Tools and methods in participatory modeling: selecting the right tool for the job

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Abstract

Various tools and methods are used in participatory modelling, at different stages of the process and for different purposes. The diversity of tools and methods can create challenges for stakeholders and modelers when selecting the ones most appropriate for their projects. We offer a systematic overview, assessment, and categorization of methods to assist modelers and stakeholders with their choices and decisions. Most available literature provides little justification or information on the reasons for the use of particular methods or tools in a given study. In most of the cases, it seems that the prior experience and skills of the modelers had a dominant effect on the selection of the methods used. While we have not found any real evidence of this approach being wrong, we do think that putting more thought into the method selection process and choosing the most appropriate method for the project can produce better results. Based on expert opinion and a survey of modelers engaged in participatory processes, we offer practical guidelines to improve decisions about method selection at different stages of the participatory modeling process.

Keywords

Stakeholders, collaborative learning, qualitative analysis, quantitative modeling, participatory planning, mental models

1. Introduction

Numerous tools and methods facilitate stakeholder engagement in participatory modeling (PM), which Stave (2010) defined broadly as "…an approach for including a broad group of stakeholders in the process of formal decision analysis." In the PM process, participants co-formulate a problem and use modeling to describe the problem, to identify, develop and test solutions, and to inform the decision-making and actions of the group. Therefore, we define **PM specifically as a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representations of reality**. Since PM is heavily focused on collaborative learning, the tools and methods used during PM projects are expected to promote system understanding and awareness for all stakeholders. By stakeholders we mean all who have a 'stake' in the project. This includes modelers and researchers themselves, who are often considered external to the project but still have interests in it, come with their own biases, and cannot be assumed totally objective and neutral (Voinov et al., 2014). The level of engagement differs across stakeholders and varies from one stage of the project to another (Arnstein, 1969; Hurlbert, Gupta, 2015).

Argyris and Schön (2002) showed that there are two levels of learning, referred to as "single loop" and "double loop" learning. In single loop learning, individuals and groups act within a single reference frame, where specific hypotheses, values, norms, beliefs and objectives are assumed to describe the world. Learning in these systems consists of observing the results of actions and, potentially, modifying future actions based on what is observed. In double loop learning, actors question and learn about the reference frame itself, and may change their fundamental hypotheses, values, norms, and beliefs based on what they learn about the system, as well as what they learn about the outcomes of specific actions (Zellner and Campbell, 2015).

The transition between single and double loop learning can result from the interaction between individual and organizational learning. Argyris and Schön (2002) found complex retrospection and feedback mechanisms between individual and organizational learning. The individual mental models that are used to construct shared mental models of an organization coalesce, thereby modifying the perception of the organization and transforming organizational values and paradigms. In turn, this modifies the environment of the individuals and affects their own mental models (Daré et al., 2014). As a result, the act of model co-creation is, in itself, an act of knowledge construction at both the single and double loop learning levels. In some cases, PM processes deliberately avoid formal model co-creation to first allow the identification and challenging of stakeholders' causal beliefs and expectations and, consequently, a reconstruction of knowledge (Habermas, 1990; Smajgl and Ward, 2013).

The goal of this paper is to provide an overview of some of the *methods* and *tools* for PM, identify some of their strengths and weaknesses, and provide some guidance for practitioners as they select methods for their PM projects. For the purposes of this paper, we define a *tool* as a modeling technique used to carry out a particular function to achieve a specific goal. Tools are defined, documented, do not change significantly through use, and are clearly external to their users and often not created by them. In contrast, a *method* is a way of doing something, in particular, a way of using tools. According to Mingers (2000), a *method* is "a structured set of processes and activities that includes tools, techniques, and models, that can be used in dealing with a problem or problem situation." A particular method can be supported by one or several tools. For example, in this context agent-based modeling (ABM) is a method; Netlogo, Mason, or RePast are some of the possible tools used to perform ABM. Multiple tools often exist to support a single method, and some tools also serve several methods. For example, Netlogo, AnyLogic, or Nova are tools that can be used within both ABM and System Dynamics (SD) methods.

While the choice of methods used can heavily impact both processes and decisions, there is little scholarly discussion about how tools and methods are chosen during PM. Certainly, decisions about methods are more influential for the whole process than the choice of a particular tool, and therefore should come before choice of tools. For instance, there are not many implications in deciding to use Stella rather than Vensim or Simile; all are well-established tools that support the SD method. But the decision to implement a more quantitative method rather than a qualitative or conceptual one can potentially significantly change the outcome of a PM process. For example, a companion ABM based on role-playing games (see Barreteau et al. 2001) can increase stakeholder involvement in the PM process and may generate much different results than computational ABM using only computer simulations and modelers' assumptions.

Previously, Voinov et al. (2016) reviewed several participatory tools and methods that have been used to enhance stakeholder participation for different components of the PM process. They concluded that, while many different methods are used for various stages of the process, in practice, there is rarely much justification given for the use of a particular method. It is difficult to find examples of participatory projects that used different combinations of modeling methods when dealing with the same problem. In most cases, once the method (or combination of methods) is chosen, it becomes the only one reported. We recently reviewed 180 papers related to participatory modeling as part of a SESYNC project on "Synergizing public participation and participatory modeling methods for action oriented outcomes" (https://www.sesync.org/project/enhancing-socio-environmental-research-education/participatory-modeling). We found no papers that reported using one method and then a switch to another method. This may be due to a general reluctance to report failures rather than only success stories, but it complicates the comparison of different methods. Another reason most studies report only one method might be that switching from one method to another is costly in terms of time and resources. A similar, though much more limited effort in healthcare research, which focused on comparison of three dynamic simulation methods, SD, ABM and Discrete Event simulation (Marshall, et al., 2015) also reports very few failures of particular methods that led to switching to other methods.

A careful and conscious selection of methods is important for the modelling process and its outcomes. Ideally, the selection would be accompanied by effective evaluations to monitor the impact of individual methods used during in PM (Hassenforder et al., 2015; Smajgl and Ward, 2015). However, in many case studies, the choice of methods and tools seems largely driven by the experiences of participating researchers (Prell et al. 2007). This is a manifestation of the hammer and nail' syndrome: once someone learns to use a hammer, everything starts to look like a nail. A researcher with expertise in system dynamics is very likely to apply system dynamics for the next modeling project, even if other methods could be equally or even more appropriate to address the full set of driving questions. Retraining is time-consuming and resources are always scarce. Engaging colleagues with experience in alternative approaches could help expand the scope of methods considered, but this is not always feasible. There are practical and social reasons why this experience-driven approach to method and tool selection is not optimal, especially in the field of PM. First, the value of PM in developing models that effectively and efficiently meet participants' requirements will be improved by using methods that best fit the project purpose and context. The modeling skill set available should be considered only to identify gaps in the skills required to address the problem in question. PM seeks to be transparent to the users and it is critical to make sure that PM practitioners are not treating all problems as nails just because they are good at using a hammer. Stakeholders, defined broadly as above, are expected to engage in all steps of the PM process, which includes method selection as well as the modeling steps. While the participation of various groups of stakeholders will be certainly different, at each stage, all stakeholders should understand why the chosen methods and tools are appropriate. This requires some flexibility in the PM process, whereby stakeholders move collectively from the problem to an appropriate method, and onto tools and associated skills found within the project team. A sharper focus on method and tool selection is needed. This requires understanding stakeholders' preferences and constraints, including their experience with particular methods, the availability of training for specific methodologies, the ability to use and maintain a particular tool for the long term given the costs to do so, and/or the ability to combine a new tool with existing tools or methods (Smajgl, 2015).

Second, social factors may also affect method and tool selection. The choice of methods is more than a technical decision; it can also involve ethical or other social judgments. It may make it easier or more difficult for specific groups to participate effectively, and to adequately represent specific technical aspects of the problem. In implementing a PM process, decisions must be made about who is involved and what is included (Midgley, 1995). Tradeoffs between narrow technical accuracy and more inclusive participation in the modeling processes themselves may add more legitimacy to the process (Nabavi et al., 2017), or help to "level the playing field" in the case of asymmetries in the power or knowledge of different stakeholders (e.g. Barnaud & Van Paassen, 2013, Campo et al., 2010). When the choice of modeling methods and tools becomes largely a personal decision of certain more knowledgeable stakeholders, it represents an ethical posture based on their own preferences and experiences and may not reflect the larger PM group. Methods (and tools) ought to be chosen in service to ethical or social needs. In contrast, method-driven PM practice can result in methods that are 'epistemically violent' to vulnerable participants; they forcibly replace one structure of beliefs with another. P PM. Individuals must be invited to join the process, but it is rarely possible to invite every individual who might be interested in the questions being addressed. Time and resource constraints, as well as the need to have effective and useful interactions among the participants means that some individuals are necessarily excluded. Further, because modeling often requires some element of rules or strategy guiding the approach prior to the decision-making process, certain participants may have greater power.

Power can be defined as the ability to control or influence others' actions or choices. The choice of methods and tools can significantly empower some participants at the expense of others. Often these others may already be traditionally disenfranchised. If the method chosen is one that the project leaders have a lot of experience in, that might give them substantial advantage in understanding and controlling the process, relative to other participants for whom the method is novel. The confidence and knowledge they have, make them more likely to guide the participatory process while subordinating the novices. But using a method that the practitioner is not familiar with just to maintain equality of power would be also unrealistic and unproductive. Because inequality in power can manifest itself in many ways (Kraus 2014), it is important for a truly participatory process to have all individuals informed not only about the decisions being made, but also about the decision-making process itself. Ultimately, the research team can be even assembled *after* stakeholders co-designed the project and select the most effective methods based on the policy indicators and the scale they perceived as most relevant (Smajgl, 2010; Smajgl et al., 2009).

On the positive side, methods can also empower and integrate many perspectives. Any of the methods and tools described in this paper may promote both individual and social learning through the use of the model as a "boundary object," a representation with a shared meaning that can facilitate exchanges of ideas and worldviews between participants (Schmitt Olabisi et al. 2014; Johnson et al. 2012; Zellner 2008). A boundary object implies a distance from reality and situations that are sometimes tense and painful. This distancing can allow for discussions on subjects that are conflictual or taboo. By fitting into a social issue, the model, co-designed with the stakeholders, becomes an "object of mediation" (D'Aquino et al. 2002; 2003), promoting conflict resolution and collective decision-making.

When selecting methods for participatory modeling, modelers and facilitators should consider how the methods or tools will provide evidence of learning. For example, a 'before and after' systems diagram may reveal shifts in mental models that occur as the result of a PM exercise. Discourse analysis may demonstrate changes in the ways groups conceptualize problems and problem-solve as the result of interaction with the model (Radinsky et al. 2016). Consideration of learning is therefore an integral part of method selection and process design in PM.

The selection of methods is both a critical and a difficult task that ideally requires (1) knowledge of available methods and tools, and (2) careful examination of selection criteria and trade-offs. This paper addresses both of these issues. Section 2 describes a broad array of available methods and tools available to scientists, modelers and stakeholders, and Section 3 systematically examines PM practice and the issue of method and tool selection.

2. Overview of PM methods

There are numerous methods used in PM projects. In Fig. 1, we propose a typology of methods (and some possible combinations thereof). It is sometimes difficult to distill the particular methods and tools used within the context of broader methodologies proposed for PM. These methodologies tend to cover the whole process and assume a particular type or set of tools embedded within. For example, the Soft Systems Methodology (SSM) (Checkland and Holwell, 1998), and the Companion Modeling (ComMod) approach (Bousquet et al. 2002, Barreteau et al. 2003; Etienne 2014) are two well-known broader methodologies.

SSM uses a sequence of stages. It (1) considers a problem; (2) expresses the problem using Rich Pictures, a freestyle mapping of the different elements that make up the problem (e.g. using pictures and text to represent processes, actors, issues); (3) develops conceptual models to represent possible actions to improve the situation; (4) compares models to the real world; (5) debates and identifies desirable and culturally feasible changes, and (6) takes action to improve the situation. The SSM approach may well cover the whole PM process, but mentions only one particular method, Rich Pictures.

The ComMod approach combines such methods as role-playing games and ABM to promote single and double loop learning, for both individuals and groups. For the first steps of the process concerning fact finding, the approach involves stakeholders in the co-design of a conceptual model of the system at stake, using role-playing games. This sharing of representations is done by means of a series of collective workshops during which Actors, Resources, Dynamics, and Interactions (ARDI) are identified and clarified (Etienne et al. 2011). These conceptual models are then implemented as ABMs and brought back to all stakeholders for further discussion and improvement.

