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Agent-Based Socio-Hydrological Hybrid Modeling for Water Resource Management

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Abstract Hybrid socio-hydrological modeling has become indispensable for managing water resources in an increasingly unstable ecology caused by human activity. Most work on the subject has been focused on either qualitative socio-political recommendations with an unbounded list of vague factors or complex sociological and hydrological models with many assumptions and specialized usability. In this paper, we propose a simple agent-based socio-hydrological decision modeling framework for coupling dynamics associated with social behavior and groundwater contamination. The study shows that using social health risk, instead of contaminant concentration, as an optimization variable improves water management decisions aimed at maximizing social wellbeing. The social models and computational framework are designed with enough flexibility and simplicity to encourage extensions to more general socio-hydrological dynamics without compromising either computability or complexity for better data-/model-driven environmental management.

Keywords Sociohydrology · Decision support systems · Computational social dynamics

1 Introduction

Coupling social and ecological dynamics for environmental management has become increasingly popular in recent years, due to a combination of an increase in computational

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power and an increase in human-caused environmental problems. Various such hybrid systems known as socio-ecological systems (SES) (Schlüter et al. 2012; Boone and Galvin 2014), socio-hydrology (Sivapalan et al. 2012), integrated water resources management (IWRM) (Biswas 2008), etc., aim to provide a decision support system (DSS) for improving the management of environmental resources. The modeling effort in these fields has been motivated by the need to account for social behavior under certain environmental circumstances. In practice, this helps improve socio-political decisions that aim to restore the equilibrium of the ecosystem.

In an increasingly human-impacted ecology, quantifying the social response to certain environmental problems should sometimes take precedence over developing new technologies to solve them. For example, social belief about climate change prospectives and awareness about carbon dioxide capture and storage (CCS) technologies have been shown to play a major role in the prediction and risk assessment of those systems (Rayner 2012; Dooley 2013). From a research and educational point of view, the overwhelming complexity of modern technologies necessitates sociopolitical-friendly scientific studies emphasizing health risks and social benefits (Slovic and Weber 2013). Accordingly, social-ecological models also help people (the public, managers, stakeholders and other interested parties) see alternatives and their respective impact on the environment, providing a more concrete motive for action and a reliable reference to vote for political representation.

The need to understand the impact of society on water resources (and vice-versa) has been amplified by recent irreversible water problems including the severe droughts in southern California (Mann and Gleick 2015) and the Middle East (Cook et al. 2016) as well the South Asia and Flint water crises (Hanna-Attisha et al. 2015). Although both social and hydrological dynamics in those situations are very complex, requiring an extensive study of socio-political and environmental factors, a reliable reduced-order model is useful to predict important system parameters in order to guide water resources management decisions (Akhbari and Grigg 2013).

Recently, there has been various efforts to bridge the gap between social and water resources management (Yuan et al. 2014; Nikolic and Simonovic 2015; Akhbari and Grigg 2015; Walker et al. 2015), as well as the gap between theoretical/computational modeling and practical applications (Borowski and Hare 2007). Thanks to an increasing computational power, agent-based models have become popular in social-environmental modeling which need to reflect the complexity of both social behavior and the dynamical interaction between people and their environment. Berger et al. (2007) and Akhbari and Grigg (2015) illustrate the complexity of coupling watersheds with social dynamics using agent-based models that inform water management decisions. Furthermore, such models were used to capture the economic interdependence of water resources and water users (Berger et al. 2007; Yuan et al. 2014). How well those socio-hydrological models reflect real-world dynamics depends on the parameters of interest to be used in decision making. But due to the chaotic nature and complexity of social-ecological systems the choice of pertinent parameters, such as the attributes of the agents, has to be done case by case in a framework where the sensitivity of each parameter can be easily explored by the decision makers. For this purpose, we have developed an agent-based socio-hydrological computational tool in which the attributes of the agents and the rules of social-environmental interactions can be easily configured depending on the system at hand; thus contributing to fill the gap between theoretical modeling and application (Borowski and Hare 2007). In this paper, we illustrate the usefulness of the developed modeling framework as applied to the management of water resources in a contaminated aquifer.

On the hydrological side, accurate and powerful simulation packages have been developed in the last few decades to simulate complex physics processes associated with groundwater flow and transport in geologic media. In this study, we use the Finite Element Heat and Mass (FEHM) code (http://fehm.lanl.gov/), which has been developed and tested at the Los Alamos National Laboratory. On the sociological side, we have developed models and algorithms for agent-based social dynamics, based on those in Bednar et al. (2006), framed as part of a social-ecological system. Accordingly, a hydro-sociological decision support framework combining agent-based social modeling with FEHM is presented below. The developed framework is coded in Julia and is part of the MADS framework (http://mads.lanl.gov/ and https://github.com/madsjulia/Mads.jl). Julia is a high-level, high-performance dynamic programming language for technical computing (http://julialang.org/). MADS (Model Analyses for Decision Support) is a high-performance open-source framework for model-based decision support employing system and complex physics simulation models.

Note that in this study, we use the term 'contaminated water' for water containing contaminants above the maximum contaminant level goal (MCLG) set by the US Environmental Protection Agency (EPA) but below the maximum contaminant level (MCL). EPA determines the MCLG and the MCL based on health effects data (US EPA https://www.epa.gov/ground-water-and-drinking-water/table-regulated-drinking-water-contaminants#one), but 'MCLG's are non-enforceable public health goals', thus vary across the states. This means that the MCLG is a local political and economic issue, as long as the water can still be used because it is below the MCL. Therefore, given that MCLG change according to health data as wells as political and economic issues, this study could also be useful to environmental agencies and stakeholders to evaluate MCLG's for contaminant-impacted water-supply resources.

