

Doing flood risk modelling differently: Evaluating the potential for participatory techniques to broaden flood risk management decision-making

Shaun A. Maskrey¹  | Nick J. Mount²  | Colin R. Thorne² 

¹Environment Agency, Reading, UK

²School of Geography, University of Nottingham, Nottingham, UK

Correspondence

Colin R. Thorne, School of Geography, University of Nottingham, NG7 2RD, Nottingham, UK.

Email: colin.thorne@nottingham.ac.uk

Funding information

Engineering and Physical Sciences Research Council, Grant/Award Numbers: EP/K01366/1, EP/N008103/1, EP/P004180/1; EPSRC PhD studentship, Grant/Award Number: 1230597

Abstract

Responsibility for flood risk management (FRM) is increasingly being devolved to a wider set of stakeholders, and effective participation by multiple FRM agencies and communities at risk calls for engagement approaches that supplement and make the best possible use of hydrologic and hydraulic flood modelling. Stakeholder engagement must strike a considered balance between participation ideals and the pragmatic realities of existing mechanisms for FRM decision-making. This article evaluates the potential for using participatory modelling to facilitate engagement and co-production of knowledge by FRM modellers, practitioners and other stakeholders. Participatory modelling offers an approach that is flexible and versatile, yet sufficiently structured that it can support meaningful representation of scientific, empirical and local knowledges in producing outcomes that can readily be integrated into existing procedures for shared decision-making. This article frames the qualities of participatory modelling useful to FRM, as being accessible, transparent, adaptable, evaluative and holistic. These qualities are used as criteria with which to assess the practical utility of three popular participatory techniques: Bayesian networks, system dynamics and fuzzy cognitive mapping. Case studies are used to illustrate how each technique might benefit FRM options appraisal and decision-making. While each technique has potential, none is ideal, and local contexts will guide selection of which technique is best suited to deliver effective stakeholder participation.

KEYWORDS

Bayesian networks, flood risk management, fuzzy cognitive mapping, participatory modelling, stakeholder engagement, system dynamics

1 | INTRODUCTION

The importance of focusing on locally tailored solutions and enhancing local capacity to mitigate flood risk is

widely accepted (e.g., Few, 2003). The inherently social issues underlying flood risk give rise to multiple constructions of both flood hazards and their consequences (Cutter et al., 2003; Lofstedt, 2004). Diversity in the way

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2021 The Authors. *Journal of Flood Risk Management* published by Chartered Institution of Water and Environmental Management and John Wiley & Sons Ltd.

flood risk is understood is a key driver of controversy concerning identification of the most appropriate flood risk management (FRM) approach for a given location at a given time. It follows that a significant challenge to practitioners lies in navigating through contested understandings of flood risk when formulating appropriate management responses (cf. Fitzpatrick, 2014; Lane et al., 2011; Lidskog, 2008).

Decision-support frameworks used in FRM attempt to meet this challenge by engaging with stakeholders, whose participation is vital because it maximises the legitimacy of the decision that is reached (Haughton et al., 2015; Reed, 2008). As used here, the term 'stakeholder' refers to 'those who are affected by the decisions and actions that are taken, and who have the power to influence their outcomes' (Freeman, 1984), and includes practitioners, modellers, project beneficiaries and members of the general public. However, decision-making procedures are seldom designed to take advantage of the multiplicity of flood knowledges that are available, or to co-produce solutions from those knowledges. Instead, conventional decision-support frameworks are designed to deliver a singular, science-based outcome indicating the most appropriate, achievable and effective adaptation. Consequently, significant tension arises between the pragmatic need to arrive at a decision, and the democratic need to account for a multiplicity of stakeholder views. This can create an impasse between stakeholders, delay in decision-making and a failure to obtain a popular mandate for the FRM solution that is selected (cf. Lane et al., 2011).

Computer modelling, which has become central in delivering evidence for flood risk decision-making, constrains modellers to specific ways of working, and uses protocols that favour options underpinned by evidence

that is scientific and certifiable (Landström et al., 2011; White, 2013). The almost exclusive use of hydrologic and hydraulic modelling to provide that evidence creates inherently technical decision-making processes that are inaccessible to most stakeholders (Prell et al., 2007). This often limits stakeholder participation to consultation at particular junctures in the decision-making process when model outcomes and alternative FRM options can be presented in ways accessible to non-specialists. Currently, efforts are underway to build computer models better suited to communicating flood risk to non-specialists, a recent example being the Flood Excess Volume method (Bokhove et al., 2019).

However, processes designed to be more 'participatory' in the ideal sense (i.e., offering partnership or citizen control) arguably achieve accessibility at the expense of the complexity necessary to create meaningful representations of the flood system (Figure 1). Placing participatory activities too far to the left on the spectrum creates a divide between modellers and other stakeholders that makes 'construction of a collective [understanding]... difficult, if not impossible' (Callon, 1999, p. 82).

Such techniques need to satisfy both the call for participation and the pragmatic reality of how FRM decision-making currently operates, by meeting the competing challenges of accessibility and complexity:

1. Accessibility challenge—techniques must be accessible to all stakeholders, many of whom will have no formal training in hydrologic or hydraulic modelling.
2. Complexity challenge—techniques must retain sufficient sophistication to support the meaningful structuring and realisation of different flood risk constructions.

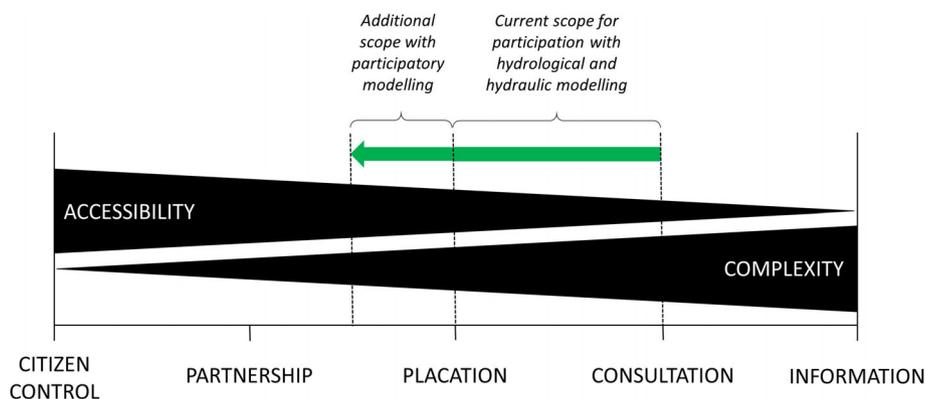


FIGURE 1 Widening participation using participatory models. Green arrow indicates how the use of conceptual participatory models could move participation in flood risk management towards partnership by offering techniques that are more accessible and less complex than traditional hydrological and hydraulic techniques, while maintaining a sufficient level of formalisation and scientific rigour that permits improved integration with existing modelling practice. Levels of participation adapted from Arnstein (1969)

There is little formal guidance on the extent to which participatory models are able to meet these challenges, or how their specific attributes influence their ability to do so. There is also little advice about how stakeholder groups might identify techniques that are appropriate given the nature and relative levels of accessibility and complexity required in a particular FRM context. This goes some way towards explaining why there has been a reluctance to co-produce shared understandings of flood risk between modellers and other stakeholders, and why there are few examples of best practice in the literature (cf. Lane et al., 2011).

In these contexts, this article examines the role of modelling in FRM in the UK, to explain why models have come to dominate decision-making processes and frameworks. We then discuss the role of participation in flood risk decision-making, and how current approaches to working with stakeholders could be modified to make better use of models. A set of simple attribute-based criteria is proposed and applied to support qualitative comparison of three popular, participatory modelling techniques that might feature in a wider suite of modelling tools to be made available for use in FRM.

2 | THE NECESSITY AND VALUE OF MODELLING

Physics-based, computer models play a key role in FRM for four main reasons. First, by predicting the probability of inundation and the likely magnitude of future floods, modelling has become increasingly important to policy-makers (Porter & Demeritt, 2012). Second, modelling enables forecasting of how flood risk might change in future as a result of climate, environmental or socio-economic changes. Third, modelling can be used to appraise the relative effectiveness of options for FRM actions under current and future scenarios. Importantly, in this context, modelling provides a degree of technical accountability with respect to both decision-making and options appraisal. Fourth, it enables production of flood maps, which are widely used in planning, development, insurance, emergency management and flood risk communication (Landström et al., 2011; Porter & Demeritt, 2012).

Conventionally, flood risk assessment and the selection of measures needed to manage that risk proceed through hydrological and hydraulic analyses. These analyses are institutionalised through the notion that any flood management scheme must be economically viable (Landström et al., 2011). Computer models are a critical source of evidence to support these processes by determining the probabilities of different hydrological events,

and generating river discharges that can then be simulated hydraulically. The outputs of hydrologic and hydraulic models, in turn, indicate spatial patterns of flood inundation associated with events with selected return periods, so providing baseline data needed to quantify the flood hazard.

3 | THE CHANGING ROLE OF PARTICIPATION IN FRM DECISION-MAKING

Participation in FRM is increasingly stipulated in national, regional and international flood management legislation, reflecting a shift from authoritative, rationalist approaches to democratic, community-based engagement. This shift reflects broader efforts to democratise decision-making (e.g., McDaniels et al., 1999) and regain trust in public agencies that was eroded during the 1980s owing to a series of regulatory scandals (e.g., BSE, GM food and dioxine; Lofstedt, 2004). International policies including the Rio Declaration (UNEP, 1992), United Nations Agenda 21 (UNCED, 1992), Aarhus Convention (UNECE, 1998), Dublin Statement on Water and Sustainable Development (ICWE, 1992), Hyogo Framework for Action (UNISDR, 2005) and Sendai Framework for Risk Reduction (UNISDR, 2015) all imply active participation in FRM that, ‘brings decision-making as close as possible to those affected’ (ICWE, 1992: p. 19). These global initiatives suggest that local decision-making and the active involvement of local stakeholders are essential to democratic approaches to delivering sustainable environmental futures (e.g., McDaniels et al., 1999).

