

Setting design inflows to hydrodynamic flood models using a dependence model

Duncan Faulkner, Caroline Keef and John Martin

ABSTRACT

In setting design inflows to hydrodynamic models of flood flow along rivers, there can be a conflict between site-specific hydrological estimates of flow for a given return period and what the river model calculates as it routes flood hydrographs. This paper describes research carried out as part of the Flood Studies Update programme in Ireland, aimed at developing guidance on how to divide up river models and set the magnitude and timing of their inflows so that conditions in the model reach correspond to the expected design flood return period. A model for the joint distribution of flood peaks at pairs of catchments has been developed. The relationship between flood return periods is linked to physical differences between catchments. The model thus allows estimation of the statistical distribution of the flood return period expected at one site during a flood of specified return period elsewhere. A separate regression model predicts the relative timings of flood peaks on pairs of rivers. A summary of the resulting practitioner guidance is given, along with an overview of the testing of the method. The paper concludes with a discussion of the potential for application of the spatial dependence model to other problems in hydrology.

Key words | design event, flood modelling, spatial dependence

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INTRODUCTION

Recent advances in hydroinformatics and computational modelling capability, as well as new policies such as the European Directive (2007/60/EC) on the Assessment & Management of Flood Risk, are driving the requirement for detailed and explicit (hydraulic) flood modelling and mapping at full catchment (or river basin) scale.

This development has shifted the interaction between design flood estimation and hydraulic modelling from one of *site-specific hydrological analysis feeding the upstream boundary of a hydraulic model to complete spatial overlap of the (typically lumped) hydrological analysis and (distributed) hydraulic flow modelling*. This calls for carefully tuned consistency, at all locations, between site-specific hydrological flow estimates and hydraulic river model outputs, as the model routes flood hydrographs through the study area. A carefully thought-out approach, often iterative, is required to ensure consistency at each point where both hydrological flow estimates and modelled flow outputs are available.

A particular challenge occurs when hydraulic models are applied to long river reaches which can alter the flood hydrograph as it moves through the system, often resulting in the hydrograph shape and peak flow at the downstream end of the reach being quite different to that which would have been estimated by a hydrological assessment of the entire catchment draining to the downstream point.

In Ireland, Catchment-based Flood Risk Assessment & Management Studies are the vehicle for achieving catchment-wide flood mapping. The hydrological and hydraulic modelling requirements of such studies present many challenges, one of which is the achievement of flood mapping for a given annual exceedence probability (AEP), or return period, at all locations throughout the catchment.

Typically, design inflows to hydraulic models are set using hydrological rainfall-runoff models to generate design flow estimates for subcatchments and routing these inflows down the modelled watercourse, with additional

inflows for tributaries. A significant disadvantage of this approach is that the assumptions and limitations of design event methods often result in poorer estimates of design peak flows than those obtained from statistical analysis of flood peak data (Institute of Hydrology 1999, volume 1). Partly for this reason, the recent Flood Studies Update (FSU) research programme in Ireland (Reed & Martin 2005) has concentrated on a statistical approach to estimation of flood peaks. Shapes and durations of flood hydrographs are chosen independently of the estimation of peak flow, with characteristic hydrograph shapes being constructed from averaging of observed flood hydrographs or synthesised from physical catchment descriptors (O'Connor & Goswami 2009). This empirical method of deriving hydrograph shapes essentially replaces the Flood Studies Report rainfall–runoff model (NERC 1975; Institute of Hydrology 1999, volume 4).

Without the option of a hydrological design event method, there is therefore an increased need to develop an approach for deriving inflows for hydraulic river network models that combine to give hydrologically consistent results down through the river network. To that end, this paper describes research carried out as part of the FSU programme, the principal objective of which was to develop rules and guidelines for subdividing river models into reaches and choosing key parameters of hydrological design inputs to river modelling studies (such as peak magnitude and timing) such that conditions in the river reach correspond to the intended flood return period. A full report on the research is given in JBA Consulting (2010). This paper expands a presentation of the research by Faulkner et al. (2010).

The approach taken to meet this objective was to develop a better understanding of inter-site dependence in river flows. The problem underlying the difficulty with setting model inflows is the lack of total dependence between river flow at different sites. If all sites in a catchment always experienced the T -year return period flood during the same event, it would be more straightforward to specify inflows for river models (i.e. they could all be set to the T -year event). In reality, dependence is partial and will vary according to the location, climate and physical properties of the catchment being considered.

This paper describes how inter-site dependence models can be used to determine the dependence, and hence the respective magnitudes and timing, of inflow hydrographs

required to achieve the objective of flood mapping for a single design event of given return period at all locations throughout the catchment. The paper also considers further applications of this dependence modelling with the potential to inform other analytical and operational purposes.

CHOICE OF DEPENDENCE MODEL

To meet the objectives above, it is necessary to answer the following type of question: what flows should we enter at point B_1 or point B_2 so that the flow at A is a flood of the required return period (Figure 1)?

A straightforward way of answering this question would be to examine concurrent flows at pairs of sites, in particular those for when the flow at A is large or extreme. Data are however not always available and few data records contain floods as large as, say, the 100-year return period.

