A Framework for Capturing and Applying Models of Biological Response to Natural Resource Management

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EXTENDED ABSTRACT

Natural resource managers need to asses the impacts of different natural resource management scenarios. Increasingly, models are used to support and communicate this complex trade-off process. One of the principle motivations for natural resource management (NRM) is to improve or protect the environment. However, our capacity to model a multi-faceted ecological response in rivers has been limited to single implementations.

We present an ecological response modelling (ERM) framework to support this NRM process. The ERM framework is constructed in Microsoft .Net using The Invisible Modelling Environment (TIME) which provides the capacity for the tool to be interoperable with the e2 catchment modelling tool. This integration permits the ecological consequences of land management changes to be modelled simultaneously with predicted hydrology and nutrient changes.

The ERM framework is based on a library of models of ecological response. Each model contains a mathematical function that transforms input time series of drivers into an output time series representing the response variable. The simple architecture which constrains the input and output to a single data type allows modularity such that models can be nested, combined into larger compound models or called by 3rd party modelling applications.

The library of ecological response models has been configured to allow local (personal computer based) stand alone models or collections of models as well as an online library of models which may be downloaded and reused or modified for specific application.

A key feature of each model within the ERM framework is the meta information. The collective meta information constitutes a 'confidence' schema and includes a confidence scoring system based on the underlying source, the data and interpretation required to generate the numerical function. The confidence score is presented in the output to provide context and supports the interpretation of numerical predictions.

The history or lineage of each model is recorded along with the model author and the authors of parent models from which it has been built. Furthermore, the spatial applicability of each model is recorded as well as any other words of warning about appropriate application of the model. The final information provided by the confidence schema is an overall summary of the model that describes context, such as the reason for model development and the ability to link any associated information such as reports or web pages. Providing such information in these different forms allows an assessment of the appropriateness of the model application and robustness of the underlying science

The ecological response modelling framework allows for a range of modelling approaches and adopts a good modelling practice approach by clearly representing the underlying science used to develop each model. The models can be made available to the broader modelling community via a shared library of ecological models. The intent is that this mechanism of publishing the associated meta information along with model functions will provide a greater level of transparency in ecological modelling, discourage improper model use and highlight areas of key research need.

1. INTRODUCTION

Modelling is increasingly being applied to the assessment of natural resource management scenarios to prioritise investment, assess policy options and plan for long term impacts such as climate change. Physical process models such as hydrologic and sediment and nutrient transport models have been applied for many years to support this process. Examples include the application of SedNet to the Great Barrier Reef catchments (Bartley et al. 2007), or the Integrated Quantity Quality Model (Podger 2004) for hydrologic modelling in New South Wales and Queensland.

Natural resource managers are increasingly required to consider the ecological consequences and tradeoffs of alternate strategies. A good example is in the field of water allocation and management where the environment is recognised as having critical water needs. The process of quantifying those environmental water needs and assessing the ecological implications of alternate water management scenarios is a key area for linking physical process models (hydrology) to ecological response. The mechanism of doing this is mostly on a piecemeal, project by project basis, with a heavy reliance on expert panels to assess the ecological outcomes of alternate scenarios (Cottingham et al. 2002). The expert panel process is timely but not transparent, nor are the results transferable to other locations or to new scenarios.

In addition to predicting the ecological consequences of a given scenario, natural resource managers are also increasingly asked to consider simultaneously the implications of multiple NRM strategies such as considering the ecological value of different combinations of environmental flows, coupled with riparian revegetation and instream works. To support these decision making processes, NRM managers require a modelling capacity that allows physical process models to be integrated with quantitative models of ecological response.

We have developed an ecological response modelling (ERM) framework to support the expert interpretation process. We will briefly describe the ERM framework followed by a more detailed discussion of the key challenge of adequately representing confidence in ecological models.