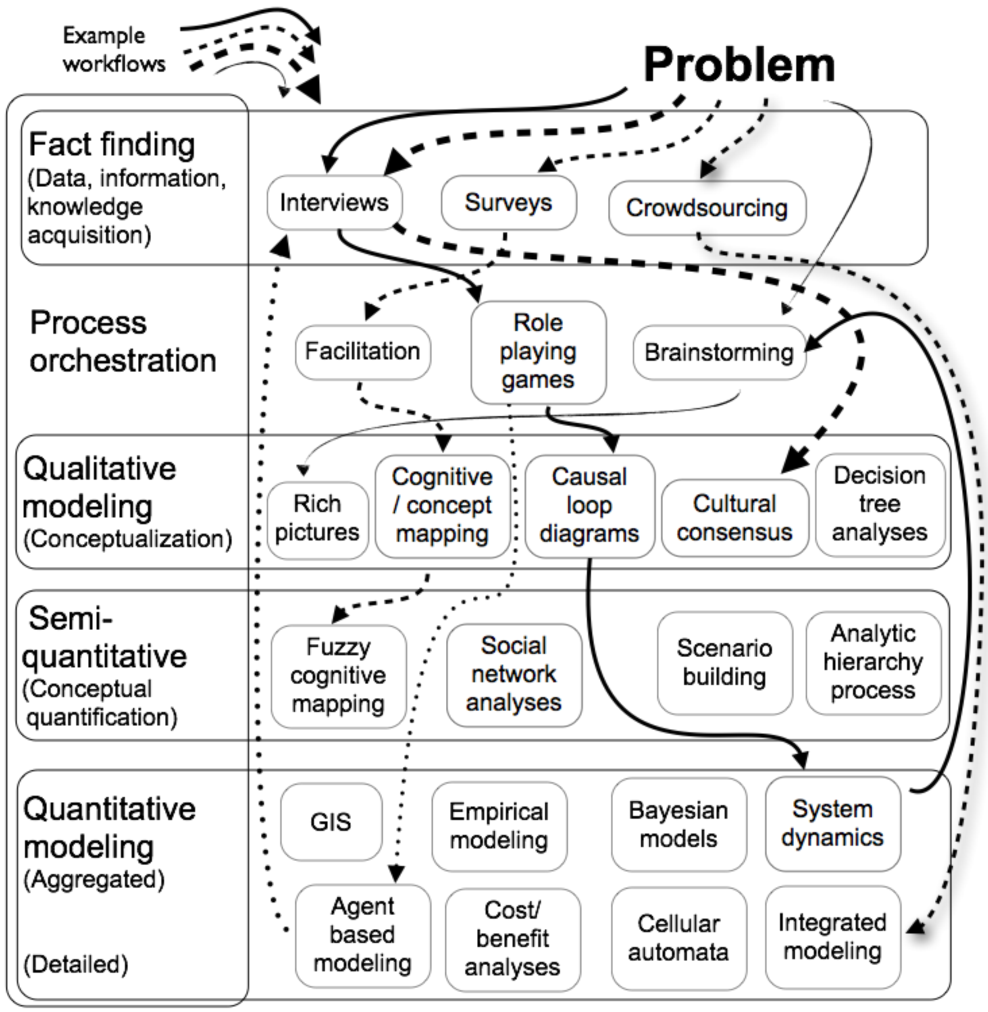

Fig.1. Typology of methods used in PM with example workflows. Most projects employ a combination of some fact-finding, process orchestration, and modeling. All projects require some facilitation or process orchestration, which continues throughout the entire project. Most projects include at least qualitative modeling; modeling can end with qualitative understanding and products, or develop further into quantitative assessments. However, projects rarely use more than one method of a particular type (e.g., both fuzzy cognitive mapping and social network analysis). Many PM projects include looping back from any stage, even from the most sophisticated quantitative modeling, to fact finding and data acquisition, and sometimes to the problem definition stage.

In the following sections, we identify and describe specific methods within each level of this typology. These methods can be, used separately or be combined within some of the more general methodologies such as SSM or ComMod described above. Here we view them as reusable components that can be reassembled in a variety of ways for future PM projects. The methods and tools discussed below are commonly used in PM but do not constitute an exhaustive list.

2.1 Fact finding

The fact finding stage(s) of PM focuses on finding, generating, and communicating data, information, and knowledge relevant to the problem being considered. This stage may continue throughout or be revisited multiple times during the PM process. In addition to standard research techniques that include literature searches and reviews, typical approaches to fact finding specific for PM are described below.

2.1.1 Surveys and Interviews

Surveys consist of a suite of questions; they can be undertaken in person, by phone, on paper, or electronically. When surveys are conducted face-to-face they are usually called interviews. These can be time-consuming but offer the possibility to clarify the questions, to gather additional valuable information not covered by the questionnaire, and to follow up conversations to explore results. Virtual surveys, collecting responses without presence of interviewer, could potentially reach a larger number of people than in-person surveys but suffer from a self-selection bias and it can be difficult to know or understand who responds and how reflective of the interests of the full group those respondents are.

It is also useful to distinguish between structured surveys or interviews and semi-structured interviews:

- Structured surveys or interviews use pre-defined questions in a set order, often with a closed response format (i.e., respondents choose from a list of possible responses). While this format limits the information that can be gathered, results are easily quantified and are relatively straightforward to analyze.
- Semi-structured interviews can include a mix of closed-ended questions, open-ended questions (i.e., respondents answer without choosing from a preset list of possible responses), and discussion. Discussion may be directed based on a particular response to a closed-ended question or may simply follow themes that arise from responses to the open-ended questions. The qualitative results of such surveys may be challenging to analyze and summarize for others, but they may allow for deeper understanding of responses.

Phone and paper-based surveys are relatively common in a variety of contexts. Telephone interviews pose recruiting, scheduling and response rate challenges; paper-based survey data are difficult to manage and process, especially when sample size is large. Studies of the potential for using 'Personal Digital Assistants' (PDAs) for gathering data electronically indicates that electronic surveys improve input data accuracy, facilitate data management and allow for automated data processing (Lane et al., 2006; Onono et al., 2011; Ficek, 2014). Recently, the increased availability of tablets and mobile phones, especially of low-end smartphones, has helped overcome some of the barriers to electronic data collection (Tomlinson et al., 2009; Kolagani and Ramu, 2017). Smartphones also permit collection of location and multimedia data, photographs, video and audio segments in addition to text, and allow better visualization, accuracy, and analysis of the data. Several free and open-source solutions, such as Open Data Kit (ODK) (https://opendatakit.org/), KoBoToolbox (http://www.kobotoolbox.org/) and Village GIS (http://www.iiits.ac.in/home/faculty/dr-nagesh-kolagani/), help users customize these solutions to their needs, and help collect, analyze and manage their data. Still, reliance on this kind of technology tool may disenfranchise the poor and less technologically facile groups of respondents. Moreover, this approach is less efficient with open-ended questions, where users are expected to enter significant amounts of text.

2.1.2 Crowdsourcing

Crowdsourcing is another data acquisition method that is becoming increasingly popular. It involves gathering data from a large number of people ('crowd'), including those unknown to the individual or organization gathering the data. Some main advantages are the relatively low cost to the data collector, quick speed, scalability, and the diversity of participation and types of data that can be obtained. However, data obtained by crowdsourcing may be hard to reproduce and its quality may be difficult to check. The data may differ significantly from the judgment of the experts, especially when more expertise is required (Sen et al., 2015). Another disadvantage from the point of view of PM is that crowdsourcing is usually used as a one-way data collection method (Voinov et al., 2016). It rarely gets used for higher levels on the participation ladder (Arnstein, 1969) that expect greater stakeholder engagement.

Individuals, either affiliated with a particular project or not, can volunteer to collect and provide data. For example, volunteered geographic information (VGI) (Goodchild, 2007) is provided by individuals associated with a specific geographic region. A prominent example of VGI is OpenStreetMap (OSM), which has the goal of creating a free editable map of the world. OSM was designed to overcome restrictions that exist on map availability in many places; it has produced spatial data of high quality, comparable to that of proprietary spatial data for most parts of the world (Haklay, 2010).

Alternatively, data can be collected from social media, derived from information provided by people even without knowing how it will be used. For example, van Zanten et al. (2016) estimated continental landscape values based on the social media data; and USGS has the Twitter Earthquake Detection data mining program which is used to help determine the intensity of earthquake energy felt by Twitter users (Earle et al., 2012)[1].

2.2 Process orchestration

By definition, PM is a process. Therefore, its success depends on how well the process is organized, managed, monitored, and reported. Process orchestration methods may overlap or combine with other methods. Note that in Fig.1, Process orchestration spans across all stages of PM. Facilitation, for example, is essential at multiple stages of a PM process. The focus of the facilitation may change (e.g. from understanding stakeholders' ideas and data to visualizing results and making decisions), but facilitation is still required. Three commonly used process orchestration approaches are described below, but there are many others.

2.2.1 Facilitation

Facilitation is key to PM processes regardless of other methods and tools used. Facilitation and the analyses that support it come with their own set of techniques and tools. For example, capability and knowledge mapping can help determine who has specific skills and capacities that are needed, and what knowledge gaps might be present. They can help map out the distribution and intensity of expertise and knowledge (Jetter et al., 2006, chapter 6). Other techniques such as diagramming, or the use of manipulatives (e.g. dice), can be used to help individuals express their ideas. Cards, stickers, or digital tools can also help facilitate and capture ideas.

Facilitation and its tools must be carefully employed and focused on moving the PM process towards attaining its goals. If mishandled, the facilitation process can become a source of frustration, and alienation. Multiple facilitators may be needed to offer different kinds of support, for example, a technician to facilitate with modeling tools, and a community leader to facilitate interaction among participants (Hovmand, 2014). The facilitation process must generally be open, accessible, and safe for honest discourse.During a facilitated participatory process, a good facilitator will strive to allow all participants to express themselves by trying to give everyone time to speak and express their points of view, to encourage mutual learning and understanding and to help foster a collaborative environment. It can be helpful for a facilitator to understand the background of the involved participants to guide their initial and continued interactions, and ultimately their perceptions of the tools, the model, and the value of the process (Kaner, 2007). An important aspect of facilitation in the PM process is the focus on modeling and the use of some of the structured modeling tools described below. At some stages of the PM process, the facilitator may need to understand the affordances and constraints of specific modeling methods, tools, and associated approaches. The facilitator role extends to encouraging all participants to see others as legitimate and valuable contributors to the development and growth of the model and associated analyses and processes. Depending on the PM problem, it may be important to consider and address cultural differences in how participants interact, and differences in their willingness to enunciate or modify beliefs or be receptive to contradicting beliefs or values. This links directly to methods such as Cultural Consensus, described below.

Good facilitation should also recognize the role of Biases, Beliefs, Heuristics, and Values (BBHV) in the PM process. According to Glynn et al. (2017), biases represent tendencies to believe in or pay attention to certain observations, ideas, or people, consciously or unconsciously, but with no good or testable reasons. This may result in decisions or actions which may be hard to explain or expect. Heuristics are

[1] https://earthquake.usgs.gov/earthquakes/ted/

https://blog.twitter.com/official/en_us/a/2015/usgs-twitter-data-earthquake-detection.html innately derived “rules of thumb,” mental shortcuts or simplifications, that help us navigate through the complexity of the world and its relationships (Kralik et al., 2012; Levine & Perlovsky, 2008). Relatedly, values are conceptions of the desirability, undesirability, or relative prioritization or importance of actions or things. Beliefs create (1) an acceptance or a conviction that something or some statement is true or real; or (2) a trust, faith, or confidence in a set of values and attitudes, in a tradition, in a thing or concept, in a “tribe”, or in a person, including oneself. Good facilitation should help participants in recognizing, mitigating or otherwise modifying or shapeing their BBHV to improve PM processes. This involves some type of reframing, personal or community questioning and learning (about oneself or itself), and training to both ease BBHV recognition and to create more effective and appropriate communication. Scientific ethics and integrity suggest that transparency and participant awareness are needed for BBHV elicitation and communication (Hill, 2012; Kelman, 1982; Cahill, et al. 2007). Different cultural norms may affect how awareness is created, or how participants are willing to enunciate or modify beliefs or are receptive to contradicting their beliefs or values. This links directly to such methods as Cultural Consensus, described below.

Facilitation can be improved and may be more useful if records of the PM activities include documentation of the facilitation processes used and the results of those processes. Such a record increases transparency and allows reconstruction and analysis of what happened, what was used and how, what the impacts and outcomes were. It creates a temporal record useful in understanding the future evolution of the system. It also aids in learning from successes and failures and provides insights that may help in applying or transferring the facilitation processes to other PM efforts. Radinsky et al. (2016) describe methods derived from the learning sciences for transcribing, coding and analyzing video-recorded discussions in participatory modeling settings. These methods help us understand how groups of participants interact with each other and with the modeling tools, how they learn about the complex problem they are facing, to what extent new knowledge and learning is translated into a plan for action, and the role facilitators played in supporting the process.

2.2.2 Role-playing games (RPG)

A role-playing game is a useful method to exchange knowledge among stakeholders in a desired context. RPGs involve creation and use of a virtual world, with simplified real-world conditions, to collect information, explore and understand context and situation, and develop and explore collectively possible solutions. A RPG comprises four main elements: environmental settings, player components, rules of operation and inputs to the game. The rules and structures of the RPGs promote player understanding by facilitating communication among stakeholders in an open environment (Eden and Ackermann 2004). In the game, different members play the role of different stakeholders and develop proposals collectively. RPGs can create more effective teams, help identify and address various stakeholders’ common or conflicting interests, effectively build a supportive coalition and increase the effectiveness of implementation. RPGs may also reveal implicit social rules and interactions between actors that might not have been evident during interviews and other interactions.

2.2.3 Brainstorming (B)

Brainstorming is a process that encourages all participants to offer ideas on a particular topic that are captured prior to any critical assessments of those ideas. Only after a robust list of ideas from the full set of participants is generated are decisions made about whether and how to exclude, include, or incorporate those ideas. Brainstorming can be used at many stages throughout the PM process, and is often used when a facilitator feels that the group has narrowed their discussions prematurely or as a tool to encourage broader thinking and participation and to ensure that all voices are being heard.

2.3 Qualitative modeling

In qualitative modeling in PM, project participants build conceptual, visual representations of the components of the problem being considered. The focus of qualitative modeling is on identifying, articulating, and representing the relationships among the many components of a problem; on the spatial, temporal relationships; and on how changes in one area affect other factors that may be important to solutions and to stakeholder concerns.

2.3.1 Rich pictures (RP)

Rich pictures is a diagramming tool that was developed as a part of the soft systems methodology (Checkland, 1999). RP makes use of cliparts, texts, and symbols to represent how a group of people think about a particular issue. Bell and Morse (2013) describe RP as a powerful intellectual and participatory device because it allows people to draw what they think but may not be able to write or speak about.

There are no strict rules or formal conventions for drawing RP. It has to make sense for those who are involved in the process, and be seen as a useful device communicating their ideas about the problem. Although this freestyle nature allows for creativity, it makes it difficult to share a rich picture outside the group without very clear explanation of the meaning embodied in the picture (Lewis, 1992). Some attempts have been made to provide general guidelines on practices for drawing coherent and useful RP (Open University, 2002; Bell et al., 2015).

2.3.2 Cognitive/Concept mapping (CCM)

Concept maps are graphical representations of organized knowledge that visually illustrate the relationships between elements within a knowledge domain. A concept map results in a network, where concepts (nodes) are connected through directed links (edges). These links are labeled to indicate semantic or otherwise meaningful relationships (e.g., “are”, “in”, “includes”). These labels allow one to logically define the structure (Novak and Cañas 2008). The argument for representing knowledge with concept maps emerges from constructivist psychology, which postulates that individuals actively construct knowledge by creating mental systems which serve to catalogue, interpret and assign meaning to environmental stimuli and experiences (Raskin 2002). Knowledge “constructed” in this manner forms the foundation of an individual’s organized understanding of the workings of the world around them, and thus influences decisions about appropriate interaction with it.

