SERIES ON MODEL CHOICE

Designed to assist you to better understand catchment modelling and model selection

www.toolkit.net.au/modelchoice

1 General approaches to modelling and practical issues of model choice.

CONTENTS

COOPERATIVE RESEARCH CENTRE FOR CATCHMENT HYDROLOGY

Summary

- There are different fundamental approaches to building models resulting in models of different structure and complexity, and there is a relationship between model complexity, data available for model development and testing, and predictive performance.
- To maximise the benefit of modelling for management actions in catchments, researchers, software developers model users and those commissioning modelling should have an understanding of basic modelling principles and the relationship between model complexity, the data available for model development and testing, and predictive performance.
- Model choice should be made using a "horses for courses" approach. There is no particular style of model that is inherently better for all applications than another. The general maxim is to choose the simplest model that will do the job required. Adding complexity can lead to reductions in predictive performance unless testing data are available.
- On practical model applications, it is critical that the context for and objectives of the modelling exercise are clear.
- There is a "model choice decision loop" to assist in choosing the right model for a particular purpose. It involves defining the objectives, assessing the availability of data, expertise, and resources and then reassessing whether the objectives can be met.
- Model users need to be realistic about the role of models in decision making
  - A perfect answer a year late is useless.
  - A model which is too simple or uncertain or inflexible to deal with the real objective/s is useless.
- Modelling is as much art as science, and the quality of the modeller is at least as important as the quality of the model.
- From a technical perspective
  - Modellers must understand the principles on which the model is based.
  - Model time and space scales must match objectives and available data.
  - Formal uncertainty estimation is likely to be impossible but an appreciation of uncertainty must be considered at each stage of the modelling and conveyed to users.
  - Availability of data for testing and expertise for interpretation must be considered up front.

Background

MODELS AND THE CRC'S CATCHMENT MODELLING TOOLKIT

There are literally thousands of models "out there" that have been designed to deal with different aspects of land and water management. Most have been built by individuals to deal with particular problems and are not available in the public domain. Many are the subject of papers in the scientific literature so the concepts are widely available, but the model code itself is not. Others are developed for commercial purposes and may be purchased. The Catchment Modelling Toolkit is adding yet more models to the confusing array already developed, so what is the advantage? Why has the CRC for Catchment Hydrology invested so much in the Toolkit?

REASONS FOR THE CATCHMENT MODELLING TOOLKIT

First and foremost, the Toolkit is the main avenue through which the outcomes of CRC research are being made available to industry. Accompanying the models in the Toolkit are data, training and background materials to enable the software to "deliver capability" to model users, not just make some code available. The knowledge that underpins the Toolkit is also considerable, providing some confidence that the models available are based on sound understanding.

USEFULNESS AND LIMITATIONS OF MODELS

It is important to remember an immutable fact about modelling:

"All models are wrong, but some are useful"!

Models can be useful because they enable the likely effects of management actions and climate scenarios to be simulated, so comparisons can be made between different options "virtually". Models can also be used to help develop targets (see *Catchword*, May 2004 www.catchment.crc.org.au/catchword), and provide a framework for interpreting data and integrating information of different types. As we seek to manage risks and predict the likely impact of decisions being made now, models are an increasingly important tool for decision makers.

But all models are a simplification of reality and the key to smart model use is knowing which model to choose for a given application and so maximise its usefulness.

SELECTING A MODEL – NEED FOR GUIDANCE

At first glance there are often many models that appear to do the same thing. Sometimes this is indeed the case, where differences are cosmetic or restricted to minor differences in concepts, but there are commonly also fundamental differences in models, particularly in the spatial and temporal scales at which they operate and in the processes they are designed to represent. There are also differences in the amount of time, data and knowledge needed to apply models and often these practical considerations have as much influence on model choice as does the fundamental model capability.

From the perspective of a model user, the choice of model style must be made using a "horses for courses" approach. There is no particular style of model that is inherently better for all applications than another. The general maxim is to choose the simplest model that will do the job required. But what are the major considerations in making this choice?

MAJOR ASPECTS IN SELECTING ALL MODELS – PURPOSE OF THIS PAPER

In this series of papers, we discuss the major considerations in selecting an appropriate model for a particular application. This first paper deals with issues that are relevant to all types of modelling.

Subsequent papers focus on models developed to deal with particular problems, namely:

i) water quality;

ii) water quantity;

iii) urban, and

iv) "whole of system" or integrated models.

In these papers, the emphasis is on how to choose between the models available in the Toolkit, although some comments are also provided on other widely available models that have similar capability.

HOW THIS PAPER IS ARRANGED AND WHAT IT COVERS

This paper has two major sections. The first covers the different fundamental approaches to modelling; the balance between data, model complexity and predictive performance; and general classifications of models, highlighting key features that indicate the likely applicability to a particular job. This first section is detailed, but is information that should be understood by anyone involved in modelling.

The second section of this paper summarises the more practical issues of choosing a model for a particular task. Readers who are familiar with modelling philosophy and modelling fundamentals may wish to skip to the second section.

Approaches to modelling

There are two basic approaches to building models, the 'downward' approach and the 'upward' approach.

DOWNWARD APPROACH

In the downward approach we begin with the simplest model that is able to reproduce a set of observations (eg. to convert rainfall to runoff) and introduce added complexity only when it:

a) consistently improves the fit to observations, and

b) makes sense in terms of our understanding of the system being modelled (i.e. implies hydrological behaviour that we know to occur).

This approach, also known as "top down" modelling, places a high priority on field data and the ability to define model parameters by calibration (i.e. choosing model parameters that provide a "best fit" between observations and simulations). It implies that we might ignore processes that we know to occur if their representation in the model does not improve measured model performance. For example, we may want a runoff model for a catchment where it can snow, but do not have enough data about the snowpack, melt rates etc. to define parameters in a specialist snowmelt model, so we just use a simple rainfall-runoff model.