In Section 2, we define a simplified problem of underground drinking water contamination within a coupled social-ecological system. In Section 3, we develop a computational sociological model that reflects the dynamics of our hybrid system. In Section 4, we describe the Finite Element Heat and Mass (FEHM) package used to simulate the spread of contaminants in the aquifer. Finally, in Section 5, we combine the social and the hydrological models within a feedback control framework and generate supporting results.

2 Problem Definition

The social-hydrological simulation is setup as follows. A small society (a few thousand people) living in a quasi-independent region has a single aquifer as a source of drinking water. Over the years, contaminants have infiltrated the aquifer due to improperly stored waste in its vicinity. Given that the water-supply pumping well is near a contamination plume (see Fig. 1), the contaminant concentration distribution in the aquifer is affected by the pumping rate. In addition, the contaminant concentration in the supplied water depends on the pumping rate, which in turn is controlled by water demand. In the simplest economic case, the pumping rate is proportional to the water demand. Furthermore, in the studied synthetic example problem, the increase in the pumping rate generally causes an increase in the contaminant concentration (Fig. 1).

By properly monitoring groundwater contamination, social regulations are created to limit the amount of pumping from the water-supply well in order to decrease its contaminant concentration, thus protecting the community from its health dangers. This creates

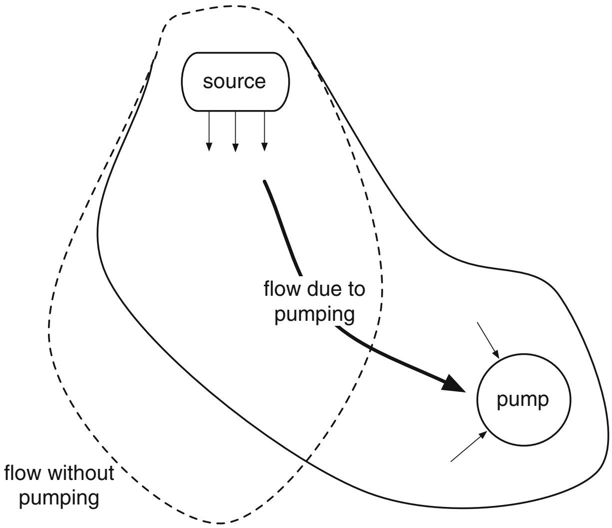

Fig. 1 Basic contamination pumping scenario

a feedback process whereby social demand affects the contaminant concentration via the pumping rate, and the contamination of the groundwater affects the demand by means of socio-political regulations and potential health hazards.

In this study, the water usage from the aquifer is regulated by two modes of policy reinforcement: media and expert influence. The media influence is characterized by spreading information across the population using awareness campaigns at a controllable frequency. The expert influence is characterized by the expert's first hand access to the actual state of the aquifer and to the expert's solid conviction of this state. Regulators, employing experts and using media outlets (as illustrated in Fig. 2), have a hydrogeological understanding of the governing physical processes controlling groundwater and available site data.

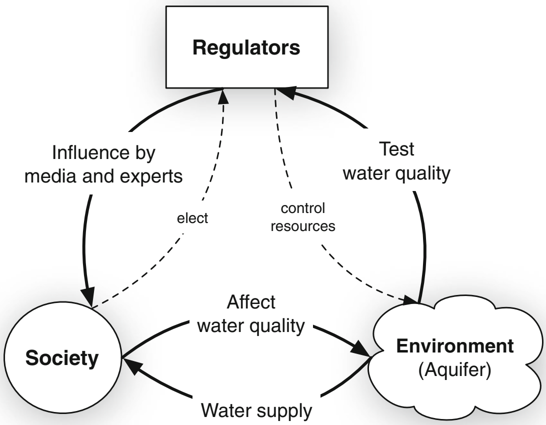

Fig. 2 Feedback model among regulators, society and aquifer

The water-supply pumping rate is controlled by two opposing factors. On one hand, the community depends on the water supplied from the aquifer and to stop using it would disrupt their economy; they would become obliged to buy water from another municipality. So, from the economic point of view water pumping from a local aquifer should be maximized. On the other hand, the more contaminated water is used by the population, the higher the health risks. From the health point of view, the pumping rate should be minimized; in our case, the lower the pumping rate, the lower contamination level in the water supply. As a result, we are faced with a constrained optimization problem such that the aquifer should be used as much as possible as long as it does not endanger the health of the community that uses it. This can be qualitatively expressed as

$$\max_{\{Q:HR(Q)\leq HR_{\text{good}}\}} EI(Q) \tag{1}$$

where EI is a measure of economic independence, HR a measure of health risk, and Q the pumping flow rate. Given the complex nonlinear dependence of the pumping rate on the contamination concentration and the unpredictability of social behavior, this management problem requires a thorough understanding of social and ecological dynamics. Furthermore, the feedback nature of the system requires that the water management is done in a closed loop. In this paper, we suggest using methods in control theory, used in a similar context by Culver and Shoemaker (1992), to regulate expert and media influence in order to optimize contaminant concentration and health risks.

Accordingly, a reliable coupled socio-hydrological data-driven modeling framework is needed. The problem described in this study is relatively simple and is therefore a starting point for building more flexible real-world simulation packages encouraging a better data-informed management of water resources.

3 Social Model

3.1 Preliminaries for Social Dynamics

We develop our social dynamics framework based on the consistency-conformity model proposed by Bednar et al. (2006). The model assumes that (a) the main driving forces of social behavior are *conformity* and *consistency*, and (b) that individuals have a finite set of attributes that define them, e.g. drinking habits, belief in global warming, reading frequency, etc. Those driving forces are phenomenological explanations deduced from many experimental sociological observations (Cialdini and Goldstein 2004; Epstein 2006).

