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A model-based policy analysis framework for social-ecological systems: Integrating uncertainty and participation in system dynamics modelling

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ABSTRACT

Problems manifested within social-ecological systems (SES) exhibit dynamic complexity and hold implications for current and future human well-being and environmental sustainability. The complexity of these issues, the ever-present uncertainty inherent to SES, and the multi-stakeholder settings in which they are discussed call for participatory modelling to support decision-making on socio-environmental issues. Yet, this challenging endeavour requires a structured approach — a modelling cycle — to facilitate engagement with the implications of participation and uncertainty as focal points for Good Modelling Practice (GMP). Here we propose an integrated policy analysis framework for SES modelling using System Dynamics (SD). This framework stems from integrating two existing modelling cycles that individually consider participation and uncertainty in SD modelling. Three global modelling phases and a set of tools to address the participation and uncertainty features in SES modelling are distinguished. The framework contributes to mainstreaming GMP, offering a structured model-based approach to enhance the robustness and social acceptance of policies on critical socio-environmental issues.

1. Introduction

Human activities are driving multiple environmental changes at a planetary scale (Folke et al., 2021). Anthropogenic pressures are linked to global issues such as climate change, environmental deterioration, resource depletion, and loss of biodiversity (Díaz et al., 2019; Nelson et al., 2006; Rockström et al., 2009; van den Heuvel et al., 2020). As humanity continues to rely on natural resources, the natural resource base (e.g. water, land, fossil fuels, minerals) is changing on a global scale along with ecosystems (cf. Armstrong McKay et al. (2022)). In turn, fast-paced environmental change is compromising human well-being and access to basic resources (Gupta et al., 2023; Watts et al., 2021). These complex interactions between humans and the natural environment act across multiple scales and exhibit bi-directional influences.

Systems thinking offers a powerful approach to conceptualise complex human-nature interactions by focusing on the interaction of interdependent elements that form a whole rather than simply on the elements themselves (Ackoff, 1971, 1994; Ison, 2008, 1997; Meadows, 2008; Mingers and White, 2010). Understanding human and natural elements as deeply intertwined is key to understanding the pressing socio-environmental challenges of our time (Folke et al., 2016). This idea has been articulated in the concept of social-ecological systems (SES) which can be defined as "interdependent and linked systems of people and nature" (Fischer et al., 2015, p. 145). SES are characterised as being nested across interacting scales (e.g. landscape, regional, and global) and embedded in the biosphere (Fischer et al., 2015; Folke et al., 2021). SES are complex systems as they are constituted relationally; adaptive; dynamic; open; contextually determined; and characterised by multiple causal pathways (Preiser, Biggs, De Vos, and Folke, 2018). These features imply that designing and implementing policies that deal with such systems is a non-trivial and complex task (de Gooyert et al., 2016; Kelly et al., 2013), likely with multiple feasible options.

Using models to represent SES is an essential part of exploring the potential impacts of socio-environmental policies. SES modelling aims "to characterise and explore complex socio-environmental issues in systematic and collaborative ways" (Elsawah et al., 2020, p. 1). This definition may be understood within a larger policy analysis framework (Mayer, van Daalen, and Bots, 2004, 2012). Among many systems approaches, policy analysis focuses on *analysing* a system to find ways to influence it towards desirable outcomes (van Daalen and Bots, 2010).

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This strongly relates to the *systematic* approach mentioned in the definition above. Likewise, developing a policy analysis approach in the context of SES has significant implications in terms of stakeholder participation (Amorocho-Daza, van der Zaag, and Sušnik, 2024; Bots and van Daalen, 2008; Clifford-Holmes et al., 2018). This relates to the challenge of developing models in *collaborative* ways. In short, SES modelling may be understood as a systems approach that takes an analytical perspective of a socio-environmental system, while recognising the criticality of having a subjective view of the problem situation at hand that arises from collaborative model building and use (van Daalen and Bots, 2010).

The ambition to engage with SES complexity in a participatory modelling setting is a formidable task for practitioners and researchers. Recent case studies (Bitterman and Webster, 2024; Mer, Vervoort, and Baethgen, 2020; Villamor et al., 2019) and reviews (Voinov et al., 2016; Whitley et al., 2024) illustrate the increasing attention toward participatory modelling approaches. Kelly et al. (2013) identified five modelling approaches that are suitable for integrating various SES processes in which stakeholders can explore, analyse, assess and communicate policy alternatives: System Dynamics, Bayesian networks, coupled component models, agent-based models and knowledge-based models. However, operationalising such modelling approaches in participatory settings remains a challenge. In a similar vein, Elsawah et al. (2020) recently identified eight grand challenges in SES modelling related to issues of epistemology, interdisciplinarity, uncertainty, scaling, and policy impact. This paper aims to explicitly engage with two of these grand challenges: (i) the integrated treatment of uncertainty in the modelling process; and (ii) the adoption of SES models to increase their impacts on policy.

The first challenge, the integrated treatment of uncertainty, recognises that uncertainty is ever-present in SES modelling (Ascough et al., 2008). Uncertainty, as defined by Walker et al.(2003, p. 8), is “any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system”. Brugnach et al. (2008, p. 5) extend this definition by including its *relational* dimension, as follows: “Uncertainty refers to the situation in which there is not a unique and complete understanding of the system to be managed”. Therefore, uncertainty takes place across all modelling phases, at different levels (from determinism to total ignorance) and exhibits distinct *natures* (e.g. knowledge or epistemic uncertainty, variability or ontological uncertainty, and ambiguity) (Kwakkel, Walker, and Marchau, 2010). In contrast to this holistic view of uncertainty, SES modelling practices related to uncertainty have often been confined to quantitative approaches to data validity, model parameter sensitivity and structural testing (Maier et al., 2016). However, recent literature highlights that activities taking place at early modelling cycle stages (e.g. scoping and conceptualisation), while qualitative in nature, represent fundamental uncertainty sources (Nabavi, Daniell, and Najafi, 2017). The lack of integrated uncertainty assessment is also connected to the challenge of communicating uncertainty to stakeholders in model-based decision-making (Palmer, 2017). Better communication regarding uncertainty implies that stakeholders and modellers engage in dialogues to discuss both qualitative aspects, such as values, representation, prioritisation, and transparency, as well as quantitative aspects, including modelling outputs, scenarios, trade-offs, and risk, across the different stages of the modelling cycle (Elsawah et al., 2020).

The second challenge connects the need for participation with the expected policy impact deriving from the use of SES models (Elsawah et al., 2020). Participation can be understood as a process in which stakeholders “choose to take an active role in the decisions that affect them” (Reed, 2008, p. 2418). The need for participation can be justified via normative and pragmatic arguments (Reed, 2008). Normative arguments are often related to the democratic right to participation (Király and Miskolczi, 2019), but also can arise from the ethical implications of building models with stakeholders (Amorocho-Daza et al., 2024; Palmer, 2017). Pragmatic arguments are related to the expected benefits of engaging stakeholders in policy-making processes, in other words, a perspective in which participation is “a means to an end”, such as enhancing the quality and durability of environmental decisions (Beierle, 2002; Reed, 2008). The latter aspect is the bridging factor between participation and policy impact. However, far from being a panacea, the successful delivery of participation “promises” is heavily context- and process-dependent (d’Hont and Slinger, 2022; Reed et al., 2017; Sarmiento et al., 2020). Narrowing down the aforementioned discussion, here we focus on the expected benefits of participation in model-based policy discussion settings around socio-environmental issues (Bots and van Daalen, 2008).

Participatory modelling settings are one of the instances in which stakeholders can take part in socio-environmental policy discussions. This generic terminology refers to the endeavour of modelling with stakeholders, very often in the context of socio-environmental issues (Videira, Antunes, Santos, and Lopes, 2010; Voinov and Bousquet, 2010). Building SES models in a participatory way is a co-creation process in which both researchers and stakeholders bring and put different perspectives and knowledge together in dialogue to improve the scope and purpose of the models (Bots and van Daalen, 2008; Norström et al., 2020; Slinger, 2023; Sterling et al., 2019; Voinov et al., 2014). Engaging stakeholders can enhance a shared understanding of complex, locally rooted, social and natural systems leading to the design of more comprehensive, locally relevant socio-environmental policies (Clifford-Holmes et al., 2018; d’Hont and Slinger, 2022; Slinger, Cunningham, and Kothuis, 2023). From a pragmatic perspective, an essential output of such dialogue is building knowledge and social capital that is reflected in the stakeholders’ commitment towards crafting and implementing informed and effective socio-environmental policies (Sterling et al., 2019). Therefore, it is critical to understand the interlinkages between participation and policy impact in the context of the SES modelling cycle (Elsawah et al., 2020).

Integrating the dimensions of uncertainty and policy impact in SES participatory modelling has proven conceptually and practically challenging, but recent advances offer promising roads ahead. Regarding the first challenge, integrating uncertainty in SES modelling, Ascough et al. (2008) set the scene by categorising various typologies and sources of uncertainty in environmental decision-making. Some of these include how knowledge uncertainty is pervasive across the modelling cycle (across the process itself, in the model, and in the modelling outputs), or the importance of linguistic uncertainty, a social aspect related to language ambiguity and vagueness in a decision-making context. More recently, Maier et al. (2016) propose that integrated uncertainty modelling needs to consider multiple future scenarios, aiming to find alternatives with *robust* performance under many plausible futures, and aim for adaptive, flexible strategies. From the participation side, there is a growing recognition of policy-relevant modelling as closely aligned with transdisciplinary participation (Moallemi, Malekpour, et al., 2020). Recent reviews show how co-produced sustainability initiatives (e.g. making use of SES models) can serve multiple purposes (Chambers et al., 2021), mirroring previous calls for adaptive and flexible strategies (Pahl-Wostl, 2007). Despite some authors highlighting the importance of participation in dealing with modelling uncertainty (e.g. Ascough et al. (2008)), or the implications of uncertainty in participatory contexts (e.g. Barnhart et al. (2018); Martinez-Fernandez, Banos-Gonzalez, and Esteve-Selma (2021); Moallemi et al. (2023)), the academic literature lacks frameworks that conceptualise the integration of both uncertainty and participation across a SES modelling cycle.

This article proposes a modelling cycle framework to support system dynamics SES modelling and policy evaluation in a stakeholder engagement context, accounting for both uncertainty assessment and participation. In addition, a range of tools and approaches are proposed at each stage in the framework to address these different facets. System Dynamics (SD) is selected as the modelling approach of choice in this context due to its analytic capabilities to simulate complex systems’ behaviour, flexibility of application, and proven use in stakeholder participatory settings (Elsawah et al., 2017). These capabilities mean that SD is being applied across various SES fields, including agriculture and natural resource management (Turner et al., 2016), water resources management (Phan, Bertone, and Stewart, 2021; Zomorodian et al., 2018), environmental health (Currie, Smith, and Jagals, 2018), and in holistic public health approaches such as One Health (i.e. health of people, animals, and the environment) (Xie et al., 2017).