The alternative is to build a model to estimate the likely flows at B_1 or B_2 when A has an extreme flow. Many different types of model exist and these range from physically based hydrological models for catchments to statistical models based purely on data. In previous studies (Calver et al. 2005; Faulkner & Wass 2005), conceptual hydrological models for catchments have been used to answer problems such as these by using continuous simulation. In a continuous simulation study, long rainfall time series are generated from a stochastic rainfall generator and this simulated rainfall is used as an input to a rainfall–runoff model to estimate flows for the catchment. Although this method has been

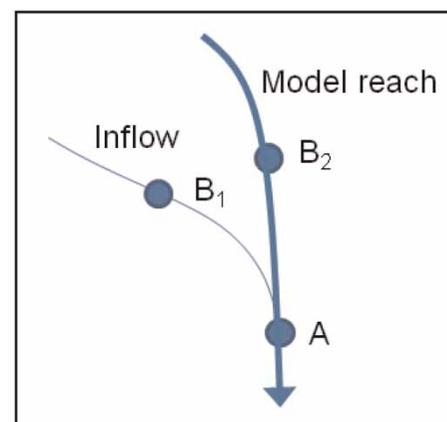


Figure 1 | Layout of sites on a river network.

used successfully in the past, there are limitations when applying it to multiple catchments: it is a time-consuming process which limits how many catchments can be included in the study; it is difficult to generalise to ungauged catchments; generation of spatially distributed rainfall is challenging; and some statistical analysis must be undertaken on the resulting simulated flows in order to answer the questions posed in this study.

In contrast, statistical models have the advantage that they are quick to fit and immediately give answers to the questions posed. When using any statistical model it is necessary to make some assumptions about the statistical behaviour of the data. It is therefore vital that the model chosen does not force the modeller to make invalid assumptions. Because the river flows requiring modelling are often larger than those that have been observed, it is necessary to use statistical dependence models that have been developed for extreme values. Many extreme-value dependence models have been developed for use with block (e.g. annual) maxima data; an example is the approach used by [Salvadori & De Michele \(2010\)](#) who modelled the joint distribution of annual maxima data from river flows in Scotland. These approaches cannot predict likely concurrent flows at tributaries, however.

A dependence study using daily data was that of [Svensson & Jones \(2002, 2004\)](#) who mapped the dependence measure χ for pairs of flood risk variables (sea surge, river flow and precipitation) around the coast of Great Britain. For the purposes of the present study, this dependence measure has two disadvantages. The first is that it is only possible to use it for pairs of variables so it would not be possible to assess likely flows at B_1 and B_2 when A has an extreme flow. The second disadvantage is that it is only suitable for a restrictive class of extremal dependence, i.e. dependence between variables as they get large. As far back as [Sibuya \(1960\)](#) and [Tiago de Oliveira \(1962/63\)](#), two types of extremal dependence were described asymptotic dependence and asymptotic independence. Two variables are asymptotically dependent if the probability of observing the very largest events on each variable at the same time is greater than zero. If two variables are not asymptotically dependent they are asymptotically independent. Asymptotic independence does not guarantee complete independence: it is possible for variables to have

asymptotic independence with positive association. This class of extremal dependence can be described by saying that, for a pair of sites, the probability of both exceeding the very largest flows (e.g. greater than the 10,000-year return period) at the same time is zero; however, large (e.g. greater than 2-year) flows occur together more often than if they were independent.

In a study of dependence of extreme river flows and precipitation in Great Britain, [Keef et al. \(2009a\)](#) found that most flows exhibited extremal dependence with positive association. The statistical model used in this study is that of [Heffernan & Tawn \(2004\)](#) which is flexible enough to handle all forms of extremal dependence, and has been extended by [Keef et al. \(2009b\)](#) to handle temporally dependent variables. The Heffernan and Tawn model uses two parameters to express the dependence between two variables, rather than the usual one parameter.

The Heffernan and Tawn model was used in this study because it can handle all forms of extremal dependence, account for the presence of simultaneous extreme and non-extreme observations and predict the likely range of flows at one site given that another site has an extreme flow of a certain value.

FITTING THE DEPENDENCE MODEL

This section gives a brief description of the method. For a fuller description see [Keef et al. \(2009a, 2009b\)](#) or [Lamb et al. \(2010\)](#). The first step in fitting the Heffernan and Tawn model is to fit a marginal distribution to the data at each station and transform the data to have Gumbel marginal distributions so that only the dependence has to be taken into account in the regression model. The transformation is carried out using the probability integral transform.

If the flows at two sites A and B after transformation to Gumbel margins are denoted by X and Y , then the Heffernan and Tawn model is given by:

$$Y = \alpha X + X^\beta Z \quad (1)$$

for X greater than a (high) threshold v . The parameter α describes the overall level of dependence between X and Y and the parameter β describes how this dependence changes

as X gets large. The residuals from this model are denoted by Z . In fitting the model the additional constraint Keef et al. (2011) was used, which helps ensure that the α and β parameters are estimated correctly.

