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Prophecy, reality and uncertainty in distributed hydrological modelling

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'To prophesy is very difficult; especially with respect to the future'

Chinese Proverb

'Nowadays model building has become a fashionable and generously supported indoor sport'

L. von Bertalanffy (1966)

Difficulties in defining truly mechanistic model structures and difficulties of model calibration and validation suggest that the application of distributed hydrological models is more an exercise in prophecy than prediction. One response to these problems is outlined in terms of a realistic assessment of uncertainty in hydrological prophecy, together with a framework (GLUE) within which such ideas can be implemented. It is suggested that a post-modernistic hydrology will recognise the uncertainties inherent in hydrological modelling and will focus attention on the value of data in conditioning hydrological prophecies.

Key words: Distributed hydrological models, calibration, validation, uncertainty estimation, value of data, Monte Carlo methods.

1 PROPHECY IN HYDROLOGY

Working hydrologists are frequently required to prophesy the future. In engineering hydrology, for example, it may be necessary to estimate the yield of a reservoir over its design lifetime, the probability of failure during drought, and the magnitude and frequency of extreme events that a spillway must cope with. Increasingly prophecies (or perhaps more correctly divination, defined by the Concise Oxford English Dictionary as the insight into or discovery of the unknown or future by supernatural† means; or skilful forecast; or good guess!) are required of the hydrological effects of land use change, such as deforestation (or reforestation). And then, of course, there is the recently fashionable activity of prophecy on the subject of the impact of climate change on hydrology.

Naturally, now that the modern science of hydrology is 50 years old or more, the traditional qualitative prophecy cannot be considered adequate. Quantitative prophecy is necessary so that the prophet is now embodied in software and the results of the deliberations displayed in impressive colour graphics. This is greatly to the advantage of the hydrological scientist, since he can now maintain a stance of scientific rigour, constructing software based on the best scientific principles and equations but distanced from the actual prophecy which is made by the computer. Assuming bug-free software that is also convergent with the original equations (a rather strong assumption?) the prophecy reflects the principles, and not the scientist directly as in the case of more traditional prophets. The underlying principles can, as in any scientific enterprise, be gradually improved as knowledge and understanding increase. The discussion that follows is primarily concerned with models based on such physical principles, particularly the use of distributed 'physically-based' models to predict hydrological responses at the catchment scale.

One implication that follows from this situation is that prophecy is no longer a dangerous activity. False

† Interpreted here, perhaps, in the sense of unrealistic beliefs.

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prophets are no longer put to the sword, although those outside the mode of current thinking might find it a little more difficult to get published. For a prophecy to be accepted (i.e. publishable) it is only necessary that the underlying principles on which it is based be accepted by the peer group of reviewers. Thus acceptability implies a proximity to consensus opinion (within the pertaining limitations of computer power and software ingenuity) which can be dangerous if the principles are not properly verified with respect to reality. Of course, in the classical scientific method, such principles should be based on testable hypotheses and consequently verifiable; this is what makes the modern method of prophecy justifiable. In practice, however, this is not so easy for open dynamic systems which depend on the specification of appropriate initial and boundary conditions (normally poorly known). Thus, although the consensus obtained by refereeing should, in principle, mitigate against the use of unrealistic descriptions, there is considerable scope for self-delusion (see discussions in Refs 2–4). A number of authors, starting with Stephenson and Freeze,[35] have pointed out the ultimate impossibility of validating the type of prophetic model we use in hydrology (see also the recent discussion of Konikow and Bredehoft).[23]

It should, however, be possible to *invalidate* the principles underlying such models. In fact, this is not at all difficult and *all* the current generation of 'physically-based' models used in catchment hydrology can be invalidated (see below). Hydrological prophecy is only considered successful at all because of a process of circular argument called parameter calibration. It follows that, as scientists, we should be much more cautious about hydrological prophecy than is currently apparent in the literature. Perhaps if prophecy was still potentially physically dangerous to the false prophet, the hydrologist would be inclined to be more circumspect.

2 REALITY AND MODEL INVALIDATION

Most of the current generation of distributed models of hillslope hydrology are based on nonlinear partial differential equations for Darcian flow in variably saturated soils, and sheet flow assumptions for surface runoff. These equations require the specification of hydraulic conductivity, porosity, soil moisture characteristic, and overland flow roughness parameters. In general, an approximate numerical solution of the equations must be used, with the flow domain divided into a number of elements or nodal domains. Different parameter values may be used in each element. The equations have been shown to reproduce small-scale laboratory and some plot-scale experiments with well-defined boundary conditions, if appropriate parameter values are used (although even at this experimental scale simulations may not be entirely successful, see for example, the study of Nieber and Walter)[32]. The derivation of appropriate parameter values remains a problem, even at small scales, since techniques for the independent definition of parameter values are lacking. Specification of parameter values generally involves back-calculation or calibration after prior experiment (often on the same experimental system), under the assumption that the equations are correct. Such an approach is clearly not well structured for testing the validity of models!

