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Integrated assessment and modelling: Overview and synthesis of salient dimensions

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A B S T R A C T

Integrated assessment and its inherent platform, integrated modelling, present an opportunity to synthesize diverse knowledge, data, methods and perspectives into an overarching framework to address complex environmental problems. However to be successful for assessment or decision making purposes, all salient dimensions of integrated modelling must be addressed with respect to its purpose and context. The key dimensions include: issues of concern; management options and governance arrangements; stakeholders; natural systems; human systems; spatial scales; temporal scales; disciplines; methods, models, tools and data; and sources and types of uncertainty. This paper aims to shed light on these ten dimensions, and how integration of the dimensions fits in the four main phases in the integrated assessment process: scoping, problem framing and formulation, assessing options, and communicating findings. We provide examples of participatory processes and modelling tools that can be used to achieve integration.

Learning objectives

- Have a basic understanding of what needs to be integrated in integrated assessment and modelling, how and why
- Identify key developments and publications in integrated assessment and modelling
- Give examples of how integration dimensions are relevant to phases of integrated assessment and modelling.

Assumed background knowledge

- Awareness of basic concepts and terminology related to integrated assessment and environmental modelling
- Awareness of the complexity and uncertainty involved in analysing environmental problems

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1. Introduction

The impacts and causes of environmental problems transcend the boundaries of sectors, disciplines, system components and other divides. This has driven the need for integrated assessment (IA), a process that combines multiple and diverse components across their social, organizational and conceptual boundaries to provide a comprehensive analysis of the problem. Integrated modelling (IM) facilitates this by providing a single platform to explore the linkages and feedbacks between different system components, including the social, economic and ecological implications of different natural or anthropogenic factors. IM is generally considered the key tool for performing the IA process as it has the capacity to help deliver a systematic and transparent approach to integration. Together, integrated assessment and modelling (IAM) can help decision-makers develop policies to managing environmental resources and assets in a way that delivers acceptable environmental and socioeconomic outcomes. More broadly, effective use of IAM supports social learning by promoting a science-informed dialogue about the future.

The meta-discipline of IA first emerged in the context of global change problems to overcome limitations of traditional disciplinary methodologies, which were ineffective in handling the complex feedbacks and interactions of socio-ecological systems (Funtowicz and Ravetz, 1993; Rotmans, 1998). On looking into the historical evolution of IAM, one can distinguish three phases. Although White (1969) has long recognized the need for integration to consider the "multiple purposes" and "multiple means" of water management, it was not until the 1990s when IAM was explicitly recognized (i.e. *the inception phase*). Mitchell (1990) talked about integrating three aspects of water systems: surface water and groundwater, and quantity and quality; water and land interactions; and interrelationships with social and economic development. During the inception phase, the concept of IAM was defined and its practices became more established, with much of this work emanating from research in climate change, energy and economics (Dowlatabadi, 1995; Risbey et al., 1996; Rotmans and van Asselt, 1996: Rotmans, 1998; Toth and Hizsnyik, 1998; Weyant et al., 1996). Reflecting on this period, Hoekstra (1998) commented that: "the [integration] concept is still crystallizing, both in theory and practice". In the 2000s, many of the foundations in the IAM were cemented (i.e. *the foundational phase*). These included: drawing frameworks, features and principles of the approach (e.g. Hare and Pahl-Wostl, 2002; Parker et al., 2002; Jakeman and Letcher, 2003); crafting the methodology (e.g. Dewulf et al., 2005; Castelletti and Soncini-Sessa, 2006; Jakeman et al., 2006; Newham et al., 2007), and showcasing its utility through case studies (e.g. Croke et al., 2007; Liu et al. 2008). The field is now in a *maturity phase*. The accumulated learning and experience as well as the advancements in related modelling and computing fields have allowed for addressing more sophisticated topics, such as good modelling practices (e.g. Van Delden et al., 2011), role of software development and computing platforms (e.g. Larocque et al., 2014), and uncertainty management (Haasnoot et al., 2014).

Whereas there is a wide consensus on the need for integration (e.g. Medema et al., 2008), there is less agreement on what integration really means (Hering and Ingold, 2012), and how it can be effectively incorporated into modelling processes. Integration is defined as "the making up or composition of a whole by adding together or combining the separate parts or elements" (Oxford English Dictionary, 2014). In this paper, we aim to shed light on what constitutes "integration" in IM, and how it is incorporated into the various activities of IA in order to improve the way we communicate about *what* and *how* to integrate. In this paper, IAM is considered as the integration of components across and within ten interrelated dimensions (Fig. 1). IAM should be a problem-driven process and the first three dimensions correspond to key drivers for integration, namely the need to account for multiple i) issues of concern, ii) governance settings, and iii) stakeholders. This in turn requires the integration of multiple, iv) natural and v) human systems, and vi) spatial and vii) temporal scales. The remaining three dimensions represent the methodological aspects related to integrating viii) disciplines, ix) methods, models, other tools and data, and x) sources and types of uncertainty. There is overlap between some of these ten dimensions, for example it is acknowledged that stakeholders and governance settings are a part of the human setting. However each of the ten dimensions is distinguished as a salient dimension of IAM. The IAM process and its outputs can be rendered inadequate with a lack of careful consideration and appropriate treatment of any one dimension.

The idea of integration as a multi-dimensional concept is not new (see Table 1 for examples). In the context of integrated assessment, Parker et al. (2002), Jakeman and Letcher (2003) and Kelly et al. (2013) consider integration across five broad categories – issues, stakeholders, disciplines, processes and models, and scales. In the context of integrated research in environmental science and policy, van Kerkhoff (2005) identified integration across 12 thematic categories; six of these categories involve integration within the research sector (e.g. disciplines, research issues, research and teaching, research methods etc.), one category represented worldviews, and the final five categories related to integration between research and non-research organisations.

Janssen (2009) considered integration as the communication process of combining different elements (including tools, disciplines, scales etc.) and identified five types of integration – methodological, social, semantic, technical and institutional. Strasser et al. (2014) distinguished three dimensions of integration from a theoretical perspective, related to the integration of different linguistic expressions and communicative practices (*communicative*), interests and activities (*social*), and knowledge bases including theoretical concepts and methods (*cognitive*). The integration dimensions by Janssen (2009) and Strasser et al. (2014) were characterised in the context of agricultural systems and climate change research, respectively, but are applicable to all interdisciplinary fields.

Jønch-Clausen and Fugl (2001) discussed the concept of integrated water resources management as the integration of two categories – the 'natural system' and the 'human system'. According to their categorisation, integration in the natural system included links between: i) land and water, ii) surface water and groundwater management, iii) water quantity and quality, iv) upstream and downstream zones, and v) freshwater and coastal zone management. The associated integration in the human system involves: i) holistic management across all levels of institutions, ii) considering water use, development and risk in all economic development planning processes for all sectors, iii) linking water resources management and poverty alleviation, iv) linking water resources management to national security and trade policies, and v) stakeholder engagement in the planning and decision process.

The ten dimensions identified in this paper are intended to capture both the integration of different components from the real world system (as in Jønch-Clausen and Fugl, 2001) and the methodological aspects related to incorporating different types of information, scales, perspectives, practices, theories, models and tools. While uncertainty has not previously been considered a dimension, its influence warrants explicit treatment. The notion of what is not known is quite distinct from what is known within each of the other dimensions, and has often been marginalised or even overlooked. There are several challenges entailed in integrating across these ten dimensions; in the next section we discuss these challenges as well as some solutions proposed by various methodological and technological advances. This is followed by a discussion on how the ten

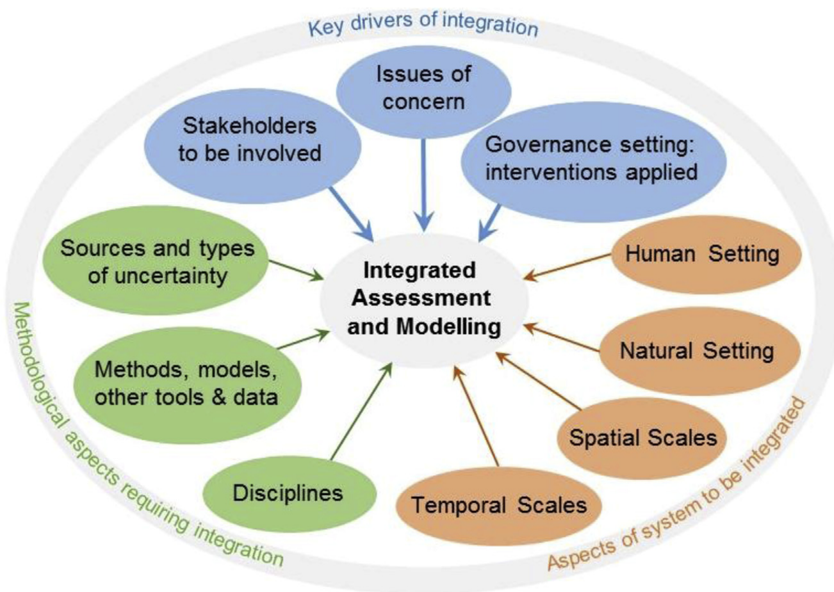

Fig. 1. The ten dimensions of integration in integrated assessment and modelling (IAM).

dimensions fit into the IAM process and how modelling and participatory tools can be used to support each step.

2. The ten dimensions of integration

2.1. Issues of concern

The need for integration arises above all from the need to tackle connected issues of concern and anticipate unexpected side-effects. The interdependent links between natural and human factors mean that one environmental problem (e.g. related to water quality or quantity, ecosystem status or extreme climate events) can affect other issues including social or economic issues (e.g. social welfare, profitability, justice), and vice versa. The linkages between issues can be direct, for example a decline in water quality is often linked to reduced flow in rivers. However, some diverse issues are linked via indirect pathways; one example is biofuels to provide clean energy and food prices. Although at first glance the two issues seem unrelated, the expansion of biofuel can lead to increases in food prices as biofuel production competes with food crops for land and water.

Issues are defined depending on stakeholders' worldviews and positions in the system (Pahl-Wostl, 2007). Many environmental problems are ‘wicked’, that is, highly complex with no clear definitions or solutions (Rittel and Webber, 1973). The challenge for managing wicked environmental problems is that stakeholders have different, and many times conflicting, views about the issue and how it may be managed. For example, Dewulf and Bouwen (2008) report a case study involving three actors, a hydropower plant, a water supply company and sand miners. For the hydropower plant, which provides electricity to the region, the key water management issue is reducing soil erosion and resultant sediment

Table 1
The dimensions of integration in this paper and how they correspond to dimensions identified in other studies.

