Attribution of flood risk in urban areas

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Abstract

Flooding in urban areas represents a particular challenge to modellers and flood risk managers because of the complex interactions of surface and sewer flows. Quantified flood risk estimates provide a common metric that can be used to compare risks from different sources. In situations where there are several organisations responsible for flood risk management we wish to be able to disaggregate the total risk and attribute it to different components in the system and/or agents with responsibility for risk reduction in order to target management actions. Two approaches to risk attribution are discussed:

1. *standards-based attribution*, which is a deterministic approach, based upon the performance of different engineering components in the system at their "design standard".
2. *sensitivity-based attribution*, which apportions risk between the variables that influence the total flood risk.

Whilst both these approaches are feasible for the small system considered here, in practice urban flooding systems involve tens of thousands of variables. The only feasible approach to tackling this problem for large urban systems is therefore by hierarchical simplification of the system, with the attribution analysis being applied in several tiers of detail. In this paper, the applicability of a hierarchical approach is demonstrated in the context of sewer pipe blockages. The results demonstrate the potential of attribution methods to support the development of integrated urban flood risk management strategies, as they can identify the forcing variables and infrastructure components that have the most influence upon flood risk.

1 Introduction

Assessment of the risk of river and coastal flooding is now becoming routine at a range of scales from national assessment through to reaches or coastal sub-cells and site-specific design (Hall *et al.*, 2003, Dawson *et al.*, 2005, Dawson and Hall, 2006). However, quantitative flood risk assessment in the urban area represents a genuine challenge as urban flooding occurs due to a complex interaction of natural and engineered processes, some of which operate at very local scales (Figure 1).

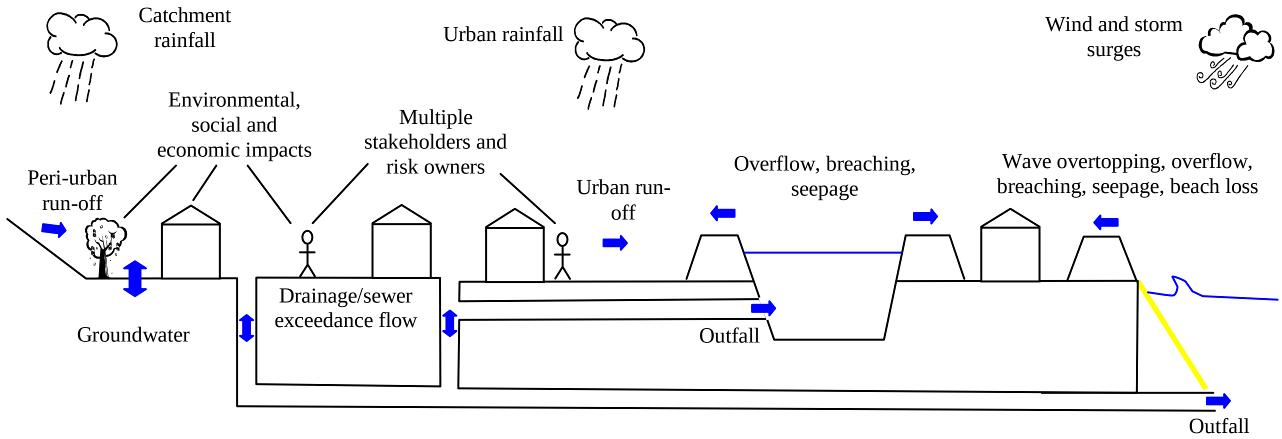


Figure 1 Key features of an integrated urban drainage system

Integrated Urban Flood Risk Management (IUFRM) explicitly recognises the interrelationships between all sources of flooding and the effectiveness and cost of flood risk management measures, within changing social, economic and environmental contexts. The main sources of flooding include intense pluvial runoff that leads to sewers surcharging and surface flows, fluvial flooding caused by high river flows, coastal storm surges and perhaps also groundwater floods. Fluvial and coastal inundation may be caused or exacerbated by the failure of flood defence infrastructure. A given flood event could be caused by a single source, or several sources acting in combination. Currently in the UK and other countries, urban flood management is fragmented, with key stakeholders being a combination of national and local government agencies and private companies, which may not have entirely congruent aims.

Urban flooding can receive less attention than other floods due to the smaller scale of individual events. However, in England and Wales alone there are 16,000 properties are at risk of sewer flooding from a 1 in 10 year event (Ofwat, 2002) and on average 5000-7000 properties (equating to <0.1% total number in England and Wales) are reported to be flooded each year by sewers, although this number may be under-reported (NAO, 2004). Of the 11,000 properties flooded in

Autumn 2000 in the UK, 83% were outside coastal and fluvial floodplains, suggesting that flooding was caused by local pluvial events, sewer flooding or groundwater. 14% (~1,400 homes) of these were flooded with sewage (Environment Agency, 2001), with disproportionately harmful effects. An individual property is much more likely to experience repeated pluvial inundation than fluvial or coastal inundation (House of Lords, 2003) and indeed the design standard of urban drainage systems is usually much lower than fluvial or coastal protection (typically 3-4% compared to 0.5-1% annual probabilities) (CIRIA, 2004). Mitigating urban flood risk can cost as much as ten times more than fluvial flooding (Green and Wilson, 2004), and the ABI (2004) estimate the cost per property of urban flood risk mitigation as being ~£5k-£8k. However, the expected annual damages from urban flooding are estimated at £0.27bn (which compares to £0.6-2.1bn for fluvial and coastal flooding (Hall *et al*., 2005a) and Evans *et al*. (2004) estimate this could be as much as £2-15bn by 2080 (compared to £1.5-20bn for fluvial and coastal flooding).

