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Policy Option Simulation in Socio-Ecological Systems

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Abstract. Social-Ecological Systems (SESs) i.e. systems linking human behavior and environmental dynamics, are characterized as complex, dynamic and heterogeneous systems. A comprehensive policy simulation in SESs has to consider all these properties. In this paper, we present a conceptual analysis on key aspects of policy simulation in SESs and introduce a combined use of Fuzzy Cognitive Mapping (FCM) and Agent-Based Modeling (ABM) methods as an approach to cover those aspects. We illustrate the applicability of this combined method for policy simulation in the case of a farming community facing water scarcity.

Keywords: Social-Ecological Systems, Policy Making, Fuzzy Cognitive Mapping, Agent-Based Modeling

1 Introduction

In a broad perspective, Social-Ecological Systems (SESs) are characterized as complex adaptive systems [1] in which wicked problems [2] may arise. While *complexity* refers to being nonlinear, causally interactive, heterogeneous and temporally dynamic [3], *wickedness* refers to data-scarce/-uncertain, multi-variable and multi-stakeholder issues [4, 5]. Accordingly, policy making in SES has to consider all these features for a holistic policy option analysis prior to their implementation in the real world [3].

Therefore, based on our experience in SESs and following complex systems' and wicked problems' literatures [1–3, 6], we categorized three main aspects that are essential to be considered in an effective policy analysis in SESs: 1) including consensus-knowledge of stakeholders and their acceptance in policy simulation 2) considering individual and spatial heterogeneity of SESs, and 3) taking into account the time-scale, causal relationships and feedback loops of social-ecological interactions.

In this paper, we first present these three main aspects. Second, we introduce a combined use of Fuzzy Cognitive Map (FCM) and Agent-Based Modeling (ABM) as an approach of policy option simulation that covers all these aspects[1].

[1] See [7] for a brief discussion on technical aspects of our proposed approach. A comprehensive framework that integrates the conceptual and methodological aspects will be presented in the long version.

Finally, relying on the results of a four years project, we presents findings of policy option analysis in a SES with combination of these two methods.

2 Conceptual Analysis

Consensus-Knowledge: In general, using consensus-knowledge of stakeholders in policy simulation—known as knowledge co-production—is a collaborative process that integrates: 1) different stakeholders' knowledge and perceptions of their environmental issues, and 2) possible stakeholders' response (e.g. acceptance and rejection) to that policy [8, 5]. This is particularly useful in policy simulation for SESs' *wicked problems* i.e. ill-formulated problems because of their multi-variables/-stakeholders environment and lack of available data for the whole system [4, 5]. Moreover, knowledge co-production helps to cover divergent knowledge of stakeholders with strong conflicting interests i.e. another feature of SESs' wicked problems [8, 5].

Hence, using knowledge co-production in policy simulation may results in improving policy effectiveness by considering important features of complex and wicked SES problems, i.e. lack of data, multi-variables environment, multi-stakeholders with conflicting interests.

Individual and Spatial Heterogeneity: Individual heterogeneity refers to various types of involved stakeholders in SESs and highlights their different preferences, available actions and long-term goals [9]. Moreover, spatial heterogeneity refers to the various environmental properties in different locations [1]. In policy making for SESs, it is important to not only aggregate knowledge of heterogeneous stakeholders, but also represent their heterogeneity in policy impact analysis. Since, impacts of different policies may vary in different locations and on different individuals. For example, in a water scarce situation different groups of farmers may have different adaptive actions based on their locations and social-economic situation i.e. from buying water and irrigation system change (expensive options) to shrinking farm area (affordable option) or well deepening where aquifer situation allows (location-specific option). Considering social-spatial varieties in such cases results in a policy toolbox that corresponds to the individual and spatial heterogeneity of SESs.