1.1. The ERM framework

The ERM framework is structured around a library of quantitative models used to predict ecological response represented as either a direct population change, or more commonly through a predicted habitat response to NRM activity. An example of modelling habitat change is to predict the change in pool habitat in a river under different water regimes. The ERM framework was initially envisaged to provide support for environmental water allocation in rivers, however it could be used to model other NRM activities. Several different types of numeric function can be stored in the ERM library, and these can be entered by any user, but would normally be entered by an aquatic ecologist due to the relatively complex aquatic systems understanding required.

The core element of the framework is a 'model' (grey area in Figure 1) which receives input as daily time series (e.g. flow and temperature), a quantitative transformation is applied to the input ('Function' in Figure 1) and a daily time-step output time series is produced. This output time series usually represents habitat availability in response to the input time series such as a binary time series identifying if fish passage is possible on any given day. This daily time-step output time series is then summarised by a season of interest to produce an annual time-step time series. An example is the number of days in spring and summer when fish passage is possible. This annual time series is then further summarised across years to produce a single summary metric, which is usually done by averaging across the annual values to give a score for the scenario. The daily and annual time series can be visualised as an output as well as the single summary metric.

A key element of this architecture is the capacity to include any style of numerical function which can take input data as time series and produce an output which can be represented as a time series. This time series based representation means that with identical data types as input and output, a generalised shell can be produced to allow models to be easily linked with each other and for 3rd party modelling software to easily call on an ERM model.

The value of the ERM framework is enhanced if it can integrate with existing physical process models, such that the ecological consequences of a change in water or nutrients can be quickly determined. Because the ERM framework is written in the TIME framework (Rahman et al. 2005) and it can be used as a 'plugin' to the e2 catchment modelling environment (Argent et al. 2005).

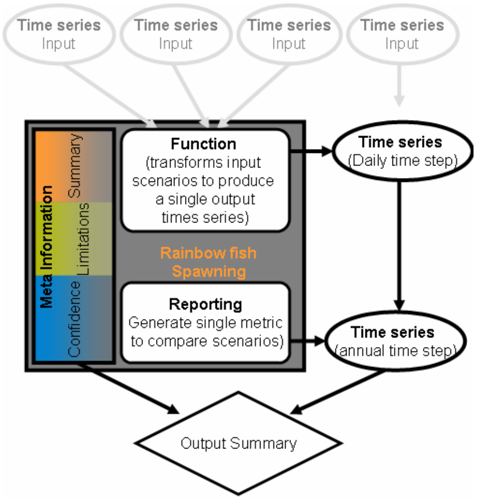

Figure 1: Architecture of an ecological response model.

1.2. Alternate numerical functions

The framework can handle different kinds of numerical functions, including rating or habitat preference curves, hydraulic rules such as water depth and velocity constraints or formula-style functions for creating complicated functions and conditional statements (Marsh et al. 2007).

In the future, the capacity to build truly networked models by joining several models will be incorporated. These networked models will allow feedback loops and time lags. An example of this type of application could be a population model for a fish which is built from several habitat-based component models such as a minimum depth to allow movement, pool habitat availability, minimum water temperature requirements and the timing of high flows which trigger spawning.

2. MODEL CONFIDENCE

One of the key facets of good model building is to ensure that model development appropriately represents the underlying science used in developing the model (Jakeman et al. 2006). Modellers tend to be inconsistent in the way in which this information is collated and presented. We have developed a schema (included as 'Meta information' in Figure 1) to manage the varying information required to adequately account for the broad range of supporting information that defines the underlying science of a model. This meta information is a critical part of the model and will be described here in some detail.

The terms 'risk', 'confidence' and 'uncertainty' have some overlap in their interpretation. We have looked to the users of the ERM framework to guide us in the development of an appropriate system. During a 6 month trial project we asked the creators and users of published models about the importance of model confidence and how they would use the concept of confidence and uncertainty in a modelling context. This is an acknowledgement that for a successful representation of confidence we require it to be both useful for supporting end users in their NRM planning decisions and accurate in its representation of the science being presented as a model.