However, even with such constraints, when moving to the hillslope and catchment scale with three-dimensional heterogeneity in soil characteristics, and variable vegetation characteristics, the problems in applying such equations become obvious. They are continuum equations and consequently require relatively smooth variations in variables such as capillary potential and overland flow depths, so that characteristic values of those variables can be defined at each 'point' in space. Further, the equations also involve gradient quantities, so that there is a requirement that gradients should also be definable. Such requirements may be satisfied in small-scale soil cores (especially if repacked in the laboratory) but not at the element scale of the solution of a distributed model, because of the heterogeneity of a structured and macroporous soil system and of surface flow over a rough or vegetated surface, where the nature of the surface also affects the pattern of input intensities (see the conceptual distribution function model discussed in Ref. 4). In a previous critique of distributed models, the author has suggested that the use of averaged variables and gradients at the element scale implies that such models should be classified as lumped conceptual models.[3]

The same problem arises with the model parameters, which may potentially reflect the heterogeneity of the system in that different values may be specified at each element of the solution grid, but which must average over the intra-element variability. There are no measurement techniques available to estimate directly the element scale values of, say, hydraulic conductivity. Measurement scales are generally much smaller. Binley *et al.*[8] have shown that the use of 'effective' values at the element scale might provide acceptable accuracy for purely subsurface flow processes (although it may be difficult to derive such values from a knowledge of the variability at the measurement scale), but that effective values will not be acceptable for the case of interacting surface and subsurface flow processes (see also the study of Loague[27] who derives effective parameters only from measured infiltration rates by the (linear) process of kriging in the application of a distributed model). There are also no measurement techniques for the estimation of hydrological *variables* at the element scale, which poses a further, as yet unresolved, question in the application of such models: what data should be collected to aid in the calibration of spatially variable element-scale parameter values.

These arguments for the invalidation of current physically-based distributed models suggests that belief in the predictions of such models is an act of faith, resting insecurely on scientific principles. Because of differences in measurement and element scales of parameter values and variables, it is unlikely that the modelling process can be redeemed satisfactorily by calibration. Thus such predictions should be treated as prophecy.

3 EQUIFINALITY IN HYDROLOGICAL PROPHECY

It does not follow, of course, that invalid physical descriptions of real world processes are not useful to the hydrologist. All models and theories are only approximations to reality and where, as in hydrology, they contain 'free' parameters that must be calibrated to a particular situation in which a model is applied, then it is usually not difficult to obtain predictions that mimic the behaviour of observed variables to a reasonable degree, at least over some range of behaviour. We also know that predictive errors do not only reflect model structural errors, but also the errors associated with the specification of input data and boundary conditions and errors of measurement of the 'observed' variables, which are usually observed only indirectly and locally.

Considerable effort has been expended in the past in the study of model calibration techniques (see, for example, the recent study of Hendrickson *et al.*[18] and references therein). Nearly all such studies have been predicated on the assumption that there is a set of parameter values within a particular model structure that is in some sense the 'optimum' set of values for a particular application, and research has been concerned with improving the techniques that will enable that optimum parameter set to be found efficiently, a search that is continuing today (for example, Ref. 10). It is generally recognised that, as with the simplest regression model in linear statistics, the optimum parameter set can only be known with some degree of uncertainty, but the effect of this uncertainty is rarely carried through into rainfall–runoff model predictions, with a few noted exceptions.[9,13,14,17,25,29,30] One reason for the common lack of any explicit consideration of predictive uncertainty following model calibration has been a lack of a firm theoretical basis for making such calculations for the highly nonlinear models used. A second limitation has been entirely practical; the constraints of available computing power. Even today, the number of runs that can be made with a physically based catchment model for a given project might be limited to tens of hundreds; barely enough for initial parameter calibration, let alone for a proper evaluation of predictive uncertainty. Fortunately, such constraints can be expected to gradually ease and the author suggests that it is time for a total reappraisal of approaches towards model calibration and prediction, in which the nature of the activity as prophecy is recognised more explicitly and honestly.

Recent increases in computer power have meant that it is now much simpler to carry out exhaustive evaluation of the parameter response surfaces, at least for simpler conceptual models. Figure 1, taken from Ref. 10, shows plots of parameter value against objective function value for a six-parameter lumped conceptual model applied to synthetic data after an exhaustive gridding of the response surface. The 'best' simulations (lowest objective function values) are clearly distributed throughout the parameter space. That this is not unusual in hydrological modelling is suggested by similar results that have been obtained at Lancaster using Monte Carlo search techniques implemented on a parallel processing computer using the semi-distributed TOPMODEL,[6,20] applied to observed catchment data, (see Fig. 2). Duan et al.[10] suggest that these results are 'disturbing' and use them to demonstrate the difficulties of finding the global optimum of the response surface. A more natural response would appear to be to question the whole concept of the optimum parameter set, given the nonlinearities and parameter interactions inherent in many hydrological models. There is no reason to expect that the physical basis of distributed models will mitigate such effects; indeed, given the numbers of parameters involved, the problem is likely to be much worse (see, for example, the example of lumped and distributed models in Ref. 21).

The concept of the optimum parameter set is flawed in a number of ways, the most important being that it discourages the consideration of uncertainty in parameter values and predictions. It is easy to show that if the same model is 'optimised' on two different periods of record, two different optimum parameter sets will be produced. Extension to multiple calibration periods, if the data were available, would yield multiple optimum parameter sets. The resulting parameter distributions would reflect the uncertainty in the parameter estimates and the interaction between the individual parameters. There may also, however, be multiple optima for a single calibration period, particularly for the physically-based hydrological models that are designed to reflect the operation of a number of different types of response processes and allow for the specification of a large number of parameter values. This would yield a type of uncertainty that should also be reflected in the predictions.

