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Imposing constraints on parameter values of a conceptual hydrological model using baseflow response

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Abstract

Calibration of conceptual hydrological models is frequently limited by a lack of data about the area that is being studied. The result is that a broad range of parameter values can be identified that will give an equally good calibration to the available observations, usually of stream flow. The use of total stream flow can bias analyses towards interpretation of rapid runoff, whereas water quality issues are more frequently associated with low flow conditions. This paper demonstrates how model distinctions between surface and sub-surface runoff can be used to define a likelihood measure based on the sub-surface (or baseflow) response. This helps to provide more information about the model behaviour, constrain the acceptable parameter sets and reduce uncertainty in streamflow prediction. A conceptual model, DIY, is applied to two contrasting catchments in Scotland, the Ythan and the Carron Valley. Parameter ranges and envelopes of prediction are identified using criteria based on total flow efficiency, baseflow efficiency and combined efficiencies. The individual parameter ranges derived using the combined efficiency measures still cover relatively wide bands, but are better constrained for the Carron than the Ythan. This reflects the fact that hydrological behaviour in the Carron is dominated by a much flashier surface response than in the Ythan. Hence, the total flow efficiency is more strongly controlled by surface runoff in the Carron and there is a greater contrast with the baseflow efficiency. Comparisons of the predictions using different efficiency measures for the Ythan also suggest that there is a danger of confusing parameter uncertainties with data and model error, if inadequate likelihood measures are defined.

Introduction

One of the main limitations to the successful application of hydrological models is the uncertainty inherent in parameter values that have been calibrated using restricted information about the system that is being modelled. The issues that most models are required to address are increasingly related to aspects of environmental change. This means that fundamental processes within the models, such as flow partitioning between the surface and sub-surface, may change. It is, therefore, important that there is a clear understanding of the relationship between the model parameters and the physical behaviour of the system. Two main approaches have been adopted to tackle this issue; the first aims to minimise the need for parameter calibration by introducing greater process understanding to models, whilst the second attempts to identify the levels of uncertainty in the parameters and to analyse the implications of the uncertainty.

The first approach has involved the development of extremely complex physically-based distributed models for which parameters can theoretically be measured in the field (Abbott *et al.*, 1986). However, application of this approach requires intensive spatial data for a large number of parameters, which still have uncertainty associated with them. Unless applied using a fine spatial discretisation, effective values for the parameters may need to be derived to account for small scale processes not included within the model, such as those effected by artificial drainage (Dunn and Mackay, 1996). Application of such models to large catchments is likely to be excessive in terms of both data and computational requirements and prohibitive of any detailed uncertainty analysis (Dunn, 1998).

The approach adopted more frequently now is to use simpler models, allowing the uncertainties associated with parameter values to be identified, and to derive an envelope of model predictions that takes into account the uncertainties in the parameter values. This concept has been formalised by the Generalized Likelihood Uncertainty Estimation (GLUE) procedure (Beven and Binley, 1992). Application of the GLUE procedure to TOPMODEL indicated that a broad range of values could be applied to many of the individual parameters to achieve the same goodness of fit to records of stream flow (Freer *et al.*, 1996).

Gupta *et al.* (1998) suggested that one of the problems in identifying model parameters lies in the limitation of using a single objective function for calibration. When model parameters are calibrated visually to stream flow records, an attempt is generally made to fit the predictions to the shape of the hydrograph recession curves and the levels of baseflow, as well as to the peaks. In doing so, the predictions are being calibrated to more than the instantaneous values of total flow, and are accounting for the hydrological behaviour in a manner that would not be achieved using an optimisation procedure blind. In their paper, Gupta *et al.* (1998) demonstrated that models can be better constrained using a multi-objective approach, based on a range of statistics to describe the agreement between predicted and observed stream flow.

A complementary approach to this issue is the idea that information about internal behaviour of catchments could be used to constrain model parameterisations more effectively. One attempt to achieve this has been described by Franks *et al.* (1998), who used representations of surface saturation derived from remotely-sensed data to condition parameter values and reduce the levels of uncertainty in model predictions. Similarly, Kuczera and Mroczkowski (1998) attempted to use groundwater level data and stream salinity in addition to streamflow to constrain parameters of a hydrochemical model. The further development of such techniques may help to provide a better understanding of how model parameters relate to the physical attributes of the catchment. The models can then be applied with greater confidence to situations involving environmental change.

However, unless they have been the subject of intensive research, the only hydrological time-series information that exists for most catchments is a historical record of stream flow. Therefore, comparisons of model predictions with the stream flow record frequently provide the only means of model calibration and validation. For catchments that are characterised by a peaky hydrograph, indicative of rapid runoff and frequent storm events, apparently good prediction of the hydrograph can be achieved provided there is a good representation of surface runoff behaviour (Jakeman and Hornberger, 1993). The baseflow and dynamics of the sub-surface will have little influence on many goodness of fit measures, unless specifically tailored to give added weight to low values by, for example, taking log values. Yapo *et al.* (1998) used a multi-objective approach to model calibration but still identified a problem in predicting low flows and recession curves using a combination of two objective functions. However, contributions from the sub-surface may still form a significant component of the total runoff, and are of particular importance where water quality, as well as quantity, is of interest.

One of the functions intrinsic to most conceptual hydrological models is the distinction between flow paths of water, represented by a separation into peak surface runoff and sub-surface (baseflow) components. The differing behaviour of these processes determines the nature of the hydrograph. Therefore, it would seem appropriate to analyse the functioning and parameterisation of the model in terms of two distinct components. The aim of this paper is to investigate whether additional information about model behaviour and parameter interpretation can be obtained from stream flow hydrographs by separating the baseflow component from the peak flow response. A modified GLUE procedure is applied using a multi-objective analysis based on hydrograph separation. Monte-Carlo simulations of random parameter combinations are performed and acceptable ranges of parameter values identified. The behaviour of the model is also examined by comparing results of a sensitivity analysis in terms of both total streamflow and baseflow response.

The DIY Model

MODEL STRUCTURE

The analysis has been carried out using a conceptual distributed hydrological model (DIY) described in detail in Dunn *et al.* (1998). The DIY model aims to provide an approach that is simple enough to permit interpretation of model behaviour and flexible enough to allow different formulations to be geared towards different applications. The model uses GIS to assign categories to cells, typically 50×50m in size, on the basis of similar topographic, climatic, soil and land use characteristics. For each cell category, a signature of hydrological response in the stream is determined, using a hillslope routing model. The catchment response is calculated by summation of the different signatures, factored by the numbers in each category. In this way, the complexity of the model is controlled by the number of characteristic categories that are assigned, and is independent of the catchment area. The definitions of the categories can be biased towards particular aspects of the catchment hydrology to suit the detail required from the model output.