Dimensions	Parker et al. (2002), Jakeman and Letcher (2003), Kelly et al. (2013)	van Kerkhoff (2005)	Janssen (2009)	Strasser et al. (2014)
Issues of concern	- Issues	- Research Issues		
Stakeholders	- Stakeholders	- Worldview	- Social[a]	- Social[a]
Governance setting	- Processes and models[a]	- Management arrangements by scale - Management by issue focus	- Institutional	
Human setting	- Processes and models[a]	- Sectors	- Social[a]	- Social[a]
Natural setting	- Processes and models[a]			
Spatial scales	- Scales[a]			
Time scales	- Scales[a]			
Disciplines	- Disciplines	- Disciplines - Research organisations - Research and teaching	- Semantic - Methodological[a]	- Cognitive[a] - Communicative[a]
Methods, models, other tools and data	- Processes and models[a]	- Data - Research methods - Research and application activities - Resources	- Methodological[a] - Technical	- Communicative[a] - Cognitive[a]
Uncertainty				

[a] Indicates dimensions from other studies that overlap more than one of the 10 dimensions identified in this paper.

flow to the reservoirs. On the other hand, miners do not frame sediment as a problem but as a source of income. The water supply company is primarily interested in providing sufficient drinking water.

A holistic treatment of issues is important to ensure that diverse stakeholder views and interests are included, to minimize conflicts, and ensure a management option implemented to address one issue does not cause unacceptable problems in other parts of the system. IM can make use of participatory and soft systems methods to identify stakeholders' key issues to be incorporated into the analysis (Ekasingh and Letcher, 2008). For example, ElSawah et al. (2013) used a cognitive mapping approach to identify and map how a group of stakeholders define water security issues in arid areas.

The integration of issues affects the IAM process practically, primarily through the selection of indicators (at appropriate scales) to assess system 'performance', under different driving conditions or scenarios, relative to some benchmark performance (e.g. business as usual). These indicators are contextual for the system of interest and vary according to which issues are being evaluated and which trade-offs are required to inform decision making. By modelling the system processes simultaneously, IM allows the evaluation and comparison of the impact of drivers on multiple issues of concern. These issues are represented in IAM as a set of indicators on the quality of the environment (e.g. biodiversity, water quality) and the community (e.g. unemployment rate, education, health).

The comparison of issues can be undertaken explicitly in IAM with methods such as multi-criteria decision analysis (MCDA) techniques, which are designed to systematically compare and rank alternative scenarios (e.g. management options) using appropriate environmental, social and/or economic indicators as evaluation criteria. In MCDA, value judgements derived from the preferences of the decision maker or stakeholders are used to weight the relative importance of each criterion. Other methods for comparing scenarios include cost benefit analysis, which assigns monetary values to the costs and benefits of each alternative, and risk analysis, which identifies and assesses the risks associated with each alternative. Using the IA framework, measures of each criterion can be estimated for various scenarios or alternatives. As environmental problems are driven by multiple objectives and criteria, a single optimal solution very rarely exists. Rather, a Pareto set of solutions can be identified, within which no single solution is strictly better than any other and a trade-off is required between the competing objectives (Bach et al., 2014). The selection of a solution is made by 'satisficing', rather than optimising the decision criteria. Satisficing refers to finding the options that are acceptable at a given level of aspiration, such as meeting the needs of stakeholders (Pidd, 2003).

An example of the treatment of multiple issues in an IM framework is the Ecosystem Portfolio Model (Labiosa et al., 2013). This is a multi-criteria decision support system (DSS) designed to allow users to simultaneously assess the impact of land-use change scenarios on a range of ecological (e.g. biodiversity potential, threatened and endangered species, rare habitats, landscape fragmentation) and socioeconomic criteria (e.g. indicators related to property values, community profile and facilities and amenities). In another example, Ausseil et al. (2013) developed an integrated model to explore the impact of land use change scenarios (afforestation) on multiple ecosystem services including climate regulation, erosion control, water-flow regulation, food, fibre and natural habitat.

2.2. Governance setting

The governance dimension relates to interventions designed and carried out to influence system processes (micro and macro) in desirable directions (Ison et al., 2013). Governance may include: public or private action; by an individual, an organisation or the government; in an operational, tactical or strategic context; and across or within institutional, sectorial and geographical boundaries. Interventions are combinations of management and administrative instruments and measures. Instruments aim to provide the context or preconditions necessary for system actors to adopt certain measures (Turner et al., 2008). Measures are "on the ground" changes that contribute to achieving objectives, and can range from technical (e.g. adoption of water-efficient irrigation systems) to behavioural changes (e.g. reducing the frequency of irrigation). Kaufmann-Hayoz et al. (2001) broadly classify instruments into six types based on how they are designed to influence the target group and micro-processes (cognitive, behavioural):

- Command and control instruments aim to restrict the scope of behaviour of a target group. These include regulatory standards, licenses, and management zones.
- Economic instruments provide economic incentives to influence choice of a target group towards a desirable option. These include price signals, taxes, and subsidies.
- Service and infrastructure instruments aim to facilitate or inhibit the behaviour of a target group (e.g. providing environmentally responsible products to help reduce impacts).
- Collaborative agreements, such as certification standards, aim to get a target group to stick to a certain course of action to achieve common goals.
- Communication and diffusion instruments, such as marketing and information campaigns, aim to trigger behavioural changes by influencing how individuals make decisions (through cognition, attitudes, or motivation).

The nub of the challenge for decision makers is to design a mix of options (i.e. strategies) that are robust under various future changes in the natural and human system settings. IM provides a framework for identifying intervention options, and assessing the risks and relative impacts (adverse and beneficial) associated with trade-offs between multiple strategies under different scenarios. Management interventions are usually treated as external input to the IM. Examples include integrated biophysical and economic models to manage water resources (Carmona et al., 2013; Qureshi et al., 2013), fishing activities (Gao and Hailu, 2012), rangelands (Ibáñez et al., 2014) and solid waste (Levis et al., 2013). An alternative approach is to examine how governance rules emerge from the system dynamics; for example Smajgl et al. (2008) present an agent-based framework for endogenously generating the emergence of rules in response to changes in the collective behaviour of individuals.

To be useful to decision and policy makers, models and scientific information in general must be (Liu et al., 2008; Laniak et al., 2013): relevant to the policy question and decision-making context; scientifically credible; transparent and lack bias; readily accessible and understandable by its users; and provided in a timely manner. Morgan and Dowlatabadi (1996) argue that the central focus of IA for decision making should be on characterizing and analysing uncertainties, and incorporating values using an iterative and adaptive approach depending on what has been learnt about the critical parts of the problem, and their relevance to the policy question. Both dimensions are covered in the issues of concern and uncertainty sections.

2.3. Stakeholders

Stakeholders can be individuals or interest groups related to the sources of the problem, as well as those affected by the problem, those with the expertise to understand them and those politically responsible for them. IA frameworks can incorporate participatory processes to ensure that a broad range of interests and perspectives are considered. Effective stakeholder engagement can also support the IA process by (van Asselt and Rijkens-Klomp, 2002; Reed, 2008; Wittmer et al., 2006):

- Providing a source of information and ideas, including: local, contextual and practical knowledge (e.g. opportunities and obstacles to management options, information sources); and stakeholder interests, perspectives and goals
- Reducing conflicts and building trust between different stakeholder groups and decision makers, helping them to move towards a 'shared vision'
- Mutually educating researchers, decision makers and other stakeholders

Involving stakeholders in the modelling process encourages them to undergo the same thinking process as the modeller, and also exposes them to the underlying assumptions, limitations and capabilities of the model (Voinov and Bousquet, 2010). This engagement helps to develop trust among stakeholder parties, and a sense of ownership and trust of the model and its use to support decisions that may affect them. If stakeholders are left feeling that the model is inaccessible and difficult to understand and trust, this may undermine the entire IAM process. Mutual learning through stakeholder engagement in IAM can also lead to changes in the participants' mental models and behaviour. In other words, outcomes can be achieved through the model development process itself. Section 3 below discusses where and how participation enters the various stages of IAM. Voinov and Bousquet (2010) is a good introduction to modelling with stakeholders and is evidence of the strong trend towards participatory modelling. For integrated models used for decision-making, stakeholder engagement can also be beneficial by: providing accountability and transparency in the decision making process; ensuring democracy and reducing suspicion of the process by allowing stakeholders to understand the problem and have the opportunity to influence the decision (i.e. stakeholder empowerment); and thereby increasing the community's acceptance of the decision and commitment to its implementation.

Stakeholder participation can occur at various stages of the IAM process, including: i) issues definition and problem formulation, ii) conceptual model development, iii) model review, iv) identification of information and data sources, v) identification of scenarios and management options, and vi) evaluation and trade-off of management alternatives (Becker et al., 2010; Carmona et al., 2013). The level and type of participatory involvement depends on the modelling purpose and context. For example, if there is a large social component to the problem and stakeholders play a crucial role in the implementation of management options, then participatory modelling may be highly valuable.

It is important that the tools used in participatory processes are suited to the audience they are intended to engage. Numerous software tools have been developed to facilitate specific participatory processes. Examples include tools developed to elicit information from stakeholders (particularly experts) by providing a consistent and structured framework to retrieve and quantify their knowledge (James et al., 2010). If models are used, it is important that the modelling approach is relatively easy to understand; for example Bayesian networks are popular for participatory modelling as they have a graphical structure based on logical cause-and-effect relationships (Castelletti and Soncini-Sessa, 2007). Complicated and highly technical models may limit the ability of non-technical stakeholders to meaningfully contribute to the process. It may be necessary to dedicate considerable time to ensure that participants understand the purpose of the modelling exercise and what models, scenarios and other relevant concepts actually mean (Becu et al., 2008). Participatory modelling is one of many tools to engage stakeholders, with others including surveys, meetings, focus groups, workshops and role playing games. It has also been found that using a combination of participatory tools allows findings to be cross-checked and validated (Becu et al., 2008). The Conflict Resolution Support System (CRSS) is an example of a tool developed as a platform for stakeholders to explore and understand the underlying causes of conflict, thereby assisting them in developing and negotiating solutions (Nandalal and Simonovic, 2003).

The design and implementation of any software application or model that is intended to support a participatory or IAM process, begins with the assessment of key systems related to a problem description. The elements of an IAM problem typically span a wide range of possible systems with aspects of the human and natural settings providing important core components, while the spatial extent and timescales are key considerations.

2.4. Human setting

The human setting relates to all human elements relevant to the problem, and may include population factors, politics, organizations, culture, technology and economic sectors (e.g. energy, agriculture, tourism). IAM can be used to investigate linkages within the human system, for example between economic sectors as in Elobeid et al. (2013) where the interplay between agricultural and energy markets caused by biofuel expansion was explored. Human behaviour and choices (e.g. social interactions between individuals or household decisions) can be represented explicitly through agent-based modelling, which is a popular approach for simulating micro-level human interactions that collectively influence macro-level patterns (Müller et al., 2013).

Human systems are also dependent on goods and services provided by the natural system and concurrently modify the processes and components of the natural system through their activities and resource use. This can directly and indirectly lead to depletion or degradation of natural resources (e.g. surface water or groundwater depletion, overfishing), production of adverse wastes (e.g. air- or water-borne pollution), disruption of processes that provide ecosystem services (e.g. erosion) and reduced health of ecological systems (e.g. biodiversity loss). Subsequently, these impacts can feedback to the human system causing social and economic problems, which can further exacerbate previous issues and cause new problems.