As a result, the paradigm within which FRM decision-making operates has shifted, not only in the UK but also globally. Recent shifts in other jurisdictions (Begg, 2018; de Brito & Evers, 2016; Seebauer et al., 2019) demonstrate the international ‘transferability’ of UK experience. In the European Union, for example, flood risk governance has moved progressively towards local decision-making based on shared, participatory processes. Previous, ‘top-down’ chains of command have been replaced by more complex, network-based structures that seek to bring multiple layers of society into decision-making processes (Rhodes, 1997). This change is reflected in statutory directives [e.g., Water Framework Directive (EC, 2000) and Floods Directive (EC, 2007)] that promote participation in flood risk decision-making at all scales, and which have fundamentally altered understandings of who is responsible for local FRM in EU member states. The implementation-working group for the Floods Directive (EC, 2007) highlight the importance of stakeholder engagement in improving, ‘the

quality of flood risk mapping and planning by bringing... local knowledge and experience in[to] the process' (EC, 2012). In the UK, strategic policies such as 'Making Space for Water' (DEFRA, 2004) and the Pitt Review (Pitt, 2008), led to the Flood and Water Act of 2010 (UK Govt., 2010), which explicitly shifted responsibility for flood risk from national to local government, with the individual citizen identified as an important agent in the delivery of local flood resilience.

Similarly, a shift towards local, partnership-based funding of FRM projects has reduced the distance between those who fund local flood risk interventions and those who benefit from them, in so doing embedding an expectation of transparent and direct accountability to local constituents in FRM decision-making processes. Steinführer et al. (2008) term this the 'privatisation of risk', and it has resulted in:

1. Transformation of a wide range of previously minimally engaged stakeholders and stakeholder groups into risk managers and active participants in local risk governance; and,
2. Inevitable diversification of the scope and types of knowledges and risk constructions that inform local flood risk decision-making processes.

The paradigm shift in local FRM policy and practice parallels significant developments in social science theory that challenge the legitimacy of expert knowledge and expert-led decision-making in FRM (cf. Healey, 1993). Of central importance have been arguments asserting that acquisition of expertise is dependent upon the acquisition of tacit knowledge, which is gained through interaction with (and immersion in) a domain, as much as through practical experience of it (Collins, 2011). From this perspective, stakeholders who are immersed in a local flood risk setting and have regular interaction with it, but have limited qualifications or technical expertise, may nonetheless be recognised as having relevant 'expertise' by means of their situated knowledge (Haraway, 1988). Consequently, the notion that evidence derived from scientifically trained, expert practitioners alone is an adequate basis for taking FRM decisions has been heavily criticised (Dooge, 1992; Jasanoff, 1998, 2003). Such criticisms recognise the different emphases of the scientific and technical knowledges of experts and the situated knowledges of local stakeholders and need to integrate the two when evaluating the effectiveness, achievability, desirability and acceptability of adaptation options for a specific flood risk context. As a result, a general consensus has emerged that recognises the usefulness of a pluralism of local flood risk domain expertise (Höppner et al., 2010; Tsouvalis & Waterton, 2012), although caution is needed against

overly-simplistic and uncritical assumptions about the benefits of incorporating situated knowledges into local FRM decision-making (e.g., Haughton et al., 2015a).

4 | MANAGING EXPECTATIONS REGARDING THE CONTRIBUTION OF PARTICIPATORY MODELS TO FRM DECISION-MAKING

The question that remains is how to balance expectations raised by the paradigm shift towards participation with the pragmatic requirement for modelling to provide certifiable evidence that can be used in existing decision-making processes and frameworks. In this context, it is important to recognise that participation may take multiple forms. This was initially represented as a 'participation ladder', extending from manipulation to citizen control (Arnstein, 1969), but later the ladder was replaced by a 'wheel', with sectors representing information, consultation, participation and empowerment (Davidson, 1998). To address the challenge of bringing together participatory activities and current flood risk modelling practices we need to move beyond the current reliance on hydrologic and hydraulic modelling, which effectively limits participation to a relatively narrow band within the right half of that spectrum (Figure 1).

Currently, accessibility is limited because in order to understand hydrologic and hydraulic modelling, stakeholders require a level of training that is, in practice, unattainable, particularly for those new to FRM. Juxtaposing expert modellers and untrained stakeholders empowers the former, disempowers the latter, and highlights the divisions between the two (Prell et al., 2007). This is, however, a stereotypical characterisation of both modellers and other stakeholders. The reality is actually more complex because neither group can be represented as a homogeneous bloc: each encompasses a host of divergent viewpoints, competing interests, and differences in technical and experiential backgrounds. Neither does such a simplistic characterisation capture other significant barriers to effective participation, such as power imbalances, politics, poverty, trust and resistance to change.

These considerations explain why participation within FRM is often limited to consultation and information (Figure 1). Arnstein (1969, p. 219) wrote that, 'inviting citizens' opinions, like informing them, can be a legitimate step towards their full participation... [however] if it is not combined with other modes of participation, ... it offers no assurance that citizen concerns and ideas will be taken into account'. To be fair, participation in FRM does sometimes go further, placating

stakeholders by giving them the opportunity to give advice. Even so, modellers (and other flood risk practitioners) retain the power to judge the legitimacy of that advice and the feasibility of acting on it. It is our belief that, as long as stakeholders have limited access to (and understanding of) modelling, they cannot move further left on the spectrum, and so are unable to become a ‘partner’ in the decision-making process (see Figure 1).

Some authors regard ‘partnership’ as being only achievable at the left, ‘accessible’ end of the spectrum, where citizen stakeholders participate fully in the decision-making processes. While there are examples of FRM decision-making that engaged practitioners with other stakeholders in truly collaborative practices that involved co-production of knowledge (cf. Lane et al., 2011), these are exceptions to the general rule, and the ideal of citizens as partners in decision making remains incompatible with the frameworks within which FRM decisions are made (Tippet and Griffiths, Tippet & Griffiths, 2007). This results in tension between modellers and other stakeholders, as most stakeholders are rarely involved in modelling, and consequently they struggle to comprehend how the FRM options discussed during their early consultation workshops have translated into the limited and/or unrecognisable choices offered following formal (i.e., model-based), options appraisal (Prell et al., 2007).

We propose that the pragmatic first step towards citizen partnership can be taken by engaging stakeholders in conceptual modelling activities that complement numerical hydrologic and hydraulic modelling, while still conforming to the protocols inherent to the existing FRM decision support framework (Figure 2).

Facilitating this change requires formalised participatory techniques that structure stakeholder knowledge into forms that can be introduced into the existing decision-making framework (Figure 2). In this context, participatory techniques will be most effective when they make that introduction easy to achieve, limiting the additional time and resources that FRM practitioners must commit to stakeholder engagement. This requires that stakeholder inputs align with existing professional practice, while still allowing stakeholders to engage effectively and on their own terms. As conceptual, co-created models can work within many of the protocols currently used by FRM practitioners, they can produce outcomes that are not only compatible with conventional models but are also realistic, and feasible; genuinely adding value to decision-making.

Participatory techniques provide the mathematical framework for capturing and analysing interdisciplinary data elicited from participants (Batchelor & Cain, 1999). They can act as the interface between modellers and other stakeholders, to formalise, structure and explore

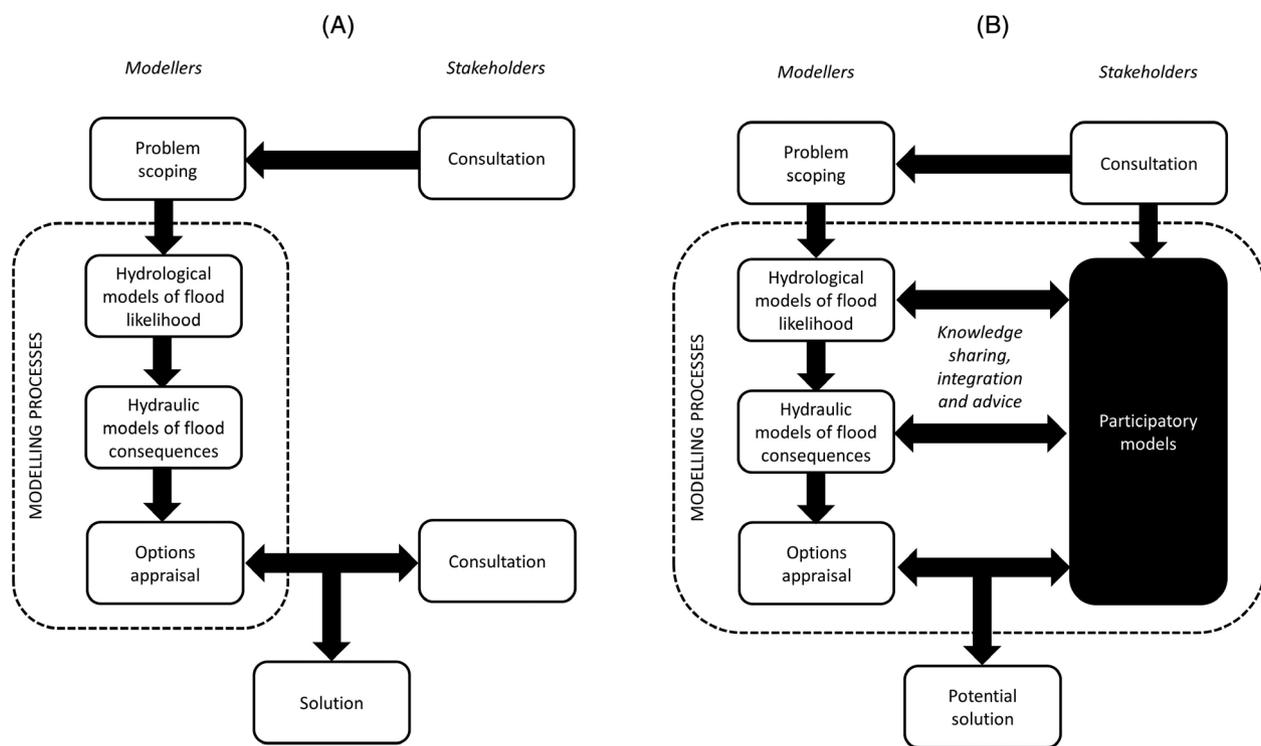


FIGURE 2 (a) Conventional modelling processes limit opportunities for stakeholders to contribute to flood risk problem solving and options appraisal. (b) Bringing participatory models into modelling processes facilitates sharing of knowledge and supports improved integration of outputs