For the decision makers (those that use model outputs to inform policy decisions), the concept of uncertainty is important when it affects the degree of confidence in the expected outcome of a decision (Refsgaard et al. 2007). It is particularly challenging for decision makers when the choice between alternate scenarios is clouded by overlapping error bounds or confidence intervals. An example would be the trade-off between allocating enough water to just wet a wetland each year compared to the value of delivering that water as an infrequent but large flood. The ecological consequences of more frequent lower volume events are known with more confidence than the value of a rarer large flood, simply because the rarity of these large events severely limits opportunity to research their impacts. In developing quantitative models to predict the value of either scenario it is important to convey the difference in the depth of science that underpins each model; the decision-maker needs to know whether any difference in model scenarios is indeed significant or whether uncertainty in the underlying science in fact overwhelms the modelled differences.

Decision makers look not only to the depth of underlying science in a model but also to the confidence that scientists place in the model. This is often manifested as a degree of consensus among scientist in the most appropriate modelling approach. Hence, any developed schema needs the support of modellers as well as decision makers.

Here the notion of uncertainty is more subjective than the traditional quantitative measures used for error propagation and statistical uncertainty analyses. Models in the ERM framework are certainly amenable to more formal uncertainty analyses, however it's important to acknowledge that the underlying ecological modelling research is not at a stage of maturity where such quantitative analyses are routine or necessarily effective. This is because there is a high level of uncertainty surrounding the underlying model conceptualisation. For this reason, a rigorous review of the conceptual representation of a model and the reputation of the scientist are important indicators of confidence for model users.

For modellers involved in this project, their requirements for a confidence schema were consistently associated with the dangers of applying models inappropriately. A model is built within a specific context and modellers are justifiably uncomfortable when their models are taken out of context. However, modellers are keen for their research to contribute to NRM decision-making processes. This apparent dichotomy can be resolved by providing appropriate contextual information with a model to encourage it to be applied within appropriate boundaries. A clear framework is needed to idenfity when a model has been applied outside its limitations.

There is a wealth of literature that highlights the need for good modelling practice and for adequately handling of uncertainty, risk and confidence. The following taxonomy to describe sources of uncertainty was presented by Refsgaard et al. (2007) but is similar to those presented elsewhere:

Context and Framing: The boundaries of the system to be modelled are not well described, such as the external economic, political and social circumstances that form the basis of model development.
Input uncertainty: The uncertainty associated with input data such as modelled or measured flow and constituent data
Model structure uncertainty: Uncertainty related to the theoretical understanding of the system being modelled.
Parameter uncertainty: Uncertainties related to appropriate model parameterisation.
Model Technical Uncertainty: Uncertainty arising from the coding of the model such as numerical approximations and necessary simplifications and lumping of some processes.

We can further break each of these five uncertainty sources into two subcomponents; nature, and level. The two elements described as the *nature* of uncertainty by Walker et al. (2003) are; 1) Epistemic uncertainty, which is the uncertainty due to imperfect knowledge and can be resolved, or at least reduced, through a maturation of the science and 2) Stochastic uncertainty, which is due to the inherent variability in systems and is non-reducible. For ecological modelling the separation and characterisation of these two key types of uncertainty is rarely possible because the data we use to verify a modelled representation represents a combination of the two. A second and critical component of uncertainty is the *level* of uncertainty which lies on a continuum between deterministic knowledge and total ignorance (Walker et al. 2003).

We can now use the uncertainty sources and their underlying components to consider the elements of uncertainty incorporated in this schema. For ecological models, the key source of uncertainty lies firstly in model structure uncertainty where we are uncertain that the quantitative representation of the system or organism is an adequate reflection of reality. Although a well-recognised and acknowledged problem, means for handling conceptual and model structural uncertainty are far less developed than those for characterising other sources of uncertainty (such as parameter uncertainty or input uncertainty due to measurement error). We're specifically interested in situations where there is a high level of uncertainty in the model structure and more broadly in epistemic uncertainty across all sources. In these situations it is generally not feasible to characterise uncertainty in a quantitative manner and there is need for other means of communicating it. The level of uncertainty in ecological models tends to fall in the category of recognised ignorance where we acknowledge that elements of the system are not necessarily well captured because our understanding is incomplete. At best our level of uncertainty could be described as scenario uncertainty; here we are confident in our ability to quantify uncertainty for the baseline case for which we have data, but we are uncomfortable with extrapolating to new scenarios where our underlying system representation may not hold.

