# The Estimation of Flood Frequency Curves by Mapping from Rainfall Frequency Curves

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**ABSTRACT**

Recent large flooding events have reinforced the need for prudent flood risk management. The July 2007 floods in Yorkshire and the Midlands and the November 2009 floods in the Lake District have highlighted the current vulnerability of key infrastructure and the built environment in the UK to flooding. This existing flood risk is coupled with concerns over the potential impacts of future climate change on flood regimes. Therefore, there is a need to develop tools and methodologies to assess the potential impact of likely climate change on flood risk.

The link between large rainfall and flow events is first examined, as well as an assessment of the seasonality of these events. This reveals a distinct east-west split in the seasonal concentration of flooding. This work provides a basis for the development of a statistical modelling technique which estimates a catchment flood record on an event basis. The model uses estimates of the flood generating storm and the antecedent conditions to estimate a flow magnitude. The modelled flood record is then transformed into a flood frequency curve using an appropriate statistical method.

Extensive testing of the model has assessed its robustness to the length of flood record used in fitting and its sensitivity to the input climate data. Several case studies using the UKCP weather generator show how the method works as well as providing an indication of how future climate changes may affect the flood frequency curve.

The frequency curve mapping method developed here performs best on catchments whose flood regime is driven by rainfall. The use of a simple antecedent rainfall accounting method has been shown to perform as well as a quasi-physical soil moisture estimation method.

The research undertaken offers several possibilities to develop understanding of flood frequency curves in catchments with short gauged records. This new methodology has the potential for further development and can be used to explore a wide range of future scenarios.

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Finally, thanks must go to everyone who has helped to keep me sane after staring at a computer screen for what seems like a rather long time. There are too many people to mention individually but special thanks must go to Carolyn for agreeing to some adventurous trips away.

**Abbreviations used within the Thesis**

| | |
|---|---|
| AEP | Annual Exceedance Probability |
| AMAX | Annual Maximum |
| API | Antecedent Precipitation Index |
| BFIHOST | Base Flow Index as derived from the Hydrology of Soil Types classification scheme. |
| CMD | Catchment Moisture Deficit |
| CS | Continuous Simulation |
| DEFRA | Department of the Environment Food and Rural Affairs |
| DEOptim | Developmental Evolution Optimisation Algorithm |
| DPLBAR | Mean of distances between each node on IHDTM grid and the catchment outlet (km) |
| DPSBAR | Mean of all the inter-nodal slops for the catchment (in km-1): characterises the overall steepness. |
| EA | Environment Agency |
| FC | Field Capacity |
| FEH | Flood Estimation Handbook |
| FRACAS | A national Flood Risk Assessment under Climate chAnge Scenarios |
| FSR | Flood Studies Report |
| GA | Genetic Algorithm |
| GCM | Global Climate Model |
| GEV | Generalised Extreme Value |
| IPCC | Intergovernmental Panel on Climate Change |
| MO | Met Office |
| MORECS | Met. Office Rainfall and Evaporation Calculation System |
| MOSES | Met. Office Surface Exchanges Scheme |
| NRFA | National River Flow Archive |
| PCD | Principal Catchment Descriptor |
| PDM | Probability Distributed Model |
| PET | Potential Evapotranspiration |
| POT | Peaks Over Threshold |

| | |
|---|---|
| PROPWET | FEH Indice; Proportion of the time a catchment has a soil moisture deficit of less than 6mm. |
| SAAR | Standard Annual Average Rainfall |
| SEPA | Scottish Environmental Protection Agency |
| ReFH | Revitalised Flood Hydrograph |
| RCM | Regional Climate Model |
| RD | Rooting Depth |
| RMED | Median Annual Maximum Rainfall Value |
| SMDBAR | Mean Soil Moisture Deficit (mm) |
| Tp | Time to Peak |
| UKCP | United Kingdom Climate Projections |
| URBEXT | Urban Extent (2000) |
| QMED | Median Annual Maximum Flow Value |
| WG | Weather Generator |

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# Chapter 1: Introduction

## 1.0 Flood Risk in the United Kingdom

In 2008 the Environment Agency calculated that around 5.2 million properties were at risk of flooding from coastal, fluvial or surface water sources in England (Environment Agency, 2009). The expected annual damage from coastal or fluvial flooding is estimated to be over £1 billion per annum, with the assets at risk from fluvial flooding alone valued at 81.7 billion pounds (FREE, 2010). In Scotland, the current average annual damage from fluvial flooding is estimated at around £20 million, with increases of up to 115% expected by 2080 (Werritty et al., 2002). Much of the UK's important infrastructure is located in areas of flood risk, posing more than just financial problems if it were inundated. This is perhaps best illustrated by the near flooding of Walham electricity sub-station during the July 2007 floods. These floods are estimated to be the most expensive floods that occurred anywhere in the world during 2007 (Pitt, 2007). While emergency defence work helped prevent any significant power failure, the situation highlighted the vulnerability of some of the key infrastructure which the UK relies upon. In 2002, Glasgow suffered from extensive surface water flooding, with 200 people evacuated from their homes and 140,000 people temporarily unable to access drinking water. In November 2009 severe flooding affected many parts of England, Ireland and Wales, with the North-West of England being the worst affected. In this case there were several fatalities and high river levels destroyed bridges and left many more unusable.

However, the problems associated with flooding and flood damage cannot be simply reduced to financial cost and economic impact. Tapsell et al. (2002) emphasise the importance of understanding the social dimensions of flooding, particularly with regards to the stress that repeated or frequent flooding can induce. In Tapsell's study, the respondents indicated that the majority of them suffered from an increase in psychological health problems due to the stress of dealing with flooding and its aftermath. Other reported health problems include illness from contact with contaminated flood waters as well as due to living in damp environments (Tapsell et al., 1999). Due to an increase in stress levels flooding can also be responsible for exacerbating pre-existing health problems.

Furthermore, as has been alluded to previously, there are clearly risks to essential services and utilities during flood events. It is difficult to put a price on services such as electricity, clean water and sewerage, where interruption of supply carries a much greater impact on society than the economic impact alone. What this means for flood risk management is that it is clear that financial cost and economic impact alone cannot be used to justify the development of flood alleviation measures.

The impact of flooding in the UK is considerable, both in monetary and social terms. Therefore, the demand for new tools to help to manage flood risk is also high. In reviewing the July 2007 floods, the Pitt review called for the development of methods to help deal with the fluvial flood problem. The research project presented in this thesis takes a much more narrow view of flood risk than the issues outlined above, it specifically considers flood frequency estimation. This is the starting point for developing more sophisticated risk assessments, whether they involve purely financial assessments or include social components as well.

This PhD research is part of the Natural Environment Research Council's (NERC) Flood Risk from Extreme Events (FREE) programme. It aims to further develop an understanding of flood risk and develop new tools to help quantify and forecast flood risk by the development of a science programme that integrates meteorological, hydrological, terrestrial and oceanographic communities (FREE, 2010).

## 1.1 Future Management of Flood Risk

Given the cost of flooding to the UK (where cost can be more than financial), there is a clear case for developing longer term management plans. These can help prioritise work as well as give an indication of the level of spending required for the future. The Environment Agency's long-term investment strategy states that the investment required to build and maintain new and existing flood and coastal defence assets would be in the region of £1040 million per annum (plus inflation) by 2035 (Environment Agency, 2009). This value excludes any measures to deal with surface and groundwater flooding and is an increase of 80 % on 2010/2011 investment levels. Exacerbation by climate change as well as societal change may impact further upon these estimates. Therefore, given the large potential costs associated with flooding in the UK, there is a need for models and decision support systems that will enable cost-effective management of future flood risk. This recommendation was made by the Pitt review (Pitt, 2007). Furthermore, there is a need to implement management strategies as soon as possible, as some evidence suggests that early action will be the better economic option in the long run (Stern, 2006).

Further demand for flood risk assessment comes from the implementation of the EU directive on the assessment and management of flood risks (European Commission, 2007). This has been transposed into UK law through the Flood Risk Management (Scotland) Act of 2009 and the Flood and Water Management Act 2010 covering England and Wales. This legislation formalises the management of flood risk from the national to local level. It sets targets for specific activities such as risk mapping and risk assessments designed to harmonise flood risk management between member states of the EU. These activities will require the use of appropriate tools, models and expertise for implementation, and it is one further reason why research on flood risk management is still active today.

## 1.2 Why Flood Frequency?

Many aspects of flood risk assessment start with an understanding of flood frequency; that is, relating the magnitude and rarity of particular flows. After the publication of the Flood Estimation Handbook (FEH) in 1999 (Reed, 1999), UK research on the topic gradually declined, apart from sporadic updates to the FEH method. More recently, driven by a concern over climate change, new work has developed methods such as the grid to grid model by CEH (see Bell et al., 2007a,b). The development of UK flood estimation guidelines are reviewed in more detail elsewhere, but it is informative to provide some context for new research here.

The main justification for this PhD research comes from the inability of existing methods to be consistently applied over many catchments while also dealing with aspects of climate change. While many catchment models exist, they are often complicated to run, require high levels of expertise and large volumes of data. Furthermore, as models often differ in their construction and operation it is not clear how results can be reliably compared between models.

The outputs from a flood frequency assessment are often used for further assessment of variables that directly affect how much flood damage is caused; namely water depths and velocities. Where only flood frequency estimates are required, many existing models complicate the analysis by providing unnecessary information. Therefore, this research focuses on the development of a simplified, alternative approach to the traditional modelling methodologies.

The work contained in this thesis makes use of the term “storm rainfall”, where a storm is a flood generating rainfall event. Rainfall is the preferred term over precipitation as this work does not explicitly make use of forms of precipitation other than rainfall. The term “extreme rainfall” is also used; this takes its definition from a traditional frequency based approach, where an extreme rainfall event is a rare event in frequency terms (such as an Annual Maximum or POT1/ 2 series).

## 1.3 Aims and Objectives

### 1.3.1 Study Aim

The aim of this study is ***to develop a method suitable for reproducing a flood frequency curve from storm rainfall and associated information, with a view to using it for the assessment of future flood risk*.**

### *1.3.2 Study Objectives*

The objectives of this study are as follows:

***-To source appropriate datasets and assess their suitability for use in the project.***

***- To investigate and develop a methodology for the transformation of rainfall to flow.***

***-To develop a robust methodology for estimating a flood frequency curve based on rainfall data and associated information on a catchment by catchment basis.***

***-To prove the use of this methodology in applications utilising future scenarios.***

While not a specific objective, it should perhaps be emphasised that this work aims to take an alternative approach to that which is being developed by the FRACAS project partners.

## 1.4 Statement of Scope and Limitations

The primary geographical focus of this investigation is the mainland UK, including England, Wales and Scotland. It does not include Northern Ireland, as flow and rainfall data are not as easily obtainable.

In terms of flood risk estimation this work is primarily concerned with fluvial flooding. Therefore, while some work considers catchments that have other components contributing to their flood behaviour, no explicit methods have been developed to take account of these. Flooding from groundwater, snowmelt, coastal flooding and extreme rainfall are present in some extent in the flow records however; the approach developed here does not take specific account of each variable. Because these mechanisms of flooding routinely interact with fluvial flooding, consideration is given to these other sources at several points within the thesis.

The method presented in this thesis uses the impact of climate change upon flood frequency as its justification. However, the work presented here details the model development as well as providing examples of applications, rather than providing a comprehensive climate change analysis of UK catchments.

## 1.5 Thesis Structure

The thesis begins with a review of the relevant literature (Chapter 2) with a view to assessing current methods and studies for aspects which can be incorporated into this work. Chapter three presents work carried out to review suitable datasets, particularly assessing the usefulness of daily data for storm estimation. This work is further developed in chapter four by combining both rainfall and flow datasets to assess the seasonality regimes of rainfall and flow before assessing the relationship between extreme rainfall and flow events.

A simple model for transforming rainfall to flow is presented in chapter five, with an exploration of the different methods of model construction. This model is further developed in chapter six, which presents the method whereby the flood frequency curve can be estimated from rainfall data and associated information. Chapter seven presents some climate change applications of the model, as well as developing the work in chapter six by presenting a validation of the model. Chapter eight presents a discussion of the research presented in the thesis, highlighting key issues within current flood frequency research and how they relate to this work. Finally, Chapter 9 presents some conclusions and summarises the achievements of this thesis..

Throughout the thesis reference is made to several catchments, often to illustrate particular aspects of the approach used. A full list of catchments referred to and their locations can be found in Appendix K.1.

# Chapter 2: Reviewing the State of the Art in Flood Frequency Estimation

## 2.1 Introduction to the Review

This literature review discusses several aspects of current scientific research which are relevant to the study as a whole. This chapter aims to put the research project into context by critically considering other relevant work. The review further illustrates the need for the research project, as well as informing the approach taken. The review structure aims to answer the following questions:

1) What is required from a flood frequency estimate and what current guidance exists on the development of an estimate?
2) What data are available for use in the project?
3) What methodologies are currently available for peak flow estimation?
4) What methodologies are currently suitable for fluvial flood frequency estimation?
5) What work has already been carried out to consider future flooding impacts on the UK?

Each question will be addressed separately, and will discuss the appropriate literature with a view to identifying issues and findings which are relevant to this study.

## 2.2 The Need for Flood Frequency Estimation and Current Guidance

In a practical setting, flood frequency estimates are typically a basis for further work, such as hydraulic modelling of inundation levels for a flood defence scheme design or flood mapping (Shaw et al., 2011). Flood frequency estimation is required not only to estimate peak flows for flood defence design, but also to estimate of the rarity of flows of a specific magnitude. This work is important for many applications – particularly the insurance and re-insurance industry. Therefore, flood frequency estimation is particularly concerned with the rarity of large flow events; it seeks to quantify these, usually in statistical terms using terminology such as return period or probability of exceedance. The return period refers to the average time interval between flows of a specific magnitude. The use of the word 'average' is important here, as in reality the fifty year flow could occur twice within five years, although the probability of this happening may be low.

In the United Kingdom there are standards to which fluvial flood schemes should be designed. In assessing risk to development, a framework is used which classifies the importance of the development in question and the associated acceptable level of flood risk. For the majority of developments, acceptable levels of risk should generally be less than the 1 in 200 year event, however for essential civil infrastructure the calculated probability of flooding should be less than the 1 in 1000 year event (Scottish Executive, 2010).

Fluvial flood management responsibilities are different depending upon the country of interest, although the recent European Union Floods Directive (European Commission, 2007) goes some way towards harmonising responsibilities and powers. In England and Wales, it is the Environment Agency's (EA) responsibility to develop flood defence schemes. The Environment Agency must also be consulted on new developments, in order to assess any possible impacts from flooding (Department for Communities and Local Government, 2007) as well as develop strategic assessments of flood risk such as flood maps. In Scotland it is currently the responsibility of the local authority to promote flood defence schemes. The Scottish Environmental Protection Agency (SEPA) has a responsibility to develop flood warning schemes as well as strategic flood risk assessments.

Current guidance on future changes to flood risk is available from DEFRA (2006). While extensive research into future changes in climate and flood risk is still ongoing, the current guidance reflects the needs of practitioners for practical and straightforward information to inform flood defence scheme design. This current guidance can be seen in Table 2.1 and provides indicative sensitivity ranges to changes in future variables such as extreme rainfall and peak river flows.

| ***Parameter*** | ***1990-2025*** | ***2025-2055*** | ***2055-2085*** | ***2085-2115*** |
|---|---|---|---|---|
| Peak rainfall intensity (preferably for small catchments) | *+5%* | **+10%** | *+20%* | *+30%* |
| Peak river flow volume (preferably for larger catchments) | +10% | **+20%** | | |
| Offshore wind speed | *+5%* | | **+10%** | *+10%* |
| Extreme wave height | *+5%* | | **+10%** | *+10%* |

**Table 2.1:** *Indicative sensitivity ranges for future variables. DEFRA (2006)*

Clearly the future changes shown in Table 2.1 are a rather broad brush approach, as they do not suggest changes based upon geographical location or return period. Guidance on smaller catchments is also non-existent. In practice this could lead to the under-estimation or overestimation of peak flows in a specific location with associated cost implications. Given that new climate scenarios such as those of UKCP09 (Murphy et al., 2010) are now available there is considerable potential to update the estimates in Table 2.1 to make them more relevant to particular locations, as well as using more up to date future climate scenarios.

The need for flood frequency estimates coupled with potential future changes in rainfall and flow regimes suggests that there is a clear need for tools and analyses which can go some way towards helping those responsible for fluvial flood management develop long-term strategies for managing future risk.

## 2.3 Assessing Flow and Rainfall Data

A study such as this, which plans to make considerable use of a variety of data sets, requires careful consideration of their attributes. As such, the work reported on here refers only to the information found in the available literature. Extensive preliminary analyses were carried out on flow and rainfall data and it is felt that this work is worthy of a separate chapter. This work can be found in Chapter 3 ‘Data Sources; Information and Assessment’.

### 2.3.1 Peak Flow Measurement

It is important to distinguish between measurement error at times of high flow, and discharge estimate. In many catchment flood records, few flow peaks have been measured directly, for the most part they are estimated from stage-discharge relationships. However, a good stage discharge relationship requires good flow estimates.

The measurement of peak flow is not straightforward. Access to rivers at times of flood can be dangerous and impractical. Herschy (2002) in his work on the worlds maximum observed floods, suggested that peak flow values in the catalogue of large observed floods had an uncertainty estimate of around 10-15 %, with lower uncertainty estimates towards the more recent end of the gauged record. One of the reasons for this may be the development of improved measurement technology such as Acoustic Doppler Current Profilers (ADCPs). Yorke and Oberg (2002) in assessing ADCP measurements suggest that they tend to fall within 8% of more conventional methods such as current metering, with the majority of measurements within 5 %. Any flow measurement is subject to some error, this is an inevitable consequence of trying to measure variable open channel flow. Whalley et al. (2001) in a study looking at flow measurement error from current meters consider than an error of +-10% of the true flow is reasonable. However, it is difficult to systematically account for measurement error where many factors influence the results. The calibration of the flow gauging equipment, the discharge measurement techniques used and the equipment operators can all influence the final results.

Where direct measurement of flow peaks is not possible, the use of a stage discharge relationship can be used to estimate the magnitude of peak flows. This usually involves relating spot discharge measurements to river level measurements. This relationship can then be extended to cover peaks not directly measured. This technique is not without uncertainty as it is possible for phase shifts to occur in the stage-discharge relationship in areas where no discharge measurements have been undertaken (Overleir and Reitan, 2009). Furthermore, it is often assumed that stage-discharge relationships are stable through time and this may not be the case where distinct seasonal changes, like vegetation growth, occur in river channels. Parodi and Ferraris (2004) present a method for stage-discharge ratings based on hydraulic modelling. The rationale for this work was the seemingly large difference in discharge estimate from one year to the next given the same stage. The stations used in the study by Parodi and Ferraris were designed primarily for low flows, and it is because of this that their operation at high flows presents problems.

While it is clear that there are problems with both the measurement and estimation of peak flows there is less research on the impact this has on the flood frequency curve. Cong and Xu (1987) suggest that small measurement errors do not adversely impact upon the estimation of the flood frequency curve. This is only valid if the measurement errors are random, as a consistent bias may prove more problematic. The results from their study used Chinese river flow data which required little extrapolation of the stage-discharge relationship and so the study results may not be so applicable to areas where considerable extrapolation is required. Overleir and Reitan (2008) show that the main problem of rating curve imprecision is to inflate the variability in the flood frequency quantile estimates. This suggests that rating curve imprecision can have an effect and that the uncertainty in the flood frequency curve estimates may increase when using uncertain rating curves.

It is difficult to determine the specific quantitative impact of data record quality upon the flood frequency curve. The literature is not conclusive; however, it is clear that using good quality data records will reduce the potential for measurement error or stage-discharge uncertainty to significantly impact upon the flood frequency estimation procedure. Therefore, the selection of good quality data records is of paramount importance.

### *2.3.2 Peak Flow Data Sources*

In the United Kingdom, most river flow records come from the designated responsible gauging authorities. In England and Wales this is the Environment Agency and in Scotland it is the Scottish Environmental Protection Agency. Flow data are archived in several locations, including with the responsible gauging authorities. Several daily time-series are hosted by the National River Flow Archive (NRFA) and are available for download online (Centre for Ecology and Hydrology, 2010). Flood peak data are also available online through the Hi-Flows project (HiFlows, 2010a). This is a joint project between UK gauging authorities to make flood peak information available online, mainly for expert users.

The Hi-flows database provides an open, online data download portal. It is maintained and updated to provide current data for those using the Flood Estimation Handbook methods for flood frequency estimation in the UK; however the format of the data is such that it can be easily used for other applications. The Hiflows project was designed to make more flood data available as well as ensuring that this data had been consistently quality controlled. These controls include a consideration of the gauging station operation, rating curve suitability and trend analysis. This aspect of data control is important as shown by the work of Shuzeng and Yinbo (1987) and Oberleir and Reitan (2008). Each catchment in the HiFlows database has been split into one of three categories giving an indicative suitability of that catchment for use either in pooling, for estimating the QMED or for neither. This is a classification used by the Hi-flows project to identify stations that have large gaps in their record or where their ratings are known to be poor at the upper end of the stage-discharge relationship. This is often due to either few gauging measurements being taken at peak flow periods or the bypassing of the gauging station at high flows. While this classification scheme represents an ‘indicative suitability’ it should be noted that it is still possible for considerable errors to occur in the peak flow records.

The flow data are available as two different series; AMAX and POT. AMAX, or annual maximum are instantaneous peak flows extracted from a continuous flow time series. Only the largest peak in a single year is extracted. Therefore a ten year continuous flow record would give an AMAX record with ten events. In the case of the HiFlows data the AMAX are extracted from a hydrological year which runs from October to September. Peaks Over Threshold (POT) data represent those peaks which exceed a specific threshold of discharge (Shaw et al., 2011, p.256). The threshold can be set according to the number of desired peaks required in the flow series. In the case of the HiFlows POT series, there are on average 5 events per year (HiFlows, 2010a).

Data can be obtained in a format suitable for direct use in the FEH software (i.e. .am,.pt and .cd files) or as POT data in .csv files. The database provides a good, easily accessible dataset which is useful to this research project.

### *2.3.3 Rainfall Record Sources*

There are many organisations within the UK that record rainfall, for a variety of purposes. Water utilities require rainfall data for resource estimation and allocation, the Environment Agency require rainfall data for water resource assessment and flood warning and the Met Office require rainfall data to assess the performance of numerical weather prediction models (among many other reasons).

There is one major source of freely available raw archived rainfall data (for research) within the UK. This is the British Atmospheric Data Centre (BADC) and it hosts gauged rainfall information from utilities, regulators and organisations such as the Met Office, as well as some private records. It has built in facilities for querying and extracting raw time series and the records it holds are considerable.

For the researcher or scientist interested in analyses using country –wide rainfall data, the use of raw BADC data requires careful consideration. If a large number of records are required, the download time and volume can be considerable. After this, a significant amount of data checking and assessment of quality is required. Issues such as the double counting of rain days or mixing hourly and daily data require that the raw data are subject to extensive quality control procedures. Finally, there is the issue of gauge location, and how many independently extracted records can be used consistently for a study. Individual rain gauge measurements are subject to a variety of errors such as outsplash (rain entering the gauge after splashing off adjacent ground), wind induced under-catch and snowmelt estimation problems. For a more detailed discussion on rain gauge measurement problems see Strangeways (2004). These problems tend to be specific to individual gauges. Regarding the impact on this study, it is important to bear these measurement problems in mind, however, they are difficult to consistently account for in a quantitative manner.

The need for consistent rainfall data for large parts of the country for both research and commercial purposes has led to the development of long term time series and gridded rainfall data products. Gridded data for the UK are produced mainly by the Met Office and sold as a commercial product to companies for application in areas such as agriculture, hydrology, ecology and forestry. Gridded datasets are also increasingly used in research for climate model inputs, model validation and trend analysis.

Perry and Hollis (2005) describe the production of a monthly gridded dataset for a range of climatic variables, including precipitation. Their use of techniques such as geographically weighted regression within a GIS allows for the interpolation of climatic variables. For rainfall, there was typically one station for every 7 x 7 km grid cell, however cover was not consistent. Areas such as the Scottish Highlands tend to suffer from sparse coverage of rainfall collection due to the low levels of habitation there, whereas the South of England tends to have better coverage. This station coverage is reflected in the accuracy of the final gridded data product, where areas of low station coverage tend to have higher errors in the gridded data set and vice versa for those areas of high station coverage.

The motivation for the development of long-term time series such as that of Alexander and Jones (2001) has been rooted in the need to put recent climate change into a longer term context. It also allows for trend analysis on a consistent dataset, something which using a series of individual gauges does not easily permit. Alexander and Jones's work considered both spatial and temporal aspects in the data comparison, and they did this by creating time-series for different regions, identified for England and Wales by Wigley et al. (1984) and extended to Scotland by Gregory et al. (1991). Their focus on using the resultant dataset for an analysis of extremes is noteworthy as it provides some basis for the use of derived products as opposed to raw data for this type of work. However, as these time-series represent a region, they may not be suitable for application over a catchment where the rainfall regime may be considerably different.

The Met. Office has produced a 5 km gridded interpolated daily rainfall data set covering the time period 1958-2002 for the UK. This data set is not freely available and is only licensed for use under certain conditions. The method used to construct this data set has not been explicitly published, although Smith (2010) provides some evidence that the method may be similar to that used to produce the monthly data as reported by Perry and Hollis (2005). Smith also undertook investigations into the use of the 5km gridded data and concluded that while concerns may exist over the lack of relevant information on its construction, the 5 km data set provides an accurate representation of extreme rainfall events. In Smiths study, the 5 km resolution was considered sufficiently small so that individual grid cells could be considered as pseudo-stations.

Fowler et al. (2005) use the 5 km gridded dataset in work that assessed regional climate model output for its ability to reproduce extremes. Their assessment used the RMED values calculated from the 5 km grid and suggests that the gridded data may have potential for use in large scale studies of extremes. There is a considerable advantage in having access to such a consistent data set over raw station data as it allows consistent temporal and spatial comparisons to be made. It is for these reasons that this type of gridded dataset is particularly useful to a study such as this.

### *2.3.4 Estimation of Extremes from data: Discretisation Effects*

While the 5 km gridded data set has some considerable advantages to its use, there are also some problems. Daily data record the rainfall ending at 9 am. However, storms rarely fit neatly within a rain day. Where they overlap the measurement boundary it can be difficult to know how to estimate the storm amount given the daily total. With hourly data, it is likely that this problem would be reduced; however, there is generally limited hourly data available. The problem of how to estimate storm rainfall from daily data can be referred to as a data discretisation effect and most research in this area tends to focus on methods for correcting fixed window measurements to reflect the true storm more accurately.

Weiss (1964) presents an analysis of the discretisation problem for the United States. The work presents correction factors in order to correct daily rainfall data to better represent their “true” amount. Weiss found average correction values of around 1.14 and recommended these be incorporated into work considering extreme rainfall events.

In the UK, the discretisation problem is well reviewed by Dwyer and Reed (1995) who report on some work undertaken to estimate correction factors between hourly and daily data. Dwyer and Reed (1995) use six sites (Eskdalemuir, Leeming, Ringway, Brisbane, Melbourne and Sydney) to calculate correction factors for a range of durations and also to produce a generalised model suitable for calculating correction factors of any duration. Their methodology for this first extracts a series of fixed and sliding maxima. Because hourly records at the time were sparse, each hourly record was two years long and then chopped into 21 day periods. For each period, a fixed and sliding maximum was extracted. This approach allowed more storms to be analysed however, it does mean there are fewer extreme events. Once the fixed and sliding maxima are extracted, their means are calculated, the correction factor being the ratio of these means. While in application it is desirable to convert individual maxima, it is tempting to calculate correction factors based on the mean of individual ratios. According to Dwyer and Reed, this is not a satisfactory estimator as it can be biased. To counteract the problem of fewer extreme events, the methodology of Dwyer and Reed gives greater weight to the larger events when calculating the correction factor. There is limited literature on the discretisation problem with regards to daily rainfall and the above studies represent the majority of the published work. While both studies present correction factors, it should also be emphasised that the length of observed record where rainfall was either recorded continuously or in hourly intervals was relatively short (2 years in the case of Dwyer and Reed). Therefore, in a two year period it is likely that there are few extreme rainfall events and so the correction factors need consideration in light of this. However, both Weiss (1964) and Dwyer and Reed (1995) provide some basis for the correction of rainfall storms estimated from daily data.

## 2.4 Hydrological Modelling of Peak Flow

In hydrology the attempt to transform estimates of rainfall to flow is often termed rainfall-runoff modelling. With all the methodologies that fall under the umbrella of this term, rainfall is transformed to a flow value through varying means, and it is these means which make the models unique. Hydrological modelling is a vast area, and it is impossible to review the large amount of literature available. For generic issues surrounding rainfall-runoff modelling the reader is directed towards books such as Beven (2008). For the purposes of this review, study is limited to those models and papers that contribute significantly to the field of peak flow modelling and which have components that are of significant importance to this study.

Before discussing the topic of peak flow modelling in more detail, it is worth providing a definition to avoid confusion. This research project is primarily concerned with flood frequency estimation. However, this section of the literature review focuses on methods suited to generating flow estimates from rainfall. This is required in the case where no observed data is available such as a future scenario or ungauged catchment.

### *2.4.1 Event Based Models*

Flow estimation models dealt with here fall in to one of two categories. The first is event based modelling, popular for peak flow estimation. Given some information on the catchment properties and a rainfall storm, the event based model will estimate the peak flow magnitude and in some cases the hydrograph. This approach has been used for several models, and a modified event based estimation forms one of the main methods of the Flood Estimation Handbook (Kjeldsen, 2007).

One of the oldest examples of an event based model was that of the rational method (ASCE, 1970). It predicts the peak runoff rate as a proportion of the storm rainfall rather than predicting the peak flow magnitude and is represented by Equation 2.1.

$$Q_{\max} = CAi \qquad \textbf{Equation 2.1}$$

Where *C* represents the coefficient of runoff, *A* is the basin area and *i* represents the rainfall intensity. *C* is chosen from a list, where different coefficients represent different land surfaces. While one of the main criticisms of the rational method is that it does not account for pre-storm ground conditions, it is still in use today as a method for runoff calculation on paved surfaces (Shaw et al., 2011, p.464). Despite the criticism, it is clear that simple models such as the rational formula still have a use in practical hydrology.

The unit hydrograph, developed by Sherman (1932) takes an alternative approach, as it predicts peak flow volume based on the rainfall input. It is a flexible model which can predict the flow hydrograph of a storm of any given duration and intensity. Various modifications of this model have occurred since its inception, but the fact that it is still in use today is testament to its applicability. Nash (1960) developed an approach that generalised the unit hydrograph. He split runoff into base flow and partitioned the rainfall by using several rules. However, the model estimate of the flow is highly dependent upon the assumptions made regarding antecedent conditions.

Event based models for peak flow estimation exist in a variety of forms, from the conceptual ideas of the rational method to more physically based models such as LISEM, as described by De Roo et al (1998). What distinguishes event based models from others is that they require initial estimates of their catchment antecedent conditions. Compared to continuous simulation models, event based modelling can be thought of as an alternative way of integrating across time. However, as their name suggests, most event based models tend to operate across a single event. More complex models such as LISEM require parameterisation and take time to set up. This makes them unsuited to the challenge of estimating a catchment flood record, where the model may need to be manually set up for each event and catchment.

While some forms of event based model assume constant catchment conditions, in practice it is now fairly well established that the hydrological response of a wet catchment to rain will be considerably different to that of a dry catchment. With regards to event based modelling, the importance of estimating these antecedent conditions has led to some significant research on the topic (see Berthet et al. 2009; Brocca et al. 2008 and Michele and Salvadori, 2002 for some examples).

### 2.4.2 Antecedent Accounting

One of the most basic ways of estimating a catchment state prior to storm arrival involves the use of antecedent rainfall. Traditionally one of the most common methods is known as the Antecedent Precipitation Index (API), first presented by Kohler and Linsley (1951). This approach weights antecedent rainfall using a decay factor, *k* in order to account for the relative importance of antecedent rainfall. Others have developed the method, such the normalised version presented by Heggen (2001), although the use of soil moisture estimates tends to be more commonplace in the literature in comparison to antecedent precipitation.

In estimating catchment antecedent conditions, no variable prevails more in the literature than soil moisture. Zehe et al. (2005) investigated the role that antecedent soil moisture plays on the resultant flood hydrograph. The results for their region (South-West Germany) suggest that at moderate and dry catchment conditions, the resulting hydrographs for the same given storm could be considerably different. However, with wetter soils, the effect on the hydrograph diminishes, therefore leading the authors to suggest that the processes of preferential and Hortonian overland flow are inherently linked with the catchment antecedent conditions. While this study made use of a relatively complex physically based model, the results suggest that threshold behaviour is an important aspect the catchment antecedent condition. Work by Berthet et al. (2009) looked at the importance of initial conditions for flood forecasting. Here they found that antecedent rainfall based approaches tended to perform poorly compared to continuous simulation methods, though they were comparing predictions based on hydrograph simulation rather than simply the peak flow or return period estimate.

The estimation of spatially coherent soil moisture estimates benefits many activities such as farming, forestry and flood management. In the UK, generalised estimates for a location were provided by the Met Office Rainfall and Evaporation Calculation System (MORECS) for many years. This was a system that provided averaged soil moisture deficit and evaporation data for 40 km grid squares on a weekly and monthly basis (Hough and Jones, 1997). This system was superseded by the amalgamation of the Met Office's Nimrod nowcasting system and its Surface Exchanges Scheme (MOSES). These improved upon MORECS by providing real time estimates of soil moisture by incorporating remotely sensed data, running on a smaller, 5 km grid (Smith et al., 2006). Both MORECS and the new amalgamated method are capable of providing estimates of surface soil moisture suitable for use in hydrological modelling. However, the data are generally expensive to obtain and require that the soil moisture model estimates can be reconciled with the hydrological model structure.

On a smaller scale, several researchers have made attempts at developing models to estimate soil moisture, given access to local climate data. Brocca et al. (2008) present the development of a soil moisture model for use in estimating initial conditions for rainfall-runoff modelling. Their results again highlight the importance of soil moisture in determining the peak discharge, and like Berthet et al. (2009) considered that methods based on antecedent precipitation did not work so well. Pan et al. (2003) present an analytical model for use in estimating soil moisture directly from rainfall data. The method is interesting from its simplified perspective as many soil moisture models incorporate significant numbers of parameters and have considerable data requirements. However, the resulting soil moisture estimates in this study were never meant for anything other than testing against spot field measurements so again it would require some work to reconcile these estimates with a hydrological model structure.

If it seems that a large proportion of the review has been devoted to antecedent conditions estimation then that is because it is perhaps one of the biggest criticisms against the use of event based models. While they have an ability to represent antecedent conditions, often through the use of soil moisture estimation or antecedent precipitation accounting, they are often considered less accurate in this respect than the continuous simulation models (Boughton and Droop, 2003). Therefore, the methods used to estimate the catchment antecedent conditions for this project will require some consideration. This is especially challenging as antecedent estimates will be required without recourse to continuous simulation type methods.

To this end, CS models are now introduced in order to highlight their structure and discuss their advantages and disadvantages. It is worth stressing however, that there is a trade-off between the two approaches, and this is considered later on.

### *2.4.3 Continuous Simulation for flow estimation*

An alternative peak flow modelling approach is that of continuous simulation (CS), where discharge is calculated at every time step of the model run and flow peaks can then be extracted from the discharge time-series. The benefit of continuous simulation is that it continually updates the model state at every time step, thereby allowing for a continual (and generally more accurate) accounting of variables such as soil moisture. There are many continuous simulation models in use today; however the method has yet to find widespread use in a commercial environment. This is perhaps due to the expertise required to parameterise, run and calibrate these types of models. They also require a considerable amount of time to set up and computational demands can be heavy. Furthermore there is limited guidance available to practitioners on the use of continuous simulation models which is probably reflected in the extent of their use in this sector.

Many models exist, and as with event based models it is not possible to review them all. Focusing on the UK, and continuous simulation in particular, one of the most widely used models is that of the Probability Distributed Model, or PDM for short. It is a lumped conceptual rainfall-runoff model which transforms rainfall and potential evapotranspiration data in to runoff (Moore, 2007). As a model, it has been well documented, first developed at the Institute of Hydrology, now CEH. The PDM model is in widespread use today, not only as a method for reproducing historical river flows, but also as a model for flood forecasting and early warning systems (Cole and Moore, 2008). Kay et al. (2006a, 2006b) apply the PDM in the ungauged situation, where parameter values are estimated through the pooling of catchments with similar characteristics (as defined by the FEH PCDs).

While continuous simulation can provide estimates of peak flow magnitude, it also provides a lot of information that may be irrelevant if only flood frequency estimates are required. For example, there is no need to estimate the entire hydrograph, only the peak flow magnitude. One of the assumptions made during the development of the aims and objectives of this thesis is that simplifications can be made to the modelling procedures currently used if only peak flow magnitudes are required. Continuous simulation is reviewed here as it is worthwhile to understand how it works, how well it performs and therefore how alternatives can be developed.

It is worth noting that in a comparison of performance, Loague and Freeze (1985) in comparing regression, event and continuous simulation models, found that there was little justification for using more complex models as they performed no better than the simple methods in a predictive mode. Where simple models are capable of carrying out the task in hand it is likely to be preferable to use them, as the model structure and assumptions are clearer. However, there will always be occasions where continuous simulation models are required, particularly where information on more than one event or variable is required.

In the case of flood frequency estimation, the use of models for peak flow estimation tends to occur where there is no observational record available. This may be in the ungauged catchment, where estimates of current flood frequency are required, or it may be for a gauged catchment where estimates of future flood frequency are required. Developing on the work that has been reported on here, the next section of the review considers how a flood frequency estimate can be developed, with a consideration of different approaches.

## 2.5 Approaches to Flood Frequency Estimation

In general, event based models are well suited to the estimation of peak flows in situations where there is little observed data. However, given the existence of a good observed flow record, statistical analysis can be undertaken for flood frequency assessment. This is the general recommended approach of the FEH (Robson and Reed, 1999). Evidently there are no future measured flood flows, and so recourse must be made to some kind of modelling if future considerations are part of the analysis.

While flood risk is a coupled problem between society and nature, most analyses tend to focus on statistical and modelling approaches to solving the problem. It could be argued that reducing flood frequency assessment to a purely statistical problem neglects the physical processes that govern flood generation. On the other hand, Reed (2002) recognises that a statistical approach makes good use of the most relevant observed data.

In some respects, these arguments generate from single site flood studies, where the analyst aims to gather as much information on the problem as he or she can. In a study taking a much broader view of the flood frequency problem, recourse to detailed information on catchment flood generation is difficult, as it is hard to develop a framework where such information can be consistently useful. This is why the review focuses almost exclusively on the mathematical and modelling methods, rather than process based studies of flood generation.

### *2.5.1 Historical Development of Flood Estimation Methodologies in the UK*

Within the United Kingdom, methodologies for flood frequency estimation have seen continual development since the 1960s. The earliest work was motivated by dam safety considerations, and the Institute of Civil Engineers published an interim report defining the first flood envelope curves for the UK in 1933 (ICE, 1933) It was twenty seven years later that this work was updated by Allard et al. (1960). In 1967, the Institute of Civil Engineers published a report recommending a detailed investigation of floods should be undertaken and that all aspects of flood hydrology in all regions should be examined. The resulting work was known as the Flood Studies Report (FSR) (Institute of Hydrology, 1975). It provided users with the ability to produce either a flow hydrograph or calculate an instantaneous peak flow value. The recommended method was dependent upon the user's requirements and the availability of observed data. The FSR includes regression equations to estimate statistics such as the mean annual flood from catchment characteristics. This was one of the first methodologies that allowed a design flood to be estimated from rainfall. In this respect the FSR can be seen as the fore-runner to the ReFH method currently in use today. The rainfall-runoff method of the FSR was in large part the same method used later in the publication of the Flood Estimation Handbook (FEH) (Reed, 1999). The FSR provided the first consistent set of guidelines for practitioners in the flood risk management field. By the early 1990s it was realised that not only was there a relatively large amount of observed data available that was not used in the FSR, but also that the large number of updates to the original method meant it had lost some of its clarity to practitioners. As a result, the Institute of Hydrology (IH) along with partners commissioned a research project to develop new guidelines and software for use by those involved in flood estimation.

The result of this project was a publication and associated software known as the Flood Estimation Handbook (FEH). The FEH incorporated a rainfall-runoff method, largely based on the FSR and a statistical method. In 2007 the FEH rainfall runoff method was revised to produce the Revitalised Flood Hydrograph (Kjeldsen, 2007). The two methodologies of the FEH tend to still be the main methods for flood frequency investigations in the United Kingdom.

However, at the time of writing there is limited potential for using these methods to look at how future fluvial flood frequency may change. Design estimates from both the statistical and design event methods can be altered using the DEFRA (2006) indicative sensitivities, but this is a reasonably crude approach which does not account for differences between individual catchments. A smaller number of applications have seen the use of continuous simulation methodologies, although these tend to be more for research purposes as opposed to scheme design.

### *2.5.2 Event Based Methodologies for Flood Frequency Estimation*

What distinguishes an event based model used for flood frequency estimation compared to a generic hydrological model is that the model used for flood frequency estimation is used to estimate an event of a particular rarity. In this form, the event in question is often known as a design event. In essence this requires a link between a rainfall event of specific magnitude and rarity (the design rainfall) and the flow that the user wishes to estimate.

As previously introduced, the standard model for use in design event flood frequency estimation within England and Wales is that of the ReFH model (Kjeldsen, 2007). At the time of writing the ReFH approach has not been validated for Scotland. The ReFH addresses some of the criticisms levelled at the original rainfall-runoff method after the publication of the FEH. The model uses a design storm estimated by the FEH Depth-Duration-Frequency (DDF) rainfall model. This is a fitted model which provides return period estimates of rainfall for any given duration for a specific location within the UK. The ReFH model itself has accounting for antecedent conditions, a losses and baseflow model as well as a more flexible unit hydrograph shape compared to its FEH predecessor. Other improvements include updates to the regression equations used to estimate some of the variables such as the time to peak parameter (Tp) and the median annual maximum flood equations (QMED). The ReFH was published as a separate report along with a software update (Kjeldsen, 2007).

The design event method can be consistently applied at any given location, its advantage is that it can be parameterised and transferred to work in ungauged catchments. The method has been developed for the design event; hence it generally only estimates one event at a time. The ReFH method is known to perform poorly on permeable catchments and in this situation the general recommendation is to use the statistical method of the FEH (Kjeldsen, 2007). It is perhaps representative of event based models in general that this is the case, as they tend to be reliant on rainfall as the predictor of the flood peak, modified by antecedent conditions.

However, despite the potential pitfalls of event based modelling, several aspects of the method have an attractiveness about them which may be helpful to this study. Specifically the handling of antecedent conditions and storm estimation are issues which are important to this research project. However, the approach taken by the ReFH to estimating pre-storm catchment conditions is still reasonably complex and may not be suitable for consistent application over a large number of events.

### 2.5.3 Statistical Methods for Flood Frequency Estimation

As previously mentioned, the use of observed flow data is preferable to that which is modelled. Observed flow data contain a wealth of information on frequency, and using supporting methodologies can be successfully extended to develop flood frequency estimates for engineering design. Little effort has been devoted to developing the kind of links possible between the rainfall and flood frequency curves as proposed by this research. One project that has examined these relationships is that of the GRADEX method. The method allows for the extrapolation of the flood frequency curve using the rainfall frequency curve (Beran, 1981). It therefore makes the assumption that at high return periods, rainfall is the dominating flood generating factor, with other influences much less important. It has seen some severe criticism from UK practitioners (e.g. Reed, 1994) from the choice of the distribution for rainfall modelling to the absence of regionalization. It is clear that extending the flood frequency curve is not a trivial issue.

The Flood Estimation Handbook (Volume 3) contains a considerable amount of information on statistical procedures for flood frequency estimation. Where observational data are present at a site of interest, these can be fitted to an extreme value distribution and flood frequency estimates produced. This is known as a single site estimate. This tends to not be recommended for many practical situations as the resultant return period estimates for rare events (i.e. T=100) are not particularly robust.

Because of the short length of many flow records, the FEH recommends pooling as the main method for estimating a flood frequency curve from observed data. This is where data from hydrologically similar catchments are pooled to create a longer time series on which to base the flood frequency curve. This approach is generally thought of as being more robust than simply using the data from the site of interest. Generally a pooled record length of five times the return period being estimated is suggested. For example, the ten year return period flow would require a record length of around fifty years for its accurate estimation. Once the flow record has been collated, the data is standardised by one of several methods. This standardised data is then fitted to an extreme value model, which is then used to estimate the design flood at a specified return period. Typical models include the Generalised Extreme Value (GEV) model, General Logistic (GL) model and Gumbel model which are suggested for use with annual maximum data and the Generalised Pareto (GPD) model, recommended for working with POT data.

Further extending the pooling method, several researchers have investigated the use of seasonality as a measure for pooling. Ouarda et al (2006) compare several seasonality indices and recommend calculating seasonality measures on POT data. Generally the use of seasonality improves the results of pooling compared to the use of traditional catchment descriptors. Cunderlik and Burn (2002) report on the use of rainfall seasonality to pool similar catchments. Here, the use of directional statistics was employed to describe the rainfall seasonality. This approach has the advantage that it can be applied to catchments which have rainfall, but no flow record. Where catchments have a fairly close linkage between the rainfall and flow regime, this approach is considered to be at least as good as that of the FEH pooling method. Archer (1981) makes the case not just for the use of seasonality measures, but for a seasonal assessment of flooding. This suggestion has never been fully implemented in products such as the FEH, but it has its uses by giving more detailed information on risk at certain times of the year. This may be important to farmers as well for construction projects working in or near rivers at risk of flood.

When working with the statistical method, it is difficult to assess the impact of potential future change on the flood frequency curve. Because the method uses observed data, it is not clear how to perturb these data to represent a future time series. It is also unclear, if catchments undergo significant change in the future, how a pooling method might work. The Flood Estimation Handbook, at the time of publication, looked at the problem of non-stationarity from a climate change perspective (Robson and Reed, 1999). The conclusions reached from this work suggested that climate change was not an important issue and that causes of non-stationarity in the observed flow record were dominated by short record lengths and changes to gauging structures (Robson and Reed, 1999). It is because of these difficulties in determining the precise causes of change to flood frequency curves that the research community have moved towards alternative methods for future flood frequency estimation.

### *2.5.4 Recent Developments*

Currently, the Flood Estimation Handbook represents the standard methodology used by practitioners in UK flood estimation. However, there are several limitations to the methods outlined, and as a result, the use of continuous simulation is being promoted, although to date it tends to be used mainly for research purposes.

With regards to flood frequency estimation, the continuous simulation approach is relatively simple. Assuming a model has been set up and run, the output in the form of a discharge time-series will be available. From this, the flow peaks can be extracted (in either AMAX or POT form) and treated statistically as per the statistical method previously described. However, one of the potential advantages over the statistical method as detailed by the FEH is that in the CS case, the number of flood peaks can be considerably increased by using a long discharge time series. These are usually generated by the use of a synthetic rainfall model, parameterised on observed data. This approach is only valid where the long rainfall time series can adequately capture the extremes found in the catchment of interest.

In terms of flood frequency estimation, continuous simulation has the potential advantage of giving an insight into how all the variables affecting the flood regime may change. Therefore the researcher gains an understanding, not just of potential future changes in magnitude but also depending upon the model, the processes driving these changes. The disadvantages of CS approaches usually centre on the computational time required to carry out a simulation as well as associated problems of model parameterisation, both for current and future climates. There is also the question of how the methodology can be adapted in order to be consistent across the UK. This problem is the result of the parameterisation required to get the models to produce outputs of a satisfactory quality.

The use of continuous simulation for river flood frequency estimation has been demonstrated for the United Kingdom (Calver et al., 2005). This work was carried out to develop a national method for river flood frequency estimation based on using continuous simulation rainfall-runoff models. Their work makes several recommendations; however, at the time of writing there is not currently a single standard modelling strategy (such as the FEH) for practitioners. A large amount of preparatory work is required in gathering meteorological input data, estimating parameter values and calibrating the model. It is perhaps a further reason that continuous simulation has yet to see significant uptake amongst the practitioners of flood frequency estimation.

In the UK, the Centre for Ecology and Hydrology (CEH) has been central to the development of a consistent CS methodology (see Bell et al., 2007a, 2007b). Two methods have been developed, both of which allow consistent application over UK catchments. The first approach uses a model known as the Probability Distributed Model (PDM) which is run for individual catchments. Parameterisation is by reference to the catchment properties, with regression analysis linking the two.

The second approach uses a spatially generalised runoff and routing model at a 1 km resolution across the UK. Current work suggests that it is found that groundwater based catchments are particularly hard to represent using this approach as the models main control is relief or topography (Bell et al., 2007a). Regional Climate Model inputs on a 25km grid cell size were used as the inputs for both the control and future scenarios. This approach is known as grid-to-grid (G2G) as the model takes gridded meteorological data as the input for the gridded hydrological model.

Continuous simulation is the main focus of the FRACAS project to estimate future flood risk. DEFRA and the Environment Agency (EA) published a technical report (Calver et al., 2005) looking at a national river catchment flood frequency method using continuous simulation. The essence of the approach behind this report is to calibrate a catchment rainfall-runoff model for a representative group of sites with river flow and rainfall time series data. The ability to use continuous simulation in an ungauged catchment is important, but is evidently complicated by the lack of calibration flow data. To parameterise rainfall-runoff models, catchment properties must be linked to model parameters. The continuous simulation approach requires good quality, high resolution data to run. The time step at which continuous simulation models are run is also an important consideration. Using daily data on small catchments has problems as these catchments may have too fast a response time to be represented by a model which runs on daily data. The time step at which a model is run is likely to be decided by a combination of the available input data time step, the size of the catchment under investigation and the available computational time.

### *2.5.5 Comparing Approaches*

Calver et al. (2009) undertook research to investigate different approaches to river flood frequency investigation for the current time period. FEH methods (both event modelling and statistical) and continuous simulation were implemented over a subset of around 100 catchments. The results reinforced the FEH preference for using the statistical method wherever possible. Continuous simulation was considered to show good potential for representing flow peaks. The event based method showed considerable error and this reflects its generalised methodology. The use of design rainfall information, as well as design discharge is thought to contribute significantly to the errors shown by this technique. In a more qualitative review, Boughton and Droop (2003) assess several continuous simulation models and provide a qualitative comparison between them and design event models. Their conclusions highlight the inadequacies of event based models such as the subjective nature of streamflow partitioning as well as the need to select a design rainfall storm structure. However, the relative complexity of continuous simulation models is also noted. Boughton and Droop's review only really considers the application of models to single catchments and it may be likely that simple models can work just as well as more complex models when consistently applied over multiple catchments. While much is made of the potential benefits of the CS approach, there is little quantitative evidence to justify the additional complexity of CS models.

## 2.6 The effect of Climatic Change on Future Flood Frequency

### *2.6.1 Studies on the Changing Climate*

The case for a changing climate has been made by several authors. Palmer and Raisanen (2002) state that increasing atmospheric carbon dioxide concentrations will almost certainly lead to changes in the global mean climate. What is less well understood is how future extremes may be affected, especially at a local scale. It is evident, that changes in extreme rainfall have the potential to severely impact many aspects of society such as flood risk management, agriculture and water resources. One of the most authoritative reviews on climate change is that of the Intergovernmental Panel on Climate Change (IPCC) who have published a synthesis report of many GCM and RCM studies (Christensen et al., 2007) as well as impact assessments. While this provides a considerable amount of background material on the subject, several selected references on the UK are presented in order to highlight specific issues.

Fowler et al. (2005) provide an assessment of the HadRM3H regional climate model (RCM) and consider its future projections of extreme rainfall. Their conclusions suggest that HadRM3H shows some skill in reproducing rainfall extremes up to the 50 year return period across the UK. In terms of future changes, there was a mixed pattern across the UK. In Scotland and parts of England, there are projected increases in the magnitude of long duration rainfall events. However, the absolute figures in this paper must be treated with caution, as this study considered only one model (HadRM3H) and one emissions scenario. If decision relevant information is required, there needs to be a much wider appreciation of the uncertainty in model formulation, natural variability and emissions scenario. Fowler et al. (2005) use the HadRM3H model for two purposes. The first is to assess the performance of RCM data in simulating current rainfall extremes; the second purpose is to assess any potential future changes to extremes using future generated time-series. The methodology took a two track approach, using both individual grid box analysis and the regional frequency analysis methodology as implemented by Hosking and Wallis (1997). Using this RCM the authors concluded that the model gave a reasonable interpretation of rainfall extremes up to the 50 year return period, though there was a tendency for overestimation in high elevation western areas. In eastern areas there was an underestimation leading the authors to suggest that the east-west rainfall gradient was perhaps exaggerated. Overall, the RCM data was considered to have some skill in predicting how rainfall extremes may change. This assessment was followed up by the use of future scenarios as described by the RCMs. The results are described in detail by Ekstrom et al. (2005) and describe the changes to different durations and return periods of events.

Deque et al. (2007) report on work that considered the problem of uncertainties in model projections. By using a combination of RCMs, GCMs and emissions scenarios they considered the most important driving forces in determining the uncertainty. Overall, it was considered that the choice of GCM introduced the largest source of uncertainty. In summer, the choice of RCM was significant, reflecting the fact that some RCMs currently show a poor ability to represent summer rainfall.

Climate projections are continually being updated as climate models change and process understanding and resolution increases. Major effort has recently focused on using climate model outputs for hydrological modelling. In particular this involves developing scenarios suitable for use with hydrological models. The use of these outputs for assessing changes to hydrological extremes is still early work, as scenario representation of extremes is limited to some extent. The next section of the review considers climate impact assessment studies that have been carried out to consider the effect on flooding.

### *2.6.1 Climate Impact Assessment*

There are some important links between climate change and hydrological change. Understanding the uncertainties and complexities of future climate projections are important if an assessment is to be made as to the overall robustness of any method claiming to assess changes to future flood frequency. For example, in certain geographical locations the annual average rainfall may not change significantly, but this may hide important seasonal changes in rainfall that has the potential to affect flood risk. Within this ever changing landscape of climate information, practitioners of climate impact assessment studies must make some important decisions about how to use climate projections and what their limitations are. Raff et al. (2009) introduce a method for the assessment of the impacts of climate change on flood frequency in the Western United States. Their study is insightful, as it provides an assessment of some of the problems facing the practitioner. For example, the issue of downscaling GCM outputs for use at a temporal and spatial resolution that is appropriate to those modelling peak or flood flows. Raff et al. also consider the problem of stationarity and the issue of using the return period as an assessment of flood frequency. In the case of the 100 year return period flood, how appropriate, or possible, is it to calculate this value for future time periods when our knowledge of how fast the climate will change is uncertain? Some have attempted to solve this by comparing a specific current time period peak flow with the same flow in the future and estimating return periods for both.

### *2.6.2 Overview of Methods and Previous Studies*

Methods for assessing how future flood frequency may change broadly fall into two categories. The first uses the analysis of trends in observed historic data; the second approach uses synthetic climate data coupled to a hydrological model to simulate a future river discharge scenario.

Hannaford and Marsh (2008) used a group of near pristine catchments with good flow records in order to examine the trends in peak flows. Their results were mixed, with little compelling evidence for any strong long term trends. They concluded that care was required in flood peak trend analysis, particularly with regard to the start of the flow records. The group of catchments considered in Hannaford and Marsh's study had station start dates during the late 1950s and early 1960s. This was considered by the authors to be a relatively quiet hydrological period. Since then, while there has been a slight increasing trend in flood 'richness', the authors are cautious about attributing this to climate change as there is some correlation with a strengthening North Atlantic Oscillation. This work helps to put the impact of climate change into perspective, as the issue of natural variability both in hydrology and climatology is an important factor in future flood frequency assessment. Similar results were reported by Robson (2002) and Robson et al. (1998).

Given that there is little trend seen in UK flood data, it is clear that there is little room for extrapolation to the future using this method. It is also questionable whether trend analysis can be extended for predictive purposes, as future changes may be non-linear. An alternative approach is to use a continuous simulation model in conjunction with current and future generated climate scenarios. The broad methodology used by most researchers is as follows. A hydrological model is set up for a catchment in question, calibrated and validated against observed data. Once this has occurred, one or more scenarios of the future are generated and the hydrological model is then re-run. The resultant output discharge time series can then be analysed for changes compared to the baseline. One of the advantages of continuous simulation results are that the resultant discharge time series can be analysed for a range of changes in duration and frequency, rather than simply considering the daily maximum flow.

Boorman and Sefton (1997) consider the use of two separate rainfall-runoff models to assess the impacts of future climate change on river flows. This work provides a good background to the generic methodology of rainfall runoff modelling for flood frequency estimation, particularly with regards to recognising the uncertainty in the modelling process. The uncertainty analysis work of this project used climate sensitivity tests as well as two different climate scenarios in order to look at how the conceptual models responded. It was found that one of the models gave results that were not appropriate for this application. As with the results of other studies, it was found that the two climate scenarios gave contrasting results with regards to future flow regimes.

Cameron et al. (1999) report on the use of TOPMODEL applied to the Wye catchment in mid-Wales. This work assessed the usefulness of continuous simulation as a method for reproducing the flood frequency curve. Using an observed 21 year rainfall record the hydrological model was calibrated with a parameter set. The flood frequency curve was then created by using a 1000 year synthetic rainfall record. This work showed the potential of continuous simulation as the authors concluded that the method was suitable for developing flood frequency estimates. However, further model improvements were considered necessary as the results indicated that flood peak rank and timings were not predicted fully. In a development of this work, Cameron (2000) used the same methodology to investigate how climate change may affect flood frequency on the Wye. The UKCIP98 simulations were used for this. These were generated from the HADCM2 GCM simulations. While there was a subtle shift in the risk of a particular flood peak occurring within a distribution, there was little change in the modelled uncertainty bounds. The authors concluded that being able to explicitly account for uncertainty in the hydrological modelling was important, as any climate change signal could be subtle and may be lost in model noise. As the development of climate scenarios continued, so too did the potential for their incorporation in hydrological modelling studies. Reynard et al. (2001) investigated climate change impacts on the Thames and Severn catchments. For the 2050s climate scenarios resulted in increases in frequency and magnitude of flooding events. The results were considered to be dependent upon the way the GCM rainfall outputs were applied to the hydrological model. As the GCMs operate on a coarse spatial resolution there was a need for them to be downscaled. While daily rainfall data were available, they were not considered to be reliable at that time; there was more confidence in the monthly aggregated totals. This study concluded that further work was needed to assess possible seasonal changes to climate as well as interactions with land use.

Pilling and Jones (2002) present an alternative to that of Cameron et al. (2000) in investigating the impact of future climate change on the Wye. This study made use of statistical relationships between atmospheric circulation variables such as vorticity and catchment daily precipitation and potential evapotranspiration. This work suggests an increased seasonality to the future flows, with drier summers. There is also evidence to suggest that peak flow events may increase in frequency. Cameron (2006) investigated the use of the UKCIP02 scenarios on a single catchment, the River Lossie in North-East Scotland. With these updated scenarios there was the choice of emissions scenario, and the modelling results suggested that there were no consistent changes in magnitude or direction in the flood frequency curves produced. Changes tended to be specific to the scenario chosen. Therefore using a single scenario is particularly limiting from a decision making point of view. Looking at a range of scenarios, especially given an uncertain future, is a key component of any climate change impact study.

The question of how to use climate model outputs for hydrological modelling is a growing research area. Kay et al. (2006a) report on the assessment of RCM data for use in flood frequency estimation. Their use of a spatially generalised hydrological model with few parameters means that some site specific performance is sacrificed. The goal of this project was to allow flood frequency assessments on ungauged catchments, so the modelling methodology must reflect this. The study took the approach of using RCM derived rainfall for both the current and future time periods. The RCM data was used for the current time-step in order to allow for an assessment of its suitability in flood frequency estimation. This work proved the potential of RCM data for hydrological modelling, though it was noted that there was a tendency for underestimation of hydrological extremes. As further development of RCM's continues with improvements in physical process understanding and a reduction in the spatial resolution it is likely that RCM data will become more appealing for use in flood frequency estimation. Kay et al. (2006b) report on a further development of this method where future RCM runs are used. In some cases, changes are significant, however, as with many other studies the authors recommend caution in interpreting the results, as they are based on only a single RCM experiment.

One relatively recent UK development for future flood frequency estimation has been the use of grid based data products and models. This setup has been described previously in Section 2.4.4 concerned with continuous simulation modelling. Bell et al. (2007b) report on the use of two sets of RCM derived precipitation for the period 2070 to 2100. Their results illustrate the problem of dependence upon only one or two future time series. The authors report that one extreme rainfall event has the ability to significantly affect the upper tail of the flood frequency curve, and that care is required in comparing baseline and future flood frequency curves when using only one or two future scenarios. It is also clear that there is less confidence in changes to events of higher return periods, despite the fact that it is these events which are of most interest to scientists, engineers and policy makers. There is an inherent link between the meteorological input data and the resultant flood frequency curve. If (for whatever reason) it is not possible to simulate a long-term rainfall time series, then the resultant flood frequency curve is likely to be limited in its application.

## 2.7 Conclusions

There is a clear need for fluvial flood frequency estimation for activities such as flood defence engineering, flood mapping and other risk analyses. For the most part these requirements come from legislative and statutory instruments, themselves driven by the extensive damage caused by flooding within the UK.

In comparison to many parts of the world, the UK is blessed with a relatively rich spatial and temporal coverage of data. These data sets have been reviewed with the HiFlows database and the Met. Office's 5km gridded datasets having been identified as suitable for future investigation. The impact of peak flow records on the flood frequency estimation process has been highlighted as an important aspect with a strong emphasis on the need for good quality flow records.

Methods for flood peak estimation and flood frequency estimation have also been reviewed, with an emphasis on identifying aspects which will be important to this research project. The estimation of antecedent conditions is one such area where there is a diverse range of possible approaches. Understanding the limits of current methodologies allows for an assessment of where improvements might be made over current methods.

Finally, the need for design flood estimates spans a time period where the evolution of the climate is uncertain. To this end, a consideration of possible future climatic changes, along with methods and studies for fluvial flood frequency impact assessment has been undertaken. The need for a reliable, simple method for estimating flood frequency curves has been highlighted, as many studies either focus on a single catchment or use complex hydrological models when looking at future change.

# Chapter 3: Data Assessment for Flood Frequency Curve Estimation

## 3.1 Introduction

Developing a link between rainfall and flood frequency requires good data records. This study makes use of a considerable amount of data, as it is UK wide in scope. Chapter 2 provides some understanding of how the key datasets were collected and processed. However, further work is required to characterise the datasets available for use by assessing where they may hold errors, what they can potentially be used for as well as the limitations of their use. The key question answered by this work is whether the chosen datasets are reliable enough to help meet the objectives laid out in Chapter 1.

## 3.2 Statistical Flood Frequency Estimation Methodology

The quality of observed data is an important aspect of flood frequency assessment, as this data can often be used for the estimation of return period flows far in excess of anything in the observed record. It is therefore appropriate to introduce some concepts surrounding flood frequency estimation, which makes use of observed data as the methods and terminology will be continually referred to throughout the thesis. A statistical methodology for carrying our flood frequency estimation is outlined here. The methodology described focuses on the use of AMAX flow series, although the process for estimating a flood frequency curve from POT data is similar.

### *3.2.1 General Overview*

The general purpose of flood frequency estimation is to assess the frequency with which discharges of a specific magnitude are exceeded. This exceedance is often known as the annual exceedance probability, or AEP. The return period is also used to describe flood magnitude-rarity relationships and can be related to the AEP as:

$$AEP = \frac{1}{T} \qquad \textbf{Equation 3.1}$$

Where *AEP* is the Annual Exceedance Probability and *T* is the return period (also known as the average recurrence interval). The cumulative probability *F* (or non-exceedance probability) can be related to both the *AEP* and *T* as:

$$F = 1 - AEP$$ **Equation 3.2**

and

$$F = \frac{T-1}{T}$$ **Equation 3.3**

It is important to note that the return period is an average recurrence interval. Therefore, it is possible for the 50 year event to be exceeded within a ten year time period, although the probability of such occurrence is small. While it is easy to convert between terms, to avoid confusion the return period is used throughout the rest of this thesis, both within the text and on plots.

The general procedure for annual maximum flood frequency estimation takes a set of *n* annual maximum discharges and then fits a statistical model to these to allow for consistent estimation of return period magnitudes. The statistical distribution usually takes the form of one of a number of extreme value distributions, depending upon the application in question.

One common tool used within flood frequency assessment is the flood frequency curve which can be plotted graphically. Figure 3.1 gives an example of this. The plots shows an annual maximum flood frequency curve for the Clyde, located in south-west Scotland. The annual maximum series has been fitted to a Gumbel distribution. The plot shows a reduced variate x-axis, allowing the empirical data to be plotted as well as the curve. The y-axis shows the estimated flow magnitude.

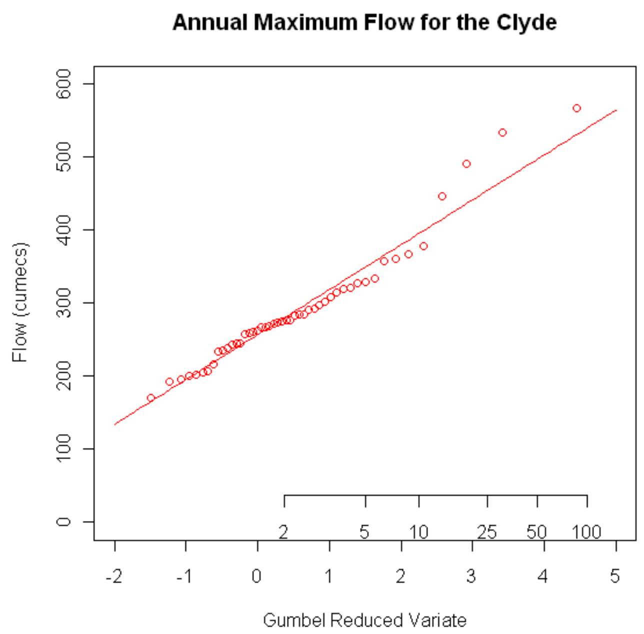



***Figure 3.1*** *Example of a catchment flood frequency plot. The catchment is the Clyde and is located in south west Scotland.*

### *3.2.2 Distributions and Distribution Fitting for Flood Frequency Estimation*

Given a set of *n* annual maximum discharges for a catchment, a flood frequency assessment is typically undertaken by fitting these *n* discharges to a distribution suitable for estimating a desired return period flow magnitude, *T*. There is no single distribution that is consistently recommended in the literature. The Flood Estimation Handbook recommends the use of two or three parameter distributions, but does not specifically state a single distribution that should be used. It recommends the use of the Generalised Logistic (GL) distribution for annual maximum flow data, but also suggests the use of the GEV and Gumbel (amongst others). The Gumbel distribution (also known as EV1) is a special 2 parameter case of the GEV where the shape parameter is fixed at 1. The GEV is a 3 parameter distribution (also known as EV3) that has some theoretical justification for use in flood frequency estimation, but is also commonly used (and recommended for use) in rainfall frequency analysis. Shaw et al. (2011) state that as the annual maximum flood series sample size increases, it should approach the form of the GEV.

In practice the distribution used for a single flood study is usually determined through an assessment of how well different distributions fit the empirical data. This assessment can be made in many ways, through observation of the graphical fit through to tests such as the Kolmogorov-Smirnov test (Cunnane, 1985).

Given the number of catchments this research deals with, it was not felt practical to select individual distributions for each catchment. Early work used the three parameter GEV distribution. While this is not always the first choice for annual maximum flood data, the reason for choosing it was that it was felt it would simplify the overall modelling approach if annual maximum rainfall and annual maximum floods could be modelled using the same distribution. While this gave reasonable results, there was concern over the values taken by the shape parameter for some catchments when estimating the flood frequency curve, resulting in some flood frequency plots that appeared to have visually poor graphical fits to the observed data.

Therefore, the approach taken by this work is to use the simplest distribution possible without heavily penalising the resulting flood frequency estimates. To this end, the two parameter Gumbel distribution has been adopted. A description of the Gumbel distribution now follows, with details being taken from Hosking (1990).

