

BRITISH HYDROLOGICAL SOCIETY

Flood forecasting:

What does current research offer the practitioner?

BHS National Meeting
University of Bristol
28th March 2000

Edited by Matthew Lees and Peter Walsh

BHS Occasional Paper No. 12

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Preface

The papers contained in this Occasional Paper are based on presentations made at the national meeting of the same title held at Bristol University on 28th March 2000.

The aim of the meeting, proposed by BHS President Professor Howard Wheater, was to present recent research on Flood Forecasting and for the research community to share this with the user community. The Easter 1998 Floods drew attention to the limited application of state of the art flood forecasting techniques in real time use, as well as identifying the need for a major overhaul of the arrangements for and the content of warning messages. New flood warning codes were introduced in England and Wales on 12th September 2000.

In addition to papers from many UK leading research centres, the meeting included a paper on recent developments to the weather radar network and the products produced by the Meteorological Office. These products are an invaluable source of input data to flood forecasting models. The meeting also learnt about proposed changes to the form of warning messages and other aspects of the Environment Agency's response to the Independent Review of the Easter 1998 Floods (Bye Report).

Over 80 people, representing a good mix of research and operational forecasting practitioners, attended the meeting and contributed to a lively discussion.

These papers provide a valuable overview of current research into flood forecasting and should contribute to wider appreciation of their potential to improve the flood forecasting and warning process.

Matthew Lees and Peter Walsh

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Developments in Weather Radar and Weather Services

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1. Introduction

The UK weather radar network in England and Wales has existed in its present form since 1989. The investment in the network has been justified on the basis of the timeliness and the spatial coverage of the data compared to those from feasible networks of gauges. The main limitation in its usage has been the uncertainty in the quantitative estimates of rainfall that can be inferred from radar data. During the last decade, development work has therefore concentrated on improving the quality of the rainfall products. In particular, some long-standing faults in the radar hardware have been revealed by improved monitoring. Introduction of radar data quality control and correction routines in the Nimrod system has resulted in a measurable improvement in the quality of the rainfall estimates (see e.g. Harrison et al. 2000, Kitchen, 1999).

A recent flooding case which both demonstrates the potential of weather radar in flood forecasting; and also suggests some further development priorities, is illustrated in Figs. 1 and 2 (taken from Johnson, 1999). This relates to flooding in the town of Freshwater on the western tip of the I.O.W. On the 1st June 1999, approximately 40-50mm of rain fell over a few hours in a small, ungauged catchment that has a time-to-peak of less than 1 hour. Although the nearest real-time raingauge was only a few kilometres away at Calbourne it recorded only about half the rainfall that fell at Freshwater.



Figure 1. *Map showing the location of Freshwater.*

The case highlights the following issues:-

- The radar data correctly identified a local maximum in storm rainfall in the affected catchment and showed that the available gauge data were not representative. Radar could have been the crucial observational input into the flood forecasting process. Flood warnings based mainly upon radar products would require the data to be reliable and of known accuracy.

- The available 5km resolution data was inadequate to properly resolve the spatial variations in rainfall, even those in the storm total accumulations.
- The very short time available for flood warning highlights the importance of rainfall forecasts, which also must be available at high enough resolution.

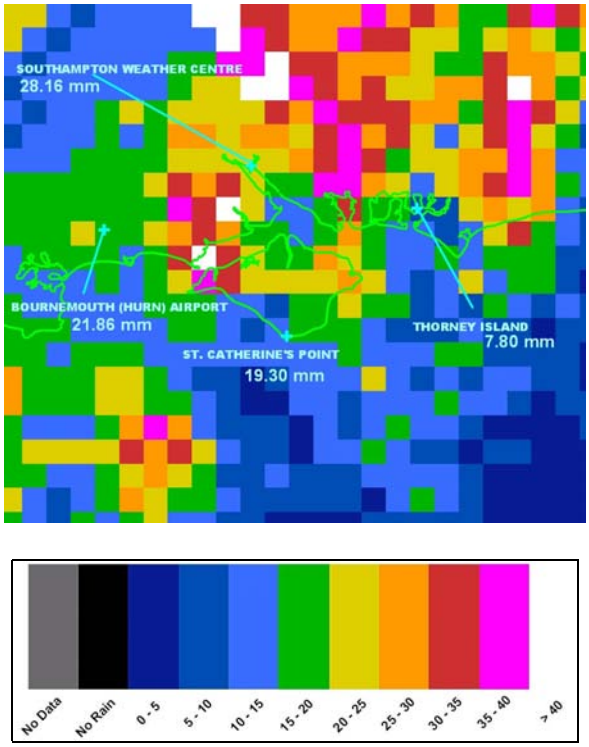


***Figure 2**. Radar accumulations in mm for the period 2100UTC 1st June – 0600UTC 2nd June 1999, with some gauge accumulations overlaid.*

The Met. Office and the Environment Agency, as joint owners of the radar network in England and Wales, are now funding work to secure the future of this network. The opportunity is being taken to make improvements in the above areas, where this can be done cost-effectively. These improvements are described in section 2 below.

The high spatial variability in the rainfall exhibited in the Freshwater case, among others, suggests that systems for the automated monitoring of radar accumulations are essential to be able to make the best use of the data. Analysis of the larger scale flood events of recent years have suggested that some other improvements in hydrometeorological data are required to better support flood forecasting. For example, antecedent catchment conditions were important in the Easter 1998 floods and melting snow contributed to the 1999 flooding in the Derwent valley. These issues are being addressed through development of higher resolution and timely hydrometeorological information, additional raingauge data, display and management software and experimentation with impact modelling. These concepts are explored in section 3.

2. Radar Developments

2.1. 1km resolution radar data

A new radar site processor has been developed by The Met. Office to replace obsolete equipment dating from the initial radar installations. The new processor is currently operational at Chenies and will be rolled out to

other sites in the network during 2000/1. The increased processing power has enabled a new 1km / 5 minute resolution product to be generated which includes data out to a range of 50 km from the radar. Beyond 57 km range, the radar beam is itself more than 1km wide and so there is little advantage in processing data at this resolution from longer ranges.

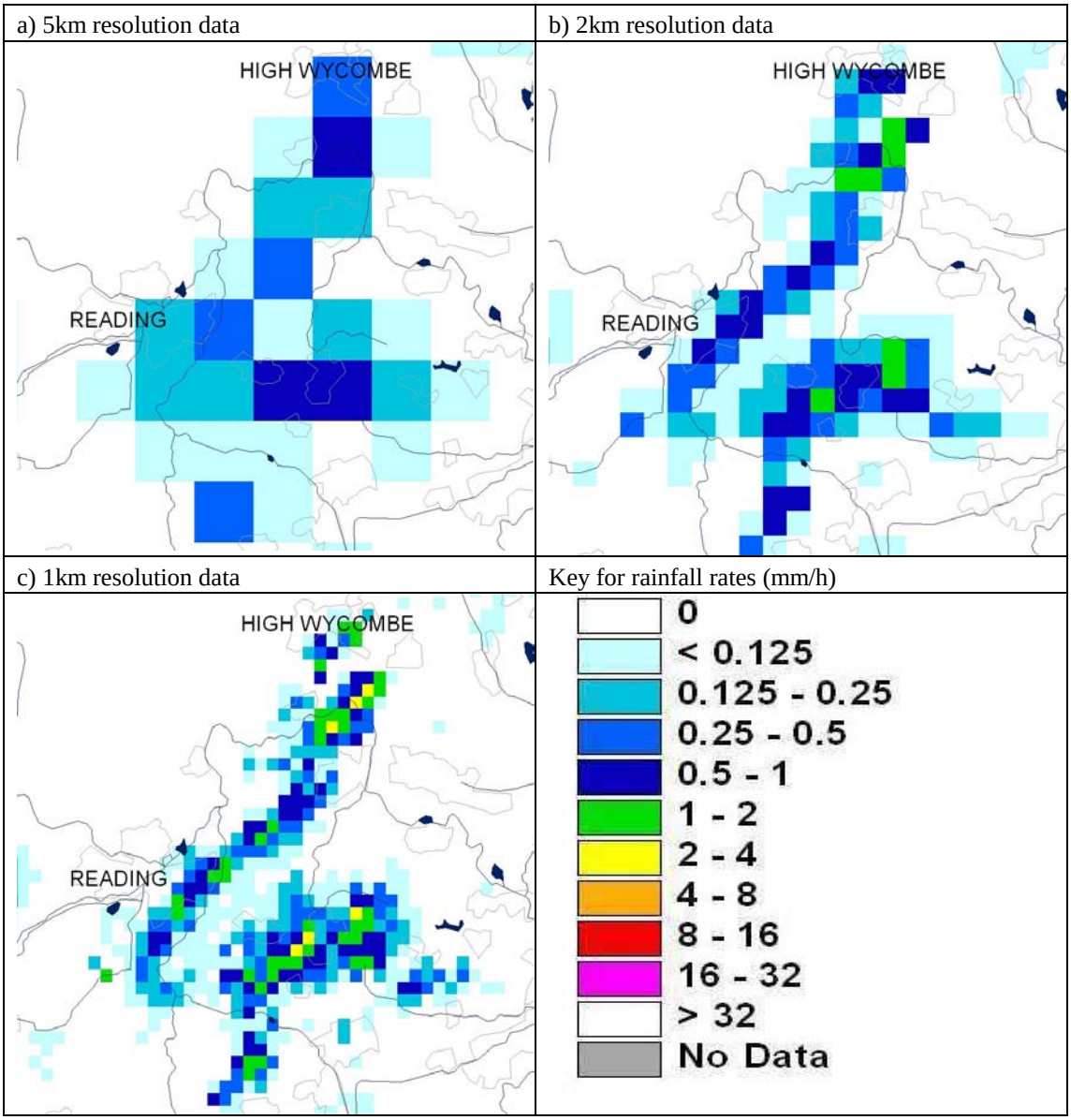


Figure 3. *Example of radar images at different horizontal resolutions – Chenies radar, 15/09/99 at 1800UTC*

Fig 3 shows a set of radar images, all from the same time, but at 5, 2 and 1km horizontal resolutions. They show areas of mainly light rain over East Berkshire. The higher resolution 2 and 1km images reveal the presence of embedded convective cells producing moderate rainfall rates. 1km data will soon be available covering some of the major conurbations in England, and this resolution may be of value in flood forecasting within small urban catchments.

2.2. Improved Rainfall Detection

The new radar site processor has also provided an opportunity to improve more fundamental aspects of the radar signal processing. It has proved possible to lower the minimum detectable signal without causing an increase in the number of spurious echoes detected. In some cases of light rain, the area of rainfall detected by the Chenies radar has been increased by more than 50%. The benefits are not confined to light rain cases, because weak signals from storms at long range are also now more likely to be detected, unless all the rainfall is beneath the radar beam. This improvement justifies an increase in the radar coverage at 5km resolution from the current maximum range of 210km up to 250km.

2.3. 2km Resolution Radar Products

2km resolution data have always been available from individual radar sites. Currently, almost all the composite radar products provided to the Environment Agency from the Met. Office are at 5km resolution. 2km resolution data currently extends out to a range of 75km from each radar, and the coverage is far from complete (Fig 4).

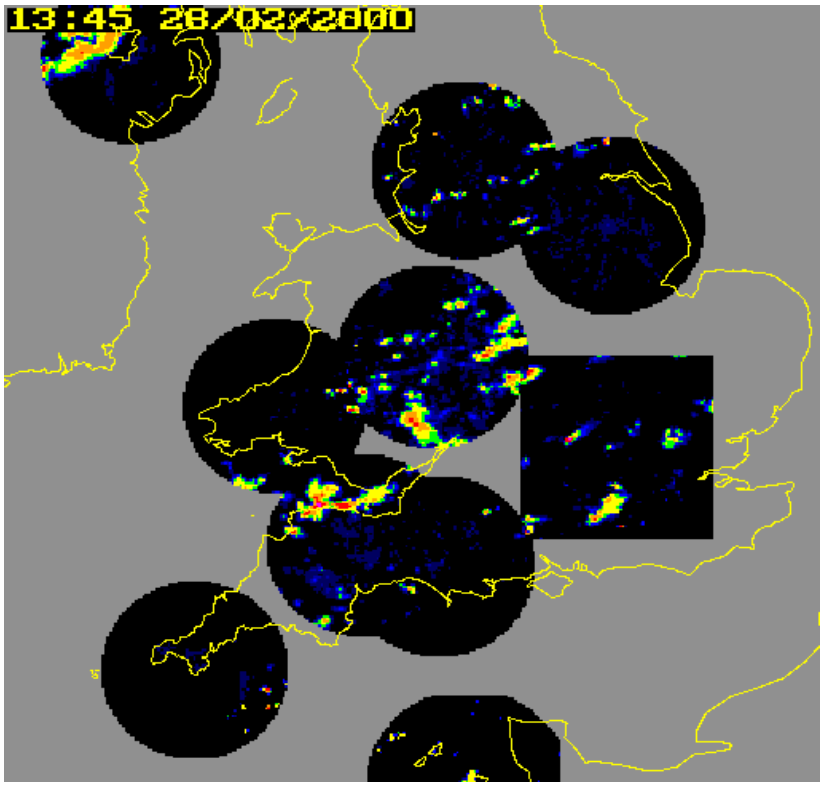


Figure 4. *Example of a 2km resolution radar composite.*

Currently, in 2km resolution network products, the gaps in coverage are ‘filled in’ by substituting 5km resolution data. However, as the processors at the radar site are being replaced, the opportunity is being taken to increase the domain of 2km coverage out to 100km range from the radar. This will remove some of the more important ‘gaps’ over the land area of England and Wales which are apparent in Fig 4.

This in turn will pave the way for production of 2km resolution rainfall forecasts. These will then be capable of being integrated with forecasts from the Gandolf thunderstorm forecasting system, which already provides products at 2km resolution.

2.4. European Radar Data

Radar coverage is being further improved by integrating data from radar sites on the near continent into standard radar products. Acquiring data direct from the radar sites is necessary to enable the Nimrod quality control and correction procedures to be applied. It has been facilitated by the recent adoption of a standard format for exchange of radar data within Europe.

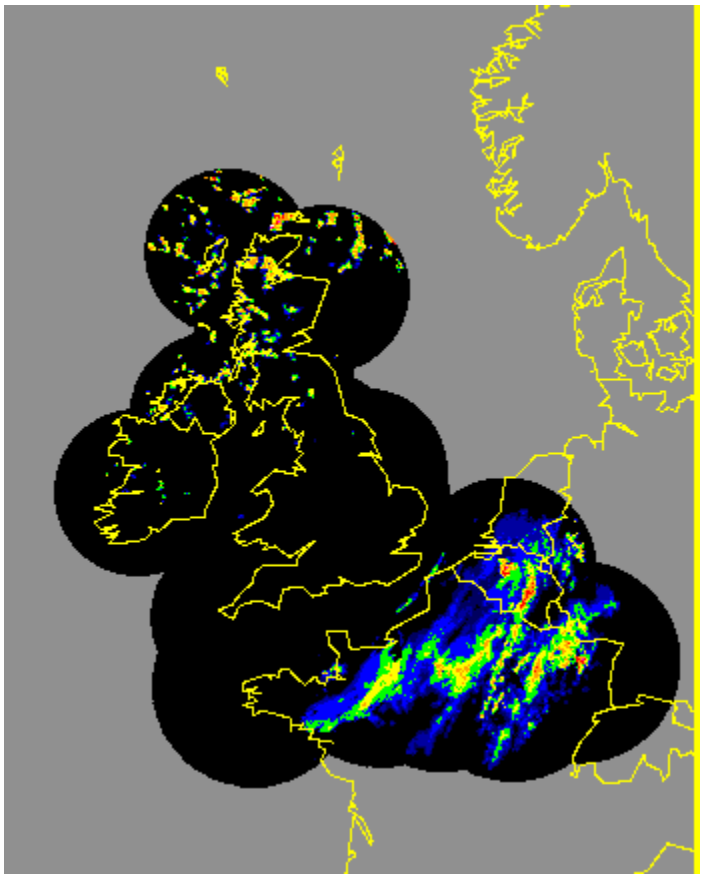


Figure 5. *Example of a Nimrod composite incorporating data from radars in Northern France and Belgium.*

By the end of 2000, it is hoped to routinely incorporate data from Northern France, Belgium and Holland. The benefits for flood forecasting are anticipated to be:-

- Improved forecasts of severe summertime thunderstorms moving up from France to affect Southern Counties (specifically longer lead-times).
- Improved forecasts of convective storms generated over the North Sea and affecting the East Anglian coast.
- Backup radar coverage over Kent.

3. Development of Weather Services

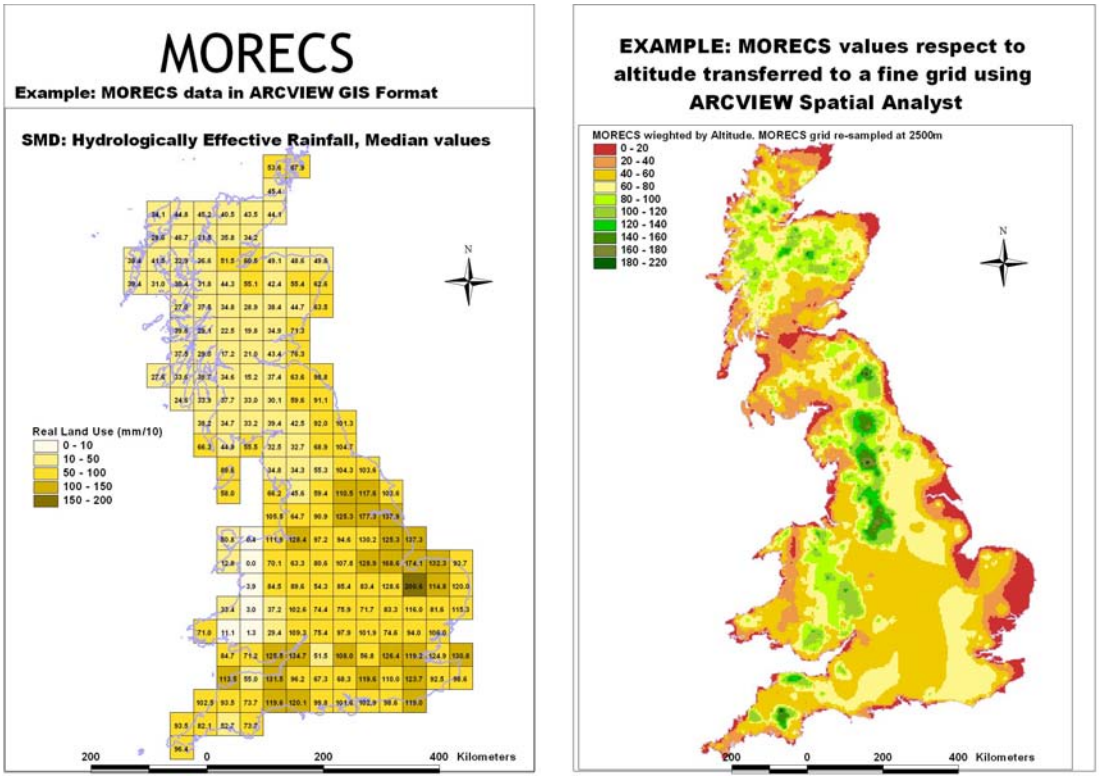
3.1. Telemetered raingauge data

Despite the improvements in the radar performance described in section 2, there are fundamental limitations in data quality at long range because of the height of the radar beam above the ground. The Met. Office and the

Environment Agency will be conducting a review of radar coverage over England and Wales during 2000 to see where improvements are required. Complimentary to this activity is another joint project to look at each organisations requirement for raingauge data. Following on from the latter will be an implementation project to collect timely raingauge information from over 900 telemetered gauges and integrate these readings with the radar information. Better resolution and more accurate rainfall accumulation estimates are anticipated from this initiative. It is anticipated that a primary product will be daily rainfall totals on a 5km grid for use in the calculation of antecedent catchment conditions.

3.2. Antecedent conditions

The independent report on the Easter 1998 floods (Bye, 1998) pointed to the need for raingauge network collaboration and for better information on catchment conditions to be made available to flood warning officers. Currently soil moisture deficits and estimates of Hydrologically Effective Rainfall (HER) are calculated by MORECS (Hough et al, 1996) for 40km squares on a weekly basis. Whilst this provides a good overview of the soil moisture status on a regional scale, it is inadequate for monitoring and modelling small catchments such as those involved in the Freshwater Flood (see section 1). Most meteorological parameters used in the calculations, (radiation, wind speed, temperature and vapour pressure) are spatially relatively consistent. But the factors giving rise to most variability in the calculations are land use, soil type and most significantly rainfall. High-resolution datasets are now available to adequately describe the first two. With the prospect of better quality rainfall totals from the projects described in section 3.1, it is planned to provide MORECS calculations at 5km resolution on a daily basis. An example of a current MORECS product alongside a simulation of a new high-resolution product is shown in Fig 6.



(a) (b)

Figure 6. *Comparison between an example of a current MORECS 40km resolution product (a) and a mock-up of a new 5km resolution product (b).*

These developments will provide better assessments of catchment scale effective rainfall for flood warning officers. More timely information on soil moisture deficits will also improve low-flow modelling and aid water resource management. Other relevant parameters which exhibit high spatial variability are snow depth and snow melt rate, both of which can be included in the new system.

3.3. Improved data handling

These improvements are of little value if users cannot receive meteorological data and products and manipulate the information for their own purposes. Historically systems have been developed that manage a defined data stream and provide a bespoke display and/or user interface. Obviously there are various degrees of sophistication in these systems, but changes to either data input or display functionality requires significant software modification. With the advent of GIS software, users have much greater flexibility to choose both inputs and display options. For example, a user may wish to show rainfall accumulations over various time scales, display with river gauge information, and overlay with catchment boundaries or urban areas. Road and rail operators will want to overlay different weather parameters on their own networks. GIS applications can be constructed which are able to ingest a variety of meteorological fields. An example of rainfall totals using Nimrod data is given in figure 7.

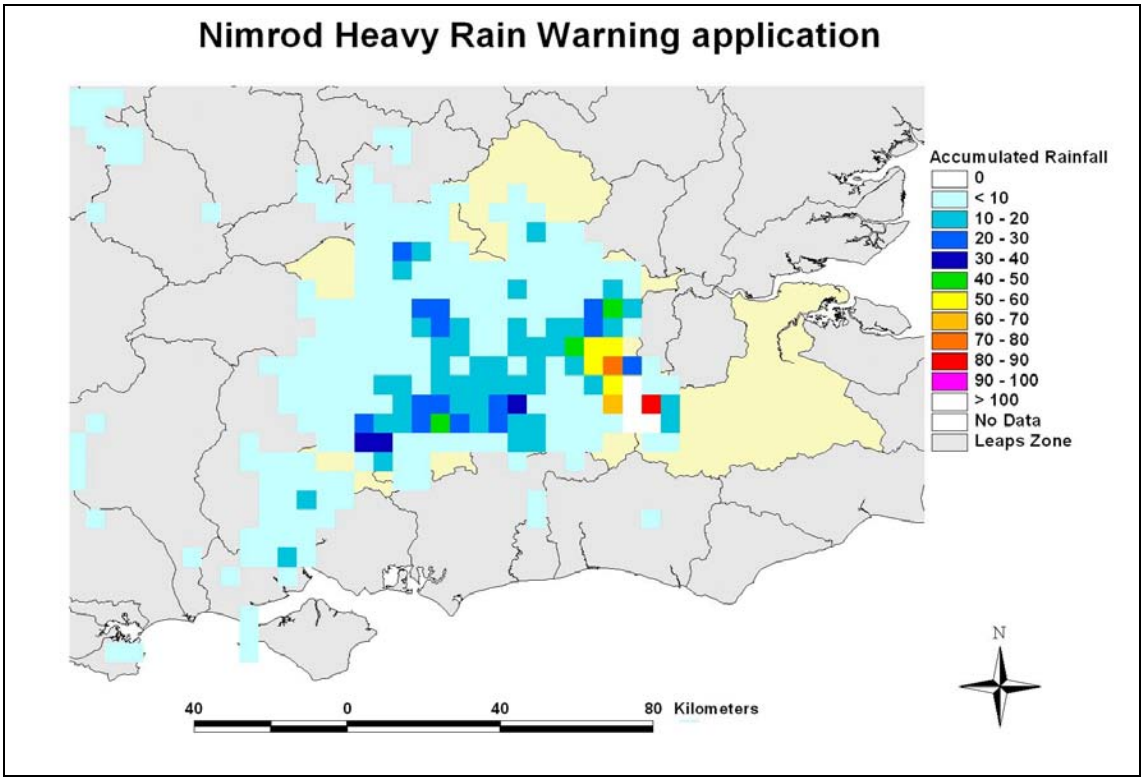


***Figure 7**. Example of rainfall accumulation data displayed using a GIS.*

3.4. Impact Modelling

So far, we have considered improvements that can be made to hydrometeorological data that is input into the flood warning process. Any benefits should be realisable because the Environment Agency have established methods of relating meteorological factors to the incidence of flooding. However, relatively few of the potential

users of weather information are in a position to interpret data in terms of likely the impact of weather upon their business or operations. Accordingly, the Met. Office has been working on a severe weather impact model, which aims to assist users in this respect and provide some guidance as to the likely impact on society. As the name implies, it has been developed for several classifications of severe weather - fog, wind, snow and rime ice. Table 1 shows the weather variables and areas or assets upon which they are judged to have a significant impact.

Table 1. *Weather Variables and Affected Assets included in the Impact Model*

Asset Sectors	*Severe Weather Parameter*				
	Wind	Snow	Rain	Fog	Ice
Residential	*		*		
Commercial	*		*		
Local Authority	*	*	*		*
Transport	*	*	*	*	*
Emergency Services	*	*	*		*
Telecommunications	*				*
Electricity	*				*

An underlying assumption within the model is that, over the course of time, the infrastructure in each of the asset sectors have largely adapted to prevalent climatology. Forecast weather events are then categorised according to their severity based upon their return period for that parameter and geographical area. Physically based algorithms are then used to calculate damage which is then related to the underlying assets within affected postcode districts. Use is made of a GIS database in the last two processes. Note that fluvial and coastal flooding is outside the scope of the model at present; the only modelled impact of heavy rainfall is through surface water flooding.

The model is about halfway through its development cycle and only a single pluvial flood case has been tested to date. This is the Folkestone storm case of 12 August 1996 when over 100mm of rain fell in a period of a few hours. 464 properties were flooded internally and the cost to the local authority was £430,000 (Russell, 1996). Given the observed rainfall (i.e. the model was not run in forecast mode), the severe weather impacts model calculated that 417 homes would have been damaged.

Although this level of agreement is fortuitous, it suggests potential to extend these techniques to aid flood warning officers and emergency authorities. Over the coming year the model will be refined and tested expanded to include other heavy rainfall events, including the Freshwater flooding case described in Section 1.

4. Conclusions

- The potential for weather radar as a flood warning tool has been reinforced and several developments identified. Notably new site processors have been installed and a replacement programme initiated which will lead to the availability of 1km resolution data every 5 minutes out to 50km range of each radar.
- Improved coverage at 2km resolution which will enable further development of rainfall forecasts at this resolution. Incorporating data from radars in Northern France, Belgium and Holland will also improve rainfall forecasts in Southern England.
- The combination of data from the radar network with that from Met. Office and Agency real-time gauge networks should improve the quality of daily accumulation fields over what can be achieved

using any of the networks independently. Reliable, high spatial resolution, daily totals should be available on a 5km, or possibly even 2km grid and will be used to improve the information on antecedent conditions available to flood warning officers. It will enable closer monitoring of soil moisture conditions within individual catchments.

- GIS technology can provide the tools to more easily access and manipulate hydrometeorological products.
- Impact modelling is a real possibility in the near future enabling emergency authorities to have a better understanding of the likely scale of damage and disruption caused by severe weather events.
- The Met. Office, through these initiatives is addressing 16 of the 40 main weather related recommendations made in the Bye report.

