Groundwater

Technical Commentary/

Groundwater Modeling with Stakeholders: Finding the Complexity that Matters

by Juan Carlos Castilla-Rho

Introduction

Many groundwater modelers believe that numbers and statistics are all they need to deliver to inform decision making. Representing competing stakeholder perspectives however remains the missing element in groundwater models of many important systems that stakeholders would urgently like to forecast and test interventions upon. In this article, I argue that agent-based modeling (ABM) is well-suited to address this challenge due to its ability to engage stakeholders in our scientific investigations. When used as "management flight simulators", ABMs can help stakeholders better understand the impacts and feedbacks of their decisions, reveal trade-offs, and generate systematic comparisons of alternative management and policy options under complexity and uncertainty. The opportunities, limitations, and our ongoing efforts to unleash the full potential of agent-based policy simulators in the field of groundwater hydrology are discussed.

First Things First: We Are Dealing with Complex Systems

We could develop more useful decision-support tools by incorporating the breadth of perspective of "complex systems" thinking via participatory ABM. In this approach, decision-support games are used to enable stakeholders explore, visualize, and interact with groundwater policy simulators in real time, to elicit their preferences for different impacts and management options (Wu and Lee 2015).

To see how this is possible, we need to start by acknowledging that the systems that groundwater hydrologists and stakeholders are concerned with—that is, coupled systems of people and water—are complex systems (Miller and Page 2009). A complex system has three key features. First, it has components that are independent and interacting. Second, there is often some selection process at work on those components and on the results of their interactions. Third, variation and novelty are constantly being added. A groundwater system is far from simple: the hydrogeology, the climate, the mining companies, the farmers, the farming practices, the crops, the soils they grow on, the markets where they are sold in, the water regulations, and the acceptance of these regulations by landowners all interact and change over time. This is a complex system.

This insight has profound implications for management and policy decisions. Critically, complex systems can cross "tipping points" where they start behaving in a different and often undesirable way (Walker and Salt 2012a). The onset of land subsidence and dryland salinity are examples of tipping points in a groundwater system. Another, perhaps more profound implication, is that complex systems are virtually impossible to control or hold in an optimal state (Walker and Salt 2012b): it is possible to control parts of the system for a limited time, yet never be in control. Complex systems also exhibit emergent behaviours, meaning that outcomes cannot be predicted from the properties and interactions of the system's components (Miller and Page 2009). We might spend decades designing laws and regulations to limit groundwater abstraction, with no certainty about the response of landholders when these regulations are finally introduced (Glodzik 2017).

ABM to the Rescue

ABM is a unique approach to study complex social systems through the analysis of computer simulations (Zellner 2008; Reeves and Zellner 2010). It is different from other forms of modeling in that real-world people, entities, and groups are represented as heterogeneous decision makers (agents) that interact between themselves