Several other mapping approaches are related to concept maps. A cognitive map usually represents an individual’s knowledge or beliefs about a particular issue or system of interest, whereas a concept map represents the perspectives of several individuals who worked together to identify key concepts, link them, and decide on the most appropriate labels describing the nature of each link (Eden and Ackermann, 1998). Additional constraints or steps can be imposed to create different types of maps. For instance, a ‘mind map’ follows a similar process to a concept map, but the core idea(s) would be positioned in the center of the map with all other ideas branching off radially. Differences between these maps, and implications for research, have been discussed by Davies (2011).

2.3.3 Causal loop diagram (CLD)

CLD is commonly used in system dynamics modelling to represent the key variables and relationships that are assumed to explain dynamic behavior. The CLD method uses a relatively small number of conventions, making it simple to use, even for a non-technical audience (Lane, 2000). Arrows represent causal relationships, where relationships are indicated by direction (i.e. positive, or negative). The emphasis in drawing a CLD is on eliciting and representing feedback loops and delays that explain the problem behavior. Lane (2008) presents a critical review of the use of CLD in system dynamics, and notes that the role of CLD changed from a back-end tool to communicate about the output behavior from the simulation model (i.e. expository mode) to a front-end model conceptualization tool. CLD can be used as a standalone method for model conceptualization, without being necessarily extended to the stage of a System-Dynamics simulation model. The CLD method has been credited for its simplicity and ability to give an aggregate or strategic view of the problem structure which helps to keep focus on feedback loops rather than on details. The method has been criticized (see Morecroft, 1982; Richardson, 1997 for more details), for example for not adhering to fundamental principles of accumulation which could lead to ambiguous and flawed inferences about problem dynamics. In the context of PM, Sedlacko et al. (2014) examined the use of CLD as a tool for promoting knowledge co-production and facilitating group learning. They found that to be effective, CLD require that groups have an agreed ontology about what variables mean and how the system works. Otherwise, there is a risk of producing shallow diagrams that hide both unexpected depths about given problems, and interesting insights in the differences between various stakeholders’ mental models and views.

2.3.4 Cultural consensus (CC)

Cultural consensus is a collection of analytical techniques and models that can be used to estimate cultural beliefs and the degree to which individuals know or report those beliefs (Weller 2007: 339). Formally, CC theory estimates the culturally "correct" answers to a series of questions (group beliefs), based on responses to similar questions, and simultaneously estimates each respondent's knowledge or degree of sharing of beliefs (Romney, Weller and Batchelder 1986). A structured questionnaire is used to collect nominal or ordinal data on set of relevant questions. Those questions are typically designed after interviews, participant observation, and direct input from stakeholders. Statements that capture key themes and knowledge are elicited from stakeholders (Paolisso 2015). Descriptive statistics can be applied to stakeholder responses to identify any within and between group patterns in the answers. Individual responses are processed through factor analysis to produce estimates of degree of sharing between individual and group cultural knowledge. The method assumes that there is only a single factor solution, which represents the cultural consensus. Stakeholders can be brought in again at this point to help interpret the pattern of responses.

In the informal model, the competence scores tell how well the responses of each individual correspond with those of the group. Stakeholder engagement is critical to interpret these results since CC does not provide definitive answers to what are the nature and boundaries of the shared underlying knowledge, only that there is a shared knowledge system underlying the pattern of responses (Paolisso 2015). CC complements BBHV recognition (above) in that it formalizes a methodological approach that captures the implicit and tacit knowledge that help drive behaviors, beliefs and values.

2.3.5 Decision tree analyses (DTA)

A variety of approaches can be used in qualitative modeling that emphasize identifying and illustrating the relationships between decisions – actions that can be taken to influence the situation of interest – and the outcomes of interest to stakeholders in the context of the PM study – their objectives. For example, decision trees (Kirkwood 2002) are used to illustrate the sequence of decisions and system changes that occur over time, and how they affect the outcomes that stakeholders care about. DTA are also used in quantitative modeling but can be used primarily as a qualitative structuring tool.

A more general name for these methods would be Decision-focused structuring (DFS). Both Adaptive Management (Holling 1978, Williams and Brown 2012) and Dynamic Adaptive Policy Pathways (DAPP) (Haasnoot et al. 2013) are decision-focused structuring and modeling methods that clearly differentiate actions, system uncertainties and evolution, and stakeholder objectives early in the model-structuring phases. These methods are designed to stimulate thinking about how decisions may change, or other decisions may need to be taken, as the system evolves; they focus on the concepts of dynamic change and adaptation of actions. As with decision trees, these methods can be useful in qualitative modeling to provide both structure and explicit consideration of timing; they can also be carried further into semi-quantitative or fully quantitative modeling. A recent case study using DAPP (Lawrence and Haasnoot 2017) highlighted the benefit of this approach in stimulating discussion among decision makers, planners and stakeholders on future actions by making uncertainty explicit, making the modelling process much more transparent, and connecting decisions to outcomes of interest.

2.4 Semi-quantitative modeling (conceptual quantification)

The distinction between qualitative and quantitative methods is not always clear cut. Quantitative methods use formulas and equations and make calculations based on data. However, in many cases the data are qualitative or semi-quantitative: the data may consist explicitly of qualitative information; they may be numeric estimates of values that are agreed upon or negotiated among participants; or they may be based on experimental data but have significant uncertainty about them.

In our typology, a method is classified as quantitative if, technically, there are ways to quantify most of the information used. This can be done through experiments, monitoring, surveying, etc. If it is impossible or very difficult to obtain or use numeric information, then the method is considered qualitative. Some methods are semi-quantitative. For example, we categorize fuzzy cognitive mapping (FCM) as semi-quantitative, since it employs some numerical analyses of the values assumed in the model, but the values themselves are most likely to be only qualitative or conceptual. On the other hand, Bayesian belief networks (BBN) are considered as quantitative because experiments can potentially be designed to measure some of the probabilities used in the method.

2.4.1 Fuzzy cognitive mapping (FCM)

FCM allows groups to share and negotiate knowledge about a problem and build semi-quantitative conceptual models. FCM facilitates the explicit representation of group assumptions or beliefs about a system being modeled through parameterized cognitive mapping (Ozesmi & Ozesmi 2004; Gray et al. 2014; Example: https://participatorymodeling.org/node/36). As in CCM, FCM starts with defining the most relevant variables that comprise a system, and the dynamic relationships between these variables, and then extends the CCM method by assigning the degree of influence (either positive or negative) that one variable can have on another.

FCM has three specific strengths compared to qualitative concept mapping techniques, which have led to their increased use in futures studies, scenario planning and complex systems modeling (Jetter and Kok 2014; Papageorgiou and Salmeron 2013). First, since the models created are semi-quantitative, they can be evaluated to understand system trends based on ‘what if’ scenarios. In a PM context, this allows stakeholders to contrast and compare the effect of different scenarios or evaluate the effectiveness of different management interventions in a given a socio-environmental problem (see Gray et al. 2015). Second, an FCM can be constructed in many ways, providing a way to combine the experiences or expertise of several individuals with various qualitative data sources (see for examples Singer et al. 2017). For instance, individuals can share their experiences and understandings, and these can be aggregate to create a group-level map (Gray et al. 2014). If the right data is available, the model can be derived entirely from the data using learning algorithms (Papageorgiou and Salmeron 2013). Third, FCM can be subjected to a range of network metrics allowing researchers to contrast the ways in which individuals or groups think about a potential problem (Lavin et al., 2018), measure the degree of structural variation across stakeholders and hence provide insight into uncertainty and complex socio-environmental problems that groups seek to understand.

There are numerous extensions to the FCM methodology, and software tools have been developed specifically to support participatory FCM (see www.mentalmodeler.org (Gray et al. 2013)). FCM can be employed with a stakeholder group to build and evaluate, through scenario analysis, a model in a short time (1-2 hours) or through individual interviews that take less than 30 minutes. However, such quick analysis comes at a cost since FCM does not represent specific quantities and is largely limited to defining linear relationships between concepts. Additionally, time and thus delays are not represented in FCM, as the system changes in ‘steps’ that bear no connection to real-world time. Therefore, although a useful tool to quickly and efficiently evaluate the structure and function of a dynamic problem, the model output is limited to conceptual and qualitative units with no real-time reference for how dimensions of a system may change over any real time horizon that stakeholders may desire for their decision-making.

2.4.2 Scenario building (SB)

Scenario building (or planning, or exploration) (Amer et al., 2013) is a practical approach to dealing with uncertainties about the future. Scenario planning relies on a broad analysis of trends and policies to cover a range of plausible futures -- it is distinct from forecasting or predicting a specific future. Each scenario should be internally consistent, meaning that - given current conditions and trends - it is plausible that the different aspects of the scenario could play out in the described way. Each scenario is designed to be substantially different from other scenarios and to highlight a unique and interesting possible future. In participatory modeling, scenarios can build from quantitative models (e.g. Systems Dynamics). In this approach, stakeholders provide knowledge about the structure of these models and indicate which input variables are critical and uncertain. A quantitative model is run for multiple input combinations within the plausible range, and the results provide the final value/state for each system element. The resulting internally consistent scenario may then be described in qualitative terms, in the form of a “scenario narrative”. Other PM approaches create scenarios in a fully qualitative fashion (“stories”). Scenarios are used to identify robust policies that are successful in most or all future scenarios, as well as to proactively develop backup plans.

2.4.3 Social network analysis (SNA)

SNA is a method for studying a set of social relations among actors, and how these relations and their patterning can impact or be impacted by actors' views, behavior, perceptions, and by learning (Prell, 2012). "Actors" can be individual persons or social entities such as organizations or even countries (e.g. Prell and Feng, 2016). Social relations can represent friendship, communication or trust, or can refer to other types of flows such as membership, trade, or various kinds of resources. A relation in SNA usually involves at most two entities, which allows SNA to use analytical tools from network/graph theory, in contrast to relations with three or more entities which are grounded in hypergraph theory.

Data on social relation networks can be binary or valued, although most analyses ultimately require that the analyst decides on a cut-off value used to dichotomize the data before modeling. The modeling of networks ranges in complexity. Simple, descriptive measures and/or visual digraphs of a network can be helpful in identifying which stakeholders are more popular or powerful, which are more peripheral, and how stakeholders might cluster together. Such simple descriptives can be helpful in designing participatory workshops and/or helping stakeholders understand the social context in which they are embedded (Prell et al., 2008; 2009). More complex stochastic models have been designed for handling network independencies, such as Exponential Random Graph Models, or ERGMs (Robins et al., 2007) and Stochastic Actor Oriented Models (SAOMs) (Snijders et al., 2010). These stochastic models can help analysts better understand, with greater precision, the decisions, perceptions or behaviors of stakeholders, especially in the context of natural resource management, or governance (Bodin et al, 2016; Matous and Todo, 2015; Prell et al, 2017)

2.4.4 Analytic hierarchy process (AHP)

During the PM process, it is often useful to consider the effects of scenarios or alternatives on a diverse set of criteria or objectives identified by the participants. While economic or cost-benefit analysis is sometimes used to summarize the impacts, it can be helpful to combine those effects into a summary metric through a model that explicitly accounts for conflicts and tradeoffs among those criteria, including criteria not easily monetized. Several approaches for evaluating options against multiple criteria, assessing tradeoffs among those criteria, and recombining results into a summary metric have been used in PM.

A popular method is Analytic Hierarchy Process (AHP) (Saaty, 1980). In AHP, tradeoffs among criteria are derived as "criteria weights" from stakeholder input on the pairwise relative importance of all criteria; alternatives are evaluated against those criteria using similar stakeholder input; and the results are combined in a weighted linear summation (Hajkowicz and Higgins, 2008; Howard, 1991; Example: https://www.participatorymodeling.org/node/45). Criteria weights are often assessed from individual stakeholders. When there is significant variability among weights obtained from different stakeholders, it may be challenging to identify an appropriate "group summary" metric. Means (Ryu et al., 2011; Tian et al., 2013), medians (Kolagani et al., 2015), and even the geometric mean (Saengsupavanich, 2013) have been proposed. Some modelers preserve the range of values by propagating the variability across stakeholders through the model using the Monte Carlo simulation approach (Rosenbloom, 1996; Hauser and Tadikamalla, 1996; Lafleur, 2011; Kolagani et al., 2016).

AHP is a special case of a more general approach known as multiple criteria decision analysis (MCDA) (Greco et al., 2016). Other popular approaches for MCDA in environmental decision making are multi-attribute utility theory and outranking approaches (Huang et al., 2011). Any of these approaches can be used at various levels of quantification: they can be used as qualitative tools to support problem structuring, and they can be partially or entirely quantified to create and support concrete valuation and comparison of values-tradeoffs necessary in any decision.

2.5 Quantitative modeling

2.5.1 Geographic Information Systems (GIS)

Geographical Information Systems (GIS) is a computer-based mapping framework that can be used to help stakeholders in visualizing and modelling their problems spatially. For example, GIS can be used to analyze and display how various scenarios play out on the landscape being considered, and how those changes provide benefits or costs to various stakeholders. GIS can also be used to provide inputs to other models. For example, stakeholders can map the land use and soil characteristics of their land parcels in a GIS, and use these maps to measure quantitatively extent of land parcels under various land use and soil categories. In participatory mapping, local stakeholders can sketch out spatial features on the ground, paper, or a touch screen on top of remote sensing imagery (Chambers, 2006). Such use of GIS by ordinary stakeholders has been termed public participation GIS (PP-GIS) (Sieber, 2006). However, implementation of quantitative GIS models typically requires quite a high level of technical skill; and over-reliance on the technical aspects of GIS may alienate less-skilled stakeholders (Chambers, 2008). There are several efforts to simplify GIS tools to facilitate use by less-technically-trained stakeholders, taking advantage for example of the increasing popularity of mobile and web technologies (Kolagani and Ramu, 2017; Example: https://participatorymodeling.org/node/38; https://participatorymodeling.org/node/121).

