CATERING FOR UNCERTAINTY IN A CONCEPTUAL RAINFALL RUNOFF MODEL: MODEL PREPARATION FOR CLIMATE CHANGE IMPACT ASSESSMENT AND THE APPLICATION OF GLUE USING LATIN HYPERCUBE SAMPLING.

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ABSTRACT

Changes in Irish climate may pose a number of obstacles for water resource management. There is a need to approach this problem using the catchment as the basic unit of analysis. The application of a lumped conceptual rainfall-runoff model for simulating beyond a baseline calibration set is a major challenge for climate change impact assessment. This is due in no small part to the limitations associated with the use of these models, with uncertainty in model output being associated with model structure and the non-uniqueness of optimised parameter sets. In this paper, HYSIM, an "off-the-shelf" conceptual rainfall runoff model using data on a daily time-step is applied to a suite of catchments throughout Ireland in preparation for use with downscaled climate data. Uncertainties relating to process parameter calibration due to parameter interaction and equifinality are highlighted. In an attempt to improve the reliability of model output the generalised likelihood uncertainty estimation (GLUE) framework is adopted to analyse the uncertainty in model output derived from parametric sources. Traditionally this approach has been applied using Monte Carlo random sampling (MCRS). However, when using an "off-the-shelf" type model, source code may not be available and it may not be feasible to run the model for large MCRS samples without user intervention. In order to make the propagation of uncertainty through the model more efficient, input parameter sets are generated using Latin Hypercube sampling (LHS). A number of acceptable parameter sets are generated and uncertainty bounds are constructed for each time step using the 5th and 95th percentile at each temporal interval. These uncertainty bounds will be used to quantify the uncertainty in simulations carried out beyond the baseline calibration period as they include the error derived from data measurement, model structure, and parameterisation.

INTRODUCTION

Conceptual rainfall runoff (CRR) models have been the most widely used by hydrologists, engineers and environmental consultants for assessing the impacts of climate change on water resources (Arnell, 2003; Charlton and Moore, 2003; Pilling and Jones, 1999; Sefton and Boorman, 1997; Arnell and Reynard, 1996; Cunnane and Regan, 1994;). Constraints are placed on such an approach by a lack of knowledge of the workings of the hydrological system, a lack of data and by the volume of complex computations required to simulate every process within the hydrological sphere. Consequently CRR models incorporate large simplifications in order to represent catchment hydrology. One of the major consequences of such simplifications has been the generation of uncertainty within the modelling framework. Oberkampf (2002) divides uncertainty into aleatory and epistemic uncertainty. The former describes the inherent variation associated with the physical system or environment and is irreducible. Epistemic uncertainty is a potential inaccuracy in any phase or activity of the modelling process that is due to lack of knowledge and is thus referred to as cognitive, subjective and reducible uncertainty. Such uncertainty can be seen in the process of parameter estimation with well known limitations being attributable to parameter identifiability, parameter stability, uncertainty and the equifinality of outputs arising from different combinations of model parameters. In many cases where "off-the-shelf" CRR models are applied they are done so without any prior knowledge of the uncertainty associated with model output due to parametric sources. Where uncertainty is catered for, the vast majority of work has used probabilistic methods to represent sources of uncertainty and then sampling methods, such as Monte Carlo sampling, to propagate these sources through the model (Khu and Werner, 2003). Such sampling requires considerable computer power and in situations where the end user was not involved in model construction access to the model source code may be problematic with, the ability to run the model for large samples without intervention being inhibited. In an attempt to overcome some of these problems, this work details the preparation of an "off-the-shelf" type CRR model and the reduction of epistemic uncertainty, derived from parameterisation, for use in climate impact assessment.

GENERAL METHODOLOGY

Daily precipitation and evaporation data obtained from Met Eireann were used to drive the model for a baseline period of forty years (1961-2000). Daily streamflow data for the baseline period were obtained from the Office of Public Works (OPW). For ease of presentation only the river Suir will be dealt with here. The methodology was divided into a number of steps beginning with an analysis of the sensitivity of model output to individual parameters. Parameter specification was aided by the incorporation of a GIS. A split sample procedure based on the baseline 1961-2000 was used for calibration and validation with the latter half of the data being used for calibration given the fact that the 1990's have been the warmest decade on the instrumental record. Problems within the calibration procedure are highlighted and the final step in the methodology was that of uncertainty quantification and the construction of uncertainty bounds for use with downscaled climatic data.

THE HYDROLOGICAL MODEL: HYSIM

HYSIM, is a hydrological simulation model, which uses rainfall and potential evaporation data to simulate river flow using parameters for hydrology and hydraulics that define the river basin and channels in a realistic way. Although spatially lumped and hydrologically conceptual in nature, the model contains many parameters that can be measured from physical reality. HYSIM has been used for a variety of hydrological applications including assessing the impacts of climate change on the hydrological cycle (Pilling and Jones, 1999, Charlton and Moore, 2003). The mathematical model is built around two sub-routines. The first of these simulates the hydrology of the catchment while the second simulates the hydraulics. The complete flow diagram of the structure of the model is given in fig. 1.