The model was fitted to daily maximum flows from pairs of gauging stations in Ireland, drawn from a set of 166 stations with at least 10 years of high-quality digital flow data available. It was necessary to use continuous data rather than just flood peak data as used in previous dependence modelling studies such as Reed (2002), because the dependence analysis needs to account for dependence between locations or variables that are not extreme. This is because several locations may experience conditions that are not extreme, but which combine to produce more extreme conditions further downstream. Daily maxima (calculated from 15-minute data) rather than daily means were chosen to ensure that the analysis captured the peak flows during flood events on small flashy watercourses.

All data were quality controlled using visual assessment of time series to check for trends, step changes, unrealistic outliers and periods of missing data. At 20 stations flow data from earlier periods were excluded to reduce the influence of trends or changes due to arterial drainage schemes. The average record length was 31 years. The stations covered a wide range of catchment sizes from 6 to 3,100 km². Six thousand five hundred and sixty-one pairs of stations had enough overlapping record to enable calculation of their dependence.

Dependence model results were calculated for lag times of up to ± 5 days between the flows occurring at each pair of gauging stations. The maximum dependence over all lag times was taken as the result for each station pair.

APPLYING THE DEPENDENCE MODEL

From the Heffernan and Tawn model, five quantiles of the conditional distribution of the flows Y at site B were estimated, given the flow X at site A has a return period of T years. These quantiles are denoted $q_{Y|X_T}(p)$ and defined in Equation (2), where $p = 0.025, 0.25, 0.5, 0.75$ and 0.975 :

$$\Pr(Y > q_{Y|X_T}(p) | X > x_T) = p(2)$$

For example, if we wish to model the 100-year flood for a particular reach (denoted A), and this reach is joined by a tributary (denoted B), it will be possible to find values of the flow most likely to occur at B (the median, $q_{Y|X_{100}}(0.5)$) and also give an estimation of the likely range in return period at B when A experiences the 100-year flow.

To apply the model it is necessary to express these flows in terms of yearly return periods. These return periods are estimated from the daily non-exceedance probability p_d using the formula:

$$T = \frac{k}{365.25(1 - p_d)} \quad (3)$$

where p_d is the probability of exceeding the T -year flood on a particular day and k is the average number of consecutive days a flow record is extreme. This expression is only really interpretable for $T > 1$ year as it does not account for seasonality and these return periods only give a good agreement with those from annual maxima for large values of T .

Because it was necessary to apply the results from the modelling at sites other than the gauging stations included in the study, the modelling was not carried out directly with flows. Instead it was done in terms of return periods, estimating the likely return period at B given that A has a T -year return period flow. This was achieved by transforming the flows $q_{Y|X_T}(p)$ to the return period scale using Equation (3). The return period at B given that A has a T -year flow is denoted $T_{B|A_T}$; the quantiles of $T_{B|A_T}$ are denoted by $T_{B|A_T}(p)$.

The results quoted in this paper focus on estimating the likely flow at one site given that another site experiences a 100-year flood, which is often the primary return period of interest in flood studies. There is a considerable amount of uncertainty associated with estimating such extreme flows which we have not accounted for in this paper. It is however safe to assume that, although subject to a considerable amount of estimation variance, each individual estimate is unbiased.

It was decided that the dependence modelling and testing of the research should be carried out for the types of event for which the research will be used. The alternative would have been to develop the guidance for more frequent

(and therefore more certain) design events and then extrapolate these results to higher return periods; this extrapolation procedure would however have a significant amount of uncertainty associated with it.

RESULTS OF DEPENDENCE MODEL

To give a geographic overview of the results, Figure 2 shows lines connecting the pairs of gauging stations that were found to have the highest dependence. In the pairs shown, the upper quartile of the distribution of return period at the dependent site exceeds 100 years, given a 100-year event at the conditioning site. This is equivalent to saying that $T_{B|A,100}(0.75) > B_{100}$. The number of such high-dependence station pairs found was 355, 70 of which were upstream and downstream on the same watercourse. This constitutes 5% of all station pairs.