2.5.2 Empirical modeling (EM)

Empirical modeling refers to the process of identifying and quantifying relationships among factors of interest using observed and experimental data. EM is sometimes called "best fit" modeling and is contrasted with mechanistic process-based modeling (Voinov, 2008). In best-fit or empirical models, mathematical relationships are derived from data; they may or may not represent actual physical relationships between those factors. They are often used early in modeling projects to explore, interpret and understand available quantitative data. These models are sometimes referred to as black-box models, because they operate as closed devices that process information with no explanation of processes or parameters involved (Serrat-Capdevila et al., 2011; Refsgaard et al. 2005). These models are entirely driven by the specific data available, and they are risky to use outside the ranges covered by that data (extrapolation). Because they do not necessarily explain real-world relationships between factors, they can be difficult to use or communicate in a PM process (Basco-Carrerra, et al. 2017a), though their accuracy can be very high.

2.5.3 Cost-benefit and other economic analyses (CBA)

Economic analysis may be conducted as part of the PM process, especially in the latest stages of the planning cycle, to help assess the benefits and costs of alternative decisions (or investments). An economic analysis may help guide the design and ultimate choice of policy alternatives and associated system scenarios and forecasts. Economic analyses may be used to place a total monetary value on specific outcomes of interest. This approach spread into the environmental arena with the concept of 'ecosystem services' (National Research Council, 2005). Total value is generally composed of "use values" and "non-use values". Use values can further be parsed into "direct use values" (e.g. fishing), "ecological function" values (e.g. water availability), and "option" values (e.g. potential protection from floods). Non-use values can take the form of an "existence value" (e.g. satisfaction of knowing that a species exists) or a "bequest value" (e.g. preserving a resource for the next generation). Economic analysis can also be used to help determine the worth or benefits of acquiring additional data or information (cf. Young MD, 1992).

Cost-benefit (or Benefit-cost) analysis (CBA) (e.g. Hanley et al., 2009; NASA primer, 2013) is a commonly used methodology for assessing the anticipated costs and benefits of an investment or policy change compared to those that would accrue without an investment or policy change. The credibility of the "no change" scenario is essential in assessing the credibility of the CBA. In each case, the analysis generally requires developing a time series of costs and benefits that would accrue under each scenario, and then using a discounting hypothesis to summarize that time-stream in a given reference year. The assessment of both costs and benefits is likely to consider only a subset of the potential costs and benefits and is also likely to miss indirect costs and benefits that may result from a particular application or policy choice. There are many examples of CBA including one undertaken by the U.S. Geological Survey to assess the value of creating a National Map (Halsing et al., 2004). Different levels of implementation of a National

Map were compared to the counterfactual of not creating a National Map.

2.5.4 System dynamics (SD)

System dynamics is a simulation-based method used to articulate and understand the causal interactions that explain how the system behavior changes over time. Key to the SD method is the representation of a system in terms of stocks (where material, energy, or items are stored and accumulated) and flows (which are rates of exchange between stocks). An SD model provides useful insights into the feedbacks, delays, and nonlinear interactions helping decision makers to see the long-term, system-wide, and sometimes counterintuitive, outcomes of their decisions (Example: https://participatorymodeling.org/node/39; https://participatorymodeling.org/node/82). SD is the foundation method for several participatory modelling methodologies, such as: Group Model Building (Vennix, 1999), Mediated Modelling (van den Belt, 2004), participatory SD (Antunes et al., 2015), SD learning laboratories (Nguyen et al., 2011; Bosch et al., 2013).

System dynamics models were initially developed to investigate the temporal dimension in non-spatial systems. Some efforts have focused on extending the capability of systems dynamics to spatial modelling (i.e. Spatial System Dynamics Modelling) to investigate the effects of spatial characteristics on the problem behavior over time (Ahmad and Simonovic, 2004; BenDor and Kaza, 2012; Costanza and Voinov, 2003). These efforts include: (1) breaking down the system into zones where each zone is represented as system dynamics model (Ford, 1999), and (2) coupling system dynamics models with GIS to exchange information between spatially-distributed models over the simulation time (Neuwirth et al., 2015).

2.5.5 Bayesian networks (BN)

Bayesian networks are a statistical modelling method where the model takes the form of a unidirectional network, a directed acyclic graph (DAG). Nodes represent variables in the problem, while links represent the causal relationships among these variables. Variables usually take discrete states with certain probabilities. The graphical representation makes BN intuitive and useful for communicating model assumptions, uncertainty and the complex interactions among variables, especially with non-technical stakeholder groups (Carmona et al., 2013; Castelletti and Soncini-Sessa, 2007; Chen and Pollino, 2012). In addition to the qualitative and graphical component, i.e., the DAG, Bayesian networks also use conditional probability tables (CPTs) to quantify the strengths and probabilistic relationship between the causal variables (parent nodes) and children variables (Pearl, 2009). BNs can use and integrate qualitative data (e.g., the prior knowledge gained from experts or literature) and quantitative data (e.g., survey data). BNs also have other advantages such as: a capability to handle missing observations, potentially high accuracy for small amounts of data, and the possible support of scenario-based analyses.

2.5.6 Cellular automata (CA)

CA is a simple yet powerful modeling method developed by Ulam and von Neumann in the 1940s. A CA model is composed of cells with finite and discrete states, located in a regular lattice space (e.g., a square grid). The state of each cell is updated at each discrete time step based on rules taking into account the state of the cell and its neighbors up to a certain distance. This modeling method is especially suitable for spatial modeling, where the landscape is represented as a grid of cells, each cell described by a certain state that can change to one of other states, depending on its current state and interactions with other cells. This method is often used to model land-use change (Veldkamp, Fresco, 1996; Verburg et al., 2006; Batty et al., 1999). Parallel computations can be implemented by partitioning the lattice space into smaller spaces, which allows one to model large landscapes and/or at a detailed spatial resolution (Sun et al., 2009).

CA can also be used in conjunction with other types of models, to bring a spatially explicit component. In spatial versions of SD models, local SD models are replicated over the grid of cells (Costanza and Voinov, 2003). When SD is involved, the models usually turn out to be quite complicated and may require substantial computer power to run.

2.5.7 Agent based modeling (ABM)

Similar to SD, Agent-Based Modeling is a simulation method used to articulate system behavior and state changes over time. Instead of considering aggregates, global variables representing whole entities (populations, amounts of water, energy, material, etc.), ABM aims at the system level and macro-patterns that emerge from individual behavior of elements and interactions between them; it is a bottom-up process (Bonabeau 2002). The main elements of ABM are called agents, represented by attributes (state, location etc.), behavioral rules, and interactions with other agents and with the environment. Some agents are able to take decisions based on certain rules or goals (e.g., maximize profit) and even learn and adjust their behavior (adapt) based on past experience and performance of other agents. Where Cellular Automata are focused on landscapes and transitions, ABMs focus on individual actions and behavior. Agents vary in their preferences and abilities to act on their environment, as well as their ability to learn and adopt new practices, spreading them via their social network.

ABMs are particularly well suited for representing complex spatial interactions under heterogeneous conditions and for modeling decentralized, autonomous decision making (Parker et al., 2003; Zellner, 2008; Filatova et al., 2013). They have been widely used to study socio-ecological systems (Bousquet and Le Page, 2004; Schulze et al., 2017; An, 2012; Examples: https://participatorymodeling.org/node/36; https://participatorymodeling.org/node/37; https://participatorymodeling.org/node/74; https://participatorymodeling.org/node/75). Abat et al. (2017) provide an impressive list of ABM tools available to support this method.

2.5.8 Integrated modeling (IM)

Integrated modeling is a way of building models by combining or coupling existing models used as components to represent complex systems (Laniak, et al., 2013; Belete et al., 2017). Output from one model becomes input for another model. Since component models can come from different disciplines, IM is often seen as transdisciplinary exercise. Complex and powerful simulation models can be created by finding existing well-tested modules and plugging them together to represent the systems of interest. With properly documented models and with appropriate user-friendly interfaces, this could potentially be done on the fly, with stakeholder participation (Example: https://participatorymodeling.org/node/90).

In particular, Fast Integrated Systems Modelling (FISM), including meta-models, integrates and simplifies interactions and relevant feedbacks among complex systems into a fast, low-resolution model necessary for high-level reasoning and communication, and for exploratory analysis and long-term decision support that takes uncertainties into consideration. Metamodels are models of models intended to mimic the behaviour of complex models (see e.g. Davis and Bigelow 2003; Walker and Van Daalen 2013). FISM and the use of meta-models normally requires pre-running the complex models, saving their output under various combinations of parameters and then using the output instead of running the actual models. Such models are also known as ‘low resolution models’, ‘repro models’ or ‘fast and simple models’. FISM builds upon the concept of collaborative prototyping (Example: https://participatorymodeling.org/node/119). FISM models use something as widely available as Excel as a front end or more sophisticated tools, such as Python or PC Raster, depending on the needs of the process (resolution in time, space and system processes to be included). FISM models have been built for simulating rainfall-runoff (Jakeman and Hornberger, 1993), analyzing airport policies (Kwakkel et al., 2010), assessing flood risks (Ward et al., 2011), and screening of management actions (Haasnoot et al. 2014).

3. Selecting appropriate methods

As summarized above, there are a large number of methods and tools that can and have been used in PM processes. Yet it is difficult to identify the best strategy for deciding on what methods and tools and/or combinations thereof are most appropriate for a particular PM project. What makes these decisions especially difficult is that, as previously mentioned, there are hardly any reported cases where more than one method has been tried for the same problem within the same project. Combining several methods is quite common but replacing one method for another is not. In operational research, the mixing of methods has been viewed as a positive trend. Howick and Ackermann (2011) have produced an extensive review of papers on mixing methods but were not able to produce any general recommendations on what methods to mix and how. The selection and mixing of methods and tools is a decision-making process on its own (see Ormerod, 1997), that, clearly, one expects would be driven by the specifics of the problems being addressed. However, current practice reported in published literature tells a different story. Rarely is there much justification provided for the methods used, either individually or in combination.

This section offers support for researchers as they consider and select methods and tools. The first subsection reviews three PM case studies, with a focus on the methods selected for each. The next subsection describes some problem characteristics that should be taken into account when selecting PM methods, followed by the results of a survey of modelers engaged in PM that explored their perceptions of the PM methods described in Section 2. We end the section with some recommendations on the process and criteria for selecting methods and tools.

3.1 Methods used in case studies

How are methods chosen in real PM case studies? This section describes three studies, identifying the methods and tools used in each, and explaining the rationale for their selection. n two of the three examples presented, there was not much discussion about methods used: they were determined by the modelers. In the Indian case study however, the stakeholders moved from one method to another one choosing what worked best for them at each stage. This was the one project that was not funded by any major external donors: it was implemented largely through volunteer efforts of the participants.

3.1.1 Modeling the causes, consequences and solutions of the Flint Water Crisis

Residents of Flint, Michigan experienced a serious compromise in their water quality beginning with an Emergency Manager's decision to switch the city's water source to the Flint River in 2014. By 2016, thousands of Flint residents had been exposed to unsafe levels of lead in their drinking water, and the governor of Michigan had declared a state of emergency. A modeling team from Michigan State University was asked by the Community Foundation of Greater Flint to conduct a modeling exercise to capture the voices and views of Flint residents around the causes and consequences of, and potential solutions to, the Flint Water Crisis (Gray et al. 2017; Singer et al. 2017). The goal of this exercise was to represent Flint resident views in a manner that could be communicated to city leadership and to the state-appointed team in charge of developing a response to the Water Crisis. The timeline for this exercise was very short; community partners wanted a modeling product within a few months, in order for the results to be timely and relevant to the Water Crisis response. This short timeline effectively ruled out a simulation modeling approach, which would have taken significantly longer. Given the goals of the exercise, it was important to select a tool which could easily capture and synthesize Flint residents' views and knowledge about the systemic nature of the Water Crisis, and which could represent those views in an easily understandable format. The Fuzzy Cognitive Mapping (**FCM**) method was selected, implemented with the Mental Modeler (Gray et al. 2013) online tool (Fig. 2).

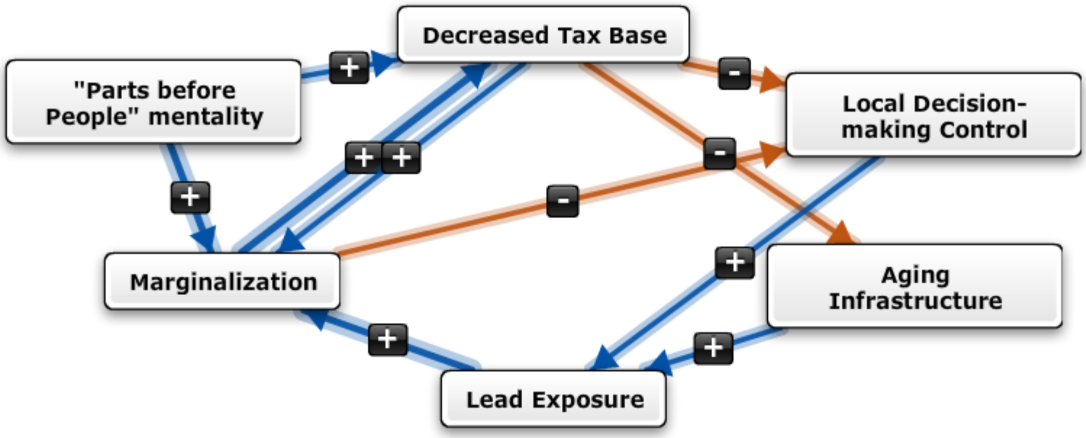

Figure 2. Example of subgraph of the concept map collected during a workshop indicated that residents felt that the City of Flint was locked into a “vicious cycle” and that an economic atmosphere of “parts before people” and loss of manufacturing jobs in the Flint led to “marginalization” and a “decreased tax base” that led to a decrease in “local decision-making control” and facilitated a lack of investment in “aging infrastructure”. These two factors in particular increased lead exposure through the Flint water crisis, which in turn increase further marginalization.