The Gumbel distribution can be identified as:

$$F(X) = \xi - \alpha \, log(-log F) \qquad \textbf{Equation 3.4}$$

(Hosking, 1990)

The Gumbel distribution has two parameters, ξ is the location and α is the scale. In the case of a finite sample, such as an annual maximum flood series, these parameters can only be estimated from the moments of the sample data. In this work parameter estimation is carried out using an l-moment routine (Hosking and Wallis, 1997). *F(X)* is the probability of an annual maximum *(Q) <X.*

The GEV (EV3) can be identified as:

$$F(X) = \xi + \alpha \frac{\{1-(-logF)^k\}}{k}$$ **Equation 3.5**

(Hosking, 1990)

where $\xi$ is the location, α is the scale and *k* is the shape (Hosking, 1990). Again, these parameters can be estimated from the sample data using the method of l-moments.

L-moment estimation is now a popular choice in hydrology (Robson and Reed, 1999). As a method, it is considered to have lower statistical errors than other methods, has more robust parameter estimates when outliers are present in the data and is generally better for use with short records.

L-moments are useful measures for summarising distributions or samples as well as estimating parameters from samples. Comparison with distribution parameters can be made. $\lambda_1$ (first moment) can be regarded as a measure of location, $\lambda_2$ as a measure of scale, $\tau_3$ as a measure of skewness and $\tau_4$ as a measure of kurtosis. $\tau_3$ and $\tau_4$ are analogues of $\lambda_3$ and $\lambda_4$ (Hosking, 1990).

For this research, the l-moments were calculated using the R software "lmom", an R routine adapted from the original FORTRAN version of Hosking and Wallis's code (Hosking and Wallis, 1997). This routine also allows for parameter estimation for a selection of distributions.

As well as showing the Gumbel flood frequency curve, Figure 3.1 also shows the empirical data. In order to be shown on the flood frequency plot, these observed AMAX data must be transformed. There are several methods for estimating plotting positions of empirical data, this study makes use of the Gringorten method, recommended by Shaw et al. (2011). The Gringorten formula is defined as:

$$P(X) = \frac{r-0.44}{N+0.12}$$ **Equation 3.6**

(Shaw et al., 2011, pp.261)

Where *r* is the rank of *X* and *N* is the number of data values.

### *3.2.3 Growth Factors and the Flood Growth Curve*

In certain circumstances it may be desirable to compare catchment flood frequency curves. This is possible by comparing catchment growth curves. Growth curves are produced by normalising the annual maximum flood record by an index flood or growth factor. The work presented in this thesis follows the convention of the Flood Estimation Handbook and uses the median annual maximum flood (QMED) as the growth factor. By normalising with QMED, the annual maximum growth curve will always have a growth factor of 1 for the two year return period flood. Figure 3.2 shows the flood growth curve for the Clyde, this can be compared with the annual maximum flood frequency curve in Figure 3.1.

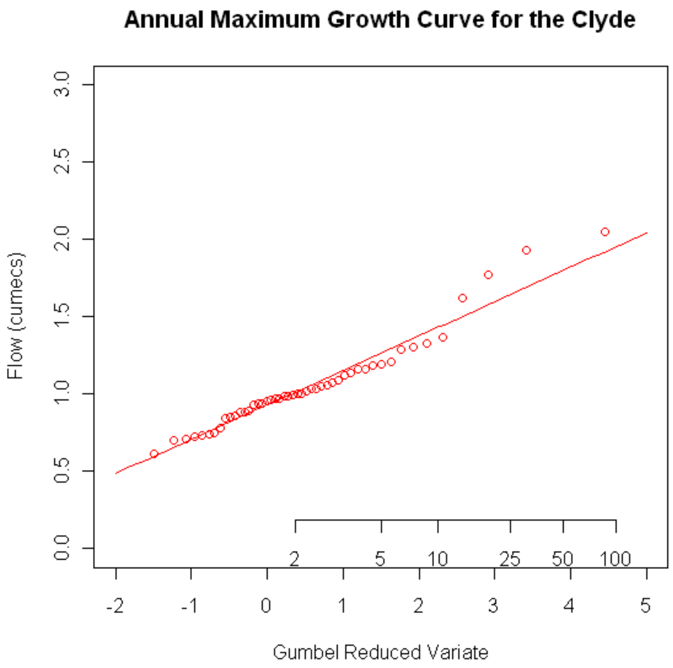



***Figure 3.2*** *The annual maximum growth curve for the Clyde*

For analysing rainfall, the approach is the same, with the growth factor referring to the median annual maximum rainfall event (RMED). The RMED value can be calculated for a range of durations such as 1 hour, 1 day, 5 day and it will depend upon the rainfall analysis as to which is appropriate.

### 3.2.4 Peaks Over Threshold Flood Frequency Estimation

While this thesis makes used of both POT and AMAX data sets, the flood frequency work deals almost exclusively with AMAX data. The Peaks Over Threshold series makes use of more of the available data, but as the number of peaks increases there is more chance that consecutive peaks may be related. This may affect the assumption of statistical independence of peaks which is necessary for a formal frequency assessment (Shaw et al. 2011). Peaks Over Threshold flood frequency estimation can be undertaken in a similar manner to that of the AMAX, with a few alterations. The recommended distribution for use with POT data is the Generalised Pareto (GPO) (Robson and Reed, 1999). No further information on POT frequency analysis is included as it is not carried out however, Robson and Reed (1999) contains extensive information on the use of POT series for UK flood frequency estimation.

## 3.3 Flow Data Assessment

### 3.3.1 Assessing the Spatial and Temporal Coverage of the Peak Flow Data

Peak flow estimation is rarely straightforward. Herschy (2002) estimates errors in discharge measurements of around 10-15 %. A key component of this error is likely to be attributable to the uncertainty in the stage-discharge relationship when extrapolated to high flows. Nevertheless, this does not mean that all high flows are erroneous. Estimated peak flows are still valuable in trying to understand how a river behaves. Realistically assessing gauging station operation and rating curves is impractical for a station set of 500+ catchments and therefore any potential error should be borne in mind for future work. However, it is possible to assess data record consistency as well as the spatial and temporal coverage of the data.

Early work assessing flow record quality concentrated on developing a set of catchments suitable for future modelling work. In order to deal with a reasonable number of catchments with records of good quality it was decided to initially concentrate on those catchments considered “suitable for pooling”. This did not preclude using catchments with different quality ratings; however, it provided a basis for starting the analysis undertaken throughout the rest of this chapter. Using these stations gave an initial subset of just over 500 catchments (for the spatial distribution see Figure 3.3). This subset was considered suitably spread to capture a variety of hydrological regimes, containing both surface and groundwater dominated catchments. Summary maps of catchment properties can be found in Appendix A.1.

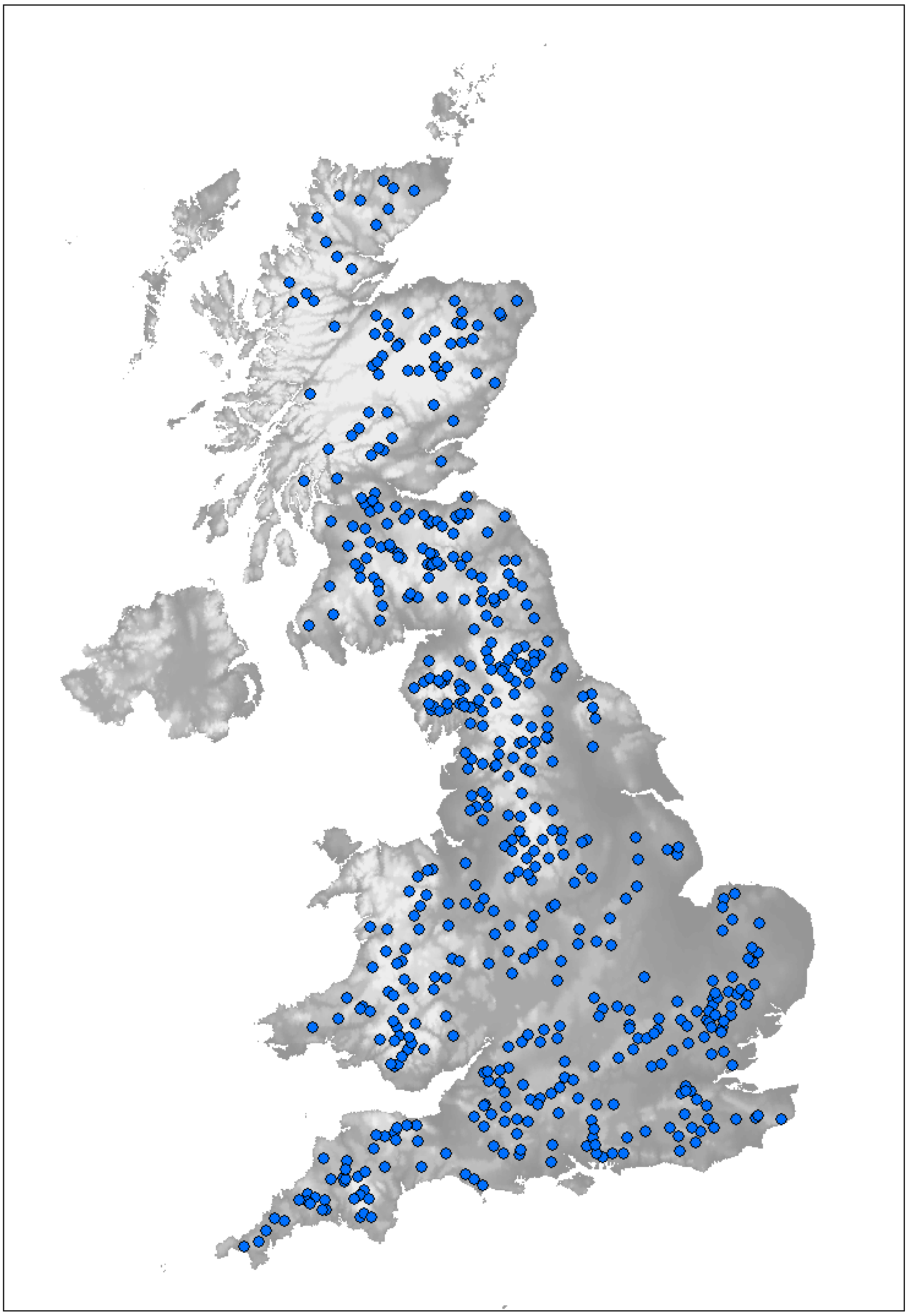


***Figure 3.3*** *The location of the flow gauging stations considered "suitable for pooling" by HiFlows*

Stations shown in Figure 3.3 have both AMAX and POT records. Figure's 3.4 and 3.5 give two different indications of the spread of record lengths for the

AMAX dataset. Figure 3.2 shows the length of records available for analysis when the flow data are cut to fit within the same time period as the gridded rainfall (1958-2002). The rainfall dataset is the MO 5 km gridded daily rainfall dataset. Figure 3.5 shows the total length of record when uncut. For a few flow records it is clear that several years of useful data may be lost, as rainfall data are not available to cover their time spans (those flow gauges installed pre 1958 and gauges still operational after 2003). However, this problem affects few station records and is therefore likely to have little impact on the overall analysis. The UK gauging station network increased rapidly during the 1960s and 1970s (NRFA, 2011) and therefore using the above rainfall and flow datasets makes good use of the available data. The mean length of station record before the removal of unusable events (due to no rainfall data being available) is around 35 years; this drops to 33 years after event removal.

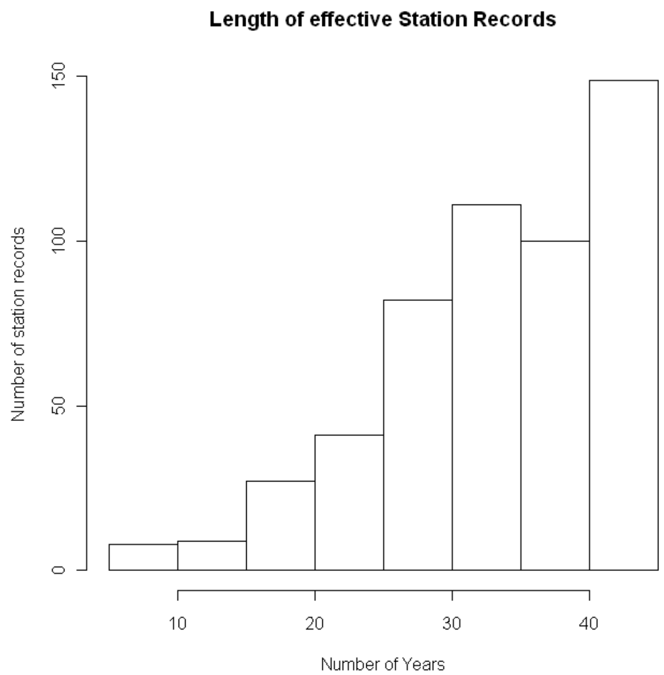



***Figure 3.4*** *The spread of the effective length of station records in the annual maximum flow data set.*

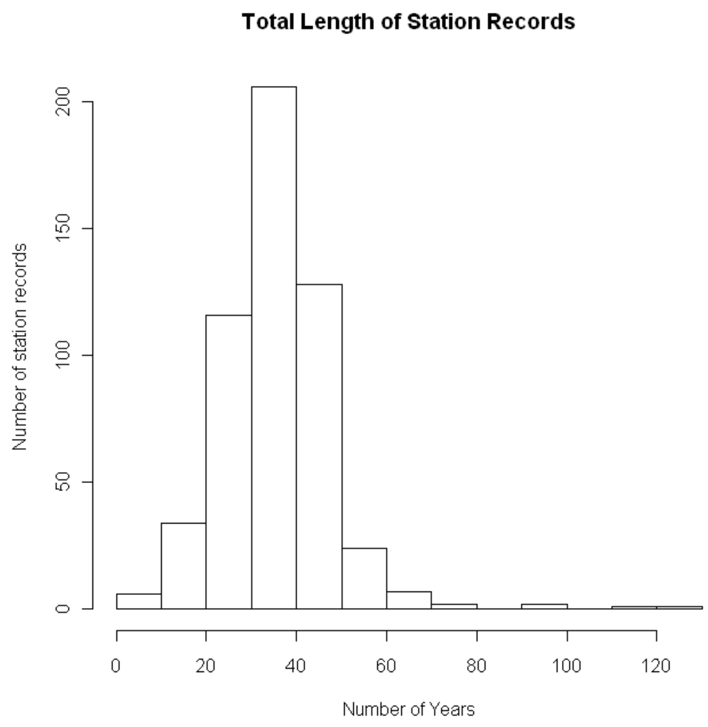



***Figure 3.5*** *The spread of the total length of station records in the annual maximum flow data set.*

Despite the quality classification by HiFlows, there still remains the potential for error in the flow station records. The use of rating curves, the design and operation of the gauging station and the recording and processing of raw data all offer potential for errors to be introduced into the final peak flow records. The HiFlows data comes from several sources (FEH dataset, digital, written and microfiche records) and rating histories are often complex due to changes in channel morphology as well as upstream catchment modifications such as abstraction. Furthermore, there is often uncertainty surrounding the behaviour of some stations at high flows, especially when they were originally designed to measure low flows. There is a significant issue in how well station ratings perform at high flows, for an example of the problem of estimating large flood peaks, see Figure 3.6. This plot shows how the station in question (the Darent at Hawley) contains many peaks at around 3 cumecs, but with one peak at around 49 cumecs. This large peak was well documented, as it was generated from a storm that affected several catchments in 1968 (Sevenoaks District Council, 2008). In terms of the physical mechanisms responsible for this flood there is a suggestion that soil capping was responsible, therefore creating a magnitude of flood that is unusual in the observed record (Sevenoaks District Council, 2008). Soil capping is a reasonably rare mechanism for extreme flooding in the UK, but it can occur. Extended periods of low rainfall combined with high temperatures can lead to the soil surface drying out and providing an impermeable barrier to heavy rainfall. The mechanism of flooding is therefore similar to that of an urbanised catchment where high rates of overland flow are observed. However, it is questionable as to how accurate the peak discharge estimate of 49 cumecs is; as it is unlikely flow gauging would have been carried out to measure this peak directly. A simple extrapolation from the original stage-discharge record is likely to show considerable error, as there are no other peaks of the same or even similar magnitude to compare this extreme event to. The case of the Darent has been included here only for an illustration of the potential problems contained within the peak flow dataset. However, the influence of rating curves on the released HiFlows dataset have the potential to be considerable. In terms of the impact on this project, it is recognised that rating curves may be an inherent source of error, and therefore in future work rating curves should always be considered as a possible error source.

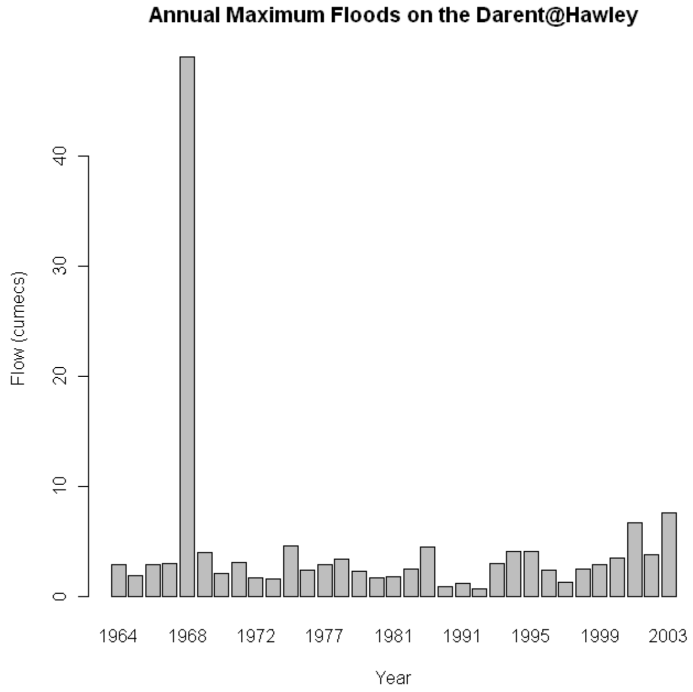



***Figure 3.6*** *The Annual Maximum Flow time series for the Darent at Hawley.*

### *3.3.2 Error Checking the Peak Flow Data*

While some sources of error, such as rating curve uncertainty, cannot be practically assessed, other error sources can. Errors in the creation of the final HiFlows data files can be identified by cross-checking the different file types against each other. The flow data from HiFlows have been produced automatically from a variety of sources with some expert user input (HiFlows, 2010). However, not all data files have been manually checked. For this reason one of the first checks carried out was to assess the consistency of the datasets, and to highlight stations which contained potential errors in their records. Specifically, the following issues were highlighted as suggesting that certain stations records might contain errors:

- Where two different POT file types (.pt and .csv) did not contain matching POT series
- Where AM or POT files contained daily time-series of flow
- Where AM or POT files contained gaps not identified by Hi –Flows

As this project was making extensive use of the HiFlows data, any errors or potential problems were highlighted to the HiFlows project and/or the responsible gauging authority. In general, the extensive record checking undertaken as part of the HiFlows project has been successful for the most part, as few records contained obvious errors. In all, 5 files contained erroneous readings, all in .csv files. These were dealt with by recourse to the original data held by the gauging authorities. Station 20006 contained continuous flow time series for one month which was considered a processing error during the original HiFlows cataloguing. The other gauges had similar problems. After contact with the gauging authorities it was concluded that the .pt files can be considered as good records (pers. Comm. Derek Fraser, SEPA, 2009).

### *3.3.3 Flood peak independence*

In flood frequency estimation, it is usual for flood events to be included in the analysis if they are "independent". One of the most important reasons for this relates to the use of observed data in flood frequency analysis. If two non-independent events are included in the frequency analysis, the resulting flood frequency estimates can be biased (Rao and Hamed, 2000). For use within a statistical flood frequency assessment there is a requirement for extreme event independence. Therefore, to ensure independence it is usual for the analyst to impose some pre-defined criteria on the flow time series. The HiFlows dataset has been extracted and checked for peak independence according to criteria defined by the HiFlows project. A consistent definition of independence was required for all catchments and this is defined as follows:

*"The extraction criteria used are broadly those set out in the FEH Volume 3, section 23.5.1 (page 275). The procedure described there is suitable for automatic data extraction followed by inspection to remove any remaining erroneous peaks. However, for the entirely automated procedure within HiFlows-UK the FEH's independence criteria of the trough between two peaks having to be less than 2/3 of the magnitude of the first of the two peaks was modified such that the trough had to be less than 2/3 of the magnitude of both peaks. This was done in order to exclude minor blips on the recession limb (such as might occur due to a very small amount of rain at the end of a long recession limb)."* Definition taken from Hi-Flows (2010b).

This was the definition used in the automated production of the POT records. However, the resulting dataset is not completely appropriate for use in linking rainfall and flow.

### *3.3.4 Flood Peak Independence and the Use of Daily Rainfall Data*

The gridded MO 5 km rainfall dataset is of a daily time resolution. It was evident at the beginning of this project that storm estimation using daily data may prove problematic. In relation to flow data, the use of daily rainfall has some particular bearing on how flow events can be analysed. For example, where two POT peaks appear in a 24 hour period this can cause problems when using daily rainfall data to estimate the storm associated with a specific flow event.

There are several assumptions that can be made when linking daily rainfall to a flow event. For a catchment with a fixed time to peak (that is, the length of time between the storm centroid and flow peak), it is theoretically possible for the same rainfall day to be selected from a record as the storm that generated two separate (under the HiFlows UK criteria) flood peaks.

Take, for example, the following two events from station 96004's POT record:

| **Date** | **Time** | **Stage** | **Flow (cumecs)** | **Rating Quality** | **Source** |
|---|---|---|---|---|---|
| 08/09/1995 | 00:30 | 2.422 | 192.47 | 2a | Digital Archive |
| 08/09/1995 | 09:00 | 2.088 | 126.77 | 2a | Digital Archive |

***Table 3.1*** *Two POT flow events occurring within a single hydrological day**.***

Using daily rainfall data to estimate the storm that generated these flow events would result in the selection of the same storm estimate for both events as, based on that catchment's typical time to peak (TP), the same hydrological day's rainfall would be associated to both flow events. In the case of this catchment, the estimated time to peak is around two hours. Therefore, for both the events listed in Table 3.1, the same hydrological day ending on 08/09/1995 would be required to characterise the one day storm contributing to those flow peaks. However, the flow peaks have a difference of around 65 cumecs. It is clear that the use of daily rainfall data in this case, and others, may present some difficulty in estimating peak flow.

In any method that attempts to relate rainfall information to flow, this is clearly an undesirable situation. It should also be noted that this problem is almost exclusively related to the use of POT datasets as the selection criteria for annual maximum data implicitly reduce the chance of two events in the record occurring so close together. To deal with this, the catchment set was analysed to highlight catchments where this problem might exist. The previously identified catchment set was analysed to look for situations where the same rainfall day was likely to be associated with two or more flow events. Out of the c. 500 catchment set, around 400 catchments were highlighted as suffering from this problem to some extent.

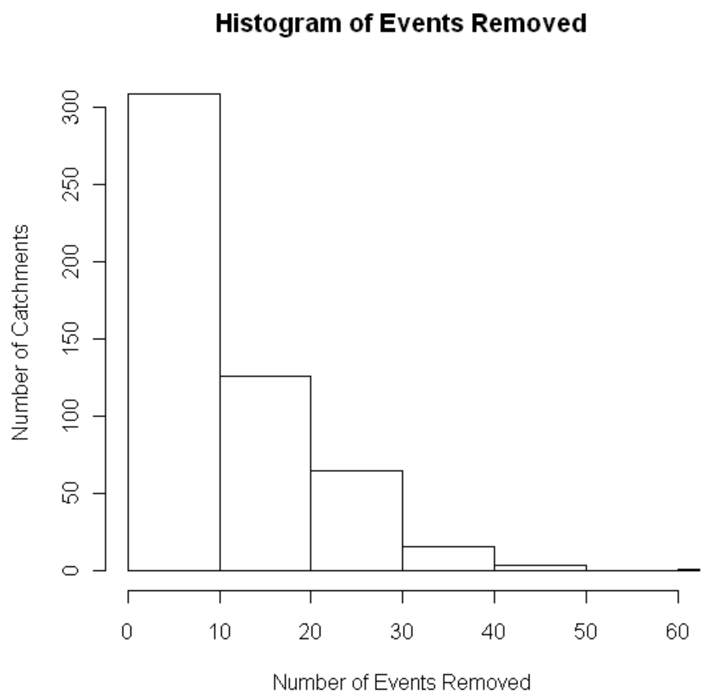



***Figure 3.7*** *Histogram Showing the Number of events removed to ensure daily peak independence.*

Where catchments records were identified as containing a problem, events were removed. Where two events occurred within a twenty four hour period, the smaller event was removed. A log was kept of removed events, as it is important to understand the effect of removing events from the record on subsequent flood frequency analysis. An altered POT record may produce unreliable flood frequency estimates; however, for the purposes of this work it was important to have a flow dataset suitable for use with the daily rainfall data. The majority of affected catchments tend to have less than 16 events removed by the filtering process from a typical POT record of around 250-300 events (see Figure 3.7). Some of the catchments with extremely high numbers of events removed are a result of data errors in the HiFlows files: where daily time series information has been included in error (as discussed previously in Section 3.3.2). These events have also been removed, but can contribute significantly to the total number of events removed. Despite this, relatively few events have been removed when compared to the overall number of events in the catchment records (see Figure 3.8)

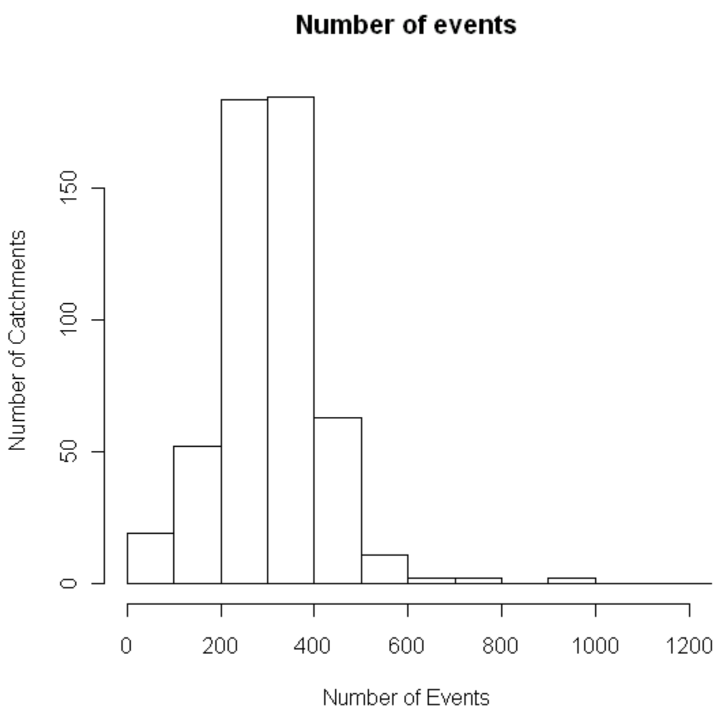



***Figure 3.8*** *Total Number of events in the catchment POT record before event removal.*

## 3.4 Storm Analysis

Any study which purports to link rainfall to flow, must demonstrate that the rainfall data sets used are suitable for that purpose. Therefore, Section 3.3 uses both hourly and daily data to investigate rainfall characteristics as well as develop a conceptual method for linking between rainfall and flow. The aim to show that daily rainfall can be used to estimate flood-generating storms. This involves assessing storm profiles from hourly data and relating this to estimation from the daily record.

### *3.4.1 Rainfall Datasets*

The primary rainfall dataset identified for use is the MO 5 km gridded daily rainfall dataset. The reasons for this are primarily due to the dataset completeness, spatial and temporal coverage and ease of access. One further advantage of this data set is that it provides a consistent method with which to estimate catchment averaged rainfall for the large subset of catchments selected for this study. The gridded data were accessed through a SQL database as created and used by Smith (2010). However, recourse was made to several hourly records in order to investigate the potential limitations and effects of using the daily data. Figure 3.9 shows the hourly gauges used for analysis. Two hourly records for each of the hydrological regions as defined by Wigley et al. (1984) and updated by Gregory et al. (1991) were also used. These records were obtained from the BADC and have already been cleaned for use in previous rainfall research work (Smith, 2010).

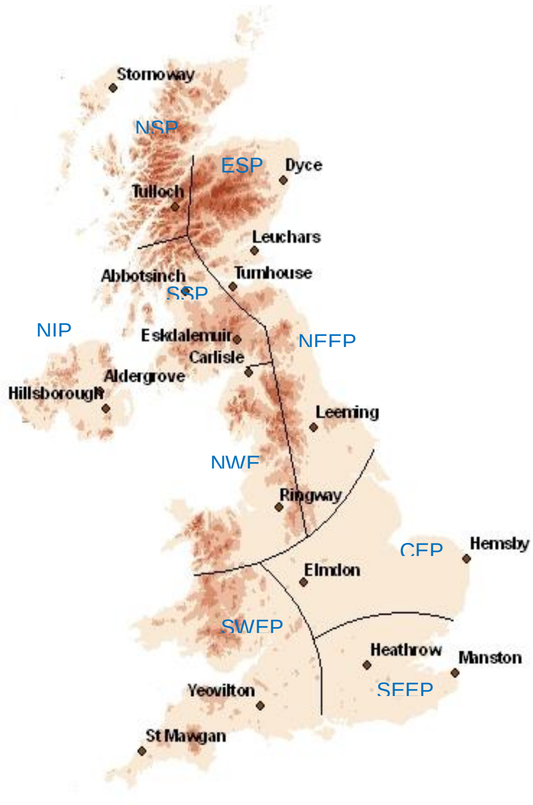



***Figure 3.9*** *The location of the 18 hourly records used in the analysis. Rainfall records in Northern Ireland were analysed as rainfall however flow data from that region are not available for analysis in this study. The black lines show the hydrological regions within the United Kingdom as defined by Wigley et al. (1984) and Gregory et al. (1991). Hydrological region codes are highlighted in blue.*

For use within this research project, catchment averaged time-series were developed from the gridded daily data. Using the catchment boundaries supplied in a format suitable for ArcGIS, the relevant 5 km cell ID's were extracted. These were then used within the SQL database in order to calculate the catchment averaged rainfall. This value was a simple arithmetic average of all the cells falling within the catchment boundary.

The use of daily data carries several potential problems. Perhaps one of the most important issues, was that of how well daily rainfall data would estimate a true storm amount and what error in estimation might arise from using daily data compared to hourly. In order to consider these issues it is worth stating some terminology which future investigative work will use.

### *3.4.2 Terminology*

This section of the thesis deals primarily with fixed and sliding window rainfall maxima. In reality, there are three terms - fixed, sliding and true. These three terms are explained in order to illustrate some of the issues associated with storm estimation from hourly rainfall records.

A fixed maxima refers to the maximum value recorded from a fixed window measurement period. The fixed maxima used in this work focuses on hourly rainfall measured on a 0900 to 0900 basis. The start and end period of the measurement window is fixed at 0900 and the maxima is based upon the maximum rainfall amount as taken from one of these 24 hour measurement windows.

A sliding window measurement period shunts along in increments. For this work, the duration of the sliding window period is the same as that of the fixed window period (24 hrs) however the start and end times of the sliding window period are not fixed at 0900. This allows the sliding window period to move around until it records the maxima over any given period.

Finally, the true maxima represents the actual amount of rain that fell as a result of the storm that we are trying to capture with fixed and sliding window measurement periods. In practice it is difficult to measure this, but the shorter the measurement window, the more likely the true storm amount can be accurately captured (for a point location). The fixed and sliding window periods are both estimates of the true storm amount. The sliding window estimate is likely to be closer to the true storm amount, but may not exactly represent it as in this case the data is still discretised in hourly intervals. Rainfall recorded in one minute intervals would likely produce a closer estimation of the true maximum, however recording data at such a high resolution is rarely undertaken, not least because of the massive amount of data it would produce as well as the known errors that arise from using tipping bucket rain gauges to estimate total volumes of rainfall. Finally, there is the terminology relating to the window duration used. A two day window uses data that have been aggregated from daily data as opposed to a forty eight hour window, which covers the same duration however, the data are constructed from hourly values.

In addition to the problem of temporal resolution, the estimation of spatial rainfall is also a problem. However, the hourly records are located far away from each other, they cannot be combined to look at a single catchment averaged rainfall value. This being the case, it is worth stating that the hourly records cannot be used to estimate catchment averaged rainfall and this is not the purpose of this piece of work.

### *3.4.3 Time Series Aggregation*

In order to investigate different aspects of rainfall characteristics, the previously introduced hourly records were used. The first analysis considered the duration of storms in the UK. This was to estimate the proportion of a flood generating storm that was likely to be included in an 0900 to 0900 observational window. This is essential in order to understand the potential for error when using the daily rainfall dataset, however, in the first instance the error can only be assessed by using hourly records.

For each hourly record, the data were aggregated to produce a twenty four hour fixed window time series, starting and ending at 0900. In order to ensure that no partial days were constructed, the original hourly record was cut to begin at 1000 on the first day and end at 0900 on the last day. As the hourly reading at 1000 includes the measured rainfall in the hour from 0900-1000 this ensures an 0900-0900 time series would be created. After checking the record to ensure that no data was missing it was then possible to aggregate the data to the fixed window record.

The sliding window analysis allowed different information about storm characteristics to be extracted. The sliding window time-series was based on a twenty four window where a new sliding window total was calculated every hour. This leaves two time-series, fixed and sliding window.

### *3.4.4 Fixed Window Storm Duration*

The fixed window records were then ranked by the rainfall amount, and the fifty highest windows were extracted. For each of the fifty windows, recourse was made to the original hourly record where the twenty four hour period of the window plus the twelve hours either side of it were extracted to create a forty-eight hour window. Hourly records were typically between fifteen and twenty years long and therefore this gave an average of around two to four rainfall events per year. This approach ensures that only larger rainfall events are included in the analysis. This work was carried out for all of the eighteen hourly rainfall records.

It was assumed that for most of the high twenty-four hour period aggregated values (selected from the ranked twenty-four hour totals), only one storm would be likely to contribute to this total. This assumption allows for storms with multiple peaks as long as the storm fits in with pre-defined storm criteria.

The criteria for defining a storm are inherently subjective. In this case, an algorithm was run to identify a storm from the forty eight hour period previously extracted as described in Section 3.4.3. This algorithm defined a storm start as a period where rainfall was greater than or equal to one mm for two hours and defined a storm end as a two hour dry period. In the case of the algorithm returning two storms from the forty- eight hour period, the storm with the highest total amount was retained. The storm definition was developed through visual checking of the extraction criteria against plots of high twenty four hour totals.

Once these storms were extracted, their centroids were found using Equation 3.7.

$$\overline{tr} = \frac{\sum Pi\left(i - \frac{1}{2}\right)\Delta t}{\sum Pi}$$

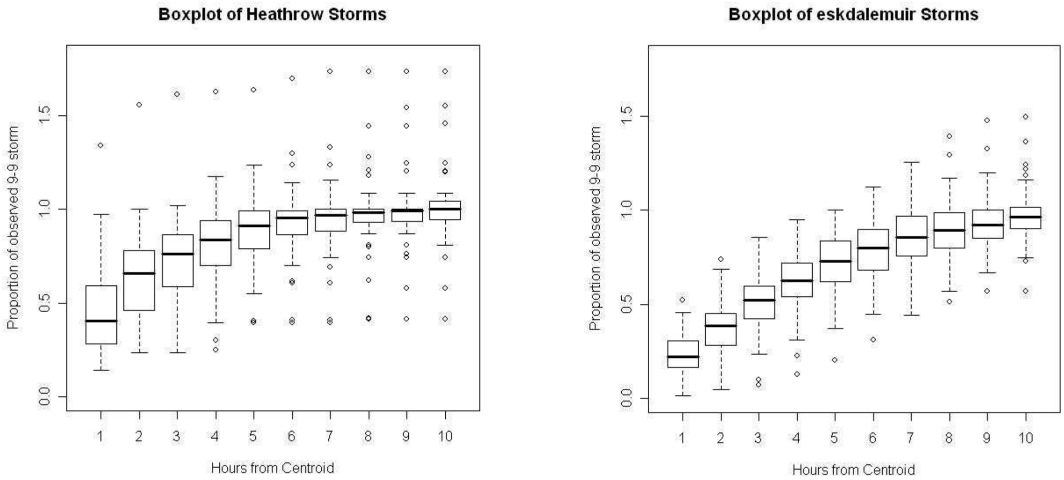
**Equation 3.7**

Where tr denotes the rainfall centroid, Pi denotes the rainfall at time i and $\Delta$t denotes the discrete time interval used in hours.

In order to investigate storm duration, for each storm, a function was used for one hour steps either side of the centroid, and for each step this function determined the percentage that the cumulative window contributed to the twenty four hour total previously extracted. This was repeated for each of the fifty storms and the results were then box plotted (see Figures 3.8 and 3.9) These plots give an indication of how far out from a storm centroid it is necessary to go in order to capture the majority of the storm. This aids an understanding of how storm duration may affect the estimation of a storm total from daily data. The longer the duration of a storm, the more likely it is to cross an 0900 measurement boundary. Because of the added twelve hour period at the beginning and end of the twenty four hour fixed period this meant that the results can show more than one hundred percent of the observed twenty four hour period. This allows for consideration of how a rainfall event may be overestimated if too large a duration is used to characterise an extreme flood-causing rainfall event. For many storms, this work shows that the twenty four hour period is adequate to characterise the storm rainfall event, however some events overlap the 0900 boundary.

### *3.4.5 Discussion on Storm Duration*

There is inherent variability in meteorological phenomena. The rainfall events that generate flooding are likely to exhibit a wide variety of durations, intensities and shapes. This work has looked at average storm shape and duration, examining storms to consider if there are geographical differences in the average storm shape. In order to highlight some differences, the contrasting cases of Heathrow (SEE) and Eskdalemuir (SS) are presented. Further plots for the other hourly stations can be found in Appendix B.1. The plots shown here are those of the sliding-window analyses.



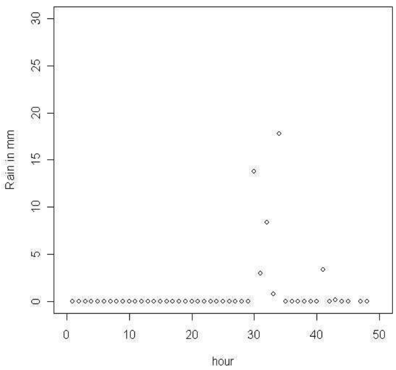

a b

***Figures 3.10a and b*** *Boxplots showing the percentage of the one day storm total captured for one hour steps from the storm centroid (calculated using the original hourly data). The thick black line shows the median, with the upper and lower ends of the boxes representing the upper and lower quartiles respectively. The dashed lines extend to the maximum and minimum values, unless there is an outlier. In this case the outlier is shown as a small circle.*

The results of the fixed window analyses showed that typical storm durations differ, depending on location. The y axis on Figures 3.10 a and 3.10 b show increases of up to 1.5 times the measured storm total. Fixed window daily storm totals are defined as the 0900 to 0900 accumulation, however for the analysis of individual storms, the centroid was identified and the accumulations at hourly intervals were calculated as previously described. This meant that it was possible for more than one hundred percent of the original 0900 to 0900 window to be included in the hourly analysis.

In general, for the Eskdalemuir record, storms required around seven or eight hours worth of data either side of the storm centroid in order to capture approximately 90 % of the storm when measured on an hourly basis. For the same 90 % value, at Heathrow, a median time of four to five hours either side of the centroid is required. Heathrow tends to have shorter rainfall events with clearly defined peaks, whereas Eskdalemuir tends to have longer events, often with a less defined peak. The 50 % value is, on average, achieved within the first hour at Heathrow, whereas three or four hours are required at Eskdalemuir for the same value. Again, this suggests that Eskdalemuir experiences events of lower intensity, where each hour of rainfall contains a smaller proportion of the total rainfall event (storm) than at Heathrow.

Figure 3.10 illustrates some of the different characteristics of storms between Heathrow and Eskdalemuir. Generally, the storms with the highest 24 hour totals at Heathrow tend to be shorter and more intense than those at Eskdalemuir. This is why the earlier work suggested that for many larger storms at Heathrow, a shorter window could be used to estimate the storm total.

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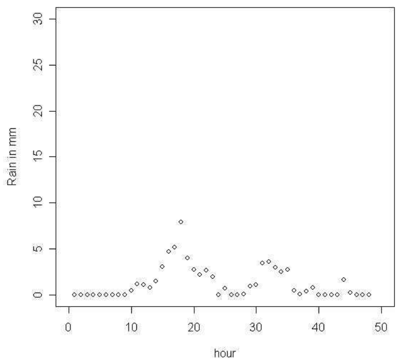


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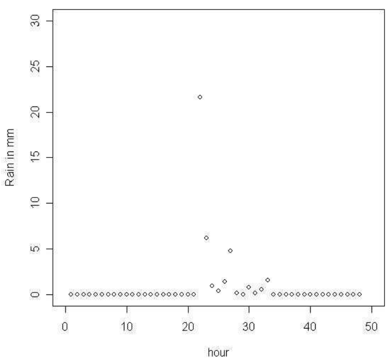


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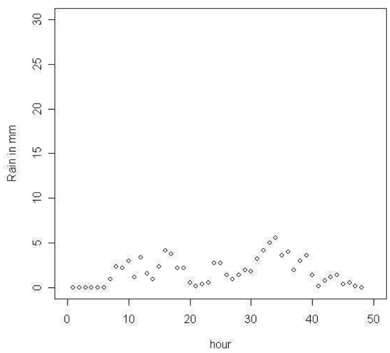


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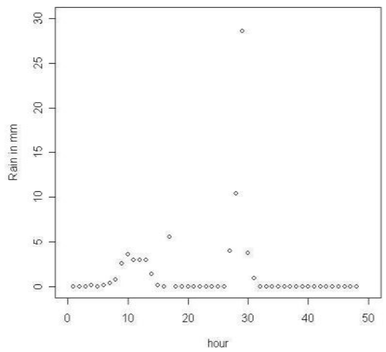


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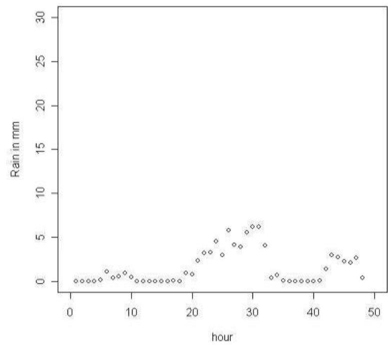


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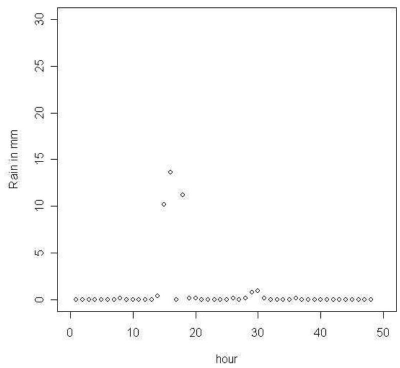


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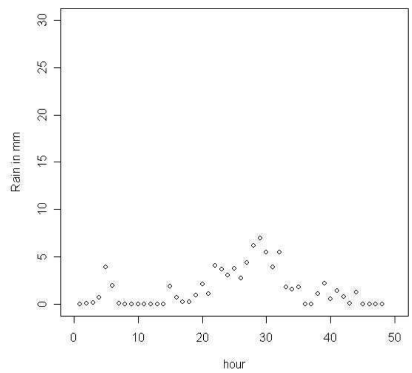



h

***Figure 3.11*** *Panels a to d show typical storms extracted from the Heathrow hourly rainfall record. Figures e to h show typical storms extracted from the Eskdalemuir hourly rainfall record.*

### 3.5 Data Discretisation; Impacts on the Estimation of Extremes

Discretisation considers the effect that data measurement intervals have on phenomena of interest. Often, data are measured at fixed, discrete time intervals. This measurement interval can often affect the estimation of the phenomenon of interest, for example rain storms. Therefore this section considers the importance of data discretisation and how it might affect the work carried out as part of this research project.

The recording of rainfall data inevitably involves some discretisation. This problem occurs when the phenomena of interest, for example a rain-storm straddles two different measurement periods. If a storm of interest starts at 7 am and finishes at 11 am, the use of either day's rainfall will not truly reflect the storm rainfall. It is likely that using either day's rainfall would underestimate the true maxima. This is an important issue when estimating storms from recorded data. This is the problem of discretisation, and is illustrated by Figure 3.12. In order to account for the fact that storm rainfall cannot be well characterised by daily rainfall, a correction factor is often applied. This factor tries to correct the fixed window observations based on the average fixed-sliding window ratio.

It should also be noted that if a typical storm at a site arises from a relatively few hours of intense rainfall, there is less chance of this event overlapping the fixed measurement boundary than at a site that experiences

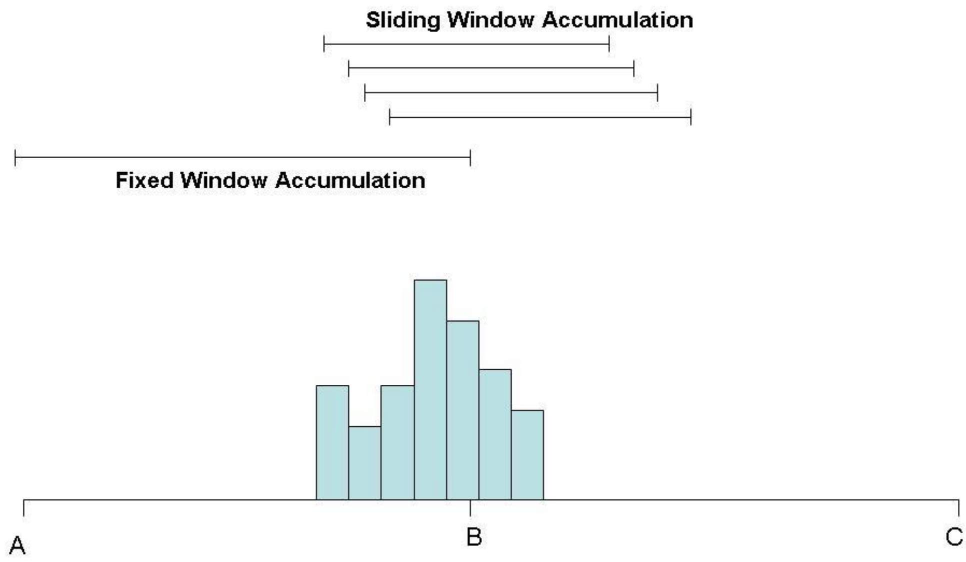



***Figure 3.12**. The diagram shows how a sliding window accumulation better represents storm rainfall than the fixed accumulation. A, B and C represent the fixed measurement intervals, with the storm shown in blue straddling the two fixed periods AB and BC.*

longer duration events. In this case, the correction factors are likely to be lower. Dwyer and Reeds (1995) work recommends a correction value of 1.15-1.17 to convert observational day rainfall into 24 hour rainfall. This is recommended as replacing the older recommended FSR values of 1.13 to 1.14 (FSR, 1975).

The Institute of Hydrology work (Dwyer and Reed) was carried out in 1995, and with the longer hourly records it was thought prudent to re-consider this work.

### 3.5.1 Investigating the Effect of Discretisation on Storm Estimation

The methodology broadly followed that of Dwyer and Reed with several differences. For each hourly record, a fixed and sliding window time series was created. The top fifty fixed window accumulations were extracted by ranking the fixed window time series. For the sliding window time series, an algorithm was run to extract the top fifty storms from that time series (as per the work reported in Section 3.4.6). Therefore to investigate the difference in the estimation of storms, there were fifty fixed and sliding window storms available for each site.

In estimating population ratios from a sample, Barnett (1981) recognises that when using a small sample, there is a skew in the distribution of the ratios and therefore r (the correction factor, or the fixed to sliding ratio) turns out to be biased. The larger the sample becomes, the more the distribution of individual ratios tends towards normality and therefore r is less biased. Because of this, Dwyer and Reed recommend calculating r as the difference between the mean fixed and mean sliding window storms. If, as Barnett recommends, the sample size was to increase, it is likely that the proportion of the sample that contains those events that are more extreme would decrease, and non-extreme events would make up a greater proportion of the sample. This in turn would likely cause the correction factor to be biased towards less extreme events.

Because of the longer record lengths and more extreme events used in this study, the correction factors were calculated as the mean of the 50 individual storm ratios. Tables of individual station correction factors can be found in Appendix C.1. The mean value of all 18 gauges is 1.14, which is similar to the recommended value from the Flood Studies Report (1975).

The mean r correction value is also close to the recommendations of Dwyer and Reed (1995). Their work recommended a correction value of somewhere between 1.15 and 1.17. The differences may be explained by several factors. Firstly, Dywer and Reed (1995) looked at only three records from the UK, whereas this work considers around eighteen. Secondly, at the time of their work, hourly rainfall records were limited and so their methodology naturally led to the use of smaller storms in the analysis in order to gather enough data. This work has perhaps improved upon that of Dwyer and Reed (1995) as the longer record lengths available for this work have allowed the selection of more extreme events.

## 3.6 Matching Rainfall to Flow

### *3.6.1 Implications for Storm Identification and Matching*

It is necessary to investigate how useful daily rainfall records are in characterising flood producing storm events. Previous work has looked at storm duration; this allows a basic assessment of the percentage of flow events that can be characterised from a single daily rainfall measurement. What follows is an example for one catchment, however this reasoning is also applicable to the set of catchments suitable for pooling derived from HiFlows.

### *3.6.2 Time to Peak (Tp) and the storm-flow link*

Time to peak (Tp) describes the length of time from the centroid of a storm to the flow peak in a river. It is a useful indicator of how responsive a catchment is to rainfall. For all the catchments used in this study, time to peak has been calculated with a regression equation from Kjeldsen (2007) using readily available catchment descriptors (see Equation 3.2).

$$Tp = 1.56PROPWET^{-1.09}DPLBAR^{0.60}(1 + URBEXT_{1990})^{-3.34}DPSBAR^{-0.28}$$

**Equation 3.8**

This links catchment properties to a time to peak value (in hours). The descriptors used in this equation all relate to properties that affect the speed at which a flood peak can travel through a catchment. PROPWET is an indicator of average catchment wetness, DPLBAR describes the drainage path length, URBEXT indicates the proportion of the catchment covered by urban area and DPSBAR is the mean slope of the drainage path. This is the most consistent and realistic way to estimate the time to peak value for this study. In the case of dealing with hourly data from one or two good catchments, then it would be possible to estimate Tp empirically. However, given the lack of availability of data to calculate Tp empirically, recourse to existing regression equations seems suitable. The following description (illustrated by Figure 3.13) provides an outline for a conceptual model that could be used to readily link rainfall to flow, given the time of the flow event.

Here, a nameless catchment is presented purely to illustrate the concept. First, assume each hour (1-24) is likely to contain a representative portion of the entire flow record. Therefore each hour is likely to contain 4.16 % of the flow record (i.e. 100 % of the record divided by 24 hours leaves 4.16 % of the flow record for each hour). Further assume that the catchment has a fixed time to peak (Tp) of around nine hours and that on average around seven hours either side of the storm centroid is required to capture around ninety percent of the storm (see earlier work on hourly data for justification). It then follows that for the storm to be captured in one observational day, the centroid of the rainfall event must occur between the hours of 1600-0200 for the centroid plus seven hours either side. With a fixed time to peak of nine hours, this means that the flow peak must occur between the hours of 0100 and 1100 for a single observational rain day to be chosen. Because the window in which ninety percent of the storm can be captured in one observational day is ten hours long, it follows that around forty two percent of flood events in this catchment could be characterised using a single measurement day's rainfall (i.e. 4.16 % multiplied by ten hours gives around 42 %).

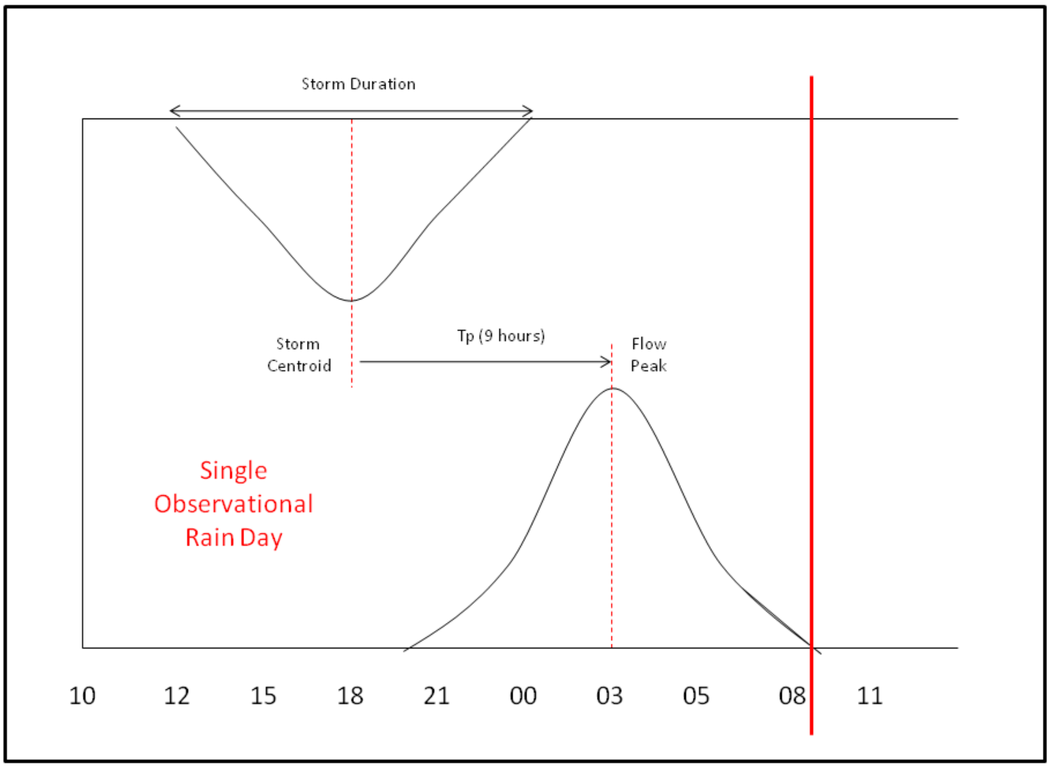



***Figure 3.13*** *An illustration of how it is possible to link a storm to flow event, given that the storm has fallen within one observational rain day.*

This model is essentially an adaptation of the ReFH rainfall runoff model, made simpler through concentrating only on storm rainfall and ignoring baseflow and losses. However, it provides a framework for connecting the storm event to a peak flow event from the HiFlows data set.

The above case makes several assumptions. Specifically:

- That peak flows are distributed evenly throughout the 24 hour period. While there is no physical reason for peak flows being biased towards certain times of the day, short records are unlikely to show a uniform distribution of flow events within each hour.
- The time to peak (Tp) value is an estimate produced from regression equations, it may contain significant error for individual catchments and it may also not be fixed for all storms in a single catchment.

- The average storm duration is simply that. This figure represents the results of analysis of several hourly records, and from this it is recommended that most storms can be captured within a 24 hour period. However, it is recognised that this approach cannot capture multi-day storms, some of which are responsible for extreme flood events.

Using the simplified model linking time to peak and storm duration, the model can be changed using different Tp values and different storm durations. Where multi-day storms are involved, there is less emphasis on selecting only one day of rainfall, and therefore the timings become relatively less important.

However, from a practical point of view, the potential to implement a working method of the above concept is limited due to the fact that timing data for peak flows is only known for short periods of record. Therefore while the concept described above provides a working model it cannot be used to its full extent in this research.

## 3.7 Conclusions from the Data Assessment Work

This first look at the data available to this project helped to develop a basis for its future use. Initial error checking of the flow data files has meant that the selected catchment set can be considered relatively error free. It allows some degree of confidence that the flood peak data are as free from error as possible and suitable for use in flood frequency estimation. This early work has also allowed the identification of some specific problems with the flow data files which has proved useful for this study and, hopefully, the HiFlows project as a whole. A separate flow data set has been created, allowing for a slightly stricter definition of what a flood peak is. This has been necessary due to the use of daily rainfall data, where two flood peaks within the same day cannot be characterised by the same rain storm.

The analysis of the rainfall data is perhaps more important, as it provides key information on the limitations and uses of daily rainfall. Initial work has shown the potential for error to be introduced when using daily rainfall data to estimate a storm value. Using hourly rainfall records has shown how this error can be corrected with a discretisation factor. Further analysis of these hourly records has shown how the majority of storms can be captured within a 24 hour period, thereby proving that daily rainfall data can be used in many cases to estimate a storm event. Some geographical differences in storm shape have also been shown.

The theory of how rain and flow events may be matched with each other has also been demonstrated with a generic example. This is a first attempt, but it provides a framework for use in the more advanced work when trying to transform between rainfall and flood frequency.

Overall, this work does not provide a strict methodology for the future use of the data sets described. Rather it seeks to provide examples of what is possible as well as examples of what is not. Future combined use of the rainfall and flow data sets largely depends on the evolution of the modelling strategy.

# Chapter 4: Seasonality and Analysis of Flood and Rainfall Regimes

## 4.1 Introduction

Seasonality has been considered an important aspect of flood frequency analysis by several authors. Archer (1981) provides a detailed overview of the seasonal hydrology in North-East England with a view to improving the FSR methods. Black and Werritty (1997) study the seasonal flooding patterns of POT flow data in order to further understand flood generation. Castellarin et al. (2001) prove the use of seasonality measures in characterising catchment hydrological behaviour. Developing from this, other authors such as Ouarda et al. (2006) and Reed et al. (1995) use seasonality indices as a method of regionalising catchments for flood frequency estimation. Seasonal variations in flood patterns are significant for flood estimation, as individual methods may not perform well on catchments which exhibit two or more seasonal flooding regimes.

In the context of the research work presented in this thesis, seasonal assessment of rainfall and flow provides a good assessment of the links between the rainfall and flood regimes of individual catchments. For example, if most catchments have the majority of their heaviest rainfall events in October or November and their largest flow events in January or February, it is clear that something other than heavy rainfall may be playing a part in the generation of flood flows. To that end, the first analysis considers measures to assess the seasonality of flood and rainfall regimes separately. By then comparing these statistics between rainfall and flow, a first assessment can be made as to how well these match.

The second piece of analysis considers the linkage between extreme rainfall and flow in a much more direct manner. It considers the proportion of extreme rainfall events responsible for generating extreme flood flows. Two different criteria for matching these events are introduced.

## 4.2 Assessing Seasonality

In order to consider seasonality, two different approaches have been used. Graphical approaches, such as polar plots are useful for assessing patterns in individual catchments. However, they are not particularly useful for comparing catchments with each other and looking at the UK as a whole. Statistical assessments of seasonality are useful both for comparison between individual catchments and national scale assessments. Therefore, both approaches have been used.

### *4.2.1 Graphical Assessments of Seasonality*

For visual assessment, polar plots of Annual Maximum rainfall and flow were produced using the statistical processing software R. The date of the annual maximum event was converted into a Julian day (1 to 365 – 366 in a leap year, where 1 is the 1st of January, 365 is the 31st of December), before then being converted into an angle using the following equation.

$$\theta = (JD - 0.5)\frac{2\pi}{365} \qquad \textbf{Equation 4.1}$$

Where θ is the angle of the annual maximum event on the polar plot, and JD is the Julian day. The modification by 0.5 moves the event to the middle of that day for plotting as an angle. This then allowed each event to be plotted on the polar plot. Magnitude values were scaled by the median annual maximum flow value (QMED) for flow and the median annual maximum rainfall value (RMED) for rainfall. An example of a rainfall polar plot can be seen in Figure 4.1. The year is plotted following the arithmetic convention as used by Robson and Reed (1999), with successive months plotted in an anticlockwise direction starting with January as the eastern most month. This practice is not followed by all authors as both Black and Werritty (1997) and Macdonald et al. (2010) use the 31st of May as the start date to avoid a discontinuity in the dates of flooding when examining event frequencies. This essentially avoids splitting the potential flood year into two, but does not affect the calculation of the MDF. This approach was not used within this study, as consistency was required in the extraction of AMAX and POT events for all analysis. Furthermore, this work does not examine the frequency of events on a monthly basis.

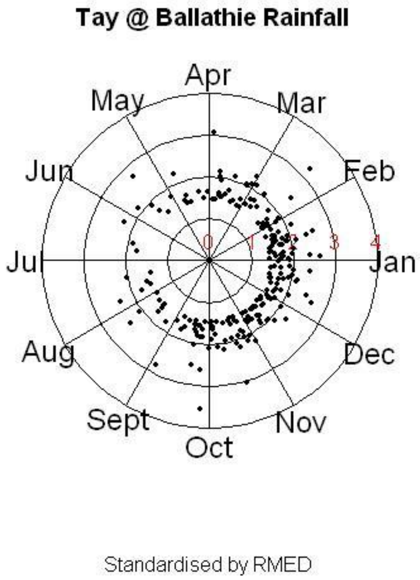



***Figure 4.1*** *A polar plot showing the seasonality of POT rainfall for the Tay catchment.*

### *4.2.2 Statistical methods of Seasonality*

Graphical methods provide a neat and easily understandable method of assessing the flow regime of individual catchments. However, they are not practical for assessing the catchment set of 520. Statistical methods provide an easily comparable alternative way of assessing flow regimes. Assessing statistics like the mean day of flood as well as variance and dispersion measures requires the use of more specialist statistics. When calculating a mean from circular data, a simple arithmetic value is not sufficient. Figure 4.2 provides an illustration of the problem.

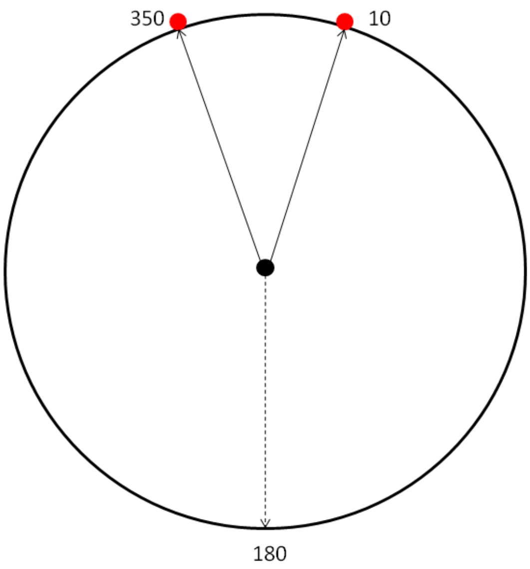



***Figure 4.2*** *The problem of using traditional statistics on circular data.*

The two red points on Figure 4.2 represent the data of interest. If we wish to calculate a statistic like the mean, then by using traditional statistics we would end up with a value of 180°. Clearly, this is not a good measure of where the mean is likely to lie based on these two data points. In using the arithmetic mean it becomes clear that it is more a function of the choice of zero direction and sense of rotation, rather than simply assessing the centre of a set of observations (Jammalamadaka and SenGupta, 2001). Circular statistics provide an appropriate alternative for assessing calendar data.

Circular statistics used here follow the approach of Robson and Reed (1999). As with the polar plots, the observed data are each referenced by the Julian day on which they occurred. This is then transformed to an angle using the Equation in 4.2.1. To calculate the mean statistic each observation is treated as a vector and they are then summed to give the resultant vector. The centroid of the event dates are represented by the co-ordinates XFLOOD and YFLOOD.

$$XFLOOD = \bar{X} = \frac{1}{n}\sum_{i=1}^{n} \cos\theta_i$$

$$YFLOOD = \bar{Y} = \frac{1}{n}\sum_{i=1}^{n} \sin\theta_i \qquad \textbf{Equation 4.2}$$

$$\bar{R} = \sqrt{\bar{X}^2 + \bar{Y}^2}$$

$\bar{R}$ represents the length of the resultant vector, and can be considered as a measure of the dispersion of events. The direction of the resultant vector can be considered the circular mean direction, defined as

$$\bar{\theta} = \begin{cases} tan^{-1}\left(\frac{y}{x}\right) & \bar{X} \geq 0, \bar{Y} \geq 0 \\ tan^{-1}\left(\frac{y}{x}\right) + \pi & \bar{X} < 0 \\ tan^{-1}\left(\frac{y}{x}\right) + 2\pi & \bar{X} \geq 0, \bar{Y} < 0 \end{cases}$$ **Equation 4.3**

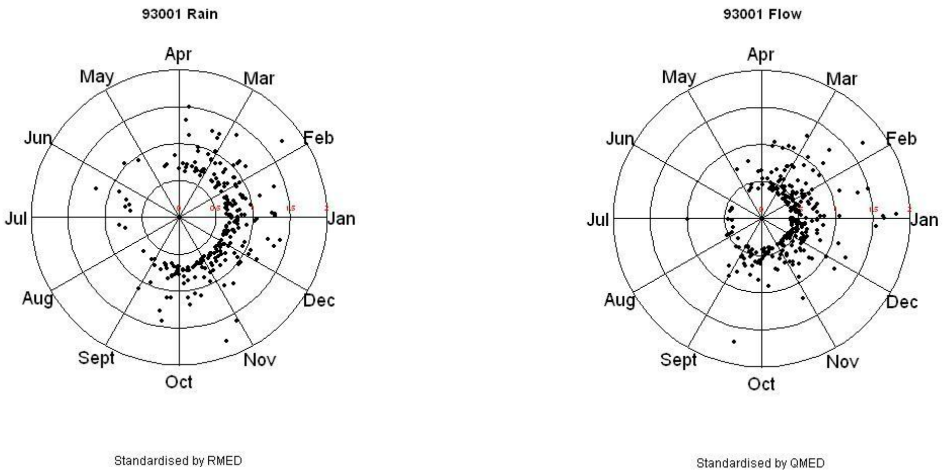
In order to relate back to the original flow and rainfall records, the circular mean direction can be transformed into the mean Julian day by

$$JD = \frac{\theta}{360} \times 365$$ **Equation 4.4**

The value R is a useful measure of how concentrated the data is towards its particular mean value. Where R tends towards n, the data are concentrated in the same direction. Where R tends towards 0, the data are more likely to be evenly spread around the circle. Because n differs between catchments, the R value in this case has been normalised by n to allow for inter catchment comparison. Therefore r values are in the range [0,1].

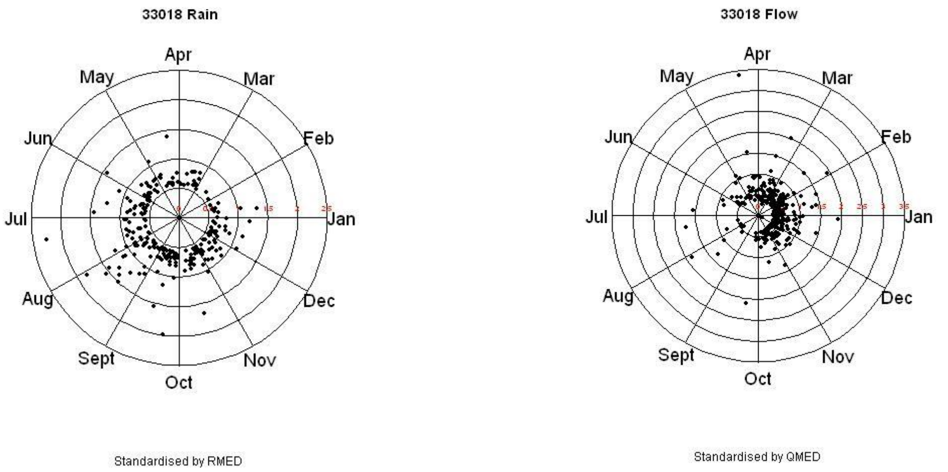
### 4.3 Seasonality Assessment; Results and Discussion

Figures 4.3 through to 4.6 provide two examples of rainfall and flow polar plots for catchments within the UK. These have been plotted for every catchment in the set. The catchments presented here have been chosen because they illustrate interesting and useful examples of seasonal rainfall and flow characteristics which are discussed further. In this analysis and the work that follows, use has been made of POT data to allow the use of a larger data set.




a b

***Figure 4.3*** *POT Rainfall (a) and flow (b) seasonality for the Carron at New Kelso.*




*a* *b*

***Figure 4.4*** *POT Rainfall (a) and flow (b)seasonality for the Tove at Cappenham.*

Seasonality information can reveal interesting behaviour in catchment hydrology. In the case of the Carron, rainfall and flow events tend to be concentrated in the Winter months of October through to March. It is clear that most of the Carron’s heavy rainfall events occur during the Winter, therefore it is not surprising that the majority of flood events also occur then. The mechanism behind this is likely to be related to catchment conditions. In Winter, when heavy rainfall is more prevalent (as evidenced by Figure 4.3 a) the catchment soils tend to be more saturated due to increased rainfall and lower evapotranspiration values. Therefore heavy rai nfall events produce more runoff and higher peak flows in the river (Figure 4.3b).