Multiple similar frameworks can be designed, none of them fully comprehensive, yet here we propose a framework that aims to be useful in mainstreaming Good Modelling Practice (GMP) in the context of complex SES modelling settings. In the introductory article of this Joint Special Issue, Jakeman et al. (2024) argue that transitioning toward the widespread adoption of GMP requires enhancing reflexivity and transparency in SES modelling practices. As recognised by the authors, reaching this vision requires a whole-cycle perspective that addresses uncertainty while promoting stakeholder participation as focal points of GMP. Here we aim to contribute to such a purpose with a framework that aligns the dimensions of uncertainty and stakeholder participation into a single modelling cycle using SD. This synthesis may be useful for SES modellers in devising a modelling roadmap that explicitly engages with the implications of uncertainty in already complex participatory settings. In addition, the present framework could facilitate transparent communication regarding the model's *crafting*— that is, *how* an SES model is built and used (Jakeman et al., 2024). In other words, researchers and practitioners can use the framework to better communicate the rationale behind the decision points that drive the modelling process. Examples of suitable modelling tools and approaches are included across the different modelling phases to offer concrete ways to operationalise the framework.

2. Developing a unified SD modelling framework for SES policy evaluation

This section presents the approach to integrating uncertainty and participation in an SD modelling framework. Section 2.1 justifies this endeavour. Section 2.2 presents two modelling frameworks that engage with uncertainty and participation aspects separately. In Section 2.3, we conceptually align these frameworks into a unified framework, distinguishing three main modelling phases. Section 2.4 describes the iterative revision cycle that facilitates applying the modelling framework. Section 2.5 presents a summary of the modelling tools and techniques that can be deployed at different stages of the modelling cycle.

2.1. Why integrate uncertainty and participation in an SD modelling framework?

SD is deeply rooted in systems thinking and possesses both qualitative and quantitative attributes, making it well-suited to address the implications of uncertainty and participation in complex socio-ecological systems (Lane, 2010). The qualitative SD stream has a long history of building systems models with stakeholders, e.g. group model building and participatory modelling (Király and Miskolczi, 2019). This literature not only focuses on the output of SD participation (e.g. SD models) but also on the complexities of the process itself (Freebairn et al., 2019; Hovmand et al., 2012; Vennix, 2000), as well as on the transformative social outputs it that may derive (Hovmand, 2014; Luna-Reyes et al., 2018; Rouwette et al., 2010). The quantitative SD stream focuses on using models to make sense of complex policy questions through numerical simulation (Meadows and Robinson, 1985; Sterman, 2002). Quantitative SD models are flexible in accommodating quantitative uncertainties in the form of parameter variations, and scenario and sensitivity analyses to make sense of possible futures in a complex and rapidly changing world (Kwakkel and Pruyt, 2013b; Moallemi, Kwakkel et al., 2020). Despite a mixed qualitative and quantitative modelling approach lying at the foundation of SD (Lane, 2010; Sterman, 2002), current SD socio-environmental practice evidences a lack of such integration (Moallemi et al., 2021).

Participation and uncertainty can seem very distinct in the SD practice, yet are closely related, impacting each other. Qualitative approaches usually have a rich understanding of a problematic situation but do not benefit from the possibility of testing desired policies (under uncertainty) in a simulation environment, assessing their impacts under myriad futures. Quantitative SD that engages with uncertainty assessment offers a rich vision of the uncertain future but it can be out of context if not discussed with stakeholders who want to use the model to answer difficult questions. A recent review of SD in the context of sustainable development provides further insights on the level of integration and identifies two requisite improvements (Moallemi et al., 2021): (i) more stakeholder participation is necessary, as >70 % of SD sustainability applications do not include any form of participation; and (ii) SD could benefit from incorporating interdisciplinary perspectives, particularly by developing robust models that can explicitly deal with deep uncertainties about the future. These are important gaps that could be bridged by better integration of the qualitative and quantitative capabilities of SD, more specifically by aligning participation and uncertainty across the modelling process (Moallemi et al., 2023).

Recent advances in integrating SD approaches with other problem-structuring methods represent a way forward for an integrated multi-method perspective for policy analysis and decision-making (Rouwette and Franco, 2024). Similarly, here we propose a framework that aims to articulate the seemingly opposite features of participation and uncertainty in SD modelling. Perhaps the common thread between the two is to understand *ambiguity* as an essential dimension of uncertainty (Brugnach et al., 2008). Ambiguity implies that uncertainty is not only an issue of objective knowledge, but mostly about *whose* knowledge is considered. In short, considering ambiguity implies that uncertainty is also an issue of knowledge plurality. This is particularly relevant for SES-related issues, in which people and the environment are so intertwined that local stakeholders should have a say in modelling endeavours that could be used to inform policies that affect them (Amorocho-Daza et al. 2024).

Such a broader perspective on uncertainty bridges model-related uncertainty, which focuses on quantitative aspects like parameters and scenarios, with participatory uncertainty that arises from the deliberation on the problem and potential solutions. Uncertainty, therefore, manifests in both the quantitative and qualitative dimensions of SD modelling practice, yet it is often treated separately. This paper aims to align and integrate these two dimensions into a coherent modelling cycle as a GMP. More specifically, here we contribute to normalising GMP by exploring the interactions between uncertainty and participatory aspects in SD modelling and how they can be understood and structured in the context of a modelling framework.

2.2. Two SD modelling frameworks incorporating participation and uncertainty

SD practice conceptualises the different stages in a structured, iterative modelling process as a cycle. It is only recently that uncertainty has been considered across the SD modelling cycle. This research builds upon the SD modelling cycle proposed by Auping (2018) which consists of a five-step cycle modifying the steps of Sterman (2000): (1) Problem articulation; (2) Conceptualisation; (3) Formulation; (4) Evaluation; and (5) Policy Testing. A strength of this new approach lies in incorporating uncertainty throughout this cycle. Fig. 1a depicts the inclusion of uncertainty in SD modelling.

At the same time, a comprehensive participatory SD modelling framework should involve stakeholders throughout. This paper builds on the framework of Videira et al. (2010), as a relevant SD-based participatory framework in the context of sustainability. The Videira et al. framework considers various phases, including: (1) Scoping and abstraction; (2) Envisioning and goal setting; (3) Model formulation and confidence-building, (4) Simulation and assessment, and (5) Evaluating

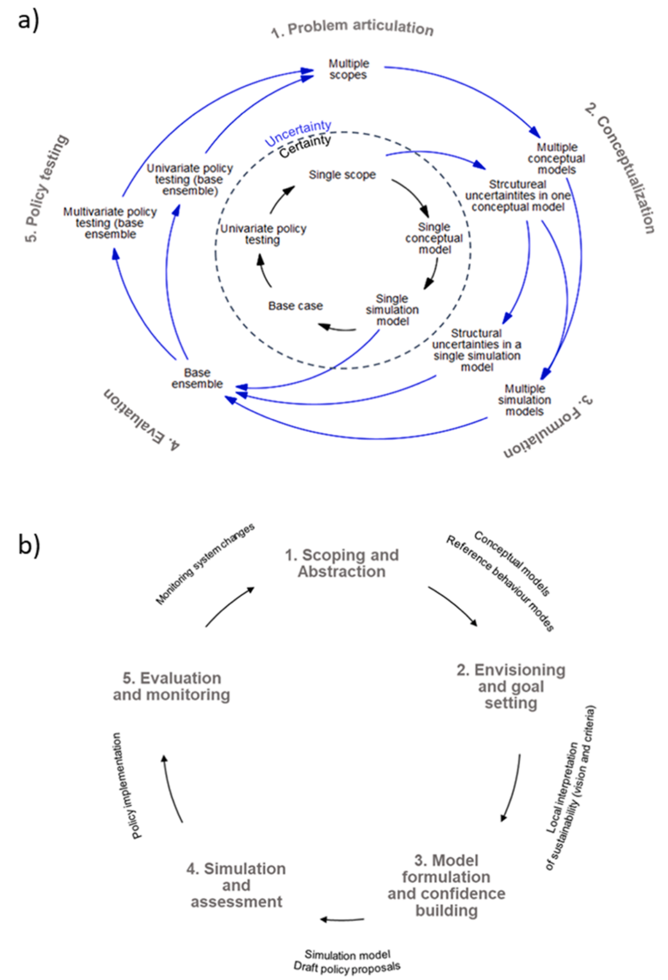

Fig. 1. System dynamics modelling frameworks for (a) considering uncertainty in the model development cycle (modified from Auping (2018)) and (b) implementing a participatory approach (modified from Videira et al. (2010)).

and monitoring. The approach identifies how the outputs of each phase become inputs for the next phases. For example, conceptual models (Mirchi et al., 2012; Purwanto et al., 2019) from the “Scoping and abstraction” phase can be useful in the “Envisioning and goal setting” phase. Fig. 1b summarises the SD participatory modelling framework.

This paper aligns the modelling cycle under uncertainty proposed by Auping (2018) with the participation stages identified by Videira et al. (2010). We integrate both approaches into a single modelling framework accounting for both participation and uncertainty analysis with two main variations. First, we adapt Auping’s (2018) problem articulation phase by not only recognising multiple scopes in the modelling process but also aiming to integrate them into a negotiated scope that will guide the rest of the process. This aims to synthesise the various scopes that emerge within a multi-stakeholder setting (Ackermann, 2012; Rosenhead, 2006). Despite being challenging, this effort is consistent with a paradigm of dialogical learning in socio-environmental participatory modelling (Brugnach et al., 2011; Brugnach and Ingram, 2012). Second, we exclude the last stage of the Videira et al. (2010) cycle (“Evaluating and monitoring”) as the current framework is oriented to policy decision analysis rather than the implementation and subsequent evaluation of policy actions in the environmental system itself. This simplification remains consistent with recognising the importance of linking model-based analysis with policy implementation, which becomes evident when viewing policy-making as a multi-stage iterative process (see Walker et al. (2003) and Sterman (1994; 2000, p. 88)). This article solely addresses the model-based policy cycle, which is nested within the broader policy implementation process.

2.3. A unified SD modelling framework aligning participation and uncertainty

A participatory modelling framework to integrate SD with other modelling tools to support SES policy decision-making under uncertainty is presented (Fig. 2). By adapting and extending the approaches proposed by Auping (2018) and Videira et al. (2010), this *unified* framework considers the implications of uncertainty and stakeholder participation in SES modelling. Fig. 2 shows the unified modelling cycle and a suggestion of modelling tools that can be useful in each part of the cycle. The innermost part of Fig. 2 highlights the structural implications of uncertainty (see Fig. 1a). The *traditional* modelling cycle is shown in the inner ring. The outer ring represents the stages of stakeholder participation, mapped to both the modelling cycle and how uncertainty plays a role. The outer *gears* refer to potentially suitable tools, methods, and techniques that could be implemented at each stage. A detailed account of each of the cycle’s phases follows. The dynamic interconnectedness between the (SD) modelling cycle and the stages of stakeholder participation is apparent in Fig. 2, with each of the participation and modelling stages influencing and complementing each other.