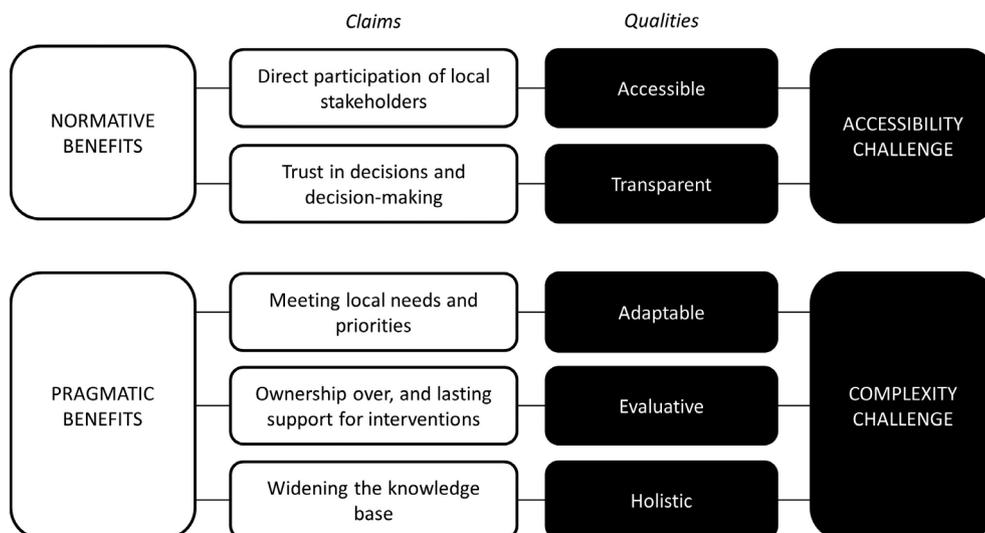


FIGURE 3 Claims made for, and qualities of, participatory modelling

knowledge through co-production, evaluation and application of the outputs of conceptual flood risk models. Conceptual models cope well with a range of quantitative and qualitative data inputs, gaps in knowledge and data uncertainty; and rather than having strict data requirements, they are adaptable to the best available data and learn from any new data that is subsequently made available. Conceptual models do not replicate and cannot replace computational hydrologic and hydraulic models, but they can complement them, providing stakeholders with the opportunity to formalise and deliver their own constructions of flooding and flood risk. It follows that, depending on the stage in the decision-making process, participatory modelling can help to inform, prioritise, shortlist, test, appraise or review FRM options (Figure 2).

5 | 'QUALITY-BASED' CRITERIA FOR PARTICIPATORY TECHNIQUE SELECTION

Mapping the accessibility and complexity challenges onto normative and pragmatic claims made concerning different techniques for participatory modelling can help establish the potential benefits to stakeholders (cf. Reed, 2008). Based on these claims, five desirable, technical attributes or qualities are identified in Figure 3 and described in Table 1.

Participatory modelling is *accessible* when normative claims to the effect that a technique allows all stakeholders to participate in modelling are justified. In essence, the modelling technique must, therefore, be such that lack of formal training or technical expertise is not a barrier to participation. Further, stakeholders must be able to trust that decisions based on model outcomes

TABLE 1 Qualities sought for participatory modelling

Qualities	Potential benefits for flood risk decision-making
Accessible	The ability to enable a wide range of stakeholders to be involved in the development, evaluation and refinement of flood risk models. Interfaces are simplified—possibly graphical—and knowledge is represented conceptually. Methods used to structure knowledge have low complexity.
Transparent	The ability to quantify and communicate the impact, limitations and uncertainties associated with different potential decisions and actions. Knowledge representation is sufficiently clear that it can be traced, along with the reasons behind different outcomes.
Adaptable	The ability to encapsulate the specific realities and dynamics of local flood contexts and be readily updated as more knowledge is acquired and/or as social and hydrologic systems change. Methods by which knowledge is structured support easy adjustment and extensibility.
Evaluative	The ability to facilitate the exploration of scenarios and direct stakeholders and decision-makers towards consensus about preferred options. Re-instantiation and/or recalibration of knowledge representation are straightforward.
Holistic	The ability to incorporate and integrate a broad knowledge base, including physically and socially derived information, into models. Holistic techniques will also be able to support the structuring, representation and integration of knowledge as both quantitative and qualitative data.

are sound. In this respect, participatory models must be *transparent* because this helps to build that trust through promoting open knowledge exchange and frank discussion of the reliabilities of key sources of data and knowledges (Evans & Plows, 2007; Jasanoff, 2003).

The *complexity* challenge is addressed through the realisation of three pragmatic claims. First, participatory modelling techniques need to be *adaptable*. That is, sufficiently flexible to represent the local context; able to develop interventions that are bespoke to local cultural, social and environmental conditions; and easily updatable as new information becomes available. Second, techniques must be *evaluative*, with stakeholders exploring future scenarios and building consensus on the preferred option. This fosters enduring support for, and a sense of ownership over, model outcomes and FRM decisions based on them. Third, the participatory model should be *holistic*: structuring and representing knowledge from physical and social sources; integrating quantitative data and qualitative information; and supporting high quality decision-making by widening the knowledge base (Bulkeley & Mol, 2003; Reed et al., 2009).

6 | CHARACTERISING AND EVALUATING CANDIDATE PARTICIPATORY MODELLING TECHNIQUES

If the outcomes of participatory modelling are to support improved FRM decision-making, it is vital that participatory models represent and aid understanding of causal relationships between the hydrologic, hydraulic, social and engineering dimensions of the flooding system. By these terms, techniques with obvious potential reside in the realm of causality and systems modelling. Three of the more popular approaches are considered here, using the quality-based criteria illustrated in Figure 3 and described in Table 1, above. These are Bayesian belief networks (Pearl, 1985, 1988), systems dynamics (Forrester, 1961) and fuzzy cognitive mapping (FCM; Axelrod, 1976; Harary et al., 1965).

These approaches were scored (on a dimensionless scale of 0–5) based on the expert judgement of the authors, and their experiences using the techniques in a range of FRM contexts. Examples are provided in Boxes 1–3. Our scoring is not intended to be definitive: we invite practitioners, drawing on their own experiences and understanding, to come to their own conclusions, using the framework provided.

6.1 | Bayesian networks

Bayesian networks (BN) are a special type of graphical causal model, consisting of a directed, acyclic graph

BOX 1 Case example of using a Bayesian network model in FRM decision-making

The aim was to facilitate stakeholder participation in FRM decision-making. The objectives were: (1) to identify FRM objectives and options by bringing stakeholders and practitioners together to develop a Bayesian network (BN), based on their shared understanding of the flooding system; and (2) to use the BN to explore and appraise the performance of alternative FRM options (and combinations of options) in meeting those objectives. Simplifications had to be made during the study to keep the model *accessible* and *transparent*. These included use of binary states and interpolating conditional probability tables from a subset elicited from stakeholders (Cain, 2001).

Qualities identified during this BN case study include:

- Usable by stakeholders with limited technical backgrounds and no prior training (*accessible*);
- Identifies a wide range of options, many being community-driven, social FRM solutions that are rarely integrated into projects based on numerical flood modelling (*adaptable/holistic*);
- Explicit and tacit knowledges can be structured and formalised with relative ease (*adaptable/holistic*);
- Ability to reveal misconceptions and knowledge gaps, while offering insights into the different risk perceptions of the participants (*accessible/transparent*);
- Capacity to identify options that merit further exploration using numerical modelling (i.e., those that are hydrologically or hydraulically complex but have high potential to help the FRM project achieve the agreed objectives) (*evaluative*).

For more information on this case study, see Maskrey et al. (2016).

(i.e., where no directed path forms a closed loop), with relationships between variables defined using conditional probabilities (Pearl, 1985, 1988). BNs have been applied to a very wide range of environmental systems, including management of a range of environmental hazards and risks (Aguilera et al., 2011; Kaikkonen et al., 2021; Moe et al., 2021; Penman et al., 2020).

BOX 2 Case example of using a system dynamics model to develop community flood risk resilience

The aim was to inform and empower the local stakeholders, who wished to be more involved in managing their own flood risk. The objectives were to: identify areas at risk during flood events with different return periods; and, determine the extent to which community-led FRM actions could reduce levels of vulnerability and exposure in Southwell.

Qualities identified during this SD application include:

- Key concepts were easy to grasp, making the model *accessible*, though specialist language required clear explanation early on, and effective communication and ‘behind the scenes’ work was needed to throughout the project to support stakeholder understanding;
- Facilitated identification of, focus on, and consensus around, those community-led FRM options with potential for the greatest flood risk reduction across the town (*adaptable/transparent/evaluative*);
- Effective in bringing together a range of different knowledges and sources (e.g., personal experience alongside rainfall data and flood depths) (*holistic*);
- While SD could not provide precise effectiveness projections for individual options, it engaged stakeholders in discussing flood risk hotspots, and allowed the Southwell Flood Forum to pass key messages to a wider audience (*adaptable/accessible*).

An incomplete understanding of feedback mechanisms within the system resulted in causal loop diagrams that were not translated into a simulation (stock and flow) model. Instead, and to maintain accessibility, a hybrid model was constructed that used elements of system dynamics.