Thus, one starting point for the proposed reappraisal would be to replace the concept of the 'optimum' set of parameter values. One alternative concept is that of equifinality in the application of different model

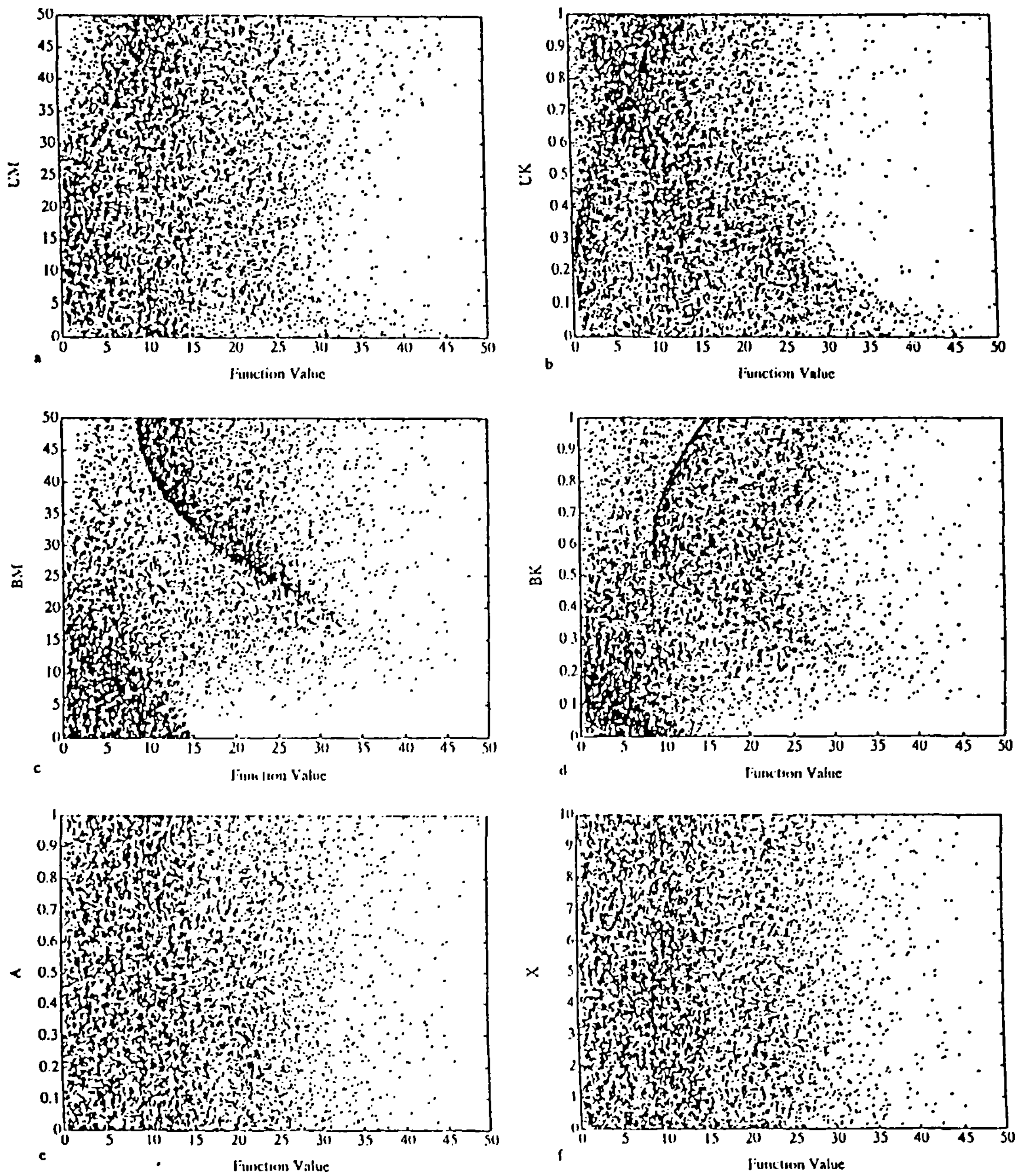
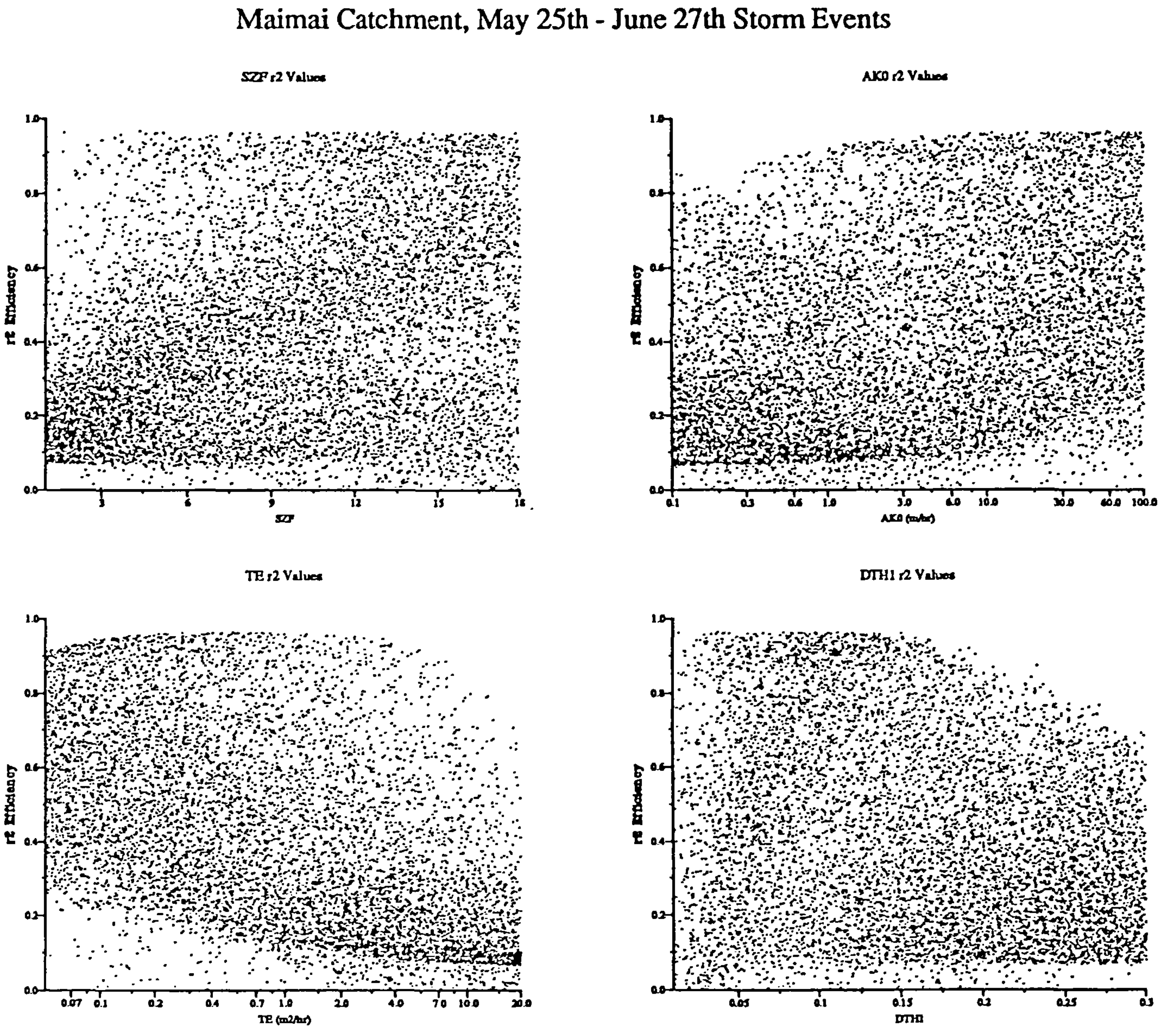


