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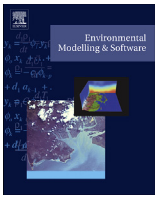

Dilemmas of modelling and decision-making in environmental research

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ABSTRACT

Multiple dilemmas confound social-ecological modelling. This review paper focuses on two: a modeller's dilemma associated with determining appropriate levels of model simplification, and a dilemma of decision-making relating to the use of models that were never designed to predict. We analyse approaches for addressing these dilemmas as they relate to shallow coastal systems and conclude that wicked problems cannot be adequately addressed using traditional disciplinary or systems engineering modelling. Simplified inter- and trans-disciplinary models have the potential to identify directions of system change, challenge thinking in disciplinary silos, and ultimately confront the dilemmas of social-ecological modelling.

Contents

1. Introduction

This paper examines two dilemmas prevalent in environmental research: a modeller's dilemma and a dilemma of decision-making. Modellers' face many dilemmas, but a central issue relates to tradeoffs between simplifications that are necessary to represent certain characteristics of a system, and the need also to represent intricacies within the system in sufficient detail in order to produce outputs that are useful in some way. This dilemma is particularly challenging in the case of social-ecological systems, which have interacting physical, ecological, and social components. How should these components be treated within models? A related

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dilemma confounds environmental management: models not intended for decision-support have nevertheless become a crutch on which decision-making often relies, with insufficient critical consideration of model limitations in the planning process, and application of models in ways that modellers may not have intended (Groeneveld et al., 2017; Kelly et al., 2013). Improved environmental planning requires progress in resolving these related dilemmas.

This paper reviews literature with an aim of identifying approaches of addressing and minimising these two dilemmas confronting modellers and decision makers. The dilemmas are recognisable across much environmental research, but we focus on shallow coastal systems, particularly estuaries, which are highly valued for providing essential ecosystem services and contributing to wider marine ecosystem function, but are also vulnerable due to their physical properties (e.g. shallow water depths) and processes such as increasing population, urbanisation, and changes in climate and land use (McNamara and Werner, 2008a; IPCC, 2014).

Box 1 sets out some of the key concepts used in this review paper. The approach has involved critiquing literature from diverse fields pertaining to social-ecological modelling, wicked problems, trans- and interdisciplinary research, ABM, estuarine modelling and estuarine management. The review is concerned with determining appropriate methods for approaching uncertainty in complex social-ecological systems and selecting suitable techniques for modelling feedbacks between, and interactions within these systems, as set out in Schlüter et al. (2012), but with a specific focus on how the two dilemmas impact upon model form, function and use.

Systems engineering models differ from the other definitions in Box 1 as they represent a single-discipline way of approaching a problem. This type of model represents a traditional approach to environmental management, as opposed to a holistic post-normal science approach. Schlüter et al. (2012) set out the main differences between traditional and social-ecological systems approaches to the management of human-environment systems, chief among which is that traditional methods utilise a ‘command and control’ technique whereas social-ecological systems management aim to enhance system resilience. The three other concepts are fundamentally intertwined; the post-normal science approach is a methodology that often incorporates transdisciplinarity when attempting to address wicked problems in complex social-ecological systems. This review was undertaken using a post-normal science approach, reviewing literature from the fields of social-ecological modelling, wicked problems, trans- and interdisciplinary research, agent-based modelling (ABM), estuarine modelling and estuarine management. Our review is concerned with determining appropriate methods for approaching uncertainty in complex social-ecological systems and selecting suitable techniques for modelling feedbacks between and interactions within these systems, as set out in Schlüter et al. (2012), but with a specific focus on how the two dilemmas impact upon model form, function and use.

Box 1
Terminology.

Post-normal science approach – A “systematic, synthetic and humanist” (Funtowicz and Ravetz, 1993: 739) approach to science in which human-environmental systems are viewed and treated holistically. The approach explicitly recognises human agency in an environmental system, and stakeholder values and opinions are taken into account. This is considered an appropriate approach for tackling wicked problems (Konig et al., 2017).

Social-ecological system - We use the term ‘social-ecological’ system to recognise that there is a fundamental connection between ‘the human’ and ‘the natural’, but that each functions as an independent system.

Systems engineering models – a ‘socio-technical’ approach to modelling requires as many facets of system form as possible to be included in a highly complicated model so as to streamline a system for human benefit (Baxter and Sommerville, 2011).

Transdisciplinarity - pertains to a research methodology where stakeholders and researchers from multiple disciplines come together during a research project in order to facilitate highly integrated research (Klein, 2014)

Wicked problem - an issue beset by uncertainty, plurality, and interdependence and that are unable to be convincingly defined (Rittel and Webber, 1973).

The review paper focuses on shallow coastal areas that occur at the downstream end of terrestrial drainage systems and are highly exposed to anthropogenically-derived pollution (Davies, 2015; Millennium Ecosystem Assessment, 2005a). Worldwide, shallow coastal ecosystems are undergoing rapid changes creating a research imperative to understand the complex interrelationships between ecological, physical and social processes that drive environmental change (e.g. McGranahan et al., 2007; Moser et al., 2012; Nicholls et al., 2011; Small and Nicholls, 2003). Rapid urbanisation and increasing population in coastal areas can stress the existing social-ecological systems while climate change is making these areas increasingly less suitable to sustain human populations (Crossett et al., 2004; Moser et al., 2012). The consequences of sea-level rise are already being felt in some of the least developed countries such as Bangladesh where some 46% of the population lived within 10 m of mean sea level in 2007 (McGranahan et al., 2007). However, sea-level rise is a global problem with 10% of world population concentrated in only 2% of the land area (McGranahan et al., 2007) and 2.4% of global population at risk of displacement by sea-level rise by the end of the 21st century (Nicholls et al., 2011). Anthropogenic alteration of natural systems makes natural processes (e.g. rainfall, flooding, storm surge) more complex by introducing runoff channelisation, water treatment and discharge, interfering with natural flow regulation. In particular, urbanised systems experience exacerbated impacts of relatively common events due to a combination of expanded impervious surfaces and channelised drainage networks (Baird, 2009; Schiff and Benoit, 2007).

Computational models can help understand these complexities and should therefore be an important resource for decision-makers in avoiding or mitigating impacts that reduce environmental, ecological, social and economic resilience. However, progress has been limited by the two dilemmas. Modellers are confronted with the challenge of how to adequately represent the physical, ecological and social dimensions of shallow coastal systems, and decision-makers are challenged by how to utilise models that are designed for social learning or developing system understanding, when a predictive model is desired for decision-making purposes.

Our aim in this paper is to reconcile the two dilemmas by identifying optimum modelling approach(es) for fully integrated consideration of social, ecological and geophysical systems in a single model. To accomplish this, we review literature so as to explore the potential for post-normal science, transdisciplinarity and particularly ABM to understand complex environmental problems and suggest a way forward. The review paper is structured as follows: first, the nature of the two dilemmas are elaborated and environmental problems are categorised as tame, complicated, and wicked (see Box 2); second; literature relevant to modelling shallow coastal social-ecological systems is reviewed, providing a foundation for the third and final section that outlines a path forward for modelling.

