Environmental Modelling and Software 112 (2019) 82–94

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

A tiered, system-of-systems modeling framework for resolving complex socio-environmental policy issues

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ARTICLE INFO

Keywords:
Deep uncertainty
Integrated assessment
Resilience
Stakeholders
Sustainability
Systemic

ABSTRACT

Many of the world's greatest challenges are complex socio-environmental problems, often framed in terms of integrated assessment, resilience or sustainability. To resolve any of these challenges, it is essential to elicit and integrate knowledge across a range of systems, informing the design of solutions that take into account the complex and uncertain nature of the individual systems and their interrelationships. To meet this scientific challenge, we propose a tiered, system-of-systems modeling framework with these elements: a component-based, software framework that couples a wide range of relevant systems using a modular, system-of-systems structure; a tiered structure with different levels of abstraction that spans bottom-up and top-down approaches; the ability to inform robust decisions in the face of deep uncertainty; and the systematic integration of multiple knowledge domains and disciplines. We illustrate the application of the framework, and identify research and education initiatives that are needed to facilitate its development and implementation.

1. Introduction

Many of the world's greatest challenges, including those associated with climate change, environmental contamination, groundwater depletion, biodiversity loss, biological invasions, disease outbreaks, the food/energy/water nexus, coastal and inland flooding, interdependent infrastructure systems, disaster management and urban planning, are complex and socio-environmental in the nature of their drivers, interactions and impacts. Concepts that are often used to frame and study these problems include integrated assessment (Hamilton et al., 2015), resilience (Hosseini et al., 2016; Righi et al., 2015) and sustainability (Bettencourt and Kaur, 2011; Bond and Morrison-Saunders, 2011; Little et al., 2016; Miller et al., 2014). To briefly illustrate the collective nature of these challenges, a simple representation of a socio-environmental system is provided in Fig. 1, showing how environmental, economic and social systems form a system of interdependent systems. Examples of such real systems include watersheds, land-use, coastal systems, ecosystems, agriculture, forestry, fisheries, climate, energy, transportation, communication, as well as economic, legal and other social systems. In this article we focus on sustainability as the ultimate goal in treating these complex problems because assessing and enhancing sustainability requires integration across a wide range of environmental, economic and social systems. The other, somewhat narrower but still complex, socio-environmental problems listed above are not as comprehensive as the goal of sustainability, requiring integration across fewer systems. In general, however, to resolve any socio-environmental problems, we need to elicit and integrate knowledge and explicit assumptions across a range of systems, informing the design of solutions that take into account the complex and uncertain nature of the individual systems themselves and their interrelationships. In Sections 1.1 through 1.6, we discuss the five primary challenges that prevent us from surmounting this collective scientific challenge. We then sketch the four elements of a proposed tiered, system-of-systems modeling framework that addresses the collective challenge. Key concepts and terms are defined in Table 1.

1.1. Primary challenge #1 – the need for a comprehensive and consistent characterization of socio-environmental policy goals

The objective of any progressive examination of a specific socio-

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https://doi.org/10.1016/j.envsoft.2018.11.011
Received 5 February 2018; Received in revised form 14 November 2018; Accepted 20 November 2018
Available online 23 November 2018
1364-8152/

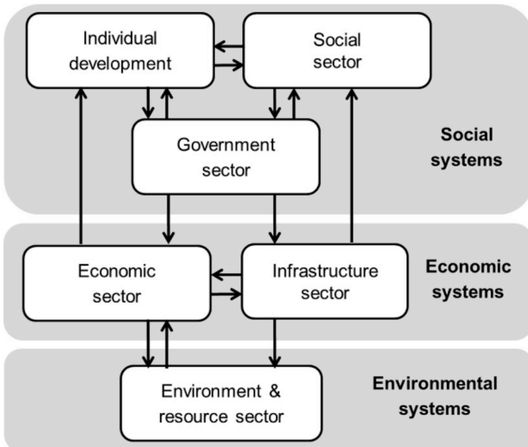

Fig. 1. A simple representation of a socio-environmental system (also referred to as a socio-environmental-technical system) showing how environmental, economic and social systems form a system of interdependent systems (adapted from Bossel (2007)).

environmental policy issue is achieving a better balance over time and space among socio-economic and environmental outcomes. We use the goal of sustainability in the following to motivate the need to explictly characterize and mechanize the goals of any challenging socio-environmental problem because we see the approach to characterizing sustainability as analogous to the other more tractable, but still extremely challenging, policy problems. For an overview of the field of sustainability, readers are referred to a recent conceptual review (Little et al., 2016), which identifies the collective limitations of the existing approaches for characterizing sustainability and briefly motivates the need for the proposed framework.

Many authors have pointed out the difficulty of defining sustainability and sustainable development (e.g., (Bare, 2014; Bond and Morrison-Saunders, 2011; Bossel, 1999; Costanza and Patten, 1995; Graedel and Klee, 2002; Griggs et al., 2014; Kuhlman and Farrington, 2010; Lélé, 1991; Pope et al., 2004). In practice, the definition of sustainability tends to be determined by the specific assessment approach being used, and these vary widely (Little et al., 2016).

To characterize the sustainability of a socio-environmental system, the definition of sustainability must be applied comprehensively and consistently. Bossel proposed a way of doing this (Bossel, 1996, 1999, 2007), suggesting that the sustainability of autonomous, self-organizing systems (which include both ecosystems and human systems) is determined by several basic orientors, including existence, effectiveness, security, adaptability and coexistence for both humans and ecosystems, and freedom of action and psychological needs for humans, as summarized in Table 1 in Little et al. (2016). According to Bossel (1999), the set of basic orientors is complete and covers all essential aspects of the supreme orientor, which in this case is sustainability, and each basic orientor is unique and cannot be replaced by the other basic orientors. Because the basic orientors are abstract in nature, they need to be translated into a broad range of concrete operational orientors that can be more easily quantified (Bossel, 1996, 1999, 2007). Sustainability is then assessed, as shown in Fig. 2, by comparing the operational orientors (which reflect the desired state of the system) to associated indicators (which reflect the actual state of the system), and evaluating the extent of orientor satisfaction. In addition, some orientors and indicators are inherently more important than others (Bossel, 1999, 2007) and relative weights are assigned (Fraser et al., 2006; Paracchini et al., 2011) in a procedure which is guided by stakeholders (Voinov and Bousquet, 2010; Voinov et al., 2016). Assigning weights does, however, require value judgements (Glynn et al., 2017; Voinov et al., 2014), which may differ from person to person and from culture to culture, making the process in which a group of stakeholders must reach agreement more difficult. On the other hand, this orientor-based approach provides a flexible and systematic method that can be expanded and adjusted (with stakeholder input) as systems are added to the system of systems.

There is also the common assumption that sustainability can be achieved by simply identifying an appropriately comprehensive set of indicators (although this in itself is difficult), which overlooks the fact that most indicators are integrated within a system of complex, interdependent systems, as shown in Fig. 1, and are often context-dependent. As an example, we refer to the 17 Sustainable Development Goals, which together with 169 targets and 230 indicators (Allen et al., 2016; Sridhar, 2016), were recently identified by the United Nations (UN, 2015). Concerted efforts to achieve these goals/targets/indicators without taking into account their interdependencies, while entirely laudable, will surely lead to unintended consequences (Sterman, 2001, 2012) because so many of them are causally related. For instance, some approaches to increasing food security may negatively affect the global climate system, putting food security itself at risk (Griggs et al., 2014). In fact, it might well be argued that it is futile to make adjustments to the indicators in a complex system and expect positive outcomes without an understanding of the causal relationships that connect them. Because many indicators are integrated within a wide range of interdependent systems, there needs to be a clear connection between the orientors and associated indicators, which are used to quantify the supreme orientor (sustainability or resilience, for example), and the conceptual framework (defined in Table 1) which is used to account for the drivers and causal relationships that govern the behavior of the system of systems (defined in Table 1).