Fig. 1. Plots of parameter value against a sum of squares objective function for the SIXPAR lumped conceptual rainfall–runoff model of Duan *et al.*[10] applied to a 200-day synthetic sequence of daily rainfall and runoff values generated using the same model. The 'best' model simulations have the lowest function values.

structures and parameter sets. Equifinality, is used here in the sense of an expectation that the same end, in this case an acceptable model prediction, might be achieved in many different ways, i.e. different model structures or parameter sets. This is not to say that every simulation is equally acceptable as a simulator of the system. Each simulation can be evaluated as part of the calibration process and ranked in terms of performance or likelihood of being an acceptable simulator, if some criterion of evaluation (either qualitative or quantitative) can be specified. In prophecy, however, it may often be difficult to specify such criteria, and it follows that many prophecies may be equally acceptable. In addition, this equifinality concept would allow that such likelihood rankings would need to be revised as more data are taken into account in the calibration. When used to prophecy, each of these model structure/parameter set combinations will, of course, make different predictions. The range of predictive behaviours can then be used to assess the uncertainty in the predictions, taking account of the performance ranking if desired.



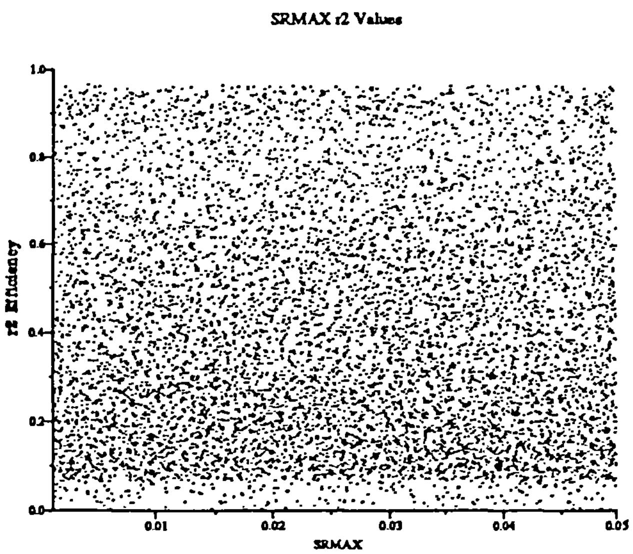


Fig. 2. Maimai catchment, 25 May–27 June, storm events. Plots of parameter value against the model efficiency objective function of Nash and Sutcliffe[31] for runs of TOPMODEL, in an application to the Maimai catchment ($3{\cdot}54\,km^2$) in New Zealand. The 'best' model simulations have the highest efficiency values.

4 DELPHIC MONKEYS AND HYDROLOGICAL PROPHECY

Physically-based models, by their nature, are designed to have parameters that are physically measurable. While measurement may not always be possible, the sheer number of parameters involved in any distributed model at the catchment scale will generally mean that some form of estimation of parameter values will be required based on a consideration of the physical characteristics of the catchment under study, even if followed by some form of calibration to refine those initial estimates. There are hydrologists who believe that, because of the physical basis of such models, sufficiently accurate estimates of parameters such as overland flow roughness, or hydraulic conductivity can be made on the basis of land use type or soil textural parameters. The concept of equifinality is not inconsistent with such a view, but implies that there may be many such sets of parameter estimates (or model structures) that might be accepted as being sufficiently accurate.

In the case of no observations being available for parameter estimation or calibration (a situation common in prophecy), the hydrologist is forced back upon *a priori* parameter estimation. Depending on the resources available, the resulting prophecy may be based only on a single 'best estimate' parameter set, perhaps with some analysis of the sensitivity to variations around those best estimate values. The equifinality concept, however, would suggest that we should take a much wider view of the scope for acceptable parameter sets in making such predictions, since the 'best estimate' set will depend upon the hydrologist making the estimate and the techniques used. What is required perhaps is a process akin to the 'Delphi technique' (see, for example, Ref. 26) in which a number of experts are asked to give opinions or predictions on the future. The range of these predictions may then be used in a variety of ways.

