FCM are listed in supplementary C. These data-driven values were used instead of perceived
281 values in all three group-specific FCMs, to cover the ecological and data-abundant part of the system
282 (red connections in figure 2). Yet all other connections, including those representing the impacts of
283 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

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

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

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

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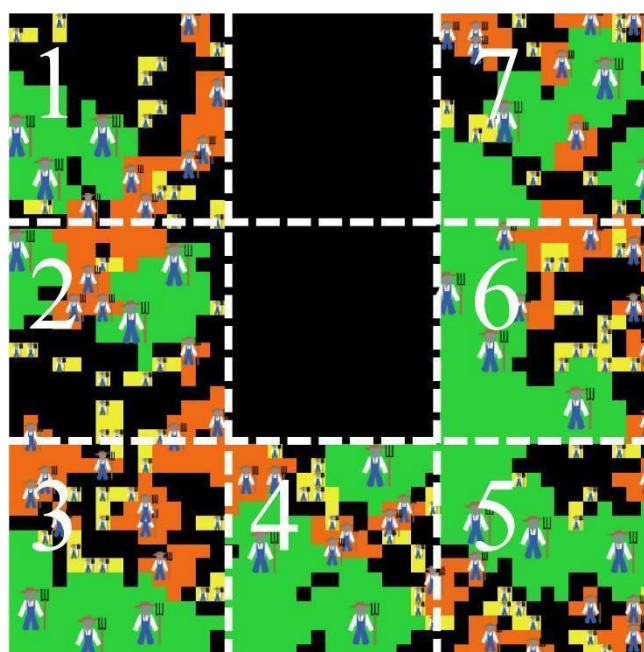
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308 Figure 3. Set-up and allocation of farmers and farms in Netlogo. Green, orange and yellow cells represent large,
309 medium and small farms, respectively. The two black regions in the middle are not farming regions (to represent
310 the real U-shape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

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

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

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

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

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

330

331 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

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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.

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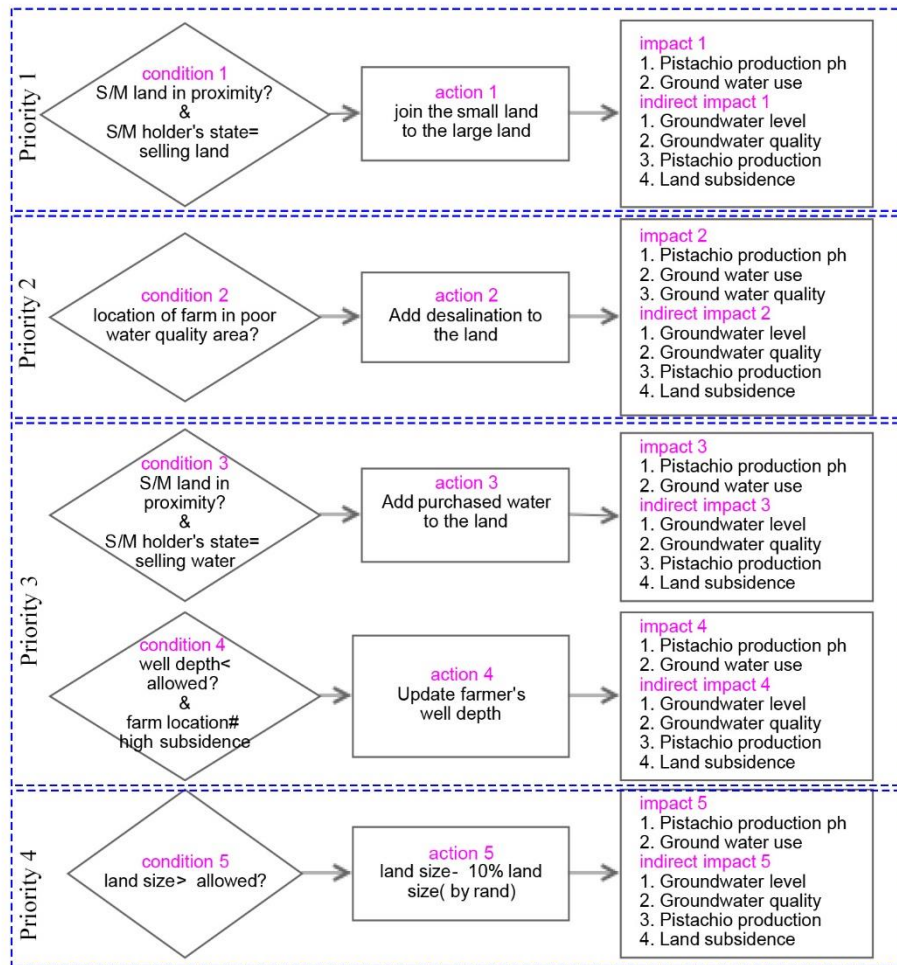
365   Figure 4: CAI of large farmers that represents set of conditions and impacts for each specific action. S/M:
366   Small/Medium, ph: per hectare.