The model is driven by daily inputs of rainfall and evapotranspiration and has seven fundamental parameters; two of which define the topographic structure of the catchment and the remaining five relate to the soil and drainage system. The parameters are listed in Table 1 together with an outline of their function. The topographic parameters (slope to stream and flow path distance to stream) are derived directly from the GIS, but calibration is necessary for the five soil and drainage parameters. The saturated hydraulic conductivity and threshold storage parameters are described as 'effective', because the technique applied to disaggregate flow down to individual cell contributions results in a modified form of sub-surface routing. When taken in combination, the effective KSAT and THMAX parameters generate a more physically realistic transmissivity value. The fast response also uses the KSAT parameter, as the response is assumed to be based on the travel

Table 1. *DIY model parameters.*

Parameter	Variable	Function
Effective saturated hydraulic conductivity	KSAT	Control rate of slow response runoff
Soil porosity	PORE	Define relationship between soil storage and head
Effective threshold storage for fast response	THMAX	Soil moisture level at which fast runoff response is initiated and effective depth for transmissivity
Fast response	FASTD	Define density of localised drainage network for fast flow routing (related to macropores, artificial drainage or rill generation)
Minimum soil storage–slope	VMIN	Set lower limit on sub-surface flow
Slope to stream	SLOPE	Define the hydraulic gradient for hill-slope model
Flow path distance to stream	DIST	Define the hill-slope routing distance for each cell

times to reach the drainage network, the density of which is defined by the fast response distance. The equations governing these flow processes are set out in Dunn *et al.* (1998).

MODEL BEHAVIOUR

The function of the various model parameters can be demonstrated in a simplified manner through model sensitivity analysis. A basic sensitivity analysis of the model has been carried out by varying each parameter, individually, from values defined by a baseline parameter set for a catchment model. This allows the relative significance of each parameter to be evaluated and the nature of its influence to be identified in terms of its effect on different flows across the hydrograph. The observed behaviour will be affected to a certain extent by the choice of the baseline parameter set and, therefore, this analysis does not give the full picture. A more comprehensive sensitivity analysis using the results of Monte-Carlo simulations is presented later in the paper. However, the results of the Monte-Carlo simulations are presented in terms of an objective function measure that summarises the overall behaviour of a simulation, but does not demonstrate the nature of the behaviour in terms of changes to different levels of flow.

The baseline parameter set for the basic sensitivity analysis was selected on the basis that it gave a good simulation of streamflow, and individual parameter values lay towards the centre of identified acceptable ranges. Factors ranging from 0.1 to 10 were applied to the baseline values. The structure of the DIY flow code permits the total catchment runoff to be separated into two components, representing the slow sub-surface response (or baseflow) and the fast storm response. The sensitivity has, therefore, been analysed in terms of both total streamflow and baseflow.

Some results from this analysis are presented in Figs. 1 and 2, for the case where each baseline parameter was modified by a factor of 0.2. The results for modifications by different factors showed similar behaviour. Figure 1 shows scatter plots of the predicted total flow for the baseline simulation, against the predicted total flow for the modified simulation, for each parameter individually. Figure 2 shows a similar set of plots but, in this case, for predictions of baseflow.

It is clear from these figures that the influence of parameters on baseflows is much stronger, in relative terms, than on total flows. The porosity parameter (PORE) has the greatest affect on the total flow, reducing the average flow by 30%, but all other parameters affect the average flow by less than 10%, and show relatively little scatter about the average. By contrast, the saturated hydraulic conductivity (KSAT), threshold storage (THMAX) and slope parameters (SLOPE) all reduce the average baseflow by a factor of 5, with considerable scatter caused by the changes to saturated hydraulic conductivity and slope. The same predicted baseline flow for these two parameters can vary by a factor of 3 in the modified simulation. The minimum storage (VMIN), flow path distance (DIST) and fast response distance (FASTD) parameters are quite insensitive in terms of their average baseflow prediction, although the flow path distance affects the behaviour of the baseflow significantly. The porosity parameter (PORE), increases average baseflows by a factor of 2.3 and also has a very significant affect on behaviour.

These results demonstrate the increased utility of separating off the baseflow for analysis. Taking only the total flow, it is hard to interpret the behaviour of the model, because flows are dominated by the storm response component. In practice, most of the model parameters have greater influence on the baseflow. This should not be too surprising, as recession and baseflow behaviour is much

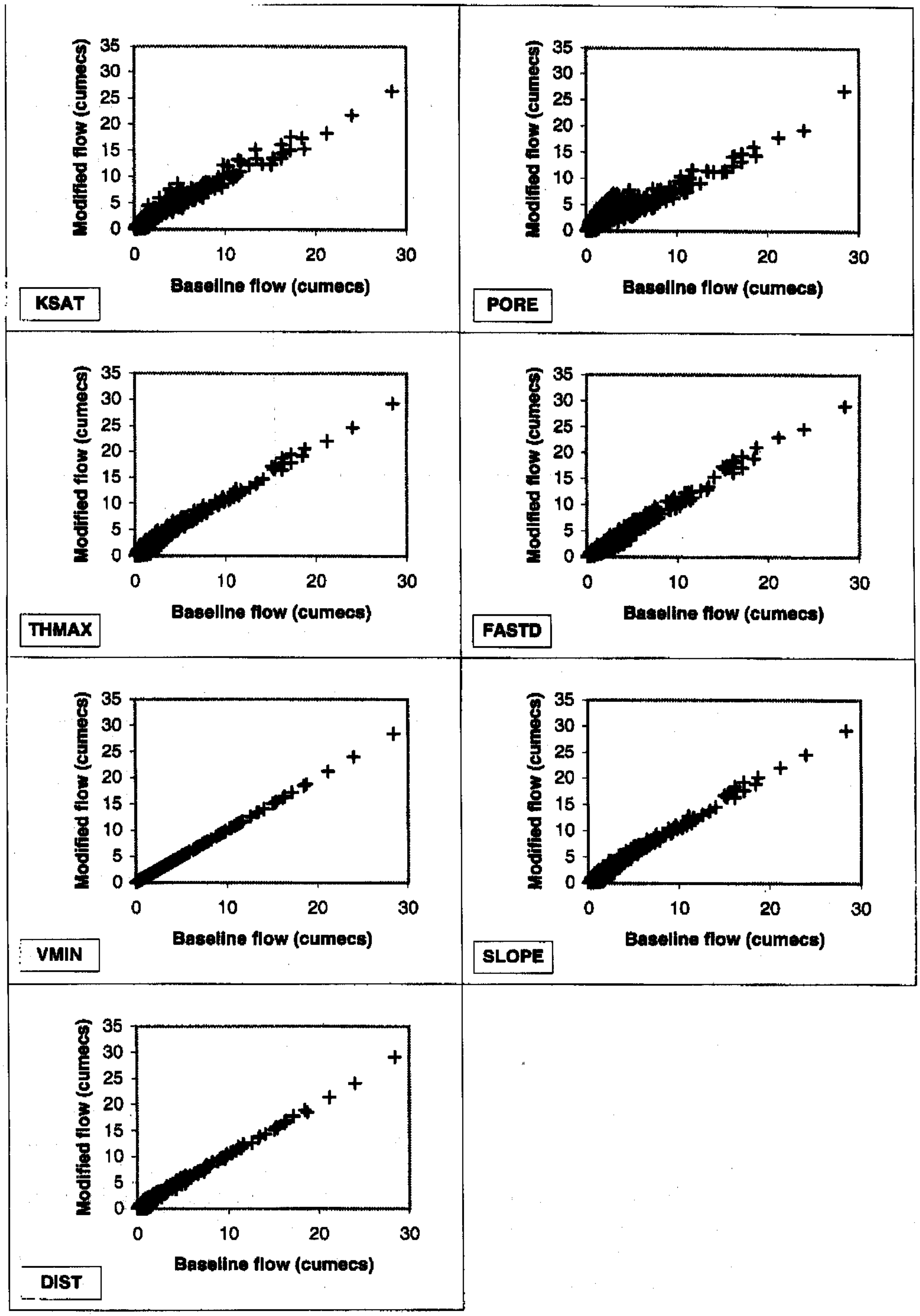

Fig. 1. *Effect of modifying individual DIY parameters by a factor of 0.2 on total flow prediction.*

more dependent on soil conditions and physical structure, whilst storm responses are dominated by the structure of a particular rainfall event.