During the spring of 2016, a series of four mental modeling workshops was conducted throughout the city of Flint, attended by a total of 36 residents. A screen projecting the Mental Modeler software was displayed in front of the workshop participants, and a facilitator led the group through a discussion of the causes, consequences, and solutions of the Flint water crisis, posed as broad questions. Concepts and relationships between concepts were suggested by workshop participants and captured by the facilitator for all to see. When necessary, the facilitator posed clarification questions for discussion around the meaning of specific concepts, or the nature of the relationships between concepts. After the final workshop, the modeling team aggregated the four models developed by residents and shared the aggregate model, as well as the similarities and differences between the community models, with Flint residents in a final workshop.

The results of the modeling process were shared widely through public meetings and an online report. When reflecting on the modeling experience, Flint residents and Flint-based members of the research team expressed satisfaction with the modeling exercise in meeting its goals as a tool to communicate community views to the officials responsible for responding to the Water Crisis. Residents appreciated the opportunity to see their views and experiences reflected in a modeling product. Workshop participants also liked Mental Modeler’s ability to run ‘scenarios’ examining how changing one variable would affect other variables in the model. Several participants expressed interest in using Mental Modeler to address other community problems, and a desire to be trained in the software. Thus, the selection of a method with a software tool that s relatively accessible to non-modelers was an appropriate choice. A few Flint residents did express a desire to see the modeling results integrated with spatial information about lead exposure (Hanna-Atisha et al. 2016). A lack of spatial capability is a weakness of the FCM method.

3.1.2 Indian groundwater crisis

In an Indian village of about 240 households, a major problem in the recent past has been drought and over-extraction of groundwater, a typical 'tragedy of the commons' problem. Over several years, local leaders have used various informal tools to better understand the causes of the problem and come up with sustainable solutions. They organized and facilitated village meetings (i.e. 'focus groups'), field visits (i.e. 'transect walks') and individual discussions (i.e. 'semi-structured individual interviews'). As spatial information was increasingly needed to better visualize and understand the problem, villagers and leaders began using handheld GPS units to plot the locations of their farms and wells on paper. They then made the process less time-consuming and less error-prone by moving to public participation GIS ('**PP-GIS**') tools (Kolagani and Ramu, 2017; Example: https://www.participatorymodeling.org/node/45) with the help of their school-going children who were in turn assisted by their computer-literate teachers (Fig. 3). They started showing the maps to other stakeholders in an effort to come up with potential solutions (Fig. 4). Emphasis was placed on the use of simple calculations and visualizations to plan and implement rainwater harvesting (RWH) systems (Kolagani et al., 2015) and other solutions that were found most appropriate to the context.

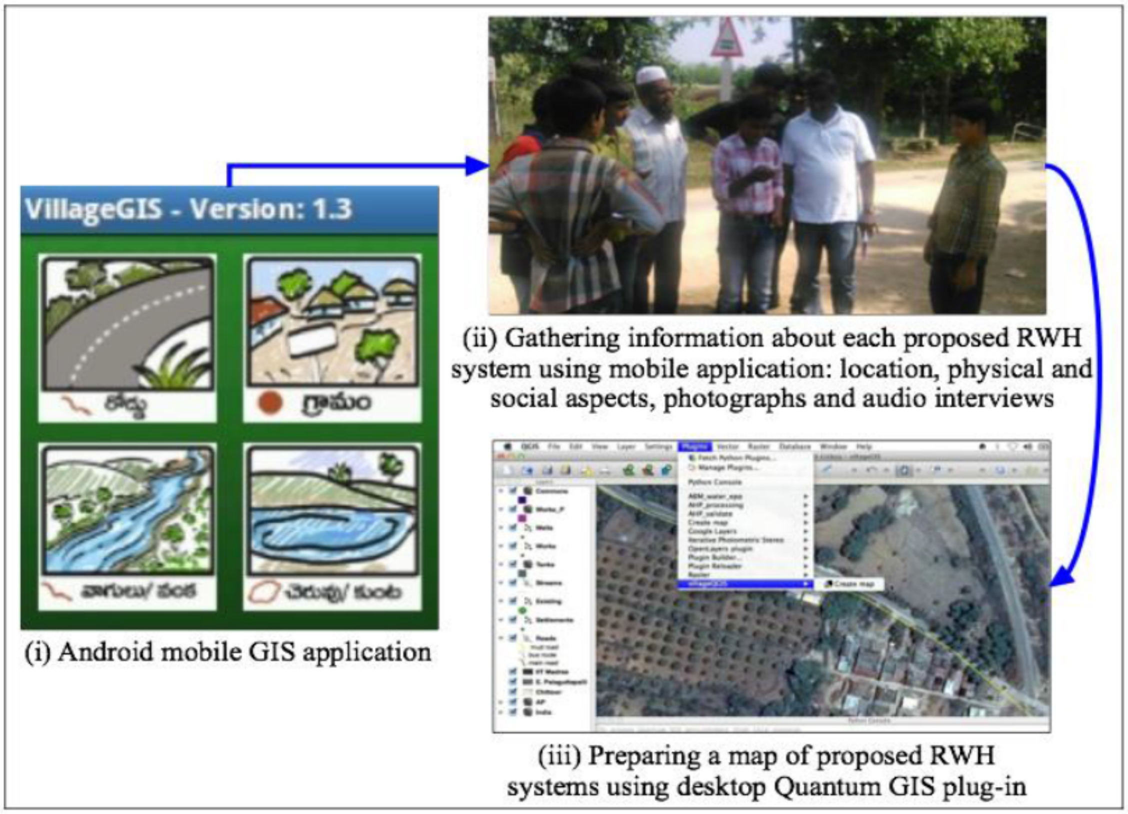

Fig. 3. Mobile GPS data collection and GIS map preparation by school children with the help of their teachers

Fig. 4. Use of PP-GIS maps, against a background of Google imagery, by stakeholders for designing village water grid: Inter-connecting tube wells to facilitate water lending (or selling) between stakeholders to provide irrigation to their crops in critical times, e.g. long dry spells that have become endemic over the last 10-20 years.

With some extensions to capture temporal dynamics, they were able to do participatory water accounting (Gray et al., 2018; Example: https://www.participatorymodeling.org/node/38). This helped them understand that increasing water recharge through RWH systems was only a short-term solution. RWH alone would not solve the problems unless water discharge was also controlled. However, discharge regulation is a socially and politically sensitive issue that requires buy-in and voluntary participation from all stakeholders. The leaders then felt that quantitative 'what-if' scenario analysis would greatly help convince the stakeholders of the need for discharge regulations. It is difficult to do 'what-if' scenario analysis with PP-GIS, however, and project leaders looked for more formal, yet simple, quantitative models that could predict the future, at least in the short term, while remaining themselves in full control of the process. They looked for a PM method that was easy to use yet had the power to answer their questions. They considered SD, ABM, BN, and FCM approaches. With the help of researchers from a nearby academic institute, they recently started using **SD**. As they got comfortable with quantitative models, they also started looking at **ABM** using rules they developed from their collective experience. Initial results seem to point to the need for a hybrid approach. An easy-to-use platform that facilitates such learning and use of different modelling methodologies might really help such innovations in participatory modelling efforts, especially by making stakeholders own and extend the models themselves.

3.1.3 Territorial transformations in the Amazon

In the Amazonian floodplains (i.e. várzea forests), climate change is disrupting the frequencies and magnitudes of floods, leading to great uncertainties for local populations. A project focused on the flooding of Curuaí big lake, a territory with 30,000 inhabitants spread over 133 communities in the Para State (Brazil), investigated how these populations were adapting their production systems to changes in flooding. A multidisciplinary research team collaborated with Feagle[2], a civil organization in charge of monitoring agrarian reforms by granting deforestation permits and hunting and fishing licenses. Today, regional conflicts and pressures from mining and timber extraction companies, and the complex landuse situation, threaten Feagle's existence and the future of the small-scale farmers in the area.

Given the vulnerability expressed by the social actors, the research team first studied their concerns and strategies through field visits and semi-structured individual **interviews** in several communities, and then collectively discussed most probable **scenarios**. To better understand ongoing dynamics regarding landuse activities on medium-term futures, a **RPG** was collectively designed with students of a rural school (around 30 future farmers). The RPG was organized as a board game that roughly displayed four communities on a transect from the lake to the forest. In this game, all players managed their respective farms according to their own strategies within the constraints of the game, considering issues such as labor, money, land cover, livestock, and so forth. By observing how players act in the game, all participants were able to better understand how people behave in real situations. The fun aspect of the game was also fundamental in freeing up conversations. The RPG debriefings enabled rich exchanges with farmers and fishermen, especially about the various constraints in the region. They spontaneously addressed the impact of their activities on natural resources, even if they were not always capable of explaining causal relationships. The main drawback of this game was its slowness: half a day of play was needed to simulate 4 to 5 years. Consequently, to better formalize the relationship between human activities and environment, and to increase the time horizons of the sessions, an **ABM** (Le Page et al., 2011) was implemented. Any of the 16 agents representing 4 smallholders from 4 communities could be controlled by participants, while the not-under-control agents performed computerized decision-making algorithms. Both types of agents simultaneously made seasonal decisions on agriculture, fishing and animal husbandry, while the computer also simulated biophysical processes by integrating their activities. The ABM was built as a continuation of the RPG. Based on the structure of the game that had been validated by the actors, it also seeks to specify the impacts of the activities based on research data. Moving from RPG to ABM enabled sophisticated calculations and scenarios on a broader timeframe. This allowed improved visualization and understanding of pasture degradation and dwindling fish stocks (Fig.5).

[2] http://governancaflorestal.iieb.org.br/manejos/view/10

Figure 5. (Left) - Workshop with the RPG at a rural school; (Right) - A snapshot of the ABM.

Through collective analysis resulting from the sessions, socio-economic and demographic changes were identified as additional factors, along with climate change, that contribute to water shortages and to the difficulties of addressing related issues. For example, without sewage-treatment systems, population growth could impact water quality and lead to the proliferation of cyanobacteria threatening human and animal health, as well as fish stocks that are already under pressure from commercial fishing and non-compliance with community fishing rules (Bommel et al., 2016).

3.2 Problem characteristics

From the examples above and from our experience running PM projects, we identified some characteristics to take into account when deciding on particular methods to use for a given problem.

3.2.1 Nature of the problem

The nature of the problem is critical. For example, a problem may focus on how to manage a common resource; acute risks; or slowly emerging risks. It may involve tradeoffs between conservation and economic development, or it may relate to environmental protection issues. Researchers considering the nature of the problem at hand may need to think about some of the following issues:

- The range of domain-specific expertise needed for the PM study: for example, expertise needed in such fields as public health, natural resource management, business organization, and others.
- The spatial and temporal scales of the system studied; and whether and how specific methods and tools used will be suitable given those spatial and temporal dimensions.
- The characteristics of the boundaries of the system relative to its processes, stocks, and flows: isolated, closed, or open.
- The structure of the problem or issue, and its degree of ‘wickedness’.
- The characterization of the level and types of uncertainties involved.

3.2.2 Nature of community engagement

The participatory process largely relies on who is playing a role in decision-making. Therefore, it is important to understand not only who is participating, but also how they are participating. This depends on one’s capacity to participate and both realized and perceived divisions of power. Not all tools are appropriate for all user groups. By considering the nature of the community, stakeholders and practitioners can choose the methods and tools that will be most effective. Researchers and participants may want to consider factors such as the:

- Number, diversity, background, and skills of the stakeholders, and also their social/political positions and roles, education, age, sex…
- Level and intensity of stakeholder participation -- low participation groups, those on the lower end of Arnstein’s participation ladder (i.e. ignorance, awareness, or information) may benefit from an entirely different set of methods or tools than those on the higher end (Lynam, et al., 2007) of the participation ladder (e.g., consultation, discussion, co-design, co-decision making).
- Timing and stages of participation -- some stakeholders may desire to participate in all stages of the PM process; others may want to focus on specific areas or may have skills and information that makes their input for specific PM stages particularly useful.
- Interaction context -- it is important to understand the level of cooperation or conflict among stakeholders: it affects the facilitation approaches and techniques that might be used, and possibly the selection of modeling methods.
- Power asymmetries -- where significant power asymmetries exist, the choice of process orchestration methods and the composition of the modeling and facilitation team may strongly influence which groups have stronger or weaker voices in the PM process. The team may need to take special care to assure that specific values or beliefs are recognized. Power asymmetries may also complicate the question of how much transparency the methods and tools should promote.

Power asymmetries have both methodological and ethical implications. The question arises as to whether some powerful actors whose actions contribute significantly to the evolution of a socio-ecological system should be included in the PM process or not. In some situations, social violence is part of everyday life and extreme pressure is often exerted on the weak. By inviting powerful actors to PM workshops, there is a risk of inciting more of this social violence. This issue creates a dilemma: claiming a "neutral posture" by inviting all relevant people may further strengthen the most powerful actors, while adopting a non-neutral posture to empower the weakest actors may compromise the legitimacy of the process (Barnaud and Van Paassen 2013). The proper balance should be taken into account in choosing facilitation approaches, although it may be difficult to translate these issues into selection criteria for other methods. In some cases, the level of power may correlate with level of education, which directly correlates with what tools are more likely to be understood and used effectively by given constituencies.

Stakeholder preferences and constraints can be driven by existing skills and experiences in particular methods or by the availability of training for newly suggested methods (Smajgl, 2015a). This depends on the level of co-implementation (e.g. model co-construction) and the expectation that methods that result from the PM process will continue to be used. In these cases, stakeholders may often consider the complementarity of the new proposed methods with the models and instruments they had been previously using. Stakeholders rarely advocate for the replacement of existing capacity. Stakeholders are also often concerned about the maintenance of methods (e.g. requirements for model re-parameterisations) if they are to be used beyond the near-term PM study.

3.2.3 Desired results

The goals of the PM process also have a strong influence on the methods and tools that should be used. For example, a focus primarily on building trust and understanding among stakeholders may rely more on qualitative tools and on process orchestration. In contrast, a focus on helping a small group of decision-makers “solve” a particular problem may require use of more sophisticated quantitative modeling approaches. Questions that can be asked include:

- What is the intent and prospective use of the modeling process and model outputs? Will the PM process help to make a decision, build trust, understand spatial distribution, temporal dynamics, and causality relationships, or is there another intent?
- Is descriptive analysis sufficient, or are prediction and scenario analyses also expected?