Time-scale, Causal relationship, and Feedback loop: Next to the heterogeneity, these are the main features of complex systems—including SESs:

- In a SES, there are different time scales in variables' changes and agents' actions. For example, slowly changing variables (e.g. population change) vs fast changing variables (e.g. government policies) or high frequency actions (e.g. farm irrigation) and low frequency actions (e.g. buying lands).

- Causal relationships in human-environment interactions represent how a network of social and ecological factors influences humans' decisions and actions, and vice versa. For instance, if farmers start to adapt a new irrigation technology, how much this adaptive action impacts on their groundwater use first and thereby, overall groundwater level and production of region, and eventually vulnerability and emigration of farmers. Capturing causality of SES variables is not possible via empirical correlations or a snapshot of causal relationships at one moment in time [10].

– Feedback loops in SESs are fundamental to understand both direct interaction of agents, i.e. how individual-level behavior and actions influence other individuals' actions, and indirect interaction of agents, i.e. how the outcome of performed behavior or actions impacts other factors of SESs which indirectly reinforce the same or other individual actions.

Considering these three properties in a policy simulation results in capturing the dynamicity of complex SESs.

3 Policy Simulation Models and Results

In this section, we illustrate how the consensus-knowledge of stakeholders can be captured using a participatory method, i.e. Fuzzy Cognitive Map (FCM). Then we show how social-spatial heterogeneity can be addressed using a dynamic modeling method, i.e. Agent-Based Modeling (ABM). Finally, we present how a combined use of FCM and ABM methods can capture all important aspects of policy simulation in SESs. To illustrate the applicability of these methods, we rely on the results of a four year project that studies a farming community facing water scarcity in Iran.

Fuzzy Cognitive Mapping and aggregated knowledge : FCM uncovers the causal relationships between social and ecological factors by representing the SES with nodes (concepts), weighted links (connections), and many feedback loops. Methodologically, it collects the rich qualitative knowledge of stakeholders, aggregates them and represents a semi-quantitative outcome. This makes FCM an appropriate methodology for knowledge co-production. We developed two FCM models of 40 policy makers and 60 farmers in a farming community, to capture their knowledge of causes and impacts of water scarcity as well as farmers' adaptive actions toward water scarcity [4]. Then, the impacts of different policy options (e.g. economic diversification, technology adaptation and monitoring policies) on the SES were simulated. Results of FCM model and simulation in this case study showed that among four policy options suggested by the government in Rafsanjan, farmers strongly believe in the impact of economic diversification on reducing water shortage, whereas the policy makers focus on the role of government control and monitoring policies to deal with water scarcity [4]. This methodology was useful for knowledge co-production in data-scarce situations as well as comparing the acceptability of different policy options. However, it does not represent the individual heterogeneity nor the spatio-temporal dynamics of the SES.

Agent-Based Modeling and interactive agents : Farmers' decisions and adaptive actions toward water scarcity in Rafsanjan can be very different based on their location and economic situation (heterogeneity). For example, large farmers tend to expand their lands and production by buying small farmers' lands and water. On the other hand, medium farmers look for collaborative farming and irrigation mechanisms with other medium-farmers to increase efficiency of their groundwater use. Finally, small-farmers prefer to sell-off or shrink (dry-off) their lands to adapt with water shortage. In this case, ABM [1, 11, 12] has been used to model farmers' collective behavior and simulate its impact on overall groundwater use. However, ABMs often have the problem of identification and justification of agents' behavioral rules as well as the causal relationships and nonlinear feedbacks in human-environment interactions [10, 3]. Hence, we used the FCM's output knowledge for ABM model justifications and to provide causal relationships and feedback loops of SES for ABM development.