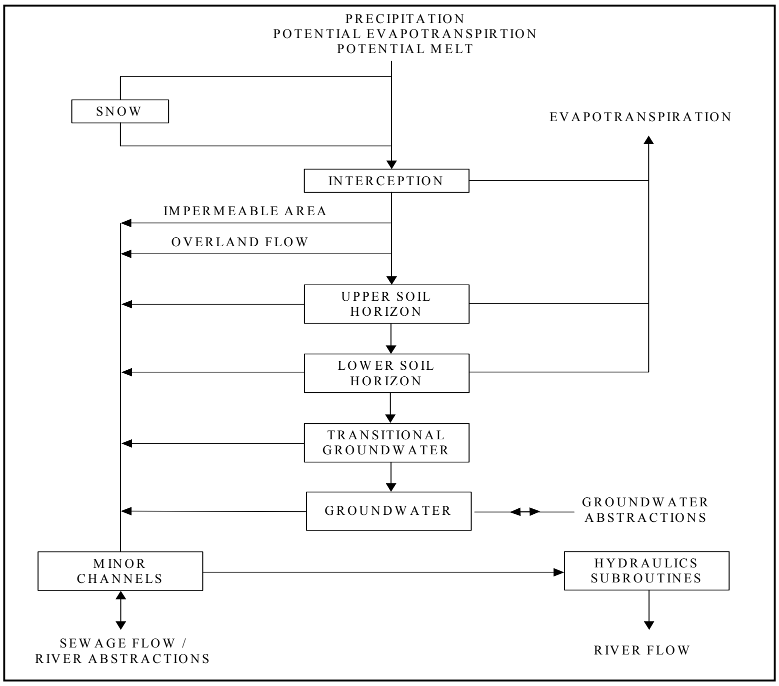


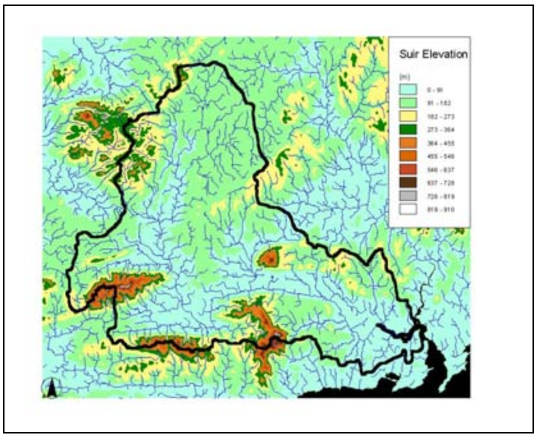
Figure 1: HYSIM Model Structure

Parameters within HYSIM can be broken down into two groups; the physical parameters and the process or "free" parameters (Sorooshian and Gupta, 1995). The former represent physically measurable properties of the watershed whereas process parameters represent watershed characteristics that are not directly measurable such as the lateral interflow rate. There are two approaches to fitting the model that can be taken. The first approach is that of parameter specification. Within this process prior knowledge about watershed properties and behaviour is used to specify estimates for the physical parameters of the model. In relation to the process parameters the idea of specification can only be extended to defining parameter ranges (minimum and maximum values) (Sorooshian and Gupta, 1995). Uncertainty in the parameter estimates is then reduced by the process of calibration using an automatic search algorithm.