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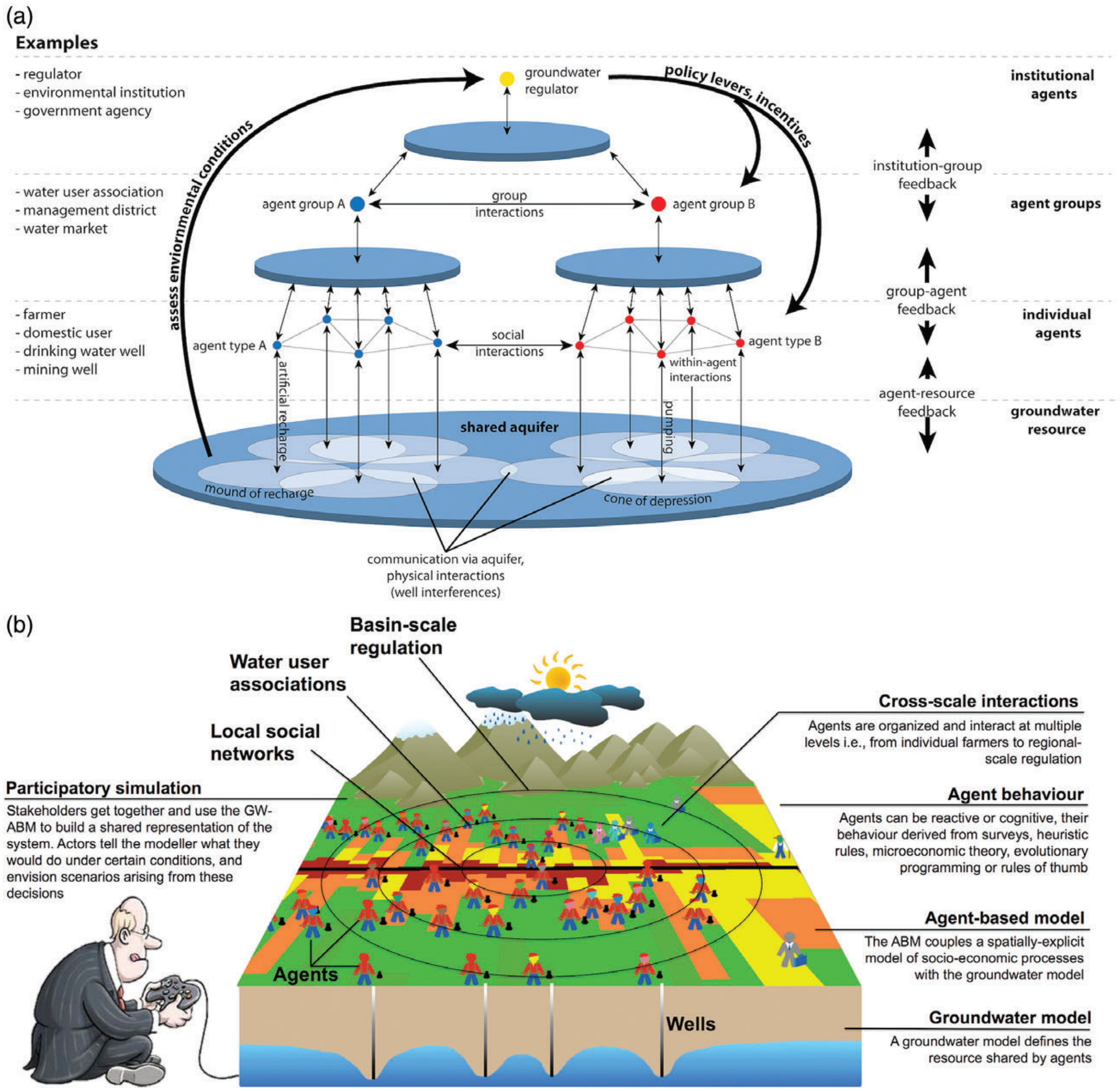

Figure 1. A conceptual framework for groundwater ABMs. (a) Agents, scales of decision making and interactions (Castilla-Rho et al. 2015). (b) The mine-landowner problem implemented in a groundwater ABM.

and with their environment (in our case, the groundwater hydrology), leading to emergent system outcomes. Although assumptions about agent behaviors and interactions may be simple, the results are seldom obvious (Epstein and Axtell 1996; de Marchi and Page 2014; Macal 2016). The goal of ABM is not prediction: it is aiding intuition, seeing interconnections, asking what-if questions about future behaviors, and being creative about system redesign (Meadows and Wright 2008; Miller and Page 2009). Our community has only recently began reaping the benefits of this modeling practice (Reeves and Zellner 2010; Barthel et al. 2012; Mulligan et al. 2014; Castilla-Rho et al. 2015; Noël and Cai 2017).

