Environmental Modelling & Software 93 (2017) 127–145

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

An overview of the system dynamics process for integrated modelling of socio-ecological systems: Lessons on good modelling practice from five case studies

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ARTICLE INFO

Article history:
Received 14 December 2016
Accepted 1 March 2017
Available online 23 March 2017

Keywords:
System dynamics
Integrated assessment
Integrated modelling
Socio-ecological systems
Modelling practices
Decision support

ABSTRACT

Similar to other modelling methodologies, the potential of system dynamics to contribute to system understanding and decision making depends upon the practices applied by the modeller. However lessons about many of these practices are often unreported. This paper contributes to the methodology of system dynamics modelling of socio-ecological systems by 1) examining issues modellers face during the modelling process, and 2) providing guidance on how to effectively design and implement system dynamics modelling. This is achieved through an investigation of five case studies, drawing on lessons from these experiences. This is complemented by a literature review of system dynamics applied within the context of integrated modelling and environmental DSS. The case studies cover a variety of environmental issues and system dynamics modelling methods and tools. Although we used system dynamics as the common lens from which lessons are drawn, many of these insights transcend to other integrated modelling approaches.

1. Background

Modelling, and Integrated assessment and modelling (IAM) in particular, provides tools and techniques that can promote dialogue among stakeholders about how a system operates, as well as facilitate policy assessment to identify acceptable interventions or strategies for change (Parker et al., 2002; Jakeman and Letcher, 2003; Van Delden et al., 2011; Hamilton et al., 2015). The modelling process is valuable despite the fact that models, both conceptual and numerical, are approximations or simplified representations of the system of interest (Jakeman et al., 2006). A wide range of modelling techniques is used to develop integrated models that combine socio-economic, ecological and other biophysical elements, with efforts increasingly revolving around environmental decision support tools (Laniak et al., 2013). Examples of common integrated modelling approaches include system dynamics (SD), knowledge-based models, Bayesian networks, coupled models and agent-based models (Croke et al., 2007; Kelly et al., 2013). Modelling approaches vary in their capacity to represent elements of complexity and uncertainty in the modelled system. Many factors determine the suitability of a modelling approach to a particular situation such as model purpose, availability of data and the functional form of the interactions of interest (Jakeman et al., 2006;

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http://dx.doi.org/10.1016/j.envsoft.2017.03.001
1364-8152/

Chen et al., 2008; Kelly et al., 2013). In this article, we focus on the application of SD for IAM and environmental modelling in general.

1.1. System dynamics

System dynamics (SD) was developed in the late 1950s by Jay Forrester and a group of researchers from the Massachusetts Institute of Technology under the name of “industrial dynamics” (Forrester, 1961). Forrester (1969) extended SD applications to include large socio-economic problems, such as urban modelling. Later, Meadows et al. (1972) presented the revolutionary best-seller “Limits to growth” for which they made use of systems thinking and SD concepts to explain how short-term development policies can lead to “overshoot and collapse” behaviour of socio-ecological systems. “Limits to growth” has exemplified the potential of SD as a tool to help understand complex socio-ecological systems, and is still regarded as a valuable resource for thinking about sustainable futures (e.g. Turner, 2012).

Grounded in control theory and systems thinking (Richardson, 1999), SD provides a set of conceptual and quantitative methods that can be used to represent, explore and simulate the complex feedback and non-linear interactions among system elements, management actions, and performance measures. In SD, a problem is represented as a network of cause-effect and feedback loops, with state variables represented by ‘stocks’ and rate of change in stocks represented by ‘flows’. SD models are generally not used to search for steady-state solutions like many other modelling paradigms, but instead are used to simulate dynamic behaviour through time. They (re)create dynamic behaviour by tracking the change in the values of stocks and flows over time, and explicitly mapping information transfers among stocks and flows to model feedback interactions (Sterman, 2000). This explicit representation of the causal relationships that derive the problem behaviour (i.e. known as problem structure) makes SD particularly well suited to improving system understanding and exploring the unexpected effects that may play out when these causal relationships run their course.

1.2. SD in the context of environmental modelling and IAM

There have been an increasing number of studies using SD for environmental modelling and IAM. These studies can be categorised according to their main problem focus (Simonovic, 2009; Winz et al., 2009) and the approach for the SD application (Mirchi et al., 2012). Thus, SD has been applied to a wide range of problems including: urban water planning (Qi and Chang, 2011; Zhang et al., 2017), water-groundwater interactions (Safavi et al., 2015), climate change vulnerability assessment (Sahin and Mohamed, 2014), regional analysis (e.g. Guo et al., 2001), trans-border water issues (e.g. Duran-Encalada et al., 2017), and more recently water-energy-food nexus issues (e.g. Akhtar et al., 2013). In general, there are three approaches for applying SD in the context of environmental modelling and decision support (Mirchi et al., 2012). First is the use of SD models as predictive tools to simulate the biophysical processes within an environmental system. For example, Venkatesan et al. (2011a, 2011b) develop an SD model of the processes of water use, water quality, and hydrology in order to forecast salinity loads in return flows. The second approach is the use of SD as a holistic framework to examine the feedback interactions among several biophysical and socio-economic systems. The purpose of these models is usually to support integrated assessment of policies by examining the broad and long term decision outcomes. For example, Gastélum et al. (2009) and Ahmad and Prashar (2010) develop basin-scale models which integrate hydrological, agricultural, economic, and ecological subsystems to examine the long term socio-economic and ecological impacts of water allocation policies. The third approach is the use of SD as a platform for participatory modelling in order to engage stakeholders and build a shared systems understanding. This approach includes studies reported in the areas of mediated modelling (van den Belt, 2004), participatory SD (Antunes et al., 2015), SD learning laboratories (Bosch et al., 2013), and Group Model Building (Chen et al., 2014). For example, Vugteveen et al. (2015) use SD to help stakeholders build consensus on the important socio-ecological indicators for managing the coastal region.

The complex nature of environmental problems and decision-making needs presents a series of challenges for using SD as a modelling methodology of environmental modelling, and in particular IAM. First IAM of socio-ecological systems requires input from a wide range of sources and types of knowledge (Jakeman et al., 2006). This includes qualitative and quantitative data from various stakeholder groups, including scientists, policy makers, and community members. To collect, synthesise and use these data in useful ways, IAM needs to utilise and combine different methods (i.e. conceptual, numerical, and participatory) in appropriate methodological designs that best fit the project's context, objectives, and constraints, in the latter case including resource availability (Kelly et al., 2013).

SD offers a portfolio of methods that can be used to support data collection (Luna-Reyes and Andersen, 2003), problem conceptualization (Lane, 2008), systems thinking and learning (Sterman, 2001), and stakeholder participation (Hovmand et al., 2012). The variety of options leads to questions around the best mix of methods to use in an SD modelling process while considering the problem context (Howick and Ackermann, 2011). Part of this challenge facing modellers is associated with the choice of SD simulation software to use given the variety available in the market place. Nabavi et al. (2017) argue that modellers' judgments on methodologies (i.e. methods and tools) for developing SD models is crucial not only for the quality of the model's results, but also to determine if the method has been used in an ethical manner by considering possible interests, decision options, and impacts.

Secondly, IAM promises to offer an integrated view of systems and processes that cause the problem. Depending on the model's purpose, these processes can be modelled with different representations and levels of aggregation (Kelly et al., 2013). This may require coupling SD with other modelling techniques and computational algorithms. Chen and Wei (2014) reviewed the applications of SD in water security applications, and concluded that there is still limited progress in integrating SD with other modelling techniques. Thirdly, IAM deals with spatially distributed biophysical and socio-economic systems, where spatial heterogeneity significantly affects system behaviour, and therefore how they respond to decision making (Hamilton et al., 2015). BenDor and Kaza (2012) reviewed how the spatial dimension has been incorporated in SD models, and found that little work has been done into rigorously selecting and implementing approaches to build spatial SD models.

Finally, given the complex nature of problems addressed, the modelling process of IAM projects tends to be non-trivial (Jakeman and Letcher, 2003), particularly for those projects with a strong social component. Developing a reliable SD model is time and resource consuming, requiring intensive engagement with users and stakeholders as well as expertise in SD modelling and facilitation. There have been efforts, however, towards developing more efficient and leaner SD modelling processes (Warren, 2014) by utilizing reusable modelling components which can help in problem structuring by focusing on the key feedback loops, and expediting the model development by providing ready-to-use validated components.

While many arguments can be correctly made about the need for future research into theoretical and methodological development to address the above challenges, one promising area is in communicating lessons and sharing experiences about good modelling practices when using SD for environmental modelling and IAM. The potential and importance of this research area have been recognized by scholars in SD, environmental modelling, and IAM (e.g. Tress et al., 2005; Phillips et al., 2010; Stave, 2010; Ravera et al., 2011). This is the research area where this article aims to contribute.

1.3. This article

The premise for this article is that much of the literature on SD applications in environmental modelling tends to embody a technical reporting view. By this, we mean that reported applications focus merely on describing the logical steps of model development and the technical aspects of the model structure, and how results can be used to feed policy design (e.g. Qaiser et al., 2011). In many cases, authors tend to give little attention to reflecting and reporting on the lessons and practices gained through the modelling process, due to limits on the paper length and the necessity of having a focused scope. According to Morris (1967), the approach of presenting models with the view of "*See how logical, how methodical, how brilliantly inevitable was our progress in this study*" may invite some misperceptions about how the modelling process unfolds by hiding many of the ad-hoc decisions, serendipities, and failures involved. We aim to demystify the SD modelling process and investigate some of the important issues faced when developing and evaluating SD models in practice. The contribution of this article lies in illuminating and consolidating the practical challenges and lessons from the application of SD to address socio-ecological problems: specifically around how the problem is scoped, selecting techniques and software tools, progressing from the conceptual to the numerical model, model testing, and combining SD with other modelling techniques. The study is also of interest to the broader IAM community, as many of the practical challenges are likely to be applicable to other modelling and integrated modelling approaches.