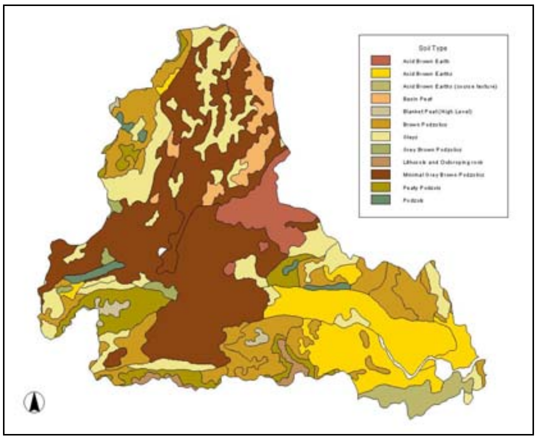
PARAMETERISATION

Parameter Specification

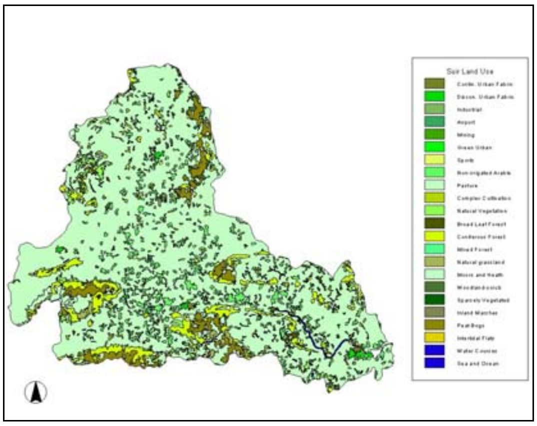
A methodology was established that would result in efficient and accurate parameterisation of the model, especially of those most sensitive parameters highlighted in the sensitivity analysis. Furthermore, this methodology had to be easy to reproduce. Traditionally, such information has been derived manually from maps, aerial photographs and field surveys. These approaches are often tedious and time consuming and subject to considerable subjectivity. Geographical Information Systems (GIS) have been increasingly employed to assist hydrologists with the task of model parameterisation. Since all of these factors vary in both space and time, the use of a GIS offers considerable potential.



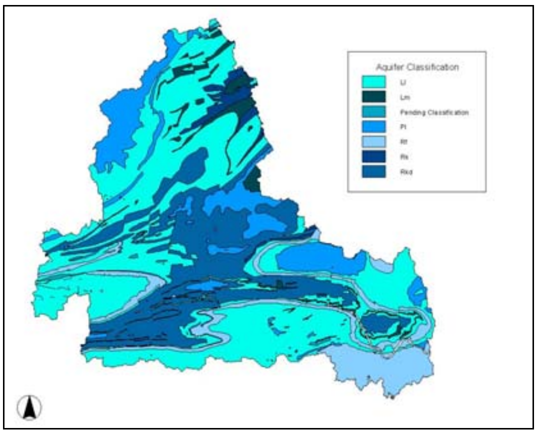
a)Suir Catchment Delineation and Stream Network



b) Suir Soil-type map



c) Suir Land-use map



d) Suir Aquifer map

Figure 2: Parameter Specification

The first method to consider when parameterising the model was that of catchment delineation. In order to derive catchments a Digital Elevation Model (DEM) was used. The DEM has a resolution of twenty metres and comes in a number of different sheets with one DEM grid-file for each EPA hydrometric area. For the purpose of this work the Arc View extension BASIN was used. BASIN extends the spatial analyst interface by allowing the user to perform a number of tasks such as catchment delineation from a point on a stream and the generation of a stream network (fig. 2a).

In order to calculate soil hydrological properties the General Soils Map of Ireland (Gardiner and Radford, 1980) was used. The principle soil and the associated soils are given in each association together with an estimate of their extent and a definition of the association in terms of a profile analysis. Once delineated, the catchment boundary was used to cookie cut the soils data included within the catchment outline (fig. 2b). Textures were found for the top two soil horizons, as HYSIM deals with both the upper and lower layers of the soil. Each association within the catchment was examined and the proportions of the soil type and its location within the catchment were considered. Calculating the area occupied by each association derived the dominant soil texture with this being used to calculate the soil parameters.

Parameters related to vegetation and land use characteristics include impermeable areas, the permeability of the soil surface and the rainfall intercepted by different types of vegetation. Values for these parameters were obtained using the CORINE dataset (Coordination of Information on the Environment) (O'Sullivan, 1994). CORINE provides comprehensive data on biophysical land occupation that are consistent and comparable across Europe. Land use or occupation is divided into 44 classifications at a scale of 1:100000. These classifications are derived by computer-assisted photo-interpretation of satellite images. The catchment area was overlaid on the land use map and the catchment shape was used to extract the relevant information on land use (see fig. 2c). Again, due to the lumped nature of the model the land use with the highest percentage was used to derive the land use parameters.

Groundwater parameters include groundwater recession, the proportion of the catchment with no groundwater, transitional recession, the proportion of the recession that is transitional and the ratio of groundwater to surface catchment. From the sensitivity analysis the most sensitive of these parameters is the groundwater recession rate. Other less sensitive groundwater parameters to be estimated include the proportion of the catchment with no groundwater and the ratio of groundwater to surface catchment area. In order to estimate parameters such as these the Aquifer Map of Ireland (GSI, 2003) data set was employed (figure 2d).