In comparison to this, the Tove plots (Figures 4.4 a and 4.4 b) show that the seasonality of rainfall and flow events is different. Rainfall events are more spread out throughout the year, whereas flow events tend to still be concentrated in the Winter months of November through to March. Given its location in the South of England, it is probable that the Tove has high soil moisture deficits in summer thus reducing the likelihood of flooding in this season. It is clear that there is potential for Summer flooding, as large rainfall events occur all year round. However, due to the higher soil moisture deficits in Summer there is little chance of these storms becoming effective enough to generate a flood. The exception to this is the relatively rare occurrence of heavy monthly rainfall followed by an extreme single day rainfall event that is heavy enough to generate a flood. This was the mechanism behind the Summer 2000 floods (Met. Office, 2010).

From these plots, it is clear that the seasonal rainfall and flood regimes of these two catchments are different. In the case of the Tove it is likely that the high soil moisture deficits typically experienced in summer reduce the likelihood of flooding during those months, despite the occurrence of large rainfall events. The Carron experiences fewer heavy rainfall events in summer; however, it is likely that it does not experience soil moisture deficits as high as those on the Tove.

Comparing these plots provides interesting insights into rain and flow seasonality. However, to consider seasonality at larger scales, statistics such as those presented in Figures 4.5 and 4.7 provide a more useful basis for assessment.

Figures 4.5 and 4.7 show the pattern of the dispersion and mean day statistic for the POT rainfall and flood records for the catchment set. On these maps, values close to 0 represent records that are well distributed throughout the year, whereas the higher values represent records that are more concentrated towards a particular point on the circle. In a hypothetical case where all events occurred on the same Julian day, the dispersion indice would be exactly, 1. However, given that the data represent natural systems it would be unrealistic to expect such high values.  Mean day statistics represent the mean Julian day of flood or rainfall as calculated using Equations 4.2 and 4.3. The direction of the arrow on the plot is calculated anticlockwise from the x axis. In order to compare and contrast the plotted maps with polar plots, some example polar plots along with their dispersion indices are presented along with the maps of indices.

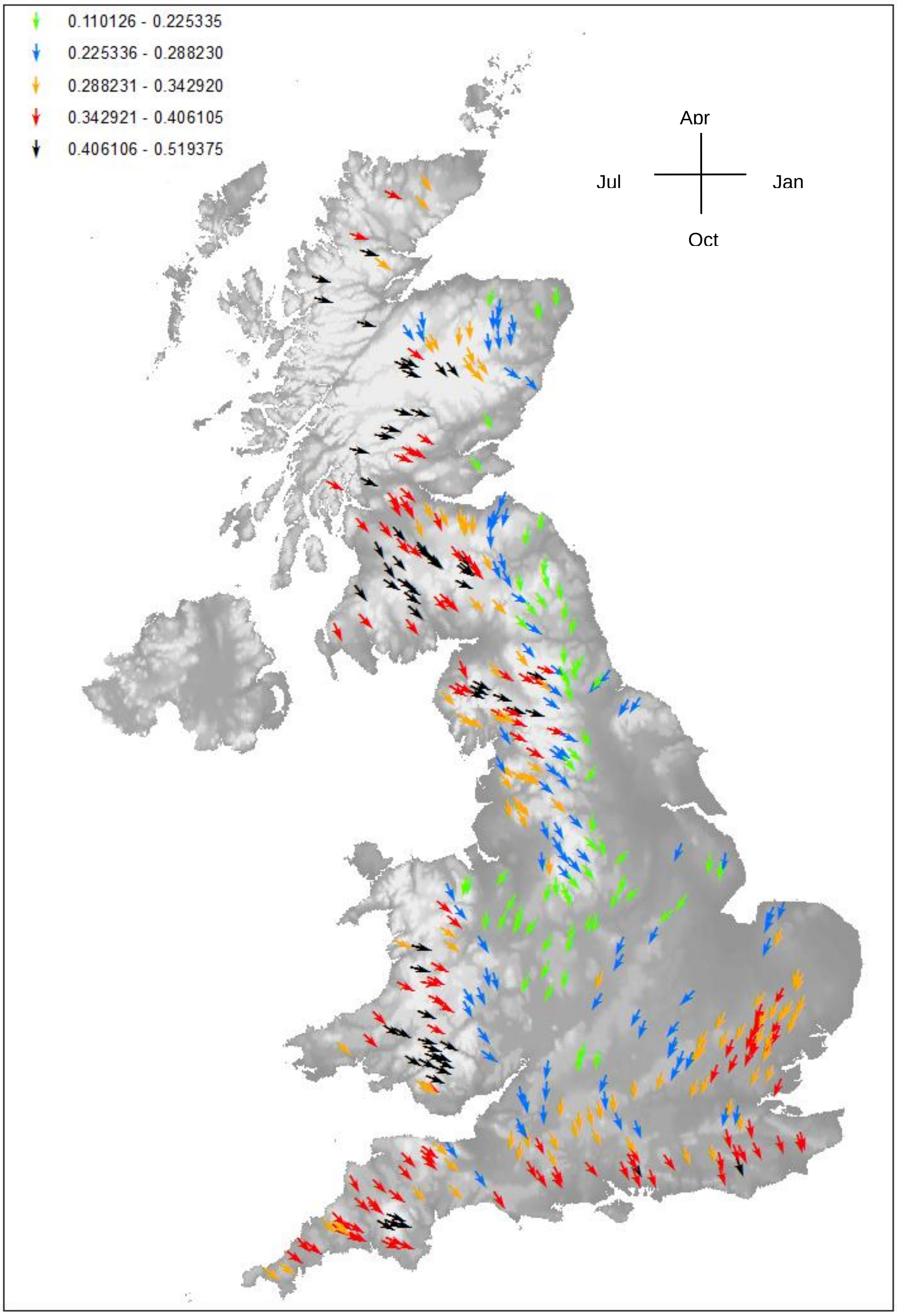
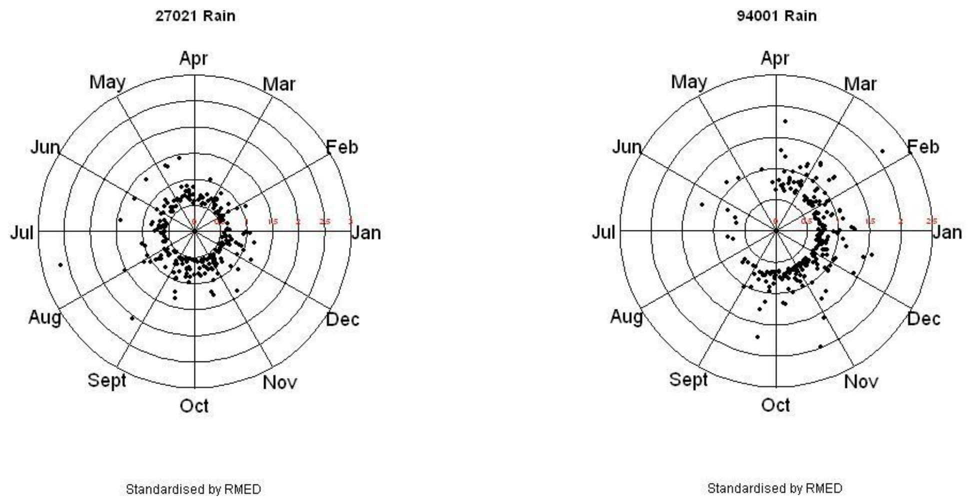



***Figure 4.5*** *Dispersion and Mean Day of Rain for the POT rainfall*




a b

***Figures 4.6*** *Two examples of rainfall polar plots, the Don at Doncaster (27021) and the Ewe at Poolewe (94001).*

Rainfall dispersion (Figure 4.5) shows some pattern. The East of the UK and Midlands tend to show highly dispersed rainfall regimes. This is due to the higher frequency of heavy rainfall events occurring in summer. Strong westerly weather systems will often track across the UK from west to east, however, the same cannot be said for easterly systems which tend to be weaker and occur more frequently in summer. This results in eastern catchments showing a more dispersed rainfall regime compared to their western counterparts as they experience more variety in the storm systems that cross them. Areas in the West and North of the UK tend to show heavy rainfall events that are more concentrated towards specific times of the year. The polar plots of rainfall in Figures 4.6a and 4.6b are further evidence of this. Figure 4.6a shows a polar plot of the POT rainfall for the Don at Doncaster (27021). Heavy rainfall events do not appear to concentrate towards a particular time of year; this is confirmed by the low dispersion index (0.13). In contrast, Figure 4.6b shows the rainfall regime for the Ewe at Poolewe (94001) in the North-West of the UK. Here, rainfall appears to be predominant in the Winter. The dispersion index is also higher than for the Don (0.51). Figure 4.5 also provides an interesting illustration of mean day statistics. In general the West of the UK tends to show a mean day of rainfall that is later in the year (around December to January time) whereas further East and South the mean day of rainfall occurs earlier (around September/October time). It is worth stressing that for catchments with highly dispersed rainfall and flow regimes, mean day statistics are not particularly useful. However, in this case there is a sufficient geographic spread of catchments with higher dispersion indices to warrant the general conclusions described above.

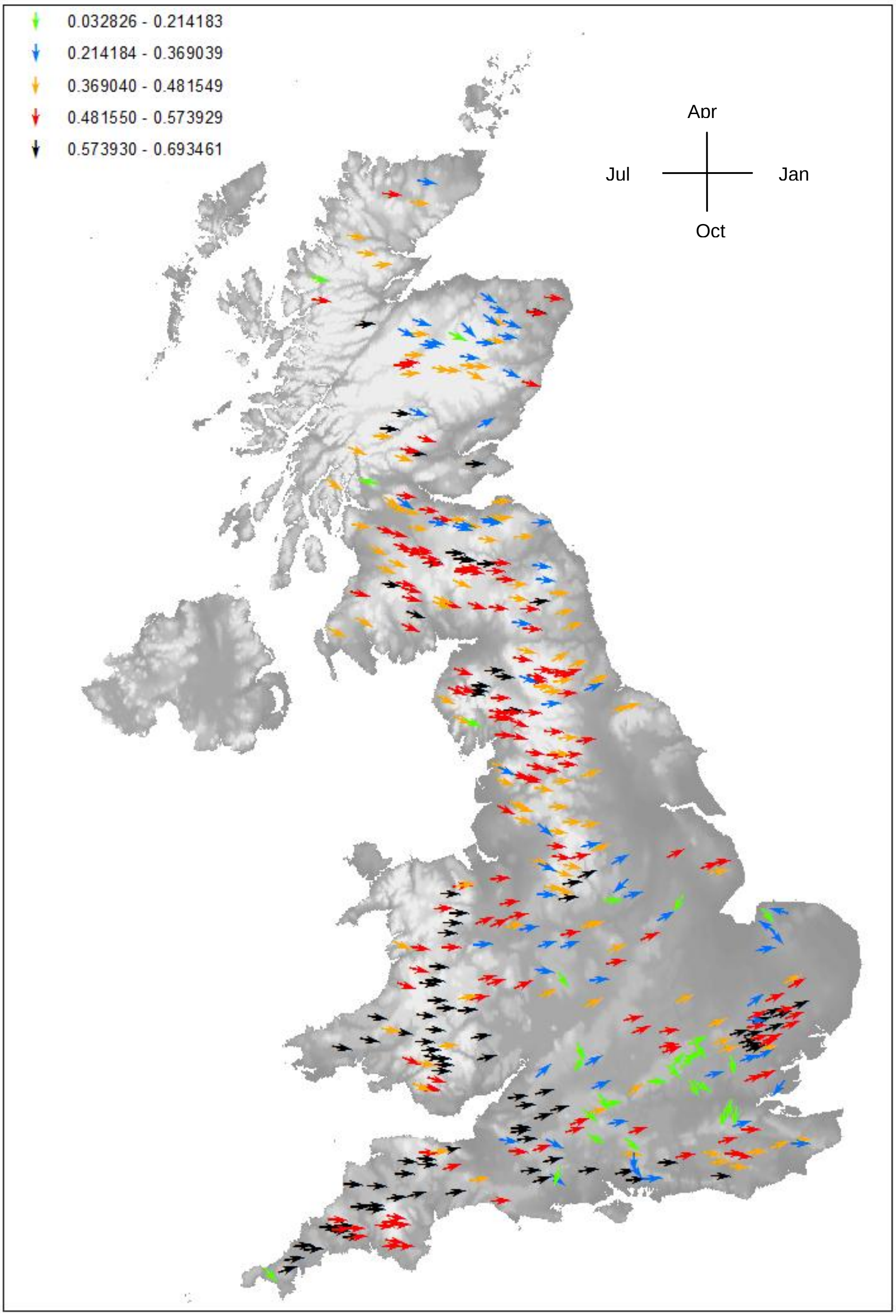
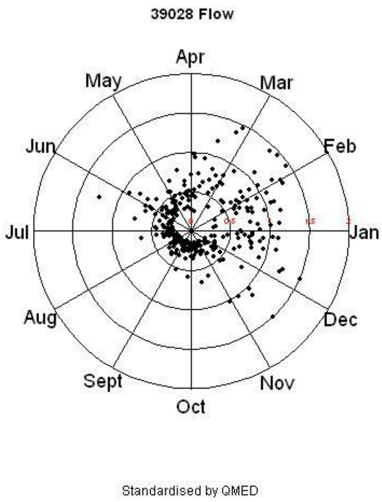
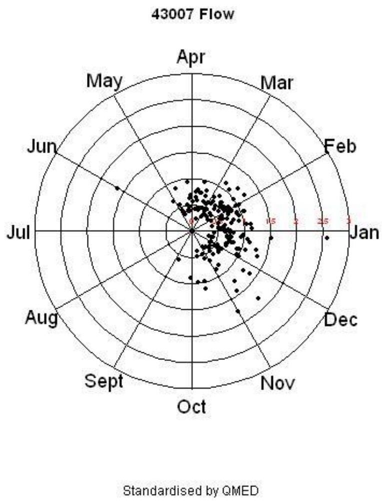



***Figure 4.7*** *Dispersion and Mean Day of Flood for the POT flood peak data*




a




b

***Figures 4.8*** *Two examples of Flow polar plots, (a) The Dun @ Hunderford and (b) The Stour @ Throop.*

| **Gauge Number and Variable** | **Dispersion Indice** |
|---|---|
| 27021 Rainfall | 0.13 |
| 94001 Rainfall | 0.51 |
| 39028 Flow | 0.04 |
| 43007 Flow | 0.68 |

***Table 4.1*** *Selected catchments and Dispersion indices*

Flood dispersion shows a similar pattern to rainfall, although not as strong (Figure 4.7). It is likely that the mean day of flood is, in some cases, heavily influenced by the mean day of rainfall. However, catchment characteristics may act as a 'buffer' to climate, thereby complicating the link between rainfall and flood dispersion. Catchments which are groundwater dominated, or typically experience spring snowmelt flooding (such as the Tay) may not show a strong link between rainfall and flood dispersion or mean dates. Several eastern Scottish catchments and catchments located in north-east England may be susceptible to this problem. This is one of the reasons why seasonality is important, and why understanding rainfall and flood seasonality can aid an understanding of flood risk. As with rainfall, individual polar plots show evidence of both dispersed and non-dispersed flow regimes (see Figures

4.8 a and 4.8 b for example). It is also the case, that many of the concentrated flow polar plots show a higher degree of concentration than the rainfall. This can be seen in Table 4.1, where the flow dispersion indices reach a higher value than the rainfall dispersion indices (0.68 compared to 0.51 for rainfall dispersion). Generally, the more clustered catchment records are found in the West, with increasingly dispersed records further East. The most highly dispersed catchments are found in the South East of the UK and the Midlands. In these areas, as mentioned above, mean day statistics are of little value. There are exceptions to this rule. In the midlands, there are a group of catchments exhibiting unusually high dispersion values compared to their neighbours. In this case it is possible that catchment characteristics play a much larger role than climate. The physical mechanism behind this clustering of flood dates towards a particular time of year may lie in regional groundwater levels, which tend to peak at specific times of year after responding to long duration rainfall. Several other high HOSTBFI catchments along the south coast would also tend to suggest that groundwater may play a part in flood dispersion. However, overall, there is a clear pattern in the mean day of flood. Western catchments tend to show a mean day of flood in November or December. Further East, catchments tend to show mean days of flood occurring in January or later. While catchment characteristics may play a role in this, it is likely that as eastern catchments tend to be drier in general, they take longer to 'wet up' and therefore their mean day of flood arrives later in the year. Western catchments are subject to a high number of heavy rainfall events and exhibit high annual rainfall totals which may explain why their mean day of flood occurs earlier.

Seasonality has held interest for several authors, though there is little published work covering rainfall and flow seasonality for the whole of the UK. Bayliss and Jones (1993) summarise the Peak over Threshold flood database of the time, including summary statistics on seasonality. Work by Black and Werritty (1997) on flow and rainfall has shown similar results for Scotland as has been found in this work. The MDF pattern for Wales shows agreement with published work by Macdonald et al. (2010). Therefore, this analysis provides a timely update of previous work, by extending the time period of data used, by extending the analysis to rainfall and also by extending the space coverage to the majority of the UK in cases where this has not occurred before.

Rainfall seasonality results show an increasing dispersion the further East a catchment is located. Black and Burns (2002) have shown this to be due to Eastern areas experiencing higher rainfall event frequencies in the summer months compared to Western areas. Black and Werritty (1997) show how four factors (peak rainfall seasonality, soil moisture deficits, catchment size and reservoir storage) can generally be used to characterise the flood regime of a basin. Similarily, Macdonald et al. (2010) found that catchment wetness was an important determinant in correlating rainfall and flow seasonality. Robson and Reed (1999) present the use of seasonality statistics for pooling. Their approach to statistic calculation was similar to that used here, however, only the flood regime was considered. Results are similar with later mean days of flood in the South and East of the country.

## 4.4 Developing the Seasonality Work; Annual Maximum Matching

As a first assessment of the linkage between rainfall and flow regimes, assessing seasonal statistics can provide some useful insights. To further develop this work, a matching analysis was undertaken. This involved the use of annual maximum rainfall and flow series for each catchment. The flow events were then matched to the annual maximum rainfall events, and a record was kept of this matching. In essence, this work considers to what extent annual maximum rainfall events are responsible for the annual maximum flow record. The analysis does not, at this stage, consider the magnitude of the events in either record.

The matching process works by taking the dates of the annual maximum flow and rainfall events and then matching them. The matching aims to attribute an annual maximum rainfall event to a flow where it is reasonable to assume that the rainfall event generated the flow. This allows for cases where the annual maximum flow and rainfall events do not fall on the same day. In the case of using a hydrological day to record rainfall it is important to remember that a hydrological day ending 3/2/2010 may be an annual maximum rainfall event that generated an annual maximum flow on 2/2/2010 for example.

Figure 4.9 presents the results of this work, mapped across the UK. As shown, the catchments that exhibit low levels of matching tend to be located in the South and East of the country, whereas the catchments that show higher levels of matching tend to be located in the North and West, with a few exceptions. This pattern resembles the spatial distributions of catchment characteristics quite strongly. In wet, upland catchments in the North and West, typically assumed to have reduced surface permeability, the map shows higher levels of percentage matching compared to catchments in the South and East which tend to be more groundwater dominated, drier, permeable type catchments. In these groundwater dominated catchments, it is reasonable to expect that large rainfall events may not always give rise to large flows, as the storage capacity of the catchment has the ability to act as a buffer. In contrast, upland catchments tend to have little storage capacity due to the relatively thinner soils. In these cases, it is reasonable to expect that the larger rainfall events are more likely to cause flood flows. Overall, a large proportion of catchments have matching values of around 20 to 50 %, with a smaller number of catchments having higher and lower matching values. This is shown graphically in Figure 4.10.

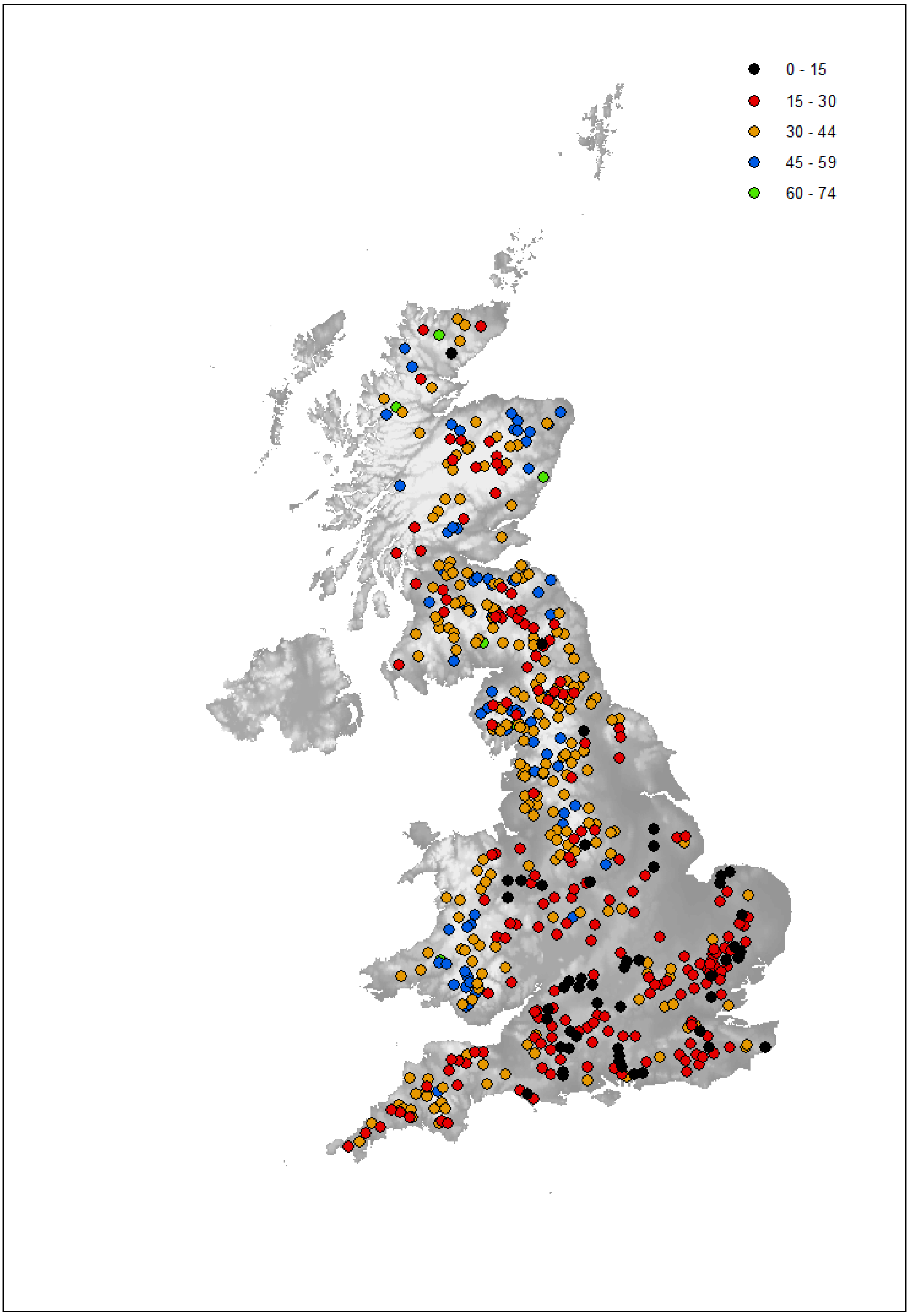



***Figure 4.9*** *The results of the annual maximum matching process. Each circle represents a gauging station and the colour refers to the percentage of events matched, as shown in the legend.*

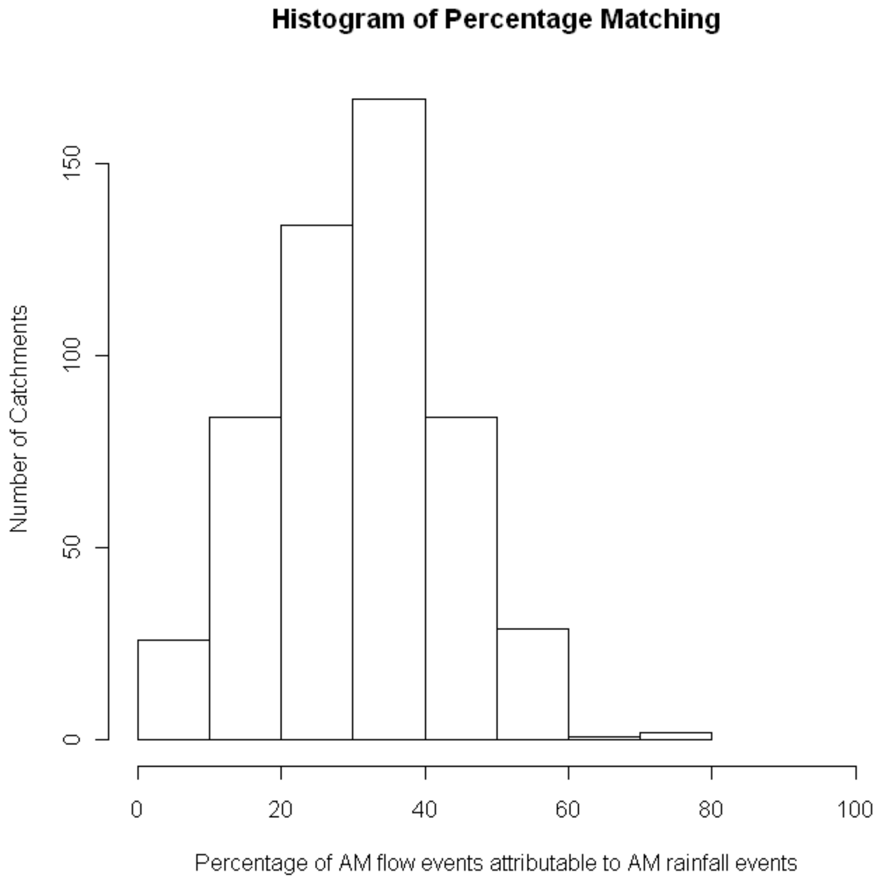



***Figure 4.10** A Histogram showing the results of the percentage matching methodology*

### *4.4.1 Relaxing the Matching Criteria*

The matching methodology described above is a relatively harsh test of a catchments flow and rainfall record. In an ideal situation, there would be a 1:1 relationship between the two records. In practice, this is not apparent, as the results of the first matching procedure show that no catchments achieve a 100 % matching record. Theoretically, it is possible for two heavy rainfall events to be of a similar size and yet have strikingly different effects on the flow peak. Therefore if the rainfall event ranked second to the annual maximum is of a similar size, it is important to recognise that it may be responsible for the annual maximum flow. The same could be said for a number of rainfall events. For this work it was assumed that this problem was unlikely to extend beyond the top three rainfall events in any hydrological year.

In order to examine the records further, the matching procedure was repeated with a relaxation of the matching criteria. In this case, the annual maximum flow record was allowed to match against any of the top three rainfall events for that year.

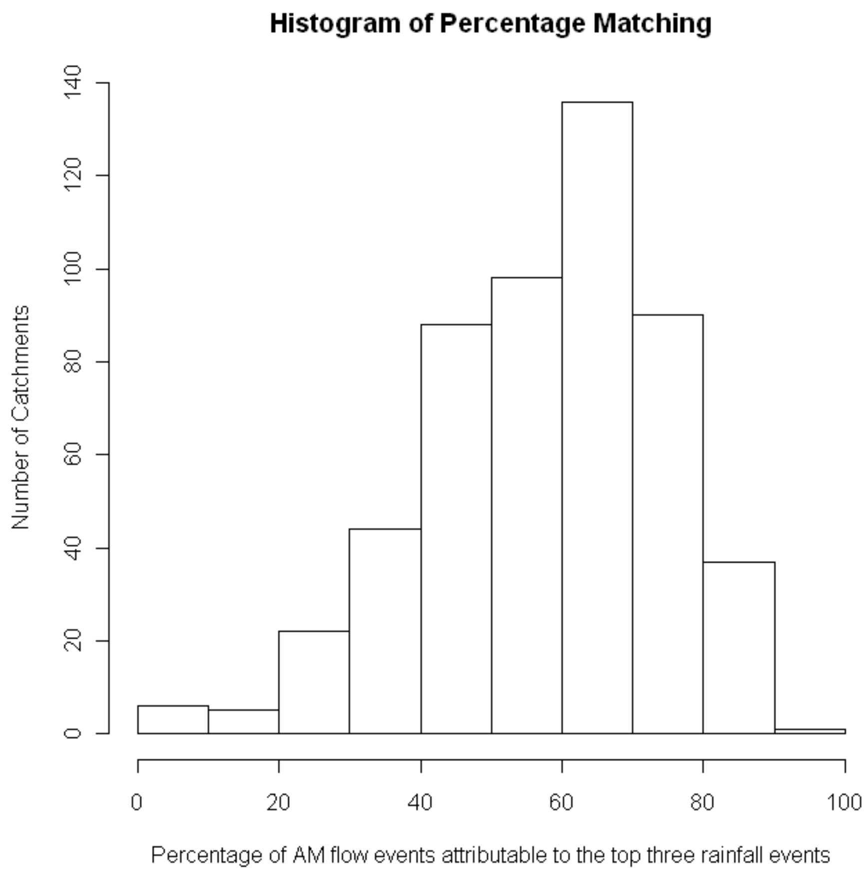



***Figure 4.11*** *A Histogram showing the results of the relaxed percentage matching methodology where the flow event was allowed to match with any of the top three rainfall events from that year.*

Figure 4.11 provides an assessment of how well the top three matching procedure works across the catchment set. The majority of catchments improve their matching values over the annual maximum approach with values approaching 90 % being reached. Using the same colour classification as for Figure 4.9, Figure 4.12 shows the percentage matching results for the UK plotted as a map. Again, the general pattern shown previously prevails, with Western and higher elevation areas showing higher levels of matching.

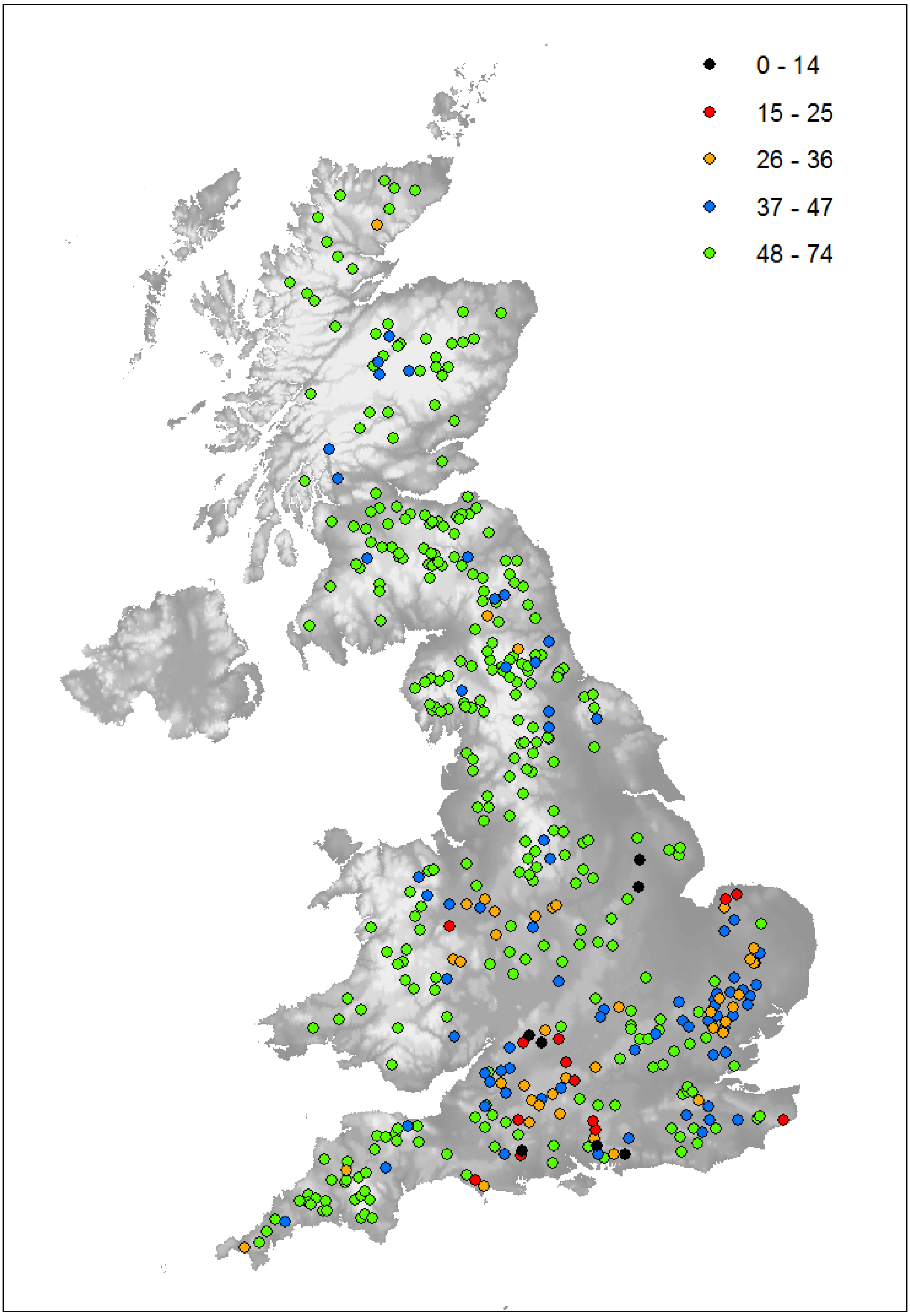



***Figure 4.12*** *Matched percentages with the top three matching approach.*

### *4.4.2 Comparison of Approaches*

While the original matching methodology is a relatively strict test, it does provide some information on those catchments where a rainfall-flood frequency link might be expected. In cases with a high matching percentage, it is possible that using the rainfall frequency curve as a guide to the flood frequency curve may be a good starting point.

The top three matching method exhibits much higher matching values than the original matching method. For the majority of catchments, around 50 to 80 % of their records are matched; this is evidently higher than for the singular annual maximum matching approach. This is not surprising, as generally, floods are caused by large rainfall events. However, they are not always caused by the largest rainfall events. What this work does not consider, is how much those top three rainfall events differ in their magnitude. A stricter test of the top three matching methodology might allow matching on three events only where these events are of similar size.

## 4.5 Conclusions

This seasonality analysis is a necessary precursor to the development of a model capable of estimating a flood frequency curve. The use of seasonality statistics has shown two different ways of assessing a catchments rainfall and flow regime. Essentially, these can be thought of as useful additions to the principal catchment descriptor set available through the FEH. However, this work further develops the published work on rainfall and flow seasonality by extending it both temporally and spatially. Seasonality information can show, and has shown some striking geographical differences in flood and rainfall regimes.

The annual maximum matching work has shown how rainfall and flow events can be matched in a simple way. However, the main insight from this work is in being able to assess how common it is for large rainfall events to generate large flow events. This work is important in developing a frequency curve matching methodology as it allows for a simple assessment of where more sophisticated predictive methods may work.

The consideration of matching has important implications from a predictive point of view. If a large proportion of a catchments annual maximum flow record has been generated from its annual maximum rainfall record, then it is perhaps indicative of a relationship which can be usefully used in the future. Where the annual maximum flow and rainfall regimes are not well aligned, it is clear that further work will be required to characterise the rainfall and flow relationship.

Both pieces of analysis presented here provide a useful basis for the development of more advanced work. In the first instance, this involves how to consistently estimate a peak flow from rainfall. This work is presented in the next chapter “Event Based Flow Estimation”.

# Chapter 5: Event Based Flow Estimation

## 5.1 Introduction

The approach to flood frequency curve estimation presented in this thesis requires the estimation of flood peaks. Previous work has considered the appropriateness of the data sets selected for use (Chapter 3) as well as providing a first look at seasonal and climatic linkages between rainfall and flow (Chapter 4). Chapter 5 now develops a method suitable to the estimation of a series of flow peaks, given some information on the climatic conditions that generated them.

### *5.1.1 Modelling Justification and Requirements*

Several researchers have published details of event based models for flood frequency estimation. These have a range of purposes, from the commercial flood estimation interests of the ReFH model (Kjeldsen, 2007) to answering questions on the use of antecedent information, like the model of Brocca et al. (2008). This being the case, it is worthwhile outlining why a new model was developed as part of this project.

The FRACAS project as a whole is concerned with the problem of how a changing climate may affect the flood regime of rivers within the United Kingdom. The approach being taken within this thesis focuses on a simplified event rainfall to flood frequency transformation, suitable for use with future scenarios. In order to achieve this, there is a requirement for the estimation of flood peaks, before a suitable flood frequency curve estimation procedure can be employed.

While there are many event based models available for peak flow estimation, none suit the purposes of this study. Models such as the unit hydrograph require inputs in the form of rainfall hyetographs to produce flood hydrographs. At a sub-daily level, the MO 5 km daily data does not allow for the estimation of rainfall hyetographs. Furthermore, this study does not require the flood hydrograph to be estimated, only the peak flow. Therefore these event models are unsuited to this work as they require inputs not easily available and produce outputs which, while suitable, are excessive in their detail. Secondly, an inability to clearly cope with future climate information and a reliance on parameters which are unknown in the future also make some event based models unsuitable for use in this study. However, there are some important features of existing models that have been incorporated into the research presented in this thesis. Where this occurs, specific reference is given in the text.

To meet the aims and objectives laid out in Chapter 1, the event model must be able to transform rainfall into flow on an event basis, but it must do this in an automated fashion and without reference to catchment characteristics. Given the large number of catchments and events in the study records, it is clearly unrealistic to have the model set up to work on an individual event basis. To meet the requirements of the research project, the model must therefore be simple (otherwise one may simply adopt a CS approach), it must be flexible (to deal with several different catchment types) and it must be capable of using future scenarios. Obviously it should also show some skill in estimating the catchment flood record.

### *5.1.2 Modelling Strategy and Initial Concept*

The event based estimation detailed in this Chapter provides a basis on which to assess the potential for catchment rainfall estimates to generate the catchment flood record. The modelling work provides a basis for later use in the frequency curve mapping which is presented in Chapter 6.

The concept behind the model uses a simple transformation of rainfall and associated information to estimate a flow value (see Figure 5.1)

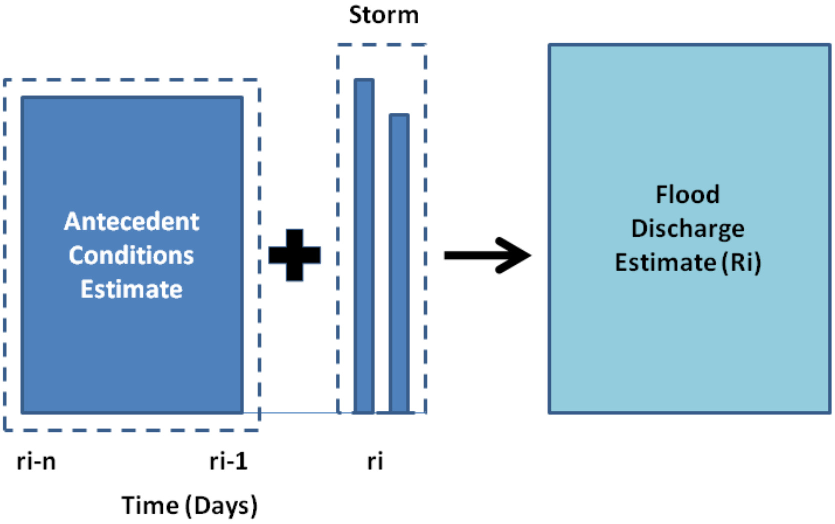



***Figure 5.1*** *The concept behind the event based model. ri is the day of the storm, ri-1,ri-2 are 1 and 2 days before the storm occurs.*

The assumption behind the concept in Figure 5.1 is that the majority of peak flow events can be estimated by reference to the storm that generated them, with an improvement in estimation by the incorporation of some information on the catchment state prior to the storm occurring. This is unlikely to be the case where catchments are subject to alterations such as significant water transfers, heavy urbanisation or flood attenuation by reservoirs.

Antecedent information used within the model can be in one of two forms. Both antecedent rainfall and simple soil moisture estimates are used as indicators of pre-storm catchment conditions. The generic flow estimation model is highly flexible. This is of considerable benefit as it allows the investigation of the effects of using different antecedent indicators and their influence on the estimation of peak flow. These different model combinations are explored in more detail in later sections.

### *5.1.3 Event Based Modelling Development; Generic Flow Estimation for One Catchment*

In simple terms, a flow estimate is obtained by applying a coefficient to the storm rainfall estimate and adding in an estimate of catchment antecedent conditions (also modified by a coefficient). The coefficients are determined by optimisation against the observed flow values over the whole catchment flood record. The aim is to minimise an objective function which calculates the absolute sum of errors between the observed and modelled estimate of the flow. All values are in growth factors for ease of processing; these can be scaled back to their true values using the appropriate RMED (or QMED in case of flow). Growth factors used in this study are median values. Therefore the flood growth factor for a particular catchment is the median annual maximum flood. Growth factors standardise the values used within the model. Therefore, where two catchments of significantly different size are modeled, the flow values used in processing fall within a reasonably small range (compared to using their true values). This is important as it allows for comparison between catchments of different size. Catchment area therefore becomes less of a factor affecting the model results as area and QMED are related. Figure 5.2 shows the relationship between these two variables. The difference (or scatter) shown in Figure 5.2 can possibly be explained by different climatic conditions found across the country. For example, the largest catchment in the set, the Thames, has an area of 9959 $km^2$, a QMED of 329 cumecs and a SAAR of 706 mm. The Tay, which has an area less than half that of the Thames (4586 $km^2$) has a QMED value of 963 cumecs, more than double the QMED value of the Thames. However, the SAAR value of the Tay, is 1425 mm, which perhaps explains the difference in QMED between these catchments. Therefore, scaling by the QMED allows for a comparison between catchments of different sizes, but it does not mean that catchment area can be disregarded after scaling has taken place.

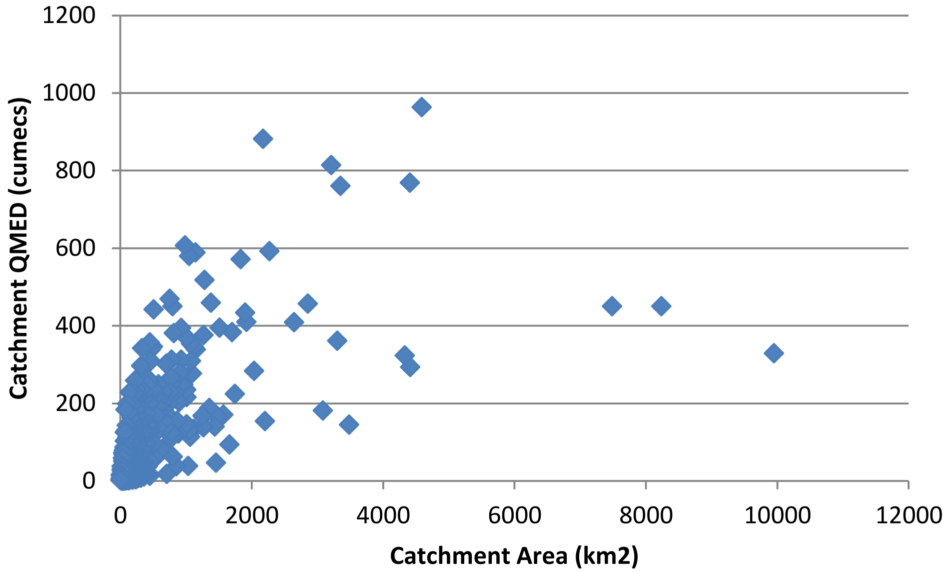



***Figure 5.2*** *Comparing Catchment Area and QMED for the entire catchment set.*

One example of how a flow estimate might be obtained is Equation 5.1 In this case antecedent rainfall is used as the estimator of antecedent conditions.

$$Qest_i = (a \times r_i) + \left(b \times (r_{i-1} + r_{i-2})\right)$$ **Equation 5.1**

*Qest* is the processed flow growth estimate, *a,* and *b* are optimised coefficients, $r_i$ is the storm rainfall growth factor that contributes to the discharge estimate (*Qest*). $r_{i-1}$, $r_{i-2}$ etc represent the rainfall on one and two days before the storm respectively. In practice the above equation could take one of several formulations in order to consider how different blocks of rainfall might capture antecedent conditions, however; this example is presented only in order to illustrate the method. The above equation is applied to all events in the catchment flood record, and the coefficients *a* and *b* are modified at each iteration of the optimisation.

The weights are optimised using the function

$$F = \sum abs(Qobs_i - Qest_i)$$ **Equation 5.2**

This is the sum of the absolute errors between the processed flood estimates (*Qest*) and the true discharge values (*Qobs*). The errors are summed for all events across a single gauged record. The aim is to minimise this function. This approach is preferred as it uses absolute error values. This allows individual events, which may have large estimation errors, to affect the overall error indice. Other error estimation indices such as the RMSE (Root Mean Square Error) use a mean error, which, while still informative, do not allow individual events to affect the overall error indice as much. Normally this would not be desirable; however, in this case it is important to account for individual events which have large estimation errors, as they may cause problems later on in flood frequency assessment. The use of an absolute sum of errors prevents positive and negative errors from cancelling each other out.

The work presented in this chapter uses the Peaks Over Threshold flood data taken from the HiFlows database. These provide a much larger dataset than the annual maximum when testing any flow estimation work. Due to the increased number of events over the annual maximum series the POT data span a wider range of hydroclimatic variation and so provide a more robust test of flow estimation. The generic method described above can be applied to all of the 520 catchments.

### *5.1.4 Model Formulations*

Three different model formulations are tested, with different levels of complexity in the way they estimate the peak flow. Table 5.1 summarises these formulations. One model estimates peak flow using only storm rainfall, one model estimates peak flow using storm rainfall and antecedent rainfall and the third model estimates peak flow using storm rainfall, antecedent rainfall and an estimate of the catchment soil moisture deficit.

| Model ID | Model Formulation | Antecedent Estimator | Number of Coefficients |
|---|---|---|---|
| *1* | *Qesti = a x Storm* | None | 1 |
| *2* | *$Qest_i$= (b x Storm )+ (c x 30 Day Rainfall )* | Rainfall | 2 |
| *3* | *$Qest_i$ = (a xStorm) + (b x 30 day Rainfall-CMD)* | Rainfall and Soil Moisture | 2 |

**Table 5.1** *Summary of Model Formulations used in Assessment. The model ID is used within the results and discussion to refer to individual models.*

The notation is similar to that of Equation 5.1. *Qest* is the estimated flow, *Storm* is the estimated storm as a growth factor, *30 Day Rainfall* is the growth factor of the thirty day rainfall prior to storm arrival and *CMD* is the catchment moisture deficit estimate at the beginning of the 30 day antecedent rainfall period. The assessment and selection of individual model components such as the storm and antecedent rainfall is detailed in Section 5.2.

### *5.1.5 Model Assessment*

A first assessment of the different storm estimation methods uses objective error indices (Equations 5.3 and 5.4), combined with graphical plots and maps of errors. Maps are useful in showing the spatial distribution of errors, whereas the seasonality plots tend to be more useful for interpreting the temporal behaviour of the model for individual catchments.

As this is an event based model, developed to estimate peak flow values, the model is assessed based on its ability to estimate the peak flow from the rainfall information. Errors are expressed in growth factors (standardised by QMED) and represent the differences between the observed and modelled peak flow. Hence, for an event with an error of + 0.5, this means that the model is underestimating the peak flow by a growth value of 0.5. From Equation 5.2 it should be remembered that this error value is the observed minus the estimated growth value. The growth error can be converted to an absolute discharge error by scaling with the QMED value. However, the use of growth factors is preferred as it provides a relatively easy way of comparing errors between catchments whose flow records are composed of significantly different magnitudes.

As the objective function shows, the optimisation method was carried out by using the sum of the absolute differences between observed and estimated flow peaks to develop the coefficients. This error index was used as an indicator of overall optimisation performance for each catchment, modified as shown in Equation 5.3 in order to compare results between catchments.

In order to assess the model between catchments, the error indices should be able to be compared against one another. The objective function as specified in Equation 5.2 was used as an estimator of model performance for the original fitting. On its own, this cannot be used to compare residual errors between catchments, as it is affected by the number of events over which the model is run. In order to allow a direct comparison, the error index as calculated in Equation 5.2 was adjusted to give an average error per event (for each catchment). This can be seen in Equation 5.3

$$F = \frac{\sum abs(Qobsi - Qesti)}{n}$$ **Equation 5.3**

Where *n* is the number of events analysed by the model for each catchment. This method of processing the error index allows for a comparison between catchments, where the record length of individual stations does not impact upon the overall error magnitude. Equation 5.3 is used to assess model performance between catchments and in order to avoid confusion is termed the 'mean error per event'.

$$G = \frac{\sum F}{j}$$ **Equation 5.4**

In certain cases it is not practical to look at the distribution of this mean error per event value for every single catchment, for every different model run. In these cases, the mean of the 'mean error per event' can be calculated, to give a single value for each model run across the entire catchment set (See Equation 5.4). Equation 5.4 outlines this calculation, where j is the total number of catchments modelled. *F* the objective function error from Equation 5.3 for a single catchment. In Equation 5.4 this *F* value is summed across all catchments and then divided by the number of catchments. This index is termed the 'mean catchment error' and is represented by *G* in Equation 5.4. While it is recognised as being a reasonably crude approach, it does provide a fast and easily understandable way of assessing model performance. Throughout the rest of this chapter both indexes are used, as both have relevance.

## 5.2 Model Components

In order to carry out the flow estimation the raw rainfall and flow data require some pre-processing.

### *5.2.1 Storm Estimation*

Different methods of storm estimation are outlined as methods *a* to *d* in the following text. In order to reduce complication, no antecedent term was included; therefore the flow estimation model used only the storm to estimate the peak flow. This allows for a better assessment of rainfall storm estimation methods. The method of estimating peak flow is represented by Equation 5.5. For each method (*a* to *d*) Equation 5.5 was used to estimate the peak flow record.

$$Qest = a \times Pi \qquad \textbf{Equation 5.5}$$

Where *Qest* is the estimated flow, *a* is the optimised coefficient and *Pi* is the storm total estimate, expressed as a growth factor.

#### *(a) Using a single day of flood approach*

The simplest method tested used the day of the peak flow, and the corresponding day of rainfall as the storm that generated it. This method performed reasonably well, however, it does not take account of measurement timing differences and so required modification. As an example, take a flow peak occurring on 2/1/2010. In most historical cases, the time of the flow peak is not known. However if it is assumed that the flow peak occurs close to midnight on 2/1/2010, then using the rainfall day 3/1/2010 may be more appropriate to describe the flood than using 2/1/2010. If the flow peak occurred earlier during the day 2/1/2010 (say around 0900) then it is likely that using the rainfall day ending 2/1/2010 is more appropriate.

***(b) Modified single day of flood approach***

This method assumes no knowledge of the time of the flood peak. It ranks the days of rainfall either side of (and including) the day of the flood by their total. The day with the highest total is then chosen as the single day of rainfall contributing to the generation of the peak flow. This method was developed to try and overcome the problems mentioned in the original single day of flood approach.

***(c) Developing a multiple day estimate of a storm***

Methods (a) and (b) make the simplifying assumption that one rain day only is responsible for producing a flow peak. However, it is acknowledged that a single day's rainfall is not always solely responsible for a peak flow value. Two recent flood events (see Table 5.2) make the case for this quite clearly. Furthermore the discretisation work and storm assessment work in Chapter 3 highlighted the problem of the storm crossing a measurement boundary. Therefore to develop an estimate of a multi-day storm, the days either side of the first estimate of the storm are checked. If their value is above a certain threshold then these days are also included in the storm total.

| **Date** | **Location** | **Event** |
|---|---|---|
| 3-6th August 1997 | Somerset | 280mm rainfall, properties inundated. |
| 5-10th January 2005 | Inveruglas, Loch Lomond | 120mm rainfall resulting in high summer flows. |

***Table 5.2*** *Two examples of documented multi-day rainfall events that have led to flooding. Examples extracted from the Chronology of British Hydrological Events (CBHE), accessed online 17/1/2010.*

The choice of threshold was developed after testing several different storm estimation procedures within the optimisation. What was clear was that different thresholds appeared to have little effect on the overall performance of the optimisation. The value of 0.5 RMED (for each individual catchment) was chosen as it allows for the different climatological conditions found in the United Kingdom. This is a scaling by the median maximum rainfall for each individual catchment, therefore the threshold will vary by catchment depending upon the rainfall characteristics. Initial choices of fixed thresholds using arbitrary values such as 5, 10 and 20 mm of rainfall do not reflect the varied climatological conditions found if they are applied as a constant over all catchments. Using a value dependent on the rainfall characteristics of the catchment accounts for the geographic spread of what might be considered 'important' rainfall.

***(d) Using Date, Time and Time to Peak to estimate storm***

The rationale and method behind this approach has already been introduced in Chapter 3 (see Section 3.6). This approach was introduced in order to provide a framework to make better use of information on the time of occurrence of the flow peak. After several initial runs it was clear that this approach was not producing results that were any better than the two simpler methods described in (a) and (b) above. It is perhaps indicative of the number of simplifying assumptions that this approach makes which cause it to perform so poorly. In particular the use of a fixed time to peak for all events as well as assuming a fixed duration storm and fixed storm shape mean that there is little flexibility in the method to deal with variation in storm and catchment characteristics.

All methods introduced (in *a* to *d*) were tested. Three methods – the 'single day of flood' estimate, the 'modified single day of flood' estimate and the multiple day estimates were chosen for assessment. The approach using the time of day of flood was discarded, as it was not possible to use this over the entire catchment record. This is due to peak flow timings only being available for short periods of record and then only in some catchments. In order to assess the performance of each method in estimating peak flow, Equation 5.5 was used to estimate peak flow.

By ignoring antecedent conditions, a true assessment of the different methods of estimating a storm could be made. It is expected that further work on antecedent conditions will have less of an impact on the overall model performance than getting the estimate of the storm rainfall right.

The results of running the model (Equation 5.5) for the three storm estimation methods are shown in Table 5.2. The values refer to the objective function error from the optimised run (see Equation 5.4). As previously introduced, this is the sum of absolute errors between the observed and modelled peak flows divided by the number of peak flow events. It can therefore be thought of as a measure of mean error within the peak flow estimation model. The mean and standard deviation are computed across all catchments in the set to give the values in Table 5.3 (as described by Equation 5.4). These are proposed as simple, but effective, measures of the validity of each storm estimation approach.

| **Storm Estimation Approach** | **Mean Error** | **Standard Deviation** |
|---|---|---|
| Single Day of Flood | 0.48 | 0.14 |
| Modified Single Day of Flood | 0.35 | 0.14 |
| Multiple Day Estimate | 0.34 | 0.13 |

***Table 5.3*** *Comparing mean catchment error indices for the different storm estimation methods. Errors are in growth factors.*

It is clear that timing information is important. Table 5.3 suggests that by assuming that the date of the peak flow occurs on the same day as the storm rainfall (i.e. the single day of flood approach), poorer performance is seen in the peak flow estimation model. A slightly more sophisticated method is to use the heaviest day's rainfall (i.e. the modified single day of flood approach). The multiple day method, while a slight improvement over the modified one day method, does not significantly improve results. However, by capturing more of the important contributing rainfall it is clear that it too is capable of characterising the storm.

In terms of future work, using either a multiple day estimate or a modified single day estimate of the storm rainfall is suggested as being the best way forward. While neither capture longer duration storms (i.e. 5 day), this problem can be dealt with separately by the inclusion of antecedent rainfall estimates. This work is necessary to provide a basis for the future development of a more complex model incorporating antecedent conditions. Collier and Hardaker (1996) suggest that the majority of the heaviest UK rainfall events fell within 8 hours, although these are more likely to be associated with convective fronts. Depression type systems have the potential to be much longer lasting and these provide the main mechanism for multi-day storms within the UK.

The work carried out as part of the storm estimation process takes an alternative approach to that of many studies. By selecting the storm based on the timing of the flood (i.e. using the same or previous day's rainfall) it can be reasonably assumed that the majority of the flood generating storm is captured. This may not be the case if an approach was used where storm events are selected based on their rainfall characteristics only. In this case many storms might be selected which do not result in a flood event. In many design event based modeling studies, the selection of a design rainfall is often one of the first steps in order to develop a flood estimate of a particular magnitude and frequency (see Kjeldsen, 2007 for an example). One of the important aspects of the model development presented in this chapter is the link between observed flood events and the storms that generated them. In some respects the use of the date of flood to estimate the storm could be seen as a backwards step, as evidently any predictive work will not have access to flood dates. Predictive work is considered separately later in the thesis, however, for the present work the storm estimation procedure is considered to be adequately specified for the purposes of this work.

### *5.2.2 Optimisation Methods*

As previously explained, the optimisation method used here finds the coefficients used to modify the storm rainfall and antecedent rainfall growth factors in order to estimate a flow. The scientific computing literature on optimisation is vast, here, a justification for the approach taken to optimisation is presented. For generic background information on optimisation the reader is referred to a book such as Miller (2000).

During early formulations of the flow estimation method developed here, simple gradient algorithms were involved such as the simplex method (see Miller, 2000 p.316 for more detail). Optimisation routines, as with all other processing, were carried out using the R statistical programming language. In the case of the optimisation, one of the early trialled methods was a box-constrained implementation of the Nelder-Mead algorithm (Zhu et al., 1997). Using a flow estimation model with two coefficients, weighting the storm and 30 day rainfall respectively it was found that the optimisation methods chosen were not only slow, but they failed to find the global optimum. Algorithms such as the Nelder-Mead are disadvantaged by the fact that they can end up finding local rather than global minima, although this is generally compensated for by a faster computational time. Versions of the Nelder-Mead designed to avoid local minima are available, but have not been developed for use within the R language as yet.

Therefore, the optimisation method chosen for the majority of the work presented here uses a genetic algorithm (GA) to develop the weights. The specific algorithm used is the Differential Evolution (DE) optimisation algorithm (Mullen et al., 2009). This method is implemented in R through the use of the package DEoptim. This was adopted after trialling several different methods such as gradient and line search techniques. Genetic algorithms tend to be better at finding global optima than some other line based search techniques, although the computational time can be heavy depending upon the application.

### *5.2.3 Antecedent Rainfall Estimation*

Several researchers have noted the importance of catchment antecedent conditions in altering peak flow volumes (See Beven,1993). The estimation of the optimal antecedent rainfall window length was undertaken by assessing the mean catchment error indice against the length of window used in flow estimation. Peak flow estimation was undertaken using model 2 in Table 5.1, varying the length of the antecedent window. The flow estimation model was run several times with different antecedent window sizes in order to estimate the optimal window length from Figure 5.3. At around 30 to 40 days worth of antecedent rainfall, there is very little improvement in the model mean error relative to extending the antecedent rainfall window.

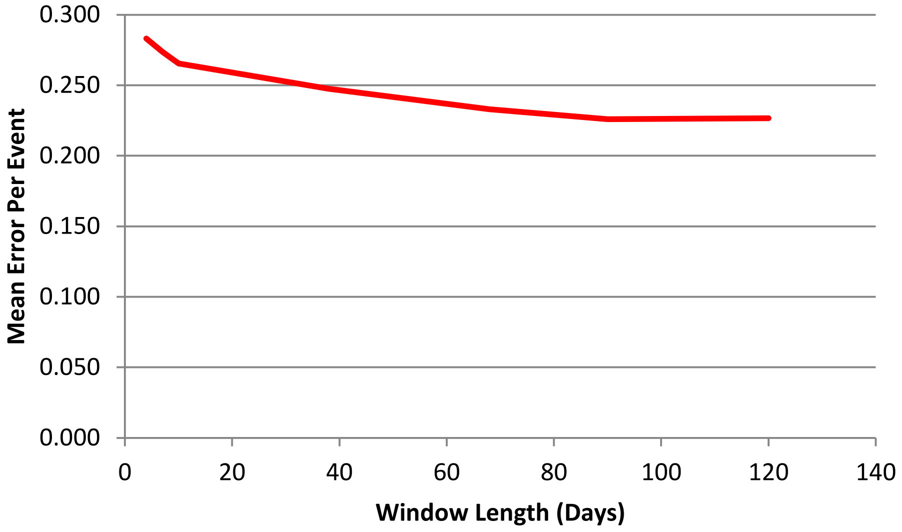



***Figure 5.3*** *Plot showing the relationship between the total length of the antecedent window used and the mean error in the growth value for each flow event.*

### *5.2.4 Soil Moisture Model Definition and Construction*

The catchment soil moisture deficit was created as a time series from which the catchment moisture deficit linked to the flood generating storm could be extracted. The model development has made extensive use of the ReFH approach (Kjeldsen, 2007), although it is not as complex as the ReFH model itself. The ReFH design event method uses regression equations to estimate the design soil moisture for its event based model (see page 33 of Kjeldsen, 2007). These regression equations have been developed from estimates of soil moisture time-series, details of which can also be found in Kjeldsen (2007, p 58). The soil moisture time-series for the ReFH are more complex, involving differential equations to model soil moisture for three different soil zones.

The relatively simple soil moisture balance model developed as part of this work includes a precipitation, evapotranspiration and a drainage term (k). Figure 5.4 provides a conceptual outline of the model.

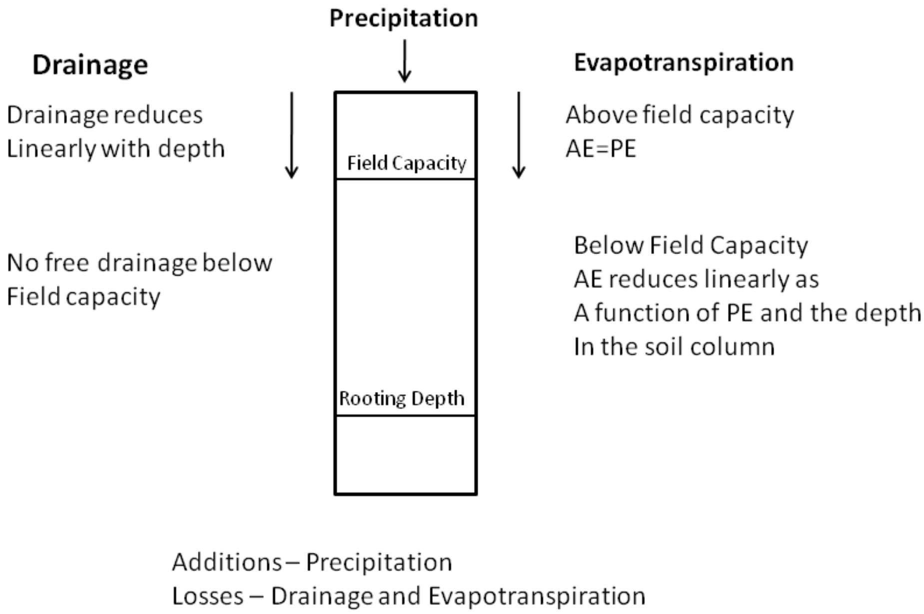



***Figure 5.4*** *Conceptual model of Soil Moisture (after ReFH)*

The soil moisture deficit on any particular day is a result of the preceding day's soil moisture, plus the rainfall, minus the evapotranspiration and a drainage component. Equation 5.6 states the first approximation of the Catchment Moisture Deficit (CMD) in mm.

$$CMD_i = CMD_{i-1} + P_i - AE_i - FC \times k \qquad \textbf{Equation 5.6}$$

$CMD_1$ is set to 0 at the beginning of the time series, occurring on the calendar date of the 1st January. This will be realistic for most catchments at this time of year. $P_i$ is the precipitation occurring at time step *i*. $AE_i$ is the actual evapotranpiration at time step *i*. *FC* is the Field Capacity and *k* is the drainage coefficient. The FC is a value in mm designed to approximate the saturated water storage in the soil column. The overall soil moisture balance equation is broadly similar in concept to that of Kjeldsen (2007,p.58) however, the solution of this equation is simplified. Actual Evapotranspiration is dependent upon the soil state of the previous days calculation. *AE* is considered to be at the potential rate down to a specified rooting depth (Kjeldsen, 2007). Below this, *AE* reduces as follows:

$$AE_i = \frac{CMD_i}{RD} \times PE_i$$ **Equation 5.7**

(From Kjeldsen, 2007, p.17)

Rooting depth (RD) is calculated as a function of field capacity, as taken from the ReFH method. Therefore rooting depth can be calculated as:

$$RD = 0.3FC$$ **Equation 5.8**

(From Kjeldsen, 2007, p.16)

Where the Field Capacity is calculated as:

$$FC = 49.9PROPWET^{-0.51}BFIHOST^{0.23}$$ **Equation 5.9**

(From Kjeldsen, 2007, p.16)

Potential Evapotranpiration $(PE_i)$ is calculated as a catchment average. For the period under study, catchment average potential evapotranspiration on an annual average basis has been calculated using the EARWIG software (see Kilsby et al., 2007 for details). To estimate the PE on a specific Julian Day, suitable for the time series model presented here, the Annual Average PE values have been distributed using a sine function, as recommended in Kjeldsen (2007,p.13). This function is:

$$Ep_i = \propto \left(1 + sin\left(2\pi \frac{i-90}{365}\right)\right)$$ **Equation 5.10**

Where *i* is the Julian day and *i*=1 would be the first of January.

In the case where the soil moisture deficit is less than the field capacity:

$$CMD_{i-1} + P_i - Ep_i < FC$$ **Equation 5.11**

then the soil moisture can simply be calculated as

$$CMD_i = CMD_{i-1} + P_i - Ep_i$$ **Equation 5.12**

As the solution assumes no free drainage below field capacity, there is no need for a drainage term if Equation 5.11 is valid. Absolute drainage reduces as the soil moisture content also reduces when above field capacity. While the above formulation calculates drainage using a multiplication factor (k, range[0,1]), this can be thought of as a specified mm of drainage per day, reducing as the soil moisture content approaches FC.

The drainage parameter (*k*) is calculated by optimising a single drainage parameter across the whole time-series. For all catchments the initial *k* value at the start of the optimisation is set to 1 (this assumes soils at or near saturation due to early winter rainfall). This value is then modified and, at each iteration of the optimisation, the indices PROPWET and SMDBAR are calculated for the time-series and checked against the catchments corresponding values in the FEH catchment descriptors data set.

PROPWET is the proportion of the time the catchment moisture deficit was less than 6mm during the period 1961-1990. It is an index calculated from the MORECS model and it essentially describes, on average, how wet or dry a catchment is. SMDBAR is the mean soil moisture deficit (in mm) for the catchment for the same time period.

The drainage parameter has an important controlling influence on drainage when the catchment is wet, as proportionally this is the time when the *k* factor has the largest influence. Once it gets closer to FC, it removes less water due to the lower soil moisture content.

### *5.2.5 Assessment of the Soil Moisture Estimates*

There are a number of other models/indices that these soil moisture indices could be tested against. For example the soil moisture deficit time-series could be directly assessed against a commercially available product such as MORECS. However, when testing against other model results it is difficult to tell if any mismatch is the result of a true error in the estimate of soil moisture or simply a different (but entirely appropriate) model structure. Because other models such as MORECS have not been validated against field data (as this is not possible due to the reasons discussed earlier) it cannot be assumed that they are entirely accurate. For the purposes of this model, the test of the soil moisture deficit estimates are in how well they estimate the flow and whether there is any improvement over the approach using only antecedent rainfall. It is debatable as to how appropriate it is to optimise the drainage parameter against the MORECS derived SMDBAR and PROPWET values as well as incorporating the FC and RD values from ReFH. However, given the lack of any large scale data sets available for either calibration or validation, using these indices is more appropriate than simply developing a model without reference to them at all.

