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Editorial

Advances in Ecological Water System Modeling: Integration and Leanification as a Basis for Application in Environmental Management

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Abstract: The art of applied modeling is determining an appropriate balance between integration of more processes and variables for the sake of increasing representativeness and reliability of the models, while also avoiding too long development and simulation times. The latter can be achieved via leanification, which can be based on reducing the number of variables and processes by focusing on key processes in the system and its management, but can be as well induced by using simplified methods for the description of relations among variables (such as regression and probabilistic methods) to, for instance, reduce the simulation time. In this way, integration and leanification can be combined and together contribute to models that are more relevant and convenient for use by water managers. In particular, it is crucial to find a good balance between the integration level of ecological processes answering environmental challenges in a relevant manner and costs for data collection and model development (and application).

Keywords: integrated water modeling; model applicability; water management; model simplification

1. Introduction

Water system models and ecological models have a long history [1]. Nevertheless, the practical use of integrated ecosystem models for decision-making in water management remains very limited and confined to specific applications [2].

This special issue presents case-studies and reviews related to the practical integration of relevant key components and processes, as well as the 'leanification' of water system models. Leanification can be based on the reduction of the number of variables and processes by focusing on key processes in a system and its management, but it can also be as induced by using simplified methods for the description of relations among variables (such as regression and probabilistic methods) to reduce the simulation time. In this way, integration and leanification can be combined and together contribute to models that are more relevant and convenient for use by water managers (Figure 1). Many water-related problems constitute diverse interactions and are part of a complex sustainable development challenge [3]. The art of applied modeling is determining an appropriate balance between the integration of more processes and variables for the sake of increasing representativeness and reliability of the models, while avoiding too long development and simulation times. The range in Figure 1 indicates that for some cases, very lean and simple models are very convenient (e.g., for the exploration and for real-time-control applications, as well as for education purposes), whereas for other applications, a higher level of integration and reliability are most critical and the objectives can allow for a longer development and simulation time. For the latter, reliability, detailed resolution, and a higher level of completeness are of paramount importance, such as for large-scale environmental design studies characterized by high investment, operational costs, and challenging risks.

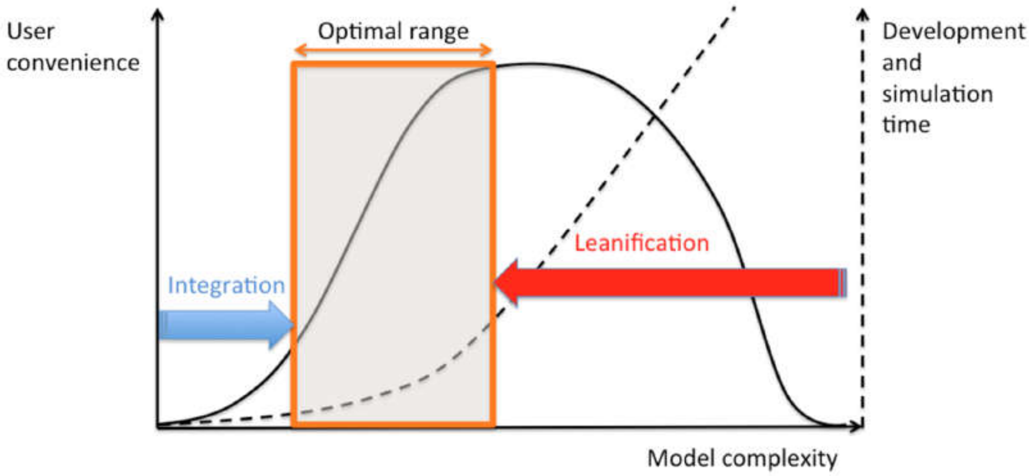

Figure 1. User convenience in relation to the level of complexity. Many water-related problems constitute many interactions. Thus, the art of applied modeling determines an appropriate balance between integration of more processes and variables while avoiding too long development and simulations times. The range indicates that for some cases, very lean and simple models are very convenient (e.g., for exploration of potential solutions and for real-time control applications), whereas for other applications, a higher level of integration is more critical than a fast simulation time.

2. Potential Applications of Models in Water Management

Integrated ecological models can support environmental management and policy development in various ways. These models provide insights into water-related disease control [4], assessments of environmental impact of wastewater and combined sewer overflows [5], wastewater treatment selection [6] and improvement [7], ecosystem services analysis [8,9], effects of land use on water quality [10] and aquatic community composition [11], as well as ecological water quality [12], determination of habitat restoration projects [13,14], distribution prediction and control of invasive species [15], integration of ecological insights into flood mitigation [16], and flow control related to reservoir management [17]. Moreover, models can be used for exploration purposes [18] and trade-off analysis [19], and environmental impact assessment [20] to inspire stakeholders and to support decision-making for policy developers. The effect of tipping points and environmental standards [21] can be analysed via models, as well as the uncertainty of assessment methods [22,23], or effects of particular choices made during assessments [24]. Models can also contribute to the leanification of data collection [5] and interpretation of data [25]. More conceptual approaches and (model) reviews can contribute to the overall improvement of the analysis of uncertainty, model development, and general applicability in water management, effective policy development, and improving water governance [26].