Parameter Estimation

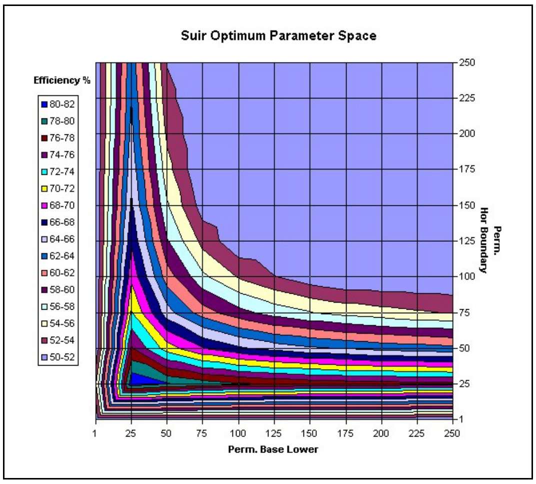
To estimate values for the process parameters the procedure of calibration was initiated. Within HYSIM this is catered for by a multi-parameter optimisation procedure, in which several parameters are changed, using an optimisation algorithm, in order to find the best value of an objective function in the parameter space or response surface. Many different optimisation strategies and computer codes are available with virtually all methods belonging to a class of mathematical procedures called improvement strategies. These begin with a first guess of the solution and then progress iteratively within bounds in order to improve the initial guess by following a set of guessing rules (Sorooshian and Gupta, 1995). HYSIM employs the Rosenbrock method, a local search algorithm using a direct search method. These algorithms search along trial directions from a point until an improvement in the objective function is found (Beven, 2000), with different algorithms varying in the search strategies used. The Rosenbrock method can be imagined as searching for a minimum contour in multi-dimensional space (Manley, 1993). The algorithm places the greatest weight on the first parameter made active for optimisation (Blackie et al, 1985). The strategy starts by incrementing each parameter by 10%. If this is successful then the step is multiplied by a factor of three, if it is unsuccessful then the step is multiplied by a factor of -0.5. On completion of the first direct search iteration, the parameter axis or direction of the search is changed by aligning the axis of the prime parameter with the vector joining the origin and the latest minimum contour value (Blackie et al, 1985). A trial is considered successful if it does not lead to a worsening of the objective function. This, rather than an improvement is used as the criteria to enable the algorithm to exit even if a parameter has effect on the results (Manley, 1993) This process is continued for each parameter until either an improvement followed by a failure has occurred for that parameter, or an almost negligible improvement has been followed by another. A new set of directions is then searched. This process is repeated until either the maximum permissible number of iterations is exceeded, or the improvement between stages is less than a specified amount. The cessation of the search strategy indicates the arrival at the optimum parameter set.

Problems associated with calibration

Once the optimum parameter set was realised it was necessary to examine if the results relate to a local or global optimum. One satisfactory way of doing this is to restart the algorithm iterations with the new set of parameters. By repeating the process from a new starting point a larger area around the optimum may be searched (Blackie et al, 1985). In doing this, a number of problems were encountered. When different starting points were used, different end values were encountered due to problems related to the parameter response surface and the obstacles confronted by the search algorithm given the non-linearity of the model. Sorooshian and Gupta (1995) highlight a number of difficulties associated with the parameter response surfaces that apply to CRR models. These include the presence of several major regions of attraction, into which the search algorithm may converge, with each major region of attraction containing numerous local minima. Furthermore, where parameters exhibit varying degrees of sensitivity a great deal of interaction and compensation may be evident, with much of this interaction being highly non-linear (Sorooshian and Gupta, 1995).

These obstacles make it very difficult if not impossible for a local search strategy such as the Rosenbrock method to progress towards a global optimum. Such obstacles are displayed in the contour plots produced for selected process parameters where the concept of parameter interaction in the form of log narrow ridges is present in fig. 3a and multi-modality is shown in fig.3b, making progression from these areas very difficult. As a result no confidence can be placed in the optimum parameter set achieved by this procedure and a large amount of uncertainty is introduced to output from the HYSIM model. As a result the concept of the existence of an optimal parameter set was rejected and replaced with the concept of equifinality. Equifinality rejects the existence of an optimal parameter set in favour of multiple possibilities for producing simulations that are acceptable simulators (Beven and Freer, 2001).

3a



3b

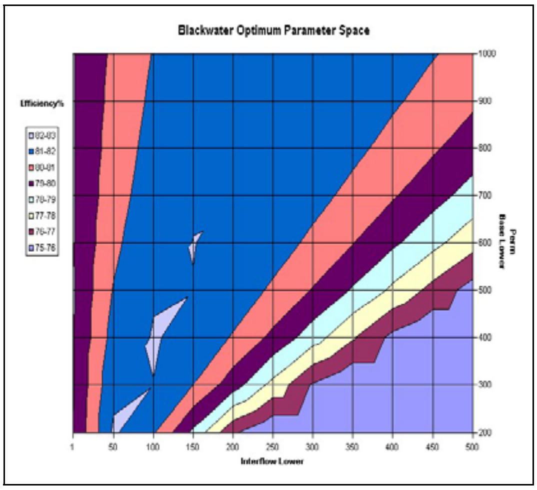


Figure 3: (a) Long narrow ridges in response surface making it difficult for optimisation strategy to progress and (b) multiple peaks highlighting the concept of equifinality.