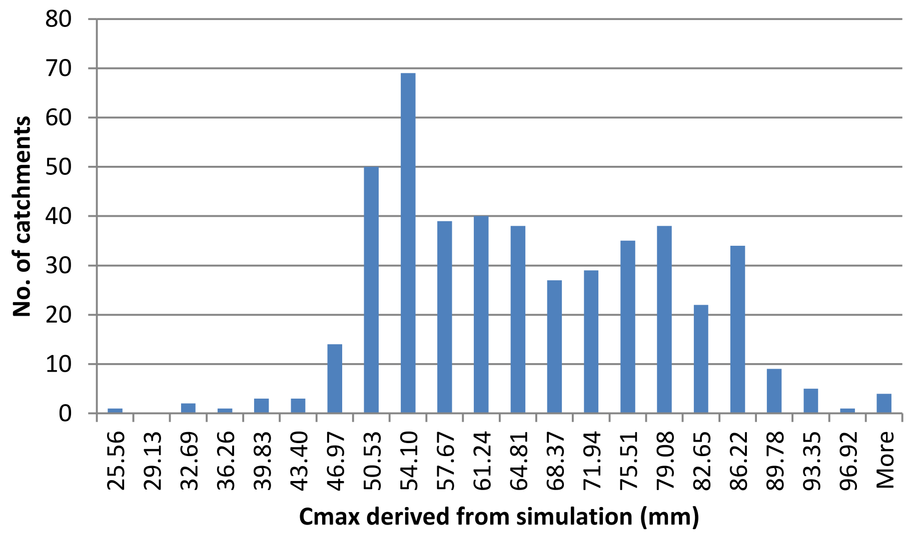



***Figure 5.5*** *Histogram of the Cmax values (in mm) from simulation. Cmax is the maximum soil moisture deficit possible in the catchment.*

Figure 5.5 shows the Cmax values from simulation. Cmax is the maximum soil moisture deficit possible. Relative to other methods, such as the ReFH the values here would appear to be low. This is a direct result of the model structure, as the FC value more or less defines the range which the soil moisture values take, and the FC values tend to be relatively low. However, the general pattern is similar, with small sets of catchments taking very low and high values and the majority of catchments falling in between.

### *5.2.6 Comparison of Soil Moisture Estimates and Inclusion into the Flow Estimation Equation*

The drainage parameters do not alter much, the lowest value being around 0.86, with the majority of values around 0.97-0.99. Therefore there may be a case for averaging the drainage term at around 0.9 in the way that the ReFH does.

In creating the soil moisture deficit time-series the optimisation objective function aims to reduce the sum of the errors between the FEH and simulated PROPWET and normalised SMDBAR values. Resultant errors are minimal. It is not worth worrying about small errors, considering the possible errors in the original model used to derive these properties.

Figures 5.6 and 5.7 show indices of PROPWET and SMDBAR as calculated from the generated soil moisture time-series. The values shown have been scaled to the range [0,1] for both the FEH and time-series values to allow for easier comparison. The FEH model is formulated in a slightly different way, and therefore scaling both outputs to the same range allows a relative comparison of results. Any remaining absolute difference can be dealt with in optimisation through the alteration of the coefficients. As Figures 5.6 and 5.7 show, indices of PROPWET and SMDBAR as calculated from the generated time-series compare reasonably well with the corresponding FEH values. These results do not mean that the soil moisture model is accurate, but it goes some way to showing that the time-series it produces have characteristics similar to other well used models.

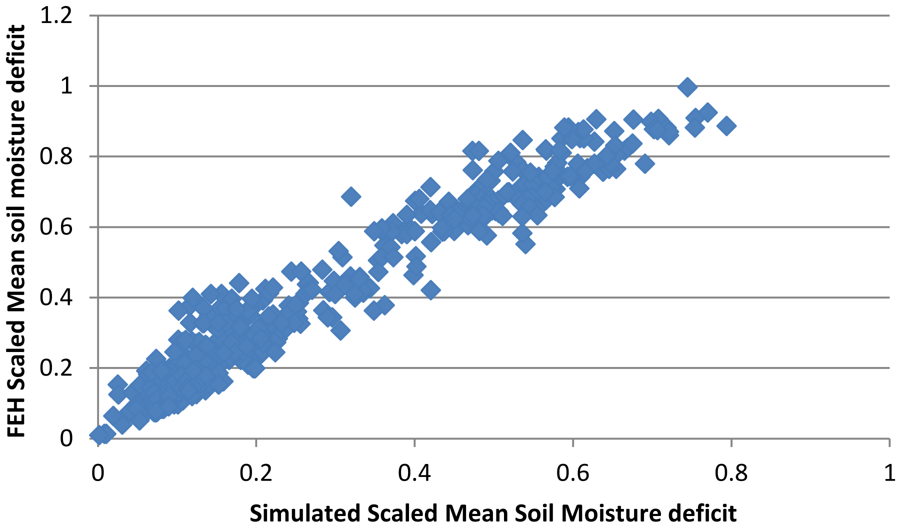



***Figure 5.6*** *Compares normalised mean soil moisture values from the model to FEH estimates (SMDBAR).*

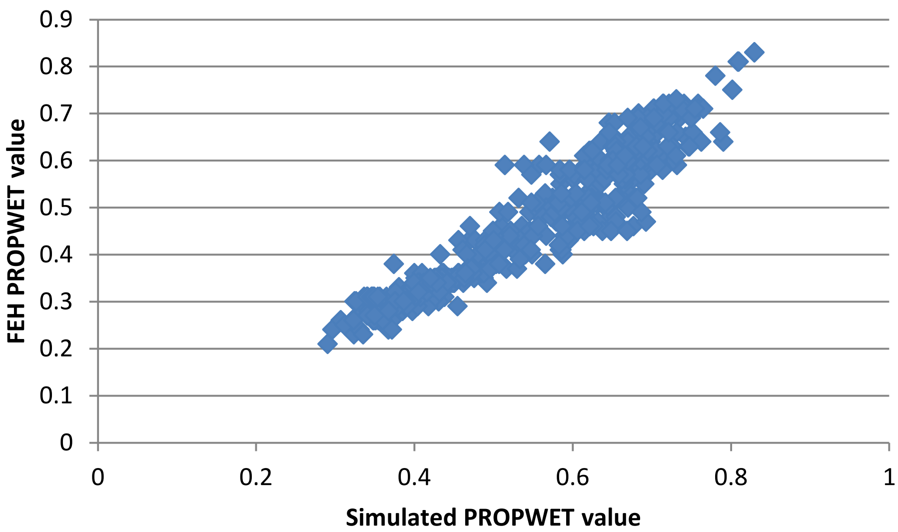



***Figure 5.7*** *A comparison of PROPWET values from the soil moisture model to FEH PROPWET values.*

To provide a comparison with the storm + 30 day rainfall only approach the soil moisture deficit model formulation followed a similar approach to that of model 2 which uses only antecedent rainfall as its antecedent conditions estimator. CMD refers to the Catchment Moisture Deficit estimate, with the CMD model referring to the flow estimation model that incorporates the antecedent soil moisture deficit estimate.

The CMD formulation takes the same blocks of rainfall as that of the model using only antecedent rainfall. However, the estimated antecedent moisture deficit at the beginning of the summed blocks (i.e. 30 days prior to storm arrival) was subtracted from the 30 day total. Two coefficients were still applied to these blocks, one to the storm estimate and one to the antecedent conditions estimate. It was felt that the inclusion of some measured local information on antecedent rainfall would provide benefits over simply using the catchment moisture deficit estimate in conjunction with the storm rainfall.

## 5.3 Peak Flow Model Results

The development of the model components is a necessary first step in testing different model formulations for peak flow estimation. These models are assessed with regards to their spatial and temporal performance, using both plots for visual assessment and simple statistics as a numerical comparison.

### *5.3.1 Spatial Comparison of Model Results*

The first assessment of model results compares model performance between catchments. For each of the three models, the mean error per event has been calculated and plotted on a map. These errors are classified by colour to allow the identification of any pattern to the spatial distribution of error.

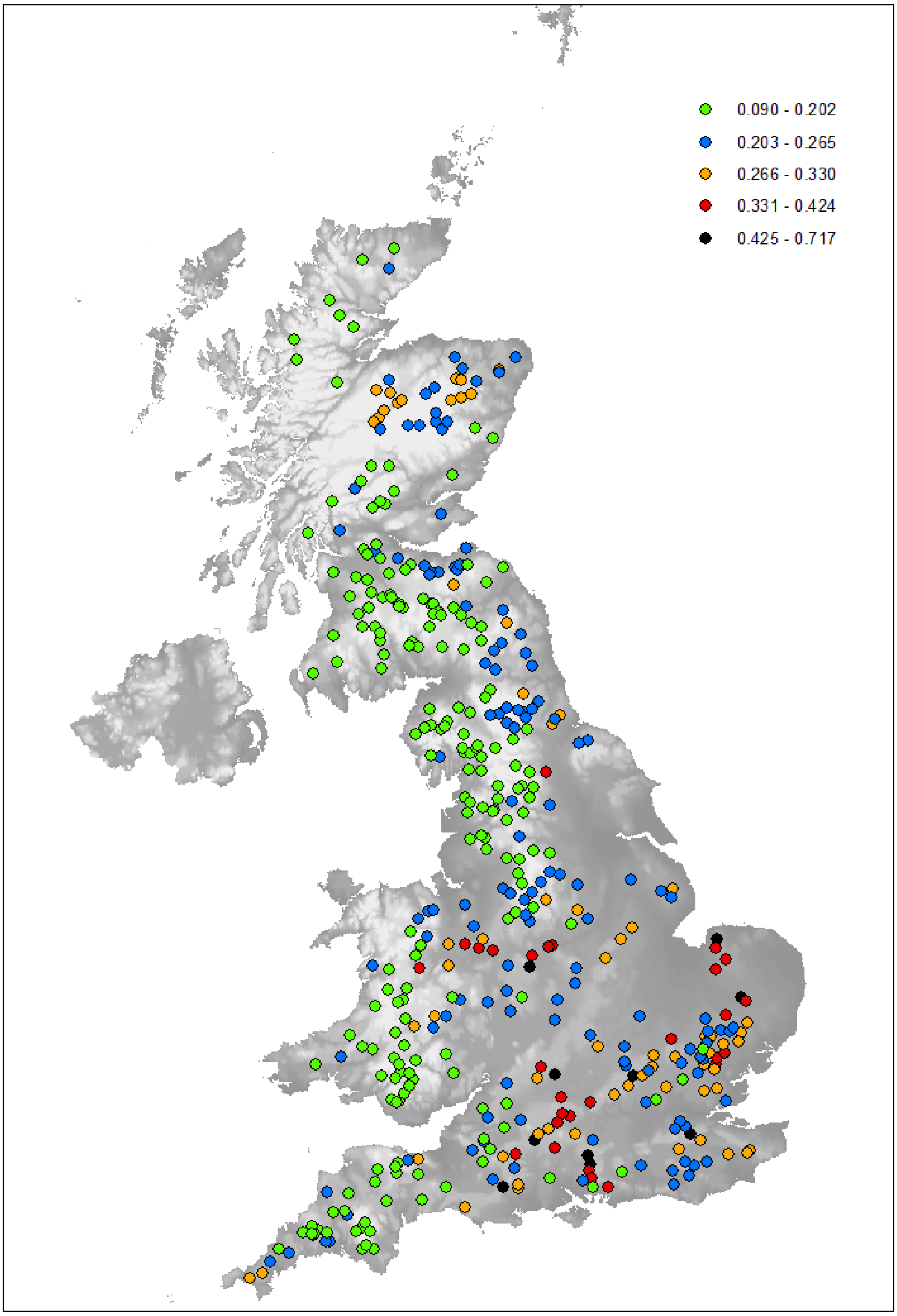



***Figure 5.8*** *The Distribution of Peak Flow Model Errors for the Storm only Model.*

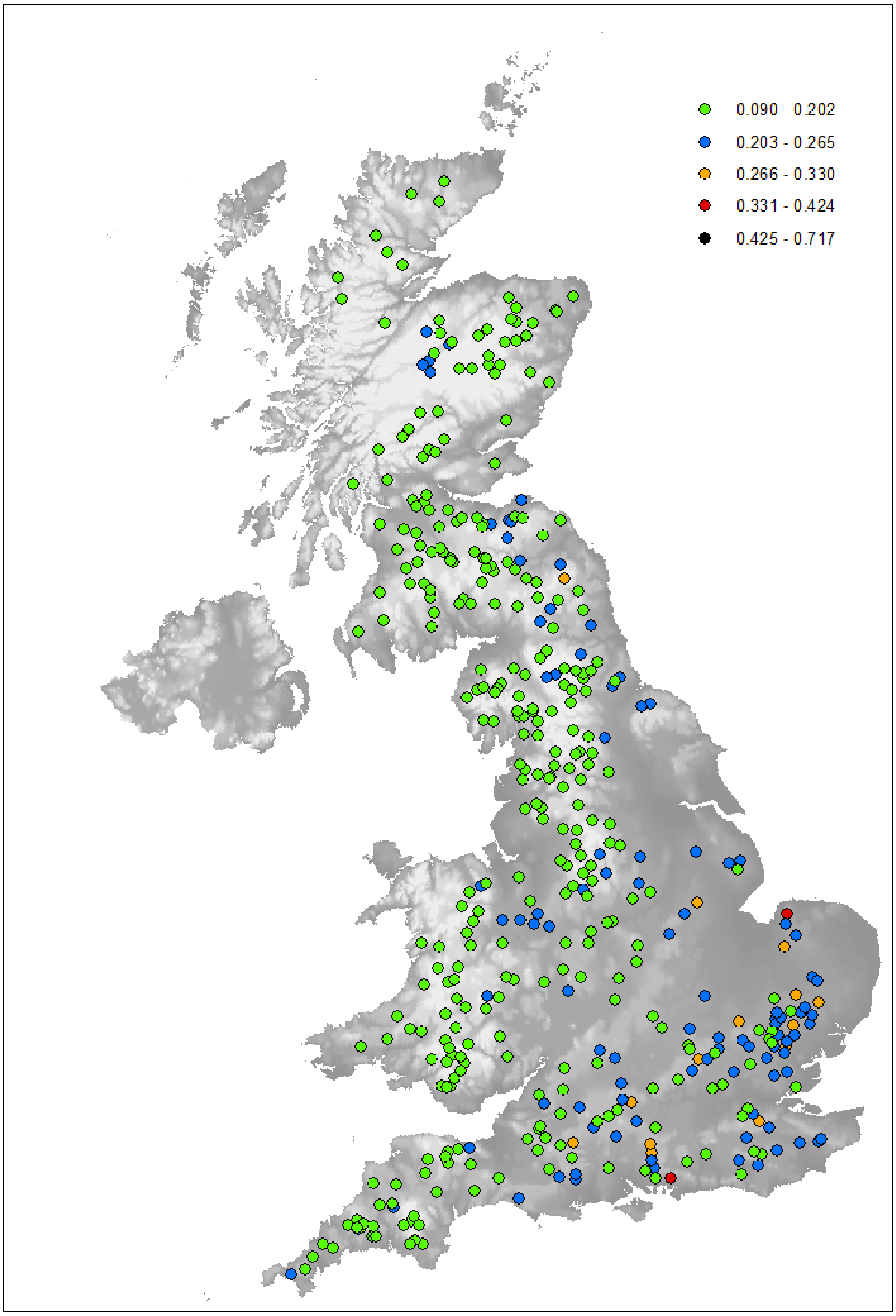



***Figure 5.9*** *Colour coded error indices of model performance. Error values are the 'mean error per event'. The model formulation incorporates antecedent rainfall.*

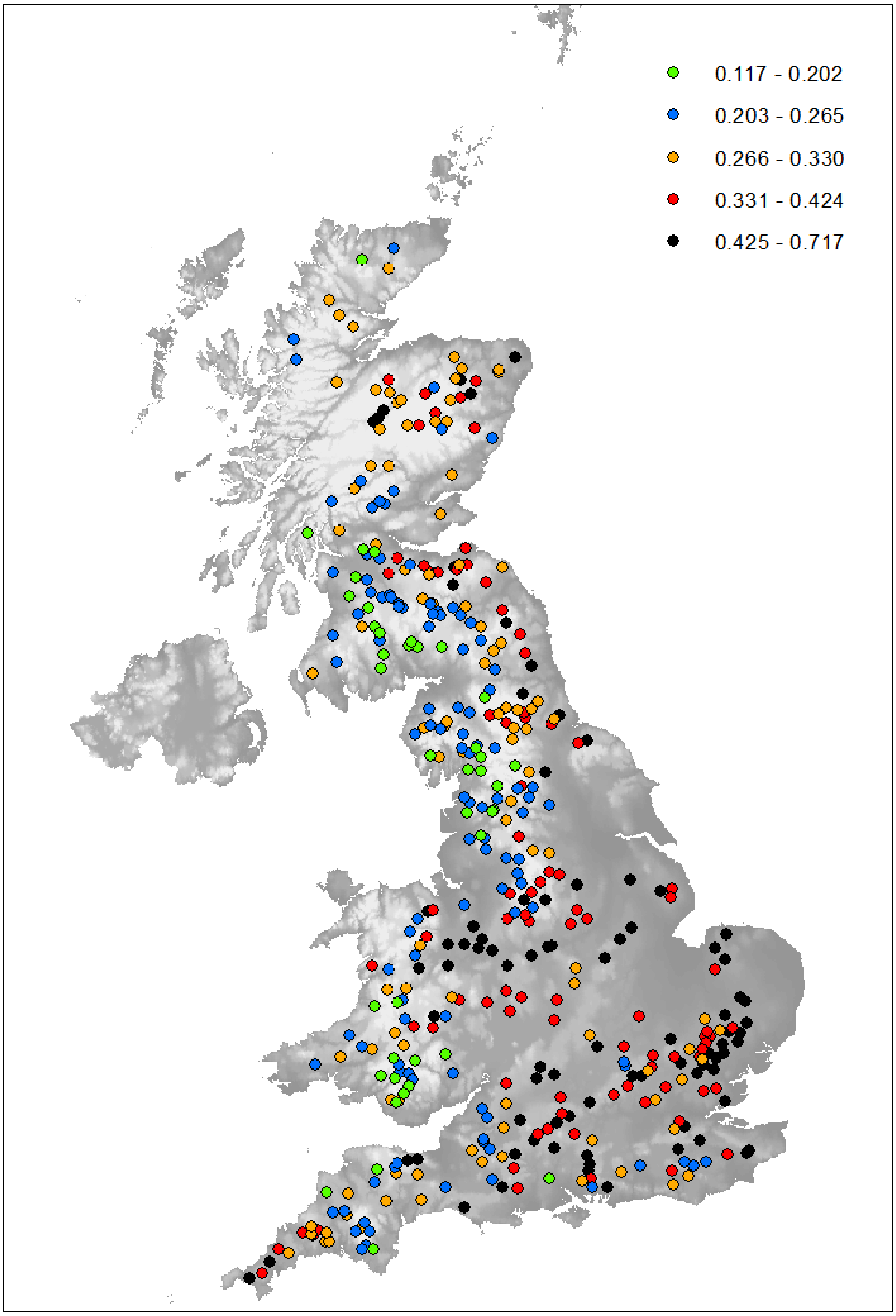



***Figure 5.10*** *Error indices from the model run incorporating the catchment moisture deficit estimations. Error values are the 'mean error per event'.*

Figures 5.8 to 5.10 give an overview of how the model performs across the whole catchment set for the three different model formulations. Results are colour coded for ease of viewing, with the graduation from green, blue, orange, red through to black signifying decreasing model performance.

In comparing the three maps, there are some similarities which can be drawn. To some extent, the pattern of performance is replicated across the three maps, with the worst performing catchments clearly identifiable in the south and east of the UK. This in part reflects the catchment characteristics. Catchments in the South and East tend to have higher HOSTBFI values (see map of HOSTBFI in Appendix A.2). This area is also one of the driest in the UK, which may contribute to higher soil moisture deficits impairing model performance. There is a clear east-west divide in the ability of the model to estimate the catchment peak flow record. Catchments in the west of the UK tend to experience higher rainfall due to prevailing westerly weather systems, and also tend to experience lower annual average temperatures compared to the east. Furthermore, western areas tend to have thinner, more impermeable soils, with much of the east of the UK having thicker, more permeable soils which can exhibit marked differences in runoff response (Boorman et al., 1995).

The maps are not however, identical. Figure 5.8, showing the spatial distribution of the error for the storm only model appears to show a considerable grouping of catchments by error. This grouping pattern is not replicated to the same extent in either of the maps showing models using antecedent conditions estimators. It is likely that the storm only model shows not only where storm estimation can estimate flow well, but also it identifies those catchments where antecedent conditions play a considerable role in flood generation. This pattern is then not replicated in further plots as the models may have accounted (to some extent) for antecedent conditions.

These patterns tend to suggest that it is possible to understand in which areas the peak flow estimation models will perform well compared to areas where it will not work. Furthermore, the areas where the models perform well tend to have a particular set of characteristics which can give a guide as to how well the peak flow estimation model will work.

The general pattern is evidently susceptible to exceptions. As Figure 5.9 shows, the north-east of England has two catchments which perform particularly poorly, and it is not clear why this is the case. Part of the perception of poor performance when looking at the map may be due to the error classification boundaries used. It may be that the two worst catchments in the north-east on the map are in fact not particularly far away from the next map colour class. While there may be some limitations to what these maps can show, they are valuable in order to examine the spatial patterns of extreme rainfall and flooding.

### *5.3.2 Temporal Assessment of Model Performance*

Assessing the spatial distribution of error indices is useful in gaining an understanding of the relative performance of the model across the UK. However, the error indices used are reasonably crude, and give little detail as to how well the peak flow estimation models perform temporally. Furthermore, the error indices used in the maps are not particularly easy to interpret in an absolute sense, and so they are only useful for a relative comparison against other catchments. Therefore, to investigate the model results in more detail, a comparison of the three model's performance throughout time was undertaken.

To assess the temporal performance of the model, plots of the growth error (i.e. observed-modelled growth values) associated with each peak flow event and the Julian day on which that event occurred are presented. Due to the objective function used, positive errors suggest an underestimation by the model, whereas negative errors suggest an overestimation. These plots help to assess whether there are any seasonal patterns to the error signal. For several different catchments, all three model runs are shown; the storm only model (model 1), the antecedent rainfall model (model 2) and the soil moisture estimation model (model 3). The error plots show the difference between the growth factor of the measured flood peak and the estimated or modelled flood peak. This error is then plotted against the Julian day on which the event in question occurred.

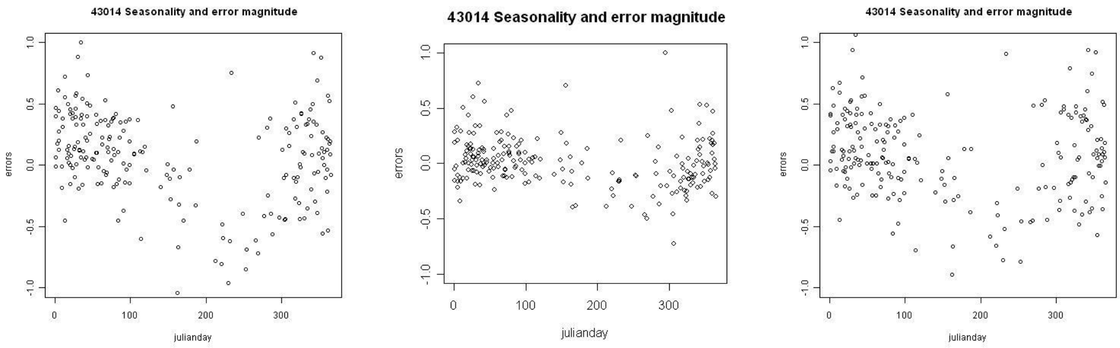
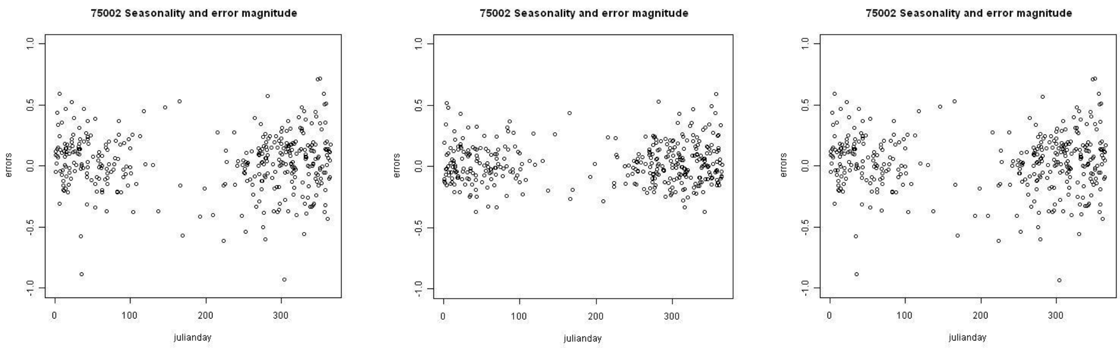



***Figure 5.11*** *The East Avon @ Upavon (South-West). From L-R, Shows the storm only approach, the storm and antecedent rainfall approach and the storm, antecedent rainfall and soil moisture deficit approach.*




***Figures 5.12*** *The Derwent (NW-England). From L-R, Shows the storm only approach, the storm and antecedent rainfall approach and the storm, antecedent rainfall and soil moisture deficit approach.*

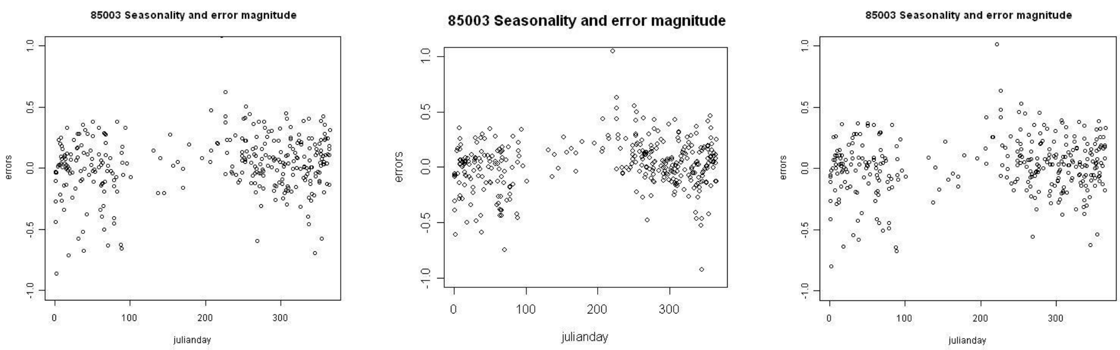



***Figure 5.13*** *The Falloch @ Glen Falloch (West Scotland). From L-R, Shows the storm only approach, the storm and antecedent rainfall approach and the storm, antecedent rainfall and soil moisture deficit approach.*

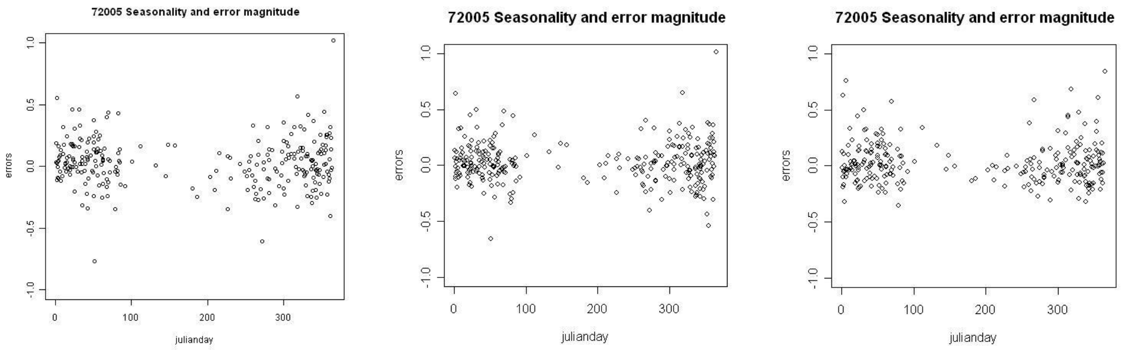



***Figure 5.14*** *The Lune @ Killington (North-west England). From L-R, Shows the storm only approach, the storm and antecedent rainfall approach and the storm, antecedent rainfall and soil moisture deficit approach.*

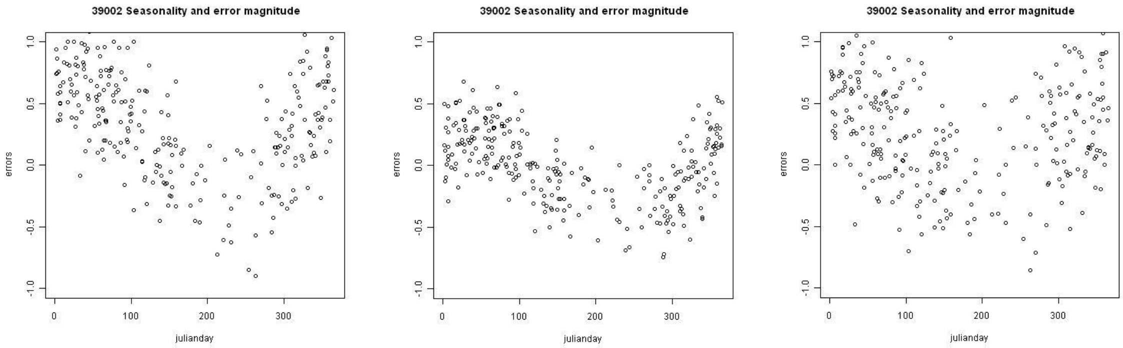



***Figure 5.15*** *The Thames@ Days Weir (South England). From L-R, Shows the storm only approach, the storm and antecedent rainfall approach and the storm, antecedent rainfall and soil moisture deficit approach.*

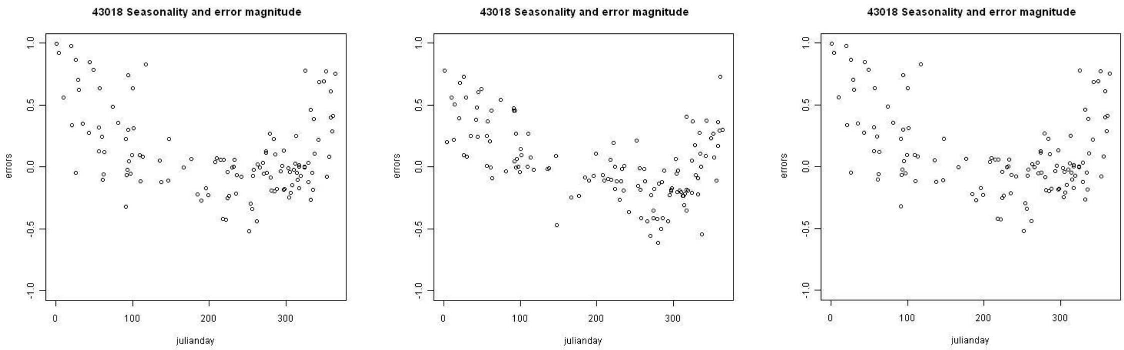



***Figure 5.16*** *The Allen @ Walford Mill (South-west England) From L-R, Shows the storm only approach, the storm and antecedent rainfall approach and the storm, antecedent rainfall and soil moisture deficit approach.*

Figures 5.11 to 5.16 give a general impression of how the three different model formulations perform. Y-axis errors are differences in growth factors between the measured and modelled flows. Generally, models 1 and 3 demonstrate more scatter in their temporal error distribution compared to model 2 where the errors are more constrained. Comparing these plots is illustrative, as it shows the benefit of adding information on antecedent rainfall conditions in to the model estimation of flow. If no improvement in the error spread was seen between models 1 and 2, then simply using the storm rainfall as an estimate of the flow peak would be the best option. It is also the case that, in general, model 3 consistently demonstrates more scatter in error distribution compared to the other two modeling formulations. This suggests that the addition of catchment moisture deficit estimates has not significantly improved the model estimation of peak flow.

The plots give a good indication of how well the flow estimation model performs seasonally. For Figures 5.11, 5.15 and 5.16 there is a pronounced dip to the error scatter, occurring in mid to late summer (around Julian Day 250-300). This is likely to be caused by antecedent conditions during the summer, when rainfall is less effective. The overestimation of peak flow events during the late summer period is likely to be caused by a lack of seasonal information within the model structure. This occurs despite the addition of soil moisture deficit estimates which further suggests that these estimates have not adequately captured catchment antecedent conditions.

Figures 5.11 and 5.12 show another seasonal aspect of model performance. The Derwent (Figure 5.12) has a relatively low HOSTBFI value (0.437) compared to the Avon (Figure 5.11). Both the Avon and the Derwent show a general constraining of the error scatter for model 2, compared to model 1 which shows how adding in the antecedent rainfall information to the model can help in the estimation of peak flows compared to using the storm only model. However, in the case of the Derwent, it does not appear to suffer from the seasonal difference in errors like the Avon. In terms of flood seasonality in the Derwent, winter flooding predominates. Because of this seasonal shift in flood dominance, it is likely that the range of antecedent conditions for flooding that the Derwent experiences are limited compared to the Avon. In terms of performance, the Derwent is one of the better performing catchments. Figure

5.12 is illustrative of this, where the events occur in winter months and tend to be bunched around relatively low model errors.

Figures 5.15 (Thames) and 5.16 (Allen) show two cases where the implementation of the three model formulations shows a seasonal signal to the error distribution throughout the year. Both catchments have a low annual rainfall (c.700-850 mm/year) and a high HOSTBFI (c. 0.65-0.8). It is suggested that within these catchments, antecedent rainfall and antecedent soil moisture is not capable of adequately representing the catchment conditions prior to storm arrival. The reason for this is suspected to be due to antecedent conditions not being adequately characterized by the soil moisture deficit or antecedent rainfall. In these catchments it is suggested that groundwater levels may have a significant effect on flood generation.

In order to understand how individual catchment plots (such as those shown in Figures 5.11 to 5.16) relate to the wider performance of the model, the results for individual catchments are summarised in Table 5.4.

| Gauge ID | Catchment | Error | Colour Code |
|---|---|---|---|
| 43014 | East Avon | 0.17 | Green |
| 75002 | Derwent | 0.12 | Green |
| 39002 | Thames | 0.34 | Red |
| 43018 | Allen | 0.27 | Orange |
| 85003 | Falloch | 0.16 | Green |
| 72005 | Lune | 0.13 | Green |

**Table 5.4** *Mean error per event values and colour codes relating the temporal plots in Figures 5.11 to 5.16 to the map of spatial errors in Figure 5.9. This is for model 2 only, the model incorporating antecedent rainfall.*

### *5.3.3 Statistical Comparison of Model Performance*

Table 5.5 summarises the three key model formulations used within this chapter along with average error statistics. They include flow estimation models using the storm only, a model incorporating antecedent rainfall and a model incorporating antecedent rainfall and the catchment moisture deficit estimates.

| Model Run | Mean Catchment Error | Standard Deviation |
|---|---|---|
| Single Day of Flood Model | 0.227 | 0.069 |
| Antecedent Rainfall Model | 0.179 | 0.043 |
| CMD Model | 0.219 | 0.061 |

**Table 5.5** *The results of using different model formulations to estimate flow. Error statistics are calculated across all catchments in the set (mean catchment error).*

These summary statistics again highlight that the incorporation of estimates of antecedent soil moisture have not had the desired effect of reducing the objective error. In comparison to the model run using only antecedent rainfall, the run incorporating soil moisture information appears to show poorer results. The general pattern of performance across the UK is the same, with the higher HOSTBFI catchments showing an increase in error between the two runs.

Figure 5.17 shows the errors presented in Figure 5.9, as a histogram. This shows the statistical distribution of errors, and provides a good basis for assessing the performance of different methods by the shape of their histograms. Simple statistics such as the mean and standard deviation, computed as a single value across all catchments, may not always give the most informative view of how different methods perform. Mean values can stay the same, yet a significant change in the distribution of error can occur. It is for this reason that assessing the distribution of error is worthwhile.

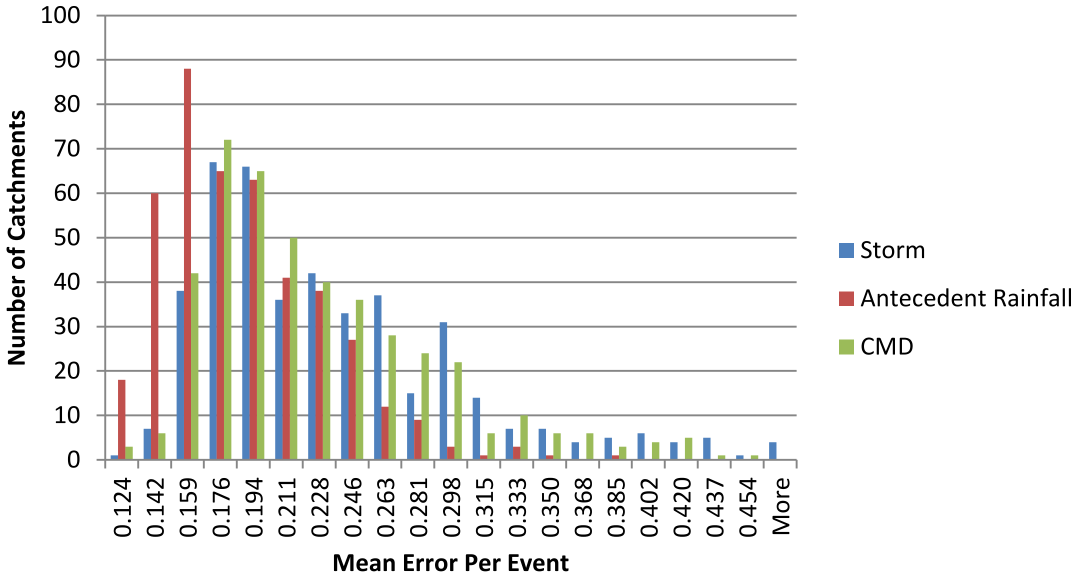



***Figure 5.17*** *The distribution of mean errors per event across the whole catchment set using the three different model formulations.*

### *5.3.4 Explaining Model Performance*

From the work shown in previous sections, there is little improvement in the flow estimation model error statistic when using the soil moisture deficit model formulation. It is possible that capturing antecedent conditions in flashy upland catchments is easier. However, the CMD model does not capture the complex regime of flooding that occurs in groundwater based catchments, where groundwater (in addition to soil moisture) plays a large role in flood generation. This limits the possible improvement that can be made to peak flow estimation with the use of the current antecedent estimates.

Figure 5.18 shows how mean error statistics can take high values in catchments with a high HOSTBFI. Figure 5.18 also illustrates the generally poor relationship between individual PCDs and model performance. While it may be possible to estimate which catchments perform the worst, it is difficult to separate the rest of the catchment set based on a single indicator such as HOSTBFI. This is perhaps due to the complex interplay between many catchment physical features and flood generation which are difficult to represent using PCDs.

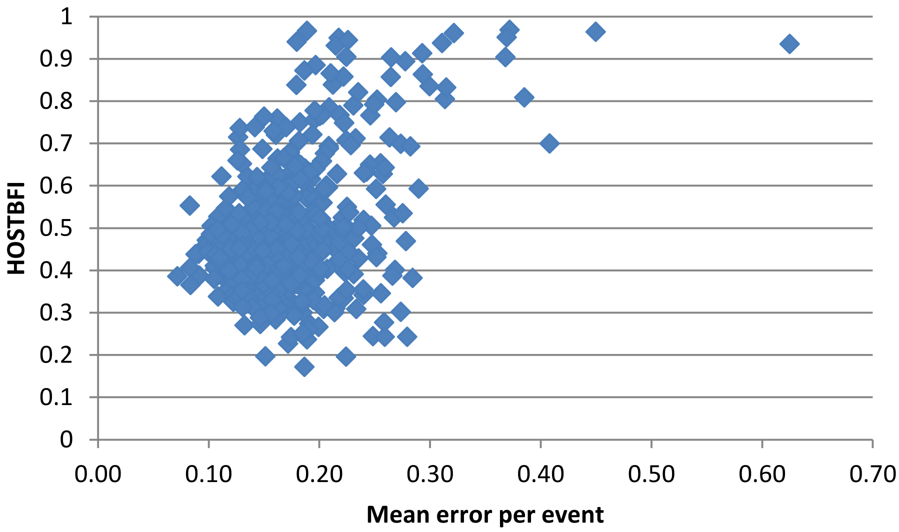



***Figure 5.18*** *The relationship between the mean error per event for model 2 (incorporating antecedent rainfall) and the catchment type. This plot suggests that the antecedent rainfall model does not adequately represent the processes governing flooding in higher base flow index catchments. (i.e. >0.8).*

Figure 5.19 shows the mean error for each catchment and the SAAR value for each catchment plotted against each other for all the catchments in the set. As antecedent conditions become better accounted for, there is likely to be less structure in the error. Nonetheless, it is clear that there is still some structure to the error as Figure 5.19 shows, with the higher errors found in catchments with lower SAAR values. In comparison to Figure 5.18, there appears to be more relationship between SAAR and model error than HOSTBFI and model error. This would suggest that rainfall (or catchment wetness) is more important than HOSTBFI in determining how well the model works. It may be that HOSTBFI provides an additional complicating factor, with ‘dry’, high HOSTBFI catchment performing much worse than ‘wet’ high HOSTBFI catchments.

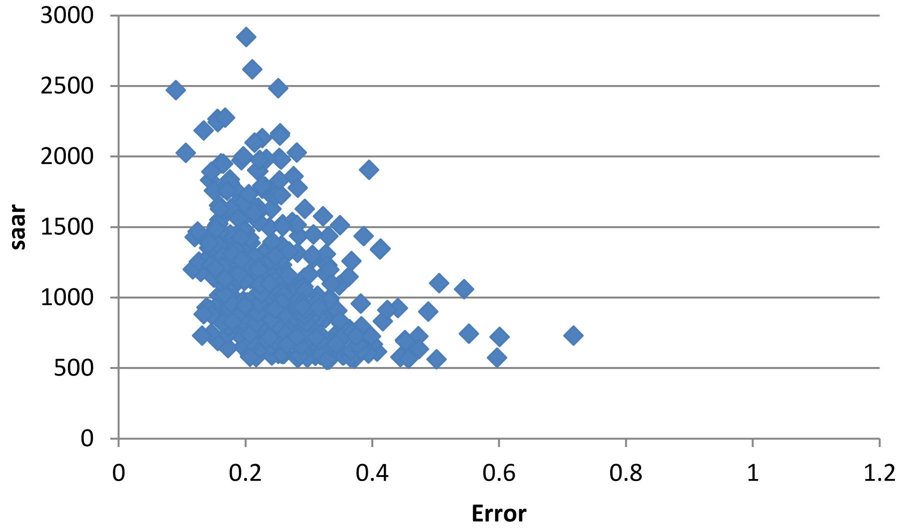



***Figure 5.19*** *Plotting SAAR against the mean error per event value*

Figure 5.20 shows the error scatter compared against catchment area. There is little distinguishable pattern to the error, although it is noteworthy that the largest errors are in the smaller catchments. Kjeldsen (2007) notes that the application of the event based ReFH model in larger catchments is suspect due to the simplifying assumption of a single storm affecting large catchments. The relatively good performance of the antecedent rainfall model in larger catchments does not mean that this assumption can be ignored. However, the fact that larger catchment errors compare well with smaller catchments suggests that catchment AREA is not a significant limiting factor in determining model performance. At larger catchment scales there can be complex interactions between sub catchments and the issue of dependency between these sub catchments becomes apparent. It is beyond the scope of this study to quantify statistical spatial dependence within the catchment set. This area is an emerging topic of interest within flood frequency estimation. Keef et al. (2009) present a model which quantifies the level of dependence between catchments for flood and rainfall events of different return periods. They show how dependence levels between catchments tend to drop in areas of diverse catchment characteristics.

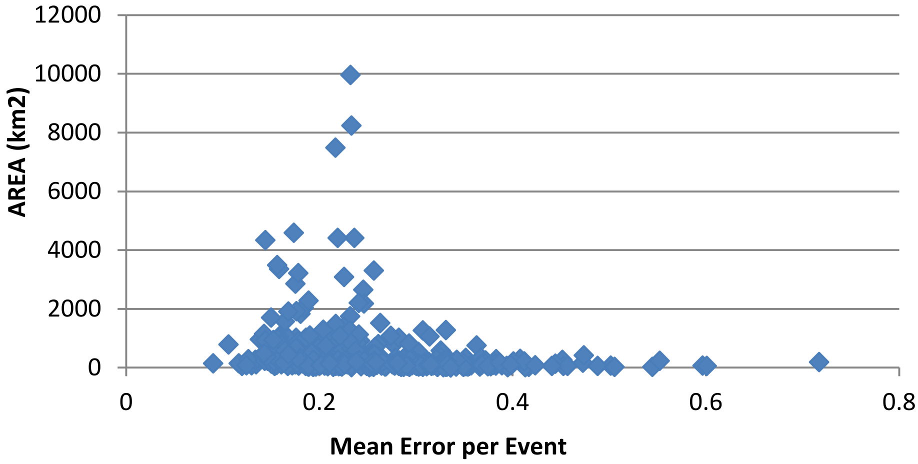



***Figure 5.20*** *Plotting the results of the objective function mean error against the catchment AREA.*

The catchment indicators used within this work are relatively crude, having been generated automatically through the use of large scale digital datasets. One of the questions that remains a considerable research challenge is just how well these indicators represent catchment hydrology. The catchment descriptors used in this study form the main method of classifying catchments in commercial flood frequency estimation software such as the FEH (Reed et al., 1999). However, in some work carried out to compare model behaviour with catchment descriptors, Oudin et al. (2010) suggested that for a significant number of catchments, the PCDs did not adequately capture catchment hydrological behaviour. They suggest that this is due to some catchments having quite specific hydrological behaviour as well as underground catchment properties not being adequately described by the available indicators such as HOSTBFI. This may go some way towards explaining why there is not a good relationship between catchment descriptors and model performance. However, the PCDs used within this study are the only readily available descriptors of catchment hydrological behaviour over a wide area, and therefore were the most appropriate to use.

## 5.4 Discussion of the Event Based Modelling Approach and Results

Perrin et al. (2001) suggest that in many cases there is little to be gained by increasing the complexity of rainfall-runoff models. Further to this, they also highlight a method whereby models should be assessed based not only on their performance, but also on their complexity. The three different models detailed within Chapter 5 use varying levels of complexity in their estimation of peak flow. This complexity is not weighted when assessing model performance, therefore, it is perhaps not surprising that the storm only model does not perform as well as the model incorporating antecedent rainfall. The poor performance of the catchment moisture deficit estimation model is more surprising. All three models make some simplifying assumptions and this discussion is devoted to a consideration of different model aspects and their influence on the peak flow estimation procedure.

Estimating peak flows using only storm rainfall should perhaps be viewed with caution, given the large amount of literature that promotes the role of antecedent conditions in determining peak flow. The main purpose for doing so here is to develop a consistent and reliable way of estimating a storm. However, in certain situations, antecedent conditions may play less of a role in defining the magnitude of peak flows. In particular, highly impervious catchments such as urbanized catchments and potentially some small, steep, upland catchments may not require much in the way of antecedent conditions estimation. That simple models such as the rational method are still used in practical hydrology suggests that in certain cases, runoff estimation can still be characterised in a simple way.

While relating model performance to catchment characteristics is difficult, the temporal error scatter plots of Figures 5.11 to 5.16 suggest that there is some benefit to including antecedent rainfall within the peak flow estimation model. The use of a rainfall block to estimate antecedent rainfall is a simple way of estimating antecedent conditions compared to more traditional methods such as the Antecedent Precipitation Index (API), described and used by many authors such as Heggen (2001). The API usually utilizes a decay function in order to estimate the importance of antecedent rainfall on a particular day prior to storm arrival. However, according to Heggen it is most often used to highlight a qualitative hydrological condition, rather than being used for hydrological prediction. This is one of the reasons why it was not employed within this model. Furthermore, the estimation of the decay coefficient is specific to season and watershed. This then involves a complexity which does not lend itself well to automation, and would not have been easy to implement over the catchment set.

While it is clear that adding antecedent rainfall has some benefit, it is less clear as to why this is. Antecedent conditions generally refer to the condition of the catchment surface prior to storm arrival. One of the specific physical processes governing the state of the antecedent condition is the infiltration capacity. Where there is a high soil moisture deficit the infiltration capacity is increased and therefore any storm rainfall that falls will be less effective. The current antecedent rainfall model definition uses the 30 day antecedent rainfall period as the estimator of antecedent conditions (and is therefore also a proxy for soil moisture). This model formulation uses a coefficient ($c$) that can be optimized along with an indicator of catchment antecedent conditions (the 30 day rainfall) to improve the flow estimation. Given the improvements seen in adding antecedent rainfall in to the flow estimation equation, it is clear that antecedent rainfall can go some way towards being a reasonable estimator of the antecedent condition. One of the major assumptions that this model formulation makes is that it assumes that the coefficient can be fixed across all flood events, with the variation in the 30 day rainfall total representing the different antecedent conditions. What this does not allow for is any other factor influencing the antecedent conditions. In particular any seasonal change to soil moisture caused by another variable such as PET would not be represented in an antecedent conditions estimator that uses only rainfall.

The incorporation of estimates of antecedent soil moisture have not had the desired effect of reducing the objective error. In comparison to the model run using only antecedent rainfall, the run incorporating soil moisture information appears to show poorer results. The general pattern of performance across the UK is the same, with the drier catchments/higher HOSTBFI catchments showing an increase in error between the two runs.

There are several possible reasons why the soil moisture estimates have not had the desired effect. There are potentially two stages where errors may be introduced, firstly in the creation of the soil moisture time-series and secondly in the incorporation of those estimates in to the flow estimation.

This work made use of catchment properties such as PROPWET and SMDBAR, themselves derived from models checked against available measurements. While the soil moisture models developed as part of this work compared well against these properties it should be emphasised that PROPWET and SMDBAR are averages. Therefore, it is quite possible for this soil moisture model to represent averages well, but perhaps not capture the extremes. This is important for flood estimation, as floods tend not be generated from 'average' conditions, they are often the result of periods where ground conditions are exceedingly wet and where evapotranspiration is perhaps low.

One of the suggested reasons why the soil moisture model does not perhaps represent the extreme conditions well is that it uses generalised PET estimates. These are not likely to reflect periods when evapotranspiration was low in reality, and so may overestimate the amount of water removed from the soil. Unfortunately, at the time this work was undertaken, there were no available data products representing historical PET over the space and time required by this study.

Regarding the incorporation of the CMD estimates into the flow estimation equation, it is likely that this is also a potential source of error. The reason for this is that the flow estimation equation is flexible, and the coefficients can vary according to the variables over which they operate. So while different formulations of the flow estimation equation can vary slightly, in general the coefficients can vary according to different model set-ups. It is thought that the larger source of error is likely to be in the inconsistent estimation of the soil moisture. In this case there is little the optimisation process can do to alter the results.

The approach taken throughout this chapter to estimate peak flow has been referred to as an event based model. However, the operation, structure, inputs and outputs of the model bear little resemblance to other traditional event based models such as the unit hydrograph. The flow estimation model presented in this chapter allows for the consistent estimation of a flow record, rather than single events. Similarly, it does not simulate an entire flood event, it only estimates the peak. However, the work carried out within this chapter is still referred to as an event based model because the method is still centred around peak flow events, albeit multiples of them.

## 5.5 Conclusions

This work has provided a basis for developing a flood frequency curve estimation model. The consistent transformation of rainfall to flow was outlined as one of the requirements of the modelling exercise, and a method for doing so has been tested on a variety of catchments within the UK. Several approaches have been identified with differing levels of complexity in the estimation of antecedent conditions.

Three different methods of estimating peak flow records have been detailed; a model using only storm rainfall, a model using storm rainfall and antecedent rainfall and a model using storm rainfall, antecedent rainfall and an estimate of the catchment moisture deficit. Through testing different storm estimation methods, timing has shown to be a key factor.

The overall results show that the addition of some antecedent information into the flow estimation equation is beneficial. The storm, 5 day rainfall and 30 day rainfall model appears to give the best results. The reasons for the poor improvement shown by the catchment moisture deficit approach are suggested as being due to the number of simplifying assumptions that the soil moisture model makes. The poor performance of the event based model when applied to permeable catchments is not unique to the approach developed within this chapter. Kjeldsen (2007) notes the relatively poor performance of the ReFH method in these circumstances, with recommendations that a statistical approach to flood frequency estimation is used.

Whatever model is used for peak flood estimation, there is a clear geographical pattern in the ability of the model to replicate peak flow estimates. Some of the structure in the error can be related to annual rainfall and HOSTBFI, whereas some of the error appears to be random. It is also likely that issues such as measurement error, the spatial variation in rainfall, routing time and artificial effects influence the performance of the models presented. However, it is difficult to account for these factors in a systematic way. Therefore, it is suggested that they are factors that should be borne in mind when assessing model performance.

Despite the issues mentioned above, the antecedent rainfall model has an ability to replicate peak flows to a reasonable level, as shown by the temporal error plots in Section 5.3.4. Therefore, the next stage in the research can use the antecedent rainfall model structure investigated here to work towards the generation of flood frequency curves. This work is now presented in "*Chapter 6: Frequency Curve Estimation*"

# Chapter 6: Frequency Curve Mapping

## 6.1 Introducing the Frequency Curve Mapping Work

Flood Frequency curves are traditionally developed using observed data. Usually this data comes from gauged river records, although some studies such as McEwen (1987) and MacDonald et al. (2006) have successfully used historical data in addition to more modern instrumental sources. More recently, continuous simulation has successfully been used for flood frequency assessment on both an individual catchment (Cameron, 2006) and national scale assessment (Bell et al. 2007; Kay et al. 2006a). This usually involves the simulation of a flow time-series from which peak flow events can be extracted and used in a statistical flood frequency assessment.

This study takes an alternative approach. First, by simulating a catchment flood record (Chapter 5) and then using this flood record in a traditional flood frequency assessment, as if it were a gauged record. Therefore, one of the key differences compared to that of continuous simulation methods is that only the flood record is estimated, rather than the whole flow time-series.

### *6.1.1 Development of the Event Based Model For Flood Frequency Curve Estimation*

As described in Chapter 5, the event based model was developed to consistently estimate flow peaks from rainfall. Here, the focus is on estimating a flood frequency curve, rather than a set of discharge estimates for individual events. Given a generic flow estimation model formula such as that presented in Chapter 5:

$$Q_{est} = (b \text{ x } storm) + (c \text{ x } thirty\ day\ rainfall) \qquad \textbf{Equation 6.1}$$

Where *b* and *c* are the optimised coefficients and the storm and thirty day rainfall are growth factors, the outputs will be in the form of a set of discharges $Q_{est1}, Q_{est2}, \ldots., Q_{estn}$ where *n* is the number of events evaluated.

These discharges can then be used in a standard statistical flood frequency analysis, such as that introduced in Chapter 3 in order to estimate specific return period magnitudes from a flood frequency curve.

One of the main differences with this work compared to the previous event based work is that, apart from developing flood frequency estimates, the performance of the model is assessed on its ability to reproduce the flood frequency curve. In this case, the new set of discharges are assessed on the criterion of how well they estimate the observed flood frequency curve; here by calculating the RMSE of selected return period estimates between the observed and modelled flood frequency curve (see Equation 6.2).

The use of an alternative performance measure is justified by the objective of the new method. Previously, the sum of the errors represented an appropriate measure of how well the flow estimation methodology estimated the magnitude of certain events. However, to reflect the new emphasis on frequency curve estimation there was a need to develop a more appropriate measure of model performance. Assessing the model based on it’s ability to replicate specific magnitude-rarity relationships better reflects the objectives of this piece of work as a whole.

$$\sqrt{\frac{\sum\left(obs_Q - mod_Q\right)^2}{n}} \qquad \textbf{Equation 6.2}$$

Where $obs_Q$ and $mod_Q$ are the observed and modelled return period estimates calculated from the fitted distribution and $n$ is the number of return period estimates calculated (in this case 4).

The RMSE calculation, however, estimates specific return period events based on the observed and modelled distributions and then calculates the sum of the root of the mean squared error (RMSE) between them. As previously mentioned, estimating higher return periods robustly is likely to be difficult given the length of flow records available. Therefore the RMS error is currently calculated as a single measure over the 2, 5 10 and 15 year return period estimates only.

The estimated flood discharges are developed as before, using the same objective function as in Chapter 5. It evaluates the sum of the errors between observed and modelled flow values.

### 6.1.2 Flood Frequency Curve Estimation Procedures and Error Assessment

As outlined in Chapter 3, the procedure used to estimate the flood frequency curve was broadly the same as that of the FEH volume 3 (Robson and Reed, 1999). The flow estimates created from the rain storm and antecedent data were treated as peak flows in a statistical flood frequency estimation procedure. As the flow estimates were known to estimate annual maxima (as they were estimated based on the date of the AM flood) they could be used directly within the flood frequency estimation procedure already outlined.

The flow estimation models developed flow estimates as growth factors, therefore to treat them as peak flows they required scaling by the catchment QMED value before any further work was carried out. The procedure for the estimation of a flood frequency curve is summarised by the flowchart in Appendix D.1.

## 6.2 Model Formulations and Frequency Curve Estimates

Initially two different model formulations were trialled with a view to establishing a single model for further use. The different model formulations used rainfall and PET as inputs to different model setups, with the use of two different distributions for flood frequency assessment also considered. The earlier work that considered the rainfall blocks was also helpful in developing these model formulations.

The models can be clearly split- one using only antecedent rainfall and one using antecedent rainfall and potential evapotranspiration (PET) data. As PET data has not been previously introduced, this model is explained in slightly more detail in Section 6.2.2.

### 6.2.1 Antecedent Rainfall Model

A rainfall only model has been used previously in Chapter 5, and so requires less introduction. The antecedent rainfall model used here takes a similar structure to that identified in Chapter 5. There are two coefficients for optimisation. One coefficient (*b*) weights the storm estimate and one (*c*) weights the antecedent estimate. The notation is retained from Chapter 5 in order to avoid confusion with the earlier event based work that used a single coefficient (*a*) to weight a storm only.

Therefore the model formulation to estimate flow is:

*Q(est) = b x storm + c x 30 day rainfall* **Equation 6.3**

This model is optimised using the same routine as described in Chapter 5, leaving each catchment with a pair of coefficients and a set of peak flows. From this, an appropriate distribution can be fitted and the flood frequency curve can be estimated.

### 6.2.2 Antecedent Rainfall and PET Model

In Chapter 5, attempts to use soil moisture were not justified as there was little return on the considerable computational and model complexity of adding a soil moisture estimation component. However, justification for the new approach outlined here is that historically derived estimates of PET on a 5 km grid for the UK were made available, and as such it was felt that these might represent a significant improvement over the generalised estimates used in the earlier work. The full complexity of a soil moisture model was still not felt to be worthwhile due to the numerous assumptions that need to be made; however, potential evapotranspiration on its own may be able to provide some significant benefits to the modelling of the flood frequency curve.

As a single variable, PET does not directly affect runoff. However, over a longer period of time, potential evapotranspiration can cause considerable differences in soil moisture deficits. These soil moisture deficits then have the potential to moderate the flood behaviour of a catchment. The interplay between rainfall and PET is a subtle, but important, process in flood generation and this is why some time is given to considering its role here.

The Potential Evapotranspiration data were calculated on a 5km grid over the UK and stored in a SQL database. Using gridded, observed temperature, humidity and windspeed data, the Penman-Montieth equation was used for the calculation of PET (Leathard, unpublished). The gridded variables were available for the time period covering 1961 to 2002. The potential benefit of using these PET data is felt to outweigh the negative aspect of using a shorter record (as rainfall data start in 1958).

As with previous work, the relevant catchment boundaries were defined in ArcMap, then the relevant 5 km grid cells from within these catchments were extracted from the SQL database. The catchment averaged values were then simply calculated using an arithmetic average of all grid squares within the catchment boundary. These time-series could then be used within the flow estimation model.

PET tends to affect soil moisture over longer timescales than rainfall. Rainfall can wet up a catchment in a matter of hours whereas PET tends to be significant only over weeks and months. As with rainfall, the PET values are simply estimates and so their incorporation into the flow estimation model still requires some flexibility in the form of a modifying coefficient.

For these reasons a longer block of PET was used, when compared to that used to describe the antecedent rainfall conditions in the previously presented rainfall-only model. An index of the thirty days prior to the flow/storm event was used. This sum of the thirty day PET prior to the storm was then divided by the median annual maximum PET for the whole of the UK. A single standardisation value has the benefit of slightly modifying the PET index dependent upon location of an individual catchment.

For example, the South of the UK is generally warmer and can expect higher PET values in Summer and it may be that PET is more important in this location for the flood frequency curve compared to an area further north. By using a single standardisation figure, the PET index can better reflect the importance of the PET value to an individual catchment.

The second reason for using an index of PET, rather than the raw values is that the range of values taken by the index fits in better with the other variables in the flow estimation equation. This therefore allows the use of the PET indice in the flow equation.

$$Qest = (b\ x\ storm) + (c\ x\ (Thirty\ Day\ Rainfall - Thirty\ Day\ PET)$$

**Equation 6.4**

In terms of incorporation of the PET index, a similar approach was taken to that of the soil moisture modelling approach tried earlier. A model formulation using two coefficients (See Equation 6.4) was used. One coefficient, *b*, modifies the storm rainfall component of the model, as per usual. The second coefficient, *c*, modifies a block of antecedent rainfall minus the PET index, created to represent catchment antecedent conditions. This block uses a growth factor value of the 30 day rainfall modified by subtracting the thirty day PET index. This allows for a direct comparison between the frequency curve estimation model using only antecedent rainfall and the frequency curve estimation model using antecedent rainfall and antecedent PET.

### *6.2.3 Model implementation*

The process for the estimation of the flood frequency curve has already been described in previous sections, however, the full method is re-iterated here for completeness.

The catchment peak flow record is estimated using one of the two model flow formulations shown in Equations 6.3 and 6.4 This peak flow record is then treated as the catchment AMAX record and an appropriate statistical flood frequency analysis is then employed. This involves the estimation of an extreme value distributions parameters through an l-moments routine. This then allows a flood frequency curve to be plotted. The observed flood frequency curve can also be treated in the same way to allow for a comparison between modelled and observed flood frequency curves.

Error assessment uses the RMSE as shown in Equation 6.2. The return period estimates are calculated using equation 6.5 shown below (for the Gumbel distribution) before being used within the RMSE calculation.

$$Q_T = \xi + \alpha(-\log(-\log(f)) \quad \textbf{Equation 6.5}$$

Where $Q_T$ is the estimated flow magnitude at the specific return period ($T$). ξ is the gumbel distribution location and α is the scale. $f$ is the non-exceedance probability. For the RMSE calculations, the return periods for the 2, 5, 10 and 15 year return period events were calculated, the non exceedance probabilities for these events are 0.5, 0.8, 0.9 and 0.93 (approx.).

This process allows for the production of graphical plots for visual assessment of the estimation of the flood frequency curve as well as a numerical assessment using the RMSE value. The process is summarised diagrammatically in Appendix D.1.

### *6.2.4 Spatial Assessment of Model Performance*

The distribution of the RMSE values for the rainfall only model across the UK can be seen in Figure 6.5 which uses a similar colour coding scheme developed during the earlier work in Chapter 5. This uses the colours green, blue, orange, red and black to indicate decreasing model performance. The categories used in Chapter 6 are different to previous work as they use the RMSE value for error analysis. The specific colours and RMSE values can be found in the key of Figure 6.5. Summary statistics from each model run can be found in Table 6.2.

Results presented here use the Gumbel distribution when calculating the RMS errors, as the Gumbel distribution is recommended for use with UK annual maximum data (Robson and Reed, 1999).

The results show a similar geographical distribution to the event estimation work presented in Chapter 5 (see Figure 5.9 for comparison). Southern areas contain the catchments with the highest RMSE values while western and northern areas contain catchments with lower RMSE values.

In order to assess how these mapped values relate to return period estimation performance, Section 6.3.3 now looks at some specific examples of modelled and observed flood frequency curves and explains how these relate to the colour coding scheme shown in Figure 6.5.

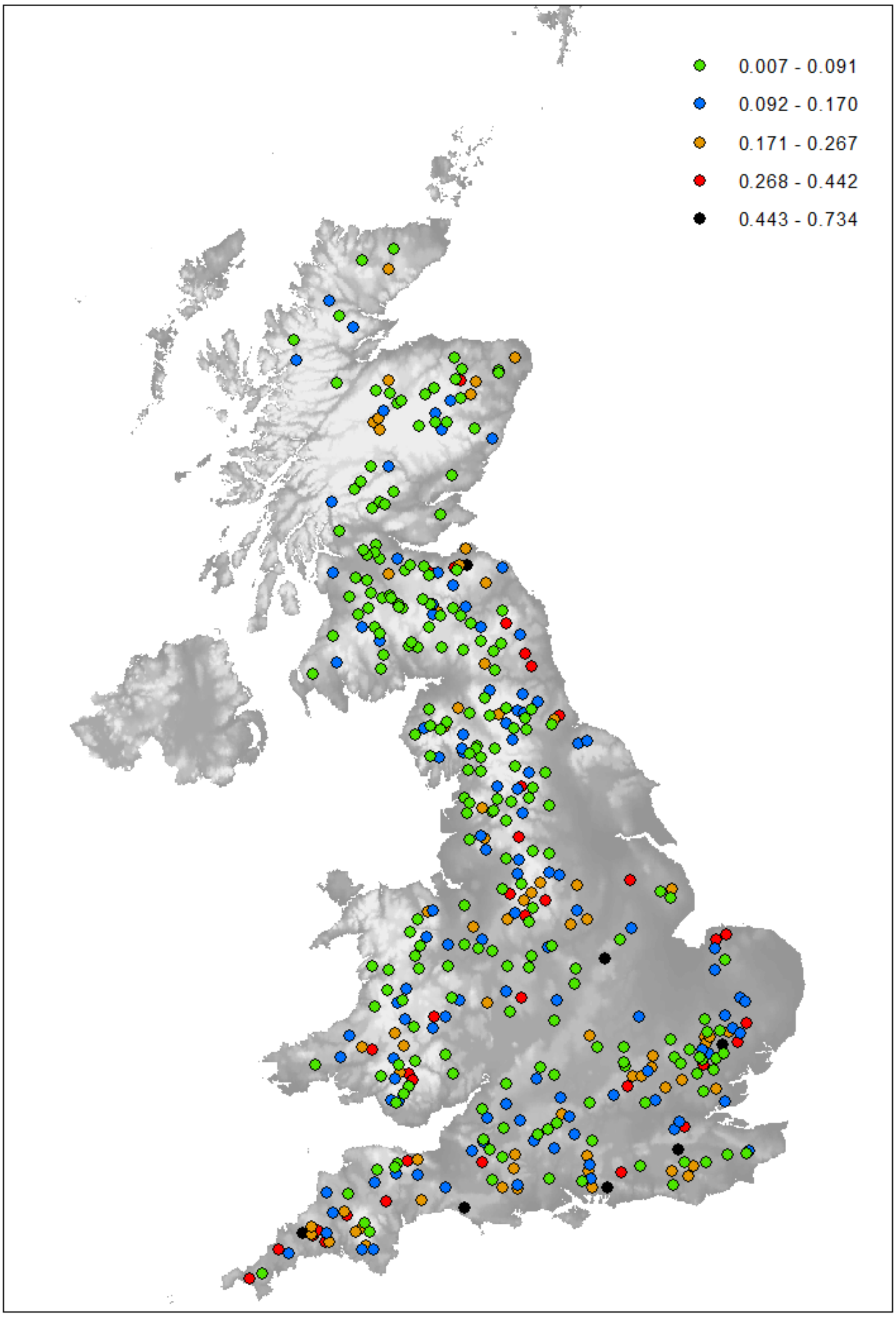



***Figure 6.1*** *The spatial distribution of RMS error for UK catchments as calculated for the rainfall only model using a Gumbel fit for the flood frequency estimation.*

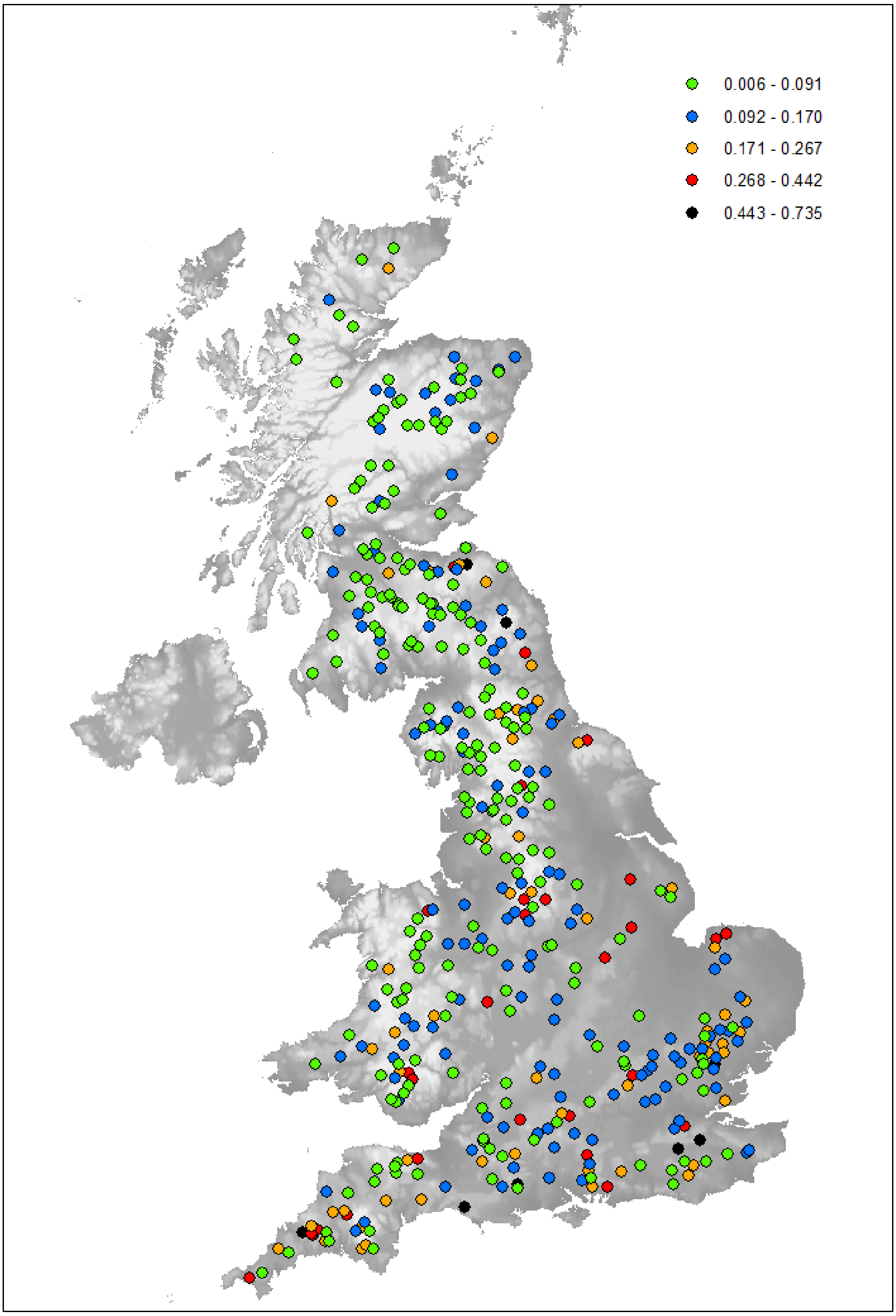


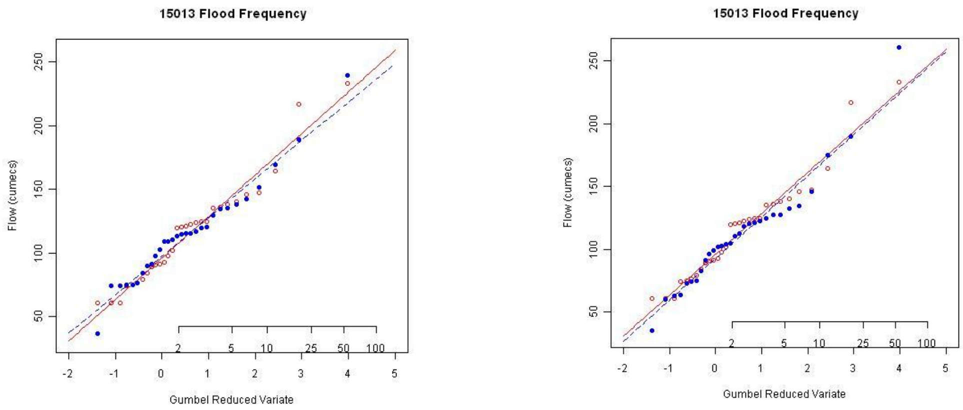

***Figure 6.2*** *The spatial distribution of the RMS error. Model run includes PET as a variable and RMS errors are calculated from the Gumbel distribution.*

Figure 6.2 shows a map of the rainfall and PET model spatial performance for individual UK catchments using the same colour classification scheme as the model using only rainfall. The distribution of results is similar to that of the rainfall only model (see Figure 6.1 for comparison).