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Snowmelt Forecasting for Flood Warning in Upland Britain

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1. Introduction

Only three of the eight regions responsible for flood warning in England and Wales operate forecasting systems that incorporate explicit monitoring and modelling of snowmelt; in Scotland there are none. However, snowmelt can be a significant contributor to winter flooding, especially when warm, moist, turbulent air from the Atlantic causes rapid melting of the snowpack and brings heavy rain. High melt rates in these conditions will be largely due to turbulent exchange of heat. This dominance of turbulent heat flux contrasts with conditions experienced in North America, Scandinavia and Alpine regions where radiation melt often prevails. There is a large literature on the snowmelt process and its modelling; the majority deal with the aforementioned regions along with significant contributions from Eastern Europe and Japan. Studies undertaken in the UK are limited, with those by Archer and Johnson in north-east England providing good examples (Johnson and Archer, 1972; Archer 1981, 1983). Some work has also been done in the Cairngorms in the Scottish Highlands by Ferguson (1984) and Morris (1982). These local studies are of most relevance to flood forecasting in Britain.

Snowpacks, at least in lowland and upland Britain, are typically shallow and ephemeral in nature, and require modelling at an interval of an hour or less to capture their dynamic behaviour. Current models take a simple lumped form, employ temperature excess melt principles and, due to a lack of data for model calibration, employ literature-derived parameter values. Moore *et al.* (1996, 1999) responded to the need for improved snowmelt forecasting methods by establishing a UK Snowmelt Database and investigating alternative methods for snowmelt forecasting. A snowmelt model, 'PACK', was developed which was coupled with two forms of catchment runoff model, the lumped 'Probability Distributed Moisture' model (PDM) and a Simple Distributed Model (SDM) based on saturation excess runoff production and an isochrone-configured kinematic wave routing translation function. The spatial variation of temperature and precipitation across the catchment was incorporated through the use of elevation zones, and was shown to be beneficial for some catchments. The PACK snowmelt module included an extended melt equation incorporating wind and rain heating effects, with the simple temperature excess (or index) method as a special case. The option of a full energy budget melt equation was also included in the model formulation. Initial model assessments were encouraging, showing that significant improvement could be gained in runoff simulation during periods of lying snow through the use of a snowmelt module. However, the study highlighted the need for further work in model development, and the need for more extensive data records for model assessment and evaluation.

Three years on, the UK Snowmelt Database now includes data from the IH experimental catchments in Balquhidder, the Dove in the Peak District, and additional data from catchments in the Upper Tees, Plynlimon and the Upper Aire. The aim of this paper is to present recent work on model development and evaluation using the extended datasets for Balquhidder and the Upper Tees. Sections 2 and 3 outline the current formulation of the snowmelt catchment model developed for real-time flood forecasting. They describe how a catchment is sub-divided into elevation zones to represent the change in temperature with altitude and, in turn, the effect of temperature on melt and whether precipitation falls as rain or snow. A hypsometric curve allows for a flexible choice of zone number with a near-continuous distribution of elevation in a catchment being possible. The PACK module used to represent snowmelt in each zone is coupled to a lumped conceptual rainfall-runoff model, the PDM (Probability Distributed Moisture), which provides alternative ways to transform the meltwater draining from the snowpack into flow at the basin outlet. A full energy budget melt formulation which uses additional radiation and humidity data is evaluated alongside the simple temperature excess and extended melt

equations. Section 4 discusses how point snow core observations are used to update the modelled snowpack in each elevation zone. Section 5 presents the results of calibration and assessment of the different model formulations with reference to snow water equivalent at the snow survey site and flow at the catchment outlet. Finally, Section 6 provides a summary and discusses some prospects for future research.

2. Snowmelt model formulation

The new snowmelt catchment model comprises a snowmelt module, "PACK", linked to a dynamic rainfall-runoff model, in this case, the PDM (Probability Distributed Moisture model). The snowmelt module conceptualises snow as being made up of dry snow (fresh snow that has not yet melted) and wet snow (melted snow) as illustrated in Figure 1. One of the most important controls on melt in the UK is temperature, which is dependent on elevation. In high relief catchments one way of incorporating the change in melt rate with elevation is by dividing the catchment into elevation zones with a snowmelt module operating within each zone. Incorporating elevation zones provides a simple way of representing the change in temperature with elevation in a catchment and its effect on melt and the rain/snow partition, through the use of a temperature lapse rate.

The concern here is to formulate a model that can define the number of elevation zones flexibly and can accommodate a near-continuous distribution of elevation in the catchment. This is accomplished using the well-known hypsometric curve (for example, see Bras, 1990). The hypsometric curve, *F(z)*, is a distribution function which defines the proportion of a catchment that lies below a given elevation, *z*. It can be computed easily from a digital terrain model (DTM) and can also be related to the frequency function of catchment elevation through $f(z)=dF/dz$. By way of illustration, Figure 2 shows hypsometric curves for the three catchments modelled here: Monachyle Burn in Scotland and Trout Beck and Harwood Beck in the Upper Tees. The importance of the distribution function, *F(z)*, is that it can be coupled with a temperature-elevation relation to define the proportion of the catchment over which snow melts, or the proportion that receives its precipitation in the form of rain rather than snow (if a simple temperature threshold is used to discriminate between rain and snow). Figure 3 illustrates the zones of melt and snowfall for a cross-section through a typical catchment. In the applications that follow, temperature is taken from one weather station in each catchment and a fixed temperature (wet adiabatic) lapse rate of 0.0059ºC m^{-1} is assumed.

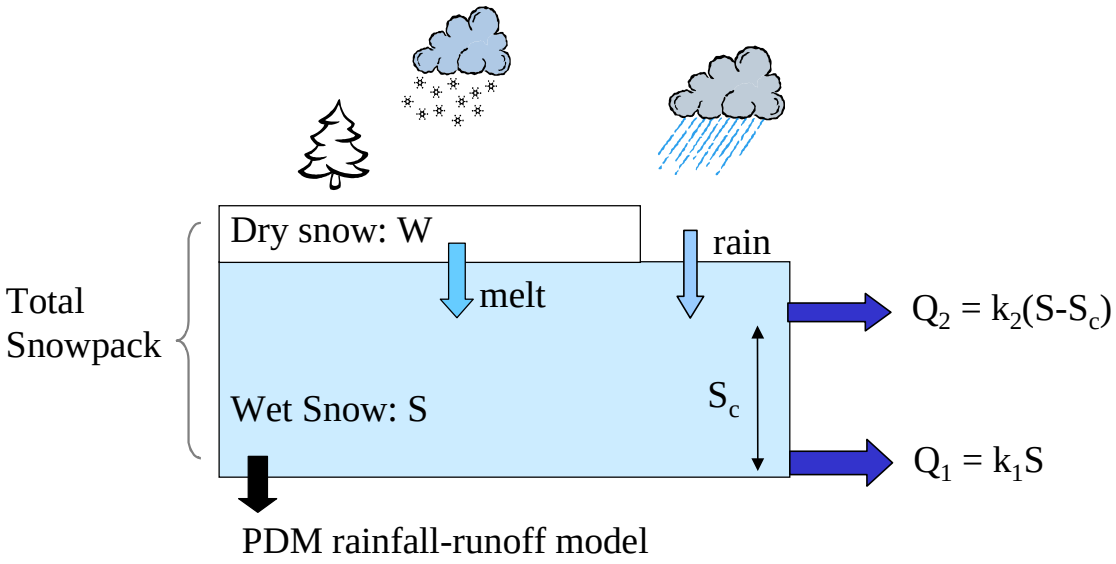


Figure 1. *Schematic of the PACK snowmelt module showing dry and wet snow stores*

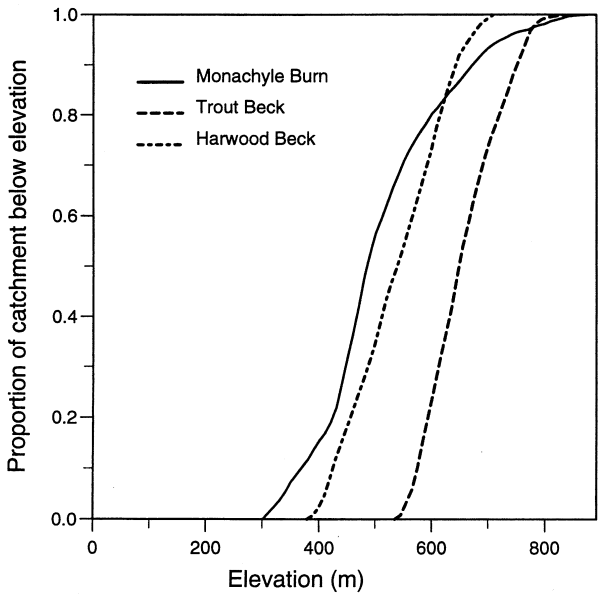


Figure 2. *Hypsometric curves for Monachyle Burn, Trout Beck and Harwood Beck*

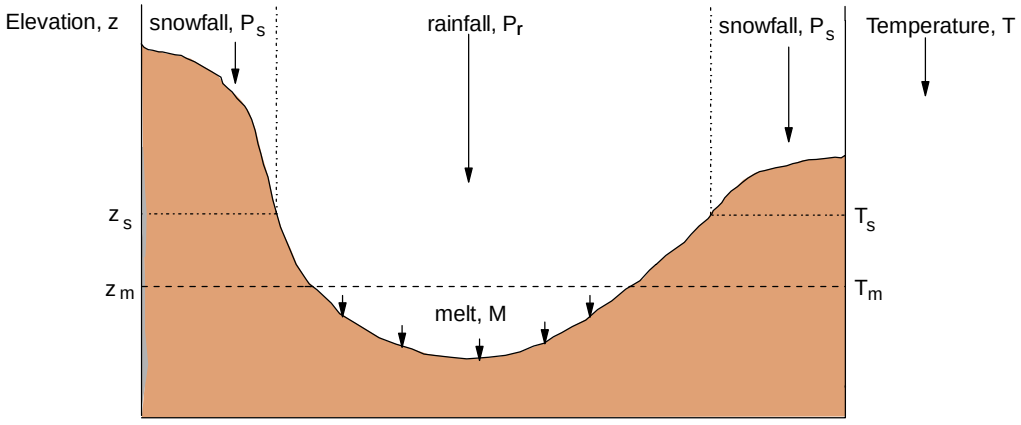


Figure 3. *Cross section through a catchment showing zones of snowfall and melting*

Making the assumption that snow/rain occurrence and melting are dependent only on the temperature at a point, and in turn dependent only on elevation through a temperature lapse rate relation, then the contents of the dry and wet snow stores, *W* and *S* respectively, are also only dependent on *z*: that is $W = W(z)$ and $S = S(z)$. This also assumes that precipitation is uniform over the catchment, or varies under the control of a precipitation lapse rate that is solely elevation dependent. Hence each contour in the catchment is assumed to have the same snowpack.

The total input of water over the catchment from snowpack drainage and rainfall is

$$I = \int_{z_1}^{z_2} I(z) f(z) dz \, . \qquad (1)$$

Here *I(z)* is the melt water released form the snowpack at elevation *z*, and *f(z)= dF(z)/dt* is the frequency function of catchment elevation; *F(z)* is the hypsometric curve. The integral limits z_1 and z_2 are usually taken to be z_{min} and z_{max}, the lower and upper elevation limits of the catchment.

The distributed nature of the model formulation means that it is more sensitive to the rain/snow temperature threshold which now governs the proportion of the catchment receiving snow (or rain) and not just whether the catchment receives rain or snow. The formulation allows greater flexibility in the use of either a finite number, or near-continuous distribution, of elevation zones in a catchment. It also permits the use of a parametric probability distribution function of elevation where a DTM of the catchment is unavailable to calculate one empirically.

The overall snowmelt model is comprised of PACK snowmelt modules operating within each elevation zone of the catchment. The resulting modelled snowmelt forms part of the input to a rainfall-runoff model which transforms rainfall together with drainage melt from the snowpack into catchment runoff. The rainfall-runoff model evaluated here is the PDM (Probability Distributed Moisture) model. The PDM (Moore, 1985, 1999; Institute of Hydrology, 1992, 1996) is a conceptual rainfall-runoff model which uses a probability distribution to describe the spatial variation of water storage capacity across a catchment. This allows saturation excess runoff at any point to be integrated over the catchment to yield the total runoff entering fast response pathways (principally stream channels) to the catchment outlet. Groundwater recharge from soil drainage passes through slower subsurface pathways and finally combines with output from the fast response pathways to give the total flow from the catchment.

3. Melt equations

The previous section provided a description of the basic form of snowmelt model together with a brief outline of the PDM rainfall-runoff model that converts snowpack drainage and rainfall to flow at the basin outlet. The formulation has assumed that a simple temperature excess model for melt applies. Here, two additional melt formulations are introduced. The first is a simple extension of the temperature excess model to include the effects of wind and rain on melt. Secondly, a full energy balance formulation is considered. These three formulations are described below. With each additional increase in snowmelt model complexity additional data are required to support the formulation. Table 1 summarises the data requirements of snowmelt models used with each type of melt equation; the data needs of a rainfall-runoff model with no snowmelt model component are presented by way of contrast.

3.1. Temperature excess melt equation

Current operational practice in the UK is that the surface melt component is approximated by a very simple temperature excess formulation which requires only measurement of temperature. The *potential* melt at an elevation *z*, M , is given by

$$M(z) = \max\{\beta(T(z) - T_m), 0\} \tag{2}$$

where β is the melt factor, α is the temperature lapse rate (fixed at 0.0059°C m^{-1}), T is the air temperature measured by an AWS, and T_m is the temperature above which melt occurs (usually taken to be at or above 0°C).

3.2 Extended melt equation

The extended melt equation of Moore *et al*. (1996) incorporates the effects of temperature, *T*, wind, *u*, and rain, *R*, on melt into a single parameterised expression:

$$M = \beta(1 - \gamma u)(T - T_m)^x + \mu RT, \tag{3}$$

where T_m is the threshold temperature above which melt occurs and β, γ *and* x are parameters (x is currently set to 1). The quantity μ is normally defined physically as the reciprocal of the latent heat of fusion, 80 cal g^{-1}. To allow for lack of representativeness in measured values of R and T, μ has been treated as a parameter available for optimisation and is referred to as the rain heating factor.

Table 1. *Data requirements of snowmelt model variants*

Model variant / *Data*	*Rainfall - runoff model*	*Snowmelt model with temperature excess melt equation*	*Snowmelt model with extended melt equation*	*Snowmelt model with energy-budget melt formulation*
Rainfall	✓	✓	✓	✓
Flow	✓	✓	✓	✓
Potential evaporation	✓	✓	✓	✓
Snow depth		✓	✓	✓
Snow water equivalent		✓	✓	✓
Temperature		✓	✓	✓
Wet bulb temperature				✓
Wind			✓	✓
Net radiation				✓
Incident solar				✓ (optional)
Reflected solar				✓ (optional)
Soil temperature				✓ (optional)
Soil heat flux				✓ (optional)

3.3. Energy budget melt formulation

When measurements of net all-wave radiation and humidity are available in addition to temperature and wind speed, it is then possible to consider the full energy balance approach for melt estimation. The energy budget approach to melt estimation reviewed in Moore *et al.* (1996) is used here to provide a formal means of assessing the potential value of additional weather measurements for improved snowmelt forecasting.

The energy budget formulation calculates the average temperature of the snowpack in terms of energy fluxes calculated from measured meteorological quantities such as net radiation and wet bulb temperature. If the average temperature of the snowpack at the next time step is calculated to be greater than $0\,^{\circ}C$, then this quantity of heat is ascribed to the heat carried away by the melt water and the temperature of the snowpack is reset to $0\,^{\circ}C$. The snowmelt rate per unit area per unit time can then be determined in terms of the heat carried away by the melt water. The approach neglects any calculations of the internal distribution of water and heat, and treats the snowpack as lumped in the vertical direction.

The many physical parameters within the energy balance equations can make it a difficult technique to apply. However, for a particular catchment a number of parameters can be set to constant values, such as latitude and longitude, and the zenith and azimuth angles used in radiation calculations. A sensitivity analysis undertaken by Moore *et al.* (1996) suggested that under UK conditions the most critical parameter was the aerodynamic roughness length controlling convective heat loss; the model was found to be only weakly sensitive to the initial pack temperature. As a result, only the roughness length features as a parameter to be optimised in the energy budget melt

formulation.; this contrasts with two parameters in the simple temperature excess model (the melt factor and threshold temperature).

The current energy budget formulation is only curently available for use with a single elevation-zone model of the catchment. Use of the approach with multiple elevation zones requires an extension involving extrapolation across the catchment of meteorological variables, in addition to temperature, such as radiation and wind. This is seen as an opportunity for further research.

4. Updating of the snowmelt model

Assimilation of snow measurements into the model in near real-time so as to improve forecast accuracy is accomplished by a novel updating scheme (Moore *et al.*, 1999). This involves operating a "point" PACK model at the snow measurement site in parallel to PACK modules in each elevation zone. Point model errors are transferred using a proportioning scheme to adjust the snowpack water contents of each elevation zone. The scheme can make use of either hourly measurements from a snow pillow (Archer and Stewart, 1995) or measurements from snow cores made once a day.

The correction to the point model ensures that the water equivalent and density of the modelled and measured packs agree, and also establishes the partition between wet and dry pack water storage in the modelled pack. The correction applied to snow water equivalent for each elevation zone is in proportion to that applied in the point model. A partition between wet and dry packs is established by maintaining the same density as at the measurement site.

5. Catchment and model database

5.1. Introduction

The Lower Monachyle catchment near Balquhidder in Scotland has been the subject of a special snow monitoring programme over a three year period beginning in 1995/6 (Bell and Moore, 1999b). However, due to a paucity of historical data and infrequent snowfall over the programme period, the records are not extensive. Additional data are used here from Trout Beck and Harwood Beck in the Upper Tees, north-east England. Details of the catchments are presented below.

5.2. Balquhidder

The Balquhidder experimental catchments, Monachyle and Kirkton Burn, were established in 1981 to study the effects of forestry on water resources. The nature of the Balquhidder catchments is significantly different to other UK experimental catchments, such as Plynlimon, in that they have a more rugged relief and coarser vegetation and experience a higher proportion of annual precipitation falling as snow. Consequently the measurement of snow proves critically important. The special monitoring programme has focussed on the Monachyle Burn catchment, which is the larger of the two catchments and without the added complexity of forestry.

Monachyle Burn, shown in Figure 4(a), drains an area of 7.7 km^2 with an elevation range of 302 to 892 metres and natural vegetation of heather, bracken and coarse grass. It has a distinct upper catchment of 2.24 km^2 containing a large undulating peat area with a heather cover. The automatic weather station (AWS) used here is sited near the outlet of this upper catchment in a fairly central location with respect to the catchment as a whole. Measurements from the AWS relate to an hourly time-step, and raingauge values are for a 15 minute time-step. In addition, daily snowcore measurements of depth, density and water equivalent, together with approximate snowline observations are made, but not on a regular basis. An inspection of historical and special monitoring programme data records revealed only two snow periods, in 1984 and during the programme in 1995/96, as adequate for model development. For the 1984 snow events, daily snow cores were made at Tulloch Farm (elevation 135 m), situated outside the catchment approximately 5 km south-east of the Lower Monachyle

gauging station. The snow cores for the 1995/96 period were taken in the vicinity of the Lower Monachyle AWS site which is located at a height of 470 m.

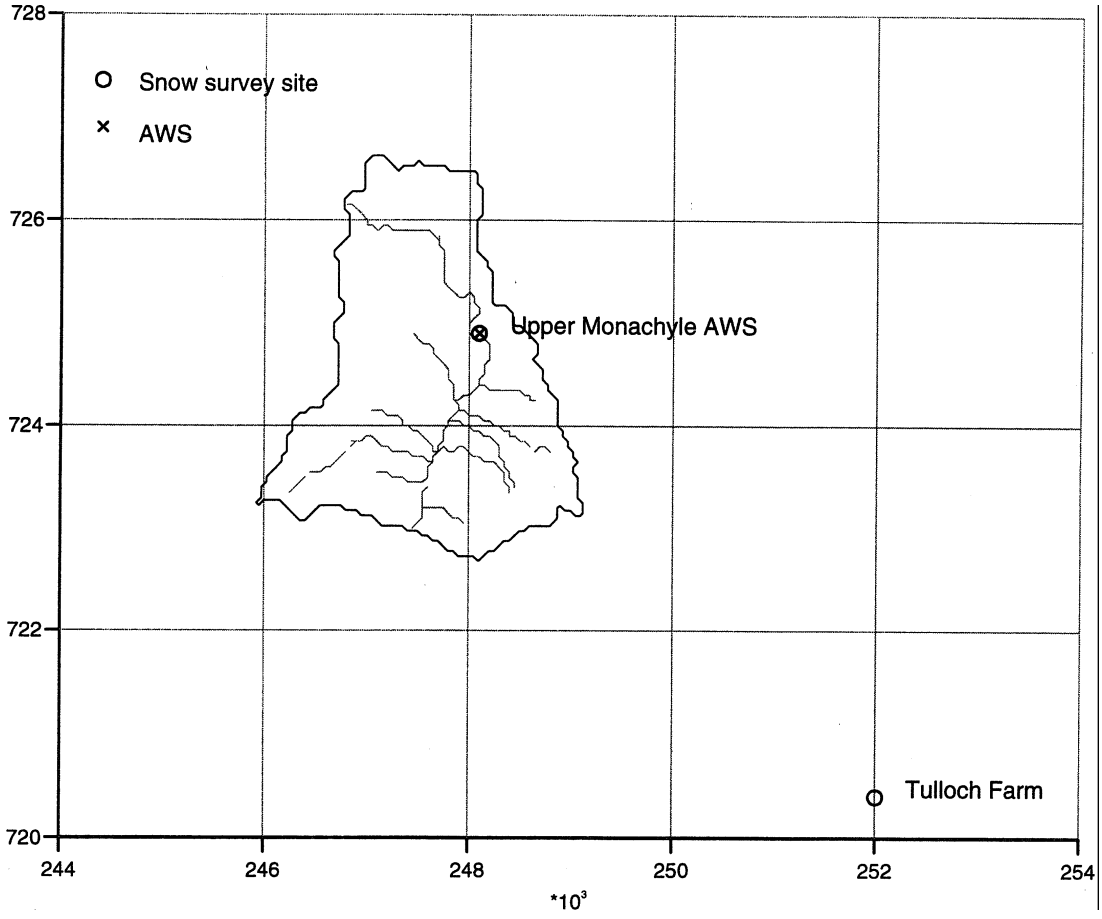
5.3. Upper Tees

The Upper Tees catchments, Trout Beck and Harwood Beck, are shown in Figure 4(b). Trout Beck drains a heather moorland area of 11.4 km^2 to its gauging station near Moor House with an elevation range of 553 to 857 metres. An automatic weather station (elevation 556 m) is located at Moor House near the catchment outlet whilst a snow-pillow (elevation 500 m) is situated about 8 km to the south-east, near Cow Green Reservoir Dam. The AWS provides hourly rainfall measurements and a recording raingauge (elevation 494 m) near Cow Green reservoir provides 15 minute rainfall data. A snow survey site at Widdibank Fell (elevation 513 m) was closed in December 1995. Since then, an observer has taken daily readings at the nearby Hunt Hall Farm situated about 200m north of Widdibank Fell.

Harwood Beck is situated approximately 4 km east of Trout Beck and drains an area of 24.7 km^2 with an elevation range of 378 to 713 metres. Rainfall measurements are provided by gauges located at nearby Cow Green Reservoir and at Burnhope Reservoir, situated about 8 km north of the catchment. The nearest AWS is at Moor House in Trout Beck. A snow survey site at Greenhills Farm has snow-survey records dating from 1991.

The snow pillow at Cow Green Reservoir was installed in February 1993 (Archer and Stewart, 1995). It is comprised of a hypalon bladder, 3 m in diameter and 250 mm deep, filled with 50:50 water and antifreeze (ethyl glycol). A manometer arrangement records hourly values of snow water equivalent.

(a) Lower Monachyle



(b) Trout Beck and Harwood Beck

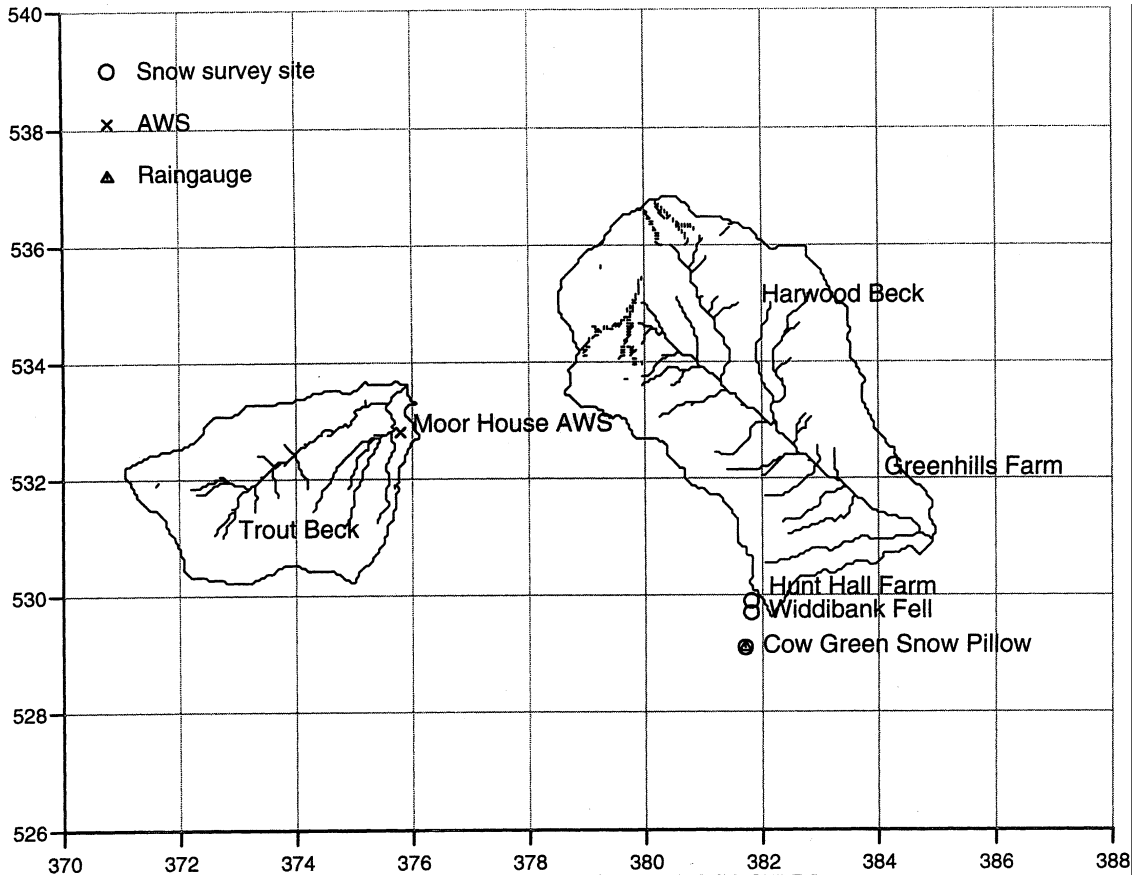


Figure 4. *Maps of the study catchments in the Monachyle Glen and the Upper Tees (Trout Beck and Harwood Beck) showing the river network and the position of weather station and snow survey sites (grid coordinates in km)*

6. Model evaluation

The different snowmelt model variants outlined previously were assessed on three catchments: Monachyle Burn, Harwood Beck and Trout Beck. The following questions were investigated:

(i) How many elevation zones should be used?
- Single zone
- Multiple zones
- Continuous distribution of zones

(ii) What is the best melt formulation to use?
- Simple temperature excess equation
- Extended melt equation
- Energy-budget approach (used with single elevation zone model only)

(iii) Is use of hourly snow pillow data beneficial?

The evaluation framework used to answer these questions is outlined below. Results from the evaluation are then used to answer each of these question in turn and to determine, in general, whether the use of a snowmelt module with a rainfall-runoff model is beneficial for flood forecasting.