UNCERTAINTY ANALYSIS

Given the epistemic uncertainty derived from the calibration procedure it is necessary to quantify the propagated uncertainty associated with model output. Uncertainty analysis can be viewed as the study of functions of the form $Y=f(x)$. Where the function f represents the model under study, $x=(x_1, x_2, \ldots)$ is a vector of model inputs and $Y=(Y_1, Y_2, \ldots)$ is a vector of model predictions. The goal of uncertainty analysis is to determine the uncertainty in the elements of Y that result from uncertainty in the elements of x. One established method that can be used in uncertainty analysis is the Generalised Likelihood Uncertainty Estimation (GLUE) procedure developed by Beven and Binley (1992). GLUE recognises the need to quantify the reliability of model simulations and starts with the recognition that many model structures or parameter sets within a given model framework will simulate a required output. Given this concept of equifinality it follows that no single optimum set of model parameters can be readily identified (Beven, 1993). Consequently it is only possible to assign a likelihood value to each parameter set, indicating that it can predict the system and that the set of parameters provides an acceptable or behavioural simulation of the observed flow (Beven and Binley, 1992). The GLUE procedure has five main steps:

1. The first and most subjective part of the procedure is the definition of a likelihood measure. This is chosen on the basis of an objective function to determine model performance. The choice of likelihood measure has significant influence on the results obtained as it influences the likelihoods found for parameter sets and their distribution as well as altering the posterior distribution and associated uncertainty bounds calculated for model output.
2. For each of the parameters a prior distribution must be defined, from which parameter sets will be sampled. These prior distributions reflect the prior knowledge on this parameter, with the range of the distribution being based on reasonable values from literature and expert knowledge.
3. A large number of parameter sets are sampled using Monte Carlo Random Sampling (MCRS) from the prior distributions (Brazier et al, 2000 used up to 3 million, Beven and Freer, 2001 used 60,000). The model is then run using these parameter sets and the model outcome of each run is compared to the observed values using the selected objective function. Based on the value of this objective function a likelihood value is assigned to each parameter set, the distribution of the likelihood function is then normalised to create a posterior distribution of likelihoods (Beven and Binley, 1992).
4. Each parameter set is classified as behavioural or non-behavioural through assessing whether it performs above or below a pre-defined threshold. All non-behavioural parameter sets are removed from the analysis. The likelihood values of the behavioural parameter sets are again normalised.
5. Subsequent predictive model runs generate results from each of the parameter sets that yield acceptable calibration simulations, thus satisfying the likelihood threshold. These combined simulations are in turn used to determine the weighted mean discharge and simulation probability bounds (Melching, 1995).

In many applications of conceptual rainfall-runoff models where the user is not the original author of the model, the program source code is not available. In such “off the shelf” type models the modeller is often unable to alter the model code so as multiple model runs can be made without user intervention. This can be problematic when using MCRS as described in the Glue methodology where many thousands or even tens of thousands of model runs are required to adequately sample the entire parameter space.

In order to overcome this obstacle, quasi-stratified sampling in the form of Latin Hypercube Sampling (LHS) (McKay et al, 1979) can be applied. LHS selects n different values from each of k variables $x_1 \ldots x_k$, by dividing the range of each variable into n non-overlapping intervals on the basis of equal probability. One value from each interval is selected at random with respect to the probability density in the interval. The n values thus obtained for x_1 are paired in a random manner with the n values of x_2. These n pairs are combined in a random manner with the n values of x_3 to form n triplets, and so on until n k-tuplets are formed (Iman and Helton, 1988). In comparing uncertainty analysis methods Yu et al (2001) and Melching (1992) have investigated the success achieved in adopting a number of different procedures, including MCRS and LHS. Yu et al (2001) used three verification storm events to compare various methods of uncertainty analysis by examining derived uncertainty bounds. The results obtained from the MCRS (1000 runs) were assumed to be the standard outcome. Findings indicated that only LHS produces results similar to the Monte Carlo approach. The authors concluded that LHS could generate representative samples more efficiently than MCRS due to characteristic uniform sampling of the parameter space. By comparing the convergence rates of the two sampling procedures it was found that for LHS both the mean and standard deviation of model output statistics converge to constant values when the number of samples are equal to 100. On the other hand MCRS required approximately 1000 realisations in order to converge to constant values.

Taking the above results into consideration and given the inability to automate the modelling procedure a technique based on the GLUE methodology is adopted here, with MCRS being replaced with Latin Hypercube sampling. This approach has been widely used in environmental modelling studies, however, examples using hydrological models are less numerous and the majority of applications have been in the context of complex, spatially distributed models.