In a practical application, the downward approach may result in a model that is too simple to address the problem of interest. For example, if we want to explore the effects of land-use change on runoff water quality, the model must have a "knob to turn" that represents the effects of different types of land-use. There may be insufficient data available to derive such effects directly from observations so in this "downward approach", the land uses may be combined in a way that is too coarse to explore the sort of management actions proposed. We may believe we know approximately what the effects of a different land use might be, but because we do not have the data to prove it, it cannot be included in the model.

UPWARD APPROACH

The second approach to model building is to represent all the processes thought to be important, and assume that because our understanding and representation of individual processes are "right", the overall model is "right". In the example above, we could include a snowmelt model in our rainfall-runoff model, but now we would have many more parameters (perhaps too many to define a single optimal set) and have to "guess" or "fix" some in order to apply the model. The "upward" approach is also known as "bottom up" modelling.

IN THIS SECTION:

IN THIS SECTION:

COMMON PRACTICE IN CATCHMENT MODELLING – COMPLEXITY AND ACCURACY ISSUES

Something closer to the "bottom up" approach has been common practice in catchment modelling, but can lead to models that are too complex and that cannot be properly tested.

The large number of model parameters that result from this approach leads to numerous combinations of parameter values giving predictions of similar quality. So there is no single best parameter set able to be defined. Modellers refer to this by saying that the parameters are not *identifiable* (see Beven, 1989; Grayson et al., 1992a, b).

In other words, when simulations based on different parameter sets are compared to observations, it is not clear which set of the parameters gives a better fit to the data. This is another way of saying that we are not really sure how good our model is. It also means that even if a model is able to simulate a particular type of observation, it does not indicate that other predictions made by the model are correct. For example, a model may give good fits to streamflow data at a catchment outlet, but this does not guarantee that there will be accurate simulation of streamflow at internal gauging stations. This has been clearly shown by many studies, yet is commonly ignored by model users who confidently display, for example, spatial predictions assuming that because the outflow hydrograph was correct, the internal predictions must also be accurate.

'TUNING' AND REPRESENTATION OF PARAMETERS - CALIBRATION

A fundamental problem is that many of the equations we use to represent processes require calibration – i.e. "tuning" of the parameters to provide a good fit to observations. This is necessary because the parameters cannot be directly measured in the field or from data. This is true even of "physically based" equations because they are invariably applied at a scale different to that at which they were derived. They then become conceptual representations with parameter values that depend on the scale at which the equations are applied.

A classic example of a "physical parameter" that becomes a conceptual representation is the hydraulic conductivity of soil; this is often measured in a laboratory on relatively small samples, yet in models, these values are applied to scales many thousands of times larger than the sample, where the direct physical measurement in the laboratory is unlikely to represent the effective value across the large area. There is also a strong argument that some of these equations are wrong at different scales (eg. Beven, 1996 argues that the equations commonly used to describe flow through soil are simply wrong at the field scale).

In any case, every time a new (or more complex) process description is included in a model, more parameters are added, each of which must either be calibrated or have a value assigned. If these parameter values cannot be determined accurately,

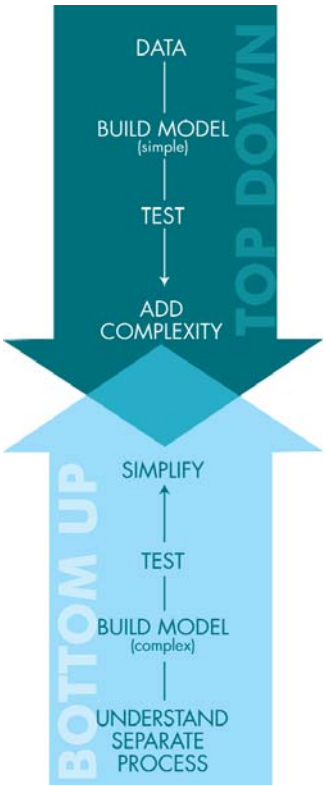

FIGURE 1. CONVERGENCE OF TOP-DOWN AND BOTTOM UP APPROACHES TO MODELLING.

the addition of model capability can increase uncertainty in predictions. This is explored further in the next section.

AIMING FOR CONVERGENCE – FULLY TESTED PROCESSES IN MODELS

Ultimately the simple "downward" and complex "upward" approaches should converge (Figure 1) since we want models that represent important processes but that can be fully tested – at least to an extent where we are comfortable in using model outputs for comparative purposes. They need to be tested well enough for us to know they are producing the 'right' results for the 'right' reasons. This will be possible only when there are sufficient observations to enable each component of the model and the interaction between the components to be tested.

Data, Model Complexity and Predictive Performance[1]

PRAGMATIC CHOICES AND TRADE-OFFS

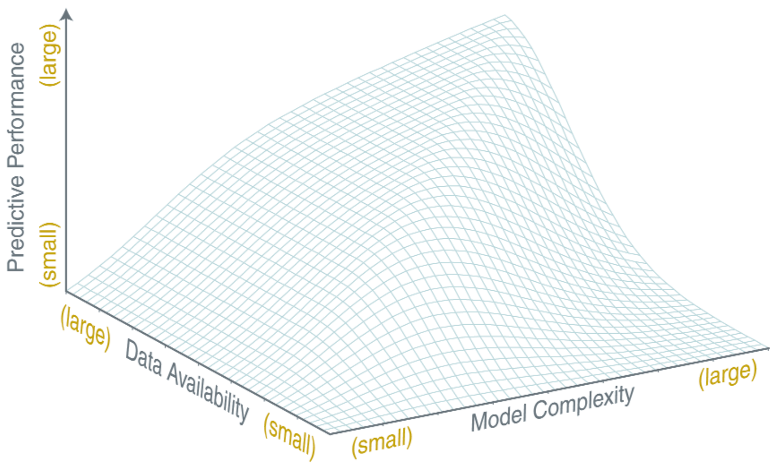

FIGURE 2A. CONCEPTUAL RELATIONSHIP BETWEEN DATA AVAILABILITY, MODEL COMPLEXITY AND PREDICTIVE PERFORMANCE (AFTER GRAYSON & BLOSCHL, 2000)

In practice, pragmatic choices have to be made regarding the appropriate level of model complexity and the consequences of those choices. Figure 2A illustrates the conceptual relationship between model complexity, the availability of data for model testing, and predictive performance of the model. The term "data availability" means the amount, quality and "information content" of the data available for model testing. The term "model complexity" means the detail of process representation. Complex models simulate more physical processes and so are likely to have more parameters. "Predictive performance" means how much confidence we can have in the model outputs when used to predict future events. We want this confidence to be as high as possible, given the model and/or data we have available.