2. A modeller's dilemma

The phrase 'modeller's dilemma' was used by Singh and Mishra (2008) in relation to conflict resolution among various model averaging techniques used in groundwater modelling. A different 'modeller's dilemma' as discussed here concerns the struggle to determine the appropriate level of simplification and imitation of reality necessary to produce useful model outcomes, while preserving the necessary particulars of the system to be studied.

In selecting an approach to model complex social-ecological systems it is necessary to first determine the purpose of the modelling endeavour as discussed by Kelly et al. (2013), and then decide upon an appropriate level of model complicatedness (Murray, 2007; Sun et al., 2016). Following Sun et al. (2016) our use of the term 'complicatedness' pertains to model structure, whereas 'complexity' is used to describe model outputs. The choice between high and low model complicatedness is determined by multiple factors, but the existing level of system understanding is perhaps most important. Murray (2007) points out that highly complicated models offer limited explanatory insight, whereas highly simple models are unable to make numerically reliable predictions. Sun et al. (2016) note that increasing the complicatedness of a model can result in a decrease in the complexity of model outputs. Reducing model complicatedness can be achieved by omitting (or approximating) poorly understood components and components that are believed to have minimal systemic effect; but these types of simplifications may also reduce the ability of the model to achieve research goals by altering model complexity. All models are by definition abstract representations (simplifications) of reality, and no model can be considered 'correct', but the degree of simplification employed in different models varies enormously (Murray, 2007, 2013; O'Sullivan et al., 2012; Simandan, 2010; Sun et al., 2016).

Determining the appropriate level of simplification is especially pertinent for a social-ecological model being developed with the intention of investigating social-ecological change and the interactions between physical, ecological and social components at various scales, as these systems are inherently highly complex yet poorly understood and notoriously difficult to manage using a traditional command-and-control approach (Voinov et al., 2016). In such poorly understood social-ecological systems, having a predictive or forecasting focus is difficult due to the presence of unknown system variables (Kelly et al., 2013). A more realistic goal is to improve system understanding by developing a very simple model that is useful, even if its assumptions and workings are not strictly correct (O'Sullivan et al., 2012; Murray, 2013). Such simple models also go some way to mitigate a dilemma that faces decision-makers.

2.1. A dilemma of decision-making

Computational models have come to occupy a position that they were never designed for; treated as infallible by those who rely on them but not by their creators (Meadows and Robinson, 2002). An increasing reliance on models to guide decision-making (e.g. Carnavale et al., 2012; Oxley et al., 2004) suggests that decision-makers prefer a predictive tool. Policy makers have historically had difficulty in comprehending and counteracting wicked problems (Davies, 2015; Head, 2014; Stirling, 2010), exemplified by the detachment between the time of decision-making and the subsequent effects being observed (Rammer and Seidl, 2015). In this context, model results provide a decision-making crutch: models can make decisions for decision-makers.

Devolution of responsibility from decision-maker to model can be traced to a number of factors including the search for simple solutions by decision-makers that thwarts the longer-term perspective necessary to approach wicked problems (Head, 2014), as well as ignoring the unintended consequences of wicked problems. There is frequent miscommunication about the role of both science (Lave, 2015) and modelling (Schneider, 1997) in decision-making and policy development. The purpose and practical limitations of a model must always be made clear to end users and decision-makers (Schneider, 1997). In turn, decision-makers have a responsibility to understand the practical limitations of a model and to avoid using it in ways and for reasons that it is incapable. Additionally, while scientists may openly express the subjective elements of their work in professional discussions (Morgan and Keith, 1995), they should also do so in relation to decision-making (Wright, 2015). Research suggests that including stakeholders and decision-makers in the development and testing of models is a valuable way of improving their understanding of model purpose (Bousquet and Le Page, 2004; Schneider, 1997; Seidl, 2015; Voinov and Bousquet, 2010; Yearley, 2006). Seidl (2015) discusses various methods of participation and potential benefits from participatory modelling in this regard.

3. Dilemmas in practice: Chesapeake Bay Modelling System

Shallow coastal areas are increasingly becoming the subject of modelling exercises aimed at deciphering potential impacts and ways to mitigate or avoid them. Dilemmas facing both modellers and decision makers are accompanying these efforts (e.g. Lloyd et al., 2015; Malzone et al., 2009). One notable example of a major social-ecological coastal modelling project is the Chesapeake Bay Modelling System (CBMS) developed by the Chesapeake Bay Program. It uses an ecosystem-based management approach to simulate social-ecological system function and the impacts of change at the catchment scale using a coupled-component model (Boesch and Goldman, 2009; Paolisso et al., 2015). Calibrated through direct comparison with observed condition, the model was initially used to assist voluntary restoration projects but is increasingly guiding official Watershed Implementation Plans that aim to reduce human impacts on the Chesapeake Bay ecosystem (Paolisso et al., 2015). The modelling endeavour has expanded since its establishment in 1983 and now encompasses airshed, watershed and a model of the shallow coastal portions of Chesapeake Bay itself (e.g. Cerco et al., 2013; Keisman and Shenk, 2013; Linker et al., 2013).

The CBMS program was not successful in achieving some of its early management goals; however, a more holistic and integrated management approach was implemented once managers recognised the interrelated nature of the issues facing the bay (Boesch and Goldman, 2009). Similar management schemes based on the principles of post-normal science, ecosystem-based management and transdisciplinary research are increasingly viewed as superior to traditional command-and-control management at addressing wicked problems (Biggs et al., 2010; Davies, 2015; Funtowicz and Ravetz, 1993). Since its inception, the CBMS has become increasingly complicated as the airshed and watershed models have been linked to the original bay model (Paolisso et al., 2015). The creation of the present coupled-component model highlights the aforementioned modeller's dilemma of determining an appropriate level of model simplicity vs. complicatedness and the dilemma of decision-making concerning changing use of the model(s) over time; the increasing complicatedness of the CBMS highlights a major issue facing modellers (a modeller's dilemma) and impacting on decision-makers (a decision-maker's dilemma) when attempting to address wicked problems.

4. Categorising problems

Rittel and Webber (1973) noted that scientific practices were failing to address issues characterised by uncertainty, plurality, interdependence, and a lack of agreement over what the problem actually was. They coined the term 'wicked' problems as a means of conveying the inherent complexity of the joint system-problem and showed that conventional methods of addressing comparatively 'tame' (relatively simple and solvable) problems were inadequate when applied to more complex problems. Balint et al. (2011) added 'complicated' problems as a middle-ground between tame and wicked, and suggested that the three major features distinguishing wicked from tame and complicated problems are values, risk and uncertainty. We use 'complicated' to refer to problems that are not necessarily simple or solvable (tame), but where research is able to gain greater traction and deliver more useful prediction and forecasting of system attributes than research addressing wicked problems. Use of the term 'wicked' implies difficulty in understanding and addressing complex problems. Almost all problems in social-ecological systems can be considered 'wicked', in large part because human interventions, intended or not, add risk, uncertainty and multiple values, creating a challenging environment for coping with this complex reality.

Box 2 illustrates some of the ways in which tame, complicated and wicked problems can be approached through disciplinary, interdisciplinary and transdisciplinary research. Tame problems are generally tackled by a single academic discipline, whereas complicated problems are best addressed through interdisciplinary research (Folke, 2006), and transdisciplinarity is emerging as an important approach for tackling wicked problems (Brown et al., 2010). Participatory modelling is an important transdisciplinary/post-normal science method of approaching wicked problems that has become increasingly important during recent years (Robson, 2014; Seidl, 2015).