For more information on this case study, see Maskrey (2017).

In the convergent graph structure illustrated in Figure 4, which is important because it is the primitive demonstration of how dependencies and probabilities propagate through a BN, nodes A and B are conditionally

BOX 3 Case example of using fuzzy cognitive mapping in water management

Ziv et al. (2018) employed fuzzy cognitive mapping to investigate how different services in the energy-water-food (EWF) nexus might be impacted by the UK's exit from the European Union (EU). The objectives were: (1) understand what different stakeholders perceive to be the influences on the EWF nexus; and (2) to predict how the demand for energy, water and food might change as the UK leaves the EU. In order to reduce the integrated map to a workable size, related concepts had to be combined between workshops. Much of the computational work also went on behind the scenes, including scenarios analysis, thereby limiting *accessibility* and *transparency*.

Qualities identified during this fuzzy cognitive mapping case study include:

- Ability to combine maps from different experts/stakeholders—thus capturing the diversity of expert perspectives about a complex change in policy (*holistic*);
- Capturing key concepts (variables), interactions between concepts and their strengths, and combining the maps was completed during a single workshop (*accessible*);
- Specialist software (Mental Modeller) was available to help code the paper maps created in the first workshop (*accessible*);
- The integrated map could be applied to explore future scenarios, placing a potentially abstract within a real-world context (*evaluative*);
- The modellers were able to present the maps using visual representations in which one can easily identify key concepts and key relationships under different scenarios (*holistic*).

independent of one another, while C is conditionally dependent on both A and B.

To transform the graphic in Figure 4 into a BN, it is necessary to estimate the prior probability distributions: $P(A)$ and $P(B)$, and the conditional probability $P(C|A,B)$ (i.e., the probability of C, given A and B). To simplify estimation of these probabilities, the variables A, B and C are given distinct states, allowing characterisation of their continuous probability distributions through a discretised, conditional probability table.

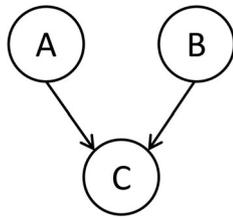


FIGURE 4 Convergent graph structure. This simple figure is the primitive demonstration, showing how dependencies and probabilities propagate through any and all Bayesian networks

The BN is completed by constructing a conditional probability table showing the probability of each state of C for all possible combinations of its parents (A and B). Propagation of information through the completed conditional probability table can be used to explore how observed conditions or decisions (referred to as ‘evidence’) affect the probable conditions of other nodes.

For example, A and B may each have two states, *a1* and *a2*, and *b1* and *b2*. Back propagation of evidence through the Bayesian network is then described by Bayes’ Theorem (Equation (1)).

$$P(a1, b1 | c1) = \frac{P(c1 | a1, b1) \cdot P(a1, b1)}{P(c1)} \quad (1)$$

BN have a number of known strengths:

1. Encouragement of ‘whole system’ thinking and understanding;
2. Scope for either bottom-up (diagnostic) or top-down (exploratory) reasoning;
3. Capacity to work with the best available (often scarce or missing) data;
4. Capacity to combine knowledges from a range of different sources;
5. Explicit treatment and communication of uncertainty and risk.

These strengths map conformably onto the qualities sought for effective participation (Figure 5).

Accessibility is promoted by the systematic treatment and clear representation of uncertainty. Both the conditional probability tables and variable state ranges describe the uncertainty at each node, and in solving the network the modeller establishes how uncertainty is propagated through to the final outcomes (cf. Marcot et al., 2001). Consequently, BN can estimate uncertainty more accurately than models that produce mean values as outputs (Aguilera et al., 2011). Sensitivity analysis helps to prioritise interventions and knowledge gaps, by identifying both the areas of greatest uncertainty and

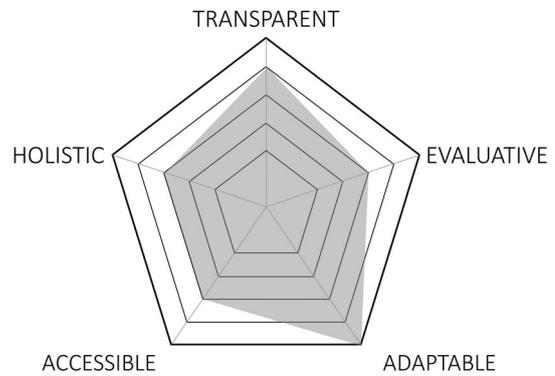


FIGURE 5 Strengths of Bayesian networks

those that have the greatest influence on stakeholder-defined objectives or FRM options, under different assumptions (Sendzimir et al., 2007). The processes of conditional probability table population, sensitivity analysis and model validation can all be carried out with the participation of stakeholders, reducing the need for extensive behind the scenes work. These strengths add to the *transparency* of the technique.

The structure of BN provides two technical strengths that together meet the complexity challenge: two-way reasoning and local updating. Reasoning may be conducted both from the bottom-up (exploring the likely causes given evidence on the outcome) and the top-down (exploring the likely outcome given evidence on the inputs, either by intervention or through evidence on their states) (Castelletti & Soncini-Sessa, 2006). Updating the BN as new data or knowledge becomes available is possible, because the values underlying each node are independent of the values underlying others nodes. Algorithms such as expectation maximisation allow this process to be automated, with the model using case-study data to calibrate conditional probability tables (cf. Marcot et al., 2006). These strengths make BN particularly *adaptable* to local flood risk contexts. Limitations of BN are listed in Table 2.

The practical utility of BN as a technique for participatory modelling was explored through its application to improving stakeholder engagement in Hebden Bridge, Yorkshire, following a series of damaging floods. In this study, a Bayesian network model was co-produced with local stakeholders (Maskrey et al., 2016; Box 1).

6.2 | System dynamics

System dynamics (SD) focuses on representing feedback loops that govern the dynamic behaviour of complex systems (Ahmad & Simonovic, 2000; Forrester, 1961). SD has been used in environmental management for a wide

TABLE 2 Limitations of Bayesian networks

Limitation	Description
1. Supporting feedback loops	The acyclic nature of Bayesian networks does not support feedback loops, making representation of spatial and temporal dynamics a challenge. Introducing time steps to overcome this is possible, but quickly causes networks to become intractable. On occasion networks are coupled with other simulation techniques that support feedback (Aguilera et al., 2011; Marcot et al., 2001; van Kouwen et al., 2008).
2. Handling of continuous data	In general, Bayesian networks were developed for discrete random variables. However, most available data are continuous or hybrid, and though these data can be handled by Bayesian networks, restrictive limitations apply (van Kouwen et al., 2008). The most common solution is for continuous variables to be discretised, which implies a loss of information and can lead to finer relationships being masked. Restricting the number of intervals (states) for computational savings (see, Point 3) can further diminish the effect of complex empirical distributions (van Kouwen et al., 2008). More complex new mathematical solutions have been proposed for handling continuous variables, but these are not commonly incorporated into currently available software (Aguilera et al., 2011).
3. Over-reliance on expert opinion	Populating conditional probability tables from a limited number of expert opinions is challenging, particularly in larger models (Landuyt et al., 2013). This is often tackled by dividing the model into sub-networks that span a scientific discipline closer in scope to that with which experts are more comfortable working (cf. Morgan et al., 1990). Over-reliance on expert opinion in the definition of conditional probability tables may be perceived as subjective or unscientific, reduce model acceptance by policy-makers, and/or lead to misinterpretation or misuse of results (Zorrilla et al., 2010). Validation is achieved by comparison with results from different models, independent experts/stakeholder groups, and the literature. Sensitivity testing can help further evaluate the relationships in the network (Aguilera et al., 2011).

range of applications including: river basin planning (Palmer, 1994; Palmer et al., 1993, 1995; Simonovic et al., 1997; Simonovic & Fahmy, 1999); air quality analysis (Stave, 2002); and, water resources management (Fletcher, 1998; Stave, 2003; Tidwell et al., 2004).

SD models may be qualitative (e.g., causal loop diagrams) or quantitative (e.g., stock and flow diagrams). Causal loop diagrams describe system structure, and help users generate a dynamic hypothesis that can be formally tested and validated (Homer & Oliva, 2001; Richardson, 1999). Stock and flow diagrams describe the condition of the system at a specified time (stocks), and how fast those stocks are filling or emptying (flows) (Ahmad & Simonovic, 2000). Figure 6 depicts two stocks, A and B, connected by a flow (hourglass symbol), with additional variables (C, D and E) forming two feedback loops that influence both the levels of A and B, and the rate of flow between them.

Causal relationships between the variables are indicated by single arrows labelled to indicate either positive or negative polarity. In Figure 6, a positive feedback loop extends from $B \rightarrow C \rightarrow D \rightarrow B$, while a negative feedback loop extends from $A \rightarrow E \rightarrow D \rightarrow A$ (e.g., Sterman, 2001). When two or more feedback loops interact (as in Figure 6) it is necessary to determine dynamic behaviour using computer simulation, in which the modeller enters parameters and initial conditions and the model iteratively updates system variables during a prescribed number of time steps (Guo et al., 2001).

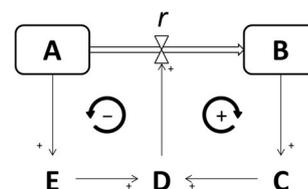


FIGURE 6 Stock and flow diagram

SD models have a number of known strengths:

1. Emphasis on system structure as starting point;
2. Capacity for construction and evaluation of multiple 'what if...?' scenarios;
3. Widely available and intuitive software;
4. Flexibility in model structure;
5. Capability to incorporate delayed responses.

These strengths map conformably onto the qualities sought for participatory modelling (Figure 7).