Severe flooding in urban areas in the UK in autumn 2000 acted as a stimulus to the development of more integrated approaches to urban flood risk management. Ownership and responsibility for urban infrastructure continues to be in the hands of a variety of public and private actors, but Defra, the government department with lead responsibility for flooding, is promoting a more integrated approach to urban flood risk management (DEFRA *et al*., 2005) in which the various organisations with a role in urban flooding work together to understand the processes of flooding and develop integrated solutions that tackle flooding in an efficient way. Integrated solutions may involve a number of measures, for example infrastructure investments and spatial planning regulations, which are designed together to achieve the desired level of risk reduction. Although the organisational context differs in many countries, the challenge of addressing integrated urban flood risk analysis has been identified in the USA (Rangarajan, 2005) and elsewhere (Andjelkovic, 2001).

There is potential to support these institutional initiatives with a new generation of flood modelling tools that can simulate the effects of sewer and surface flows (Mark and Djordjevic, 2006). Flood simulations can act as a vehicle for collective learning about system performance by various stakeholders in FRM. However, for this to be achieved a transformation of the standard approach to urban drainage modelling is necessary. In the past modelling systems were designed and used with the prime objective of sewer design to a certain standard and little consideration of the hydrodynamics of situations that exceeded that standard. A risk-based approach, by contrast, involves consideration of a wide range of loading conditions, including conditions that exceed the design standard and lead to extensive surface flooding (Hall et al. 2003). A precondition for this transformation is the development of core concepts for a framework for unified systems-based flood risk analysis:

1) *Risk is a 'common currency'*, which can be used to compare risks from different sources on a common basis.
2) *Risk is a multi-dimensional measure* and needs to include all losses (and gains) including social, environmental and economic. These may be accounted implicitly, for example through economic valuation, or explicitly, through multi-attribute measures.
3) *Spatial and temporal profiles* of this multi-attribute measure of risk need to be constructed to support broad scale and long term planning.
4) *Attribution of risk.* In a situation where there are several organisations responsible for risk management we wish to be able to disaggregate the total risk and attribute it to different components in the system and/or agents with responsibility for risk reduction.

This paper expands upon these principles by, in the following section, setting out the theoretical framework for risk calculation and then in Section 3 presenting alternative approaches to risk attribution. A synthetic example of urban flooding is established in Section 4 and standards-based and variance-based attribution methods are applied in Section 5. An example is also provided of analysis of sensitivity to pipe blockage. The paper concludes in Section 6.

2 Formulation of the risk problem

Consider a system that is described by a vector of loading variables S and a vector of variables that describe the flood management infrastructure system R. We write all of the basic variables as $X = (S, R)$. The resistance variables R might include the height or other dimensions of dikes, the dimensions of surface water courses or the dimensions of the sewer system. Their variation might be continuous (*e.g.* a height variable) or discrete (*e.g.* a 'blocked' or 'not blocked' descriptor of a pipe). We use capital notation (e.g. X) to denote a random variable and lower case (e.g. x) to denote a fixed value of that variable.

The variability in the loading and resistance is described by a joint probability distribution $\rho(x) : x \geq 0$. We may often be able to assume that many of the variables in R are statistically independent and we will often assume that S and R are independent. There is a damage function $e(x)$, where the units of e are £(British pounds) or some suitable currency, which gives the flood damage in the systems for a given vector x that complete describes the system state. For many states of the system $e(x) = 0$. Indeed we only expect $e(x) > 0$ when S is large or when there are some inadequacies in system design or some failure, for example due to deterioration or blockage. The risk r associated with the system is:

$$r = \int_0^\infty \rho(x)e(x)dx \tag{1}$$

The temporal dimension of this risk estimate is implicit in $\rho(x)$, so when, for example, $\rho(x)$ measures annual probability then r is an expected annual damage (EAD).

One version of this problem is a system of fluvial flood defences alongside a river with discharge probability distribution $\rho(q)$ and a series system of dikes with n dike sections, each of which may be in a 'breached' or 'not breached' state, so there are 2^n dike system states, $c_j : j = 1, ..., 2^n$. Given a flow q and a dike state c_j there is a damage function $e(q, c_j)$, *i.e.* in this case we calculate damage on the basis of two variables, the discharge Q and the indicator of dike state. Obviously damage will be least when c_j indicates that all of the dike sections are in the 'not breached' state and in this case will be zero unless q is sufficiently large for the water level to exceed the crest level of one or more of the dike sections. The total flood risk, in terms of EAD, is therefore given by:

$$r = \int_0^\infty \sum_{j=1}^{2^n} P(c_j|q)\rho(q)e(q, c_j)dq \tag{2}$$

where by definition

$\sum_{j=1}^{2^n} P(c_j|q) = 1$ and $\int_0^\infty \rho(q)dq = 1$.

The risk integral can be further extended to address antecedent conditions either by including antecedent variables in the loading vector S, or, alternatively, by extending the analysis so that S is a function of time. At any point t in time the damage is $e(x_t)$ and the risk is the instantaneous expected value this function. A further attraction of the approach is that it can deal with other variations in the system state variables with time, for example due to deterioration in the condition in the variables describing the system state or changes in the loading due to climate change or other environmental changes.

3 Risk attribution

We have introduced risk attribution as the process of calculating the relative contribution towards risk from different flooding sources and components of flooding pathways, including infrastructure components. Risk attribution provides essential information for a number of IUFRM purposes:

1) *Risk ownership*. There are several organisations with a role in flood risk management. We wish to know, in broad terms, what proportion of the risk each is responsible for.

2) *Estimation of capacity to reduce risk*. Ideally, risk should be owned by organisations with the greatest capacity to manage it. Capacity to reduce flood risk is related to the potential to change the characteristics of the flooding system, e.g. by replacing drainage infrastructure or modifying surface flow paths. We wish to identify those organisations with the capacity to reduce risk.
3) *Asset management*. Given limited resources, an organisation with responsibility for management of flood defence or drainage infrastructure should rationally invest those resources so that they maximise impact in terms of risk reduction. Within a specified set of system components we therefore with to identify those components that contribute most to risk, and to compare potential measures to reduce risk with the cost of implementing those measures in order to develop an optimum intervention strategy. A secondary problem is to target monitoring strategies so that resources are invested in data acquisition that makes the greatest contribution to reducing uncertainty.