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

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

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

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

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

385   *Equation 2:*

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

3.3.3.   UML diagram

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

404   ● **Time scale**: Actions may be taken by farmers every month, every six months or every year.
405   Moreover, some actions can be taken by farmers only once (e.g. desalination or irrigation system
406   change), whereas other actions can be taken several times until their limits are reached (e.g. well
407   deepening or land shrinking). Therefore, the time scale (i.e. frequency and one-time or repetitive)
408   are added to the condition of each action. Thus, if an action is executed annually, the condition for
409   this action is *to be in time step multiples of 12*.

410   ● **Randomness:** Randomness is added to the priority set of actions in the behavioral rules of agents
411   as well as in the initialization of parameters' values. In the priority set of actions, some actions have
412   the same or very similar priority[5]. In these cases, one action is randomly chosen to have priority
413   over the other. Applying randomness in the agent's behavior also helps to include the outliers'
414   behavior who may not follow the same behavior rules as other agents. Randomness is also used in
415   the distribution of agents over the seven sub-regions, as well as their farm sizes within the ranges of
416   small, medium and large farms' area mentioned in section 3.2.2. For the initialization of parameters'
417   values, an interval of initial values was collected for each parameter in each sub-region and
418   randomly distributed over the farm patches (supplementary A, section 3.1).

419   ● **Spatial dimension:** Some environmental properties have significantly different values in different
420   regions of Rafsanjan. For example, groundwater quality and land subsidence level are different in
421   each of the seven sub-regions and thus have a different impact on farmers' decisions. This spatial
422   heterogeneity is represented in the cells' properties and added to the conditions of each action.

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

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[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.

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

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

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

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

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

3.4.3. Sensitivity analysis

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

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

4. Results

4.1. Validation

524 We used the FGLS estimation procedure to compare simulation run and historical data of groundwater
525 use per each time step (considering the run time autocorrelations). Results show that our simulation
526 model explains around 81% of variation in historical data, though the relationship is not one to one and
527 the simulation does not explain all the temporal trend in data (details of the FGLS can be seen in
528 supplementary G). There are two specific peaks of groundwater use, both in the simulation and in the

529 real data (Figure 5A). Such peaks (in reality) are because of significant well deepening in different
530 regions (i.e. first in sub-regions 1 and 2 and later in sub-regions 6 and 7), where around 2015 most of
531 the wells have already reached their maximum depth.

4.2. Baseline scenario

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

536 Regions 4 and 5: Farmers in these two regions still can deepen their wells at the beginning of the
537 simulation, while other regions have either very poor water quality or very high land subsidence that
538 prohibit more *well deepening* (supplementary A). *Well deepening* and *water marketing* in regions 4 and
539 5 results in a rapid rise in their aggregated groundwater use. The peaks of groundwater use in these two
540 regions occur when farmers reach their permitted well depth, at which time further deepening stops.
541 Hereafter, trends of groundwater use are followed by a slight decrease due to actions like *shrinking lands*
542 and *buying/integrating farms*. Since region 5 has better access to groundwater than region 4
543 (supplementary A), farmers in region 5 start taking adaptive actions later than those in region 4.
544 Therefore, the groundwater use in region 5 lags slightly behind that of region 4.

