Making use of Fuzzy Cognitive Maps in Agent-Based Modeling

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Abstract. One of the main challenges in Agent-Based Modeling (ABM) is to model agents' preferences and behavioral rules such that the knowledge and decision-making processes of real-life stakeholders will be reflected. To tackle this challenge, we demonstrate the potential use of a participatory method, Fuzzy Cognitive Mapping (FCM), that aggregates agents' qualitative knowledge (i.e., knowledge co-production). In our proposed approach, the outcome of FCM would be a basis for designing agents' preferences and behavioral rules in ABM. We apply this method to a social-ecological system of a farming community facing water scarcity.

Keywords: Knowledge Co-Production, Participatory Modeling, Fuzzy Cognitive Mapping, Agent-Based Modeling

1 Introduction

Agent-Based Modeling (ABM) is a dynamic method for understanding and predicting the collective behavior of multi-agent systems, given the motives and preferences of individuals [1]. In principle, ABM requires specifying agents' available *actions*, behavioral *rules*, and decisions' *impacts* in each specific situation. To employ ABM in real world applications, one main challenge is to formalize these three aspects (i.e. actions, rules and impacts) such that the qualitative and quantitative knowledge and decision-making processes of stakeholders will be reflected. Many ABMs avoid addressing this challenge by relying on rational choice theory to describe their agents behavior [2, 3]. However, stakeholders' behavior is usually not purely rational and often far more complex than assumed in such theories [4, 5]. In particular, this is a problematic assumption in cases where preferences and decisions of agents highly depend on environmental dynamics, emerging social norms, and information accessibility. An alternative approach in such cases would be to inform ABM with participatory methods that collect qualitative data from stakeholders.

In this paper, we employ a Fuzzy Cognitive Mapping (FCM) method [6] to formulate and parametrize the qualitative knowledge gained by stakeholders (i.e. co-produced knowledge) and translate the FCMs to be used in ABM (section 2). This methodology is demonstrated with the case of a farming community facing water scarcity.

2 Methodology

In general, FCM method enables collecting and representing stakeholders' knowledge about a particular problem [7]. More specifically, stakeholders' perception about influential variables and causal relations among these variables are represented in a directed graph structure. In this graph, variables appear as nodes (concepts) and causal relations as weighted links (connections) [8]. Below, we introduce a method that enables translating the knowledge represented in FCM for ABM development.

Collecting Knowledge : FCM models are usually developed with a participatory approach. Stakeholders who are familiar with the operation and behavior of the system or specific problem of the system are asked to mention the most important concepts (environmental, social, ecological or economic variables), their causal relations, and weights of the connections (i.e. how much a change of one concept causes a change in another concept) [8]. To be able to use FCM results for ABM, stakeholders should also be asked about their 1) responses (actions) to the system or that specific problem, and 2) causes and impacts of their actions from/on environment variables (conditions and impacts).

Representing Knowledge : The data gathered during the interviews can be categorized and represented in a graph structure as follows (figure 1):

1. Action concepts: which are the concepts mentioned by stakeholders as their responses to the system. For ABM use, they represent the set of possible actions that can be taken by agents. Size of concepts in FCM can be shown by the number of times they have been mentioned by stakeholders. Therefore, size of actions in FCM can represent *order* (*preferences*) of agents required in ABM.
2. Impact concepts: which are output concepts of each action along with their causal network, i.e. direct and indirect impacts of that action. Impact concepts are usually dynamic variables (with changing states) e.g. agriculture production, precipitation or population change.
3. Condition concepts: which are input concepts of each action representing driving forces or causes of that action. Condition actions can be either dynamic—e.g. access to groundwater—or fixed (true/false) variables—e.g. having document or legal permission.
4. Driving connections: connections linking conditions and actions. These connections are not accompanied with causal weights, rather they represent implication and are interpreted as may "lead to" [9].
5. Impact connections: connections linking actions-impacts and impacts-impacts. These connections have causal weights, which reflect direct and indirect impact of actions on dynamic variables.