[1] The topic of model complexity has been a source of stimulating discussion in the literature, particularly in the 1980s and early 1990s when modelling was "taking off". Interested readers may wish to consult some of the following (Bair, 1994; Bathurst and O'Connell, 1992; Beck, 1987, Beven, 1987, 1989, 1996; Bergström, 1991; Grayson et al, 1992; Jakeman and Hornberger, 1993; Hillel, 1986; Konikow and Bredehoeft, 1992; Kleme, 1983, 1986; James and Burges, 1982; Morton, 1993; Oreskes et al., 1994; Philip, 1975 ; Refsgaard et al., 1996; Smith et al., 1994).

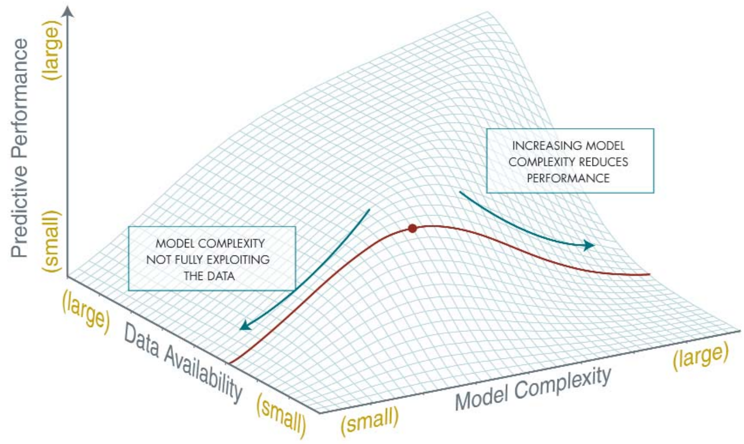

FIGURE 2B

If we have a certain availability of data (eg. solid line in Figure 2B), there is an "optimum model complexity" beyond which the problems of properly defining the model parameter values described previously become important and *reduce the predictive performance*. There are too many model parameters and not enough data to test whether the model is working, or is working for the right reasons. If we use a simpler model than the optimum, we will not fully exploit the information in the data.

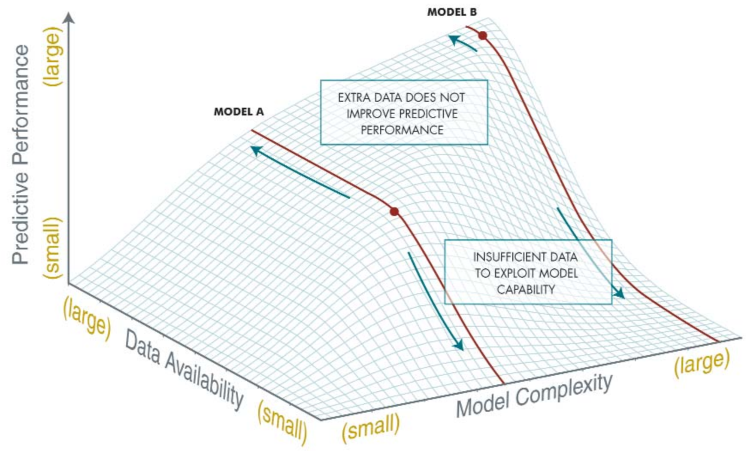

FIGURE 2C

For given model complexities (eg. Model A and Model B in Figure 2C), increasing data availability leads to better predictive performance up to a point, after which the data contains no more "information" to improve predictions i.e. we have reached the best a particular model can do and more data does not help improve performance (the lines flatten out as data availability increases). This is not a particular problem, except that we could possibly do better. In this case, we could consider a more complex model to better exploit the information in the data.

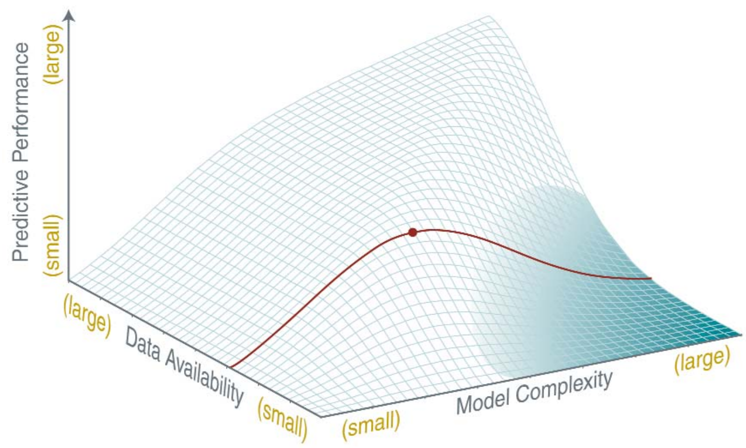

FIGURE 2D

The more common situation for practical applications of catchment modelling is represented by the shaded area in Figure 2D, where we are using too complex a model with limited data and so cannot define an optimum set of parameters with confidence.

GETTING THE RIGHT LEVEL OF COMPLEXITY

Ultimately the answer to "what model complexity is warranted" depends on the objectives of the modelling exercise and knowledge of the system being modelled. The key point is that it is not useful to add complexity when we have no way of testing whether this improves a model or makes it worse. In general it is most efficient to start simple, gaining initial insights quickly and making it easier to determine how much additional complexity is warranted.