5. Modelling

5.1. Revisiting modelling

According to Kelly et al. (2013), the five potential purposes of modelling are developing system understanding; facilitating social learning; predicting the behavior of variables when other variables are known; forecasting the behavior of variables when other variables are not known; and management and decision-making under uncertainty. Sun et al. (2016) set out six similar purposes for modelling: prediction; theory building; decision-making; case-specific analysis; to illuminate core dynamics; and education. Social-ecological models can be developed and subsequently used for any

Box 2

Tame, Complicated and Wicked Problems

Transdisciplinary research and stakeholder participation facilitate the improvement of system understanding allowing researchers to come to terms with the complexity of wicked problems (Moser et al., 2012; Voinov and Brown-Gaddis, 2008). The multiple dimensions of complexity require that multiple viewpoints are needed to scope out a wicked problem and begin to address it. Characterised by bringing together two or more disciplines from the very beginning of the venture to allow for truly integrated research (Klein, 1990, 2014), transdisciplinarity attempts to remove disciplinary barriers in order to allow for focus on multiple interpretations of information simultaneously, rather than solely disciplinary interpretations of it. This allows for stakeholder involvement from the earliest possible stage (Laniak et al., 2013; Tress et al., 2005; Turner II et al., 2016). Transdisciplinary research into wicked problems is problem oriented, asking 'what is the problem?' rather than pursuing the 'what are we trying to fix?' approach of traditional systems engineering.

Fig. 1 shows a representation of the relationships between (i) tame, complicated and wicked problems, (ii) three forms of disciplinarity, and (iii) an increasing intensity of the two dilemmas facing decision makers and modellers. Three models are placed in the matrix to illustrate how different types of problems require different approaches to address them. Tame problems can generally be addressed by a single discipline, and the two dilemmas are weak. Complicated problems require an interdisciplinary approach, and the two dilemmas are present. The two dilemmas are fully developed where wicked problems occur, and these are best addressed through transdisciplinary research.

Point 1 is based on the work of McMahon et al. (2017), which evaluated the controlling variables on riverbank erosion in subtropical Australia. Being a natural physical process, albeit one that can be altered by human agency, riverbank erosion is an example of a tame problem. It can be addressed within a single disciplinary silo and when modelling such an issue the two dilemmas described in this paper are weak.

Point 2, based on the work of Qin et al. (2017), positions a model for forecasting coastal pollutant movement in the zone of complicated problems, interdisciplinarity, and developing dilemmas. The researchers come from multiple agencies, allowing expertise from different disciplines to shape the research. The problem is created by human agency, making it complicated, but it is potentially solvable. The modeller's dilemma begins to show as model accuracy relies on quality input data, which as the authors note may not be available in all circumstances. Additionally, the dilemma of decision-making is developing as the model is intended for an environmental management application where persons detached from the model development will operate it; the limitations of operating such a model using lower-quality data may not be understood and appropriately accounted for by the end-users.

Point 3 is based on the work of Le Cozzanet et al. (2015) analysing uncertainties of flooding under future sea-level rise. Sea-level rise and its impacts are very wicked problems, requiring the efforts of multiple disciplines. Transdisciplinarity is best suited to deal with climate change due to the holistic systems thinking required to address the problem. As problems become increasingly wicked, uncertainty in both model inputs and outputs also increase. The two dilemmas are both present in this case as despite the modeller's knowing what model inputs to use they become increasingly uncertain into the future, and hence decision-makers will likely have trouble using a model such as this one in environmental planning applications.

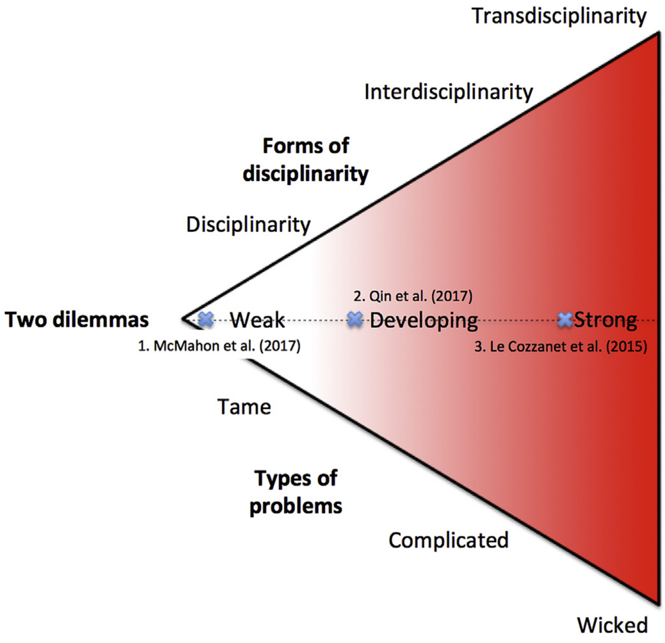

Fig. 1. Tame, complicated and wicked problems, three forms of disciplinarity, and the development of the two dilemmas in relation to three hypothetical environmental issues. Points 1, 2 and 3 represent positions within the matrix of three models published between 2015 and 2017 in *Environmental Modelling and Software*.

of these purposes, or a combination thereof; model developers and end-users may view and utilise the same model in different ways (Schneider, 1997), creating the potential for a dilemma of decision-making to emerge.

Many approaches to integrated inter- and transdisciplinary social-ecological modelling exist: Bayesian networks; system dynamics modelling; ABM; knowledge-based modelling; and coupled-component modelling (among others), have diverse strengths and weaknesses and are subsequently suited to achieving different modelling aims (Gilbert et al., 2008; Kelly et al., 2013). No approach to environmental modelling is applicable in all situations. The principal consideration when selecting a modelling technique and level of complicatedness is determining the purpose of the research. (Kelly et al., 2013; Sun et al., 2016). For instance, if the investigation is focused on developing greater system understanding or facilitating social learning or in research with a significant spatial component then ABM is a suitable approach (Kelly et al., 2013). However, system dynamics modelling may be a better option in cases without major spatial constituents (Voinov and Bousquet, 2010). As a way of accommodating the strengths and avoiding the weaknesses of the available techniques, coupled-component modelling attempts to bring the best of each system together to facilitate interdisciplinary modelling, albeit it in a highly complex manner (Kelly et al., 2013). While coupled-component modelling increases model complicatedness, it can facilitate understanding of both individual interactions and their aggregate effects. This is useful when attempting to improve understanding of the system. Coupled components models may, however, exacerbate a modeller's dilemma as the combination of existing models can easily result in the development of a highly complicated model when a simpler original model would be better suited to address the issues facing the system.

While system dynamics and ABMs are both well suited to developing system understanding and facilitating social learning, the spatial properties of ABM means that it is generally superior for social-ecological applications (Bousquet and Le Page, 2004; Kelly et al., 2013; Sun et al., 2016; Voinov and Bousquet, 2010). ABMs tend to be more complicated than system dynamics models, but are more revealing of the interactions between individual variables and agents (Clifford, 2008; O'Sullivan et al., 2012). The approach selected should be determined by whether the research project is more interested in these individual interactions or only aggregate effects (Kelly et al., 2013).