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

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

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

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

570

A) Overall groundwater use, 2044-2011

B) Geoundwater per each region (2015 - 2030)
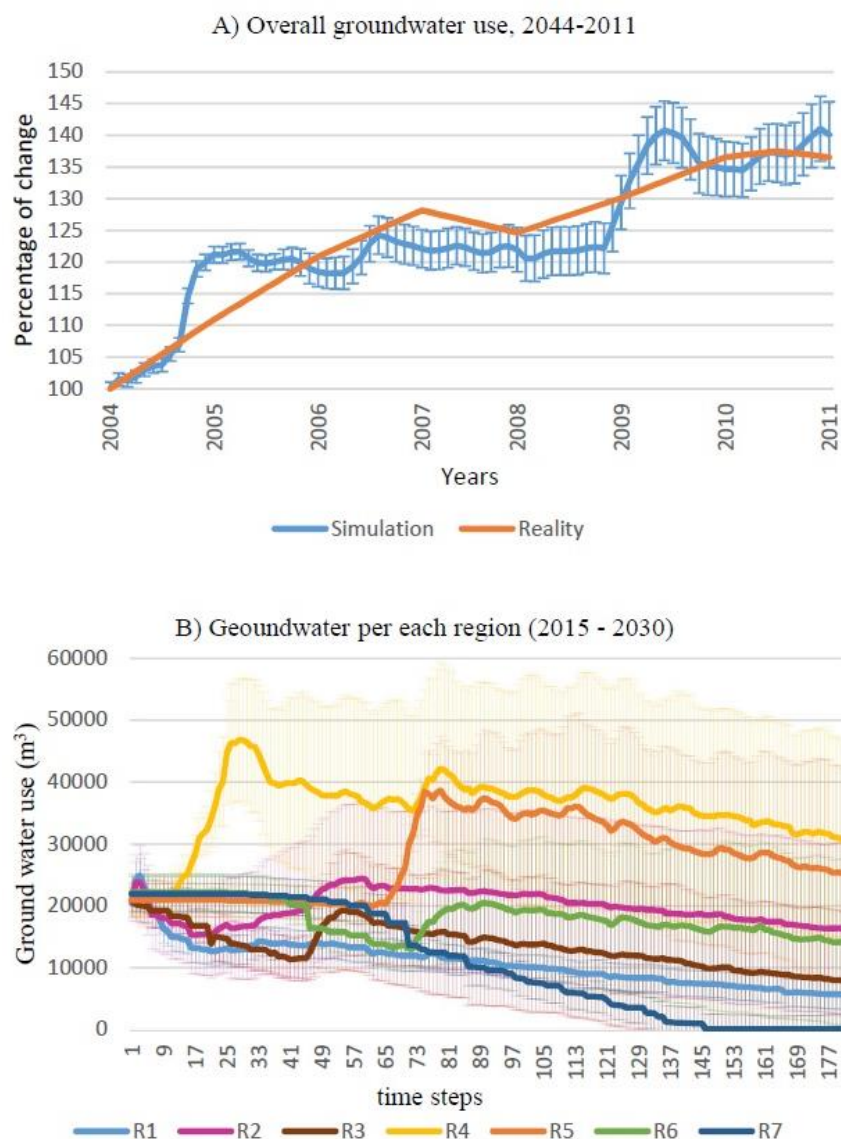
Figure 5. A) Validation using groundwater use of whole Rafsanjan in simulation and reality over the period 2004-2011. Due to difference in initial values of simulation and reality, their data-sets are normalized to show the *percentage* of changes. The bars depict confidence intervals (with confidence 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.
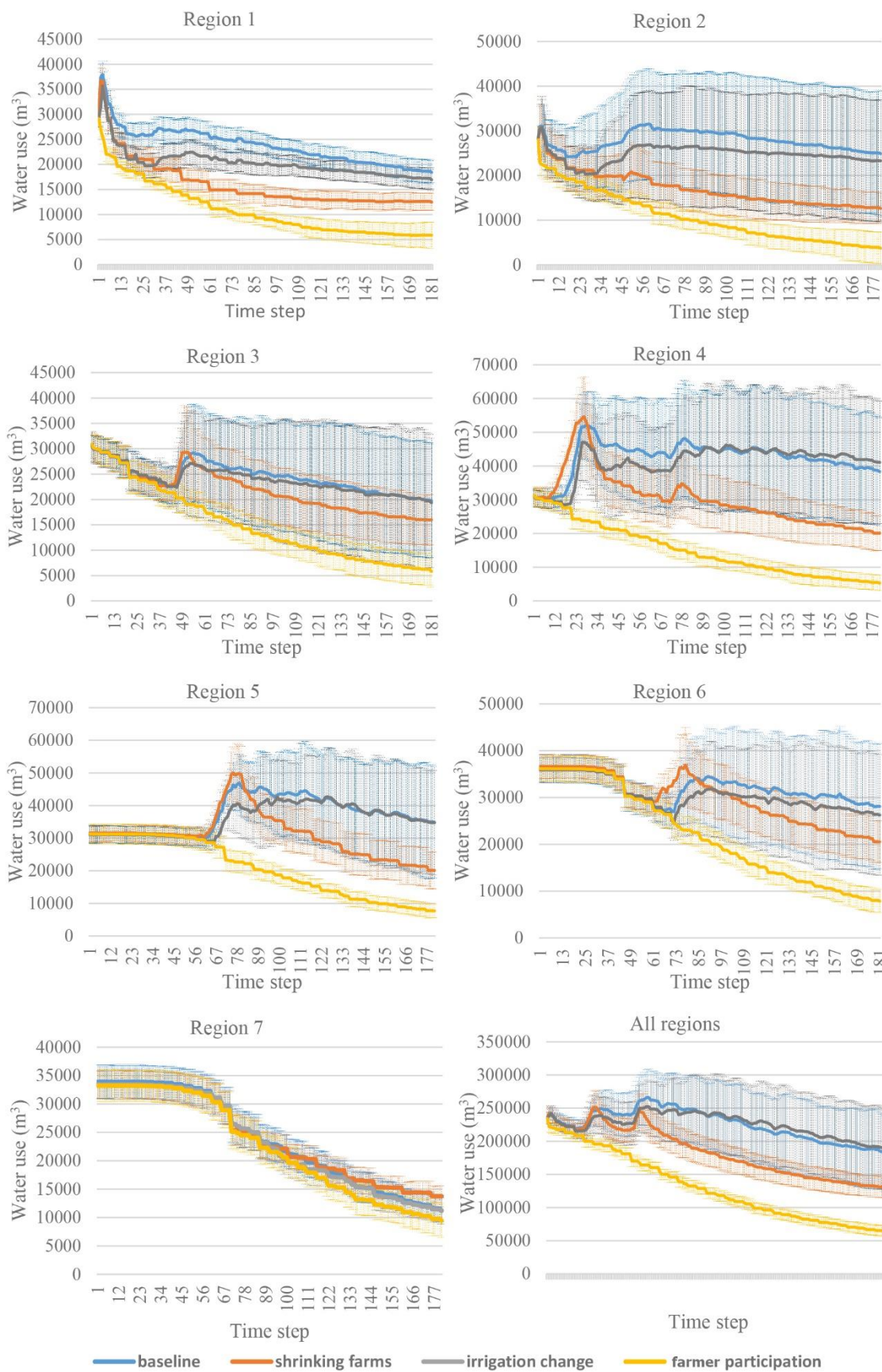
4.3. Policy options simulations