Three distinct phases facilitate the analysis of the interactive nature of dealing with uncertainty and participation in SD. The first *modelling foundations* phase focuses on all the activities developed before starting a quantitative modelling exercise, such as defining and conceptualising the issues at hand, and defining desirable futures in which such issues are addressed. The second phase, *model building and testing*, deals with the intricacies of crafting and testing a quantitative model within the boundaries and purposes defined in phase one. The third and last phase, *model use and policy evaluation* involves the use of the quantitative model, particularly as a decision-support tool to test policy alternatives to deal with the issue identified in phase one. Below we present a detailed account of the activities in each phase.

The modelling cycle is an idealised version of logical, step-wise phases and stages that go from defining a problem to selecting a solution. A disclaimer is that implementing such a cycle will be *messy* in reality. In a practical case, we would expect feedback and reprocessing across and within the modelling stages. A second point of attention is that this cycle can only take place in a participatory setting where the interested parties (i.e., stakeholders and modellers) agree on the modelling process, an approach in line with what other authors have called a *dialogical learning strategy* (Brugnach et al., 2011). Agreeing on the process implies valuing the rationale behind the participatory modelling exercise; it does not mean agreeing on other specific aspects such as the problem definition or the key variables to be considered. However, not agreeing on the process also implies that parties who do not agree may need to withdraw from the modelling process and that engaging them will require other strategies (Brugnach et al., 2011). This practical implication demonstrates that a participatory modelling process occurs within a larger policy arena (see McEvoy, 2019, pp. 32–36).

A useful conceptualisation for the relevance of a participatory modelling process is to understand it as nested within a larger policy implementation cycle (Sterman, 2000; Walker et al., 2003). In other words, a policy recommendation arising from a modelling exercise can be ideally implemented and monitored, as part of a larger policy implementation cycle. SD researchers and practitioners have continuously pursued policy relevance since the field’s inception (Buzogany, Kopainsky, and Gonçalves, 2024; Forrester, 1994, 2007; Ghaffarzadegan, Lyneis, and Richardson, 2010). Here we aim to contribute towards this overarching objective by proposing a structured approach to support socio-environmental policy-making. Yet, our proposed framework does not offer a guide for policy implementation, monitoring, and evaluation. Understanding this limitation is crucial for building bridges between policy evaluation and application. Hence, our proposed three-phase framework can better elucidate the essence of what a

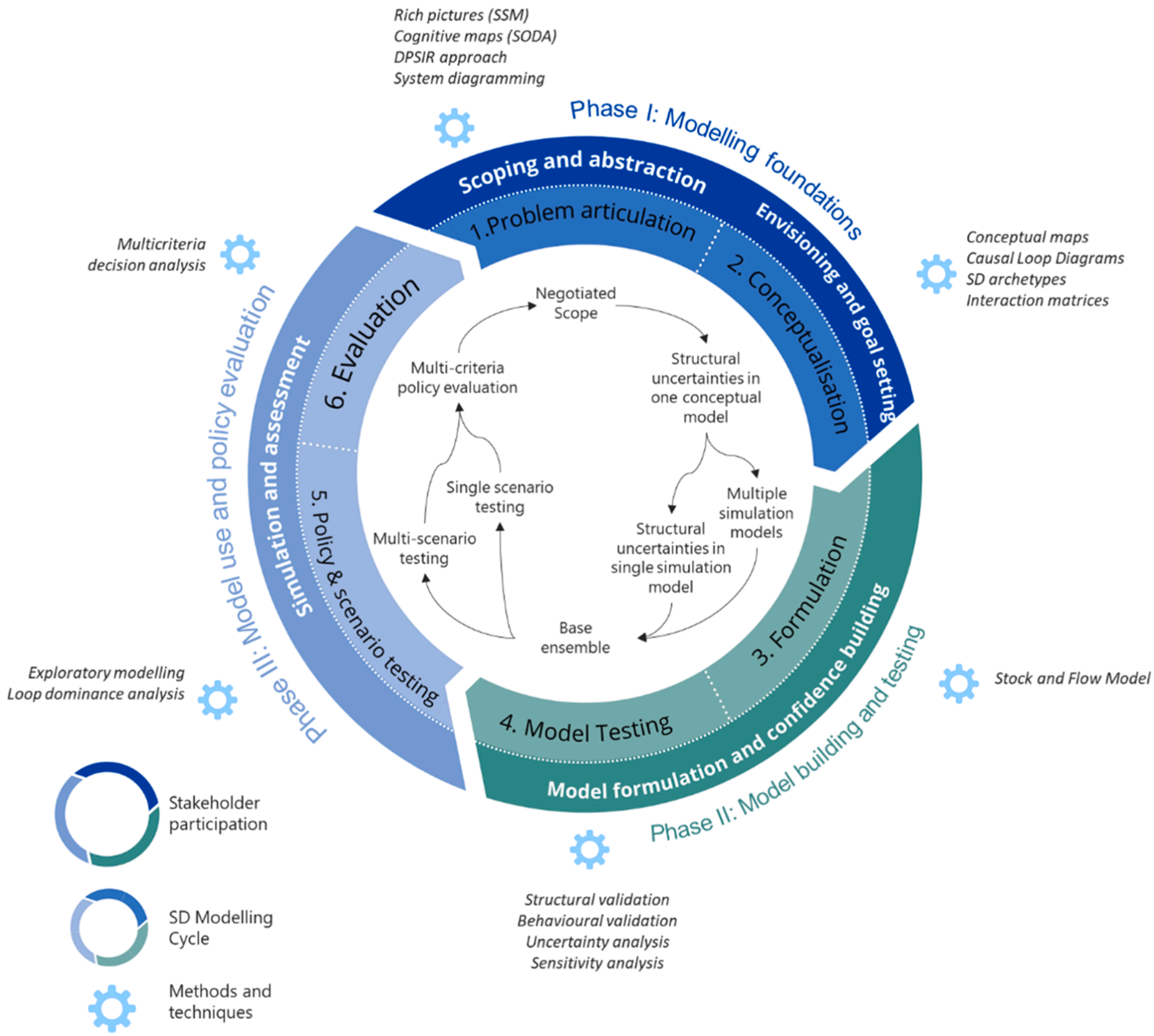

Fig. 2. The unified SD modelling framework distinguishes three primary phases in the modelling cycle: Modelling foundations (dark blue), Model building and testing (green), Model use and policy evaluation (light blue) and comprises the modelling process cycle (inner circle) under uncertainty (circle centre) (adapted from Auping (2018), stakeholder participation (outer circle) (adapted from Videira et al. (2010)) and relevant modelling tools (outer 'gears').

modelling exercise can offer within a larger socio-environmental policy setting.

2.3.1. *Phase I: modelling foundations*

During phase I, the modelling foundations are established. Here we first describe the corresponding stages of the SD modelling cycle under uncertainty, followed by the parallel modelling stages using a participatory modelling perspective.

2.3.1.1. *SD modelling under uncertainty (inner circle and centre in Fig. 2).*

Two stages are relevant for establishing modelling foundations using a modelling cycle under an uncertainty approach: problem articulation, and conceptualisation.

2.3.1.1.1. *Problem articulation.* The problem articulation phase defines the model's purpose (Sterman, 2000) or "aims at articulating the central problem which needs to be researched" (Auping, 2018, p. viii), and determines the next phases in the cycle. Auping (2018) highlights that as SD usually deals with *wicked* problems, multiple scopes (potentially leading to multiple models) could be suitable for studying a problem under uncertainty. The involvement of various stakeholders with differing perspectives in socio-environmental debates often results in multiple, sometimes conflicting, framings and scopes, leading to ambiguity (Dewulf et al., 2005), another dimension of uncertainty (Brugnach et al., 2008). Brugnach et al. (2011) identified various strategies that can be used to cope with such ambiguity: rational problem-solving, persuasion, dialogical learning, negotiation and opposition. From the previous list, a participatory modelling approach is primarily consistent with a dialogical learning strategy, as it assumes that stakeholders have a legitimate interest in co-producing a model in an active dialogue with their counterparts (Amorocho-Daza et al., 2024; Videira et al., 2010). Accordingly, a stakeholder dialogical strategy facilitates a transition from multiple problem scopes to a joint problem definition (i.e. negotiated scope) that is meaningful and relevant for the participants in the overarching process (Brugnach et al., 2011). In this paper, we consider that problem articulation under ambiguity (a dimension of uncertainty) involves integrating multiple scopes (i.e. Auping (2018)) rather than simply adopting a single scope (i.e. Sterman (2000)) into a negotiated scope arising from stakeholder dialogue (Ackermann, 2012; Rosenhead, 2006).

2.3.1.1.2. *Conceptualisation.* The conceptualisation phase's primary aim is to identify the main relations between key variables, which often build on the mental models of stakeholders and experts (Auping, 2018), demonstrating a clear link to stakeholder participation. Mental models are "internal representations of external reality that people use to interact with the world" (Jones et al.,2011, p. 1). During conceptualisation, mental models are translated into tangible conceptual representations. Tools like conceptual maps and causal loop diagrams help visualise and characterise system relationships (Ford, 2010; Voinov et al., 2018). However, collaborative conceptualisation is a complex process itself (Luna-Reyes et al., 2006). To cope with it, SD practitioners use *scripts*, as a "tool for helping facilitation teams visualize and solve problems in the design of group model building sessions" (Hovmand et al., 2012, p. 183). Hovmand et al. (2012) initiated a collaborative platform, *Scriptapedia*, to document and expand the group model-building practice in the SD community. An example of the deployment of a group model-building script in the context of a contested socio-environmental system is described in Purwanto et al. (2019).

Modelling scripts are helpful in structuring the use of complementary tools to support system conceptualisation with multiple stakeholders. Choosing among which tools to use varies on a case-to-case basis, but the display of such tools needs to happen in a structured and purposely crafted way. Tools and techniques useful to support the conceptualisation process include the use of SD archetypes (Mirchi et al., 2012); interaction (or causal) matrices (Sanò, Richards, and Medina, 2014); and more general methods such as participatory scenario planning and SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis (Barnaud et al., 2013; Ritzema et al., 2010; Voinov et al., 2016).

The conceptualisation phase deals with uncertainty in different dimensions. First, as conceptualisation follows problem formulation, it is also subject to the ambiguity derived from the presence of multiple stakeholders, and therefore, multiple mental models (Brugnach et al., 2011). Thus, participatory system conceptualisation is not a deterministic task; rather, it depends on the participants involved, the facilitation method employed (e.g. scripts), and notably, the interaction among stakeholders throughout the process. Knowledge, or epistemic, uncertainty is also present due to the limited knowledge about the system components and their interactions. Conceptualisation is the first stage in which structural uncertainties (i.e. how model variables are connected/related) are identified to be assessed in later stages of the modelling cycle. This is evident in discussions about the polarity and global relevance of certain variable relations and feedback loops in causal loop diagrams (CLDs) (Sanò et al., 2014). This challenge can inspire early conversations on how to account for *scenarios* (e.g. changes in external influences, new variables, relations and influences to consider) from the beginning of the modelling cycle. In sum, embracing ambiguity and knowledge uncertainty implies the recognition of going beyond a *deterministic*, to a *structurally uncertain* conceptual model.