A typical aim of modelling is to achieve a level of consistency between model components, particularly scale, as it is simpler to investigate interactions between the constituent parts when they are similarly scaled (Murray et al., 2009). Explicit numerical reductionism involves modelling on the smallest and fastest scales, whereas top-down exploratory modelling operates on the largest and slowest scales (Murray et al., 2009). As different components may act and interact at vastly different scales, utilising only a single scale risks oversimplification of some components if top-down modelling is used, or over-complication of model structure if numerical reductionism is applied. Dealing with this requires use of a scale appropriate for the system under consideration; a scale that captures the requisite level of complexity needed to address the problem being investigated (O'Sullivan et al., 2012).

Our literature review suggests that key to social-ecological modelling endeavours are four actions: coming to know the system under consideration; identifying the constituent components of the system; identifying the connections between these components; and reconciling both component scale and disciplinarity. Attempts at modelling for the purpose of developing system understanding tend to limit the number of components included in the model or reduce their scale or other attributes (e.g. Becu et al., 2003; Huang et al., 2014), whereas attempts at quantifying the nature of interactions between components tend to have increased complicatedness. In many situations where some facets of system form and function are not well understood, the inclusion of poorly understood components will reduce numerical precision and the robustness of model outputs. Some of these unknown quantities can be approximated (Gonzalez et al., 2008), or proxies used (Drobinski et al., 2012; McGranahan et al., 2007) but when they cannot, limiting the number of model components can both increase model accuracy and enhance system understanding.

5.2. Modelling shallow coastal systems

When developing a model to investigate changes in shallow coastal systems the developers should be explicit as to whether it is designed to investigate the mean values of system change or the extreme conditions caused by these changes. Mean values drive an average condition and are widely used in models operating over decadal or longer time scales (e.g. Holgate, 2007; Nicholls et al., 2008). Incremental stressors occurring over a longer timeframe can trigger state changes in shallow coastal social-ecological systems (Hughes et al., 2017); for example, the impacts of rising water temperatures on coral reefs or a gradual long-term increase in nitrogen in estuarine systems. However, investigating the incremental changes that produce 'average' system conditions do not shed light on the extreme events that might provide the impetus for sudden state changes in a system. In local and regional scale investigations of climate change impacts on coastal areas, the extreme values constitute the greatest risk to people and property – subsequently, they are among the best studied facets of climate change (e.g. Chini and Stansby, 2012; Kirwin et al., 2008; Nicholls et al., 2011).

Modelling the impacts of environmental change on shallow coastal social-ecological systems occupies a position near point 3 in Fig. 1. The problem is wicked and multiple disciplines need to cooperate and contribute toward addressing it (Berkes, 2010; Learmonth et al., 2011). Utilising simple computational modelling for shallow coastal systems research allows for development of understanding of system form and function, while avoiding unnecessary complicatedness in model design, testing and operation. Modelling specific components of the social-ecological aspect of coastal catchments can allow researchers to develop understanding of the potential directions of climate change, environmental change, and changes in collective human behavior on the shallow coastal areas of the system. Such a model may be intended for use in forecasting or predicting system responses, but there are significant challenges associated with this aim. Local-scale research is much more likely to achieve success if it has alternate purposes such as facilitating social learning among stakeholders, or to *assist* (but not *drive*) decision-making under uncertainty in the future. If such a model is to be used in decision-making, it is vital to explain to the decision-makers the reasons a model was constructed, what its limitations are, and that model intent may not be forecasting or prediction (Schneider, 1997), rather that it can demonstrate the potential for non-linear and complex responses to the wicked problem of climate change. Such a model could be used to guide decision-making by encouraging the fostering of resilience within the social-ecological system under consideration (Murray et al., 2009).

5.3. *What models suit?*

In a recent review of participatory modelling ventures, Seidl (2015) found participatory ABM to be the most commonly used participatory modelling approach, and Simon and Etienne (2010) concluded that ABM is the most appropriate modelling approach to facilitate stakeholder participation. In the literature, ABM stands out as the technique most suited to investigating dynamic human-environmental interactions in a shallow coastal social-ecological system due to its explicit focus on investigating interactions between individuals; other techniques are more concerned with analysis of the aggregated effects of such interactions (Kelly et al., 2013; Schlüter et al., 2012). However, ABM approaches often produce more complicated models than other approaches due to the large numbers of model inputs (Sun et al., 2016), exacerbating the modeller's dilemma. Of significance to the intricacy of the model are: simulation of the interactions between inputs; a continually changing spatial setting; and potentially, changing boundary conditions (Bousquet and Le Page, 2004; Kelly et al., 2013; O'Sullivan et al., 2012).

ABMs can expand researcher and stakeholder understanding of complex social-ecological systems by simulating interactions between autonomous entities within the system, making this approach particularly appealing for modelling the interaction between social and ecological agents in coastal systems research (e.g. Luo et al., 2012; McNamara and Keeler, 2013). However, depending on the level of model simplification desired, complicated model structure can be considered a weakness of an ABM approach when addressing the modeller's dilemma (Kelly et al., 2013; O'Sullivan et al., 2012; Sun et al., 2016). Hence, there is a trade-off when using an ABM approach between the strength of simulating agent interactions and the potential weakness of high model complicatedness (Sun et al., 2016). The inability of ABMs to accurately predict outcomes without making the model overly complicated due to the inclusion of poorly understood system components is a limitation (Kelly et al., 2013; Sun et al., 2016). As stated, this can be remedied by reducing model complicatedness, but in doing so the modeller runs the risk of also reducing model complexity, which may adversely impact on research outcomes. While the intricacy of ABM makes it a complicated and time-consuming approach, its significant strength in developing system understanding can often justify these factors (O'Sullivan et al., 2012). If prediction of system behavior is the purpose of modelling, more suitable approaches than ABM are available, such as system dynamics and potentially coupled component modelling. When developed in conjunction with stakeholders and/or end-users, an ABM can help mitigate the dilemma of decision-making by explicitly demonstrating model limitations to end-users (deReynier et al., 2010; Robson, 2014). This kind of end-user participation in model development can also mitigate the modeller's dilemma as all parties collaboratively decide upon an appropriate level of complicatedness, rather than just the modeller determining this.

Agent behavior and interactions are fundamental concerns in developing understanding and modelling coastal social-ecological system structure (Bousquet and Le Page. 2004). ABMs provide a well-founded framework aimed at incorporating this integration of behavior and interactions, as well as stakeholder knowledge and perspectives, within a numerical model (Berger, 2001; Elsawah et al., 2015; Fulton et al., 2015; Kelly et al., 2013; Voinov and Bousquet, 2010; Voinov et al., 2016). Their ability to handle spatial data and dynamics gives ABMs an advantage over other approaches to modelling (Kelly et al., 2013; Sun et al., 2016). ABM has been used to model various social-ecological systems at the catchment-scale (e.g. Barreteau et al., 2001; Barthel et al., 2009; Becu et al., 2003) and is particularly useful when investigating human settlement and other social-ecological systems (O'Sullivan et al., 2012; Sun et al., 2016). Modelling of shallow coastal environments using an ABM approach is also becoming increasingly common (e.g. Brush and Nixon, 2010; Canal-Vergés et al., 2014; Zhang and Gorelick, 2014).