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.

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

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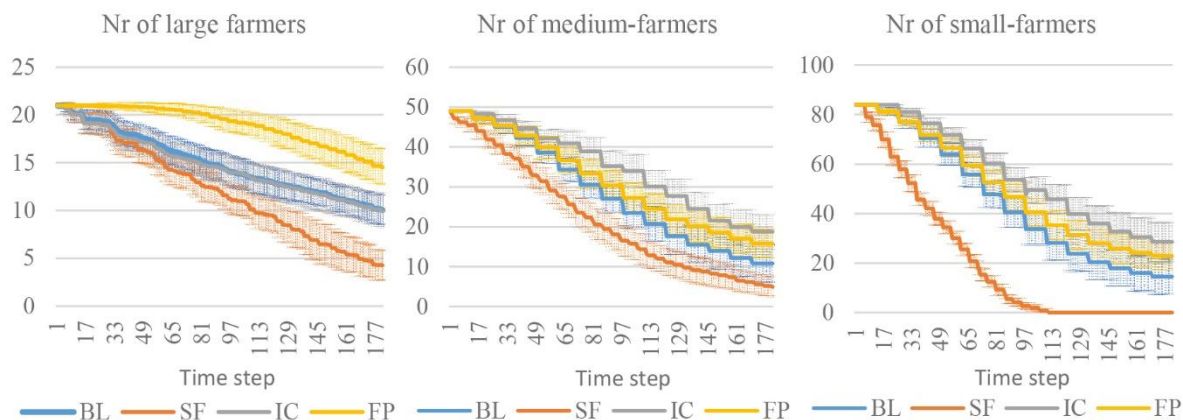601   range in all regions (orange and yellow lines in figure 6).

