Build-in Uncertainty in Agent-Based Model and Its Impact on Social-Ecological System Decision-Making under Deep uncertainty

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Abstract: Social-Ecological System is a complex system and often confronts tipping points under deep uncertainty. These uncertainties come from both social and natural processes and most current studies payed more attention to natural part than social. In this study, we construct two models, agent-based model (ABM) and system dynamics (SD) model, based on the same assumption to describe the same social system and the same process where house owners update their Onsite Sewage System which would then affect nutrient level in a shallow lake. ABM has its build-in uncertainty and we believe the uncertainty can present part of deep uncertainties in social system. Our multi-objective decision making problem is to find a control policy that can avoid regime shift in ecological system under deep uncertainty. Robustness index, reliability and other indicators are used to measure the performance of one decision. Then we can see to what extent the uncertainty in social part affects decision making. Results show that if both ABM and SD have similar overall behaviour and all the objectives are average indicators, their recommended decision will be similar. However, SD which does not include uncertainty in social part fail to inform decision's performance under extreme states of world. Uncertainties increase system vulnerability considering extreme cases. Since our study is based on the model containing simple process, following works should base on real case study to test this conclusion in more complex system.

Keywords: deep uncertainty; social-ecological system; agent-based model; robustness

1 INTRODUCTION

There are numerous unpredictable processes existing in both social and ecological system and, therefore, over the last decade more and more studies shifted their focus from stochastic uncertainty to deep uncertainty (Bankes, 2002; Milly et al., 2008; Galloway, 2011). Deep uncertainty affects the strategy performance in many ways and one of them is that strategy derived from traditional methods may lead to unintended system deterioration (Herman et al., 2014). Some of system changes are irreversible, which are also called “regime shift”: Once system goes through a certain tipping point, it will be impossible or cost too much to back to former state (Walker and Salt, 2006). As a result, recent studies tried to find the way that could prevent system away from tipping point under deep uncertainty (Kasprzyk et al., 2013; Ward et al., 2015).

Many factors result in deep uncertainty. One of the them is climate change which is widely studied recent years (Lempert, 2002; Gober et al., 2010; Mortazavi-Naeini et al., 2015). The size of decision timescale also affects the scale of deep uncertainty. For example, in a long term water supply system planning deep uncertainty become significant because it is too hard to determine the change of parameters over a long period of time (Lempert et al., 2003). Deep uncertainty not only exists in ecological system but also can be found in social system since social system is also complex. For example, some economic assumption would not be true and related parameters are treated as “unresolvable uncertainty” (Newell and Pizer, 2000; Hadka et al., 2015).
However, studies tend to overvalue the uncertainty because of scientific background and undervalue the socio-economic uncertainties and the importance of human decisions (Trutnevyte et al., 2016). Back to the time when deep uncertainty was proposed, we can see that deep uncertainty was also aimed at agent-based model (ABM) (Bankes et al., 2001; Bankes, 2002; Lempert, 2002), which is a modelling technique describing complex adaptive social system while in the following years few studies focused on decision making based on ABM under deep uncertainty. Social uncertainty may also lead to decision failure because recent studies found that social system only is enough to drive the whole social-ecological system (SES) experience a regime shift (Lade et al., 2013) so that a sound decision aimed at regulating SES should base on the model where social system and ecological system are treated “equally” (Binder et al., 2013). This means these two parts need to have almost the same model complexity.

This study follows the model LimnoSES, developed by Martin and Schlüter (2015), which uses a hybrid model technique to model a SES confronting tipping point. We take the ecological part of LimnoSES to formulate a decision making problem under deep uncertainty and explore the influence of deep uncertainty generated from social system on final decision making. To achieve this, besides the ABM used in LimnoSES to model social system, we also construct a system dynamics (SD) based on the same assumption to describe social part. Due to the build-in uncertainty caused by inadequate information resources or irregular arrangement of houses, ABM contains some deep uncertainty while SD does not. In this way, we compare how deep uncertainty in social part affects decisions on SES.

2 MODELLING SES

In LimnoSES, individual house owners release sewage water unless they update their Onsite Sewage System (OSS). Nutrients will affect the density of two kinds of fish, pike and bream, and their densities are used to indicate whether the shallow lake is in clear (high pike and low bream) or turbid (low pike and high bream) state. Ecological model was developed by Scheffer (1989), which is a minimal model about alternative stable state in eutrophic, shallow lake system and represented by (Scheffer, 1989; Martin and Schlüter, 2015):

\[
\frac{dbream}{dt} = ib + r \frac{nutr}{nutr + H_1} - cb \cdot bream^2 - \frac{bream^2}{bream^2 + H_2} \cdot pike \cdot pred,
\]

\[
\frac{dpike}{dt} = ip + pike \cdot pred_r \cdot pred_e \cdot \frac{bream^2}{bream^2 + H_4} \cdot \frac{V}{V + H_5} - pike \cdot mort - cp \cdot pike^2
\]

\[V = \frac{K \cdot H_3^2}{H_3^2 + bream^2}\]

Where See Table 1 for details.