In order to understand environmental problems and help design effective policies, it is essential to understand the underlying human drivers, for example barriers to adoption of potential solutions. Socio-ecological research has emerged in recognition of the dynamic and coupled interactions between human and natural systems (e.g. Young et al., 2006). It emphasises the co-evolution of natural and social systems, where understanding changes in one requires understanding of changes in the other, rather than treating them separately (Folke, 2006; Vespignani, 2012). IM can be a useful tool for investigating interactions between human-environment systems. For example integrated models of global climate change have been developed to explore human impacts and feedbacks on greenhouse gas emissions and climate change by considering a range of processes that influence mitigation such as social and cultural change, institutional change, economic development, energy transition and technological change (Schwanitz, 2013). The integration of socioeconomic and environmental considerations through IM is becoming increasingly common for assessing and managing natural resources (Laniak et al., 2013; Kragt et al., 2011) and agricultural systems (van Ittersum et al., 2008).

2.5. Natural setting

This dimension relates to the integration of components of the biophysical systems of interest (climate, land, water, atmospheric and/or ecological systems). In the past, a fragmented, piecemeal approach was taken to managing natural resources, disregarding the interdependence of system components (Katsanevakis et al., 2011). For example, until recently, surface water and groundwater development were considered separately. There has been increasing recognition that such system components do not operate in isolation and require a holistic approach to assessment and management. For instance, an integrated approach to water resources management may involve joint consideration of surface water, groundwater, climate, vegetation, fauna, soils, wetlands and/or estuaries.

In IM, connecting different system components can involve linking sub-models that represent relevant processes such that the model output(s) of one sub-model is treated as input(s) for another, or sub-models share inputs. For example, Dyer et al. (2014) linked output from down-scaled climate scenarios and river management models to hydrological, water quality, and ecological response models to predict the flow-on impacts of combined changes in climate and management conditions. Holguin-Gonzalez et al. (2013) developed an integrated model to assess the impact of waste water on the habitat suitability of macroinvertebrates, where a water quantity and quality sub-model produced data for six variables (e.g. temperature, flow, DO, water depth etc.) that were fed into the ecological models. In another example, Borusk et al. (2004) combined several sub-models representing different physical, chemical and biological estuarine processes to form a eutrophication model to predict ecosystem response to various nutrient management options. By considering the system (including the human system components) as a whole, IAM improves understanding of the problem and may help elucidate underlying causes and point to potential longer term solutions.

2.6. Spatial scale

There are different spatial scales at which the various important processes of a system occur or can be represented by data or a model. The system's drivers, characteristics and processes at one scale are important determinants of environmental conditions at subordinate scales (Stewart-Koster et al., 2007). For example climate processes (regional scale) are one of the key drivers of stream flow (catchment-scale), which interacts with finer-scale processes to determine microhabitat-scale properties such as velocity and depth. On the other hand, large-scale properties can emerge from interactions at the fine-scale; for example large-scale land cover changes resulting from social processes at a neighbourhood-scale that influence farm practices (Caillault et al., 2013). Also, the same type of process may occur at vastly different scales depending on the characteristics of the system component; for example, a single groundwater system can range from less than 100 km^2 to over 100 000 km^2 in size.

Common approaches to conceptually represent the spatial dimension in models include: being spatially non-specific (*non-spatial*); spatially averaging values for the entire area (*lumped*) or homogeneous sub-areas (*compartmental*); discretising the units into uniform cells (*grid-based*); or allowing *continuous* distribution over space (Kelly et al., 2013). IM must accommodate multiple spatial scales of system processes; in addition, the stakeholders or IM users may be interested in issues that occur at different scales. Knowledge, data and computational constraints can require a compromise between the scales of interest and the different scales of the biophysical and socioeconomic processes (Van Delden et al., 2011). There are two main approaches to resolving the mismatch of scales in IM frameworks: 1) upscaling or downscaling processes to a single targeted scale; and 2) using a nested or multi-scale approach (Voinov and Shugart, 2013).

Using the first approach, the targeted scale should be in line with the objectives of the IM and may be that of the key processes or critical thresholds. Processes occurring at finer scales can be upscaled, in other words aggregated to a larger scale, using simple functions (e.g. mean, median, x-percentile, variance) or more complex techniques such as block kriging (Bastin et al., 2013). Aggregated values can also be calculated using statistical modelling as in Pérez Domínguez et al. (2009) where farm-level bio-economic processes were upscaled to analyse market processes at a regional level. Downscaling to a finer resolution often requires information on auxiliary environmental variables to provide information about fine scale heterogeneity and the use of statistical techniques such as regression analysis to estimate the disaggregated values (Park, 2013). Upscaling can help reduce computational time, but the process may lead to important patterns being overlooked (Voinov and Shugart, 2013). It is essential that the scale-dependency of the processes is considered, as a mismatch between the process and scale of study can lead to misleading results (Anselin, 2001).

If practical and knowledge constraints permit, it is possible to incorporate multiple scales into an IM framework (Scholes et al., 2013). For example, the SAHRA project integrated three resolutions into a single IM to address multiple questions related to eco-hydrological (plot-scale), engineering and land management (medium-scale), and institutional and socioeconomic (sub-basin-scale) issues (Liu et al., 2008). The integration of GIS within the modelling framework in Labiosa et al. (2013) allowed users to analyse trade-offs between multiple criteria at the scale of the 30 m $\times$ 30 m cells or of groups of cells (e.g. user-defined or pre-defined land parcels).

Other challenges related to spatial scales to be accounted for include capturing emergent behaviour at a larger scale that emanates from local-scale processes, and spatially disjunct processes where cause and effect do not occur in the same or adjacent area (e.g. El Nino phenomena) (Scholes et al., 2013).

2.7. Time scale

Temporal scales of processes are often related to their spatial scale, and many of the challenges and approaches to deal with the spatial scales are relevant to those for temporal issues. Phenomena observed at a given scale are influenced by constraints imposed by broader-scale system dynamics which are typically slower and larger processes, and by finer-scale system dynamics which are typically faster and smaller (Cash and Moser, 2000). Processes can occur over timeframes spanning minutes to hours or less (e.g. some biological or chemical functions), or days to weeks (e.g. ecological processes), whilst others may occur over years (e.g. socioeconomic processes), decades or longer (e.g. species assemblage shift, climate change). Due to time lags, cause and effect may not be obvious, especially if other disturbances have occurred in the intervening period. For the same reason, it can be difficult to attribute present-day disturbances to ecological condition due to legacy effects from past disturbances (Allan, 2004).

Models can be static (non-temporal), lumped over a given time period, dynamic or continuous (Kelly et al., 2013). As with spatial issues, multiple temporal scales can be reconciled in IM frameworks by upscaling and downscaling processes or using a multi-scale approach. The IM goal should dictate the appropriate choice of time horizon (*extent*) and time step (*resolution*) to ensure that the important processes and responses are captured by the model.

There are also differences between space and time. Time is intrinsically directional. A static model generally still captures a notion of cause-and-effect that occurs over time. There is a strong distinction between past, present and future that separates events and circumstances that cannot be changed from those that are simultaneous and those that can still be influenced. What has been done cannot be undone. This results in concepts such as the precautionary principle and adaptive management that explicitly tackle the temporal permanence of impacts. This is in stark contrast to spatial differences where, in principle, conditions in different locations are always open to being modified.

2.8. Disciplines

In addressing the preceding dimensions, many complex environmental problems require integration of knowledge and competencies from a broad range of paradigms (e.g. positivist, interpretive) and disciplines (e.g. ecology, economics, hydrology, geomorphology, engineering, computer science, sociology, political science and psychology). A paradigm represents the very general philosophical assumptions underlying the research intervention. Differences in paradigms lie in their assumptions about both the nature of reality and knowledge. Positivistic disciplines, such as ecology and hydrology, assume that systems have objective boundaries independent from the subjective views of observers. On the other hand, interpretive disciplines (e.g. cognitive psychology) assume that our very subjective views and underpinning values determine how we make sense of surrounding systems and the way we produce and interpret our knowledge about these systems.

Traditionally, disciplines have been fragmented into intellectual silos and developed their own set of theories, assumptions and research methods. IM provides a platform to bring together multiple disciplines and provide a shared understanding of the system. It is however faced with challenges associated with incorporating the divergent views, types and formats of information, languages, methodologies and tools of the different science domains (Voinov and Shugart, 2013; Laniak et al., 2013; Kragt et al., 2013).

Although the call for integration across disciplines is not a new one, the actual development of inter-disciplinary research to address environmental problems is still lagging behind (Pahl-Wostl et al., 2013). This lag is due to three main barriers to integration across disciplines: 1) cultural and historical; 2) conceptual; and 3) technical. Cultural barriers include individuals and research groups who are territorial of their disciplinary field, driven by fear and lack of trust, as well as discipline-based funding and institutional arrangements. Newell et al. (2005) argue that this is the more challenging barrier because it is rooted in our education systems which promote "the only right answer" mindset. Pahl-Wostl et al. (2013) assert that the academic reward system hinders integration of disciplines, and discourages scientists from bridging their disciplinary silos.

Conceptual understanding of a system may differ across disciplines because of differences in their phenomena of interest, as well as the way they perceive the system processes (e.g. type, resolution and scale of data collected) and frame the issues. Divergent characterisations of a phenomenon can arise from differences in the chosen boundaries of the issue (i.e. the inclusion/exclusion of specific elements), the focal point, and the assumptions regarding the nature of the phenomena (Dewulf et al., 2007). To bridge these gaps, it is important for the different researchers to: acknowledge one another's perspectives; explore incompatible and complementary contributions of the different knowledge frames; and be willing to incorporate other concepts into their previously held frames as well as establish new frames (Dewulf et al., 2007). In order to overcome some of these conceptual barriers, Newell et al. (2005) developed a conceptual template to capture an interdisciplinary view of concepts used to represent aspects of environmental problems. The template categorises a broad list of concepts across disciplines into six conceptual clusters: i) dynamics and system, ii) organisation and scale, iii) controlling models, iv) management and policy, v) adaptation and learning, and vi) history.

The technical barrier relates to the differing research practices and tools adopted by the various disciplines. We discuss the integration of diverse methods, models, other tools and data in the section below. Related to this is the use of different linguistics and semantics, with disciplines potentially assigning different meanings to the same term or using different terminology to describe the same phenomena. Knowledge representation through formal ontologies is one way to overcome this 'confusion of tongues' (Voinov and Shugart, 2013). Ontologies explicitly express all concepts, system properties and processes in a man- and machine-readable format such that they are unambiguously defined. Standard ontologies (e.g. OWL, RDF) help facilitate the flow of communication between cross-disciplinary teams, including interoperability between their models (Janssen et al., 2009; Arnold, 2013). Ontologies also support declarative modelling, where the model is specified according to the components and variables of the system and the functional relationships between them (rather than the algorithms that perform the calculations), allowing more efficient re-use and integration of models from divergent disciplines (Rizzoli et al., 2008; Villa et al., 2009).