### *6.2.5 Performance By Catchment*

Figure 6.3a shows a good example of a model reproduction of a flood frequency curve by the rainfall only model. In this plot, the solid red line represents a flood frequency curve estimated from observed flood peak data (in this case the annual maximum flood series). The red circles are the empirical data. The dashed blue line represents the modelled flood frequency curve, which has been fitted to the model estimates of annual maximum data. This colour coding of flood frequency plots has been adopted throughout the rest of this thesis.

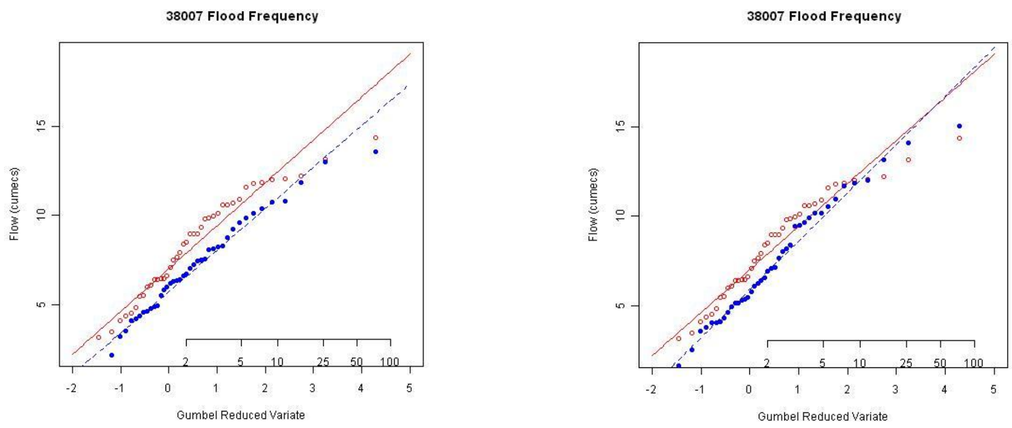
This particular gauge has an RMSE value of 0.037 and according to the coloured classification scheme shown in Figure 6.5; this would give it a green coding. The RMSE value is calculated over the 2,5,10 and 15 year return period estimates. Therefore, if the observed and modelled flood frequency curves show significant divergence above the 15 year return period, this will not be reflected in the RMSE value. The reason for this is that given the length of flow and rainfall records available for use, the observed flood frequency curve is still likely to be sensitive to outlier events above the 15 year return period estimate and so comparing it to the modelled curve is unrealistic above this level.




*a* *b*

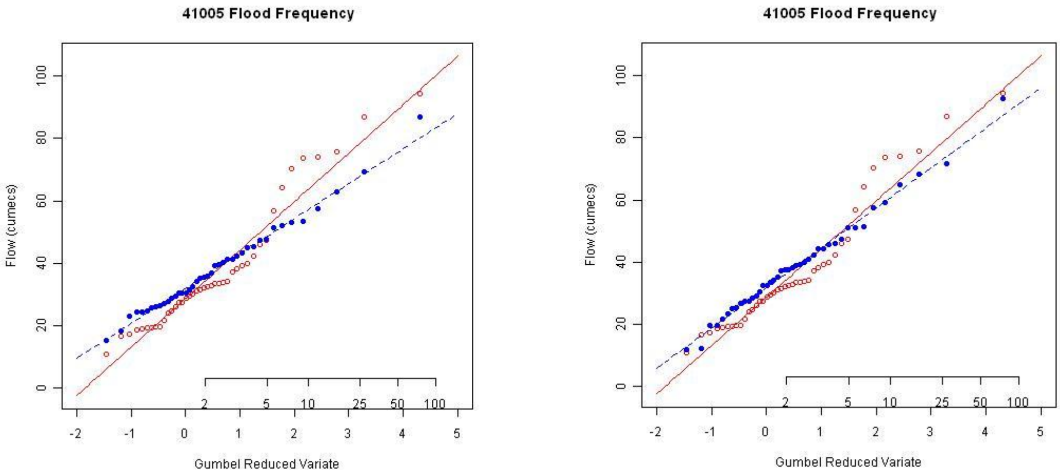
***Figure 6.3*** *Flood frequency curve estimation for the Almond at Almondbank (located in south-east Scotland). (a) shows the modelled flood frequency curve estimate from the antecedent rainfall model, (b) shows the modelled flood frequency curve estimate from the antecedent rainfall and PET model.*

In the case of the Almond, the modelled flood frequency curve is able to estimate the observed flood frequency curve reasonably well, however, there is some divergence at higher return periods. This can be explained by the way the model is fitted using only return periods up to and including 15 years. To some extent the use of the Gumbel distribution resolves this problem.



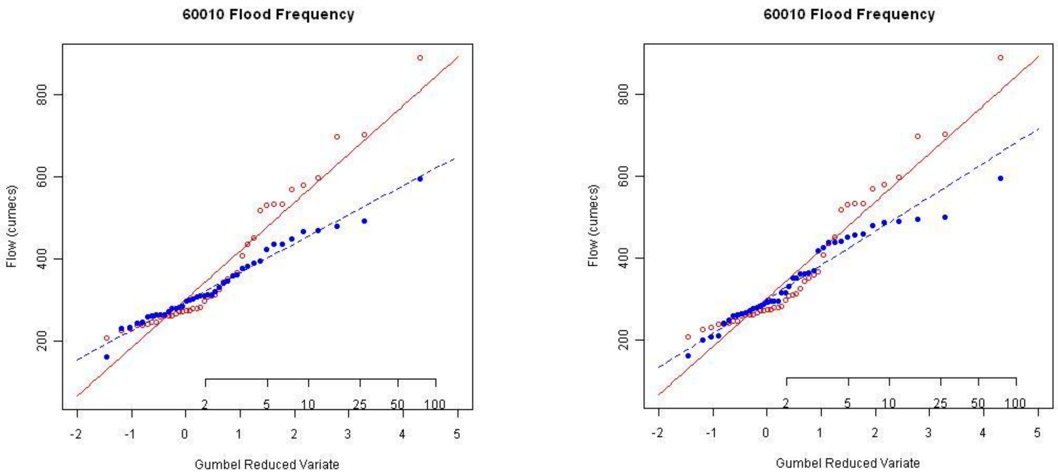

a b

**Figure 6.4** Blue category. Catchment is the Canons Brook, located in SE England. (a) shows the antecedent rainfall model estimates of the flood frequency curve, (b) shows the antecedent rainfall and PET model estimates.



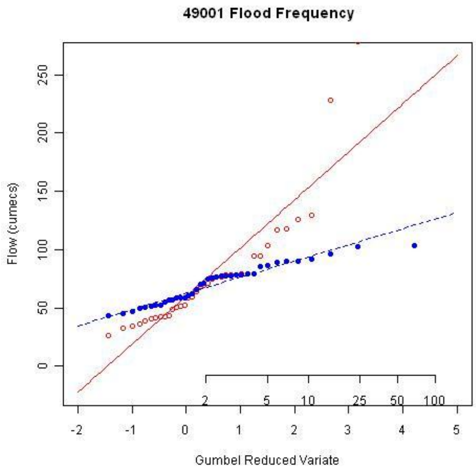

a b

***Figure 6.5*** *Orange category. Catchment is the Ouse, located in the south of England.*




a b

**Figure 6.6** Red category. Catchment is the Tywi, located in SW Wales.

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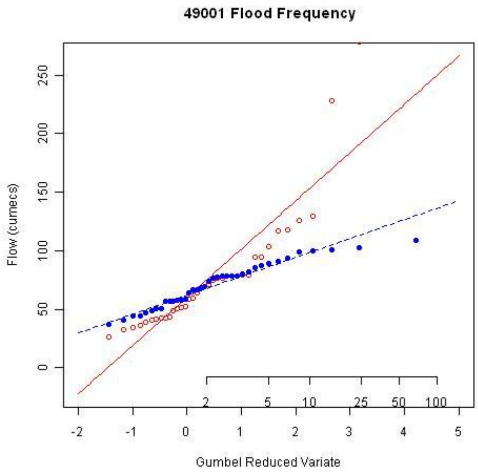



b

***Figure 6.7*** *Black category. Catchment is the Camel, located in SW England.*

Figures 6.3 through to 6.7 show how the RMSE performance measure relates the estimated flood frequency curve to the observed flood frequency curve and the maps of spatial performance in Figures 6.1 and 5.2. The flood frequency plots give an example of a catchment flood frequency curve associated with a particular colour classification on the map of spatial performance. They are ordered by decreasing performance in terms of RMSE (or green through to black). In general the plots show an ever widening disparity between the observed and modelled flood frequency curves as the RSME value increases. The RMSE values and the location of the stations associated with each of the plots can be found in Table 6.1.

| **Gauge** | **Station** | **RMSE (Gumbel)** | **Colour** | **Number of Catchments in Category** |
|---|---|---|---|---|
| 15013 | Almond | 0.037 | Green | 197 |
| 38007 | Canons Brook | 0.170 | Blue | 123 |
| 41005 | Ouse | 0.173 | Orange | 67 |
| 60010 | Tywi | 0.274 | Red | 32 |
| 49001 | Camel | 0.603 | Black | 12 |

**Table 6.1** *Summary of model performance for Figures 6.6 to 6.10 along with an overall categorisation of the performance measure. 431 Catchments were used in the model run, their performance can be judged by assessing the number of catchments in each colour category on the right hand side of the table.*

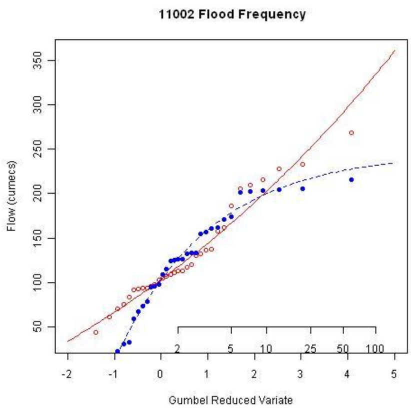
In terms of overall model performance, almost three quarters of the catchments are contained in the first two categories (green and blue – RMSE of less than 0.17). The choice of categorisation evidently affects how the results are perceived. While the worst category (black) contains only twelve stations it covers a large range (RMSE of 0.443 to 0.734) when compared to the blue category (RMSE of 0.092 to 0.170). Using the categorisation in this way suggests that there are a small subset of catchments that tend to perform very poorly compared to the majority when using the RMSE as an indicator of model performance.

From the map of the spatial distribution of the error it can be seen that most of the worst performing catchments tend to be located in the South and East of the country, with a smaller number located in the South-West. These values are revealing, as when they are compared to the green category, there are some significant differences. The green category of catchments has a group mean Base Flow Index (HOSTBFI) of 0.47 and group mean Annual Rainfall (SAAR) value of 1155 mm and group mean PROPWET value of 0.51. In contrast, the worst performing group of catchments has a mean HOSTBFI value of 0.62, a mean SAAR value of 859 mm and a mean PROPWET value of 0.35.

These summary catchment statistics suggest that to some extent, that the worst performing catchments tend to be groundwater based and are often reasonably dry throughout the year (as evidenced by the PROPWET and SAAR values). Therefore, similar to the event based model, it is likely that it is the models handling of the antecedent condition which is causing the poor performance in flood frequency curve estimation.

### *6.2.6 GEV vs. Gumbel Distribution*

As has been previously discussed, the choice of statistical distribution for use in flood frequency estimation is not straightforward. In some cases, where record lengths are reasonably short, when using the GEV distribution, the shape parameter has the tendency to take some rather extreme values which are unlikely to represent a real-world situation.

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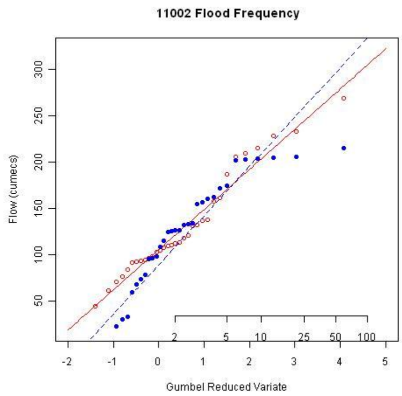


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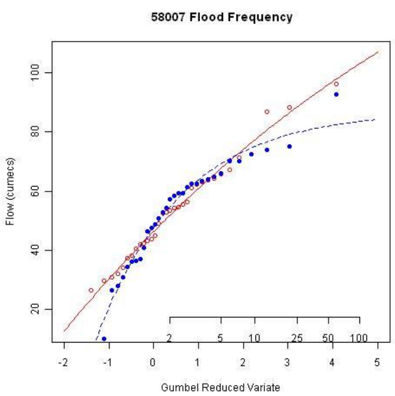


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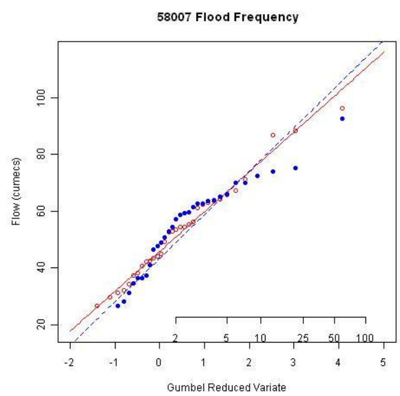



d

***Figure 6.8*** *Two examples of GEV distribution fits (plots a and c) and Gumbel fits (plots b and d).*

This issue is highlighted in Figure 6.8 (a and c) where modelled flood frequency curves using the GEV distribution, while having reasonably good RMS errors, evidently have problems with the shape of the flood frequency curve, most notably at higher return periods. This is perhaps due to the shape parameter being unbounded in the GEV fitting procedure, although determining valid bounds for this parameter is difficult (as this may depend on catchment type as well as the dominant rainfall type in the catchment – convective or frontal). It is likely that using a statistical distribution with a fixed shape parameter (i.e. the Gumbel) will partly alleviate these problems.

It is for this reason that the Gumbel distribution was adopted for use in this study across all catchments. For the rest of this thesis, all reference to RMS errors and flood frequency plots will use the Gumbel distribution as their basis.

### *6.2.7 Comparing the Two Frequency Curve Model Formulations*

Summary statistics between the two different model runs are presented in Table 6.1. These statistics are computed across the whole catchment set. Figure 6.9 shows the distribution of error for the two model runs.

| **Model Run** | **Mean RMS Error** | **St. Dev. RMS Error** |
|---|---|---|
| Rainfall | 0.136 | 0.116 |
| Rainfall and PET | 0.128 | 0.106 |

**Table 6.2** *RMSE Summary Statistics from the two different model runs.*

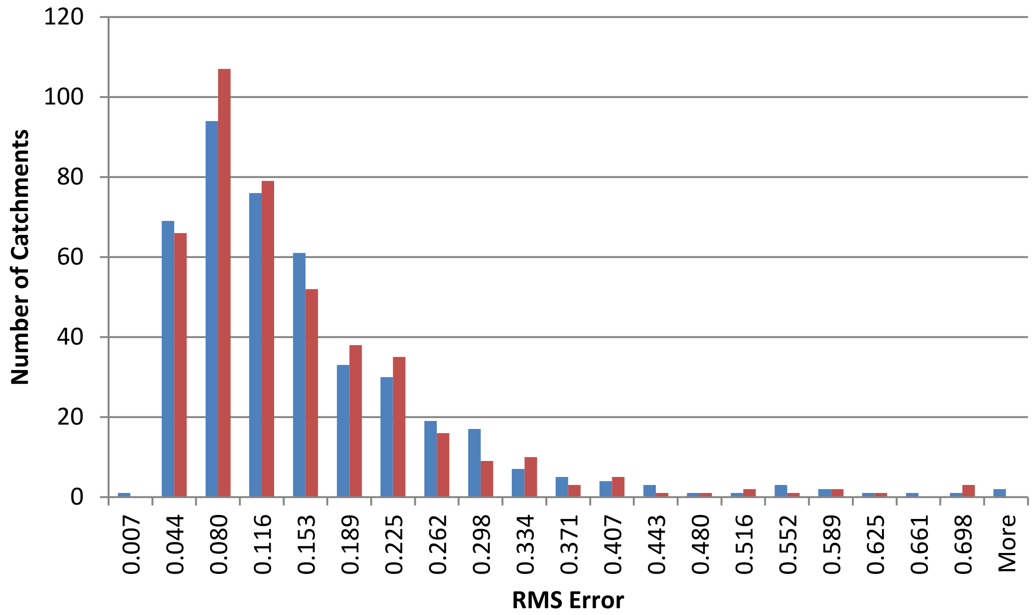



***Figure 6.9*** *The distribution of the RMS error for two different model formulations. Blue represents the rain only mode, red represents the model including PET*

Along with maps of the spatial distribution of error, these results suggest that adding antecedent PET into the estimation of the flood frequency curve does not significantly alter the model performance over the larger catchment set. However, unlike the soil moisture modelling approach of Chapter 5, model performance does not significantly decrease when the PET estimates are used. One of the main justifications for using PET as an antecedent indicator is that it may change under future conditions, and so must be accounted for in current flow estimation in order to be included in a future case. This work does not test how influential the PET is in the model formulation and this is important if it is to be used as an antecedent indicator in the future. Therefore further work is carried out to test the sensitivity of the model to changes in the input climate in order to further understand how the models operate. This work is reported on in Section 6.5.

## 6.3 Linking Coefficients to Catchment Type

Several authors have considered the problem of linking catchment model parameters to catchment characteristics. The spatially generalised PDM model of Kay et al. (2006a) links the PDM model parameters to the FEH catchment descriptor set through regression equations. Model performance showed mixed results, with groundwater based catchment performing worse than their surface water counterparts (Kay et al. 2006a). However, Oudin et al. (2010) suggest that physically similar catchments (as defined by simple catchment descriptors) may not be hydrologically similar. This then poses a problem for parameter estimation using simple catchment descriptors.

While it may be beyond the scope of this work to develop a comprehensive framework for model coefficient estimation from catchment descriptors, the simplistic structure of the frequency curve model allows for an investigation of the coefficients, particularly whether they show any pattern with regards to the catchment type.

To this end, analysis considered whether links could be made between the coefficients and the catchment type. The catchments were subset into groups based on catchment descriptors such as AREA (threshold 500 $km^2$), SAAR (threshold 1100 mm), PROPWET (threshold 0.47) and HOSTBFI (threshold 0.49) in order to see if their flood frequency estimation model coefficients showed any tendency to group based on these categories. The thresholds for splitting use the median value of the catchment descriptor as calculated across the whole catchment set.

Figure 6.10 shows these results. While no significant grouping occurs, it is clear that wetter catchments tend to take a much narrower range of values compared to dry catchments (as shown by the considerable scatter of coefficient values for dry catchments compared to wet). The plots split by SAAR and PROPWET both appear to show this. HOSTBFI shows little grouping. AREA perhaps shows some, but not enough for any justification to allow the estimation of the coefficient based upon the AREA value.

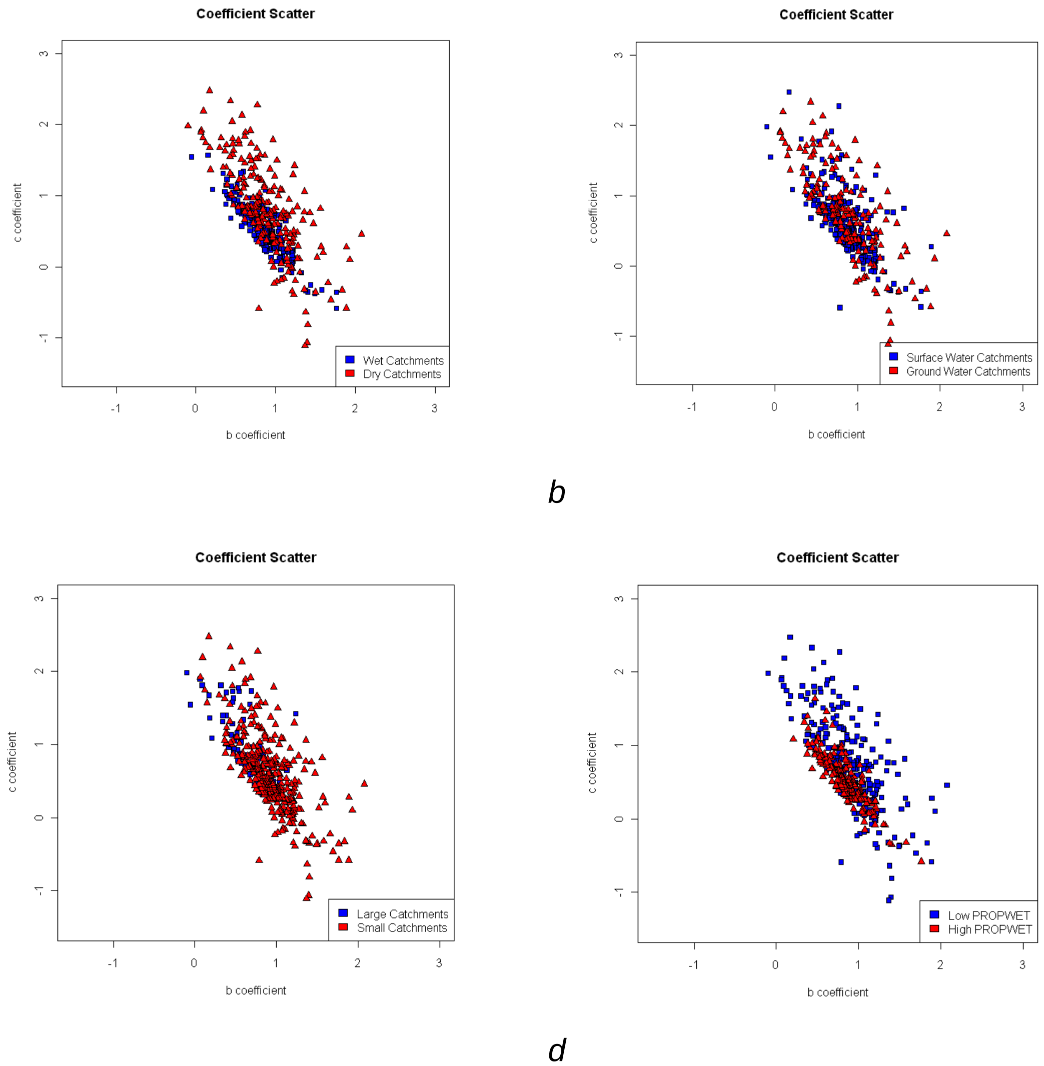



***Figure 6.10*** *Scatter plots of the b and c coefficients subset into groups based on pcds. From top left clockwise, split by (a) SAAR, (b) HOSTBFI, (c) PROPWET and (d) AREA.*

As previously explained, it may not be valid to use the optimised model coefficients under a future climate. Therefore part of this work looking at the coefficient values was developed in order to understand how model performance may be impacted by using estimated coefficients for the future case. While coefficients cannot be estimated through regression equations to the PCDs (as there is too poor a relationship for this to work), it is possible to narrow the range that coefficients could take for a specific type of catchment given some basic information on its physical and climatological conditions.

## 6.4 Poorly Performing Catchments

### *6.4.1 Case study of a poorly performing catchment*

It has previously been explained that the model performs poorly in reproducing the flood frequency curve for high base flow index catchments when modelled with either of the model formulations presented in this chapter. Here, a case study of one such catchment is provided to try and explain why this is the case. This also helps understand how the models work and the situations in which they can be applied. For clarity, the model formulation incorporating antecedent rainfall and antecedent PET is used.

The catchment which will be presented is the Slea @ Leasingham Mill. It is a reasonably small catchment located in south-east England, covering an area of around 50 km$^2$, has a SAAR of 601 mm, a PROPWET value of 0.23 and a BFIHOST value of 0.809. From the Hi-Flows gauging notes it suggests that this is a predominantly limestone catchment, which does not respond to rainfall.

Figure 6.11 presents the original fit. There is a clear underestimation in the modelled flood frequency curve. It is suggested that the reason for this is because storm rainfall is not the primary mechanism for generating a flood flow. Therefore, because the model has little knowledge of the antecedent channel water level it cannot estimate peak flows from rainfall storms alone.

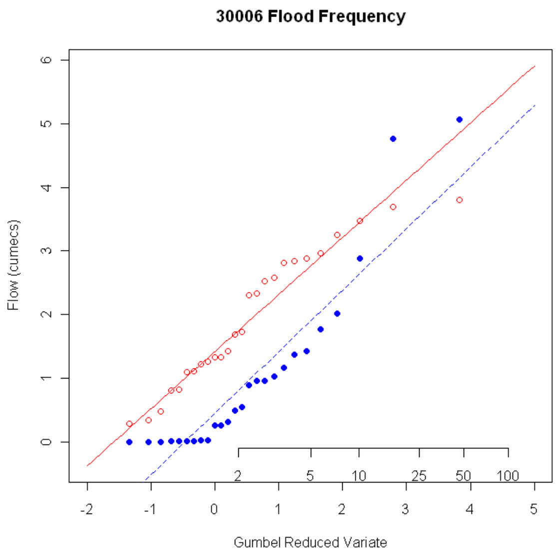
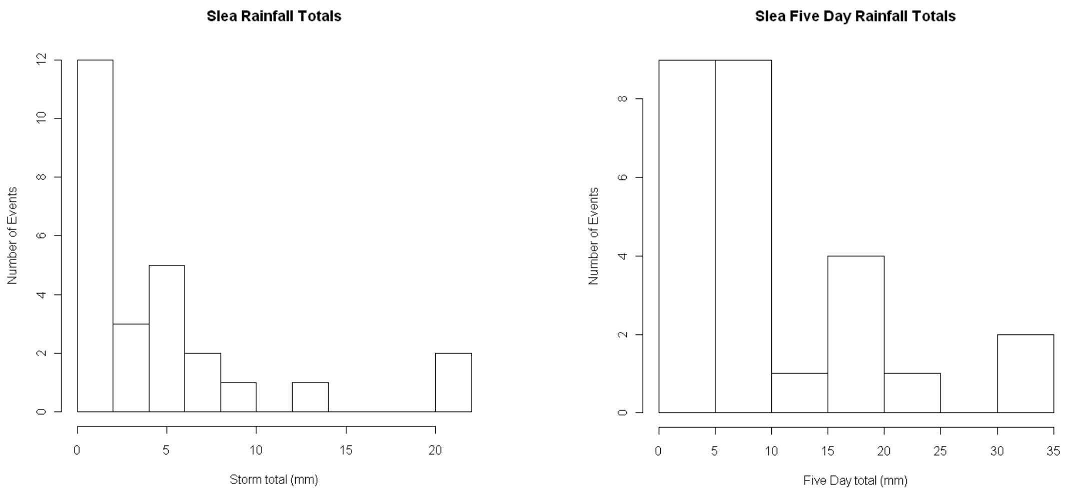



***Figure 6.11*** *The observed and modelled flood frequency curve for the Slea using optimised coefficients for the modelled version.*

Therefore, the current model structure for this catchment evidently neglects some aspect of the catchments flood generation process. Further evidence for this catchments behaviour can be found in Figure 6.12, a histogram of the rainfall totals associated with the annual maximum flow events used in fitting the flood frequency curve.




*a* *b*

***Figure 6.12*** *A Histogram of storm totals (a) and five day antecedent rainfall totals (b) associated with the annual maximum flow events for the Slea.*

Out of the 26 annual maximum flow events, over half had a storm total of less than 5 mm. Similarly, over half had a five day rainfall total of less than 10 mm.

It is suggested that due to the evidence presented above, as well as the information provided in the station gauging notes, that catchments' with properties similar to the Slea are inherently unsuited to the modelling method developed here. In particular, because of their hydrogeology it is likely that groundwater levels play a large part in flooding in these catchments. With regards to hydrogeology, catchment boundaries often do not follow surface watershed boundaries, and this makes the process of modelling them difficult. Regional groundwater levels are often responsible for flooding in these types of catchment, combined with occasional preferential flow along lines of weakness (Finch et al., 2004). Furthermore, these catchments are also dry, as they experience relatively low annual rainfall compared to the rest of the UK. This in turn makes them more susceptible to experiencing a wide range of antecedent conditions which are harder to model.

What this means for the method presented here, is that where catchments are unresponsive to rainfall, and where antecedent conditions estimation is challenging, a method which uses storm and antecedent rainfall/PET will inevitably fail to work. Discussion on how these catchments could be modelled in a similar way, but using different information is included in the discussion and conclusions in Chapter 8.

### *6.4.2 Identifying Poorly Performing Catchments*

The case of the Slea shows how the current frequency curve estimation model structure cannot deal with flooding generated from sources other than extreme rainfall. The model coefficients are essentially a function of both the catchment physical characteristics and the hydroclimate of the catchment in question. Therefore, it is important to test if a catchment's estimated coefficients can still be used if its hydroclimate changes in the future. In this section, the FEH catchment descriptor PROPWET is used to identify poorly performing catchments. Further to this, a method whereby PROPWET can be estimated for the future is also introduced, therefore allowing for application of the model to future climates.

Previous work has suggested that there are limits to how well catchment characteristics can be related to model performance. However, as Figure 6.13 shows, PROPWET can be used in this case to highlight the worst performing catchments. Linear relationships between catchment characteristics and model performance are perhaps optimistic, as in reality there is a considerable interaction between catchment physical characteristics, resulting in a degree of complexity not suitably represented by a single characteristic.

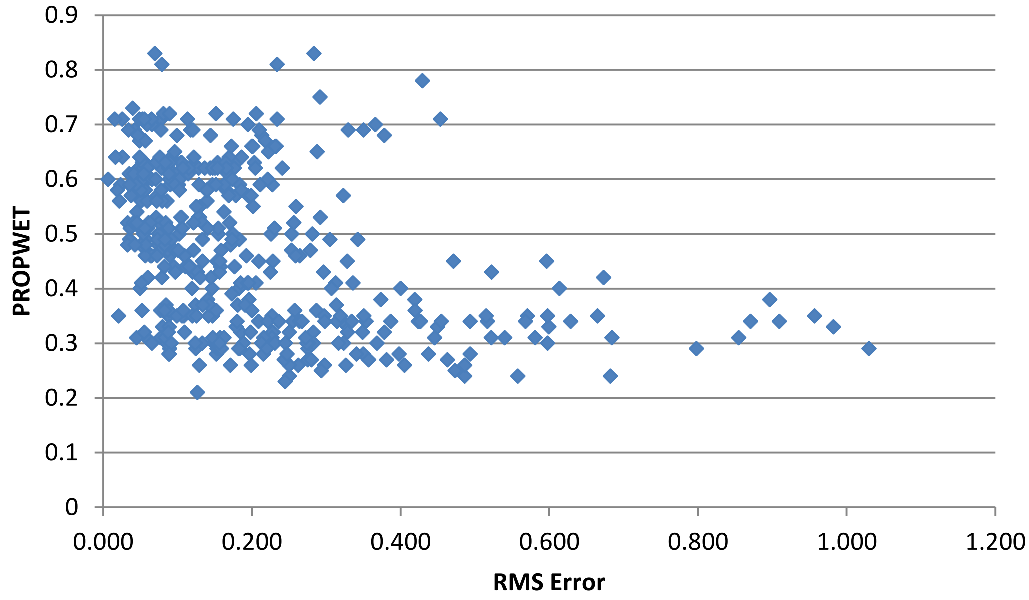



***Figure 6.13*** *Comparing Model RMS Error and PROPWET*

Figure 6.13 uses the FEH PROPWET index to highlight catchments that perform particularly badly. In this case, catchments with a low PROPWET value tend to show the highest errors, although for any particular low value of PROPWET (i.e. <0.4), the model error could span a wide range. In practice this could lead to discarding some catchments where the model performs well, where they cannot be identified as such.

The identification of this subset of poorly performing catchments is useful, as it provides a basis for estimating whether or not a catchment can be considered suitable for frequency curve estimation. Under a future climate, the PROPWET index may change; therefore there is a requirement for the estimation of this index under a future climate. In this way, the poorly performing catchments can be identified.

PROPWET is the proportion of the period 1961-1990 where the catchment soil moisture deficit was below 6 mm (Bayliss, 1999). Therefore wet catchments tend to have high PROPWET values and dry catchments tend to have low PROPWET values. For the future case, PROPWET has been estimated through regression, using the current relationship between annual PET and SAAR. Figure 6.14 compares the estimated PROPWET through regression with the FEH values.

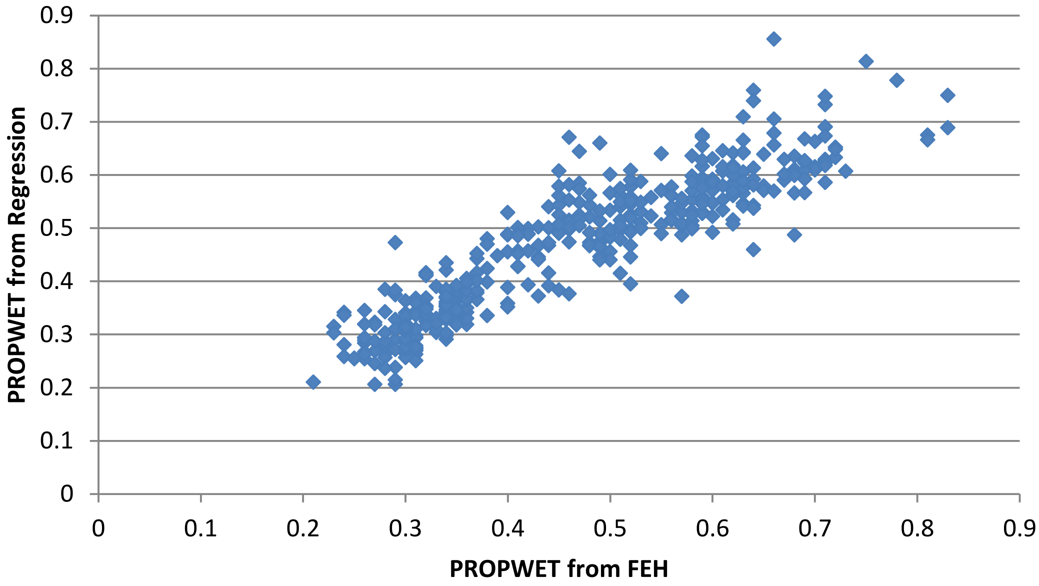



***Figure 6.14*** *Comparing FEH and estimated PROPWET values.*

The regression equation for the estimation of PROPWET is:

*PROPWET = 1.07 – 0.00144 PET + 0.000148 SAAR* **Equation 6.6**

The regression has an R-squared value of 0.83. This equation only uses PET and SAAR as they are readily available estimates of future climate. The comparison of estimated and observed PROPWET values shows a reasonable agreement, suitable for the purposes outlined at the beginning of this section. This allows the estimation of a catchment's PROPWET index for now or a future climate, given some information on its climate.

### *6.4.3 Catchments which are unsuited to modelling*

This leads on to a consideration of defining the catchments for which the flood frequency curve cannot be reliably estimated using the models presented in this thesis. The catchment descriptor which is most apt with regards to the work presented above is the PROPWET characteristic. The PROPWET value represents the average proportion of time during which the catchments soil moisture deficit is less than 6 mm. Therefore the higher the value, the wetter the catchment generally is. Catchments whose flow regimes tend to be dominated by groundwater inputs are likely to show low PROPWET values, due to their permeability (as seen in Figure 6.15). However, dry catchments (those with a low PROPWET value) do not always show high HOSTBFI values. The relationship shown in Figure 6.15 is reflected in the maps of catchment properties in Appendix A. HOSTBFI as an indicator of the groundwater component in a catchment, is not singly responsible for determining the wetness/dryness of a catchment. The east-west rainfall gradient across the country combined with the spatial variation in PET is also likely to play a part.

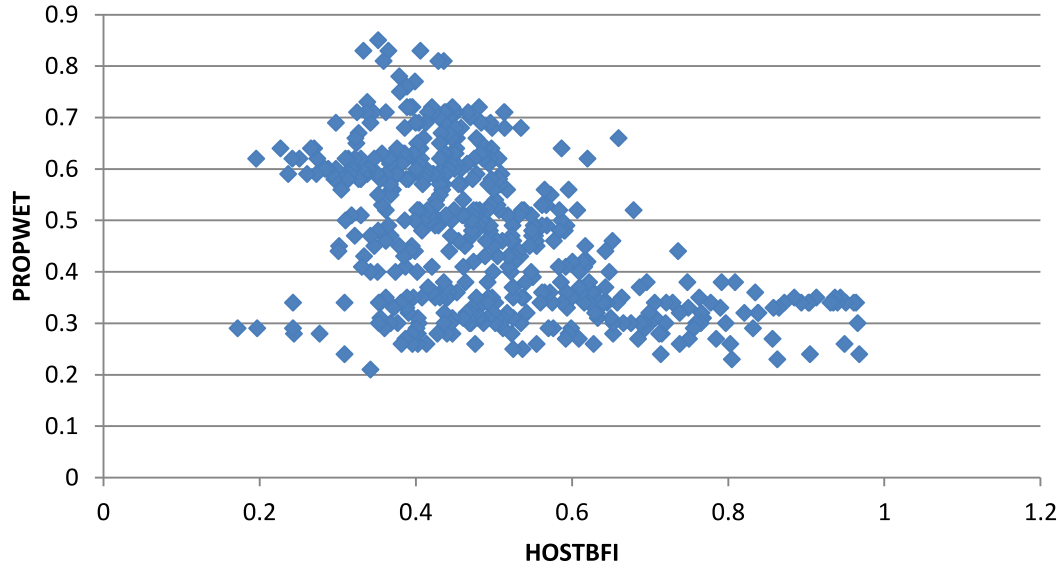



***Figure 6.15*** *Comparing Catchment HOSTBFI and PROPWET values*

It is not particularly easy to define at what point a catchments PROPWET value is likely to make it unsuited to modelling; however, it is suggested that a value of 0.45 be used as an initial threshold. Clearly this is a somewhat arbitrary approach; however, Figure 6.13 provides some basis for the choice of threshold. Were this flood frequency curve estimation method developed further it is likely that a threshold could be set in order to achieve a minimum level of model performance. This would evidently depend on the end user and application.

Figure 6.16 shows the distribution of catchments after those with low PROPWET values are removed.

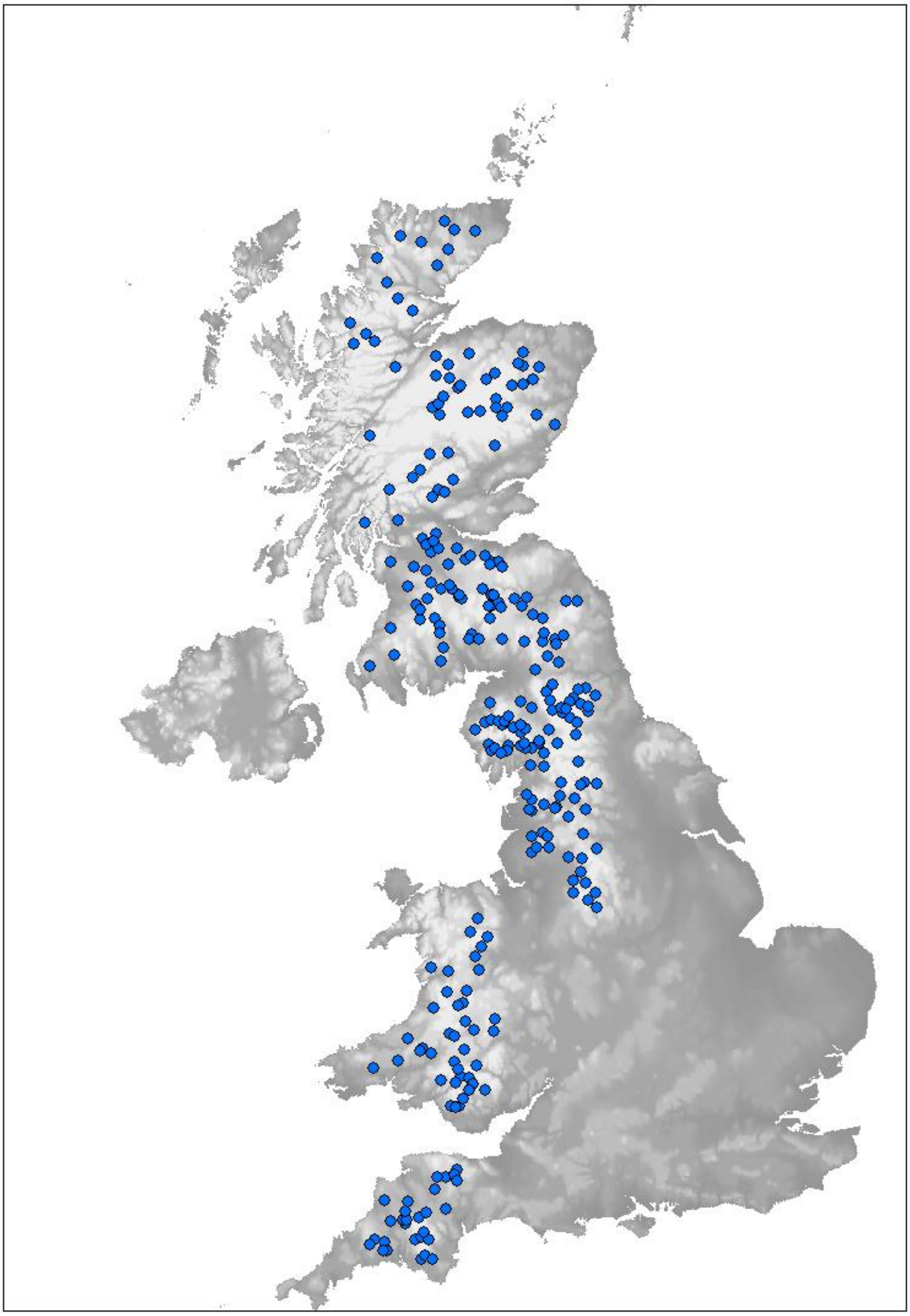


***Figure 6.16*** *Catchments with PROPWET values of 0.45 or above which can be modelled using the approach contained within this thesis.*

Overall, the removal of catchments with low PROPWET values reduces the size of the catchment set available for analysis by 84, leaving a set of 347 catchments. As Figure 6.16 highlights, the most noticeable gap in geographical catchment distribution exists in the south of England.

Because certain types of catchments are not suited to modelling using the method presented in this thesis, these catchments will not be used in further work. However, consideration will be given to how it may be possible to work with other catchment types in the discussion.

### *6.4.4 Case Study Catchments*

In order to illustrate some results, six catchments have been selected as case studies. These catchments are used throughout the rest of this chapter, not only to illustrate various tests of the model, but also as examples of future applications. This smaller set of catchments is used primarily because of the time required to generate the synthetic climate records. These catchments are listed in Table 6.3. A map detailing the location of each catchment can be found in Appendix E.1.

| **Station ID** | **Length of Record (yrs)** | **Station Name** | **AREA (km2)** | **HOSTBFI** | **SAAR (mm)** | **PROPWET** | **1 Day RMED** |
|---|---|---|---|---|---|---|---|
| 16003 | 43 | Ruchill Water | 98.58 | 0.428 | 1901 | 0.59 | 52.5 |
| 25001 | 47 | Tees | 815.69 | 0.355 | 1140 | 0.58 | 40 |
| 25005 | 46 | Leven | 193.57 | 0.381 | 726 | 0.34 | 33.3 |
| 53005 | 41 | Midford Brook | 147.4 | 0.625 | 965 | 0.36 | 37.9 |
| 71001 | 43 | Ribble | 1146.1 | 0.371 | 1350 | 0.56 | 43.9 |
| 84003 | 47 | Clyde | 1093.2 | 0.45 | 1165 | 0.6 | 37.5 |

***Table 6.3*** *A list of the catchments used as case studies in this chapter and some of their key attributes.*

Catchments were chosen primarily based upon their record length, with the selected catchments having the longest flow records out of the larger catchment set. Within the small group of case study catchments detailed in Table 7.1 there is a mix of both catchment size and SAAR. One catchment has a slightly higher HOSTBFI value than the rest, however, catchments with higher HOSTBFI values were generally disregarded.

## 6.5 Model Sensitivity

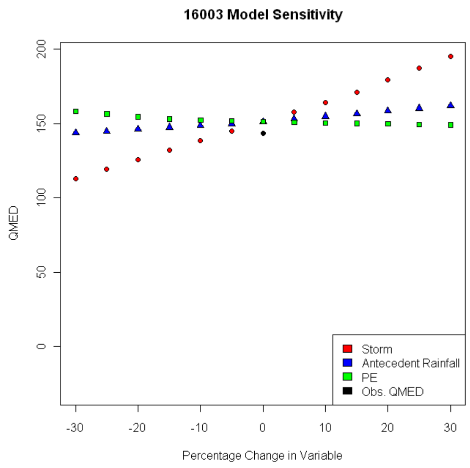
### *6.5.1 Model Sensitivity to Input Data*

Hashemi et al. (2000) highlighted the role of soil moisture in modifying the flood frequency curve. Elsewhere in this thesis, the importance of antecedent conditions has already been referred to. Therefore, a consideration of model sensitivity to antecedent conditions and storm magnitude is informative. This provides a useful check on the model concept and allows for an assessment of how well the modelling theory is reflected in practice. As has been previously explained, the antecedent estimates used here are reasonably crude – certainly no recourse has been made to soil moisture estimates in the case of the flood frequency curve estimation model. However, if the model setup is more sensitive to small changes in the antecedent conditions than to the storm rainfall it may be a problem, particularly as the antecedent estimates in this case are reasonably rough. Here, consideration is given to how sensitive the model is to PET, as well as the antecedent rainfall and storm rainfall. In general it would be expected that the current model setup is most sensitive to the storm rainfall and that any change in this variable would have a more significant effect on the flood frequency curve than changes to the antecedent PET or rainfall inputs.

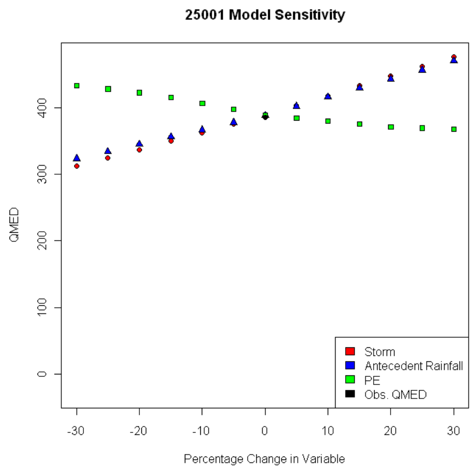
The sensitivity testing of input data modifies the three variables (storm rainfall, antecedent rainfall and antecedent PET) in five percent increments from minus thirty percent to plus thirty percent. Only one variable is modified at a time. For each percentage modification of the input climate, the frequency curve estimation model is run as per normal, using optimised coefficients. The flow estimation equation used is the same as that detailed earlier in Chapter 6 and can be seen in Equation 6.7. From each run, the

QMED value is calculated from the estimated flood frequency curve and then plotted against the modification percentage of the input variable. These plots are presented in Figure 6.17(a-f).

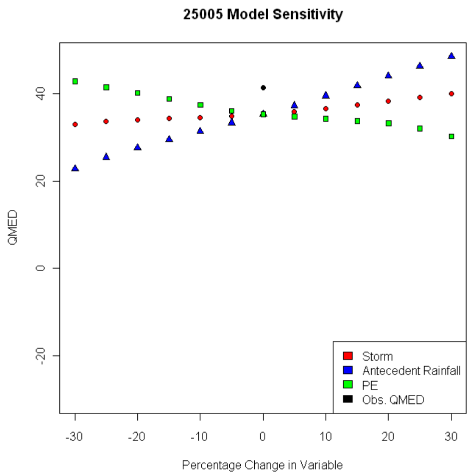
*Qest = b x storm + c x (30 day rainfall – 30 day PET)* **Equation 6.7**




*a*




*b*

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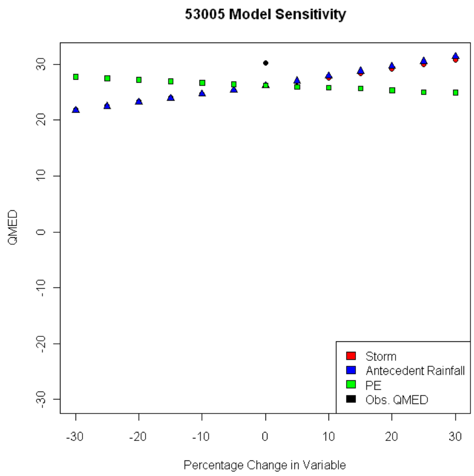


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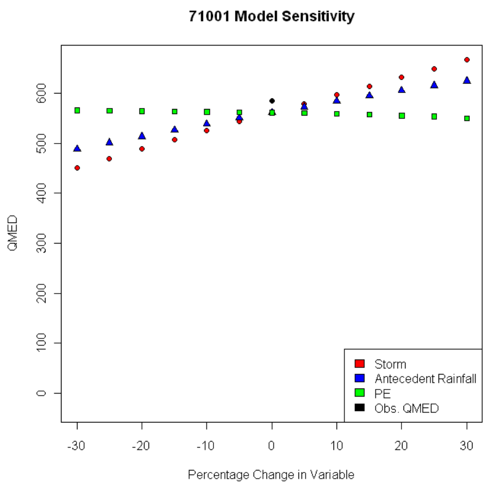


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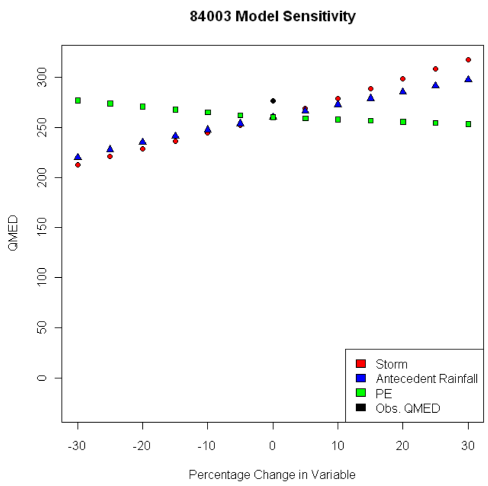


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***Figure 6.17**. Plots indicating model sensitivity for the six case-study catchments. The y-axis shows the estimated QMED, the x-axis shows the percentage change in the model input variable.*

The model appears most sensitive to changes in the storm rainfall, followed by antecedent rainfall and then PET. This is to be expected as it is partly a reflection on the model coefficients, where the coefficient applied to the storm tends to be higher than that applied to the antecedent block (average storm coefficient is 0.867 compared to 0.67 on the antecedent block). This is partly a reflection of reality in surface water driven catchments where antecedent conditions may modify a flood frequency curve, but it is principally determined through the storm rainfall amount, intensity and duration.

Station 25005 (Tees) is an exception to this; it is more sensitive to the antecedent rainfall (see Figure 6.16 (c)). It is located in the East of England and has reasonably low rainfall (SAAR of around 726 mm). It might be expected that in certain catchments, the antecedent conditions play a more important role than in others and therefore during model optimisation the objective function increases the weight on the antecedent conditions more than on the storm rainfall. However, the optimisation function evidently has no direct knowledge of catchment physical characteristics. The method assumes that catchment physical characteristics will influence the rainfall-flow transformation and therefore influence the optimised coefficients. It is also possible that in some circumstances the coefficients reached their final values because their respective storm and antecedent estimate sets took specific values which made it easier to minimise the objective function by increasing the weight on the antecedent condition coefficient. This, in itself, does not mean that antecedent conditions are more important in a catchment, it is merely the result of the mathematics involved in optimisation. This problem is considered later in the thesis where the optimised coefficients are tested in order to see how stable they are.

In terms of future changes to flood frequency curves, a simple change in one variable would produce a change in the flood frequency curve. However, changes to future climate may be more complex, possibly involving changing seasonality of PET and rainfall as well as changes to magnitudes of all three variables used as model inputs. In this case, the corresponding change in the flood frequency curve will not be so easy to determine and it is because of this that a model, such as the one outlined in this thesis can help to provide predictions of future behaviour. Before the model can be used for future projections, it is necessary to look at the assumptions built into the modelling structure as well as the model performance. These are now considered in more detail.

### *6.5.2 Model Sensitivity to Record Length*

The current model setup uses the derived coefficients (b and c) from the optimisation process for use in the predictive mode of the model. Gaining an understanding of how reliable these coefficients are is important, as their usefulness may be limited if they vary considerably between different model runs when using the same input data. Similarly, it is also useful to know what length of flow record is required in order for the coefficients to be considered stable.

To test the robustness of coefficient estimation, a bootstrap assessment of the coefficient estimation was undertaken. Bootstrapping is a re-sampling method that calculates the accuracy of a value when estimated from a specific set of data. Four catchments with long flow records were selected for the bootstrap assessment. For five different record lengths (5,10,15,20 and 25 years) the assessment estimated the optimised model coefficients from 100 bootstrap samples of AMAX flow events. The flow estimation model used PET and antecedent rainfall for coefficient estimation; however, the choice of model does not make a significant impact upon the results; rather it is the length of the record which determines how robust the coefficient is. These results are equally applicable to the flow estimation model using only rainfall as its antecedent indicator. From the coefficient estimates, a standard error was calculated (as per Equation 6.8). The results are shown in Figure 6.18.

$$SE = \frac{s}{\sqrt{n}}$$ **Equation 6.8**

Where S represents the sample standard deviation and n represents the number of observations in the sample. Based on the results shown in Figure 6.18, a record length of less than fifteen years should be considered unsuitable for use in coefficient estimation using the model developed in this thesis. For the four stations shown in Figure 6.18 a station record that is less than fifteen years tends to show a steady increase in the error as the record length is shortened. Record lengths greater than 15 years show a much more gentle increase in error up to this point. However, the error increases for all catchments as the record length is shortened.

This assessment demonstrates that the minimum record length suitable for use within the coefficient optimisation method demonstrated in this thesis is 15 years. However, it should also be stressed that, with regards to a flood frequency assessment, a record length of fifteen years is generally considered to be short, as only low return period flows can be estimated with any confidence

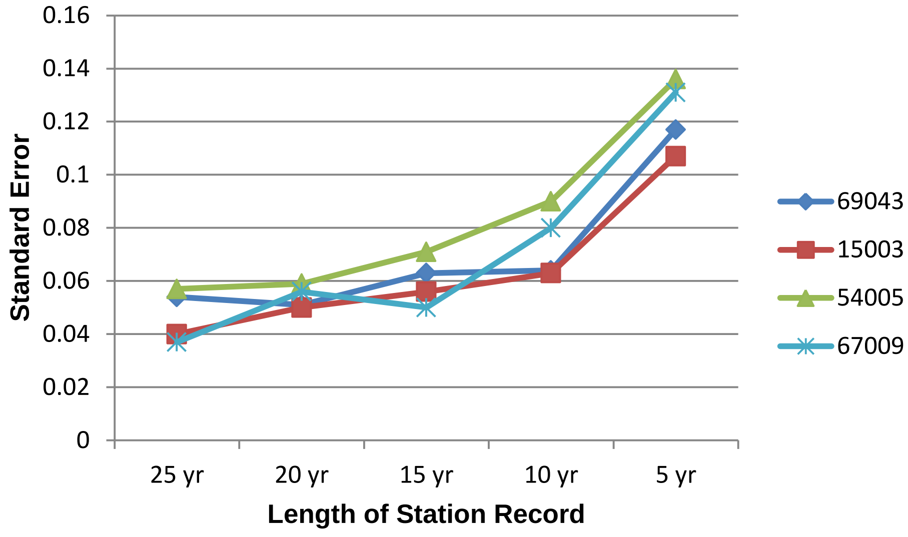



***Figure 6.18*** *Relationship between the length of record over which the coefficients were estimated and the standard error estimate for each catchment. The standard error calculation was carried out for four catchments, identified by their gauge ID's.*

## 6.6 Discussion

### *6.6.1 Assessing Performance*

The spatial distribution of results as shown in Figures 6.1 and 6.2 are similar to those of the event based model shown in Chapter 5. The distribution of results is also similar to other national scale modelling work such as the g2g modelling of Bell et al. (2007a). The g2g model performs best on catchments whose hydrological regime is dominated by topography and so it performs relatively poorly on catchments which have a strong groundwater component. This seems to suggest that modelling groundwater based catchments requires an alternative approach to both the frequency curve mapping work carried out here as well as the g2g method.

Section 6.4.2 highlighted how the catchment descriptor PROPWET could be used to identify poorly performing catchments. PROPWET is not a direct indicator of the groundwater component present in a catchment, it is a more general description of catchment wetness. On its own, HOSTBFI does not show any particularly good relationship with model performance, yet PROPWET can clearly identify the poorly performing catchments. It may be that certain high HOSTBFI catchments do not suffer so much from low groundwater levels and so the frequency curve estimation model performs better in these catchments. Yet other high HOSTBFI catchments do not perform well using any frequency curve estimation method. From the distribution of high HOSTBFI catchments as shown in Appendix A.2, it is the eastern catchments which show higher errors. This may be because of their tendency to experience lower rainfall and higher PET than their western counterparts. This would tend to agree with work showing poorer model performance in the lower PROPWET catchments. This was one of the reasons why PROPWET was chosen as the indicator which could be used to identify poorly performing catchments. The second reason is that as shown, it can be reasonably estimated from simple climate data, allowing for its use in future projection studies. Estimating HOSTBFI may require a more complex approach and on its own it does not particularly highlight the poorly performing catchments.

### *6.6.2 Antecedent Conditions Estimation*

Chapter 5 showed how the complexity of the catchment moisture deficit model did not improve flow estimation compared to the model using only antecedent rainfall. Therefore, the work presented in this chapter concerning frequency curve mapping made no use of the catchment moisture deficit estimates. It did however introduce the use of a new source of PET data. Justification for the testing of a frequency curve model which includes PET lies in both the source of the data as well as the future requirements of the model. The PET data were calculated from observed, gridded datasets and so it likely that these PET estimates are more locally representative of actual conditions than the generalised PET estimates used in Chapter 5. These calculated PET estimates from gridded data were only available later on during the research project which is why they were never used in the original soil moisture estimation model. Nevertheless, they are still reasonably rough estimates and do not estimate actual evapotranspiration.

Irrespective of the impact that PET has on the model, accounting for antecedent conditions is clearly important. Future climate changes may be complex, involving changing seasonality of both rainfall and PET. If the flood frequency curve estimation model cannot account for these future changes then any future predictions of change are likely to be flawed. While antecedent PET does not significantly improve the performance measures of the frequency curve estimation model, the sensitivity testing work has shown that the models are sensitive to it as an input variable.

To some extent antecedent conditions have already been included within the modelling procedure for the rainfall-only model, as the use of antecedent rainfall blocks in the flow estimation formula gives an indication of how wet the weather has been over the catchment before the storm event (and therefore an indication of how wet the catchment may be). Over a longer period however, potential evapotranspiration (PET) can play a significant role in controlling soil moisture, and therefore it was felt necessary to include this within the model formulation.

Hashemi et al. (2000) and Franchini et al. (2000) have shown the importance of antecedent conditions through simulation. In particular, they emphasise how soil moisture variability at the time of arrival of a flood generating storm can affect the shape of the flood frequency curve. In another simulation study, Zehe et al. (2005) suggest that given different realisations of initial soil moisture, intermediate and dry catchment soil moisture states can produce strongly different hydrographs, whereas the effect from a wet catchment is much less noticeable. The physical explanation for this may lie in thresholding behaviour, particularly where overland flow generation is present.

## 6.7 Conclusions and Implications.

The work presented in Chapter 6 shows how the modelled annual maximum time-series can be used to estimate the catchment flood frequency curve. However, a good estimation of the flood frequency curve does not on its own show that the model can reliably estimate the flood frequency curve nor be suitable to work with future projections. Therefore the work presented within this chapter only shows how the rainfall to flood frequency transformation can take place; it does not prove that it is reliable for use with future projections. In order to show this, more extensive testing of the model is required and this work is presented in Chapter 7.

# Chapter 7: Validation and Application

## 7.1 Introduction

The flood frequency curve estimation model has been developed with future scenarios in mind, evidently a situation where no validation of the model output can take place, as there is no observed flow data for the future. Furthermore, as available climate model outputs produce scenarios of change, the frequency curve mapping model can only be used to make projections of future impact upon flood frequency rather than making specific predictions.

Determining a specific definition of model validation is difficult, as there is little agreement on what it constitutes (Hassanizadah and Carrera, 1992). It is an undeniable fact that earth systems models can never be proven right, but they can be proven wrong (Oreskes et al., 1994). Therefore, even exhaustive testing of a model still leaves some uncertainty in its ability to make predictions. Despite this fact, testing models on data and situations outside those on which they were developed can provide some significant insights into the limitations of model operation as well as patterns of model performance. Chapter 7 builds on the previous model development of Chapter 6 by developing specific tests of the flood frequency curve estimation model, designed to assess the model behaviour under different criteria.

As the flood frequency curve estimation model has previously been shown not to work well on catchments with a high HOSTBFI value, the work presented in this chapter uses a smaller subset of catchments (removing those with high BFIHOST values from the analysis) when compared to the work presented in previous chapters. In certain circumstances the amount of work required for the analysis prohibits application across a large catchment set, and in these circumstances only a few catchments have been selected for assessment.

A single model formulation is tested in this Chapter. This formulation can be seen in Equation 7.1. It includes PET and antecedent rainfall as the antecedent conditions estimator. Due to the potential for PET to alter in the future, it is an important variable to include in the model formulation.

$$Qest = (b\ x\ storm) + (c\ x\ (Thirty\ Day\ Rainfall - Thirty\ Day\ PET)$$

**Equation 7.1**

## 7.2 Model Validation

Hassanizadah and Carrera (1992) suggest full model validation is impossible, and therefore models can only be referred to as partially validated or semi-validated. Despite this they note several common reasons why model validation is undertaken, namely; establishing the ability of the model to make predictions, comparing model predictions to measurements and quantifying uncertainty and inaccuracies. Konikow and Bredehoeft (1992) suggest that validation demonstrates the ability of a site specific model to represent cause and effect relations at a particular field area. Oreskes et al. (1994) argue that the primary value of models is heuristic and that because of the impossibility of validation, predictive modelling is less important. Philosophical arguments surrounding validation are abundant and it is difficult to develop an overarching definition of what it is. Even if this were possible, the practical problem of how to meet that definition still remains. Here, validation testing of the frequency curve estimation model uses the reasons (stated earlier) of Hassanizadah and Carrera (1992) as a guide in order to develop some specific tests of the flood frequency curve estimation model. Three tests of the model are used as a basis for validation. The tests have been designed specifically for this modelling approach. This is important as the model structure and operation is different to that of many other catchment models. The tests examine different aspects of the models predictive behaviour, but on their own they do not show that the model can be reliably used with future projections. This work is considered separately in Section 7.3.

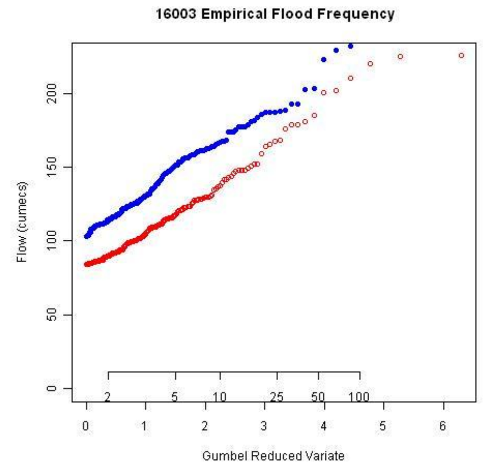
### *7.2.1 Testing on Unused Data*

The first test involves assessing how well the model can estimate flood frequency with data that was not used in the fitting process. Peaks over Threshold (POT) data is used in order to test how well the model is able to transform rainfall inputs into flows using the previously optimised coefficients from the model fitting in Chapter 6. The model structure is of particular importance, as any assumptions may invalidate the model in an alternative situation. Therefore, this test assesses the models ability to work with data on which it was not fitted.

The coefficients have previously been optimised against the observed AMAX flow and rainfall data. They are therefore, to some extent, a product of catchment physical characteristics as well as the catchment hydroclimatology represented through the AMAX series. Under a future climate scenario, it may be valid to assume that catchment physical characteristics will remain reasonably unchanged, but, if the coefficients are a product of the catchment's hydroclimatology, it may not be valid to use them for future scenarios where the climate is significantly altered. By using a separate set of flow data, that spans a wider range of hydroclimatic variability, the usefulness of the coefficients for predictive use can be assessed. This is a check to ensure that the model fitted using the AMAX data was not simply an optimised model which would only work well on that data; it needs to have applicability to any combination of large rainfall and flow events.