Classification of models

BASIC FEATURES FOR CLASSIFICATION

A general classification of models can be useful for giving an indication of model structure or complexity. The modelling literature is replete with different ways of classifying models. Refsgaard (1996) presents an excellent description of model types and definitions relevant to modelling. Singh (1995) discusses classifications in terms of how processes are represented, what time and space scales are used and what methods of solution to equations are used. Here we focus on three basic features, useful for distinguishing approaches to modelling in catchment hydrology – these are:

(i) the nature of the basic algorithms (empirical, conceptual or process-based),

(ii) whether a statistical or deterministic approach is taken to input or parameter specification, and

(iii) whether the spatial representation is lumped or distributed.

EMPIRICAL, REGRESSION OR "BLACK-BOX" MODELS

The first question in classification is whether any attempt is made to represent the basic processes. Models that simply calibrate a relationship between inputs and outputs are known as empirical, regression or "black-box" models. They are based on input-output relationships without any attempt to describe the behaviour caused by individual processes. An example is:

$$\textbf{Runoff} = a\cdot(\textbf{rainfall})^{b}$$

where we derive the parameters a and b via a regression between measured rainfall and runoff.

CONCEPTUAL-EMPIRICAL MODELS

The next step in complexity is conceptual-empirical models where, in the case of catchment modelling, the basic processes such as interception, infiltration, evaporation, surface and subsurface runoff etc. are separated to some extent. However, the equations that are used to describe the processes are essentially calibrated input-output relationships, formulated to mimic the functional behaviour of the process in question. The classical example is the STANFORD watershed model (Crawford and Linsley, 1966), and derivatives of this modelling genre are still in use all over the world (eg. SIMHYD in many of the CRC models).

IN THIS SECTION:

APPROACHES TO MODELLING

DATA, MODEL COMPLEXITY AND PREDICTIVE PERFORMANCE

CLASSIFICATION OF MODELS

BASICS OF TEMPORAL AND SPATIAL DISCRETISATION/RESOLUTION

PHYSICALLY-BASED OR PROCESS-BASED MODELS - COMPLEX CONCEPTUAL MODELS

As the quest for deeper understanding of hydrological processes has progressed, models based on the fundamental physics and governing equations of water flow over and through soil and vegetation have been developed. For example the water balance model in CLASS (See *Catchword*, September, 2004) solves the Richard's equation (a fundamental equation for flow through porous media) for flow through soil and includes functions to represent the distribution of plant roots, different types of soils etc. These are often called physically-based or process-based models. They are intended to minimise the need for calibration by using relationships in which the parameters are, in principle, measurable physical quantities. In practice these parameters can be difficult to measure (at least everywhere that is needed for modelling and at the right scale) so these models are best thought of as complex conceptual models (Beven, 1989).

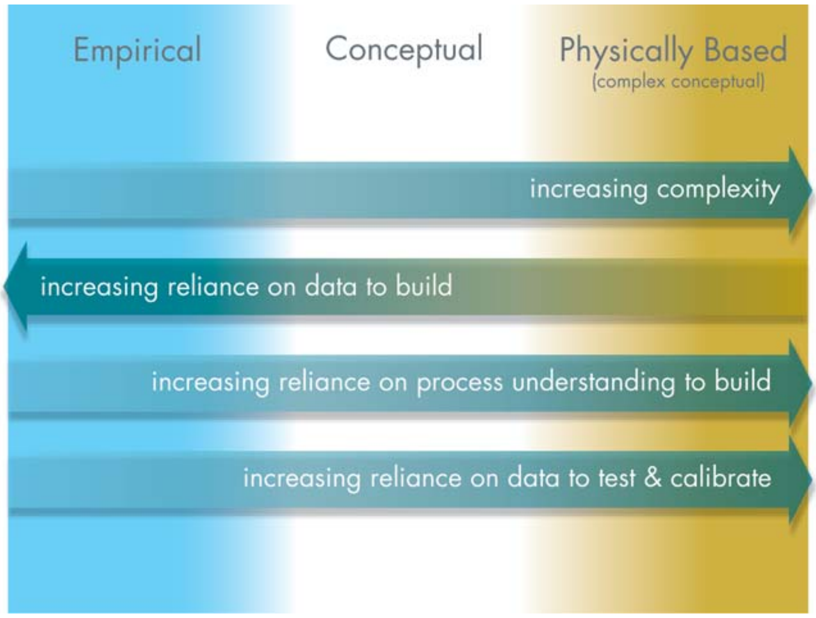

FIGURE 3. SOME FEATURES OF DIFFERENT TYPES OF MODELS. (NOTE THAT THESE CLASSIFICATIONS ARE NOT THREE CLEARLY DISTINCT GROUPS BUT RATHER REPRESENT POINTS ALONG A CONTINUUM.)

STOCHASTIC OR DETERMINISTIC REPRESENTATIONS

Another basic distinction between models is whether stochastic or deterministic representations and inputs are to be used.

Most models are deterministic, meaning that a single set of input values and a single parameter set is used to generate a single set of output.

In stochastic models[2], some or all of the inputs and parameters are represented by statistical distributions, rather than single values. For example, instead of a single value of, say infiltration capacity, a range is defined, perhaps represented by a mean and standard deviation (based for example, on a large number of field experiments). Similarly if we know there is some error associated with an input, rather than use a single value of, say, daily rainfall, we could define a range (or distribution). There is then a range of output sets, each derived from different combinations of the inputs and parameters and/or each of them associated with a certain probability of occurrence.

[2] "Stochastic" is also used in relation to data generation (eg. The Stochastic Climate Library in the Toolkit). This is a different concept where many (thousands) of data sequences are generated in a way that maintains the overall statistics of an observed data series. These data are very useful for design and testing when we want to see how, say, a reservoir may behave under different (but equally likely) periods of data.

Stochastic modelling generally requires the model to be run many many times, each with different combinations of parameters or model inputs that are "possible", resulting in many outputs that can be analysed to define a probability distribution of outputs (Figure 4). Stochastic modelling can be very useful, particularly when we are uncertain about the exact values of model parameters or model inputs, but running a model many times (perhaps tens of thousands of times) can be time consuming.