2.3.1.2. Stakeholder participation (outer circle, Fig. 2). Two stages are relevant for establishing modelling foundations using a participatory modelling approach: scoping and abstraction; and envisioning and goal setting.

2.3.1.2.1. Scoping and abstraction. The scoping and abstraction phase relates to the problem articulation and conceptualisation stages of the modelling cycle. Scoping or framing a problematic socio-environmental situation is not an objective exercise (Dewulf et al., 2005; Dewulf, Craps, and Dercon, 2004), as it deals with important value-related questions that will frame the rest of the modelling process (Amorocho-Daza et al., 2024; Gregory et al., 2020). Abstraction-related activities coincide with the conceptualisation stage in the modelling cycle, as they depart from a problem situation and aim to translate stakeholders' mental models of the problem into qualitative models based on a deliberation process (Vennix, 2000). At this stage, uncertainty is evidenced by the ambiguity arising from multiple problem frames, as well as by the limited knowledge regarding the variables (and their interaction) that are relevant to understanding the problem itself. Problem structuring methods (PSMs) are helpful to engage with the aforementioned complexities.

PSMs are qualitative approaches to making sense of ill-structured problems (Smith and Shaw, 2019), i.e. problems arising from "situations characterised by multiple actors, differing perspectives, partially conflicting interests, significant intangibles and perplexing uncertainties" (Rosenhead, 2006, p. 762). PSMs have been established in the management literature for over 40 years (Mingers, 2011; Smith and Shaw, 2019), and they remain relevant across several fields of research and practice (Gomes Júnior and Schramm, 2021; Mingers and White, 2010). The three most established PSMs are Soft Systems Methodology (SSM), Strategic Options Development and Analysis (SODA) and the Strategic Choice approach (Ackermann, 2012; Wright et al., 2019). However, other frameworks such as DPSIR (Drivers, Pressures, State, Impact and Response) (Bell, 2012) and systems diagramming (Enserink et al., 2022; van der Lei et al., 2011) can be deployed as PSMs. A recent review indicates that the primary applications of PSMs are found in the business management domain, while environmental applications are relatively scarce, comprising only 17 % of the reported case studies in academic literature (Gomes Júnior and Schramm, 2021). Relevant applications of PSMs in complex socio-environmental problems have been reported using different methods: SSM (Bunch, 2003; Suriya and Mudgal, 2012), SODA (Elsawah et al., 2015; Hjortsø, 2004), and DPSIR (Gregory et al., 2013; Wantzen et al., 2019).

Scoping and abstraction activities often result in building qualitative system representations that give a rich understanding of the problem under consideration. Examples of these representations are the *rich pictures* of SSM (see Bunch (2003)) or the *collective cognitive maps* of SODA (see Elsawah et al., 2015) or the *systems diagrams* of policy analysis (Enserink et al., 2022; van der Lei et al., 2011). These representations can be integrated with other tools as part of a broader modelling cycle (Elsawah et al., 2015; Howick and Ackermann, 2011; Nijmeijer, 2018; Rodriguez-Ulloa and Paucar-Caceres, 2005). For instance, a PSM (e.g. SSM) can be incorporated into the SD modelling cycle in the shape of qualitative system representations such as causal loop diagrams (Paucar-Caceres and Rodriguez-Ulloa, 2007). Building such qualitative models has several benefits, including (a) adding rigor to the analysis and discussion; (b) scoping a concise and shared understanding of a problem; (c) serving as a group memory of participatory sessions (Vennix, 2000). However, both individual and group dimensions are sources of 'messy problems' in participatory modelling settings (Vennix, 2000). This is why successful participatory modelling sessions with stakeholders should have structured planning, often in the form of SD scripts (Andersen and Richardson, 1997; Hovmand et al., 2012; Luna-Reyes et al., 2006), and facilitators with the right set of attitudes and skills (Vennix, 2000) to arrive at an adequate scoping and abstraction of a socio-environmental problem in the form of a meaningful system representation (Sterling et al., 2019).

In summary, scoping and abstraction activities within a participatory process offer a meaningful approach to navigating the complexity of socio-environmental problems and the ambiguity arising from the multiple possible frames to define them. By engaging with a rich problem definition, abstraction follows as a way to a shared understanding in the form of a qualitative system representation. This highlights the essential connection between an active stakeholder dialogue and uncertainty (i.e. ambiguity), even before defining the first equation of a quantitative environmental model.

2.3.1.2.2. Envisioning and goal setting. After scoping a problem and advancing in its conceptualisation, the engagement of stakeholders in SES will focus on envisioning and goal setting. The purpose of this phase is to develop shared visions of the future of the system, and discuss sustainability criteria (Videira et al., 2010). Visioning engages with uncertainty by connecting current trends to (un)desired futures (Slinger et al., 2023). Conceptualisation can go beyond current issues by considering future trends. This activity can take place in stakeholder workshops and encourage the use of conceptual maps and CLDs as a common ground to discuss and set priorities for later stages of the modelling cycle (e.g. formulation and evaluation). This stage might be the starting point to ask questions related to simulation capabilities (e.g. what will the simulation model be able to measure?) and policy opportunities (e.g. which kind of policy interventions are associated with a desired future?). Discussions around the concept of sustainability may reflect stakeholders' values and preferences. A discussion around sustainability could help stakeholders to clarify "*what* they want to sustain and *for how long*" (Stave, 2010, p. 2765). Sustainability policies can have goals that reflect diverse values, such as integration, anticipation, precaution, participation, and equity (Gasparatos, El-Haram, and Horner, 2008). The deliberation should end with a context-specific interpretation of sustainability (Videira et al., 2010). This will be crucial for later stages of the modelling cycle (i.e. policy - scenario testing and evaluation).

2.3.2. Phase II: model building and testing

During phase II the model is built and tested. Here we first describe the corresponding stages of the SD modelling cycle under uncertainty, followed by the parallel modelling stages using a participatory modelling perspective.

2.3.2.1. SD modelling cycle under uncertainty (inner circle and diagram, Fig. 2). Two stages are relevant for building and testing the model using a modelling cycle under uncertainty: formulation, and model testing.

2.3.2.1.1. Formulation. During model formulation, the model is specified mathematically and simulated using computational tools (Auping, 2018; Sterman, 2000). An SD simulation model is a quantitative representation of the variables and relations that were identified during conceptualisation with each variable and relation specified in terms of stocks, flows and associated parameters. The resulting system of non-linear first-order differential equations, visualised as a Stock and Flow Model (SFM), is solved numerically to yield graphs of the time varying dynamics of the complex system (Banks and Slinger, 2011; Ford, 2010 - Part I). Much of the SD literature covers the conceptual and mathematical foundations that underlie the relations between a system's stock structure and the dynamic behaviour emerging from it (Ford, 2010 - Part I; Meadows, 2008 - Part I; Naugle, Langarudi, and Clancy, 2024; Sterman, 2000 - Parts II-V). Conceptual models serve as a guide to formalising a quantitative model of a system. The translation process can be challenging because not every detail of the conceptualisation can be formally quantified. Therefore, model formulation requires balancing the complexity reflected in the CLD with the simplicity needed for quantification (Amorocho-Daza et al., 2024). Freebairn et al. (2019) propose a conceptual framework focused on this challenge.

Formulating an SD modelling exercise under uncertainty builds on the structural uncertainties identified during the first phase of the modelling cycle. More specifically, having a structurally uncertain CLD that reflects the complexity of the issue and the intrinsic ambiguity of its conceptualisation has implications for the formulation phase. Auping (2018) highlights that structural uncertainty can be captured in single or multiple models derived from a structurally uncertain CLD. A single quantitative simulation model can incorporate uncertainty in different ways. As the modelling exercise enters the quantitative realm, a quantitative assessment of uncertainty becomes possible, for example, in the form of statistical and scenario uncertainty. Statistical uncertainty may be captured by variations in models' parameters (Ford and Flynn, 2005; Kwakkel and Pruyt, 2013a). Scenario uncertainty uses scenarios to capture diverging trends or driving forces beyond the model's scope, such as climate change or socioeconomic pathways (Moss et al., 2010). Maier et al. (2016) highlight conceptual and practical aspects of considering statistical and scenario uncertainty in the context of modelling under deep uncertainty. Furthermore, considering multiple models might be an option when having a single simulation model is unfeasible or undesirable. This, however, comes at the cost of increasing the analysis complexity at later stages in the modelling cycle, such as when using the model for decision-making.

2.3.2.1.2. Model testing[1]. The model testing phase aims to increase stakeholder confidence in the model (Forrester and Senge, 1980), further demonstrating the link to stakeholder participation. During this phase, various tests are performed to check whether the model has been correctly constructed (i.e., verification) and whether it is fit for purpose (i.e., validation) (Auping, 2018). Not limited to statistical validation, structural and behavioural validation tools are suitable for this purpose (Forrester and Senge, 1980). After testing, the model is acknowledged to reproduce the general behaviour of the system. This is often done via a base modelling run representing the behaviour of the variables of interest over time.

Incorporating uncertainty during model testing involves moving beyond a base case, to a base ensemble. A base case results from a single (deterministic) run of the simulation model for specific variables of interest. In contrast, an uncertainty approach considers a base *ensemble*, a set of bundled simulations, that capture multiple modelling runs (from individual or multiple models) that represent a broad spectrum of system trajectories to understand the range and distribution of the output variables of interest when the parameters and structure of the model are considered stochastic (Auping, 2018; Bankes, 2002; Kwakkel and Pruyt, 2013a; Maier et al., 2016). Fig. 3, illustrates how a system can have different trajectories in different scenarios, but there is statistical uncertainty associated with each of the trajectories, illustrated by the translucent bands (Fig. 3). In sum, instead of simulating a single future, an ensemble of model runs (in different scenarios) is a relatively straightforward way to represent several possible futures based on a wide range of model outcomes and scenarios. In addition to the aforementioned uncertainty analysis, performing a sensitivity analysis can provide additional insights into the main factors (parameters) which drive the model's overall output uncertainty (Saltelli et al., 2019). Sophisticated methods for testing the sensitivity of the models' outputs to changes in (non-linear) graphical functions are also available (Eker, Slinger, van Daalen, and Yücel, 2014).

Having a range of plausible values for a variable of interest provides

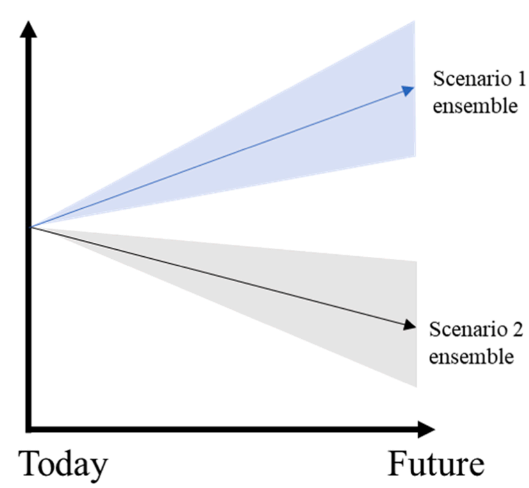

Fig. 3. Conceptual representations of statistical and scenario uncertainty, the two trends represent diverging scenarios with increasing uncertainty over time (shaded area), modified from (Maier et al., 2016).