RESULTS

In the work conducted here for the Suir Catchment at Clonmel, the Nash-Sutcliffe efficiency criterion was adopted as the likelihood measure with behavioural parameter sets taken as those with an efficiency value above 70%, with 60% being indicative of a satisfactory model. A uniform distribution was attributed to each process parameter (as proposed by Beven, 2001) and samples were generated using LHS. Recommendations for the necessary number of model runs vary in the literature. Iman and Helton (1985) suggest sampling two to five times the number of varied model parameters. Selection of runs in this way is rather subjective. Melching (1995) proposed to define the number of model runs necessary by checking for convergence of statistical measures of model output on the number of executed model runs. The analysis of convergence rates for the HYSIM model show that the generation of 100 samples is adequate (fig.4).

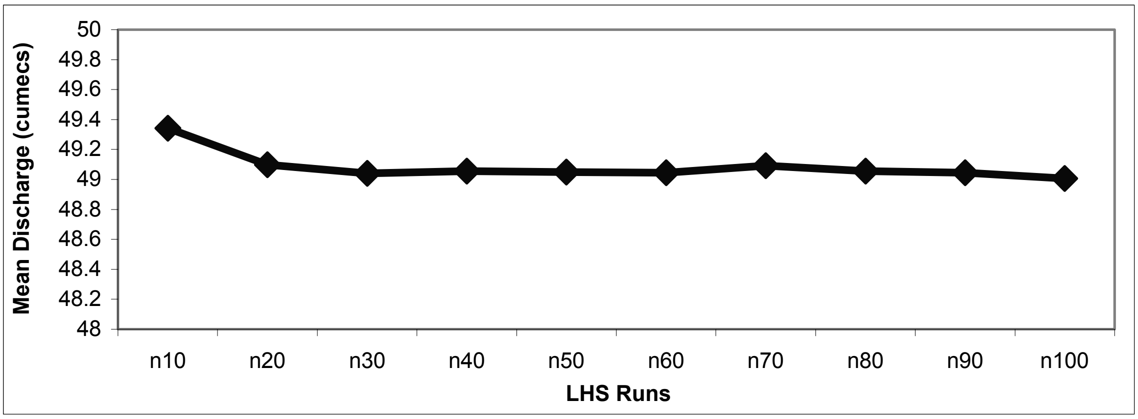


Figure 4: Mean discharge convergence for Suir LHS

From these samples 43 were retained as behavioural parameter sets. These parameter sets were in turn used to calculate the probability distribution of model output for each modelling time step and uncertainty bounds for model output were generated using the 5th and 95th percentiles at each temporal interval. From the uncertainty bounds constructed for the period of October to November 2000 (**fig.5**), it can be seen that the measured data are contained quite well within the upper and lower percentiles. Minimum and maximum values are plotted as uncertainty bounds or confidence limits, chosen to represent model uncertainty at each time-step. These uncertainty bounds incorporate the epistemic uncertainty derived from uncertainties associated with data measurement, model structure, and parameterisation.

When comparing the results obtained by the optimisation procedure and the GLUE approach for the validation period 1961-80, the GLUE methodology is more successful. In order to assess how each set performs model output was assessed both on a seasonal basis (DJF, MAM, JJA, SON) and in terms of the entire validation period (1961-80). The measurements employed include the coefficient of efficiency (CE), the coefficient of determination (R^2), the index of agreement (d), the mean actual error (MAE) and the percent bias (PBIAS). Both correlation and relative error measures were included as the use of correlation-based measures alone can be over sensitive to extreme values and are insensitive to additive and proportional differences between model predictions and observations (Legates et al, 1999). The modelled and observed means are also compared. In order to aid in the visualisation of model performance scatter plots were constructed on a seasonal basis.