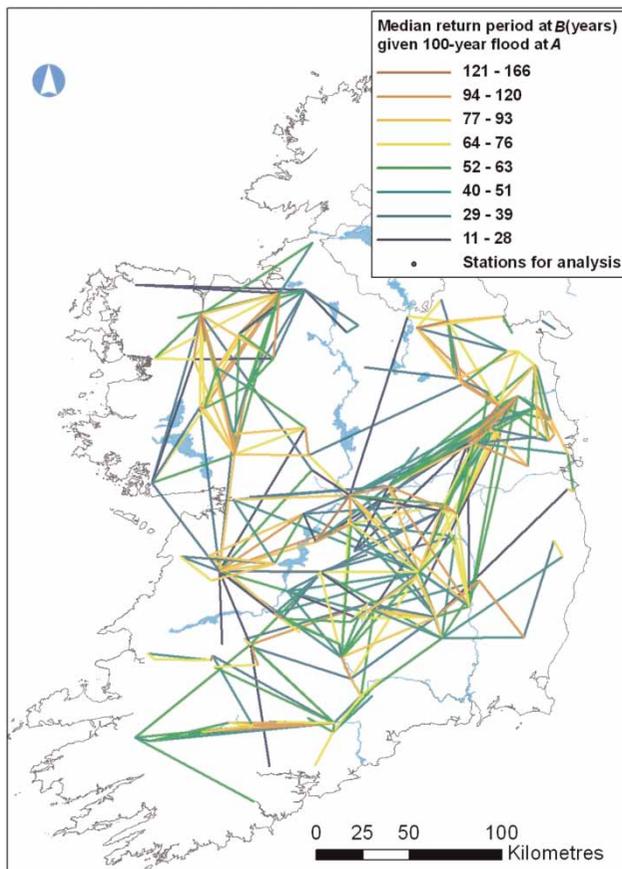


Figure 2 | Lines connecting station pairs with high dependence.

The colour (see online version, <http://www.iwaponline.com/nh/toc.htm>) or shade of lines on Figure 2 indicate the degree of dependence. Eighty-five of the high-dependence station pairs have catchment centroids separated by more than 50 km, demonstrating that sometimes stations separated by long distances can be highly dependent. The longest separation is just over 100 km for two catchments (Deel at Killyon and Ballyfinboy at Ballyhooney) that are similar in size, altitude, rainfall, permeability and soil wetness. The station pairs with the longest separations generally appear to have lower dependence (indicated by blue and green lines in colour version, see <http://www.iwaponline.com/nh/toc.htm>).

A feature of Figure 2 is that some stations appear to have a high dependence with many others. The station with the largest number of links is the Nore at McMahon's Bridge, which is highly dependent on 20 other stations. This suggests that high dependence is more likely to occur for some types of catchment, rather than merely being a function of the similarity between catchments in the pair. One complicating factor that is likely to influence the results is that the record length varies between stations. Stations with longer records will appear in more pairs because there will be more stations with which they have a long enough overlapping record. There is therefore more opportunity for long-record stations to exhibit high dependence with other stations.

Relation of dependence to catchment properties

To use the dependence model to set inflows to river models, it is desirable to generalise it so that it can apply on ungauged catchments. It was decided to investigate relationships between the degree of dependence for station pairs and absolute differences between the physical properties of catchments: pairwise catchment descriptors ΔCD , defined as $|CD_A - CD_B|$ for a pair of sites A and B . The pairwise descriptors examined were chosen in accordance with findings from previous research (Keef et al. 2009a):

- distance between catchment centroids;
- difference between soil permeability as indexed by base-flow index modelled from soil type (BFI_{soil}) using a relationship between BFI calculated from hydrometric

data at gauging stations and digital mapping of soils, subsoils and aquifer types (Fealy *et al.* 2004);

- difference in logarithm of catchment area (AREA); and
- difference in an index of flood attenuation due to reservoirs and lakes (FARL), which varies between 0 and 1 with lower values indicating more attenuation.

These catchment descriptors have been derived for locations at 500 m spacing throughout the Irish river network (Mills 2009).

The correlations (measured by Kendall's tau) between the conditional median flood probability $T_B|A_{100}(0.5)$ (i.e. strength of dependence) and each pairwise catchment descriptor were:

- distance between catchment centroids: -0.24
- difference between BFI_{soil} : -0.15
- difference in $\log(AREA)$: -0.10
- difference in FARL: -0.22

The fact that all of these values are negative indicates that, in general, increasing differences between catchment descriptors correspond with reducing dependence. The values are all closer to 0 than to -1 however, indicating that the strength of this relationship is rather weak (similar results were found by Keef *et al.* 2009b using UK data).

As an example, Figure 3 shows how dependence varies with distance between catchment centroids. The graph plots the median flood probability at a site conditional on the 100-year return period flood occurring at another site. Each point on the plot represents a pair of gauging stations. The colours of the points distinguish between upstream/downstream station pairs ('connected') and other pairs ('unconnected'). For a connected pair, flow recorded at one site will influence the flow downstream at the other site (e.g. A and B_1 or A and B_2 on Figure 1). Unconnected pairs may be on watercourses that are eventually confluent (e.g. B_1 and B_2 on Figure 1) or on watercourses that diverge and flow into the sea in different locations. Little difference in dependence was found between confluent and divergent pairs, so it was decided to analyse them as one group in order to increase the sample size.