- Is the goal only to promulgate or achieve greater system understanding? Or is there a desire to create forecasts, or produce quantitative estimates? Is the description of trends sufficient, or is the elucidation of actual process dynamics needed?
- What are specific social objectives for the PM process (e.g. decision making, collaborative learning (shared or social learning), mediation, model improvement)?
- What are the political (or governance) types of actions that may result from the process (e.g. unilateral action, coordination, collaboration, joint action)?

3.2.4 Resources available

The final critical factor to be considered in selecting methods and tools relates to the type and amount of available resources. Resources required include time and money, people, skills, information and data. These resources are often limited, so method selection should be informed by considering:

- Types, quantity, and quality of available data and the time and expertise required for any additional fact finding.
- Available analytical tools, platforms, and visualization / communication tools that can be used by the full project team.
- Human resources and expertise: the types and levels of expertise among project participants; and how their expertise aligns with their desired level of participation.
- Timing: the length of time needed for various approaches or methodologies varies greatly, depending also on the level and expertise of participants. Considering when results from the project are expected and when they will have the most impact may suggest which methods have the greatest chance of success to meet the needs of the project and its stakeholders.
- Financial resources available to support process orchestration (meetings and workshops), model implementation, and consensus-building around possible outcomes or recommendations.

The importance of these factors was confirmed through the survey described in the next section.

3.3 Survey of PM practitioners

To understand how PM researchers typically select methods, we administered an online survey of PM practitioners. The survey included four main parts that elicited:

(1) Experience in the use of different methods: participants indicated their level of experience with each of the 23 methods shown in Fig. 1, using a 3-point scale (not experienced, somewhat experienced, or very experienced).

(2) Most preferred modeling methods: participants were provided with a list of the 18 methods from the modeling portions of Fig. 1 and asked to indicate their first, second, and third most preferred.

(3) Ways of selecting different modeling methods: participants were asked to rate their level of agreement, on a 1 to 5 scale, with each of the following statements regarding their choice of methods in their past PM projects:

- I used the method(s) with which I am most familiar.
- I explored all options and then chose the methods that were most appropriate, even if I was not experienced with them.
- I started with the method that I thought was most appropriate. If I found that it did not work, then I switched to another one (trial and error approach).
- I have only chosen to work on projects that can be addressed with the methods I already know.
- I typically selected methods based on the nature of the problem at hand.
- I typically selected methods based on the nature of the community involved in the project.

(4) The importance of different factors that may influence the selection of methods; participants were given a list of factors derived from the discussion above and were asked to rate the importance of each

factor to them when they select a method, using a 1 to 5 Likert-type scale (from a “strongly agree” to a “strongly disagree”).

3.3.1 Survey Administration

Survey responses were solicited through a listserv to more than 1,000 individuals included on a mailing list from the Innovations in Collaborative Modelling group as well as through convenience sampling to various colleagues and collaborators of the authors. To ensure the respondents were professionals in the field of PM, the first question included the following statement “We define participatory modeling or collaborative modeling as a purposeful learning process for action that engages the implicit and explicit knowledge of stakeholders to create formalized and shared representation(s) of reality. Have you participated as a modeler or researcher in a project that involved participatory modeling?” If respondents indicated “no” to this question they were excluded from taking the survey. In total, 93 respondents identified themselves as having experience in PM and 84 completed the entire survey for which results are shown.

3.3.2 Survey Results and Discussion

On the subject of experience with different tools, survey responses indicated some unevenness across the different methods (Fig 6). While it could be expected that some of the fact-finding methods such as Surveys and Interviews are quite well known, and similarly for some of the Facilitation methods such as Brainstorming, it was surprising to find that System Dynamics was as well-known as Interviews, and better known than Causal loop diagrams (CLD), which in a way are embedded in System Dynamics. Overall, our results indicated that respondents were knowledgeable of a diversity of methods.

The preference for methods used (Fig.7) aligned with responses regarding experience with the methods, except for some cases. For example, many respondents (> 60%) indicated that they were experienced in Cost-Benefit Analysis, but just a few (< 5%) preferred that method. System dynamics was the most preferred method (26%), followed by CLD (22%) and then Scenario building (20%), and these were also methods that many respondents had experience using.

For the most preferred method, we also asked respondents to specify the strengths and weaknesses of the method in the context of PM. These comments have been taken into account in describing the methods in Section 2 above.

Interesting results emerged from questions about how participants chose methods for their recent PM projects (Fig.8). On the one hand, respondents clearly admit that they choose methods that they are most familiar with: 92% totally agree or strongly agree with this statement. At the same time, 60% claim that they choose the most appropriate methods. This suggests that perhaps researchers choose the projects that where their methods-expertise is the most appropriate choice, yet only 35% of our participants said that was a factor. Indeed, the vast majority say that they choose methods based on the problem characteristics (87%) and on the nature of the community involved (73%). These responses are difficult to reconcile.

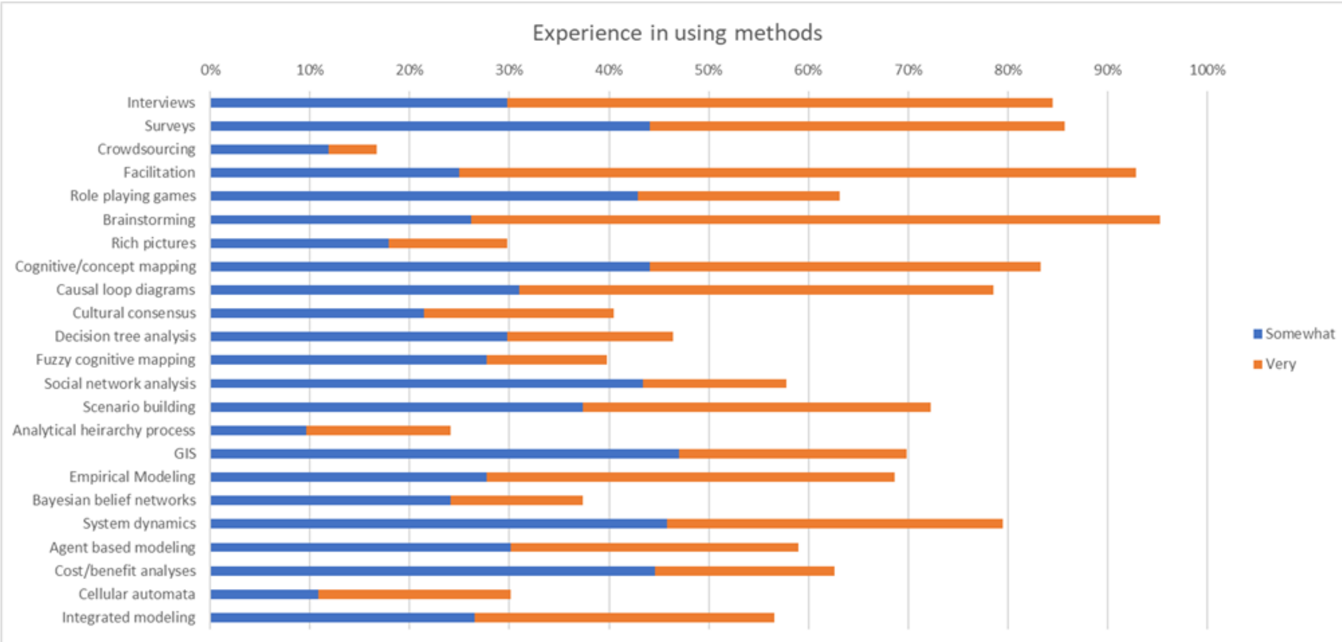

Figure 6. Percentage of respondents that are "very" and "somewhat" experienced with the various PM methods.

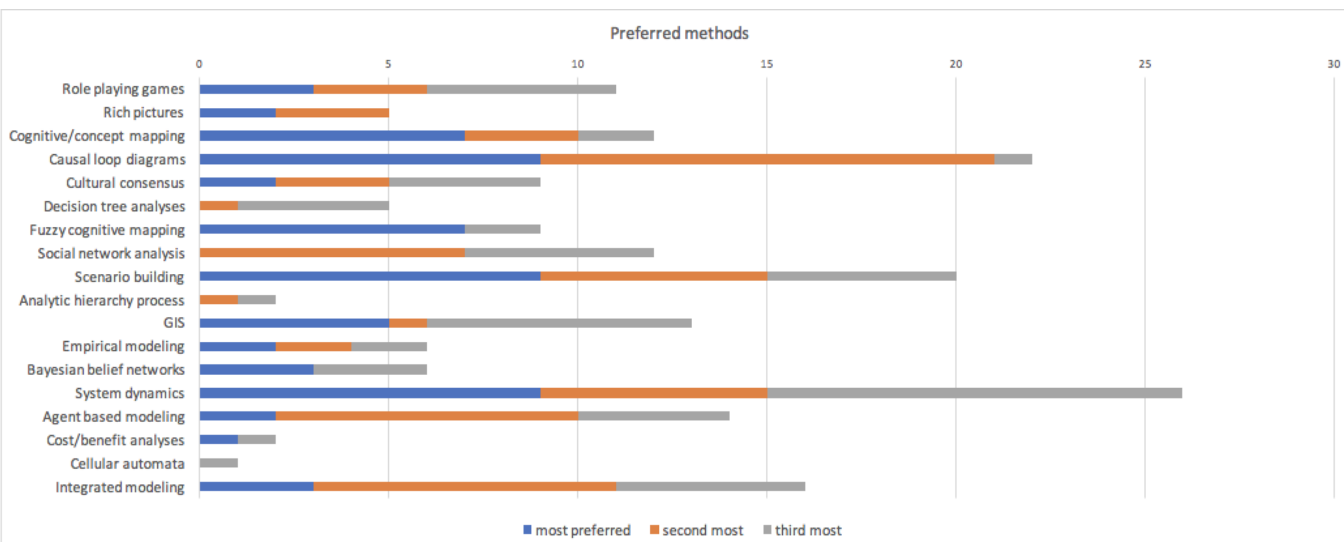

Figure 7. Numbers of respondents who indicated their preference for using a particular PM modeling method.

When asked to rate factors in terms of how important each is when selecting a method, all the identified factors were considered important. Time, money, and level of stakeholder involvement required, as well as the availability of data had the highest importance (Fig.9). Skills and education of stakeholders were of lower importance in the survey, though still important.

Overall, the survey suggests that practitioners consider many things when selecting methods, but that they do not necessarily have a clear hierarchy of criteria or approach for choosing those methods. One interpretation of the results in Figures 6 and 7 is that our respondents are guilty of a hammer-and-nail' interpretation, where they simply believe the tools they know best are the most appropriate and may be imposing their favorite tools on the stakeholders involved. Another interpretation is that our particular respondents were quite knowledgeable about the various methods of PM. Out of the 23 methods listed, all respondents indicated they were experienced in at least 5, one claimed experience in all 23, and on average respondents were "very" or "somewhat" experienced with 14 methods. This level of experience might allow them to choose both methods they are familiar with and those that are most appropriate to the problem. They may also tend to choose projects where there expertise is most relevant. .

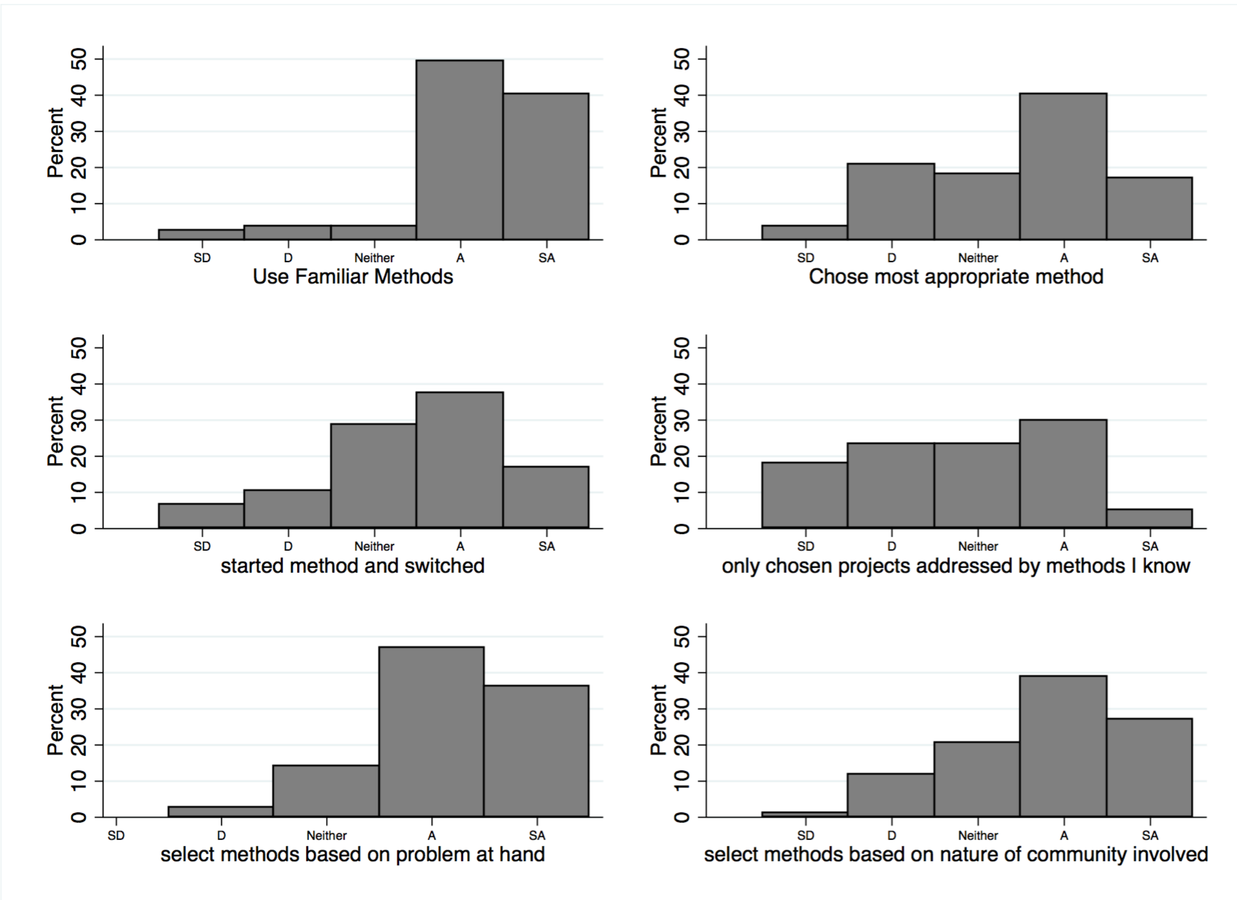

Figure 8. Distribution of responses to questions about the method selection process. Full questions described in text.