2.9. Methods, models, other tools and data

This dimension concerns the technical integration of different methods, models, other tools and data from various disciplines and/or representing different processes or perspectives. There is a plethora of modelling and analytical tools that can be used in the IA process as summarised in Table 2. In this paper IM is emphasized as the key tool for performing IA, but other various tools are applicable depending on the purpose of the task. For example participatory methods seek contribution from stakeholders through their expression of knowledge, ideas, preferences or values, and are suitable for identifying objectives, issues of concern, performance measures and management alternatives. This section focuses on modelling tools; participatory tools are discussed in more detail in Section 3 below. While the IA process can involve the use of multiple tools separately, tools can be integrated as in integrated models, which can be useful for simultaneously modelling the impact of management scenarios on different system components or criteria.

Voinov and Shugart (2013) distinguish two main approaches to IM: 1) developing the model, typically from scratch, using one modelling methodology to represent the whole system (*integral models*); and 2) coupling existing models such that the models operate together and exchange information (*assemblage approach*). The first approach can also incorporate existent models, however those component models are translated and reprogrammed to fit into the whole model (Voinov and Shugart, 2013). As this type of IM is generally developed by one team using a single formalism, the model tends to be more cohesive both conceptually and technically. The second approach reuses models developed and tested by specialists in that particular area, which can be advantageous if complex processes need representation and can also reduce model development cost, time and effort. However coupling model components involves challenges related to interfacing, interoperability, information exchange between models and the organisation of components (Rizzoli et al., 2008).

Table 2
Categorisation of tools to support the IA process.

Tool Category	Examples of tools	Application	Purpose
Exploratory tools	Statistical analysis, data mining, multivariate exploratory techniques, data-based models	Search for patterns in data and relationships between variables	• Improve system understanding • Identify indicators and criteria
Knowledge representation tools	Process-based models, integrated models such as Bayesian networks, decision trees, conceptual models, mind maps, spatial analysis, mapping	Summarize and represent what is understood about the system by integrating or encoding knowledge and data	• Improve system understanding • Communication of knowledge • Social learning • Identify knowledge gaps
Optimisation tools	Multi-objective optimisation models, genetic algorithms, cost-benefit analysis	Find the solution that optimises the objective function based on a single criterion, or finds the set of solutions at the Pareto frontier when multiple criteria are involved	• Improve system understanding • Screen or evaluate alternative management options
Participatory tools	Participatory modelling, focus groups, scenario analysis, stakeholder workshops, role playing games	Interactive or deliberative approaches where stakeholders contribute by expressing their knowledge, ideas, preferences and/or values	• Identify objectives, issues, preferences, management options • Obtain information from stakeholders • Improve system understanding • Social learning • Support negotiation, reduce conflict and build trust
Prediction tools	Data-based models, process-based models, integrated models	Estimate impacts of alternative scenarios on criteria of interest	• Improve system understanding • Evaluate alternative management options
Trade-off tools	Integrated models, MCDA	Explore trade-offs involved with different alternatives based on two or more criteria	• Improve system understanding • Evaluate alternative management options • Facilitate negotiation and conflict resolution

There are several IM frameworks available, each having different properties and requirements, and suited to different contexts and applications. Kelly et al. (2013) reviewed five common types of models for integrated assessment: coupled component models, system dynamics, Bayesian networks, agent-based models and knowledge-based models. The suitability of IM modelling type depends on the purpose of the model, the type of data available, the type of processes of interest (e.g. interactions between individuals, aggregated effects, feedback loops, etc.) and whether the focus of the model is to represent depth in specific processes or breadth of the whole system (see Kelly et al., 2013). Researchers tend to use tools they are familiar with rather than those most appropriate for the study conditions. Guidelines such as Kelly et al. (2013) can help to inform the appropriate selection of tools.

A third alternative approach to IM is developing meta-models or emulation models, which are simplified or more computationally efficient versions of other models, and provide similar outputs for given inputs (Castelletti et al., 2012). Where the original model is complex, speeding up computation might allow more runs to be made to allow exploration of uncertainty, or might allow the model to be used in an interactive setting with stakeholders. The simplification might also help identify dominant characteristics of the system that are not otherwise obvious (e.g. Young et al., 1996), or allow the efficient derivation of model properties, such as sensitivities to changes in inputs (e.g. Blatman and Sudret, 2010).

IM also involves integrating different types of data (e.g. nominal, ordinal, binary, numeric) from various sources. Data pre-processing or manipulation can be applied in some cases to make the data compatible for use, for example transforming continuous data to discrete data. However in other cases, disparate data (e.g. qualitative vs. quantitative data) can be difficult to meaningfully transform. Often the type of data available will dictate what models or tools can be applied.

Linking or incorporating models built under different modelling paradigms, semantics, programming languages and scales, is a challenge when using components based on existent models. This becomes especially difficult if the legacy models or code are poorly documented. Appropriate model documentation should include clear definition of model objectives and all model inputs/outputs, including data format, scales, units and data sources (Jakeman et al., 2006). Also, if the original data, model or software code have been altered in any way (including data pre-processing), the changes should be tracked and recorded (e.g. version control). If models are coupled under inappropriate conditions or translated incorrectly, there is a high risk of the IM being unsuccessful, referred to by Voinov and Shugart (2013) as ugly constructs or 'integronsters'. This includes when a model is applied beyond their intended capabilities or validated range. Transparent reporting and documentation of models facilitates communication between modellers, model users, and other experts and stakeholders involved to ensure the model is not re-used in the wrong context or misinterpreted.

There has also been a call for the establishment of standard protocols in data management and modelling to increase interoperability between tools (Castronova et al., 2013). The need for standardisation of modelling processes becomes more crucial when models are linked with other models. There are general guidelines for modelling practice standards such as Jakeman et al. (2006), which details ten iterative steps to model development and evaluation. However documentation protocols also need to be designed in a way that accommodates a modelling paradigm's theoretical and conceptual foundation, for example the ODD protocol in agent based modelling (Grimm et al., 2006), the SDM-Doc in systems dynamics (Martinez-Moyano, 2012), and the good practice guidelines for BN modelling (Chen and Pollino, 2012). Similarly, guidelines for good practice in participatory modelling have been outlined in Korfmacher (2001) and Langsdale et al. (2013).

Another advancement toward greater interoperability between tools has been through shared semantics. As discussed in the 'Disciplines' section, integration of semantics can be achieved through ontologies to provide a standardised data and knowledge structure, to resolve ambiguities about concepts and relationships. There are two main approaches to making an existing model interoperable with other disparate models: 1) rewrite the code to make their language compatible, or 2) to use a wrapper, which acts as an interface that converts the code or data into a compatible form (Bastin et al., 2013; Castronova et al., 2013). Model integration frameworks such as OpenMI and TIME have created software interface specification standards to allow compliant model components and tools to readily exchange data (Rahman et al., 2003; Gregersen et al., 2007; Knapen et al., 2013). OpenMI and other software standards support two-way linkages of existing and new model components from different developers, across multiple disciplines and scales, and are therefore highly suitable for developing integrated models of complex systems (Knapen et al., 2013).

Other technologies, particularly web-based platforms, have enabled collaboration and information exchange between experts and stakeholders in different locales, greatly facilitating large IAM projects that often involve multiple research teams (Arnold, 2013; Bastin et al., 2013). Also, data sharing has become supported by web-based data repositories, such as the Long Term Ecological Research Network (www.lternet.edu), USGS National Water Information System (waterdata.usgs.gov/nwis) and STORET (Storage and Retrieval) Data Warehouse (www.epa.gov/storet). Although IAM is faced with many technical challenges related to gathering information and representing such complex systems, there are many promising technologies and approaches being developed to overcome them.

2.10. Uncertainty

Uncertainty is widely accepted to be pervasive in any attempt to manage and understand environmental problems. Uncertainty can be interpreted in different ways depending on the discipline, and the context of application. Ascough et al. (2008) presented a typology for uncertainty in environmental decision making, which includes knowledge uncertainty, variability uncertainty, linguistic uncertainty, and decision making uncertainty.

Uncertainty can be characterised by: 1) its source and location within the IA process (e.g. problem framing, model structure, model inputs/outputs) (Refsgaard et al., 2007); 2) its level along the spectrum from determinism to total ignorance; and 3) its nature (epistemic, stochastic or ambiguity uncertainty) (Walker et al., 2003). IM must address integration of these three dimensions of uncertainty both within and across the model components. Integrated models encompass multiple models, often from a broad scope, and therefore take on an even higher level of abstraction and require a larger number of assumptions. This results in an “explosion of uncertainty” (Jones, 2001) not only through the accumulation of uncertainty stemming from the individual sub-models but also from the integration of those models.

Guillaume et al. (2012) propose an uncertainty management framework containing seven iterative steps: (i) identifying the uncertainties, (ii) prioritising resources to address them, (iii) reducing the uncertainty, (iv) describing the uncertainty, (v) propagating it through the model, (vi) communicating the uncertainty to model users and (vii) anticipating residual uncertainty. When integrating several different model or system components, it may not be useful to invest considerable effort and resources toward reducing uncertainty in one area if the results are dominated by uncertainty in another area (Guillaume et al., 2012). In other words, to be effective uncertainty management should be prioritised toward uncertainties that are most relevant to the IA task.

The uncertainty of data or model components may take a variety of forms, such as measures of performance (Bennett et al., 2013), bounds, scenarios or probability distributions. Transformation may be needed if they are to be combined (Bastin et al., 2013). The propagation of uncertainties through integrated models involves determining the effect on the output of changes in the inputs. This may be as simple as running alternate scenarios, or a Monte Carlo method, consisting of running random samples from a distribution. Some forms of uncertainty, for example ‘unknown unknowns’, cannot be quantitatively measured (Bastin et al., 2013). Quantifying structural uncertainty remains a challenge in environmental modelling in general, although peer review and comparison of models with alternative structures has been found to be useful in assessing this type of uncertainty and helping to understand its causes and effects (e.g. Gupta et al., 2012; Rosenzweig et al., 2013).

IA may also require the integration of different epistemological and pragmatic attitudes toward uncertainty and how it should be addressed. Differences may arise from contrasting goals and interests (e.g. management vs science), views of model usage or attitudes toward risk (van Asselt et al., 1996). Depending on perspective, the appropriate treatment of uncertainty may be eliminating it with further research, quantifying it, having managers actively manage issues that arise, or simply ignoring it until it becomes a more pressing issue. It is increasingly being accepted that the pervasiveness of uncertainty in models means that uncertainty cannot be fully quantified let alone reduced; this has led to the increasing popularity toward adaptive and learning-oriented approaches (Cundill and Fabricius, 2009; Crona and Parker, 2012).

Due to the dynamic nature of biophysical and socioeconomic systems, uncertainty can also vary as a function of time. Uncertainties increase as projections are made further into the future. Scenario analysis may be suitable for planning over long horizons or when the outcomes of alternatives are difficult to estimate (e.g. climate change). Rather than attempting to make these predictions, a representative spectrum of plausible scenarios can be constructed and evaluated to assess possible risks and opportunities, and strategies to respond to them (Liu et al., 2008; Mahmoud et al., 2009).