6.1. Evaluation framework

The main criterion used to compare model performance is the R^2 statistic, giving the proportion of the variability in the observations accounted for by the model. The performance statistic is calculated for both snow water equivalent at the snow survey (or pillow) site and for flow at the catchment outlet. This formal statistic is complemented by time-series plots of flow and snow water equivalent, as observed and forecast, which provide an informal visual assessment of performance of the point and catchment scale models.

Since direct measurements of snowfall are not available, the snowpack water equivalent is reset to the observed snow (survey or pillow) value on occasions when it is seen to increase. This is accomplished using the updating scheme discussed in Section 4 where a point snowmelt model for the snow survey (or pillow) site is reset using the observed value and the adjustment involved transferred to each elevation zone of the catchment snowmelt model. At other times the snowmelt component is operated in "simulation mode" without updating with reference to observations. Also, the initial assessment of the catchment model component is operated in simulation mode, with no updating using observed flows at the basin outlet. This approach allows the evaluation to focus on the choice of appropriate model dynamics, without the added confusion of the effect of updating. In an operational context the snowpack would be updated with reference to all available snow observations and the rainfall-runoff model updated using observed flows. This would most likely yield a more accurate flow forecast and thus the results presented here might be regarded as conservative in terms of forecast performance.

The strategy for model calibration first employs a period when snow is absent to calibrate the underlying rainfall-runoff model. Then a period of lying snow is used for calibration, fixing the rainfall-runoff parameters and optimising those of the snowmelt component. Optimisation is carried out using flow and water equivalent in turn in forming the objective functions and performance is assessed in terms of both variables. Flow measurements used for model calibration and assessment were for a 15 minute time interval, the same as the model time-step adopted here.

The strategy for evaluation was restricted to the use of long continuous periods of snow activity for each of the study catchments, each period encompassing a number of snowmelt episodes. This has the advantage of allowing (i) continuous water accounting to be maintained throughout the period and (ii) calibration of a model optimised over the range of conditions experienced. It also avoids the further complication of pooling the objective function across several discrete events to obtain a single parameter set, or the disadvantage of obtaining several model parameter sets for each event calibrated separately. Use of a long period containing several snowmelt episodes avoids the danger of overfitting and lessens the need for independent validation using records not used for model calibration. The strategy was also practical since the number of snow events well-suited to model evaluation were rather restricted, particularly in the case of Monachyle Burn where only two periods of lying snow were available.

6.2. How many elevation zones should be used?

To determine the number of elevation zones that yields the optimal model performance, the snowmelt model used in conjunction with the PDM rainfall-runoff model was assessed on two catchments: Monachyle Burn and Trout Beck. However, for brevity, results from Monachyle Burn only are presented here.

Use by the model of a hypsometric curve, discretised to 1 metre, means that Monachyle Burn was effectively split into a maximum of 590, with the zones actually used being readily changed in number. For a smaller number of zones the data describing the hypsometric curve are aggregated to determine the proportion of the catchment that lies below each elevation zone together with the area of each zone. Model performance was assessed for different numbers of elevation zones in order to determine the optimum number of zones to use for each catchment. Illustrative results for the period 9 January to 28 February 1984 for Monachyle Burn are presented in Figure 5. The figure reveals that while a poor result is obtained using one elevation zone, and a good consistent performance is obtained using more than 20 elevation zones, there is a marked fluctuation in

performance between these limits. The best result was obtained using five elevation zones and the fluctuation in performance ceases beyond around 20 elevation zones, corresponding to an elevation band of 30 m (590/20 $\cong$ 30).

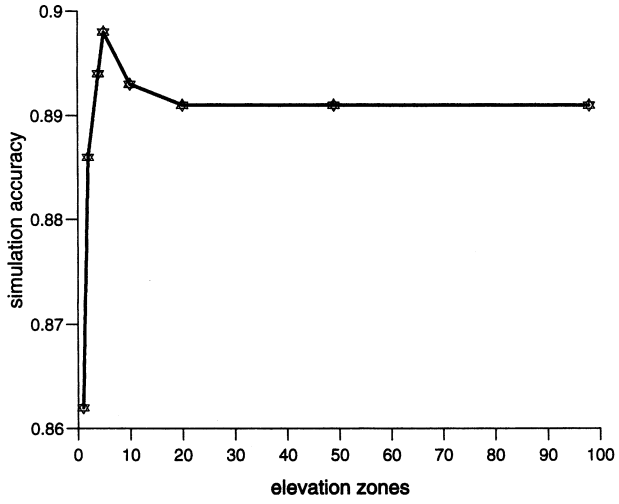


Figure 5. *Sensitivity of model performance (R^2 statistic for flow) to the number of elevation zones used: Monachyle Burn, 9 January to 28 February 1984*

Overall the results presented here, and other results obtained for Trout Beck, suggest that more than one elevation zone is optimal, with performance varying between one and 20 zones. One reason fro this variation may be that the model is simply very sensitive to the use of a small number of zones that split the catchment into a few very large regions. This may introduce errors in partitioning the catchment into areas experiencing melt and receiving precipitation as rain rather than snow. In certain cases these errors may be beneficial leading to improvement in model performance whilst for other numbers of zones model performance could suffer. The results suggest that a conservative selection for the number of zones to use might be 15 to 20, placing the model in the region where it is relatively insensitive to changes in the number of zones. Subsequent results employ models with 10 zones for the Monachyle Burn and Trout Beck and 15 zones in Harwood Beck; these numbers achieve good model performance while minimising computational time during model calibration and evaluation.

6.3. What is the best melt formulation to use?

Both the simple temperature excess melt formulation and the extended melt equation are evaluated in Table 2. Results suggest that there is some slight benefit to be gained by the use of the extended melt formulation (equation (3)) which introduces the effect of wind and rain on snowmelt. Figure 6 compares simulated melt (mm/15 minute time-step) from these two melt formulations alongside the melt obtained using the energy-budget. Figure 6(a) shows a time-series of melt from the simple temperature excess melt formulation alongside one from the energy-budget approach. The time-series illustrate the dependence of the temperature excess melt on air temperature, which is displayed below, and shows how the magnitude of the melt is often 50% below that obtained using the energy-budget melt formulation, and sometimes misses the melt 'peaks' altogether (for example days 39 and days 47 to 54). When the effect of rain and wind is introduced in Figure 6(b) the melt is increased dramatically, often leading to a higher melt rate than that obtained from the energy-budget formulation. The melt 'peak' of day 39 is similar to that obtained from the energy-budget method, though there are large differences in melt simulation in the first ten days of the calibration period.

Table 2. *Assessment of model performance using temperature excess and extended melt formulations: Harwood Beck, calibration period 1 January to 6 March 1994*

Melt formulation	*Flow R^2*
Snow ignored	0.528
Snow included + temperature excess	0.668
Temperature excess + rain	0.714
Temperature excess + wind	0.670
Temperature excess + rain and wind	0.714

Building on these exploratory results, Table 3 presents the main snowmelt model evaluation in terms of the R^2 statistic for flow. Four periods of lying snow not used in model calibration are simulated using the snowmelt model coupled with the PDM rainfall-runoff model. Two forms of the snowmelt model are evaluated. The left hand side of Table 3 presents results obtained using the extended melt equation with 15 elevation zones, while the right hand side displays results obtained using the energy-budget melt formulation and representation of the catchment by a single elevation zone (multiple zones are not available for use with the energy-budget melt formulation).

Table 3. *Model performance using extended melt and energy-budget melt formulations using daily snow survey measurements: Harwood Beck*

(a) Daily snow survey measurements

Period	*Model*	*Extended melt Flow R^2*	*Energy-budget Flow R^2*
Calibration			
1 Jan- 6 Mar 1994	Snow ignored	0.528	0.528
		0.714	0.640
Assessment			
1 Jan – 1 Feb 1993	Snow ignored	0.362	0.362
	Snow included	0.440	0.543
	and recalibrate	0.528	0.614
27 Dec 1994 – 6 Feb 1995	Snow ignored	-0.072	-0.072
	Snow included	0.054	0.228
	and recalibrate	0.935	0.786
27 Dec 1994 – 30 Jan 1995	Snow ignored	0.350	0.350
	Snow included	0.581	0.619
	and recalibrate	0.705	0.709
2 Dec 1997 – 6 Mar 1998	Snow ignored	0.663	0.663
	Snow included	0.751	0.742
	and recalibrate	0.776	-

(b) Hourly snow pillow measurements

Event	*Model*	*Extended melt Flow R^2*	*Energy-budget Flow R^2*
Calibration			

1 Jan- 6 Mar 1994	Flow calibration	0.546	0.518
Assessment			
27 Dec 1994 – 6 Feb 1995	Snow included	-0.037	-0.074
	and recalibrate	0.066	-0.008

For each period the model is evaluated in three ways:

(i) ignoring the presence of snow with no additional calibration (PDM only).

(ii) including snow observations, using parameters obtained by calibration from the January 1994 period with no additional calibration; and

(iii) including snow observations and recalibrating to achieve the best possible flow result for that period.

In the third way of evaluation, the optimal model performance achieved using recalibration provides a benchmark against which evaluation (ii) can be compared. This may be used to determine how robust the snowmelt parameter set is when applied to different events.

Overall, Table 3 reveals that for the events tested, the snowmelt model can be improved through the use of a full energy-budget melt formulation; and has a robust parameter set which gives reasonable results when applied to different periods of snowmelt. In general over the three catchments used for evaluation, inclusion of rain and wind heating terms in an extended temperature melt equation was found to provide some benefit in model performance. A comparison between melt calculated using the extended melt equation and the energy-budget formulation suggested that the inclusion of wind and rain effects in the simple temperature excess equation could reproduce some of the variation seen in the energy-budget melt approach. Figure 7 illustrates the benefits to be gained for flow simulation through the use of a snowmelt model compared to use of a rainfall-runoff model alone. Figure 7(a) shows the observed and simulated flow hydrographs obtained for Trout Beck for the period 4 to 30 December 1993 using the PDM alone. The improved result shown in Figure 7(b) was obtained using the snowmelt model with an energy-budget melt equation coupled with the PDM. Figure 7(c), which shows components of the energy-budget, indicates that the significant components of the energy-budget under UK conditions are sensible heating from the atmosphere and latent heat of condensation.

6.4. Is use of hourly snow pillow data beneficial?

Table 4.5 presents the snowmelt model results obtained using hourly snow pillow measurements in place of daily snow survey observations. When compared to Table 4.4, which shows model performance using snow survey observations, it is apparent that model performance is worsened by the use of snow pillow data. For the calibration period 1 January to 6 March 1994 the best R^2 of 0.714 is obtained using daily snow core observations whilst the use of snow pillow data results in an R^2 of 0.546. The main reasons for the difference in performance appear to be the preferential rate of melt from the pillow causing some peaks to occur too soon, and an underestimation in measured water equivalent from the snow pillow compared to snow core measurements, which affects some days more than others. Similar results are obtained for the period 27 December 1994 to 6 February 1995 and the change from snow core to snow pillow observations did not improve simulation of the high flow peak on 31 January 1995.

7. Summary

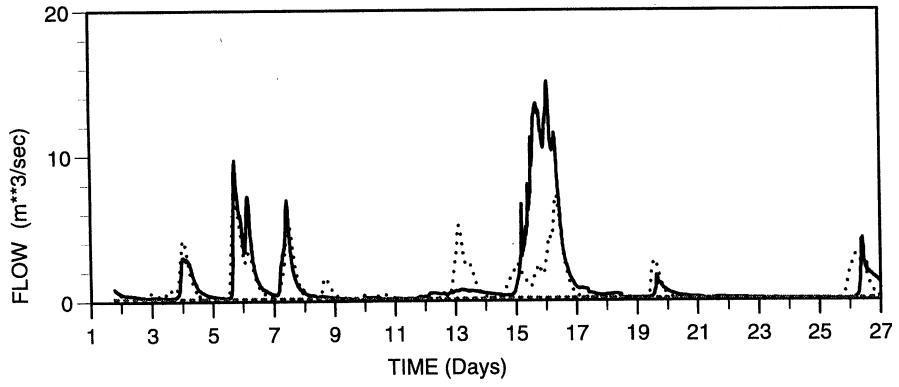
A new snowmelt model for flood forecasting in upland Britain has been developed which can use either a finite number or continuous distribution of elevation zones in a catchment. Two different melt formulations can be used with the new model: the extended melt equation, which uses measurements of temperature, wind and

rainfall to determine the potential melt experienced by the snowpack, and the energy-budget melt formulation which requires additional weather station data in the form of radiation and wet bulb temperature.

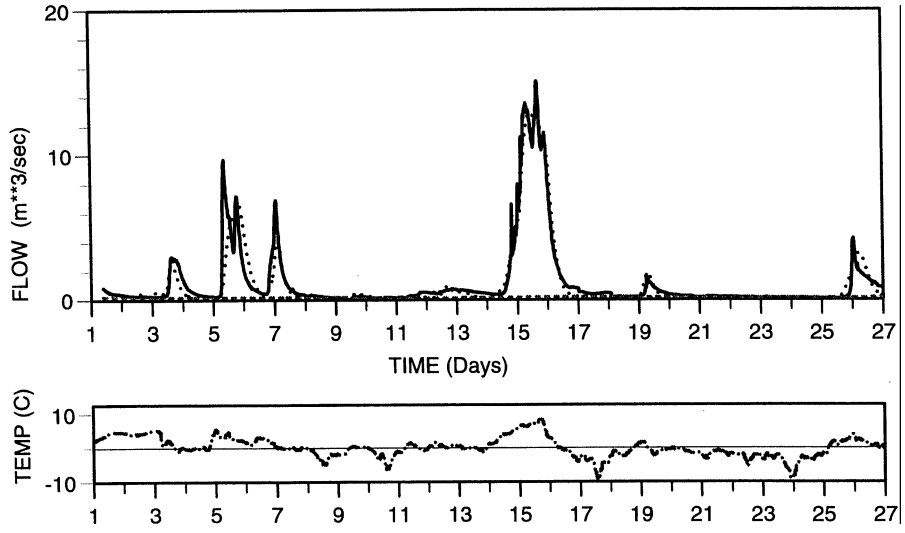
The research reported here builds on the work of Moore *et al*. (1996) which developed a range of model variants and a snowmelt database to support future research relating to snowmelt in the UK. This database has since been extended to include recent data and the inclusion of data from Balquhidder in Scotland. A new elevation-dependent snowmelt model has been formulated and evaluated in Monachyle Burn near Balquhidder and two catchments in the Upper Tees: Harwood Beck and Trout Beck. These developments are reported more fully in Bell and Moore (1999a and b).

Model calibration and assessment on the extended dataset allows the following conclusions to be drawn. A sensitivity analysis of the snowmelt model to the number of elevation zones employed suggests that the use of multiple elevation zones in upland catchments can improve flood forecasting during periods of lying snow. A single zone model is nearly always improved upon by the use of multiple elevation zones, which take into account the variation in temperature with elevation in a catchment and its effect on rain/snow separation and melt. A continuous distribution of elevation zones in a snowmelt model tends to give similar results to a model with 10 to 20 zones. The continuous formulation may be of use for catchments where a DTM cannot be used to derive the hypsometric curve and a parametric function is used instead to represent the distribution function of elevation within a catchment.

(a) Flow hydrograph: no snowmelt component



(b) Flow hydrograph: snowmelt model with energy-budget melt formulation



(c) Components of the energy-budget

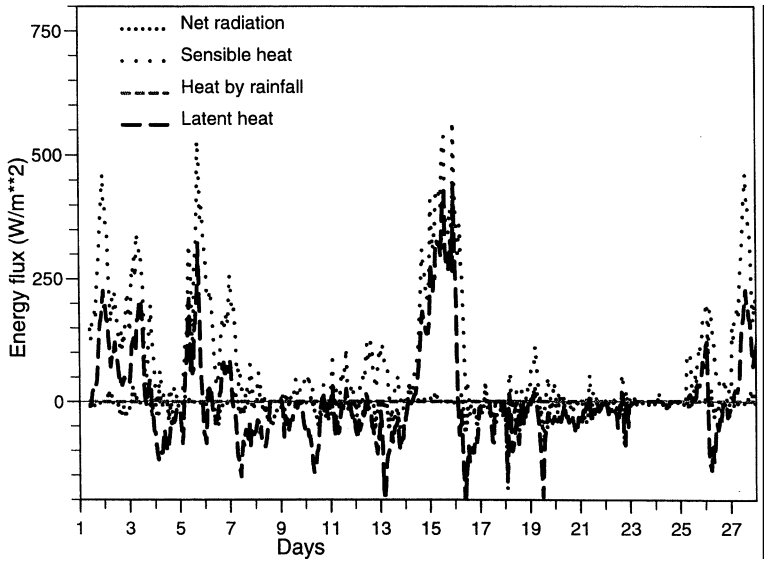


Figure 6. *Time-series of flow and energy-budget melt components: Trout Beck, 4 to 30 December 1993. Observed flow: bold line, predicted total flow: dotted line*

Inclusion of rain and wind heating terms in an extended temperature melt equation was found to provide some benefit in model performance. A comparison between melt calculated using the extended melt equation and the energy-budget formulation suggested that the inclusion of wind and rain effects in the simple temperature excess equation could reproduce some of the variation seen in the energy-budget melt approach.

Extensive model calibration and evaluation across three upland catchments reveals that the snowmelt model always improves upon flow results obtained using a rainfall-runoff model without a snowmelt model component. Typically, the use of a snowmelt model during periods of melting snow can improve flow forecast performance, with R^2 values around 0.35 using the PDM rainfall-runoff model alone increasing to around 0.55 when the snowmelt component is incorporated. Further calibration on each event can improve model performance still further to give R^2 values of around 0.7. Although no one model variant can be relied upon to give optimal model performance, the energy-budget melt formulation used with the single zone snowmelt model can often give very good performance. The snowmelt model can be calibrated to give a robust parameter set and gives acceptable results when applied across different periods of melting snow.

While the Cow Green snow pillow in the Upper Tees was found to be of value to modelling, comparisons with daily snow core measurements suggested that use of the hourly snow pillow data could not easily improve on flow modelling results obtained using daily snow core observations.

A fundamental problem in snowmelt modelling is the difficulty of reliable snowfall measurement. An exploratory study of the use of Met. Office Numerical Weather Prediction (NWP) model estimates of snowfall, for both past and forecast amounts, as input to the snowmelt model would be of value. This might extend to include NWP estimates of other quantities involved in snowmelt forecasting, particularly temperature and wind. Future work should also further examine the use of snow pillow data to improve forecast performance, and assess the snowmelt model in a simulated real-time context with full updating.

8. Acknowledgements

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Data-Based Mechanistic Modelling and Adaptive Flow Forecasting

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1. Introduction

One of the most interesting modelling problems in hydrology is the characterisation of the nonlinear dynamic relationship between rainfall and runoff and the use of such models as a basis for flow forecasting and flood warning. This has received considerable attention over the past thirty years, with mathematical and computer-based models ranging from simple 'black-box' representations to complex, physically-based catchment models. Wheater et al. (1993) have categorised such models into the following four, broad types: Metric (black-box); Conceptual, Physics-Based; and Hybrid Metric-Conceptual (HMC). HMC models are in quite a useful form for flow forecasting applications because they are normally quite simple, hydrologically meaningful characterisations of the rainfall-flow process and they are identified and estimated against the available data using statistical methods of time series analysis. This approach not only yields estimates of the model parameters but it also provides measures of the uncertainty associated with the parameter estimates and model disturbances; measures that are essential to the implementation of stochastic forecasting methods. In a very real sense, these HMC models are an attempt to combine the ability of black box models, such as transfer functions, to efficiently characterise the observational data in a statistical terms (the principle of parsimony: Box and Jenkins, 1970), with the advantages of conceptual models that have a prescribed physical interpretation within the current scientific paradigm.

Two main approaches to HMC modelling can be discerned; approaches which, not surprisingly, can be related to the more general deductive and inductive approaches to scientific inference that have been identified by philosophers of science from Francis Bacon, to Karl Popper and Thomas Kuhn. In the first hypothetico-deductive approach, the *a priori* conceptual model structure is effectively a theory of hydrological behaviour based on the perception of the hydrologist/modeller and is strongly conditioned by assumptions that derive from current hydrological paradigms. Typical and practically useful examples of this type of HMC model are the Bedford-Ouse model (Young, 1974; Whitehead and Young, 1975) and its successor, the IHACRES model (Jakeman et al 1990; Jakeman and Hornberger, 1993). The alternative *Data-Based Mechanistic* (DBM) approach is basically inductive, in the sense that it tries to avoid theoretical preconceptions as much as possible in the initial stages of the analysis. In particular, the DBM model structure is not pre-specified by the modeller but, wherever possible, is inferred directly from the observational data in relation to a more general class of models. Only then is the model interpreted in a physically meaningful manner, most often (but not always) within the context of the current hydrological paradigm: e.g. the DBM models of rainfall-flow data in Young (1993, 1998, 1999a), Young and Beven (1991, 1994), Young *et al* (1997, 1998) and Lees (2000).

Since the DBM approach is inductive, it is not wedded as strongly to the current paradigms as the hypothetico-deductive approach: indeed, its intention is always to respect these paradigms but not allow them to dictate the structure of models (here rainfall-flow) if the data suggest otherwise. In other words and to use a Kuhnian interpretation of science (Kuhn, 1980), the DBM approach encourages the continual questioning of current paradigms and rejoices in its ability to promote paradigm change if this is supported by observational data. Examples of this ability to promote paradigm change in an evolutionary manner, based primarily on the statistical analysis of data, are the development of the Aggregated Dead Zone (ADZ) model for solute transport in rivers (e.g. Beer and Young, 1983; Wallis et al, 1989; Young and Wallis, 1994); and recent research on *Active*

[1] Now with the Environment Agency

Mixing Volume (AMV) models in mass and energy transfer processes (Young and Lees, 1993; Price *et al*, 1999).

On the basis of the above observations, the present chapter discusses briefly the DBM approach to rainfall-flow modelling and shows how, in conjunction with associated DBM flow routing models, it can form the basis for the development of adaptive flow forecasting algorithms. These algorithms utilise a special, stochastic state-space formulation of the DBM models in which the physically meaningful 'quick-flow' and 'slow-flow' components identified in the DBM model identification and estimation analysis are defined as the stochastic state variables. The resulting forecasting algorithm is recursive in form and exploits a modified and data-optimised version the well known Kalman Filter (KF) to allow for adaptive updating of these physically meaningful state variables on the basis of the monitored rainfall and flow measurements.

2. Data-Based Mechanistic (DBM) Hydrological Models

In the Flow forecasting context, DBM models are required to represent the rainfall-flow and flow routing (flow-flow) processes in stochastic, dynamic terms. As we shall see, these two types of model are able to describe the dominant modes of hydrological behaviour in typical catchments and they can be identified and estimated from rainfall-flow measurements made on the catchment. By *identification*, we mean here the identification of the structural form of a model that can be uniquely estimated from the measured data with the minimum number of parameters; and by *estimation*, we mean the statistical estimation of these parameters.

2.1. The DBM Rainfall-Flow Model

In the case of a uniform sampling interval Δt, the discrete-time (sampled data) DBM rainfall-flow model (see the above references) takes the following form:

$$x_t = \frac{B(z^{-1})}{A(z^{-1})} u_{t-\delta} \quad ; \qquad t = 1, 2, ..., N \tag{1}$$

$$u_t = c \cdot f\{s_t\} \cdot r_t \tag{2}$$

where $A(z^{-1})$ and $B(z^{-1})$ are the following discrete-time operator polynomials,

$$A(z^{-1}) = 1 + a_1 z^{-1} + ... + a_n z^{-n} \quad ; \qquad B(z^{-1}) = b_0 + b_1 z^{-1} + ... + b_m z^{-m}$$

in which z^{-i} is the i^{th} the backward shift operator; i.e. $z^{-i} y_t = y_{t-i}$. Equation (1) is a linear Transfer Function (TF) relationship between the effective rainfall (rainfall excess) input u_t at the t^{th} sampling instant and the flow x_t at the same sampling instant. Equation (2) describes the nonlinear relationship between the measured rainfall r_t and u_t, which takes the form of a multiplicative nonlinearity between r_t and a nonlinear function $f\{s_t\}$ of the soil moisture s_t. This soil moisture variable can be considered as an unobserved state of the system that either has to be estimated from the data in some manner, or replaced by some surrogate that reflects changes in soil moisture (see later discussion). The parameters of both the linear TF model (1) and the nonlinear model (2) are all unknown *a priori* and need to be estimated from the rainfall, flow and (if available) temperature and/or soil moisture measurements. In addition, the TF polynomial orders (which are normally ≤ 3), and any associated time delay δ, need to be identified as part of the identification and estimation procedure.

Equations (1) and (2) are purely deterministic. In order to introduce stochasticity into the formulation, it is assumed that the flow x_t is affected by noise ξ_t that reflects the combined effects of measurement noise, unmeasured disturbances and imperfections in the model: i.e. $y_t = x_t + \xi_t$. Then, the model can be written in the following discrete-time equation form relating the measured variables y_t and u_t,

$$y_t = -a_1 y_{t-1} - ... - a_n y_{t-n} + b_0 u_{t-\delta} + b_1 u_{t-\delta-1} + ... + b_m u_{t-\delta-m} + \eta_t \quad (3)$$

where $\eta_t = \xi_t + a_1 \xi_{t-1} + ... + a_n \xi_{t-n}$. The noise ξ_t can be modelled in various ways, e.g. as a zero mean white noise sequence or as an AutoRegressive (AR) or AutoRegressive-Moving Average (ARMA) stochastic process (see e.g. Box and Jenkins, 1970; Young, 1984). However, these noise models are hardly ever entirely appropriate in the case of rainfall-flow data, where the noise does not necessarily conform to such regularity and can be affected by problems such as non-stationarity (e.g. heteroscedasticity or changing variance) and nonlinearity. Thus, while such simplifying assumptions can be introduced at this stage for theoretical convenience, it is important to subsequently utilise statistical methods of model identification and estimation that are not sensitive to these assumptions.

The conceptual justification for the TF model (1) is straightforward: it can be considered in its alternative infinite dimensional 'convolution equation' form,

$$x_t = \sum_{i=0}^{\infty} g_i . u_{t-\delta-i} \quad (4)$$

as obtained by simply dividing the numerator polynomial $B(z^{-1})$ by the denominator polynomial $A(z^{-1})$. This form of the model is interesting because the coefficients g_i are the ordinates of the impulse response function; or, in hydrological terms, the associated infinite dimensional unit hydrograph (IUH). The more conventional finite dimensional approximation of the IUH (the Finite Impulse Response (FIR) in systems terms) is obtained from the g_i by curtailing the number of these coefficients to only those that are numerically significant. This interpretation demonstrates that the TF model is a parametrically efficient ('parsimonious') representation of the unit hydrograph model. This has important implications on the statistically efficient identification and estimation of the model (e.g. Young, 1999a).

The nonlinear equation (2) is an attempt to represent, in a simple manner, the soil-moisture and evapo-transpiration mechanisms in the system and modify the rainfall to account for these effects. In this regard, equation (2) multiplies the 'raw' rainfall measurements r_t by the function $f\{s_t\}$ of the soil moisture, so modifying the measured rainfall to reflect the antecedent rainfall effects on the catchment. Interpreted in these terms, the input nonlinearity can be considered as an alternative to the well known, and conventional 'Antecedent Precipitation Index' (API) approach (e.g. Weyman, 1975) that has been used for many years in rainfall-runoff models. In HCM models, such as the Bedford-Ouse and IHACRES models mentioned previously, $f\{s_t\}$ is formulated as a simple, hydrologically meaningful conceptualisation of the soil-moisture and evapo-transpiration mechanisms. In fact, the main 'catchment storage equation' for s_t, in the Bedford-Ouse model can be considered as a parametrically efficient alternative to the API.