Conformity is the tendency of individuals to mirror their social circle. For example, people tend to have the same dietary habits as their family in particular and as their compatriots in general. Conformity dynamics take some time to propagate into the rest of one's social circle depending on the elasticity of the habits involved. Although conformity dynamics depend on various unknown factors, the main kinematics can be reduced to a simple model that captures the time for conformity as a function of interaction rate. Accordingly, interaction between two individuals in a social context synchronizes their beliefs and actions. For instance, a person tends to have the same drinking habits and using the same drinking source as his family and friends.

Consistency is the tendency of individuals to have consistent attributes by minimizing the contradictions within their own beliefs and actions. The desire to be consistent results from the fact that people try to minimize the discomfort of having inconsistent attributes.

For example, if one believes that a certain type of food is not healthy, they tend to stop eating it. As in conformity, consistency can be reduced to a simple model where each individual matches his own relevant attributes together.

In our study, we use two binary attributes, as shown in Fig. 3. Belief in 'tap water contamination' and 'usage of tap water': one can either believe that the tap water is contaminated or not, and one can either drink the tap water or not. The belief attribute is the one through which people are informed about tap water contamination by certain informative events that propagate in society via conformity dynamics. Having two attributes ensures that people who believe that the water is contaminated do not automatically stop using the water due to the inertia of their habits, but rather take some time to match their belief and usage attributes via consistency dynamics. The usage attribute is the one contributing to water demand.

This simple but powerful social model makes it very easy to increase the complexity of the dynamics by simply adding attributes and the rules that relate them. Also, in a more realistic light, the 'usage of tap water' attribute can be reinterpreted as using a residential water filtration system or not; except in this case, the pumping rate would not be affected by social behavior, making the problem significantly simpler.

Based on this computational framework, we develop models that organize the population of a society into interacting users and regulators, as shown in Fig. 2. Regulators, being part of a governmental or social management institution, influence people's opinion (i.e. flip their belief bit) by informing them about the state of contamination in the aquifer. Consistency dynamics takes care of changing their usage habits (or bit). In the following, we postulate two ways of influencing people's belief of 'tap water contamination':

1. Expert influence: a set of people with access to contaminant concentration data in the pumped water, have an unwavering knowledge (i.e. fixed belief bits) of water contamination, thus acting as a source of factual belief in society.
2. Media influence: a hypothetical external media outlet with an equally precise knowledge of water contamination, persuades (i.e. flips the belief bit of) a finite set of individuals in the population at every broadcasting event.

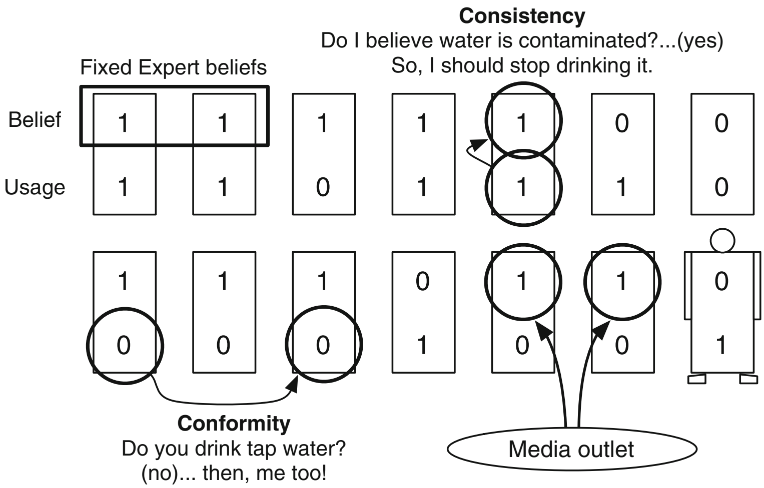

Fig. 3 Summary of social dynamics

Those two simple ways of affecting public opinion can be superposed into a combined expert-media influence.

3.1.1 Expert Influence

Given a population that initially uses the water from a local supply well, the pumping rate at the well is assumed to operate at its maximum capacity. At some point in time, a small portion of people in the population, so-called 'experts', change their belief attribute upon detection of contaminants in the water supply. In this model, the belief of the experts is assumed to be fixed and unaffected by the rest of the population or by their own usage habits.

In this context, a useful measure of "belief diffusion" in society is the time it takes a single expert to transform a community into a fully conforming-consistent society that match his belief. A society converges to a fully conforming-consistent (with all its individuals having attributes [1, 1] or [0, 0]) after many iterations of full social interactions. In every full social interaction, an individual either conforms his belief to another's or equates his own attributes once. The dynamics are illustrated by this example (see Fig. 3). Say an agent A who believes that the water is contaminated and does not drink it (with attributes [1, 1]), meets with agent B who drinks the water and does not believe it is contaminated (with attributes [0, 0]). Agent A influences agent B's opinion about tap water contamination, thus changing his attributes to [0, 1]. However, Agent B still drinks the water due to the inertia of habits. Later, agent B's usage habit can be influenced by C who believes that tap water is contaminated but does not drink it, with attributes [1, 0], making B's attributes [1, 1]. Before interacting with C, B can also change his usage attribute (from [0, 1]) to match his belief attribute (to [1, 1]), because he's a rational agent (i.e. by consistency dynamics). Normal individuals in a society can influence each other equally (A can influence B as much as B can influence A). Experts, however, can only influence other people's beliefs without being influenced by anyone. Therefore, eventually, everyone will come to believe what experts believe, and will also change their habits accordingly.

In order to characterize the 'diffusivity' (or the rate of spread) of belief and usage attributes, we simulate the number of full social interaction steps it takes a community of 200 people and one expert to converge. Here, the choice of the $1/200$ expert-to-people ratio is arbitrary because the purpose of this preliminary experiment is to reveal the qualitative characteristics of the social dynamics. At the initial time, when everyone believes that tap water is clean and uses it, the unaffected belief of the expert is switched to 'believe water is contaminated'. Therefore, this experiment is akin to a step response in the context of expert dynamics.