1.2. Primary challenge #2 – the need for a system-of-systems structure

While there is growing recognition of the need for a systems approach to effectively characterize sustainability (e.g. (An and López-Carr, 2012; Fiksel, 2012; Hadian and Madani, 2015; Housh et al., 2014; Little et al., 2016; Liu et al., 2015; Ramaswami et al., 2012),) and other socio-environmental problems, there is no agreement on what a systems approach entails. Usefully, a recent review (Arnold and Wade, 2015) clarified the meaning of a systems approach by identifying eight key elements: recognizing interconnections; identifying and understanding feedback; understanding system structure; differentiating types of stocks, flows, and variables; identifying and understanding non-linear relationships; understanding dynamic behavior; understanding systems at different scales; and reducing complexity by modeling systems conceptually. While all eight elements are needed, the use of models is especially important when attempting to understand and represent complex systems because the complexity of such systems overwhelms our ability to understand them (Sterman, 2001, 2012). This phenomenon, which is sometimes referred to as policy resistance, arises because complex systems are constantly changing, tightly coupled, governed by feedbacks, nonlinear, history-dependent, self-organizing, adaptive and evolving, characterized by trade-offs, and counterintuitive (Sterman, 2012). As a result, many seemingly obvious solutions to problems fail or actually worsen the situation (Sterman, 2012), causing what are more commonly known as unintended consequences. Mathematical models are thus the primary tools available for understanding complex systems and are essential ingredients for adaptive management (defined in Table 1) of interconnected complex systems. Models are therefore needed for each of the systems that are included in the system of systems. With a large number of systems that are potentially involved and a need for systems integration (Liu et al., 2015), a conceptual framework which is based on a system-of-systems (DeLaurentis and Crossley, 2005; Keating et al., 2003; Maier, 1996; Nielsen et al., 2015) notion is required. Here, we define a system of systems as a collection of independent constituent systems, in which each fulfills its own purpose while acting jointly towards a common goal.

Given the spatial scale of the various socio-environmental systems

Table 1
Definition of key concepts and terms.

Concept or term	Definition
Adaptive management	Adaptive management, which may be a part of the integrated assessment process, views policies as if they were experiments, with results from one generation of study informing subsequent decisions (Holling, 1978). A range of participatory mechanisms can be employed at different stages of the adaptive management cycle to create favorable outcomes for diverse stakeholders (Stringer et al., 2006).
Conceptual framework	A conceptual framework is the basic structure underlying a concept or system. The conceptual framework is used to organize and manage information about the concept or system, and is sometimes simply referred to as a framework.
Deep uncertainty	Deep uncertainty exists when there is “fundamental disagreement about the driving forces that will shape the future, the probability distributions used to represent uncertainty and key variables, and how to value alternative outcomes” (Lempert, 2002).
Integrated assessment	Integrated assessment is a well-established approach for evaluating environmental science, technology, and policy problems (Hamilton et al., 2015; Laniak et al., 2013a; Rotmans and van Asselt, 2001; Schneider, 1997), having been used extensively for climate change (Morgan and Dowlatabadi, 1996; Patt et al., 2010; Schneider, 1997), and more recently for sustainability (Hacking and Guthrie, 2008). Integrated assessment may include adaptive management and often employs scenarios to characterize hypothetical future pathways. Scenarios typically describe sequences of events over a period of time, and consist of states, driving forces, events, consequences and actions which are causally related (Rotmans et al., 2000).
Social learning	In the context of the integrated management of natural resources, social learning (Berkes, 2009; Pahl-Wostl et al., 2007; Pahl-Wostl and Hare, 2004) can be defined as “the collective action and reflection that takes place among both individuals and groups when they work to understand the relations between social and ecological systems; it is conceptualized as a process of transformative social change in which participants critically question and potentially discard existing norms, values, institutions and interests to pursue actions that are desirable to them” (Cundill et al., 2012).
Software framework	A software framework (Lloyd et al., 2011) provides a reusable design which guides software developers in partitioning functionality into components, and specifies how the components communicate and manage the order of execution.
Systems thinking	Although there remains considerable debate about exactly what constitutes a systems approach (Demetis and Lee, 2016; Mingers, 2017) a recent definition of systems thinking considers it to be a system for thinking about systems (Arnold and Wade, 2015), with eight key interconnected elements: recognizing interconnections; identifying and understanding feedback; understanding system structure; differentiating types of stocks, flows, and variables; identifying and understanding non-linear relationships; understanding dynamic behavior; reducing complexity by modeling systems conceptually; and understanding systems at different scales. These elements form a system with a series of feedback loops (see Fig. 3 in Arnold and Wade (2015)), which results in continuous improvement of each of the elements, and a concomitant continuous improvement of the “systems thinking” system itself.
System of systems	There is no precise and widely accepted definition of a system of systems (Nielsen et al., 2015), a term which has been used since the 1950s (Boardman and Sauser, 2006; DeLaurentis and Crossley, 2005; Keating et al., 2003) to describe systems that are composed of independent constituent systems, which act jointly towards a common goal through the synergism between them (Nielsen et al., 2015). A system of systems has been used in many fields, including energy (Agusdinata and DeLaurentis, 2008), healthcare (Grigoroudis and Phillis, 2013), emergency management (Liu, 2011), engineering (Keating and Katina, 2011; Keating et al., 2008), as well as infrastructure, transportation, and defense (Nielsen et al., 2015). Here, we define a system of systems as a collection of independent constituent systems, in which each fulfills its own purpose while acting jointly towards a common goal.

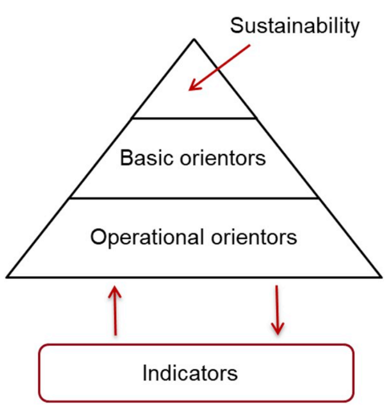

Fig. 2. Sustainability, which is the supreme orientor, is determined by several basic orientors. The basic orientors are abstract and are translated into more concrete operational orientors, which are compared to a range of associated indicators (adapted from (Bossel, 1999, 2007)). Other supreme orientors include resilience, human health or ecosystem health, for example.

that need to be coupled when focusing on the specific supreme orientor of interest (sustainability, resilience, human health or ecosystem health, for example), it makes sense to begin at a regional scale keeping in mind the socioeconomic and policy drivers and impacts. As the systems-level conceptual approach is established, we would map out the component systems in more detail, keeping in mind that some of the relevant systems may be at a sub-regional scale. Once the initial application is successful, it could be applied across many regions, with a need for repeated applications of models of similar systems. The coupling of many models within a system of systems would be greatly facilitated with a component-based software framework (also defined in Table 1).

1.3. Primary challenge #3 – the need for a tiered structure

The third challenge is the vast gap between bottom-up (with a high level of detail) and top-down (with a lower level of detail) approaches (Little et al., 2016). We again use sustainability to motivate the need to ensure that bottom-up and top-down approaches are consistent. For example, top-down sustainable development goals may be useful as a diagnostic test for assessing the state of nations, but what detailed bottom-up actions do we take if the indicators inform us that change is needed? How do we know that the detailed actions we do take to improve sustainability will not result in unintended consequences? To emphasize the point, there have been relatively few attempts to synthesize multiple bottom-up indicators to attain a more holistic perspective (Hester and Little, 2013; Huber et al., 2015).