This simple sensitivity analysis also demonstrates that several of the soil and drainage parameters are equally as significant as the more identifiable topographic parameters in determining model behaviour. Therefore, it is important that the uncertainty in these parameters is identified.

Uncertainty Analysis Approach

Having demonstrated the utility of separating off baseflow for interpretation of parameter functions, the next step is to investigate whether the same technique can be used to reduce uncertainty in predictions and constrain the values of parameters more effectively. The individual parameter sensitivities do not define integral model behaviour,

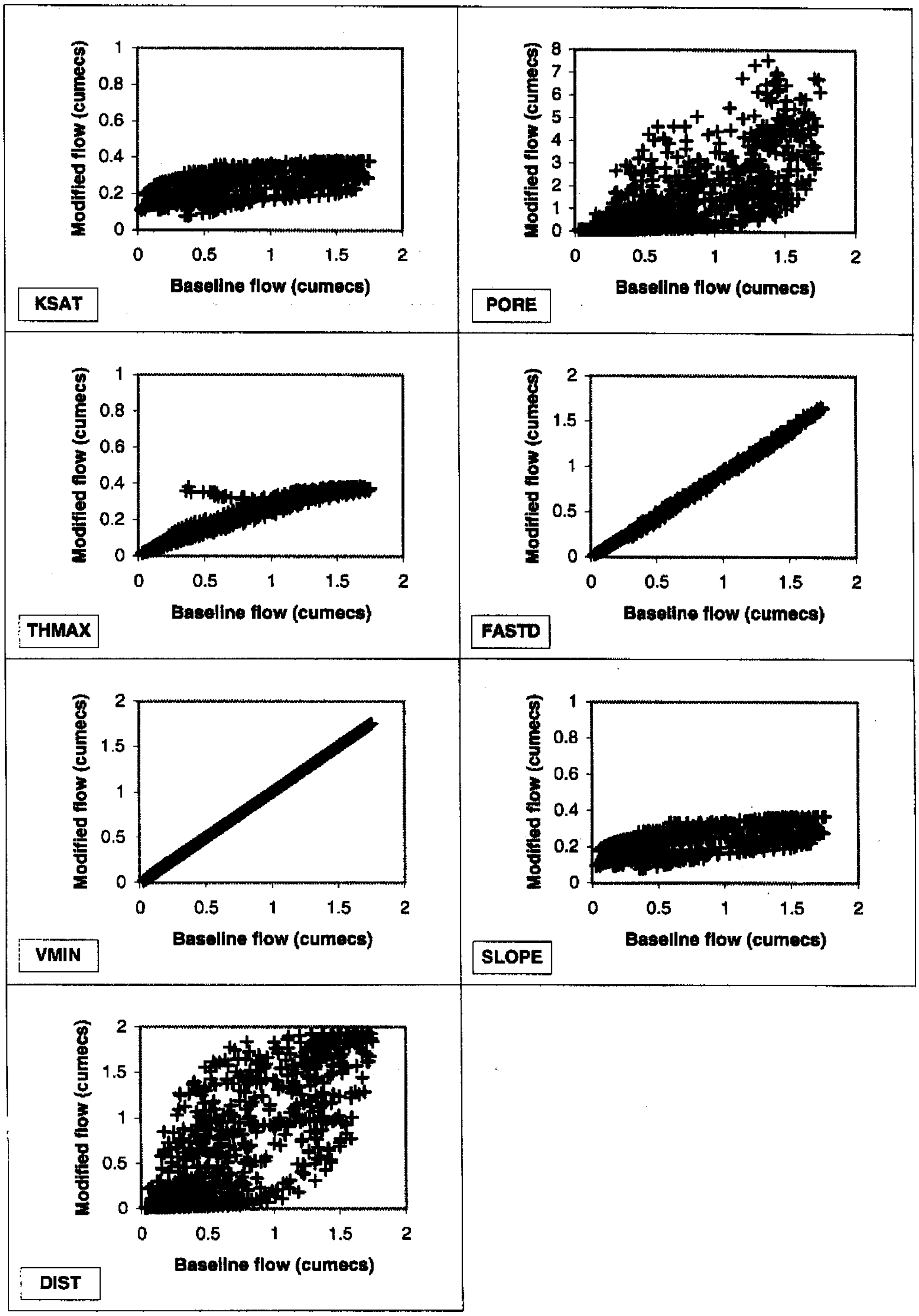

Fig. 2. *Effect of modifying individual DIY parameters by a factor of 0.2 on baseflow prediction.*

because it is clear that several parameters affect the model behaviour in a similar manner. Therefore, it is highly likely that completely different combinations of parameter values could be equally good predictors of stream flow. This is the logic behind the GLUE approach developed by Beven and Binley (1992). The extension to the approach investigated here is to use the model distinction between surface and sub-surface runoff, in a similar manner to the sensitivity analysis, to define a second likelihood measure for stream flow prediction.

Following the approach adopted by GLUE, multiple simulations of the model are performed using random combinations of parameter values, which are set within specified ranges believed to represent their practical limits. A likelihood measure, in this case defined by the Nash and Sutcliffe efficiency (Nash and Sutcliffe, 1970) for predic-

Table 2. *Characteristics of the Carron Valley and Ythan catchments*

Catchment	Area (km^2)	Mean ann. rainfall (mm)	Dominant land cover	Mean slope (m/m)	Mean flow (eq. mm/d)
Carron Valley	120	1450	Moorland	0.076	3.0
Ythan	548	750	Arable land	0.050	1.1

tion of total stream flow, η_t, is calculated for each simulation, as a measure of the performance of that particular combination of parameter values:

$$\eta_t = \sum_{i=1}^{n} \frac{(q_{oi} - q_{om})^2 - (q_{oi} - q_{pi})^2}{(q_{oi} - q_{om})^2} \qquad (2)$$

where q_o is the measured stream flow, q_p is the calculated stream flow and other subscripts are defined by i for each time point, and m for the mean value averaged over n time points.

The approach is extended by using the model predictions to identify days on which the catchment runoff is dominated by baseflow. Calibration of the flow record using only these days will bias the model towards accurate prediction of baseflow response rather than peak flow response. In this way, the behaviour of the baseflow runoff component may be analysed independently from the total runoff and used to provide additional information about acceptable parameter ranges. A second likelihood measure, based on the Nash and Sutcliffe efficiency for prediction of baseflow, η_b, can be calculated for each simulation:

$$\eta_b = \sum_{i=1}^{n} \frac{(b_{oi} - b_{om})^2 - (b_{oi} - b_{pi})^2}{(b_{oi} - b_{om})^2} \qquad (2)$$

where subscripts are as above and b refers to the flow only for time points where predicted flows are identified as baseflow dominated. The identification of baseflow dominated days has been performed using a prior set of 100 test simulations. For each of these simulations each day has been classified as either baseflow or stormflow dominated, where baseflow dominated days satisfy the criterion, *baseflow* ≥ 0.95 × *total flow*. A fixed set of baseflow dominated days was then identified for calculation of the second likelihood measure, using the criterion that 85% of the test simulations identified a day as baseflow dominated. This was found to give a visually acceptable definition of baseflow dominated periods on examination of the hydrographs.