Knowing that the dynamics are stochastic, we perform this simulation 100,000 times to deduce the distribution of time to convergence; it represents the discrete probability density function when normalized. The histogram in Fig. 4 shows that this distribution is binomial. The tail of the distribution shows that the time to a full convergence might take much longer than expected due to the finite probability that some people will never conform.

3.1.2 Media Influence

In contrast to expert influence, a media oriented approach to spreading information does not assume a set of individuals in society to have fixed beliefs. In this model, a randomly chosen portion of the population is persuaded by media outlets (e.g. advertisements, fliers, awareness campaigns) that the water is contaminated. As expected, the frequency of informative

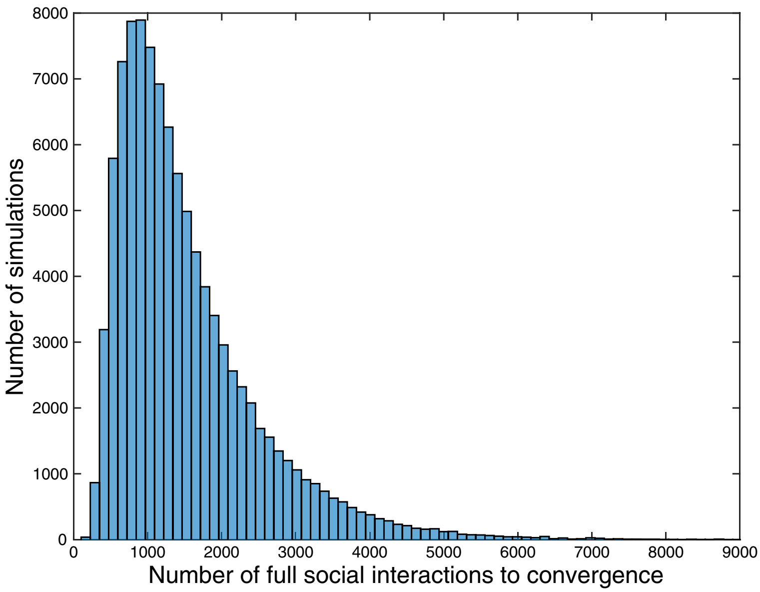

Fig. 4 Expert belief diffusion: distribution of time steps to convergence in a community of 200 people and 1 expert

events correlates positively with the convergence rate. Here, individuals are persuaded in steps assuming they are done in discrete chunks by, for example, advertisements on TV or distribution of fliers once a month.

3.2 Social Hierarchy and Generalized Consistency-Conformity Dynamics

Expert and media dynamics take into account the organization of a society into regulators and users. However, they do not take into account the multi-scale social structure of users which makes their interactions very heterogeneous thus hampering the smooth propagation of beliefs. In reality, it is much more likely for someone to interact with a relative, friend or acquaintances rather than a random person. Social networks today make it possible to get accurate data on social connections from which interaction likelihood can be calculated. Accordingly, a social network can always be transformed into a classification tree according to the probability of interaction, as illustrated in Fig. 5. In this representation, the nodes act as gateways of interaction having a decreasing probability as one gets closer to the top.

Furthermore, this hierarchy unifies conformity and consistency social dynamics into a coherence tree, where consistency is a property of the lowest branches and conformity a property of those above it.

3.3 Social Dynamics Results

Before doing any coupling of sociology with hydrology, we need to understand the general trends of social response to media and expert influence. Becoming familiar with the qualitative response of the average social behavior helps with improving management strategies aimed at making the population most compliant to expert opinion and media outlets. In particular, the rate of propagation of usage habits and beliefs are one of the principle parameters to be considered in the context of socio-hydrological decision making.

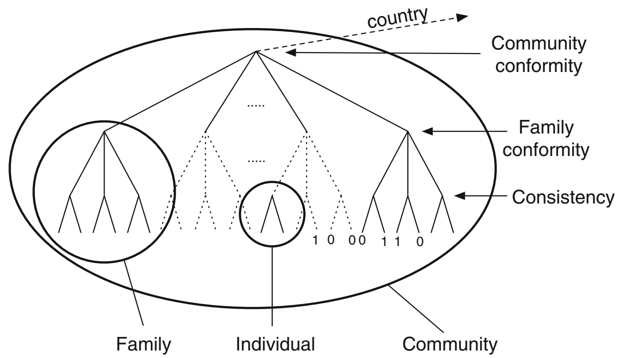

Fig. 5 Simplified representation a social hierarchy

Should we use more awareness campaigns or employ more experts to prevent the population from panicking at the news that the water is contaminated? Which management decision would minimize the time before optimal water usage is achieved?

Some of those questions become clearer when we compare the social response of the various models developed in the previous sections. Given the fact that each agent-based simulation is inherently stochastic, we run multiple realizations to deduce the average behavior, as shown in Fig. 6. In this case, we compare expert dynamics (for populations where 3% and 6% of the people are experts) and media dynamics for both hierarchical and unstructured populations. It can be seen that expert dynamics in a hierarchical population requires much more time for convergence than in an unstructured population. However, the opposite effect is observed in media dynamics where the hierarchy is more conducive to belief diffusion. This shows the different impact that a hierarchy of interactions has on media and expert dynamics.