To connect bottom-up and top-down approaches in complex socio-environmental problems, we need a tiered structure with different levels of abstraction (Borshchev, 2013; Borshchev and Filippov, 2004). Assuming only two levels for now, one can envision more detailed process models at the process level, and less detailed system models at the systems level, with a consistent way of scaling the models from the process level to the systems level. In addition to the tiered structure with different levels of abstraction, we also need a way of connecting the tiers, albeit loosely, so that critical information can be passed among them (Little et al., 2016).

A further justification for the tiered structure pertains to the large number of systems that are potentially involved in any socio-environmental problem. If we only have a small number of process models of not inordinate complexity to couple, we may be able to couple them directly at the process level. But if we have many complex process level models that are highly-resolved, both spatially and temporally, there is simply too much detail, especially if we are coupling them with other models that have much lower resolution. In these cases reduced-order models, also known as meta-models or emulators (Castelletti et al., 2012; Ratto et al., 2012), will be needed.

Finally, we note that all socio-environmental problems involve policy decisions and that a tiered structure with a coupled system-of-systems model at the systems level would be especially advantageous because most policy decisions need to be implemented at the systems level, and not at the process level. Of course, options assessed at each level need to be clearly linked to actionable measures in the real systems so that suggested improvements can be translated into actions.

1.4. Primary challenge #4 – the problem of deep uncertainty

With the preceding discussion in mind, sustainability, resilience and other complex socio-environmental problems generally qualify as "wicked" problems (Churchman, 1967; Rittel and Webber, 1973; Xiang, 2013). Because the problems are embedded within a wide range of complex, interdependent systems, there is no optimal solution, uncertainty is pervasive (Bammer, 2008) and the stakes are contested. A closely-related concept with increasing currency is that of deep uncertainty (defined in Table 1), which exists when there is "fundamental disagreement about the driving forces that will shape the future, the probability distributions used to represent uncertainty and key variables, and how to value alternative outcomes" (Lempert, 2002; Lempert et al., 2003). Although uncertainty assessment is essential for making robust decisions in the face of deep uncertainty, a qualitative grasp of uncertainties may suffice in some cases, such as when stakeholders are engaged in social learning (defined in Table 1) so that future decisions can be made on a more informed and less contested basis. On the other hand, when quantitative assessment of uncertainties is needed for decision-making, novel computational experiments that sample the range of uncertainties and analyse the results will be required to address the problem of keeping the sampling efficient yet produce model outputs that cover the response behavior space of the model(s). This will be essential when models have long runtimes for any given parameter sample. In some cases, as mentioned in Section 1.3, model emulators (Castelletti et al., 2012; Ratto et al., 2012) may be built to achieve a faster running model under certain acceptable conditions.

1.5. Primary challenge #5 – the fragmented nature of the disciplinary landscape

When dealing with complex socio-environmental problems, the disciplinary landscape is fragmented with a wide range of professional and academic groups pursuing related goals, but without effective interdisciplinary coordination. In the case of sustainability (Little et al., 2016), for example, many disciplines have added elements of sustainability to their historical approaches, resulting, for example, in green accounting, green chemistry and green engineering. Professional societies are also engaged in initiatives that broaden their sphere of influence to include sustainability but, here too, the initiatives tend to begin with the traditional focus area of the society (water or energy or transportation or ecology or economics, for example) and then extend to include other aspects of sustainability. Although these initiatives can only be applauded, they collectively guarantee a fragmentation in approaches to assessing and enhancing sustainability.

Integrated assessment (defined in Table 1) is a well-established approach for evaluating environmental science, technology and policy problems (Hamilton et al., 2015; Jakeman and Letcher, 2003; Laniak et al., 2013a; Rotmans and van Asselt, 2001; Schneider, 1997). The approach was designed as a meta-discipline to overcome fragmentation, and has been used extensively for climate change (Morgan and Dowlatabadi, 1996; Patt et al., 2010; Schneider, 1997), integrated water resources management (Jakeman and Letcher, 2003) and more recently for sustainability (Hacking and Guthrie, 2008). A methodology for the design and development of integrated assessment decision support systems (McIntosh et al., 2011) focuses on the overall iterative development process and includes stakeholders and policy makers, scientists and engineers, IT-specialists and the architect(s) of the decision support system (van Delden et al., 2011). Although integrated assessment emphasizes, for example, the integration of socio-economic and ecological models (Jakeman and Letcher, 2003) to address policy questions that are derived from engagement with interest groups, a more systematic approach that combines a system-of-systems framework with the integrated assessment methodology would be of considerable benefit for the fields of sustainability and resilience in particular, and for resolving complex socio-environmental problems in general.

1.6. This article – surmounting the collective scientific challenge

In Section 2, we sketch the outline of a tiered, system-of-systems modeling framework for resolving complex socio-environmental problems with four key elements:

- A component-based, systems-level software framework that can couple a wide range of relevant systems using a modular, system-of-systems structure;
- A tiered structure with different levels of abstraction that spans bottom-up and top-down approaches and establishes a systematic connection among the tiers;
- The ability to inform robust decisions in the face of deep uncertainty; and
- The systematic integration of multiple knowledge domains and disciplines.

The first two elements describe the structure of the framework while the last two elements describe ways in which the framework is implemented. In Section 3, we briefly illustrate the application of the framework, arguing that while sustainability represents the most comprehensive socio-environmental problem, the other narrower socio-environmental problems (for example, food, energy and water systems and interdependent infrastructure systems) are essentially subsets of the more comprehensive problem. By initially focusing on the narrower problems, but keeping the more comprehensive longer-term goal in mind, we can build confidence in the proposed framework. In Section 4 we identify research and education initiatives that are needed to facilitate the development and implementation of the framework, and in Section 5 we identify various barriers and enablers that will impede or expedite the implementation of the framework. We conclude by acknowledging that the proposed framework represents a daunting challenge, especially in the case of sustainability, but argue that progress could be accelerated by initially focusing on the narrower socio-environmental problems in a concerted and systematic fashion.

2. Outline of a tiered, system-of-systems modeling framework

In this section, we describe the four key elements of the proposed framework.

2.1. A component-based, modeling and software framework

When developing a system of systems based on mathematical models within a conceptual framework, we need to distinguish between the modeling approach (e.g. system dynamics, agent-based models or mere linking of any style of computational models as in Kelly et al. (2013)), and the software framework itself. In this section, we first provide further justification for the system-of-systems modeling framework and the range of available modeling approaches, and then discuss the development of the component-based, systems-level software framework.

2.1.1. A system-of-systems modeling framework

A simplified systems approach is already being implemented by the climate change community, with integrated assessment models that include key features of human systems, such as demography, energy use, technology, the economy, agriculture, forestry and land use (Moss et al., 2010). These models incorporate simplified representations of the climate system, ecosystems, and in some cases, climate impacts, and are calibrated against more complex climate and impact models. The models are used to develop emissions scenarios, simulate feedbacks, estimate the potential economic impacts of climate change, evaluate the costs and benefits of mitigation and evaluate uncertainties (Moss et al., 2010). The development of these integrated assessment models involves two conceptual steps – the first being the creation of reduced-order models from more complex ones, also known as "up-scaling", and the second being the coupling of the "up-scaled" components using a common computational structure. Thus, we envisage a process level with process models that have a lower degree of abstraction and more detail, as well as a systems level with system models that have a higher degree of abstraction and less detail. We note here that the preference would often be for mechanistic models, but that machine-learning algorithms, or expert systems (Krueger et al., 2012), or even empirical relationships could suffice, at least initially or when mechanistic understanding and/or data are too limited. The primary distinction is that the process models operate at a finer level of detail than the system models.