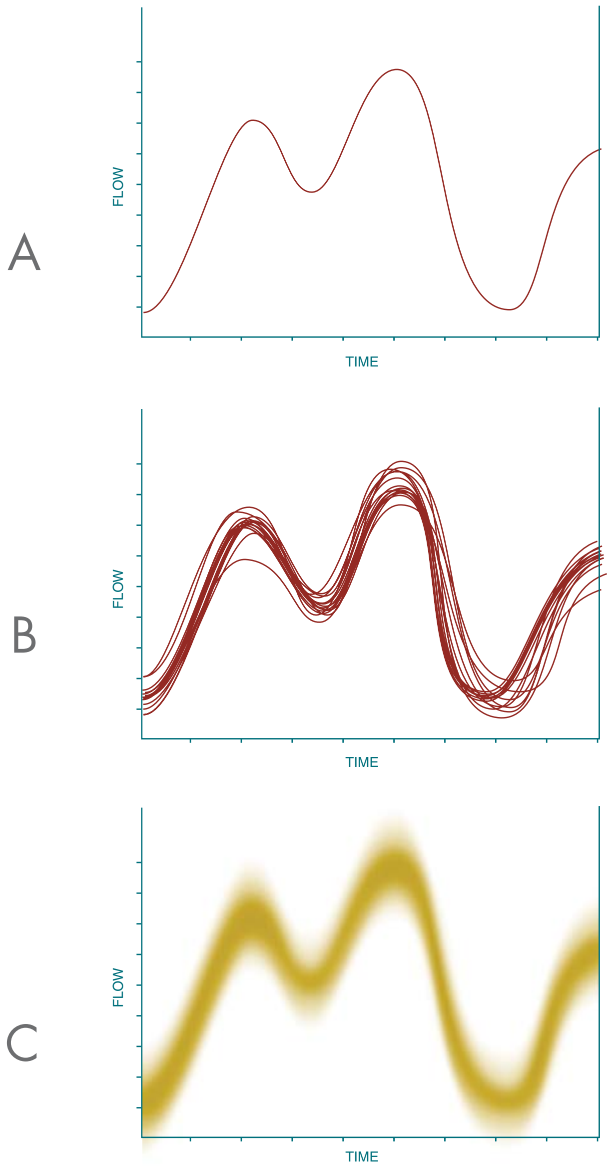

FIGURE 4. MODEL OUTPUT FROM: A) A SINGLE DETERMINISTIC MODEL RUN ; (B) 15 MODEL RUNS (EG. WITH PARAMETER VALUES CHOSEN STOCHASTICALLY FROM A DISTRIBUTION); (C) THOUSANDS OF MODEL RUNS, WHERE THE SHADING OF THE GRAPH INDICATES THE PROBABILITY OF A PARTICULAR FLOW VALUE AT A POINT IN TIME.

IN THIS SECTION:

APPROACHES TO MODELLING

DATA, MODEL COMPLEXITY AND PREDICTIVE PERFORMANCE

CLASSIFICATION OF MODELS

BASICS OF TEMPORAL AND SPATIAL DISCRETISATION/RESOLUTION

REPRESENTING SPATIAL DETAIL

Finally, models differ in how they represent spatial detail.

Spatially lumped models treat the modelled area (eg. a sub-catchment) as a single unit and average the effects of variability over that unit.

Spatially distributed models separate the region to be modelled into discrete units, enabling different model inputs or parameters to be used to represent spatial variability.

These notions of "lumped" or "distributed" do not indicate anything particular about the methods used for representing individual processes, but simply indicate the approach to spatial representation. This is discussed in more detail in the next section.

Basics of temporal and spatial discretisation or resolution

REPRESENTING TIMING VARIATIONS

The distinction between lumped and distributed catchment models can also be made in the time domain. Some models are designed to give output that represents "average" or "long term" values, whereas others are "time stepping" models where output is produced hourly, daily, monthly etc. The simplest models are lumped in both time and space while the more complex models tend to be distributed in both time and space.

SELECTING TIME AND SPACE RESOLUTION IN MODELS

The temporal and spatial discretisation (or resolution) has a major impact on the sorts of questions that can be answered with the models. Table 1 gives some examples of the temporal and spatial discretisation of models in the Catchment Modelling Toolkit.

The temporal and spatial resolutions most appropriate for addressing a given management question must be selected together. For a given amount of data on catchment behaviour, the spatial accuracy available is usually influenced by the temporal resolution and vice

TABLE 1. EXAMPLES OF THE TEMPORAL AND SPATIAL DISCRETISATION OF MODELS IN THE TOOLKIT.

	Spatially Lumped	Spatially Distributed
Temporally Lumped	Chute RipRap* Forest change*	CMSS SedNet BC2C* Aquacycle*
Temporally Distributed	Models in the RRL RAP	EMSS E2* 2C* CLASS* MUSIC

* indicates models that are expected in 2005

versa. This is because increases in both spatial and temporal resolution generally require increases in model complexity (eg. Jothityangkoon et al., 2001), and there is an optimum model complexity for a given data availability (Figure 2).

- SPATIAL RESOLUTION ISSUES

In catchment management applications, models are commonly used to run a series of scenarios representing different management options and assess the impact on various model outputs. For example, we may want to simulate the effect on sediment and nutrient loads of several options for reducing catchment sediment and nutrient supply. But what spatial resolution do we require for specifying where the options will be implemented? If we want to know exactly where the sediment or nutrient comes from in the catchment, we will need a spatially distributed model, but if we are happy to just know the total amount of load, a spatially lumped model (with say land-uses defined by percentage of total area) would suffice.