The value of the approach has been investigated through application of the DIY model to two contrasting catchments; the Ythan above Ellon (NGR 3947 8303) in NE Scotland and the Carron Valley above Headswood (NGR 2832 6820) in Central Scotland. Both catchments have been the subject of previous modelling studies, described in Dunn *et al.* (1998) and Dunn and Ferrier (1999). Flow duration curves for the two catchments are illustrated in Fig. 3 and physical characteristics of the catchments are summarised in Table 2. The Ythan catchment has a high baseflow index of around 0.75. The 5% exceedance flow of 16.4 m^3/s is only 2.4 times the mean daily flow of 6.8 m^3/s. The Carron Valley catchment, despite being heavily managed as a water resource, is much flashier and has a similar 5% exceedance flow of 16.5 m^3/s, but this is almost 4 times the mean daily flow. Bearing this in mind, it would be expected that the added value gained by conditioning parameter values on baseflow response would be less for the Ythan than for the Carron, because the behaviour of the total flow will be closer to that of the baseflow in this catchment.

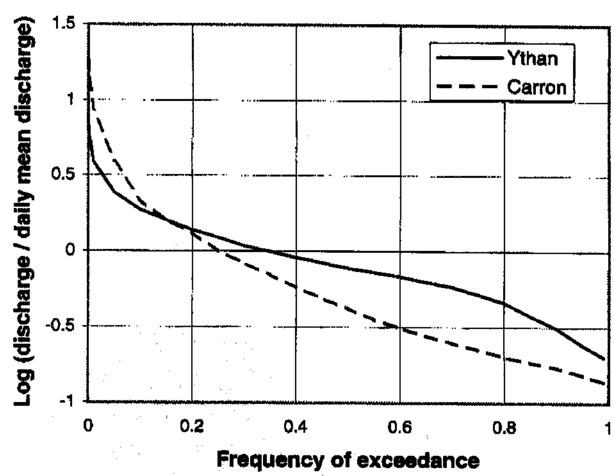

Fig. 3. *Flow duration curves for the Ythan and the Carron plotted relative to mean daily flow*

Ranges for the DIY model parameters were defined, taking as broad limits as was considered practical. Table 3 lists the values for the Carron and Ythan respectively. The slope and flow path distance are spatially variable. Therefore, a range of factors (FSLOP and FDIST) has been defined to apply to the baseline values (SLOPE and DIST), which were derived from the GIS analysis of the topography. It would not be anticipated that the topographic parameters would be modified, but the analysis will permit the acceptability of their values to be checked and their sensitivity to be evaluated relative to the soil parameters.

Table 3. *Parameter ranges and constraints for efficiency criteria for the Carron Valley and Ythan*

Parameter	Parameter range	Total flow efficiency	Baseflow efficiency	Combined efficiencies
Carron Valley		> 0.75	> 0.3	
KSAT (m/day)	10–200	10–200	40–200	90–190
PORE (-)	0.1–0.4	0.1–0.4	0.1–0.37	0.1–0.37
THMAX (m)	0.0001–0.03	0.0001–0.03	0.0001–0.013	0.0001–0.0015
FASTD (m)	1–15	1–12	1.2–13	1.8–6.2
VMIN (m)	0.000002–0.00001	0.000002–0.00001	0.000002–0.000009	0.000002–0.000009
FSLOP (-)	0.2–2	0.2–2	0.3–2	0.8–1.9
FDIST (-)	0.2–2	0.2–2	0.7–2	1.2–2
Ythan		> 0.7	> 0.6	
KSAT (m/day)	10–150	10–150	35–145	35–120
PORE (-)	0.3–0.8	0.3–0.8	0.25–0.8	0.34–0.78
THMAX (m)	0.0025–0.04	0.0025–0.04	0.008–0.027	0.008–0.018
FASTD (m)	2–50	5–50	4–48	12–37
VMIN (m)	0.00002–0.00008	0.00002–0.00008	0.00002–0.00008	0.00002–0.00006
FSLOP (-)	0.2–2	0.2–2	0.2–2	0.4–1.6
FDIST (-)	0.2–2	0.2–2	0.3–1.4	0.25–1.3

For each catchment 2500 model simulations were performed. For each model run, a random number generator was used to select a parameter set that falls within the defined limits. The predictions of flow were then compared with observed data to calculate the Nash and Sutcliffe efficiencies for both total stream flow and baseflow.

Results of Uncertainty Analysis

The results of the multiple simulations for both catchments demonstrated that, in general, a wide range of values for each parameter can be found to give an acceptable prediction of total stream flow. In Fig. 4 the efficiency for total flow is plotted against the parameter values for each of the Carron simulations, for four different parameters. Only the fast response distance shows any clear relationship, with a gradual reduction in efficiency for all values greater than 5m. The threshold storage and slope factor parameters both show that there were fewer simulations with low efficiencies for parameter values at the lower end of the defined range but that acceptable combinations could be found throughout the parameter space. The saturated conductivity parameter appeared largely unconstrained, as did the remaining parameters not shown.

For prediction of baseflow, the results of the multiple simulations are quite different. Figure 5 shows an equivalent set of plots to Fig. 4, with the efficiency calculated using predictions only from those periods that are baseflow dominated. In general, the efficiencies for the model predictions are much lower and reflect the fact that small absolute errors in prediction are much more significant during low flow periods. The number of simulations achieving good efficiencies is also fewer and the behaviour over the parameter space differs from the total flow comparisons. By contrast to the results for total flow efficiency, the baseflow efficiencies for threshold storage are clearly highest for low values of the parameter. Only one simulation with a threshold storage, $THMAX > 0.003$m had a baseflow efficiency, $\eta_b > 0.3$. Saturated conductivity is slightly better constrained by the baseflow efficiency, with a lower value of 40 m day^{-1} necessary to achieve $\eta_b > 0.3$. It should be emphasised that this parameter has a conceptual function within the model structure and also represents catchment scale behaviour; thus, it includes macro-pore and drainage effects as well as basic soil hydraulics. For other parameters, the best simulations are again spread across the parameter ranges, although there is an indication that the best flow path distance and slope factors lie in the upper half of the range.

The results for the Ythan simulations were very similar. The analysis based on total flow efficiencies placed a lower limit on the fast response distance of 5m, but other parameters were largely unconstrained. The baseflow analysis provided lower limits to the values of saturated conductivity and threshold storage and an upper limit to the threshold storage and flow path distance factors, but again other parameters appeared largely unconstrained.