The process for testing is as follows. First, the HiFlows POT flow records are filtered by removing the AMAX data. This process ensures that the test is being conducted on independent data compared to the model fitting, and that the AMAX do not influence the results on any testing. The test of the flood frequency curve models predictive ability then takes the filtered POT flow data and for each event estimates a storm using the date of the event by utilising the storm estimation procedures already developed. Antecedent rainfall and PET are estimated as previously also using the date of the POT flood event. From this, the previously derived coefficient sets (from Chapter 6) are used to transform the storm and antecedent estimates into flows, leaving a set of POT flows. Finally, an observed and modelled flood frequency curve can be constructed using the observed and modelled POT flood series. In this case a distribution was not used, and so results are plotted as empirical frequency plots only.

Traditionally, a POT based flood frequency assessment would utilise the Generalised Pareto Distribution (GPD) (Robson and Reed, 1999). However, fitting a distribution to a POT series requires considerable work, with recommendations that the use of the specific threshold needs careful testing in conjunction with a GPD distribution (Coles, 2001). Therefore, to remove any ambiguity about the influence of the choice of distribution and method of fitting, observed and modelled data are presented as empirical frequency plots only. Therefore, performance can only be assessed graphically and subjectively. The above process has been carried out for the selected catchment set introduced in Section 7.1.1 and the results are presented in Figure 7.1.

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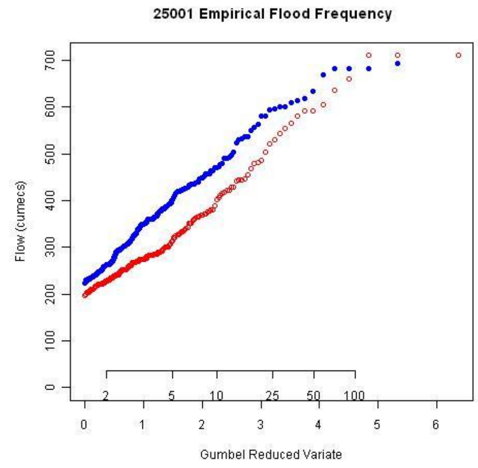


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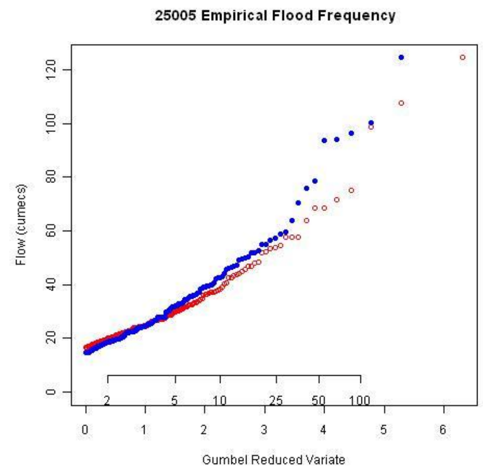


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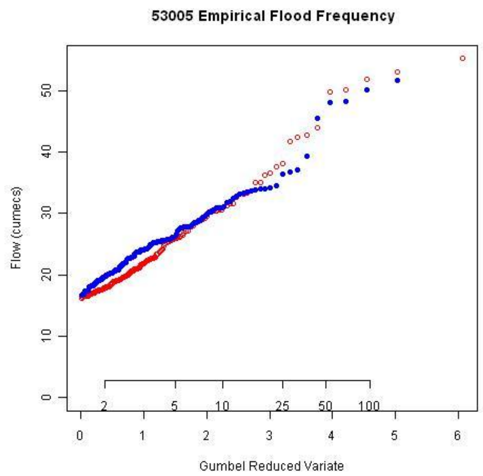


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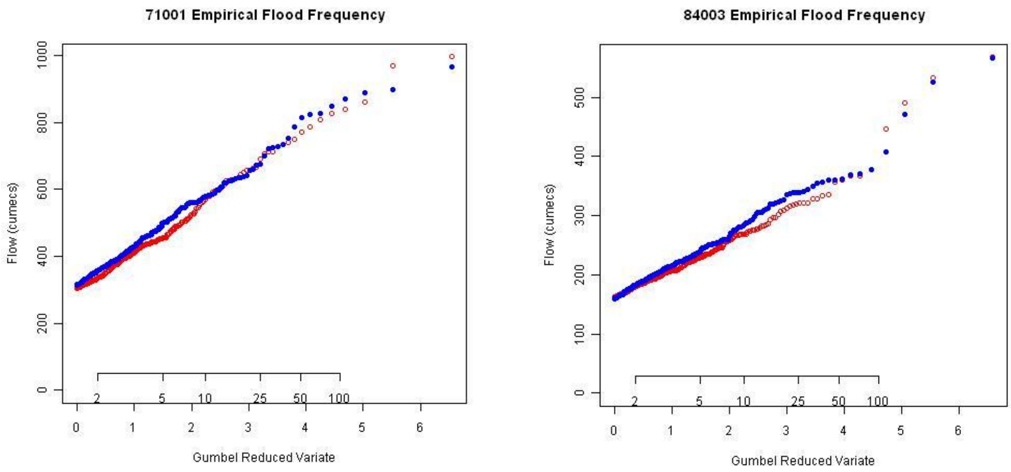


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***Figure 7.1*** *Plots of observed (red) and modelled (blue) POT data using the model developed in Chapter 6. Plots show empirical frequency on a Gumbel reduced variate scale.*

The model appears reasonably capable of estimating the observed empirical frequency curve for most catchments. However, for catchments Ruchill Water (16003) and Tees (25001) there is an overestimation of the empirical flood frequency curve. Figure 7.2 shows the original comparison between observed and modelled flood frequency for the coefficient fitting as undertaken in Chapter 6. Both catchments show good agreement with the observed flood frequency curve.

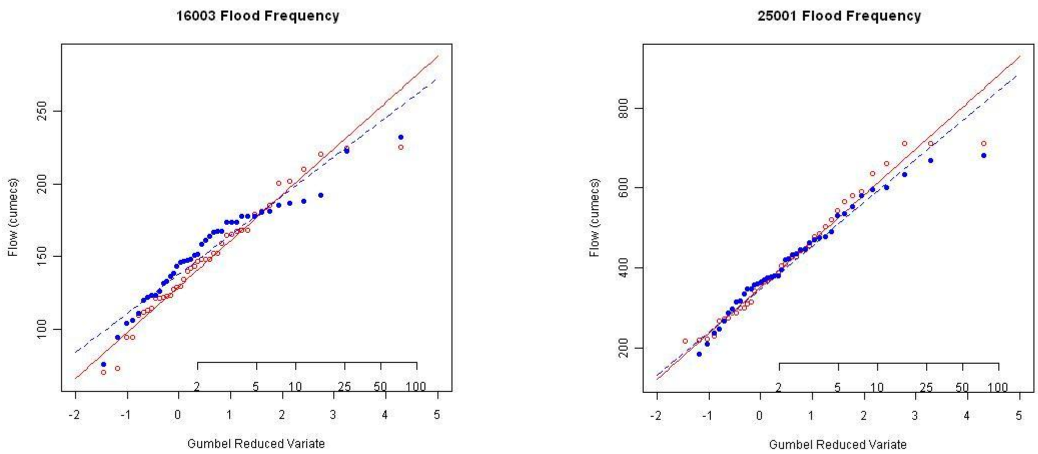



***Figure 7.2*** *Comparing observed (red) and modelled (blue) flood frequency curves from the original fitting in Chapter 6. The catchments are Ruchill Water (16003) and the Leven (25001). The model uses PET and antecedent rainfall.*

What is not clear is why these catchments do not perform well under the POT test. The problem is more than one of a few rogue events, or extreme cases, as Figures 7.1a and 7.1b show a consistent overestimation. This suggests that a good fit from the flood frequency curve estimation work carried out in Chapter 6 is not on its own indicative of a model which is suitable for use in future projection work. This test suggests that in order to use the flood frequency curve estimation model in the future, it must first be fitted (as in Chapter 6) and then tested on some unseen data (as carried out here). Only if this is successful can work using future climate scenarios be considered. As the POT modelling work was carried out over all catchments, further examples of comparative plots between model fitting and application to the POT data can be found in Appendix F.1.

The results give some confidence in the estimation of flow peaks and hence the estimated flood frequency curve. While the model developed in this thesis was fitted to the AMAX series, the validation of its predictive ability using the POT series (with the AMAX data removed) suggests that the model has some predictive power. In relation to the purposes of validation stated by Hassanizadah and Carrera (1992) this test is one of how the model performs when tested on a set of unseen data. The work has shown that the optimised coefficients can be used on a wider set of data than that to which they were originally fitted. This gives some confidence in the ability of the model to estimate a series of flow peaks which were not used when fitting the model.

### *7.2.2 Testing Predictive Ability*

The second test of the model involves predicting the flood frequency curve from rainfall without recourse to the flow record for storm estimation. This is important, as when used for future projection work the model will have no knowledge of the date of occurrence of any flood. As a validation test, this aims to assess one aspect of the predictive power of them model. The process of estimating the catchment flood frequency curve without reference to the date of flood is as follows.

1) A POT rainfall series is extracted from the observed rainfall record. This POT series averages five events per year over the length of the record.

2) The POT rainfall series are converted to flow. This step uses Equation 7.1 to estimate flows, and antecedent information calculated based on the date of the POT rainfall event. The coefficients for flow estimation are those estimated through optimisation during the model fitting phase. Once completed, this leaves a series of estimated flow peaks (with retained dates).

3) From the flow series in step 2, the AMAX flow values can be extracted.

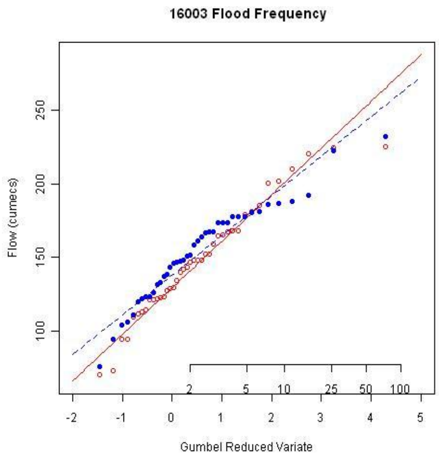
4) Flood frequency curves of observed and estimated AMAX data are then produced and assessed on their RMS error as for previous work. These flood frequency curves can also be compared to those produced during the fitting phase in order to assess any change in model performance between fitting and the test of predictive power.

This process recognises that the AMAX rainfall event is not always responsible for generating the AMAX flow event (and that the extent to which this is the case differs between catchments). Chapter 4 provided extensive evidence of this. Therefore, it would not be appropriate to simply extract the AMAX rainfall series and convert it to flow.

Figure 7.3 shows observed flood frequency curves (red) along with the modelled curves (blue) for the 6 case-study catchments. For each catchment, the blue curve in the left panel shows the original model fit, and the blue curve in the right panel shows the validation test estimate of the flood frequency curve. In this case the modelled curves have been estimated through the validation procedure as described above, with the coefficients b and c taking the optimised values.

Original Fit

*Validation*

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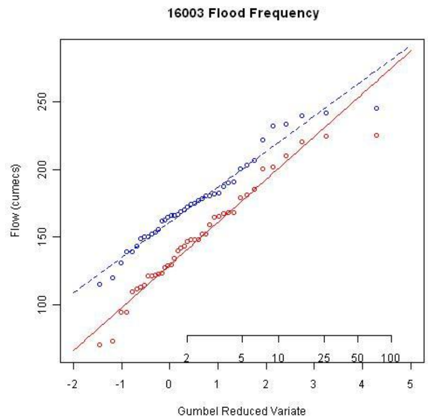


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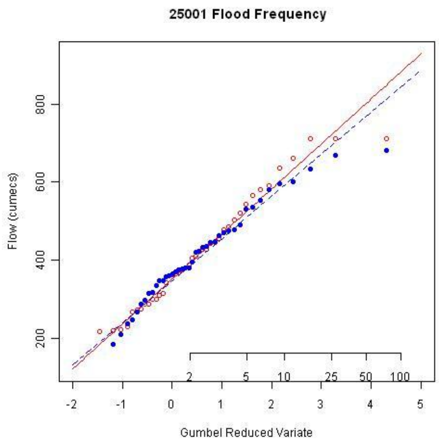


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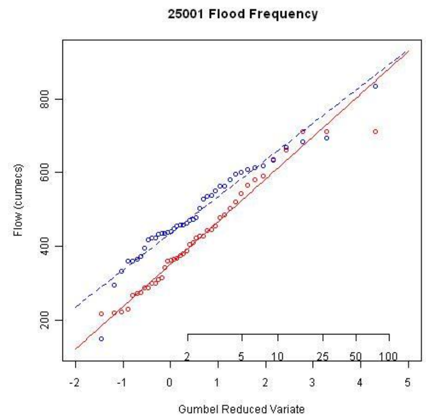


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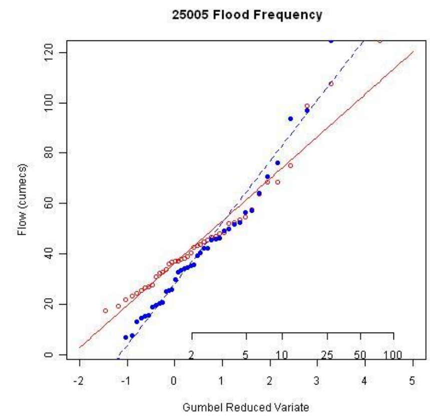


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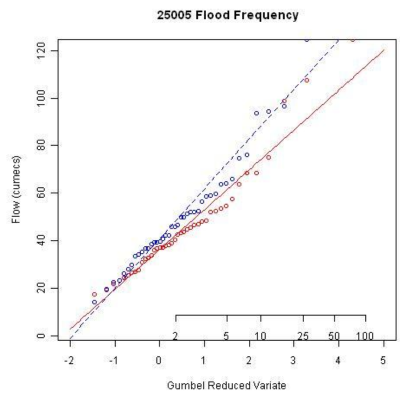


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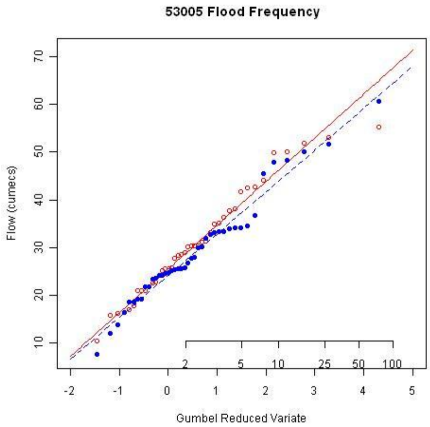
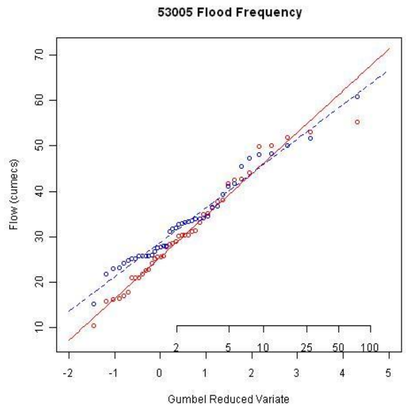
Original Fit | *Validation*

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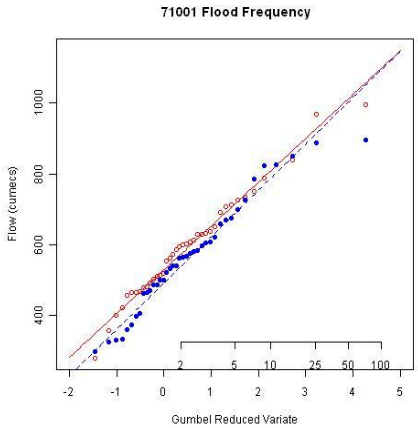


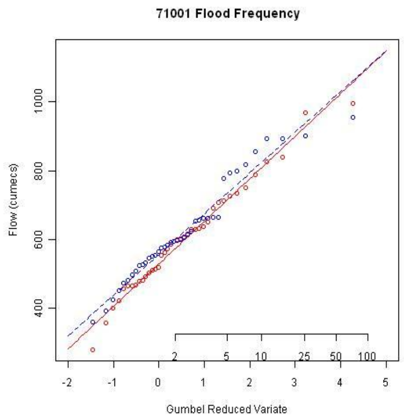


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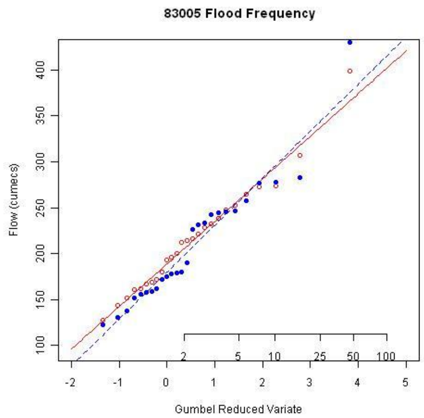


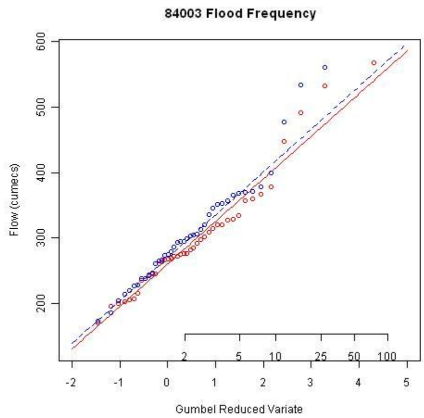


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***Figure 7.3*** *Fitting (left) and validation (right) flood frequency curves created using optimised coefficients. Solid red lines represent the observed frequency curve; dashed blue lines represent the modelled frequency curve.*

There is a general degradation in model performance between fitting and validation steps, although some stations show little change. Ruchill Water (16003) and the Tees (25001) show the most degradation between fitting and validation; the reason for this is unclear as they are both considered relatively wet catchments with a low HOSTBFI. These catchments also performed poorly in the first test using POT data. It is difficult to know why Ruchill Water and the Tees do not work well in either validation test, however, these results re-inforce the need for fitting the model and then testing it before predictive use. The poorer performance shown by the two catchments mentioned above is further evidence of the poor link between catchment type and model performance.

Figure 7.4 provides a more general understanding of how the RMS error changes between fitting and validation, this time across the larger catchment set. As expected, there is a general increase in the higher RMS errors in the validation test model compared to the original fit, although few catchments show particularly high RMS errors at the validation stage. As the change in distribution of the RMS errors is reasonably small, there is some confidence in the ability of the model to estimate the AMAX flood frequency curve when timing information on flooding is not available.

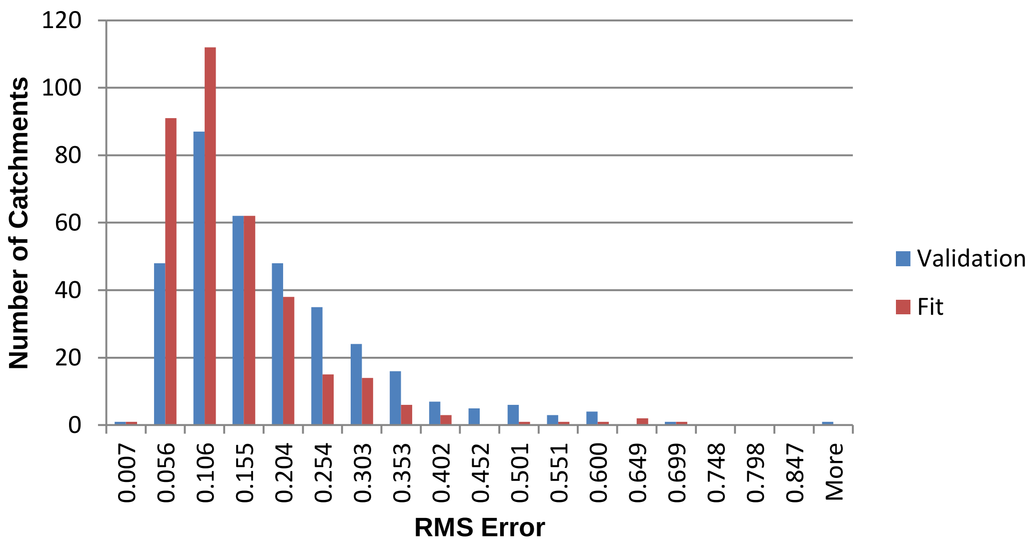



***Figure 7.4*** *A comparison of the RMS error for between fitting and validation.*

An alternative assessment of error calculates the percentage difference between specific return periods for the observed and modelled flood frequency curves. This assessment gives a direct and easily understandable quantification of the error between the modelled and the observed flood frequency curves in terms of the model's predictive ability. A negative error represents an underestimation by the model whereas a positive error suggests an overestimation by the model. The percentage errors for the validation plots in Figure 7.3 are presented in Table 7.1. This shows the percentage error between the observed and modelled flood frequency curve at the ten year return period. These values tend to reflect what the visual assessment of Figure 7.3 shows. However, even for some of the poorly modelled catchments, the percentage errors are still encouraging, given that the potential for errors in the measurement of high flows can be around 10-15 % (Herschy, 2002). Ruchill Water and the Tees appear to show such low percentage error because of the shape of the modelled flood frequency curves which tend to agree more with the observed flood frequency curves at higher return periods. This explains why the percentage error cannot be used on its own to assess model performance as it could be prone to give misleading results.

| **Gauge** | **Percentage Error** |
|---|---|
| 16003 | -9.9 |
| 25001 | -11.2 |
| 25005 | -21.1 |
| 53005 | -1.3 |
| 71001 | -0.9 |
| 83005 | 0.1 |

**Table 7.1** *Percentage errors between the magnitude of the ten year return period event as calculated using an observed AMAX flood frequency curve and the model validation flood frequency curve from Figure 7.3.*

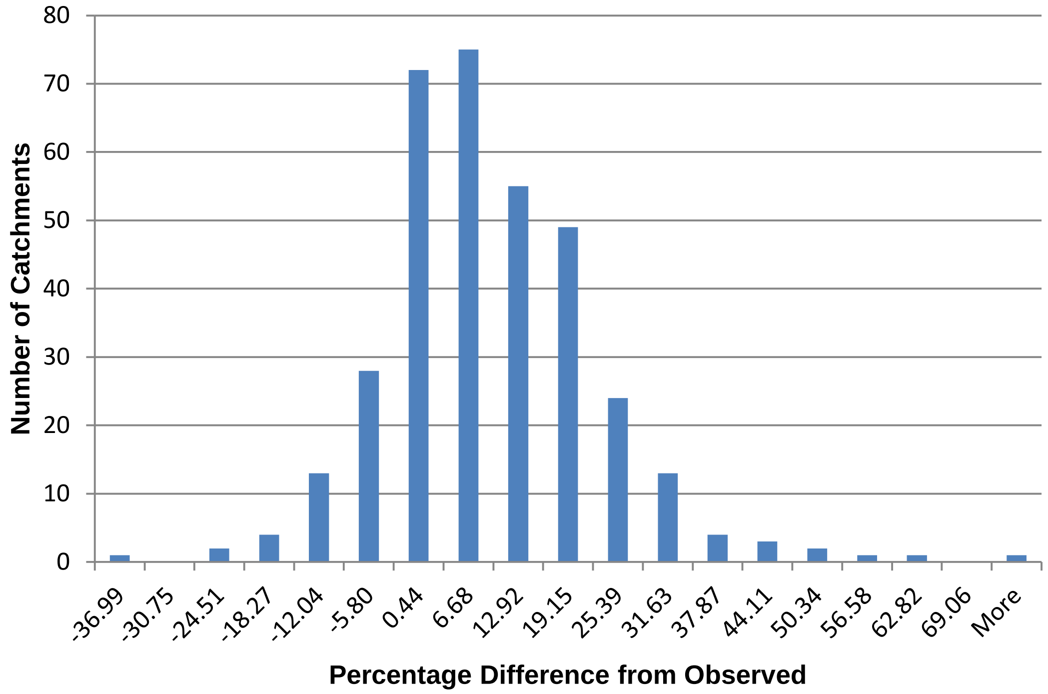



***Figure 7.5*** *The percentage error between the estimated magnitude of a ten year return period event, as calculated using an observed AMAX flood frequency curve and the model validation flood frequency curve estimated using observed rainfall data for the whole catchment set (excluding low PROPWET catchments).*

Figure 7.5 provides evidence of the distribution of percentage error for the estimated magnitude of the ten year return period event between the observed and modelled flood frequency curves across the catchment set (low PROPWET catchments excluded). The majority of catchments have a low percentage error of between -5 % and 20 % and this gives some confidence in the ability of the model to estimate return period values. There is, however, a slight tendency for overestimation. The selection of a single return period is intentional, as it provides a more understandable assessment of model performance than the RMSE value used previously.

From the individual catchments plots in Figure 7.3 the change in percentage error can be assessed against the change in return period visually. For the majority of catchments, the difference is minimal at different return periods. However, for the Leven there is a significant change in the percentage error with return period due to the poor estimation of the modelled flood frequency curve.

Figure 7.6 shows the spatial distribution of the percentage error. The pattern of error is similar to that of previous model fitting errors, with western catchments showing the lowest percentage error estimation (typically +-10 %). The low PROPWET catchments have been included here in order to illustrate their high percentage error values at the ten year return period. In a few cases these percentage errors are upwards of 50 % and reinforce why flood frequency estimation in these catchments is not appropriate given the current model setup. It is however, encouraging that the general spatial pattern of percentage error is similar to the earlier work, reflecting consistency in the model performance when applied in different circumstances. Furthermore, there is a reasonable distribution of catchments with errors of +-10 % for use in a large scale flood frequency assessment.

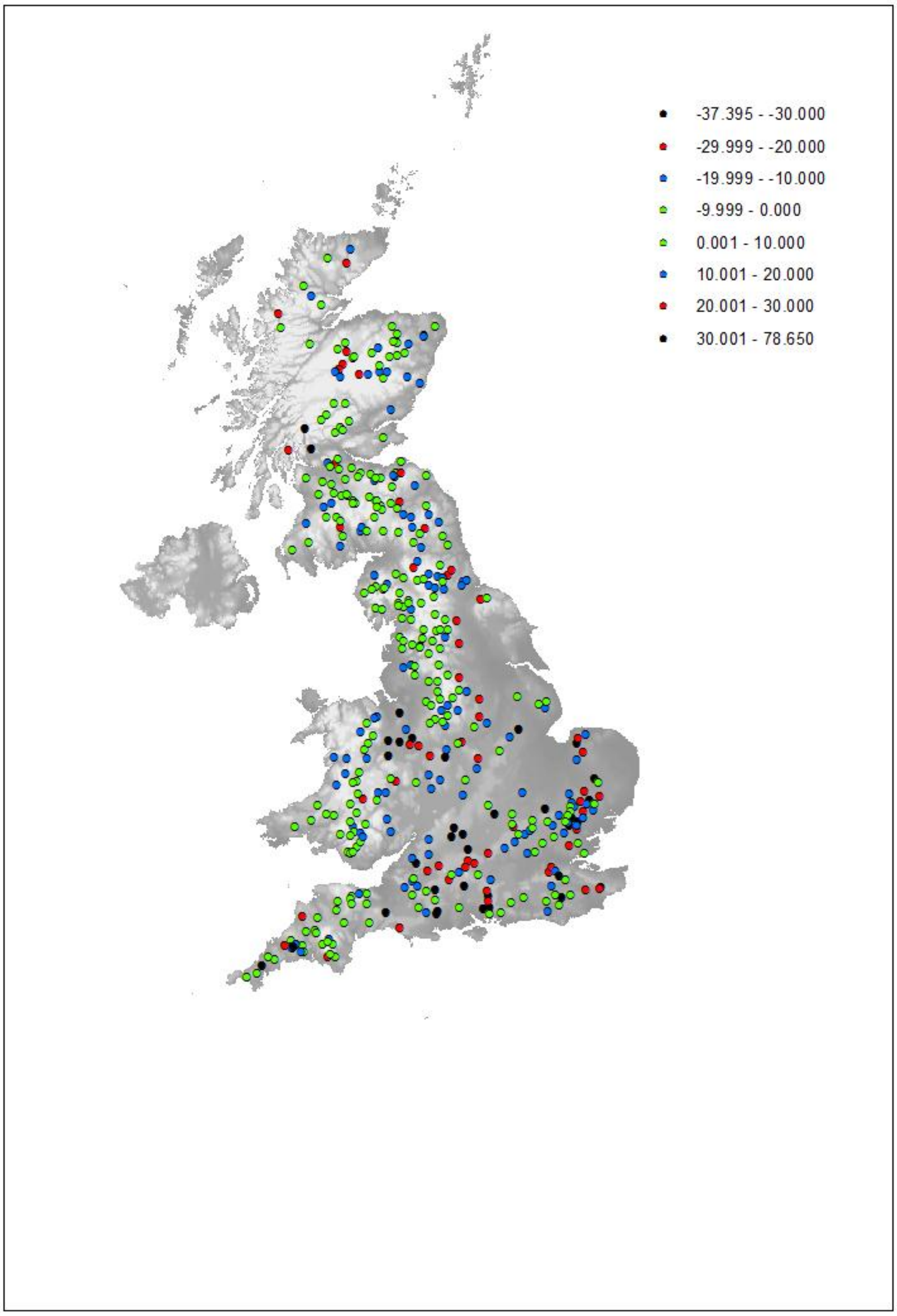



***Figure 7.6*** *The percentage difference between the magnitudes of the 10 year RP event estimated from observed and modelled flood frequency curves. The flow estimation model uses PET and antecedent rainfall. Note that the scale can take positive and negative values reflecting over and underestimation of the RP value by the model.*

The second validation test has shown how the model can estimate the catchment AMAX flood frequency curve from POT rainfall. The relatively small change in RMS error distribution between the fitting and validation test is encouraging. Furthermore, the use of a percentage error provides a more understandable way of assessing model performance compared to the RMS error and gives confidence in the model ability to estimate the flood frequency curve.

### *7.2.3 Testing Transferability of the Model Coefficients*

The third test of the frequency curve estimation model involves estimating the model coefficients for a target catchment by transferring the coefficients from another catchment with similar physical characteristics to that of the target. This is a test of the transferability of model coefficients, and, as such is not strictly necessary for model operation. However, it provides interesting insights in to the ability of the model to work with estimated, rather than optimised coefficients.

The use of a donor catchment is tested. This assumes that no coefficient set is available for the catchment of interest. Therefore, the method chooses a coefficient set from another 'similar' catchment. This could be thought of as addressing the ungauged catchment problem. Depending upon performance, this method may be the most suitable for selecting catchment coefficients under a radically different climate.

The 'similar' catchment is chosen as being the closest to the target catchment in Euclidean space in terms of three catchment descriptors from the FEH, through the use of the following equation:

$$d = \sqrt{\left(\frac{BFI_g - BFI_{tg}}{\sigma BFI}\right)^2 + \left(\frac{AREA_g - AREA_{tg}}{\sigma AREA}\right)^2 + \left(\frac{SAAR_g - SAAR_{tg}}{\sigma SAAR}\right)^2} \qquad \textbf{Equation 7.3}$$

Where *tg* is the target flow gauge (for coefficient estimation) and *g* is the potential donor gauge. *D* represents the distance in catchment descriptor space between the target and potential donor. Evidently, the smaller the distance, the more representative the potential donor is of the target. This assumes that the coefficient sets are related to the catchment characteristics selected within the equation. However, the relationship between FEH catchment descriptors and model coefficients is not straightforward as has previously been shown. It also assumes that the selected catchment characteristics can adequately characterise catchment hydrology, and this may not be the case.

Donor catchments were chosen based on their hydrological and climatological characteristics, rather than through a geographical proximity method. This is the approach taken by the FEH in pooling catchments. The FEH catchment descriptors or characteristics chosen for catchment estimation are HOSTBFI, AREA and SAAR. While other characteristics like PROPWET and RMED could also have been used, these tend to show a close agreement with properties like SAAR and therefore including them would only replicate these properties.

The estimated coefficients are then used within the frequency curve estimation model as detailed in Chapter 6. This uses the observed peak flow data to estimate the storm and antecedent conditions. The estimation model is stated in Equation 7.1 at the beginning of this chapter. This allows for direct comparison against the fitting procedure, but not against the second validation test of predictive performance.

Figure 7.7 outlines the distribution of results for the donor coefficient estimation method as well as the optimised coefficient method. In general, the model using the optimised coefficient set performs best, however; this is perhaps to be expected. The donor catchment method appears to contain more catchments on the upper tail of the error distribution in Figure 7.7.

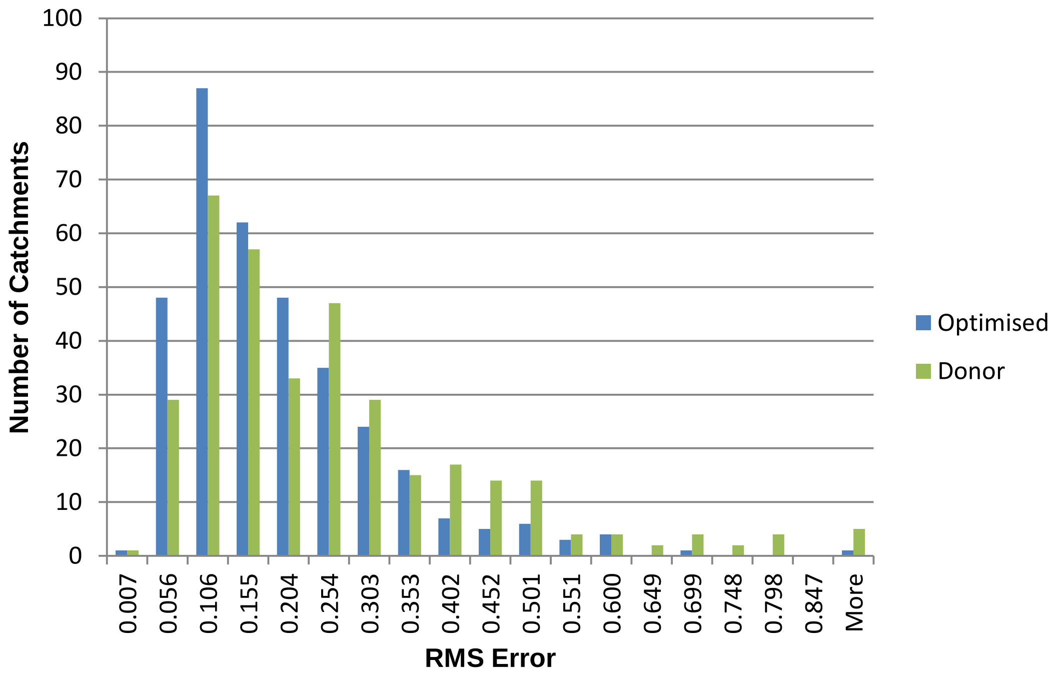



***Figure 7.7*** *RMS errors for model runs using different coefficient sets*

The error distribution results suggest that a higher overall error could be expected if a set of donor coefficients was used compared to an optimised set. However, some catchments, when used with donor coefficients, still show a reasonably small RMS error, suggesting that in some catchments a donor estimation method may prove acceptable.

The summary statistics for each model run are presented in Table 7.2. Summary statistics are computed across all the catchments used for analysis (does not include low PROPWET catchments). It appears that estimating catchment coefficients using optimisation is the better performing method for estimation of the flood frequency curve. The donor method has a larger spread of results and this is reflected in the higher mean error statistics in Table 7.2. Examples of catchment plots provide further evidence of the relatively poor performance of the donor method relative to optimisation; these can be found in Appendix G.1.

| Model Run | Mean | Standard Deviation | Max | Min |
|---|---|---|---|---|
| INDIV_OPTIM | 0.169 | 0.126 | 0.897 | 0.007 |
| DONOR | 0.232 | 0.190 | 1.396 | 0.003 |

**Table 7.2** *Summary of Statistics for model runs using different coefficient sets. Summary statistics refer to RMS error, here calculated as a mean across the catchment set.*

The work suggests that using coefficients from a hydrologically similar catchment (where hydrologically similar is defined by HOSTBFI, AREA and SAAR) is not better than an optimised coefficient. The relatively poor performance of the donor estimation method compared to optimised coefficients is perhaps not surprising given previous work trying to link model performance with catchment characteristics. What is not clear is whether this is a result of the donor catchment being insufficiently identified or because there is a poor relationship between coefficients and catchment types. There are many other factors that may affect coefficient optimisation, such as rainfall and flow seasonality in the catchment, artificial influences such as urbanisation and reservoirs, geographical location and altitude amongst others.

This work plays an important part in understanding the limitations of the model. The predictive capability can be thought of as a trade-off. Individually optimised coefficients can clearly give better estimates of the current flood frequency curve compared to donor coefficients. Therefore, in choosing a model it is a trade-off between increased accuracy and reduced validity. However, the use of optimised coefficients has already been partially validated by the first test using the Peaks Over Threshold data. A consideration of how to develop the ungauged catchment problem further will be given in the discussion.

## 7.3 Method Validation

The validation work carried out here is considered distinct from the previous work. Section 7.2 tests different aspects of model predictive behaviour, one at time. The validation work presented in this section tests the ability of the method to work with future projections, building upon the validation tests already undertaken. Previous model validation tests have shown how the model can work in a predictive sense, but only using the observed data, some of which was used in fitting. Because of this, the frequency curve estimation method needs to be tested on an alternative dataset in order to show that it can be reliably used in future projection studies.

For this validation, a single test is carried out. This involves the use of simulated climate data. It will assess how well the model and its coefficient sets can reproduce a flood frequency curve, given a different input climate data set. The test is similar to that of Section 7.2, where there is no knowledge of flood dates. The synthetic climate data represent the climate at a particular location for a specific time period; they do not aim to reproduce historical weather events or time-series. Therefore, no dates or timing information of observed peak flows would be of use. Instead, the test aims to show that a simulated climate record is sufficiently representative of the observed climate that generates an observed flood frequency curve.

Two sources of climate data have been identified for further investigation of model performance. The first source is the UK Climate Impacts Programme (UKCP) weather generator. Weather generators can be used to downscale RCM estimates to make them suitable for use at a local scale. The UKCP weather generator produces probabilistic estimates of future climate scenarios from a combination of model runs. Murphy et al. (2009) provide a comprehensive overview of the development of the UKCP probabilistic projections. Jones et al. (2010) detail the construction and use of the weather generator.

The UKCP weather generator allows for the estimation of selected climate variables for a particular location within the UK. The user can select a location based upon a 5 km grid, select the temporal resolution of the data, the emissions scenario and the time-slice. As part of the climate generation process, the weather generator also produces a baseline climate. It is worth emphasising that while the climate projections are labelled as probabilistic, when assessed in impact studies they do not provide predictive probabilities of change, as this is dependent upon the emissions scenario used. Currently, there are no probabilities attached to emission scenarios, reflecting the uncertainty in the evolution of future emissions. The probabilistic element can be thought of as giving an estimate of uncertainty in the modelled impacts for a given scenario (Shaw et al., 2011, pp. 497).

In previous validations, only a single thirty year period of rainfall data has been available. This is unlikely to represent the full range of variability seen in the climate. By using simulated data with a wider variability, the uncertainty in the flood frequency curve can be estimated better. In order to investigate the issue of climatic variability, 100 thirty year time-series were generated in each case for the baseline climate (1961-1990). This then allowed the estimation of multiple possible flood frequency curves for the same catchment. This is an additional benefit to the assessment of the model estimation of flood frequency curves using an alternative data source.

For each case study catchment introduced in Section 7.1.1, a representative 5km grid cell at the catchment centroid was identified. Rainfall and PET were then generated for this grid cell using the UKCP weather generator and assumed to be reasonably representative of the catchment in question. This may not be so valid for larger catchments, and were these to be studied a catchment averaged time-series might need to be generated. Because the time-series generation was carried out manually using the weather generator, only the case studies introduced in Section 7.1.1 have been considered. In order to investigate the issue of climatic variability, 100 thirty year time-series were generated in each case for the baseline climate (1961-1990). This then allowed the estimation of multiple possible flood frequency curves for the same catchment.

The second source of climate data used was an eleven-member ensemble of Regional Climate Model (RCM) runs from the Met Office HadRM3H model which were used to construct the UKCP09 scenarios. These runs provide a more limited insight into uncertainty compared to the probabilistic projections provided by the UKCP weather generator. The RCM’s dynamically downscale GCM outputs, however, they are run on a grid that is coarser than both the MO observed gridded dataset and the weather generator (5 km resolution in both cases). The RCM’s operate over a 25 km grid resolution and the outputs are available from the BADC through the ClimateLink project (Met. Office, Hadley Centre, 2010). The eleven RCM outputs are provided in addition to the main UKCP products and the data outputs exists in a raw form. Rainfall data were sourced from the model outputs directly. For each case study the grid cell which covered the catchment centroid was chosen. This inevitably involved some subjectivity due to the larger grid resolution of the RCM. Details on the 11 member ensemble are available in Chapter 5 of Murphy et al. (2009).

### *7.3.1 Areal Reduction Factors*

As the rainfall time series from the UKCP weather generator (WG) (http://ukclimateprojections.defra.gov.uk/) estimates are representative of point rainfall, they require some modification before they can be compared with the observed 5 km series and also before they can be used in the frequency curve estimation model. The 5 km observed time series used in model fitting (Chapters 5 and 6) were calculated as a catchment average. The weather generator data was not calculated as a catchment average due to the difficulty in using the weather generator to extract catchment averaged values when using the online user interface. Therefore, the storms extracted from the weather generator runs were altered with an Areal Reduction Factor (ARF). This is standard practice when transforming point rainfall to areal rainfall and is recommended by the FEH. An ARF essentially represents a ratio between the catchment averaged rainfall and the point rainfall within that catchment. ARF's are specific to both catchment area and rainfall duration.

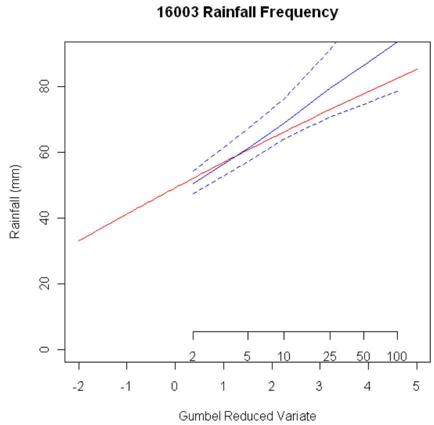
The ARF values were estimated using the FSR areal reduction factors. These are still recommended as being the most appropriate reduction factors for use today (Kjeldsen et al., 2005). The generalised method for estimating an ARF can be seen in Equation 7.5. The equation coefficients are displayed in Appendix H.1.

$$ARF = 1 - bD^{-a} \qquad \textbf{Equation 7.5}$$

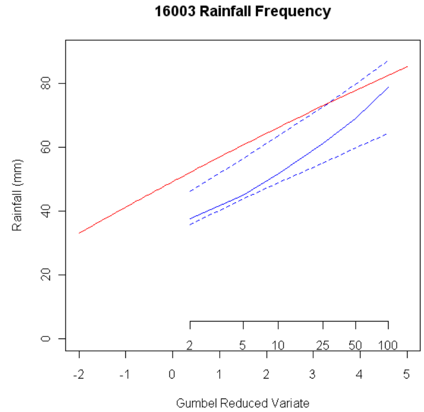
Where $D$ represents the rainfall duration in hours. $b$ and $a$ are set coefficients, and are dependent upon catchment area. The resulting Areal Reduction Factor is a value between 0 and 1, applied to the storm amount in order to better estimate the catchment averaged storm. The ARF is not applied to the entire rainfall time-series, only to the storm.

### 7.3.2 Assessment of Rainfall Reproduction

Before the weather generator or RCM data can be used within the flood frequency curve estimation model, an assessment is required as to how well they represent the benchmark climate. It is assumed that the MO 5 km gridded daily rainfall dataset introduced in Chapter 3 is a reasonable representation of the current climate, as it has been generated from observed rainfall data. Therefore the assessment of the simulated data uses the 5 km gridded dataset as a benchmark. Because of the importance of rainfall estimates to the model, the simulated rainfall data is assessed with regards to both the frequency of heavy rainfall events and the mean monthly rainfall. The assessment of frequency uses the AMAX rainfall estimates, fitted to a GEV distribution. This is considered the most suitable distribution for use in conjunction with annual maximum rainfall (Robson and Reed, 1999). In Figure 7.8 (see overleaf) the dashed blue lines show the calculated 10$^{th}$ and 90$^{th}$ percentile estimates of annual maximum rainfall at specific return periods (2,5,10,15,25 and 50). This should be compared to the red line which shows the rainfall frequency curve estimated from the MO 5 km observed rainfall dataset. The left panels show the results for the WG, whereas the right panels show the same results for the direct RCM outputs.


16003 Rainfall Frequency
Rainfall (mm)
Gumbel Reduced Variate
2 5 10 25 50 100

a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Rainfall (mm)
Gumbel Reduced Variate
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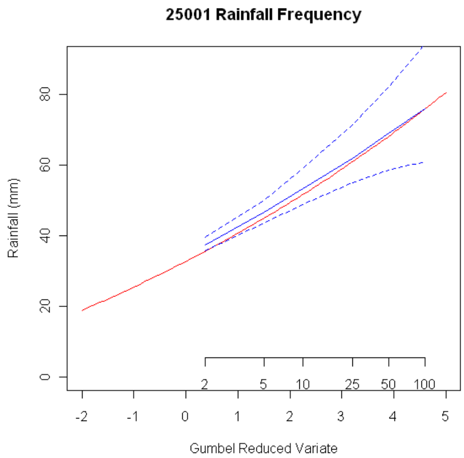
g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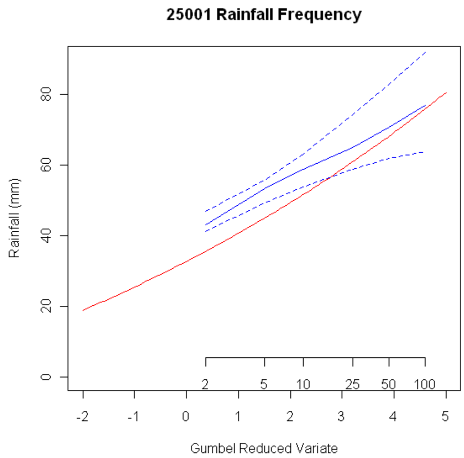
Rainfall (mm)
Gumbel Reduced Variate
2 5 10 25 50 100

b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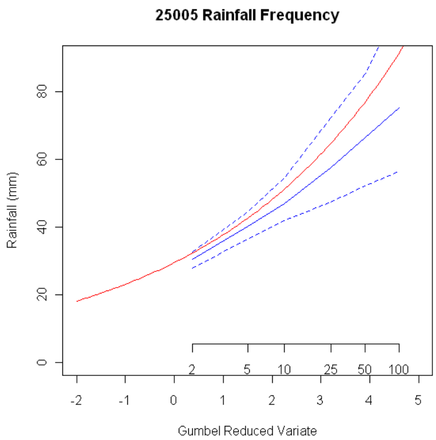
Rainfall (mm)
Gumbel Reduced Variate
2 5 10 25 50 100

h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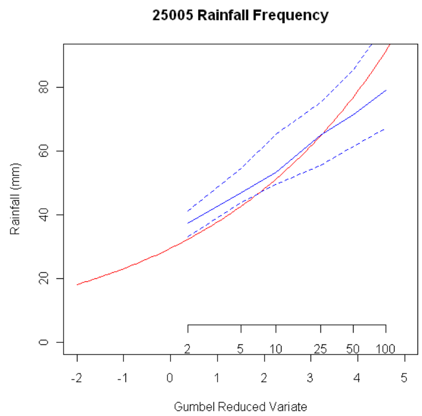
Rainfall (mm)
Gumbel Reduced Variate
2 5 10 25 50 100

c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Rainfall (mm)
Gumbel Reduced Variate
2 5 10 25 50 100

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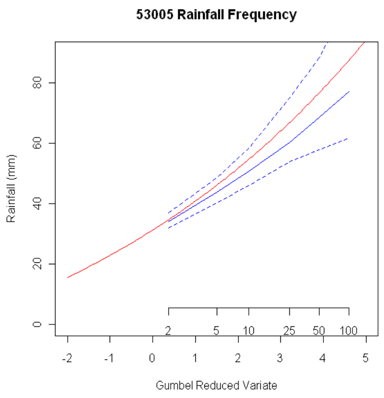
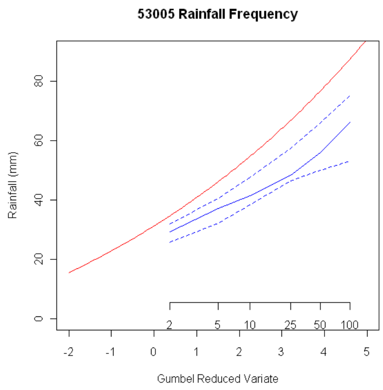
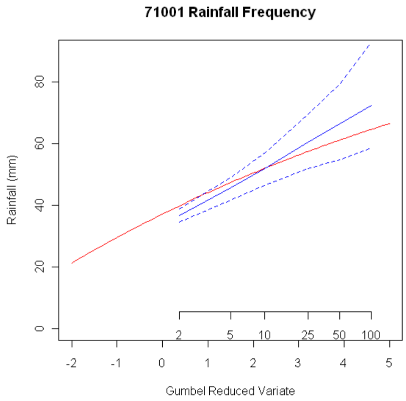
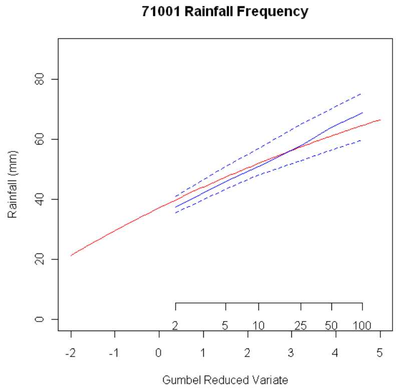


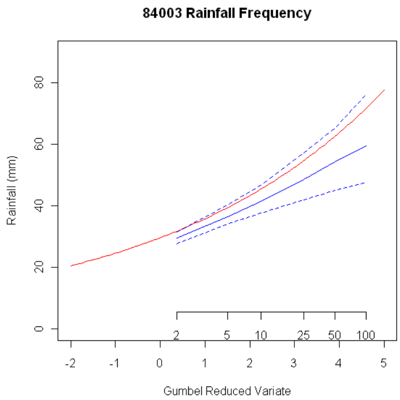



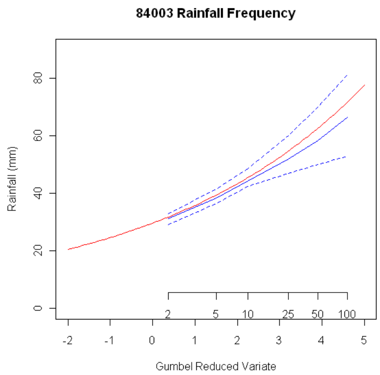

*d* *j*




*e* *k*



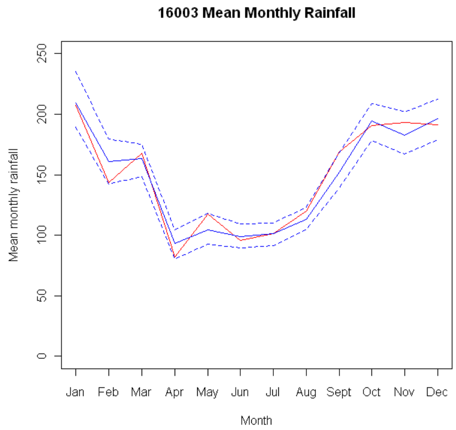

*f* *l*

***Figure 7.8*** *Rainfall Frequency Curves comparing the MO 5 km gridded AMAX (red line) with simulated data for the 6 case study catchments. Plots (a-f) show UKCP WG estimates, plots (g-l) show UKCP RCM estimates. Dashed blue lines show 10th and 90th percentile estimates from the modelled data. Solid blue lines show the median estimates from the modelled data.*

The weather generator (plots a to f in Figure 7.8) values for AMAX show a reasonable agreement with the observed values. In all catchments the weather generator $10^{th}$ and $90^{th}$ percentile estimates bound the observed, and for all return periods. It should be noted that the MO 5 km gridded data is used as a catchment average, whereas the weather generator data is a single cell, which according to Murphy et al. (2009) can be used as point estimate, although this has been adjusted by an ARF as detailed above. Figure 7.8 shows that the weather generator gives a good estimate of heavy rainfall events in the case study catchments in comparison to observations.

The RCM estimates do not look as good. For four out of the six catchments, the observed rainfall frequency curve lies outside the RCM $10^{th}$ and 90th percentile estimates. There appears to be no clear bias, as the RCMs underestimate the observed rainfall frequency curve for two catchments and overestimate this for two catchments. The RCM works on a coarser grid compared to the weather generator (25 km compared to 5 km) and so it inevitably does not resolve detail as well. It might be argued that it does not operate on a level suitable for rainfall estimation in small-medium sized catchments. The two catchments which show the best RCM agreement with the observed also happen to be the largest (71001 and 84003).

Irrespective of the resolution over which they are run, it is clear that there are several differences between the final products. It is acknowledged that the RCM runs have some bias and have had no error correction (Jenkins et al., 2010). Figure 7.9 shows similar results, comparing mean monthly rainfall between the UKCP weather generator, RCM runs and the MO 5 km observed data.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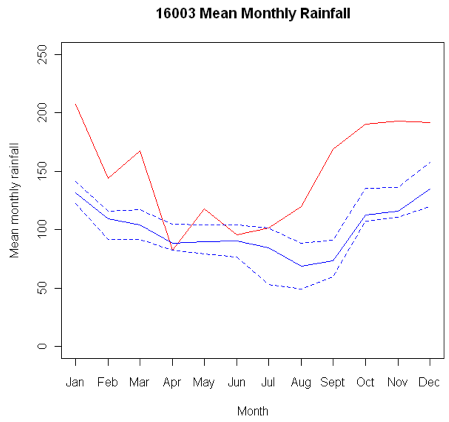
Mean monthly rainfall
0 50 100 150 200 250
Jan Feb Mar Apr May Jun Jul Aug Sept Oct Nov Dec
Month

a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Mean monthly rainfall
0 50 100 150 200 250
Jan Feb Mar Apr May Jun Jul Aug Sept Oct Nov Dec
Month

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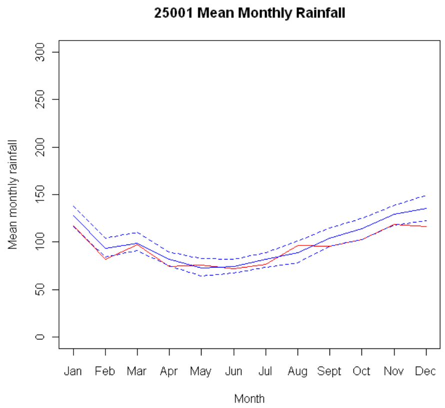
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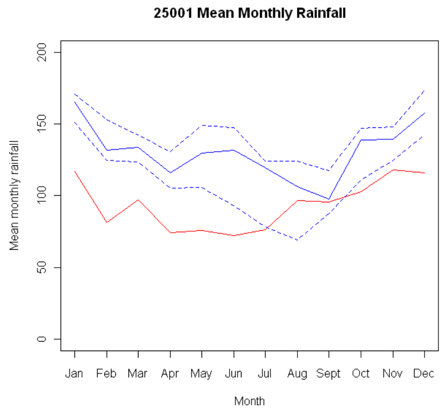
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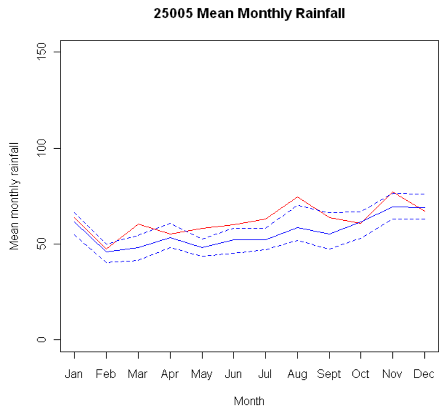
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Mean monthly rainfall
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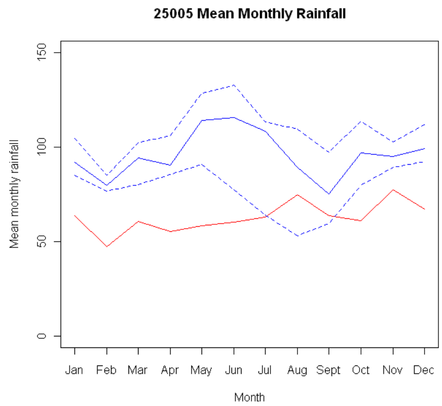
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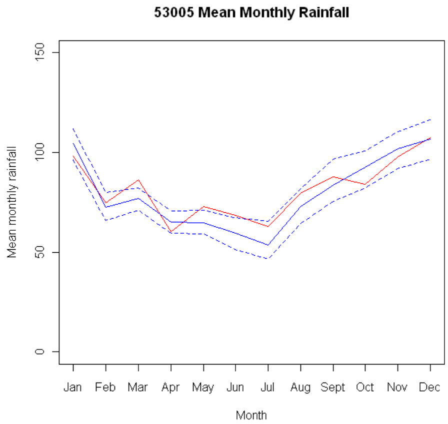


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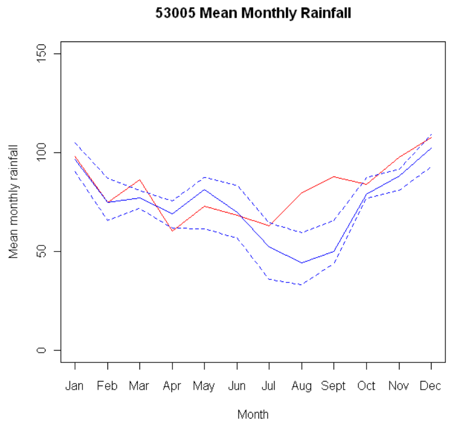


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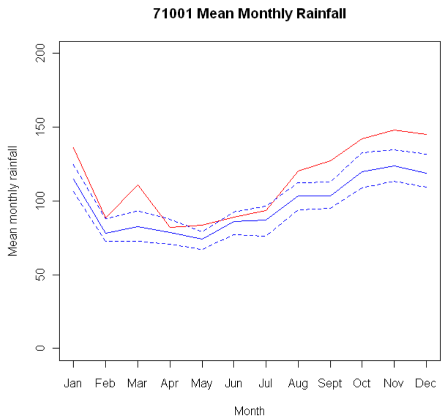


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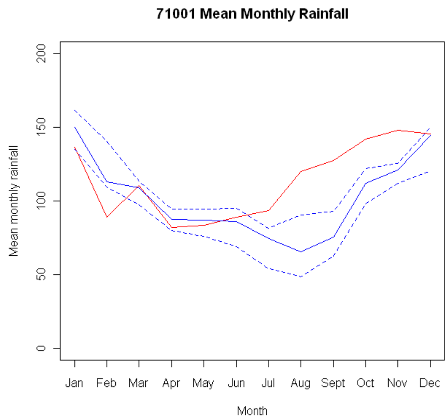


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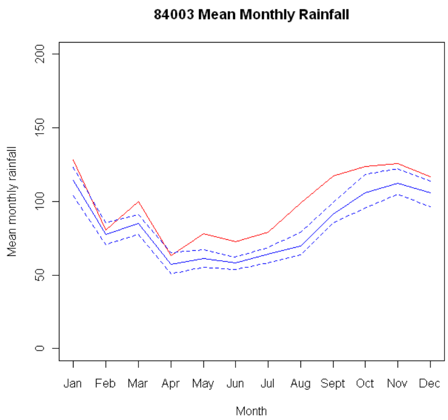


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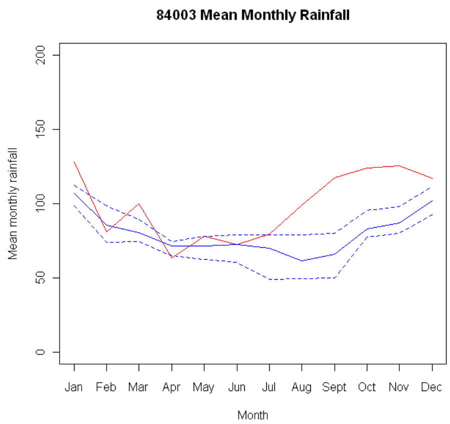



l

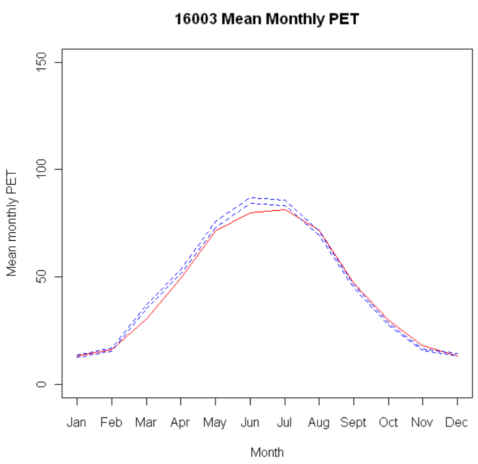
***Figure 7.9*** *Comparing Mean Monthly Rainfall from the UKCP Weather Generator (left) and the RCM runs (right). The red line is the MO 5 km observed data, blue dashed lines represent the 10th and 90th percentiles respectively. The solid blue line represents the median modelled estimate.*

The comparison of mean rainfall shows similar results to the heavy rainfall analysis presented previously. In general, the weather generator results show a good agreement with the MO 5 km data and this is much better than for the RCM runs. While the 10th and 90th percentile bounds do not always encompass the MO gridded data, the seasonality of rainfall is well represented.

The RCM runs show generally poor agreement with the MO gridded data and for most catchments do not adequately represent the seasonality. This is most pronounced in (but not limited to) the wetter catchments. The poor representation of the observed mean rainfall climatology by the RCMs gives a reason for the poor performance in representing heavy rainfall shown in Figure 7.8.

### *7.3.3 Assessment of PET reproduction*

A similar analysis has also been undertaken for the PET estimation, and these results can be seen in Figure 7.10. PET is assessed with regards to the mean monthly values only, the dashed lines also represent the 10th and 90th percentile estimates. PET is only used over longer time periods in the flow estimation model (currently a 30 day index) and so there is no need to assess PET extremes. Because of the poor representation of rainfall by the eleven member RCM ensemble, no attempt has been made to consider the estimation of PET by these models.

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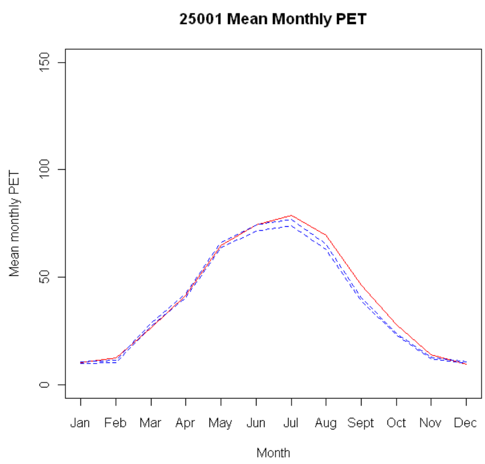


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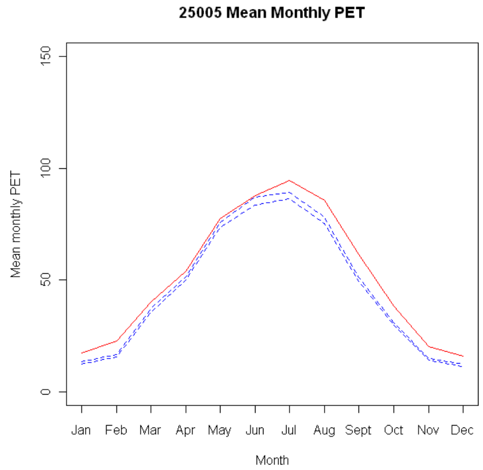


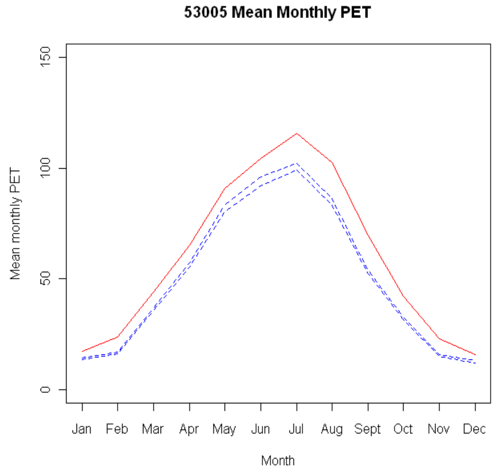


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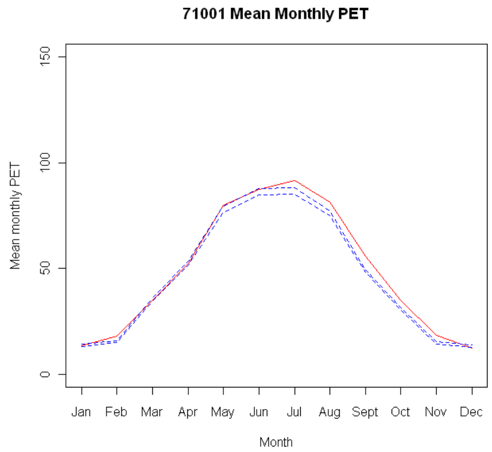


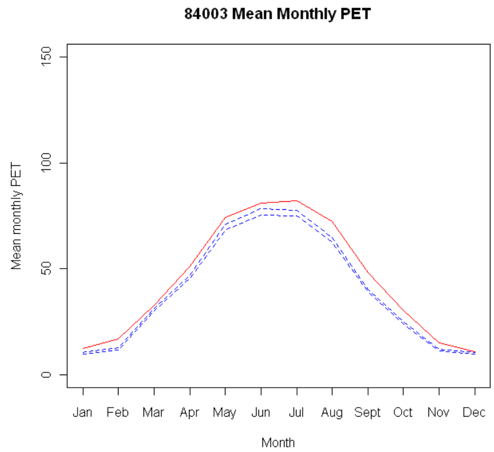


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***Figure 7.10*** *A comparison of PET between the UKCP weather generator and the calculated observed data used in this study. The solid red line represents the mean monthly PET calculated from observed climate variables, the blue dashed lines represent the 10 and 90$^{th}$ percentiles from the UKCP weather generator respectively.*

PET is strongly driven by temperature, which, as a climate variable, is much less temporally and spatially variable than rainfall. Therefore, the modelled estimates of PET from the weather generator tend to show a reasonably good agreement with the PET estimates calculated from the observed climate variables. Because PET is used over long periods in the frequency curve estimation model it is more appropriate to consider mean values than extremes for this climate variable.

The analysis of the simulated climate data suggests that the weather generator can be used with some confidence to construct a flood frequency curve. The RCM data is less useful and there is no clear benefit to running poor RCM estimates through the flood frequency curve estimation model. The continuous simulation approach to flood frequency curve estimation taken by the FRACAS partners has utilised the RCM model runs and this was the main reason for using it in an assessment here. However, the RCM data will not be used further in this thesis.

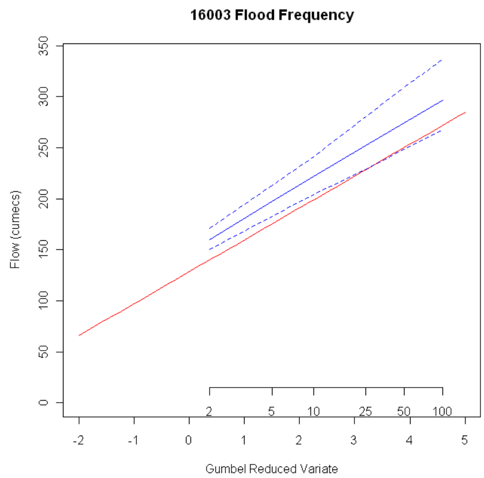
## 7.4 Application of Simulated Climate Data to the Flood Frequency Model

Given that the simulated weather generator baseline climate data for 1961-1990 is reasonably representative of the observed data used for model fitting, it can be used to assess how well the flood frequency curve estimation model performs. While it is important to assess how well the climate is reproduced by the UKCP weather generator and RCM models, good representation on its own does not necessarily mean that the data is useful for frequency curve estimation. Until now, climate variables have been assessed individually. However, the frequency curve estimation model uses a summation of storm rainfall, antecedent rainfall and antecedent PET.

The method of frequency curve estimation used in this section is similar to that introduced in the second validation test of Section 7.2.2. However, the method is restated here for completeness. First, a Peaks Over Threshold rain storm extraction is applied to the time series of daily rainfall data from the weather generator runs. Using the previously derived optimised coefficients along with the antecedent rainfall and PET estimates from the weather generator runs, these POT storms are transformed into flow events, retaining the date of the POT event. From the estimated flow series, an AMAX series can be extracted fitted to an extreme value distribution (the Gumbel) and a flood frequency curve constructed.