4 Hydrological Contamination Model

We apply physics-based model to predict the contamination of water supply based on the production rate of a water-supply wells. The groundwater flow and transport in the aquifer

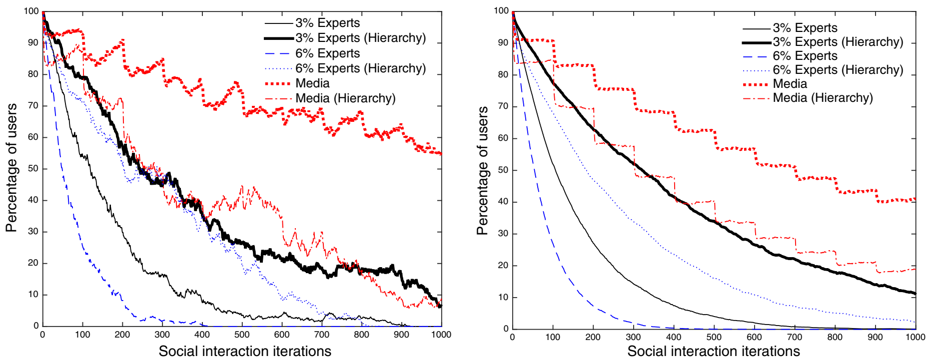

Fig. 6 Comparison of single realization (*left*) and mean (*right*) hierarchical and non-hierarchical media and expert social dynamics

is simulated using the code FEHM (Finite Element Heat and Mass Transfer code; https://fehm.lanl.gov). The numerical model is applied to predict a spatial and temporal behavior of a contaminants plume originating with a constant mass flux from a source with a radius of 100 $[m]$. The model is executed to make predictions over a time period of 100 to 200 years (depending on the case studies discussed below) since the contaminant was released. Most of the simulations are conducted using a model assuming homogeneous aquifer parameters. The model simulates advection and diffusion of contaminants in the aquifer. The model parameters are listed in Table 1.

Note that the water supply well is located at the periphery of the contamination plume (see Fig. 1). When the well is not pumping, the groundwater at the well contains a background contamination concentration. However, due to the proximity of the contaminant plume to the well, the concentrations increase with the pumping rate, as shown in Fig. 1.

5 Coupled Socio-Hydrological Contamination Model

In this section, we demonstrate the use coupling of the social and hydrological models. First, we define the model parameters. Second, we show the incompleteness of making open loop decisions without a regular feedback from the state of the aquifer and that of the population. Third, we demonstrate the use of 'Proportional-Integral-Derivative (PID) decision making' related to water resource management in analogy to its counterpart in control theory in decision support systems. Finally, we prove the necessity of using health risk-based control rather than contamination control.

5.1 Model Parameters

In the groundwater flow and transport simulations, the pumping rate is assumed to be proportional the public demand as in a free market. The social sample is a community of 10,000 people using 26.6 L/day each. The interaction frequency of people communicating their beliefs about water contaminations is assumed to be once every 15 days. The age limit of each individual is assumed to be 100 years old. The contaminants are released in 1964 and are tracked throughout 100 to 200 years depending on the study. The background concentration of contaminants is 5 parts per billion (ppb). In general, the rates of consistency and conformity are difficult to identify and uncertain (Bednar et al. 2006); in our experiments, we assume that people tend to be slightly more conforming (65%) than consistent (35%).

Table 1 The parameters used in the flow and transport model

Parameter	Value
Hydraulic Gradient	0.001 [–]
Hydraulic Conductivity	3.0×10^{-3} $[m/s]$
Specific Storage	2.2×10^{-4} $[1/m]$
Transport Porosity	0.12 $[-]$
Longitudinal Dispersivity	60 [m]
Transverse Dispersivity	4 [m]

5.2 Open Loop Decision Making

We start by testing a simple open loop coupling from the social to the physical model. This setup can be seen as a fixed long-term management decision analysis without the need to predict coupled socio-hydrological interactions. The awareness campaigns and expert beliefs are pre-decided accordingly. The results in Fig. 7 show that the transients of the contaminant concentration in the water supply under different decision open-loop scenarios accounting for water usage as well as media and expert interferences. The figure also show how the concentration decrease at late times depends on the number of experts (i.e., individuals with fixed beliefs), and on the rate of awareness campaigns coming from media outlets.

However, something peculiar is observed: if the entire population uses the groundwater water supply, contamination levels are lower after few decades of use when compared to the case in which only half the population uses the water supply (Fig. 7). It can be also observed, that regular awareness campaigns (or ads) are not necessarily an optimal solution in the long run. Such unintuitive consequences are mainly due to processes causing nonlinear effects of mixing clean and contaminated water in the aquifer which impact the contamination levels of the pumped water supply. If there were more complex governing processes accounting for complex biogeochemical reactions involving the contaminant, the transients on the contamination level transients might be even more complicated.

When making decisions in an open loop system, i.e. without a constant feedback about the concentration in time, one should always have in mind that coupling the aquifer response with the social response is highly nonlinear and their synthesis is not predictable in advance; thus making the effect of decisions often unintuitive. Hence, the need for a closed loop data-informed simulation framework.

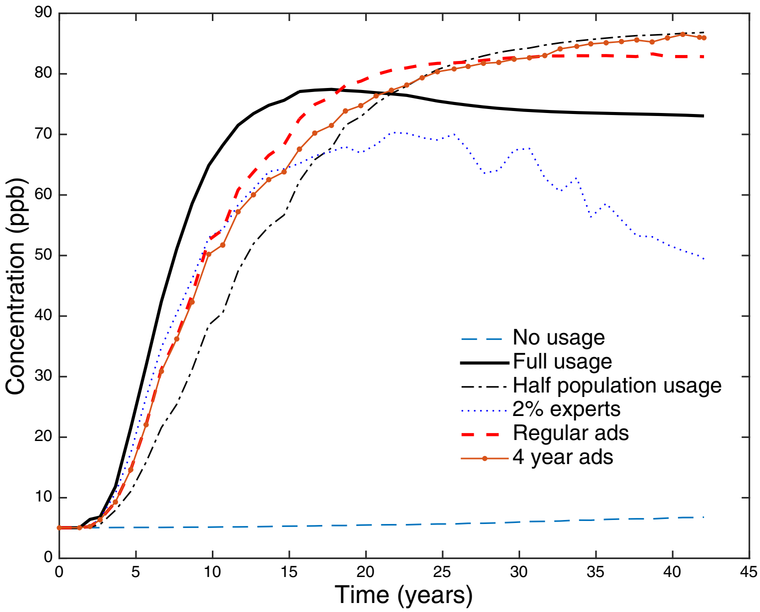

Fig. 7 Contaminant concentration in the water supply over time under various decision open-loop scenarios accounting for water usage as well as media and expert interferences