The integration of the system of systems involves several important challenges. The models operate naturally at different temporal and spatial scales, and individual models have different mathematical underpinnings. Although the systems are coupled through information exchange, their models may have different inputs and outputs, which must be logically connected and scaled. There is also new emergent behavior of the coupled models due to interconnectivity, which can exercise the individual models in new regimes (Vespignani, 2010). To bridge the difference in spatial and temporal scales among the models, and to harmonize the inputs and outputs, scale issues would need to be addressed for each individual model, such that models have similar spatial and temporal scales at their points of interaction, and have compatible inputs and outputs.

There are many approaches used for modeling complex systems. Kelly et al. (2013) reviewed five of these, including system dynamics, Bayesian networks, coupled component models (which may also be thought of as hybrid models because they are assembled from a variety of different components), agent-based models and knowledge-based models (also known as expert systems). Kelly et al. characterized the contexts in which each may be preferred. Others have been more definitive and restrictive in their regard as to appropriate approaches. Thus Borshchev (2013) argues that system dynamics, agent-based models and discrete-event models, which employ a detailed, process-based approach, are the three essential modeling approaches for simulating complex systems. Mobus and Kalton (2015) identified system dynamics, agent-based models, operations research (or optimization) and evolutionary models (Maier et al., 2014) as the primary approaches for modeling complex systems, concluding that a hybrid version of these approaches (which they refer to as complex, adaptive and evolvable systems) is ultimately needed. Indeed, hybrid or mixed method approaches are gaining in popularity (e.g. (Howick et al., 2016; Morgan et al., 2017; Vincenot et al., 2016)).

The required characteristics of the component-based, systems-level conceptual framework must be considered at an early stage in the development of the overall framework. System dynamics and agent-based models would clearly be strong candidates as both of these approaches are currently employed in simulating socio-environmental systems. System dynamics models (Elsawah et al., 2017; Sterman, 2012) are already being used extensively in evaluating the sustainability of natural, social and engineered systems (Little et al., 2016). Agent-based models are also used for natural, social and engineered systems (Wilensky and Rand, 2015), and appear especially promising for ecosystems (Grimm and Berger, 2016; Railsback and Grimm, 2011), economics (Farmer and Foley, 2009) and quantitative social science (Byrne and Callaghan, 2014; Macy and Willer, 2002), primarily because of their emergent properties.

2.1.2. A component-based, systems-level software framework

Component-based approaches compartmentalize each model that represents a system of interest into individual components. The approach is widely adopted in the environmental modeling arena to facilitate the incorporation of existing models while making the development and coupling of new models more efficient (de Kok et al., 2015). For example, Malard et al. (2017) couple system dynamics with physically-based models using a "wrapper" approach to represent a socio-economic system and the effects on soil salinity in a farming system. Such "wrappers" compartmentalize and separate a model while handling the inter-model data exchange processes (Laniak et al., 2013a). Likewise, a systems-level software framework that implements such an approach across systems would greatly facilitate the development and implementation of the framework.

Software frameworks, as described by Lloyd et al. (2011), provide a reusable design, which guides software developers in partitioning functionality into components, and specify how components communicate and manage the order of execution. Generic frameworks provide support for general software elements such as database access, enterprise services, graphical interface design, and transaction management, while domain specific frameworks provide reusable design and functionality for specific knowledge domains. Frameworks themselves support model development by providing tools (for example, libraries of components) as well as steps and processes that guide modelers.

For example, the most recent version (v3) of the Object Modeling System (OMS) (David et al., 2013) includes a non-invasive lightweight framework design supporting component-based model development, the use of domain specific language design patterns and provides a cloud-based foundation for computational scalability. As the framework is non-invasive, little to no change is required of a target model for its use within the framework. Once implemented, components can be re-used in other models coded to the same framework with little migration effort (Lloyd et al., 2011). The Community Surface Dynamics Modeling System (CSDMS) approaches model integration in a similar manner through the Basic Modeling Interface (BMI) standard (Peckham et al., 2013). Yet another example is the Open Modeling Interface (OpenMI) standard (Gregersen et al., 2007; Moore and Tindall, 2005), which was originally developed for the hydrological sciences, but has since been expanded to better represent processes in other domains.

Recent advances in model integration frameworks and interoperability standards have lowered the technical barriers to achieving model integration. The frameworks are largely method and programming language agnostic. Although interoperability between computational languages remains an issue, the situation is improving. The envisioned software framework would allow modelers to quickly develop component-based models facilitating common activities in the development process. These include component interaction and communication, spatial-temporal stepping and iteration, up/downscaling of spatial data, multi-threading/multiprocessor support, cross language interoperability and reusable tools for data integration, analysis and visualization. Such a framework could, for example, be developed with Python – a general-purpose programming language widely used in the computational sciences – and implemented in one (or more) of the existing standards for inter-model data exchange and communication. In this manner existing integration frameworks and standards could be leveraged for these purposes. Interoperability among the frameworks may also be desirable and indeed a future possibility. This would allow, for example, models developed with BMI to almost seamlessly interact with OpenMI wrapped models (Goodall and Peckham, 2016).

These frameworks and standards aim to offer a consistent yet flexible approach to achieving model integration. That said, further investment may be needed to support an integrated system-of-systems framework. Including capabilities for meta-model generation (see Section 2.2), data integration and other visualization capabilities, as well as uncertainty analysis (see Section 2.3) could facilitate progress towards the proposed goal.

2.2. A tiered structure

To connect bottom-up and top-down approaches at both high and low levels of detail, we need a tiered structure with different levels of abstraction (Borshchev, 2013; Borshchev and Filippov, 2004). Having established this tiered structure, we need to ensure that the coupled models at the systems level capture the essential features of the process level. A consistent way of up-scaling from the process level to the systems level is therefore needed, as well as a way of connecting the tiers or levels so that critical information can be passed among them. A variety of up-scaling approaches, also known as emulation modeling or meta-modeling, have been suggested for objectively identifying such dominant processes or influences (Ratto et al., 2012). Dynamic emulation modeling can be achieved in two ways (Castelletti et al., 2012): structure-based methods, where the mathematical structure of the original model is manipulated to a simpler, more computationally efficient form; and data-based methods, where the emulator is identified from a data-set generated via numerical experiments conducted on the large simulation model. The two methods can be combined to improve accuracy while maintaining efficiency. Finally, we note that emulation modeling is closely related to multiscale modeling (Hoekstra et al., 2014; Karabasov et al., 2014), which usually involves one-way or two-way coupling between the scales. In what we are proposing, however, the process level and systems level models are not intimately coupled.

When applying this up-scaling approach to process models, the indicators must also be up-scaled. Indicators at the systems level will be, by definition, broader and more comprehensive than those at the process level, with pure, absolute or mid-point indicators more common at the process level, and integrated, relative or end point indicators more common at the systems level (for a brief review of absolute versus relative and mid-point versus end point indicators, see Hester and Little (2013)). Similar to the up-scaling of mechanisms from the process models, up-scaling of indicators will invariably result in some loss of information. It is therefore critical to identify which indicators or types of indicators dominate the characterization of the socio-environmental problem at the process level, and prioritize these for inclusion at the systems level. It may well be the case that some of the indicators are not integrated within the models that form the system of systems. These could initially be connected using a simple knowledge-based system. Depending on their relative importance, efforts could subsequently be made to include additional models that allow these indicators to be causally connected within the system of systems. The up-scaling of indicators will be an iterative process that is interconnected with, and inseparable from, the up-scaling of the process models.