It is possible to devise a number of alternative approaches to risk attribution:

1. *Standards-based attribution* quantifies the performance of different engineering components in the system at their "design standard".
2. *Sensitivity-based attribution* apportions risk between the system variables that influence the total flood risk on the basis of estimates of actual or potential variation.
3. *Source attribution* uses hydrodynamic particle tracking methods to understand the sources of water that result in flood damage.

3.1 Standards based attribution

Consider an organisation with responsibility for urban drainage (hereafter a UDO), providing a specified level of service to discharge rainfall events up to return period T_s. If the system floods in any rainfall event with return period $T_s' \leq T_s$, then the flood damage is the responsibility of the UDO as they have not fulfilled the standard to which they are committed. If the system floods only in events for which $T > T_s$ then the damage is not the responsibility of the UDO. However, if the system has capacity $T_s' \leq T_s$, and an event with return period $T > T_s$ occurs, then a proportion of the damages is the responsibility of the UDO. A flood model can be used to estimate the damage $e(l_T)$ given rainfall l_T with return period T. By definition $e(l_T) = 0$ when $T \leq T_s'$. Therefore the expected damage attributable to the UDO, r_{UDO}, given a probability density $\rho(l)$ of rainfall is:

$$r_{UDO} = \int_0^{l_{T_s}} \rho(l)e(l)dl + e(l_{T_s}) \int_{l_{T_s}}^{\infty} \rho(l)dl \tag{3}$$

This may be extended further to consider the situation in which due to blockage or some other sewer failure the damage is not $e(l_T)$ but $e(l_T, F_j)$ where F_j indicates some failure event in the sewer system attributable to the UDO. The damage not attributable to the UDO in events for which $T > T_s$ is still $e(l_T, \bar{F}) - e(l_{T_s}, \bar{F})$, where $\bar{F}$ denotes non-failure. Therefore the damage that is attributable to the UDO is now $e(l_T, F_j) - e(l_T, \bar{F}) + e(l_{T_s}, \bar{F}) : T > T_s$. For $T \leq T_s$ the damage that is attributable is simply $e(l_T, F_j)$. The expected attributed damage calculation now requires a probability distribution over the n various possible blockage states $F_j : j = 1, \ldots, n$ and the non-failed state $\bar{F}$, which we now write as F_{n+1}

$$
\begin{aligned}
r_{UDO} = & \int_0^{l_{T_s}} \sum_{j=1}^{n+1} \rho(l) e(l, F_j) P(F_j) dl \\
& + \int_{l_{T_s}}^{\infty} \sum_{j=1}^{n} \rho(l) \left[e(l, F_j) - e(l, F_{n+1}) \right] dl \\
& + e(l_{t_s}, F_{n+1}) \int_{l_{T_s}}^{\infty} \rho(l) dl
\end{aligned}
\tag{4}
$$

However, n may be very large and estimation of $P(F_j) : j = 1, \ldots, n$ can be difficult to estimate for sewer systems and so application of Equation 4 is likely to be limited.

3.2 Sensitivity-based attribution

An intuitive measure of influence or sensitivity is the extent to which variation in a factor of interest (or a set of factors) has on a system performance, in our case flood risk r. This is the classical sensitivity analysis problem to which there are a number of more or less well known solutions (Saltelli et al. 2000). Sensitivity-based attribution particularly helps to identify those variables in the system that might be most influential in risk reduction. It can also, incidentally, help to identify uncertain variables that should be the target for data collection in order efficiently to improve the accuracy of flood risk estimates.

If each of the loading variables, S, (e.g. fluvial flows, rainfall, surge tides) were the unequivocally responsibility of a particular agent, then sensitivity analysis would provide a useful basis for definition of risk ownership. Risk ownership could be disaggregated on the basis of sensitivity to the relevant loading variable. However, rainfall, for example, is dealt with in sewer and highway drainage systems as well as urban water courses. In that case it is necessary to also consider the variables R that define system performance.

Sensitivity-based attribution, in the form described here, relies upon knowledge of a (continuous or discrete) probability function over the variables to which risk is to be attributed. For some variables, such as rainfall as we have already seen, existence of such function is a natural requirement for flood risk analysis. Similarly, the notion of a discrete probability distribution over infrastructure system states has already been introduced. However, there are other variables that may for practical purposes known precisely (to within some tolerance) e.g. pipe diameter, but we nonetheless wish to understand the potential for risk reduction by changing the value of such a variable, and under these circumstances we have to specify a range of potential variation and corresponding probability distribution.

Here we briefly consider the sensitivity techniques applied later in the case study. A full review of these and other sensitivity measures in hydraulic engineering is provided by Hall *et al*. (in review). In all cases we consider a model numerical model, f, with k inputs, $X_1, \ldots, X_k$, which we shall refer to as 'input factors', and a scalar output $D : D = f(X_1, \ldots, X_k)$. As previously, we use capital notation (e.g. D) to denote a random variable and lower case (e.g. d) to denote a fixed value of that variable.

3.2.1 Linear regression

For a linear model, the linear regression coefficients between input and output provide natural sensitivity indices such that the model can be approximated by the form:

$$d = b_0 + \sum_{i=1}^{k} b_i x_i \tag{5}$$

where b_0 is a constant and b_i are fixed regression coefficients. The linear regression coefficients will usually have dimensions but can be standardized so that:

$$\tilde{D} = \beta_0 + \sum_{i=1}^{k} \beta_i \tilde{X}_i \tag{6}$$

where $\tilde{D} = \frac{D-\mu_D}{\sigma_D}$, $\tilde{X}_i = \frac{X_i-\mu_i}{\sigma_i}$ and $\beta_i = \frac{\sigma_D}{\sigma_i} b_i$. $\tilde{D}$and $\tilde{X}_i$are the standardized variables, μ_D, σ_D and μ_i, σ_i are the means and standard deviations of the output and input factors respectively and β_i are known as standardized regression coefficients (SRCs) (Saltelli *et al*., 2005). Even if the model is mildly non-linear, SRCs are still a reflection of the contribution of the variance of each input factor to the overall output variance and offer a measure of the effect of each given factor on D, which is averaged over a sample of possible values, as they are not calculated at a fixed point.