[1] A change in the terminology from Auping (2018) is proposed: "Model testing" is proposed instead of "Evaluation". This change is similar to the terminology originally proposed by Sterman (2000). The term "Evaluation" is used for the last stage in the modelling cycle in Fig. 2.

richer modelling results to stakeholders when compared with a single model-run approach. This might enable discussions to determine if such a range is consistent with real-world expectations or available data, thereby providing an opportunity for exploring empirical grounds for validating the modelling outputs. Nonetheless, this expected benefit comes at the cost of communicating quantitative uncertainty features to a diverse stakeholder audience, likely unfamiliar with such jargon and thinking (van der Bles et al., 2019). Another point of attention arises when only ranges are considered in the ensemble. In such a case, the system's intrinsic behaviour may be difficult to observe or may even be obscured. This practice may limit the observation of recurrent modes of dynamic behaviour (e.g. a system that exhibits oscillation vs. goal seeking), important in SD practice (Mirchi et al., 2012; Sterman, 2000).

2.3.2.2. Participatory modelling cycle (outer circle, Fig. 2). There is one relevant stage for building and testing the model using a participatory modelling approach: model formulation and confidence building.

2.3.2.2.1. Model formulation and confidence building. During the formulation and model testing phases, the qualitative models developed with stakeholders are translated into simulation models while gaining confidence in their capabilities (e.g. see model testing section above). Collaborative SD development may foster learning, co-production of knowledge and development of innovative solutions (Videira et al., 2010). However, this process involves a tension between complexity (the system described in causal loop diagrams) and simplicity (i.e. feasibility of creating a simulation model based on such diagrams) (Barreteau et al., 2014; Freebairn et al., 2019). Freebairn et al. (2019) propose a structured process to guide this translation process illustrated with a case study. In a context with uncertainty, stakeholders and analysts should agree on how to best estimate parametric uncertainty, as well as possibly formulate various simulation models that account for structural uncertainty.

Stakeholders can increase their confidence in the simulation model by providing input about a model's *structure* and its capabilities in representing the *behaviour* of the real system. Freebairn et al. (2019, p. 16) also highlight the importance of this phase and describe it as a process of "engaging with and communicating the model's results". Slinger (2023) provides a detailed and practical illustration of validation activities in an SES participatory modelling setting. The model testing process can go beyond a deterministic assessment and integrate the dimension of uncertainty by going from a base case to a base ensemble (described above). Stakeholders can discuss the quantitative effect of uncertainty in terms of output variables' ranges, but qualitative understanding can also be valuable, for example, by assessing possible changes in the system's modes of behaviour due to parametric variation in some of the simulations (Kruseman Aretz, 2023; Nava Guerrero, Schwarz, and Slinger, 2016).

2.3.3. Phase III: model use and policy evaluation

During Phase III, the model is put to use and can support policy evaluation. First, we describe the corresponding stages of the SD modelling cycle under uncertainty, followed by the parallel modelling stages using a participatory modelling perspective.

2.3.3.1. SD modelling cycle under uncertainty (inner circle and diagram, Fig. 2). Two stages are relevant for model use and policy evaluation using a modelling cycle under an uncertainty approach: policy and scenario testing, and evaluation.

2.3.3.1.1. Policy and scenario testing[2]. At this stage, the model is used to test policies under different scenarios. Policies are intended changes to modify the system's performance (Sterman, 2000). Scenarios represent exogenous visions of the future, for example in terms of climate change and/or socio-economic development (Enserink et al., 2022; Moss et al., 2010). Scenario thinking is increasingly critical in the discussion around SES (O'Neill et al., 2020). Therefore, accounting for the performance of policies in various climate and societal pathways provides a better understanding of the system's exogenous sources of uncertainty (Wu, Elshorbagy, and Alam, 2022). Following the Maier et al. (2016) conceptualisation, engaging with both endogenous and exogenous sources of uncertainty requires estimating endogenous uncertainty on top of different scenarios (see Fig. 3). This allows for estimating initial base ensembles (see Phase II, model testing). In other words, it is possible to consider various scenarios (exogenous uncertainty) and explore their associated parametrical variability (endogenous uncertainty).

At the policy testing stage, the base ensemble can be compared with a 'policy ensemble' to explore how activating policies may affect system behaviour compared to the base ensemble scenario. This relatively straightforward approach is known as the *design of experiments* in the exploratory modelling literature. However, the exploratory modelling perspective offers a repertoire of approaches that combine different strategies based on the assumptions made about the decision and uncertainty space (Moallemi, Kwakkel, et al., 2020). This perspective actively engages with exploring robust policies—those that perform well regardless of deep uncertainty conditions (Kwakkel, Walker, and Haasnoot, 2016; Moallemi, Kwakkel, et al., 2020).

Other analytical approaches can be useful at the policy testing stage. For example, system interventions, i.e., policies, can be designed based on the leverage points proposed by Meadows (1999). Policies can be designed to deal with shallow (at the level of parameters and feedback structures) or deep (at the level of design and intent) leverage points (Abson et al., 2017). Shallow points can be easily incorporated into an SD model. For example, some authors have suggested that policy testing can be made more systematic and automated by evaluating changes in multiple parameters to achieve a desired outcome (Auping, 2018; Moallemi, Kwakkel, et al., 2020). A more efficient approach according to Meadows would be to focus on dominant feedback loops that drive the system's behaviour. Tools such as "Loops that Matter" facilitate this identification to focus on policies that directly intervene in dominant loops to obtain the desired effects on the system (Schoenberg, Davidsen, and Eberlein, 2020). Deeper leverage points in the domain of design (e.g. rules of the system and information flows) are effective in creating wide system changes (Abson et al., 2017), and may potentially be incorporated in a quantitative SD model. However, despite the potentially transformative efficacy of the deepest leverage points, they remain difficult to capture in policies. Formulating a co-creation dialogue in which increasingly deeper leverage points are considered, and incorporated into SD model structures, would likely provide learning opportunities on ever-effective changes in SES.

2.3.3.1.2. Evaluation[3]. In the evaluation phase, policies are evaluated and ranked according to stakeholders' priorities. Contrary to Sterman (2000), the current framework decouples policy testing from policy evaluation. Practicality is one reason, as there is already substantial complexity in the stage of *policy and scenario testing* (under uncertainty). Second, the evaluation phase resembles a decision analysis or decision-making process that can be done outside the SD simulation environment (Slinger and van Daalen, 2003). The Multi-Criteria Decision Analysis (MCDA) approach is useful for addressing the challenge of structuring decision-making problems with multiple alternatives, indicators and objectives, particularly in complex socio-environmental settings (Amorocho-Daza et al., 2019; Giove et al., 2009; Lahdelma, Salminen, and Hokkanen, 2000). Indeed, the SD approach can provide a

[2] A change in the terminology from Auping (2018) is proposed: "Policy and scenario testing" is proposed instead of "Policy testing" to explicitly account for the interaction between policies and scenarios.

[3] This phase was not included in the framework of Auping (2018). The term "Evaluation" is inspired by Sterman (2000), who proposes to include "policy formulation and evaluation" in a single phase.

simulation environment where it is possible to go from *what if* policy exploration towards more structured decision-making (Phan et al., 2021). Coupling SD models with MCDA methods represents a research opportunity to expand SD capabilities in complex decision-making problems (Elsawah et al., 2017; Phan et al., 2021; Zomorodian et al., 2018). SD can be merged with MCDA by, for example, deriving indicators and scenarios directly from the SD models while estimating relevant criteria and their weights in discussion with stakeholders. Yet, relatively few case studies showcase this integration in fields such as water resources management (Elshorbagy, 2006; Momeni et al., 2021; Xi and Poh, 2014) and solid waste management (Gul and Haydar, 2024).

Performing the evaluation stage under uncertainty adds a layer of complexity to the decision-making process. While traditional MCDA assumes deterministic conditions to structure the decision-making process, emerging advances examine how it is possible to consider uncertainty in the evaluation of policies (Durbach and Stewart, 2012). Some literature case studies illustrate how to incorporate quantitative uncertainty in MCDA using stochastic parameters (Scholten et al., 2015) and scenarios (Lienert et al., 2015; Ram, Montibeller, and Morton, 2011). This stage of the modelling cycle offers the opportunity to incorporate the estimated quantitative uncertainties from the SD model through both statistical and scenario analyses into a structured decision-making approach. It is noteworthy that when undertaken within the SD modelling cycle under uncertainty process, such a structured and computationally based decision analysis does not necessarily involve multiple stakeholders.

2.3.3.2. Stakeholder participation (outer circle, Fig. 2). There is one relevant stage for model use and policy evaluation using a participatory modelling approach: simulation and assessment.

2.3.3.2.1. Simulation and assessment. During the final phases of the participatory SD modelling cycle that concentrate on policy and scenario testing as well as evaluation, stakeholders are involved in assessing the outcomes of model simulations. This contrasts with the SD modelling cycle under uncertainty where the inclusion of stakeholders in the evaluation phase is optional. However, Lahdelma et al. (2000) consider assessing policies against multiple criteria a difficult task that requires structured approaches and stakeholder participation. Accordingly, in the simulation and assessment phase, SD modelling can be combined with other methods so that the performance of policy initiatives in complex socio-environmental settings can be evaluated effectively. As described above, multi-criteria decision analysis techniques help bring structure to the evaluation process (Videira et al., 2010). Likewise, considering long-term diverging system trajectories can help to account for structural uncertainty in policy evaluation (Moss et al., 2010). For instance, recent modelling efforts have assessed critical socio-environmental issues considering multiple socioeconomic and climate scenarios (Alizadeh, Adamowski, and Inam, 2022; Graham et al., 2020). Integrating scenarios in a MCDA support framework is an approach that promises to improve policy evaluation (Ram et al., 2011), and can help stakeholders to prioritise amongst many potentially feasible options.

Here, the criteria and priorities identified in the *Envisioning and goal-setting* stage are operationalised to serve as criteria for assessing the performance of the different policies considered. The engagement of stakeholders across the model-building process may increase their confidence in the model outcomes. This, in turn, is expected to increase the likelihood of using SD models as decision-support tools to engage in desired policy paths (Stave, 2010). Participation is therefore key for moving from concept to action in SD applications (Stave, 2002). Participatory modelling may enhance not only stakeholders' general understanding of the system but, more specifically, their awareness about the likely outcomes of policy changes that they help to design and test. Despite the achievement of these potential benefits being a desired outcome of the participatory process, engaging stakeholders up to this stage remains a challenging endeavour as it requires acknowledging and addressing both the methodological and social complexity of the participatory modelling process (Voinov and Bousquet, 2010).