Combined FCM and ABM methods and Results : While FCM covered consensus-knowledge and ABM enabled modeling our heterogeneous farming community, only a combination could cover the last aspect i.e. time-scale, causal relationship, and feedback loop. Time scale in agents' actions and environment variables could be represented by ABM, whereas causal relationships and feedback loops in social-ecological interactions were shown by FCM. Moreover, with this combined method, we could simulate impact of policies considering preferences, interactions and dynamic response of farmers over time which resulted in different outcomes comparing with those of FCM simulation. For example, real impact of the irrigation system change policy i.e. subsidizing new irrigation system for farmers, depends on priority of this action for farmers comparing to their other possible adaptive actions. Results of policy option simulations with a combined FCM-ABM modeling methodology showed that 1. policy options (i.e. government control and monitoring, adapting new technologies, and participatory water management) have different long-term impacts in different locations of our case study, 2. overall, policy of facilitating people participation in management and control of their groundwater use has the highest impact in reducing groundwater use. Surprisingly, adapting new irrigation technologies does not have any significant impact on reducing overall groundwater use in the region.

4 Conclusions

Policy option simulation in SES has to consider various features of complex adaptive systems and wicked problems. It is essential for an effective policy analysis in a SES to 1) include consensus-knowledge of stakeholders and their acceptance in policy simulation 2) consider individual and spatial heterogeneity of SESs, and 3) take into account the time-scale, causal relationships and feedback loops of social-ecological interactions. FCM can cover the first aspect, ABM the second, and only combination of these two can provide all three aspects. However, some social-political aspects, e.g. cultural differences and power relations, can be investigated in future studies.

References

1. Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A.: Spatial agent-based models for socio-ecological systems: Challenges and prospects. Environmental modelling & software **45** (2013) 1–7
2. Xiang, W.N.: Working with wicked problems in socio-ecological systems: Awareness, acceptance, and adaptation. Landscape and Urban Planning (110) (2013) 1–4
3. Levin, S., Xepapadeas, T., Crépin, A.S., Norberg, J., De Zeeuw, A., Folke, C., Hughes, T., Arrow, K., Barrett, S., Daily, G., et al.: Social-ecological systems as complex adaptive systems: modeling and policy implications. Environment and Development Economics **18**(2) (2013) 111–132
4. Mehryar, S., Sliuzas, R., Sharifi, A., Reckien, D., van Maarseveen, M.: A structured participatory method to support policy option analysis in a social-ecological system. Journal of environmental management **197** (2017) 360–372
5. Olazabal, M., Chiabai, A., Foudi, S., Neumann, M.B.: Emergence of new knowledge for climate change adaptation. Environmental Science & Policy **83** (2018) 46–53
6. Liu, J., Dietz, T., Carpenter, S.R., Alberti, M., Folke, C., Moran, E., Pell, A.N., Deadman, P., Kratz, T., Lubchenco, J., et al.: Complexity of coupled human and natural systems. science **317**(5844) (2007) 1513–1516
7. Mehryar, S., Schwarz, N., Sliuzas, R., van Maarseveen, M.: Making use of fuzzy cognitive maps in agent-based modeling. In: Proceedings of the 14th Social Simulation Conference. (2018)
8. Gaddis, E.J.B., Falk, H.H., Ginger, C., Voinov, A.: Effectiveness of a participatory modeling effort to identify and advance community water resource goals in st. albans, vermont. Environmental Modelling & Software **25**(11) (2010) 1428–1438
9. Macy, M.W., Willer, R.: From factors to factors: computational sociology and agent-based modeling. Annual review of sociology **28**(1) (2002) 143–166
10. Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., Janssen, M.A., McAllister, R.R., Müller, B., Orach, K., et al.: A framework for mapping and comparing behavioural theories in models of social-ecological systems. Ecological economics **131** (2017) 21–35
11. An, L.: Modeling human decisions in coupled human and natural systems: Review of agent-based models. Ecological Modelling **229** (2012) 25–36
12. Matthews, R.B., Gilbert, N.G., Roach, A., Polhill, J.G., Gotts, N.M.: Agent-based land-use models: a review of applications. Landscape Ecology **22**(10) (2007) 1447–1459