The situation relevant to hydrological prophecy may be illustrated by the tale of the Delphic monkeys, first told in a discussion session at the NATO Advanced Study Institute on Recent Advances in the Modelling of Hydrological Systems organised by David Bowles and Enda O'Connell in Sintra, Portugal. The situation to be considered is that of estimating the hydrological response before and after the development of a construction project which covers the major part of a small forested basin. No existing hydrological data are available, although maps exist of the present topography, land use and soil classification. The model structure to be used has already been chosen by the agency responsible for assessing the environmental impact of the proposal. It is a model based on infiltration excess overland flow runoff generation and kinematic routing on hillslope elements and within the channel network. It is not dissimilar to a number of models used by agencies and consultants today. The question of whether it is an appropriate model for the type of hydrological responses on that particular basin remains open (see, for example, the results of Loague and Freeze[28]), although let us accept that a field visit suggests that there is at least local evidence of overland flow during rainstorms within the basin in the past.

Application of the model to simulate the existing hydrology requires specification of a discretisation of the hillslopes, specification of vegetation, soil infiltration, overland flow roughness and channel dimension and roughness parameters, for each element of the discretisaton, as well as appropriate initial and boundary conditions. Application to prophesy the changed response after development requires the specification of a new set of parameters. The developer employs a consultant to estimate the parameters in both cases, define a design storm, or sequence of storms on the basis of nearby rain-gauge data and make 'best estimate' predictions. The accuracy in the predictions will depend very much on the past experience of the consultant and the way in which (s)he might have been able to evaluate past performance of the model and parameter estimation techniques.

In fact, such a project would provide a very useful training exercise, and since the basic understanding required is not great it could be carried out by a group of hydrologically and computer literate monkeys (borrowed, perhaps, from the best University graduate schools). Each monkey is given the same brief and computer running the modelling software, and taken on a field visit around the basin. Each makes his or her own basin discretisation and estimates of parameter values (or, if (s)he has been taught properly, ranges of parameter values), simulates the current and post-development responses, and prepares a report. The result to be expected is a whole range of predictions, some of which will be more extreme than others.

As a training exercise, of course, the results should be assessed, both for errors in the mechanics of the exercise (since even monkeys make the occasional typing error, *vide* the plays of Shakespeare) but also for the acceptability of the predictions. For the purpose of this particular exercise, it would seem sensible to ask a group of assessors to look at all the reports (together with that of the original consultant), including both practising hydrologists in agencies and consultancies and the University professors who taught the monkeys. It seems possible that the grades given to the different simulations might vary widely, since University professors in particular are not noted for their ability to agree. Indeed, some might well reject *all* the simulations with this model structure on the basis that, in such a catchment prior to development, infiltration excess overland flow is most unlikely to occur and that any evidence of overland flow is more likely to result from a saturation excess mechanism.

Combining the grades given to the individual simulations provides an overall weight or degree of acceptability that can be used in an assessment of the uncertainty associated with the predictions. There are, of course, many different ways in which this may be done. An *a priori* weighting on the basis of the experience of the original consultant relative to the inexperienced monkeys might also be taken into account. The important point to note is that, prior to the data obtained from such an evaluation, all the simulations were equally acceptable and it is unlikely that the evaluation would produce a clear 'optimum' set of simulations.

5 UNCERTAIN PROPHECY: A GENERALISED LIKELIHOOD APPROACH

One possible formal implementation of the concepts discussed above is the Generalised Likelihood Uncertainty Estimation (GLUE) technique of Beven and Binley.[5] The GLUE procedure explicitly recognises the equivalence or near-equivalence of different parameter sets or model structures in the representation of hydrological responses. Rather than monkeys, a Monte Carlo procedure is used to generate multiple simulations using parameter values for each model structure drawn from specified distributions. The parameter set may include some definition of initial and boundary conditions for the model. Where observations are available to evaluate the performance of the model, each set of parameter values is assigned a likelihood of being an acceptable simulator of the system under study. The term 'likelihood' is used here in the sense of a fuzzy measure of acceptability rather than in the more restrictive sense of maximum likelihood theory. The equivalence with maximum likelihood theory can be established but appears to require the identification of the likelihood maximum and associated error structure beforehand. It is worth noting that the parameter values are not considered independently in this procedure but only as members of the set. Sets of initial and boundary conditions may also be evaluated in this way. All the simulations with a likelihood measure significantly greater than zero are retained for consideration. Rescaling the likelihood measures of the retained 'behavioural' set to have a sum of 1·0 yields a relative probability of acceptability scale for the parameter sets. Predictions or prophecies from these simulations are made and the scaled likelihood weights used in estimating the uncertainty associated with the predictions. Searching for an optimum parameter set is clearly a special case of this procedure in which the optimum set as measured by some objective function is given a likelihood value of 1·0 and all others are given a likelihood of zero. The distribution of likelihoods may be updated as more data become available.

Further background and a detailed description of the GLUE technique are given in Refs 4,5 and 7, and only the briefest outline will be given here. One important characteristic of the procedure is that it incorporates a formal methodology for some of the subjective elements of model calibration. The following elements must be defined.

5.1 The likelihood measure or set of likelihood measures

As with the objective functions of optimisation methods, the choice of a likelihood measure is inherently subjective. Continuous measures, set measures and binary (acceptable behaviour/non-behaviour) measures may all be used. If no observations are available for comparison with model predictions then some judgmental measure based on the experience of the modeller can be defined. Where multiple measures are used, some means of combining them into a single index must be specified. Some possibilities are discussed in Ref. 5.