The nonlinear part of the DBM model is much simpler than in either of the two previous HCM models. Following the DBM approach discussed briefly in the last section, it is based on a special form of non-parametric estimation from the data (e.g. Young, 2000) and takes the form,

$$u_t = c \cdot f\{y_t\} \cdot r_t \quad (5)$$

where c is a scaling factor chosen in some appropriate manner: e.g., as in the example below, so that the volume of the effective rainfall is equal to the total stream flow volume over the estimation period. In other words, the nonlinear function $f\{s_t\}$ in the HCM models is replaced by $f\{y_t\}$. As pointed out in the above references on DBM rainfall-flow models, this relationship should not be interpreted as saying that effective rainfall is *physically* a function of flow, which is obviously impossible. Rather, the measured flow y_t is effectively acting here as an objectively identified *surrogate* for the catchment storage. This seems sensible from a hydrological standpoint, since flow is clearly a function of the catchment storage and its pattern of temporal change is likely to be similar. A typical nonlinear function that is able to parameterise the non-parametric estimate of the nonlinearity $f\{y_t\}$ is the power law, i.e. $f\{y_t\} = y_t^{\vartheta}$ (see later example). However, in DBM terms, the functional form of the nonlinearity is not necessarily of a particular, pre-specified form; rather the functional form is identified from the measured data as a stage in the modelling process. For example, in the case of the

well known Coweeta catchment (Young, 1999a, 2000) either a polynomial relationship or an exponentially rising function appear more appropriate than a power law.

It will be noted that the DBM model (equations (1) and (2)) does not include any temperature dependent terms and so, in this basic form, it cannot account for seasonal effects that appear to be temperature dependent. Following the DBM approach, however, these should be identified and estimated from the data, rather than included *a priori*, as in the Bedford-Ouse and IHACRES models. In the case of the Coweeta data (Young, 1998, 1999a, 2000), for instance, such an approach suggests strongly that the temperature dependency enters through a separate linear TF relationship. However, the present paper considers hourly rainfall-flow data from the Ribble catchment in North West England and this does not reveal any significant temperature dependency. For this reason, and because temperature data were not available, the effective rainfall nonlinearity is identified simply as a power law $f\{y_t\} = y_t^{\vartheta}$.

2.2. The DBM Flow Routing (Flow-Flow) Model

The rainfall-flow process is a nonlinear dynamic process consisting of the effective rainfall nonlinearity in series with a linear TF. Once the soil moisture dynamics have been accounted for, however, the flow routing process down the river is much simpler. It is now well established in the hydrological literature that linear TF models can characterise well the dynamic relationship between either flows or levels in river channels. Typically, the TF model relating the measured flows at adjacent measurement locations on the river takes the form:

$$y_t^i = \frac{D_i(z^{-1})}{C_i(z^{-1})} y_{t-\delta i}^{i-1} + \mu_t^i \quad ; \qquad i = 1, 2, ..., n_r \tag{6}$$

where,

$$C_i(z^{-1}) = 1 + c_{i,1}z^{-1} + ... + c_{i,p}z^{-ni} \quad ; \qquad D_i(z^{-1}) = d_{i,0} + d_{i,1}z^{-1} + ... + d_{i,q}z^{-mi}$$

Here, y_t^i is the measured flow (or level) at the i^{th} reach downstream; δi is the associated advective time delay; μ_t^i is the associated noise process; and n_r is the total number of reaches in the modelled stretch of the river.

2.3. Physically Meaningful Decompositions of TF models

If the TF associated with either the rainfall-flow model or the flow routing model is greater than first order and characterised by real eigenvalues (the roots of the $A(z^{-1})$ or $C_i(z^{-1})$ polynomials: see below), then the TF can be decomposed into serial, parallel or feedback forms. This decomposition is ambiguous, in the sense that the decompositions are all equally acceptable from a mathematical standpoint and they all represent the parent TF exactly. This ambiguity can be removed, however, by considering the physical implications of the decompositions, in line with the DBM philosophy. In the present context, for instance, the parallel decomposition makes most sense, since parallel behaviour of flow processes seems most reasonable in hydrological and water quality systems (e.g. Young, 1992).

Considering the linear part of the rainfall-flow model described by equation (1), the parallel flow decomposition takes the form:

$$\frac{B(z^{-1})}{A(z^{-1})} = \frac{\beta_1}{1 + \alpha_1 z^{-1}} + ... + \frac{\beta_n}{1 + \alpha_n z^{-1}} \tag{7}$$

where α_i and $\beta_i, i = 1, 2, ..., n$ are, respectively, the eigenvalues (roots) of $A(z^{-1})$ and the associated residues in the partial fraction expansion of the TF (the *residue.m* m-file in MATLAB). It is clear from (7) that the effective rainfall $u_{t-\delta}$ can be partitioned into *i* parallel pathways resulting in *i* component flows which, when added

together, yield the total measured river flow. In effect, therefore, the decomposition provides estimates of i 'unobserved' ('hidden' or 'latent') flow states and their associated rainfall-flow dynamics. The advantage of this decomposition is that these unobserved flow states and the dynamics have an obvious and, as we shall see useful, physical interpretation. Before discussing this physical interpretation, however, it is convenient to introduce the following parametric definitions in relation to the i^{th} decomposed, first order TF:

5. **Steady State Gain**, $G_i = \beta_i / (1 + \alpha_i)$: this defines the 'steady state gain' between the input effective rainfall and the unobserved flow in the i^{th} pathway. In the present context, if the input and output variables are similar physical variables and can be interpreted in volume or mass terms, the steady state gain is a measure of conservativity, with a gain of unity indicating a conservative (loss-less) system.
6. **Residence Time or Time Constant**, $T_i = -\Delta t / \log_e(-\alpha_i)$: this is the residence time of the water in the i^{th} pathway. Together with the steady state gain and the advective time delay δ, it defines completely the dynamics of the water passing through the i^{th} pathway. The associated travel time is defined as $t_i = T_i + \delta$.
7. **Partition Fraction**, $p_i = G_i / (\sum_{j=1}^{j=n} G_j)$: this is the inferred fraction of flow passing through the i^{th} pathway ($100 \cdot p_i$ is the percentage partition).
8. **Active Volumes**, $v_{i,t} = p_i \cdot T_i \cdot y_t$: this is the inferred volume associated with the water transfer through the i^{th} pathway at the t^{th} sampling instant (this is obtained from the conventional definition of residence time as volume divided by flow rate: here the flow rate in the i^{th} pathway might be inferred as $p_i \cdot y_t$).
9. **Volume Fraction**, $d_{i,t} = v_{i,t} / V$, where V is the total volume of water: this defines the volume of water passing through the i^{th} pathway at the t^{th} sampling instant, in relation to the total volume of water.

The latter two definitions follow from similarly defined parameters in the case of water quality models, where they are very significant in terms of their physical interpretation (see e.g. Young, 1999b and the previous references therein: in this other application, they are termed the 'active mixing volume' and 'dispersive fraction', respectively). In the present rainfall-flow and flow routing context, they appear to be less obvious and useful parameters but are included here for completeness.

Given these definitions, the hydrological interpretation of each decomposed TF is revealed by considering the unobserved flow component $x_{i,t}$ in the i^{th} pathway. From (7), this is generated by the equation:

$$x_{i,t} = \frac{\beta_i}{1 + \alpha_i z^{-1}} u_{t-\delta} \quad \text{or} \quad x_{i,t} = -\alpha_i x_{i,t-1} + \beta_i u_{t-\delta} \tag{8}$$

This can be interpreted (see e.g. Young, 1984) as the discrete-time version of a first order differential equation of the form[2]:

$$T_i \frac{dx_i(t)}{dt} = G_i \; u(t - \delta\Delta t) - x_i(t) \tag{9}$$

where T_i and G_i, i=1,2, are, respectively, the associated time constant and steady-state gain of the TF; $u(t - \delta\Delta t)$ is the continuous-time equivalent of the sampled effective rainfall measure, $u_{t-\delta}$;and $x_i(t)$ is the continuous-time equivalent of the sampled flow variable $x_{i,t}$. It is straightforward to see how equation (9) can be interpreted as a dynamic mass balance or storage equation[3] by defining the rate of change of water storage $S_i(t)$ in the i^{th} pathway as the volume of water entering the pathway in unit time minus the volume leaving in the same time interval, i.e.,

[2] Indeed, it is possible to estimate the TF model directly in such differential equation terms using the rivcid.m tool in the MATLAB CAPTAIN Toolbox (see Conclusions Section 6)

[3] See Young and Lees (1992) for a more general environmental interpretation as an *Active Mixing Volume* (AMV) model.

$$\frac{dS_i(t)}{dt} = G_i\ u(t-\delta\Delta t)\ -\ x_i(t) \tag{10}$$

where $G_i\,u(t-\delta\Delta t)$ represents the volume equivalent of the rainfall input entering the i^{th} pathway, having accounted for the advective time delay (δ sampling intervals is equivalent to a temporal delay of $\delta\Delta t$ time units). Now, by making the physically reasonable assumption that the outflow $x_i(t)$ is proportional to the storage $S_i(t)$ at any time, i.e.,

$$x_i(t) = \gamma_i\ S_i(t) \quad \text{or} \quad S_i(t) = T_i\ x_i(t); \quad T_i = 1/\gamma_i \tag{11}$$

and substituting from equation (11) into (10), we obtain the identified equation (9) provided T_i is a constant. The derivation of equation (9) in this manner is perfectly credible in physical terms: indeed, the derivation, including the assumption (11), is the basis of the physically-based 'lag-and-route' models that have been used for some considerable time by hydrologists (see e.g. Young, 1986).

2.3.1 A Typical Example

A typical example of parallel decomposition is the following rainfall-flow model identified and estimated from hourly data for the River Hodder at Hodder Place in the River Ribble Catchment (see later) in December 1993:

$$x_t = \frac{b_0 + b_1 z^{-1}}{1 + a_1 z^{-1} + a_2 z^{-2}}\, u_{t-\delta} \quad ; \quad y_t = x_t + \xi_t \tag{12}$$

Here, the effective rainfall is generated from the power-law equation:

$$u_t = c \cdot y_t^{\vartheta} \cdot r_t \tag{13}$$

from the rainfall r_t, which was obtained as a Thiessen Polygon average of all the rain gauges in the vicinity of the River Hodder. The resulting model parameter estimates, together with their standard errors (shown in parentheses), are given in the first column of Table 1. The physically meaningful parameters discussed above are easily derived from these parameter estimates and are also shown in the Table 1. The TF parameter estimates were obtained using a special optimisation procedure based around the statistically robust (see earlier comments) SRIV method of *Instrumental Variable* estimation (see e.g. Young, 1984, 1985) which is not sensitive to nature of the noise on the data (see also the Appendix in Young and Beven, 1994). Given these estimates of the TF parameters, the modelling error is defined as the difference between the measured flow y_t and the deterministic model output $\hat{x}_t$ given by,

$$\hat{x}_t = \frac{\hat{b}_0 + \hat{b}_1 z^{-1}}{1 + \hat{a}_1 z^{-1} + \hat{a}_2 z^{-2}}\, u_{t-\delta} \tag{14}$$

A normalised measure of how well the model has explained the data is then provided by the *Coefficient of Determination* (or *Efficiency*), R_T^2, which is defined as follows:

$$R_T^2 = 1 - [\sigma_\varepsilon^2 / \sigma_y^2] \tag{15}$$

where σ_e^2 is the variance of the model fitting error $\varepsilon_t = y_t - \hat{x}_t$ and σ_y^2 the variance of the flow series y_t. In this case, $R_T^2 = 0.872$ (i.e. 87.2% of the output river flow variations are explained by the deterministic model output), so we can conclude that the model provides a relatively good description of the data. The noise ξ_t can be explained approximately by a 6^{th} order AutoRegressive (AR(6)) model; and the equivalent coefficient of

determination based on one-step-ahead prediction errors incorporating this model is $R^2 = 0.96$. The residuals from the model including this AR(6) noise model are not significantly correlated and have a variance 0.005. However, there are clear signs of heteroscedasticity, as usual in rainfall-flow models.

Table 1. *Derived Physically Meaningful Parameters for Equation (12)*

Parameter Estimates	*Physical Meaningful Derived Parameters*	*'Slow-Flow' Pathway*	*'Quick-Flow' Pathway*
$\hat{a}_1 = -1.7394(0.015)$; $\hat{a}_2 = 0.7428(0.014)$	SSG, G_i	0.40	0.60
$\hat{b}_0 = 0.1529(0.006)$; $\hat{b}_1 = -0.1495(0.005)$	Residence Time, T_i	73 hours	3.5 hours
$\hat{\alpha}_1 = 0.9864$; $\hat{\alpha}_2 = 0.7530$	Advective Delay, δ	4 hours	4 hours
$\hat{\beta}_1 = 0.0055$; $\hat{\beta}_1 = 0.1474$			
$\hat{c} = 0.847$; $\hat{\vartheta} = 0.16(0.0001)$	Partition %, p_i	40%	60%

The derived parameters in Table 1 reveal that the two pathways have very different dynamics: the 'quick-flow' pathway has a residence time of 3.5 hours which, together with the advective time delay of 4 hours, produces a total travel time of 7.5 hours; in contrast, the 'slow-flow' pathway has a residence time of 73 hours and a total travel time of 77 hours. The associated partition percentages of 60% and 40%, respectively, suggest that more of the effective rainfall affects the quick-flow pathway than the slow-flow pathway. However, a word of caution is necessary when considering these figures: if the uncertainty in the parameter estimates is taken into account (see e.g. Young, 1999b), then some of the derived parameters in Table 1 have wide confidence intervals and non-gaussian distributions. In particular, and not surprisingly, the 'slow' flow dynamics are much more poorly defined than the 'quick' flow dynamics.

Given the parameters in Table 1, the most obvious physical interpretation of the model (12) is that the effective rainfall affects the river flow via two main pathways. First, the initial rapid rise in the hydrograph derives from the 'quick-flow' pathway, probably as the aggregate result of the many surface processes active in the catchment. And the long tail in the recession of the hydrograph arises from the 'slow-flow' component, probably as the result of water displacement (probably of 'old water') within the groundwater system. Note that the estimate of the flow contribution of this 'slow-flow' component is also practically useful: it provides a relatively objective estimate of the total 'base-flow' in the river and, as such, can be utilised for base flow quantification removal, if this is required (but again noting our comments on the implications of uncertainty).

3. The Stochastic State Space Formulation of the DBM Model

The rainfall-flow and flow routing models given by equations (1), (2) and (6) are useful in analysing the rainfall-flow processes in the catchment, as revealed by the rainfall-flow data. In the present flow forecasting context, however, they are just as important in providing the basis for the development of an adaptive forecasting algorithm. In this paper, we develop this algorithm via stochastic State-Space (SS) theory, exploiting recursive estimation (see e.g. Young, 1984). The first stage in this development is the conversion of the above TF models into a suitable stochastic SS form.

There is no unique state space equivalent of a TF model since the formulation of such a model depends upon the definition of the stochastic state variables. For this reason, many past applications of this approach in flow forecasting have tended to utilise special 'canonical' SS forms, where the state variables are defined in a manner which is convenient mathematically but normally has little physical significance. We have found, however, that this rather arbitrary specification of the state space model can result in poor forecasting performance. Superior results are obtained if the SS model form is chosen to conform to the TF decomposition discussed above. For example, equation (12) can be converted to the following SS model:

$$\begin{aligned} \mathbf{x}_t &= \mathbf{F}\mathbf{x}_{t-1} + \mathbf{G}u_{t-\delta} + \varsigma_t \\ y_t &= \mathbf{H}\mathbf{x}_t + e_t \end{aligned} \tag{16}$$

where,

$$\mathbf{x}_t = \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} \quad ; \quad \mathbf{F} = \begin{bmatrix} -\alpha_1 & 0 \\ 0 & -\alpha_2 \end{bmatrix} \quad ; \quad \mathbf{G} = \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \quad ; \quad \mathbf{H} = \begin{bmatrix} 1 & 1 \end{bmatrix};$$

Here e_t is the observational error on the flow measurement which, for simplicity, is assumed here to have zero mean and variance σ^2; and ς_t is the 2x1 vector of stochastic disturbances to the state equations (system noise), which is assumed, again for simplicity, to be composed of independent white noise elements with a diagonal covariance matrix $\mathbf{Q}$. In other words, the stochastic state variables are selected as the two flow components defined by the parallel flow decomposition of the TF model and the stochastic description is completed by the introduction of the white noise inputs e_t and ς_t. In terms of the TF model (12), ξ_t is an easily derivable function of ς_t and e_t but this is not utilised in the subsequent use of the SS equations because the required statistical properties of ς_t and e_t are estimated directly from the data within this SS formulation, given the above definitions of **F**, **G**, and **H**.

4. The State Adaptive Forecasting Algorithm: A Special Form of the Kalman Filter

Let us consider, once more, the simple example discussed above, with e_t in (16) assumed to be zero mean white noise with variance σ^2. Given on-line inputs of the measured rainfall-flow data, $\{y_t, r_t\}, t = 1, 2, ..., N$ (e.g. by telecommunication from remote sensors), equation (13) provides an estimate of the effective rainfall u_t. Recursive estimates $\hat{\mathbf{x}}_t$ of the state vector $\mathbf{x}_t$ and, from this, a recursive estimate $\hat{y}_t$ of the river flow y_t, can then be obtained from the following special form of the Kalman Filter algorithm, written conveniently in a prediction-correction form:

Recursive State Adaptation Algorithm (e.g. Young, 1999c; after Kalman, 1960)

Repeat for $t = 1, 2, \cdots, N$

Prediction:

$$\begin{aligned} \hat{\mathbf{x}}_{t|t-1} &= \mathbf{F}\hat{\mathbf{x}}_{t-1} + \mathbf{G}u_{t-\delta} \\ \mathbf{P}_{t|t-1} &= \mathbf{F}\mathbf{P}_{t-1}\mathbf{F}^T + \mathbf{Q}_r \\ \hat{y}_{t|t-1} &= \mathbf{H}\hat{\mathbf{x}}_{t|t-1} \end{aligned} \tag{17a}$$

Correction:

$$\begin{aligned} \hat{\mathbf{x}}_t &= \hat{\mathbf{x}}_{t|t-1} + \mathbf{P}_{t|t-1}\mathbf{H}^T[1 + \mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}^T]^{-1}\{y_t - \hat{y}_{t|t-1}\} \\ \mathbf{P}_t &= \mathbf{P}_{t|t-1} - \mathbf{P}_{t|t-1}\mathbf{H}^T[1 + \mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}^T]^{-1}\mathbf{H}\mathbf{P}_{t|t-1} \\ \hat{y}_t &= \mathbf{H}\hat{\mathbf{x}}_t \end{aligned} \tag{17b}$$

where $\mathbf{P}_t$ is a 2x2 matrix, related to the parametric covariance matrix $\mathbf{P}_t^*$ by $\mathbf{P}_t^* = \sigma^2\mathbf{P}_t$; and $\mathbf{Q}_r$ is defined as the 2x2 *Noise Variance Ratio* (NVR) matrix,

$$\mathbf{Q}_r = \frac{\mathbf{Q}}{\sigma^2} = \begin{bmatrix} q_{r1} & 0 \\ 0 & q_{r2} \end{bmatrix} \tag{17c}$$

We see that, based on the SS model (16), the previous estimate of the state vector $\hat{\mathbf{x}}_{t-1}$ and its associated covariance matrix $\mathbf{P}_{t-1}$ (as obtained at the previous recursion) are predicted forward one sampling interval by the first two equations in (17a) to yield $\hat{\mathbf{x}}_{t|t-1}$ and $\mathbf{P}_{t|t-1}$, respectively. The total one-step-ahead flow prediction $\hat{y}_{t|t-1}$

is then obtained trivially from the third equation in (17a), as the sum of the two elements in $\hat{\mathbf{x}}_{t|t-1}$ (the predicted quick and slow-flow components). If multi-step forecasts are required, they are obtained by repeating the equations in (17a) for the requisite number of times, before proceeding to the correction equations (17b). Note that this is a very simple process if the forecasting interval f is less than or equal to the advective delay δ: however, larger prediction horizons than this require simultaneous prediction of the input effective rainfall, which is clearly a much more difficult problem, particularly in the UK![4] (normally, the most convenient approach, given $f > \delta$ and no available rainfall forecasts, is to assume that the future rainfall is zero or some prescribed percentage of current rainfall in the case of flood warning). Finally, in the correction equations (17b), the one-step-ahead predictions are updated, based on the one-step-ahead prediction error (innovations process) $v_t = y_t - \hat{y}_{t|t-1}$, to yield the estimated state vector, covariance matrix and flow estimates, $\hat{\mathbf{x}}_t$, $\mathbf{P}_t$ and $\hat{y}_t$ respectively, at the t^{th} sampling instant. These then become the initial conditions for the next recursion.

All of the parameters required to implement the above KF algorithm are available from the prior model identification and estimation analysis, except the NVR matrix $\mathbf{Q}_r$. This is normally assumed to be diagonal in form and its two diagonal elements, the 'hyper-parameters' q_{r1} and q_{r2}, need to be estimated in some manner. The most convenient approach is to utilise Maximum Likelihood (ML) optimisation based on *Prediction Error Decomposition*, as described for example in Young (1999c) and Lees (2000). An alternative, used in the later example, is to optimise the NVR values so that they minimise the variance of the multi-step ahead forecasting errors, based on past data. This NVR optimisation is important, since the NVR parameters q_{11} and q_{22} control the memory of the forecasting algorithm and, thence, the rate of the state adaptation. If the NVR values are small, the memory is long and the predicted state variables (component flows) are determined largely by the model predictions, with only minor adjustments in the correction step. If they are large, however, the memory is short and the predicted state variables can be modified considerably at the corrective step, should the one step ahead prediction error v_t be large. This is clearly an advantage in robustness terms, particularly since this corrective action is data-based and, therefore, fully automatic.

So far, for simplicity and clarity, we have limited discussion to the simple rainfall-flow model (12). In practice, of course, it is necessary to expand the model and the forecasting algorithm to represent the whole of the catchment being considered. This requires the formulation of the complete catchment model from the component rainfall-flow and flow routing sub-models. Although this appears complex, particularly for a large catchment with many sub-models, it is a straightforward operation and presents no major difficulties, given the power and flexibility of modern computer systems.

Note finally that the approach to adaptive forecasting based on state adaptation outlined here should be differentiated from adaptive forecasting based on *parameter adaptation*, where a recursive estimation algorithm is used to sequentially update the parameters in the rainfall-flow model (e.g. Lees *et al*, 1994) and/or any hyper-parameters, such as the NVR values in $\mathbf{Q}_r$. Of course, it is possible to combine both state and parameter adaptation but this is not considered here (see Conclusions Section 6). However, the state adaptation algorithm (17), on its own, is well tried in practice and is known to be robust to violation of the theoretical assumptions (e.g. here the assumption that e_t and ξ_t are zero mean, white noise processes). Note that the algorithm (17) is sometimes referred to as a 'data assimilation' procedure, since equation (17a) allows the data to be assimilated on-line in order improve the deterministic model predictions produced by equation (17a).

5. A Typical Practical Example: Multi-Step Forecasting in The River Ribble Catchment

This example is based on the results of an investigation in which different rainfall estimation methods and flow forecasting methods were compared using data from the catchment of the River Ribble in North West England. One main aim of the study was to evaluate the performance of the state adaptive approach to forecasting, as

[4] It is sometimes possible to partially solve this problem by introducing a longer, *false* time delay and estimating the TF model with this false delay included. While this results in larger fitting errors, it can substantially improve forecasting accuracy (see Lees *et al.*, 1994).

outlined above, in comparison with its predecessor at Lancaster, the parameter adaptive forecasting system developed for the Solway River Purification Board as a flood warning system for the town of Dumfries in Scotland (e.g. Lees *et al*, 1994). The other objective, following from the development of the Lancaster Adaptive Radar Calibration (ARC) system for the National Rivers Authority/Environment Agency (Lord *et al*, 1995), was to consider how well forecasting performance using weather radar measured rainfall compared with the performance using more conventional ground-based methods of rainfall measurement.

The Ribble rises at Dodd Fell in the Pennine Hills and flows through a long narrow valley and the Arnford gauging station, before being joined by the its major tributaries, the Rivers Hodder (thinly populated and largely rural) and Calder (extensively urbanised with considerable industrial and agricultural abstraction). Downstream of its confluence with the Calder, the river passes through the New Jumbles Rock gauging station and enters a relatively flat, narrow valley without significant tributaries until it reaches the lowest non-tidal gauging station at Salmesbury, which marks the downstream limit of the study area. The total catchment area to the Salmesbury station is 1145 km^2 and its elevation ranges from 6m AOD at Salmesbury, to 880m AOD at Whernside. The solid geology of the catchment consists of a mixture of carboniferous limestone in part of the catchment north of the Arnford gauging station and millstone grit in the sub-catchments of the Rivers Hodder and Calder. The remainder of the catchment, below 350m AOD, is covered by a thin layer of glacial and alluvial drift deposits, generally less than 20m thick. The main data base consists of six separate periods of rainfall-flow data all sampled at an hourly sampling interval, as outlined in Table 2. All the flow data are converted from $m^3 s^{-1}$ to mm hr^{-1} equivalent; and the rainfall data are measured in mm hr^{-1}.

Table 2. *Summary of Rainfall-Flow Data from the Ribble Catchment used in the Study*

Date of Sample Set	*Identification Letter*	*Number of Hourly samples*
December 1990-January 1991	**A**	392
August-September 1992	**B**	552
January 1993	**C**	720
November-December 1992	**D**	288
December 1993	**E**	480
October- November 1991	**F**	624

Typical DBM model identification and estimation results for data set E have been discussed in sub-section 2.3.1 based on data from the River Hodder at Hodder Place. Typical modelling results across the whole catchment are given in Table 3 (Tomlin, 1999), for a later data set in February 1997. This also compares the results obtained with different rainfall measures, including those obtained from the Lancaster ARC and other weather radar calibration methods, applied to weather radar data from the Hameldon Hill Station.

Except for the results based on the use of the default and Meteorological Office calibrated radar measurement of rainfall, the estimated models explain the data well, with an average $R_T^2 = 0.85$. The best results are obtained using English's method (1973), based on the gauge data. However, those obtained using ARC calibrated radar data have an average $R_T^2 = 0.80$ and are quite reasonable, illustrating how, with improved calibration and spatial interpolation methods, weather radar derived rainfall measurement is becoming competitive with gauge based methods. Indeed, later research, based on improved stochastic spatial interpolation of the ARC calibration results (Brown *et al*, 2000)[5], has yielded better results than those shown here.

[5] Interestingly, this approach also uses optimal recursive estimation procedures similar to those used here.

The state adaptive, four-hour-ahead, forecasting results for the example in sub-section 2.3.1 are shown graphically in figure 1. Here, NVR optimisation was accomplished on the basis of minimising the variance of the four-step-ahead forecasting errors, yielding $q_{r,1} = 0$ and $q_{r,2} = 0.0234$. The forecasting performance could be improved somewhat if the AR noise model was incorporated into the forecasting algorithm design. Even without this, however, the performance is very good and this is reflected in the statistical properties of the forecast errors, which have a mean value near to zero (0.0032 mm hr^{-1}) and a standard deviation $\sigma_{e4} = 0.132$ mm hr^{-1}. The coefficient of determination based on the variance of the four-step-ahead-prediction errors, σ^2_{e4}, is defined as $R^2_4 = 1 - \sigma^2_{e4} / \sigma^2_y$, where the four-step-ahead-prediction error is defined as $e4_t = y_{t+4} - \hat{y}_{t+4|t}$. Here, $R^2_4 = 0.871$, compared with $R^2_4 = 0.484$ for the naïve ('persistence') forecast, where the predicted four-hour-ahead flow is equal to current flow; and $R^2_4 = 0.405$ for the deterministic forecast based on the TF model (as generated, for instance, by the MATLAB 'compare.m' function). This latter performance is so poor because of the considerable noise amplification introduced by the fact that the two coefficients in the numerator polynomial $\hat{B}(z^{-1}) = 0.1529 - 0.1495z^{-1}$ are almost equal and opposite in sign, so that the forecasts are very volatile. It is improved considerably if the deterministic forecast is based on the decomposed parallel pathway form of the TF, when the performance, in this particular case, is only a little worse that with state adaptation. The advantages of the parallel pathway model in forecasting terms are very clear from these results.