5.3 Closed Loop Decision Making

Figure 8 illustrates the feedback decision making framework for adjusting social policies based on knowledge of social dynamics and hydrology. There are two stages of coupling between the physical model (FEHM) and the social model. First, the supply-demand economics unit is assumed to proportionally map usage rate unto pumping rate. This simplified coupling is only used as a first approximation to avoid increasing the number of variables in this study, but it can be independently extended to better existing supply-demand economic models (Tietenberg and Lewis 2016; Berger et al. 2007). Second, the management decision happens between the measurement of contaminant concentration in the water supply and the specification of social regulation parameters. That is, which management decisions are most appropriate to minimize health risk and maximize economic independence? (see Eq. 1)

In our study, we simplify the general problem posed in Eq. 1 by assuming that the economic independence is maximized as long as the health risk is maintained at its desired limit. This general assumption allows us to frame our system as a Proportional-Integral-Derivative (PID) control problem.

5.3.1 Proportional-Integral-Derivative (PID) Decision Making

When the input of a dynamical system depends on its output, and when its difference with a desirable output is being minimized, we are faced with a closed loop control problem. Basic closed loop control systems have three main components: a controller, a plant, and a feedback sensor. In the context of water resources management, the managers are the controller, the environment and the society are the plant, and the measurement of water quality and social wellbeing are the feedback sensor. Figure 12 (in Appendix B) demonstrates these interactions. Along the lines of this analogy, we can use methods in control theory to design a computational decision support system for finding optimal water resources decisions. Here, we show how proportional-integral-derivative (PID) can be used in this context. PID control minimizes the time it takes to reach a target concentration or risk by taking into account the past (from the integral of the error), the present (from the error), and the future (from the rate of change of the error). Here, the error $e(t)$ at a given time t is the difference between a target value v^* of the control variable (e.g. concentration threshold) and the

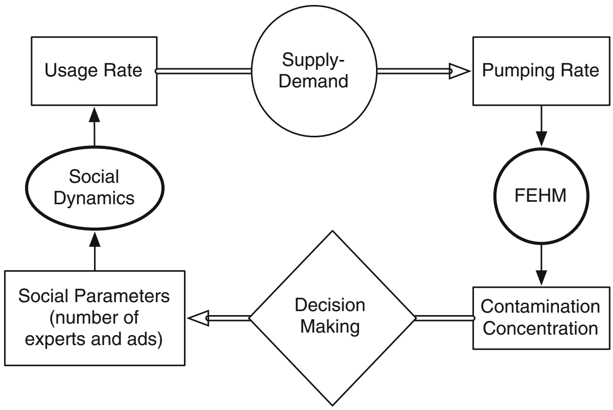

Fig. 8 Diagram of the coupled socio-hydrological model

value of the variable $v(t)$ at that time, such that $e(t) = v^* - v(t)$. This is especially useful for managing water resources where the time-dependent dynamics leading to a better social-ecological equilibrium should be taken into account; not only the present state of the environment.

In the real world, there are a great number of social parameters that could be tuned to change the state of the environment. However, limiting ourselves to a few predictable social parameters gives us a better understanding of the sensitivity and the reliability of the decision strategy. Using the social models developed in Section 3.3, the influence of regulators on social behavior is done by controlling the *number* of experts and the *frequency* of awareness campaigns.

The advantage of using control theory for the proper tuning of social influence is demonstrated in Fig. 9. The figure presents the contaminant concentration transients in the water supply for the case of proportional and fixed 'on-off' toggle control. The results clearly show that the 'social-ecological pendulum' (Kandasamy et al. 2014), expressed as concentration fluctuations in Fig. 9, is much better controlled when the number of experts is proportionally weighed against the difference between the desired and current concentrations. Otherwise, as frequently observed, the system would be in a perpetual state of reaction.

5.3.2 Risk Versus Concentration Control

When faced with a environmental management crisis such as water-supply contamination, the remediation goal is reducing the contamination levels to the maximum contaminant level (MCL) at points of compliance. However, in public policies in general, and groundwater contamination in particular, management decisions ultimately aim at reducing the factors

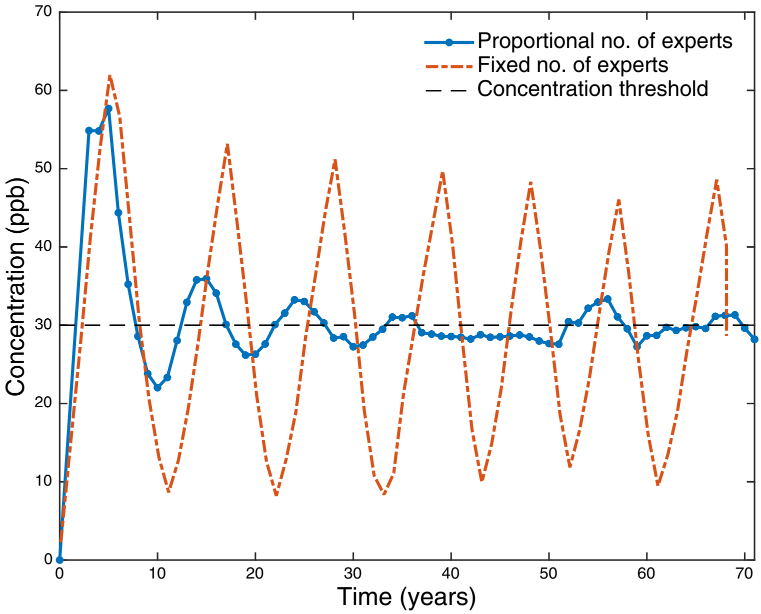

Fig. 9 Contaminant concentration in the water supply (with a target concentration of 30 ppb) for the case of proportional and fixed (3% experts) 'on-off' toggle control