To achieve this, based on the argument we have laid earlier that many of these applications do not explicitly report on these practical challenge, we provide detailed insights into the modelling process by drawing on the collective experience and lessons from five case studies where the authors were closely involved. The case studies examined cover a variety of environmental issues (i.e. urban and regional development, groundwater, urban water management) as well as SD modelling methods and tools. Moreover, we review literature on the application of system dynamics within the context of environmental modelling and IAM, with focus on eliciting the insights provided about the model development process. By combining findings from the case studies and literature review, we aim to contextualise our findings in the existing literature and consolidate lessons from a wide set of case studies.

Following this background section, the article is organized as follows: we introduce both our research design and methods in Section 2. In Section 3, we present and discuss the findings from the case studies, along with relevant literature. Section 4 synthesizes our recommendations for good practices. Section 5 wraps-up with the conclusion and outlines some priorities for future work.

2. Research design

We design this inquiry as a multi-method approach where the modelling lifecycle is the central focus or the unit of analysis. A typical SD modelling lifecycle contains the following four main phases (Luna-Reyes and Andersen, 2003): (1) *conceptualization*, which focuses on model scoping and system conceptualization, (2) *formulation*, which focuses on model formulation and coding, (3) *verification and validation*, which focuses on testing model structure and behaviour, and (4) *implementation*, which focuses on active model use and application. These phases could be viewed as a summary of the ten iterative steps to model development and evaluation in Jakeman et al. (2006) and subsequent papers by Robson et al. (2008), Welsh (2008), and Blocken and Gualtieri (2012). In our research design, we collect and analyse data from the reviewed case studies across the four phases of the modelling lifecycle while using the lens of the ten steps in model development and evaluation as a guiding framework (Table 1). Additionally, we collect and analyse data related to the model support aspects of the model lifecycle, including a myriad of ancillary considerations that are integral to the creation of an SD model for IAM cases, such as the modelling platform and computational architecture.

2.1. Data collection and analysis

We developed and used a survey tool to provide a structured and systematic way for collecting, analysing, and comparing data across the case studies (See Table 1). The design of the survey was informed by some of the modelling practice considerations present in the SD literature (Winz et al., 2009; Martinez-Moyano and Richardson, 2013; Martinez and Luna, 2001; Lane, 1993), as well as practices and considerations from integrated environmental modelling (e.g. Jakeman et al., 2006; Kelly et al., 2013; Hamilton et al., 2015). Data analysis and review passed through several iterations where case study authors were asked to comment and elaborate on their responses. Results from the initial analysis round were published in (Elsawah et al., 2012). To add rigor to the analysis, one of the co-authors (i.e. an experienced modeller who was not part of any of the case studies) was tasked with synthesizing results by promoting questions around the linkages among cases, looking closely at the evidence to support results, and commenting on the breadth and details reported on individual cases. Moreover, we conducted a literature review on the use of SD in the application of system dynamics within the context of environmental modelling and IAM, with a focus on eliciting the insights provided about the four modelling phases.

2.2. Five case studies

We collected information with respect to experiences of the modelling process from five case studies that were selected to cover a variety of environmental issues as well as modelling methods (including knowledge elicitation, knowledge mapping) and tools. Case studies satisfied the following requirements in relation to the paper's aims:

- They represent an SD-based IAM application to support broader functions related to decision making
- They are publicly available as peer-reviewed publications (i.e. journal articles, dissertations, conference papers) to allow readers to scrutinize the technical details of the model
- They have a clear participatory component
- Participant co-authors have direct and intimate knowledge of the process and outcomes to be able to provide insights

The five case studies are listed below; see Table 2 for an overview of the different aspects of the cases.

1) The *Berlin Urban Development* case study examined land use development and population dynamics in the metropolitan region of Berlin, Germany (Lauf et al., 2012). The SD model

Table 1
Description of the survey tool used to collect data from case studies.

Survey Part	Survey questions	Corresponding steps from Jakeman et al. (2006)
Model Conceptualization Phase		
I. Model purpose and end users	• What is the modelling purpose? • Who are the (intended) users? • Which stage of the planning/decision-making process, does the modelling process/output feed into? • What is the level of experience model users have about system dynamic concepts and techniques?	1. Define model purpose 2. Specify modelling context
II. Conceptualizing the dynamic hypothesis	• Did relevant stakeholder groups (including end users) contribute to the process of formulating the dynamic hypothesis? • Which methods did you use to engage stakeholders in formulating the dynamic hypothesis? • Do you think the engagement method has an impact on the conceptualization process, and the resulting dynamic hypothesis? How? • Which conceptual system dynamic technique did you use for mapping the dynamic hypothesis? How did you use each method? • What are the strengths and weaknesses of the different mapping techniques? • Do you think the mapping method has an impact on the conceptualization process, and on the characteristics of the final model? • How did you deal with the limitations of the mapping methods?	3. Conceptualize system, specify data and other prior knowledge
Model Formulation Phase		
III. Formulation and development of the simulation model	• Did you have to add more detail into the model that may not be necessary to explain the output behaviour? How and why? • Do you think that adding these details has affected the learning insights that can be gained from the model? • In the progression from the dynamic hypothesis to the numerical system dynamics model, what were the most challenging tasks you faced and how did you handle them?	4. Select the model features 5. Determine how to find model structure and parameter values 6. Select estimation/ performance criteria and algorithm 7. Identify model structure and parameters
Model Verification and Validation Phase		
IV. Testing model structure and behaviour	• How was the model structure evaluated? • How was the model behaviour evaluated?	8. Verification and diagnostic testing 9. Quantify uncertainty 10. Model evaluation and testing
Model Use and Applications Phase		
V. Model use	• Who were the actual users? • Did the model meet the objective(s)? What insights were obtained through the use? • In hindsight, what "insights" to the system/problem did system dynamics provide that may not be achieved by other modelling techniques?	Revisit Steps 1 (model purpose) and 2 (modelling context)
Software Platforms, Integration Architecture and Model Coupling		
VI. Coupling system dynamics with other modelling techniques	• How did you select your SD modelling software? What are the strengths and limitations of the software based on your experience from the case study? • Why did you (not) choose a "purely" system dynamics modelling approach? • How did coupling affect your system dynamics modelling practices through each modelling phase?	Reconsider all Steps (1–10) in its entirety
VII. System dynamics strengths, weakness, and "good practices"	• From your modelling experience, please provide evidence to support or falsify claims made about system dynamics (e.g. ability to model/communicate feedback, etc.) • From your modelling experience, if you were offering advice on the best way to undertake system dynamics modelling, what are the most important modelling practices in each step of the modelling process?	

simulates the effect of demographic, economic and planning changes on residential housing demand-supply, which feeds into a coupled cellular automaton model representing land use change.

2) The *Gnangara Groundwater DSS* (Decision Support System) was developed as part of the Gnangara Sustainability Strategy to assess the impacts of water and land use decisions on the Gnangara groundwater system in Perth, Australia (Elmahdi, 2009; Elmahdi and McFarlane, 2010, 2012). SD was used to model the inter-relationships between climate, land use, agricultural water use and productivity, domestic water use, and groundwater recharge and storage, in order to analyse the effects of various scenarios on economic, social and environmental indicators (e.g. agricultural revenues, wetland values, groundwater levels).
3) The *Texas Groundwater* DSS was built to determine the sustainable yield for an aquifer system in central Texas, United States (Pierce, 2006). SD modelling was used to incorporate socio-economic influences (e.g. land use change, water demand, community preferences) with the physical (hydrogeological) system, to enable exploration of how different water allocation, extraction rates, and other management strategies affect aquifer yield and meet multiple stakeholder objectives.
4) *MedAction* is a generic policy support system (PSS) for river basin management in arid and semi-arid regions, incorporating a range of issues including land degradation and desertification, water management, and sustainable farming (Van Delden et al., 2007; Van Delden et al., 2009). SD was used to simulate the interactions between bio-physical and socio-economic developments in the region, to show the possible impact of

Table 2
Overview summary of the key characteristics of the five case studies.

Case study	Berlin urban development	Gnangara groundwater	Texas groundwater	MedAction	ACT water management
Citation(s)	Lauf et al. (2012)	ElMahdi (2009); ElMahdi and McFarlane (2010; 2012)	Pierce (2006); Passarello et al. (2014)	Van Delden et al. (2007)	Elsawah (2010); Elsawah et al. (2015)
Location	Metropolitan region of Berlin, Germany	Gnangara region, Western Australia	Central Texas, USA	Mediterranean region, Europe and Africa	Australian Capital Territory
Modelling objective	To simulate the functional relations of urban land-use development and household dynamics, creating feedback of residential choices	To assess the impacts of water and land use management on groundwater	To determine sustainable yield for aquifer systems and define science-based management/policy recommendations.	To support policy makers in understanding the impacts of autonomous developments within and external to the region	To simulate changes in water storage levels, and water use under different climate and policy scenarios
Model purpose (see Kelly et al., 2013)	• Prediction • Social learning	• Decision support • Stakeholder engagement	• Decision support • Social learning • Conflict Resolution	• Decision support	• Social learning • Public outreach and education
Policy area	• Urban development planning	• River system planning • Groundwater allocation planning	• Groundwater allocation planning • Urban Development	• Regional land and water management	• Urban water management
Uncontrollable drivers	• Economic development • Global and national or local investments in the housing market • Environmental state in the city except greenspace areas (e.g. air pollution)	• Natural hazards including unplanned fires • Climate changes • Economic and social development or changes • Population growth	• Population growth • Climate conditions • Groundwater-dependent flow requirements for environment and habitat protection	• Population growth • Climate conditions • Macro-economic developments (e.g. GDP, crop pricing)	• Population growth • Climate conditions • Environmental water requirements
Management decision	• Demand-supply decision making including individual preferences	• Public water supply and wastewater management • Land use and land management including urbanization • Water use and management • Environmental water provisions	• Drought policy settings (alarm and cutback levels) • Pumping restrictions • Pumping Location and volumes • Urban land cover as impervious level settings • Urban land use as density settings	• Subsidies and taxes • Spatial planning • Construction of infrastructure • Afforestation • Water pricing • Water use restrictions and prioritization • Restriction on salt concentration of irrigation water • Sedimentation control (check dams versus dredging) • Land management (ploughing, terracing, irrigation)	• Water supply management options (e.g. building dams) • Water demand management options
Stage in the policy making process the model is used to support	• Scoping and issues definition • Designing of alternatives • Evaluating alternatives	• Scoping and issues definition • Designing of alternatives • Evaluating alternatives	• Scoping and issues definition • Designing of alternatives • Evaluating alternatives	• Scoping and issues definition • Designing of alternatives • Evaluating alternatives	• Policy communication
Model end user	Social scientists	Land and water managers	Groundwater planning agencies	Regional policy makers	General public
Issues addressed	• Urban land use change • Demographic change	• Groundwater decline • Water demand and allocation • Climate change • Land use change	• Groundwater allocation • Urban Land Use • Drought risk and resilience	• Urban and rural land use change • Land degradation • Desertification • Water management • Sustainable farming • Regional development	• Urban water security • Climate change
Modelling approach	SD model coupled with Cellular Automata	SD model coupled with MODFLOW groundwater model and agro-economic models	SD model coupled with MODFLOW groundwater model and optimization (tabu) search algorithm	SD used to integrate different sets of biophysical and socio-economic models	Purely an SD model
Users' experience in system dynamics	Minimal	None	None	None	None
Software	Simile (version 4.7) by Simulistics	Vensim	PowerSim coupled to hybrid decision support	Geonamica software environment	PowerSim