A simple illustrative example is helpful in understanding what ABMs are. I will use the mine-landowner water resources problem described in (Ferre 2017), where a mine aims to dewater an ore body located in a shallow unconfined aquifer and nearby landowners are concerned about the impacts of the proposed pumping. The agents in the ABM would be the mine (operating a network of production wells), the landowners, the regulator, and any groundwater-dependent assets (e.g., wetlands, riparian vegetation) that could potentially be affected by the mine's operations. All of these agents can be made as diverse as they are in the real-world. For example, landowner agents can be programmed to represent different agricultural practices (e.g., crop choices and irrigation technology), and varying degrees of tolerance and concern about impacts on their wells. Further, each agent can operate under different decision-making strategies (optimize capital returns, imitate others, a rule-of-thumb, etc.) and constraints (well depth, local hydrogeology, crop choice/water requirements, proximity to a wetland, etc.). The interactions between landowner agents can be modeled, for instance, using opinion diffusion models and social networks, by which agents can adjust their tolerance for impacts on the landscape, or alter their decision-making strategies in response to changing groundwater conditions. Based on the simulated environmental condition of agents that represent environmental assets and the economic performance of landowner agents, the regulator agent may choose between a number of management decisions such as amending water allocations, providing landowner subsidies, altering water trading rules, or establishing well protection areas. Figure 1 presents a conceptual framework for developing groundwater ABMs, like the one described above.

Groundwater ABMs enable us to conduct management experiments that would be either impossible or impractical to deploy in the field. In developing the "Groundwater Commons Game" (Castilla-Rho et al. 2017), for example, we tested hundreds of permutations of monitoring and enforcement powers in three regions currently experiencing long-term groundwater depletion: the Murray-Darling Basin (Australia), the California Central Valley (USA), and the Punjab (India and Pakistan). In this work, we combined principles of cognitive science, human cooperation, and collective action, to figure out whether and when farming communities might comply with groundwater conservation policies. Our findings were indeed surprising: collective attitudes towards groundwater conservation policies are governed by tipping points. Using the ABM, we were able to characterize and examine these tipping points in relation to cultural values and human behavior, leading us to identify a number of interactions and nonlinearities in the system that might exploited to trigger compliance with groundwater conservation. With these new insights in hand, our knowledge of the system became a little more complete, and we learned how to look for new leverage points for change.

Eliciting Preferences: Bring All Stakeholders into the Room, but Leave Utility Functions Out

The first challenge that the 2016 Darcy Lecture laid out is that we need to have active conversations with stakeholders to identify which system responses have the greatest influence on their decisions, in other words, define the benefits and costs that stakeholders expect due to predicted system responses (Ferre 2017; Peeters 2017). The Achilles' heel of this approach, however, is defining preferences using utility functions.

We need to remind ourselves that stakeholders are part of a complex system. Groundwater and its many users are immersed in dynamic, nonlinear feedbacks and collateral interactions at multiple scales. In this context, we cannot expect stakeholder preferences to be predictable or easily quantifiable, but constantly evolving in response to social, cultural, political, economic, environmental, and regulatory drivers and constraints. It is often assumed when applying utility functions that: (1) stakeholders have fixed preferences; (2) that these preferences are the same for everyone; (3) that people have complete information about the system at any given point in time; and (4) that people are fully rational optimizers (Epstein and Axtell 1996). Decades of research on human behavior and practical experience suggests otherwise (Simon 1955; Gigerenzer and Selten 2002; Gigerenzer 2007; Todd and Gigerenzer 2012). It is not surprising that *Socio-Hydrology*—the new science of people and water (Sivapalan et al. 2012; Sivapalan 2015)—has set out to redefine the way stakeholder preferences and decisions are represented in hydrologic models.

The way we currently develop and apply groundwater models makes it practically impossible to meaningfully take stakeholders and their preferences into account in defining the outcomes of concern. We make assumptions about the system and what is important, we model, we write a report, make a presentation, and then we leave. We can, and should, do this more collaboratively (Guthke 2017 makes a similar point) by involving stakeholders in identifying those important outcomes (Ferre 2017), as they are unlikely to *know* a priori what could be outcomes that really concern them. I believe we can go a long way in dealing with these issues using participatory groundwater ABMs.

Learning about the System through Participatory Modeling

I colloquially refer to participatory groundwater ABMs as "management flight simulators." Just like pilots use flight simulators to hone their judgment and make sound decisions in the face of uncertain flight conditions, a management flight simulator allows stakeholders to identify robust policy options under uncertainty. The management flight simulator becomes a laboratory in which a wide range of policies, decisions, and models can be tried and tested, without the risk of making mistakes on the real groundwater system. The idea is simple: groundwater modelers and stakeholders get together to describe the system, conceptualize and develop an ABM of given problem, and subsequently use this ABM to test policy interventions, interpret simulation results, suggest scenarios, and propose solutions. There are multiple benefits from using this technique, including a high degree of ownership and motivation towards change for the people involved in the modeling process (Ruankaew et al. 2010). The proposed approach is presented in Figure 2, and it relies on the affinity of ABM to intuitive visual representations of complex systems and user-friendly interfaces. These features have been effectively used to engage stakeholders in formulating policy decisions to many environmental problems (Poteete et al. 2010, Voinov and Bousquet 2010; Etienne 2013).