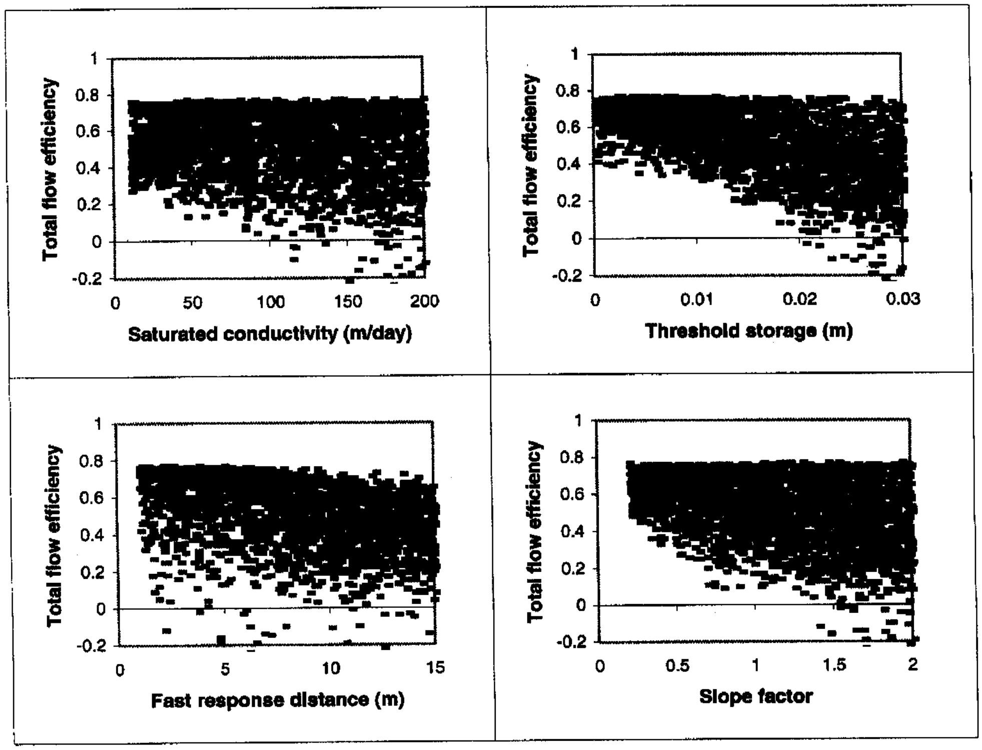

Fig. 4. *Scatter plots of model efficiency for total flow in the Carron over specified parameter ranges*

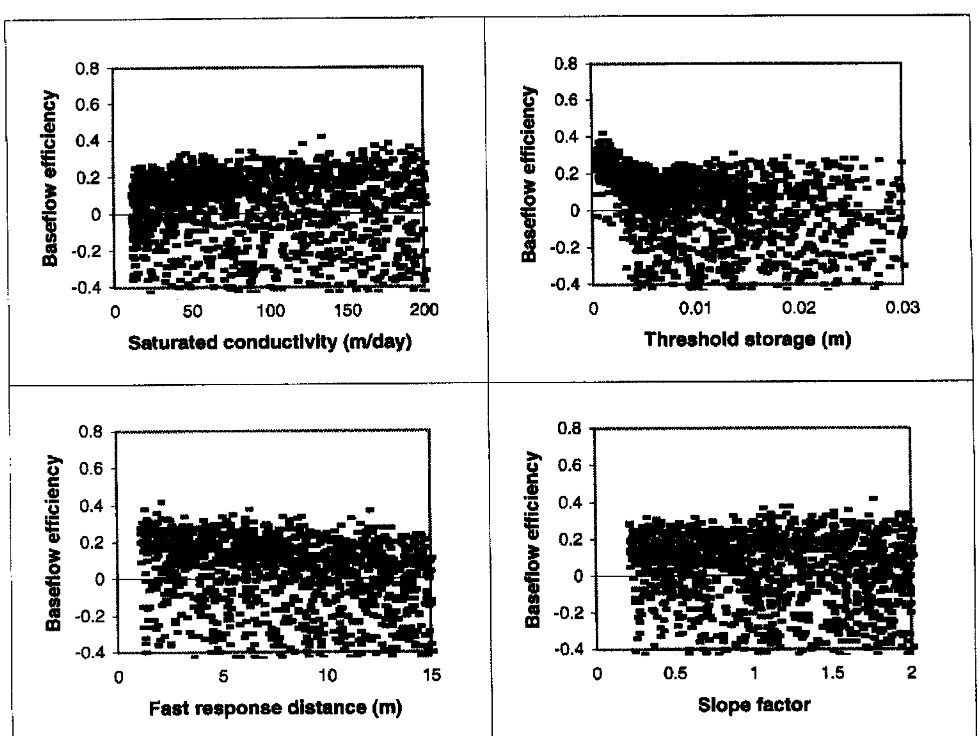

Fig. 5. *Scatter plots of model efficiency for baseflow in the Carron over specified parameter ranges*

However, the key to identifying acceptable parameter ranges lies in combining the results from the predictions for total flow with those for baseflow. This can be achieved by defining criteria for an acceptable simulation, on the basis of both total flow and baseflow. From the results, for the Carron, these criteria were set as a Nash and Sutcliffe efficiency for total flow, $\eta_t > 0.75$ and for baseflow, $\eta_b > 0.3$, and for the Ythan, $\eta_t > 0.7$ and $\eta_b > 0.6$. This eliminates all simulations that were good at predicting either total flow or baseflow, but not both. The resulting acceptable parameter space is significantly better constrained than either of the two components individually. Table 3 summarises the parameter ranges that satisfy the individual and combined efficiency criteria for the Carron and Ythan respectively.

The method has had slightly greater success in defining parameter values for the Carron Valley catchment than for the Ythan. This was expected because the distinction between the total flow and baseflow response is much stronger in the Carron, making the parameters more identifiable. In both catchments, the minimum storage parameter appears unconstrained. Again this was expected, because the parameter effectively takes account of a deep groundwater contribution, by ensuring that a certain minimum flow is maintained during exceptionally dry spells and, at other times, the parameter has no function. A value for the parameter could be determined by focusing on the dry periods when it is operational. The porosity is also poorly constrained by the method, although the conceptual baseline range is narrower than for other parameters in any case.

Generalised Sensitivity Analysis

The results from the Monte-Carlo analysis also permit a more comprehensive sensitivity analysis to be performed, following the procedure of Spear and Hornberger (1980). The sensitivity analysis here is carried out in a form very similar to that presented by Freer *et al.* (1996). The first step in this analysis requires a subjective distinction to be made between behavioural and non-behavioural parameter sets from the Monte-Carlo simulations. In order to compare the parameter sensitivities in terms of both the total flow and baseflow efficiency measures, the same number of simulations was assumed to be behavioural for both measures. For the Carron Valley model, taking all simulations with a positive baseflow efficiency (i.e. better predictors than taking the mean), this gave a criterion of $\eta_t \geq 0.64$ for total flow efficiency and included one third of the simulations. Only around 65% of the simulations identified as behavioural in terms of baseflow were coincident with the behavioural simulations for total flow.

The behavioural simulations were then separated into 10 sets, according to the efficiency values, and are plotted as cumulative distributions for each individual parameter value, and for the two objective functions, in Figs. 6 and 7. Only 40% of the top set of simulations were the same for both objective functions. Figures 6 and 7 show how sensitive the model predictions are to each parameter across their defined range. A large difference in the cumulative distribution curves between sets indicates high sensitivity. Curves lying close to each other indicate low sensitivity. In addition, the gradients of the curves indicate areas of the parameter ranges where changes in parameter values have a strong or weak effect. The importance of the value of THMAX on baseflow efficiency is shown clearly by the sharp gradient at the lower end of the range for the best set in Fig. 7.

The results presented in Figs. 6 and 7 reinforce the findings of the simple sensitivity analysis by demonstrating how the total flow and baseflow efficiencies provide different information about the model behaviour. In general, the baseflow efficiency measure is seen to be more sensitive to parameter values.

Flow Predictions Including Parameter Uncertainties

The results of the uncertainty analysis have illustrated how baseflow can be used to define a second likelihood measure that helps to constrain flow predictions. One of the main purposes of the uncertainty analysis is to enable an envelope of flow predictions to be derived. The value in achieving greater parameter constraints is that the width of this envelope will be narrowed. The effect of the constraints defined by setting criteria for total flow efficiency, baseflow efficiency and the combined efficiencies has been investigated by extracting, from the simulations, the most extreme values at each time step that satisfy the different efficiency criteria. Figures 8 and 9 compare the envelopes of prediction for one year of the Carron and Ythan predictions, for each case. These have been derived using the efficiency value as the likelihood measure, and do not include accentuated weightings for better simulations, such as those described by Freer *et al.* (1996).