6. Reintroducing social elements

Wicked problems are ubiquitous within interconnected social-ecological systems (Balint et al., 2011; Brown et al., 2010; Turnpenny et al., 2009). Shallow coastal social-ecological systems are highly interconnected and often produce non-linear emergent responses to a change in one system component, resulting in changes across scales and affecting multiple system attributes (McNamara and Werner, 2008a; Moser et al., 2012; Williams et al., 2013). Hence, the human element must be meaningfully embraced in shallow coastal social-ecological modelling, which requires a multifaceted approach. Historically, when disciplinary research programmes have attempted to grapple with wicked problems that transcend disciplinary boundaries, one discipline tends to dominate the discourse and research agenda with the result that either human or non-human system attributes are poorly incorporated or oversimplified to the point of irrelevance (Davies, 2015; Lave et al., 2014; Turner II et al., 2016). Previous work on resilience in social-ecological systems has tended to either disconnect the social components of systems from the whole (Brown Gaddis et al., 2010), reduce them to economic factors or simple demographics (Cote and Nightingale, 2012), or represent the connections between the subsystems as unidirectional (Filatova et al., 2013), while failing to acknowledge the singular, complex and intertwined entity that is a social-ecological system (Berkes, 2007). This pitfall can be avoided by investigating the nature of relevant human variables from the outset of research, particularly through application of a post-normal science/participatory modelling approach (Funtowicz and Ravetz, 1993; Turnpenny et al., 2009; Voinov et al., 2016).

Stakeholder participation provides the opportunity to learn about concealed characteristics of the system (Voinov and Brown Gaddis, 2008), such as how resident and non-residents utilise and interact with a shallow coastal system. Social-ecological research can use stakeholder participation to make visible the range of values held (Davies, 2015; Balint et al., 2011), and to build a shared understanding of a system and the issues facing it both for social learning purposes, and to link findings to decision-making processes (Fulton et al., 2015; Yearley, 2006), mitigating the dilemma of decision-making. The knowledge derived from stakeholders, participants and end-users can be used by modellers to develop a richer understanding of the system, so that the model under development can more accurately represent the social characteristics of the system and assist in developing ways to address the wicked problems afflicting it. An analysis of integrated coastal management in New Zealand found that increased collaboration across the ‘science-policy interface’ facilitates the production of higher-quality science and better management outcomes for coastal zones (Bremer and Glavovic, 2013).

When studying a wicked problem, separate handling of the social components could easily result in unrealistic representation of system functions, subsequent production of imprecise model outputs and an exacerbation of the modeller's dilemma through inclusion of unnecessary variables or oversimplification of the social system. Cote and Nightingale (2012) noted that work on resilience in social-ecological systems has proceeded in ‘remarkable isolation’ from human geography and other social sciences, despite the notable commonalities in research foci. A holistic, broad-scale envisioning of the system using a post-normal science approach is desirable when researching and modelling social-ecological impacts of climate change on shallow coastal systems. Viewing shallow coasts as comprised of separate social, geophysical, ecological, economic, political, etc. subsystems is commonplace in the Anglophone world as a way of making sense of complexity (Castree, 2014). In practice, there is considerable difference between understanding a system as the sum of its parts and dealing with system complexity in a way that does not recognise artificial conceptual boundaries between subsystems.

In developing simple models that aim to grow understanding of an entire shallow coastal social-ecological system, there is little point in treating perceived subsystems as distinct entities. The components of any system are not solely responsible for its behavior; rather, the interactions between components create system form and function (Castree, 2014; Thrift, 1996 in Simandan, 2010: 393), and those components need not belong to any one category or subsystem. Simandan (2010:391), writing on contingency and necessity within human belief systems, highlights a major issue with a non-holistic research approach:

> “Binary distinctions yield artificial borders, and as soon as one faces borders, one faces the quandary of border cases and the ensuing temptation to fudge them so as to fit neatly into one box or the other.”

True transdisciplinary environmental research ought to accept that boundaries between ‘social’, ‘ecological’ and ‘geophysical’ systems are socially constructed and that their use may lead to potentially inadequate representations of any system as a whole. Traditional disciplinary understandings and representations of subsystems are not obsolete: epistemic communities remain vital to disciplinary and interdisciplinary knowledge production, but the different disciplinary viewpoints need to be proactively discussed and blended in the early stages of a research project (Turner II et al., 2016).

This review paper indicates that the best path is to: (1) identify those variables in a system whose interactions have the greatest influence on whatever is of interest; and (2) model their interrelations (Lynam et al., 2007) and effects on overall system form and function, regardless of which subsystem they are perceived to occupy. Such a holistic treatment of the overall social-ecological system can mitigate the modeller's dilemma as the inclusion of only the necessary variables reduces model complicatedness. In turn, simpler models can mitigate the dilemma of decision-making as the model can be easier to comprehend and limitations of the model will be more obvious.

7. A way forward

Participatory ABM can help to mitigate the dilemma of decision-making by ensuring that stakeholders and decision-makers are engaged in the development of model form and function and so understand when it is and is not appropriate to use a model to assist with the decision-making process. By encouraging end-user participation, the modeller's dilemma can be lessened, as the modeller no longer needs to give as much concern to misuse of the model, and has more leeway to determine how complicated model structure should be so as to appropriately model the system in question.

Shallow coastal ecosystems have unknown variables and myriad complex interactions across human and biophysical domains. Hence, social-ecological models are more suited to producing information on the likely *direction* of environmental changes through developing system understanding than to making accurate predictions of exactly *what* change will occur. Models may be heuristic, imperfect representations of reality, but they can serve to achieve research and environmental management goals (Murray, 2007). In social-ecological systems not all system components need to be modeled in order to investigate outcomes of interactions between other system components.

In a transdisciplinary setting, developing a model allows for improving researcher and stakeholder understanding of the system in question, which in turn helps in addressing the problems affecting the system. High numerical precision of outputs might be achieved through increasing model complicatedness, but this is less important in this type of work than the robustness of results pertaining to the directions of change.

The need for balance between model simplification and complicatedness is mirrored in efforts to achieve parity between the various disciplines involved. Wicked problems in social-ecological systems cannot be adequately addressed using traditional disciplinary or systems engineering modelling due to the interplay of social variables (Wu et al., 2015). Instead, use of interdisciplinary and transdisciplinary modelling enables a holistic systems view: this is a prerequisite for grappling with wicked problems in shallow coastal social-ecological systems.

Anthropogenically induced changes to shallow coastal systems are present worldwide, yet the changes that are occurring are often poorly understood. These changes do not occur in isolation, but impact upon other facets of these systems. Understanding how these changes occur and spread is vital to avoiding or reducing the impacts of human actions. Simple models developed for the purpose of identifying directions of system change under various stressors are a valuable tool in achieving this. Inter- or transdisciplinary research that considers the relevant factors in system form, function and change can help challenge the thinking in disciplinary silos where knowledge has historically been produced and can help societies confront wicked environmental problems. A post-normal science approach, particularly participatory modelling facilitates the development of understanding of complex systems (Voinov et al., 2016), and provides a valuable tool to help address the issues faced by social-ecological systems in a holistic, transdisciplinary manner.