climate, economic (e.g. crop prices, management costs), policy (e.g. subsidies, regulation), and land management (e.g. ploughing, irrigation) scenarios on a range of indicators (e.g. environmental, water shortage, farmer profit).

5) The *ACT Water Management* tool simulates water supply and demand in response to uncontrollable drivers (e.g. climate) and management decisions in the Australian Capital Territory (Elsawah, 2010; Elsawah et al., 2015). The SD model was developed as a tool for improving learning and communication with stakeholders and experts about urban water issues and management.

3. Results and discussion

3.1. Model conceptualization

The initial phase of any modelling process is a critical determinant of the final outcomes - from defining the reasons and motivations behind the creation of a model, identifying the key aspects of the modelling context, and conceptualizing the important data, information or knowledge elements. The inclusion of model users and other stakeholders at this stage can generate trust and enhance their later acceptance of the model and the probability of its use in practice (Van Delden et al., 2011). Stakeholders are also a valuable source of information, including local contextual knowledge, perspectives, preferences and values. Wolstenholme (1999) refers to this initial stage as qualitative SD because it is intended to qualitatively reflect on the situation in order to identify the variables and causal interrelationships that derive the problematic behaviour, and to examine the rules and policies that govern the way actors make decisions.

3.1.1. Model purpose and scope

Like other problem solving and modelling methodologies, the SD modelling process starts with a scoping phase, where the focus is on defining the problem and deciding how it will be addressed by the model (i.e. model purpose/use). The scope of the problem and boundary of the system to be modelled is also determined during this initial step. There must also be consideration of the suitability of SD for addressing the particular problem, the resources (i.e. time, funds, data, and skills) available for the project, as well as identification of the relevant users and stakeholders. This initial step is critical as it guides the rest of the modelling process (Sterman, 2000; Jakeman et al., 2006; Van Delden et al., 2011).

The case studies illustrate that SD can be applied to a broad range of problems and settings, including local and regional scale water allocation, land use change, and land degradation. In terms of modelling purpose, the case studies indicate the propensity for SD models being used for decision support and social learning, although other purposes such as prediction, stakeholder engagement and public outreach and education were noted. The first four case studies used the SD modelling in the policy-making process to scope and define issues, and design and evaluate alternatives. For the remaining case study on ACT water management, the model was developed to support policy communication.

In regard to the scoping process, case study authors agree that defining the model purpose can be a very challenging and lengthy task in practice, and may involve several iterations before the modeller(s) and stakeholders agree on the 'right' objective. This observation concurs with the recent discussion on the challenge of boundary setting in SD modelling process by Nabavi et al. (2017), who describe this task as an inherently social process involving practical and ethical considerations. The ethical concern of boundary setting relates to the judgements required in defining a particular view of the system and its workings, and "what *ought* to be done" to the system (Nabavi et al., 2017).

At the outset of the scoping process, it cannot be assumed that stakeholders know what the problem is and how the SD or IAM process may contribute; it is the modeller's responsibility to explain how the modelling process may contribute to the problem at hand. For example, in the Gnangara DSS, it took almost 6 months to set the right objective that met with the goals of the multiple management agencies involved in the project. The project team introduced the need for an integrated multi-agency approach as a logical way forward to achieving long-term sustainable groundwater management. In the ACT case, the modeller identified the opportunity of using SD models to improve public perception of water resource issues during a severe drought episode (known as the Millennium Drought), and approached the local water industry with ideas about how SD models could be used to communicate about current and future policies.

It is important to consider in this early step whether or not SD is a suitable approach for the assigned problem and budget. All the case study projects were conducted over several years. All projects also involved systems that were relatively well understood and had a fair amount of data describing key variables — at a minimum, the system feedbacks were understood well enough to provide plausible estimates that described the relationships mathematically.

3.1.2. Conceptualizing the dynamic hypothesis

The term dynamic hypothesis is commonly used in the SD literature to describe a conceptual model that explains how structure and policies generate the dynamic behaviour (Sterman, 2000, p.86). Formulation of the dynamic hypothesis includes a clear definition of endogenous variables, exogenous variables, feedback loops, and time delays. Randers (1980, p.131 and 134) notes that the dynamic hypothesis remains an assumption until it is either refuted or proven based on how well the simulated model reproduces historic behaviour. Different knowledge elicitation and mapping techniques are used throughout the process of conceptualizing the dynamic hypothesis (Luna-Reyes and Andersen, 2003). Based on the findings from the literature review and the case studies, the following methods are used for knowledge elicitation:

- *Document analysis:* The analysis of policy and planning documents may provide a good "initial understanding" of the problem by enabling the modeller to "get a sense" of the issues, and start sketching out the dynamic hypothesis. However, document analysis on its own is not sufficient for scoping the model, as it may lead to unclear, less explicit, and "incorrect" assumptions about how the system works. Simply, documents cannot be questioned, and therefore do not provide modellers with the necessary knowledge and feedback.
- *Interviews:* Direct interviews (informal or formal) with individuals and groups provide deep understanding of subjective views or mental models about how the system functions, with opportunities for clarification, follow-up questions and feedback. The interview process also helps build familiarity and rapport with or among stakeholders. Interviews can be a more 'safe' environment for a non-experienced modeller to start the process before they gain the confidence to take part in group activities. On the other hand, the interviewing process can be time consuming.
- *Workshops and focus group meetings:* Group data collection methods, such as focus groups, are used to represent the group view. Compared to working with individuals, groups provide a broader source of expertise and knowledge, and are more capable of filtering out erroneous information. Working with groups also allows an exchange of views, facilitating social learning. Case study authors noted the discussion with the

group often led to the view that was dominant among participants. Beall et al. (2011) advise to move away from potentially heated and value-laden questions (e.g. "tell us when we are going to run out of water") to consensus-building and action-oriented queries (e.g. "what would we do as a community if we knew").
- *Data analysis:* Analysis of existing data (e.g. GIS layers, point information, parameter priors) can provide useful information on the characteristics of system variables or the nature of the relationships between some variables. This information can complement data from other elicitation methods.

3.1.3. Knowledge mapping

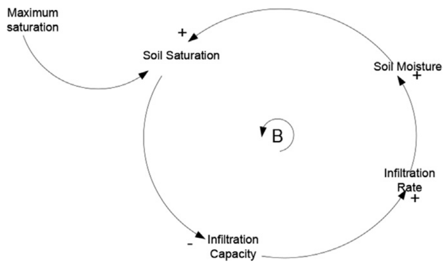
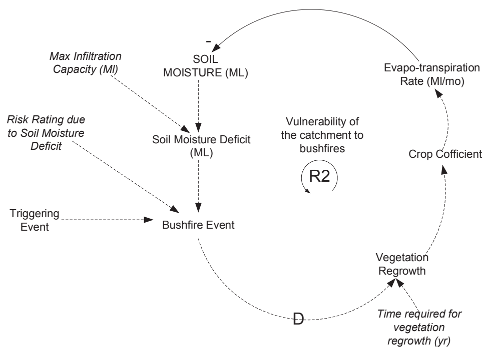
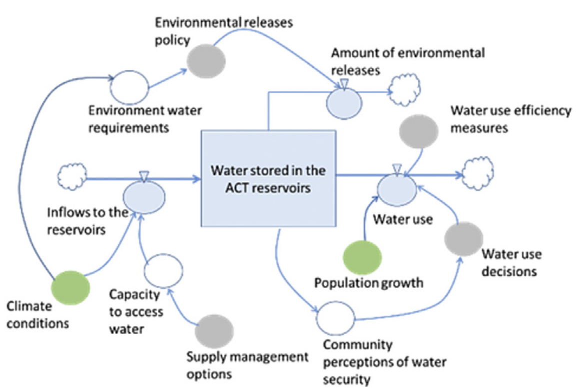
Throughout the conceptualization process, a sequence of conceptual diagrams is used to refine the dynamic hypothesis, provide more detail, and communicate with stakeholders. Different knowledge mapping techniques can be used to formulate and represent the dynamic hypothesis, including causal loop diagrams, influence diagrams, stock and flow diagrams, system archetypes or policy structure diagrams (Sterman, 2000; Lane, 2008; Mirchi et al., 2012). Table 3 provides descriptions of the strengths and weaknesses of the methods reported in reviewed case studies, including:

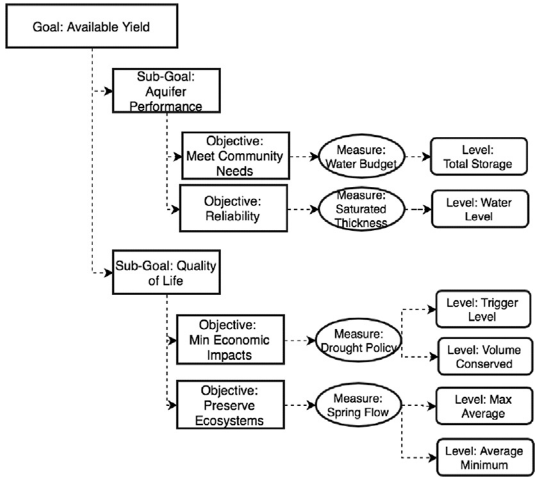
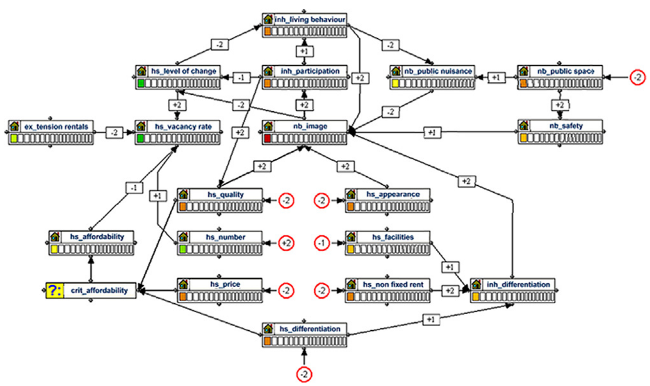
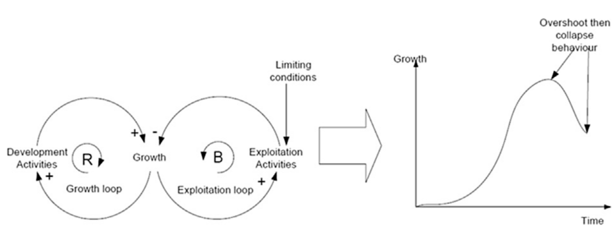
- *Goals and Objectives Hierarchy (GOH):* GOH involves explicitly defining the goals and objectives of stakeholders in the modelling process and delineating a hierarchy with respect to the modelled elements (Pierce, 2006). This method is particularly useful for formulating the problem in such a way that the objective function clearly links to principle stakeholder values. GOH supports the process of connecting stakeholder concerns and motivations with performance measures, which can be used to design an SD model, but it does not address the functional behaviour of model components.
- *Causal loop diagrams (CLDs):* CLDs are one of the most simple and commonly used diagramming tools in SD. They are easy to use at the beginning of the modelling exercise in order to develop a preliminary dynamic hypothesis. Because of their simplicity, CLDs are valuable tools for eliciting and mapping mental models, especially from inexperienced stakeholders. Sedlacko et al. (2014) find that CLDs help stakeholders focus their attention on the assumptions behind causal links. However, they also find using CLDs without having an agreed ontology among stakeholders about what words and links mean may lead to unwieldy maps. Moreover, CLDs can be somewhat ambiguous in representing system processes, which can potentially lead to misinterpretations when formulating the quantitative model (especially for inexperienced modellers). For more on the limitations of CLDs, readers are referred to Morecroft (1982) and Richardson (1997).
- *Influence diagrams (IDs):* IDs provide a more explicit and rigorous graphical representation of the casual structure than CLDs (McLucas, 2005). Unlike CLDs, IDs make distinctions between stocks, flows, information flows, and physical flows, thereby forcing the modeller to think about the operational model early in the process (Coyle, 1996). The greater level of detail of IDs requires many conventions and rules which may not be easy to master especially for those used to CLD or new to SD. The term (IDs) is used by some authors to describe CLDs.
- *Fuzzy Cognitive Maps (FCM):* FCM is a semi-quantitative diagramming tool that represents the belief system about the causal structure of the problem, including the relative strength of the links between variables (Kok, 2009). The variables are described as fuzzy values, which are neither numeric nor exact, but are interpreted in a linguistic manner. The polarity and strength of these links are expressed as weights on an ordinal scale, allowing relationships that are typically difficult to quantify or be estimated.
- *Stock and flow diagrams (SFDs):* SFDs represent the problem as stocks (or state levels) that change over time through flows (or mechanisms). These diagrams encourage numerical thinking, and have the virtue of being more transparent and explicit for thinking about the problem processes and how they can be represented in the model. However these diagrams are much more difficult for stakeholders to understand, let alone co-develop. Case study authors found that training is needed to allow users and stakeholders develop SFDs.
- *System archetypes*: system archetypes are high-level conceptualizations (represented as causal loop diagrams) which give insights about common patterns of behaviour in systems (Wolstenholme, 2003). These insights can be transferred across various problem situations and domains. For example, Gohari et al. (2013) used the 'fixes that can backfire' archetype as a basis to conceptualize the water shortage problem. However, there is a risk of force-fitting a particular archetype to the problem, especially if the modeller is not experienced (Corben, 1994; Sterman, 1994).

The case study authors agree that the selection of mapping method affects the quality of the resulting dynamic hypothesis, and therefore, the final SD. The same principle applies for all IAM modelling paradigms, with the conceptualization process forming the foundation of the integrated model, including many of its underlying assumptions (Jakeman et al., 2006). The case study authors identified several considerations they took into account when deciding on the mapping methods to be used in the process, including:

- The mapping methods need to be commensurate with the capacity of participants involved in the modelling exercise. This adherence will enable the modeller to elicit as much knowledge and information as practically possible and therefore may lead to better model design. In all case studies, stakeholders had no or minimal SD knowledge. In these circumstances, case study authors agree that it is more effective to use CLDs at the early stages in a wider group of participants and, in later steps, use more elaborate methods (e.g. stock and flow diagrams) with those having experience and/or affinity for SD modelling. For example, in the MedAction and ACT water case studies, CLDs were co-developed with users, while SFDs and IDs were developed by the modellers in a subsequent step.
- Differences in the way mapping methods represent problems will create an emphasis on different aspects of the system through the conceptualization process. For example, stock and flow diagrams are very functionally focused while GOH create a bridge between stakeholder preference sets and the metrics or measures used to assess performance. In the MedAction case study, the development process first involved creating a table of the goals and objectives ('what really matters'), followed by a CLD to link these through processes ('what is connected'), which were then further detailed using IDs, FCMs and SFDs ('how it works').
- Methods need to be selected and mixed in a way that improves model transparency and ease of communication. In the Texas groundwater DSS case study, reference modes (representations of pattern of change based on historical data) were used along with narrative analysis early in the participatory process as a guide to dialogue with both individuals and the group about their beliefs regarding the system behaviour under various conditions (e.g. how they expected water quality to behave as

Table 3
The strengths and weakness of some of the methods used to conceptualize the "dynamic hypothesis".

Mapping method	Example	Features	Strengths	Limitations	Examples in literature
Causal loop diagrams (CLDs)		• Map casual structure and delays in the system • Network of variables are connected by arrows indicating casual links • Links/loops are marked with symbols/letters to indicate their polarity (−/+)	• Provide an aggregate or strategic view of the problem structure, which helps to keep focus on the feedback loops and away from unnecessary details (if developed and presented with some caution) • Relatively intuitive, and easy to explain to non-modellers • Encourage stakeholders to think of the assumptions underpinning the causal links (Sedlacko et al., 2014)	• May lead to incorrect inferences about the dynamics, and therefore faulty models (Mirchi et al., 2012) • Do not distinguish between physical and information links, or stocks and flows • Do not distinguish non-linear relationships • Need to be used with an agreed ontology about what the words and links mean, otherwise can lead to unwieldy maps (Sedlacko et al., 2014)	Hassanzadeh et al. (2014); Kotir et al. (2016); Madani and Mariño (2009); Rehan et al. (2011); Sedlacko et al. (2014)
Influence diagrams (IDs)		• Map causal interrelationships in greater detail than CLDs • Network of variables are connected by arrows indicating casual links (Coyle, 1996 p.21)	• Explicit way for thinking about the system dynamics, and how they will be represented in the operational model • The level of details considered on developing ID facilitates transition to a quantitative model. • Distinguish information and physical flows, and different types of variables and parameters	• Too many conventions and rules that take time to master • Can be difficult to explain to non-modellers • Like CLDs, do not distinguish non-linear relationships	Elsawah et al. (2015)
Stock and flow diagrams (SFDs)		• Problem is represented by stocks that change over time through flows • Problem elements are represented by shapes (rectangles, valves, circles, clouds, etc.) that represent different types of elements (stocks, flows, converters, connectors, sources/sinks)	• Good for showing a step-wise flow through the model. • Good for visualizing the problem processes and the physics of changing these processes • Good to communicate about quantifying relationships and units consistency	• Can be hard for non-modellers to follow and understand	Elsawah et al. (2015); Zhang et al. (2017); Liu et al. (2015)

Goals and Objectives Hierarchy (GOH)		• Displays relationships among goals and objectives and their attributes in a hierarchy	• Useful for structuring the problem with multiple goals and motivational constructs • Supports links between activation or trigger levels for goals and measures of performance • Helps connect measurements to motivation and actions/ intervention strategies	• Difficult to merge goal structure across individuals or stakeholder groups when significantly different • Fits well with soft-computing, but must be manually adapted and input for use in SD model	Pierce (2006)
Fuzzy cognitive maps		• Combination of fuzzy logic and cognitive mapping. • Map the important elements of a system in nodes and provide the relationship between nodes in terms of direction and strength	• Explicit way of thinking about the system components and their relations • Ability to examine feedback effects in systems where exact relations are hard to quantify	• Results from FCM calculations can be difficult to explain to non-modellers	Van Delden et al. (2008b)
System archetype		Descriptive qualitative tools, applicable to classes of problems that share one or more modes of dynamic behaviour	• Provide a generic structure that can help with the initial conceptualization and development of the dynamic hypothesis • Provide insights into the interpretation of the model results	• Risk of force-fitting an archetype to the problem situation rather than a lens to look at the situation from different perspectives	Gohari et al. (2013); Mirchi et al. (2012)

urbanization increases). Stakeholders answered reference mode questions during open elicitation and then confirmed their individual expectations with facilitators and modellers. Finally, the reference modes were used in group settings to initiate discussion about possible differences in expectations among stakeholders.