- TEMPORAL RESOLUTION ISSUES

We also need to ask, what temporal resolution do we require in the predicted loads? For the response of long-term average loads to long-term changes, such as riparian revegetation, we could use a temporally lumped model, as long as it represents the effect on sediment and nutrient loads of this management activity. Such a model would predict a temporal average of load under the alternative scenario. However, if we are interested in temporal variation in the resulting loads, for example, storm or baseflow conditions, or loads at a particular time of year, we may require a temporally distributed model.

- MODELLING TO REFLECT MANAGEMENT CHANGES

A further consideration is that model complexity can also be increased by the need to represent particular catchment processes so that the effect of management changes can be captured. Increasing model complexity to represent catchment processes can limit the amount of spatial and temporal resolution achievable for optimum model predictive performance. For example, a model such as SedNet represents sediment generation from hillslope, gully and streambank erosion separately, but these are averaged over the long-term. Conversely models such as EMSS (Environmental Management Support System) predict daily or monthly sediment generation but from different broad land-uses, so they give a general indication of sediment source localities, but not the detailed source.

TRADE-OFFS BETWEEN MODEL COMPLEXITY AND PREDICTIVE PERFORMANCE

A model that can satisfy all our requirements for spatial and temporal resolution, and representations of particular catchment processes may be overly complex, and so provide poor predictive performance. Then it becomes a process of deciding which of the requirements has highest priority, and compromising one or more of the other requirements to achieve acceptable predictive performance. For example, if the highest priority is to determine the spatial location and specific type of source control, then the model with best spatial resolution and representing the impact of those options should be used. If the highest priority is to determine the temporal pattern in loads then the model with the best temporal resolution should be used.

It is also possible to achieve requirements that are of lesser importance by modifying the inputs or outputs from the model that addresses the requirement of highest priority. For example, the long-term average loads from temporally lumped models can be temporally disaggregated to indicate the temporal variation in load. This requires knowledge on the present temporal pattern, and assumptions about how the management scenario will affect this pattern.

MODELLING FOR TARGET SETTING, OR ASSESSMENT OF PERFORMANCE

When using models for target setting, or assessment of performance against targets, there needs to be a matching of temporal and spatial resolution between the modelling and the time frames for reporting (and time over which some changes due to management intervention might be expected). This matching will also be constrained by the predictive performance of the modelling and the details of the monitoring used to assess targets. The data and modelling used in assessing targets may be so uncertain as to make the targets virtually untestable. There is an urgent need for much more careful analysis of modelling and data needs to assist with achievable target setting. Over time we hope the Toolkit will assist in this endeavour (*Catchword*, May 2004).

OVERALL CONSIDERATIONS WITH SPATIAL AND TEMPORAL RESOLUTION

Two final things to consider when deciding on the appropriate spatial and temporal resolution, are:

(i) that the finer the resolution, the slower the computational time and often the slower the process to collate and prepare the data and

(ii) for a given data availability, it is likely that the finer the resolution, the greater the uncertainty in the output.

Just as with the earlier discussion on model complexity, there is no guarantee that the "finer resolution the better". The most important thing is to match the temporal and spatial detail and model complexity to the problem at hand – fine enough to answer the questions posed and commensurate with available data, expertise and resources, but no more.

A GENERAL RULE IN CHOOSING THE STYLE OF MODEL

As noted earlier, the choice of model style must be made using a "horses for courses" approach. There is no particular style of model that is inherently better for all applications than another. The general maxim is to choose the simplest model that will do the job required.

The following section addresses this issue of choosing a model in more detail. In the papers that follow in the Model Choice Series, these considerations will be discussed in relation to particular models in the Catchment Modelling Toolkit.

Basic considerations

There are four basic considerations in choosing the right model for a particular job:

1. Objectives of the overall exercise
2. Access to data
3. Access to expertise
4. Availability of resources (time and money)

These need to be considered iteratively, since limitations in one of the four areas may restrict choices and so require a re-evaluation of the objectives, the personnel involved, cost of the exercise etc. In choosing a modelling approach, close communication is needed between all those involved in the modelling, and it is often valuable to talk with colleagues who have been involved in similar exercises.

One of the purposes of the Toolkit web site (www.toolkit.net.au) is to provide information to assist with model selection, as well as provide a forum for benefiting from other's expertise.

Objectives of the overall exercise

This first consideration is easy to say, but difficult to do, and is absolutely central to a successful modelling exercise. Key questions include:

- Is the broader context of the modelling clear?
- How are the results of the modelling going to be used?
- What specific output is needed?
- Where will the model be applied?
- What are the proposed actions that need to be represented?
- Who will be interpreting the results and what decisions will they be making?

Answers to these questions provide an outline of the basic capabilities required of the models under consideration.

Defining the "output needs" tells you what the model must be able to compute, including the appropriate time and space scales. For example, "daily runoff from catchments ranging in size from 1-100 km^2"or "average annual sediment load from streambank erosion".

IN THIS SECTION:

IN THIS SECTION:

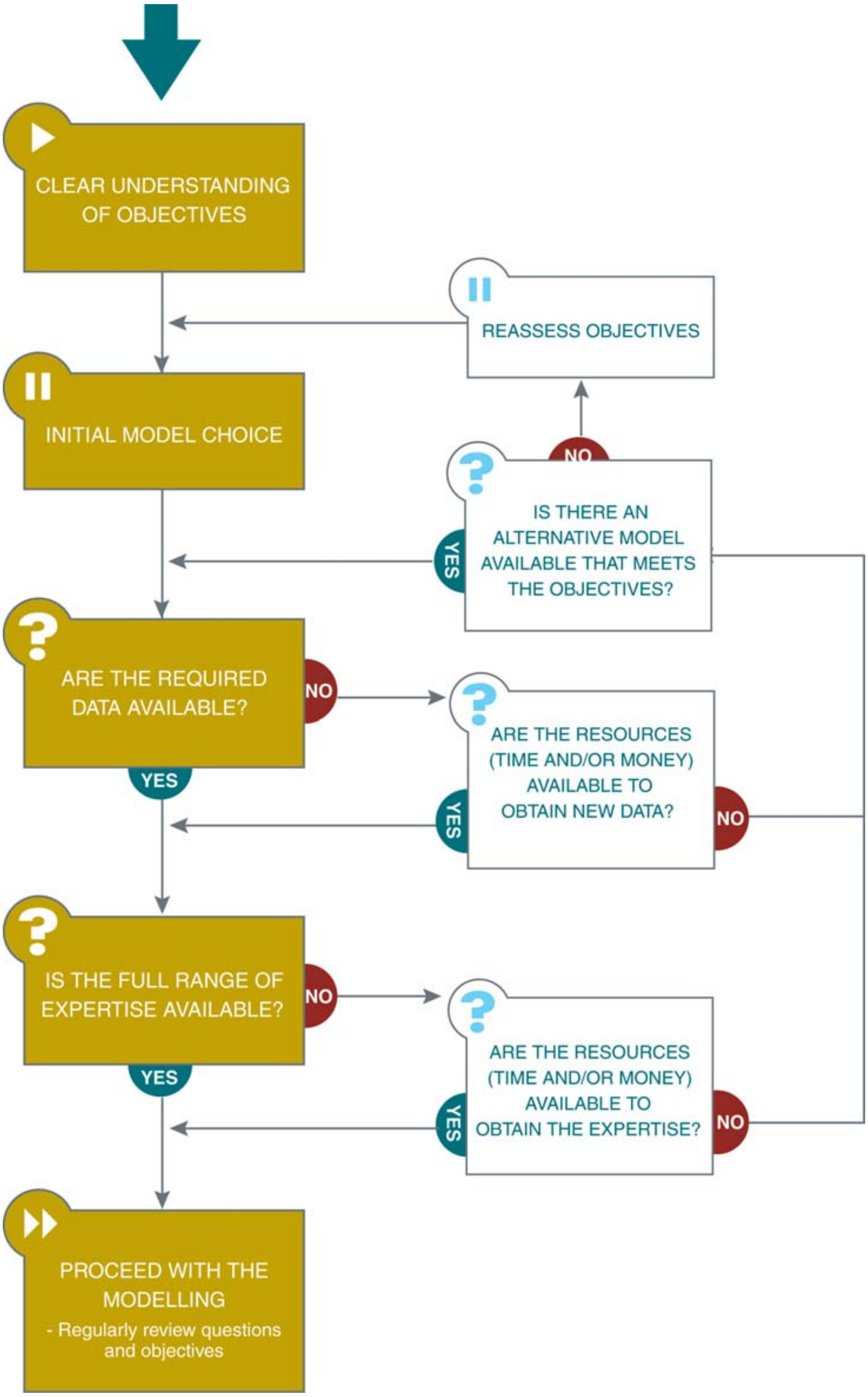

FIGURE 5. FLOWCHART SUMMARISING KEY QUESTIONS IN CHOOSING A MODEL FOR PRACTICAL APPLICATION.

Knowing about the proposed management actions to be simulated indicates what "knobs or levers" are needed in the model. For example, if an action involves land-use change, or riparian vegetation management, or modification of water released from a storage, the model must obviously have parameters that can be modified to reflect these management actions.

The importance of clarifying modelling objectives and context (and revisiting them regularly) cannot be overstated. It is vital that "clients" and "consultants" have shared expectations about exactly how the modelling will assist in a decision making process (or as part of an education activity etc.). This also provides an opportunity to discuss the pros and cons of different approaches and some of the broad principles outlined in Part 1.

People are often polarised in their approach to output from models – either blind-faith or total disbelief. Both approaches are counter-productive and can be overcome via improved understanding of just what models can and cannot do. This step of clarifying objectives, leading to an initial choice of model is also a chance for the client to gain confidence in the knowledge and abilities of the modelling team. Ultimately this will be central to the whether the modelling achieves the overall objectives.

Access to data

A clear articulation of the objectives will lead to an initial model choice and so define the general data needs. Data limitations are the single biggest constraint to model choice and confidence in results. Virtually anything can be simulated, but whether it bears any relationship to reality is dependent on the availability of data for development and testing.

Key questions include:

- Are data at the right spatial and temporal resolution available now?
- Is there a good understanding of the data accuracy?
- Do you have the expertise and time to get/interpret new data?
- How much work is needed to make the data usable in a model? (there is often a lot of work in reformatting, pre-processing etc. that can eat up a large proportion of a modelling exercise)

If data are not available, or cannot be easily collected, the objectives of the modelling may need to be revisited. Failure to do this will likely lead to model results in which there is little confidence.

Access to expertise

Different models require different levels and types of skill to apply and interpret including:

- an understanding of the physical processes and catchment behaviour
- interpretive and technical understanding about models and algorithms

- community consultation skills
- numerical and data manipulation skills
- discipline specific knowledge
- communication skills (particularly if the modelling is part of a wider process)

An honest assessment of the capabilities of the team early on will identify major gaps and may limit the type of model you choose (and therefore possibly the extent to which your original objectives can be met). It is important at this point to consider the non-technical skills that may be needed for the broader activity of which the modelling is a part. It is relatively common for poor communication of model capabilities and limitations to result in a less than optimal outcome.

The overall confidence in a modelling exercise is generally more dependent on the quality of the modelling team than on the model itself.

Availability of resources (time and money)

Modelling and data collection/manipulation are time consuming. Data are of little use without the expertise for interpretation, and expertise (both technical and non-technical) can be expensive.

There will be constraints on total time and money available, again possibly limiting the extent to which the original objectives can be met. There will invariably be a trade-off between resources and the extent to which objectives can be met, and this trade-off needs to be discussed with clients.

The modelling team needs to be able to clearly articulate "this is what you will get for this many resources" and how a change in resources will specifically affect the utility of the modelling.

So what tends to happen in reality?

In practice, these four considerations are rarely addressed explicitly.