Up-scaling of process models and indicators will result in the creation of a series of system models that are coupled at the systems level. If up-scaled indicators at the systems level reveal that mechanisms represented at the process level are either missing or incomplete, the process level models may also be adjusted. This approach may similarly reveal the need for new or additional indicators at the process level, consistent with the process of deriving indicators from the basic orientors (Bossel, 2007). A simple representation of the proposed framework is shown in Fig. 3.

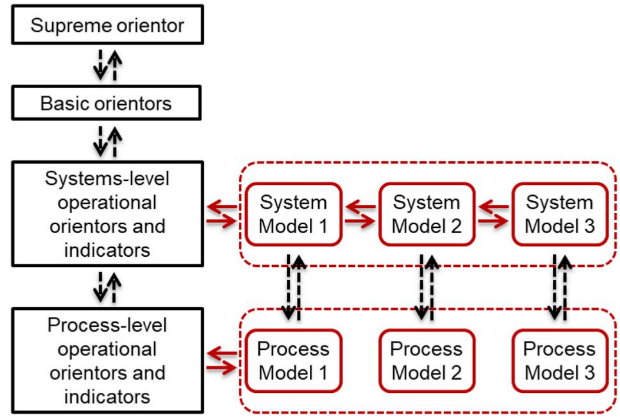

Fig. 3. The tiered, system-of-systems modeling framework, which refers to the entire framework, has more-detailed process models at the process level and less-detailed system models at the systems level. The component-based software framework couples the system models at the systems level.

In the tiered, system-of-systems modeling framework, important mechanisms are rooted in the process level and propagate upward, while a comprehensive definition of the supreme orientor is rooted at the systems level (ultimately in the basic orientors) and propagates downwards. The framework can be applied to resolve a wide range of socio-environmental policy issues, primarily by defining appropriate basic orientors for the supreme orientor of interest (sustainability, resilience, human health or ecosystem health, for example) and by selecting the appropriate set of socio-environmental systems to include in the system of systems.

The development and implementation of the framework would proceed in an iterative and modular fashion, starting with process models that are already available and using the integrated assessment methodology (as a reminder, see definition in Table 1) and the coupled models at the systems level. However, the iterative procedure may in time lead to the identification of a more appropriately scaled set of orientors and indicators for each process-level model and it may then be possible to use the individual process models themselves to resolve socio-environmental problems at the process level.

2.3. The ability to inform decisions in the face of deep uncertainty

The identification and management of uncertainty is a crucial task for resolving complex socio-environmental problems. While there has been considerable development of integrated environmental and socio-economic models (Laniak et al., 2013b), there has been much less (but growing) generation of information about uncertainty and sensitivity in those models, very little frank reporting of uncertainties, and very little trust in, or explicit use of, uncertainty information by users of models (Jakeman et al., 2006). As summarized in Table 2, the sources of uncertainty that need to be considered and managed derive from data, future forcing conditions, parameters and/or initial/boundary conditions, prior knowledge (formal and informal), model formulation (assumptions), model parameters and objective functions, the value of the verification/validation process, and the uncertainty communication process. Model components of problems subject to deep uncertainty are uncertain for most, if not all, of these reasons. Uncertainties propagate among components and propagation is not effectively dealt with in an analytic framework due to there typically being a mix of model types. Uncertainties also arise in situations where results are contested, due to the fact that multiple outputs may need to be weighted in different ways to try and recognise stakeholders with different values. Above all, uncertainties and the process of deriving them need to be reported as a

Table 2
Sources of uncertainty applicable to problems characterized by deep uncertainty.

Source	Brief description
Data	Imprecise, often sparse data in space and/or time with systematic and/or random errors and/or inadequate coverage of conditions. These errors affect calibration of the model while data input errors also affect outputs when using the model in predictive/simulation mode.
Future forcing conditions	Unknown variables or states of the model such as climate, demography, prices, and sectoral and cross-sectoral policy changes.
Parameters and/or initial/boundary conditions	Estimated parameters will always have uncertainty, but so will parameters that are considered known or can be measured.
Prior knowledge	Prior knowledge may be used to constrain parameters, formally or informally, in the formulated model structure. Inappropriate constraints may underestimate or overestimate uncertainty.
Model formulation	This may be known but non-identifiable in that there are multiple sets of parameter values that explain the model output. This non-uniqueness may apply to the model itself, even with exact/ideal data (a priori non-identifiability) or due to data being insufficiently informative (a posteriori non-identifiability). There may also be multiple model formulations (same type with varying structure, for example polynomials of different degree) or even paradigms (different types, for example, partial differential equations versus lumped transfer functions) used because processes are represented in different ways.
Model and/or objectives	These must address the real issues. There has often not been a thorough investigative and engagement process to identify the issues at stake, due for instance to resource limitations, lack of experts and perspectives, oversimplification of the issues or lopsided scientist push.
Verification/validation process	If this step is inadequate there may be an overconfidence in the model's capacity and limitations. The less comprehensive this step, the less certain the model results. A common glaring deficiency is the omission of a cross-correlation analysis between model residuals (predictions minus corresponding observations) and model inputs to assess if there is something missing in the model's explanation of outputs.
Communication process	There is often a disconnect between decision makers and the people undertaking modeling and simulation. The metrics presented to decision makers can be too complex and the amount of data overwhelming. The communication process needs to be iterative with the modelers providing information on what is most scientifically relevant and the decision makers communicating what is important to them.

matter of course and in a more complete and hence transparent way.

There are useful existing methods and concepts that can be invoked in the quest for enhancing the treatment of uncertainty. Existing methods, such as Monte Carlo based techniques, including formal Bayesian methods, are well developed and can be used. But the treatment of uncertainty might also vary depending on the objectives of the modeling exercise. If it is to increase social learning about a problem among stakeholders, then uncertainty can be handled more easily as it may only require participants to understand qualitative relationships and their implications. However, if the objective is prediction, then a more sophisticated treatment of uncertainty would be required. If, however, the objective is to discriminate among management alternatives, then outcomes can be evaluated based on the difference or change in outcomes of interest for a given scenario relative to some benchmark scenario. As shown by Reichert and Borsuk (2005), uncertainties in such differentials are lower than with absolutes.

Concepts such as risk and vulnerability are also often relevant for focusing the task of managing uncertainty. They can be invoked to simplify the questions being asked of a modeling problem and thereby reduce the demands on uncertainty characterization. Thus one may attempt to assess the risk of a bad outcome rather than trying to obtain a picture of all outcomes under all conditions.

Most of the quantitative methods for characterizing model uncertainty focus on the prediction objective and involve running the model many times. The most utilised is Monte Carlo sampling of model parameter space where each sample provides a prediction of outcomes so that multiple runs generate a distribution of outcomes. Invoking this in a probabilistic Bayesian setting is becoming popular though many assumptions about prior parameter values and errors may be required and convergence can be a problem. There are also more brute force techniques, often non-probabilistic, that aim to stress-test a model to assess under what conditions acceptable and non-acceptable outcomes are predicted.

A qualitative approach in complex modeling situations should not be under-valued. Indeed it may be sufficient or at least be a useful adjunct in some cases. One way of approaching this is through quality assurance of the modeling process (Refsgaard et al., 2007) and its constituent assumptions, while another is to include qualitative judgements about the information and how it is produced (Van Der Sluijs et al., 2005). We also note that adaptive management, which views policies as if they were experiments with results from one generation of study informing subsequent decisions, is a useful tool when dealing with uncertainty and which can enhance social learning.