Based on the requirements of decision makers and model users and our understanding of the key limitations in confidence for ecological modelling we have devised a schema to capture these more qualitative aspects of confidence associated with each ecological model. The schema has two major categories of information. The first contains a systematic confidence scoring system based on the rigor of the underlying science to allow model users to compare across models and to allow model output to be tagged with a meaningful confidence score to inform interpretation. The second area allows the capture of contextual information to inform appropriate model selection. These two areas are described in more detail below.

2.1. Confidence scoring

We have devised a confidence scoring system based on the 'Pedigree' element of the Numerical Unit Spread Assessment Pedigree (NUSAP) system described by Funtowicz and Ravetz (1991). The pedigree is the scientific status of the information developed through expert judgement based on set criteria (Van der Sluijs et al 2005). The scoring system is similar to the multiple lines and levels of evidence (MLLE) approach (Norris et al. 2005) whereby lines or categories of evidence are collated across multiple evidence sources. The MLLE approach differs from the NUSAP system in that it is a generalised system to be applied across any problem which allows the scores to be directly compared, where as the NUSAP system is generally tailored to a specific application.

Our category system adopts the MLLE approach but is simpler to implement because it does not rely on a comprehensive literature review to complete. The ERM confidence scoring system is not a hypothesis testing procedure. We are not testing if a model is likely to be true by weight of evidence approach of randomly sampling an underlying population of potential information as you may do in the MLLE approach (Norris et al. 2005). We focus here on gathering supporting evidence. Where there is contrary information, this can be presented in the caveats, or can be used to produce a competing model.

The ERM confidence scoring system has three lines of evidence, and each line has three levels of scoring (Table 1). This scoring is applied across all evidence sources and then combined to give a single confidence score for each line of evidence.

Table 1: ERM confidence scoring.

Confidence	Source (Where was the model published)	Data (what is the data that underpins the model)	Specificity (how specific is the published form of the model)
High	Peer reviewed publication	Multiple sites and/or times	No interpretation required
Medium	Non-peer reviewed publication	Single site and/or time	Some interpretation required
Low	Unpublished expert opinion	No data expert judgement	Major interpretation required

We think that an explicit numeric representation based on data from a robust experimental design published in a peer reviewed journal constitutes a high level of confidence in the model. The method of aggregating confidence levels across different sources or evidence and combing lines of evidence should reflect this perception of high confidence.

In many ways it would be preferable to keep the confidence scoring in its disaggregated form, as any form of aggregation is somewhat arbitrary (particularly given the qualitative nature of the scoring system). Some aggregation is desirable, however, if only to ensure that some indication of confidence can be communicated easily with model results. In choosing an aggregate scare, we wanted to ensure that all sources of evidence could be considered, whether published or not, and that those sources of information that scored well across all lines of evidence make a greater contribution to the overall confidence.

We considered four alternative techniques for aggregating the confidence scores for each line of evidence across multiple sources of evidence. To illustrate the different techniques consider an example model with three key sources of information which have been used in the model development. The first is a peer reviewed journal paper that presents the concept of the system understanding but is data free, the second is a local unpublished study based on a sound experimental design and the third is the advice of an expert group generated via a workshop. Table 2 has the base confidence values presented for each information source across all three lines of evidence. The bottom half of Table 2 represents the results from the four aggregation techniques:1) take the highest of each confidence line; 2) take the lowest of each confidence line; 3) averaging the levels of evidence for each line of evidence; and 4) moderate the confidence line by the other lines that correspond to that piece of evidence (achieved by dropping the value of each element in a line of evidence by one score if an associated line of evidence is lower, and then the highest level of evidence for each line of evidence is adopted).