Having such information, for each action a set of Conditions-Action-Impacts (CAI) can be extracted from FCMs to be used in ABM development. In addition to the sequence of actions and their conditions and impacts, ABM development requires timing of certain actions (frequency of actions and one time actions vs repeating actions), randomness (in behavioral rules of agents) and spatial dimension (in case of varying spatial attributes). Since these aspects can not be represented in a FCM, they should be added via quantitative data, complementary literature review and local knowledge of experts collected during interviews.

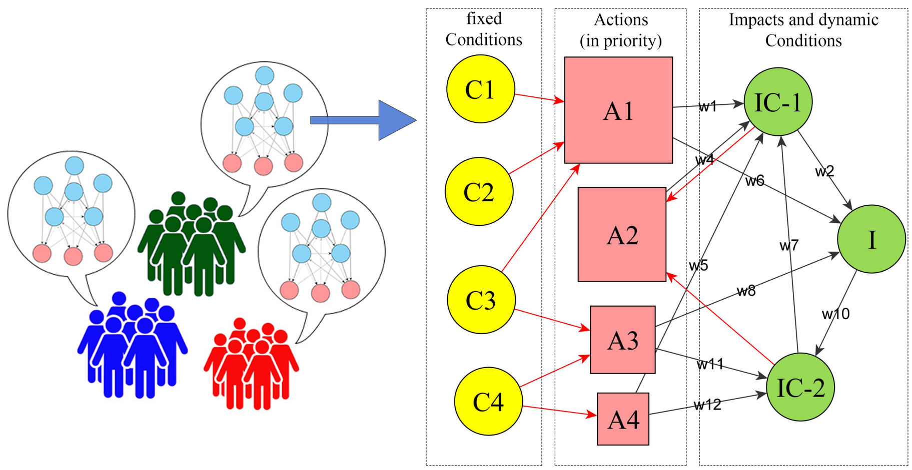

Fig. 1. Translating FCM model into the CAI map. Red and black arrows show driver and impact connections, respectively. A: Action, C: Condition, I: Impact,

3 Case Study and Preliminary Results

To illustrate the proposed methodology, we used the case study of a farming community facing water scarcity in Rafsanjan, Iran. Farmers take different kinds of adaptive actions (based on their social-spatial situation) to satisfy their water demand for pistachio production. Farmers' actions have different impacts (based on location and size of farms) on environmental properties as well as on other farmers decisions and actions. The main objective is to simulate the impact of aggregated farmers' adaptive actions on overall groundwater use in the region. For this objective, we used the FCM data collected in our previous study [10].

Therefore, the individual FCMs were developed by interviewing 60 farmers from different locations and social-economic situations. The farmers' knowledge about the main causes and impacts of water scarcity in their regions, their adaptive actions toward water scarcity, and influence of those actions on other variables of the system have been collected.

Although agents have the same preference, i.e. satisfying their water access, their decision making mechanisms to achieve this goal are significantly different based on their economic situation. Therefore, the farmers' FCMs were developed within three groups of small, medium and large farmers. The group-specific FCMs represent the