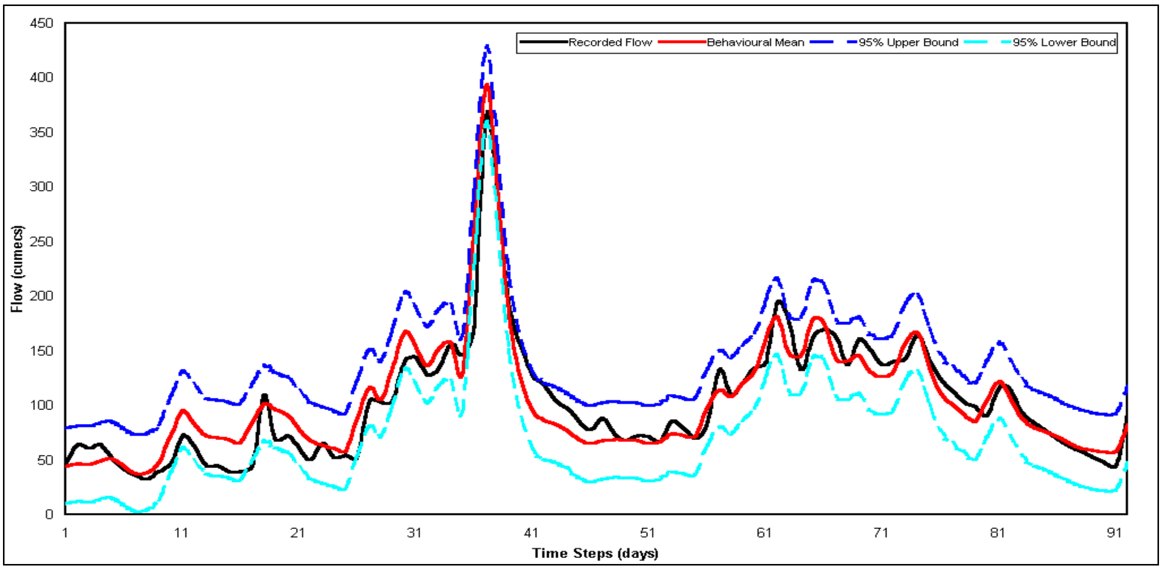


Figure 5:Uncertainty bounds calculated for the river Suir at Clonmel (10/2000 to 12/2000).

On every level of comparison the behavioural mean performs better in terms of the correlation based measures with the relative error being slightly more on a number of occasions such as the MAE and PBIAS for winter and summer. Consistently higher values of CE are particularly reassuring as this measure is sensitive to differences in the observed and modelled means and variances. The limitations of the optimisation routine are evident with the mean behavioural parameter set providing a better fit to the observed data than the parameter set optimised by the Rosenbrock method.
In terms of seasonal performance both models perform quite well during times of high flow with good results being achieved during winter and spring. Summer simulations are more problematic with correlation-based measures being quite low with only around 50% of the variance in observed flows being captured by both parameter sets. However, the relative error based measures are reassuring.

An improvement in error measurements is found during august given the recharge of stores. This pattern is again evident when scatter graphs are constructed on a seasonal basis for the validation period (**Figure 6**). Both models perform reasonably well for the wetter seasons of winter and spring with the behavioural mean again showing itself to perform marginally better. However, summer results again prove to be more problematic. From the scatter graph for the summer season the graphs show a distinct V-shape or funnelling providing evidence of heteroscedacity. This is indicative of a changing variance as flows increase with poorer results evident as summer flows increase. This may be due to the inability of the model to represent streamflow from summer convective storms producing high volumes of precipitation in a small space of time. Once again the performance of both parameter sets improves for the autumn season.

Figure 7 shows the comparison between the behavioural mean and the optimised model output in relation to observed flows for four selected years. For each year good simulations of mean and low flow conditions are achieved for both procedures with the behavioural mean again performing slightly better. This is especially encouraging for the years 1975 and 1997 with the former being the representative year for a change point in observed trends in Irish streamflow records (Kiely, 1999), whereas 1997 was the warmest year recorded for Ireland in the 1990s, the warmest decade in the global instrumental record. In relation to high flows there are flood events for which both approaches fail to capture the peaks adequately. For the optimisation procedure this is a major limitation and no confidence can be placed in how this single parameter set will perform outside of the calibration conditions. In relation to the behavioural parameter set it must be remembered that given the large number of behavioural parameter sets captured, these flood peaks will be included within the uncertainty bounds.