The sum of the squares of the SRCs represents the proportion of the model output variance explained by the regression model and gives insight into model linearity and is expressed as the model coefficient of determination, R_D^2:

$$R_D^2 = \sum_{i=1}^{m} \frac{d_i^* - \mu_D}{d_i - \mu_D} \tag{7}$$

where m is the number of model simulations, d_i are the simulation outputs for model realisation i and d_i^* are the values of d provided by the regression model for input vector x_i. R_D^2 is a positive number in [0,1] which indicates which fraction of the original model variance is explained by the regression model. When R_D^2 is high, *e.g.* 0.7 or higher, then the SRCs are suitable for use as a sensitivity measure, albeit at the price of remaining ignorant about that fraction of the model variance not explained by the SRCs. Standardised rank regression coefficients (SRRCs) can also be calculated using a rank transformation method so the regression analysis is based on the strength of monotonic relationship between the variables using the normal regression procedures (Helton and Davis, 2000).

3.2.2 Variance-based attribution methods

Equation (1) shows that risk is a probability weighted integral of damage. If X is a vector random variable then $e(X)$ is also a random variable $D = e(X)$ with some variance, whilst the mean value is the risk. A natural sensitivity measure is the amount by which the variance in D would be reduced if one or more of X_i were fixed at some value. This is the basis for variance-based sensitivity analysis (VBSA) (Saltelli et al. 2000).

The variance V can be decomposed into contributions from each of the input factors acting on their own or in increasingly high order interactions: (Sobol, 1993, Saltelli et al., 1999):

$$V = \sum_i V_i + \sum_{\substack{i,j \\ i<j}} V_{ij} + \sum_{\substack{i,j,l \\ i<j<l}} V_{ijl} + \ldots + V_{12\ldots k} \tag{8}$$

where

$$V_i = V[E(D|X_i = x_i^*)] \tag{9}$$

$$V_{ij} = V[E(D|X_i = x_i^*, X_j = x_j^*)] - V_i - V_j \tag{10}$$

and so on. $V[E(D|X_i = x_i^*)]$ is referred to as the Variance of the Conditional Expectation (VCE) and is the variance over all values of x_i^* in the expectation of D given that X_i has a fixed valuex_i^* and measures the amount by which $E(D|X_i = x_i^*)$ varies with the value of x_i^*, while all the effects of the X_j's, $j \neq i$, are averaged. The ratio $S_i = \frac{V_i}{V}$ is therefore a measure of the sensitivity of D with respect to X_i. It is worth noting that for linear models $\beta_i^2 = S_i$.

Also of interest is the influence of factor X_i when acting in combination with other factors. There are $2^k - 1$ of such interactions, so it is usually impractical to estimate the effect of all of them. A more practical approach is to estimate the k total sensitivity indices, S_{T_i}, where (Homma and Saltelli 1996):

$$S_{T_i} = 1 - \frac{V[E(D|X_{\sim i} = x^*_{\sim i})]}{V(D)} \tag{11}$$

where $X_{\sim i}$ denotes all of the factors other than X_i. The total sensitivity index therefore represents the average variance that would remain as long as X_i stays unknown. The total sensitivity indices provide an indicator of interactions within the model. For example, factors with small first order indices but high total sensitivity indices affect the model output D mainly through interactions – the presence of such factors is indicative of redundancy in the model parameterisation.

3.3 Source attribution

In situations of flooding from multiple sources, urban flood risk managers may be interested in the sources of water that led to a particular flood event. For example if flooding was caused by a combination of sewer surcharging and overland flow, then flood risk managers will wish to know the proportions of water, at a particular site, that originated from these two sources. Hydrodynamic modelling potentially provides solutions to the problem of source attribution, though these solutions are discussed only in outline here. Particle tracking methods (Fischer et al., 1979) enable the water that ends in a particular location to be tracked back to its sources. The proportions of water in that location can then be allocated to those sources. A less sophisticated approach may be achievable where the flows paths are well understood and not strongly interacting. For example where flooding in a particular low-lying area is due to a combination of overland flow and discharge from known sewer man-holes then the fluxes of overland flow into the low-lying area and discharges from the manholes can be extracted from a numerical model and used in an attribution calculation without recourse to particle tracking methods. An approach of this type was applied in Glasgow (UK) after urban flooding in 2002 (CIRIA, 2004), in which a hydraulic model was used to calculate the total flood volumes conveyed in the sewers, overland and in the urban water courses. However, the analysis was conducted for only one event, whereas, in keeping with the principles outlined in the previous sections, a calculation of this type should be repeated over a range of events, so that the attribution measure is calculated as an expected value over a range of loading events.

4 Risk analysis for an urban drainage system

4.1 The flood risk calculation

A synthetic integrated urban drainage system that has been parameterised such that it represents a realistic, albeit small system has been established to demonstrate the risk analysis methodologies introduced above. An overview of the various processes in the flood damage simulation for an urban area situated near a fluvial watercourse is shown in Figure 2. Consistent meteorological boundary conditions drive a hydrological model of an upstream catchment and provide direct rainfall inputs to the urban catchment. The upstream hydrology model provides boundary conditions of river flow next to the urban area which input to a coupled surface and sewer flow model of the urban area. Flood depths are subsequently extracted from the model and integrated with depth-damage curves to estimate damages for a given flood event, and subsequently risks. Multiple samples of the model variables are generated and used to attribute risk to infrastructure and other system components. It is important to note that the risk attribution methodology is not tied to the specific model components used in this study and will be suited to any system of models and methodologies that calculates flood damage according to any metric(s) of interest.