Accessibility is enhanced by the availability of intuitive, widely available software. Many SD packages offer extensive user-support systems/tutorials which, when supported by effective facilitation, can lead to model results being output within hours of a stakeholder-expert group first adopting an SD approach (Coyle, 1996; Kampmann & Oliva, 2020; Sterman, 2001, 2018). The rapidity with which models can be derived and results generated enables iterative improvements to be made

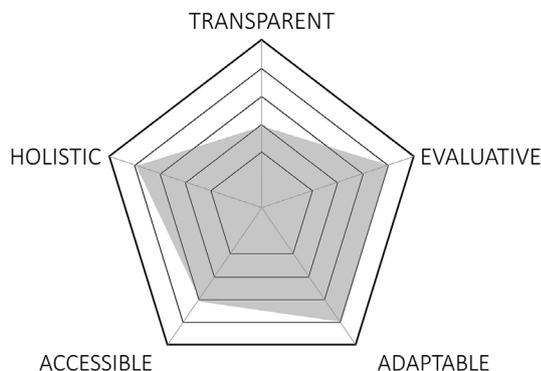


FIGURE 7 Strengths of system dynamics

during participatory modelling sessions. Potential issues with more complex modelling tasks, such as sensitivity testing, are largely avoided because they are automated. While the automation of these tasks adds to the *accessibility* of SD for modellers, it means that large stages of the modelling process happen behind the scene, significantly reducing *transparency* for other stakeholders.

The focus of SD on system structure and behaviour from the outset forces participants to think *holistically* throughout the participatory modelling process (Randers, 1973; Winz et al., 2009). SD supports *evaluation* first, because it takes a strategic approach, identifying potential ‘policy levers’ (elements of the system where policy changes are especially effective), rather than focusing on external causes or sources that are more challenging to manage (Stave, 2002) and, second, through its suitability for scenario testing, which can demonstrate how different options shift the system towards alternative future states (Nandalal & Simonovic, 2003).

Technically, SD is one of the most *adaptable* participatory modelling methods available (Winz et al., 2009) because it: can handle both qualitative and quantitative variables; can consist of nested, cross-scalar models; and can be constructed from modules that are interchangeable and re-usable. Furthermore, the ability to simulate delayed responses allows SD to represent feedback that is not realised immediately, a feature unavailable in FCM (Tidwell et al., 2004). However, a significant limitation on SD’s *adaptability* stems from its low capacity to model or make precise projections regarding SD specific to a given locale. This and other limitations of SD are listed in Table 3.

To investigate the practical utility of this technique, a conceptual SD model was co-produced with stakeholders in Southwell, Nottinghamshire. The group included residents (of whom many were members of Southwell Flood Forum) and experts from the Environment Agency, water utilities and local government. This research followed two closely spaced, damaging floods in 2007 and 2013 (Box 2).

TABLE 3 Limitations of system dynamics

Limitation	Description
1. Social nature of model validation	When a problem is characterised by high uncertainty and complexity, it becomes harder to validate a model by comparing its predictions with observed data. Validation becomes largely a social process, whereby the model structure and its outcomes are evaluated and refined by all involved parties (Barlas & Carpenter, 1990). Structure tests (comparison with experts’ mental models); behaviour tests (comparison with real world behaviour) and policy implication tests (comparisons with observed system responses to policy change) can all be conducted to gain confidence in models (Winz et al., 2009)
2. Predictive capabilities	Due to the uncertainties in complex open systems, system dynamics modelling cannot provide exact solutions, and is thus poorly suited to addressing well-defined operational problems (Winz et al., 2009). Authors found that treating system dynamics models as predictive tools can cause concern amongst modellers and stakeholders alike, while treating them as instructive tools does not (Tidwell et al., 2004; Xu et al., 2002).
3. Long-term focus	Often, system dynamics is focussed on long-term patterns and trends, while social decisions (including those made by flood risk managers) are plagued by short-term pressures (funding, government policy, staffing, etc.; Stave, 2002). Participants’ goals of finding a quick solution may not align with those of system dynamics modellers, leading to potential tension. Recommended solutions may require structural changes, and revision of objectives and responsibilities; which are often politically unacceptable.

6.3 | Fuzzy cognitive mapping

FCM uses signed fuzzy weighted digraphs, usually involving feedback, which consist of nodes and the directed edges between them (Axelrod, 1976; Harary et al., 1965; Kosko, 1986). FCMs have been used in ecosystem management (Dadaser & Özesmi, 2002; Hobbs et al., 2002; Özesmi, 1999); forestry (Hjortsø, 2004;

Mendoza & Prabhu, 2003; Skov & Svenning, 2003); agriculture (McRoberts et al., 1995; McRoberts & Hughes, 2001); and, catchment management (Kafetzis et al., 2010; Mouratiadou & Moran, 2007).

In FCM, a collection of concepts, C_i , is represented by a series of nodes linked by causal relationships ($C_i \rightarrow C_{i+1}$), that are represented by arrows (Figure 8). For the divergent graph structure shown in Figure 8, A is the cause of both B and C. Each concept is given an initial value α , $\alpha \in [-1, 1]$, and each edge is quantified by a weight defining the polarity and strength of the causal relationship between two concepts. Weights can be based on empirical data and/or expert opinion (Hobbs et al., 2002).

An iterative stabilisation process produces a set of stable concept values. An FCM is interpreted by comparing these final values, which provide an indication to the level of importance each concept plays in determining and influencing system structure. The most influential concepts are termed central concepts. Stability is usually achieved after a few iterations. For example, in an exploration of the determinants of land-cover changes in the Brazilian Amazon, Soler et al. (2011) found that FCM values stabilised after 10 iterations, and that final values could be used to identify the most influential factors determining land-cover, which included agro-pasture expansion and dry season severity (Figure 9).

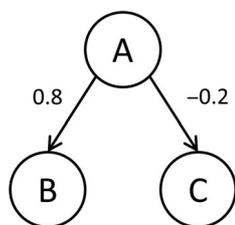


FIGURE 8 Divergent graph structure. An increase in A leads to a minor decrease in C, and a substantial increase in B. Weightings are in the range $[-1, 1]$

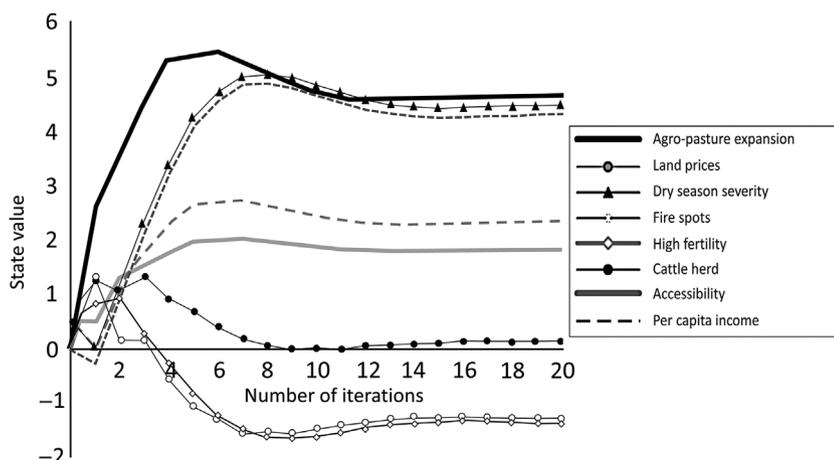


FIGURE 9 Example graphical output from a fuzzy cognitive map, showing system stabilisation and the subsequent ranking of system variables by influence on system structure (adapted from Soler et al., 2011)

The ranking of system variables produced by FCM also provides a basis on which to test how the system responds under different scenarios. This is usually achieved by attaching external drivers to the FCM model and then changing their initial values to represent the selected scenario.

FCM models have a number of known strengths:

1. Elicitation and management of expert knowledges (especially in data-poor situations);
2. Development of goals and objectives;
3. The speed and ease with which maps can be obtained, combined, and evaluated;
4. Identification of central (i.e., most influential) concepts and/or management actions;
5. Capacity for feedback processes and system evolution through time.

These strengths map conformably onto the qualities sought for participatory modelling (Figure 10).

FCM is an intellectually demanding activity that challenges stakeholders to test new ideas, question assumptions and draw system-level conclusions (Eden & Ackermann, 2004; Hobbs et al., 2002). Professional facilitation in a series of participatory modelling sessions is essential, with particular attention being paid to reducing biases created by stakeholder power imbalances. The need for facilitation and the intense thought processes required to build an FCM may negatively affect *accessibility*. However, with sufficient expertise and support, the basic structure of an FCM can be co-constructed quickly, permitting the dynamic output from the model to be generated and evaluated during a single session (Ackermann & Eden, 2005; Kok, 2009). FCM's capacity to self-adapt with increasing data availability speeds up the participatory modelling process, increasing its *adaptability*. While model creation and development is fast, those stakeholders less familiar with the technique may

struggle to understand how their inputs are being translated through to an end result. Although technically these processes take place with the stakeholders present, it inevitably leads to a loss of *transparency* (Papageorgiou & Salmeron, 2013).

The structure of FCM supports *evaluation* because it allows early identification of central concepts, which indicates which FRM options should be the focus of subsequent, scenario-based investigations. In scenario-based options appraisal, FCM can model the variables that drive changes in the central concepts, providing a vehicle with which to build group consensus about how drivers

and FRM responses can best be managed (Ackermann & Eden, 2005; Özesmi & Özesmi, 2003). The ability to produce a composite influence map promotes *holism* by integrating the views, beliefs and knowledge bases of different participants (Hobbs et al., 2002; Khan & Quaddus, 2004). Combining maps produced by sub-groups or individuals allows them to make unique contributions while ensuring that their views, beliefs and data are considered in the wider context. This holistic approach facilitates consensus building and the emergence of common goals. Finally, the presence of feedback in fuzzy cognitive maps adds a temporal dimension that enables observation of system changes as they unfold, especially when used in conjunction with scenario analysis (Khan & Quaddus, 2004), which further enhances the holistic and evaluative qualities of FCM. The limitations of FCM are listed in Table 4.