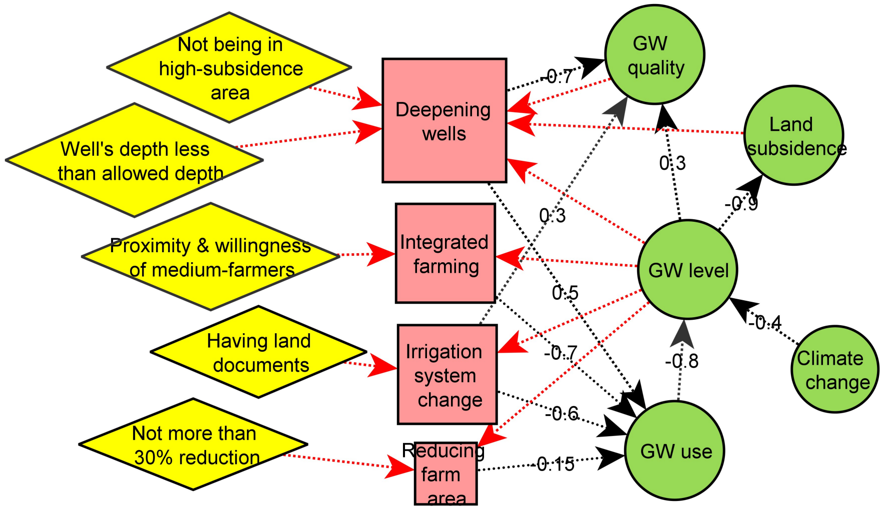

Fig. 2. CAI map of medium farmers based on their FCM. Red and black arrows show driver and impact connections, respectively. GW: Ground Water.

set of farmers' actions to adapt with water scarcity in the order of farmers' preferences (node size in FCM). For example, large farmers' set of actions are *buying small farms* from medium and small holders, *desalination*, *purchasing water* from medium and small holders, *deepening wells*, *reducing farm's area* and *relocating farms* in order. While medium farmers do not afford first three actions of large farmers, their set of actions include *deepening wells*, *integrated farming* with other medium farmers, *irrigation system change* and *reducing farm's area* (figure 2). Small farmers have few options in their set of actions, which are basically *irrigation system change* or *turning off their well pumps* during the night or over winter. In addition to the set of actions and order of actions, CAI maps gave us the conditions for each action as well as the impact weights of each action on environment variables. As figure 2 shows, each action has condition concepts along with driver connections and a network of impact concepts along with impact connections. Thereby, the set of CAI for all actions have been extracted and combined with 1) time scale, 2) randomness and 3) spatial diversity of the system to be used in an ABM model development. For example, randomness has been used for the actions with same priority—e.g. *integrated farming* and *irrigation system change* in medium farmers' FCM—, and time scale and spatial heterogeneity have been added to the conditions of actions to specify the frequency of actions—e.g. *integrating farm* as a one-time actions vs *deepening wells* that may happen several times before reaching the permitted wells depth—and the place of actions—e.g. *desalination* only happens in areas with poor quality of groundwater—(table 1). Preliminary results of this model shows aggregation of groundwater use in different regions of this case study considering different farmers' actions, adaptations and interactions with changing environment.

Having the current situation of groundwater use by farmers, impacts of different policy alternatives can be simulated on changing overall groundwater use of region [3].

Table 1. CAI table of medium farmers.

	Conditions	Actions	Impacts
Priority 1	• Well depth < allowed well depth • Farm location is not in high subsidence and poor GW quality areas	**Deepening wells**	• Direct impacts: GW use • Indirect impacts: GW level, land subsidence, and GW quality
Priority 2	• Medium land in neighbor • Neighbor medium-farmer is willing to integrate his/her farm • Action has not been executed	**Integrating farming**	• Direct impacts: GW use & quality • Indirect impacts: GW level and land subsidence
	• Farmer has land document • Action has not been executed	**Irrigation system change**	• Direct impacts: GW use & quality • Indirect impacts: GW level and land subsidence
Priority 3	• Land size >= 70% initial land size	**Reducing farm area**	• Direct impacts: GW use • Indirect impacts: GW level, land subsidence and GW quality

4 Conclusion

We presented a method that enables translating qualitative co-produced knowledge (from FCM outputs) as an input for ABM development. Our proposed method includes aggregating individual interviews into group-specific FCMs and setting up CAI diagrams that provides inputs for ABM development. We also illustrated the applicability of this method using a case study in a farming community facing water scarcity. However, this method does not provide all information required in an ABM (e.g. temporal and spatial dynamics, stochasticity, ...). Therefore, quantitative and objective data (e.g. from literatures, reports, surveys, historical data) is complementary next to FCM to provide data for ABM.

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[3] Detailed description on implementation of this method and results of case study have been presented in [11, 12]

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