By bringing people together to identify relevant criteria to assess policies, uncertainty appears again in the form of ambiguity. Here we move back into the realm of values and subjective priorities that dominate the early stages of the modelling cycle (Amorocho-Daza et al., 2024). Recent research suggests that enlarging the value and time spectrum (e.g. considering intra-intergenerational justice) in complex socio-environmental issues has several implications for model-based decision-making (Jafino, Kwakkel, and Taebi, 2021). Interestingly, even a single decision-maker can show inconsistency in ranking criteria and alternatives when they are framed distinctly (Tversky and Kahneman, 1981). Recent research shows that the framing effect also occurs when stakeholders establish priorities for environmental problems with a focus on future generations (Kuroda et al., 2021). Therefore, the estimated criteria weights after deploying an MCDA are inherently uncertain (Durbach and Stewart, 2012). Exploring policy ranking variation via sensitivity analysis over the weights and reframing questions of value (e.g., in terms of benefits vs. losses or present vs. future generations) can offer insights and trigger discussions about which policies seem to be more desirable and *robust* in the face of uncertainty.

2.4. Iterative revision

The 6-step SD modelling cycle (inner circle, Fig. 2) can itself be understood as an adaptive feedback cycle or iteration (Fig. 4). In the first iteration of the cycle (blue arrows, Fig. 4) all phases from problem articulation to evaluation are executed, after which a second iteration (dashed green arrows, Fig. 4) can be considered as a refinement guided by stakeholders' feedback and evaluation. The main purpose of the initial cycle is to build and gain confidence in a model (or a set of differently structured models) that accurately represents the behaviour of the system. The revision iteration focuses on enhancing the capabilities of the model(s) as a decision-support tool. Therefore, the emphasis of the revision cycle is on adapting the simulation model(s) to test new policies or incorporate new insights of interest to the stakeholders. Often, the revision is quicker than the initial cycle, as it does not focus on conceptualisation nor on model testing. Instead, it is assumed that the changes proposed by the stakeholders can either be included fairly easily in a revision of the model(s) or can be simulated directly in the existing model(s). This is a plausible assumption as the overall structure of the

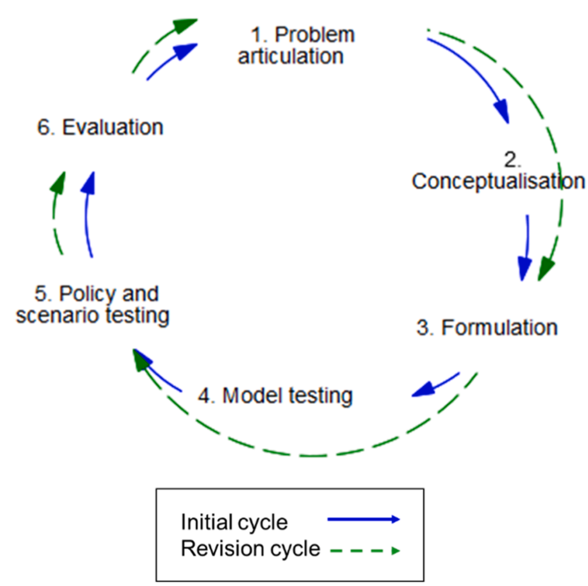

Fig. 4. Initial and revision iterations of the SD modelling cycle.

complex social-ecological issue is already systemically captured in the simulation model(s). Likewise, an extensive model testing phase is not required because (i) each model has already been tested and (ii) the stakeholders' confidence in the capabilities of the model(s) is already established.

The iterative steps described above can be understood through the concept of *self-reference* (Hofstadter, 1979). That is, the modelling process evolves in reference to itself. This idea becomes clearer once we distinguish between a problem situation and a problem-solving system (van Daalen and Bots, 2010). For instance, a problem situation can be an SES issue; such as water pollution affecting human and environmental health. In contrast, a problem-solving system could be formed by actors that participate in a policy analysis process and how they interact among themselves and with models of the issue; for example, this could involve a riparian community, local public servants, and a group of modellers collaborating to develop a model for supporting decision-making about water quality and health concerns. The self-reference perspective helps to highlight that it is the people engaged throughout the modelling cycle who ultimately determine the process's outcomes. Here we show how such interactions can converge to support stakeholders to identify and commit towards ways that improve a socio-environmental problem.

Embracing a self-reference perspective is useful to clarify the close interaction between the *problem* and the *problem-solving system*. For instance, stakeholder interactions could have at least two main effects, one on the problem-solving system progress itself (i.e. modelling cycle), and the second on the *real-life* problem situation. This in turn may also change further interactions and discussions among stakeholders. There is therefore a mutual self-referencing between the *real-life* problematic situation and the concrete group of actors participating in a modelling cycle. According to Hofstadter (1979), understanding such complex self-referencing interactions can be aided by visual representations such as the M.C. Escher's paradoxes (e.g. *Print Gallery* - Escher in het Palais (n. d.)).

2.5. *Methods and techniques (outer "gears", Fig. 2) to support the process*

In Table 1, we provide a detailed but non-comprehensive account of useful tools to support the modelling process, structured according to the three main modelling stages proposed in Section 2.3. The table provides specific information on where to implement the tools throughout the modelling stages, along with a brief description of each tool's features, as well as their benefits, limitations, and illustrative references.

3. Concluding remarks

3.1. *The dynamic relation between uncertainty and participation in model-based decision-making*

3.1.1. *Phase I: modelling foundations*

Dealing with a complex and problematic socio-environmental issue can be overwhelming, while making sense of intricate systems of people and nature, interacting at different scales remains an epistemological challenge. Trying to address the overwhelming knowledge uncertainty by acquiring more knowledge (e.g. more variables, measurements, and observations) is a strategy that can backfire. Various authors highlight the existence of an epistemology paradox: the more you know about a system the more complexity it exhibits (Brugnach et al., 2011; Brugnach et al., 2008; Dewulf et al., 2005). One way of dealing with this paradox comes from a clear definition of the problem using a systemic perspective. For instance, defining a relevant system boundary helps to better understand a socio-environmental problem (Nabavi et al., 2017). Defining what the issue is, in which geographical and time scale it operates, and who is part of it, are questions that can help to frame the problem to be explored. Addressing such questions is not an objective exercise. On the contrary, useful answers or approaches should be co-created with stakeholders relevant to the problem situation rather than derived by modellers only (Amorocho-Daza et al., 2024). Developing a participatory problem definition can help in tackling knowledge uncertainty.

Involving stakeholders in the modelling process can help in dealing with knowledge uncertainty, but inherently increases ambiguity, another dimension of uncertainty (Brugnach et al., 2008). Stakeholders that commit to a co-creation process agree to engage in a common process, but may continue to hold different perceptions, particularly concerning the problem definition and their system understanding. Indeed, ambiguity in perceptions can go beyond diversity in preferences regarding the system boundaries and extends deeply into the conceptualisation of the relations within such a system. Despite the diversity and range in perceptions associated with multiple stakeholders, expert knowledge and locally relevant experience from different stakeholders are useful at this stage to ensure that key variables and interlinkages are included and that the system boundary is well defined. Additionally, early participatory conceptualisation activities taking place after defining a relevant system boundary can help to lower ambiguity further by engaging again with knowledge about the system relations and structure. Interestingly, without participation, ambiguity is minimised but knowledge uncertainty can become overwhelming. With participation, despite ambiguity explicitly being present, more appropriate boundary conditions present opportunities to better deal with knowledge uncertainties about the relations within the system's boundaries.

3.1.2. *Phase II: model building and testing*

It is primarily epistemological and ontological uncertainty that dominates this phase (Kwakkel, 2010; Wang, 2015). Epistemic uncertainty comes from the difficulty of translating the interlinkages found in conceptual models as mathematical equations in a simulation model. In this process, the modeller plays a crucial role, by making decisions about which simplifications, adaptations, and assumptions to apply based on the available data, system knowledge, physical constraints, and other factors. This translation process is a significant source of epistemic uncertainty. Ontological, or aleatory, uncertainty refers to the inherent variability observed in biophysical and social systems. For example, biophysical processes such as the nutrient and water cycles exhibit intrinsic stochastic behaviour. Socially driven trends can also be deeply uncertain, for example, socio-economic development pathways. Some of this variability can be quantified in the simulation model as statistical and scenario uncertainty.

Participation is central to the model testing stage. Here, key output variables of the model, in the form of scenario ensembles, can be estimated and compared with available field data and stakeholder knowledge. Quantitative estimation of uncertainty in the form of averages and ranges provides insight into the model's ability to accurately estimate the patterns, and trends observed in the real-world system. Even where information is available to quantitatively validate a model, stakeholders' input is essential for crosschecking whether the model behaviour aligns with their empirical knowledge about the system. In sum, testing activities help determine if the uncertainty inherent in the quantitative translation of the model is reasonable and appropriately captured for the socio-environmental problem at hand.

3.1.3. *Phase III: model use and policy evaluation*

Towards the end of the first iteration of the modelling cycle, different sources of uncertainty have been accommodated into a simulation model. Utilising such a model to evaluate policies amidst uncertainty again necessitates the participation of stakeholders. The social use of the model as a decision support system means that ambiguity resurfaces. This occurs because pondering criteria and aggregating indicators brings forth value-based questions and links back to earlier modelling choices and stages such as envisioning. Moreover, human priorities are likely to fluctuate and be influenced by framing effects, such as focusing on gains

Table 1
Modelling tools and techniques to support different phases of the unified SD modelling framework.