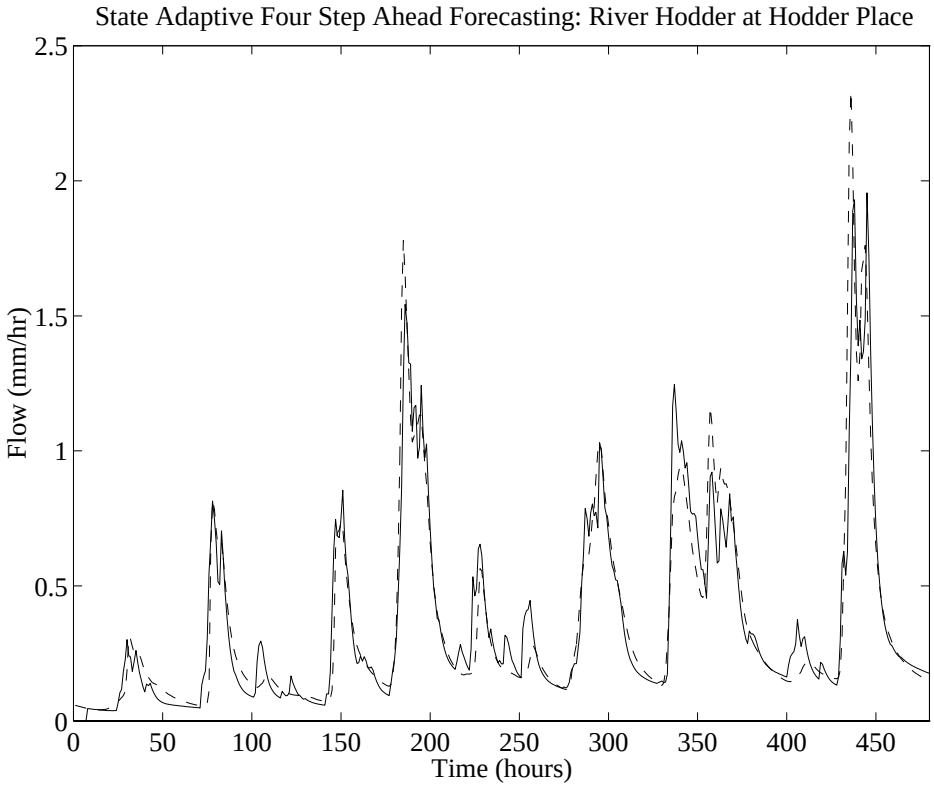


Figure 1. *Four-step-ahead forecasting results for the River Hodder at Hodder Place in December 1993: forecasts (full line) compared with measured flow series (dashed).*

Table 4 summarises the full, four-hour-ahead, state adaptive forecasting results over the Ribble catchment. It should be noted that the results in this Table were obtained without hyper-parameter optimisation, using default, short memory NVR settings of 100. In the present context, these are effectively 'worst-case' scenarios and are selected here to illustrate the robustness of the forecasting algorithm to poor optimisation. It must be emphasised, however, that the results obtained using optimised hyper-parameters can be much superior

to this: e.g. compare the coefficient of determination in the above detailed example for the Hodder at Hodder Place ($R_T^2 = 0.872$) with the results in Table 3a, where the $R_T^2 = 0.8015$. Despite this sub-optimality, however, state adaptation still yields overall better performance than for Dumfries parameter adaptation (Tomlin, 1999). It is only in the case of the Salmesbury station that some of the parameter adaptive results are marginally better than those obtained with state adaptation.

Table 3. *Typical Model Fitting Results for the Ribble Catchment Using Different Rainfall Measures*

Rainfall-flow model location	*Rainfall estimation method*	*Model order*	*Coefficient of Determination* R_T^2
River Ribble at Henthorn	Simple average	(2,1,3)	0.8369
	Thiessen Polygons	(2,1,3)	0.8610
	Inverse distance	(2,1,3)	0.8422
	English's Method	(2,1,3)	0.8718
	Default radar	(2,1,3)	0.6430
	Met Office radar	(2,1,1)	0.4541
	ARC radar	(2,1,3)	0.7920
River Hodder at Hodder Place	Simple average	(2,2,4)	0.8401
	Thiessen Polygons	(2,2,4)	0.8414
	Inverse distance	(2,2,4)	0.8646
	English's Method	(2,2,4)	0.8452
	Default radar	(2,2,4)	0.6979
	Met Office radar	(2,2,3)	0.7872
	ARC radar	(2,2,5)	0.8174
River Calder at Whalley Weir	Simple average	(2,2,4)	0.8910
	Thiessen Polygons	(2,2,4)	0.9064
	Inverse distance	(2,2,4)	0.8557
	English's Method	(2,2,4)	0.8955
	Default radar	(2,2,4)	0.5592
	Met Office radar	(2,2,4)	0.6637
	ARC radar	(2,2,4)	0.7879

Table 4. *Four Hour Ahead Forecasting Results (R_4^2) for the Ribble Catchment: State Adaptive Algorithm*

Data Set	*Ribble at Henthorn*	*Hodder at Hodder Place*	*Calder at Whalley Weir*	*Ribble at NJ Rock*	*Ribble at Samlesbury*
A	0.7688	0.8456	0.9217	0.8851	0.8851
B	0.8236	0.7978	0.8442	0.8893	0.9408
C	0.8314	0.8317	0.9015	0.8995	0.9382
D	0.8848	0.9014	0.7800	0.8753	0.9547
E	0.8649	0.8015	0.8773	0.9039	0.9540
F	0.8403	0.8562	0.4495	0.8819	0.9314

6. Conclusions

This paper has outlined how the *Data-based Mechanistic* (DBM) approach to modelling is able to produce parametrically efficient rainfall-flow and flow routing transfer function models that can be decomposed to reveal interesting and physically meaningful parallel-pathway mechanisms. These DBM models are also in an ideal form for development of an advanced, parameter or state-adaptive flow forecasting algorithm based on a stochastic state space formulation of the parallel-pathway models.

The state adaptive forecasting algorithm has been evaluated extensively by application to the catchment of the River Ribble in North West England, where it has been compared with a previous parameter adaptive forecasting algorithm developed as the basis of a flood warning system for the town of Dumfries in Scotland. It is concluded that the new algorithm performs better than its Dumfries predecessor but that the differences are not all that significant. Nevertheless, the state adaptive algorithm is simpler and more elegant than the parameter adaptive alternative and so should prove to be more robust in practical application. It must be emphasised, however, that the historical Ribble catchment data are very good, so that the DBM models, on which the forecasting algorithm design is based, are of excellent quality. In cases where the prior historical data are not so good, it may well be advantageous to have a parameter adaptive features which are able to 'tune' the forecasting algorithm on-line and so achieve increasingly better performance. For this reason, future research will seek to combine the two methods, so providing a parameter adaptive capability to the state adaptive system.

The Ribble study has also evaluated the performance of the algorithm using various different methods of rainfall measurement, including ones based on weather radar. Although the performance of the state adaptive forecasting system using rain-gauge-based rainfall measurement is still superior to that using weather radar, the difference in performance is no longer all that significant. In particular, the performance using the Lancaster Adaptive Radar Calibration (ARC) system is approaching that of the ground-based methods and is much better than that obtained with other existing weather radar calibration methods. And it appears that recent improvements to the ARC system, in the area of stochastically-based spatial interpolation, will improve the forecasting performance based on weather radar still further.

Finally, note that all of the computations and modelling in this paper was carried out in MATLAB using the CAPTAIN Toolbox (see http://cres1.lancs.ac.uk/systems.html for further information). This Toolbox, which is in the final stages of beta-testing, provides a kit of computational tools for stochastic modelling, time series analysis, forecasting and signal processing. These include: linear TF model identification and estimation for all of the main operator models (discrete, z^{-1}; continuous, s or d/dt; and delta); nonstationary time series analysis; adaptive forecasting based on recursive estimation and fixed interval smoothing; time variable parameter regression (linear, harmonic, auto and the *Auto-Regressive eXogenous variables*, ARX, model); unbiased time variable parameter TF estimation; and *state dependent parameter* estimation for the identification and estimation of nonlinear, stochastic dynamic systems.

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Advances in Transfer Function Based Flood Forecasting

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1. Introduction

The use of linear transfer function models as the basis of real-time flood forecasting systems is well established with many such operational systems in place world-wide. The main attraction of the transfer function approach over the use of conceptual hydrological models is the simplicity of the forecast model that can be represented as a simple difference equation, which is then exceptionally easy to implement in a real-time forecasting system. Disadvantages of commonly applied transfer function methods include the inappropriate use of a linear model when in fact the rainfall-runoff process is highly nonlinear due to dynamic catchment conditions, and the use of the transfer function as a black box model without consideration of physical model constraints. This paper presents extensions to the development and calibration of transfer function models that address these two problems, i.e. by the development of nonlinear physically reasonable transfer functions. The paper also discusses the use of real-time updating, which although it should be a key component of any short lead-time forecasting system, is often omitted in operational systems, and suggests a simple method of calculating probabilistic forecasts. Forecast uncertainty estimation is becoming an increasingly important component of the forecasting procedure as it is recognised that since both data and models are uncertain then our forecasts are inherently also uncertain. Some aspects of the methods presented for real-time updating and uncertainty estimation are equally applicable to forecasting systems based on other models such as artificial neural networks, and flow routing models.

2. Physically reasonable transfer functions

There are many different forms of transfer function (TF) models that differ according to the assumed noise model component; however, the most commonly utilised is the multi-input single-output (MISO) dynamic autoregressive exogenous (DARX) model,

$$y_t = \sum_{i=1}^{r} \frac{B_i(z^{-1})}{A(z^{-1})} u_{i,t-\delta_i} + \frac{1}{A(z^{-1})} e_t \tag{1}$$

where,

$$\begin{aligned} B_i(z^{-1}) &= b_{0_i} + b_{1_i} z^{-1} + \cdots + b_{m_i} z^{-m_i} \\ A(z^{-1}) &= 1 + a_1 + a_2 z^{-1} + \cdots + a_n z^{-n} \end{aligned} \tag{2}$$

Here u_i, $i = 1, 2, \cdots r$ are input variables; the triad $[\, n,\ m_i + 1,\ \delta_i \,]$ defines the model structure; z^{-p} is the backward shift operator, *i.e.* $z^{-p} x_t = x_{t-p}$; and $a_1 \cdots a_n, b_{0_i} \cdots b_{m_i}$ are the parameters. If $i = 1$, then the model reduces to a single-input, single-output (SISO) transfer function model. SISO models are typically used to model rainfall-runoff relationships, while MISO models are used in flow-flow forecasting applications where there are a number of gauging stations on upstream tributaries. Although the parameters of the DARX model are commonly estimated using a simple least squares methods, there is evidence (e.g. Lees, 2000) that more sophisticated system identification methods such as the simplified refined instrumental variable (SRIV) method

(Young, 1984) produce more certain parameter estimates, which in turn leads to the identification of different model structures with significantly improved performance.

One of the major advantages of the TF model over other conceptual hydrological models is that the structure [n, m_i+1, δ_i] is objectively identified as part of the modelling procedure so resulting in parsimonious models. At first sight to many hydrologists, this feature places the TF model in the group of black-box models along with artificial neural network models since the estimated model parameters do not appear to have a physical interpretation. Indeed, TF models identified in this way can have undesirable characteristics such as oscillatory responses that are clearly not physically reasonable given our current knowledge of hydrological processes. However, an investigation of any identified models to check that they are physically reasonable should also be performed prior to acceptance of the TF as a predictive model of the system. This additional modelling step is particularly important in ensuring good forecasting performance during events with greater magnitude than events contained within the calibration data.

At this stage, it is useful to examine the relationship between certain single-input single-output TF model structures, as defined by the triad [n, m+1, δ], with more traditional rainfall-runoff models. It is easy to show that discretisation of the well-known linear storage model,

$$\frac{d\hat{Q}}{dt} = \frac{1}{T}\left[u(t) - Q(t)\right] \tag{3}$$

where $\hat{Q}(t)$ is the model outflow at time t; $u(t)$ is the inflow at time t; and T is the residence (mean travel) time, results in the following first order discrete TF [1, 1, 0],

$$\hat{Q}_t = \frac{b_0}{1 - a_1 z^{-1}} u_t \,;\; b_0 = \frac{\Delta t}{T},\;\; a_1 = 1 - \frac{\Delta t}{T} \tag{4}$$

where Δt is the discretisation step size. Introducing a lag element δ results in a TF with a [1, 1, δ] structure that can be rearranging into the following difference equation form,

$$\hat{Q}_{t+\delta} = b_0 u_t + a_1 \hat{Q}_{t+\delta-1} \tag{5}$$

revealing that the model is identical to commonly applied flood forecasting models such as the linear input-storage-output (ISO, Lambert, 1972). Using block diagram analysis it is easy to show that the SISO version of the transfer function model (1) can represent any combination of linear storage models as is shown in Fig 1. In order to decompose an identified TF into its constituent linear storage structure requires partial fraction expansion (see, Young, 1992). Note that the transfer function is not constrained to the linear storage parameter relationship $a_1 = 1 - b_0$, *i.e.* mass can be generated or lost, which is a very useful feature in cases where additional inflow such as flow from ungauged tributaries or lateral inflow occurs.

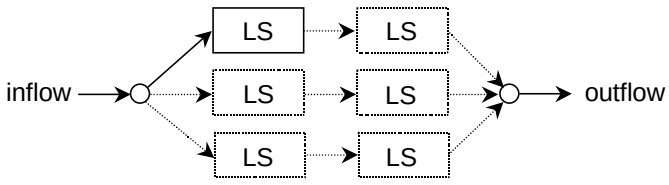


Figure 1. *General linear storage model (each linear store takes the form of Equation 3)*

Having ascertained that the SISO TF can be considered to be a representation of many common conceptual hydrological models questions the usefulness of the TF approach. However, there are a number of advantages of posing the modelling problem in TF form including the availability of powerful system identification techniques for optimal parameter estimation; and the ability to use state estimation methods to improve on-line forecasts. In particular, most simple conceptual and unit hydrograph based models do not attempt to include baseflow as an integral model component although it is well known that second order flow dynamics can represent an important component of flood flows. TF modelling objectively reveals the most appropriate model structure for the study catchment as part of the modelling procedure, and the majority of cases studied so far suggest that the most appropriate structure is second order which can be decomposed into two linear stores representing 'quick' and 'slow' flow processes. Such a parallel storage structure is a common feature of a number of accepted rainfall-runoff models including PDM (Moore, 1985) and IHACRES (Jakeman and Hornberger, 1993).

3. Nonlinear transfer functions

The rainfall runoff process is inherently nonlinear due to antecedent catchment wetness and the effect of dynamic contributing areas on runoff production. Some operational flood forecasting models ignore this nonlinearity completely, while many incorporate very simple rainfall loss methods of calculating an effective rainfall for input to the routing component of the model (e.g. RORB, Mein *et al*., 1974). Although real-time model correction can be implemented to improve the performance of linear models, a nonlinear model in addition to a suitable real-time correction model is likely to produce superior performance.

The first nonlinear extension of a TF based rainfall runoff model, which is presented in Whitehead and Young (1975), consists of a rainfall pre-processor that calculates effective rainfall (*er*) as the product of rainfall (*r*) with a catchment wetness index (*CWI*) that is simply filtered rainfall,

$$er_t = r_t \times CWI_t ;\; CWI_t = \frac{1}{1 + dz^{-1}} r_t \tag{6}$$

Here d is related to the time constant (memory) of the filter through,

$$T_c = \Delta t / \ln(-d) \tag{7}$$

This rainfall loss function is closely related to the antecedent precipitation method of effective rainfall calculation (Linsley *et al*., 1988) since it can be shown that the output of a first order filter is the summation of exponentially weighted past inputs. Extensions to this loss function have since been made to incorporate the effects of long-term changes in evaporation resulting in models such as the IHACRES model (Jakeman and Hornberger, 1993), which is one example of a new class of hybrid conceptual-metric continuous simulation models that combine various conceptual loss functions with a metric TF routing model (Wheater *et al*., 1993). Figure 2 shows the hybrid conceptual-metric model structure.

While a conceptual loss function is required for simulation purposes, in real-time flow forecasting applications measurements of antecedent flow are likely to provide a good surrogate of catchment wetness. To this end, Young and Beven (1994) proposed the following simple loss function,

$$er_t = r_t \times Q_{t-\tau}^{\alpha} \tag{8}$$

where τ is a shift parameter that is usually zero, and α is optimised using a suitable nonlinear optimisation method. Excellent results have been reported for this loss function in a number of applications when it is

combined with a parallel structure TF model (e.g., Young *et al*., 1997). Figure 3, which shows the loss function for $\alpha = 1$ (termed bi-linear) and $\alpha = 0.3$, reveals the form of the loss function which simply states that as flow increases the proportion of rainfall that is effective increases. The power law relationship is clearly more physically reasonable than the bi-linear relationship since as the catchment saturates the proportion of rainfall that is effective tends to unity.

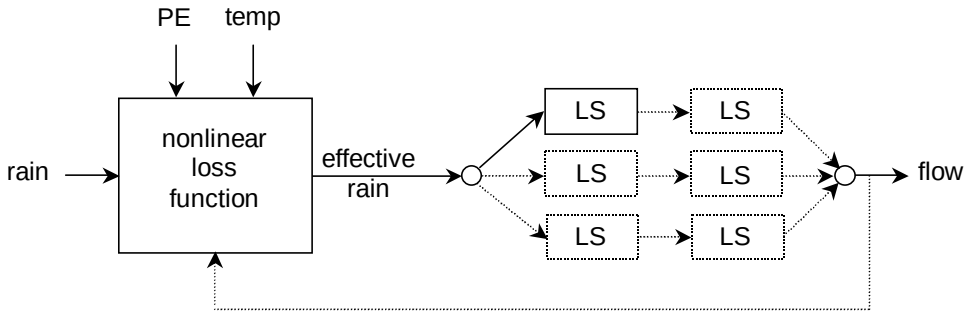


Figure 2. *Hybrid conceptual-metric model structure*

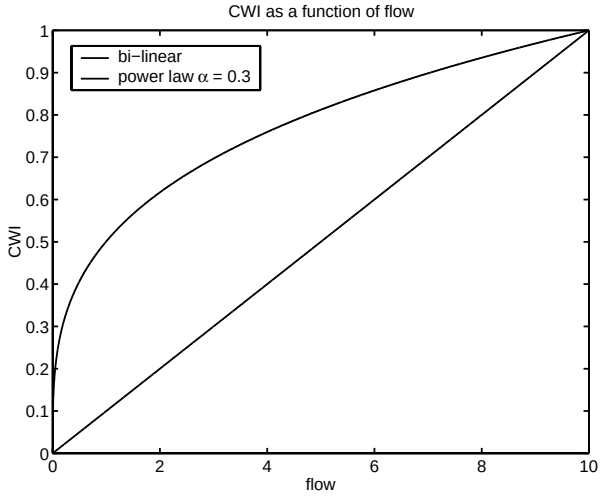


Figure 3. *Flow based nonlinear loss function*

The power law form of this loss function is *subjective* and many other forms could be appropriate according to the specific catchment characteristics. However, the form of this nonlinearity can be objectively identified using the state dependent modelling technique outlined by Young and Beven (1994) and Lees (2000). In the state dependent modelling method a time varying parameter version of the DARX model (1) is used to investigate relationships between parameter variations and states providing a non-parametric representation of the nonlinearity. For example, it has been found that for the rainfall-runoff case the numerator parameter of a first order model varies with flow in a manner that can often be approximated as a power law relationship, and since this parameter acts solely on the input variable, the nonlinearity can be simplified to an input form. Although state dependent parameter modelling provides an objective method of identifying the nature of the rainfall-runoff nonlinearity; at this point in time, due to the complexity of the methodology, it is more useful as a research tool to investigate the nature of other suitable nonlinear functions that would then be optimised using simpler numerical optimisation techniques. Note that there are clear parallels here between the nature of this

nonlinearity and the dynamic contributing area concept of models such as PDM (Moore, 1985) and TOPMODEL (Beven and Kirkby, 1979).

4. Real-time forecast updating

It has long been recognised by researchers that on-line forecast correction using the latest available flow data should be an important component of a real-time flood forecasting system. However, with a couple of notable exceptions, many areas of the UK currently rely on forecasting systems that do not have any mechanism for the automatic real-time correction of flood forecasts. Although experienced operators can take account of systematic errors in hindcasts there is a concern that errors can be made under the pressurised conditions that occur during flood events. Figure 4, which shows a schematic of a forecasting system with real-time updating, reveals that elements of the forecasting system are updated (modified) using a procedure that is driven by the error between past forecasts and the current measured output.

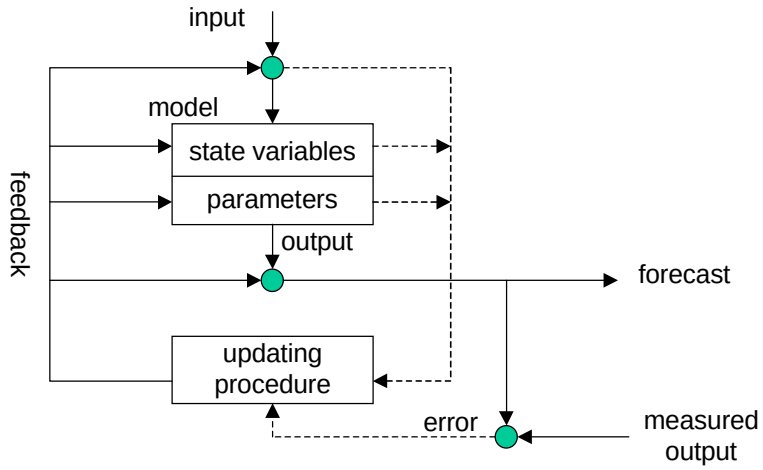


Figure 4. *Schematic of a real-time forecasting system with updating*

A number of different updating techniques exist that attempt to improve forecasts by examination of past forecast performance, and as such they can be thought of as an automation of the intuitive correction applied by a human operative. Most techniques can be classified as either state updating, parameter updating or error prediction methods. Error prediction, which can be applied to any type of forecasting model (including ANNs, see Imrie *et al*., 2000), is based on time-series modelling of the forecast residuals (Bell and Moore, 1998). State updating and parameter updating can be performed using a Kalman filter if the model is linear, or by an extended Kalman filter if the model is nonlinear (Wood and Szöllösi-Nagy, 1980). Bell and Moore (1998) also present an empirical state updating method for nonlinear forecasting models.

As state earlier, one advantage of the TF approach is that the TF model can be easily converted to a stochastic state space form and therefore the Kalman filter can be used to estimate an optimal state estimate, which in this case is flow. A common simplification of the KF state-updating technique is state replacement where the latest available flow measurements replace model output in forecast calculations. For example, the state updated forecasts for a first order transfer function model with a 2 sample lead time can be calculated at each step by,

$$\begin{aligned} \hat{Q}_{t+1} &= a_1 Q_t + b_0 u_{t-1} \\ \hat{Q}_{t+2} &= a_1 \hat{Q}_{t+1} + b_0 u_t \end{aligned} \qquad (9)$$

where $\hat{Q}_t$ is the flow forecast and Q_t is the measured flow. This method is of course equivalent to KF state updating with the covariance of the observation noise set to a low value relative to the system noise covariance, such that the KF estimate closely tracks the output. Although this method is very simple in comparison to the KF, it has the disadvantage that probabilistic forecasts cannot be produced.

Parameter updating refers to the on-line estimation of model parameters using a recursive estimator such as the KF with the system equations reformulated so that the state vector contains the TF parameters. However, due to the limited information content contained within individual flood events, it is not possible to robustly estimate a large number of model parameters on-line. In many situations it is sufficient to estimate a scalar gain parameter that does not change the 'shape' of the hydrograph but simply shifts the output up or down. State and parameter updating can be combined where parameter updating is used to correct long-term changes in the system caused by physical changes such as land-use changes in the case of rainfall-runoff modelling, or channel properties in the case of flood routing, and state-updating is used to incorporate past observations into forecasts in an optimal manner. This combined approach has been successfully used in practice in an operational flood forecasting system developed for Dumfries in SW Scotland (Lees *et al.*, 1994).

5. Estimating forecast uncertainty

In many forecasting fields such as meteorological forecasting it is becoming accepted practice to disseminate forecasts with some associated estimate of the forecast confidence. For instance, rainfall forecasts are commonly presented in a probabilistic way, for example stating that there is a 30% probability of rain tomorrow. Acknowledgement that uncertainty exists in forecasts is an honest approach to modelling since expert modellers realise that inevitable uncertainties arise as a result of data errors, model structure error, and calibration errors. The capability to automatically estimate forecast uncertainty could be of great potential operational use since the generated uncertainty mimics an experienced operative's intuition because it is driven by past forecast performance.

There are a number of possible approaches to estimating this uncertainty including: real-time estimation using a Kalman filter; estimation of parameter probability distributions as part of the model calibration procedure; and fitting of an error model to the residuals generated from past model performance. A full description of the use of a Kalman filter to produce confidence intervals can be found in Lees (2000), and a description of the GLUE method of parameter based uncertainty estimation as used for estimating flood inundation uncertainty can be found in the Beven *et al*. paper in this issue.

The simplest method of calculating forecast confidence limits is to fit an error model to the residuals generated by validating the model on historic events. This method is an empirical approach that essentially aims to capture the effect of all uncertainties on forecast performance. As such it is clearly limited to situations where a reasonably long historic data set is available, and relies on the residuals taking the form of a know theoretical distribution such as normal or log-normal. A useful transformation in this latter regard is the Box-Cox parametric family of power transformations (Kottegoda and Rosso, 1998),

$$e(\lambda) = \begin{cases} \dfrac{e^{\lambda} - 1}{\lambda} & \lambda \neq 0 \\ \ln(e) & \lambda = 0 \end{cases} \tag{10}$$

where a suitable value of the λ parameter is found in order to producer normality in the residuals e.

6. An illustrative example: flood forecasting for the River Bollyneendorish

To demonstrate the performance of the nonlinear transfer function model and different real-time updating and uncertainty estimation techniques, a limited modelling exercise has been performed using data from the River Bollyneendorish catchment in the Galway region of Ireland (see Fig. 5 for location). This hydrometric network, which was set up as part of an investigation into flood problems in the region (Lees *et al.*, 1998), is selected since the rainfall-runoff response is similar to many fast responding UK catchments where production of flood forecasts typically relies on a rainfall-runoff model, and also because the data is of marginal quality with the rainfall measured using a single tipping bucket gauge (indicated as FG on Fig. 5.) and flow estimated using a transducer situated in a natural section control (indicated as SA2 on Fig. 5.) with a relatively uncertain rating curve. Further details of the catchment's climatic regime, geology and instrumentation can be found in Lees *et al*. (1998). Calibration was carried out on a 2 week period of hourly data in January 1996 and verification over the whole data period, although verification attention is focussed on the three separate high flow periods that occurred in February, March and October 1996: see Fig. 6.