It is clear that using a single efficiency criterion based on total flow (Figs. 8(a), 9(a)), the envelope of flow predictions is very broad, and the uncertainty in low flow predictions is very high, particularly for the Carron. Using only the baseflow efficiency criterion for the Carron (Fig. 8(b)), the envelope is much narrower for the low flow predictions and only slightly broader for the peak flows. However, there is less improvement for the Ythan using the baseflow efficiency alone (Fig. 9(b)). Taking the combined efficiency criterion for total flow and baseflow, the envelope of flow is narrowed further for both catchments (Figs. 8(c), 9(c)). The resulting hydrograph prediction for the Carron is very good, with the measured flow hydrograph falling within a narrow envelope of predictions for the majority of the simulation. The results for the Ythan are not so good. Although the envelope is narrower and

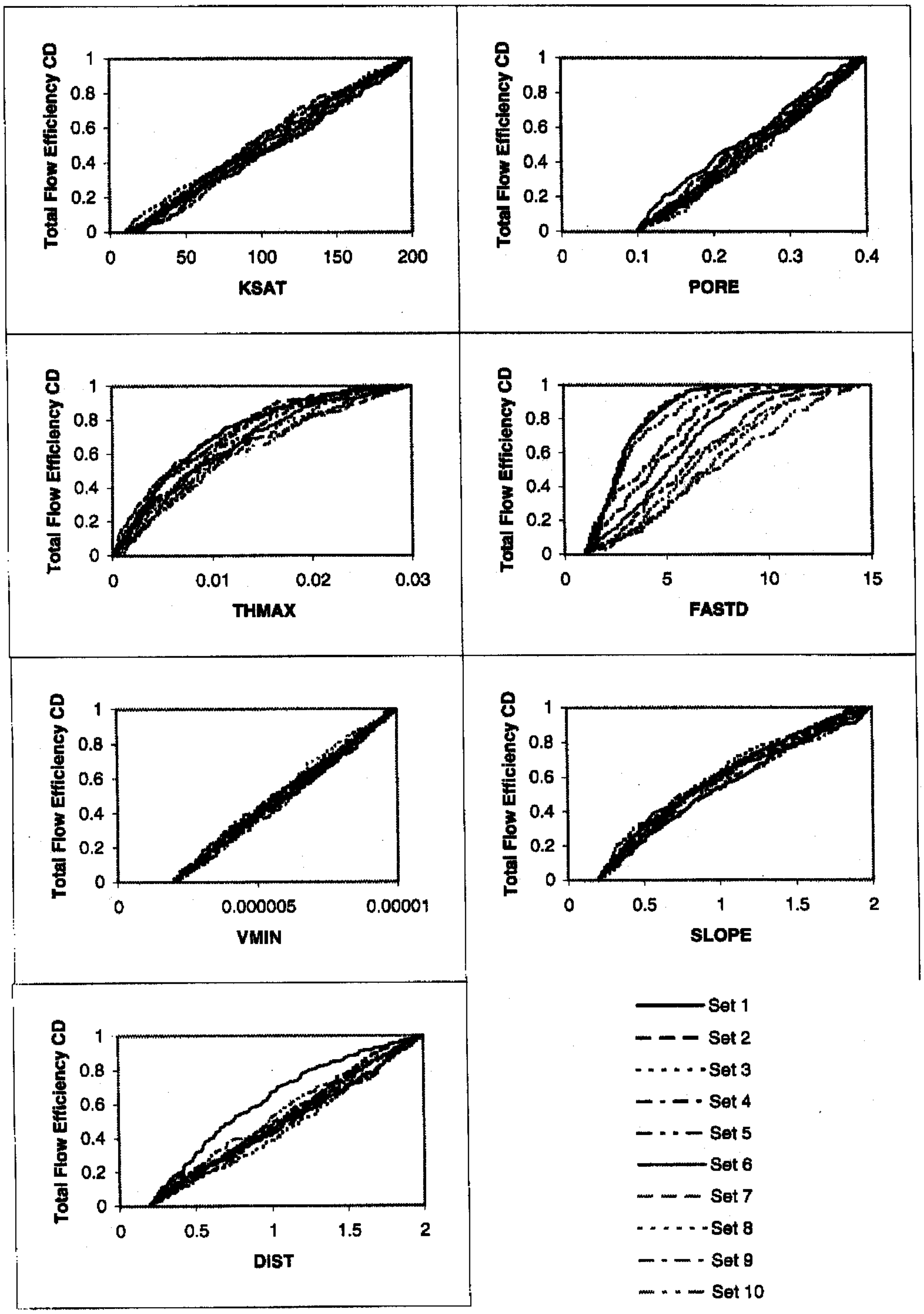

Fig. 6. *Sensitivity of individual parameters expressed as cumulative distributions of values, in 10 equal sets of retained simulations with total flow efficiency >= 0.64 (set 1 highest efficiencies, set 10 lowest efficiencies)*

the model is better constrained when combined efficiency criteria are used, the measured flow lies outside the envelope during periods in spring and autumn, although parts of these periods were used to define the baseflow efficiency. This suggests that the model is not capable of predicting behaviour correctly during these periods and, hence, that there are either data or model errors in addition to the parameter uncertainties. Taking the broader envelope based on total flow efficiency, these errors are less obvious, demonstrating that there is a danger of masking model and data errors, by using a poor likelihood measure for defining parameter uncertainties. Similar observations