More commonly, the objectives are not entirely clear and one uses gut feeling, or chooses whatever models happen to be most easily available (or have been used before) or perhaps even whatever might most impress the client! These approaches result in an implicit commitment to the expertise, data and resources required to apply that particular model. This can lead to a disappointing result and has been the cause of modelling getting a "bad name" in some circles.

The management of expectations in all modelling is difficult, but made even more so if these four issues are not dealt with up-front and rigorously. Figure 5 provides a simple flow-chart linking the four areas.

Concluding comments

This paper provides a background to the fundamental approaches to modelling and practical considerations in choosing a model for a particular task.

It is intended to provide some guiding principles and key questions to ask to help make an informed model choice. In the papers to follow, we will apply the "practical considerations in model choice" to the models in the Catchment Modelling Toolkit and to some models widely used in the industry.

One of the important principles that underlies the Toolkit is flexibility. In the past there has been a problem of choosing a model and being "stuck with it forever". Modelling approaches such as E2 (Argent et al., 2005), and having several models available of different complexity, enables a user to apply a hierarchical approach to modelling – start simple and get more complex as needed.

In the papers that follow, we will group the models around the following basic types of application:

- water quality – sediment and nutrients, salinity;
- water quantity;
- urban models; and
- "systems" or "whole of catchment" models designed to look simultaneously at several types of output.

The use of modelling in natural resource management is increasing rapidly, and with it must come an increase in the general level of understanding of models and modelling by those commissioning modelling exercises, model users and model developers.

We hope this series of papers contributes to improving that level of understanding.

References

Argent, R.M., Grayson, R.B. and Rahman, J.M. (2005). Model selection and the Catchment Modelling Toolkit Proceedings, 29th Hydrology and Water Resources Symposium 21-23 February 2005, Canberra, Engineers Australia.

Bair, E.S. (1994). Model (in)validation – a view from the courtroom, Ground Water 32(4):530-531.

Bathurst, J.C. and O'Connell, P. E. (1992). The future of distributed modelling: The Systéme Hydrologique Europeen. Hydrol. Proc., 6:265-277.

Beck, M.B.(1987). Water quality modelling: a review of the analysis of uncertainty. Water. Resour. Res. 23:1393-1442.

Bergström, S. (1991) Principles and confidence in hydrological modelling. Nordic Hydrol., 22, 123-136.

Beven, K.J. (1987). Towards a new paradigm in hydrology. In Water for the future: Hydrology in perspective. IAHS Publ. No. 164:393-403.

Beven, K. (1989) Changing ideas in hydrology - the case of physically based models, Journal of Hydrology, 105, 157-172.

Beven, K. (1996) A discussion of distributed hydrological modelling. In: Refsgaard, J. C and Abbott, M. B. (Eds.) Distributed Hydrological Modelling, Kluwer, 255-278.

Crawford, N.H. and Linsley, R.S. (1966). Digital simulation in hydrology: The Stanford Watershed model IV. Technical Report No. 39. Dept. Civil Engineering, Stanford University, Palo Alto, California.

Grayson, R.B. and Blöschl, G. (2000). Spatial Patterns in Catchment Hydrology: Observations and Modelling. Cambridge University Press. 404p.

Grayson, R. B., Moore, I. D. and McMahon, T. A. (1992a) Physically based hydrologic modeling, 1. A terrain-based model for investigative purposes. Water Resour. Res., 28, 2639-2658.

Grayson, R. B., Moore, I. D. and McMahon, T. A. (1992b) Physically-based hydrologic modelling, 2. Is the concept realistic? Water Resour. Res., 26, 2659-2666.

Hillel, D. (1986). Modelling in Soil Physics: A Critical Review. In Future Developments in Soil Science Research. A collection of Soil Sci. Soc. Am. Golden Anniversary contributions presented at Annual Meeting, New Orleans. p.35-42.

Jakeman, A. and Hornberger, G. M. (1993) How Much Complexity Is Warranted in a Rainfall-Runoff Model? Water Resour. Res. Vol. 29 , No. 8 , p. 2637-2649.

James, L.D. and Burges, S.J. (1982). Selection, calibration and testing of hydrological models. In hydrological modelling of small watersheds, Ed. C.T. Haan, H.P. Johnson and D.L. Brakenseik. Am. Soc. Agr. Eng. Monogr. Series Vol. 5, pp.435-472.

Jothityangkoon, C.; Sivapalan, M., and Farmer, D. L. (2001) Process controls on water balance variability in a large semi-arid catchment: downward approach to hydrological model development. Journal of Hydrology; 254:174-198.

Kleme, V. (1983) Conceptualisation and scale in hydrology. Journal of Hydrology, 65, 1-23.

Kleme, V. (1986) Dilettantism in hydrology: transition or destiny? Water Resour. Res., 22, 177S-188S.

Konikow, L. F. and Bredehoeft, J. D. (1992) Ground-water models cannot be validated. Adv. in Water Resour., 15, 75-83.

Morton, A. (1993). Mathematical models: Questions of trustworthiness. Brit. J. Phil. Soc. 44:659-674.

Oreskes, N., Shrader-Frechette, K. and Belitz, K. (1994) Verification, validation and confirmation of numerical models in the earth sciences. Science, 264, 641-646.

Philip, J.R. 1975; Some remarks on science in catchment prediction. In: Prediction in Catchment Hydrology: A National Symposium on Hydrology. Ed. T.G. Chapman and F.X. Dunin, Australian Academy of Science, pp.23-30.

Refsgaard, J.C. (1996) Terminology, modelling protocol and classification of hydrological model codes. In: Refsgaard, J. C and Abbott, M. B. (Eds.) Distributed Hydrological Modelling, Kluwer, 17-40.

Singh, V. P. (Ed.) (1995) Computer Models of Watershed Hydrology. Water Resources Publications, Highlands Ranch, Colorado, 1130pp.

Smith, R.E., Goodrich, D.R., Woolhiser, D.A. and Simanton, J.R. (1994). Comment on “Physically based hydrological modelling 2: Is the concept realistic?” by Grayson, Moore and McMahon. Water. Resour. Res., 30:851-854 .