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References

Baird, R.C., 2009. Coastal urbanization: the challenge of management lag. Manag. Environ. Qual. 20 (4), 371–382.

Balint, P.J., Stewart, R.E., Desai, A., Walters, L.C., 2011. Wicked Environmental Problems: Managing Uncertainty and Conflict. Island Press, Washington, D.C.

Barreteau, O., Bousquet, F., Attonaty, J.-M., 2001. Role-playing games for opening the black box of multi-agent systems: method and lessons of its application to Senegal River Valley irrigated systems. J. Artif. Soc. Soc. Simul. 4 (2).

Barthel, R., Janisch, S., Nickel, D., Trifkovic, A., Hörhan, T., 2009. Using the multiactor-approach in GLOWA-danube to simulate decisions for the water supply sector under conditions of global climate change. Water Resour. Manag. 24 (2), 239–275.

Baxter, G., Sommerville, I., 2011. Socio-technical systems: from design methods to systems engineering. Interact. Comput. 23, 4–17.

Becu, N., Perez, P., Walker, A., Barreteau, O., Le Page, C., 2003. Agent based simulation of a small catchment water management in northern Thailand. Description of the CATCHSCAPE model. Ecol. Model. 170, 319–331.

Berger, T., 2001. Agent-based spatial models applied to agriculture: a simulation tool for technology diffusion, resource use changes and policy analysis. Agric. Econ. 25, 245–260.

Berkes, F., 2007. Understanding uncertainty and reducing vulnerability: lessons from resilience thinking. Nat. Hazards 41, 283–295.

Berkes, F., 2010. Devolution of environment and resources governance: trends and future. Environ. Conserv. 37 (4), 489–500.

Biggs, R., Diebel, M.W., Gilroy, D., Kamarainen, A.M., Kornis, M.S., Preston, N.D., Schmitz, J.E., Uejio, C.K., Van De Bogert, M.C., Weidel, B.C., West, P.C., Zaks, D.P.M., Carpenter, S.R., 2010. Preparing for the future: teaching scenario planning at the graduate level. Front. Ecol. Environ. 8 (5), 267–273.

Boesch, D.F., Goldman, E.B., 2009. Chesapeake bay, USA. In: McLeod, K., Leslie, H.M., Aburto, M. (Eds.), Ecosystem-based Management for the Oceans. Island Press, Washington, D.C, pp. 268–293.

Bousquet, F., Le Page, C., 2004. Multi-agent simulations and ecosystem management: a review. Ecol. Model. 176, 313–332.

Bremer, S., Glavovic, B., 2013. Exploring the science-policy interface for integrated coastal management in New Zealand. Ocean Coast. Manag. 84, 107–118.

Brown Gaddis, E.J., Harp Falk, H., Ginger, C., Voinov, A., 2010. Effectiveness of a participatory modeling effort to identify and advance community water resource goals in St Albans, Vermont. Environ. Model. Softw. 25 (11), 1428–1438.

Brown, V.A., Harris, J.A., Russell, J.Y., 2010. Tackling Wicked Problems: through the Transdisciplinary Imagination. Earthscan, London.

Brush, M.J., Nixon, S.W., 2010. Modeling the role of macroalgae in a shallow subestuary of Narragansett Bay, RI (USA). Ecol. Model. 221, 1065–1079.

Canal-Vergés, P., Potthoff, M., Thorbjørn Hansen, F., Holmboe, N., Rasmussen, E.K., Flindt, M.R., 2014. Eelgrass re-establishment in shallow estuaries is affected by drifting macroalgae – evaluated by agent-based modeling. Ecol. Model. 272, 116–128.

Carnavale, C., Finzi, G., Pisoni, E., Volta, M., Guariso, G., Gianfreeda, R., Maffeis, G., Thunis, P., White, L., Triacchini, G., 2012. An integrated assessment tool to define air quality policies at the regional scale. Environ. Model. Softw. 38, 306–315.

Castree, N., 2014. Making Sense of Nature. Routledge, London.

Cerco, C.F., Noel, M.R., Wang, P., 2013. The shallow-water component of the Chesapeake Bay environmental model package. J. Am. Water Resour. Assoc. 49 (5), 1091–1102.

Chini, N., Stansby, P.K., 2012. Extreme values of coastal wave overtopping accounting for climate change and sea level rise. Coast. Eng. 65, 27–37.

Clifford, N.J., 2008. Models in geography revisited. Geoforum 39, 675–686.

Cote, M., Nightingale, A.J., 2012. Resilience thinking meets social theory: situating social change in socio-ecological systems (socio-ecological system) research. Prog. Hum. Geogr. 36 (4), 475–489.

Crossett, K.M., Culliton, T.J., Wiley, P.C., Goodspeed, T.R., 2004. Population Trends along the Coastal United States: 1980-2008. Silver Spring (M.D: National Oceanic and Atmospheric Administration/National Ocean Service, Management and Budget Office, Special Projects.).

Davies, K., 2015. Many voices of the Manukau: Participatory Modelling, Ecosystem Services and Decision Making in New Zealand. PhD Thesis. University of Auckland, p. 276.

deReynier, Y.L., Levin, P.S., Shoji, N.L., 2010. Bringing stakeholders, scientists, and managers together through an integrated ecosystem assessment process. Mar. Policy 34, 534–540.

Drobinski, P., Anav, A., Brossier, C.L., Samson, G., Stéfanon, M., Bastin, S., Baklouti, M., Béranger, K., Beuvier, J., Bourdallé-Badie, R., Coquart, L., D'Andrea, F., de Noblet-Ducoudré, N., Diaz, F., Dutay, J.-C., Ethe, C., Foujols, M.-A., Khvorostyanov, D., Madec, G., Mancip, M., Masson, S., Menut, L., Palmieri, J., Polcher, J., Turquety, S., Valcke, S., Viovy, N., 2012. Model of the Regional Coupled Earth system (MORCE): application to process and climate studies in vulnerable regions. Environ. Model. Softw. 35, 1–18.

Elsawah, S., Guillaume, J.H.A., Filatova, T., Rook, J., Jakeman, A.J., 2015. A methodology for eliciting, representing, and analysing stakeholder knowledge for decision-making on complex socio-ecological systems: from cognitive maps to agent-based models. J. Environ. Manag. 151, 500–516.

Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A., 2013. Spatial agent-based models for socio-ecological systems: challenges and prospects. Environ. Model. Softw. 45, 1–7.

Folke, C., 2006. Resilience: the emergence of a perspective for social-ecological systems analysis. Glob. Environ. Change 16 (3), 253–267.

Fulton, E.A., Boschetti, E., Sporcic, M., Jones, T., Little, L.R., Dambacher, J.M., Gray, R., Scott, R., Gorton, R., 2015. A multi-model approach to engaging stakeholders and modellers in complex environmental problems. Environ. Sci. Policy 48, 44–56.

Funtowicz, S.O., Ravetz, J.R., 1993. Science for the post-normal age. Futures 25 (7), 739–755.