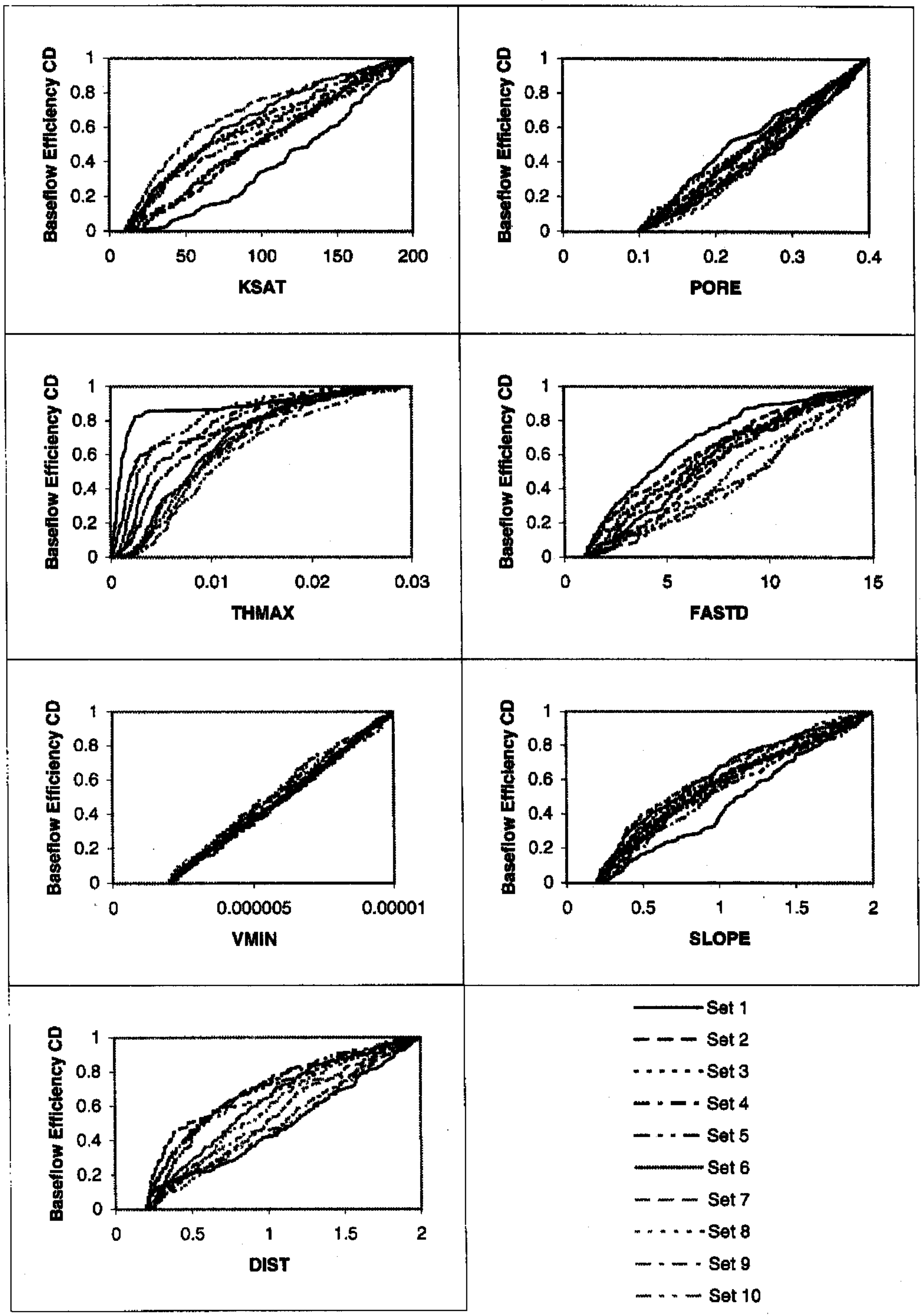

Fig. 7. *Sensitivity of individual parameters expressed as cumulative distributions of values, in 10 equal sets of retained simulations with total flow efficiency >= 0.0 (set 1 highest efficiencies, set 10 lowest efficiencies)*

about model error were also made by Gupta *et al.* (1998) in their multi-objective analysis.

Discussion and Conclusions

The analysis carried out in this paper has demonstrated how hydrograph separation can be used to derive additional information about catchment behaviour from stream flow records. From the Monte-Carlo simulations, it is clear that acceptable combinations of values can be found throughout the parameter space that will give an equally good prediction of total stream flow, using the Nash and Sutcliffe efficiency as a likelihood measure. However, the introduction of an efficiency criterion for baseflow helps to

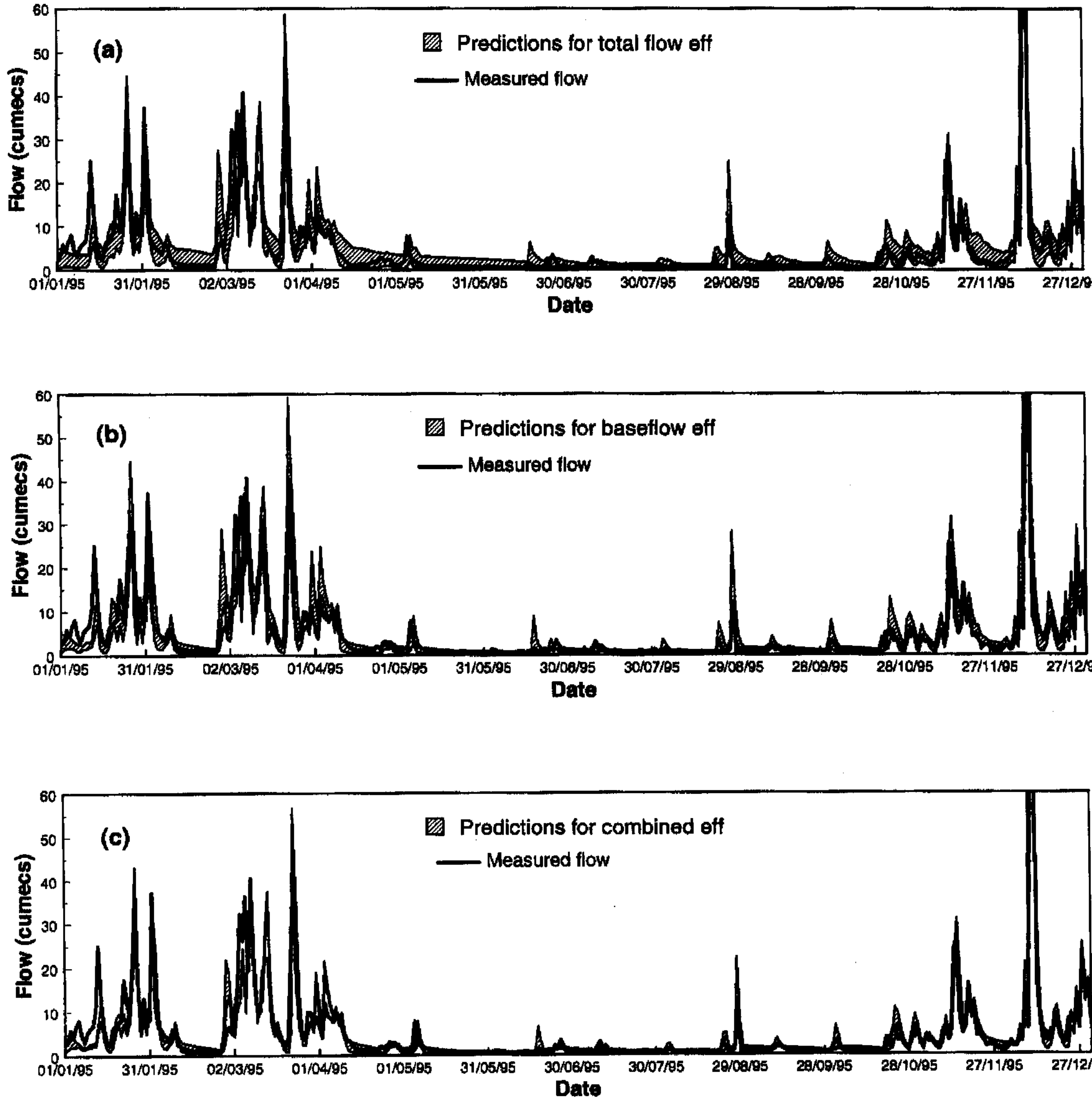

Fig. 8. *Envelope of flow predictions for Carron using different efficiency criteria (a) total flow efficiency > 0.75, (b) baseflow efficiency > 0.3, (c) combined total and baseflow efficiency*

constrain the acceptable parameter ranges. Taking both likelihood measures, in combination, to provide a multi-objective framework, constrains the parameters further.

The sensitivity analysis showed that the baseflow component is generally more sensitive to parameter values than the total flow, and that the greatest sensitivities lie in different regions of the parameter space. As such, the baseflow efficiency provides additional information about the model. The sensitivity analysis also demonstrated that several of the calibrated model parameters, relating to the soil and drainage system, are of equal importance to the topographic parameters. An understanding of the constraints on the parameter values is therefore important, if methods of relating the parameters to physical properties are to be developed.