In the case of the simulated WG data, the process described above was followed. However, one hundred 30 year climate time-series were produced from the weather generator. Therefore this allowed the generation of one hundred AMAX flood frequency curves. To show all of these on a plot would be uninformative; therefore for the one hundred time series, the 10th and 90th percentile estimates were calculated at specific return period intervals (2, 5, 10, 15, 25 and 50 years). These RP values were then plotted on a flood frequency plot for comparison against the observed flood frequency curve (see Figure 7.11).

It is important to emphasise that the dashed lines in Figure 7.11 do not represent a flood frequency curve. They represent the percentile estimates at that return period from all 100 simulated flood frequency curves. These percentile estimates are then joined for convenience, but like a single site flood frequency curve they should not be extrapolated.

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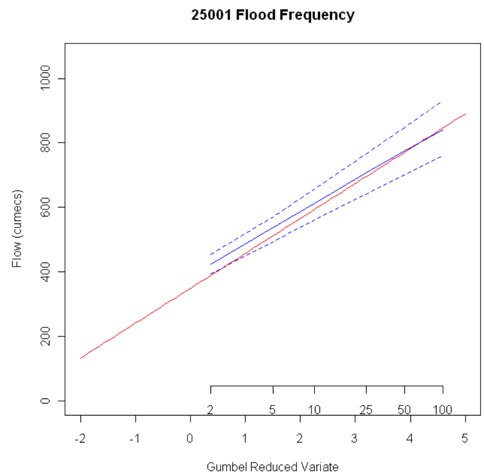


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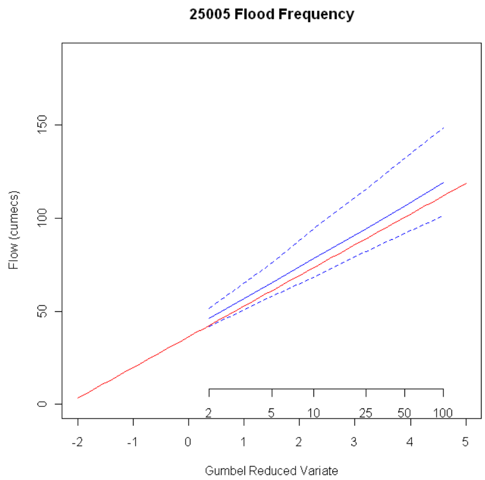


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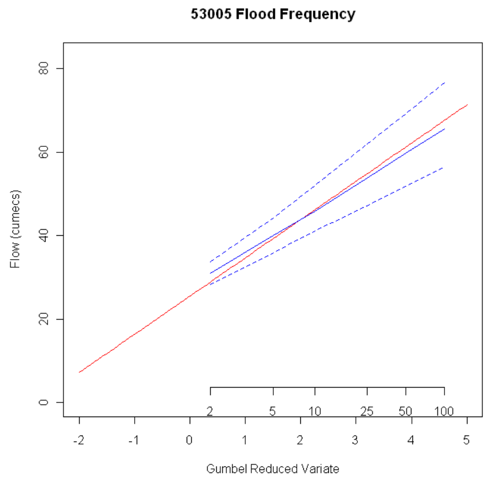


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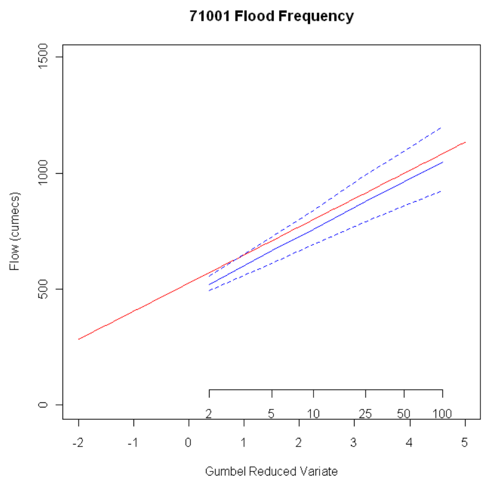


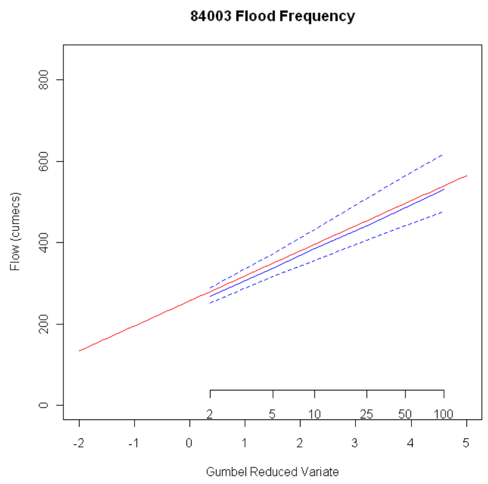


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***Figure 7.11*** *The results of running the baseline UKCP WG scenarios through the flood frequency estimation model for the six case study catchments. The observed flood frequency curve is shown in red. The dashed blue lines represent the 10$^{th}$ and 90$^{th}$ percentile estimates. Solid blue lines represent the median estimates from the WG runs.*

Figure 7.11 plots a to f (weather generator runs) show the observed AMAX flood frequency curves compared to the simulated flood frequency curves (10$^{th}$, 90$^{th}$ and 50$^{th}$ percentiles) from the WG runs. Because the flood frequency estimation model uses storm rainfall, antecedent rainfall and antecedent PET, there is the potential for significant variability between weather generator runs. Therefore the flood frequency curves plotted here can be thought of as multiple realisations of the flood frequency curves that could be created by the current climate. They represent multiple combinations of the three flow estimation variables which would not be found in a single observed record. Therefore, if it was assumed that the climate is stationary, and another thirty years of annual maximum peak flow data were recorded, it is likely that the new curve would fit within the percentile bounds plotted in Figure 7.11.

Overall, for the weather generator runs, the results are encouraging. In five out of six cases the observed flood frequency curve is bounded by the 10$^{th}$ and 90$^{th}$ percentile estimates for the RPs calculated from the one hundred weather generator runs, although one station, Ruchill Water, has the percentile bounds on the edge of the observed flood frequency curves. This flood frequency curve estimation model for this catchment overestimated the flood frequency curve in the first two validation tests reported on in Section 7.2 and such is less reliable for future projection work.

## 7.5 Climate Change Applications

It is not intended that this thesis should present a full blown climate change analysis over the whole of the UK. Rather it has sought to prove the use of the modelling method through case studies. The source of the future scenarios has already been introduced in Section 7.6.1 which seeks to assess baseline data for 1961-1990 between the observed and modelled climate. It is not intended that the models structures, forcings, parameterisations, validity of future projections or specific projections of future change will be considered in any great detail. While an important aspect of climate change impact assessment, this is a significant task in its own right and therefore is not particularly feasible to undertake given the timescale available for this research. Because of this, less emphasis is placed on the specific magnitudes of change shown by the models in the climate change applications. Instead, the use of these data sources is considered in light of the potential for future model development. The case studies introduced in Section 7.1.1 are used to outline the method for future climate. A medium emissions scenario has been used for the example future cases shown here. This is a 30 year window centred over the 2050s and as with the baseline work, 100 time-series have been generated for each example catchment. The work required to extend this analysis to the full catchment set is considerable, and has already been discussed previously as the main reason for not doing so.

### *7.5.1 PROPWET Estimation*

Chapter 6 introduced the idea of using the PROPWET indicator to highlight catchments which were unsuited to flood frequency curve estimation. Section 6.4.2 also introduced a method whereby PROPWET could be estimated through regression using the catchment SAAR and annual PET values. Therefore, before any future flood frequency curves are presented, the future

PROPWET values are estimated. From Section 6.4.2 (Equation 6.6) the PROPWET estimation equation is:

$$PROPWET = 1.07 - 0.00144\ PET + 0.000148\ SAAR \qquad \textbf{Equation 6.6}$$

To estimate a single PROPWET value for the future, the mean SAAR and annual PET for all future weather generator runs for each catchment were calculated. This was also carried out for the baseline period 1961-1990, in order to compare whether the WG is able to provide a good estimate of PROPWET for the baseline climate when compared to the FEH PROPWET values. The baseline SAAR and PET values are displayed in Table 7.3 along with baseline estimated PROPWET values and the original PROPWET values from FEH. Table 7.4 contains the same variables for the future values (minus the FEH values).

| GAUGE | SAAR | Annual PET | Estimated PROPWET | FEH PROPWET |
|---|---|---|---|---|
| Ruchill | 1734.9 | 529.9 | 0.56 | 0.59 |
| Tees | 1186.2 | 445.3 | 0.60 | 0.58 |
| Leven | 660.7 | 540.1 | 0.39 | 0.34 |
| Midford | 930.6 | 587.7 | 0.36 | 0.36 |
| Ribble | 1163.4 | 541.9 | 0.46 | 0.56 |
| Clyde | 990.6 | 464.2 | 0.55 | 0.6 |

**Table 7.3** *Comparing PROPWET values estimated from regression and the FEH values. Both represent the baseline time period (i.e. 1961-1990). SAAR and Annual PET values are also shown for comparison.*

The FEH and estimated PROPWET values displayed in Table 7.3 show a reasonable agreement. The Ribble shows the largest error in PROPWET estimation. While the original PROPWET regression in Section 6.4.2 used the observed 5km data, here the PROPWET estimation uses the weather generator data. It was unfeasible to generate climate scenarios for every catchment with the WG, hence why the original PROPWET regression was undertaken using the larger observed MO 5 km data set. Despite this, the estimated PROPWET values provide some confidence in the use of the regression with the weather generator data.

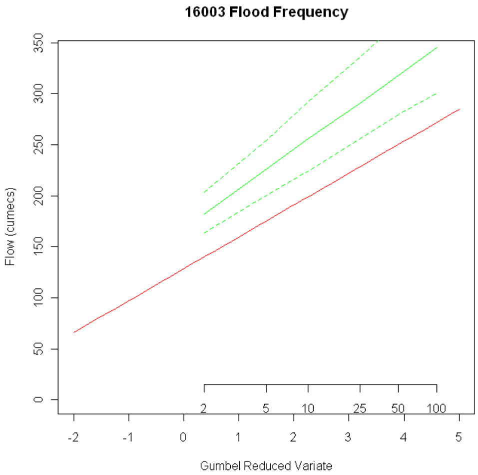
| GAUGE | SAAR | Annual PET | Estimated PROPWET |
|---|---|---|---|
| Ruchill | 1818.5 | 606.3 | 0.47 |
| Tees | 1169.9 | 574.1 | 0.42 |
| Leven | 655.93 | 623.4 | 0.27 |
| Midford | 939.5 | 684.1 | 0.22 |
| Ribble | 1157.2 | 650.6 | 0.30 |
| Clyde | 1021.8 | 551.43 | 0.43 |

**Table 7.4** *Estimating future PROPWET values through regression. The climate data are centred over the 2050s for a medium emission scenario.*

For all catchments, the future estimated PROPWET values decrease (see Table 7.4). This can be explained by a general increase in the annual PET. Rainfall totals do not follow such a simple pattern. As previously outlined in Section 7.5.2, catchments with a PROPWET value of less than 0.4 tend to be susceptible to higher errors. This being the case, the Leven, Midford and Ribble might be considered unsuited to the future frequency curve estimation method outlined here. However, from Table 7.3, it should be remembered that the Ribble PROPWET value was underestimated by about 0.1 for the current time period. If the assumption is made that the same happens in the future, it may be possible to use the method for this catchment. The Leven and Midford had low PROPWET values from the FEH, and therefore there is a higher level of uncertainty surrounding their flood frequency curve estimation for the baseline time period. However, because observed data is available it is possible to assess how well the Leven and Midford perform based on these. Current fits appear reasonable, and so this puts them within the subset of catchments that have a low PROPWET value, but also have a low error.

### 7.5.2 Future Flood Frequency Curve Estimation

Figure 7.12 shows the results of applying the future WG scenarios to the frequency curve estimation model. The procedure for doing so is identical to that outlined for the baseline climate and so is not repeated here. The plots use an alternative colour scheme in order to make them distinct from the baseline case.

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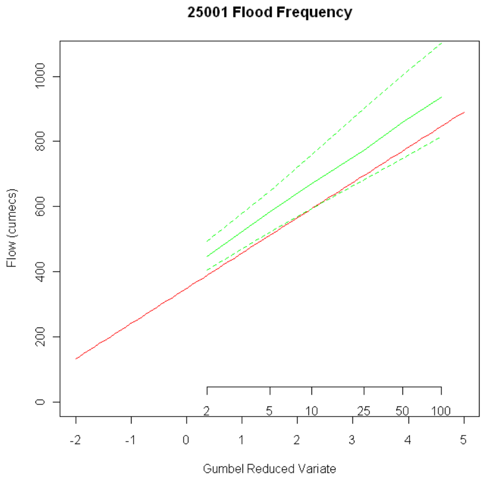


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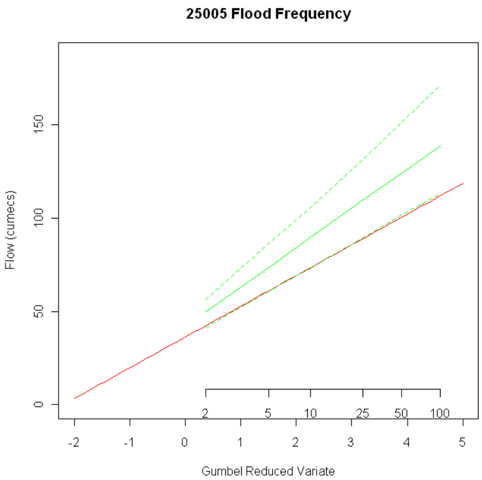


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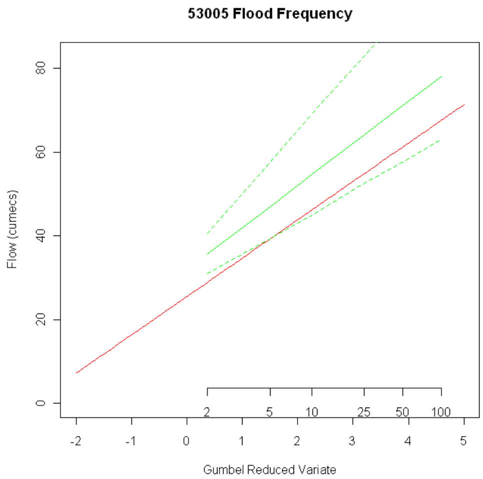


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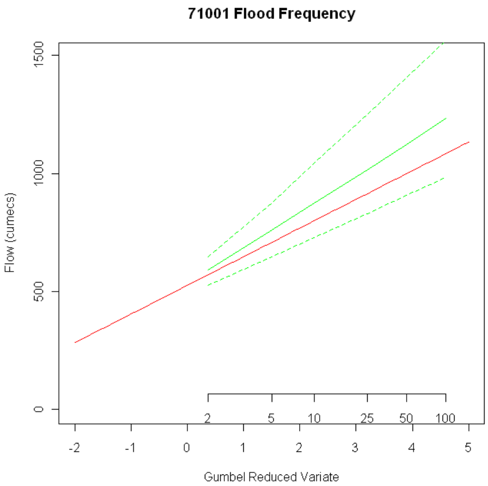


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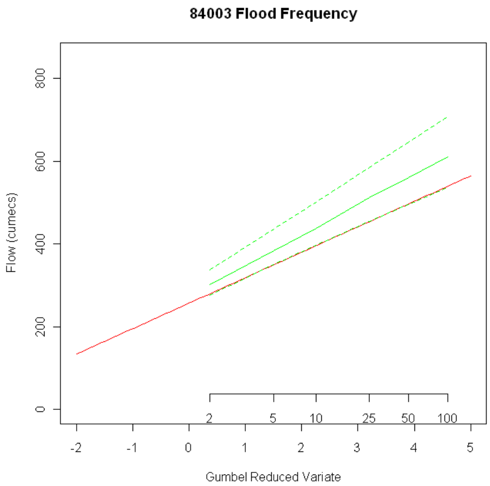


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***Figure 7.12*** *The result of applying a medium emissions climate scenario to the flood frequency curve estimation model for the 2050s for the six case-study catchments. The solid red line is the observed ffc, the dashed green lines represent the 10th and 90$^{th}$ percentile estimates and the solid green line represents the median estimate of the ffc using WG data.*

The process of using the future climate change scenarios with the model is reasonably simple; however, in order for the results to be meaningful; some care may be required in the interpretation of the results. In all cases, median and other percentile estimates of the frequency curves increase. While stations such as Ruchill Water show a fairly large change in the modelled curves compared to the observed, it should be remembered that the original fit using the baseline weather generator runs was not perfect and therefore caution is advised in interpreting the future changes.

| Station | Percentile | | |
|---|---|---|---|
| | 10 | 50 | 90 |
| **Ruchill** | 2.0 | 6.0 | 13.5 |
| **Tees** | 1.9 | 2.7 | 9.5 |
| **Leven** | 4.2 | 6.0 | 8.7 |
| **Midford Brook** | 4.7 | 6.1 | 17.5 |
| **Ribble** | 1.3 | 5.5 | 13.9 |
| **Clyde** | 0.8 | 6.8 | 9.5 |

***Table 7.5*** *Percentage changes between percentile values as calculated from the baseline estimated flood frequency curves and the future estimated flood frequency curves for the 10 year return period flow. All values are positive and therefore show future increases.*

Table 7.6 shows the percentage changes between baseline and future runs for the ten year return period flow. The raw values used to calculate these changes are tabulated in Appendix I.1. There is a tendency for the lower percentile estimates to increase only slightly, whereas upper percentile values show much larger increases. The analysis carried out here is not extensive enough to infer anything about spatial patterns of flooding under projected future climate change.

The percentage changes shown in Table 7.6 should be considered as relative changes. Earlier work in Section 7.2.2 showed the percentage error in the estimation of the ten year return period event by comparing modelled and observed flows. In several cases the models overestimated the flood frequency curve compared to the observed and in some cases the percentage errors exceed any projected future difference under climate change as shown by Table 7.6. The uncertainty in estimating rare events can be considerable. Given that most of the observed flow records average 30 years of data there is still a considerable uncertainty in the estimation of the observed ten year return period event. Despite this, the relative percentage changes can still give some useful projections of how fluvial flood frequency may change in the future.

## 7.6 Discussion of Validation and Application Work

### *7.6.1 Test results and Model Structure*

One of the main limitations highlighted within this chapter concerns the use of a donor catchment for flood frequency curve estimation at an ungauged site. This work was carried out as the Flood Estimation Handbook uses a similar approach to the estimation of QMED at a target site and therefore it was felt worthwhile to test a similar approach to the estimation of the flood frequency model coefficients. The relatively poor result obtained from this test partly reflects the reasonably weak links between model coefficients and catchment characteristics, as described at the end of Chapter 6. Were an alternative approach to be taken, whereby model coefficients were determined principally through catchment characteristics (and not through optimisation), then the estimation of donor catchment coefficients would perhaps be more straightforward. On the other hand, this may lead to greater modelling errors. Model parameterisation from PCDs is the approach taken by the parameter-generalised PDM model of Kay et al. (2006a) which has been successfully used to estimate flood frequency at ungauged sites. However, designing a framework for estimating model coefficients from PCDs requires some care, not least because some of the PCDs are themselves a product of the climate and therefore subject to change under an altered climate. Assuming time-invariant model parameters has the potential to increase the uncertainty in model projections of future flood frequency. Merz et al. (2011) highlight this problem through a modelling study for a future case that shows increasing uncertainty above that which would normally be expected from a hydrological simulation. Two approaches to deal with this problem exist. The first involves a calibration procedure which estimates time-stable parameters. The second approach involves developing a framework for estimating time-varying parameters, so that given any future scenario, model parameters can then be estimated. With this second option, no calibration occurs, as parameters are estimated directly. As no calibration takes place there is an increase in the possibility of model bias with this option (Merz et al. (2011). Section 7.5 has shown how the PCD PROPWET can be estimated for future cases from simple climate data. This shows that if PCDs are to be used for estimating model coefficients or parameters, then they can be estimated for both current and future cases. Within this work, the PROPWET value is mainly used to highlight poorly performing catchments, but the same regression could also be used if PROPWET was more directly involved in coefficient estimation. The use of a donor catchment has only been tested on the flood frequency curve model using rainfall and PET. Earlier work on event based peak flow estimation suggested that catchments tended to be grouped by performance when using a storm only model, as this highlights groups of catchments where antecedent conditions play similar roles in flood generation. Therefore, if donor estimation was a key requirement, using a storm only model for flood frequency curve estimation may be more useful. This is evidently offset by reduced model performance as antecedent conditions are not accounted for. The limitation of the flood frequency curve estimation model being unreliable for donor catchment transfer is not crucial to the method described in this thesis, but it does provide some interesting insights into the model structure and performance.

While the donor transfer method does not perform particularly well, the other tests of the model and method are encouraging. The first model test, involving POT flow data was a useful check in assessing the model against data on which it was not fitted. The removal of the AMAX data from the POT series was important to avoid the AMAX data influencing the results too much. However, the removal of large events poses another problem; that of extrapolation. The use of POT data does not test the extrapolation ability of the model. Specifically it does not test whether model estimates of flood frequency curves are reliable if the frequency curves have been estimated from events which are larger than those on which the model was fitted. With rainfall extremes in some areas increasing, and predicted to increase further (see Fowler and Kilsby (2003) and Buonomo et al. (2007) for examples), it could be argued that the validation testing does not go far enough in this respect. The current model takes a simplified view of the mechanisms of flood generation. It assumes that the same processes are responsible for flood generation over the entire flow record, whether that is AMAX or POT. This is perhaps unlikely to be representative of real life conditions where large flood peaks and small flood peaks may have been generated through different physical processes. Modelling of earth systems in general always involves some simplifying assumptions in order to develop a suitable model. The frequency curve estimation model was originally fitted to the whole AMAX record in order for it to be able to estimate a similar curve in the future. It is acknowledged that the validation work does not test the extrapolation ability of the model. One of the problems with testing this is the limited number of extreme events available for assessment. Furthermore, it is possible that modelled floods events that are larger than those in the observed record are generated from processes which are radically different to those processes responsible for generating the peak flows in the observed record. Kusumastuti et al. (2007) provide some evidence for the importance of thresholds on controlling flood frequency and magnitude. This means that it is difficult to design an extrapolation test which can give confidence in the models ability to estimate the flood frequency curve from events which are considerably larger than those in the observed record. This problem is not unique to the model developed in this thesis. It affects any model where assumptions are made surrounding process conceptualisation, especially where there are limited data to do so.

The method validation has been considered clearly distinct from that of model validation. The test of method validation applied the model to a set of simulated climate time-series, generated specifically for the catchments of interest. The relatively poor performance of the RCM data compared to the WG estimates was the main reason for not using it any further as little can be gained from using a model with poor input data. Using RCM data is a raw, uncorrected form is generally discouraged, and so were any modelling work to use it, some form of downscaling or correction would be necessary. The UKCP weather generator is one method of downscaling from RCMs with the raw eleven member UKCP ensemble RCMs also contributing to the weather generator output. Other methods include the use of bias correction, change factors and statistical downscaling methods (Chen et al., 2011). All involve the use of observed data in some way to develop relationships between locally observed climate and simulated climate. While the RCM data was considered poor, it was assessed against specific criteria for this study. It may be that RCM rainfall is more suited to modelling large catchments as the RCM rainfall better represented the observed rainfall in the larger case study catchments used in this study. RCM rainfall has been used directly in modelling studies such as that of Kay et al. (2006) where it has driven a spatially generalised version of the PDM model. Their approach linked residual modelling errors to the representation of rainfall by the RCMs and therefore provides some confidence in the ability of RCMs to be used directly in modelling studies as they improve their ability to capture rainfall characteristics.

Chen et al. (2011) caution on the use of only a single downscaling method in climate impact studies. This research has made use of only a single source; the UKCP weather generator. However, the aim of the work was not to determine magnitudes or directions of hydrological change, rather it was to prove the use of the frequency curve mapping methodology with data sets other than that on which it was fitted. The use of the weather generator showed that this was possible. The use of the baseline WG time-series provided some interesting insights into flood frequency variability. The use of a number of time series (100) allowed for an assessment of some of the uncertainty in a single site observed flood record. By increasing the variability in the baseline climate, a more robust estimate of the flood frequency curve can be made. This approach is similar to that of continuous simulation, where long time series are often used to represent climate variability at the site of interest. Shaw et al. (2011) recommend the use of confidence limits with a single site approach using short observed records and this can be considered similar to the use of a large number of time-series to estimate bounds on return period magnitudes. The ability of the frequency curve mapping methodology to be able to deal with large numbers of time-series is one of its benefits over single site approaches using observed data, as it can deal with climatic variability in an explicit way. While the original aim of the research project was to develop a methodology suited to the estimation of future flood frequency curves, the current model, when used properly, can give useful insights into current flood variability. This approach of estimating variability within a single time-slice assumes that flood frequency is stationary, and this may not be the case. The ability of the frequency curve estimation model allows it to work with other data products developed to produce future projections of climate. Median estimates of future changes to the ten year return period floods all show increases in the range two to seven percent compared to the baseline. Current design guidelines for estimating future changes to peak flows use an indicative sensitivity of somewhere between ten and twenty percent (DEFRA, 2006), although this is acknowledged as being a precautionary upper envelope (Shaw et al., 2011). These estimates are applicable to all areas of Britain, reflecting a lack of knowledge at the time of any spatial pattern of change. However, Kay et al. (2006) found changes of between -7 percent and +32 percent for the 10 year return period flood across the UK for the period 2071-2100. This shows a much larger range of change than either the results shown in Section 7.5 or the DEFRA recommendations. Direct comparison is not possible due to the small set of catchments used in the frequency curve estimation model as well as the different time-slice used for analysis (2050 compared to 2070-2100). It should be emphasised that agreement with other recommendations is not evidence of a definite change, but to some extent it can give confidence in the ability of the frequency curve mapping methodology to be used for more extensive future flood frequency assessments.

### *7.6.2 Implications for a National Flood Frequency Assessment*

While this work has not undertaken a national flood frequency assessment will be made for the future, it is worth considering what the validation work has shown and how this can be used to design an extension of the work already carried out. Validation work has shown that the frequency curve estimation model must be fitted and tested before it can be used for future projection work, as a good fit in optimisation is no guarantee of predictive ability. In order for a future study to be of use, a good geographical distribution of catchments should be available where the model can be reliably used. In some respects, the poor relationship between PCDs and model performance is useful here. PCDs show distinctive geographical patterns to their distribution (see Appendix A), therefore should the model not work particularly well for a certain subset of a single PCD, it is likely that a specific geographical area would not be able to be modelled. Whilst in general, the model does not work well in low

PROPWET/high HOSTBFI catchments, there is still a reasonable geographic spread of catchments in areas with these characteristics (see Figure 6.16).

A good geographic spread of catchments is clearly useful to be able to infer any pattern to future change. However, the models used for this must also show good predictive power. The estimates of the percentage error in the modelled flood frequency curves give some confidence in the model's ability to estimate a rare flood event magnitude and the percentage errors compare well with other work such as that of Kay et al., (2006). However, the first validation test using POT data still requires visual assessment in order to gain an understanding of how suitable a catchment is to modelling work in the future. Extrapolation from the six case studies in this chapter is difficult, as they were presented to give a good representation of catchment characteristics rather than model performance. The further examples shown in Appendix F.1 suggest that out of the ten catchments with good original fits, (i.e. RMS error of < or below) seven of them show reasonable results when used with POT data. Further work is required to characterise this over the larger catchments set, however, these results are encouraging as they would allow application of the method over a larger number of catchments.

## 7.7 Chapter Conclusions

Chapter 7 has developed further understanding of the model presented in Chapter 6, designed to estimate the flood frequency curve.

Model validation has shown that the frequency curve estimation model has some predictive power, as it can be successfully used on data to which it was not fitted. For the six catchments chosen, the derived model structure appears to be capable of reproducing the empirical POT frequency curve well in four catchments, with two catchments performing poorly in both model validation tests.

The second model validation test outlined a method whereby future annual maximum flood frequency curves can be estimated. As has already been shown, the use of annual maximum rainfall for this purpose is fraught with complication. Therefore, a method using POT rainfall has been introduced and has been shown to adequately estimate the annual maximum flood frequency curve without reference to timing information on floods.

The coefficient transfer test was not so successful and this has been attributed to the relatively poor relationship between coefficients and catchment types. Further improvements to this method are discussed in Chapter 8.

Finally, the model has been shown to work with outputs from a weather generator, another key consideration if the use of the model to explore the potential impacts of future climate change on the flood frequency curve is desired. It is suggested that RCM data on their own are not capable of adequately representing the baseline rainfall climatology in the catchments of interest and for this reason the raw RCM outputs have not been used for baseline or future assessment. The results from Chapter 7 are taken forward in the discussion by critically considering how the problem of developing projections of future climate impacts on flooding can be achieved, given the work that has been carried out.

As with all the work undertaken in this thesis, there are alternative approaches and other methods that may be suited to the work carried out here. Therefore, Chapter 8 also presents an exploration of the work presented in this thesis by critically considering what has been achieved as well as developing ideas for future work.

# Chapter 8: Discussion and Suggestions for Further Work

## 8.1 Introduction

A catchment does not "have" a flood frequency curve. In its simplest form a flood frequency curve can be considered as a tool for extracting useful information from observed data regarding the flood regime of a catchment. Therefore, the flood frequency curve is more a function of the data that creates it as opposed to being an attribute of the catchment itself. This point might seem obvious, however, it is often easy to overlook the influence that a data record may have on the catchment flood frequency curve. Similarly, the importance of the underlying data to the modelling work presented in this thesis should not be underestimated. It is therefore appropriate that a discussion of the approach and performance of the flood frequency curve estimation model takes place.

Chapter 8 provides a discussion on the work carried out and presented in this thesis, as well as considering issues not explicitly dealt with elsewhere in the text. Principally, it will consider to what extent the work carried out meet the aims and objectives laid out in Chapter 1. It will consider various aspects of the approach taken with reference to other work and consider the implications of the findings detailed in the previous chapters. Finally, some consideration will be given to the future development of this work.

## 8.2 Summary of Research and Key Findings

This thesis has presented work that has been carried out to develop a method of estimating a flood frequency curve from rainfall and potential evapotranspiration inputs. Early work assessed the datasets available for use. This work highlighted the importance of good flow datasets as well as showing that stricter independence criteria are required when using flow data in conjunction with daily rainfall. This work was developed by assessing how well peak flow and daily rainfall datasets could be used together. This provided an interesting look at UK hydrological behaviour, revealing geographical patterns on the links between extreme rainfall events and floods in a variety of catchments. This work was considered as a useful first step in assessing frequency relationships between rainfall and flow.

Initial modelling work considered how to estimate a flow peak only. While the proposed model may be simple, extensive work was required to characterise the performance and identify sources (and structures) of error. This work showed the importance of timing with regards to storm estimation, as using the date of flood can be misleading. The model results show a temporal structure to the error pattern in some catchments, with the suggestion that the model's ability to replicate seasonal antecedent conditions was at fault. This prompted the development of soil moisture deficit estimates, however in terms of flow estimation, the model results showed little improvement.

The event based work allowed the subsequent development of a model to estimate an annual maximum flood frequency curve. In order to be suitable for future work, this model incorporates PET. The flood frequency estimation model has been tested in order to determine how robust it is, as well as how it may be used with alternative input meteorological data. The results of this work provide clear limits to the applicability of the model, with the indicator PROPWET used to highlight those catchments where the flood frequency curve estimation model does not work.

Finally, while this thesis does not attempt to provide an extensive climate change impact assessment of the UK, several catchments have been selected in order to prove the use of the model in developing projections of future flood frequency curves. The use of the UKCP weather generator allows multiple future projections of climate to be used within the frequency curve estimation model. The rest of this chapter considers some aspects of the work in more detail, particularly with regards to how well the objectives stated in Chapter 1 are met.

## 8.3 Sourcing and Assessing Appropriate Datasets

Based on the approach that this study has taken to the problem of flood frequency estimation, significant amounts of data have been used. Initial work involved sourcing and assessing these data for use in the study. Quite clearly, the use of environmental data requires some consideration, as the potential for errors introduced during collection and processing is significant. The HiFlows data, while containing some known problems, are considered the most suitable flow data for this type of work.

Within the UK, there are few alternatives suited to the demands of this project. The National River Flow Archive (NRFA) hosts mean daily flow series. It is conceivable that the modelling approach presented in this thesis could be used on mean daily data. It is not clear how useful mean daily data are to flood frequency estimation, as they do not represent flow peaks well, although the G2G model has made use of this type of data. Similarly, the use of continuous river flow time-series could be considered. This would give considerable information on antecedent conditions and may provide further insights into how different catchments perform in frequency curve estimation. However, continuous river flow time-series may not be particularly suited to a predictive model, as evidently no time series would be available for the future.

Rainfall data are also prone to some potential measurement error. The spatial extent of data required for this project is considerable. This led to the use of gridded data, in this case the MO 5 km daily dataset. While there may be some concerns about the lack of published information on the dataset construction, others have shown the dataset to give reasonable representation of extremes (Smith, 2010).

The use of alternative rainfall datasets may be worthy of consideration. The current model takes advantage of the gridded daily rainfall data because it is widely available and requires very little pre-processing. However, in the future, or for a small group of catchments, it is conceivable that sub-daily rainfall information may be utilised. This may bring benefits in frequency curve estimation in smaller catchments, where daily data mask the intricacies of rainfall hyetographs and catchments respond quickly. With regards to this study, hourly data was never used as available records tend to be short and do not cover the spatial extent required for the national scale study. One of the advantages of the flood frequency curve estimation model is that it has the ability to be adapted to different datasets depending upon requirements. This is essential if the model is to be used for future prediction.

The first objective of this study was to consider appropriate datasets for use within the modelling methodology. Chapters 2 and 3 form the main bulk of this work, with Chapter 4 also giving some summary information on dataset characteristics. It is considered that this objective has been met, as the datasets used within the rest of this work (namely the gridded MO 5 km daily rainfall data and the HiFlows peak flow data) are considered the most appropriate for the task in hand. While this first objective may seem a simple one to achieve, it is crucial that it is adequately addressed as the rest of the study relies upon good rainfall and flow datasets.

## 8.4 Developing an event based peak flow estimation methodology

The development of the event based model for peak flow estimation began in Chapter 4, with an initial assessment of the seasonality and links between the rainfall and flood regimes of catchments. While seasonality analysis of UK catchments has been reported on in parts elsewhere (see Black and Werritty, 1997; Robson and Reed, 1999; Archer, 1981, Macdonald et al., 2010), there is little published work which considers the whole of the UK comparing both rainfall and flow. Seasonality as an indicator of a catchment flood regime is not typically used in flood frequency assessment, although some have called for its inclusion (Reed, 2002; Cunderlik and Ourda, 2009). In Chapter 4, the seasonality analysis provided a reasonably rough method for assessing where later work might be appropriate. Circular statistics can be used to highlight where there is a disparity between catchment rainfall and flow regimes. The results from the seasonality work were primarily responsible for the subsequent approach taken of only including one or two days' worth of storm rainfall. The AMAX and POT matching work suggested that this approach could be adopted due to the high levels of matching between one day storms and AMAX floods. The use of a one day storm is not justified entirely by this matching work; further investigations were undertaken as part of the peak flow modelling work in Chapter 5.

### 8.4.1 Catchment Moisture Deficit Estimates

With regards to the results contained in Chapter 5, it is interesting to note the relatively poor performance of incorporating the catchment soil moisture deficit estimates. In general, literature on antecedent conditions estimation tends to suggest that soil moisture is preferred as an indicator of antecedent conditions over antecedent precipitation (e.g. Brocca et al., 2008). The primary reason for this is because antecedent precipitation on its own gives no indication as to the effectiveness of a rain storm. In the case of the modelling carried out in Chapter 5, it is clear that the formulation of the soil moisture time-series is not suited to flow estimation. It is highly likely that the generalised soil moisture model cannot capture antecedent catchment conditions well enough to improve flow estimation. This problem may be a combination of (1) the model not capturing local infiltration characteristics and (2) the model not adequately capturing the groundwater regime where flooding can be generated from relatively little rainfall. The soil moisture model drainage coefficient k was allowed to vary in order to represent local conditions. It may be that this does not go far enough in capturing the wide variety of soil characteristics necessary for accurate soil moisture simulation. The use of generalised PET within the soil moisture model as well as generalised regression equations from the ReFH may also contribute further to the problems associated with this approach.

Whatever the source of the error in the soil moisture modelling, there is one further characteristic of this approach that makes it undesirable. The modelling strategy was designed to take an alternative approach to that of CS, as this is being developed elsewhere. Therefore the creation of a soil moisture time-series, that updates itself at every time step is perhaps not in the spirit of what was originally envisaged for this project. Furthermore, the creation of the soil moisture time-series used variables that may change in the future (such as the Field Capacity) and it is not clear how these can be reasonably adjusted to account for future change. To that end, the further development and use of the soil moisture deficit model was reasonably discontinued at this stage.

Chapter 5 presented an outline model for the estimation of peak flows, as this was felt to be an important first step in frequency curve construction. For the majority of catchments, the model can reasonably be considered to estimate a catchment flow record, albeit with some catchments performing better than others. With the soil moisture time-series not improving flow estimation, some catchments still suffer from a distinctly seasonal signal to their temporal error plots. While this could be due to the poor construction of the soil moisture model, it is also likely that other effects such as groundwater storage and possibly snowmelt affect the results.

### *8.4.2 Snowmelt Influences*

The issue of snowmelt has not been dealt with specifically in the modelling process. The development of a snowmelt component to the model is recommended as further work however, it would require the sourcing and processing of additional datasets. This has not been carried out due to time constraints. Appendix J.1 highlights those catchments which are likely to be prone to snowmelt floods. By definition these are high altitude catchments, primarily, but not exclusively, in the North and East of the UK (Watson et al., 1994). While this study does not deal with the problem of snowmelt flood estimation, it does highlight catchments where snowmelt floods may be a problem. This would allow any flood frequency assessment to be more sympathetic to the issues in the specific catchment under investigation.

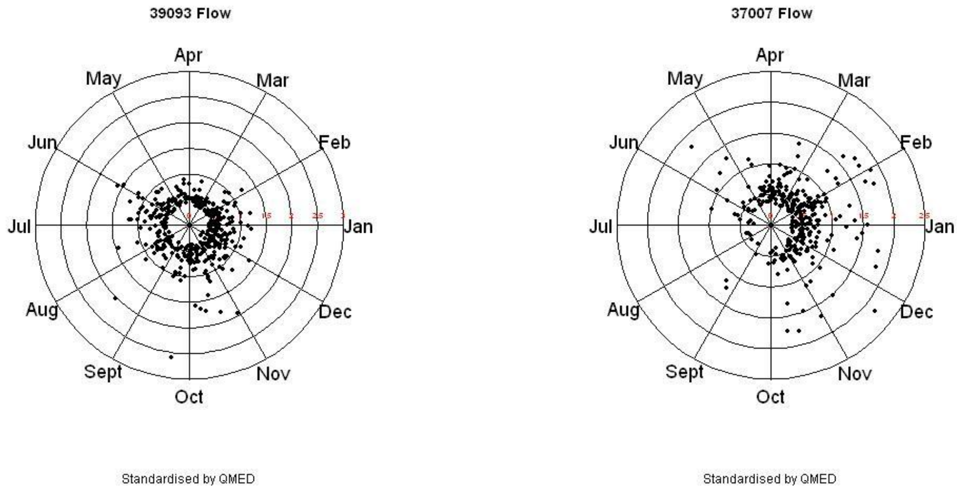
Guidance on snowmelt flood estimation is limited. This probably reflects the fact that the problem only affects a small number of catchments. However, it is not clear how snowmelt influences may impact upon a flood frequency estimate. Because snowmelt influences are not accounted for in any of the FEH PCDs, care may be needed when forming pooling groups for a target catchment that is prone to snowmelt generated floods. In terms of estimating potential melt values, Hough and Hollis (1998) provides a useful basis for snowmelt estimation however, to be of use to this work it is likely that a joint probability approach would be required between melt rates and storm rainfall.

### *8.4.3 Urbanisation Effects*

The physical processes behind urbanisation effects on hydrology are well documented (see Hollis and Lucket, 1976 and Packman, 1980 for two examples). Impervious ground such as paving and concrete can lead to high rates of runoff, thereby exacerbating the effects of flooding. But while the local scale effects are reasonably well understood, it is less clear what effect urbanisation has at larger catchment scales.

The FEH includes the variable URBEXT as a descriptor which characterises the extent of urbanisation in a catchment. For the majority of catchments in this study, URBEXT values are low. However, there are a small number of catchments which have significantly higher URBEXT values (up to around 0.4).

Typically, the effects of urbanisation cause faster runoff, higher volumes of runoff and a reduced sensitivity to antecedent conditions (Robson and Reed, 1999). These effects can manifest themselves in a catchments flood record, as typically urbanised catchment's are prone to year round flooding compared to a seasonal partitioning of flooding in their counterparts. This is mainly because rainfall effectiveness varies less over an urbanised catchment (or rainfall has the same effectiveness all year round). Figure 8.1 shows two polar plots which compare a heavily urbanised catchment and a catchment with very little urbanisation. The catchments are similar in all other respects such as AREA, HOSTBFI, PROPWET, SAAR and FARL. In addition they are also located close to each other. The change in flow seasonality, with flood events spread throughout the year in the more urbanised catchment can be clearly seen.




*a* *b*

***Figure 8.1*** *Two examples of Polar plots of POT flow seasonality. (a) shows a catchment with a high URBEXT value, (b) shows a similar catchment nearby with a low URBEXT value.*

With regards to the event based modelling work, the influence of urban extent on the residual peak flow model error is likely to be small. Because the coefficients are optimised, it is likely that they can deal with urbanisation effects. However, the model coefficients do not vary through time. Therefore, a catchment with a gradually expanding urban area may require some adjustment or re-fitting of coefficients in the future.

With regards to the current model structure, it is not specifically tuned to urbanised catchments. However, highly urbanised catchments are likely to experience an almost direct transformation of rainfall to flow, and therefore would be well suited to an event based modelling approach with a crude estimation of antecedent conditions as developed in this thesis. Developing a specific model for use on a set of these catchments may be a worthwhile exercise, as current commercial flood estimation work is heavily focused on urban areas to assess the risks to new and existing urban developments. However, the current urbanised catchment set is too small to be able to reliably infer anything about a suitable model structure for urbanised catchments.

### *8.4.4 Event Based Model Structure*

The structure of the event based model (either with or without the soil moisture estimates) is a simple one, albeit with some complexity in the work required to prove its worth. There are several advantages to keeping the model this way, not least because its simplicity allows for a greater understanding of how the model works and its performance over a large number of catchments. Furthermore, as the model contains few coefficients, it is simple to use for the future case, as there are fewer ambiguities about how to alter model parameters to represent a future climate. Perrin et al. (2001) have shown that, in many cases, simple models with few parameters can perform as well as, and in some cases better than, more complex models with many parameters. In practice, certain models will always perform better under specific sets of conditions and using certain model assessment indices and so it is unlikely that any single model can ever be considered as the best model to use in any given situation.

One of the major findings during the development of the event based model was that the inclusion of the catchment moisture deficit estimates could not be justified due to the relatively poor performance of these indices. However, from the error plots contained in Section 5.3.2 there is a clear need to try and account for seasonally effective rainfall. An alternative model structure might use a seasonally varying coefficient to modify the antecedent rainfall. It is currently unclear how well a generalised seasonal coefficient would work though the seasonal error signal to the plots shown in Chapter 5 provides some evidence that a seasonal correction might be suitable. If a seasonal correction was implemented statistically, then there would evidently be a requirement that this correction can be altered in the future should the seasonality of rainfall (and/or PET) change.

The second objective introduced in Section 1.3.1 was to develop a methodology for the estimation of peak flow from rainfall. This work has been reported on in Chapters 4 and 5. While many flow estimation methods currently exist, the event based method outlined in Chapter 5 allows for the estimation of peak flows in the entire flow record. This was necessary in order to allow for the estimation of the catchment flood frequency curve. The methodology used is reasonably flexible and allows for a different model specification depending upon the available data. It is acknowledged that some catchments still have remaining errors, and therefore further work might be required in order for this second objective to have been considered to be fully met for all UK catchments.

## 8.5 Developing a methodology for the reproduction of catchment flood frequency curves

This thesis uses the title ‘The Estimation of Flood Frequency Curves by Mapping from Rainfall Frequency Curves’. In practice, the flood frequency curve estimation model does this using rainfall frequency data and supporting information. It is a rapid statistical method which can use estimates of rainfall from different sources and which with care, can be used to examine future projections of change.

Objective three in Section 1.3.1 was to develop a method suitable for the estimation of flood frequency curves. Chapters 6 and 7 report on the development and testing of the flood frequency curve estimation model.

### *8.5.1 Model Formulation and Structure*

The frequency curve estimation model formulation follows a similar structure to that of the event based model. The estimation of flow peaks was seen as an important first step, prior to the estimation of the flood frequency curve. The use of observed data allows for interesting insights into the rainfall to flood transformation and this was partly the reason for choosing this approach over other possible methods.

An alternative approach could have been to take a rainfall frequency curve, and then directly estimate the flood frequency curve through an analysis of the extreme value distribution parameters. As a method, this is simple and is conceptually appealing due to the direct frequency curve transformation. However, a simple mathematical transformation of distribution parameters may hide the intricate details such as the influence of antecedent conditions or the problems of flood estimation in groundwater based catchments. Chapter 2 highlighted a similar method, known as GRADEX (Beran, 1981) which extends the flood frequency curve based on the rainfall frequency curve. However, the underlying assumptions regarding appropriate distributions may not be valid, and the method is not particularly suited to future climate applications.

The modelling approach which this research has developed can be described as relatively non-complex. In both the event based estimation and the estimation of the flood frequency curve there are only ever a maximum of two coefficients in use. Both the event based model and the frequency curve estimation model use a maximum of three terms and this simplified approach has been intentional throughout. However, in any environmental modelling approach there is a balance to be struck between the complexity of the model and the aim of the modelling project. Highly parameterised physically based models used for flow and flood frequency estimation such as SHETRAN (Ewen et al., 2000) can represent a wide variety of conditions and processes, but this is at the expense of the complex parameterisation which is often non-trivial to implement. On the other hand, simple models require far less parameterisation but often sacrifice site-specific performance in order to do this (Kay et al., 2006).

### *8.5.2 Robustness and Applicability of Return Period Estimates*

The estimation of the flood frequency curve in Chapter 6 allows for the calculation of selected return period magnitudes. However, as the flood frequency curve estimation method generally uses short records to estimate the flood frequency curve for a single site, the ability of the method to estimate high return period events is limited.

To some extent, the frequency curve estimation method is limited by the rainfall records that drive it. If the estimation of extremes in the rainfall records is poor, then the flood frequency curve model cannot be expected to reproduce higher return period events with any accuracy. On the other hand, where the fitting of the flood frequency model is poor, it does not matter how good the rainfall estimates are.

The FEH recommends that to estimate a target return period magnitude, the data record used for estimation should be at least five times as long as the return period desired (Robson and Reed, 1999). In the case of the records used for the fitting in this study, most are around 30-40 years long. Using the

FEH guidelines, this would allow the estimation of only the 6-8 year return period event from a single observed rainfall record.

If used in a predictive mode, the flood frequency curve estimation model developed in Chapters 6 and 7 can be used to estimate frequency curves when used with synthetic rainfall data. The flood frequency plots shown in Section 7.6.2 illustrate the uncertainty in the single site flood frequency curve. However, the use of multiple synthetic rainfall time-series for frequency curve estimation allows for a more robust estimate of the frequency curve and its associated uncertainty, similar to the advantage gained from the use of continuous simulation models. Therefore the estimation of a target return period can be extended beyond the 5x record length rule of the FEH, as multiple realisations of the flood frequency curve are produced which to some extent reduce the uncertainty in the flood frequency estimate.

Flood frequency estimation for floods in excess of the 100 year return period is challenging (Macdonald et al., 2006). Even if the most rigorous approach is taken, all relevant data is collected and the analysis is appropriate, there is still a significant amount of uncertainty involved. The estimation of a design event for which there is no comparable entry in the observed record is evidently problematic and will inevitably involve some degree of uncertainty.

This being the case, it is clear that the flood frequency estimates developed here will not be immune to this uncertainty. The results from the catchments selected for a future flood frequency assessment (see Section 7.7) all tend to show an increase in the median, 10$^{th}$ and 90$^{th}$ percentile bounds under the future case compared to the current and all show increases in the modelled flood frequency curves. Furthermore, the distance between the 10$^{th}$ and 90$^{th}$ percentile bounds increases under the future scenario. This is in agreement with other published work such as that of Arnell (2003) which found that streamflow values under future conditions could take on an increased range and that the climate change signal was not always easy to distinguish from decadal variability.

Generally, the results from Section 7.7 compare well with other published work. Reynard et al. (2001) considered future changes to the Thames and Severn around the 2050s. Their results suggested increases in the peak daily discharge of between 2 and 45 percent for all return periods up to 50 years. Similar results were found by Kay et al. (2006b) when looking at a larger catchment set, although interestingly in some locations (notably the South east of England) flood magnitudes for specific return periods decreased. It should be noted that agreement with other published research on its own is not an indication that the future change identified is probable. The changes identified can be considered as best estimates, and need to be considered in light of the stated uncertainties.

In terms of quantifying the error associated with the modelled estimates, Chapter 7 provided the results of assessing the percentage difference between the observed and modelled flood frequency curve. This gives a reasonable indication of how well the model can estimate one selected return period. This index was chosen as it is reasonably easy to interpret its implications, unlike the RMS error which is calculated over several return periods and normalised by QMED. While it might seem desirable for this percentage error to be minimised there is a danger of model over fitting if the optimisation is too tight. Specifically, it should be remembered from Chapter 2 that the potential error in the observed discharge record could be as much as ten to fifteen percent. Therefore an error of this magnitude between the observed and modelled return period estimates is not significant. From a practical perspective, there are clearly catchments that are unsuited to frequency curve estimation using the method developed in this thesis due to the size of the errors between their observed and modelled return period estimates. For the rest of the catchment set, the acceptable error between observed and modelled estimates will likely depend on the user and the application.

One further aspect of uncertainty within flood frequency estimation which should not be overlooked is that of stationarity. For a traditional statistical flood frequency assessment, it is assumed that the observed series are stationary, that is, they are stable throughout time. It is recommended that non-stationary series are not used within traditional statistical analyses. This problem is significant within flood frequency analysis as while practitioners may wish to use long time series for robust return period estimation, the longer the time series, the greater the chance that that it is non-stationary. Recently, it has been noted that in several areas, stationarity is no longer a viable assumption to make with regards to some environmental records (Milly et al., 2008). For the frequency curve estimation model developed as part of this work, stationarity has been assumed, mainly to make the frequency curve estimation process as simple as possible. However, it likely that this assumption is not viable in all catchments and therefore the work may require further development in order for robust frequency curve estimation to be ahcieved. Villarina et al. (2009) recognise land use change as a cause of non-stationarity in observed AMAX records and propose a method to model time-series under non-stationary conditions. Cunderlik and Burn (2003) and Leclerc and Ourda (2007) both advocate the use of time-dependent distribution parameters for flood quantile estimation. This recognises the change in distribution parameterisation throughout time and, as an approach, could reasonably be used with the flood frequency curve estimation model developed as part of this work.

### *8.5.3 Improving Frequency Curve Estimates*

One potential way of improving flood frequency curve estimates is by the inclusion of historical estimates of extreme floods. While there are several uses for this type of work, there could be significant benefits to a frequency analysis by including historic data. In using historic data, care needs to be taken with frequency analysis as it may be that not all significant floods are reported. However, where instrumental records are short, there are clear benefits to improving frequency analysis by adding data obtained from other sources.

McEwen (1987) investigated the use of historic rainfall data to help extend the flood record of the upper Dee in Aberdeenshire. The complication in this work is in trying to develop a link between the recurrence interval of rainfall and the flow that it generates. Historical flood evidence can come in many forms, such as estate and community records, bridge marks and documentary evidence. However, the incorporation of historic floods peaks into a modern flood frequency assessment is difficult and should not be undertaken lightly. The frequency analysis procedure that includes historic data should be seen as augmenting the modern approach which uses instrumental records. However, the benefits can be significant and in the UK guidance on the use of historic flood data was published by Bayliss and Reed (2001). MacDonald et al. (2006) recommend the use of historic data where return period estimates in excess of 100 years are to be assessed. The incorporation of historic data within the flood frequency curve estimation model is only worth considering if rainfall is available as well. Given that rainfall records tend to be more extensive than flow records, there is some potential for more direct use of the frequency curve estimation model in extending the flow series.

### *8.5.4 Model Use and Limitations*

While the flood frequency curve estimation model has been developed with future applications in mind, it can provide a useful way of looking at current variability within the flood frequency curve. The ability to work with synthetic rainfall time-series means that, where the observed flood frequency curve can be adequately estimated, it is possible to develop more robust estimates of current flood frequency. This advantage is similar to that provided by continuous simulation (CS), where long climate time series can be used to develop more robust estimates of flood frequency. The advantage of the frequency curve simulation model is that it does not require the extensive parameterisation and computational complexity and time of CS modelling, as it focuses on developing estimates of instantaneous flood peaks rather than the whole flow series.

With regards to the approach detailed in this thesis, the flood frequency estimation method clearly has some limitations. Catchment types not suited to the approach have been clearly identified; these tend to be permeable catchments, where the response to rainfall is severely dampened. In particular this affects the South of England, where chalk and limestone geology is abundant. Furthermore, it is clear that dry catchments do not perform particularly well, as shown by the relationship between model performance and the PROPWET catchment descriptor. However, most other approaches, including CS, are poor in representing flood peaks in these types of catchments so this is not a problem unique to this approach.

#### 8.5.5 Using Principal Catchment Descriptors (PCDs) to assess Performance

One of the more difficult issues that this thesis has approached is that of how model performance may relate to catchment characteristics, as well as how the coefficient structure may relate to catchment characteristics. Ideally, coefficient values would relate to catchment physical characteristics and model performance would also be related to catchment type. However, this is not the case. The reasons for this may vary. Firstly, it is perhaps unrealistic to expect that any single catchment descriptor would control model performance, where many interacting factors may be responsible for the flood regime. In terms of identifying these factors this is perhaps further complicated as their relative importance may change between catchments. Furthermore, physically similar catchments may not prove to be hydrologically similar. The PCDs used in this study provide a limited description of the catchment hydrology. Oudin et al (2010) describe how PCD's often do not adequately characterise the underground catchment properties and therefore do not fully represent catchment hydrological behaviour. Their study compared catchment physical descriptors with catchment behaviour from hydrological modelling, and only in 60% of the catchments studied did the two approaches agree with each other. This suggests that there may be limits to how well PCDs can be used to characterise catchment hydrology. In work comparing different methods of regionalisation, Merz and Bloschl (2005) suggest that spatial proximity is a significantly better predictor of regional flood frequency than catchment attributes. While their study was carried out on Austrian catchments, the results suggest that an alternative coefficient estimation method based on spatial proximity may be useful to the model developed within this thesis.

The third objective set out in Section 1.3.1 was to develop a method suitable for the estimation of the flood frequency curve. This work builds considerably on that reported on in Chapters 1 to 5 and is presented in Chapters 6 and 7. It is acknowledged that there are some weaknesses in the developed method, and these are stated within the chapters mentioned. Therefore, it is considered that this third objective has been partially met, despite the inability of the model to deal with certain situations.

## 8.6 Using the Method for Future Flood Frequency Estimation

The question of how fluvial flood frequency may alter in the future is a difficult one to address. There is considerable uncertainty in how the climate will evolve (Prudhomme et al., 2003). There is uncertainty in how catchments might change, therefore affecting the physical processes that govern runoff and ultimately affect the flood frequency curve.

The current frequency curve estimation model requires little in the way of alteration for use under a future environment; this is the main attraction of using the method. However, care must be exercised in the use of the model under certain futures, where it may not be appropriate to use the optimised coefficients under a radically different climate.

### *8.6.1 Climate Scenarios For Flood Frequency Estimation*

This work has made use of a single source of future climate data; the UKCP weather generator. This product was chosen mainly because of its availability, but also because of its good representation of the current climate. In contrast, the raw RCM data shows a reasonably poor representation of the current climate in its control climate. This being the case, it is clear that little can be gained by using poor climate estimates and so the RCM data was not used in any flood frequency curve estimation work. In practice, the direct use of raw RCM data for catchment modelling is generally discouraged without some sort of bias-correction. Kay et al. (2006) demonstrate a simple method to estimate catchment averaged rainfall using the ratio between RCM grid rainfall and SAAR on a 1km grid. Were the RCM rainfall assessed in this study to be used any further it is likely that an approach similar to that of Kay et al. (2006) could be used. However, the UKCP user guide acknowledges that the RCM data contains some model bias with respect to historical observations and it is provided with caveats attached (UKCP, 2011).

In terms of processing the RCM data to make it more suitable for use, one of a number of methods could be used. One of the simplest methods is that of bias correction. With this technique, a correction factor is calculated between some observed dataset and the RCM output, usually on a month by month basis. This same correction factor would normally then be applied to the

RCM output in the future (Hay et al., 2002). This approach makes the assumption that in order to apply the bias corrections in the future the RCM error structure will essentially be the same and this may not be true.

An alternative and slightly more sophisticated approach is called quantile correction, where the aim is to shift the distribution of the RCM output to match with the distribution of the observed. Again, this still suffers from the problem of how valid any corrections might be in the future (Wood et al., 2004).

### *8.6.2 Predictive Ability of the Model when working with future scenarios*

Future scenarios of climate used within this thesis can be considered as multiple realisations of how the climate may evolve in the future. The climate scenarios used in Chapter 7 do not encompass all of the potential climate model and emissions variability possible in the future. Nevertheless, it is useful to consider how well the modelling strategy developed in Chapters 4 to 7 is able to provide future estimates of the flood frequency curve.

The question of how flood frequency may change in the future is an inherently difficult one to answer, mainly because it is not possible to assess projected future changes in flood behaviour against any observed data. Many studies tend to focus on the uncertainty in climate scenarios (e.g. Fowler and Wilby, 2010; Bell et al., 2007b). It is clear that if there is an important link between climate and flood frequency, then any error associated with the projected climate will be propagated into future projections of flood frequency. Estimates of future climates are continually evolving, therefore it is highly likely that the best estimates of today will be superseded as models are run at higher resolutions and process understanding improves. As an example, all current RCMs exhibit poor skill in reproducing extreme summer rainfall; this has been attributed to their poor representation of convective rainfall events (Fowler et al., 2005) as these convective systems tend to have a smaller footprint than the RCMs current resolution (~25-50 km). Therefore, the impact on any flood frequency assessment is that the results need to be interpreted with caution, especially where flooding occurs during the summer.

While many studies look at the effect of the future climate estimates on an impact assessment, fewer studies compare the uncertainties in the hydrological model itself. Traditional methodologies for assessing future hydrological change often use a rainfall-runoff model calibrated for a baseline period against some observed flow data. This same model can then be used with a future climate to assess future projected changes. However, this method assumes that the model parameterisation stays the same between the baseline and future periods. Where any calibration takes place, it is clear that the resulting parameter set is then influenced by the hydroclimatology. The question then arises as to how these parameters can be used in the future if the hydroclimatology changes? This problem is common to many modelling studies, including the work carried out here. The work in Chapter 7 attempted to address this issue by applying the coefficient sets estimated through optimisation in Chapter 6 to a set of unused data spanning a wider range of hydroclimatological variability. This work highlighted the clear need to do this before a catchment can be used with the future scenarios and modelling method outlined in the thesis. In two cases, where original fits were good, there was a considerable overestimation of the empirical frequency curve when the frequency curve estimation models were used with the POT data. The reasons for this are unclear. Merz et al. (2011) look at the problem of assuming time invariant parameters when modelling baseline and future hydrology. They found trends in parameter time-series when estimated from consecutive short baseline records. With regards to the plots in Figure 7.3 of this thesis concerning the use of the POT data, it could be that there was a lack of variability in the original flood records and this then led to the overestimation of the empirical frequency curves in two cases when using the POT data. Whatever, the reason for the mismatch between the fitting and validation of the frequency curve estimation model, one clear message from the work is that a second assessment (in this case the assessment on unseen POT data) is important if any confidence is to be placed in the future projection work. Understanding how the model behaves on different sets of data as well as understanding coefficient stability gives confidence in the modelling procedure; these tests are recommended by Wilby (2005) in a study looking at model parameter stability for water resources.

The development of the flood frequency curve estimation model was specifically focused on providing a rapid means of assessing changes to future flood frequency based on changes to future climate. While this work has not carried out in depth analyses of country-wide changes to future flood frequency, it has provided a model structure and method for doing so. The last objective set out in Chapter 1 was to develop a method suitable for developing projections of future change. It is considered that this objective has also been partly met, as there are circumstances where the current modelling methodology will not work.

## 8.7 Suggestions for Further Development of this Work

The development of this model has thrown up several interesting avenues for future research. Here, some selected possibilities are presented. These have been chosen specifically because it is felt they would enhance the practical application of the flood frequency curve estimation method.

### *8.7.1 Extending Frequency Curve Estimates to Higher Return Periods*

The design of many engineering structures for flood risk management requires estimates of flood frequency typically in excess of the 100 year return period. It is acknowledged that the frequency curve estimation method presented in this thesis does not achieve this, as it currently estimates a single site frequency curve.

With this in mind, the development of a method suitable for estimating high return period events would seem a worthwhile piece of work. Within traditional methodologies such as the FEH statistical method, the pooling of hydrologically similar catchments is used to develop an extended flood frequency curve. Pooling allows the creation of a time-series longer than the original target site which is better suited to the robust estimation of higher return period events.

With regards to the frequency curve estimation method outlined in this thesis, further work would need to identify how catchments could be pooled. While the hydrological similarity of catchments has been identified as a suitable method for pooling it would need to be shown that this was compatible with the flow estimation coefficients that are used in the frequency curve estimation model. To further develop this, it may be appropriate to identify groups of catchments with similar hydrological characteristics and similar coefficient values. This may allow the use of a single set of coefficients for a small group of catchments. Therefore, if this was found to be the case, it might be possible to develop a long flow series using a set of catchments.

This approach may only develop the method for estimating current return period values. Pooling is often used for short records because short records do not exhibit the full range of hydrological variability necessary for robust frequency estimation. An alternative approach to the estimation of high-return period events might be to use long-term synthetic rainfall records which can then be run through the frequency curve estimation model. In essence this approach would be similar to CS, albeit without continual accounting of river flow and soil moisture etc. Evidently the ability of the future climate scenarios to represent extreme rainfall is still a constraint on how well high return period flood events can be modelled.

The study is primarily forward looking in its use of data. While considerable use of instrumental records is made, the work is designed to try and develop a method which predicts future flood frequency curves. However, an alternative method might be to use the method and data in a historical analysis. There are several possibilities with regards to this idea. Several authors recognise the benefit of including historical data in flood frequency analysis (for example see McEwen (1987) and Black and Fadipe (2009)). It can give insights into flood clustering as well as improve frequency estimates through the inclusion of a greater number of large flow peaks. With information on longer term rainfall it would be possible to include these historic flood data in an analysis such as the one which has been carried out as part of this work. The use of historic flood data to improve flood frequency estimates is discussed further in Section 8.5.3.

Assuming that a method for peak flow estimation has been developed for a catchment, it might be possible to reconstruct the peak flow magnitude, given some information on the storm that generated it. This could be used either as an estimate of the peak flow, or as a check on estimates developed from other documentary sources. It may also be possible to reverse the method to take a discharge measurement and then estimate the magnitude of the rainfall event that caused it. Given that rainfall data tend to be more abundant than flow data, there is a significant potential for the use of the model in this respect.

#### *8.7.2 Developing the Method for Ungauged Catchment Use*

To some extent, this problem is linked to the work described in Section 8.8.1 on the estimation of higher return period events. A pooling approach allows the estimation of flow in ungauged catchments as long as the pooling group and the target catchment can be considered homogenous. As previously described, the problem with applying a pooling method to the modelling approach here is that flow estimation coefficients can vary between hydrologically similar catchments.

Therefore, the estimation of flood frequency curves in the ungauged catchment requires some development to work with the modelling method presented here. In particular it would be desirable to relate model coefficients to catchment characteristics. This is the approach that the parameter generalised g2g model takes (Kay et al., 2006). However, with regards to this work it is clear from the work on donor coefficient estimation in Section 7.4.2 that there would be a loss of performance in the model with the current coefficient estimation strategy. Suggested further work could take one of two approaches. The first would be to re-visit the optimisation procedure in order to force the coefficients to be better linked to catchment characteristics. If the current optimisation routine finds many local optima then this approach may prove to be useful. Secondly, further work could be done on the estimation of the donor coefficient. This work might consider a much wider range of variables that characterise catchment hydrological functioning. Variables such as seasonality statistics, matching percentages and other non-traditional measures of hydrological functioning may prove useful.

### 8.7.3 Improving Frequency Curve Estimation in High HOSTBFI Catchments

The current flood frequency curve estimation method does not work particularly well on dry catchments, as well as those with high HOSTBFI values. The reasons for this and an assessment of the impact on the method can be found in Section 6.4.2. Groundwater flooding as a phenomenon has physical causes which are considerably different from typical fluvial flooding in surface water driven catchments. Therefore to adequately characterise the problem of groundwater flooding it is likely that there would be a need for an alternative approach to that which is taken for the work presented in this thesis.

As a suggested method, it may be useful to characterise rainfall on much longer time-scales than the method currently uses. An initial analysis of flow and rainfall regimes may help identify these time-scales with more confidence but it may be in the region of 3 to 6 months (or longer) of rainfall which is required. Furthermore, from the work carried out here it is clear that storm rainfall has considerably less influence on flood generation in groundwater catchments compared to their surface water counterparts. Therefore it is also likely that new flow estimation formula would be required compared to the current method.

While continuous simulation methods are often presented as the most appropriate method for dealing with groundwater flooding, there is no reason why an appropriately specified event-based model cannot deal with the problem. Compared to CS, event based models deal with time-varying hydrology in a different way however, as long as this method is appropriate it should be possible to characterise groundwater flooding. The use of seasonality information may prove to be of considerable use in this approach.

### 8.7.4 Extension of the Climate Change Impact Assessment Work

This thesis has primarily dealt with developing and testing a model that could be used to estimate the flood frequency curve. The work considering future applications proves the use of the model, but it does not provide an in depth analysis of climate change in the UK. Reasons for not doing so are primarily due to time constraints.

Future work in this area would benefit from looking at a much wider selection of catchments. It would be sensible to select these catchments based upon performance measures already outlined in this thesis. A group of around 150-200 catchments with a good geographical distribution could reasonably be selected. In conjunction, the use of future climate scenarios would need to consider a wider range of emissions scenarios, as only medium emissions have been considered as part of this work. If these two additional bits of work can be completed, then it would be possible to develop a climate impact assessment of the UK which can deal with some of the uncertainty currently inherent in the use of climate scenarios. On a practical level, this work could also be compared with that of the g2g model outputs.

#### *8.7.5 Extension of the Method to Other Areas*

In some respects the geographical area covered by the model has benefitted its development. The UK exhibits a reasonably wide variety of climatic conditions and hydrological characteristics. Therefore, in terms of understanding how this model works, the variability over the country has provided some interesting insights.

However, this variability perhaps makes the modelling task harder, particularly when only one model formulation is applied to catchments with widely varying hydrological conditions. If the modelling technique applied here was transferred to an area that exhibits homogenous hydrological conditions, then it may be that the modelling process would be simpler and more successful. This would likely require a different specification of model which better represents catchment response to the climate. It is inevitable that a single model will not perform as well as several different models which have been better specified for a particular set of circumstances. This has been recognised by the authors of comparative model studies such as Perrin et al. (2001).

Were the modelling technique developed in this thesis applied elsewhere, it would require reasonable records for fitting and assessment. The UK is blessed with reasonably good rainfall and flow records, therefore this type of approach can be implemented with relative ease. It would not be easily applied in cases where only short flow records exist (or none at all) and in cases where only short flow records exist it may be more suited to the use of CS approaches which could be calibrated on reasonably short flow time series compared to this method.

However, given an understanding of the hydrology and catchment functioning, it would be possible to prescribe an event based model that adequately captures the catchment response. The difficulty in using this for extremes lies in the uncertainty of the estimates due to limited model assessment.