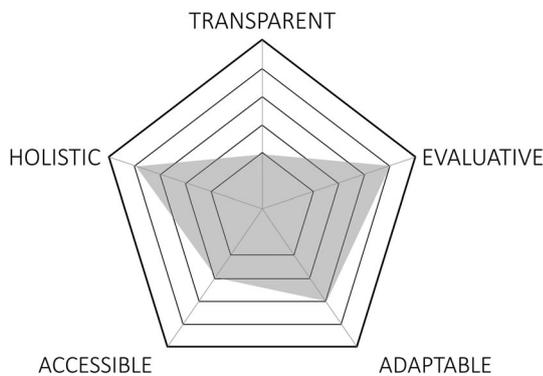


FIGURE 10 Strengths of fuzzy cognitive mapping

6.4 | Role of local context in technique selection

In addition to using these five qualities to help select the appropriate technique, the local context must also be taken into account. The local context extends to include: the resources available to allocate to the project

TABLE 4 Limitations of fuzzy cognitive maps

Limitation	Description
1. Risk of over-tuning	Fuzzy cognitive mappings (FCMs) are fundamentally a qualitative technique for capturing expert judgement, with subsequent testing and tuning necessarily a subjective process. This gives rise to concerns over replicability, and introduces the risk of over-tuning the model, such that anticipated values of all outputs are obtained, leaving one in the position where nothing new can be learned from the model (Hobbs et al., 2002). This is overcome by not tuning the model to preconceived notions that have little or no empirical foundation.
2. Subjective nature of inputs	Any conclusions drawn from fuzzy cognitive maps must be carefully qualified bearing in mind that they are: (a) ultimately based on expert opinion about processes for which there may be little data; and (b) based therefore on a restrictive description of the causal relationships. Wherever possible it is desirable to evaluate models by comparison with those built using empirical data, or by consulting a set of independent experts (Hobbs et al., 2002).
3. Sensitivity to method selection	Different mapping methods can have a larger effect on the model outputs than changes to the structure of the maps themselves (Penn et al., 2013). The literature suggests using multiple techniques and then comparing outputs as part of a wider validation process, to highlight how robust the model outputs are to specific techniques.
4. Identifying individual contributions	Where there are large discrepancies between the individual maps that form the composite map, it can be difficult for stakeholders to recognise their individual contribution to the model (Eden & Ackermann, 2004; Penn et al., 2013).
5. Semi-quantified relationships	FCMs assume relationships to be linear and require them to be semi-quantified. However, in many environmental systems relationships are not always linear and quantitative information is often sparse or unavailable. If these weights are not specified correctly then the outcomes of the FCM may appear unrealistic (Eden & Ackermann, 2004). As relationships are only semi-quantified, interpretation in absolute terms is obstructed and the output from an FCM (after several iterations) cannot be directly translated into time (Kok, 2009).

(e.g., expertise, existing models/data, time and money); the complexity of the system being modelled; the number of stakeholders; and their commitment to the participatory process. The participatory process involved in delivering any of the techniques explored in this article can be adapted to meet these local conditions. The critical aspect of local context that cannot be met by adapting the process is the desired outcome, and this aspect is likely to have an impact on technique selection. BN lend themselves to situations where you are exploring cause and effect, and how the system state alters given different antecedent conditions (e.g., how different choices of interventions affect the current state of the system). SD introduces the dimension of time, and is useful for looking at how different policies (or actions) might affect the future of the system (e.g., effects of climate change on the benefits of different interventions). FCM focuses on relationships between different system elements, and is more useful for exploring how different system-wide levers might be used to alter the path that the system is taking (e.g., modelling how a system might respond to a change in policy).

7 | CLOSURE

Use of flood risk modelling to inform FRM decision-making provides the scientific evidence necessary to achieve technical credibility and demonstrate a sound business case when appraising options and designing FRM projects. By its simplest definition, flood risk is the probability of a flood event multiplied by consequences should it occur (Hall et al., 2003). Hydrological and hydraulic inundation models, coupled with well-established depth-damage curves (Penning-Rowsell et al., 2005), provide plausible estimates of physical, financial and economic flood risks under current and future (with-project) scenarios (Thorne et al., 2007). However, FRM modelling processes are generally inaccessible to non-specialist stakeholders. This is unfortunate as situated and experiential knowledges of previous flood events held by local stakeholders (including, for example, details of flood water dynamics and inundation outlines, and rafts of relevant information on community impacts) can (a) add value to inundation models and (b) are critical to understanding and accounting for the social consequences of flooding (Brown & Damery, 2002).

The level of complexity inherent to hydrological and hydraulic modelling limits accessibility to those with technical expertise and training, resulting in stakeholder engagement being limited to consultation that takes place at junctures in the decision-making process when stakeholder-accessible model outcomes can be shared.

The level of engagement possible during consultation is so far removed from participation in the decision-making process that stakeholders often feel that their involvement is no more than symbolic.

In this article, we have explored whether participatory modelling can provide a mechanism for stakeholders to partner more effectively with flood modellers and FRM practitioners, moving towards true participation in decision-making processes. Our review of the challenges and benefits of participation reported in the environmental management literature identified techniques that might be applicable in flood risk modelling. We concluded that, for stakeholders to participate effectively, participatory modelling should be accessible, transparent, adaptable, evaluative and holistic, and we then examined the performance of three popular participatory modelling techniques according to these qualities.

Accessibility and transparency require that participatory models can be undertaken and fully understood by stakeholders with limited or no technical expertise. However, accessible techniques must also be holistic (embracing all significant aspects of the flood risk system) and capable of reproducing the causal links and feedback loops responsible for complexity in the behaviours of real flood risk systems. In these contexts, suitable participatory techniques must guide inexperienced users through the steps necessary to co-produce a holistic conceptual model that adequately replicates the complexity in the local flood risk system in question, with each step being accessible and transparent. Such techniques have the potential to structure participants' prior knowledges of how the flood system operates, and how its individual elements are causally related. Once the model has been co-produced, it must have the adaptive capacity to benefit from later inputs of data or information, and the capability to compare and evaluate alternative options for FRM interventions in the system. The final requirement is that the outcomes of participatory modelling must be easily integrated with those of hydrological and hydraulic models, so that they can feed seamlessly into existing, pragmatic decision-making processes and frameworks.

Investigation of BN, SD and FCM as candidate techniques to deliver participatory modelling reveals that each displays the five qualities, but in different ways and to different extents. Each technique also has limitations, and these must be recognised and borne in mind. These findings indicate that none of these techniques is ideal, though each has merit. It follows that none of the three techniques investigated in our study represents a 'silver bullet' that can meet the participation challenge, and that local context and the research question will play significant roles in technique selection. Applying these techniques and standardising the steps required for

inexperienced stakeholders to co-create models remains one of the outstanding challenges in FRM. Further research, applying these and other participatory modelling techniques in the field of FRM, is needed to improve our understanding of what each technique can deliver in practice, and in which contexts its use in participatory FRM is appropriate.

ACKNOWLEDGEMENTS

The research reported in this article was performed by the first author as part of doctoral research supervised by the second and third authors. The research was supported by the Engineering and Physical Sciences Research Council [grant numbers EP/K01366/1; EP/N008103/1 and EP/P004180/1] as part of the Blue-Green Cities Research Consortium (<http://www.bluegreencities.ac.uk/>), and through a block-funded EPSRC PhD studentship (number 1230597). The authors thank Stuart Lane for encouraging the first author to publish this article and suggesting its submission to JFRM.

DATA AVAILABILITY STATEMENT

All data referred to herein is available from the first author's thesis, which is published online.