The real power of participatory modeling rests in the possibility to visualize system trajectories (Figures 2 and 3). This means that the ABM has the ability to simulate and graphically portray the most likely states of the system for all outcomes of concern (e.g., economic,

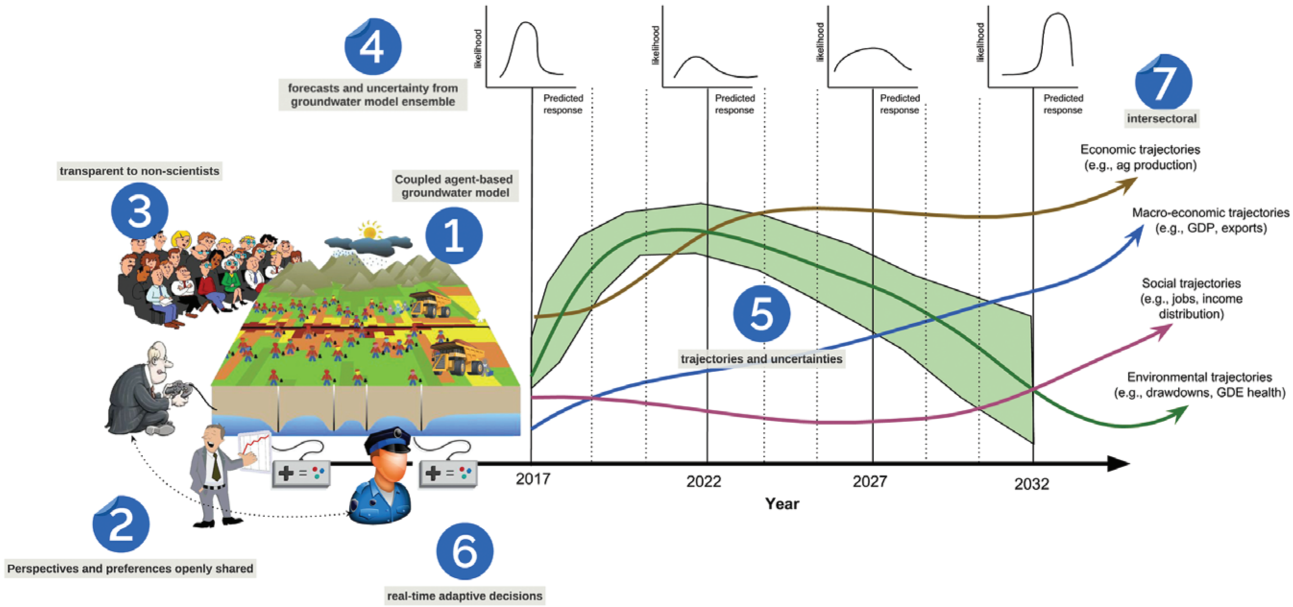

Figure 2. The proposed approach to integrating scientific uncertainty and stakeholder valuation in groundwater studies. (1) An agent-based policy simulator is coupled with groundwater model(s). (2) The coupled model is deployed in a participatory modeling activity where multiple stakeholder perspectives and narratives are openly shared. (3) The activity can also be attended and receive input by an audience of nonscientists (journalists, politicians, media, etc.). (4) During the simulation, game play decisions are made in light of scientific uncertainty provided by advocate groundwater models. (5) System trajectories are graphically portrayed and evaluated by stakeholders to make adaptive decisions during the simulations (6). (7) The ABM represented intersectoral trajectories, meaning that all stakeholder concerns (context) are incorporated to game play decisions.

social, environmental, regulatory, etc.). To me, this is the key to making better decisions under uncertainty. Trajectories, as opposed to point estimates and statistical distributions, tell a story about where the system has been and where it might be headed. As their physical counterparts, trajectories have inertia and may be difficult to correct in the short term. It is important that these dynamics are communicated and understood by all stakeholders, and then incorporated into their decisions.