There is a great deal of scatter on Figure 3 and on equivalent plots for other pairwise descriptors. It is possible for very close station pairs (with catchment centroids within

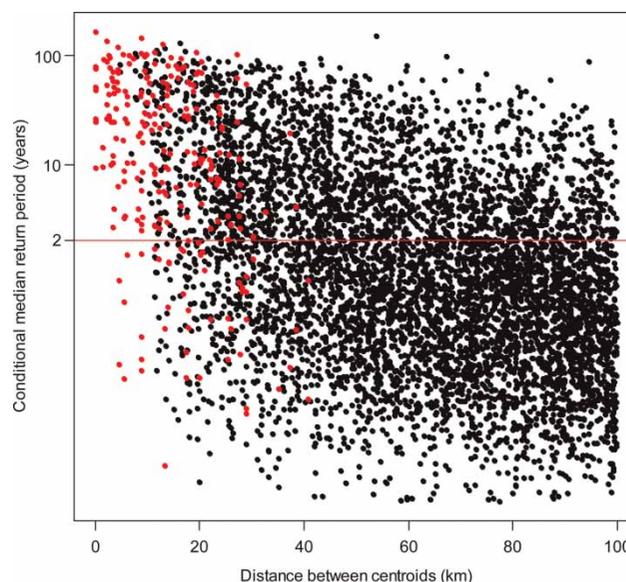


Figure 3 | Conditional median flood probability versus distance between catchment centroids; grey (red in colour version, available online at <http://www.iwaponline.com/nh/toc.htm>) points indicate 'connected' pairs, i.e. on the same watercourse.

10 km) to exhibit either high dependence or complete independence, even if the stations are on the same watercourse.

An attempt was made to develop multiple regression models to explain the relationship between dependence and pairwise catchment descriptors. As expected from the weak correlation described above, the regression models did not perform well, with R^2 values lower than 0.2. Rather than persisting with attempts to develop regression models, it was decided to develop a classification of the results using ranges of pairwise catchment descriptors.

Threshold values were selected for various pairwise catchment descriptors from examination of the scatter plots described above and other visualisations of the model results. Pairs of sites whose pairwise descriptors fall below the thresholds are likely to have higher dependence. Five characteristics were selected:

- whether the sites are connected (i.e. upstream and downstream on the same watercourse);
- distance between catchment centroids (far if greater than 25 km);
- absolute difference between BFI_{soil} (large if greater than 0.3);

- absolute difference between log AREA (large if greater than 1, which corresponds to a factor of approximately 2.7 for the ratio of AREA values); and
- absolute difference between FARL (large if greater than 0.07).

Each of the above characteristics can take two possible values. The total number of combinations is 2^5 , i.e. 32. The 6,561 pairs of gauging stations were sorted into these 32 classes, and the median dependence calculated for each class (apart from those that contained no or very few pairs). For each class, the aim was to identify the likely value of the return period at *B* given a 100-year flood at *A*, i.e. $T_{B|A_{100}}(p)$. To do this, the median of $T_{B|A_{100}}(p)$ was calculated for the pairs within each class for $P = 0.5$, i.e. the median of the expected (median) return periods for each pair. These values can be used to set input flows to river models, because the median ($P = 0.5$) can be regarded as the most likely return period at station *B*, given a 100-year return period at station *A*. The median of $T_{B|A_{100}}(p)$ was also calculated for other

values of p : 0.05, 0.25, 0.75 and 0.95. These give information on the maximum and minimum probable return periods at station *B*, and the upper and lower quartiles. Results for classes containing eight or more station pairs are shown in Table 1 for $P = 0.025, 0.5$ (the median) and 0.975.

The highest conditional median return period (i.e. the strongest dependence) is found for connected pairs of stations with similar catchment properties BFI_{soil} , AREA and FARL but a large distance between their centroids. For this class, given a 100-year return period flood at one station, a 63-year return period is the median outcome at the other station. There is no obvious physical explanation why dependence for this class of station pairs should be stronger than for connected pairs that are similar and nearby. The difference in results is probably an artefact of the small number of pairs in this class (nine). Note the range between the 5 and 95 percentile return periods: 9–279 years. This range gives an indication of the uncertainty in the results and can be used to explore the sensitivity of river models to different combinations of inflow return

Table 1 | Results from dependence model for a conditioning return period of 100 years

BFI_{soil} difference large	Centroids far apart	AREA difference large	FARL difference large	5%ile return period (years)	Median return period at dependent site (years)	95%ile return period (years)	No. of pairs in data
Connected pairs of stations (upstream/downstream)							
FALSE	TRUE	TRUE	FALSE	0.1	3.5	117	8
FALSE	TRUE	FALSE	FALSE	9.5	62.6	279	9
FALSE	FALSE	TRUE	TRUE	3.9	25.1	67.8	8
FALSE	FALSE	TRUE	FALSE	1.6	15.8	117	51
FALSE	FALSE	FALSE	TRUE	2	21.6	233	13
FALSE	FALSE	FALSE	FALSE	9.4	42.8	230	102
Non-connected pairs							
TRUE	TRUE	TRUE	TRUE	0	0.1	2	40
TRUE	TRUE	TRUE	FALSE	0	0.2	6.6	86
TRUE	TRUE	FALSE	TRUE	0	0.6	35.5	63
TRUE	TRUE	FALSE	FALSE	0	0.6	36.3	159
FALSE	TRUE	TRUE	TRUE	0.1	0.8	16.1	258
FALSE	TRUE	TRUE	FALSE	0.1	1.3	51.3	981
FALSE	TRUE	FALSE	TRUE	0.2	2	74.2	681
FALSE	TRUE	FALSE	FALSE	0.2	2.6	108	2,255
FALSE	FALSE	TRUE	FALSE	0.6	7.7	133	78
FALSE	FALSE	FALSE	TRUE	0.8	11.9	156	36
FALSE	FALSE	FALSE	FALSE	2.4	19.8	203	245

periods. In general, a wider range of uncertainty (on a factorial scale) is seen for the classes of catchment pairs that are more dissimilar, indicating the potential for a few dissimilar catchments to show moderate dependence.