Phase	Methods/ techniques	Implementation stage	Description	General benefits	General limitations	Key references for applications
I: Modelling foundations	Rich pictures (SSM)	- Stakeholder participation cycle: Scoping and abstraction. - SD modelling cycle: Problem definition	A *rich picture* is a pictorial overview that "portrays actors and elements in a problematic situation and indicates relationships among them" (Bunch, 2003)	- Promotes holistic thinking, as "pictures are a better medium than linear prose for expressing [multiple and interacting] relationships" (Checkland, 2000) - Rich pictures can be constantly upgraded based on the stakeholder's understanding of the problematic situation (Bunch, 2003)	- Making system pictures is a skill that comes naturally and easily to some people, while others may find it challenging (Checkland, 2000). Therefore, the role of facilitators is critical in developing system representations that reflect the *richness* of the problematic situation, including the perspectives of people with varying communication skills. - Getting from *messy* to *meaningful* system representations (i.e. rich pictures) and stakeholder discussion may require deploying other complementary SSM tools (see *root definition* and *CATWOE analysis* – Checkland (2000))	Bunch (2003) Suriya and Mudgal (2012)
	Cognitive maps (SODA)	- Stakeholder participation cycle: Scoping and abstraction. - SD modelling cycle: Problem definition	Cognitive maps are "a picture or visual aid in comprehending the mappers' understanding of particular, and selective, elements of the thoughts (rather than thinking) of an individual, group or organisation" (Eden, 1992)	- Combining individual into collective cognitive maps is possible using specialised software tools (i.e. Decision Explorer) (Ackermann, 2012; Elsawah et al., 2015). - Collective maps offer the opportunity to observe collective convergent representations of a problem emerging from seemingly diverging points of view (Ackermann, 2012) - It is a transparent, and systematic approach helpful to connect qualitative to quantitative modelling approaches (Eden, 1988; Elsawah et al., 2015).	- Translating the mappers' narratives into maps can be overwhelming. This 'rich qualitative source' needs to be narrowed down according to the specific objectives of building the maps (Elsawah et al., 2015). - The maps are restricted by what people are willing to share. Inquiring about a controversial issue could generate resistance among the participants to explain their inner rationale and motivations (Elsawah et al., 2015).	Elsawah et al. (2015)
	DPSIR	- Stakeholder participation cycle: Scoping and abstraction. - SD modelling cycle: Problem definition	It is a systems framework that explores the complex relationship between human and natural systems through a conceptual understanding of interconnected Drivers, Pressures, State, Impact, and Responses (EEA, 1999).	- Facilitates a systemic understanding of the origins and consequences of environmental problems, explicitly incorporating feedback structures to do so. - Can be easily integrated with other methodologies to explore specific social-ecological problems in further detail. - Its simplicity facilitates co-creation and communication among various environmental stakeholders (e.g., policymakers, local communities, academics).	- Implementing the framework requires a deep and participatory understanding of the socio-environmental problem at hand. If multiple perspectives are not included, the analytical usefulness of the tool can be hindered. - The conceptual characterisation is flexible but might be insufficient to represent the complexity and cross-scale nature of environmental issues.	Bell (2012) Gregory et al. (2013) Wantzen et al. (2019) Zare et al. (2019)
	System diagramming	- Stakeholder participation cycle: Scoping and abstraction. - SD modelling cycle: Problem definition.	It is a simple system representation resulting from an iterative process of establishing a boundary and elucidating the following elements: external factors, internal factors and their relationships, means (or levers or steering factors), and measurable criteria (or objectives) (Enserink et al., 2022). The representation is built based on seven critical guiding questions (van der Lei et al., 2011). System diagramming is closely aligned with the XLRM framework (Lempert et al., 2003).	- It focuses on analytical rigour, consistency and conceptual clarity - It is more easily transferable (e.g. to students and practitioners) than traditional PSMs. - Being easy to communicate and revise, "the approach leads to an internally consistent systems model that represents the problem definition and delineation" (van der Lei et al., 2011, p. 1401)	- It is consistent with a 'consultancy setting' with a clear problem owner. The allied XLRM framework has been used extensively in this way. The multi-actor version can become rather complex. - The approach is suited to demarcating an appropriate system boundary, external factors, means and criteria, but must be deployed alongside other tools such as conceptual maps and CLDs to avoid a *black-box* model.	Hidayatno, Rahman, and Muliadi (2015) Nijmeijer (2018)

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Table 1 (*continued*)

Phase	Methods/ techniques	Implementation stage	Description	General benefits	General limitations	Key references for applications
	SD archetypes	- Stakeholder participation cycle: Envisioning and goal setting. - SD modelling cycle: Conceptualisation.	System archetypes are generic system structures showing common or generic patterns of behaviour over time (Mirchi et al., 2012; Wolstenholme, 2003).	- They synthesize "much qualitative and quantitative modelling effort cumulated over many years by many analysts", offering learning systemic opportunities in new problems and domains (Wolstenholme, 2003) - They represent a structured and *free-standing* way to understand the reason behind complex systems' counterintuitive behaviour (Wolstenholme, 2003)	- The archetype provides a starting assumption but it has to be empirically tested (Oberlack et al., 2019). - There might be specific conditions in which certain archetypes are applicable (or not) to a particular context (Magliocca et al., 2018)	Bahri (2020) Edwards et al. (2023) Gohari et al. (2013) Moallemi et al. (2022) Phelan et al. (2020)
	Causal matrices	SD modelling cycle: Conceptualisation.	Causal matrices help identify relationships and polarities among several variables (Sanò and Medina, 2012; Sanò et al., 2014).	- A causal matrix can be easily transformed into a causal loop diagram (Sanò et al., 2014) - Individual matrices can be aggregated into a *group* matrix that potentially leads to a shared causal loop diagram on the problem at hand (Sanò and Medina, 2012)	- A set of initial variables is a prerequisite of the method. These could be obtained with participatory scripts e.g. Nominal Group Technique (see Scriptapedia) - The method starts from a reductionist approach, so it might not help to develop a "system perspective" from the very beginning of the modelling process	Sanò and Medina (2012) Sanò et al. (2014)
	Conceptual maps	SD modelling cycle: Conceptualisation.	Conceptual maps are qualitative system representations that include key variables and describe how they are connected.	A comprehensive conceptual map can synthesize an important amount of information that can be very useful in later modelling stages. It provides a shared vision of the system as well as its main components and connections.	Building conceptual maps is a creative and open-ended process. Without facilitation, it can grow too complex to handle and connect with later modelling stages (Freebairn et al., 2019).	Purwanto et al. (2019) Sušnik et al. (2021)
	Causal Loop Diagrams (CLDs)	SD modelling cycle: Conceptualisation.	CLDs go beyond conceptual maps by characterising the causal relations among system variables. They are developed following a standard notation to describe the balancing or reinforcing influences between variable pairs, as well as feedback loops (Mirchi et al., 2012).	CLDs provide important learning opportunities by allowing stakeholders to understand the system as a whole and identify their key feedback relationships.	Just as with the conceptual maps, CLDs can easily grow too complex. Additionally, identifying polarities for every relationship adds a layer of complexity, as there are interlinkages where it is not easy, intuitive, or even possible to assign a polarity.	Bahri (2020) Purwanto et al. (2019) Zhao et al. (2021)
II: Model building and testing	Stock and Flow Model	- Stakeholder participation cycle: Model formulation and confidence building. - SD modelling cycle: Formulation	Stock and flow models (SFMs; cf. Ford (2010)) aim to simulate a complex system. Often built based on CLDs, SFMs represent a quantitative effort to characterise the behaviour of complex systems.	SFMs can serve as platforms for policy experimentation to address complex issues. Stakeholders can use them to learn about complex systems (e.g., SES) and to further develop policy discussions around them.	SFMs are simpler than CLDs. Not all qualitative complexity can be integrated into a quantitative model. Additionally, some stakeholders may face difficulties when interpreting the quantitative results of a simulation model. Effectively communicating insights from quantitative models is a challenge for modellers.	Prasad et al. (2022) Turner et al. (2016)
	Structural validation	- Stakeholder participation cycle: Model formulation and confidence building. - SD modelling cycle: Model testing	It is a set of qualitative tests that aim to compare the structure of the real system with the structure of the model that represents it (Forrester and Senge, 1980).	Test various model features (see Barlas (1996)): - Parameter-confirmation: To establish the conceptual and numerical validity of model's the parameters (i.e. constants) when compared with the real system - Extreme condition: To anticipate the model's behaviour under extreme conditions (e.g. parameters and equations) and compare it with the expected real system's behaviour - Dimensional consistency: To check dimensional consistency in both sides of the model's equations	Identifying the 'real system' features can be problematic. For the parameter confirmation, available information about the system's variables might be limited, non-existent, or anecdotical. This also applies to extreme condition tests, for SES it can be simply too difficult to know what would be the real-life behaviour of a system if such extreme conditions have not been previously identified or measured.	Barlas (1996) Qudrat-Ullah and Seong (2010)

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Table 1 (*continued*)

Phase	Methods/ techniques	Implementation stage	Description	General benefits	General limitations	Key references for applications
	Behavioural validation	- Stakeholder participation cycle: Model formulation and confidence building. - SD modelling cycle: Model testing	It is a set of qualitative and quantitative tests to evaluate "the adequacy of model structure through analysis of behaviour generated by the structure" (Forrester and Senge, 1980).	Test various model features (see Barlas (1996)): - Extreme condition: To compare the model's behaviour under extreme conditions (e.g. parameters and equations) and compare it with the expected real system's behaviour - Behaviour sensitivity: To identify changes in model's behaviour in response to changes in parameter values. - Behaviour reproduction. To check if the model is able to reproduce the real system's behaviour (e.g. symptom generation, frequency generation, multiple mode)	The main limitation here is obtaining sufficient and reliable information that facilitates the comparison of the modelling results with the observed behaviour of the system.	Barlas (1996) Naderi et al. (2021)
	Uncertainty analysis (UA)	- Stakeholder participation cycle: Model formulation and confidence building. - SD modelling cycle: Model testing	This umbrella term covers a set of tools that focus on characterising uncertainty in the model's output (Ghanem, Higdon, and Owhadi, 2017). Monte Carlo Methods (MCMs) are widely applied methods for model-based uncertainty analysis. MCMs can be used to do a quasi-random sampling of the parameter values using (often) pre-defined probability density functions (PDFs) to give a density distribution on the main outputs (Ford and Flynn, 2005).	SD simulation software already includes tools to perform uncertainty analysis. For example, quasi-random sampling is available on SD software (Stella, Vensim).	A good uncertainty analysis practice requires *global* analyses. That is, *global* uncertainty analysis methods test the output modelling uncertainty based on multiple simultaneous parameter variations. A local uncertainty analysis, in contrast, focuses on exploring a subset of factors or even parameters one at a time. This is a discouraged practice as it does not correctly represent models with non-linearities (Saltelli et al., 2019).	Ford and Flynn (2005) Kwakkel and Pruyt (2013b) Martinez-Fernandez et al. (2021)
	Sensitivity analysis (SA)	- Stakeholder participation cycle: Model formulation and confidence building. - SD modelling cycle: Model testing	This analytical tool aims to assess the impact of uncertain input factors on the overall uncertainty of the model's outputs (Saltelli, 2002). In other words, sensitivity analysis is useful to identify "which input factors contribute the most to model uncertainty". (Saltelli et al., 2019, p. 30).	By performing sensitivity analysis, modellers can identify which factors (parameters) contribute the most or least to the model's overall uncertainty. This information might be useful to prioritise resources to gather additional information that reduces uncertainty in the critical factors, while non-critical factors can have their values fixed (Saltelli et al., 2019)	Similar to the UA, SA should be performed using a *global* instead of a *local* approach. Global approaches consider the "factors' global influence in terms of their contribution to the variance of the model output, including the effect of interactions among factors" (Saltelli et al., 2019, p. 31). In contrast, *local* approaches consider each factor individually using a 'one at a time' strategy. The latter approach is unsuitable for non-linear systems and under-explores the uncertainty space, particularly when several factors are considered.	Dai et al. (2024) Mai et al. (2020) Puy et al. (2021)
III: Model use and policy evaluation	Exploratory modelling	- Stakeholder participation cycle: Simulation and assessment. - SD modelling cycle: Policy and scenario testing	This approach offers various tools to operationalise modelling under deep uncertainty. To do so it follows a systematic approach to exploring the implications of the model's assumptions for decision-making. Not limited to quasi-random sampling, other experiments such as stress testing, worst-case scenario, and many objective optimisation can be integrated into a larger uncertainty-rich decision-making framework (Moallemi, Kwakkel, et al., 2020).	Exploratory modelling analyses can be done using open-source tools. The Exploratory Modelling Workbench is an open-source toolkit to develop exploratory modelling analyses (Kwakkel, 2017).	As more sophisticated analyses are developed, more effort and creativity are required for communication and promoting meaningful interactions between academic and non-academics.	de Haan et al. (2016) Kalra et al. (2015) Kwakkel et al. (2015) Moallemi et al. (2017)
	Loop dominance analysis	- Stakeholder participation cycle: Simulation and assessment.	Loop dominance evaluation assesses the relative importance of feedback loops in driving a system's behaviour (Ford, 1999). *Loops that matter* (LTM), is a recent	- Identifies the dominant feedback loops driving system behaviour. - Enables understanding of changes in feedback loop dominance over time.	The loop dominance analysis adds complexity to the discussion of results. Explaining the related concepts and analysing the dominant feedback loops with stakeholders can likely	Aboah and Enahoro (2022) Phaff et al. (2006)