- The modeller needs to have a very good understanding of the weaknesses inherent in each method and take necessary measures to mitigate these. On conceptualizing the model structure, the case study authors considered the potential risk of overwhelming stakeholders or deriving erroneous dynamic inferences from using particular mapping methods, and identified several possible measures to avoid this risk. These identified measures are applicable for mitigating the weaknesses of all mapping methods:
  - Pointing out such limitations to participants
  - Breaking down the model into sub-models, and managing model complexity especially in relation to the number of feedbacks
  - Providing additional or scientifically proven knowledge to complement the mapping methods
  - Using an incremental build-and-test approach where the realism/appropriateness of each interaction and feedback loop between components is first tested and assessed by itself, then in threesomes, foursomes, etc. Testing and assessing is undertaken based on logical reasoning (expert judgment), and historic data when available.

The case study authors agree that identifying the sequence of cause-and-effect relationships that constitute feedback interactions is often challenging. Identifying, understanding and articulating feedback loops requires domain knowledge, and in-depth understanding of the views and knowledge that stakeholders have about the situation. This concurs with observations made in the literature (e.g. Warren, 2014). In the ACT water management case study, in depth interviews, followed by cognitive mapping, proved to be an effective means to tap into stakeholders' mental models so as to capture their cognitive assumptions about how the system works. This mapping revealed that the unwillingness of some stakeholders to engage in more sustainable practices (e.g. change in water consumption habits) were underlain by misconceptions and poor reasoning about the problem dynamics. This information provided insights into the important feedback loops on which to focus the modelling.

Another challenge arises when stakeholders suggest the inclusion of variables or feedback loops that do not have a clear causal relationship nor readily fit into the system conceptualization. One example from the Texas groundwater DSS was a desire to link increased obesity to land use change – this was considered a tenuous link from a causal perspective and the modellers had to carefully explain to the relevant stakeholders, why it was not a strong choice for inclusion in the model. To accommodate this perspective, the modellers included a general representation of increased commute time estimates based on land use/urbanization of a region, which served as a proxy indicator for the obesity relationship that the stakeholder wanted to represent.

This first phase of the SD modelling process is considered a valuable output in itself. Indeed, there are studies where the qualitative SD models were the end product, including Mendoza and Prabhu (2005) and Guest et al. (2010). In these two studies, qualitative SD modelling was found to be useful for structuring the problem and for identifying and understanding the interactions between system components. Some experts (e.g. Coyle, 2000; Wolstenholme and Coyle, 1983) advise against going beyond the qualitative model if the data and system understanding are inadequate.

3.2. Model formulation

In the model formulation and coding phase, the modeller translates the developed qualitative model of the dynamic hypothesis into a working, formal, quantitative model. This includes clear definition of stocks (i.e. system states that can be measured at any point of time), flows (i.e. rate of change in system stocks), auxiliary variables, parameters and equations. The way the SD modelling process is often described may give the misperception that there is a natural progression from the dynamic hypothesis to the numerical model. For example, Hassanzadeh et al. (2014) report that: "*After drawing the CLD, the model variables were transformed into stocks, which characterize the state of the system and flows, which define rates that can change stock variables. The governing equations for states are represented by finite difference expressions and solved using standard numerical schemes*". However, in reality this process is unlikely to be that straightforward. Converting a qualitative conceptual model to a working numerical model is a challenging iterative process, full of decisions that modellers need to make along the way (see Howick et al., 2008), including decisions on what to include and exclude from the conceptualization. Such choices often go unreported (e.g. Rehan et al., 2011).

In the next subsection, model formulation is discussed in terms of developing the model structure (simplicity vs. complexity) and calibrating the model (Quantifying System Relationships). We also elaborate on the reuse of existing model components and the treatment of space – two topics pertinent to SD modelling.

3.2.1. Model structure – simplicity vs. complexity

The model scope and conceptualization will govern the breadth of the system (the elements to include) and depth of the processes (the level of detail) to be represented. Widely accepted modelling principles (e.g. Occam's razor) are applicable to SD models; the model should be as simple as required (and only as complicated as necessary for the purpose). The first version of the model structure should include the key variables and functions that represent the dynamic hypothesis within the specified context. SD models tend to evolve and improve through several iterations, rather than through one attempt only. Starting with a simple working prototype, the model should be continuously reviewed and revised with consideration about whether the model adequately represents the research objectives and scope, and whether the model is behaving as expected (Sterman, 2000).

In the literature, SD modellers are sometimes criticised for building overly complex models, thereby compromising the model's parsimony and learning insights derived from the model (Kelly et al., 2013). The temptation to add unnecessary complexity to the model (i.e. components that may not have data to back up behaviours or that may not really be needed to represent the key behaviours of interest) is often attributed to the user-friendly drag-and-drop features available in most SD software. However there are situations where variables not part of the dynamic hypothesis may need to be included in an SD model, for instance, for the inner working of the model. An example of this is the inclusion of the surface water stock in the ACT water management model. In this case study the hydrological variables of direct interest were the reservoir storage level, soil moisture, evapotranspiration rate and rainfall. However, in order to model the delayed process of rainfall being infiltrated into the ground, the modeller needed to include rainfall accumulation in "surface water", which was a virtual stock for modelling purposes only. Additional variables may also be required to fulfil the information needs of users.

In the ACT water management tool and the two groundwater

DSS case studies, the authors were obliged to add more detail into the model than felt necessary for yielding the output behaviour, in order to satisfy end user requests. The main reasons for these additions in these cases were to improve the model's realism as perceived by the end users and to include measures that aligned with the end users' investigative/reporting needs. For example, in the Texas groundwater DSS case study, the representation of a drought trigger measure was modified to include an original measure (springflow) and an alternative measure (well level) at the user's request. This was due to the Groundwater Conservation District using both measures in the real world, drought indicator system. The user also requested that the interface be modified to include different drought pumping cutback levels to help with a real world debate about the best levels to set. In the ACT water management tool, the model has three categories of water saving measures according to their effect (i.e. low, medium, high). The user requested that a breakdown of these measures be added to the interface so that these measures could be communicated in the water saving campaigns.

Although there is a need to keep the model as simple as possible, the case study authors argue that adding additional detail in such cases as above was necessary. The additions provided a model that was considered to be more reasonable from the user perspective, and thus more likely to be adopted. This compromise links back to the model objectives and ensuring that the model is developed in a way that is fit-for-purpose. To achieve this, it is essential that end user requirements are properly understood, and effective communication occurs with stakeholders and the future users of the system throughout the model development process. A particular consideration in this respect is the appropriate provision of user support and training in the use of the model.

3.2.2. Quantifying system relationships

In an SD model, the causal relationships are mostly described by differential or difference equations based on evidence and/or experience. The equations can be drawn from a range of sources including empirical data, survey data, literature, anecdotal information, and logical inferences. Often parameter estimation for SD models is carried out "by hand" through a process of simulation-analysis-revision (i.e. trial and error); although this method can be effective, it is also subjective, depending heavily on the modeller's expertise and experience (Lyneis and Pugh, 1996; Yu and Wei, 2012). A large range of statistical parameter estimation methods can be used, from methods such as multivariate regression to more sophisticated optimization methods such as genetic algorithms and hill-climbing algorithms (Yu and Wei, 2012; Hassanzadeh et al., 2014). The suitability of these calibration methods can depend on the availability of data and the complexity of the model structure, and whether the method's assumptions are met (e.g. assumptions regarding normality, collinearity, etc). These parameter estimation methods are aimed at matching observed historical data with simulated output for a given structure. In other words, the calibration is also based on the assumption of correct model structure, which must be considered when validating the model (Oliva, 2003).

A challenging task in the model formulation and coding phase is the calibration and validation of feedback loops, particularly where real world data are lacking. Addressing this requires an iterative process of parameter estimation, model testing, parameter adjustment, model testing, etc. A related challenge involves the specification of measurable criteria that reflect model performance. To overcome this, one of the case study authors suggests creating and assessing multiple criteria for each model objective, to provide a broader, more robust evaluation (see also Bennett et al., 2013 for ways to characterize model performance). Various model testing techniques are elaborated in the Model Verification and Validation Section below.

An alternative to formulating and coding model components from scratch is to emulate pre-existing models from other modelling paradigms. In other words model components can be approximations of more complex models (also referred to as meta-models or surrogate models) or be pre-existing models themselves. For example, the MedAction PSS incorporated the pre-existing Metronamica land use model (Van Delden and Hurkens, 2011), and its hydrological and plant growth model components (Pattern-LITE) were simplified versions of the larger Pattern model (Mulligan and Reaney, 2000). The modular structure of SD models lends itself well to the reuse of pre-existing models.

3.2.3. Reuse of existing model components

Recently there has been growing interest in the reuse of existing model components (e.g. Donatelli et al., 2014; Stella et al., 2014), also referred to as constructs, modules (Eberlein and Hines, 1996) or building blocks, especially for more generic elements of the system. The coupling of available and tested model components is a common integrated model building strategy (*assemblage approach*, Voinov and Shugart, 2013). It essentially averts re-invention of the wheel, thus saving time, costs and efforts (Warren, 2014), providing the modeller more time to spend on high-return modelling activities, such as experimentation and results communication (Monks et al., 2016). In the ACT water management model for example, the "Bass diffusion model" described in Sterman (2000) was reused to model how people change their behaviour at a population level (compliance vs. non-compliance) based on factors such as climate, price and perceptions. The Berlin urban modelling group also built upon a pre-existing model (in Simile) for the City of Leipzig (Lauf et al., 2012).