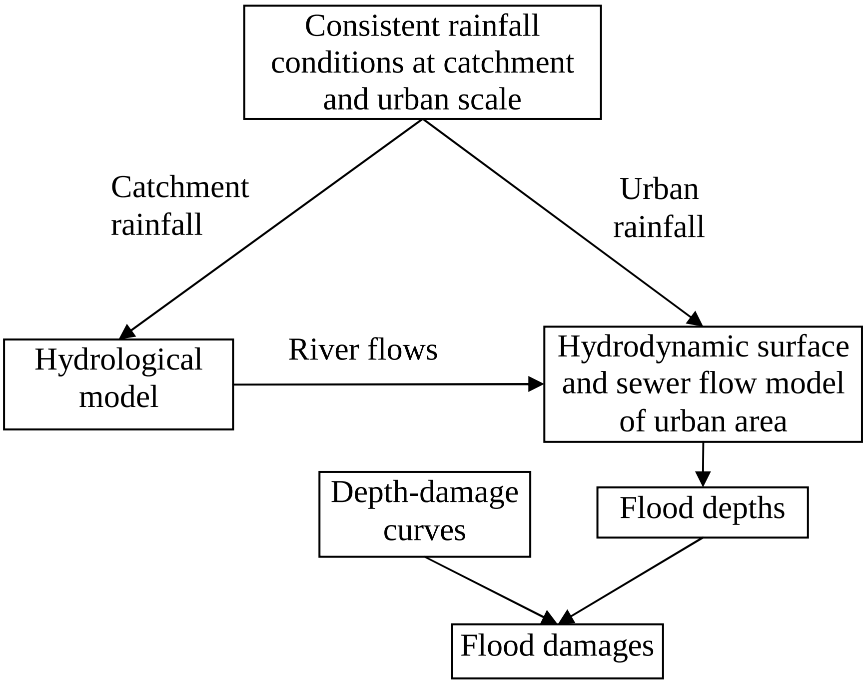


Figure 2 Overview of urban flood risk analysis modeling process

Statistical properties of rainfall data from a site in the UK were extracted using methods described by Burton *et al*. (2004) to identify design storm total rainfall and intensities for different return periods. The 50% summer storm profile, as recommended by the Wallingford Procedure in the design of urban drainage systems (Butler and Davis, 2004), was been used.

The semi-distributed Arno model of Todini (1996) was used to simulate the hydrology of the upstream catchment and generate realistic response times and flow rates in the river for given rainfall events. The output of the model is a time-varying hydrograph at the upstream end of the urban drainage system (node 26 in Figure 3). The upstream catchment was sufficiently small, $50km^2$, that spatial variability in rainfall need not be considered, and its runoff characteristics were selected (within the ranges of realistic values recommended by Todini (1996)) so that, under many rainfall conditions, there was interaction between the fluvial and pluvial components of the flood. For example, for the 100 year return rainfall event the time to peak river flow in the river for the 0.25, 6 and 24 hour duration events is 80, 300 and 800 minutes respectively.

The urban drainage model was implemented in SIPSON (described fully in Djordevic *et al.*, 2005), a coupled 1D model of surface and sewer flow. Key properties of the urban drainage system are summarised in Table 1 and Figure 3 shows its layout. The topography and pipe gradients are such that the water drains to the southeast corner of the urban area. Figure 4 and 5 demonstrate the interaction between the sub-surface and surface components – in particular the localised urban flooding in the West side of the urban area is evident at the lower return period event, but the river level dominates water levels in the catchment for more extreme events. The Northwest corner escapes flooding during the more extreme events. The cross-sections in Figure 5 illustrate the effect of rainfall falling on the road network and in the first instance draining into the sewers at low points in the road whilst in due course the water level in the river rises and inhibits drainage of the pluvial runoff into the river.

Table 1 Urban drainage system properties

Property	Value
Urban catchment area	1.5km^2
Length of streets	3.3km
Length of sewer pipes	4.6km
Number of houses	328
House spacing	20m
Proportion impervious	60%
Proportion of area roofed	10%
Runoff characteristics	1 year event: 0% runoff
	10 year event: 20% runoff
Pipe diameters	400-1000mm
River width	2.5m