that endanger the public health. Therefore, when studying a coupled system of natural and social events, the input is a management decision and the output is a rate of casualties, statistically expressed in terms of health risk. In other words, we are usually not concerned about the concentration of contaminants in absolute; but rather about how and at what rate contaminants endanger citizens. For example, the current MCL established by U.S. Environmental Protection Agency for chromium is 0.1 mg/L; however, this MCL is based on health risk caused by chromium toxicity and cancerogenicity (Dayan and Paine 2001). As a result, risk-driven remediation analyses at chromium contamination sites might provide better protection of the human health than remediation analyses driven by chromium MCL only. This motivates a proper quantification of health risk to be used as an optimization variable in dynamical social-ecological systems.

To demonstrate this point, we design a synthetic problem with a sample society containing individuals of all ages, from 0 to 100, each having a drinking water record. Each person is replaced by a newborn when dead and their record is restarted. In this study, the risk of developing cancer due to water contamination is given by Atchley et al. (2013)

$$\text{risk} = e^{-C_\text{p} A_\text{d} F} \tag{2}$$

where C_p is the cancer potency factor (given by the office of Environmental Health Hazard Assessment), A_d the average daily dose, and F a parameter specific to the contaminant. A_d is a function of the contaminant concentration, exposure duration, average lifetime and body weight, all of which are introduced in the social dynamics. Given that the exposure duration assumes individuals to have lived a complete lifetime, the contaminant concentration obtained last is assumed to be the same for the remainder of each person's life for computing the risk at each time step. Also, the control target is chosen to keep 90% of the population below the risk limit.

Given those factors, we perform a hybrid socio-hydrological analysis for 60 years such that the contaminant is detected 15 years after it has polluted the water. By comparing concentration and risk control, Fig. 10 shows that concentration control is successful in maintaining the contaminant concentration around the desired threshold. However, it can be seen that a large portion of the population is held above the risk threshold when using concentration control. Instead, controlling the risk makes sure that the water supply

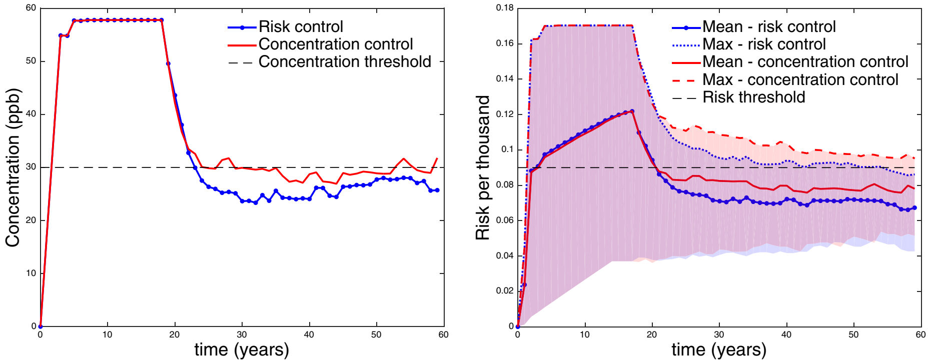

Fig. 10 Contaminant concentration in the water supply (*left*) and risk (*right*) over time for the case of risk (*blue*) vs. concentration (*red*) PID control; the *shaded areas* represent the risk range for the entire population

concentration is below allowable limit, giving people's body some time to recover from their past contaminant exposure due to water consumption. Accordingly, Fig. 10 shows that risk control minimizes the time to attain a safe social-environmental equilibrium.

5.3.3 The Effect of Heterogeneity

Most aquifers have a highly heterogeneous permeability. Due to the heterogeneity of aquifer properties, the advective and dispersive contaminant transport can be difficult to predict without extensive data collection campaigns (which may include numerous monitoring wells) and complex model analyses (for example, using hydraulic tomography approaches (Vesselinov et al. 2001; Lin et al. 2016)). In real world applications, it is important to take into account the effect of heterogeneity to avoid underestimating or overestimating contaminant predictions at the water-supply well as a consequence of the social response. For example, a heterogeneous permeability field can impact the timing and magnitude of changes in contaminant concentrations due to the social response. This being said, the same techniques and algorithms used in this paper would still hold for heterogeneous aquifers.

6 Conclusions

In this study, we developed an extendable computational agent-based social dynamics framework relevant to a hybrid socio-hydrological modeling. We demonstrated its usefulness in management decision scenarios where there is a dynamic feedback relationship between the environment and the society. This synthetic and relatively simple approach captures the dynamics of physical phenomena that lie in the "gray area" where policies and risk assessment both target and are affected by social behavior.

This being said, our hybrid modeling framework shows the possibility of designing flexible real-world simulation analyses and motivates a better data- and model-informed management of water resources. First, the developed social dynamics framework is flexible and easily extendable. It can account for deterministic and stochastic model parameters, both social and hydrological. It can account for complex attributes to individuals' social behavior and create rules that connect them. For example, it is possible to add an attribute of 'gender perception of risk', if provided with data showing a correlation between risk-perception and conformity (Flynn et al. 1994). This attribute-based social dynamics model makes it attractive for combining both power and simplicity. Second, the hierarchical setup developed in Section 3.2 enables the social models to be used in conjunction with a social networks thus providing real-world data for the rates of conformity and consistency. Third, the modular nature of this computational framework makes the economic model easily replaceable by available sophisticated financial simulators. Fourth, the analogy drawn between social-ecological management and control theory opens many possibilities for the use of more complex stochastic control and objective machine learning methods to help find the optimal management decision. Finally, this computational package is open source and distributed as a part of the MADS (Model Analyses and Decision Support; http://mads.lanl.gov). It is written in Julia, an widely-used, high-level, dynamic, and fast programming language for technical computing. The runtime of all the model analyses presented in the paper is an hour at most.