Figure 3, drawn from our recent work on the Groundwater Commons Game (Castilla-Rho et al. 2017), demonstrates the mapping of system trajectories and their uncertainty using an ABM. A simple participatory activity using this ABM would begin by showing participants a mean trajectory estimate (Figure 3a) of an outcome of concern, for example, groundwater drawdowns, as influenced by the percentage of farmers that comply with their water allocations. Then, we could simulate and present stakeholders with an ensemble of trajectories from one particular assumption about the propensity of farmers to report neighbors that pump water illegally and how important it is for them to maintain a good reputation (Figure 3b). The graphic clearly captures the complexity that emerges from farmer decisions and interactions and improves the picture depicted by the single trajectory. This ensemble of trajectories, however, still underestimates the complexity of the groundwater management problem at hand. This is shown in Figure 3c when we simulate a marginal change in preferences for reporting and reputation, which has the effect of spreading system trajectories over a wide range of possible outcomes. Although these ensembles of trajectories help visualize and clarify the complexity of plausible futures, they are rarely elaborated or reported, given that their uncertainty may appear uninformative to decision makers. To overcome this, we can take the analysis one step further by studying simulated trajectories under a wide range of assumptions, and mapping them into so-called *policy landscapes* (Bankes 2002). Figure 3d presents one such visualization. These policy landscapes reveal the hidden structure in the system's behavior.

Participatory simulation forces us to approach the groundwater modeling exercise differently. In the traditional approach, we collect and process all the knowledge and data *before* the analysis begins; scenarios are established a priori and pumping rates follow a predetermined schedule throughout the simulation. In contrast, when ABM is used interactively, knowledge, data, preferences and decisions *emerge and are used throughout the course of the iterative modeling activity*. A powerful collaboration between stakeholders, hydrogeologists, and the ABM arises when the computer's ability to execute large number of experiments is combined with the ability of humans to recognize patterns and see the big picture (Bankes 2002). This problem-solving strategy provides the necessary bridge to integrate contextual, qualitative information about people's preferences—knowledge that would be otherwise difficult to encode in an equation, probability distribution or utility function—with the more quantitative, scientific information captured by the groundwater model.