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. fast-

643 changing variables (e.g. annual agriculture production) or high-frequency actions (e.g. farm irrigation)
644 and low-frequency actions (e.g. buying lands).

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

5.2. Limitations and future studies

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

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

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

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

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

694
695 Last, ODD+D protocol (Müller et al., 2013) can also be used in this methodology instead of standard
696 ODD. This protocol rearranges the design concepts to better capture human *decision-making*.

697 **6. Conclusion**

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

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

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720 **References**

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722 An, L., 2012. Modeling human decisions in coupled human and natural systems: Review of agent-
723   based models. *Ecol. Model*. 229, 25-36. doi:10.1016/j.ecolmodel.2011.07.010

724 Bersini, H., 2012. UML for ABM. *J. Artif. Soc. Soc. Simul.* 15, 9. doi:10.18564/jasss.1897

725 Bousquet, F., Barreteau O., D'aquino P., Etienne M., Boissau S., Aubert S., Le Page C., Babin D.,
726   Castella J.-C., 2002. Multi-agent systems and role games: collective learning processes for
727   ecosystem management. *Complexity and ecosystem management: The theory and practice of
728   multi-agent systems*, 248-285

729 Carvalho, J.P., Tomè J.A., 2000. Rule based fuzzy cognitive maps-qualitative systems dynamics, in:
730   *Fuzzy Information Processing Society, 2000. NAFIPS. 19th International Conference of the
731   North American*. 2000. IEEE, pp 407-411. doi: 10.1109/NAFIPS.2000.877462

732 Castella, J.-C., Trung N., Boissau S., 2005. Participatory simulation of land-use changes in the
733   northern mountains of Vietnam: the combined use of an agent-based model, a role-playing
734   game, and a geographic information system. *Ecol. Soc.* 10, 1-32. doi:10.5751/es-01328-
735   100127

736 Edmonds, B., Moss S., 2004. From KISS to KIDS–an 'anti-simplistic'modelling approach, in:
737   *International workshop on multi-agent systems and agent-based simulation*. 2004. Springer,
738   pp 130-144

739 Elsawah, S., Guillaume J.H., Filatova T., Rook J., Jakeman A.J., 2015. A methodology for eliciting,
740   representing, and analysing stakeholder knowledge for decision making on complex socio-

ecological systems: From cognitive maps to agent-based models. *J. Environ. Manage.* 151, 500-516. doi:10.1016/j.jenvman.2014.11.028

Filatova, T., Verburg P.H., Parker D.C., Stannard C.A., 2013. Spatial agent-based models for socio-ecological systems: challenges and prospects. *Environ. Modell. Softw.* 45, 1-7. doi:10.1016/j.envsoft.2013.03.017

Ghorbani, A., Dijkema G., Schrauwen N., 2015. Structuring qualitative data for agent-based modelling. *J. Artif. Soc. Soc. Simul.* 18, 2. doi:10.18564/jasss.2573

Giabbanelli, P.J., Gray S.A., Aminpour P., 2017. Combining fuzzy cognitive maps with agent-based modeling: Frameworks and pitfalls of a powerful hybrid modeling approach to understand human-environment interactions. *Environ. Modell. Softw.* 95, 320-325. doi:10.1016/j.envsoft.2017.06.040

Giabbanelli, P.J., Torsney-Weir T., Mago V.K., 2012. A fuzzy cognitive map of the psychosocial determinants of obesity. *Applied soft computing.* 12, 3711-3724

Gilbert, N., 2008. Agent-based models. vol 153. Sage,

Gosselin, F., Cordonnier T., Bilger I., Jappiot M., Chauvin C., Gosselin M., 2018. Ecological research and environmental management: we need different interfaces based on different knowledge types. *J. Environ. Manage.* 218, 388-401. doi:10.1016/j.jenvman.2018.04.025

Gray, S.A., Zanre E., Gray S., 2014. Fuzzy cognitive maps as representations of mental models and group beliefs, in: Fuzzy cognitive maps for applied sciences and engineering. Springer, pp 29-48. doi:10.1007/978-3-642-39739-4_2

Grimm, V., Berger U., Deangelis D.L., Polhill J.G., Giske J., Railsback S.F., 2010. The ODD protocol: a review and first update. *Ecol. Model.* 221, 2760-2768. doi:10.1016/j.ecolmodel.2010.08.019

Grimm, V., Polhill G., Touza J., 2017. Documenting social simulation models: the ODD protocol as a standard, in: Simulating Social Complexity. Springer, pp 349-365. doi:10.1007/978-3-540-93813-2_7