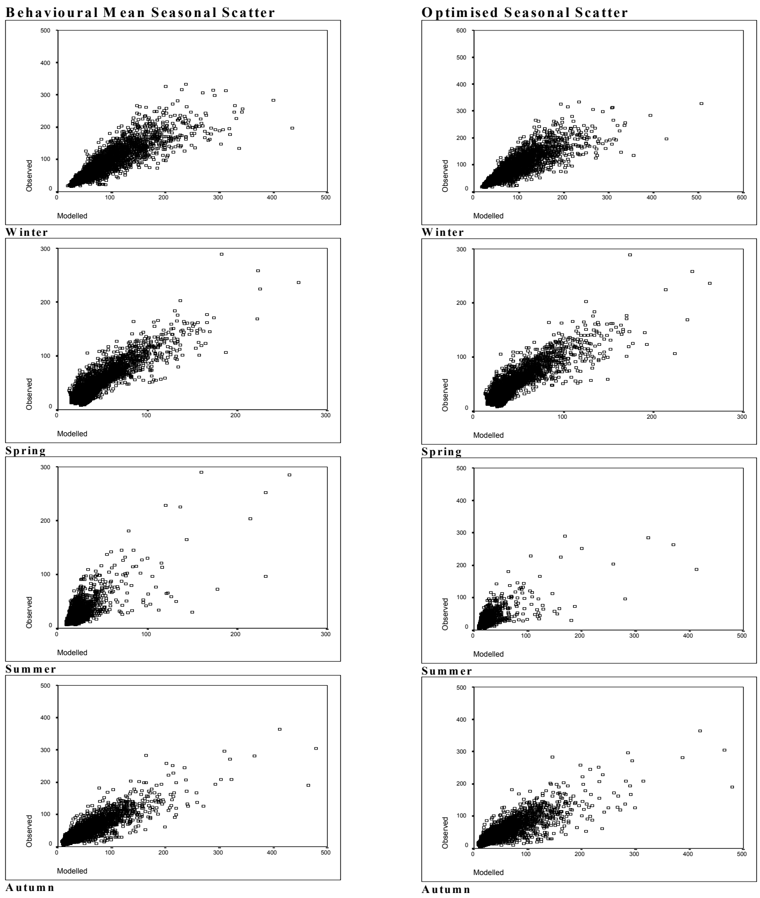


Figure 6: Scatter graphs produced for the behavioural mean and optimised models.

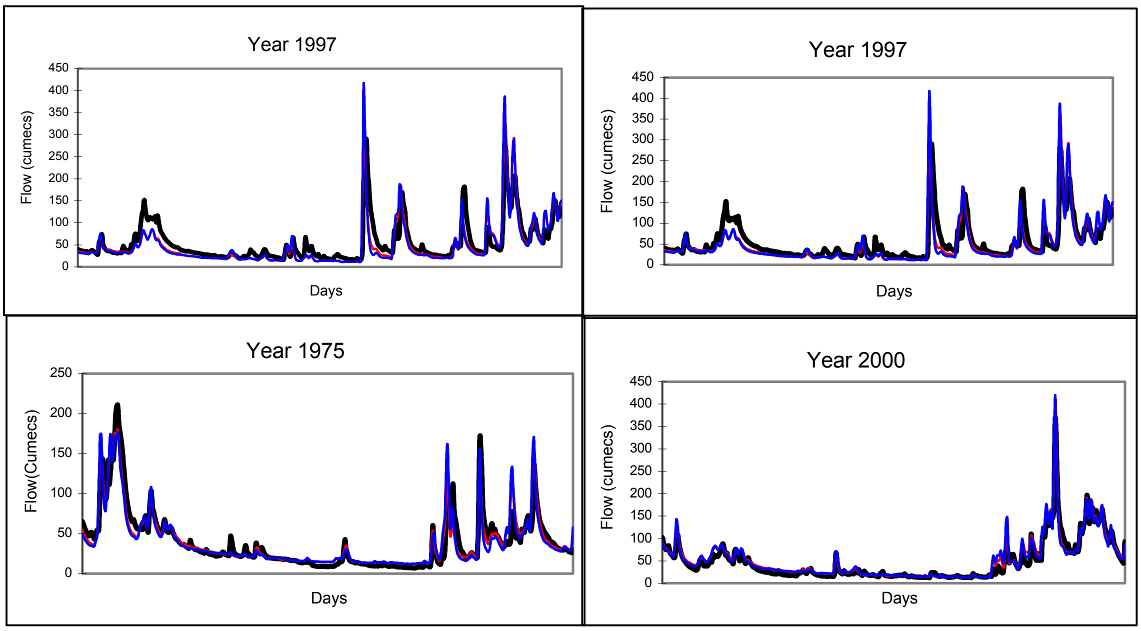


Figure 7: Comparison of behavioural mean and optimised model output for four selected years

CONCLUSION

Changes in Irish climate may pose a number of obstacles for water resource management. There is a need to approach this problem using the catchment as the basic unit of analysis. The methodology established results in the successful application of HYSIM to a suite of catchments in Ireland, with satisfactory results being obtained across a wide variety of basins. However, further analysis on the residuals of the summer results need to be undertaken. Large amounts of uncertainty can be derived from the use of CRR models in environmental impact assessment. The limitations associated with the parameterisation of an "off-the-shelf" type model and the inability to automate certain processes has been overcome by the incorporation of Latin Hypercube Sampling. This procedure provides an efficient and feasible sampling methodology in the absence of the ability to consider large Monte Carlo random samples. The uncertainty bounds constructed incorporate the error derived from model structure, data measurement, parameterisation, and lack of knowledge in the process parameters and can thus be used to quantify uncertainty in model simulations beyond the baseline calibration period. Finally, given the application of the GLUE methodology, the procedure adopted allows easy updating of the likelihood weights and thus uncertainty bounds as more data becomes available.Having successfully prepared and calibrated the model, statistically downscaled data of a daily time step from a selection of synoptic stations will be used as input to the model. Daily sequences of wet and dry days and rainfall amounts downscaled for each site and season using a generalized linear modelling technique and potential evapotranspiration (PE) will be used to drive the model for each of the selected catchments. Output will be used to answer prominent questions such as what the future is likely to hold for Irish water resources in terms of floods and droughts as well as the magnitude and frequency of their return.

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