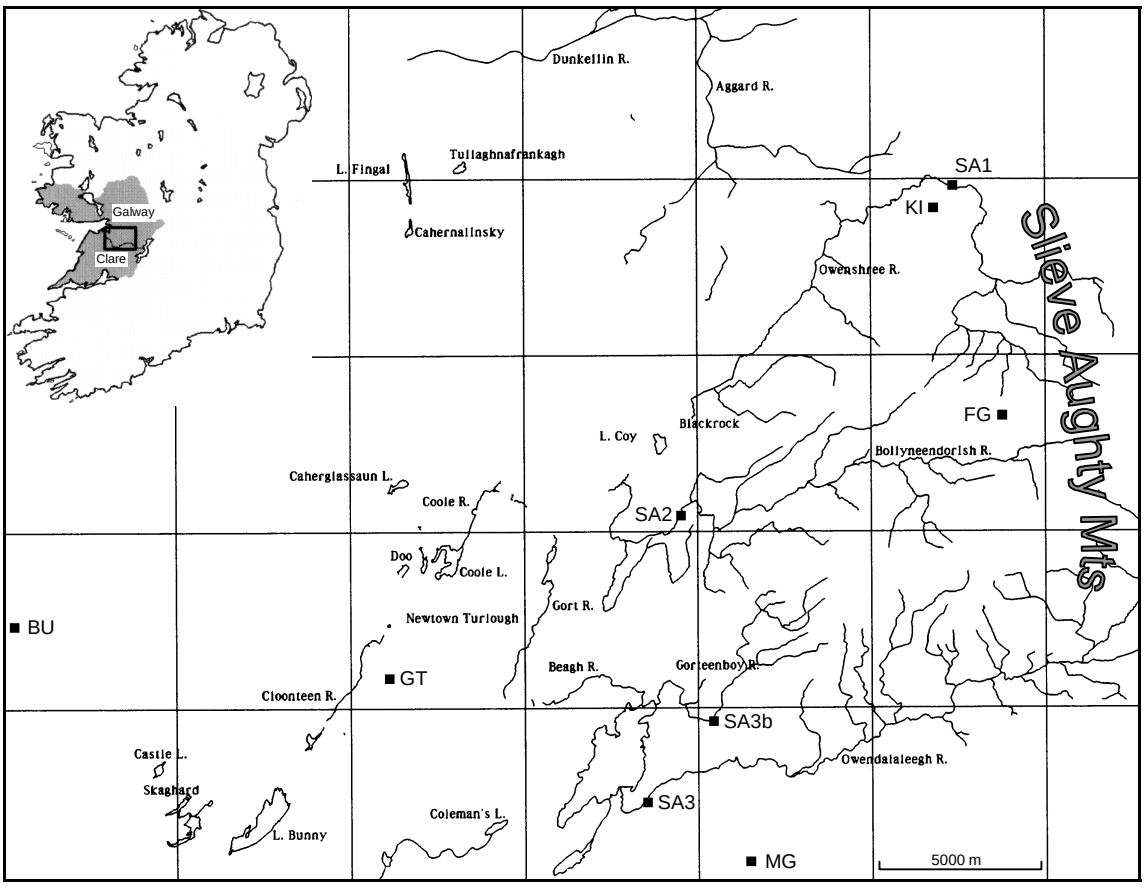


Figure 5. *Galway region: rain and flow gauging stations*

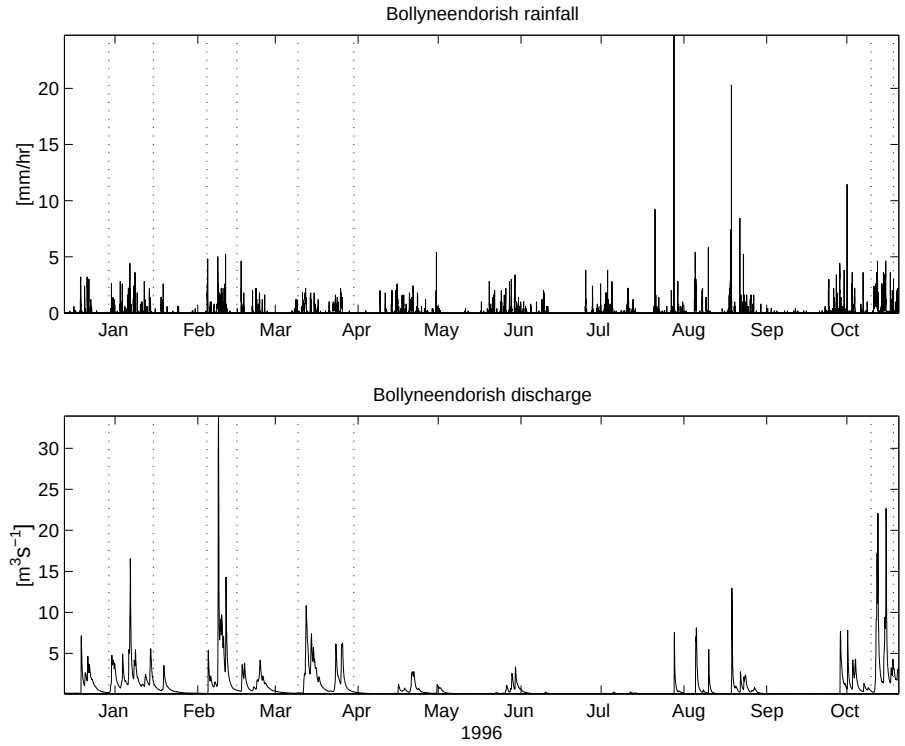


Figure 6. *River Bollyneendorish catchment rainfall and flow for 1996. High flow periods of particular interest are marked with dashed lines*

Initial *linear* TF identification using the SRIV system identification method indicates that a first order model with a 3 hour lag is the most appropriate TF structure. This model explains approximately 75% of the runoff variance (see Table 1), although examination of the model fit shown in Fig. 7 reveals that peak flows are significantly underestimated. Next a *nonlinear* TF where the nonlinearity takes the form of the power law loss function (8) is calibrated with the TF parameters again estimated using SRIV and the power law parameter α estimated using a simplex optimiser (Nelder and Mead, 1965). The nonlinear model explains 80% of the variance (see Table 1) which is a significant improvement over the linear model. Figure 7, which shows both the linear and nonlinear TF calibration fits, clearly demonstrates this superior fit at high flows and also that the shape of the nonlinear model hydrograph is better due to the incorporation of an effective rainfall model component. It is particularly important for forecasting applications that the shape of the hydrograph is predicted correctly since real-time correction is most successful when the residuals shows persistence. For completeness a nonlinear transfer function is also estimated using the state dependent modelling technique with, as in previous rainfall-runoff applications (Young and Beven, 1994; Young *et al*., 1997; Lees, 2000), the nonlinearity taking the form of an input relationship that closely resembles a power law form.

Table 1. *Calibration and verification results*

Model	*Calibration*		*Verification*	
	R^2	*Peak Error*	R^2	*Peak Error*
Linear TF	0.76	33%	0.47	41%
Power Law NL-TF	0.80	17%	0.77	43%
SDM NL-TF	0.81	4%	0.80	36%

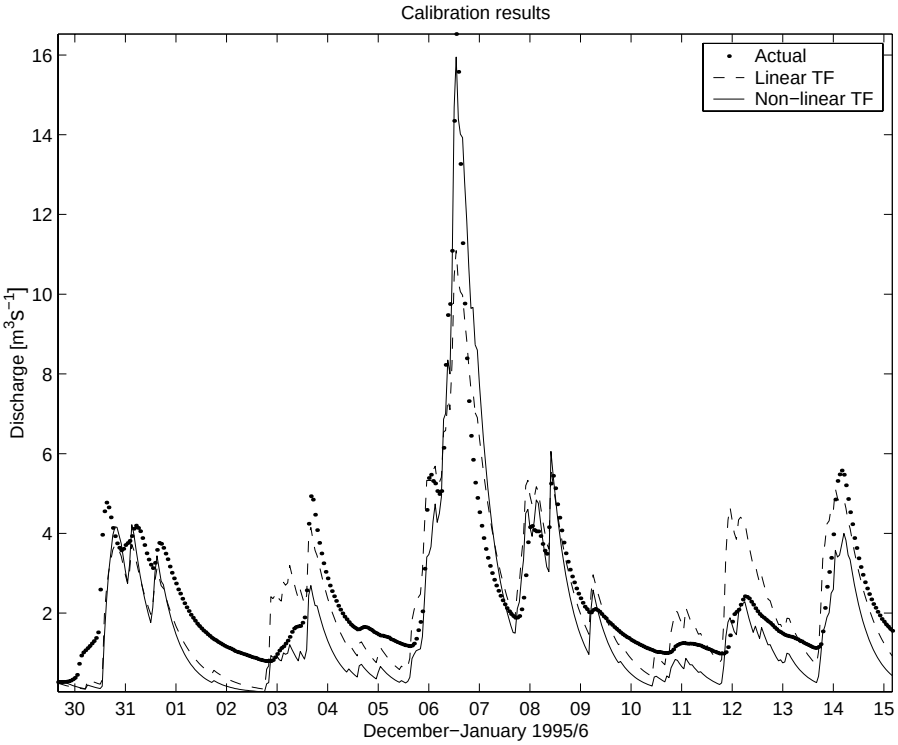


Figure 7. *Linear and nonlinear TF model calibration results*

Model verification is performed for all three models on the entire data set. Table 1 gives the performance statistics for the whole verification period, and Figure 8 shows some sample verification results for the March 1996 high flow period for the power law nonlinear TF model. Results given in Table 1 confirm that both nonlinear models significantly out perform the linear TF model confirming the requirement for a rainfall loss function component. The 3-hour ahead forecasts produced by the power law TF model, as shown in Fig. 8, are excellent. Although the performance of the nonlinear model resulting from the state dependent modelling procedure has better performance than the power law model, the improvement is only marginal. Therefore the following power law forecasting model is used as the basis for an investigation of a number of different forecast updating procedures and methods of uncertainty estimation,

$$\hat{Q}_{t+3} = a_1 \hat{Q}_{t+2} + b_0 \left(r_t \times Q_t^{\alpha} \right) \tag{9}$$

with the calibrated parameter values $a_1 = -0.9158$, $b_0 = 0.0808$, and $\alpha = 0.25$. The simplicity of this forecasting model underlines the attractiveness of the TF approach to real-time forecasting since no complex numerical procedures such as numerical integration or finite difference are required to implement the model.

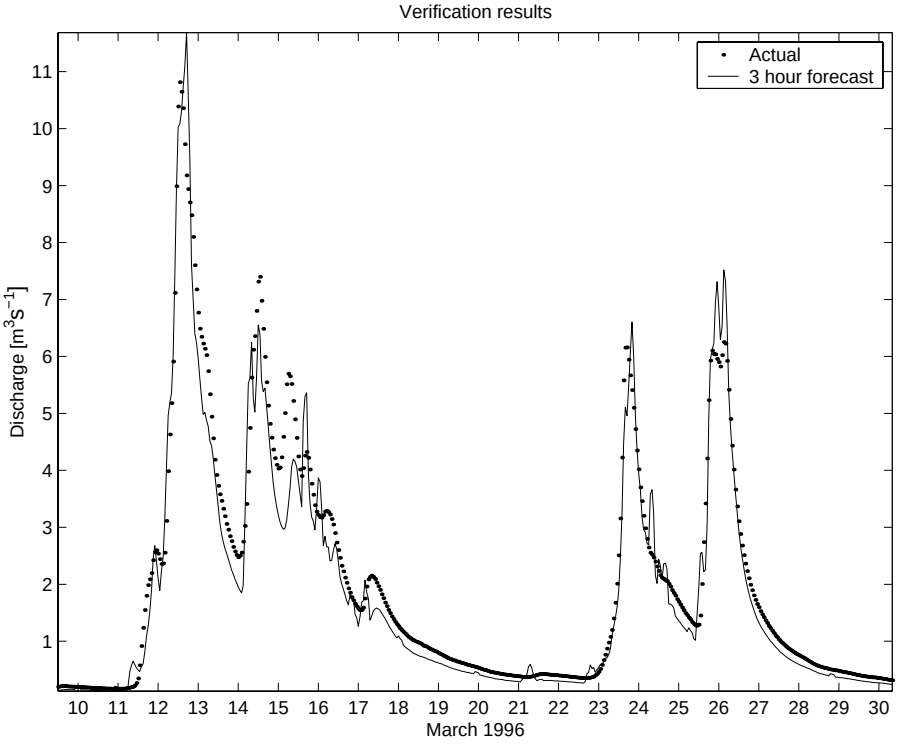


Figure 8. *Power Law nonlinear TF verification results for March 1996*

In order to compare commonly applied updating procedures the following methods are implement in conjunction with the power law TF forecast model: error prediction (EP); Kalman filter state updating (KF); simple state replacement (SR); adaptive gain updating (i.e. updating of the b_0 parameter). Figure 9, which shows the results of this investigation for different lead times compared to the forecast performance for the model with no updating, reveals the considerable performance benefits of utilising an updating procedure, especially for short lead-times. Interestingly the results for the Kalman filter, state replacement, and error prediction are almost identical, and they are significantly better than the gain adaption results. In each case that requires meta-parameter estimation (e.g. noise covariance in the Kalman filter), the parameters have been estimated using a simplex optimiser with an objective function based on the 3 step ahead forecasting period over the original model calibration period.

Over the majority of the data set, the increase in 3 hour ahead forecasting performance resulting from the use of an updating procedure is not hugely noticeable as evidenced by the increase in R^2 from 0.8 to 0.9. However examination of the forecasting results over the February high flow period reveal a dramatic difference. Verification results show that both the linear and nonlinear TF models produce poor forecast results particularly at peak flows. Figure 10, which shows the results for the power law TF model with and without Kalman filter state updating clearly reveals the large improvement in forecast performance provided by the state updating procedure with the KF state updating method reducing the percentage peak error from 60% to 22%. Examination of the rainfall time-series suggests input data error as the main cause of the poor performance of the forecast model without updating. This source of error is the most likely to be encountered operationally, and the significant improvement produced by the updating procedure points suggests that there may be significant benefits to be gained from routinely including an updating element in future flood forecasting systems.

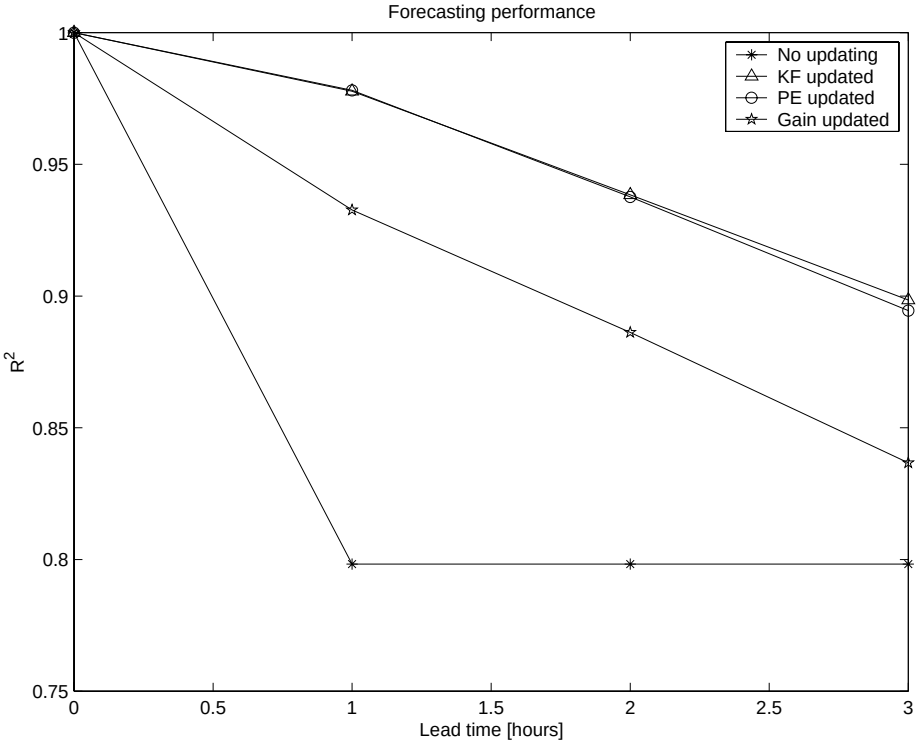


Figure 9. *Results from a comparison of forecast updating methods*

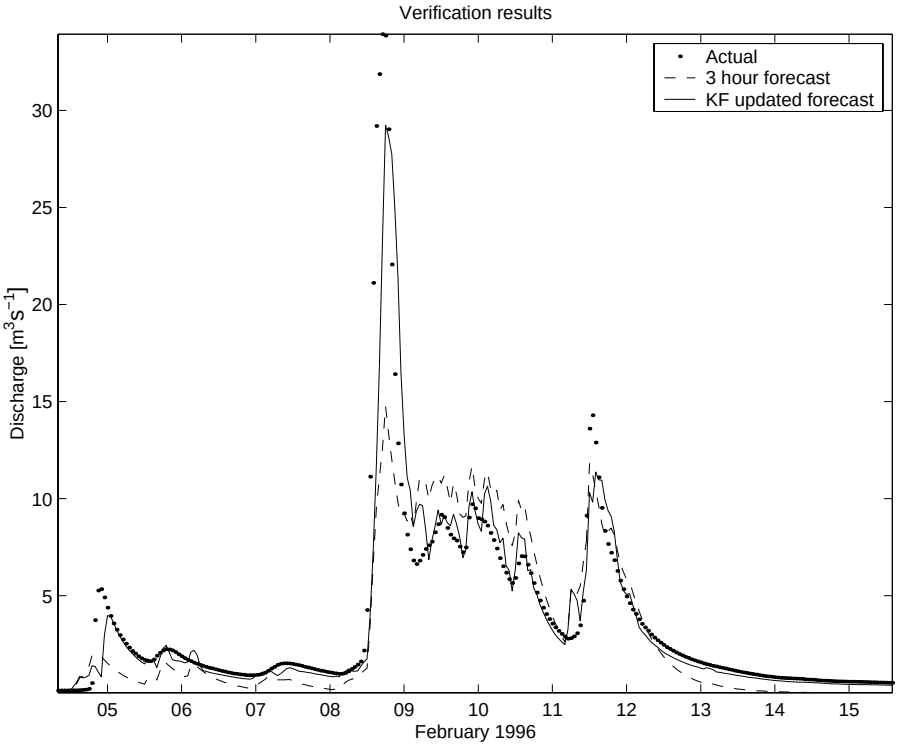


Figure 10. *Verification results for the February 1996 flood event: comparison of power law nonlinear TF model forecasts with and without Kalman filter state updating*

Turning to the problem of estimating forecast uncertainty, Figure 11 shows the power law TF model forecast with associated 95% confidence intervals calculated using a Kalman Filter for the October 1996 verification period. Examination of these results, which reveal that the uncertainty at low flows seems to be over-estimated and the uncertainty at high flows under estimated, lead to an investigation of the validity of the Kalman filter's assumptions. The main assumptions made in the application of the Kalman filter are that the model is correct, that the residuals are normally distributed, and that the residuals are homoscedastic (i.e. their variance is constant regardless of the flow value). Examination of the residuals for normality revealed that they are approximately normal, and although the model is inevitably incorrect the KF is known to be robust to model error. However, examination of the residuals by plotting them against flow reveals that they are strongly heteroscedastic (see Fig. 12). This behaviour is commonly observed in rainfall-runoff modelling and can be largely attributed to errors caused by the translation of stage into flow using a power law rating equation.

In order to produce an error model, a Box-Cox transformation is applied, with $\lambda = 0.2$ selected through trial and error, to the residuals resulting from application of the power-law TF model with prediction error updating to the calibration period. Figure 12 shows that these Box-Cox transformed residuals are homoscedastic, allowing a normal distribution error model to be fitted. This can then be used to calculated prediction confidence intervals that are then inverse Box-Cox transformed prior to plotting onto the flow forecasts. As can be seen from Figure 13, which shows the 95% confidence intervals calculated using this simple error model for the October 1996 verification period, the confidence intervals are much more sensible that the KF generated ones. In particular, the uncertainty at high flows now encompasses the observed data points.

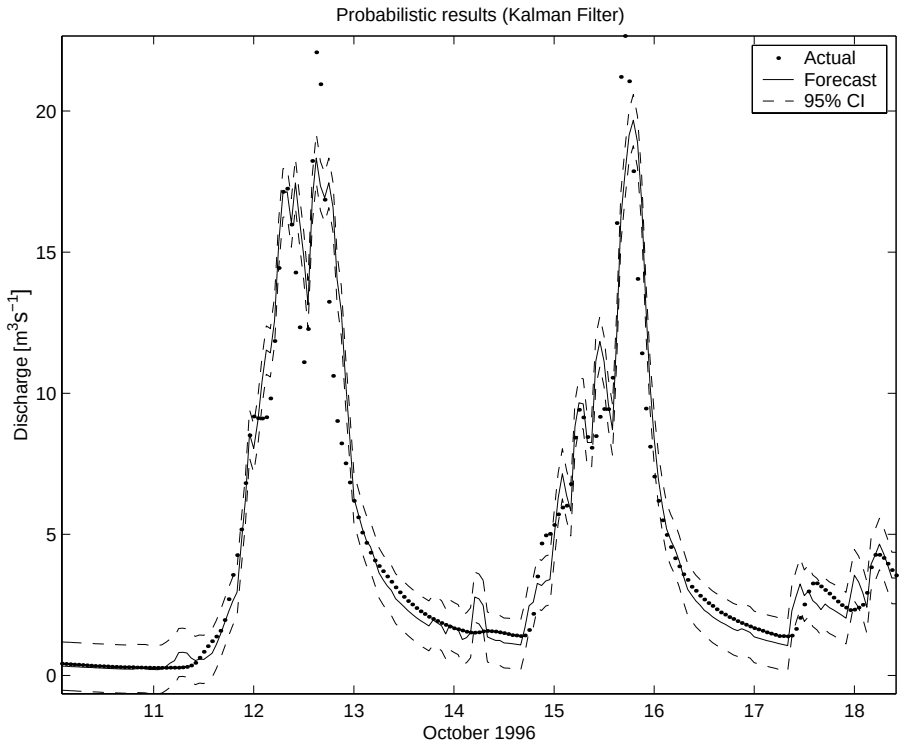


Figure 11. *Probabilistic results produced by application of a Kalman filter to the power law nonlinear TF forecasting model*

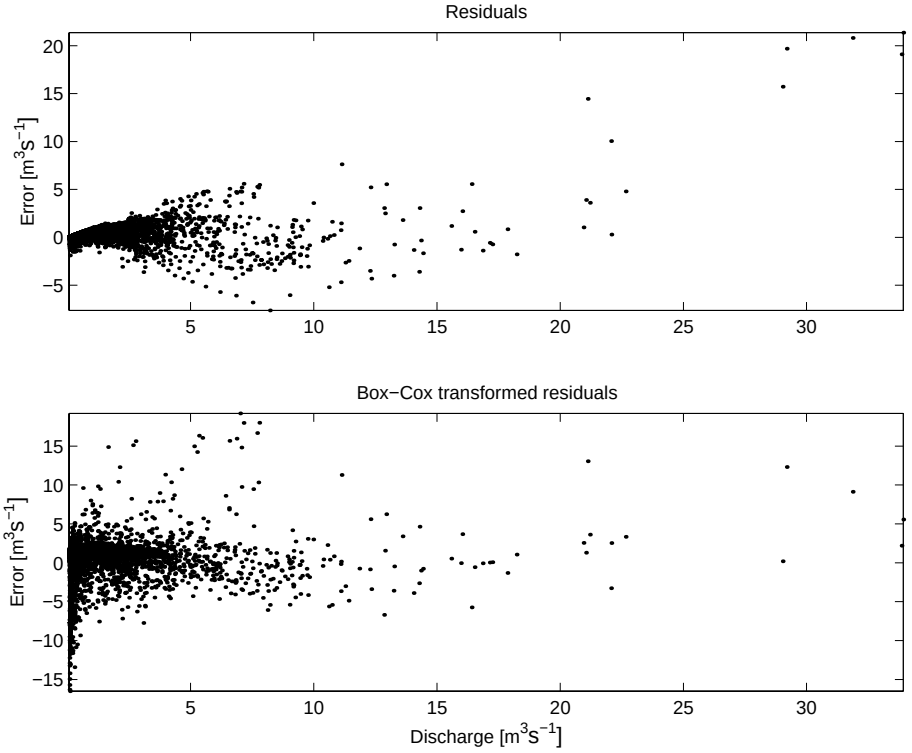


Figure 12. *Power law nonlinear TF model residuals and Box-Cox transformed residuals with* $\lambda = 0.2$

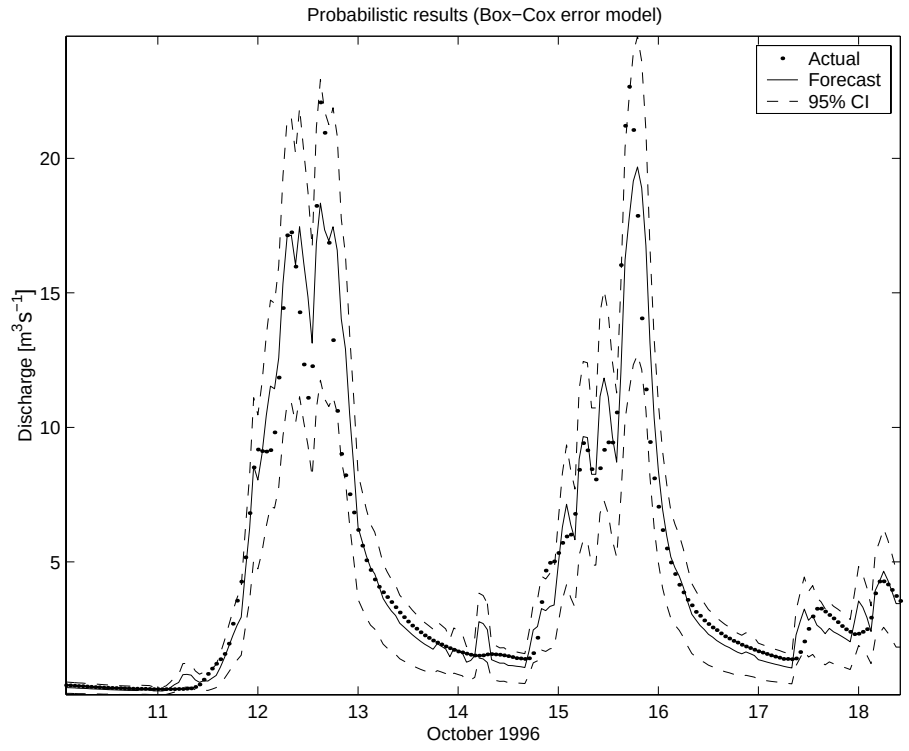


Figure 13. *Probabilistic results produced by application of a simple error model to the power law nonlinear TF forecasting model*

7. Conclusions

The paper presents an extension to traditional transfer function based flood forecasting model, the nonlinear transfer function. The nonlinearity can be characterised as either as a state dependent parameter relationship or as a power law input nonlinearity. It is suggested that for practical application the power law form is sufficient. The idea of introducing a physically reality check step into the transfer function modelling procedure is suggested as a way of ensuring the identified model is a hydrologically acceptable physical representation of the dominant dynamic processes, and is therefore likely to exhibit good out-of-sample forecasting performance. To this end, it is shown that the TF model can represent a general linear storage model that obeys the fundamental law of continuity where linear stores are combined both in series and in parallel, and that an identified TF model should not be accepted as a reasonable descriptor of the system unless it can be decomposed into a physically reasonable form. A number of real-time updating techniques are discussed and the use of an error model fitted to Box-Cox transformed historical forecast residuals is proposed as a simple alternative to more sophisticated prediction estimation techniques such as the Kalman filter.

A case study demonstrates the utility of the nonlinear transfer function modelling methodology for rainfall-runoff modelling. Excellent results are produced, and it is shown, through a comparison of real-time updating techniques, that while implementation of such a technique is high recommended, the simple prediction error technique produces comparable results to the more complex Kalman filter updating technique. It is shown that because of the problem of heteroscedastic residuals, that the simple error model method of estimating prediction uncertainty is more appropriate in this case. Forecast uncertainty can provide very useful additional information on flooding likelihood, although there is much current debate in the UK as to what form probabilistic forecasts issued to the Public should take.

In conclusion, the modelling and forecasting technique presented here are powerful objective data-driven techniques that extends a class of widely-used linear storage based hydrological models into the hydroinformatic age where data availability and increasing computing power are becoming readily available. Many of the modelling techniques used in this paper are contained in the CAPTAIN MATLAB (Mathworks, 1996) toolbox developed by the Systems and Control Group at Lancaster University, see http://es-parto.lancs.ac.uk/captain/ and others are available from the author as MATLAB functions, see http://ewre.cv.ic.ac.uk.

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Mapping the Probability of Flood Inundation (Even in Real Time)

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1. Introduction: why worry about probabilities of inundation?