<table>
<thead>
<tr>
<th>Table 1. Parameters and state variables in ecological system model.</th>
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<tbody>
<tr>
<td>Symbol</td>
</tr>
<tr>
<td>r</td>
</tr>
<tr>
<td>pred_e</td>
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<tr>
<td>cb</td>
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<tr>
<td>cp</td>
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<td>pred_r</td>
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<tr>
<td>pred_r_a</td>
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<tr>
<td>mort</td>
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<tr>
<td>ib (ip)</td>
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<td>H1</td>
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<td>H2</td>
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</tbody>
</table>
All the baseline values are taken from Martin and Schlüter (2015) and according to the original parameters determination process, we select four parameters as deep uncertain parameters which have reference range in Scheffer (1989).

Based on the report on OSS in Sweden (Wallin, 2012; Wallin et al., 2013a; Wallin et al., 2013b), Martin and Schlüter (2015) developed the ABM to simulate social system in LimnoSES. Each house owner has their own update willingness (willingness-to-update) which is equal to the probability they update OSS. Their willingness can be increased in two ways: stochastic interaction with neighbours who have updated their OSS or government inspection. No matter in which way, each time the willingness rises by 50%. At the beginning, all the agents (house owners) are distributed randomly. Once one agent updated its OSS, its willingness will not change any more. There is a tolerance level (tl) of the percentage of polluter above which pollution will happen. Also, the increase of nutrients in the lake at time t is in the proportion to difference between the percentage of polluter and tl. See Martin and Schlüter (2015) for details. In LimnoSES, observer can also monitor the status of lake and can influence agent’s willingness through social engagement. We do not include this process in our model because according to Wallin (2012), this process is not as significant as inspection.

On the other hand, based on the same assumption, we can directly deduce an ordinary system describing the same social process and this work is enlightened by Deffuant and Gilbert (2011). Therefore, we have the system:

\[
\frac{dg}{dt} = (1 - g) \cdot fp
\]

\[
\frac{dp}{dt} = q \cdot 0.5 \cdot fp + g \cdot 0.5 \cdot fp
\]

\[
\frac{dnutri}{dt} = \frac{1 - g - tl}{1 - tl} \cdot sewagemx
\]

Where g represents the percentage of house owners with OSS at time t; fp is the average willingness of house owners who have not updated their OSS; nutri is the nutrients in the lake at time t; q is the probability that each owner is inspected by government (inspection rate, that is each time q per cent agents would be inspected) and sewagemx is the maximum degree polluter could influence lake.

In this study, we set initial willingness-to-update 0.1 for all house owners, sewagemx 0.35, tl 0.1 and at the beginning, the lake is in clear state and other parameters are the same with Martin and Schlüter (2015). Both ecological model and SD for social system simulate at daily time scale and ABM runs at annual time scale.

3 SEWAGE CONTROL PROBLEM UNDER DEEP UNCERTAINTY

Martin and Schlüter (2015) provided the ecological model code and the instruction on how to analysis the model stability in MATLAB GRIND. Using the baseline value in table 1, we find that the stable equilibrium of clear state exists only when nutrient is lower than about 2.3 and for turbid state that is higher than around 0.9. Nutrient is a dimensionless variable. Another important fact is that if nutrients increase dramatically, the lake also turns into turbid state even though nutrients level is much lower than 2.3. This is a rate dependent behaviour. See Martin and Schlüter (2015) for details. Given the parameters
in section 2 and set inspection rate q 0, SES would turn into turbid state after around 10 years. However, the control policy is to increase rate q to reduce both the highest level and increase speed of the nutrients.

In section 2 we know that our ecological model is facing with deep uncertainty. As a result, the decision making the problem has to deal with both deep uncertainty and tipping point. Recently, Hadka et al., (2015) and Ward et al., (2015) developed a multi-objective optimization model for a similar problem. Based on their work, we construct our optimization model as:

$$\text{min } q$$

$$\text{max min } \frac{1}{S} \sum_{i=1}^{S} \text{pike}_{i,t}$$

$$\text{min max } \frac{1}{S} \sum_{i=1}^{S} \text{bream}_{i,j}$$

$$\text{max } RI = \frac{1}{S} \sum_{i=1}^{S} \theta_{i,j}$$

s.t.

$$\text{reliability } = \frac{1}{S \cdot T} \sum_{i=1}^{S} \sum_{j=1}^{T} I_{i,j} > 0.85$$