The ‘single highest’ approach would provide a high confidence in this model despite there being no peer reviewed interpretation of the model and thus would overstate the confidence that we should have in the model. The ‘single lowest’ approach similarly understates the confidence in the model. The ‘averaging’ approach is difficult to present because representing a fractional value of a qualitative rating would overstate the precision of the approach. Rounding to the closest whole score appears reasonable for this example. A limitation of simple averaging for each line of evidence is that valuable sources of information that contribute across all lines of evidence are not provided any additional status. The ‘moderated approach’ weights more heavily the sources of evidence that contribute across all lines of evidence.

Table 2: Example of raw confidence data for each evidence source and alternate ways to summarise the results. 'moderated' scores parenthesised.

	Lines of evidence		
source of evidence	*Source*	*Data*	Specificity
1) Peer reviewed paper	High (Medium)	Low	Low
2) Local unpublished study	Low	High (Medium)	High (Medium)
3) Data free expert panel	Low	Low	High (Medium)
Summary methods			
1) single highest	High	High	High
2) single lowest	Low	Low	Low
3) average (rounded)	Medium	Medium	High
4) Moderated	Medium	Medium	Medium

At this point we have a confidence scoring system which can be reported for all three lines of evidence. An additional summary option is also provided to make the output clearer, whereby the confidence is aggregated across the lines of evidence by presenting the value for the line of minimum confidence. For this example the overall confidence would be medium. For this scoring system a high level of confidence can only be achieved if a single source of information scores highly across all three lines of evidence. A limitation is that this scoring system does not consider a 'weight of evidence' such as when consistent results from many poorly designed experiments could add weight or increase confidence in the conclusion. Future versions will consider adoption of a weight of evidence approach.

2.2. Limitations and summary

In addition to the systematic scoring of confidence we provide a structured mechanism to capture contextual information to inform model choice. Good model building practice requires that we are clear about not only where a model could or should be used, but also where it is inappropriate to use the model. There are two main model limitations which are recorded. The first is the spatial limitation of the model, whereby the spatial extent to which the model could be applied is presented. This is critical for ecological models that may be focused on plants and animals that have finite distributions, or where behaviour may vary in different regions. The second key field under limitations is 'Words of warning' where the model author can highlight known deficiencies and reviewers of the model can also contribute to these guidelines for using the model appropriately and wisely.

A further concept which is captured is the lineage or 'model history'. This is an acknowledgement that the lineage of a model, or how it has been incrementally refined and improved, is an overall contribution to the confidence that one has in the model prediction. For example, a model that is based heavily on the universal soil loss equation (Renard et al. 1991) provides the user with some confidence that the methods are well-established and widely accepted. The model history is tracked when any new model is created based on a copy and paste and modification of an existing model.

As a part of the model history, the authorship of any model is also recorded. Authorship is a key tenant of scientific publication. A model is an extension of a person's scientific work, and we consider it important to ensure authorship is acknowledged and remains associated with any future models that evolve from it. Authorship is not simply the author of the current model, but the authors of any parent models on which the model was based.

An additional summary area of the confidence schema is provided primarily for capturing unstructured contextual information about a model such as the purpose or project for which it was developed. Any supporting or associated information can be linked to the model. An example may be a website describing where the model has been used or a schematic diagram of how the model is intended to work.

3. CONCLUSIONS

The ecological response modelling framework has been developed to support natural resource management organisations to make quantitative assessments of the ecological consequences of alternate scenarios of land and water management. The framework can be integrated with existing catchment modelling systems such as the e2 framework to provide an ecological interpretation of the modelled changes in hydrology and nutrient delivery under different scenarios. The framework allows non-developers to enter models directly into the framework and contribute them to a web-based library of models for reuse and refinement. The framework includes a comprehensive confidence schema that has been developed to support the concepts of good modelling practice, whereby the underlying science and the limitations of a model are clearly presented. The confidence schema includes a confidence scoring system that is included as one of the model outputs; the intention is that this will help establish a practice of presenting both model results and confidence in that result. We readily acknowledge that the confidence schema represents a first attempt to require greater transparency and insight into model underpinnings in a way that is easy for end-users to adopt. The Ecological Response Modelling Tool will be available on the toolkit.net.au website and through the eWater CRC.

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