5.2 The ranges or distributions of parameter values to be considered

No hydrological parameter can be specified precisely, but it may be similarly difficult to specify the range or distribution of parameter values that is appropriate to a given situation. Where observations are available with which to compare model predictions this may not be crucial to the procedure, in that an initial wide range may be used in the Monte Carlo sampling procedure, the range being later refined on the basis of the resultant likelihood measures. Initial range or distribution definition is more important in the case where no data are available since this *a priori* distribution will carry forward directly into the uncertainty calculations.

5.3 A procedure for using the rescaled likelihood weights in uncertainty estimation

The likelihood measure associated with a particular parameter set represents a degree of acceptability associated with that simulation. That degree of acceptability may be carried over into the predictions of the model made using that set of parameter values. If the rescaled distribution function of likelihood weights is treated as a probabilistic weighting function for the predicted variables, uncertainty estimates of the predicted variables may be derived directly. It is worth remembering that these uncertainty estimates are conditioned on the definition of the likelihood function, the model structure or structures, the initial and boundary conditions used (if not part of the parameter set) and the particular random sample of simulations made. There need be no inherent distributional assumptions involved in the uncertainty calculations; indeed Beven and Binley[5] have shown that the distribution of predictions may vary greatly between time steps and, in particular between peak flows and recession periods. Distributions of predicted flow peaks tend to be highly skewed; those during recession, more Gaussian. They also show how the likelihood weights can be used in parameter sensitivity analysis in an extension of the procedures developed by Hornberger and Spear.[19]

5.4 A procedure for updating the likelihood weights as more data (or likelihood measures) become available

Beven and Binley[5] have shown how updating of the likelihood weights can be carried out by a simple application of Bayes equation. The definition of an initial range or distribution of parameter values can consequently be thought of as the definition of an initial prior distribution for a particular parameter set. New data can then be used to define a new likelihood measure from which a posterior distribution of the likelihood weights can be calculated from

$$L_p\langle\Theta|y\rangle = L_y\langle\Theta|y\rangle L_o\langle\Theta\rangle$$

where L_o is the prior likelihood weight distribution of the parameter sets Θ, L_y is the calculated likelihood distribution given the new data set y, and L_p is the posterior likelihood weight distribution. It should be noted that because each parameter set is associated with its own likelihood measures, independent of all other parameter set samples, this equation may be applied on a sample by sample basis.

6 AN APPLICATION OF THE GLUE METHODOLOGY

Figure 2 is based on Monte Carlo simulations for a version of TOPMODEL applied to the Maimai catchment in New Zealand over a number of storm events. It is clear from this figure that, although some of the parameters show some sensitivity to the objective function (in this case based on the Nash and Sutcliffe[31] model efficiency measure) in part of the range considered, all the parameters have wide ranges in which different parameter values give equivalent degrees of fit to the observations. Using the efficiency as the likelihood measure with a threshold of acceptability for the simulations of an efficiency of 0·7, the resulting likelihood weighted uncertainty estimates are shown in Fig. 3. More detail can be seen for the major event of