Where $\text{pike}_c$ (0.5) and $\text{bream}_c$ (60) are the critical thresholds for pike and bream respectively,

$$I_{i,j} = \begin{cases} 1 & \text{if } \text{pike}_{i,j} > \text{pike}_c \text{ and } \text{bream}_{i,j} < \text{bream}_c \; ; \; \theta_{i,j} = \begin{cases} 1 & \text{if } \frac{1}{T} \sum_{j=1}^{T} I_{i,j} > 0.85 \; ; \; 0 & \text{otherwise} \end{cases} \\ 0 & \text{otherwise} \end{cases}$$

The first objective is to minimize management cost; the second and third are to maximize the average performance of one decision at the worst time. Instead of using reliability as both objective and constraint, we only use it as constraint and select another robustness measurement, robustness indicator (RI) as another objective. It shows the percentage of States Of World (SOWs) where the decision could achieve satisficing performance. Critical thresholds for pike and bream are determined according to the stable equilibrium diagram.

Since there are two independent deep uncertain parameters in ecological model, we use Latin Hypercube sampling to generate 100 SOWs and we also run ABM for 100 times. All the ordinary equations are solved by fourth-order Runge-Kutta method with daily step-size for 20 years. Even though it is a multi-objective optimization problem, it is still simple because we have only one decision variable. So for decision variable q, we test all possible value, 0,1%,2%...100% and then each time use the output of social system as input of ecological system. Based on the output of ecological system, we get the value of objectives above.

4 RESULTS AND DISCUSSION

We first compare overall behaviour of different social models. It can be seen from figure 1 that SD model (red line) has the same trend with ABM (grey line). However, when agents can only sense local neighbours (ABM-local) there are obvious differences on the percentage of house owners who have
updated their OSS. On the other hand, if agents can sense any other agents (ABM-global) the differences will be reduced. This is due to how better one agent can know other agents’ decision. Because in SD, we assume all the agents could sense other agents’ decision even though it may be impractical in real world. In conclusion, we could get almost the same overall behaviour from any of three models.

![Figure 1](image1.png)

**Figure 1.** Overall behavior of different models (red line: SD, grey line: ABM) when \(q=0,0.3,0.6\) and 0.9. Three kinds of output are compared, from top to down is nutrient level in lake, percentage of house owners with OSS and average willingness of owners who have not updated their OSS.

Will these difference lead to different optimal inspection rate \(q\)? Figure 2 shows line graph of RI, reliability and the average density of bream and pike at worst time along with \(q\). We can see that when \(q=0.4~0.5\), reliability will be greater than 0.85 (figure 2(a)) and we could hardly see significant improvement in terms of average performance at worst time (figure 2(b)). Since RI and Reliability increase along with \(q\) until \(q\) is higher than 0.8. An optimal decision should lie between 0.4 and 0.8 no matter which model we rely on to make decision.

![Figure 2](image2.png)

**Figure 2.** RI, reliability and the average density of bream and pike at worst time vs \(q\).

However, if we analyse the worst value among all SOWs it is another situation. Figure 3 gives us the worst density of pike for all SOWs under given \(q\).
It can be seen from figure 3 that 0.8 is not enough to guarantee system below threshold and the overall trend between SD and ABM is obviously different. If we only have SD model for social system, we may believe that 0.6 can ensure pike above critical threshold for all SOWs while according to ABM, it should be around 0.85 or higher. Even though we have one objective to indicate the density of pike at worst time but it is averaged over all SOWs.

All measures in our optimization problem are average measures so they cannot show us the influence of deep uncertainty especially for extreme cases. In fact, not only for extreme cases, but also for all SOWs near extreme cases, the performance of one decision will be significantly different between SD and ABM. If we could analyse these difference case to case and draw decision landscape vs uncertain parameters (Lempert, 2002) and then all the impacts will be clear. Furthermore, it will be helpful for analysts to use a variety of indicators to show the performance for each decision, including average measurements such as robustness index, reliability and other measurements to show extreme value for all SOWs.

Our results show that for a decision making on SES under deep uncertainty, if the model could generate considerable overall behaviour of the whole system, the final decision based on this model can give us a good estimation of average consequence over all SOWs even though the model do not contain enough deep uncertain factors. On the other hand, it would fail to inform us the performance of one decision under extreme cases.

5 CONCLUSION AND FUTURE WORK

We construct two models to describe social system based on the same assumption and study the influence of deep uncertainty in social system on decision making. Our results show that the performance of decision under extreme case will be poorly informed if we ignore deep uncertainty in social system. However, our study relies on one simple model containing simple process that enable us to derive SD model and we have to enlarge some parameters in social system to let social part have the potential to affect ecological system. Indeed, sewage water in this case only accounts for 10% local total phosphorus. Next, we will focus on developing another SES model which contains main polluting process and is able to reflect main feedback processes. Based on such kind of model, we can better analyse possible policies and their impacts on SES system under deep uncertainty.

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