Gilbert, K., Spate, J., Sanchez-Marre, M., Athanasiadis, I., Comas, J., 2008. Data mining for environmental systems. In: Jakeman, A.J., Voinov, A., Rizzoli, A., Chen, S. (Eds.), Environmental Modelling, Software and Decision Support – State of the Art and New Perspectives, vol. 3. Elsevier, Amsterdam.

Gonzalez, M.C., Hidalgo, C.A., Barabasi, A.-L., 2008. Understanding individual human mobility patterns. Nature 453 (5). https://doi.org/10.1038/nature06958.

Groeneveld, J., Muller, B., Bachmann, C.M., Dressler, G., Guo, C., Hase, N., Hoffman, F., John, F., Klassert, C., Lauf, T., Liebelt, V., Nolzen, H., Pannicke, N., Schulze, J., Weise, H., Schwarz, N., 2017. Theoretical foundations of human decision-making in agent-based land use models - a review. Environ. Model. Softw. 87, 39–48.

Head, B.W., 2014. Evidence, uncertainty, and wicked problems in climate change decision making in Australia. Environ. Plan. C Gov. Policy 32, 663–679.

Holgate, S.J., 2007. On the decadal rates of sea level change during the twentieth century. Geophys. Res. Lett. 34, L01602. https://doi.org/10.1029/2006GL028492.

Huang, Q., Parker, D.C., Filatova, T., Sun, S., 2014. A review of urban residential choice models using agent-based modeling. Environ. Plan. B Plan. Des. 41, 661–689.

Hughes, T.P., Barnes, M.L., Bellwood, D.R., Cinner, J.E., Cumming, G.S., Jackson, J.B.C., Kleypas, J., van de Leemput, I.A., Lough, J.M., Morrison, T.H., Palumbi, S.R., van Nes, E.H., Scheffer, M., 2017. Coral reefs in the anthropocene. Nature 546, 82–90.

IPCC, 2014. Climate change 2014 synthesis report. Contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change. In: Core Writing Team, Pachauri, R.K., Meyer, L.A. (Eds.), Intergovernmental Panel on Climate Change. Switzerland, Geneva, p. 151.

Keisman, J., Shenk, G., 2013. Total maximum daily load criteria assessment using monitoring and modeling data. J. Am. Water Resour. Assoc. 49 (5), 1134–1149.

Kelly (nee Letcher), R.A., Jakeman, A.J., Barreteau, O., Bursuk, M.E., Elsawah, S., Hamilton, S.H., Hendriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw. 47, 159–181.

Kirwin, M.L., Murray, A.B., Boyd, W.S., 2008. Temporary vegetation disturbance as an explanation for permanent loss of tidal wetlands. Geophys. Res. Lett. 35, L05403. https://doi.org/10.1029/2007GL032681.

Klein, J.T., 1990. Interdisciplinarity: History, Theory and Practice. Wayne State University Press, Detroit.

Klein, J.T., 2014. Discourses of transdisciplinarity: looking back to the future. Futures 63, 68–74.

Konig, N., Borsen, T., Emmeche, C., 2017. The ethos of post-normal science. Futures 91, 12–24.

Laniak, G.F., Olchin, G., Goodall, J., Vionov, A., Hill, M., Glynn, P., Whelan, G., Geller, G., Quinn, N., Blind, M., Peckham, S., Reaney, S., Gaber, N., Kennedy, R., Hughes, A., 2013. Integrated environmental modeling: a vision and roadmap for the future. Environ. Model. Softw. 39, 3–23.

Lave, R., 2015. Introduction to special issue on critical physical geography. Prog. Phys. Geogr. 39 (5), 571–575.

Lave, R., Wilson, M.W., Barron, E.S., Biermann, C., Carey, M.A., Duvall, C.S., Johnson, L., Lane, K.M., McClintock, N., Munroe, D., Pain, R., Proctor, J., Rhoads, B.L., Robertson, M.M., Rossi, J., Sayre, N.F., Simon, G., Tadaki, M., Van Dyke, C., 2014. Intervention: critical physical geography. Can. Geogr. 58 (1), 1–10.

Le Cozzanet, G., Rohmer, J., Cazenave, A., Idier, D., van de Wal, R., de Winter, R., Pedreros, R., Balouin, Y., Vinchon, C., Oliveros, C., 2015. Evaluating uncertainties of future marine flooding occurrence as sea-level rises. Environ. Model. Softw. 73, 44–56.

Learmonth Sr., G.P., Smith, D.E., Sherman, W.H., White, M.A., Plank, J., 2011. A practical approach to the complex problem of environmental sustainability: the UVa Bay Game. Innovation J. Public Sect. Innovation J. 16 (1), 1–8.

Linker, L.C., Dennis, R., Shenk, G.W., Batiuk, R.A., Grimm, J., Wang, P., 2013. Computing atmospheric nutrient loads to the Chesapeake Bay watershed and tidal waters. J. Am. Water Resour. Assoc. 49 (5), 1025–1041.

Lloyd, S.J., Kovats, R.S., Chalabi, S., Brown, S., Nicholls, R.J., 2015. Modelling the influences of climate change-associated sea-level rise and socioeconomic development on future storm surge mortality. Clim. Change. https://doi.org/10.1007/s10584-015-1376-4.

Luo, M., Opaluch, J.J., Anderson, J.L., Schnier, K., 2012. Managing the intentional introduction of nonnative species. In: Qin, J.G. (Ed.), Oysters: Physiology, Ecological Distribution and Mortality. Flinders University, Adelaide, pp. 101–145.

Lynam, T., de Jong, W., Sheil, D., Kusumanto, T., Evans, K., 2007. A review of tools for incorporating community knowledge, preferences, and values into decision making in natural resources management. Ecol. Soc. 12 (1), 5.

Malzone, C., Marcus, J., Pauly, T., 2009. Modeling the Multidimensional & Fiscal

Impacts of Storm Surge and Sea Level Rise: a Compelling View through a Powerful and Interactive 4D Data Integration, Analysis and Visualization Tool. MTS/IEEE Biloxi – Marine Technology for Our Future: Global and Local Challenges, Oceans 2009, p. 5422063.

McGranahan, G., Balk, D., Anderson, B., 2007. The rising tide: assessing the risks of climate change and human settlements in low elevation coastal zones. Environ. Urbanization 19 (1), 17–37.

McMahon, J.M., Olley, J.M., Brooks, A.P., Smart, J.C.R., Rose, C.W., Curwen, G., Spencer, J., Stewart-Koster, B., 2017. An investigation of controlling variables of riverbank erosion in sub-tropical Australia. Environ. Model. Softw. 97, 1–15.

McNamara, D.E., Werner, B.T., 2008a. Coupled barrier island-resort model: 1. Emergent instabilities induced by strong human-landscape interactions. J. Geophys. Res. 113, F01016. https://doi.org/10.1029/2007JF000840.

McNamara, D.E., Keeler, A., 2013. A coupled physical and economic model of the response of coastal real estate to climate risk. Nat. Clim. Change 3, 559–562.

Meadows, D.H., Robinson, J., 2002. The electronic oracle: computer models and social decisions. Syst. Dyn. Rev. 18 (2), 271–308.

Millennium Ecosystem Assessment, 2005a. Ecosystems and Human Well-being: Current State and Trends. Island Press, Washington D.C.