Moderately strong dependence (median return period of 15–25 years) is found for most other classes of connected station pairs. The exception is for widely separated catchments with a large difference in AREA. These show weak dependence (a median return period of 3 years), although again this result is from a small sample of just eight pairs.

Most classes of non-connected pairs show weak or negligible dependence, the exception being stations that are nearby with similar BFI_{soil} and AREA. Some pairs of gauging stations on confluent streams will fall into this category.

All classes with a large difference in soil permeability, as measured by BFI_{soil} differing by more than 0.3, show almost no dependence. However, large differences in BFI_{soil} only tend to occur (in the dataset of gauged catchments) for catchments that are far apart and so it is not safe to conclude that the lack of dependence is due entirely to the difference in soils.

The analysis was also carried out for conditioning return periods of 2, 5, 10, 20, 50, 75, 200, 500 and 1,000 years. The results are summarised in Figure 4 which plots the median

(i.e. most likely) return period at station *B* conditional on a *T*-year flood occurring at station *A*, for connected pairs of gauging stations. Higher lines indicate classes with stronger dependence.

With a few minor exceptions (indicated by crossing lines), the patterns described above for a conditioning return period of 100 years hold true for other return periods. Most lines on the graph deviate further from the 1:1 line (which marks complete dependence) at higher return periods. From this, we can conclude that dependence may reduce in more extreme events.

Timing of inflows to river models

The dependence model provides information on the relative return period, and hence magnitude, of floods at different locations. In order to define inflows for river models it is also necessary to define hydrograph shapes with a realistic relative timing of tributary hydrographs. The investigation of hydrograph shapes for the FSU research programme by O'Connor & Goswami (2009) did not include any consideration of relative timings of hydrographs at different locations. The timing of subcatchment responses is particularly important on larger catchments (Pattison *et al.* 2008).

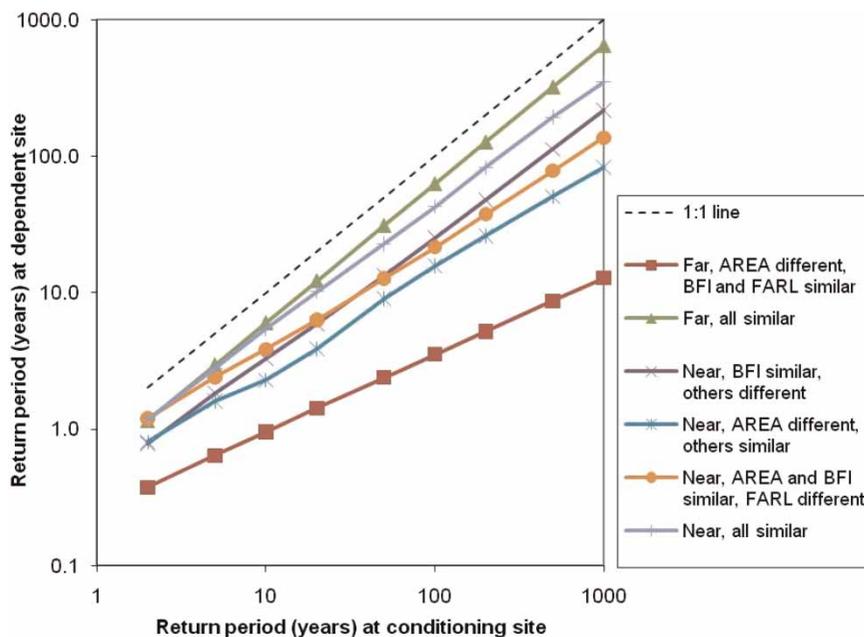


Figure 4 | Relationship between return periods at pairs of connected sites.

Realistic timing is often ensured by applying a design rainfall event to a set of rainfall–runoff models representing each subcatchment but, as explained above, the design rainfall event method has generally been avoided within Ireland’s FSU approach to flood estimation.

A regression model was developed for prediction of the median time between flood peaks for a pair of catchments from pairwise catchment descriptors. It would be expected that nearby catchments with similar properties would tend to peak at around the same time. When the regression model is applied, typically we will know the time at which the peak occurs on the model reach upstream of the confluence (B_2 on Figure 1) and will want to know the time at which the peak of the inflow from a tributary should be set (B_1). In other words, the regression model is needed for confluent site pairs rather than upstream/downstream site pairs. For reasons discussed above, the model was developed using data from all pairs of gauging stations that do not lie upstream and downstream of each other.

For each gauging station record, times of the peaks of high flow events were extracted. Events were defined as peaks over a threshold separated by 5 days where the flow was below this threshold. The threshold chosen was the 99th percentile flow on the daily scale. Peaks at two gauging stations were defined as belonging to the same event if they occurred within 48 hours of each other. Setting this time window involved striking a balance between the risk of excluding some events on pairs of very different catchments and that of including some peaks that did not arise from the same event.