3. Fitting the dimensions into the IAM process

Here we discuss how integration of the ten dimensions fits into the IAM process. We broadly describe the process in terms of four major phases (Scholes et al., 2013): 1) scoping, 2) problem framing and formulation, 3) assessing options and 4) communicating findings. IAM processes rarely follow a linear path. Therefore, these four phases tend to be iterative, and often some activities across phases occur simultaneously. For instance, the problem scope or the conceptual model may be re-examined and modified as new insights come to light. Integration can be achieved in these IAM phases using a mix of stakeholder participation processes and modelling tools (Jakeman and Letcher, 2003; Voinov and Bousquet, 2010); examples are given in Table 3.

The first phase focuses on collecting local knowledge about the system under study. Walz et al. (2007) define local system knowledge as “the insights of individuals into the socio-economic, administrative, cultural, political, and environmental dynamics with a particular region.” These data (mainly qualitative) help researchers make sense of the problem and its scope (Smith, 1989; Bardwell, 1991), including identifying the objectives, the system boundaries, the stakeholders and their issues of concern. The scoping phase of an IAM project must also consider the resources available, in terms of funds, time and skills. It is necessary for the project to set priorities based on how crucial each issue is, and to be pragmatic in selecting appropriate tools and methods. The end of the other three phases should also involve a critical review that reflects on these priorities and the project objectives. The review

Table 3
Relevance of integration of the 10 dimensions to each phase of IAM, and relevant techniques to support integration.

Dimension	Scoping	Problem framing and formulation	Analysis and assessment of options	Communication of findings
Issues of concern	Identifying important issues → *rapid appraisal*, *stakeholder workshops*, *focus groups*	Including relevant indicators to use as performance criteria → *soft systems methodologies*, *stakeholder workshops*, *focus groups*, *expert elicitation*	Evaluating alternatives based on how it is predicted to affect the performance measures → *MCDA*, *analytic hierarchy process*, *multi-objective optimisation*, *trade-off analysis*	Target communication towards issues of concern
Governance setting	Identifying connected management settings → *stakeholder workshops*, *focus groups*	Identifying management options to assess → *stakeholder workshops*, *focus groups*, *mental models*, *conceptual models*, *expert elicitation*	Modelling impacts of management alternatives → *integrated models*, *scenario analysis*	Target communication towards management interests
Stakeholders	Involving relevant stakeholders → *stakeholder analysis*; *focus groups*; *snowball sampling*	Balancing representation of stakeholder interests → *mental models*, *conceptual models*, *soft systems methodologies*, *ODD*, *Delphi method*	Involving stakeholders to assess assumptions used; Deriving preferences from stakeholders to weight criteria → *participatory modelling*, *group model building*, *Institution/actor power mapping*, *behavioural modelling*; *Delphi method*	Targeting stakeholders interests → *role playing games*
Natural setting	Including relevant natural system components → *stakeholder workshops*, *focus groups*, *expert elicitation*	Defining natural system behaviours and indicators → *stakeholder workshops*, *focus groups*, *mental models*, *conceptual models*, *expert elicitation*	Modelling natural system processes → *process-based models*, *data-based models*, *integrated models*	Reporting states of biophysical models to interested audiences
Human setting	Including relevant human system components → *stakeholder workshops*, *focus groups*, *expert elicitation*	Defining human system behaviours and indicators → *stakeholder workshops*, *focus groups*, *mental models*, *conceptual models*, *expert elicitation*	Modelling human system processes → *process-based models*, *data-based models*, *integrated models*	Expressing interactions of human behaviour and natural system
Spatial scale	Determining spatial extent of key processes	Defining spatial heterogeneity and interactions	Defining model spatial elements → *multi-resolution spatial modelling*, *cellular automata*	Spatial representation of results → *GIS tools*
Time scale	Determining relevant time scales → *space-time domain plotting*, *narrative story lines*	Determining temporal extent and resolution → *scenario analysis*, *future visioning*	Defining model time steps → *dynamic models*, *multi-scale modelling*	Temporal representation of results
Disciplines	Including relevant researchers and reviewing relevant literature	Balancing interests of researchers and level of detail of representation	Collaborative modelling; Involving researchers in assessing their connection with other components → *standard ontologies*, *declarative modelling*, *expert review*	Bridging language barriers; Interdisciplinary collaboration
Methods, models, other tools and data	Identifying relevant tools and data → *requirements identification and analysis*	Defining relationship between tools → *system analysis and design techniques*	Using tools; Combining tools → *integrated models*; *wrappers*; *Integrated modelling environments (OpenMI)*	Making tools understandable within and outside project team → *web-based technologies*; *visualisation tools*; *user-friendly GUI*
Uncertainty	Considering alternative boundaries of scope	Considering alternative problem formulations	Considering alternative model instances → *uncertainty quantification*, *hypothesis testing*, *(pseudo) Monte Carlo methods*	Conveying alternative possible answers rather than a single conclusion, and the reasons for them

should evaluate whether the past and planned activities are in line with the scope to ensure the project remains focussed. Software engineering provides techniques and tools (e.g. rapid prototyping) that allow stakeholders to try ideas, evaluate the development process, and refine modelling requirements (Verweij et al., 2010).

Ideally, all relevant stakeholder groups should be identified and appropriately engaged as early as possible to enhance the effectiveness of the IAM process and the credibility and value of its outputs (Reed, 2008; Voinov and Gaddis, 2008). Stakeholders can be broadly categorized according to their influence on and interest in the process and its outputs. For example, who has the power to block the modelling process and implementation of its results? Categorising stakeholders guides the design of the participatory component of the project (i.e. who will be involved in the modelling process, when, why and how).

Participatory methods (See Fig. 2) have an important role to play in IAM as they help:

- establish relationships with key stakeholders and interest groups;
- learn about the historical context related to stakeholders and issues; and

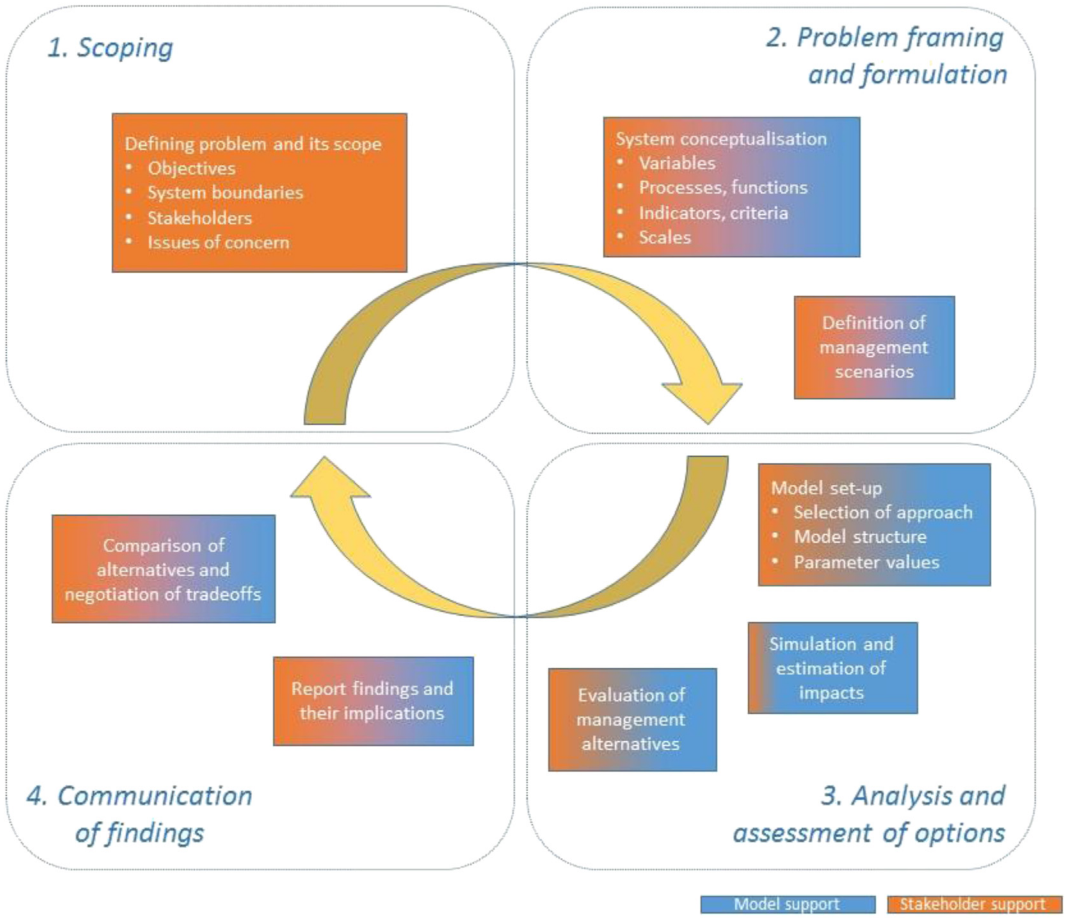

Fig. 2. The IAM process phases and steps. The level of model- and stakeholder-support required for each of the steps is indicated by the colour shading. (Adapted from Becker et al., 2010). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

- reveal the divergent and potentially conflicting values, interests and underlying objectives held by stakeholders (Voinov and Bousquet, 2010).

Depending on the modelling purpose and the local situation, various participatory approaches can be used. For example, rapid appraisal (Beebe, 1995) is an umbrella approach that covers a wide range of data collection methods, such as one-to-one interviews, field trips, and information meetings that allow the modeller to gather data quickly. Rapid appraisal might be followed with more detailed and structured discussions through stakeholder workshops or focus groups with a subset of stakeholders with a particular interest.

After all concerns and interests are expressed, it may be necessary to narrow these down to a smaller set of objectives and issues that can be fine-tuned through the process (Van Delden et al., 2011). Interactive or deliberative participatory methods can help non-experts to articulate their knowledge, preferences and values in a structured group process, and help the group reach consensus on the problem and scope to be addressed (van Asselt and Rijkens-Klomp, 2002). Related to this are soft systems thinking and problem structuring methodologies (e.g. soft systems methodologies; Checkland and Holwell, 1998) which provide a holistic framework (theories, techniques, and tools) that can support stakeholder participation through scoping and subsequent phases.

The second phase involves building the evidence base to help conceptualise the problem (Scholes et al., 2013). This evidence includes any relevant literature, data, models and hypotheses, as well as expert and stakeholder knowledge which can be obtained with elicitation tools (e.g. James et al., 2010). Logical thinking and mapping tools can be useful in representing knowledge and articulating ideas (Wolstenholme, 1999; Kelleher and Wagener, 2011). Mapping techniques vary from very simple and unstructured (e.g. mind maps), to semi-formal and moderately structured (e.g. conceptual models, causal loop diagrams), to very structured (e.g. DPSIR; Gregory et al., 2013).

Participatory methods and tools can be utilised to inform and enhance the conceptualization phase. For example through group brainstorming, a conceptual model(s) can be drawn up to show and summarise all the important variables and processes to be incorporated into the model, their linkages to one another, and to performance indicators (Vennix, 1999). This can also be a valuable opportunity for stakeholders to think critically and reflect on their understanding of the system.