Data integration, visualization and analysis tools are also needed to provide intuitive descriptions of complex and large-scale simulation data. In the face of deep uncertainty, the form and scale of model output should be more carefully considered. Many models are non-identifiable and analysis tools are needed to expose critical parameters and uncertainties so that improved, identifiable (and likely simpler) model formulations can be obtained. Simpler formulations (which include emulation models) that perform at least as well in prediction have several advantages when undertaking an uncertainty analysis. As a final note, problem framing and stakeholder engagement are now generally regarded as crucial when the problem has deep uncertainty in order to ensure the right problem is being addressed, crucial knowledge and perspectives are identified and trust is generated.

2.4. New educational and organizational support structures

As already mentioned, combining a system-of-systems modeling framework with the integrated assessment methodology could be of considerable benefit for resolving several families of complex socio-environmental problems. Because of the vast scale of the collective scientific challenge and the large number of disciplines and knowledge domains involved, we envision a new category of specially-trained "systems" scientists and engineers. They would be familiar with models at both the process and the systems level, and their role would be to couple the system models in the component-based, systems-level software framework (the solid horizontal arrows in Fig. 3). These systems scientists and engineers would orchestrate the exchange of information among the systems and would act as facilitators for communication between the two levels (the dashed vertical arrows in Fig. 3). When trying to couple a wide range of different knowledge domains, it is neither possible nor desirable for all scientists and engineers working on the problem to be actively engaged in systems integration. In fact, the vast majority of scientists and engineers would be experts in their own disciplines or domains (we refer to them as process experts), but would need to have some familiarity with systems integration and the component-based software framework. A small fraction of the total would be experts in systems integration and the component-based software framework (we refer to them as systems experts), but would also have training in one or more of the specific disciplines or domains.

As new models are acquired or developed at the systems level, they can be coupled to the existing system models, and the success of that integration checked (Bennett et al., 2013; Jakeman et al., 2006). The advantage of having a tiered structure that maintains the process-based models is that access to the more detailed mechanistic predictions that are possible with process models is maintained, even if these relationships are not hard-wired. In this way, process experts can continue to develop and validate their existing process models, and detailed expertise is maintained in those fields. Increasing communication between those working at the systems level and those working at the process level will ensure that new insights are passed between the two levels so that knowledge and understanding can be simultaneously improved at both levels. We note here that this tiered educational structure is reminiscent of the education of "T-shaped" professionals (Heinemann, 2009; McIntosh and Taylor, 2013; Uhlenbrook and de Jong, 2012), but in our case, we need the systems experts to also have detailed knowledge of their own discipline or domain so that they can be responsible for developing the emulation models from the more detailed process models in their discipline or domain. In addition, they need to use this knowledge when coupling their systems-level models with systems-level models from other disciplines or domains.

3. Illustrative examples

Here we provide a brief illustration of how one could combine the integrated assessment methodology (as a reminder, see definition in Table 1) with the proposed tiered, system-of-systems framework to address two socio-environmental issues: the food/energy/water nexus and interdependent infrastructure systems. We select sustainability as the supreme orientor for food, energy and water systems and resilience as the supreme orientor for evaluating the impact of coastal flooding on interdependent infrastructure systems, as shown in Figs. 4 and 5, respectively. In each case we begin with available models of a few systems, but implement the framework in a way that allows additional systems to be added in a modular fashion. Wherever possible, we would take advantage of existing modeling infrastructure and scientific expertise by using component models and knowledge that have accrued from intensive studies over a long period.

3.1. Sustainable food, energy and water systems

To assess and enhance the sustainability of food, energy and water systems in the Chesapeake Bay Watershed, we would build upon the integrated assessment methodology. This would produce a stakeholder-

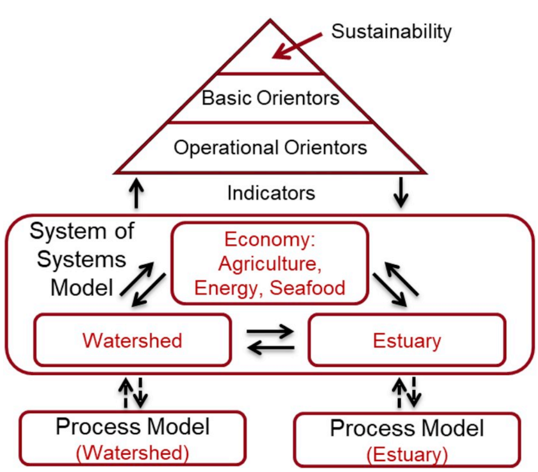

Fig. 4. Initial framework for enhancing sustainability of food/energy/water systems.

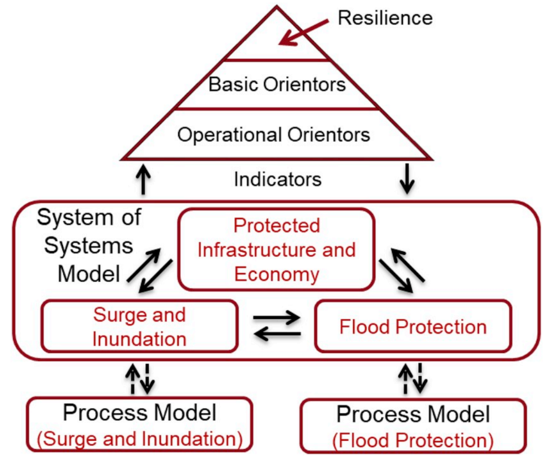

Fig. 5. Initial framework for enhancing resilience of interdependent infrastructure systems to coastal flooding.

driven (Voinov and Bousquet, 2010; Voinov et al., 2016) conceptual system-of-systems model that, as part of the joint problem framing, identifies operational orientors, indicators, and specific process models to be included, and that recognizes the context for decision-making and how the various uncertainties are to be prioritized and managed.

As shown in Fig. 4, we could take advantage of the existing Chesapeake Bay Model which comprises a suite of process-level models including watershed and estuary models (CBP, 2012; Shenk et al., 2012; Voinov and Cerco, 2010), modifying them for our purpose and identifying any process model gaps in terms of the requirements of the overall conceptual model. To represent food and energy, we could initially choose a spatially-resolved version of an economic model (Duchin, 2005; Duchin and Levine, 2012) with agriculture, seafood, and energy as three of many sectors, and with water represented by the process-level watershed and estuary models. We would then up-scale the process models to the systems level, as described in Section 2.2 and having the needs of the overall conceptual model in mind. Indeed, the dynamics of the process level models could be extracted in a way that best suits the purpose of the models at the systems level. However, the spatial resolution of the economic model is at the county scale, and it would therefore be directly coupled at the systems level, as shown in Fig. 4. The three system models would form a system of systems using the component-based software framework. The basic orientors would be used to derive appropriate operational orientors suitable for these specific systems, as well as identify associated indicators, and these would then be used to assess and enhance sustainability, recognizing that several systems would only be added at a later stage.

Once the initial set of systems were being successfully simulated, we could begin to include other systems relevant to the Chesapeake Bay Watershed. For example, we could include agriculture, fisheries and energy models at the process level, and then up-scale these to the systems level creating additional systems-level models and removing the representation of agriculture, fisheries and energy from the economic model. As already mentioned, some of the initial indicators may not be causally integrated within the models. These could initially be connected using a knowledge-based system (Krueger et al., 2012) and, depending on their relative importance, could subsequently be included in additional systems that allow these indicators to be causally integrated within the system of systems. As new systems were added, additional orientors and indicators would be added that are relevant to the new systems, making the assessment of sustainability increasingly comprehensive. Some of the knowledge domains and disciplines do not yet have appropriate models (especially social systems), but initial versions of these would need to be developed. In this way, we would build complexity as we develop confidence in the modeling framework (for example, see Jakeman et al. (1994)), keeping in mind the overall goal for the system-of-systems model.