The median, upper quartile, lower quartile and mean time difference were calculated for 6,561 pairs of gauging stations. To develop the regression model, only pairs with at least 10 events were included (to give a reliable estimate of the median), yielding 1,763 pairs.

A multiple linear regression model was developed using a large number of candidate pairwise catchment descriptors ΔCD (defined as $CD_{B_2} - CD_{B_1}$) to predict the median difference in time of peak ΔT (defined as $T_{B_2} - T_{B_1}$ in hours). Note that, unlike in the dependence model, absolute differences are not used because it is necessary to predict the sign of the time difference.

A preferred regression model was selected on the basis of R^2 , Akaike Information Criterion and physical

interpretation:

$$\begin{aligned} \Delta T = & 32.1 \Delta BFI_{\text{soil}} - 103 \Delta \text{FARL} \\ & + 1.62 \Delta \sqrt{(\text{AREA})} - 1.94 \Delta \text{TAYSLO} - 46.4 \Delta \text{ARTDRAIN} \\ & - 0.0272 \Delta \text{NETLEN} \end{aligned} \quad (4)$$

where BFI_{soil} , FARL and AREA are defined as above; TAYSLO is Taylor–Schwartz slope (dimensionless) (Taylor & Schwartz 1952); ARTDRAIN is the proportion of the catchment area affected by arterial drainage schemes; and NETLEN is the length in kilometres of the river and lake network draining the contributing catchment.

Although the square root of AREA is highly correlated with NETLEN, it was found that R^2 increased from 0.36 to 0.49 when $\sqrt{(\text{AREA})}$ was added to the regression. It appears that AREA is able to explain aspects of flood peak timing that NETLEN cannot. Note the negative coefficient on ΔNETLEN . The interpretation of the model is that larger catchments, as measured by $\sqrt{(\text{AREA})}$, will peak later; NETLEN is then used as an adjustment factor to account for the interaction between the two terms that measure the scale of the catchment.

The coefficients on the other pairwise descriptors indicate that site B_2 will peak before site B_1 (Figure 1) if the catchment of B_2 is less permeable, less influenced by standing waterbodies, steeper or more affected by arterial drainage. These are all physically realistic.

The R^2 of the final model is 0.49 and the standard error is 11.9 hours. The performance of the model is illustrated in Figure 5. There is considerable scatter in the results, and the standard error is larger than is desirable.

DEVELOPMENT OF GUIDANCE FOR RIVER MODELLING

The results of the dependence model were used to develop guidance on dividing hydrodynamic river models into reaches and choosing design inflows to such models such that the flow in the model reach corresponds to the required return period. This guidance was developed on the basis of practical experience of river modelling. An important consideration was to ensure that the guidance was easy to implement, given that it was to form part of a

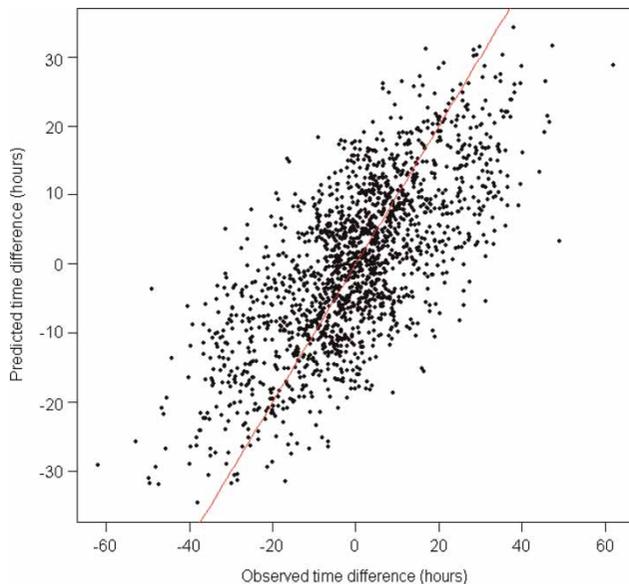


Figure 5 | Performance of regression model for difference in timing of flood peaks on pairs of catchments.

set of methods to be applied by practising hydrologists and engineers. It was developed in an evolutionary way, starting with initial ideas and then testing them using first idealised and then real river catchments. At the end of this process, the following four factors were thought to be the most important.

- The extent of the river model (for example, whether it includes just one watercourse or extends up its tributaries as well).
- The presence of gauging stations (providing good-quality flood peak data) close to points of interest within the model. This is often the largest influence on the choice of approach in flood estimation, and also affects the way in which inputs to river models are set because of the way that flood peak data implicitly account for catchment processes which may otherwise have to be modelled. It is suggested that any longer-term historical flood information should be taken into account in a similar way to gauged data.
- The degree of dependence between the flows at the upstream and downstream ends of the model, and between any tributary inflows and the main river.
- The importance of backwater effects, for example on tidal reaches or pumped watercourses, where flow is affected

by downstream hydraulic influences as well as upstream hydrological inputs.