3. The Challenging Path from Data, to Model and Environmental Manager

Although integrated ecological water system models have a high potential to contribute to a more sustainable use of water resources, there are several remaining challenges to overcome, such as data collection in a highly complex ecosystems, model uncertainties, the focus on too specific subparts (e.g., merely hydrological, chemical, or biological), the high complexity of models and their use, the continuous change in environmental conditions which can affect model accuracy and representativeness, the irrelevance of possible simulations, or a combination of these elements [27]. A key element remains that data collection is in line with model development, training, and simulation to solve environmental models, and is not, for instance, focusing too much on representativeness and reliability, or elements such as costs (thus determining also the potential benefits in the context of the model selection and use).

Another main challenge to overcome for the success of models is their midfield position between data collection and environmental management. Importantly, the fact remains that (field) data collectors, data storage and dissemination managers, model developers, and potential direct and indirect model users (environmental policy makers and managers, stakeholders, and citizens) 'live' in different worlds with (aside from the partly common and general) specific objectives and key performance indicators. Good communication via appropriate data and information flows remains a very critical element and major bottleneck, combined with discipline-specific customs and beliefs. New and more integrated roles of environmental data managers [28], in addition to stakeholder involvement and close cooperation with data collectors, are needed in the future. Furthermore, social media, citizen science, and dashboard systems might increasingly play a new and resolving role via a continuous sharing of information and insights beyond discipline and professional borders. Last but not least, new monitoring and analytical tools, as well as new insights will result in new opportunities for obtaining data that are more reliable and much more abundant, but also to challenges for incorporating new insights and elements in models, such as new molecular and other biotechnological methods.

4. Model Complexity and Functionality: The Leanest Possible While Integrating the Necessary

A key question for model application is what to include in models—within a project management triangle confined by available staff, budget, and timeframe—and reflects in particular four elements: the selection of input variables, parameters, processes, and output variables. The key to the determination of the best combination is related to what is the available budget, the timeframe for data collection, model development, and model simulation, and the required reliability and resolution of the model. To answer this question, it is moreover very crucial to know what is already available of (field) data or other existing models to further build on.

During the past years, many practical concepts and software systems were developed related to environmental decision support [29]. Basically, one can opt to build a new model for each application (integrative approach) or to utilize existing models where possible (coupling approach). The first approach has the benefit of control in the models' design and linkage, but requires a longer development time. The second approach saves on the development time, but requires additional work to link up existing models [30]. From this perspective, integration, and leanification have practical challenges even beyond the project management triangle. In particular, one has to gain insight into how much of previous modelling and data collection studies can be reused and coupled to answer a problem, and decide whether the existing models are compatible and complete enough. Moreover, it is necessary to determine whether enough data can be gathered for model training, validation, and simulation. In several cases, one can reduce the complexity via a selection of key processes (for example via network models such as Bayesian Belief Networks), or via the training of a data driven and reduced model from a set of simulations of an integrated and complex model. The latter combines the knowledge span of an integrated and complex model, while strongly reducing the simulation time. Nevertheless, one has to take care of conditions that are not covered by this derived model. Examples of this include data-driven models generated from mechanistic hydrological models, for instance, to be used for real-time control related to flood management which can practically help citizens to determine what actions they need to take in their houses in case of such events. These models might be used for this particular type of short-term simulations, continuously fed by very recent data from probes, but have for instance no use for long-term predictions needed for investments in flood-defence infrastructure related to climate change. Leanification can thus also rely on different approaches, depending on needs and priorities, as well as what is and can be available.

5. Conclusions

Although several technical and cultural challenges remain to make integrated ecological models more successfully used, several practical cases and examples have shown that a smart modeling approach is key to the benefits of the use of models. In particular, it is crucial to find a good balance between the integration level of ecological processes answering environmental challenges in a relevant manner and costs for data collection and model development and application. This can be achieved through a more thoughtful problem definition, analysis, and (re)use of existing data of the system, model selection and data collection, as well as through the optimal consideration of the project triangle (available time, staff, and budget) in relation to the problem questions (focus, level of detail, and accuracy), for which leanification is of paramount importance. Thus, the models need to provide an answer on the raised water system questions and challenges, not only clearly embedded in a context of sustainable development, but also in a feasible time and cost frame that can be achieved by the available project development and implementation team(s).

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