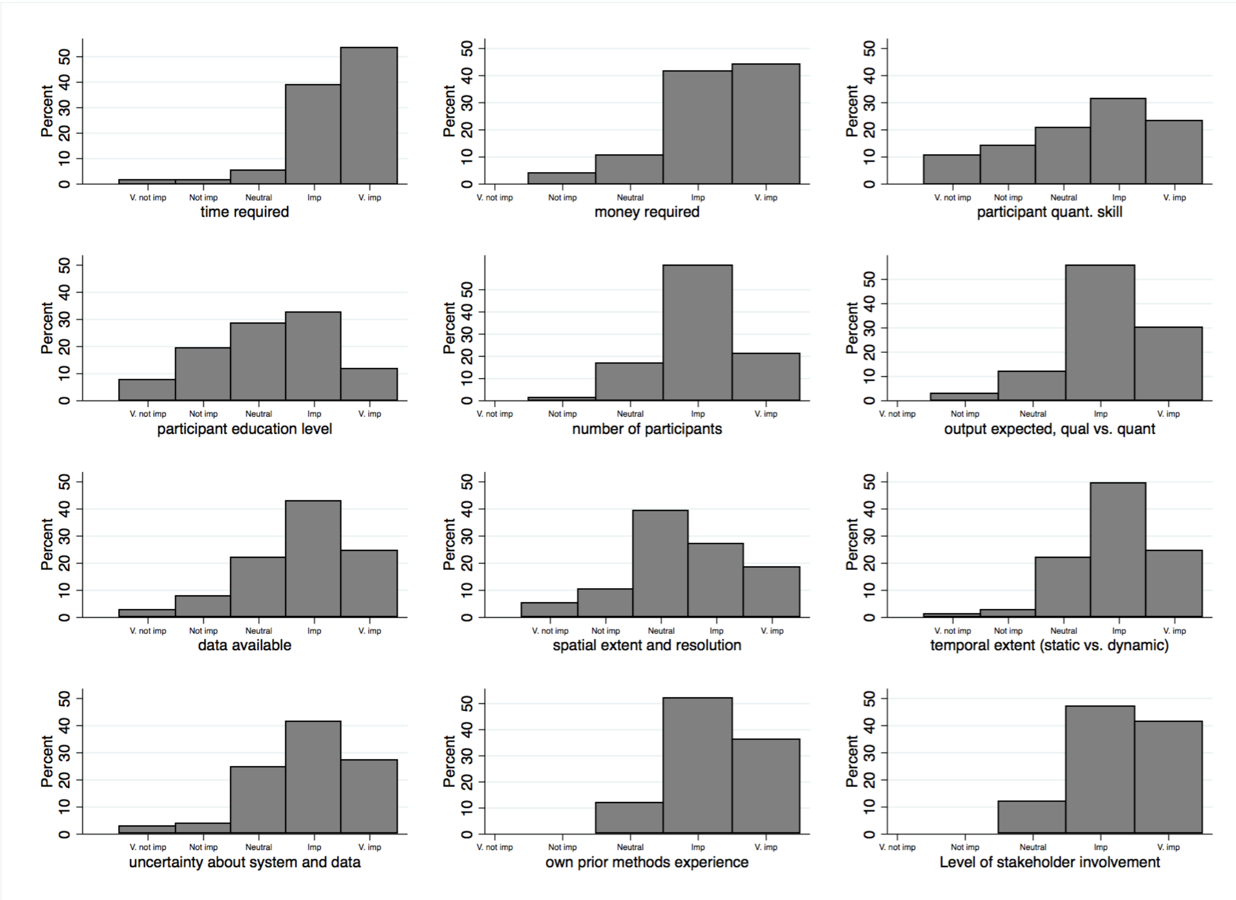

Figure 9. Importance of various factors to survey respondents when selecting the right tool for the job.

3.4 Some Recommendations

We differentiate between three types of method selection:

- The expert approach, in which modelers choose or recommend the methods and tools to be used. Their recommendation is likely to be strongly influenced by the methods and tools with which they are most familiar and most comfortable with, among those applicable to a problem. While there may be nothing wrong with this approach, there is always a risk that more appropriate methods exist that the expert is less comfortable with that would garner more effective participation in the process.
- The experimental approach, in which the stakeholders decide to experiment with new research methods or explore the applicability of existing methods in the project. This may be also driven by the modeler (usually an academic with a research agenda) wishing to learn how new methods work in new applications, using the project as a testbed. This trial and error approach has the potential to create new insights, but may be costly, both in terms of time and resources needed, and has to be well explained not to undermine stakeholder trust in the PM process.
- The participatory approach, in which all stakeholders, including modelers, take part in the process of selecting methods. Typically, this requires extensive engagement between all stakeholders at the very beginning of a project, so that all stakeholders can make an educated choice. Some stakeholders may also advocate for the use of a method that may not necessarily be the best for the task at hand.

We propose a critical approach that incorporates elements of all three types. The experts can start with a systematic comparative analysis to identify and reflect on the merits and weaknesses of various methods and their applicability to the multiple dimensions of the problem they seek to address. The other stakeholders are called in early in the PM process to learn about the existing alternatives, evaluate the options, and decide as a group on what methods to use. Experimentation with methods should be encouraged whenever sufficient time and funding are available.

There is still the problem of power and knowledge asymmetries that put experts in a favorable, dominant position. Their opinion may be hard to contest for less-educated and less-prepared stakeholders. We have started a web portal, https://www.participatorymodeling.org/, as one attempt to facilitate access to knowledge about methods and their past use, and also to promote further collaboration and communication about PM. Much of the information about methods presented in this paper is available on the web portal. The site is a content management system that uses the Drupal open-source platform and allows the users to enter and upload all sorts of information. We encourage anybody practicing PM or interested in PM to share their experience, case studies, information, and skills. To facilitate access to methods and knowledge in particular domains, we are also collecting a listing of experts, and provide a collection of other resources, such as models, videos, papers, etc.

There are several ways to guide the selection process. A decision tree may be the most straightforward and easy to follow selection technique. One previous attempt to apply such an approach to model selection was conducted by Kelly et al. (2013). However, for PM we failed to identify an appropriate set sequence of decision points that could enable building a decision tree. The process always appeared more nuanced, and too many considerations had to be simultaneously taken into account.

Mingers (2000) developed a questionnaire to help researchers think about selecting and designing multi-method processes that involve the use of participatory and numerical/analytical models. Questions are grouped into the following categories: (1) questions related to the relations between the researcher and the candidate methods (e.g. experience and skills), (2) questions asking about the relations between the researcher and the problem characteristics (e.g. interactions with stakeholders), and (3) questions connecting the problem situation and the intellectual resources, such as the suitability of methods to the organizational or situational culture. These factors are similar to the list described in Section 3.2 above. That list and the Mingers questionnaire provide useful guidance to help researchers think about what factors they need to take into consideration. However, they do not provide practical insights into how these selection methods perform.

We need a meta-tool that supports both the selection criteria and the nuanced judgments possible for each criterion. Our method-selection tables rank each of the PM methods shown in Fig 1: first against a set of desired model characteristics (Table 1), and second, against a set of resources required for implementation (Table 2). This is somewhat similar to the approach that the RAND Corporation suggests when choosing models for infection disease prevention (Manheim et al., 2016).

Table 1. Some capabilities of various PM methods, rated from Low (L) to Medium (M) to High (H). All values are relative to the suite of methods considered, and assume that each method is being considered in the context of the same problem with approximately the same levels of detail and complexity. A rating of "L" means that a method is less able to produce outputs that have the desired capability than is method rated "H" on the same capability. For example, GIS methods are better able to produce a spatial representation of a problem than are SD methods; and SD methods are better able to produce quantitative forecasts than are RPGs.

	Qualitative modeling methods					Semi-quantitative modeling methods				Quantitative modeling methods (aggregated)				Quantitative modeling methods (detailed)			
	RP	CC	RPG	CLD CCM	DTA DFS	SNA	FCM	SB	AHP	SD	EM	GIS	BM	CBA	ABM	CA	IM
Spatial representation	M	L	L	L	L	L	L	L/M	L	L	L	H	L	L	H	H	H
Temporal representation (dynamic)	L	M	M	L	L/M	M	L	H	L	H	M	L	L	L/M	H	H	H
Qualitative forecast	L/M	M	M	L/M	L/M	M	M	H	L	H	M	L	M	L/M	H	H	H
Quantitative forecast	L	L	L	L	M	M	L	M	L	H	M	L	M	M	H	H	H
Ease of communicating results	H	H	M	M/H	M	H	M/H	H	M	M	M/H	H	L/M	M/H	M	L/M	L
Transparency	H	M	M/H	H	M/H	M/H	M/H	M/H	M	M	L	M	L/M	M/H	L	M	L
Ease of modification	H	M	H	H	H	L	H	H	L	M	L	H	M	M/H	M	M	L
Feedback loops supported	L	L	H	H	L	M	H	M	L	H	M	L	L	L	H	H	H
Handling uncertainty	L	M	M	L	L	L	L	H	L	H	H	L	M	L	H	M	M

Table 2. Some requirements for implementing various PM methods, rated from Low (L) to Medium (M) to High (H). All values are relative to the suite of methods considered, and assume that each method is applied in the context of the same problem, with approximately the same levels of detail and complexity. A rating of “L” means that a method requires less of the resource than does a method rated “H” for the same requirement. For example, RPs require less time and money to implement than does IM; EM requires less systems knowledge than SD.

	Qualitative modeling methods					Semi-quantitative modeling methods				Quantitative modeling methods (aggregated)				Quantitative modeling methods (detailed)			
	RP	CC	RPG	CLD CCM	DTA (DFS)	SNA	FCM	SB	AHP	SD	EM	GIS	BM	CBA	ABM	CA	IM
Time and cost	L	M	L/M	L	M	M	L	L/M	M/H	M/H	M	M	M/H	M	M/H	M/H	H
Data (Empirical)	L	M	L	L	M	H	L	L/M	L	L/M	H	H	M	M/H	L/M	M	H
Systems Knowledge (Conceptual)	L/M	M	L/M	L/M	M	M	M	M/H	M/H	H	L	L/M	M	L/M	H	H	H
Expertise of modelers	L	M	M	L	M	M	M	M	M	H	M/H	M	M/H	L/M	H	H	H
Methodological expertise of stakeholders	L	L	L	L	M	L	L/M	L/M	L	M	L/M	L	M	L	L/M	M	M
Computer resources	L	M	L	L	L	M/H	M	L/M	M	H	M/H	H	M	M	H	H	H

The goals of a PM study should offer the starting point for any discussion about the PM methods needed. These goals may be positioned on two extreme ends of a continuum. At one end, some studies are designed to highlight knowledge diversity, to make different voices in the community heard, and to understand sources of conflict. In these studies, the models themselves are mainly boundary objects for communication of different worldviews. They do not have to be scientifically accepted representations of the real-world systems, and they may not be consolidated into a single model. Participants are chosen based on a desire and need for comprehensive representation, diversity of perspectives, and to maximize engagement and understanding. At this end of the continuum, ease of communication and interpretation might be the most important factors to consider in selecting methods. In contrast, at the other end of the continuum, some studies aim to pool expert knowledge about a system and to create a model that allows predictions to be made and that supports detailed exploration of the implications of different decisions or actions. The desired output of this kind of study may be a quantitative model in of itself that is validated against empirical data and expert knowledge. Accordingly, these studies are very concerned with the modeling process (e.g. expert selection, strategies for model validation) and emphasize consolidation and aggregation. Figure 10 is a generalized version of Figure 1, and positions different groups of modeling methods on this continuum.

Selecting methods for a participatory modeling exercise should be a flexible process. It may even involve the invention of new methods and tools if existing modeling approaches are not appropriate. Throughout the selection process, stakeholders (including modelers) are typically engaged in asking the following questions (sometimes repeating these questions at multiple stages of the modeling process):

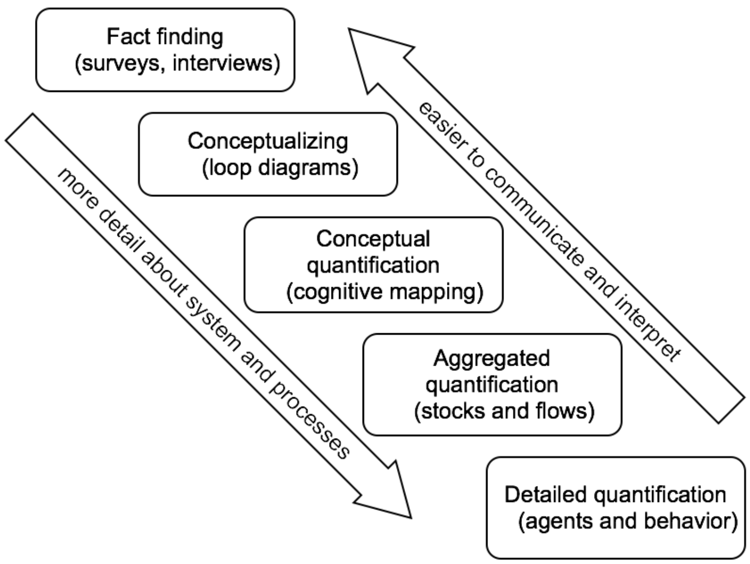

Figure 10. The modeling ladder: complexity versus communication.