However the uptake of model reuse has been limited, in part due to the difficulties in designing reusable components that are generically structured and transferable across different problems and contexts. In addition, model components still need to be carefully verified and rigorously validated for the new context (Voinov and Shugart, 2013). The MedAction PSS and its predecessor MODULUS (Oxley et al., 2004) were from the start developed as generic systems for arid and semi-arid regions, which determined the selection and development of model components included in the systems. First applications to regional case studies in Greece and Spain supported the further development of these generic components. Later applications to the Oum Zessar region in Tunisia (Van Delden et al., 2008a) as well as country level applications showed the limitations of a large coupled component model with a fixed set of individual components. This initiated the development of a more modular framework, the DeSurvey IAM, where components could be selected based on the purpose, scale and data availability (Van Delden et al., 2009).

The water balance components of the Texas and Gnangara groundwater DSS were meta-models of established hydrological modelling systems, MODFLOW and PRAMS (Perth Regional Aquifer Modelling System), respectively. In these two groundwater management case studies, the authors reported that the challenge was aggregating spatially explicit information about aquifer properties into a small subset of spatial zones with the inclusion of conductance and transfer equations between the updated cells. In effect the detailed numerical model was reformulated into a simpler and less spatially explicit implementation with calibrated responses matched between the two versions. SD models do not readily represent space; approaches to overcoming this limitation are discussed in the following section.

3.2.4. Treatment of space

The reviewed case studies showcase different approaches to incorporate the spatial dimension into SD models varying from lumped modelling, coupling the SD model with other spatially explicit models or tools (e.g. GIS), and use of modelling environments that support the development of spatially explicit SD models (e.g. Geonamica in the case of the MedAction). Selecting the appropriate approach involves trade-offs between several considerations, such as the model purpose, software flexibility, and familiarity of the modeller with particular software (i.e. popular SD software tools such as Powersim and Vensim do not support spatial treatment). In the ACT water case study, the purpose of the model was to communicate generally about water policies to the public rather than provide spatially explicit information to support decision making. Consequently the case study author made the decision to develop an aggregate or lumped sub-catchment model to simulate runoff dynamics.

In the Texas groundwater case study, the DSS offered two options for groundwater simulation during runtime. The first option used a detailed, spatially explicit (7036 grid cells) numerical model of the groundwater system in MODFLOW, which was hybridized with an SD model of the other components (e.g. land use, commute distances etc.). This version was suitable for supporting policy making as it was considered to be a more scientifically representative. The second option used a simplified, spatially aggregated (11 hydraulic conductivity zones) SD emulation of the groundwater model. This second version mimicked general groundwater behaviour and allowed users to quickly test scenarios (under 30 s per run, compared to 2–5 min for the detailed spatially explicit option), making it suitable for real-time group negotiation and conflict resolution. The DSS allowed users to toggle between the two versions, depending on user needs.

In the Berlin urban development case study, the spatially explicit process of land use change was represented through the integration of the SD model with a cellular automaton model (Metronamica). Other studies have also enabled the representation of space by coupling the SD model with other modelling paradigms (e.g. agent based models; Vincenot et al., 2011) and tools such as GIS (Ruth and Pieper, 1994; Sahin and Mohamed, 2014). The coupling of SD with other tools is discussed in more detail in 3.5.2.

3.3. Model Verification and validation

Model testing is a critical part of the modelling process that helps build confidence in the model and its insights. The evaluation of SD models centres around two types of testing: behavioural and structural. Behavioural validation tests assess how well the model outputs replicate observed system behaviour. Structural validation tests assess how well the structure of the model represents the real world structure of the system. A widely used approach to testing models is by calculating goodness-of-fit measures, which give an indication of the model's performance (see Bennett et al., 2013 for a comprehensive delineation of relevant performance measures, both quantitative and qualitative). All the case studies of this paper were faced with data limitations, a common problem in modelling such complex systems. Even when long-term datasets are available for one or a few state variables, it is rare to have sufficient data for all variables in an SD model. Formal model testing should be performed whenever data allows; this can be complemented with other forms of evaluation including peer review, sensitivity analysis, the plausibility of patterns in results, and comparison with other models.

3.3.1. Behavioural testing

The most common approach to model testing is the statistical comparison of observed data with simulated outputs. A large range of goodness-of-fit measures have been applied to test SD models, including the correlation coefficient, root mean squared error, mean absolute relative error, maximum relative error and discrepancy coefficient, in cases where adequate data were available (Wei et al., 2012; Hassanzadeh et al., 2014; Kotir et al., 2016). In most cases, SD models are not expected to reproduce outputs at a high accuracy or precision, with emphasis more on replicating system behaviour. Thus, model performance of SD can also be assessed based on the general patterns produced by the model (Saeed, 1998). For example, in the MedAction case study, in addition to cell-by-cell measures for map comparison, the similarities of historical data to the output maps were assessed at a higher level of abstraction, using fractal analysis and landscape metrics for assessing the land use patterns the model generated.

Behavioural testing can rely on multiple lines of evidence. In the Berlin Urban Development case study, for example, the SD model results were tested and compared to the one year of data available, which included satellite imagery, using a range of validation measures (kappa, mean absolute error and mean relative deviation). The simulation results were also compared with results from a null model that excluded household dynamics by keeping the housing demand/supply parameters constant. This comparison showed that the SD model not only simulated system processes more realistically but also reproduced existing land use patterns more accurately than the null model. Here it is worth repeating the old mantra: the modelling purpose determines which data patterns are important for model evaluation (Crout et al., 2008, p.20). For example, in the ACT water case study, the model output was compared to historical hydrological data (Elsawah et al., 2015). Results showed that the model does not produce an adequate representation of peak flows. Whereas the main interest is simulating base flows rather than predicting flood peaks, capturing the timing and magnitude of peak flows is irrelevant. Therefore, the model was regarded as sufficiently accurate to fit-its-purpose.

Given the modular structure of SD models, the components of the model can be tested separately to judge if they produce reference-mode behaviour. In the three water management case studies, for example, the hydrological components of the SD models were tested against observed or modelled data. The ACT Water management case study compared the water inflow and storage values simulated by the model with historical data. In the Texas and Gnangara groundwater case studies, the water balance components of their SD models were evaluated to see whether they adequately replicated the hydrological models they emulated. In the MedAction case study, in order to deal with the complexity of the system, all individual components were tested separately, then in pairs, threesomes etc., to test each individual relationship before assessing the entire integrated model.

3.3.2. Structural testing

Evaluation of the model structure is often conducted through qualitative assessment. This type of assessment is also important for behavioural testing, particularly in the absence of adequate data (Bennett et al., 2013). For structural testing, experts, users or modellers can be asked to assess the validity of the model structure. This includes questions about the model components and how well it matches knowledge about the real world system (including boundaries, problem representation, casual relationships, parameters), as well as questions about the modelling process and its usefulness or fitness-for-purpose (e.g. for capacity-building, education, social learning). If necessary, different domain experts can be used to assess the parts of the model relevant to their expertise.

In the MedAction case study, in addition to testing model components with historical data, the model was evaluated through an in-depth verification exercise with experts and users who helped assess the logic of the modelled system. They discussed assumptions and causal relations, and analysed spatial and temporal patterns produced by the model to verify whether the outputs were reasonable.

Sensitivity analysis is another valuable approach to behavioural and structural testing, whereby the effects of variations in parameter values, boundary conditions and other model inputs on model output are assessed (see Norton, 2015 for an overview). It helps provide a greater perspective on the reliability and the validity of the model and its outputs. In the MedAction case study, sensitivity analysis was performed on the parameters of the key drivers in the system; the results indicated the value ranges within which the model would be useful for policy support. In the Gnangara groundwater case study, sensitivity analysis was performed to evaluate the effect of changing uncertain parameters, such as the costs of groundwater abstraction and the discount rate, thereby providing a means to test some of the constraining model assumptions. Sensitivity analysis was also used in the Gnangara case study to assess variations from the scenarios of interest (i.e. business-as-usual and scenarios recommended by the user). In other studies, sensitivity analysis have been performed to identify model parameters that have the greatest influence on model behaviour, thereby guiding future focus for policy making (Sušnik et al., 2012).

Despite the benefits that ensue from sensitivity analysis, uncertainty analysis and robustness checks, extensive evaluations are often not performed due to resource and time constraints. As eloquently captured by Balci (2010), "*The only exhaustive testing there is, is so much testing that the tester is exhausted*". Therefore, thorough model testing should be planned and budgeted for in the early stages of the project proposal. It can reveal fundamental problems in the model, which may require intensive revisions in the model structure, or at the very least can indicate limitations of the model. Although model testing formally follows model formulation in the modelling process, it is sensible to continuously test the model's validity from the early development stage, at least informally, to avoid having to conduct major amendments later in the project (Warren, 2014). For example, in the ACT water case study, the testing process followed the systematic modular sequence of the V-methodology ("Vee model"), whereby model components are incrementally built and verified before new components are added (Forsberg and Mooz, 1991; McLucas, 2005). The V-methodology introduces testing in the early stages of model/software development, requiring the design of the testing phase to be planned in parallel with development activities.

3.4. Model use and application

SD models are strong tools with the capacity to provide interactive decision support for complex scientific problems. For example the MedAction, Gnangara groundwater and Texas groundwater SD models provided decision support by identifying the potential impacts of alternative management options, enabling the tradeoffs of associated social, economic and environmental benefits and costs to be assessed. SDs models are particularly unique in their ability to reveal important, and often counterintuitive, behaviour in systems, which can be a helpful contribution to policy making (Ghaffarzadegan et al., 2010).

SD modelling can also support social learning environments and substantive dialogue about a shared problem among stakeholders. In the ACT water case study, the SD model was used by the water authorities as an online public education tool. Similarly, Williams et al. (2009) developed a 'big picture' water-system educational tool for university students and other adults using SD. The model was found to be an effective alternative learning tool that also engaged students who were less responsive to traditional teaching methods. As an interactive learning tool, the model was reported to provide users with an understanding not only of key water resource concepts, but also of the system-wide impacts of policy alternatives, and the conflicts between users (Williams et al., 2009).