Groeneveld, J., Müller B., Buchmann C.M., Dressler G., Guo C., Hase N., Hoffmann F., John F., Klassert C., Lauf T., 2017. Theoretical foundations of human decision-making in agent-based land use models–a review. *Environ. Modell. Softw.* 87, 39-48. doi:10.1016/j.envsoft.2016.10.008

Harrell Jr, F.E., 2015. Regression modeling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis. Springer,

Hatwagner, M.F., Yesil E., Dodurka F., Papageorgiou E.I., Urbas L., Koczy L.T., 2018. Two-stage learning based fuzzy cognitive maps reduction approach. *IEEE Trans Fuzzy Syst*,

Jetter, A.J., Kok K., 2014. Fuzzy cognitive maps for futures studies—a methodological assessment of concepts and methods. *Futures*. 61, 45-57. doi:10.1016/j.futures.2014.05.002

Kerman Provincial Government 2014. Policie and directives on protection and conservation of groundwater aquifers. *In:* Affairs, D (ed.). Kerman, Iran.

Kosko, B., 1986. Fuzzy cognitive maps. *Int. J. Man. Mach. Stud.* 24, 65-75

Lavin, E.A., Giabbanelli P.J., 2017. Analyzing and simplifying model uncertainty in fuzzy cognitive maps, in: *Simulation Conference (WSC), 2017 Winter*. 2017. IEEE, pp 1868-1879

Lavin, E.A., Giabbanelli P.J., Stefanik A.T., Gray S.A., Arlinghaus R., 2018. Should we simulate mental models to assess whether they agree?, in: *Proceedings of the Annual Simulation Symposium*. 2018. Society for Computer Simulation International, p 6

Levin, S., Xepapadeas T., Crépin A.-S., Norberg J., De Zeeuw A., Folke C., Hughes T., Arrow K., Barrett S., Daily G., 2013. Social-ecological systems as complex adaptive systems: modeling and policy implications. *Environ. Dev. Econ.* 18, 111-132. doi:10.1017/S1355770X12000460

788 Macy, M.W., Willer R., 2002. From factors to actors: computational sociology and agent-based
789   modeling. *Annu. Rev. Sociol*. 28, 143-166. doi:10.1146/annurev.soc.28.110601.141117

790 Mease, L.A., Erickson A., Hicks C., 2018. Engagement takes a (fishing) village to manage a resource:
791   Principles and practice of effective stakeholder engagement. *J. Environ. Manage.* 212, 248-
792   257. doi:10.1016/j.jenvman.2018.02.015

793 Mehryar, S., Sliuzas R., Sharifi A., Reckien D., Van Maarseveen M., 2017. A structured participatory
794   method to support policy option analysis in a social-ecological system. *J. Environ. Manage.*
795   197, 360-372. doi:10.1016/j.jenvman.2017.04.017

796 Mehryar, S., Sliuzas R., Sharifi A., Van Maarseveen M., 2015. The water crisis and socio-ecological
797   development profile of Rafsanjan Township, Iran. *WIT Trans. Ecol. Environ.* 199, 271-285.
798   doi:10.2495/RAV150231

799 Mehryar, S., Sliuzas R., Sharifi A., Van Maarseveen M., 2016. The socio-ecological analytical
800   framework of water scarcity in Rafsanjan Township, Iran. *Int. J. Saf. Secur. Eng.* 6, 764-776.
801   doi:10.2495/SAFE-V6-N4-764-776

802 Mourhir, A., Papageorgiou E. 2017. Empirical comparison of fuzzy cognitive maps and dynamic rule-
803   based fuzzy cognitive maps. *In:* Westphall, CB (ed.) *ICAS 2017* Barcelona, Spain.