1) Does this problem require detailed spatial or geographic information to solve? At what scale or resolution? Are there spatial interactions to consider?
2) Is there a need to project current system conditions into the future in order to make or improve decision-making? How far into the future do we need to look, and how precisely? What level of uncertainty are we comfortable with? Are there temporal interactions to consider?
3) What is the goal of the participatory modeling process? Is it community engagement, community organization, solution-building, planning implementation?
4) How much time and how many people and resources can be devoted to the modeling effort? What skills do the people have?
5) How much does the community know about the problem being modeled? Do scientific data need to be collected and integrated into the model to help answer the community's questions? What data are available (kind, quantity, quality, scale/resolution)? What interactions with the modeling tools will different stakeholders want to have? Will they want to be consumers of outputs, users and scenario testers, developers? What capacity-building is needed for the different stakeholders to facilitate the PM process interactions they aspire to?
6) What capacity does the modeling team have to build or use appropriate modeling tools? Do other modeling or scientific experts need to be brought in, and is there sufficient time and financial resources for this? What is the ability to continue using the particular method (as output of the PM project) after project completion? How alternative methods can be linked to existing and already used data and methods?

Answering these questions and using Tables 1 and 2, the stakeholders should be able to evaluate the various methods available and choose one or a combination of methods that will be most appropriate for a given problem or situation. Subjectivity will always remain in how stakeholders treat these questions, which is why it is hard to expect that the choice of methods will be always optimal. In fact, there is probably no optimal choice. However, by designing the process as open-ended and adaptive, the project team could ensure ongoing evaluation of process outcomes and methods used, and change direction when deemed necessary.

3.5 Further considerations for method selection

Clearly, the evaluation of appropriateness of PM methods entails multiple criteria, which can be summarized as follow:

- Effectiveness: how well can a specific method succeed given the focal problem of interest, and how well it meets the goals of the PM team and the needs of the PM processes.
- Efficiency: whether the methods can achieve the PM goals in the needed time and with the appropriate use of the available human, financial, and technical resources.
- Social value added: how well the methods support the broader goals of the PM process, such as promoting gender, racial and income equality, learning and education, dialogue among diverse groups, and social capital of stakeholders (in line with the social network development mentioned below).

Evaluation of the usefulness of the method used usually occurs only at the end of the project, when time and money are most likely running out, and when participants are fully invested in what they have done. This only makes reporting of failures in addition to successes even more essential, so that everyone can learn from mistakes or problematic choices; it also explains the rarity of such reports. If instead, we evaluate the appropriateness of the methods early and throughout the PM process it is more likely that the project can adapt and change course if needed.

Some methods may offer additional benefits that go beyond questions of effectiveness, efficiency, and social value. For example, to the extent that participants can really engage (i.e., “lose themselves”) in a gaming, modeling or simulation process, some conceptual modeling and qualitative or numerical simulation tools can help the decontextualisation process and potentially reduce conflict. Modeling and simulation tools and processes that are flexible enough to effectively create abstraction while fully engaging participants may be of great interest.

The preferred approach may be a combination of methods and tools, so considering the compatibility of different methods to work together in the PM process is desirable. For example, there is theoretical and empirical support for combining mapping and SD modelling. Companion Modeling involves the combined, usually sequential, use of both RPG’s and ABM, where RPG is used to first create an engaging abstraction that can then foster more complex participant understanding and engagement in the use of ABM.

Social network analysis can be used, in conjunction with cognitive and/or behavioral measures, as a means to assess how stakeholders’ views, beliefs, and practices co-evolve with the relationships formed via the ongoing PM process. Doing so would involve measuring stakeholders’ ties with one another at various points in the PM process, and collecting, at the same points in time, relevant cognitive and behavioral data. Such a combined tool kit could thus readily be used as means to evaluate the extent to which: 1) the PM process has resulted in creating, strengthening, or improving stakeholder relations; and 2) the process has created channels through which stakeholders can mutually influence and learn from one another. The subsections below discuss some issues related to combining or using multiple methods and tools.

3.5.1 Interfacing qualitative and quantitative methods

Following the Voinov and Bousquet (2010) diagram, we can point at another version of the generic framework in which the two big leaps in the process are stressed. A first leap happens in the move from the conceptual, qualitative phase of model development to the quantitative phase of model formalization and computer runs. A second leap happens in the move back from quantitative analysis to qualitative interpretations, for example in the simplified visualizations and communications that are essential for the delivery of model results and for their translation into policy and actions (Fig. 11). This also somewhat resembles the modeling ladder in Fig.10. We go from data and concepts and gradually attempt to make sense of them through various forms of reasoning and analyses. Bridging the gaps between qualitative and quantitative modeling remains a challenge, and often disrupts the PM process. Quantitative models, especially when they become quite complex, are often built behind the scenes by experts and later on, are reintroduced to the rest of the group. A smoother transition between qualitative and quantitative phases is much needed but is yet to be achieved.

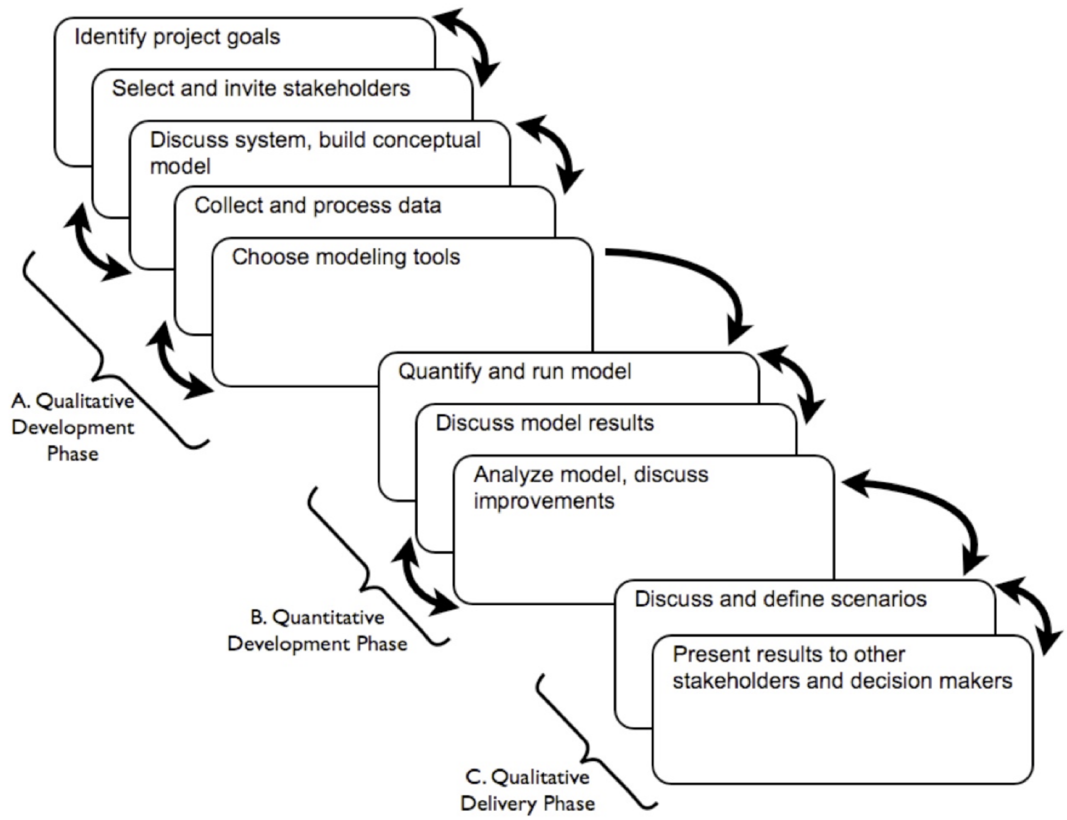

Figure 11. Gaps between qualitative and quantitative phases in the model development.

3.5.2 Interactive modelling

For true engagement of stakeholders in the modeling process, it is essential that models be transparent and easily modified and tuned according to the needs of the stakeholders. They should be able to interact and make direct changes in the models as they use them; and see the results of their changes almost instantly. Such direct interaction facilitates stakeholder understanding of complex physical processes. This does not mean that for all cases the whole PM framework has to be applied and implemented. Usually only some parts may be exposed to stakeholders. While there are many benefits of staging a full complete participatory modeling process, in reality there often exists restrictions of time, resources and needs that make it necessary to limit the PM approach to a partial implementation. Even then, there is a lot that can be derived from the connection between models and stakeholders in the process.

Following this perspective, several modeling tools are popular in the PM community for their ease of use with interactive groups. For example, *Cormas* (an ABM tool dedicated to natural resources management) has been used for collective design of models and interactive simulation (Bommel et al. 2016). Here users can interact with a simulation by manipulating avatars (the agents that represent them in the simulated word), changing their environment and their behavior (by modifying simple activity diagrams). Thus, it is possible to collectively explore medium and long-term scenarios to better understand how a desired situation may be reached.

Similar functionality explains the success of *Stella,* an SD tool, actively used by the Mediated Modeling approach (van den Belt, 2004). More recently, the use of direct dynamic visualizations of a system often in the form of interactive submersive graphics (i.e. virtual reality, mixed reality, and 3D environments[3]) is an emerging technological trend that facilitates understanding of model outputs and stimulates stakeholder engagement in modifying and refining the models (Basco-Carrera et al. 2017b; Example: https://www.participatorymodeling.org/node/117). Here also there are certain restrictions on the realism of the output generated; virtual reality may overburden stakeholders with information and hide the important message of the modeling process (Voinov, et al., 2017).

3.5.3 User interfaces

Better understanding of the interconnections among the social, behavioral, and material elements involved in the participatory modelling activities, and how these interconnections influence the participatory modelling process and outcomes is necessary to fully understand the effectiveness of different combinations of methods. Theoretical insights from relevant scientific fields, including cognitive science and user psychology, could identify the characteristics of modelling techniques that fit into a particular PM activity. For example, Golnam et al. (2012) used Cognitive Fit Theory to explain the cognitive capabilities required for building SD models, and to determine the suitability of various problem structuring and conceptualization techniques to fit to these capabilities. Herrera et al. (2016) developed an experimental framework to compare the effectiveness of (1) a single-method group-modelling process and (2) a multi-method process combining strategic options development and analysis with computer simulations at promoting changes in participants' mental models and achieving better negotiation outcomes. Shelley et al. (2010, 2011) studied how different tangible and mobile interfaces can help stakeholders state their preferences and values, collectively design scenarios and make sense of simulation outputs, and deliberate towards compromises. There is much improvement still needed in the modeling interfaces that could make model formulation, running, testing, and communication simpler for non-expert stakeholders.

4. Conclusions

There is much improvement yet to be made in how modeling methods are selected for PM projects. There are many methods already available, and choices are not simple. In too many cases, the selection process seems to be largely driven by the past experience of participants, rather than by the particular needs of the project. While logic tells us that this is probably not the best strategy, we do not have much, if any, evidence that this is a bad thing. To a large extent, this is because there are almost no method comparisons documented for PM projects, i.e. where one method was substituted by another and where results were meaningfully compared. Comparing across projects is difficult because each project is unique. While the problems may be similar, the stakeholders involved are always special, and group dynamics are hard to reproduce. There is also much subjectivity in how stakeholders perceive the outcomes of a PM process and how those processes are evaluated. What may be a success for one stakeholder group may turn out to be a failure for another. There are too many biases, beliefs, and values involved in any kind of comparison and evaluation done by stakeholder groups to assume that the evaluation is correct and universal. Post-audits and other tools to assess longer-term outcomes of PM-driven actions/decisions and provide feedbacks (i.e. PM as a part of adaptive management and governance) could certainly help but are still very rare.

The challenge here is that there are many confounding factors influencing the PM outcomes, tied to the individual and collective characteristics and relationships within the project teams, and these change over time as participants interact with each other and with the modeling approaches and tools. At best, we can

[3] Some examples include: Interactive SandBox (https://www.deltares.nl/en/news/interactive-sandbox-new-interactive-design-tool-for-the-direct-visualisation-of-coastal-interventions/), 3Di water model (http://www.3di.nu/en/international/), or flexible mesh (https://www.deltares.nl/en/software/3d-interactive-modelling-using-delft3d-flexible-mesh/)

attempt quasi-experimental setups, but controlled experiments are not possible. Despite this limitation, evaluation of each PM study should become standard practice, so that a body of knowledge can be built to inform new applications.

While all stages in the PM process assume possible iteration, method and tool selection is crucial because there may be insufficient time or resources available to go back and do the whole PM process once again with another method. The modeling method chosen depends upon, but can also determine, the types of data to be collected and processed. While the 'hammer and nail' syndrome always has a negative connotation, past experience certainly matters and, indeed, it may not be bad to use a method that someone is most comfortable with. Besides, as shown here, there is often considerable overlap between some methods: this only makes it harder to come up with a unique optimal choice.

With no strict rules or guidelines for method selection, more consultation and access to past and present experience could help. An inventory and systematic analysis of methods and tools can also provide a stronger basis for model selection and can narrow the array of choices. We hope that the web portal introduced above, https://participatorymodeling.org, will engage PM practitioners, enlist them in adding their knowledge and experiences to the web portal, and will generally serve the community of practice interested in the development of better techniques for participatory, collaborative modeling. The web portal is a community-led endeavor, and we expect the users to identify what features and functions it should provide. We will also need community suggestions regarding how to best manage and moderate the portal. For example, we would like to ensure that additional openness in project reporting, and potentially ensuing critiques from the PM community, do not discourage stakeholder groups from presenting their results and methods for public scrutiny and evaluation.

A good PM project should be open minded about the particular type of modeling methods to be employed. Itis often problematic to justify this to funders who usually want to know in advance everything about what will be done, accomplished, and how the PM process will unfold. It takes a considerable amount of trust from funding agencies and clients to devote resources to processes that are vaguely defined, and/or to rely on the project team to provide or add expertise as a problem requires (Prell et al. 2007). If it is harder to get funding for a multi-method project, such projects are likely to remain rare, offering little help in convincing the funders about the benefits of adaptive modeling approaches.

It also may sometimes be difficult for funders (and publication authors and editors) to recognize that documenting PM failures is as important as documenting PM successes, and indeed may be more important in advancing PM knowledge and best practices. This is one more reason for the PM community to organize itself, to recognize the advantages and disadvantages of the rich array of PM tools and methods that are already available, to improve and innovate as needed, and to educate itself (as well as its funders and stakeholders) on the factors that should be considered in the selection of PM methods and tools. We hope that this paper, and our creation of the https://participatorymodeling.org web site, will help in this regard.

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