Recent flood events in the UK have revealed that the flood forecasting for individual events remains a difficult problem that requires improvements in the technology of data retrieval, modelling methodologies and the dissemination of warnings (Bye report). Most flood forecasting modelling in the past has been primarily concerned with N step ahead predictions of discharges at particular sites. It has not generally been possible to address the problem of inundation predictions in real time, although deterministic 1-dimensional hydraulic models are sometimes included in operational flood prediction systems (e.g. Moore et al., 1994). Traditionally, the problem of inundation prediction, essentially a routing problem, has been considered to more amenable to deterministic modelling approaches than the problem of rainfall-runoff modelling, i.e. how much runoff to route. Hydraulic principles have always been considered better understood than the nonlinearities of complex runoff generation processes.

However, the hydraulic routing problem is not free of uncertainties. There are primarily the uncertainties in upstream hydrographs that arise directly from the problem of runoff generation. These are limited by only using a hydraulic model downstream of a gauging station, but even then there may be considerable uncertainties in the stage-discharge relationship at high flows. In some cases, there may be significant uncertainties associated with lateral and tributary inflows, which may sometimes (albeit rarely in the U.K.) be negative, i.e. losses into the bed and banks of the flood plain. There is a much neglected source of uncertainty in the specification of the geometry of the channel and floodplain, that may at least be reduced in the future with the more widespread availability of Lidar datasets. A further source of uncertainty is in the specification of effective roughness coefficients, often treated as hydraulic constants, but which are not independent of the model implementation (discretisation, solution algorithm, treatment of obstacles such as walls and hedges, identification and treatment of culverts and flood plain channels, etc). Finally, for N-step ahead event prediction in real time, there will be an uncertainty associated with projecting inputs and the approximate solution of the governing equations into the future.

Ideally, at this point the solution should be made adaptive since during a flood event there is information being transmitted back to the flood operations room about rainfalls and river levels from various points within a catchment of interest. Techniques for adaptive forecasting for predictions at a point for which observations are available in real time are well established and continuing to be improved (e.g. Lees et al., 1994; Young, this volume; Lees this volume). For distributed models, however, this is a particularly difficult problem because assimilation of observations available at a small (often very small) number of points on a river network into a distributed modelling system is not a well posed problem mathematically and can only really be done under very restrictive assumptions. In this paper, we propose an alternative computationally intensive methodology to cope with all these different sources of uncertainty within which maps of the probability of inundation on a flood plain can be displayed and continually updated as an event progresses. Such an approach was not possible until relatively recently but could now, with the advent of parallel PC systems, be implemented operationally at reasonable cost.

There are some important advantages in taking account of the uncertainties in predicting flood inundation. A single deterministic prediction will, with high probability, be wrong. It may be reasonable; it may to the

hydrologist be acceptable; but in places (and almost certainly some places where damage occurs) it will be wrong. It is even more likely to be wrong if there is no possibility of updating the forecasts as the event occurs on the basis of real time level information. Thus, the estimation of uncertainty in the predictions, and the process of updating, can be usefully be considered as a protection against being wrong, or at least a way of being wrong more gracefully.

2. Identifying the parameters of inundation models.

Distributed predictions of inundation require distributed models that discretise the channel/flood plain system into many calculation elements. Newer 2 dimensional finite element and finite volume solution algorithms, such as TELEMAC 2D require many thousands of elements to represent a significant length of reach and large amounts of computer time to make even a single model run. Each element then requires the specification of one or more parameter values (the minimum is usually a single effective roughness coefficient for each element). Thus with a large number of elements, a large number of parameters must be identified.

It is often assumed that roughness coefficients can be estimated a priori, by knowing the physical characteristics of the bed and banks (with perhaps some "tweaking" necessary in applications to specific sites). This is a convenient assumption given the number of parameters that need to be specified but it may not be a good one when the effective roughness coefficients must account for all losses of momentum within an element, including losses that are additional to the bed friction, such as those due to internal shear at the channel/flood plain boundary and those due the effects of bank vegetation, walls, hedges and other flood plain "roughness elements".

In fact, the information available for the identification of the parameters of such distributed models is invariably not sufficient. The identification problem (or even the "tweaking" problem) is not well posed in any systems identification sense and, as noted above, the effective parameters required by the model will depend on the model implementation, particularly the representation of the flood plain geometry. Thus, given all the sources of uncertainty associated with the modelling process, it is likely that no single model parameter set will give a good fit to all the observations about patterns of inundation that are available, but that many different parameter sets might provide "acceptable" simulations (see Romanowicz et al., 1996; Romanowicz and Beven, 1998). This is the equifinality problem, that has also been demonstrated in rainfall-runoff modelling and other areas of environmental modelling (Freer et al., 1996; Lamb et al., 1998, Hankin and Beven, 1998, Cameron et al., 1999; Beven, 2000a,b).

3. The GLUE Methodology

One way of taking account of such uncertainties in modelling is using the Generalised Likelihood Uncertainty Estimation (GLUE) methodology developed at Lancaster University. This is based on Monte Carlo simulation using randomly chosen parameter sets. Each realisation is compared to whatever data area available for model evaluation (here we will examine the use of maximum inundation maps from past events). Those models that are not considered to give acceptable fits to the data are rejected as non-behavioural. Those that are retained are associated with a likelihood measure based on how well the model fits the data. Such measures can be based on traditional statistical assumptions, where this is appropriate (see for example Romanowicz et al., 1996), but can also be chosen subjectively, the only requirements being that the value should be zero for non-behavioural simulations and should increase with increasing goodness of fit (however that might be defined).

In prediction, all of the behavioural models will give different predictions. These are then weighted to form a cumulative likelihood weight distribution from which prediction limits can be determined as:

$$P\left(\hat{Z}_t < z\right) = \sum_{i=1}^{i=N} L\left[M\left(\Theta_i\right) \mid \hat{Z}_{t,i} < z\right] \quad (1)$$

where $L[M(\underline{\Theta}_i)]$ is the value of the likelihood measure for the *i*th model scaled such that the sum over all the behavioural models is unity, $\hat{Z}_{t,i}$ is the predicted value of variable Z at time t simulated by model $M(\Theta_i)$ with parameter set $\underline{\Theta}_i$. Prediction limits determined in this way are conditional on the model structures used, the range of parameter values sampled, the likelihood measure used in model evaluation and the particular sequence of boundary conditions used to exercise the model. Likelihood measures can, however, be updated as more information becomes available. We will use this in the real time forecasting situation below. Further details of the GLUE methodology will be found in Beven (2000a) and Beven et al. (2000).

4. A Case Study: Using inundation maps from past events on the River Culm to condition inundation predictions.

This case study uses the same 12 km reach between Woodmill to Rewe on the River Culm in Devon as previously studied using fully 2 dimensional modelling by Bates et al. (1992) but here making use of the simpler quasi-2 dimensional model of Romanowicz et al. (1996) and Romanowicz and Beven (1998). The topography of the flood plain has been developed from the 96 cross-sections that are available using a linear interpolation designed to preserve the channel/flood plain boundary. The topographic representation remains, however, approximate. In this application, for the first time, historical inundation maps compiled by Simm (1993) are used to evaluate the inundation predictions. It was apparent early in the study that the predictions and the inundation maps were not consistent in some parts of the reach and that even the most detailed finite element representation of the flood plain could not reproduce the maximum inundation extent, as mapped. This appeared to be primarily because of inconsistencies in the representation of the flood plain topography based on the cross-sectional information, but is probably indicative of the types of problems encountered in many studies of this type.

Upstream levels and discharges were available from the Woodmill gauging station. In this study the uncertainties associated with the upstream boundary conditions were assumed to be small, although in principle such uncertainties could be taken into account within the GLUE methodology. In the inundation model, each reach of the river is treated as one channel element and two flood plain elements. From the interpolated topography between the available cross-section surveys, local water level/storage/boundary area/wetted perimeter look-up tables are developed for each channel and flood plain element. From these look-up tables, once water level in the element is known, the storage can be mapped back onto the topography to determine the area of inundation. Although the linear interpolation used here results in relatively coarse inundation maps, the same idea can be extended to cases where very detailed topographic information is available. The boundary areas and wetted perimeters will be inundation depth dependent and can be used to determine the exchanges of water between elements. This requires a conveyance coefficient for each exchange, requiring at least 5 coefficients for each of the 96 reaches. In this implementation the exchanges are determined by a Manning-Strickler relationship. In fact, at least 5 coefficients are required since, especially in the case of significant bankside vegetation, the coefficients might be expected to be level dependent. For simplicity they have here been assumed constant. This simplified model greatly reduces the computer time necessary, an important consideration in Monte Carlo simulation, but does not greatly compromise the potential accuracy of the inundation simulations.

Interestingly, a sensitivity analysis based on Monte Carlo simulations of different parameter sets reveals that predicted inundation extent is highly sensitive to the channel conveyance coefficients, and not very sensitive to the flood plain or exchange coefficients. This implies that, for the events examined on this system (up to an

estimated return period of 5 years), the role of the flood plain is primarily one of storage, and that the major control on the local discharge remains within the channel. To reduce the dimensionality of the problem, for this analysis the channel and flood plain coefficients were assumed to be constant within 6 sections of the 12 km reach, each made up of multiple elements. This reduces the number of parameters required to only 30, which is still a high dimensional problem.

Three historical events have been examined: in December 1980, January 1983 and January 1984. Simm (1993) gives maps of maximum inundation extent for these events, which had estimated peak discharges of 120, 60 and 110 m3/s respectively. From these maps vectors of (x,y) co-ordinates of the flood limits were digitised and converted to equivalent water surface elevations using interpolated elevation data. There are then three sets of event maximum water surface elevation data for comparison with the predicted discharges in each modelled reach.

There is, however, necessarily some uncertainty in this process. The original maps of Simm (1993) have an uncertainty of at least 30m in (x,y) position based on the thickness of the drawn lines. In producing a measure of performance, all models predicting within the equivalent range of maximum water surface elevation were given a high likelihood. Outside that range it was assumed that there was a parabolic decrease in likelihood with distance from the edge of this range to a zero value at the edge of the floodplain. Thus, in each reach, a form of fuzzy measure is used to assess the likelihood associated with the individual Monte Carlo simulations. Where the inundation is mapped at the edge of the topographic flood plain, such as where the flooding reaches the railway or motorway embankments, then position alone does not provide an upper limit on the elevation of the water surface. Aronica et al. (1998) provide an example of using mapped maximum inundation depths directly in assessing inundation models within the GLUE framework, but such data were not available here.

5. Uncertain N-step ahead predictions of inundation with updating

A methodology for N-step ahead predictions of inundation probabilities with updating in real time, within the GLUE framework, has been outlined by Romanowicz and Beven (1998), with an application to the River Culm. In their original study, prior likelihoods associated with behavioural models were determined by conditioning on reach scale water level information (in fact these were simulated data taken from the more detailed finite element model of Bates et al., 1992). Here, the prior likelihoods are taken from the evaluations in respect of the actual observations of maximum inundation for the events described above. The rest of the procedure is, however, the same.

Rather than attempting to update all the states in the distributed model, the procedure is based on updating the likelihood value associated with each parameter set according to how well that simulation is predicting downstream level or discharge estimates at a gauging site for which it is possible to make N-step ahead predictions, for example using the adaptive transfer function techniques described in Young (this volume) and Lees (this volume). Those forecasts at the downstream site can be made together with estimates of the uncertainty associated with them. This uncertainty is normally assumed to be Gaussian, with a variance that will be expected to grow as N increases. Figure 1 shows the results of a three hour ahead prediction of the downstream water levels at Rewe gauging station for the 1984 event, using a transfer function from Woodmill to Rewe developed from the 1980 hydrographs, with the observed water table at each time step being used recursively to condition the prediction and associated uncertainty limits.

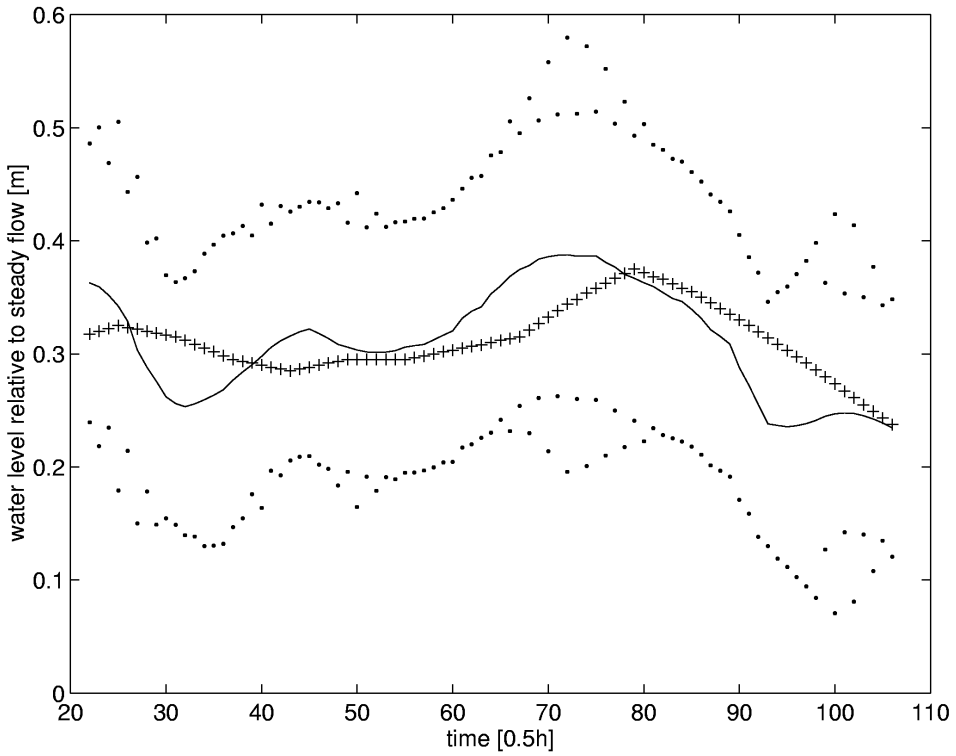


Figure 1. *Predictions of 5 time step ahead water levels at Rewe for the January 1984 event, with updating, together with 90% prediction limits using a transfer function with time variable gain given the input water levels at Woodmill. Actual water levels shown as crosses.*

These predictions can then be compared with the forecasts of the routing models at the downstream site. Since these will all be behavioural models for previous events, they will all have positive prior likelihood values. Then, the likelihoods can be updated on the basis of how well each inundation model predicts the downstream levels, N-steps ahead. This can be achieved using Bayes rule in the form:

$$L_N[M(\underline{\Theta}_i)] = L_o[M(\underline{\Theta}_i)]L\left[M(\underline{\Theta}_i \mid \hat{Z}_N, \sigma_N^2)\right] \tag{2}$$

where $L_N[M(\underline{\Theta}_i)]$ is a posterior likelihood for the N-step ahead prediction of the *i*th model $M(\underline{\Theta}_i)$, $L_o[M(\Theta_i)]$ is the prior likelihood of the *i*th model based on the historical data, $L\left[M(\underline{\Theta}_i \mid \hat{Z}_N, \sigma_N^2)\right]$ is the likelihood measure calculated for N time steps ahead with the latest adaptive forecasted level at the gauging site $\hat{Z}_N$, with variance σ_N^2. This is easily extended to multiple time step predictions. There is a possibility, of course, that after such an updating, all the predictive models have a very low posterior likelihood. This will suggest that, for this new event, the predictive ability is severely compromised (essentially that all models previously considered behavioural are being rejected) and that something seriously different is happening. The reason may become apparent (a flood bank failure, for example, or a much more extreme event than previously recorded) and may require adjustment of the model structure or resampling of the model parameter space, something that may be difficult to achieve in real time but which might form part of a post-event audit.

The results of this form of real time probabilistic prediction are shown in Figure 2. Here a section of the 12 km reach is shown at hour 35 of the January 1984 event. The mapped maximum inundation extent for this event is shown as solid lines. The inundation probabilities are here conditioned on the inundation extent maps from the earlier 1980 and 1983 events, with updating in real time. At this stage, the inundation predictions reflect the coarse nature of the available flood plain topography so that the positions of the available cross-sections are

clearly seen. The procedure will easily incorporate more detailed data in creating the reach by reach look-up tables without significant additional computational time in running the model realisations.

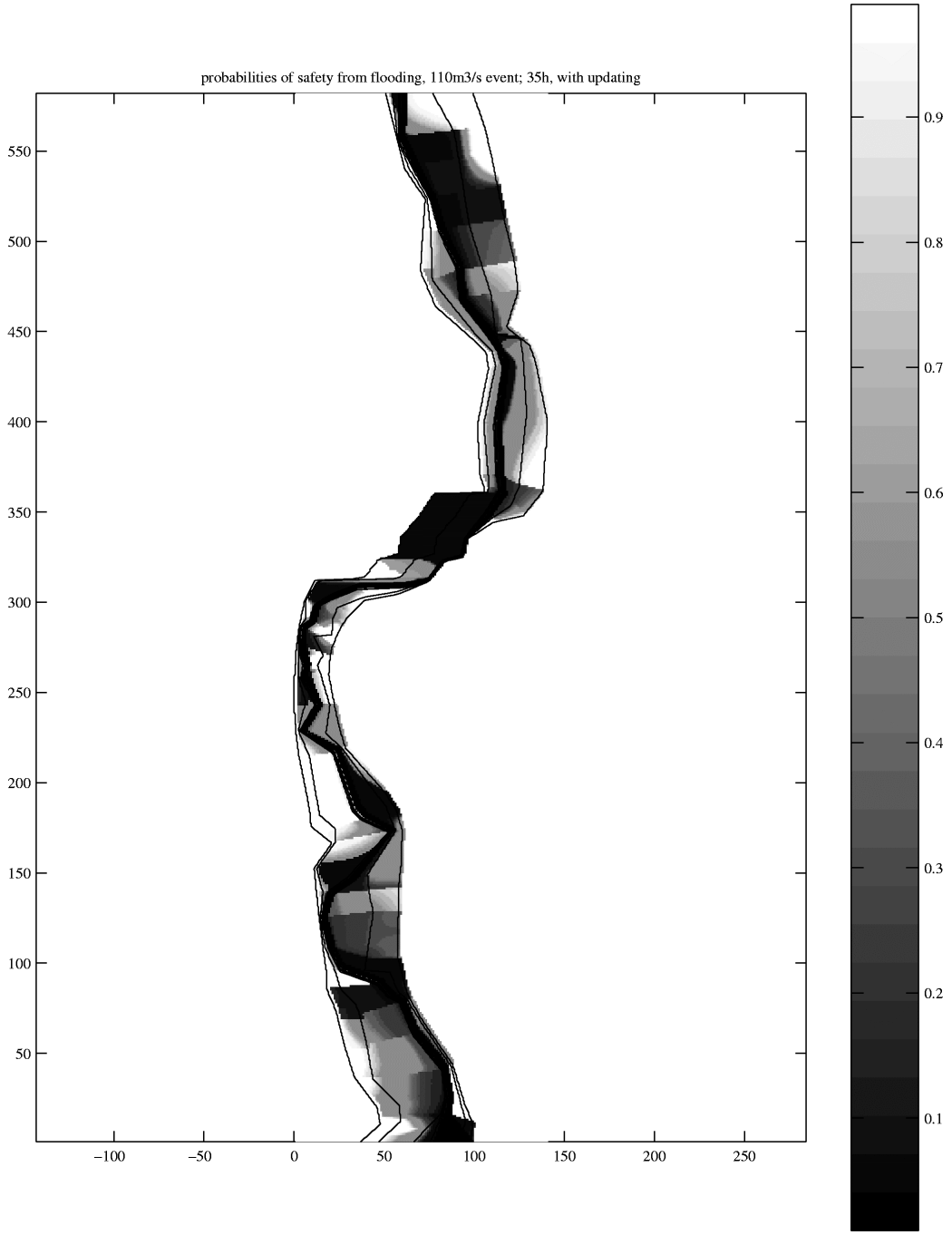


***Figure 2**. Predicted 5 time step ahead probabilities of inundation for part of the study reach on the River Culm at hour 35 of the January 1984 event with updating based on predicted water level distribution at Rewe. The predictions are made as if in real time. The limited flood plain topography data available in this case can be seen in the interpolations between the cross-section profile sites. Thin solid lines represent the edge of the topographic flood plain and the maximum inundation mapped for this event.*

6. Towards a fuzzy hydraulics

Although the methodology described above is conceptually simple, it is computationally intensive in that a sufficient sample of behavioural models will be required to adequately characterise the predictive uncertainty. Thus, there would be considerable benefit in developing approximate inundation models that would provide sufficiently accurate results when applied to ideal datasets but which could be run within the type of Monte Carlo simulation framework described above for operational real time applications. The approximate nature, and resulting uncertainty, of even the most detailed distributed flood inundation models when applied to extended reaches of real flood plains would suggest that this is a worthwhile aim. To this end we have been working on developing hydraulic models based on fuzzy rules for the integrated transfer of mass and momentum between large scale elements, in which the detail of the topography within each element is contained within the type of look-up table described for the Culm model above. In this way, the representation of the transfers is not limited to the simplistic uniform flow type relationships commonly used, but can be developed directly from observational information. The first steps in this direction have been made using laboratory flume data (see Hankin et al., submitted) but the aim is to extend the approach to larger elements and longer time steps using rules for the integrated net exchanges over those time steps. Currently, a fuzzy rules based model for part of the Thames flood plain is being tested.

7. Conclusions

There are many sources of uncertainty associated with predictions of the pattern of flood inundation during an event. It is important to evaluate the uncertainty associated with inundation predictions since any single deterministic model prediction will always be wrong, if only in places. It has been suggested that it may be more important to use an approximate inundation model that can be run many times to evaluate and map prediction limits for inundation, than to use a very detailed model that can only be run once because of the computational requirements. An approach for conditioning prediction limits based on Monte Carlo simulation within the GLUE methodology has been described and applied to a 12 km reach of the River Culm, Devon. In this case, the conditioning of model parameter sets was based on an evaluation of the predicted and observed maximum inundation extent for several historical events. It was also demonstrated how the likelihood measures determined in this way could be used in a real-time context, making use of the adaptive N-step ahead forecasts of levels at a downstream gauging station to modify the likelihoods associated with each inundation model.

It now appears that it is feasible to implement such inundation predictions for real time operational use. Further improvements in run times of the inundation model would, however, allow more Monte Carlo realisations to be used. A model based on fuzzy rules for integrated net mass and momentum fluxes between elements is currently being developed with a view to achieving such gains in computational efficiency.

8. Acknowledgements

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Environment Agency Current Practice and Planned Developments

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1. Introduction

The Environment Agency is responsible for provision of flood warning in England and Wales under Ministerial Direction derived from the Water Resources Act 1991 and the Environment Act 1995. The Agency exercises this responsibility through flood forecasting, warning and emergency response provisions applied via its eight regions. Recent floods, particularly the severe event of Easter 1998 have tested the effectiveness of the existing arrangements. These arrangements have been subject to independent review and a report by Peter Bye which identified several opportunities to improve the quality and effectiveness of the service.

In May 1997 an Advisory Committee was appointed by the Ministry of Agriculture, Fisheries and Food under the chairmanship of Professor Edmund Penning-Rowsell of Middlesex University. The purpose of the committee was, inter alia, to define the R&D requirements for flood and coastal defence for the period 1998-2003 (and beyond if appropriate) and to make recommendations for a framework of strategic and applied research which would be appropriate for MAFF and Environment Agency funding and for its effective implementation and dissemination. Flood forecasting R&D was included within this review, which was published in July 1999.

This paper sets out the changes which are in progress, or planned, to the operational delivery of the flood forecasting and warning service of the Agency and the management and promotion of flood forecasting and warning R&D as a result of the above reviews. Although the paper concentrates on the flood forecasting aspects of the service, the aim of the changes is to foster a holistic approach to flood forecasting, warning and response to provide a seamless service to the public.

2. Organisational Changes

The Agency has a legacy of different flood forecasting and warning systems and organisations. These were, in most cases, built up by predecessor water authorities to suit local operating conditions and there was no national focus. Although there were some initiatives aiming to improve consistency, these were of limited effect and the regions of the Agency operate in many and varied ways. Recommendations in the Bye Report included:

- the need for nationally consistent management procedures for flood forecasting and warning;
- increasing the importance and strength of line management from the Head of Flood Defence down;
- establishing specific accountability at region and area level for flood forecasting and warning; and
- centralising flood warning technical specialisms regionally (or nationally) to improve efficiency, effectiveness and national consistency.

In order to meet these recommendations, the Agency has undertaken a review of the flood forecasting and warning service. The following structure has been agreed and is in process of implementation:

- a National Flood Warning Centre

- regionally based monitoring and flood forecasting
- area based flood warning and emergency response

The aims of the new National Centre are:

- to be a focal point for experts and key stakeholders in the field of flood warning, including forecasting, public awareness, warning dissemination and community response to flooding;
- to enable the Agency to maintain a long-term (5-10 year) perspective on flood warning practice in order to take best advantage of emerging technologies and position England and Wales at the leading edge of the field;
- to provide high quality support, advice, guidance and direction to flood warning practitioners to enable the Agency to deliver a seamless and integrated flood warning service;
- to drive national consistency and convergence towards best practice in flood forecasting, warning and public awareness; and
- to become an internationally recognised centre of excellence for flood warning.

The NFWC is not expected to have a direct operational role, although much of its work will be closely linked to the operational requirements of flood warning practitioners.

3. Current Forecasting Practice in the Agency

As indicated in Section 2, the practices for forecasting differ widely throughout the Agency at present. Some regions rely on qualitative radar data and simple level to level flow correlations for forecasting. A variety of more sophisticated regional systems have been developed.

- Midland region operates a system developed in-house, involving 114 rainfall/runoff models, feeding into a conceptual routing model covering 100 discrete reaches, with a real-time updating model.
- South West and North West regions have supported development by Salford University of the WRIP and STORM modelling and display systems, using physically realisable transfer function (PRTF) models.
- North East region has the IoH RFFS system, developed with MAFF research funding, this system is also being installed in Thames region, incorporating the Thames Conceptual Model (TCM) developed by Thames.
- Anglian region is currently installing a new system based on Mike-11.
- North East region is trialling a system using neural networks developed by Leeds University under a MAFF R&D contract.
- Thames region uses the method developed by IoH for local recalibration of weather radar data, for comparison with NIMROD network data, and also uses the GANDOLF system for thunderstorm detection developed under a project jointly funded by the Agency and Met Office.

4. Management of R&D

In addition to the recommendations for organisational change, the Bye Report had several recommendations relating to research. There are major recommendations for restructuring of R&D contained in the Penning-Rowsell Report Following discussions between MAFF and the Agency, a paper on “Proposal for the

Implementation of the Recommendations of the Advisory Committee on Flood and Coastal Defence Research and Development Published 1999" was produced in November 1999.

The six theme areas for R&D identified in the Penning-Rowsell Report have been modified to fit with current responsibilities of MAFF and the Agency. The six theme areas now identified are:

- Engineering;
- Flood Forecasting and Warning
- Broad-Scale Modelling;
- Policy Development;
- Fluvial, Estuarine and Coastal Processes; and
- Risk Evaluation and Understanding of Uncertainty.

Theme Advisory Groups will be formed to offer guidance on the composition of the R&D programmes of MAFF and the Agency in the theme areas to ensure compatibility and consistency. It has been agreed between MAFF and the Agency that the theme area of Flood Forecasting and Warning will be administered by the Agency. The Theme Leader will be the Head of the National Flood Warning Centre.

Following the publication of the Bye Report on the Easter 1998 Floods, it became apparent that the Agency needs to ensure that the R&D programme is clearly focussed on the priority issues which will assist the implementation of an increasingly effective flood forecasting and warning system.

In order to identify and confirm priorities to address both the Bye Report and the Penning-Rowsell Report, work is being undertaken to identify where efforts should be focussed. This will be achieved by using a Concerted Action approach, as recommended in the Penning-Rowsell Report. The Concerted Action for Flood Forecasting and Warning was initiated by a Workshop held on 17 February 1999.

5. Objectives of Concerted Action Approach

The objectives of the Concerted Action approach to flood forecasting and warning R&D are to:

- focus on the business needs of the Agency,
- agree principal issues for R&D,
- establish thematic areas,
- rank the R&D programme in priority order,
- encourage ownership of the programme and process,
- promote implementation of results and
- identify opportunities for partnership.

It is important, not only that adequate research effort is devoted to the most relevant needs, but also that research results are adopted operationally in order to improve the service to the community at risk.