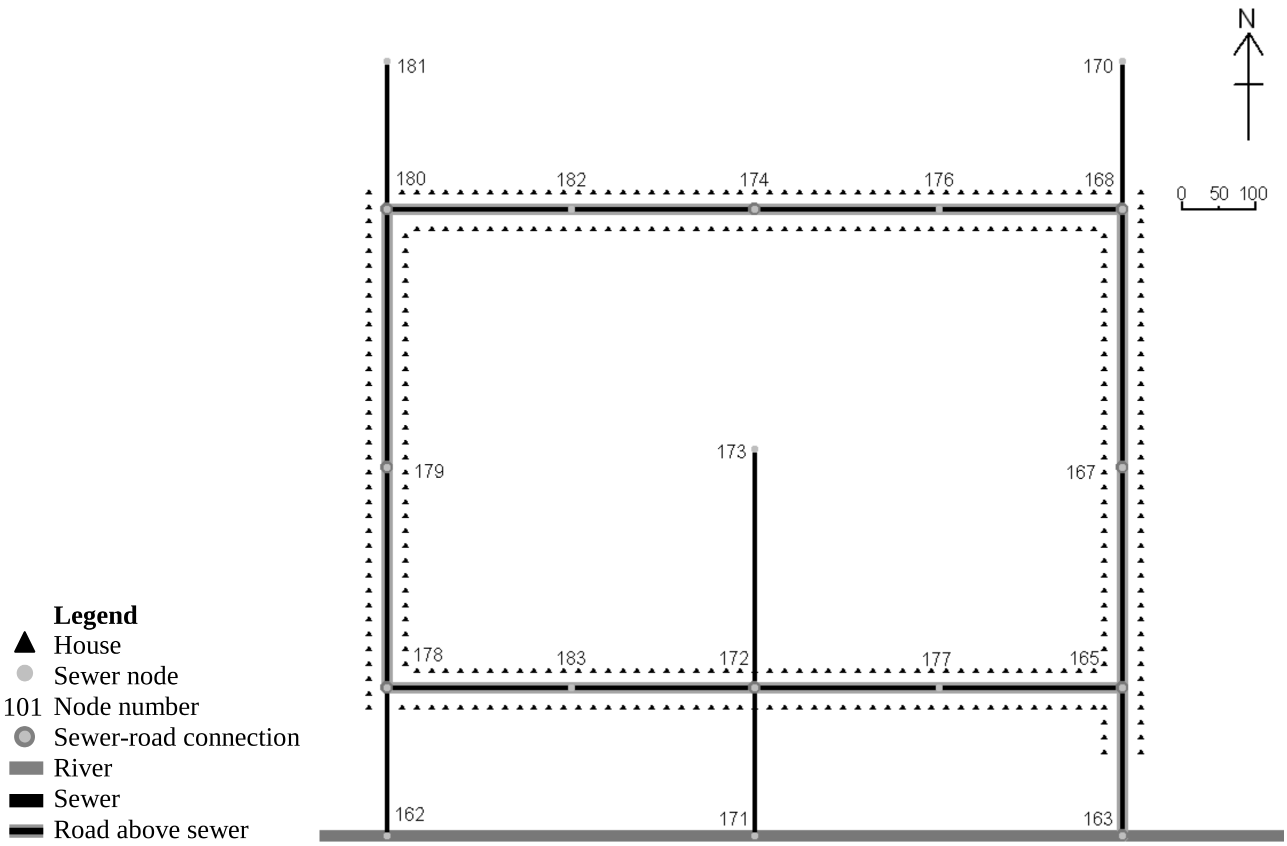
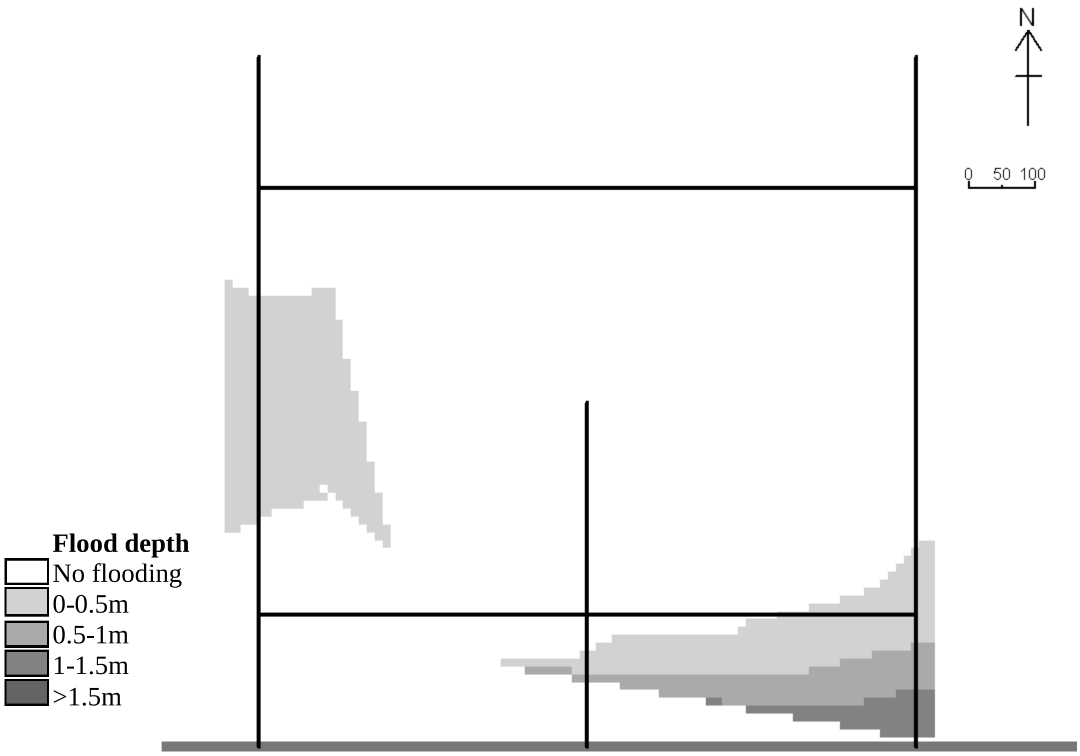
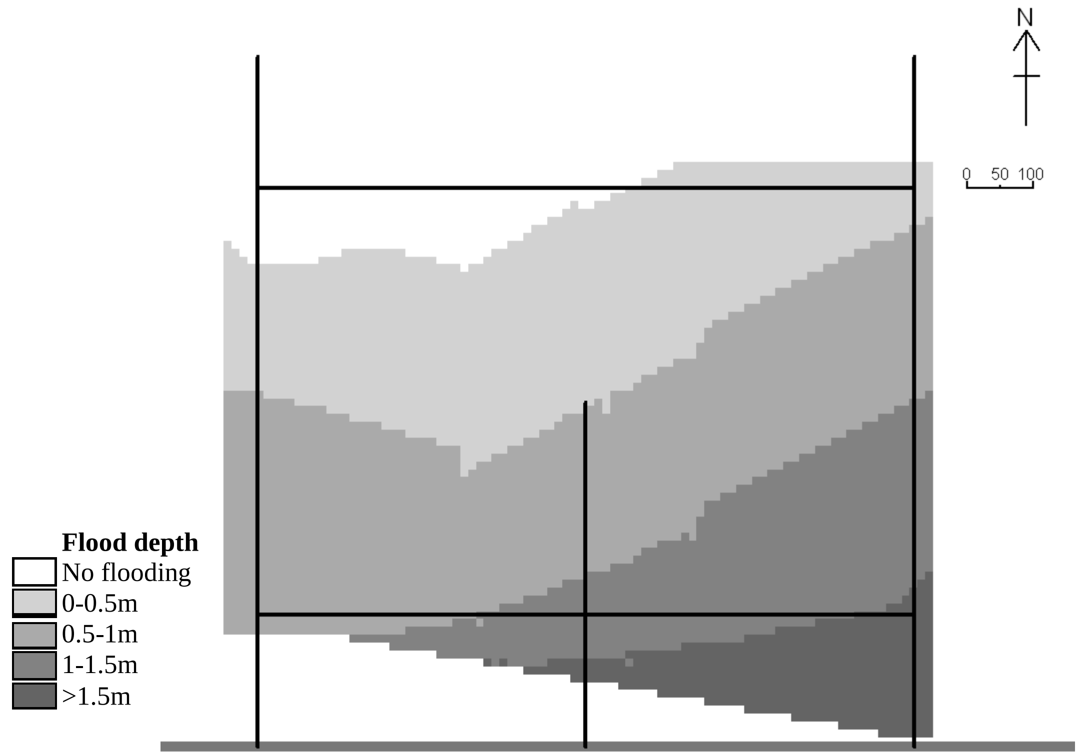