During this phase researchers and stakeholders also identify the appropriate criteria, indicators, functions and scales to represent the issues of concern and their related biophysical and socioeconomic processes (Reed et al., 2006). Scenario planning is a useful approach for helping stakeholders develop a coherent storyline about the cause-and-effect relationships that link future changes in the system drivers, processes, and dependent values (i.e. social, cultural, economic). Scenarios promote “what-if” thinking, explicitly reasoning about the consequences of alternative conceptualisations of a system, actions and events.

Selecting combinations of participatory methods may be a challenging task as it depends on several criteria, including (Hare, 2011):

- the purpose of the participatory activity in the context of the IAM objectives;
- the types and forms of data required to support model development;
- available time, skills, and resources required versus what is available; and
- the relative fit between the selected engagement methods and stakeholder preferences and capacity.

The third phase involves identifying candidate solutions and assessing the various management options or scenarios through modelling or other tools. This includes selecting the appropriate modelling approach, model structure and parameter values (e.g. Kelly et al., 2013; Jakeman et al., 2006) in conjunction with participants to assure that the modelled outputs are aligned with the relevant problem objective. The models are run to estimate the possible impacts of the alternatives on the selected criteria or indicators. If the system processes require detailed representation and appropriate disciplinary models exist, the suitable approach may be to couple the existing models into an integrated model (Voinov and Shugart, 2013). Other approaches may be more suitable under certain settings. For example system dynamics modelling is appropriate where system feedbacks are important (Winz et al., 2009), Bayesian networks are suitable when data or knowledge is limited (Chen and Pollino, 2012), and agent-based models are suitable for modelling emergent behaviour from local interactions (Filatova et al., 2013). The performance measures from the different alternative options can be compared and ranked using techniques such as multi-criteria decision analysis (MCDA), life cycle analysis (LCA), cost benefit analysis (CBA) and risk analysis (Sinclair, 2011).

The final phase is about communicating the model findings and their possible implications to the end user (e.g. decision maker). This includes reporting the uncertainties about the model output or findings. The appropriate style and language of reporting depends on the audience and the purpose of the IAM project. The integrated models and other tools may be packaged in a software platform to facilitate communication and interaction between stakeholders and/or experts (Croke et al., 2007). However, it is crucial that any software or decision support tool be designed and developed with a clear understanding of end-user needs and expectations. Many decision support tools fail to be adopted due to inadequate consultation with the intended end users; the establishment of trust and credibility during the development process can be more important than the end product itself (McIntosh et al., 2011).

It is clear that the outcome and usefulness of any IAM project hinges on adequate incorporation of each of the ten dimensions. When designing, evaluating or using findings from any IAM project, we encourage the practice of systematically and explicitly considering how each dimension is addressed, as well as uncertainties related to those left out. Ideally, this practice would involve identifying the components being integrated in each of the ten dimensions and providing a rationale for the approach to combining them. Often practical, knowledge and/or data constraints will cause discord between how the dimensions *are* and *should be* integrated. Even when integration across a dimension is not explicitly addressed, underlying assumptions are often implied. For example, by considering only a select few natural or human system components in an integrated model, it is assumed that other system components are not relevant to the problem. In another common example, if the spatial scales of processes are upscaled, it is assumed that processes occurring at finer scales are not important. Such assumptions should be made explicit and, where appropriate, assessed for their implications on the study outputs.

4. Conclusion

It is broadly recognised that the interconnectedness of our world requires integrated rather than piecemeal approaches to resolving complex environmental issues, particularly in view of the increasing speed and pervasiveness of connections associated with globalisation. Yet, there is little agreement on what and how to integrate. This paper has highlighted ten dimensions of integration that are of particular interest in integrated modelling and assessment. To go beyond integration as a buzzword, it is important that those undertaking an IAM project are aware of which of these dimensions they are actually addressing within their work, and which they are not. Inadequately integrating these dimensions and/or omitting important ones may result in impacts of interventions being overlooked, or the modelling effort being rendered irrelevant. In recommending to modellers to reflect on their practice, we would particularly emphasise the need to take a purpose-driven approach. The need for integration arises from the need to integrate issues, management and stakeholders, and the nature and level of integration of the other dimensions should always be performed with that context in mind. Integrated assessment and modelling is not about integration for its own sake. Its *raison d'être* lies in helping to tackle the complex multi-issue problems faced by coupled human-environment systems.

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References

Allan, J.D., 2004. Landscapes and riverscapes: the influence of land use on stream ecosystems. Ann. Rev. Ecol. Sys 35, 257–284.
Anselin, L., 2001. Spatial effects in econometric practice in environmental and resource economics. Am. J. Agric. Econ. 83, 705–710.
Arnold, T.R., 2013. Procedural knowledge for integrated modelling: towards the modelling playground. Environ. Model. Softw. 39, 135–148.
Ascough II, J.C., Maier, H.R., Ravalico, J.K., Strudley, M.W., 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. Ecol. Model. 219 (3), 383–399.
Ausseil, A.-G.E., Dymond, J.R., Kirschbaum, M.U.F., Andrew, R.M., Parfitt, R.L., 2013. Assessment of multiple ecosystem services in New Zealand at the catchment scale. Environ. Model. Softw. 43, 37–48.
Bach, P.M., Rauch, W., Mikkelsen, P.S., McCarthy, D.T., Deletic, A., 2014. A critical review of integrated urban water modelling – urban drainage and beyond. Environ. Model. Softw. 54, 88–107.
Bardwell, L.V., 1991. Problem-framing: a perspective on environmental problem-solving. Environ. Manag. 15 (5), 603–612.
Bastin, L., Cornford, D., Jones, R., Heuvelink, G.B.M., Pebesma, E., Stasch, C., Nativi, S., Mazzetti, P., Williams, M., 2013. Managing uncertainty in integrated environmental modelling: the UncertWeb framework. Environ. Model. Softw. 39, 116–134.
Becker, A., Soncini-Sessa, R., Castelletti, A., Hattermann, F.F., Willems, P., Stalnacke, P., Laurans, Y., de Lange, W.J., 2010. How can models help implementing the water framework directive? In: Hattermann, F.F., Kundzewicz, Z.W. (Eds.), Water Framework Directive: Model Supported Implementation. A Water Manager's Guide. IWA Publishing, London.
Becu, N., Neef, A., Schreinemachers, P., Sangkapitux, C., 2008. Participatory computer simulation to support collective decision-making: Potential and limits of stakeholder involvement. Land Use Policy 25, 498–509.
Beebe, J., 1995. Basic concepts and techniques of rapid appraisal. Hum. Organ. 54 (1), 42–51.
Bennett, N.D., Croke, B.F.W., Guariso, G., Guillaume, J.H.A., Hamilton, S.H., Jakeman, A.J., Marsilli-Libelli, S., Newham, L.T.H., Norton, J.P., Perrin, C., Pierce, S.A., Robson, B., Seppelt, R., Voinov, A.A., Fath, B.D., Andreassian, V., 2013. Characterising performance of environmental models. Environ. Model. Softw. 40, 1–20.
Blatman, G., Sudret, B., 2010. Efficient computation of global sensitivity indices using sparse polynomial chaos expansions. Reliab. Eng. Syst. Saf. 95 (11), 1216–1229.
Borusk, M.E., Stow, C.A., Reckhow, K.H., 2004. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecol. Model. 173, 219–239.
Caillault, S., Mialhe, F., Vannier, C., Delmotte, S., Kêdowidé, C., Amblard, F., Etienne, M., Bécu, N., Gautreau, P., Houet, T., 2013. Influence of incentive