ORCID

Shaun A. Maskrey  <https://orcid.org/0000-0003-4476-7783>

Nick J. Mount  <https://orcid.org/0000-0003-4443-7549>

Colin R. Thorne  <https://orcid.org/0000-0002-2450-9624>

REFERENCES

- Ackermann, F., & Eden, C. (2005). Using causal mapping with group support systems to elicit an understanding of failure in complex projects: Some implications for organizational research. *Group Decision and Negotiation*, 14, 355–376.
- Aguilera, P. A., Fernández, A., Fernández, R., Rumí, R., & Salmerón, A. (2011). Bayesian networks in environmental modelling. *Environmental Modelling & Software*, 26, 1376–1388.
- Ahmad, S., & Simonovic, S. P. (2000). System dynamics modelling of reservoir operations for flood management. *Journal of Computing in Civil Engineering*, 14(3), 190–198.
- Arnstein, S. R. (1969). A ladder of citizen participation. *Journal of the American Institute of Planners*, 35(4), 216–224.
- Axelrod, R. (1976). *Structure of decision: The cognitive maps of political elites*. Princeton University Press.
- Barlas, Y., & Carpenter, S. (1990). Philosophical roots of model validation: Two paradigms. *System Dynamics Review*, 6(2), 148–166.
- Batchelor, C., & Cain, J. (1999). Application of belief networks to water management studies. *Agricultural Water Management*, 40(1), 51–57.
- Begg, C. (2018). Power, responsibility and justice: A review of local stakeholder participation in European flood risk management. *Local Environment*, 23(4), 383–397.
- Bokhove, O., Kelmanson, M. A., Kent, T., Piton, G., & Tacnet, J. M. (2019). Communicating (nature-based) flood-mitigation schemes using flood-excess volume. *River Research and Applications*, 35(9), 1402–1414.
- Brown, J. D., & Damery, S. L. (2002). Managing flood risk in the UK: Towards an integration of social and technical perspectives. *Transactions of the Institute of British Geographers*, 27, 412–426.
- Bulkeley, H., & Mol, A. P. J. (2003). Participation and environmental governance: Consensus, ambivalence and debate. *Environmental Values*, 12, 143–154.
- Cain, J. (2001). Planning improvements in natural resources management. *Centre for Ecology and Hydrology, Wallingford, UK*, 124, 1–123.
- Callon, M. (1999). The role of lay people in the production and dissemination of scientific knowledge. *Science, Technology and Society*, 4(1), 81–94.
- Castelletti, A., & Soncini-Sessa, R. (2006). Bayesian networks and participatory modelling in water resource management. *Environmental Modelling and Software*, 22, 1075–1088.
- Collins, H. M. (2011). Language and practice. *Social Studies of Science*, 41(2), 271–300.
- Coyle, R. G. (1996). *System dynamics modelling: A practical approach*. Chapman and Hall.
- Cutter, S. L., Carolina, S., Boruff, B. J., & Shirley, W. L. (2003). Social vulnerability to environmental hazards. *Social Science Quarterly*, 84(2), 242–261.
- Dadaser, F., & Özsesmi, U. (2002). Stakeholder analysis for sultan marshes ecosystem: A fuzzy cognitive approach for conservation of ecosystems. In *EPMR2002, environmental problems of the Mediterranean region. Nicosia, North Cyprus, 12-15 April 2002*. Lefkoşa: Near East University.
- Davidson, S. (1998). Spinning the wheel of participation. *Community Planning*, 1415, 14–15.
- de Brito, M. M., & Evers, M. (2016). Multi-criteria decision-making for flood risk management: A survey of the current state of the art. *Natural Hazards and Earth System Sciences*, 16, 1019–1033.
- Department for Environment, Food and Rural Affairs (DEFRA) (2004). Making space for water. In *Developing a new government strategy for flood and coastal erosion risk management in England*. Defra.
- Dooge, J. C. I. (1992). *An agenda of science for environment and development into the 21st century*. Cambridge University Press.
- Eden, C., & Ackermann, F. (2004). Cognitive mapping expert views for policy analysis in the public sector. *European Journal of Operational Research*, 152, 615–630.
- European Communities (2000). Directive 2000/60/EC establishing a framework for community action in the field of water policy. *Official Journal of the European Union*. L327, 22/12/2000.
- European Communities (2007). Directive 2007/60/EC on the assessment and management of flood risks. *Official Journal of the European Union*. L288, 06/11/2007
- European Communities (2012). *Report of the WGF Thematic Workshop: Stakeholder involvement in flood risk management*. 17–19 April 2012, Bucharest, Romania. Retrieved from https://circabc.europa.eu/webdav/CircaBC/env/wfd/Library/framework_directive/thematic_documents/flood_management/information_exchange/documents_information_stakeholder_17-1842012/Report/WGF13-6-RO-Stakeholder%20involvement%20workshop%20report-Bucharest-Draft%20Final%20for%20CIRCA.pdf

- Evans, R., & Plows, A. (2007). Listening without prejudice? Re-discovering the value of the disinterested citizen. *Social Studies of Science*, 37, 827–853.
- Few, R. (2003). Flooding, vulnerability and coping strategies: Local responses to a global threat. *Progress in Development Studies*, 3(1), 43–58.
- Fitzpatrick, D. (2014). *Pickles-Patterson flood spat highlights true top-down nature of UK policy making*. Retrieved from <http://blog.policy.manchester.ac.uk/sci-tech/2014/02/pickles-paterson-floods-spat-highlights-true-top-down-nature-of-uk-policy-making/>
- Fletcher, E. J. (1998). The use of system dynamics as a decision support tool for the management of surface water resources. In Proceedings of the 1st International Conference on New Information Technology for Decision-Making in civil engineering. Montreal, Canada.
- Forrester, J. W. (1961). *Industrial dynamics*. MIT Press.
- Freeman, R. W. (1984). *Strategic management: A stakeholder approach*. Basic Books.
- Guo, H. C., Liu, L., Huang, G. H., Fuller, G. A., Zou, R., & Yin, Y. Y. (2001). A system dynamics approach for regional environmental planning and management: A study for the Lake Erhai Basin. *Journal of Environmental Management*, 61(1), 93–111.
- Hall, J. W., Meadowcroft, I. C., Sayers, P. B., & Bramley, M. E. (2003). Integrated flood risk management in England and Wales. *Natural Hazards Review*, 4(3), 126–135.
- Harary, F., Norman, R. Z., & Cartwright, D. (1965). *Structural models: An introduction to the theory of directed graphs*. Wiley.
- Haraway, D. (1988). Situated knowledges: The science question in feminism and the privilege of partial perspective. *Feminist Studies*, 14(3), 575–599.
- Haughton, G., Bankoff, G., & Coultard, T. J. (2015). In search of 'lost' knowledge and outsourced expertise in flood risk management. *Transactions of the Institute of British Geographers*, 40, 375–386.
- Healey, P. (1993). *Planning through debate: The communicative turn in policy analysis and planning*. Durham.
- Hjortso, C. N. (2004). Enhancing public participation in natural resource management using soft OR—An application of strategic option development and analysis in tactical forest planning. *European Journal of Operational Research*, 152, 667–683.
- Hobbs, B. F., Ludsins, S. A., Knight, R. L., Ryan, P. A., Biberhofer, J., & Ciborowski, J. J. H. (2002). Fuzzy cognitive mapping as a tool to define management objectives for complex ecosystems. *Ecological Applications*, 12(5), 1548–1565.
- Homer, J., & Oliva, R. (2001). Maps and models in system dynamics: A response to Coyle. *System Dynamics Review*, 17(4), 347–355.
- Höppner, C., Buchecker, M., & Bründl, M. (2010). *Risk communication and natural hazards*. CapHaz Project.
- International Conference on Water and the Environment (ICWE) (1992). *The Dublin statement on water and sustainable development*. 26–31 January 1992, Dublin.
- Jasanoff, S. (1998). The political science of risk perception. *Reliability Engineering and System Safety*, 59, 91–99.
- Jasanoff, S. (2003). Breaking the waves in science studies: Comment on H. M. Collins and R. Evans, 'The third wave of science studies'. *Social Studies of Science*, 33(3), 389–400.
- Kafetzis, A., McRoberts, N., & Mouratiadou, I. (2010). Using fuzzy cognitive maps to support the analysis of stakeholders' views of water resource use and water quality policy. In M. Glykas (Ed.), *Fuzzy cognitive maps: Advances in theory, methodologies, tools and applications*. Springer.
- Kaikkonen, L., Parviainen, T., Rahikainen, M., Uusitalo, L., & Lehtikainen, A. (2021). Bayesian networks in environmental risk assessment: A review. *Integrated Environmental Assessment and Management*, 17(1), 62–78.
- Kampmann, C. E., & Oliva, R. (2020). Analytical methods for structural dominance analysis in system dynamics. In B. Dangerfield (Ed.), *System dynamics. Encyclopaedia of complexity and systems science* (pp. 153–176). Springer.
- Khan, M. S., & Quaddus, M. (2004). Group decision support using fuzzy cognitive maps for causal reasoning. *Group Decision and Negotiation*, 13, 463–480.
- Kok, K. (2009). The potential of fuzzy cognitive maps for semi-quantitative scenario development, with an example from Brazil. *Global Environmental Change*, 19, 122–133.
- Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, 1, 65–75.
- Landström, C., Whatmore, S. J., & Lane, S. N. (2011). Virtual engineering: Computer simulation modelling for flood risk management in England. *Science Studies*, 24, 3–22.
- Landuyt, D., Broekx, S., D'hondt, R., Engelen, G., Aertsens, J., & Goethals, P. L. M. (2013). A review of Bayesian belief networks in ecosystem service modelling. *Environmental Modelling and Software*, 46, 1–11.
- Lane, S. N., Odoni, N., Landström, C., Whatmore, S. J., Ward, N., & Bradley, S. (2011). Doing flood risk science differently: An experiment in radical scientific method. *Transactions of the Institute of British Geographers*, 36, 15–36.
- Lidskog, F. (2008). Scientised citizens and democratised science. Re-assessing the expert-lay divide. *Journal of Risk Research*, 11, 69–86.
- Lofstedt, R. E. (2004). Risk communication and management in the twenty-first century. *International Public Management Review*, 5(2), 36–51.
- Marcot, B. G., Holthausen, R. S., Raphael, M. G., Rowland, M. M., & Wisdom, M. J. (2001). Using Bayesian belief networks to evaluate fish and wildlife population viability under land management alternatives from an environmental impact statement. *Forest Ecology and Management*, 153, 29–42.
- Marcot, B. G., Steventon, J. D., Sutherland, G. D., & McCann, R. K. (2006). Guidelines for developing and updating Bayesian belief networks applied to ecological modelling and conservation. *Canadian Journal of Forest Research*, 36, 3063–3074.
- Maskrey, S. A. (2017). *Supporting local flood risk decision-making using participatory modelling* (PhD thesis). University of Nottingham. Retrieved from <http://eprints.nottingham.ac.uk/39963/>
- Maskrey, S. A., Mount, N. J., Thorne, C. R., & Dryden, I. (2016). Participatory modelling for stakeholder involvement in the development of flood risk management intervention options. *Environmental Modelling and Software*, 82, 275–294.
- McDaniels, T. L., Gregory, R. S., & Fields, D. (1999). Democratizing risk management: Successful public involvement in local water management decisions. *Risk Analysis*, 19(3), 497–510.