804 Müller, B., Bohn F., Dreßler G., Groeneveld J., Klassert C., Martin R., Schlüter M., Schulze J., Weise
805   H., Schwarz N., 2013. Describing human decisions in agent-based models–ODD+ D, an
806   extension of the ODD protocol. *Environ. Modell. Softw.* 48, 37-48. doi:10.1007/s10584-014-
807   1275-0

808 Özesmi, U., Özesmi S.L., 2004. Ecological models based on people's knowledge: a multi-step fuzzy
809   cognitive mapping approach. *Ecol. Model.* 176, 43-64. doi:10.1016/j.ecolmodel.2003.10.027

810 Papageorgiou, E., Kontogianni A., 2012. Using fuzzy cognitive mapping in environmental decision
811   making and management: a methodological primer and an application, in: International
812   Perspectives on Global Environmental Change. InTech. doi:10.5772/29375

813 Papageorgiou, E.I., Markinos A., Gemptos T., 2009. Application of fuzzy cognitive maps for cotton
814   yield management in precision farming. *Expert systems with Applications*. 36, 12399-12413

815 Papageorgiou, E.I., Markinos A.T., Gemtos T.A., 2011. Fuzzy cognitive map based approach for
816   predicting yield in cotton crop production as a basis for decision support system in precision
817   agriculture application. *Applied Soft Computing*. 11, 3643-3657

818 Rahimi, N., Jetter A.J., Weber C.M., Wild K., 2018. Soft Data analytics with fuzzy cognitive maps:
819   modeling health technology adoption by elderly women, in: Advanced Data Analytics in
820   Health. Springer, pp 59-74

821 Reckien, D., 2014. Weather extremes and street life in India—implications of Fuzzy Cognitive
822   Mapping as a new tool for semi-quantitative impact assessment and ranking of adaptation
823   measures. *Global. Environ. Change.* 26, 1-13. doi:10.1016/j.gloenvcha.2014.03.005

824 Robinson, D.T., Brown D.G., Parker D.C., Schreinemachers P., Janssen M.A., Huigen M., Wittmer
825   H., Gotts N., Promburom P., Irwin E., 2007. Comparison of empirical methods for building
826   agent-based models in land use science. *J. Land. Use. Sci.* 2, 31-55.
827   doi:10.1080/17474230701201349

828 Schlüter, M., Baeza A., Dressler G., Frank K., Groeneveld J., Jager W., Janssen M.A., Mcallister R.R.,
829   Müller B., Orach K., 2017. A framework for mapping and comparing behavioural theories in
830   models of social-ecological systems. *Ecol. Econ.* 131, 21-35.
831   doi:10.1016/j.ecolecon.2016.08.008

832 Sun, Z., Lorscheid I., Millington J.D., Lauf S., Magliocca N.R., Groeneveld J., Balbi S., Nolzen H.,
833   Müller B., Schulze J., 2016. Simple or complicated agent-based models? A complicated issue.
834   *Environ. Modell. Softw.* 86, 56-67. doi:10.1016/j.envsoft.2016.09.006

835   Sun, Z., Müller D., 2013. A framework for modeling payments for ecosystem services with agent-
836   based models, bayesian belief networks and opinion dynamics models. *Environ. Modell.*
837   *Softw.* 45, 15-28. doi:10.1016/j.envsoft.2012.06.007

838   Ten Broeke, G., Van Voorn G., Ligtenberg A., 2016. Which sensitivity analysis method should I use
839   for my agent-based model? *J. Artif. Soc. Soc. Simul.* 19, 5. doi:10.18564/jasss.2857

840   Thiele, J.C., Kurth W., Grimm V., 2014. Facilitating parameter estimation and sensitivity analysis of
841   agent-based models: A cookbook using NetLogo and R. *J. Artif. Soc. Soc. Simul.* 17, 11.
842   doi:10.18564/jasss.2503

843   Vasslides, J.M., Jensen O.P., 2016. Fuzzy cognitive mapping in support of integrated ecosystem
844   assessments: developing a shared conceptual model among stakeholders. *J. Environ. Manage.*
845   166, 348-356. doi:10.1016/j.jenvman.2015.10.038

846   Vasslides, J.M., Jensen O.P., 2017. Quantitative vs. Semiquantitative Ecosystem Models: Comparing
847   Alternate Representations of an Estuarine Ecosystem. *Journal of Coastal Research*. 78, 287-
848   296

849   Venkatramanan, S., Lewis B., Chen J., Higdon D., Vullikanti A., Marathe M., 2017. Using data-driven
850   agent-based models for forecasting emerging infectious diseases. *Epidemics.*
851   doi:10.1016/j.epidem.2017.02.010

852   Voinov, A., Jenni K., Gray S., Kolagani N., Glynn P.D., Bommel P., Prell C., Zellner M., Paolisso M.,
853   Jordan R., 2018. Tools and methods in participatory modeling: selecting the right tool for the
854   job. *Environ. Modell. Softw.* 109, 232-255

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

857