networks on landscape changes: a simple agent-based simulation approach. Environ. Model. Softw. 45, 64–73.
Carmona, G., Varela-Ortega, C., Bromley, J., 2013. Supporting decision making under uncertainty: development of a participatory integrated model for water management in the middle Guadiana river basin. Environ. Model. Softw. 50, 144–157.
Cash, D.W., Moser, S.C., 2000. Linking global and local scales: designing dynamic assessment and management processes. Global. Environ. Chang 10, 109–120.
Castelletti, A., Soncini-Sessa, R., 2006. A procedural approach to strengthening integration and participation in water resource planning. Environ. Model. Softw. 21 (10), 1455–1470.
Castelletti, A., Soncini-Sessa, R., 2007. Bayesian networks and participatory modelling in water resource management. Environ. Model. Softw. 22, 1075–1088.
Castelletti, A., Galelli, S., Ratto, M., Soncini-Sessa, R., Young, P.C., 2012. A general framework for dynamic emulation modelling in environmental problems. Environ. Model. Softw. 34, 5–18.
Castronova, A.M., Goodall, J.L., Ercan, M.B., 2013. Integrated modelling within a hydrologic information system: an OpenMI based approach. Environ. Model. Softw. 39, 263–273.
Checkland, P., Holwell, S., 1998. Action research: its nature and validity. Syst. Pract. Action Res. 11 (1), 9–21.
Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environ. Model. Softw. 37, 134–145.
Croke, B.F.W., Ticehurst, J.L., Letcher, R.A., Norton, J.P., Newham, L.T.H., Jakeman, A.J., 2007. Integrated assessment of water resources: Australian experiences. Water Resour. Manag. 21, 351–373.
Crona, B.I., Parker, J.N., 2012. Learning in support of governance: theories, methods, and a framework to assess how bridging organizations contribute to adaptive resource governance. Ecol. Soc. 17 (1), 32.
Cundill, G., Fabricius, C., 2009. Monitoring in adaptive co-management: toward a learning based approach. J. Environ. Manag. 90 (11), 3205–3211.
Dewulf, A., Bouwen, A., 2008. Frames, scales and actors. In: Proceedings of the European Group of Public Administration Conference. Erasmus University, Rotterdam.
Dewulf, A., Craps, M., Bouwen, R., Taillieu, T., Pahl-Wostl, C., 2005. Integrated management of natural resources: dealing with ambiguous issues, multiple actors and diverging frames. Water Sci. Technol. 52 (6), 115–124.
Dewulf, A., François, G., Pahl-Wostl, C., Taillieu, T., 2007. A framing approach to cross-disciplinary research collaboration: experiences from a large-scale research project on adaptive water management. Ecol. Soc. 12 (2), 14.
Dowlatabadi, H., 1995. Integrated assessment models of climate change. Energy Policy 23, 289–296.
Dyer, F., ElSawah, S., Croke, B., Griffiths, R., Harrison, E., Lucena-Moya, P., Jakeman, A., 2014. The effects of climate change on ecologically-relevant flow regime and water quality attributes. Stoch. Environ. Res. Risk Assess. 28 (1), 67–82.
Ekasingh, B., Letcher, R.A., 2008. Successes and failures to embed socioeconomic dimensions in integrated natural resource management modeling: lessons from Thailand. Math. Comput. Simul. 78 (2), 137–145.
Elobeid, A., Tokgoz, S., Dodder, R., Johnson, T., Kaplan, O., Kurkalova, L., Secchi, S., 2013. Integration of agricultural and energy system models for biofuel assessment. Environ. Model. Softw. 48, 1–16.
ElSawah, S., Mclucas, A., Mazanov, J., 2013. Using a cognitive mapping approach to frame the perceptions of water users about managing water resources: a case study in the Australian Capital Territory. Water Resour. Manag. 27 (9), 3441–3456.
Filatova, T., Verburg, P.H., Parker, D.C., Stannard, C.A., 2013. Spatial agent-based models for socio-ecological systems: challenges and prospects. Environ. Model. Softw. 45, 1–7.
Folke, C., 2006. Resilience: the emergence of a perspective for social-ecological systems. Glob. Environ. Change-Human Policy Dimens. 16 (3), 253–267.
Funtowicz, S.O., Ravetz, J.R., 1993. Science for the post-normal age. Futures 25, 739–755.
Gao, L., Hailu, A., 2012. Ranking management strategies with complex outcomes: an AHP-fuzzy evaluation of recreational fishing using an integrated agent-based model of a coral reef ecosystem. Environ. Model. Softw. 31, 3–18.
Gregersen, J.B., Gijsbers, P.J.A., Westen, S.J.P., 2007. OpenMI: open modelling interface. J. Hydroinform. 9 (3), 175–191.
Gregory, A.J., Atkins, J.P., Burdon, D., Elliott, M., 2013. A problem structuring method for ecosystem-based management: the DPSIR modelling process. Eur. J. Op. Res. 227 (3), 558–569.
Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Peer, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E., Souissi, S., Stillman, R.A., Vabø, R., Visser, U., DeAngelis, D.L., 2006. A standard protocol for describing individual-based and agent-based models. Ecol. Model. 198 (1–2), 115–126.
Guillaume, J.H.A., Qureshi, M.E., Jakeman, A.J., 2012. A structured analysis of uncertainty surrounding modelled impacts of groundwater-extraction rules. Hydrogeol. J. 20, 915–932.
Gupta, V.G., Clark, M.P., Vrugt, J.A., Abramowitz, G., Ye, M., 2012. Towards a comprehensive assessment of model structural adequacy. Water Resour. Res. 48, W08301. http://dx.doi.org/10.1029/2011WR011044.
Haasnoot, M., Van Deursen, W.P.A., Guillaume, J.H.A., Kwakkel, J.H., Van Beek, E., Middelkoop, H., 2014. Fit for purpose? building and evaluating a fast, integrated model for exploring water policy pathways. Environ. Model. Softw. 60, 99–120.
Hare, M., 2011. Forms of participatory modelling and its potential for widespread adoption in the water sector. Environ. Policy Gov. 21, 386–402.
Hare, M., Pahl-Wostl, C., 2002. Stakeholder categorisation in participatory integrated assessment processes. Integr. Assess. 3 (1), 50–62.
Hering, J.G., Ingold, K.M., 2012. Water resources management: what should be integrated? Science 336, 1234–1235. No. 6086.
Hoekstra, A.Y., 1998. Perspectives on Water: an Integrated Model-based Exploration of the Future. International Books, Utrecht, Netherlands.
Holguin-Gonzalez, J.E., Everaert, G., Boets, P., Galvis, A., Goethals, P.L.M., 2013. Development and application of an integrated ecological modelling framework to analyze the impact of wastewater discharges on the ecological water quality of rivers. Environ. Modell. Softw 48, 27–36.
Ibáñez, J., Lavado Contador, J.F., Schnabel, S., Pulido Fernández, M., Martínez Valderrama, J., 2014. A model-based integrated assessment of land degradation by water erosion in a valuable Spanish rangeland. Environ. Model. Softw. 55, 201–213.
Ison, R., Blackmore, C., Iaquinto, B.L., 2013. Towards systemic and adaptive governance: exploring the revealing and concealing aspects of contemporary social-learning metaphors. Ecol. Econ. 87, 34–42.
Jakeman, A.J., Letcher, R.A., 2003. Integrated assessment and modelling: features, principles and examples for catchment management. Environ. Model. Softw. 18, 491–501.
Jakeman, A.J., Letcher, R.A., Norton, J.P., 2006. Ten iterative steps in development and evaluation of environmental models. Environ. Model. Softw. 21, 602–614.
James, A., Low Choy, S., Mengersen, K.L., 2010. Elicitator: an expert elicitation tool for regression in ecology. Environ. Model. Softw. 25 (1), 129–145.
Janssen, S., 2009. Managing the Hydra in Integration: Developing an Integrated Assessment Tool for Agricultural Systems (PhD thesis). Wageningen University.
Janssen, S., Ewert, F., Li, H., Athanasiadis, I.N., Wien, J.J.F., Thérond, O., Knapen, M.J.R., Bezlepkina, I., Alkan-Olsson, J., Rizzoli, A.E., Belhouchette, H., Svensson, M., van Ittersum, M.K., 2009. Defining assessment projects and scenarios for policy support: use of ontology in integrated assessment and modelling. Environ. Model. Softw. 24, 1491–1500.
Jønch-Clausen, T., Fugl, J., 2001. Firming up the conceptual basis of integrated water resources management. Water Resour. Dev. 17, 501–510.
Jones, R.N., 2001. An environmental risk assessment/management framework for climate change impact assessments. Nat. Hazards 23, 197–230.
Katsanevakis, S., Stelzenmuller, V., South, A., Sorensen, T.K., Jones, P.J.S., Kerr, S., Badalamenti, F., Anagnostou, C., Breen, P., Chust, G., D'Anna, G., Duijn, M., Filatova, T., Fiorentino, F., Hulsman, H., Johnson, K., Karageorgis, A.P., Kroncke, I., Mirto, S., Pipitone, C., Portelli, S., Qiu, W., Reiss, H., Sakellariou, D., Salomidi, M., van Hoof, L., Vassilopoulou, V., Vega Fernandez, T., Voge, S., Weber, A., Zenetos, A., Hofstede, R.T., 2011. Ecosystem-based marine spatial management: review of concepts, policies, tools, and critical issues. Ocean Coast. Manag. 54 (11), 807–820.
Kaufmann-Hayoz, R., Bättig, C., Bruppacher, S., Defila, R., Di Giulio, A., Flury-Kleubler, P., Friederich, U., Garbely, M., Gutscher, H., Jäggi, C., Jegen, M., Mosier, H.-J., Müller, A., North, N., Ulli-Beer, S., Wichtermann, J., 2001. A typology of tools for building sustainable strategies. In: Kaufmann-Hayoz, R., Gutscher, H. (Eds.), Changing Things - Moving People. Birkhäuser, Basel, Switzerland, pp. 33–108.
Kelleher, C., Wagener, T., 2011. Ten guidelines for effective data visualization in scientific publications. Environ. Model. Softw. 26 (6), 822–827.
Kelly, R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., van Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw. 47, 159–181.
Knapen, R., Janssen, S., Roosenschoon, O., Verweij, P., de Winter, W., Uiterwijk, M., Wien, J.-E., 2013. Evaluating OpenMI as a model integration platform across disciplines. Environ. Model. Softw. 39, 274–282.
Korfmacher, K.S., 2001. The politics of participation in watershed modeling. Environ. Manag 27 (2), 161–176.
Kragt, M.E., Newham, L.T.H., Bennett, J., Jakeman, A.J., 2011. An integrated approach to linking economic valuation and catchment modelling. Environ. Model. Softw. 26 (1), 92–102.
Kragt, M.E., Robson, B.J., Macleod, C.J.A., 2013. Modellers' roles in integrative research projects. Environ. Model. Softw. 39 (1), 322–330.
Labiosa, W.B., Forney, W.M., Esnard, A.-M., Mitsova-Boneva, D., Bernknopf, R., Hearn, P., Hogan, D., Pearlstine, L., Strong, D., Gladwin, H., Swain, E., 2013. An integrated multi-criteria scenario evaluation web tool for participatory land-use planning in urbanized areas: the ecosystem portfolio model. Environ. Model. Softw. 41, 210–222.
Langsdale, S., Beall, A., Bourget, E., Hagen, E., Kudlas, S., Palmer, R., Tate, D., Werick, W., 2013. Collaborative modeling for decision support in water resources: principles and best practices. J. Am. Water Resour. Assoc. 49, 629–638.
Laniak, G.F., Olchin, G., Goodall, J., Voinov, A., Hill, M., Glynn, P., Whelan, G., Geller, G., Quinn, N., Blind, M., Peckham, S., Reaney, S., Gaber, N., Kennedy, R., Hughes, A., 2013. Integrated environmental modeling: a vision and roadmap for the future. Environ. Model. Softw. 39, 3–23.
Larocque, G.R., Bhatti, J., Arsenault, A., 2014. Integrated modelling software platform development for effective use of ecosystem models. Ecol. Model. 288, 195–202.