Scenario analysis, in particular, is easy to complete using SD models, even with non-expert stakeholders. Users can easily change model inputs, values or parameters to represent different conditions in the system, enabling rapid assessment and comparison across scenarios in real time. Interactive dashboards or interfaces can help the user understand the effects of their decisions by linking changes in the model input to system behaviour.

The case study authors were asked to reflect on the value of SD with the question: "In hindsight, what 'insights' to the system/problem did SD provide that may not have been achieved by other modelling techniques?" It is noteworthy that the experts also have wide experiences in using other modelling techniques, thereby enabling them to comment on the strengths that SD brought to the analysis relative to other techniques. The notable advantages of SD modelling were seen to include:

- *A better understanding of how variables might be mutually influential.* In complex urban systems, as shown in the Berlin coupled model, we have sound knowledge about the different human and land-use variables but little understanding about their manifold interactions and feedbacks. Implementing possible attraction and repulsion mechanisms as well as feedbacks helps to better understand if, and if so how, an improvement/worsening of the environmental conditions really influences the decision-making of urban dwellers.
- *A sound analysis of the system in terms of possible feedbacks and their outcomes*. In the Texas groundwater DSS, for example, stakeholders made use of the model in group discussions to explore how land use changes affected different elements of the system and discussed, particularly the surprising, results. This helped uncover some unexpected relationships that stakeholders had not anticipated in non-model supported dialogue.
- *System dynamics provided a robust and logical way to couple various models and hence test out the feedback mechanisms incorporated*. Many insights can be gained from the development pathway or temporal dimension of the model to help understand which processes reinforce each other over time.

3.5. Software platforms, integration architecture, and model coupling

There are many software programs that can be used to develop SD models as discussed below. The nature of the software program used was found to significantly influence the modelling practices.

3.5.1. SD software platforms

There are increasing numbers and types of SD tools becoming available, with each tool offering a range of strengths and weaknesses. In the literature, there is no systematic comparison among the different software packages in terms of their capabilities to support integrated assessment modelling. Available comparisons (e.g. https://en.wikipedia.org/wiki/Comparison_of_system_dynamics_software) do not provide much information about the software functionalities and how they serve the technical and participatory requirements of the IAM process.

In this section, we discuss the key characteristics of the software platforms used in the case studies with a focus on shedding light on the trade-offs to be considered when selecting a software platform

- as reported by the case study authors. In Table 4, we compare the strengths and limitations of the four software packages used in the case studies – Powersim, Vensim, Similie and Geonamica – and another commonly used software package Stella/iThink.

Authors agree that selecting particular SD modelling software is not a decision to be taken lightly, but has to be considered closely and early in the scoping phase as it influences the final model's abilities to meet the model's objective(s). They described selecting a software package as a trade-off among several criteria, including the ease of use and flexibility (in terms of the ease in changing the model in response to stakeholder needs) on the one hand and the ability to incorporate more complexity into the model, such as spatially-explicit features. For example, (as shown in Table 4), the Geonamica framework is a software environment that supports the development of multiple spatial scales and integration of components with various spatial and temporal resolutions. Geonamica allowed the MedAction PSS to incorporate a high level of spatial detail and build a custom interface tailored towards its end users; however, it made the PSS less flexible for incorporating changes in the model structure. On the other hand, software such as Powersim and Vensim are easier to use, but do not readily support the building of models at multiple scales.

There is also a trade-off in selecting open source software versus commercially available software. Commercial software tends to provide better maintenance, documentation, and training services. However, the cost-prohibitive nature of some commercial software can also limit opportunities for collaboration in model design and testing, either with other modellers, experts or stakeholders. For example in the ACT water management model, the use of the commercial software Powersim ultimately limited the adoption of the model. The modeller was unable to put the model on the user's website without the user owning the professional license which they could not afford. Instead, the modeller had to build a database of select runs to be put online, which people could query for a restricted number of scenarios. The software costs limited the ability of the user to design experiments as well as long term model maintenance plans. Some software packages, such as Geonamica, distinguishe between developers and users, charging different fees for different users as a way to facilitate the uptake of developed systems by user organizations.

Other considerations for selecting SD software, especially from a participatory modelling perspective, include the graphical interface capabilities. In the Gnangara groundwater DSS, the modeller found Vensim to be limited in these capabilities and therefore used a general programming language C++ to develop a graphical user interface. Another consideration relates to the software's ability to support the development of hybrid decision support systems that integrate other simulation or modelling tools, as well as advanced computing applications for big data and machine learning. Simile, for example, which was used to build the Berlin SD-CA model, readily supports the coupling of different models.

3.5.2. Coupling SD models with other modelling approaches

In four of the case studies (all but the ACT water management study), SD was coupled or hybridized with other modelling approaches, including: Cellular Automata, economic models, agro-economic, and hydrogeological models. The coupling of SD with other modelling approaches is often done to overcome limitations of SD and/or leverage the strength of another modelling approach, in particular to surmount the inability of SD to model processes at different temporal and spatial scales. Model coupling also allows different parts or behaviours of the same system to be simultaneously represented and assessed (Morgan et al., 2017).

In the Berlin urban development case study, a coupled SD-CA approach was used to build a spatially explicit model that includes both system knowledge about population growth/decline and household formation, as well as household housing preferences and spatial properties like accessibility to infrastructure. As there are more than 1.5 million households in the study region, a spatially implicit SD approach was deemed appropriate to

Table 4
The strengths and limitations of various SD software. The list includes commonly used software packages and those used in the case studies.

Software name	Strengths	Limitations
Stella	• Story telling functionality • Extensive on-line support • Simple interface that is easy to use and learn, especially for beginners • Suitable for rapid prototyping of the model with stakeholders	• Difficult to build models at different spatial scales
Powersim	• Simple interface that is easy to use and learn, especially for beginners • Suitable for rapid prototyping of the model with stakeholders • Presentation and design mode toggles are useful for group model building • Drag and drop capabilities	• Commercial license makes it difficult to use for modifications with multiple stakeholders, and makes it difficult to share models and host online • Requires a commercial SDK license to connect other parts of a DSS • Difficult to integrate with an open source DSS architecture • Difficult to build models at different spatial scales • Limited modelling community support
Geonamica	• Suitable for large scale modelling with a high level of spatial detail • Suitable for inclusion of various spatial scales and integration of components with various spatial and temporal resolutions • User interface building blocks available for policy support • Drivers and parameters visible and adaptable • Modular framework with hierarchical model development structure	• No visual 'drag and drop' functionality for model development • Adaptations to model structure and equations need to be undertaken by an experienced programmer (except for those parts of the system where this is made available through the user interface). Therefore it is less flexible and not accessible for all modellers
Simile	• Simple interface with good documentation (manual) and sample models, making it easy to use and learn • Suitable for inclusion of various spatial scales and integration of components with various spatial and temporal resolutions	• The user interface is difficult to customize or modify
Vensim	• Models are constructed graphically or in a text editor, assisting in communication of modelling concepts and results • Useful features include dynamic functions, subscripting (arrays), Monte Carlo sensitivity analysis, optimization, data handling, application interfaces etc. • Vensim DLL capability is a separate program that can be called from other applications such as Visual Basic, Delphi, Excel, and multimedia authoring tools easing the linkage with other models	• Difficult to build models at different spatial scales • License restricts the use of the software to provide web or other network services

considerably reduce the run time of the complete model.

In the Texas groundwater DSS case study, SD alone did not offer the spatially explicit level of detail that was needed for the project. In addition, the project required use of a previously vetted scientific model (MODFLOW) for the groundwater component. The modellers could not use SD alone and still achieve an acceptable level of credibility required to support decision making. The SD model was therefore coupled with the spatially explicit MODFLOW-based groundwater model using a dynamic data exchange manager. Similarly, in the Gnangara groundwater DSS, an SD model linked to a crop model was developed to simulate surface and groundwater irrigation requirements. Output was fed to the groundwater model to simulate the changes in groundwater level in more spatial detail than can be offered by SD. In that case, the hybrid approach presents the advantage of linking SD to physical processes, hence providing more realistic outcomes.

The coupling of SD with other models or tools can be loose, as in Guan et al. (2011) where the SD model generated a database of predicted future indicator values, which were then spatially analysed in GIS. Tight coupling occurs with the synchronous operation of systems; the transfer of data between the SD and the other model/tool can be achieved using protocols such as dynamic data exchange (DEE) (e.g. the Texas groundwater case study; Ahmad and Simonovic, 2004) or using middleware such as Python (Neuwirth et al., 2015). Although loose coupling tends to lead to slow execution speed, it remains a relatively popular approach as it is simple to implement without the need for expertise in programming (Sahin and Mohamed, 2014). However, loose coupling may be appropriate only when the interaction between two different models is a simple, sequential one-directional flow of information such that the output of one model is input to the second model (Swinerd and McNaught, 2012). For more complex interactions between two (or more) models, including a multi-directional flow of data, there are many possible ways to couple the models, largely depending on the features of the other modelling approach. Possible permutations include the SD model being fully embedded in the other model, the other model being fully embedded in the SD model, or the two models combining to form a new method (Vincenot et al., 2011; Swinerd and McNaught, 2012; Morgan et al., 2017). The MedAction PSS is an example of the second permutation, where several models were integrated using SD.

The MedAction PSS integrated many different system components including model components represented by pre-existing models such as a land use model, a hydrological model and plant growth model. The model components were adapted (if pre-existing models were available) and created to meet the needs of the overall system, based on user feedback by the modellers and software developers. Due to the complexity of the model components incorporated (various spatial scales, high level of spatial detail at the local level and various temporal resolutions) and the development of a user-friendly interface tailored towards the needs of the end users, the flexibility for adding processes or changing existing model equations was more cumbersome and required software development. Substantial effort may be required to achieve this level of integration.