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Table 1 (*continued*)

Phase	Methods/ techniques	Implementation stage	Description	General benefits	General limitations	Key references for applications
		- SD modelling cycle: Policy and scenario testing	numerical method for loops dominance evaluation. It defines loop scores to estimate each feedback loop's contribution to the model's behaviour, ranging from -1 to +1, also indicating the loop's polarity (Schoenberg et al., 2020; Schoenberg, Hayward, and Eberlein, 2023)	- Can highlight potential resistance or counterintuitive responses to new policies, aiding in better policy design and evaluation.	generate further discussion. However, this exercise might be time-consuming and needs to be properly anticipated and scheduled.	
	Multi-criteria decision analysis (MCDA)	- Stakeholder participation cycle: Simulation and assessment. - SD modelling cycle: Evaluation	MCDA methods support decision-making processes when several criteria and alternatives are considered (Lahdelma et al., 2000). They provide a systematic approach to assess the importance of criteria and how different policies perform against them (Hajkowicz and Higgins, 2008). Among others, widely adopted MCDA methods include Analytical Hierarchical Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and ÉLimination et Choix Traduisant la REalité (ELimination and Choice Translating REality) (ELECTRE).	- MCDA methods help evaluate alternatives considering multiple factors rather than a single metric/indicator. - They enhance stakeholder dialogue and confidence in policy selection as expert judgment is used to quantify the importance of different criteria.	- Different MCDA methods have varying approaches to weighing criteria. - As stakeholders are required again to give input at the final modelling stages, this may add to the stakeholder fatigue in a co-creation project - Using models under uncertainty requires adapting deterministic MCDA methods.	Antunes et al. (2006) Amorocho-Daza et al. (2019) Momeni et al. (2021)

versus avoiding losses, or prioritising present versus future generations (Jafino et al., 2021; Tversky and Kahneman, 1981). In short, the plurality of stakeholders' values and interests and the inherent bounded rationality of humans make ambiguity an inherent property of decision-making under uncertainty.

Paradoxically, the dialogue around the modelling outputs can help navigate ambiguity by using the model to help answer relatively simple *what if* policy questions, that is, performing *experiments* in a simulation environment (Zomorodian et al., 2018). Alternatively, the simulation model could also be integrated into a more sophisticated decision support system that helps to rank multiple policies against various performance criteria. Tools like MCDA offer the opportunity to integrate the simulation model outputs into a structured decision-making process that helps to rank the more desirable policies to pursue. However, considering uncertain modelling outputs adds complexity to the decision-making process and requires extending MCDA tools to handle uncertainty. This raises a further challenge, which is to communicate uncertainty to an audience of stakeholders and model users who may be unfamiliar with such concepts (van der Bles et al., 2019). Here it might be easier to start with a deterministic ranking of alternatives and later move on to explore how such ranking could alter in the face of uncertainty. This stepwise approach could offer opportunities to learn about the system's behaviour under diverse policies and changing scenario and parametric conditions.

3.2. Future directions for model-based policy analysis in SES

In this article we provide a framework in which we enunciate the main implications of uncertainty and participation for model-based decision-making in the context of SES. By integrating and aligning two SD relevant modelling cycles, one engaging with uncertainty and the other with participation aspects, we were able to distinguish three general modelling phases, namely: 1. Modelling foundations, 2. Model building and testing, 3. Model use and policy evaluation. Here we identify future research avenues that could emerge from deploying our unified SD modelling cycle.

For Phase I, there is potential to extend the use of problem structuring methods (PSMs) to enrich the problem definition in the modelling cycle of SES as a Good Modelling Practice (GMP). Although these methods are established in sectors such as business and health, environmental applications remain limited. Integrating PSM into co-creation methods is an active area of research (Cunningham et al., 2014; Slinger et al., 2023). Incorporating such activities into the SD modelling cycle could aid in articulating the problem more effectively and in building a richer problem definition (Rouwette and Franco, 2024). This would enhance the qualitative and quantitative models resting on such system understanding. Our focused attention on reviewing and articulating Phase I's methods is a practical contribution and an invitation for further research to address the currently largely deficient practice regarding problem scoping and participation in SES modelling (See Jakeman et al., 2024, Section 4, Points 1, 10, and 19).

While a holistic uncertainty approach is recognised as a topic for enhancing GMP (See Jakeman et al., 2024, Section 4, Points 4 and 6), doing so opens up new challenges for implementing Phase II. For instance, future research can help to validate whether quantifying uncertainty is helpful in the testing stage of SES simulation models. Here we hypothesize that this would be the case, as having a wide range of probable outputs for the variables of interest will yield more information about the range of variation that such variables exhibit in relation to existing field measurements or the experiential knowledge of stakeholders. However, a caveat is that presenting ensembles and ranges may obscure the observation of (dynamic and/or recurrent) modes of behaviour in these complex systems. More research is needed to elucidate the trade-offs in accounting for uncertainty at the model testing stage in practice. Future studies are needed to understand how to communicate such sophisticated numerical treatments of uncertainty to an audience that may be unfamiliar with the concepts and jargon of uncertainty assessment.

Despite progress in model-based policy evaluation (Phase III), the SES GMP literature can benefit from understanding how this process can be structured in practice in case studies that cover a variety of environmental issues at a diversity of spatial and temporal scales, and with variously composed stakeholder groups (See Jakeman et al., 2024, Section 4, Points 9 and 10). Moreover, we advocate further research on the integration of SD quantitative models into decision support systems, whether formal or informal process-based systems. These include applications linked to MCDA or multi-model systems combining different types of qualitative and quantitative modelling (see Slinger, 2023). Indeed, future studies could investigate the benefits and challenges of developing and applying environmental decision support tools that are deterministic versus explicitly accommodating of uncertainty, versus a combination of both.

Another potential benefit of our proposed framework is to facilitate SES modelling reporting and transparency as a GMP (see Jakeman et al., 2024, Section 4, Points 2, 13, and 17). Despite SES modelling case studies often exhibiting some of the generic modelling stages described in this article (e.g. scoping, envisioning, evaluation, etc.), it is difficult to find applications that cover the whole modelling cycle. In fact, a recent participatory modelling review shows that not a single case study reported undertaking activities across all the modelling cycle stages (Voinov et al., 2016). This does not necessarily imply that these activities were not covered in practice, but may indicate that comprehensively reporting SES modelling activities in a single research article is extremely challenging. Our proposed 3-phase modelling cycle can aid with this scientific communication issue. Future case studies on SES modelling for policy evaluation could report in terms of the three modelling phases, describing the relevant activities undertaken in each phase, and making use of some of the proposed modelling tools or contributing other relevant tools. Moreover, the unified modelling framework can serve as a tool in designing a stakeholder and uncertainty-inclusive modelling process, that addresses each of the requisite activities in turn. Such future studies can also use the unified modelling framework to structure reporting on their challenges, lessons learned, and overall experience of employing a participatory modelling cycle (under uncertainty) to address a socio-environmental issue.

Nonetheless, the proposed framework has intrinsic limitations as it is tailored to modelling SES from an SD paradigm. Despite the extensive benefits that we have argued above, the SD approach has limitations as it is not spatially explicit and it focuses on modelling *wholes* rather than *individuals* or agents, both features being particularly relevant for ecological research (Vincenot et al., 2011). Therefore, adapting the proposed 3-phase framework to other SES modelling paradigms is an open avenue for future research. For instance, the framework can be adapted to model SES problems that are better addressed from an Agent-Based Modelling (ABM) perspective (e.g. see Bourceret et al. (2024)), or even, going a step forward, by integrating SD with Agent-Based-Modelling (ABM) in a single modelling cycle (Vincenot et al., 2011). Our framework can act as a baseline for such expansion and adaptation. Other modifications may come from applying the proposed SD-based framework in a more concrete type of SES (see Datola et al. (2022), for a relevant application in the context of urban resilience). This opens up ample possibilities for tailoring the overall SES framework to overarching themes, such as integrated resources management (Ghodsvali, Dane, and de Vries, 2022) and conservation science (Sala and Torchio, 2019); or to specific biophysical environments, such as coastal systems (Slinger, Taljaard, and d'Hont, 2020), river basins (Cabello et al., 2015) and forests (Fischer, 2018).

Finally, a synthesised SES policy evaluation modelling cycle opens the opportunity to connect better with policy application. Here we argue that an SES modelling exercise ideally consists of three global phases: it starts with a problem that is conceptualised, then translated into a model that facilitates collective understanding, and is finally used to evaluate policies aimed at tackling the initially identified problem. This global understanding can simplify the dialogue between the stakeholders responsible for making SES policy decisions (or providing input) and those responsible for implementing and monitoring such policies (Nuno, Bunnefeld, and Milner-Gulland, 2014). More research is needed to capture the synergies and barriers that arise from a nested policy evaluation/implementation approach in dealing with socio-environmental problems. Case studies can illustrate what happens after a policy to tackle an SES issue has been selected via a participatory modelling process (see Slinger, 2023; Clifford-Holmes et al., 2018). Who are the decision-makers and implementers? Who is part of both groups, and how do they interact? How is the policy implemented and monitored? Does the implementation align with the recommended policy path supported by the modelling cycle? How does it differ? Does the monitoring feed back into another participatory policy evaluation cycle? Does the model suggest trends that became apparent in the real world after the implementation of policies? These questions open up an exciting avenue of research to understand the factors that support or hinder a fluid and collaborative SES policy evaluation and implementation process. A better understanding of these interactions can help to design and implement sound, concerted, and impactful policies to address the critical socio-environmental issues of our time.

CRediT authorship contribution statement

Henry Amorocho-Daza: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Janez Sušnik:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Pieter van der Zaag:** Writing – review & editing, Visualization, Supervision, Conceptualization. **Jill H. Slinger:** Writing – review & editing, Supervision, Methodology, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Janez Susnik reports financial support was provided by European Union Horizon 2020 research and innovation programme. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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