Levis, J.W., Barlaz, M.A., DeCarolis, J.F., Ranjithan, S.R., 2013. A generalized multi-stage optimization modeling framework for life cycle assessment-based integrated solid waste management. Environ. Model. Softw. 50, 51–65.
Liu, Y., Gupta, H., Springer, E., Wagener, T., 2008. Linking science with environmental decision making: experiences from an integrated modelling approach to supporting sustainable water resources management. Environ. Model. Softw. 23, 846–858.
Mahmoud, M., Liu, Y., Hartmann, H., Stewart, S., Wagener, T., Semmens, D., Stewart, R., Gupta, H., Dominguez, D., Dominguez, F., Hulse, D., Letcher, R., Rashleigh, B., Smith, C., Street, R., Ticehurst, J., Twery, M., van Delden, H., Waldick, R., White, D., Winter, L., 2009. A formal framework for scenario development in support of environmental decision-making. Environ. Model. Softw 24, 798–808.
Martinez-Moyano, I.J., 2012. Documentation for model transparency. Syst. Dyn. Rev. 28, 199–208.
McIntosh, B.S., Ascough II, J.C., Twery, M., Chew, J., Elmahdi, A., Haase, D., Harou, J.J., Hepting, D., Cuddy, S., Jakeman, A.J., Chen, S., Kassahun, A., Lautenbach, S., Matthews, K., Merritt, W., Quinn, N.W.T., Rodriquez-Roda, I., Sieber, S., Stavenga, M., Sulis, A., Ticehurst, J., Volk, M., Wrobel, M., van Delden, H., El-Sawah, S., Rizzoli, A.E., Voinov, A.A., 2011. Environmental decision support systems (EDSS) development – challenges and best practices. Environ. Model. Softw. 26 (12), 1389–1402.
Medema, W., McIntosh, B.S., Jeffrey, P.J., 2008. From premise to practice: a critical assessment of integrated water resources management and adaptive management approaches in the water sector. Ecol. Soc. 13 (2), 29.
Mitchell, B., 1990. Integrated Water Management: International Experiences and Perspectives. Bel-haven Press, London, U.K.
Morgan, M.G., Dowlatabadi, H., 1996. Learning from integrated assessment of climate change. Clim. Change 34 (3–4), 337–368.
Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models – ODD + D, an extension of the ODD protocol. Environ. Model. Softw. 48, 37–48.
Nandalal, K.D.W., Simonovic, S.P., 2003. Conflict Resolution Support System. A Software for the Resolution of Conflicts in Water Resource Management. Prepared for Division of Water Sciences, UNESCO. http://webworld.unesco.org/water/wwap/pccp/phase2/crss/users_manual.pdf (accessed Oct. 2014).
Newell, B., Crumley, C.L., Hassan, N., Lambin, E.F., Pahl-Wostl, C., Underdal, A., Wasson, R., 2005. A conceptual template for integrative human–environment research. Glob. Environ. Change 15 (4), 299–307.
Newham, L.T.H., Jakeman, A.J., Letcher, R.A., 2007. Stakeholder participation in modelling for integrated catchment assessment and management: an Australian case study. Int. J. River Basin Manag. 5 (2), 79–91.
Oxford English Dictionary, 2014. OED Online. Oxford University Press. www.oed.com.
Pahl-Wostl, C., 2007. The implications of complexity for integrated resources management. Environ. Model. Softw. 22 (5), 561–569.
Pahl-Wostl, C., Giupponi, C., Richards, K., Binder, C., de Sherbinin, A., Sprinz, D., Toonen, T., van Bers, C., 2013. Transition towards a new global change science: requirements for methodologies, methods, data and knowledge. Environ. Sci. Policy 28, 36–47.
Park, N.-W., 2013. Spatial Downscaling of TRMM Precipitation Using Geostatistics and Fine Scale Environmental Variables. Advances in Meteorology 2013. Article ID 237126, 9 pp.
Parker, P., Letcher, R., Jakeman, A., Beck, M.B., Harris, G., Argent, R.M., Hare, M., Pahl-Wostl, C., Voinov, A., Janssen, M., Sullivan, P., Scoccimarro, M., Friend, A., Sonnenshein, M., Baker, D., Matejicek, L., Odulaja, D., Deadman, P., Lim, K., Larocque, G., Tarikhi, P., Fletcher, C., Put, A., Maxwell, T., Charles, A., Breeze, H., Nakatani, N., Mudgal, S., Naito, W., Osidele, O., Eriksson, I., Kautsky, U., Kautsky, E., Naeslund, B., Kumblad, L., Park, R., Maltagliati, S., Girardin, P., Rizzoli, A., Mauriello, D., Hoch, R., Pelletier, D., Reilly, J., Olafsdottir, R., Bin, S., 2002. Progress in integrated assessment and modelling. Environ. Model. Softw. 17 (3), 209–217.
Pérez Domínguez, I., Bezlepkina, I., Heckelei, T., Romstad, E., Oude Lansink, A., Kanellopoulos, A., 2009. Capturing market impacts of farm level policies: a statistical extrapolation approach using biophysical characteristics and farm resources. Environ. Sci. Policy 12 (5), 588–600.
Pidd, M., 2003. Tools for Thinking. Modelling in Management Science, second ed. John Wiley and Sons Ltd, West Sussex, England.
Qureshi, M.E., Whitten, S.M., Mainuddin, M., Marvanek, S., Elmahdi, A., 2013. A biophysical and economic model of agriculture and water in the Murray-Darling Basin, Australia. Environ. Model. Softw. 41, 98–106.
Rahman, J.M., Seaton, S.P., Perraud, J.-M., Hotham, H., Verrelli, D.I., Coleman, J.R., 2003. It's TIME for a new environmental modelling framework. In: Post, D.A. (Ed.), MODSIM 2003 International Congress on Modelling and Simulation. Modelling and Simulation Society of Australia and New Zealand Inc., Townsville, pp. 1727–1732.
Reed, M.S., 2008. Stakeholder participation for environmental management: a literature review. Biol. Conserv. 141, 2417–2431.
Reed, M.S., Fraser, E.D.G., Dougill, A.J., 2006. An adaptive learning process for developing and applying sustainability indicators with local communities. Ecol. Econ. 59 (4), 406–418.
Refsgaard, J.C., van der Sluijs, J.P., Højberg, A.L., Vanrolleghem, P.A., 2007. Uncertainty in the environmental modelling process- A framework and guidance. Environ. Model. Softw. 22 (11), 1543–1556.
Risbey, J., Kandlikar, M., Patwardhan, A., 1996. Assessing integrated assessments. Clim. Change 34, 369–395.
Rittel, H.W.J., Webber, M.M., 1973. Dilemmas in a general theory of planning. Policy Sci. 4 (2), 155–169. http://dx.doi.org/10.1007/bf01405730.
Rizzoli, A.E., Donatelli, M., Athanasiadis, I.N., Villa, F., Huber, D., 2008. Semantic links in integrated modelling frameworks. Math. Comput. Simul. 78, 412–423.
Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J.M., 2013. The agricultural model intercomparison and improvement project (AgMIP): protocols and pilot studies. Agric. For. Meteorol. 170, 166–182.
Rotmans, J., 1998. Methods for IA: the challenges and opportunities ahead. Environ. Model. Assess. 3, 155–179.
Rotmans, J., van Asselt, M., 1996. Integrated assessment: a growing child on its way to maturity. Clim. Change 34, 327–336.
Scholes, R.J., Reyers, B., Biggs, R., Spierenburg, M.J., Duriappah, A., 2013. Multi-scale and cross-scale assessments of social-ecological systems and their ecosystem services. Curr. Opin. Environ. Sustain. 5 (1), 16–25.
Schwanitz, V.J., 2013. Evaluating integrated assessment models of global climate change. Environ. Model. Softw. 50, 120–131.
Sinclair, P., 2011. "Describing the elephant": a framework for supporting sustainable development processes. Renew. Sustain. Energy Rev. 15 (6), 2990–2998.
Smajgl, A., Izquierdo, L., Huigen, M.G.A., 2008. Modelling endogenous rule changes in an institutional context: the ADICO sequence. Adv. Complex Syst. 11 (2), 199–215.
Smith, G.F., 1989. Defining managerial problems: a framework for prescriptive theorizing. Manag. Sci. 35 (8), 963–981.
Stewart-Koster, B., Kennard, M.J., Harch, B.D., Sheldon, F., Arthington, A.H., Pusey, B.J., 2007. Partitioning the variation in stream fish assemblages within a spatio-temporal hierarchy. Mar. Freshw. Res. 58, 675–686.
Strasser, U., Vilsmaier, U., Prettenhaler, F., Marke, T., Steiger, R., Damm, A., Hanzer, F., Wilcke, R.A.I., Stotter, J., 2014. Coupled component modelling for inter- and transdisciplinary climate change impact research: dimensions of integration and examples of interface design. Environ. Model. Softw. 60, 180–187.
Toth, F.L., Hizsnyik, E., 1998. Integrated environmental assessment methods: evolution and applications. Environ. Model. Assess. 3, 193–207.
Turner, A., Willetts, J., Fane, S., Giurco, D., Kazaglis, A., White, S., 2008. Guide to Demand Management. Water Services Association of Australia, Sydney.
van Asselt, M.B.A., Rijkens-Klomp, N., 2002. A look in the mirror: reflection on participation in integrated assessment from a methodological perspective. Glob. Environ. Change 12, 167–184.
van Asselt, M.B.A., Beusen, A.H.W., Hilderink, H.B.M., 1996. Uncertainty in integrated assessment: a social scientific perspective. Environ. Model. Assess. 1, 71–90.
Van Delden, H., Seppelt, R., White, R., Jakeman, A.J., 2011. A methodology for the design and development of integrated models for policy support. Environ. Model. Softw. 26, 266–279.
Van Ittersum, M.K., Ewert, F., Heckelei, T., Wery, J., Alkan Olsson, J., Andersen, E., Bezlepkina, I., Brogaard, S., Donatelli, M., Flichman, G., Olsson, L., Rizzoli, A., van der Wal, T., Wien, J.E., Wolf, J., 2008. Integrated assessment of agricultural systems – A component-based framework for the European Union (SEAMLESS). Agric. Sys 96, 150–165.
van Kerkhoff, L., 2005. Integrated research: concepts of connection in environmental science and policy. Environ. Sci. Policy 8, 452–463.
Vennix, J.A.M., 1999. Group model-building: tackling messy problems. Syst. Dyn. Rev. 15 (4), 379–401.
Verweij, P.J.F.M., Knapen, M.J.R., de Winter, W.P., Wien, J.J.F., te Roller, J.A., Sieber, S., Jansen, J.M.L., 2010. An IT perspective on integrated environmental modelling: the SIAT case. Ecol. Model. 221 (18), 2167–2176.
Vespignani, A., 2012. Modelling dynamical processes in complex socio-technical systems. Nat. Phys. 8 (1), 32–39.
Villa, F., Athanasiadis, I.N., Rizzoli, A.E., 2009. Modelling with knowledge: a review of emerging semantic approaches to environmental modelling. Environ. Model. Softw. 24, 577–589.
Voinov, A., Bousquet, F., 2010. Modelling with stakeholders. Environmental Modelling and Software 25, 1268–1281.
Voinov, A., Gaddis, E.J.B., 2008. Lessons for successful participatory watershed modeling: a perspective from modeling practitioners. Ecol. Model. 21, 197–207.
Voinov, A., Shugart, H.H., 2013. 'Integronsters', integral and integrated modeling. Environ. Model. Softw. 39, 149–158.
Walker, W.E., Harramoes, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P., Krayer von Krauss, M.P., 2003. Defining uncertainty. A conceptual basis for uncertainty management in model-based decision support. Integr. Assess 4, 5–17.
Walz, A., Lardelli, C., Behrendt, H., Grêt-Regamey, A., Lundström, C., Kytzia, S., Bebi, P., 2007. Participatory scenario analysis for integrated regional modelling. Landsc. Urban Plan. 81 (1), 114–131.
Weyant, J., Davidson, O., Dowlatabadi, H., Edmonds, J., Grubb, M., Parson, E.A., Richels, R., Rotmans, J., Shukla, P.R., Tol, R.S.J., Cline, W., Fankhauser, S., 1996. Integrated assessment of climate change: an overview and comparison of approaches and results. In: Climate Change 1995-Economic and Social Dimensions of Climate Change, IPCC. Cambridge University Press, Cambridge, pp. 367–396.
White, G.F., 1969. Strategies of American Water Management. University of Michigan Press, Ann Arbor.
Winz, I., Brierley, G., Trowsdale, S., 2009. The use of system dynamics simulation in water resources management. Water Resour. Manag. 23 (7), 1301–1323.
Wittmer, H., Rauschmayer, F., Klauer, B., 2006. How to select instruments for the resolution of environmental conflicts. Land Use Policy 23, 1–9.

Wolstenholme, E.F., 1999. Qualitative vs quantitative modelling: the evolving balance. J. Op. Res. Soc. 1999, 422–428.
Young, P., Parkinson, S., Lees, M., 1996. Simplicity out of complexity in environmental modelling: occam's razor revisited. J. Appl. Statistics 23 (2–3), 165–210.
Young, O.R., Berkhout, F., Gallopin, G.C., Janssen, M.A., Ostrom, E., van der Leeuw, S., 2006. The globalization of socio-ecological systems: an agenda for scientific research. Glob. Environ. Change 16 (3), 304–316.