As might be expected, using a coupling approach affects the SD modelling process. The following issues were raised by other case study authors:

- *Spatial mismatch is a challenge that requires downscaling and/or upscaling techniques to be applied before coupling the different models*. In the Gnangara groundwater DSS study, outputs from the PRAMS model (i.e. the model used to estimate the groundwater recharge and abstraction) fed into the SD model which simulates the triple bottom line impacts from different planning scenarios such as landuse changes. However, PRAMS and the SD model differ in their spatial resolution. The SD model considers the Gnangara mound as 6 regions divided into 29 management areas, but PRAMS uses a uniform grid of 500 m by 500 m over the entire model domain. Post-processing was required to upscale the outputs from PRAMS to match the spatial scale of the SD model.
- *Technical coupling in terms of exporting and importing output files from the SD software to other modelling platforms is a demanding task*. Although most SD software allow this feature by generating model code in general programming languages, this may not be an easy task. For example, in the Texas groundwater model, adding in SD made the simulation modelling stage significantly more difficult because so much data had to be prepared before being able to put it into a format for the SD model and connect the SD model to a numerical model. Creating the code and software interfaces to enable hybridization of the whole decision support system was a significant, time consuming and expensive task.
- *Model testing may need to be done for each model separately, and then jointly*. In the Texas groundwater case study, comparison of the SD model against the distributed MODFLOW model was a difficult challenge because the modelling team had to recreate and calibrate the SD model to assure that the simpler SD component replicated responses and behaviours across the range of possible user settings for landuse, pumping location or level, and drought policy decisions. This made the first version of the hybrid model much harder to finalize, but much more valuable when completed. Once the base hybrid model was completed uncertainty could be tested much more easily. So the heavy load was on the front end and then it was much easier after obtaining a base model.

SD can be coupled with other tools such as GIS to expand their capabilities. Given the limited spatial representation capabilities of SD models, many studies have combined SD with GIS to enable analysis of spatial-temporal interactions (e.g. Ruth and Pieper, 1994; Ahmad and Simonovic, 2004; Sahin and Mohamed, 2014). SD can be combined with multicriteria decision analysis methods to improve the provision of decision support (Pruyt, 2007). For example, in Xi and Poh (2015), the Analytic Hierarchy Process (AHP), a multi-criteria decision-making technique, was combined with an SD model of water supply. The SD model was used to simulate the implications of alternative policies under different scenarios of population growth, and AHP was then applied to compare and rank the performance of the alternative policies based on the SD simulations and the judgement of decision makers on the importance of three criteria – adequacy of water, self-sufficiency in water and cost.

There has been growing interest in the coupling of SD models with other modelling paradigms, in particular agent based models (Vincenot et al., 2011; Swinerd and McNaught, 2012). In contrast to SD models, which provide an aggregated representation of entities in the system, agent-based models represent each entity individually to understand the system properties that can emerge from their interactions. In Verburg and Overmars (2009), an agent based model was combined with an SD model to represent cross-scale interactions including local processes of vegetation dynamics and large-scale dynamics of land use change. Similarly, an agent based model was combined with a stocks and flow model in Gaube et al. (2009) to represent local processes, specifically the decision making process of stakeholders. Vincenot et al. (2011) also suggest that agent based models can provide a spatial dimension to SD models when coupled. In other fields, SD models have been hybridized with modelling approaches such as discrete event simulation

(Alvanchi et al., 2011; Morgan et al., 2017), optimization models (Azadeh and Arani, 2016), and Bayesian networks (Mohaghegh, 2010), which suggests that the full potential of SD modelling for IAM has yet to be explored.

4. Good modelling practices

Based on the collective experience of the authors, including the lessons from the five case studies, we compiled the following set of good practices for SD modelling of socio-ecological systems.

Good practices in the model scoping and conceptualization phase:

- Account for the time and resources required for evaluation and iterations in the proposal and planning phase. This accounting is often skipped or minimized due to time/budget constraints, but is crucial for producing a credible model.
- Taking a step-wise approach is critical, especially for identifying the conceptual model elements with stakeholders. The stakeholder engagement for this task should occur over multiple sessions; it can be too overwhelming (particularly for participants new to systems thinking) to build a model in one sitting.
- Remind stakeholders that modifying the hypotheses is relatively simple, so they can begin with an initial interpretation and change it easily. Also, the modeller should not assert too much pressure over including feedback loops as some stakeholders may find it difficult or irrelevant, and feedbacks add complex dynamics that require careful evaluation.
- Importantly, elicit knowledge on the formulation of decision rules as well as the system at stake.
- Be aware of the limitations related to the different methods used to elicit and visualize the dynamic hypothesis, and how they may affect the final model and its application/use.
- Flowing from the previous point, leverage the strength of various elicitation and mapping techniques throughout the modelling process utilizing approaches such as pairing methods, and detailed variant maps.

Good practices in the model formulation phase:

- Build a simple model first – identify the variables, key decisions, and main functions. Keep it very small and think about the primary behaviours to be reflected in the model first. Once one has a first simple version of the model, think about the reference behaviours, i.e. does the model behave as you expect it to? Remember that more detail, including different metrics, can be built in iteratively to represent the behaviours that are needed.
- Reflect on the model as it advances. SD modelling is a particularly reflexive and flexible process. At each model iteration, consider whether the model is aligned with its objective and scope.
- Make use of (already tested) model structures (also referred to as model modules) when pertinent and available instead of re-inventing them. This reuse may include model components built using other modelling approaches to form hybrid SD models. Sometimes other modelling approaches can simulate parts of the dynamic hypothesis better or easier than SD.
- When your model consists of various modules, first test these components individually, next in pairs, threesomes and so on, in order to manage the complexity of the integrated model and allow for a thorough investigation of each relationship between core processes.
- Make smart use of prototypes to give users an appreciation of the final model capability while avoiding the risk of over-shooting their expectations.
- Pay more attention to (spatial and temporal) scaling and reporting unit questions when considering the main objectives of the modelling exercise.
- Avoid hiding parameters in equations. Having them explicit makes the model more transparent (to stakeholders and users) and easier to update. When building the model in a participatory setting and using visual model development interfaces, this would mean that parameters become their own module. And when building models with a tailor-made user interface, this would mean including parameters in the user interface and allowing users to inspect and adapt them.
- Make use of software development methodologies (e.g. the Vee development process, rapid prototyping methods) and practices (e.g. version control) to structure the way you develop and test the model.
- Make careful use of arrays and subscripts as they can be complex to develop and test, and hide some complexity of the model structure. Develop and test a full version of the single dimension (non-arrayed) model before adding dimensions.
- Calibrate the model using historic data where possible, even if the data are only available for part of the system.

Good practices in model evaluation:

- Make use of logical reasoning and expert judgement to assess the structural validity of each of the interactions, and the complete set of interactions.
- Perform behavioural testing with data in parts of the model where they are available. Formal testing against data should be complemented with other forms of model evaluation including peer review, sensitivity analysis, uncertainty analysis, robustness checks and comparison with other models.
- Whether using specific data to populate a function or inferring a reference behaviour, be certain to stress-test to ensure that the model reproduces the system behaviour as closely as possible across the range of potential scenario or decision variable settings. Assure that the simpler model (emulation) produces relatively reliable outputs.
- Test "on the go", i.e. test small components before uncertainty grows "out of control". When all components are tested, an integrated/whole of system test is essential. The use of a formal software development and testing methodology may be useful.

Good practices in model use:

- Ensure that the final model is only delivered to end users for their purposes after it has undergone and passed rigorous model evaluation. If the model is released prematurely, errors in the model (including bugs, or model structural or behaviour errors) may diminish their confidence in using the model, discouraging them from using the model even if the errors are subsequently fixed.
- Link the model behaviour back to the sources of dynamics (e.g. feedback loops and delays). Make use of conceptual models developed throughout the process to complement the discussion. CLDs can be an effective method in communicating the core feedback interactions in the model.
- Ensure the tools are well documented with adequate help resources available online. Over-reliance on the developers for technical support is unwise and often limits uptake of the model.
- Clearly discuss or describe the limits of the model for use (based on results from testing in previous steps) and point out where there may be inconsistencies with expected behaviour. Also

note what the model best represents, including which behaviours are expected to be good indicators of response.

Good practices in software selection:

- Explore the strengths and limitations of software platforms in terms of the specific technical and participatory modelling requirements early in the project scoping phase, as software selection can have large implications for the modelling capabilities. If unsure about specific requirements, start with an easy-to-use, open access package (e.g. InsightMaker) until there is a better understanding of the required functionalities, then move to more sophisticated packages to support a spatially explicit approach and/or a user interface that meets the needs of the users.
- In general, consider the use of SD software with active user communities as they are more likely to provide adequate information, communication, and support for modellers.

5. Conclusion and future research directions

In this article, we have used a multi-case study approach to bring together some insights and lessons about the SD modelling process. The case studies were intended to expose and shed light on many of the decisions that SD modellers have to make through the modelling lifecycle. In addition, the authors shared from their experience what they consider to be good modelling practices. The good practice recommendations outlined above are intended to overcome some of the common challenges of SD modelling, and improve the efficiency and effectiveness of the SD model design and implementation process. Additionally, the guidelines are intended to lead to the development of SD models that are more credible, useful and transferable/reusable. Furthermore, better SD modelling processes and models will improve recognition of the value that the methodology offers for understanding and managing socio-ecological systems.

SD provides a strong advantage over other modelling approaches in their representation of system feedbacks. Often such interactions are poorly understood or underappreciated, despite their potential to lead to significant outcomes in the system. SD allows feedback mechanisms to be tested in a vigorous and logical way, to explore the wider implications of changes to one or more parts of the system. As found in the case studies, SD was highly beneficial for promoting systems thinking and stimulating dialogue between different stakeholder groups.

To better enable the field of SD modelling to advance, particularly when modelling complex systems, we encourage the reporting of models to not only fulfill, but go beyond, the communication of technical details so as to include more transparency in specific practices and challenges faced. Greater deliberation of challenges and subsequent lessons encountered through the modelling process, including the interactions with stakeholders, will help to build and communicate in-depth knowledge about how to carry out IAM effectively in practice.

Acknowledgement

Special thanks to Dr Michael Ryan for his helpful comments on the various versions of this manuscript.

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