There is not enough space here to present the full guidance, which can be found in [JBA Consulting \(2010\)](#). One of the main questions it addresses is what return period should be applied at a tributary inflow in order to represent the design T -year flood event on the main river. This can be answered by selecting the appropriate class of catchment pair from [Table 1](#) and using Equation (4) to set the timing of the inflow. However, if there is a gauging station downstream of the confluence, then the best estimate of design flow can usually be obtained by direct estimation using flood peak data from that station. In that case, it will often be more appropriate to adjust the magnitude or timing of the inflow from the tributary by trial and error until the flow in the model matches the preferred downstream estimate.

Example applications

The guidance was tested in four river modelling case studies on the River Suir (long and rural with significant tributaries), River Owenboy (short and rural), River Tolka (urban) and River Dodder (affected by reservoirs and urban areas). Routing models were developed for each river and inflows were set according to the guidance. Flows at key points within the model reaches were then compared with design flows estimated using flood estimation methods applied to the lumped catchment draining to the point, adjusted using local flood peak data. Details of the flood estimation methods used both for model inflows and for lumped catchments are given in [JBA Consulting \(2010\)](#). An example of the comparison of results is shown in [Figure 6](#).

Close agreement between modelled flows and lumped hydrological estimates can be seen at most locations shown in [Figure 6](#). Where there is a discrepancy between the two flows (for example at New Bridge, which is a gauging station), it is mainly due to spatial inconsistency in the design flows which show an unexpected drop between the upstream location and New Bridge, much larger than the slight attenuation that can be inferred from the change in the modelled peak flows. A common theme that emerged from the case studies is that the FSU methods

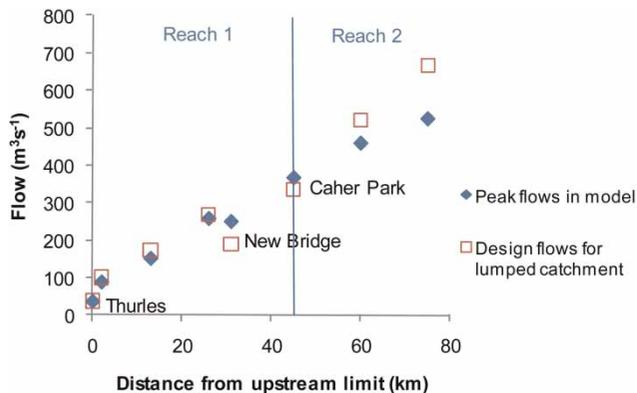


Figure 6 | Results of the River Suir case study for the 100-year return period flood.

of flood estimation, all designed for application at individual locations, do not necessarily give spatially consistent results when applied at multiple sites. This could be seen both in the magnitudes of peak flows and the durations of flood hydrographs. Both of these can lead to difficulties in river modelling, which imposes a structure on the hydrological response of the catchment which is not necessarily present in a set of design flows derived for individual locations using statistical methods.

Despite these difficulties, the case studies showed that when model inflows are set using the guidance, the resulting modelled flows generally give an acceptable agreement with lumped hydrological estimates at points within the model reaches. At the downstream end of all five reaches in the various models, the modelled flows were within 21% of the hydrological estimates.

CONCLUSIONS

The approach of setting inflows to river models based on consideration of spatial dependence is a step away from conventional river modelling methods based on a design rainfall event towards more integrated approaches such as continuous rainfall-runoff simulation modelling or direct application of the full spatial statistical approach underlying the guidance. Both would require significantly more modelling to resolve joint probabilities by simulating many different combinations of design flows. Instead, the approach developed within the research described above is to use information on spatial dependence to guide choices

for the peak flow and timing of design flood hydrographs when only one or a small number of simulations can be performed (typical in many river modelling studies). This is inevitably a compromise since it does not explore the full range of scenarios that could contribute to the design condition in a catchment model, but the guidance helps to base choice of design simulations on a consistent analysis of dependence between rivers.

One factor that makes it difficult to determine useful guidance is that there appears to be only a small amount of correlation between the difference in catchment descriptors and the level of dependence between extreme flows at different points on the river network. This lack of dependence was also found by Keef *et al.* (2009a) who analysed UK river flow gauges using a lower threshold to define extremes. To overcome this difficulty, the results presented in this paper are based on classifying pairs of sites and providing ranges of possible answers. These ranges provide the user with a sensible choice of the possible return period expected at one location given that another location experiences the T -year flood.

As well as the applications discussed above, the dependence model could be used to understand the range of possible or likely spatial patterns of flooding that could be expected during real events. Widespread flood events can show a large variation in return period even within the same catchment, as shown by Faulkner *et al.* (2008). The results in Table 1 (and equivalents for other conditioning return periods) allow the distribution of expected return period at an ungauged site to be predicted, given the occurrence of a given return period at a gauged site.

Another application of the model is to assess the return period of flood events affecting entire catchments, regions or all of Ireland. This type of analysis has been carried out in the UK, as discussed by Keef *et al.* (2010) and Lamb *et al.* (2010) who show how it is possible to use this model to answer questions about how many sites are likely to experience flooding at the same time.

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