Most importantly, this study shows that, using this computational framework, a simple change of control variable (from concentration to risk) changes the strategy to reach social-ecological equilibrium. This demonstrates the invaluable utility of this tool in changing water managers' perspective of the problem and improve their decisions and thus the social good.

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Appendix A: Social Dynamics

In this study, the results shown in Section 5 highlight the average dynamics of the entire society, expressed in terms of average social health risk and total water usage. However, it must be noted that even when the contaminant concentration or health risk reach quasi-constant value, individuals are always changing their usage habits and beliefs. This means that even though the regulators manage the average behavior and beliefs of a society, the beliefs and behavior of every single individual is uncontrollable and unpredictable. Figure 11 shows the social dynamics of a sample of the population (100 individuals) changing attributes (usage and beliefs) throughout 100 years of simulation. On the left, the population is sorted according to specialty. The first 20 individuals (shown in the bottom of the abscissa axis) are initially experts who turn into normal citizens when not employed by the regulators. The right plot shows the population sorted by attributes.

Appendix B: Analogy Between Water Resources Management and Proportional-Integral-Derivative (PID) Control

Social-ecological system management fits naturally in the framework of control theory. According to this analogy, shown in Fig. 12, the decision makers are the controllers, the

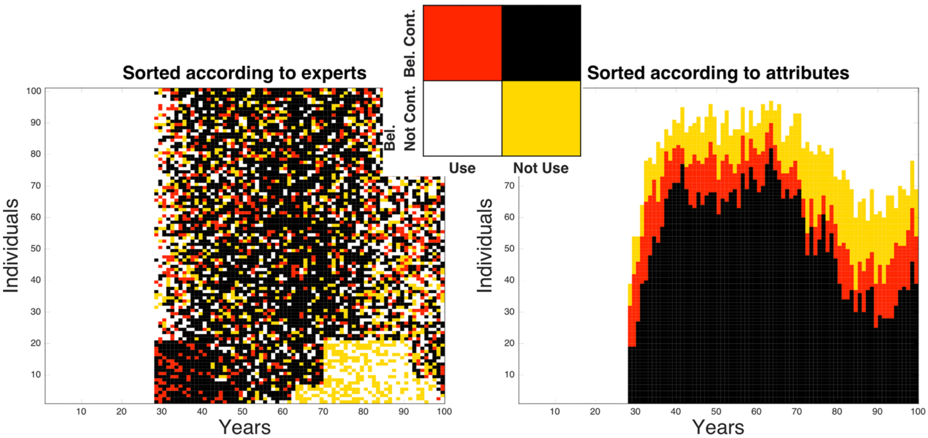

Fig. 11 Dynamics of usage and belief over time for a representative sample of the population (100 individuals); the *left subgraph* shows the changes in the social attributes over time for each individual in the sample (the first 20 people, shown at the figure bottom, are initially experts who turn into normal citizens when not employed by the regulators); the *right subgraph* shows the population sorted by attributes

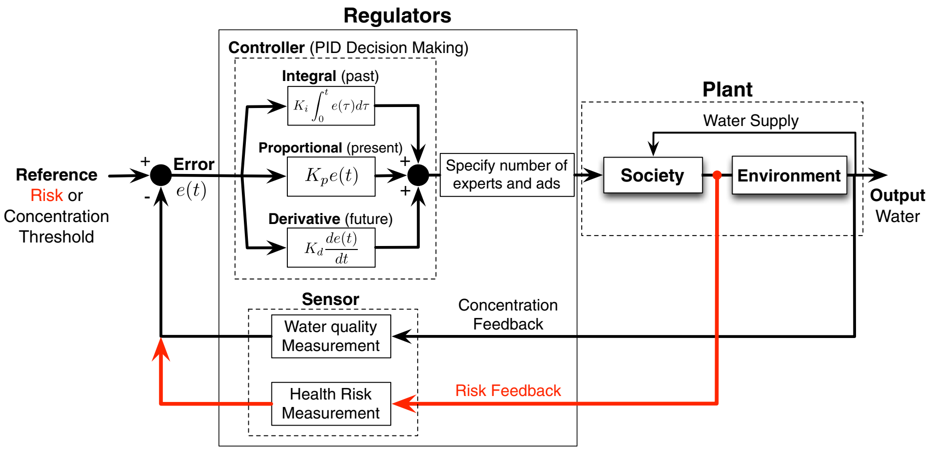

Fig. 12 Analogy between water resources management and Proportional-Integral-Derivative (PID) control; comparison between concentration and risk control is illustrated

plant is the social-environmental system and the sensors are managed by scientists and engineers. If a social-ecological system is unstable (i.e. threatens a deterioration of either the environment or social well-being) environmental management decisions aim at restoring the balance (i.e. reach a reference state) of the ecosystem (i.e. the social-environmental plant). In the context of control theory, this is done by minimizing the difference between a reference well-balanced state and a present unsustainable state. In this study, the control (management) variables of interest are health risk and contaminant concentration.

The proportional (K_{p}), integral (K_{i}) and derivative (K_{d}) constants are tweaked to minimize the rise time to steady state and dampen the oscillations as much as possible. However, the values are not optimal. The choice is only meant to illustrate the advantage of using PID control in the context of environmental management.

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