Morgan, M.G., Keith, D.W., 1995. Subjective judgments by climate experts. Environ. Sci. Technol. 29, 468A–478A.

Moser, S.C., Jeffress Williams, S., Boesch, D.F., 2012. Wicked challenges at Land's end: managing coastal vulnerability under climate change. Annu. Rev. Environ. Resour. 37, 51–78.

Murray, A.B., 2007. Reducing model complexity for explanation and prediction. Geomorphology 90, 178–191.

Murray, A.B., 2013. Which models are good (enough), and when? In: Schroder, J.F. (Ed.), Treatise on Geomorphology. Elsevier, London, pp. 50–58.

Murray, A.B., Lazarus, E., Ashton, A., Baas, A., Coco, G., Coulthard, T., Fonstad, M., Haff, P., McNamara, D., Paola, C., Pelletier, J., Reinhardt, L., 2009. Geomorphology, complexity, and the emerging science of the Earth's surface. Geomorphology 103, 496–505.

Nicholls, R.J., Marinova, N., Lowe, J.A., Brown, S., Vellinga, P., de Gusmao, D., Hinkel, J., Tol, R.S.J., 2011. Sea-level rise and its possible impacts given a 'beyond 4°C world' in the twenty-first century, Philosophical Transactions of the Royal Society A: Mathematical. Phys. Eng. Sci. 369 (1934), 161–181.

Nicholls, R.J., Wong, P.P., Burkett, V., Woodroffe, C.D., Hay, J., 2008. Climate change and coastal vulnerability assessment: scenarios for integrated assessment. Sustain. Sci. 3 (1), 89–102.

O'Sullivan, D., Millington, J., Perry, G., Wainwright, J., 2012. Agent-based models – because They're worth it? In: Heppenstall, A.J., et al. (Eds.), Agent-based Models of Geographical Systems. Springer, Dordrecht, p. 138.

Oxley, T., McIntosh, B.S., Winder, N., Mulligan, M., Engelen, G., 2004. Integrated modelling and decision-support tools: a Mediterranean example. Environ. Model. Softw. 19 (11), 999–1010.

Paolisso, M., Trombley, J., Hood, R.R., Sellner, K.G., 2015. Environmental models and public stakeholders in the Chesapeake bay watershed. Estuaries Coasts 38 (Suppl. 1), S97–S113.

Qin, R., Lin, L., Kuang, C., Su, T.-S., Mao, X., Zhou, Y., 2017. A GIS-based software for forecasting pollutant drift on coastal water surfaces using fractional Brownian motion: a case study on red tide drift. Environ. Model. Softw. 92, 252–260.

Rammer, W., Seidl, R., 2015. Coupling human and natural agents: simulating adaptive management agents in dynamically changing forest landscapes. Glob. Environ. Change 35, 475–485.

Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Policy Sci. 4, 155–169.

Robson, B.J., 2014. When do aquatic systems models provide useful predictions, what is changing, and what is next? Environ. Model. Softw. 61, 287–296.

Schiff, R., Benoit, G., 2007. Effects of impervious cover at multiple spatial scales on coastal watershed streams. J. Am. Water Resour. Assoc. 43 (3), 712–730.

Schlüter, M., McAllister, R.R.J., Arlinghaus, R., Bunnefeld, N., Eisenack, K., Hölker, F., Milner-Gulland, E.J., Müller, B., 2012. New horizons for managing the environment: a review of coupled social-ecological systems modelling. Nat. Resour. Model. 25 (1), 219–272.

Schneider, S.H., 1997. Integrated assessment modelling of global climate change: transparent rational tool for policy making or opaque screen hiding value-laden assumptions? Environ. Model. Assess. 2, 229–249.

Seidl, R., 2015. A functional-dynamic reflection on participatory processes in modeling projects. Ambio 44, 750–765.

Simandan, D., 2010. Beware of contingency. Environ. Plan. D Soc. Space 28, 388–396.

Simon, C., Etienne, M., 2010. A companion modelling approach applied to forest management planning. Environ. Model. Softw. 25, 1371–1384.

Singh, A., Mishra, S., 2008. The Modeler's Dilemma – Resolving Conflicts Among Different Model Averaging Techniques. American Geophysical Union. Fall Meeting Abstracts.

Small, C., Nicholls, R.J., 2003. A global analysis of human settlement in coastal zones. J. Coast. Res. 19, 584–599.

Stirling, A., 2010. Keep it complex. Nature 468, 1029–1031.

Sun, Z., Lorscheid, I., Millington, J.D., Lauf, S., Magliocca, N.R., Groeneveld, J., Balbi, S., Nolzen, H., Müller, B., Schulze, J., Buchmann, C.M., 2016. Simple or complicated agent-based models? A complicated issue. Environ. Model. Softw. 86, 56–67.

Thrift, N., 1996. Spatial Formations. Sage, London.

Tress, G., Tress, B., Fry, G., 2005. Clarifying integrative research concepts in landscape ecology. Landsc. Ecol. 20, 479–493.

Turner II, B.L., Esler, K.J., Bridgewater, P., Tewksbury, J., Sitas, N., Abrahams, B., Chapin III, F.S., Chowdhury, R.R., Christie, P., Diaz, S., Firth, P., Knapp, C.N., Kramer, J., Leemans, R., Palmer, M., Pietri, D., Pittman, J., Sarukhán, J., Shackleton, R., Seidler, R., van Wilgen, B., Mooney, H., 2016. Socio-Environmental Systems (SES) Research: what have we learned and how can we use this information in future research programs. Curr. Opin. Environ. Sustain. 19, 160–168.

Turnpenny, J., Lorenzoni, I., Jones, M., 2009. Noisy and definitely not normal: responding to wicked issues in the environment, energy and health. Environ. Sci. Policy 12, 347–358.

Voinov, A., Brown Gaddis, E.J., 2008. Lessons from successful participatory watershed modeling: a perspective from modeling practitioners. Ecol. Model. 216, 197–207.

Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environ. Model. Softw. 25, 1268–1281.

Voinov, A., Kolagani, N., McCall, M.K., Glynn, P.D., Kragt, M.E., Ostermann, F.O., Pierce, S.A., Ramu, P., 2016. Modelling with stakeholders- next generation. Environ. Model. Softw. 77, 196–220.

Williams, Z.C., McNamara, D.E., Smith, M.D., Murray, A.B., Gopalakrishnan, S., 2013. Coupled economic-coastline modeling with suckers and free riders. J. Geophys. Res. Earth Surf. 118, 887–899.

Wright, J., 2015. Preparing New Zealand for Rising Seas: Certainty and Uncertainty, New Zealand Parliamentary Commission for the Environment, Te Kaitiaki Taiao a Te Whare Paremata, 93 pages.

Wu, P.P.-Y., Fookes, C., Pitchforth, J., Mengersen, K., 2015. A framework for model integration and holistic modelling of socio-technical systems. Decis. Support Syst. 71, 14–27.

Yearley, S., 2006. Bridging the science-policy divide in urban air-quality management: evaluating ways to make models more robust through public engagement. Environ. Plan. C Gov. Policy 24, 701–714.

Zhang, H., Gorelick, S.M., 2014. Coupled impacts of sea-level rise and tidal marsh restoration on endangered California clapper rail. Biol. Conserv. 172, 89–100.