Once sustainability is being assessed and enhanced at the regional scale, the tiered framework could then be applied to regions of similar scale in other areas. If the approach proves successful for several regions across the globe, the potential to link across regions, nations, continents and oceans could be considered. Methods and approaches for modeling the Anthropocene are increasingly being implemented (Verburg et al., 2016) and a modular, system-of-systems framework would be of great benefit in these situations as well. To connect all regions, we would likely have to up-scale (see Section 2.2) the system models at the regional scale to the national or continental scale, creating an additional systems level, with this new set of systems again coupled using a component-based software framework. A repository of re-useable components could be made available and applied across regions, nations, continents and oceans. At that point, we would have a global model that could be used together with down-scaled orientors and up-scaled indicators to assess and enhance global sustainability, but this would clearly be a major undertaking that would need to be coordinated by an organization like the United Nations.

3.2. Resilience of infrastructure systems to coastal flooding

As modern societies become more complex, critical interdependent infrastructure systems are more likely to fail under stress unless they are designed to be resilient (Ellingwood et al., 2016; Nan and Sansavini, 2017; Zio, 2016) Resilient infrastructure systems maintain the flow of goods and services in the face of a broad range of natural and anthropogenic hazards. As shown in Fig. 5, we could use the exact same procedures outlined in Section 3.1 for sustainable food, energy and water to enhance resilience in Coastal Louisiana, which has experienced the catastrophic effects of several land-falling hurricanes in recent years.

Although widespread agreement has not been reached on a definition (Cutter et al., 2014; UNDP, 2014), a recent report (UNDP, 2014) defines resilience as the capacity to anticipate, prevent, recover from, and transform in the aftermath of shocks, stresses and changes. The report recommends that measurements of resilience need to be linked to clear targets, and that a multi-scale, generic, and multi-dimensional approach for resilience that encompasses many dimensions (including physical, technical, economic, human, social, political, institutional, ecological and environmental) should be adopted. Conceptually, these requirements are similar to those for sustainability with a need for a wide range of orientors to be compared to indicators (as shown in Fig. 2) that are integrated within a broad range of socio-environmental systems (as shown in Fig. 1). Resilience would therefore replace sustainability as the supreme orientor in Fig. 2, with several basic orientors that capture the abstract essence of resilience, and many more concrete operational orientors reflecting desired targets that are compared to the actual values of associated indicators in the system of systems.

In choosing the relevant systems for a conceptual, stakeholder driven system-of-systems model, we could initially focus on a surge and inundation model (Bilskie et al., 2014), a flood protection model (Duncan et al., 2008), and all major infrastructure sectors using a spatially-resolved, infrastructure and economic model (Haimes et al., 2005; Okuyama and Santos, 2014), as shown in Fig. 5. The surge and inundation model and the flood protection model would both be implemented at the process level and then up-scaled to the systems level, while the economic model would be less spatially resolved and would be implemented directly at the systems level. Once the initial set of systems were being successfully simulated, we could begin to include other systems relevant to Coastal Louisiana. For example, we could include models for various infrastructure systems at the process level, and then up-scale these to the systems level creating additional systems-level models and removing the representation of these infrastructure sectors from the combined infrastructure and economic model. In time, to make the assessment of resilience increasingly comprehensive, we could extend to environmental and social systems (Cutter et al., 2003, 2014; Magis, 2010), keeping in mind from the outset their role in the conceptual system-of systems model.

4. Next steps in research, education and practice

In this section we briefly discuss initiatives that are needed for the component-based, modeling and software framework, the tiered structure and scaling procedures, decision-making under deep uncertainty, new educational and organizational support structures, and specifications for the proposed framework.

4.1. A component-based, modeling and software framework

An omnipresent problem associated with coupling complex models is the vast difference in temporal and spatial scales among models. For example, climate models span global to regional spatial scales and seasonal to decadal temporal scales, while watershed models are spatially explicit at the regional and local scale and temporally explicit over timescales from hours to years. The mismatch in scales can be resolved to some extent with judicious aggregation during up-scaling from the process to the systems level, but large gaps will no doubt remain in some regions. This may require that extensive sets of new data be collected and/or that methods and expert opinion be used to fill knowledge gaps. In this regard, the convergence of pervasive sensing with location-aware and social media technologies, along with infrastructure-based sensors, is leading to the production and collection of "big data" in many areas (Rao et al., 2015; Zaslavsky et al., 2012) and it may be possible to capitalize on this proliferation to help fill in the gaps in spatial and temporal phenomena.

Further challenges include the potential for nonlinear systems to exhibit unpredictable "phase-change" behavior (Monasson et al., 1999; Solé et al., 1996), the formation of "alternate stable states" (Beisner et al., 2003; Scheffer et al., 2001; Schröder et al., 2005; Suding et al., 2004), as well as "Panarchy," which describes the conditions that control cycles of growth, accumulation, restructuring and renewal in coupled human and natural systems (Garmestani et al., 2009; Holling, 1973, 2001). We need to decide on which complex systems should be included for a specific region, the level and scope of detail that is necessary for the purpose of the overall conceptual model, and how the specific systems should be arranged and organized. The last refers to the model composition and structure, both semantic (will the model composition output useful results?) and syntactic (how the component models are coupled in a technical sense – the "nuts and bolts"). For example, do we start with a geographic basis emphasizing demographics, and then layer additional systems on top of that? What about the problem of reconciling natural features (watersheds and airsheds) with economic and political zones (cities and regions)?

Progress is also needed in identifying the scope and generic features of the specific systems that need to be included in the system of socio-environmental systems. Although there is some overlap in the systems listed in Section 1, a modular approach with a repository of system models that can be used repeatedly in different regions and in different combinations means that system models that are already coupled may need to be decomposed. Nevertheless, a systematic approach with a library of system models for a wide range of real-world systems would be extremely valuable.

4.2. Tiered structure and scaling procedures

Clearly, the necessary fundamental knowledge, mechanistic understanding, and data are not available for all systems of interest, but we can surely make useful progress if we start building on what we have. In addition, it may be that some models are initially only available at the systems level. The tiered framework would therefore be simultaneously developed at both the process level and the systems level. Procedures for the identification of appropriate sets of basic orientors, operational orientors and indicators, as well as the consistent up-scaling of indicators and process-level models and down-scaling of orientors and systems-level models are needed. Another problem is the difficulty of up-scaling systems with emergent properties from the process level to the systems level and the analogous lack of reductionism for some systems at the systems level. Finally, as discussed in Section 3.1, it may be possible to use additional, systems-level tiers in the framework so that the sustainability or resilience of large sectors of society (nations and continents) could eventually be characterized, ultimately leading to a more realistic assessment of global health.

4.3. Decision-making under deep uncertainty

A component-based modeling approach will necessarily result in integrated models of high complexity. Uncertainty assessment of the upper tier system-of-systems model must first proceed with uncertainty assessment and understanding of the components in that tier as well as uncertainty assessment in each of the lower tier process models. Generally this is not practised as integrated models have tended to be assessed as a whole and not examined for uncertainties in their component models and how they propagate through the model linkages. A new mindset is therefore required to address the challenge of analyzing component models and understanding and assessing their uncertainties as well as capturing how they propagate through the system of systems. There are however promising new Exploratory Modeling and Analysis techniques and software that analyse integrated models as a whole in an exploratory sense (e.g. (Hadka et al., 2015)) rather than in a predictive sense. These techniques are aimed at exploring the effects of policy options under uncertainties in future conditions and model assumptions, which are sometimes framed in an effort to assist robust decision making and with outputs that produce Pareto fronts that illustrate tradeoffs among the outcomes of interest (Kasprzyk et al., 2013; Watson and Kasprzyk, 2017).