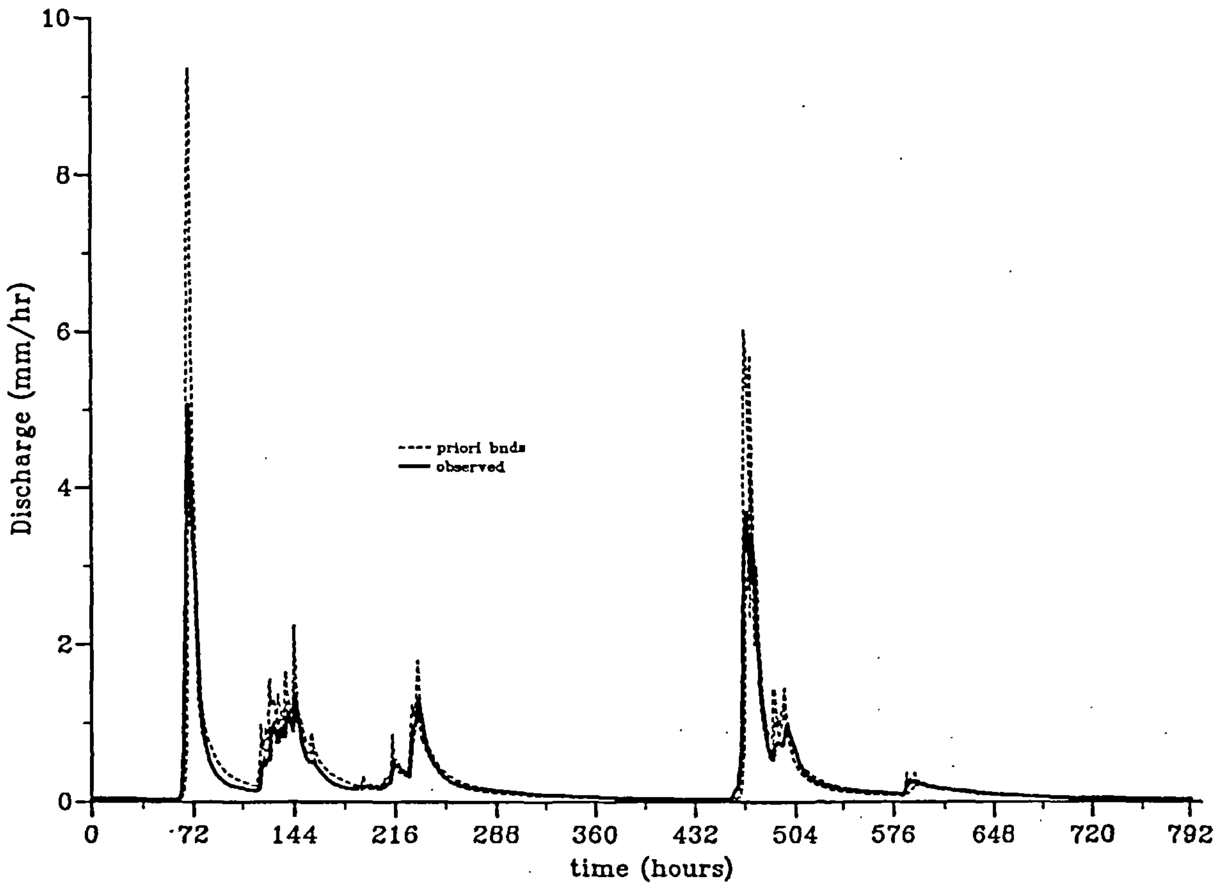


Fig. 3. Maimai catchment, 25 May–27 June, storm events. Confidence limits (5 and 95%) for the predictions of the TOPMODEL calculated using the GLUE procedure in an application to the Maimai catchment in New Zealand. Observed discharges and simulated prior confidence limits for period 25 May–27 June 1990 are shown with solid and dashed lines respectively.

this record in Fig. 4. It is seen that, with the exception of the periods around the major peaks, the uncertainty bands are relatively narrow and bracket the observed discharges, but that in the periods around the major peaks, the uncertainty in the discharge predictions remains high (see particularly Fig. 4, with 90% confidence limits for the predicted peak flows of between 4 and 10 mm/h). These results are not untypical of the application of the GLUE methodology to rainfall–runoff modelling (see also Ref. 5). This particular period of record was simulated using prior parameter distributions conditioned on the results of simulating a number of previous storm periods. Figure 4 also shows the result of using the Bayesian updating procedure described above to refine the estimates of the uncertainty limits. In this case, given the conditioning on previous data sets, there is very little difference in the prior and posterior confidence limits.

With hydrological systems, of course, it should not necessarily be expected that the addition of additional data will decrease the uncertainty in the predictions. Beven and Binley[5] give examples where the posterior limits, after taking account of the data from the largest storm in the record, are wider than the prior estimates. They also show how uncertainty in the input values can lead to cases where the observed discharges might move outside the predicted uncertainty limits. It is very difficult to predict a storm hydrograph if not enough rainfall appears in the rain-gauge records (see Ref. 20 for an even more extreme example).

One area of interest in the application of the GLUE technique is the possibility of easily defining likelihood functions that take account of internal state data, such as water-table levels, contributing area and soil moisture patterns, where of course the model structure is capable of predicting such data directly. In a hypothetical example, Binley and Beven[7] showed that water table information at a few points in a catchment was not of great value in refining uncertainty estimates, and that 90% confidence limits for the simulated water tables were generally at the surface and the base of the simulated soil! They were making use of a hypothetical data set based on a three-dimensional Richards equation simulation of a small basin being simulated by three two-dimensional planes to represent the catchment based on the same equation and solver. It appears that even in this case model structural errors were an important source of uncertainty in the predictions. It