# Chapter 9: Conclusions

## 9.1 Summary of key findings

The key findings resulting from the research are listed below, with elaboration of these points in the following sections of this chapter:

- **Modelling of peak flows using daily data requires strict independence criteria in the selection of the modelled flows**

- **There is a clear east-west distinction in rainfall and flow seasonality**

- **Simple antecedent rainfall accounting has shown to be as useful as quasi-process based soil moisture modelling.**

- **Multiple weather generator outputs can be used for flood frequency assessment.**

- **The value of the flood frequency curve estimation model lies in its simplicity, allowing for a rapid assessment of future flood frequency.**

## 9.2 Modelling peak flows using daily data requires strict independence criteria in the selection of the modelled flows.

The selection of peak flows is an essential early step in the flood frequency assessment process. Certain AMAX series (especially in lowland, groundwater dominated catchments) may contain non-flood events due to the typical temporal distribution of peak flows. These AMAX series then need to be scrutinised for non-flood events. Similarly, in POT series there is a need to ensure independence between flood events.

The early peak flow modelling work (detailed in Chapter 5) required a link between a Peak Over Threshold flow event and its generating rainfall event. This link was identified in Chapter 3 as being essential and Sections 3.3.3 and 3.3.4 introduce the concept of independence criteria for flood frequency estimation and the peak flow modelling work detailed in this thesis.

The work detailed in Chapter 3 provided a key finding that was to be incorporated throughout the peak flow modelling work. This was that strict independence criteria are required when modelling peak flow data using daily rainfall.

This independence criterion requires that only one peak flow can be modelled in any single day. If two events were modelled in a single day, using daily storm rainfall would require that the same day's storm rainfall is attributable to both flow events (which may be of considerably different magnitude). This then creates a problem for peak flow modelling using rainfall data as the primary factor in flow generation. This problem only exists with POT series, as AMAX series implicitly remove the chance of two events occurring on the same day due to the criteria that an AMAX selection imposes.

The investigations into independence criteria recommended that where two peak flow events occurred on the same day, that only the larger of the two are used in peak flow modelling. This led to the removal of several events from the original POT series, detailed in Section 3.3.4.

## 9.3 There is a clear east-west distinction in rainfall and flow seasonality

Chapter 4 detailed work undertaken to consider the seasonality of extreme rainfall and flow events across the United Kingdom. Whilst this work has been considered by others such as Macdonald et al. (2010) and Black and Werritty (1997), little work has been published on rainfall and flow seasonality across the whole of the UK.

The seasonality work detailed within this thesis not only confirmed the general findings of the previously mentioned studies, but it also provided a timely updated (both spatially and temporally) to previous work.

Both the dispersion and mean day statistics of rainfall and flow were assessed, alongside polar plots of individual catchments. Rainfall statistics highlighted the increasing dispersion of extreme rainfall events as the analyses moved from west to east across the UK. This increasing dispersion has been attributed to the higher rainfall event frequencies observed in eastern catchments in summer compared to their western counterparts (Black and Werritty, 1997).

The analysis of flood statistics revealed a mixed pattern compared to rainfall. To some extent, rainfall and flow seasonality statistics are linked. However, there are several complicating factors, mainly attributable to catchment characteristics. Generally speaking, western catchments tend to show low levels of dispersion due to the predominantly westerly weather systems that cross them combined with generally wet, upland catchment characteristics. However, some groupings of eastern catchments also show low levels of dispersion due to the flooding mechanisms that operate within them. An example of this are the low levels of dispersion found in several east Anglian catchments as groundwater flooding tends to cluster in time due to water table influences.

## 9.4 Simple antecedent rainfall accounting has shown to be as useful as quasi-process based soil moisture modelling.

The estimation of antecedent conditions for peak flow modelling has been a challenging aspect of the research presented within this thesis. Antecedent condition estimation were highlighted as being important early on, and there is a large body of research on various aspects of antecedence ranging from hydrological modelling to more detailed soil moisture modelling studies.

The approach taken within this thesis uses a simple soil moisture accounting model. It is suggested that this modelling approach can be thought of as a quasi-process based model, as it attempts to model physical processes in a simple way. The model uses physical descriptors such as rooting depth and field capacity, but estimates these from empiricial equations so they are not truly physically realistic estimates at point of interest.

The soil moisture accounting model used within this thesis represents different soil types by varying statistics such as field capacity and rooting depth. These statistics do not fully represent soil conditions and along with the generalised estimates of PET are the suggested reasons for why the soil moisture model estimates do no better in peak flow estimation than the simple antecedent rainfall accounting method.

In order to better model the soil column, details such saturated hydraulic conductivity values, soil column types and depths and more detailed climatic data would likely be of use. These are typically used in more detailed soil moisture models which attempt to model soil moisture through the use of more direct physical equations. However, gaining the data and physical lithographic information to do this is not straightforward and is one reason why this approach was never utilised as a method for antecedent accounting.

## 9.5 Multiple weather generator outputs can be used for flood frequency assessment.

To develop scenarios of future flood frequency first requires some estimates of future climate. This study has made extensive use of the United Kingdom Climate Impacts Programme (UKCP) weather generator.

Typical future scenario inputs for hydrological modelling use either RCM or WG outputs. This research has shown the benefit of using the probabilistic nature of the WG output to develop multiple estimates of the flood frequency curve; thereby giving a greater understanding of flood frequency under a stationary climate (the weather generator does not consider any observed trends in outputs).

Many other studies make use of only one or two climate scenarios. However, from a practical perspective it is important to consider all possible future scenarios, especially if it is not possible to attach a probability to a specific scenario. In practice, this allows decision makers to have a fuller understanding of the possible range of scenarios which could happen, rather than presenting them with only one or two scenarios which give a misleading interpretation of future possibilities.

The use of the weather generator has been key in this respect, as it is simple to operate and can rapidly output many different scenarios. Extending the analysis to a wider range of catchments using weather generator outputs has been identified as a key piece of future work.

## 9.6 The value of the flood frequency curve estimation model lies in its simplicity, allowing for a rapid estimation of future flood frequency curves.

It is difficult to categorise the type of approach which has been detailed within this thesis in relation to typical flood estimation methodologies. It is a rapid statistical method which employs aspects of event based simulation and statistical flood frequency estimation to arrive at a final estimate of the flood frequency curve.

The value of the method lies in its simplicity. The number of transfer coefficients used is kept to a minimum and the estimation of peak flow uses a small number of variables.

Not only does this mean that the method has relatively low computational demands, it also allows it to be applied to different WG or climate model outputs in the future. The current simplistic nature of the method provides a robust basis for the future development of other model aspects such as snowmelt flooding or flooding from groundwater, two areas identified as being important in flood generation in some parts of the UK.

## 9.7 Overview of Thesis Achievements

This thesis has considered several aspects of contemporary flood hydrology. While advances in technology and knowledge have helped develop modelling techniques, the use of flood peak data is still a challenging issue and therefore this issue forms the basis for developing the work within this thesis.

Seasonality is an aspect of flood estimation that does not receive as much attention as it may be due. As some current climate change predictions suggest an alteration to the seasonality of rainfall, it may be just as important to understand how flood seasonality may alter, particularly with regards to agricultural and construction activities. This thesis has provided a basis for developing an understanding of the seasonal aspects of flooding.

The frequency curve model developed within the thesis is as much a demonstration of the link between rainfall and flooding as it is a practical tool. The ability to link rainfall and flood frequency opens many possibilities for practical applications and the frequency curve model specified within this thesis can be adapted to suit a wide range of circumstances.

Finally, one of the key concerns within society in general, is that of how climate change may impact upon the way in which we live. Through extensive testing, this thesis has shown the possibilities for using the frequency curve estimation model with future scenarios of climate.

## 9.8 Summary

The use of rainfall as a tool in assessing flood frequency curves has been shown to be of value and offers considerable possibilities in areas where gauging station data are limited.

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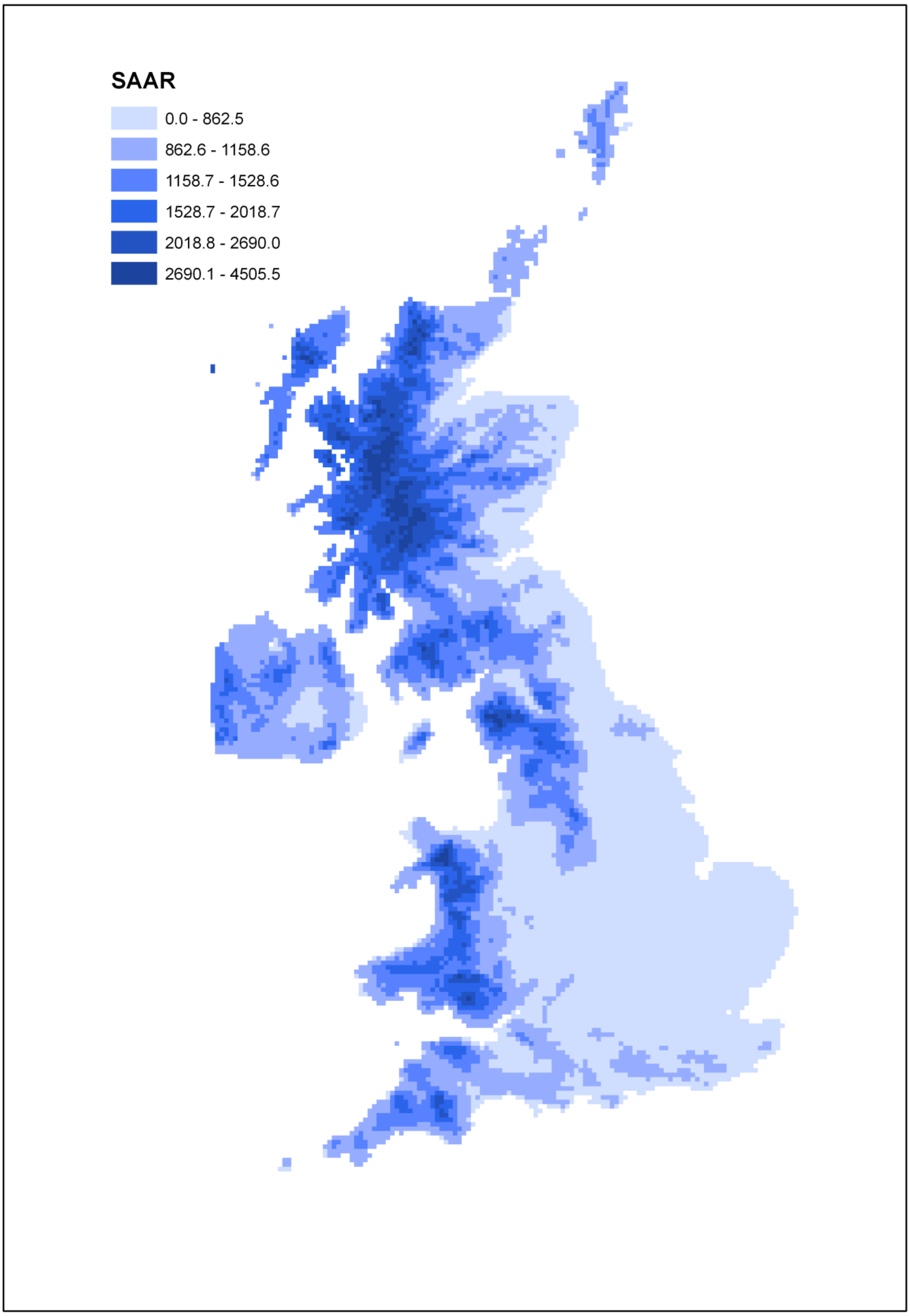
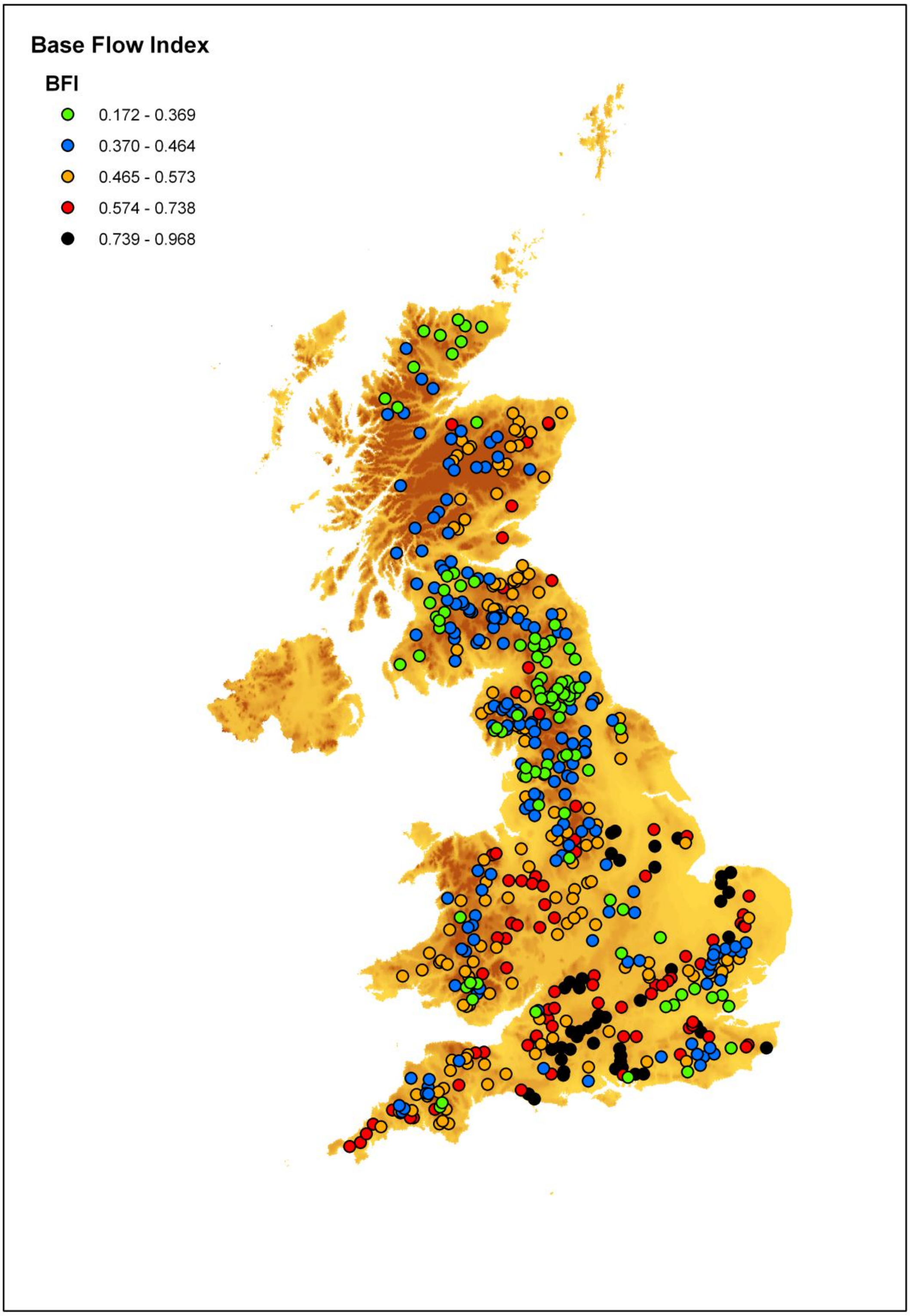
## Appendix A.1 Summary Maps of Catchment Properties



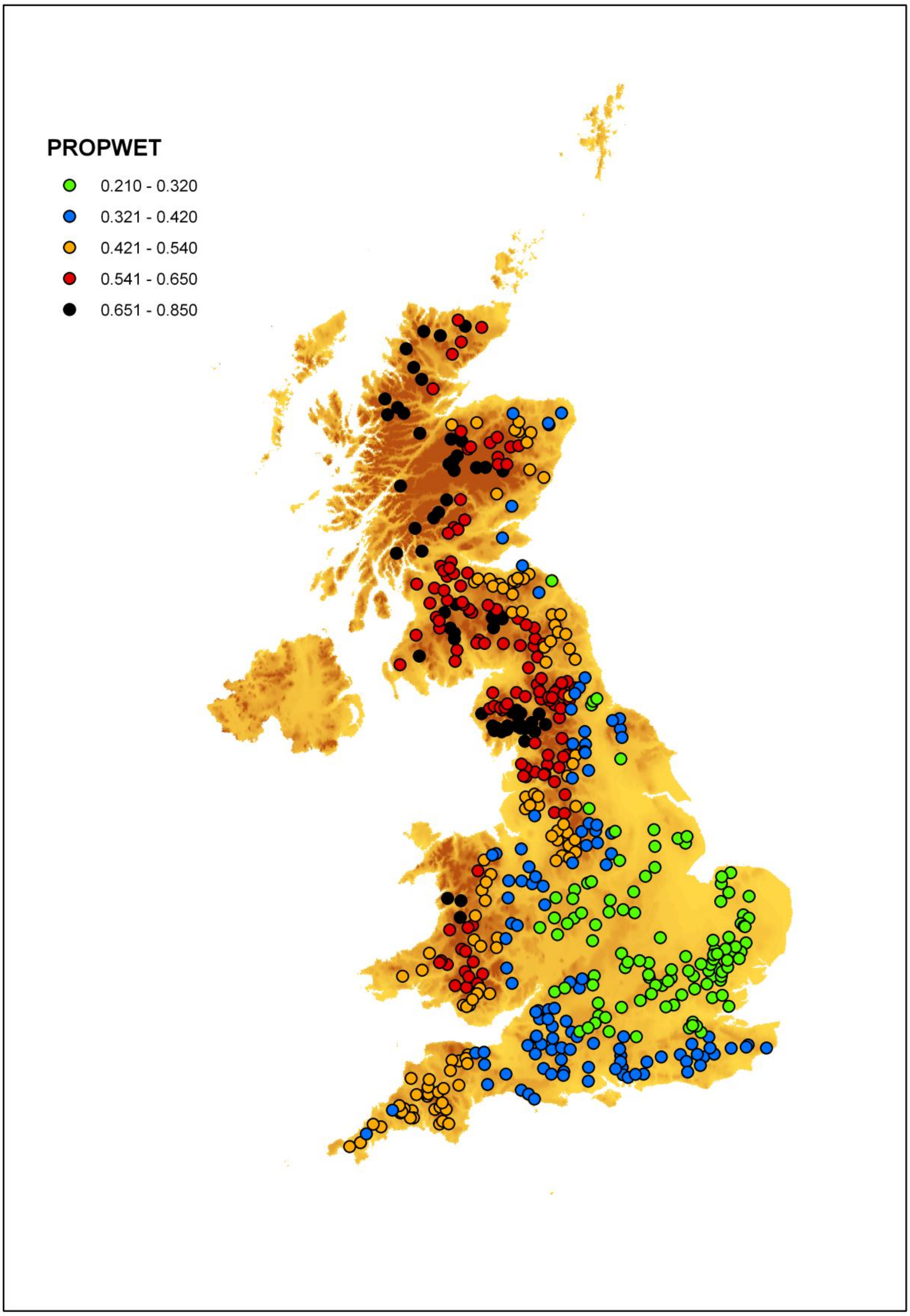

*The distribution of annual average rainfall across the UK as calculated from the MO 5km gridded dataset.*

## Appendix A.2 Summary Maps of Catchment Properties



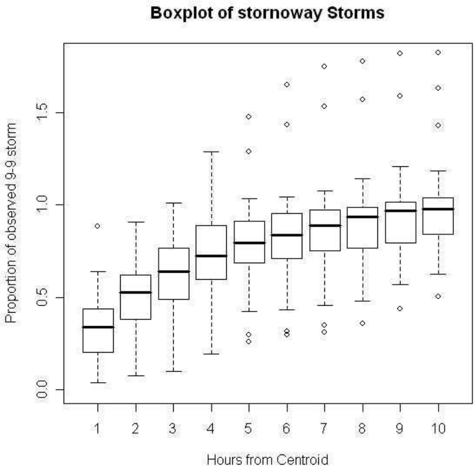

*Catchment HOSTBFI values as taken from the FEH catchment descriptor set.*

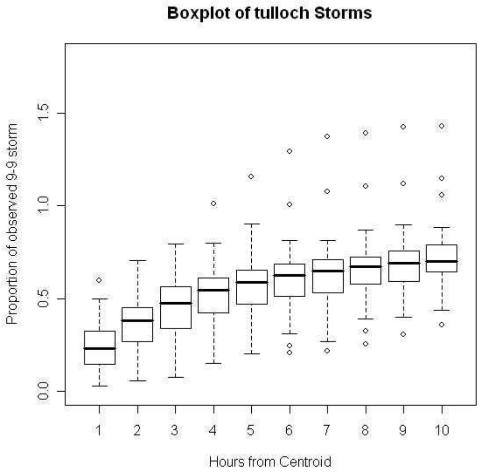
**Appendix A.3 Summary Maps of Catchment Properties-PROPWET**

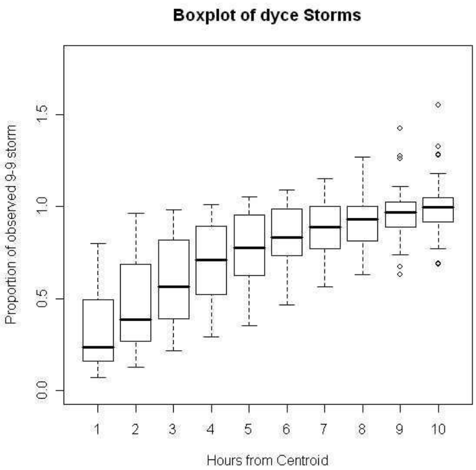


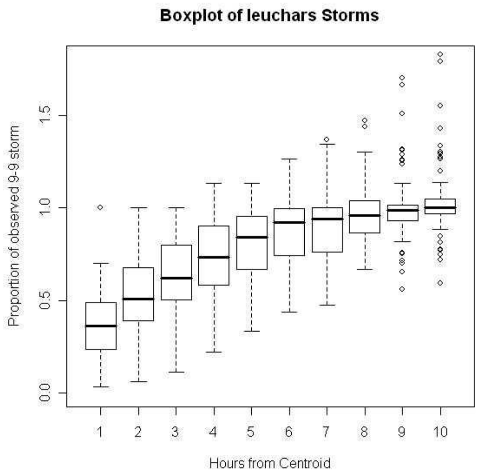

*Catchment PROPWET values as taken from the FEH catchment descriptor set.*

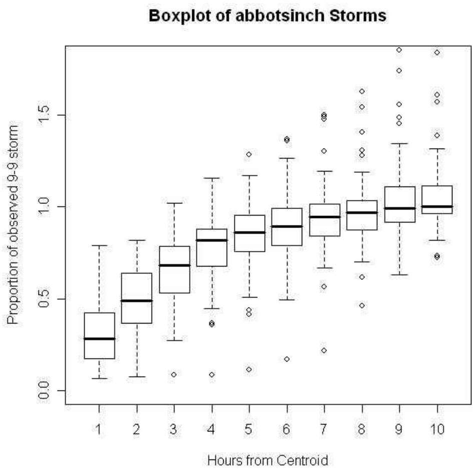
## Appendix B.1 Boxplots of Hourly Stations

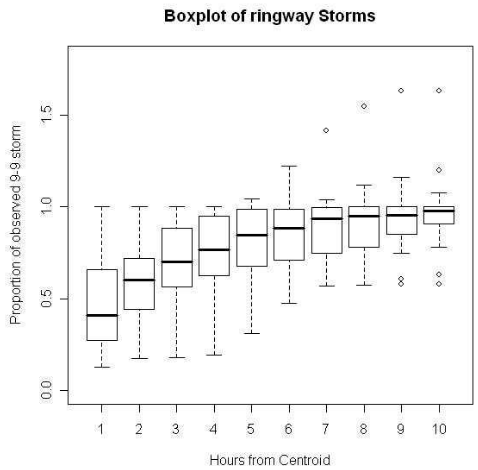


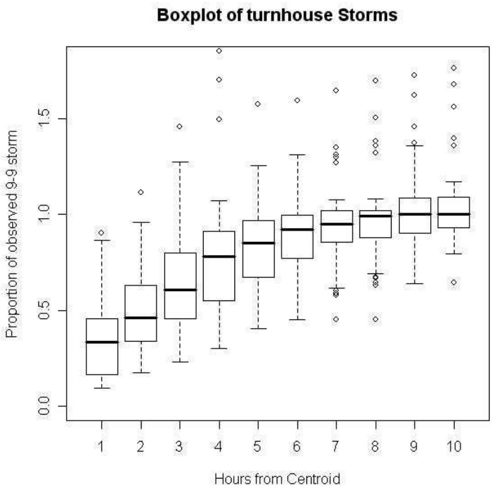



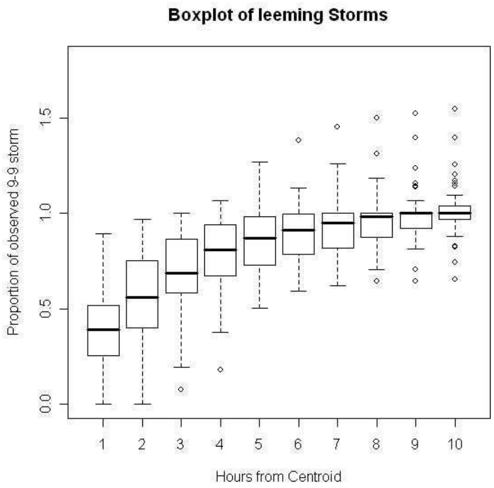



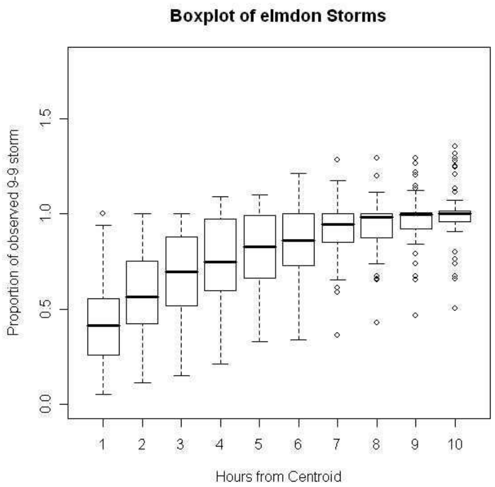



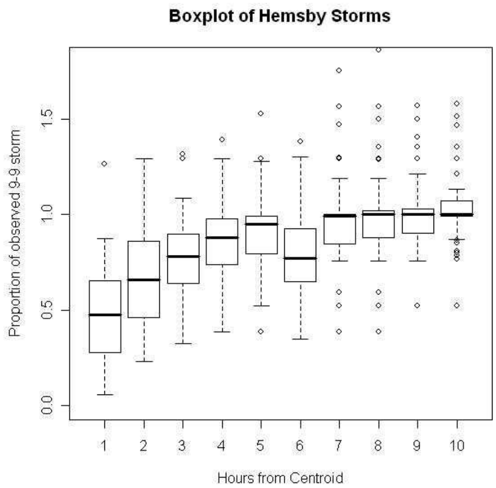



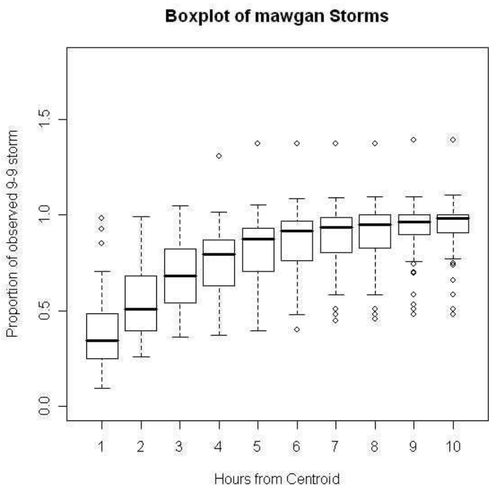



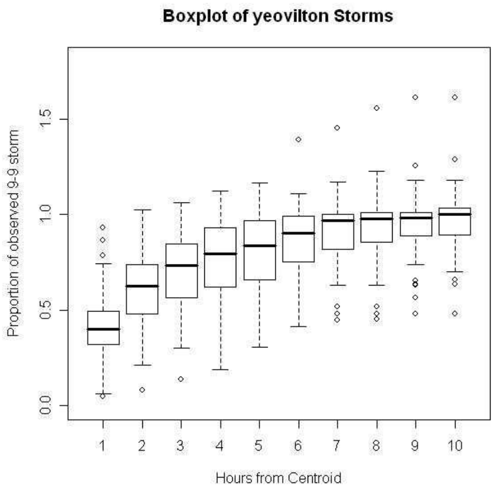

Boxplot of turnhouse Storms
Proportion of observed 9-9 storm
Hours from Centroid

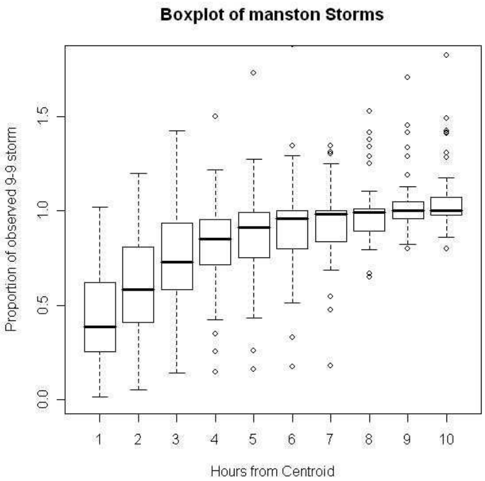

Boxplot of leeming Storms
Proportion of observed 9-9 storm
Hours from Centroid


Boxplot of elmdon Storms
Proportion of observed 9-9 storm
Hours from Centroid


Boxplot of Hemsby Storms
Proportion of observed 9-9 storm
Hours from Centroid


Boxplot of mawgan Storms
Proportion of observed 9-9 storm
Hours from Centroid


Boxplot of yeovilton Storms
Proportion of observed 9-9 storm
Hours from Centroid



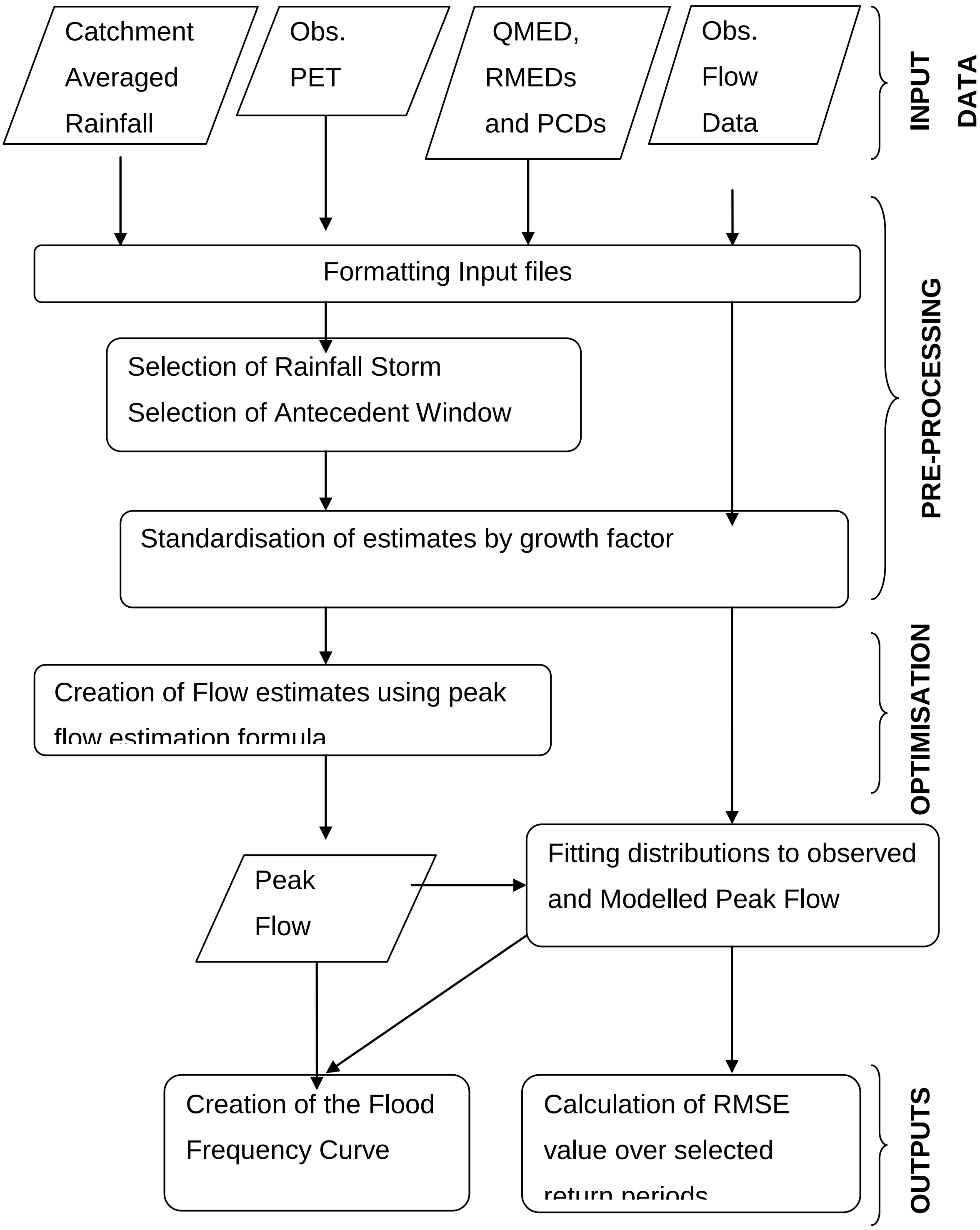

*Boxplots showing the percentage of a storm captured during a specific window. Eskadalemuir and Heathrow are shown as examples in Chapter 3. The boxplots show the smallest observation (lower bar), lower quartile (bottom of box), median (line through box), upper quartile (top of box) and largest observation (upper bar). Outliers are points that fall more than 1.5 times the interquartile range above the third quartile or below the first quartile and are indicated individually.*

## Appendix C.1 Individual Station Discretisation Values

| Site | Factor |
|---|---|
| Abbotsinch | 1.15 |
| Aldergrove | 1.14 |
| Carlisle | 1.14 |
| Dyce | 1.14 |
| Elmdon | 1.15 |
| Eskdalemuir | 1.12 |
| Heathrow | 1.13 |
| Hemsby | 1.16 |
| Hillsborough | 1.14 |
| Leeming | 1.13 |
| Leuchars | 1.20 |
| Manston | 1.19 |
| Mawgan | 1.10 |
| Ringway | 1.10 |
| Stornoway | 1.16 |
| Tulloch | 1.16 |
| Turnhouse | 1.16 |
| Yeovilton | 1.10 |

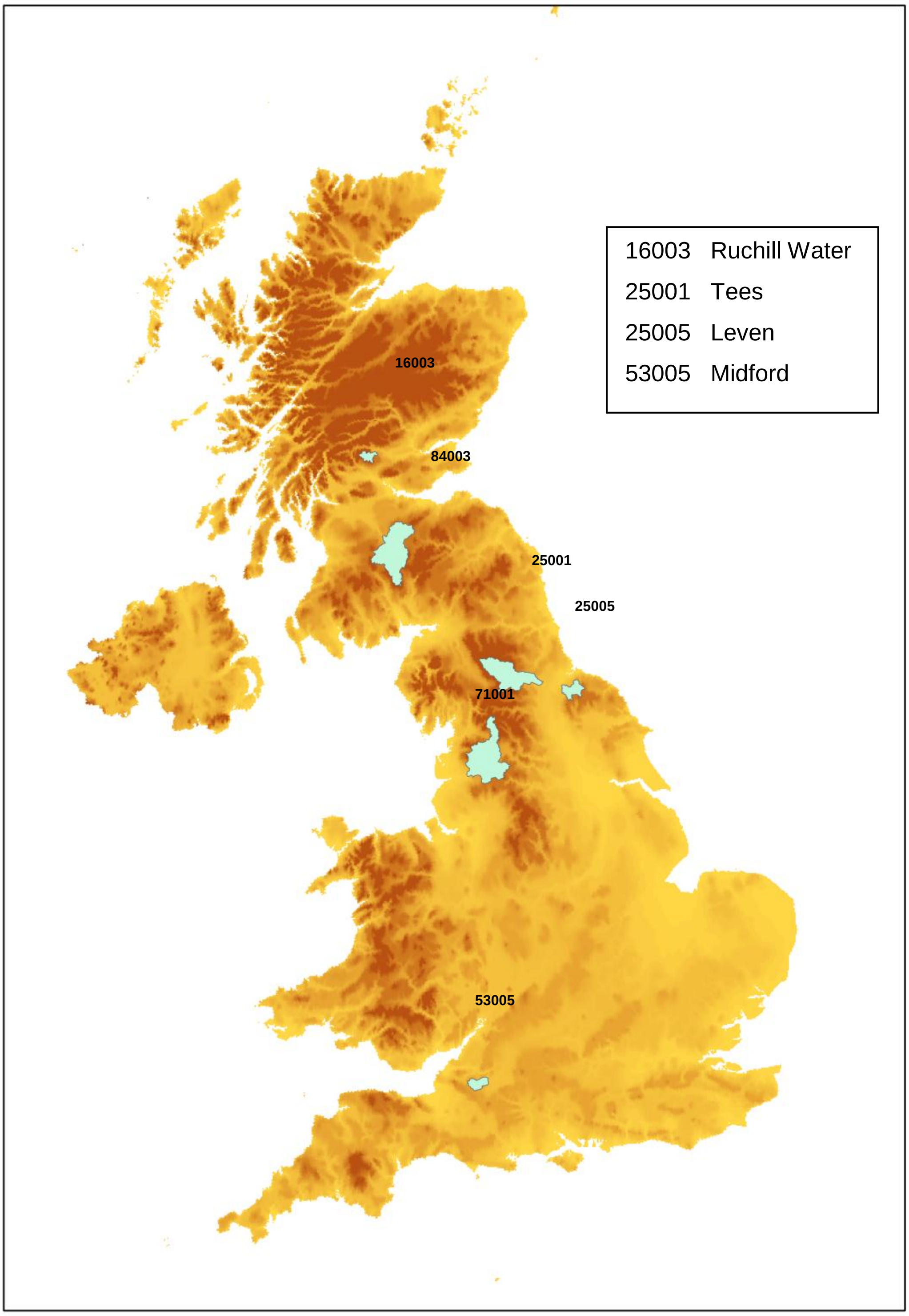
*The 18 hourly gauges used in the rainfall study and their associated mean correction factors.*

**Appendix D.1 Schematic Of Model Fitting**



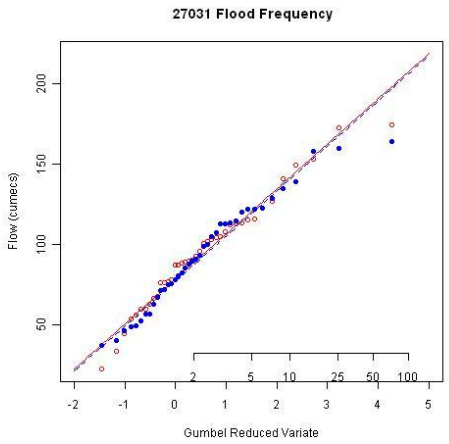

*This schematic of model fitting outlines the process used to derive the modelled flood frequency curve. The process is described in more detail in Chapter 6.*

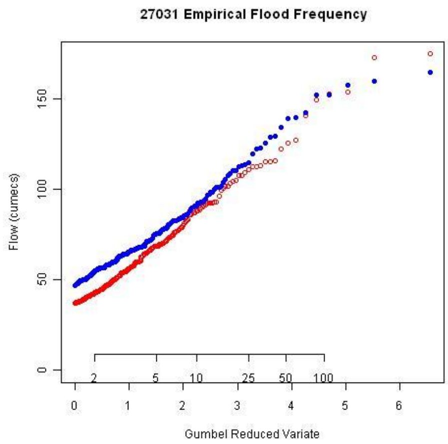
## Appendix E.1 Location of Selected Catchments Used for the Analysis in Chapter 6 and Chapter 7

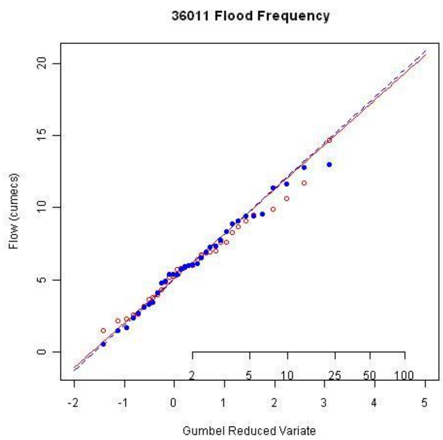


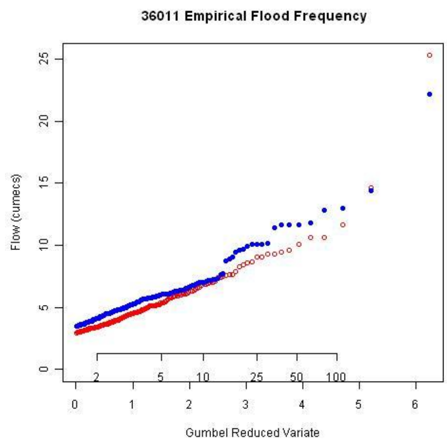

*The location of selected catchments used to illustrate the validation work in Chapter 7 and the model sensitivity work in Chapter 6.*

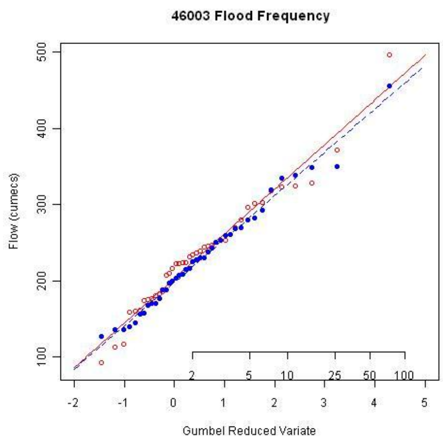
## Appendix F.1 Further Examples of Comparative plots between the model fitting work and POT assessment work carried out in Section

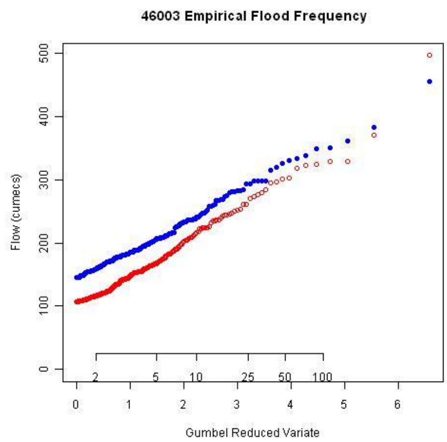


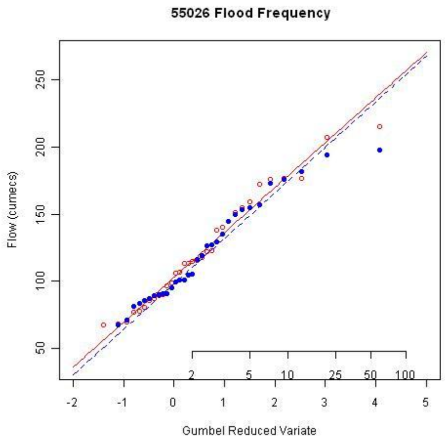



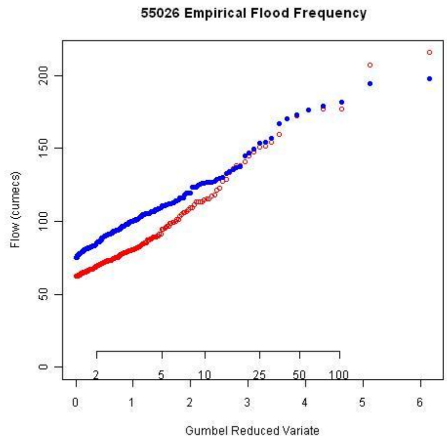



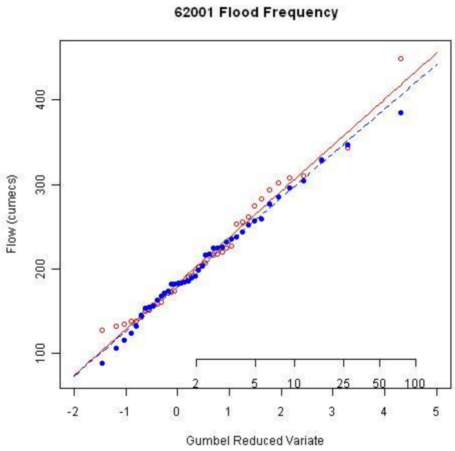



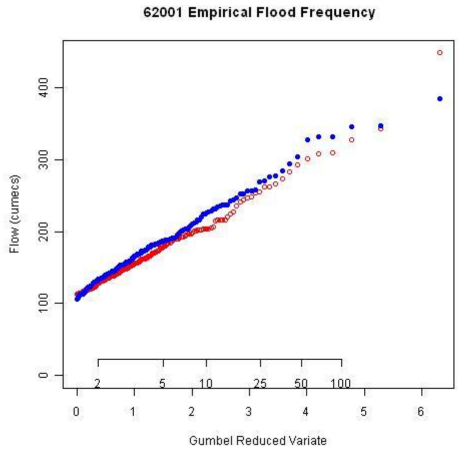



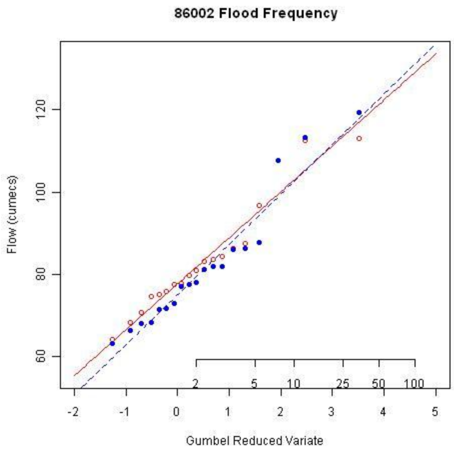



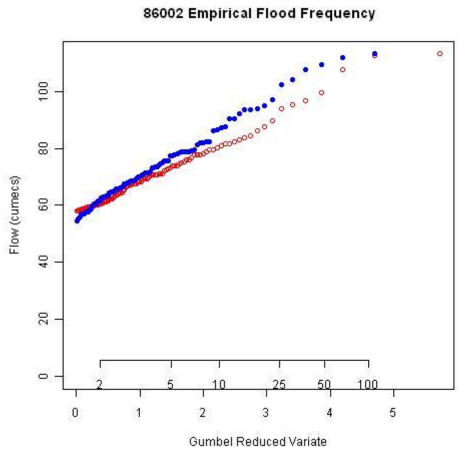

55026 Flood Frequency
Flow (cumecs)
Gumbel Reduced Variate

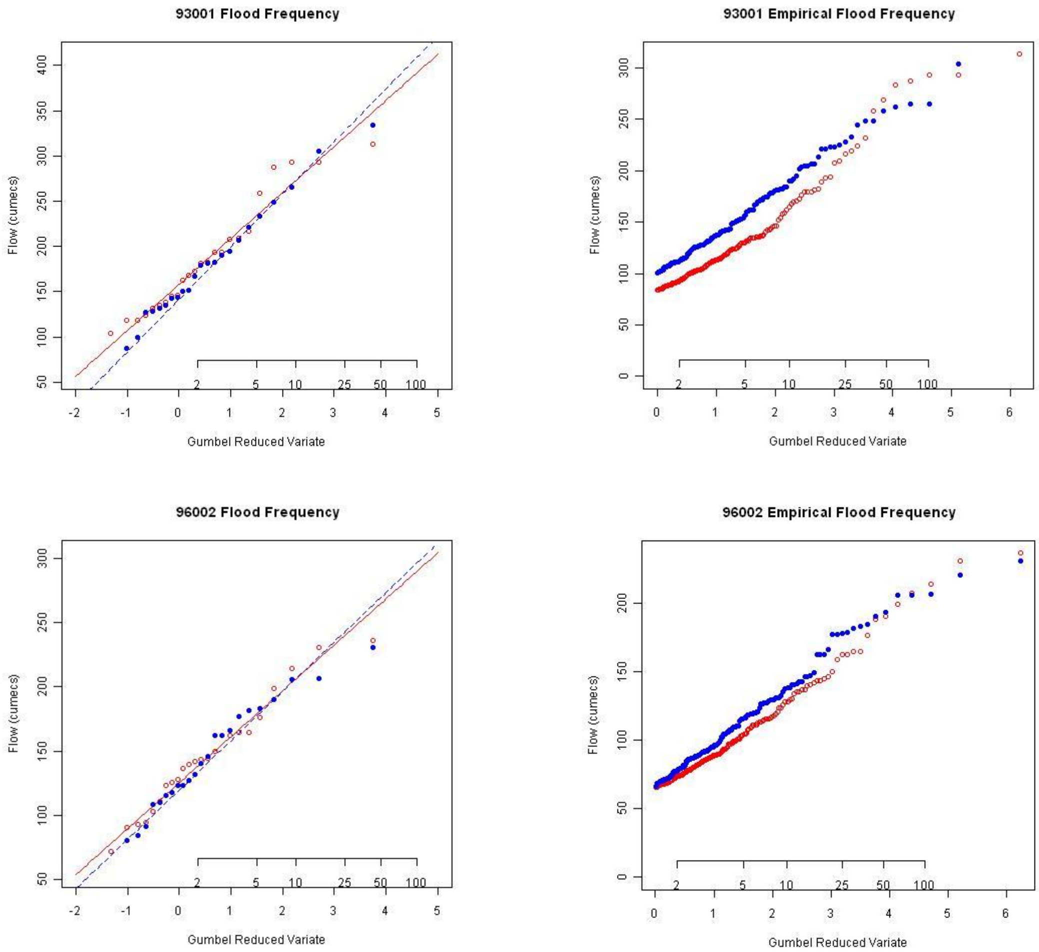

55026 Empirical Flood Frequency
Flow (cumecs)
Gumbel Reduced Variate


62001 Flood Frequency
Flow (cumecs)
Gumbel Reduced Variate


62001 Empirical Flood Frequency
Flow (cumecs)
Gumbel Reduced Variate

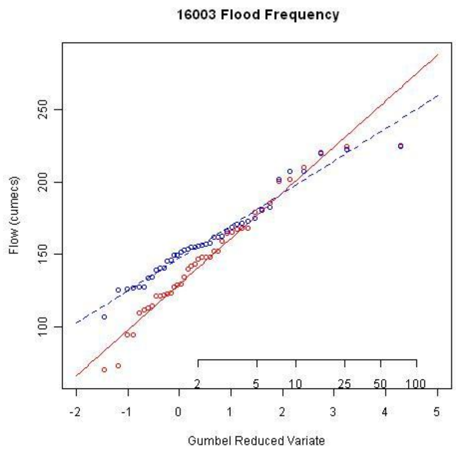

86002 Flood Frequency
Flow (cumecs)
Gumbel Reduced Variate

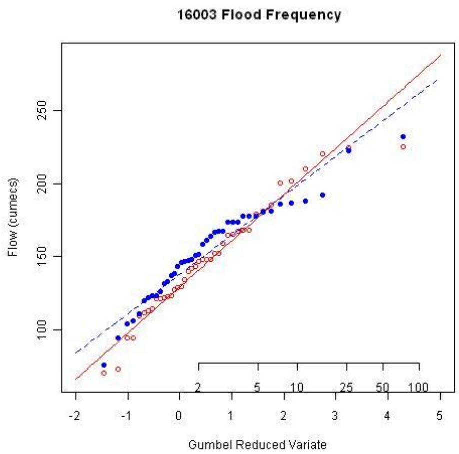

86002 Empirical Flood Frequency
Flow (cumecs)
Gumbel Reduced Variate

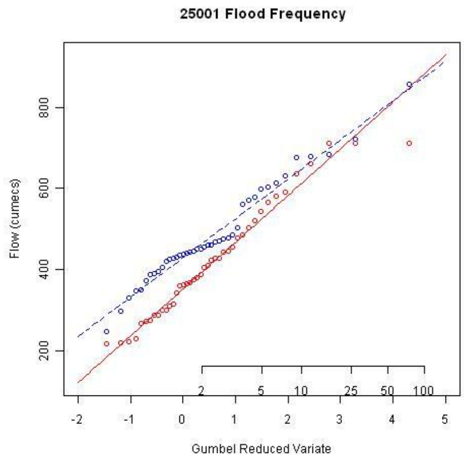


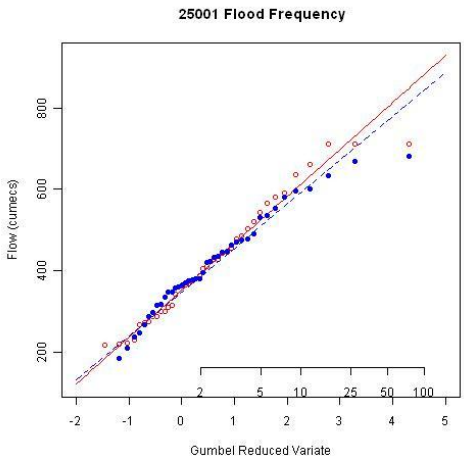

*Further examples of comparative plots between the model fitting carried out in Chapter 6 (left) and the POT testing in Chapter 7 (right). In both cases red represents the observed data, blue represents the modelled data. Distributions are not fitted to the POT data for reasons outlined in Chapter 7.*

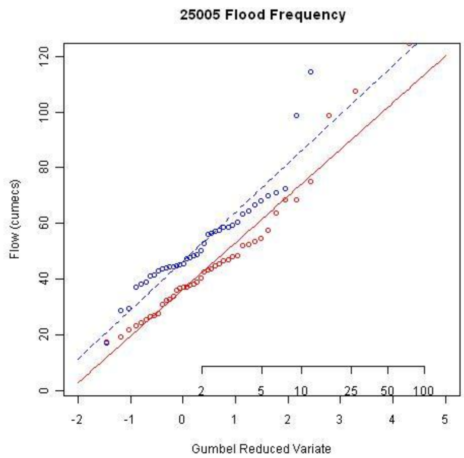
## Appendix G.1 Comparative Catchment Plots for the Donor Estimation Method

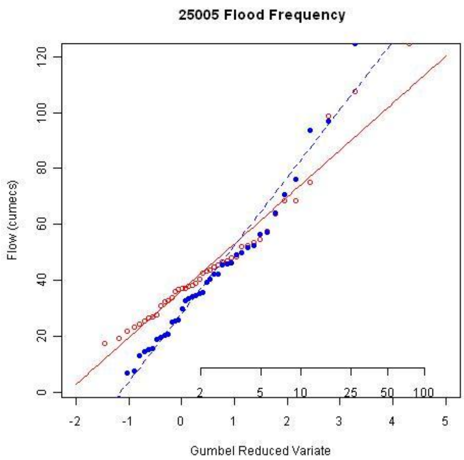


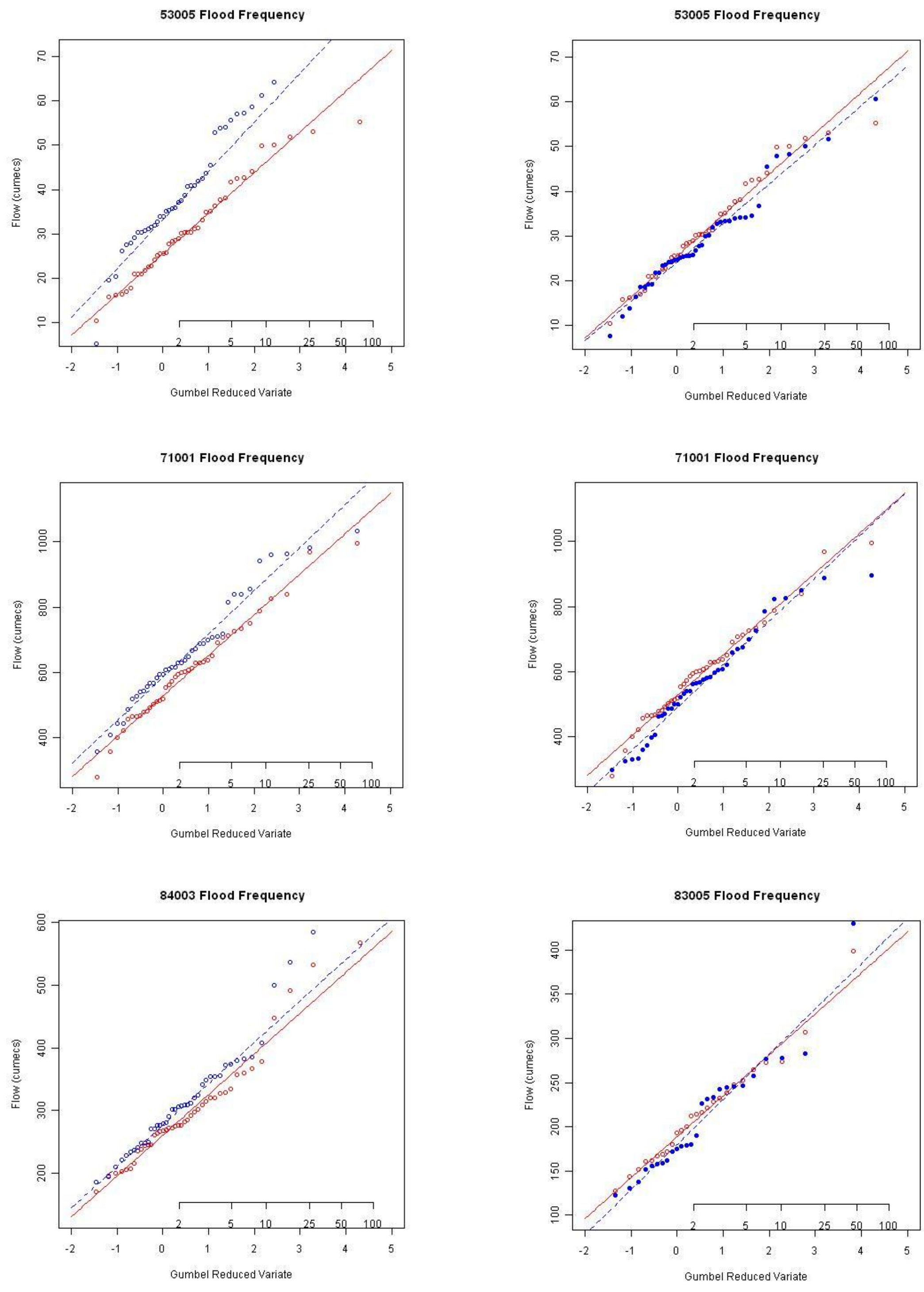






*Comparative plots between the donor estimation method (left) and the original fit from Chapter 6 (right). Red represents the observed data and fitted flood frequency curve. Blue represents the modeled data and flood frequency curve.*

**Appendix H.1 ARF Relationship Coefficients**

| **Area A ($km^2$)** | **a** | **B** |
|---|---|---|
| A≤20 | 0.40-0.0208 ln (4.6-ln(A)) | $0.0394\ A^{0.364}$ |
| 20 < A < 100 | $0.40-0.00382(4.6-\ln(A))^2$ | $0.0394\ A^{0.364}$ |
| 100 ≤ A <500 | $0.40-0.00382(4.6-\ln(A))^2$ | $0.0627\ A^{0.254}$ |
| 500 ≤ A <1000 | 0.40-0.0208 ln(ln(A)-4.6) | $0.0627\ A^{0.254}$ |
| 1000 ≤ A | 0.40-0.0208 ln(ln(A)-4.6) | $0.1050\ A^{0.180}$ |

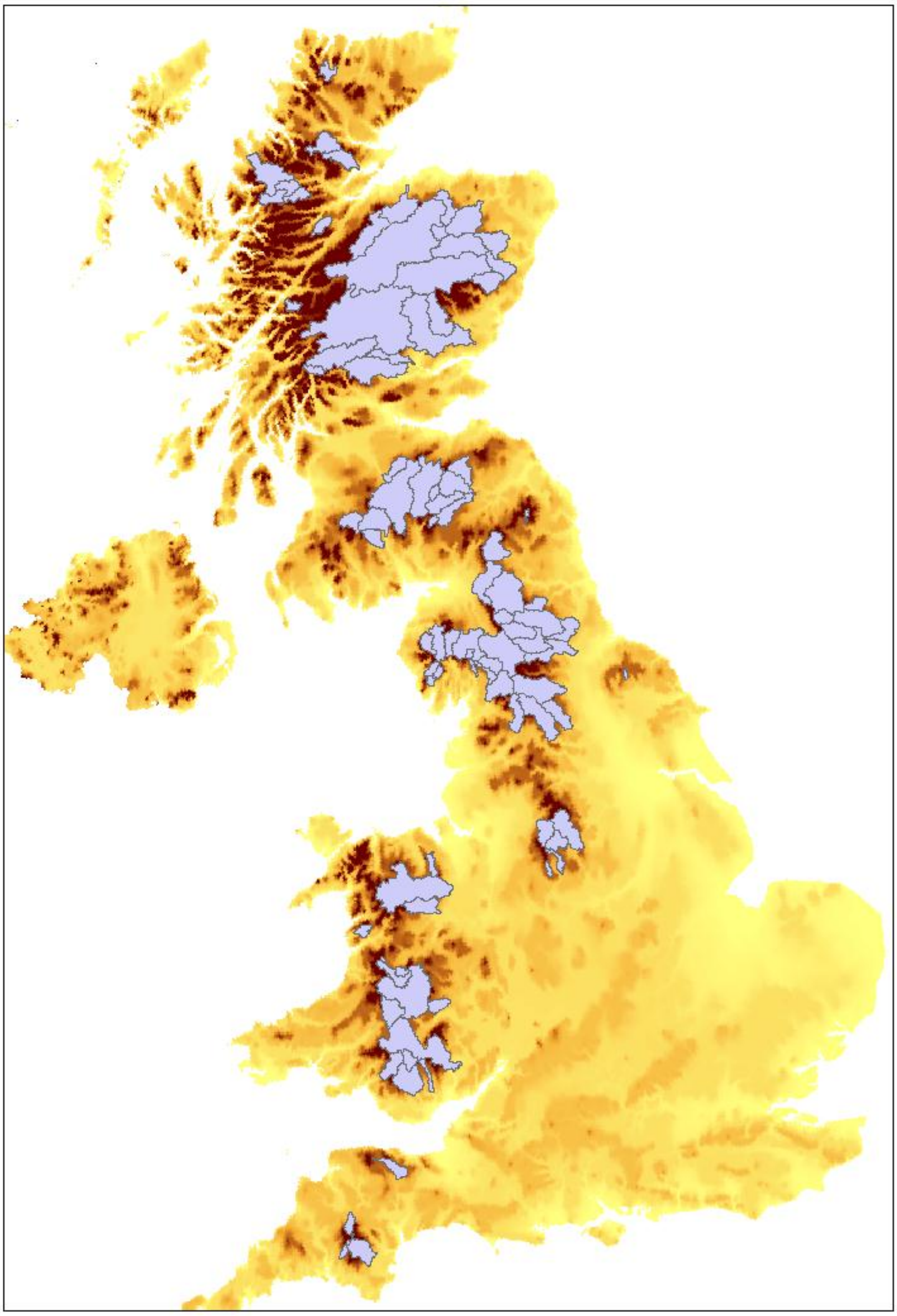
A *and B coefficient estimation for the ARF estimation. These values are taken from the FEH Volume 2, 'Rainfall Frequency Analysis'.*

**Appendix I.1 Raw Values for future changes**

| | Current | | | Future | | |
|---|---|---|---|---|---|---|
| **Station** | **10** | **50** | **90** | **10** | **50** | **90** |
| Ruchill Water | 201 | 219 | 237 | 205 | 233 | 274 |
| Tees | 561 | 614 | 656 | 572 | 631 | 725 |
| Leven | 68 | 78 | 94 | 71 | 83 | 103 |
| Midford Brook | 41 | 46 | 52 | 43 | 49 | 63 |
| Ribble | 691 | 758 | 839 | 700 | 802 | 975 |
| Clyde | 357 | 385 | 431 | 360 | 413 | 476 |

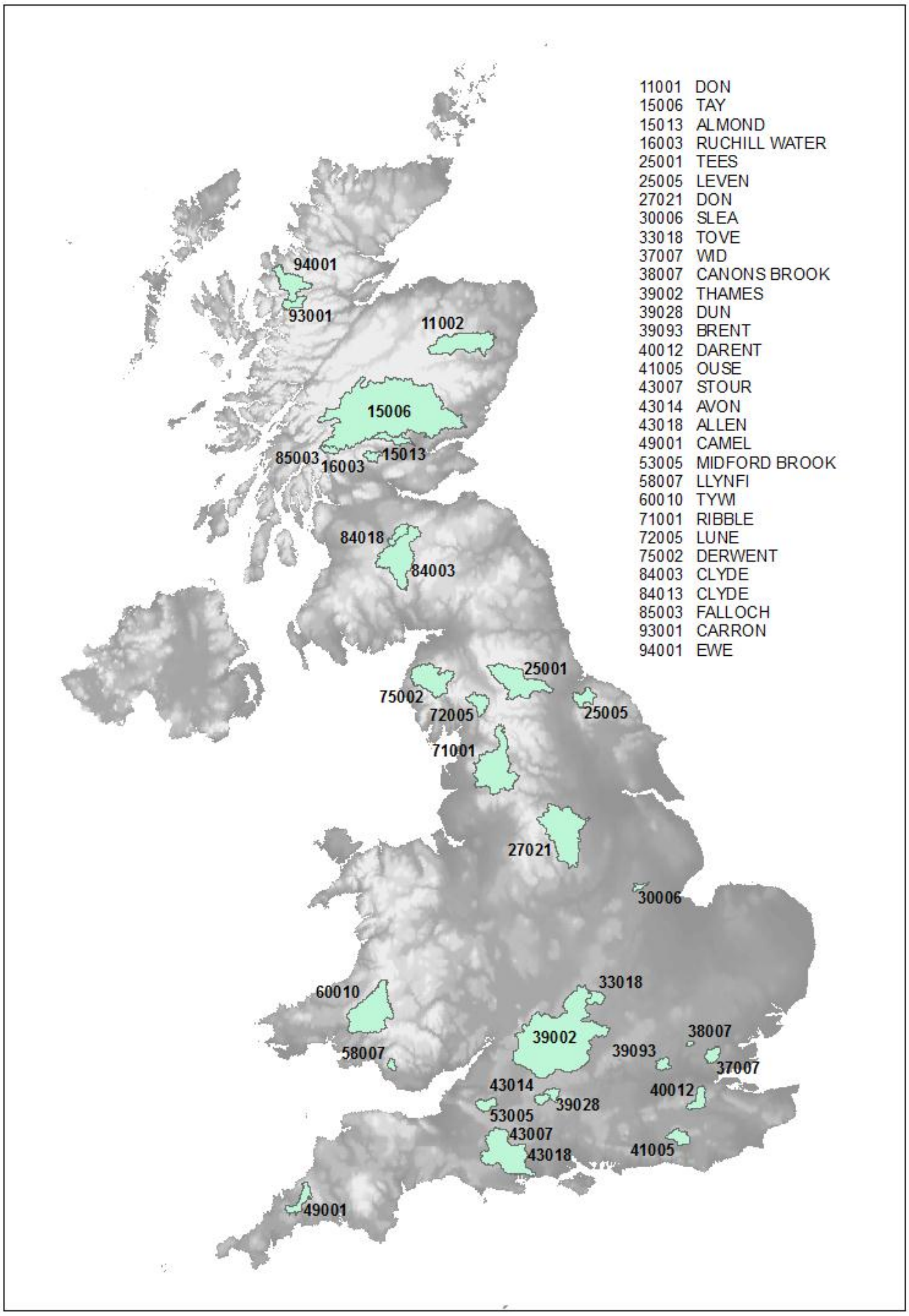
*Percentile Values for the 10 year AMAX flood as calculated from Baseline and Future Estimated Flood Frequency Curves. Percentile values are the same as for the individual plots (10$^{th}$, 50$^{th}$ and 90$^{th}$ percentiles) and have been rounded to the nearest cumec.*

**Appendix J.1 Snowmelt Flood Prone Catchments**



*Snowmelt flood prone catchments within the UK. These catchments have been selected based on their characteristics and criteria discussed in Chapter 8.*

**Appendix K.1: Catchments referred to within this Thesis**




*Selected catchments referred to within this Thesis. Catchments are referenced by their Gauge ID.*