The most basic step in uncertainty assessment is to ensure that the modeling addresses the questions being asked. This applies not just to the high-level objective (prediction, adaptive management, social learning, discriminating among management alternatives) but also to characterization of specific functions of the quantities of interest. Homing in on these functions may also serve to simplify the demands of the modeling task. For example, for a hydrological problem, one may not be concerned with the whole time series of certain fluxes, but perhaps some integral of those over time and space, thereby focusing and reducing the uncertainty requirements.

Indeed it must follow that one allows for the expense of essential analysis of model uncertainty and ascertains what uncertainties are crucial for the specific functions of the quantities of interest and concentrate on them. Attention to problem framing and stakeholder engagement is crucial when the problem has deep uncertainty in order to manage various aspects of it such as getting the problem framing right, the quantities of interest set, and soft and hard prior knowledge incorporated. Managing these uncertainties has several elements including initially identifying and ranking the importance of their sources so that it can be reduced where needed and possible, and generally appreciated.

4.4. New educational and organizational support structures

The disciplinary landscape is fragmented, with a wide range of professional and academic groups pursuing related goals, but without much formal coordination. Existing scientific and professional organizations that are focused on integrated assessment, resilience or sustainability could re-align some of their activities, or new organizations may emerge to take on the challenge. These organizations could provide independent, institutional oversight, guiding the consistent development and implementation of the proposed framework.

The strong disciplinary structure of higher education is of great value to society because it produces much-needed disciplinary experts. Unfortunately, it also severely constrains interdisciplinary interaction. Consequently, to ensure the success of the proposed framework, we need increasingly novel approaches to education that more strongly integrate across the social, physical and life sciences, and engineering to create a new generation of "systems" scientists and engineers.

In civil engineering, for example, most undergraduate programs require core competence in civil engineering plus an area of specialization, such as construction, environmental, geotechnical, materials, structural, transportation or water resources engineering. We therefore propose adding a new area of specialization to educational programs that is focused on systems. Then, as shown in Fig. 3, trained civil/systems engineers would integrate models at the systems level, working in collaboration with systems experts from other disciplines (represented by the horizontal solid arrows). The civil/systems engineers would also facilitate two-way communication between the systems level and the process level (represented by the vertical dashed arrows). The civil engineers at the process level would be introduced to the systems approach while developing new engineering knowledge at the process level. Two-way communication between the systems level and the process level, coupled with interdisciplinary communication among all disciplines and knowledge domains at the systems level, will be crucial for the successful implementation of the proposed framework.

We conclude this section by noting the similarity between what we are proposing and general systems theory (GST) (von Bertalanffy, 1950, 1972), which aims to provide a foundational theory of universal principles applying to systems in general (Rousseau, 2015). Although the ongoing fragmentation of the systems community casts a long shadow over the vision of discovering and developing GST, contemporary work suggests that GST is a realistic prospect that has the potential to support interdisciplinary communication and cooperation, facilitate scientific discoveries, promote the unity of knowledge, and provide a disciplined way to build a systematically healthy world (Rousseau, 2015). Thus, systems experts from the systems discipline could play a central role in building the proposed framework and in helping to design the curriculum associated with the training of systems experts in all other disciplines and knowledge domains.

4.5. Specifications for the proposed framework

The design principles of the new framework need to be specified. This encompasses the individual systems, the system of systems, the way the systems interact and exchange information, the tiered structure and procedures for scaling among the tiers, and the orientors and indicators. This is not to say that there are no frameworks currently available which address some of these concerns for system/model coupling and integration. There are in fact many, each with their own design philosophies and implementation approaches (Belete et al., 2017). Although a full review of available frameworks is inappropriate here, no single framework appears to have received majority support. While a common aim is to ease the technical burden of coupling models, a steep learning curve still exists. For example, in the context of applying the OpenMI framework, it has been recommended (Knapen et al., 2013) that model developers improve their understanding of software development principles before attempting model integration.

The proposed framework would ideally be made accessible for model developers within interdisciplinary teams. To cater for the diversity in technical ability this may mean making the framework extensible, preferably in its native programming language (or providing a scripting language), and facilitating direct interfaces with existing tools and models which may be written in other programming languages. Including a graphical interface to enable ease of use would be an additional desirable feature (Malard et al., 2017). A good graphical interface should enable users to more easily interact with the framework, facilitating the handover process to end users (in cases where the users are not the developers) and overcome barriers to adoption of the framework (Crout et al., 2008).

5. Looking ahead: a tiered, system-of-systems modeling framework for resolving complex socio-environmental policy issues

We have sketched the outline of a generic framework for resolving complex socio-environmental problems. In this section, we briefly identify some barriers and enablers that will impede or accelerate the implementation of the framework and conclude with a cautionary perspective on systems thinking, complexity and comprehensiveness.

Potential barriers to building a system of systems model for such socio-environmental issues include the challenge of increasing system understanding and informing robust decisions in the face of deep uncertainty, and the lack of reliable models for many of the social systems that are needed. Potential enablers include the current focus of research on deep uncertainty and the adoption of integrated uncertainty assessment approaches which consider the various sources of uncertainty throughout the modeling process and their implications for the modeling purpose (Maier et al., 2016). Another enabler is current research focused on consolidating and synthesizing knowledge about coupling environmental and social models (Schlüter et al., 2017) beyond single case studies, to generate lessons learned and illuminate promising lines of inquiry (www.sesmo.org).

An additional barrier exists because in most cases, specific socio-environmental problems are tackled separately, without acknowledging or understanding similarities across problem domains. However, as shown in Section 3, the approach to characterizing the sustainability of food, energy and water systems is analogous to the approach to characterizing the resilience of interdependent infrastructure systems to coastal flooding. In addition, only a few models are usually coupled, without much thought given to the possibility of extending to include additional systems. The proposed framework could serve as an enabler in these cases, providing a way to more effectively elicit and integrate knowledge across a wide range of systems, and across several families of socio-environmental problems.

Implementing the proposed framework represents a daunting challenge, especially in the case of sustainability, but even recognition of the need for a framework that can be commonly applied across knowledge domains and disciplines to resolve families of socio-environmental problems is a critical first step. By initially focusing on somewhat narrower socio-environmental problems, but keeping the more comprehensive longer-term sustainability goal in mind, we can build confidence in the proposed framework. To facilitate the implementation of the framework, we envision a transformation in our approach to science and engineering that spans research, education and practice. As described above, we propose new educational initiatives for training the next generation of process and systems scientists and engineers. This transformation can build upon the current science and engineering enterprise in an inclusive way such that many relevant disciplines would be engaged in the development of the framework.

Finally, we acknowledge that the field of systems thinking is rich in schools of thought with different epistemological and ontological stances (Jackson, 2010; Midgley, 2000). The same is true for environmental modeling with its epistemological pluralism (MacMynowski, 2007). The proposed framework is driven from the systems engineering field, which largely operates from a positivistic or functionalist paradigm based on ontological assumptions that systems, causes and events along with mechanisms and processes operate more or less independently of the observer. Indeed, the concept of post-structuralism (Scheele et al., 2018) warrants recognition, with choices and assumptions in modeling made as transparent as possible. As already emphasized, we propose to begin with narrower socio-environmental problems, but work towards the more comprehensive goal of sustainability. In doing so, we acknowledge the question posed by Ulrich: "How can we deal critically with the fact that our thinking and hence, our knowledge, designs, and actions, cannot possibly be comprehensive, in the sense that we never "comprehend" all that ought to be understood before we pass to judgment and action?" (Ulrich, 1993).

Acknowledgements

Partial financial support was received from the Global Change Center and the Fralin Life Science Institute at Virginia Tech, as well as the National Socio-Environmental Synthesis Center (SESYNC) at the University of Maryland.

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