The constrained parameter ranges that are generated by the method are only moderately well defined for the Carron Valley catchment. However, the levels of variability inherent in soil water transport properties at a small scale are similar in magnitude (Corwin *et al.*, 1997), and this is, perhaps, the best level of information that can be achieved at the catchment scale. The values in the calibrated range for effective saturated conductivity are high but, as discussed, this is a function of the conceptual model structure including the method by which spatially disaggregated flows are calculated using the hill-slope routing model. When taken in conjunction with the effective threshold storage, the range for a maximum transmissivity parameter, defined by *KSAT* × *THMAX*, is from 0.03 m^2 day^{-1} to 0.3 m^2 day^{-1}, which would appear to be physically realistic. The most surprising result from these simulations was the lack of constraint on the porosity parameter, although the conceptual values assigned initially were more tightly constrained than most of the other parameters.

The more damped hydrological behaviour of the Ythan resulted in poorer constraints on the parameter ranges. None the less, an improvement was achieved by using the baseflow analysis in conjunction with the total flow. Relative to the Carron Valley, the constrained parameter ranges for the Ythan reflect the conceptual physical differences between the two catchments; the higher threshold storage for the Ythan corresponds to deeper soils and the greater fast response distance reflects a slower reaction to storm events. The transmissivity range is from 0.28 m^2 day^{-1} to 2.2 m^2 day^{-1}, which is an order of magnitude higher than for the Carron Valley.

Thus, although the results are not successful in defining individual parameter values, they do constrain parameter ranges sufficiently that it should be possible to relate the ranges for the conceptual soil and drainage parameters to physical properties of the catchment. In this application, the slope and flow path distance parameters were allowed to vary but, in practice, these would be set according to the topographically derived values. The effect of this would be further to improve constraints on the soil and drainage parameters. Additional applications of the model to different catchments should also provide greater insight

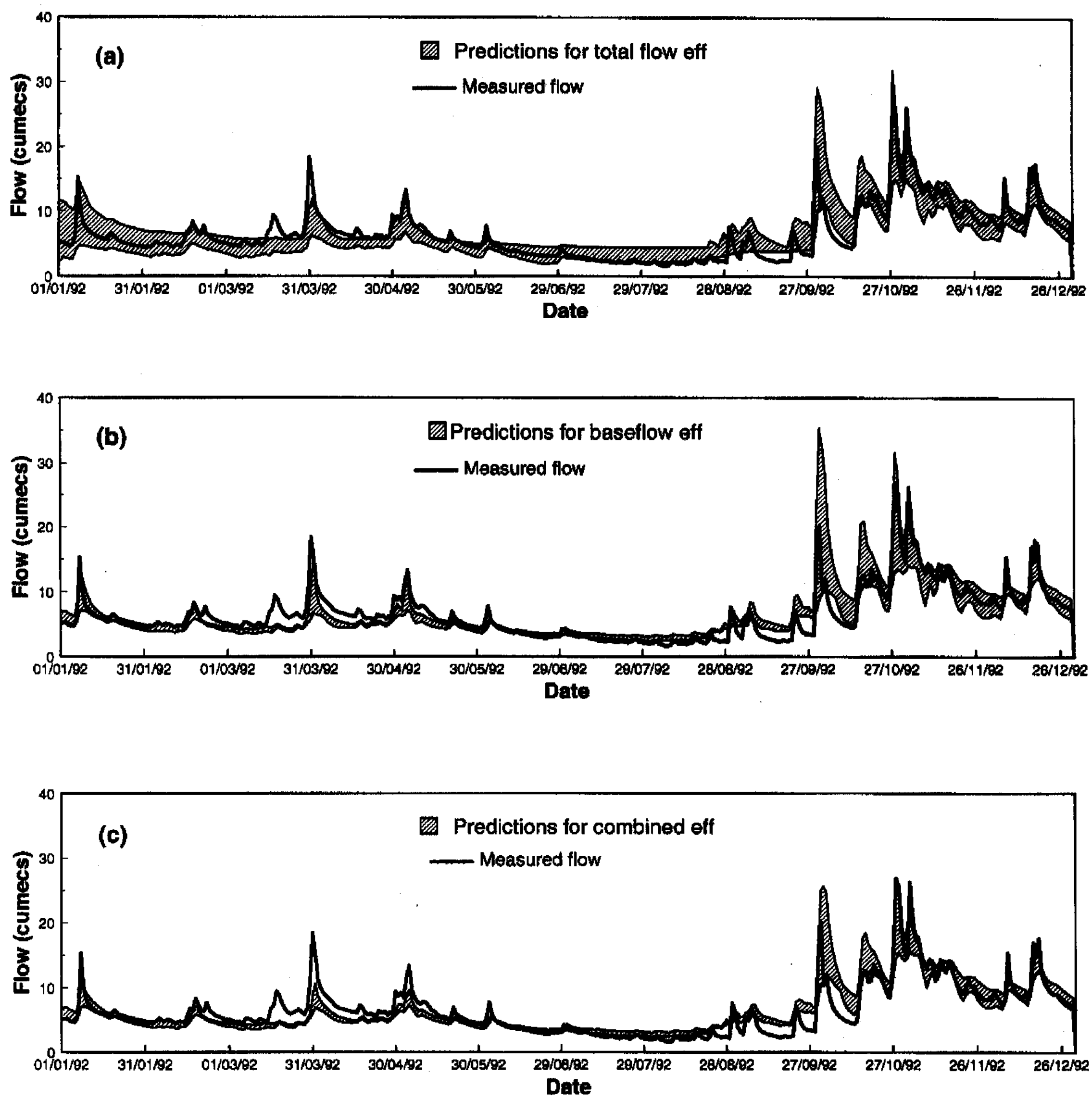

Fig. 9. *Envelope of flow predictions for Ythan using different criteria (a) total flow efficiency > 0.7, (b) baseflow efficiency > 0.6, (c) combined total and baseflow efficiency*

into the physical interpretation of the parameters. The next stage would be to develop relationships between the parameter ranges and catchment attributes such as the Hydrology of Soil Types (HOST) classification (Boorman *et al.*, 1995). This would enable greater spatial variability to be included in the models and greater confidence to be placed on their application to address issues involving environmental change. However, the modelling would still be reliant on a similar form of uncertainty analysis to that performed in this paper, to identify the combinations of parameters within ranges that generate an acceptable model.

The predicted envelopes of flow reinforce how the baseflow analysis reduces uncertainty and highlight how data error and model error can be hidden, if the bands are too wide. In the case of the Ythan simulations, the error during the spring period is probably caused by data error, as there is a fairly significant water balance error for this period, whilst in the autumn the error would appear to be more related to model structure. Model enhancements, such as a more sophisticated groundwater representation, should target this period for improvements in prediction.

Overall, the analysis has demonstrated that apparent uncertainties in parameter values are partly due to the limitations of objective functions, as well as reflecting the acceptable parameter ranges. Hydrograph separation has been shown to be an extremely useful technique for extracting additional information from standard streamflow records, particularly in catchments that are characterised by flashy surface runoff responses. Even with a well constrained set of flow predictions, there is not a unique set of parameter values, but the ranges are sufficiently narrowed that, given a diverse set of model applications, it should prove possible to relate parameter sets to physical attributes of a catchment. Clearly, in this context, catchments that have been monitored in greater detail could be of value in extending the multi-objective analysis to predict other parts of the system and internal behaviour, such as soil moisture or streamflow in different locations. This should help to further constrain parameter values and provide greater insight into their physical interpretation.

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