- McRoberts, N., Foster, G. N., Davies, D. H. K., Evans, K. A., McKinlay, R. D., & Wale, S. (1995). The role of synoptic models in the development of crop protection for sustainable crop production systems. *BCPC Proceedings*, 63, 439–446.
- McRoberts, N., & Hughes G. (2001). *Killing or culling? Is it possible to manage weeds as a resource*. BCPC annual conference 2001. Farnham, UK: BCPC.
- Mendoza, G. A., & Prabhu, R. (2003). Qualitative multi-criteria approach to assessing indicators of sustainable forest resource management. *Forest Ecology and Management*, 174, 329–343.
- Moe, S. J., Carriger, J. F., & Glendell, M. (2021). Increased use of Bayesian network models has improved environmental risk assessments. *Integrated Environmental Assessment and Management*, 17(1), 53–61.
- Morgan, M. G., Henrion, M., & Small, M. (1990). *Uncertainty: A guide to dealing with uncertainty in quantitative risk and policy analysis*. Cambridge University Press.
- Mouratiadou, I., & Moran, D. (2007). Mapping public participation in the water framework directive: A case study of the Pinios River Basin. *Greece. Ecological Economics*, 62, 66–76.
- Nandalal, K. D. W., & Simonovic, S. P. (2003). Resolving conflicts in water sharing: A systemic approach. *Water Resources Research*, 39(12), 1362–1373.
- Özesmi, U. (1999). *Conservation strategies for sustainable resource management in the Kizilirmak Delta in Turkey* (PhD thesis). University of Minnesota, Minneapolis.
- Özesmi, U., & Özesmi, S. L. (2003). A participatory approach to ecosystem conservation: Fuzzy cognitive maps and stakeholder group analysis in Ulubat Lake, Turkey. *Environmental Management*, 31(4), 518–531.
- Palmer, R. N. (1994). *ACT-ACF River Basin planning study*. Retrieved from <http://www.ce.washington.edu>
- Palmer, R. N., Hilton, K., & Hahn, M. (1995). *Willamette River Basin reauthorization feasibility study*. Retrieved from <http://www.ce.washington.edu>
- Palmer, R. N., Keyes, A. M., & Fisher, S. (1993). Empowering stakeholders through simulation in water resources planning. In K. Hon (Ed.), *Proceedings of the 20th anniversary conference of the American Society of Civil Engineers, Seattle, WA* (pp. 451–454). American Society of Civil Engineers.
- Papageorgiou, E. I., & Salmeron, J. L. (2013). A review of fuzzy cognitive maps research during the last decade. *IEEE Transactions on Fuzzy Systems*, 21(1), 66–79.
- Pearl, J. (1985). *BNS: A model of self activated memory for evidential reasoning*. Proceedings of 7th Conference on the Cognitive Science Society, 15–17 August 1985. University of California, Irvine, CA.
- Pearl, J. (1988). Probabilistic reasoning in intelligent systems: Networks of plausible inference. Representation and Reasoning Series, Morgan Kaufman, San Fransisco, California, USA.
- Penman, T. D., Cirulis, B., & Marcot, B. G. (2020). Bayesian decision network modeling for environmental risk management: A wildfire case study. *Journal of Environmental Management*, 270, 110735.
- Penn, A. S., Knight, C. J. K., Lloyd, D. J. B., Avitabile, D., Kok, K., Schiller, F., Woodward, A., Druckman, A., & Basson, L. (2013). Participatory development and analysis of a fuzzy cognitive map of the establishment of a bio-based economy in the Humber region. *PLoS One*, 8(11), 1–14.
- Penning-Rowsell, E., Johnson, C., Tunstall, S., Tapsell, S., Morris, J., Chatterton, J., & Green, C. (2005). *The benefits of flood and coastal risk management: A handbook of assessment techniques*. Flood Hazard Research Centre, Middlesex University Press.
- Pitt, M. (2008). *The Pitt review: Learning lessons from the 2007 floods* (p. 20). Cabinet Office.
- Porter, J., & Demeritt, D. (2012). Flood-risk management, mapping, and planning: The institutional politics of decision support in England. *Environment and Planning A*, 44(10), 2359–2378.
- Prell, C., Hubacek, K., Reed, M. S., Quinn, C. H., Jin, N., Holden, J., Burt, T., Kirby, M., & Sendzimir, J. (2007). If you have a hammer everything looks like a nail: ‘Traditional’ versus participatory model building. *Interdisciplinary Science Reviews*, 32(3), 263–282.
- Randers, J. (1973). *Conceptualizing dynamic models of social systems: Lessons from a study of social change* (PhD thesis). MIT Sloan School of Management, Cambridge, MA.
- Reed, M. S. (2008). Stakeholder participation for environmental management: A literature review. *Biological Conservation*, 141, 2417–2431.
- Reed, M. S., Graves, A., Dandy, N., Posthumus, H., Hubacek, K., Morris, J., Prell, C., Quinn, C. H., & Stringer, L. C. (2009). Who’s in and why? A typology of stakeholder analysis methods for natural resource management. *Journal of Environmental Management*, 90, 1933–1949.
- Rhodes, R. A. W. (1997). *Understanding governance: Policy networks, governance, reflexivity and accountability*. Open University Press.
- Richardson, G. P. (1999). Reflections on the future of system dynamics. *Journal of the Operational Research Society*, 50, 440–449.
- Seebauer, S., Ortner, S., Babicky, P., & Thaler, T. (2019). Bottom-up citizen initiatives as emergent actors in flood risk management: Mapping roles, relations and limitations. *Journal of Flood Risk Management*, 12(3), e12468.
- Sendzimir, J., Magnuszewski, P., Balogh, P., & Vári, A. (2007). Anticipatory modeling of biocomplexity in the Tisza River basin: First steps to establish a participatory adaptive framework. *Environmental Modelling and Software*, 22, 599–609.
- Simonovic, S. P., & Fahmy, H. (1999). A new modelling approach for water resources policy analysis. *Water Resources Research*, 35(1), 295–304.
- Simonovic, S. P., Fahmy, H., & El-Shorbagy, A. (1997). The use of object-orientated modelling for water resources planning in Egypt. *Water Resources Management*, 11(4), 243–261.
- Skov, F., & Svenning, J. C. (2003). Predicting plant species richness in a managed forest. *Forest Ecology and Management*, 180(1), 583–593.
- Soler, L. S., Kok, K., Camara, G., & Veldkamp, A. (2011). Using fuzzy cognitive maps to describe current system dynamics and develop land cover scenarios: A case study in the Brazilian Amazon. *Journal of Land Use Science*, 7(2), 149–175.
- Stave, K. A. (2002). Using system dynamics to improve public participation in environmental decisions. *System Dynamics Review*, 18(2), 139–167.
- Stave, K. A. (2003). A system dynamics model to facilitate public understanding of water management options in Las Vegas. *Nevada. Journal of Environmental Management*, 67, 303–313.

- Steinführer, A., Kuhliche, C., De Marchi, B., Scolobig, A., Tapsell, S., & Tunstall, S. (2008). Towards flood risk management with the people at risk: From scientific analysis to practice recommendations (and back). In P. Samuels, S. Huntington, W. Allsop, & J. Harrop (Eds.), *Flood risk management: Research and practice*. Taylor and Francis.
- Sterman, J. (2018). System dynamics at sixty: The path forward. *System Dynamics Review*, 34(1–2), 5–47.
- Sterman, J. D. (2001). System dynamics modelling: Tools for learning in a complex world. *California Management Review*, 43(4), 8–25.
- Thorne, C. R., Evans, E. P., & Penning-Rowsell, E. (Eds.). (2007). *Future flooding and coastal erosion risks* (p. 514). Thomas Telford.
- Tidwell, V. C., Passell, H. D., Conrad, S. H., & Thomas, R. P. (2004). System dynamics modelling for community-based water planning: Application to the middle Rio Grande. *Aquatic Science*, 66, 357–372.
- Tippett, J., & Griffiths, E. J. (2007). New approaches to flood risk management-implications for capacity-building. In *Advances in urban flood management* (pp. 383–413). Taylor and Francis.
- Tsouvalis, J., & Waterton, C. (2012). Building ‘participation’ upon critique: The Loweswater care project, Cumbria, UK. *Environmental Modelling & Software*, 36, 111–121.
- United Kingdom Government (2010). Flood and Water Management Act 2010. Retrieved from <https://www.legislation.gov.uk/ukpga/2010/29/contents>
- United Nations Conference on Environment and Development (UNCED). (1992). *Agenda 21*. UNCED.
- United Nations Economic Commission for Europe (UNECE). (1998). *Convention on access to information, public participation in decision-making and access to justice in environmental matters, 25 June 1998 (Aarhus convention)*. UNECE.
- United Nations Environment Programme (UNEP) (1992). *Report of the United Nations Conference on Environment and Development*. 3–15 June 1992, Rio de Janeiro.
- United Nations Office for Disaster Risk Reduction (UNISDR). (2005). *Hyogo framework for action 2005–2015: Building the resilience of nations and communities to disasters*. UNISDR.
- United Nations Office for Disaster Risk Reduction (UNISDR). (2015). *Sendai framework for disaster risk reduction 2015–2030*. UNISDR.
- van Kouwen, F., Schot, P. P., & Wassen, M. J. (2008). A framework for linking advanced simulation models with interactive cognitive maps. *Environmental Modelling and Software*, 23, 1133–1144.
- White, I. (2013). The more we know, the more we don't know: Reflections on a decade of planning, flood risk management and false precision. *Planning Theory and Practice*, 14, 106–114.
- Winz, I., Brierley, G., & Trowsdale, S. (2009). The use of system dynamics simulation in water resources management. *Water Resources Management*, 23, 1301–1323.
- Xu, Z. X., Takeuchi, K., Ishidaira, H., & Zhang, X. W. (2002). Sustainability analysis for Yellow River water resources using the system dynamics approach. *Water Resources Management*, 16, 239–261.
- Ziv, G., Watson, E., Young, D., Howard, D. C., Larcom, S. T., & Tanentzap, A. J. (2018). The potential impact of Brexit on the energy, water and food nexus in the UK: A fuzzy cognitive mapping approach. *Applied Energy*, 210, 487–498.
- Zorrilla, P., Carmona, G., de la Hera, A., Verela-Ortega, C., Martinez-Santos, P., Bromley, J., & Henriksen, H. S. (2010). Evaluation of Bayesian networks in participatory water resources management, upper Guadiana Basin, Spain. *Ecology and Society*, 15(3), 1–17.

How to cite this article: Maskrey, S. A., Mount, N. J., & Thorne, C. R. (2021). Doing flood risk modelling differently: Evaluating the potential for participatory techniques to broaden flood risk management decision-making. *Journal of Flood Risk Management*, e12757. <https://doi.org/10.1111/jfr3.12757>