Figure 3 Urban flood system showing the location of sub-surface network (black), road network (grey) and housing zones



(a) 1 in 100 year event



(b) 1 in 10,000 year event

Figure 4 Surface water depth for the 1 in 100 and 1 in 10,000 year flood events

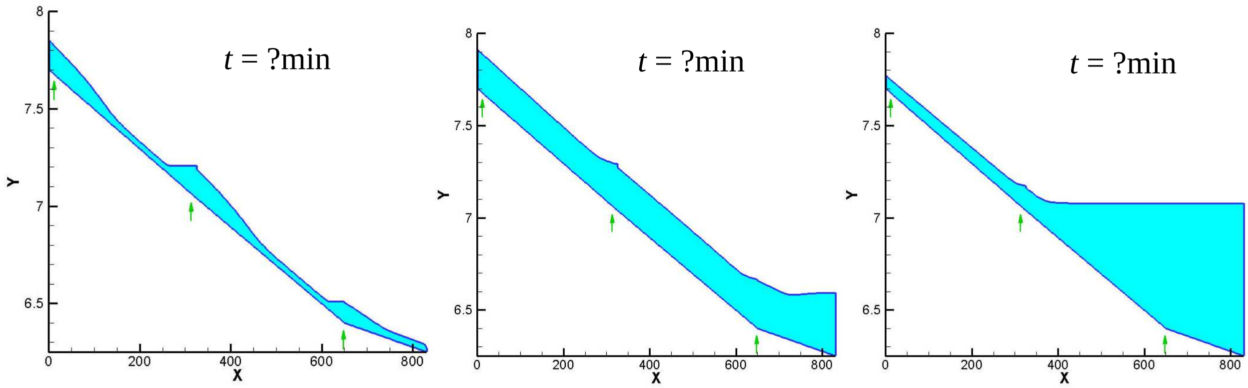


Figure 5 Water surface level along nodes 163 and 168 for 1 in 200 year rainfall event combined with the 1 in 1000 year river flow rate

Damage for each flood is calculated using standard UK depth-damage curves published by Penning-Rowsell *et al*. (2003), and each property is assumed to have no cellar and a threshold level of 0.15m above street level. The risk was calculated to be an expected annual damage of £576k (Equation 1).

5 Implementation of risk attribution methods

5.1 Standards based attribution

First we consider two different standards, of 10 and 50 years, for the urban system and fluvial flood defence systems respectively and no infrastructure failure i.e. Equation 3. Table 2 shows the damage calculated when considering predominantly river or rainfall flooding. It is clear that some damage occurs due to both sewer and river flooding at conditions below the design standard of the two systems. Applying Equation 3, the total risk attributed to the fluvial defence organisation (FDO) is £680k and the risk attributed to the urban drainage organisation (UDO) is £1080k.

Table 2 Damage associated with different fluvial and pluvial return periods

Rainfall RP	River flow RP	Damage (£k)
$T = 1$	$T = 50$	680
$T = 1$	$T = 100$	1560
$T = 1$	$T = 200$	2560
$T = 10$	$T = 1$	1080
$T = 25$	$T = 1$	3910
$T = 50$	$T = 1$	4780

5.2 Sensitivity based attribution

The steps to implementing the variance-based sensitivity method described earlier are:

1. Identify the components in the urban drainage system (and associated model parameters) to which risk is to be attributed.
2. Identify the range of variation for each parameter.
3. Sample a range of values for each parameter.
4. Run the flood model for each sample and calculate the corresponding damage.
5. Analyse the sensitivity of the system to each parameter and attribute the risk accordingly.

Six key system variables were chosen for analysis (sewer pipe diameter, impermeable area, river width, rainfall duration, total rainfall, river flow rate). The distributions of pipe diameter, impermeable area and river width are given in Table 3, whilst the rainfall duration, total rainfall and river flow rate were obtained as described previously, with estimated rank correlation coefficients given in Table 4. Both the methods of Sobol' (1993) for independent quasi random samples and also replicated Latin Hypercube Sampling (rLHS) with correlated inputs were employed. Rainfall and river flow are obviously correlated so the rLHS method is the appropriate one, but has the disadvantage of not yielding total sensitivity indices (Equation 11). Though the assumption of independence in the method of Sobol' (1993) is not tenable, it can still provide some useful insights so the results are reported here. The rLHS sample was generated by applying the method of Conover and Iman (1981). The calculation of the sensitivity indices using rLHS and the method of Sobol' is discussed elsewhere (Saltelli et al, 2000) so is not repeated here. For both the Method of Sobol' and the rLHS importance measures ~2,000 simulations were required to generate stable estimates of sensitivity. The outputs of the different methods are summarized in Table 5 for the linear regression, variance based and importance measures methods.