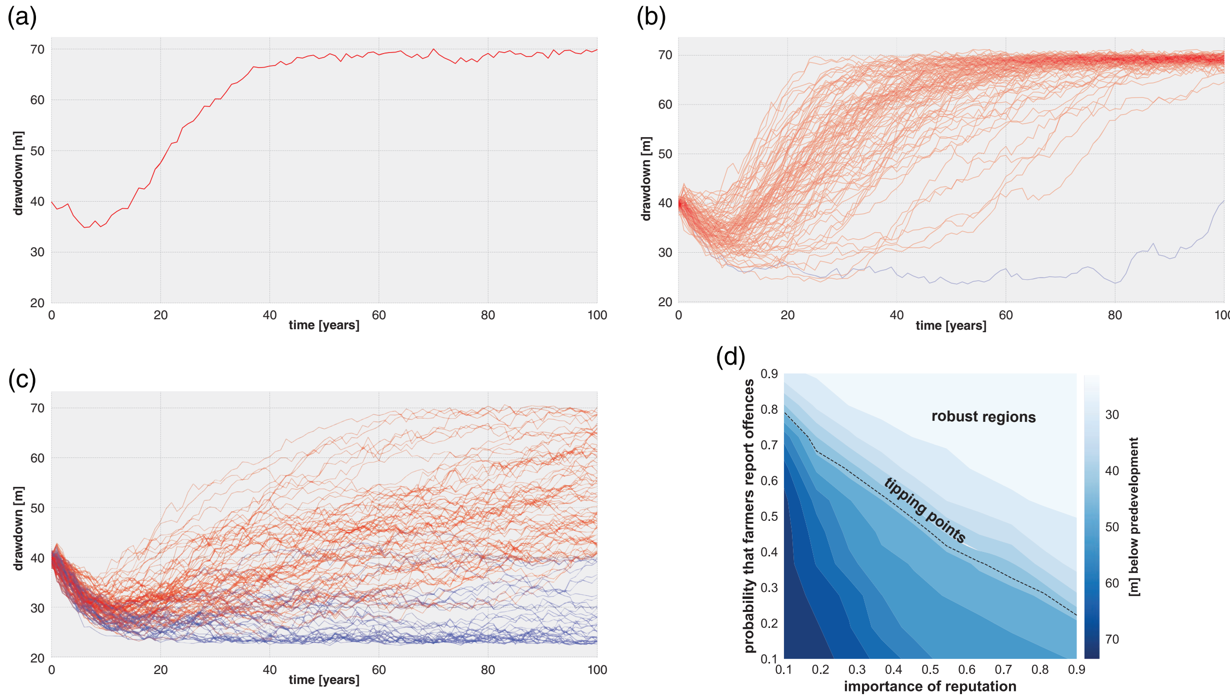

Figure 3. The concept of system trajectories. (a) Single trajectory of groundwater drawdowns under lax regulation provides little information. (b) An ensemble of possible trajectories when the ABM is run hundred times to account for stochasticity in agent's decisions provides partial indication of uncertainty. Note the two trajectories in blue where depletion does not occur despite lax monitoring and enforcement. (c) Feedbacks and nonlinear interactions in the ABM give rise to emergent behaviors when the probability that agents report offenses is increased by 20%. (d) The underlying structure of system trajectories can be revealed by mapping trajectories into "policy landscapes."

Instead of summarizing the outcomes of a groundwater study in a written report, the participatory modeling activity becomes a living document of the collective exploration and decision-making process that takes place around the ABM. It stands to reason that stakeholders will find it easier to relate to the dynamics simulated in these kinds of models, provided they can see themselves explicitly represented as an "agent" within the ABM. Crucially, we can create a space where the multiple stakeholder perspectives and narratives can be openly shared and challenged, in light of our best-available science. Within this space, stakeholders are more likely to understand the full range of futures they face and identify the main forces that drive these alternative futures.

Participatory modeling experiments can be instantiated, paused and rerun any number of times. This enables participants to gradually test and craft more robust decision which perform well under various future scenarios, rather than engineering "optimal" decisions which maximize performance under a single scenario (White 2017 makes a similar point). Preferences are revealed when stakeholders make "real-time" decisions during game play, as a result of their objective and subjective evaluation and weighting of simulated system trajectories. This stands in stark contrast to eliciting stakeholder preferences via surveys and interviews (the traditional approach), where the true preferences may never be revealed or stated.

Conclusion

Armed with the above concepts and tools, we are in a better position to project stakeholders to alternative futures where decisions need to be made in light of uncertainty. The fact we often forget is that groundwater hydrology is only one of the many inputs into the modeling process and it is no more and no less legitimate than less objective human factors. The argument that the vested interests and preferences of stakeholders are not logical and that therefore cannot be incorporated into to groundwater models needs to be challenged. Economists would argue that few things are as logical as stakeholder preferences. However, these are things that can be, and should be, modeled and plugged into the larger decision support system. Yes, we need robust and well-calibrated groundwater models to engender trust and support in our work, but the flipside of that argument is that those models will be of little value without effective stakeholder engagement.

We have already taken the first steps to develop the framework and the software needed to deploy participatory agent-based groundwater modeling applications (Castilla-Rho et al. 2015), yet there is still work to be done in order to couple "artificial agent societies" to groundwater models that incorporate more complex hydrogeological processes, including surface-groundwater interactions, three-dimensional flow, and contaminant transport. The main challenge is to achieve this sort of coupling in such way that participants can interact in real time with the

ABM during a workshop or meeting activity. The integration of model emulators, analytic element modelling and parallel computation will play an important role in increasing the speed, performance and realism of these participatory simulations. Overall, using ABM to incorporate stakeholders into the modeling workflow has great potential to fill an important gap in the groundwater modeling toolbox, and most importantly, help us find and deal with the complexity that matters.

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