6. Organisation and Management of R&D

Within the Agency, flood forecasting and warning research and development is a functional responsibility of the Head of Flood Defence, acting through a Programme Officer, responsible for all Flood Defence R&D and a Theme Leader for flood forecasting and warning, assisted by a Topic Advisor. Administrative support is also

provided from the national R&D function, through regional R&D Management Services Officers. The National Flood Warning Centre will take over the role of management of the programme in due course.

The national R&D programme has, historically, been developed from proposals submitted from Agency staff and external bodies in response to annual invitation. Proposals were considered by a functional group, drawn from Flood Defence in the case of flood forecasting and warning, and an outline annual programme prepared taking account of need and risk.

It is proposed to develop a long-term programme, in order to:

- address issues strategically, rather than the previous piecemeal approach;
- reduce delays in implementation of projects within the R&D programme, in order to deliver the EFAP, and
- promote projects which address the highest priority issues.

The programme is intended run for 5 years, with a total cost of £1million.

The Theme Leader, as Head of the National Centre, will manage the programme, in addition to co-ordinating R&D carried out by others, notably MAFF, in this field.

Two groups have been formed to provide expert advice to the Theme Leader:

- Technical Issues Advisory Group
- Social Issues Advisory Group

The intention is that these groups will identify projects for both the MAFF and Agency R&D programmes which will then be developed and promoted by the relevant body, or by joint funding with others as appropriate.

7. Future Programme

The concerted action Workshop identified key issues to be addressed to improve flood forecasting and warning. The key issues relevant to forecasting are:

Key Issue 1. To examine the provision of a range of forecasts which would reflect the uncertainty inherent in specific techniques and provide the forecaster with guidance on the best estimate for each situation.

- Probabilistic/ensemble forecasts
- Approaches to uncertainty
- Decision support systems

Key Issue 2. To improve the performance of forecasting models both by the development of experimental techniques to operational use and the employment of best practice.

- Best practice
- Alert status by catchment criteria
- Small catchment detection methods
- Antecedent catchment conditions
- New technologies for weather radar
- Forecasts at many points on the river

- Development of technical “tool kit” of best practice
- Integrated rainfall/runoff prediction

Key Issue 3. To improve the accuracy of information received from the field.

- Constraints on effective forecasting
- Data problems in extreme events
- Improvements in rainfall monitoring and forecasting
- Accuracy of data
- Improved onshore wave height measurement

Key Issue 4. To identify the conditions which give rise to extreme events in order to focus resources on those conditions likely to produce emergencies.

- What is a rare event?

8. Commissioned and Proposed R&D

One of the first projects commissioned under the new arrangements is a **Good Practice Baseline Review**. This has the objective of documenting current good practice within the Agency and provide recommendations to guide development of regional and area flood forecasting and warning systems and procedures to improve timeliness, accuracy and reliability of flood warnings.

It is not intended to cover such issues as model comparison in the above. A project on **Real-Time Modelling** has been identified as high priority in the future programme. This will review performance information on existing hydraulic and hydrological models used in real time and provide guidelines on the most suitable models for use in particular catchment conditions, including confidence limits, and to identify R&D needs. This work will clearly build on the comparison of rainfall/runoff models described in an earlier paper.

Other priority projects include;

- **Rainfall Forecasting -** a review of existing techniques of rainfall forecasting and recommendations for implementation into real-time systems to improve accuracy.
- **Extreme Event Recognition -** to review conditions which have produced extreme flood events and to identify factors which could be used for early recognition of the development of extreme events to improve response

A common factor in much of this work is the aim to make best use of existing science, rather than funding new developments. Historically, the implementation of R&D has been patchy in the Agency and the full benefits of research are not being realised. The reorganisation of the flood forecasting and warning service gives clearer lines of communication to allow improvements and good practices to be disseminated throughout the system to achieve the full benefits of the efforts which have been, and will continue to be, invested in R&D.

Intercomparison of rainfall-runoff models for flood forecasting

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1. Introduction

Choosing a rainfall-runoff model for use in flood forecasting is not a straightforward decision and indeed may involve the selection of more than one. The Environment Agency (EA), responsible for operational flood warning in England and Wales, commissioned research aimed at providing guidance on choice of model for different types and sizes of catchment and for different meteorological situations. The study began with a literature review of models, focussing first on models in operational use by the EA but expanding to include models developed elsewhere and of distributed form.

Following this review a subset of the models was chosen for inclusion in a data-based intercomparison of models. The intercomparison employed 8 models across 9 catchments of varying size, land use, relief and lithology. For three of the catchments weather radar data were used to obtain "best estimate" rainfalls as an alternative to raingauge estimates. The data record for each catchment, extending up to 10 years in duration, was split into calibration and evaluation datasets.

Models were evaluated in simulation mode and in updating (forecast) mode. The range of models included different updating methods based on error prediction, state correction and parameter adjustment. Performance was judged using a range of statistics (R^2, skill scores on threshold crossings), scatter plots of observed and forecast peaks, and hydrograph plots. The results have been used to draw up guidelines on model choice for different catchment situations. This paper presents an outline of some aspects of the study.

2. Selection of models for intercomparison

Whilst there is a plethora of "brand name" models they involve a relatively small set of model functions which are configured in a variety of different ways. A literature review of models, forming the Part 1 Report (Moore and Bell, 2000), provided a basic understanding of the types of model available, highlighting their similarities and differences. The initial selection of models for review was guided by those already in use for flood forecasting in the UK. To this were added well-known models developed overseas and those with a distributed formulation. From this menu of models, eight were selected for the data-based intercomparison detailed in the Part 2 Report (Bell *et al.*, 2000).

The chosen models encompass those used operationally by the EA together with one overseas model and a simple distributed model previously developed for the Agency. Four of the models are lumped, conceptual models with continuous water accounting procedures: the Thames Catchment Model (TCM), the Midlands Catchment Runoff Model (MCRM), the Probability Distributed Moisture model (PDM), and the US National Weather Service Sacramento model (NWS). A fifth model, the Isolated Event Model (IEM), is an event model modified to operate continuously in real-time. Water balance principles are used for soil moisture accounting and water storage routing but an empirical function links the two components, controlling runoff production as a function of soil moisture. The sixth model is a simple Transfer Function (TF) model whilst the seventh is a constrained form of TF model, referred to as the Physically Realisable Transfer Function (PRTF). The TF types of model are black-box models which empirically relate rainfall and flow, can be related to unit hydrographs and can be subject to conceptual interpretation as forms of routing function. The last model, the Grid Model, is

included as a simple form of distributed conceptual rainfall-runoff model suitable for use in flood forecasting and able to use weather radar estimates of rainfall in grid form.

The literature review also provided detailed overviews of the Input-Storage-Output or ISO-function model and the NAM model, which are both conceptual approaches. It also provided a commentary on emerging technologies for forecasting which included neural network, fuzzy rule-based and nearest neighbour methods. However, these methods were not carried through to the detailed data-based model evaluation which focussed on models in operational use by the EA.

The Part 1 Report also reviewed the methods available for forecast updating, where recent measurements of flow are used to improve upon the model forecasts in real-time. Two main methods are distinguished. Error prediction aims to predict future model errors by utilising the dependence structure in past errors. State correction makes adjustments to the model states, in the form of water storages or flows, to "steer" the model towards the observed behaviour of flows at the catchment outlet. The latter method needs to be tailored to a particular model type. State correction can take the form of full state re-initilisation, where modelled flows are replaced by observed ones. Or correction can be partial adjustments to states that are not directly observed, such as the water contents of conceptual model stores. Since error prediction can be applied independent of the form of the model, it has been adopted for use in the Part 2 study where an updating method was not well established for a given model.

3. Selection of catchments for model intercomparison

In order to draw general guidelines on model choice in different situations, a careful selection of catchments for use in the model assessment was required. The catchments chosen are presented in Table 1 and their locations mapped in Figure 1. At least one catchment was chosen from each of the eight EA regions. The final selection was guided by operational importance as well as ensuring a mix of hydrological characteristics, such as small/medium/large, upland/lowland, ground/surface water dominant, and urban/rural. Very large catchments were excluded as these would normally be represented by a network configuration of rainfall-runoff and channel flow routing models, these being outside the scope of the present study.

One catchment, the Stour to Shipston, was included during the course of the study in response to the "Easter 1998 Flood" and the need to have one catchment significantly affected by this major flood event. The conditions of super-saturation could bring into play different flood mechanisms requiring to be modelled. The Lavant was chosen as a catchment with a flood response superimposed on a dominant groundwater regime, and which has well level records and pumped abstractions. Only two of the models, the TCM and PDM, have the capability to accommodate pumped abstraction data and to represent ephemeral streamflow behaviour explicitly. As a consequence, only these models were applied to the Lavant catchment along with the TF model (using rainfall and flow data only), serving primarily as a point of reference. The Roch has been extensively used in model development work in North West Region, especially for TF and PRTF models. Use of the Brue reflects the availability of a very dense raingauge network installed under HYREX (Hydrological Radar EXperiment), a NERC Special Topic. Trout Beck, a typical small upland catchment, was the focus of a snowmelt forecasting project and an existing dataset at IH (Moore *et al*, 1995; Bell and Moore, 2000). The Dove at Izaak Walton is important for flood warning in the Midlands Region and data had been collated as part of the snowmelt forecasting project. The Silk Stream is a small urban catchment in London with a good dataset of raingauge, flow and radar data brought together under the NRA Project "Evaluation of FRONTIERS and Local Radar Rainfall Forecasts for use in Flood Forecasting Models" (Moore *et al*, 1993). TCM, PDM and IEM models had already been developed for this catchment. The Rhondda to Trehafod provides a good example of a medium-sized catchment with steep slopes. This catchment has been the subject of study in the NRA Project

"Development of Distributed Flood Forecasting Models using Weather Radar and Digital Terrain Data" (Moore *et al*, 1994), from which the Grid Model was developed and compared in performance to the PDM.

Table 1. *Catchments selected for model assessment*

	EA Region	*Catchment*	*Area* km^2	*Characteristics*
1.	North East	Trout Beck at Moorhouse	11.4	Small, upland rural.
2.	Thames	Silk Stream at Colindeep Lane	29	Small urban, clay.
3.	Midlands	Dove at Izaak Walton	83	Small/medium, high relief, rural, moorland mudstone/sandstone headwaters. Carboniferous limestone.
4.	Southern	Lavant at Graylingwell	87.2	Small/medium, ephemeral stream in a permeable (Chalk) catchment, mainly rural, groundwater abstractions, well records.
5.	Welsh	Rhondda at Trehaford	100.5	Medium, steep rural headwaters, urban/industrial development in valleys, 24% forest.
6.	South West	Brue at Lovington	135.2	Medium, rural catchment, springfed headwaters. Clays, soils and oolites. Modest relief.
7.	Midlands	Stour at Shipston	185.0	Medium, rural, Keuper Marl. Modest relief.
8.	North West	Roch at Blackford Bridge	186	Medium, highly urbanised in lower half with moorland above.
9.	Anglian	Witham at Claypole Mill	297.9	Large, mainly rural lowland catchment with clay (50%), limestone (40%) and gravel, low relief.

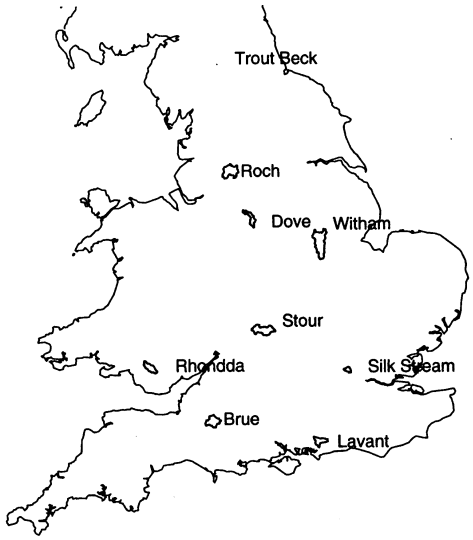


Figure 1. *Location of the study catchments*

The Witham was chosen by hydrologists in Anglian region as representative of a large, low-lying rural catchment in Eastern England and because of its importance to flooding of Lincoln.

Three of the catchments – the Silk Stream, the Stour and the Roch – were assessed using radar data, whilst all catchments were assessed using raingauge data. This reflected the cost and time-consuming nature of handling radar data off-line at the present time. Data from the Clee Hill radar were used for the Stour, the Hameldon Hill radar for the Roch and the Chenies (London) radar for the Silk Stream. Single site (Type 2) 2 km radar data (or 5 km data outside the 75 km range) were used. Nimrod corrected data (Golding, 1998) are not available over the period of a decade used for model assessment. Also, the Nimrod product has only been stable since circa 1998 and is available only for the coarser resolution of 5 km. The Grid Model was only applied to the three largest catchments – the Stour, the Roch and the Witham – where the benefit of using a distributed model formulation was thought likely to be most beneficial.

4. Strategy for model assessment

The strategy for assessment used was based on first calibrating all models in "simulation-mode", where each model is used to transform rainfall (and potential evaporation) to runoff without using flow to update the model forecast. Each model was then evaluated using periods of data not used for calibration. The simulation-mode evaluation serves to focus on the process model capabilities of a given model. Subsequently, each model was evaluated in "forecast-mode" in which an updating scheme is used to incorporate measurements of flow up to the "forecast time-origin". This emulates the forecast performance expected operationally at different forecast lead times. Perfect foreknowledge of rainfall was assumed so as not to confound the model assessment with uncertainties in rainfall forecasts. Long continuous periods of record, typically eight months in duration at a fixed 15 minute time-step, were employed for model assessment, with two to four periods being used for both model calibration and evaluation.

The statistics used for model assessment were R^2 and a Threshold CSI (Critical Success Index). The R^2 statistic, giving the proportion of the variability in the flow accounted for by the model forecasts, was used to provide a broad guide to model performance. The Threshold CSI statistic was used to judge the efficacy of a model to correctly forecast the exceedence of a set of flow thresholds, particularly relevant to the use of a forecast to trigger an alert level of a given severity. Forecasts were also judged more informally via hydrograph plots and scatter plots of observed and forecast flood peaks.

Whilst the main assessment related to the use of raingauge estimates of rainfall as input to the models, for three of the catchments the assessment extended to the use of weather radar, both in raw form and as raingauge-calibrated radar estimates of rainfall. Whilst forecast accuracy was the focus of the model assessment, other issues were considered including ease of model configuration, initialisation and calibration.

The form of model assessment used, employing long continuous periods of record rather than storm event data, meant that it proved difficult to emulate the performance of TF/PRTF models as used operationally within the Agency. These models are used in "event mode" and commonly operate on baseflow separated runoff where baseflow is taken as the flow at the start of the event. The opportunity exists to manually adjust the model parameters affecting the volume, shape and timing of the forecast as the flood develops. Also, the model time-step and model order are commonly chosen with regard to the response characteristics of the catchment. The results obtained in the model intercomparison related to TF/PRTF models without baseflow separation, using an automated method of model parameter adjustment and using a fixed model time-step and model order. An alternative formulation, using an error predictor for updating, was also included. The findings relating to TF/PRTF models need to be interpreted against this background noting that these models, as implemented here, do not reflect their application in the Environment Agency.

5. Model and data configuration tools

The extensive nature of the model assessment, involving eight models and nine catchments, required tools to be developed to ease the tasks involved. For model calibration and evaluation, all models were operated within the same River Flow Forecasting System (RFFS) Model Calibration Facility. This provided a consistent modelling framework across the set of models being assessed. It employs a modified simplex direct search procedure for model parameter estimation and produces forecasts in simulation, fixed-lead time and fixed-origin forms from which error statistics are calculated and hydrographs plotted. For the TF/PRTF models, special facilities utilising a recursive least squares algorithm were embedded within the model codes to emulate the MATH code in use by the EA . Four of the conceptual models were already available within the Model Calibration Facility. The NWS and MCRM models were modified to work within the generic Model Calibration environment and required extensions, particularly relating to model initialisation and operation at a variable time-step. It is possible with the facility to run models initially at a daily time-step, focussing on the parameters controlling the water balance, and then to operate at the chosen time-step (15 minutes here) to adjust the rate parameters and obtain a final parameter set.

Typically each catchment had no more than two reliable raingauge records with which to estimate catchment average rainfall. New automated tools were developed which employed the Digital Terrain Model (DTM) with spatial datasets of SAAR (Standard Average Annual Rainfall) to derive catchment raingauge weightings based on nearest distance principles. Distance could be defined in terms of Euclidean distance (Thiessen), elevation or SAAR, or combinations of these. In general, a closest elevation weighting was used. For the assessment using radar data, a new raingauge/radar merging technique was adopted based on a hybrid climatological adjustment and a dynamic gauge adjustment, the latter dominating closer to each gauge.

The Thames Conceptual Model sub-divides a catchment spatially into hydrological response zones. Identification of these zones was semi-automated by using the DTM with spatial datasets of urban area, 100 year flood extent and WRAP (Winter Rain Acceptance Potential) soil classes to provide an initial set of response zones which were subsequently refined as part of the model calibration process. Extensions to both the TCM and PDM were made to model ephemeral flows from groundwater catchments under the influence of pumped abstractions, underflow and external springflow.

6. Results of the model assessment

Overall, the results of the model assessment suggest that no one model consistently out-performs all others across all catchments. The TCM is one of the best performing models when judged using the R^2 statistic whilst the PDM is more successful according to the Threshold CSI criterion (relevant to the issuing of flood alerts) and in forecasting flood peaks. Whilst the TCM is the most complex model and can be a challenge to calibrate, the PDM is of intermediate complexity. For a simple model, the IEM is surprisingly successful, particularly in terms of Threshold CSI. The simplest models, the TF and PRTF, are easiest to calibrate and initialise and can provide good forecasts for some catchments. For smaller catchments in particular, TF models compare favourably with other models when used with error prediction rather than state updating. The MCRM proved sensitive to initial conditions of soil moisture but can work well on small-to-medium sized catchments. The NWS model, despite its large number of parameters, proved easy to calibrate using automatic optimisation and provided reasonable performance. Figure 2 shows how forecast performance varies with lead time for all models tested on a selection of four of the catchments. It illustrates how there is often little to choose between models in terms of the R^2 performance statistic, whereas greater separation is apparent in the Threshold CSI criterion used to judge the success in forecasting the crossing of flow thresholds.

Use of radar data gave as good, and sometimes slightly better results than using raingauge data alone, provided the radar was functioning well, and raingauge-calibration generally helped. The Grid Model was the only distributed model assessed and can utilise radar data in grid form. For the three catchments on which it was evaluated in simulation-mode it consistently gave the second best model simulations in terms of R^2 but did less well according to the Threshold CSI criterion. Figure 3 presents a selection of model hydrographs obtained for the 1998 Easter flood event in the Stour using rainfall data from both raingauges and raingauge-adjusted radar, using the Clee Hill radar. In all cases, model performance is improved through the use of raingauge-adjusted radar data although for the Grid Model the improvement is minor. Note that the apparent poor performance of the models obtained using raingauge data is in part due to the short periods used for radar data evaluation, which can have an affect on the water balance accounting in conceptual models through inadequate initialisation.

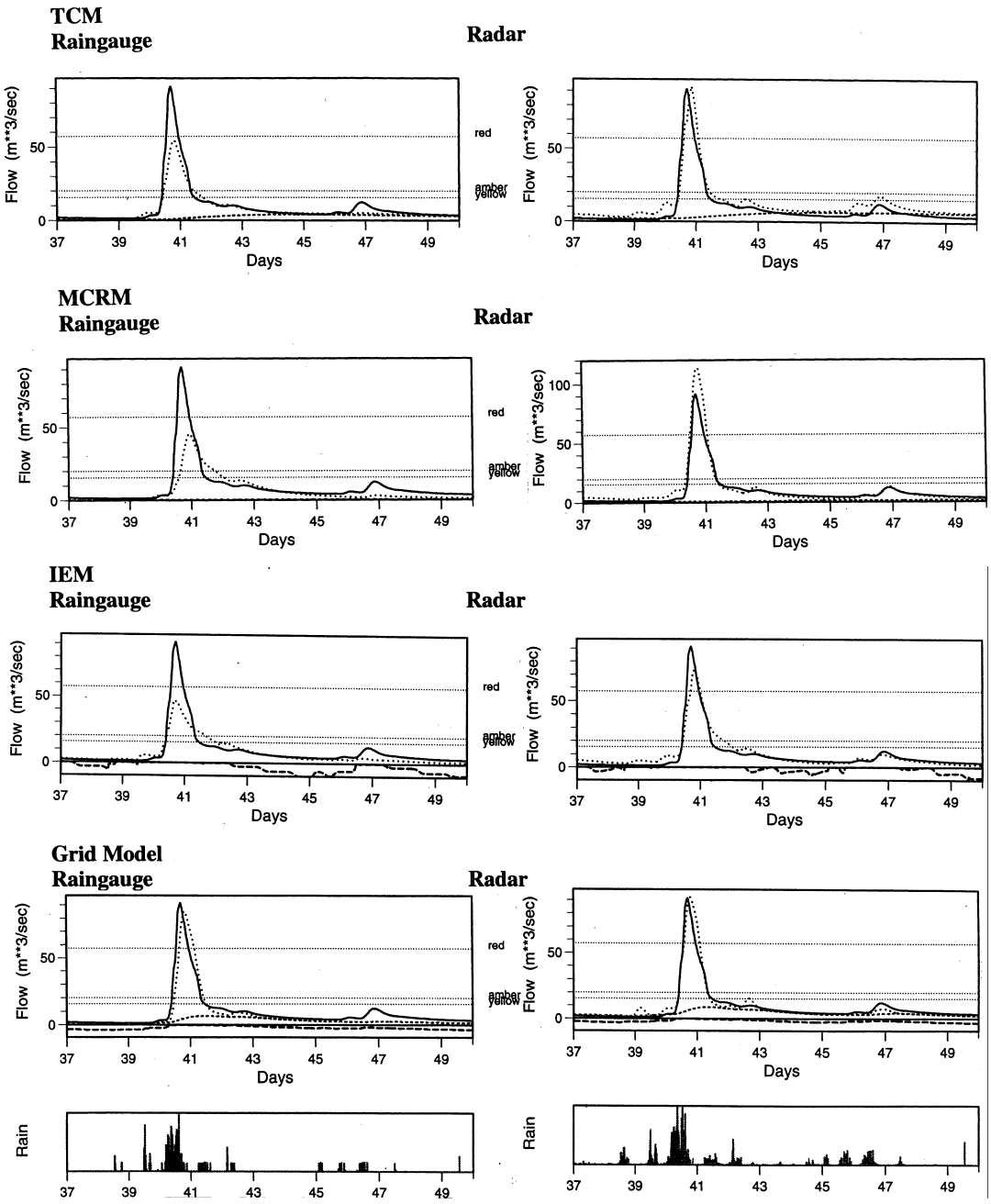


Figure 2. *Variation in forecast performance (R^2 and Threshold CSI) with forecast lead time from different models. The TF model with error prediction is indicated as tfar.*

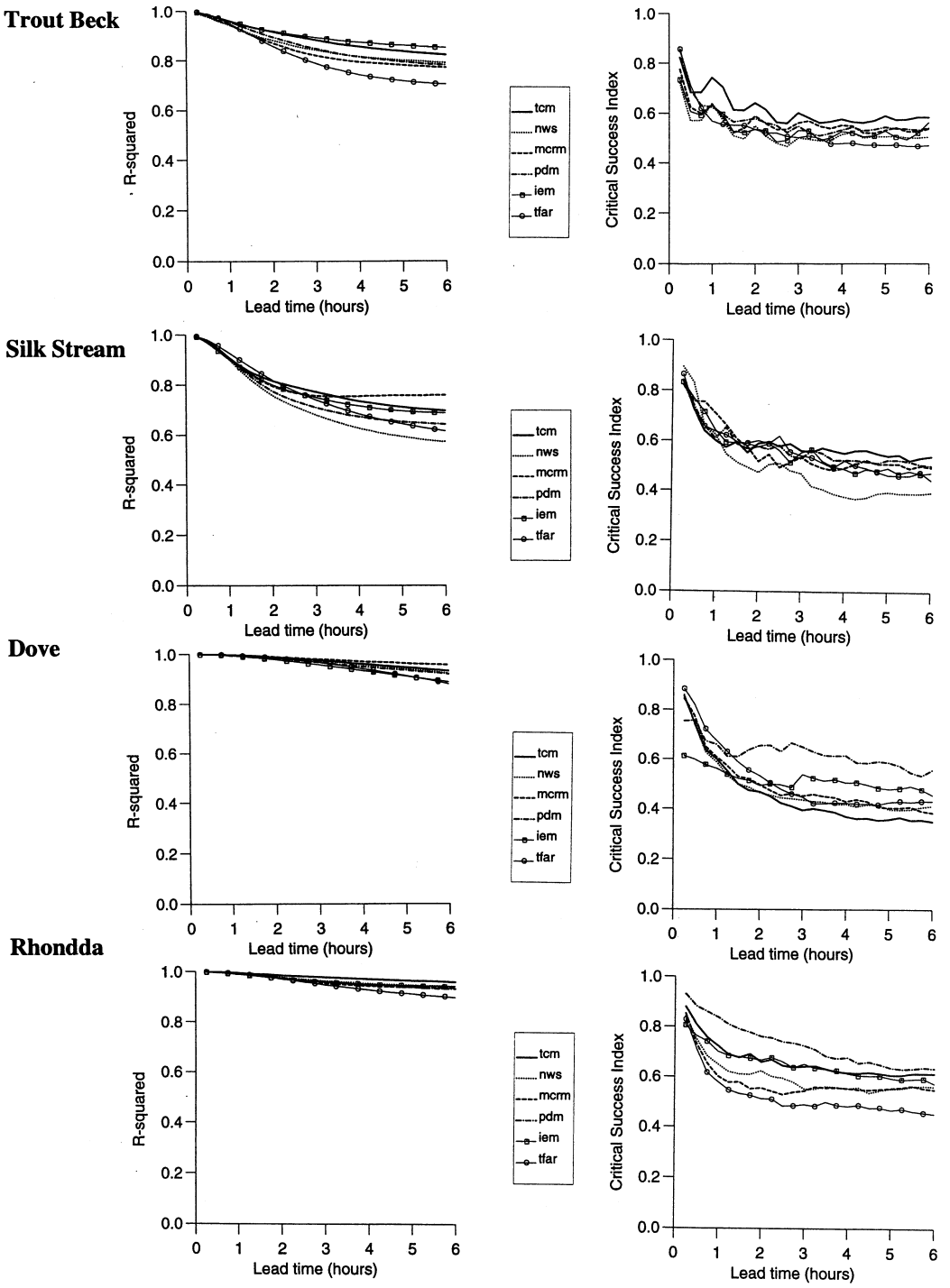


Figure 3. *Simulation-mode model hydrographs using raingauge and calibrated radar data for the Stour, 6 to 19 April 1998 (Easter 1998 Flood).*

Operationally, the TCM, PDM and IEM models appear to be the most appropriate flood forecasting models to use, of those assessed, the choice depending on the complexity of catchment response whilst all models have value in the right situation. The advantage of model familiarity acquired through past use has been employed to guide more specific recommendations for each EA region.

The assessment of TF/PRTF models proved problematic on account of their event-mode form of use, which affects both model calibration and forecasting. Operational applications commonly involve baseflow separation using the start-of-event flow and manual adjustment of the model parameters as the flood develops. These features have not been emulated here. As a consequence, it is difficult to comment objectively on the performance of TF/PRTF models, as applied operationally within the EA, in relation to the other models assessed here. However, it is recommended that more automated applications of TF/PRTF models be pursued which accommodate the effects of catchment wetness on runoff production through effective rainfall transformations and incorporate baseflow via parallel "fast" and "slow" transfer function routing components. Examples of such formulations are given by Moore (1982, 1999), Young (1992) and Lees (2000). The results obtained from such models as the PDM, which encompass certain cases of these extended forms of TF model, may be indicative of the performance that can be achieved or bettered.

Opportunities for further research on model formulation and configuration, updating schemes, and catchment-scale rainfall estimation are identified in the Part 2 Report.

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