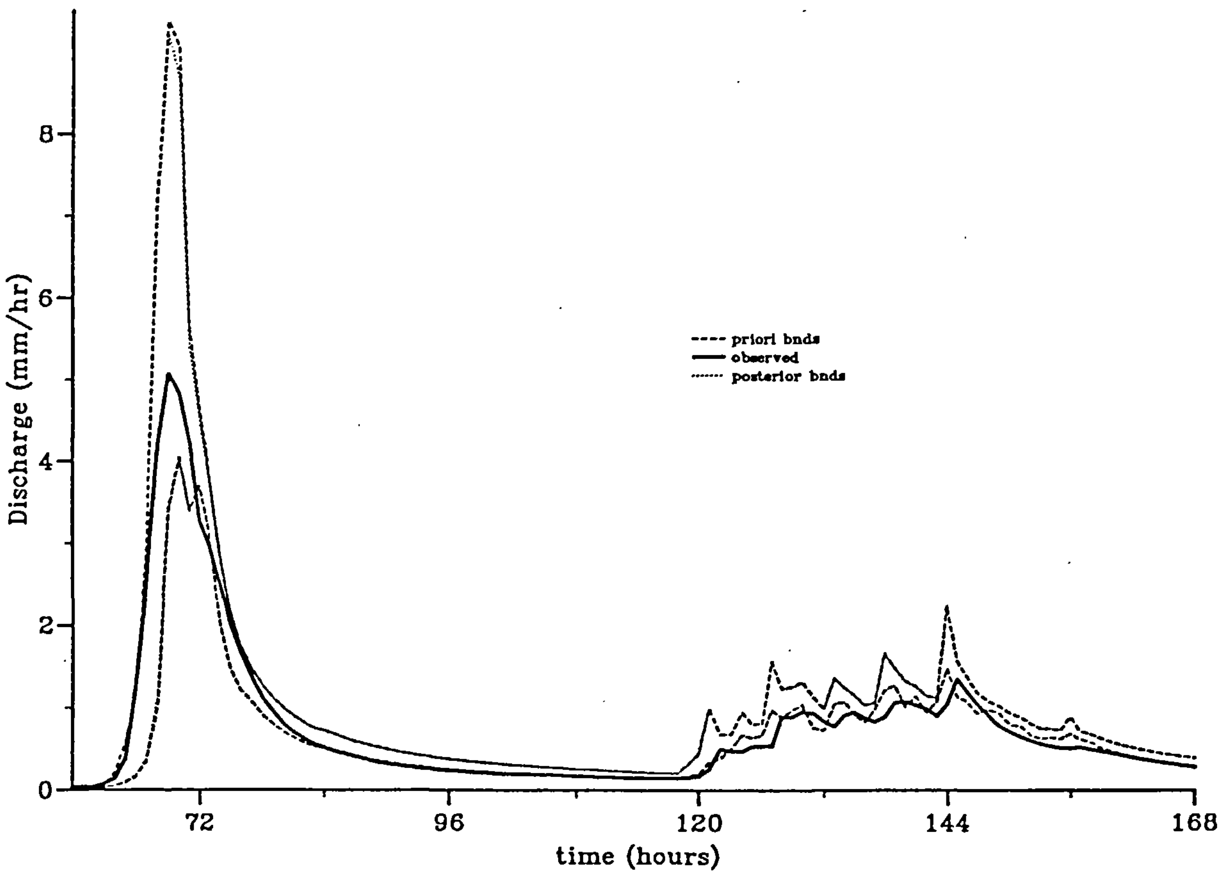


Fig. 4. Maimai catchment, 25 May–27 June, storm events in detail. 28 May 1990. Observed discharges are shown with a solid line, prior confidence limits with a dashed line and posterior confidence limits after the updating of the likelihood values using data from this storm period with a dotted line.

remains to be seen if similar conclusions will be drawn in applications to real data. This is currently being explored for the Maimai and other catchments with internal state data and will be reported in due course.

7 UNCERTAINTY, MODEL VALIDATION, AND THE VALUE OF DATA: TOWARDS A POST-MODERNIST HYDROLOGY

The argument that all hydrological models may be easily invalidated in catchment-scale applications would appear to make the notion of model validation redundant. Yet it would still be useful to be able to compare the relative merits of different model structures. Uncertainty estimation provides a methodology for such a direct comparison through calculation of a measure of the uncertainty associated with the predictions of each model structure. A number of such measures are available, including the Shannon entropy measure (see, for example, Ref. 22). Such uncertainty measures can be useful in two contexts. In the context of model validation, they may be used to rank different model structures, provided that identical likelihood measures are used in the evaluation of each model. Uncertainty in observed data and initial and boundary conditions can also be incorporated into this procedure, as may well be necessary in hydrological models as demonstrated by Stephenson and Freeze,[35] and Hornberger *et al.*[20]

A second context that has not received sufficient attention in the hydrological literature is in assessing the value of data (but see Refs 12, 15, 16, 24, 34 and 36). One criterion for the value of additional data in hydrological simulation is its effect in reducing predictive uncertainty. In the context of discharge simulation, the availability of a single discharge hydrograph might have a dramatic effect in reducing the uncertainty calculated using only the *a priori* parameter estimates. Certainly, in the example of the Delphic monkeys, such data would cause many of the monkeys to revise their parameter estimates, or the assessors to revise their previously subjective gradings. But would a discharge hydrograph be more valuable in reducing the uncertainty associated with a physically-based model than say the 157 infiltration measurements available to Loague[27] in the application of such a model to a small rangeland catchment?

Geochemical data may also yield additional insights into hydrological responses, as has been shown, for example, by the analysis of environmental isotopes. However, to model such data will require the introduction of additional parameters, so that there is an inevitable compromise between the value of additional data and the identifiability of the parameters required to take account of that data. Interactions between parameters is generally such that adding additional model components may well have repercussions for the values of parameters in existing model components. The relationship between parameter identifiability and predictive uncertainty in the context of hydrogeochemical models has been discussed by Beck *et al.*[1]

One of the aims of this work is to focus attention on the interaction between data, model structure, parameter sets and predictive uncertainty. In the application of distributed hydrological models there are never enough data. Thus, invariably, there will be an element of prophecy about predictions made with the model. The author would argue that the process of prophecy needs be examined more carefully in hydrology and that the hydrologist needs to be realistic about the uncertainties associated with his prophecies. It may be that those uncertainties are far greater than we like to think, if evaluated properly. This is not necessarily a bad thing. As well as being intellectually honest, it will highlight the value of appropriate data collection in the calibration process, uncertainty reduction, and improving the understanding incorporated into model structures, including the necessary subjective elements involved. Certainly, a proposal to evaluate data in terms of reducing model uncertainty should surely provide a compelling case for research funding for field work!

Hydrological prophecy can be considered to be a trans-scientific activity (see Ref. 33) but the implications of this have yet to permeate hydrological research and practice. The outline of a post-modernist hydrology that recognises the fundamental limitations and subjectivity of its science has already been presented in the context of groundwater contamination by Freeze *et al.*[11] This pioneering work has much in common with the aims of the GLUE methodology developed in the context of rainfall–runoff modelling, and indeed goes much further in incorporating hydrological uncertainty into a full economic decision analysis framework. The GLUE procedure provides one easily understood and implemented strategy for addressing some of the problems inherent in rainfall–runoff modelling. There are undoubtedly more refined ways of achieving the same ends. The important thing is that the problems outlined in this paper be properly recognised and researched in the future so that, in time, hydrological prophecy can be given a firmer scientific basis while also explicitly recognising the sociological context in which it takes place.

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Research Institute, Christchurch. However, not all of those friends and colleages will agree with the rather extreme views presented, and the author would welcome any comments and weightings awarded for acceptability (and/or degree of pretentiousness?) from the reader. This work has been supported in part by NERC grant GST/02/491 and the ENCORE project of the CEC.

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