Table 3 Distribution of input parameters for risk attribution

Variable	Physical range	Distribution
Pipe diameter	±50% diameter	Uniform ~ $U(-0.5, +0.5)$
Impermeable area	30%-90% of total urban area	Normal ~ $N(60, 10)$
River width	1.5m-11m	Beta ~ $\beta(2.5, 7)$

Table 4 Rank correlation coefficients of the rainfall parameters and fluvial flow

	Duration	**Total rainfall**	**Flow rate**
Duration	1	0.928	0.146
Total rainfall	0.928	1	0.360
Flow rate	0.146	0.360	1

Table 5 Sensitivity indices for key variables

Variable	**Linear regression**		**rLHS sensitivity index (1^{st} order)**	**Method of Sobol'**	
	SRC	**SRRC**		**1^{st} Order**	**Total**
Duration	0.36	0.17	0.08	0.19	0.65
Peak flow rate	0.00	0.01	0.01	0.02	0.10
Peak rainfall	0.29	0.13	0.08	0.15	0.48
Pipe diameter	0.08	0.02	0.11	0.04	0.30
River width	0.00	0.00	0.00	0.00	0.00
Impermeable area	0.01	0.01	0.01	0.01	0.03

These results show that all three methods attribute the highest proportion of the risk to the event duration, peak rainfall and pipe diameter – but by differing amounts and quantities. For the linear regression, the coefficient of determination, R^2=0.17, is significantly lower than the 0.7 minimum requirement suggested by Saltelli *et al*. (2005) for the method to be valid. This means that the analysis explains only 17% of the variation in total damage. Implementing the rank transformation gave the lower value of R^2=0.07 because the flood damage is a highly skewed function as the most likely events generate little or no damage. The first order indices, shown in Table 5, calculated by the rLHS method explain only 29% of the total variance. Though the total indices from the method of Sobol' should be treated with care, they illustrate that the same variables that dominate the first order indices (event duration, peak rainfall and pipe diameter) are also most actively involved in interaction.

Figure 6 illustrate the influence of pipe diameter, river capacity and permeability of urban surface upon the resultant flood damages. Varying pipe diameter over the range of values analysed here leads to the largest changes to flood damage. Damage increases linearly with the proportion of impervious surfaces in the urban area, but the difference between 30-90% impervious surface alters the damage by only ~£400k. Whilst river capacity shows a non-linear interaction with damage, again the maximum change in damage is ~£600k compared to £4m for the pipe diameter.

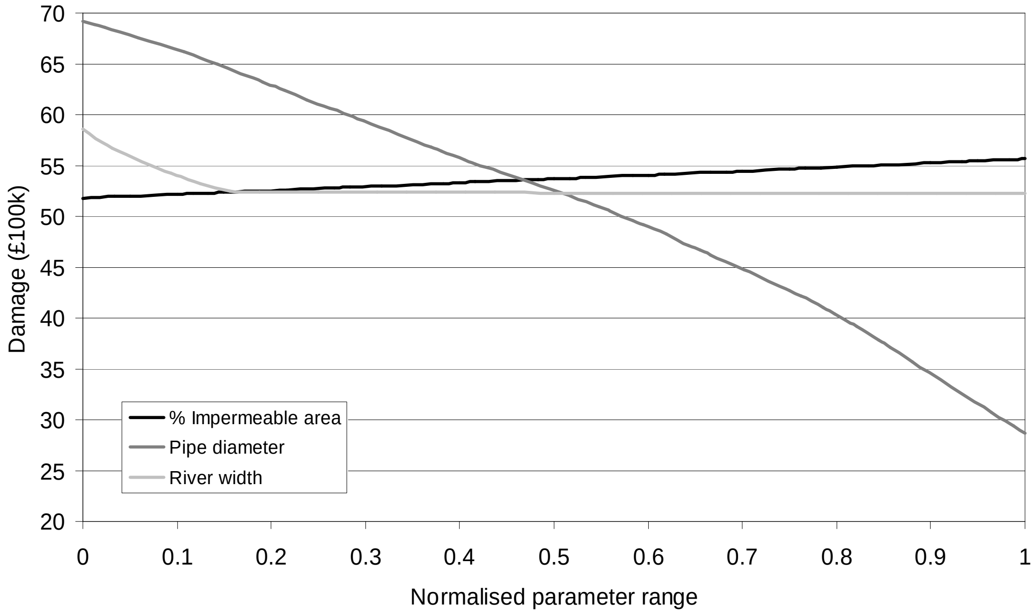


Figure 6 Influence of pipe diameter, river capacity and permeability of urban surface upon flood damage. Independent variable normalized by range.

5.3 Blockages in the urban drainage system

Given the significance of the sewer system in determining flood risk, analysis was conducted to identify the most critical pipes in the sewer network. This problem belongs to the class of discrete systems reliability problems that have been studied extensively elsewhere (Van der Borst and Schoonakker (2001), Hartford and Baecher (2004)). Even for a system of this size, it is impractical to simulate 2^n pipe blockage combinations (n is the number pipes, in this case n=18) so only single blockages were considered. The seven pipes that, when blocked, lead to the greatest increase in flood damages for the design standard (1 in 10 year event) of the sewer system were selected for further analysis. The method of Sobol' was then applied for a sample size of 2048 simulations where all combinations of pipe blockages for these seven pipes were analysed, whilst keeping all other parameters constant. The first order and total sensitivity indices for this analysis are presented in Table 6 and

Figure 7. As might be expected intuitively, important components in the urban drainage system include those nodes that drain into the watercourse. These pipes also exhibit the strongest interactions with other pipe blockages. This implies that the most successful flood risk reduction strategy would, in this case, be to increase the capacity of these pipes, whilst monitoring activities should be targeted to ensuring these pipes do not block.

Table 6 Sobol' sensitivity indices for pipe blockages

Pipe nodes	**Method of Sobol'**	
	First order	**Total**
168 - 167	0.12	0.24
167 - 165	0.15	0.33
165 - 163	0.21	0.29
171 - 172	0.00	0.00
176 - 168	0.08	0.16
180 - 179	0.08	0.09
178 - 162	0.20	0.20

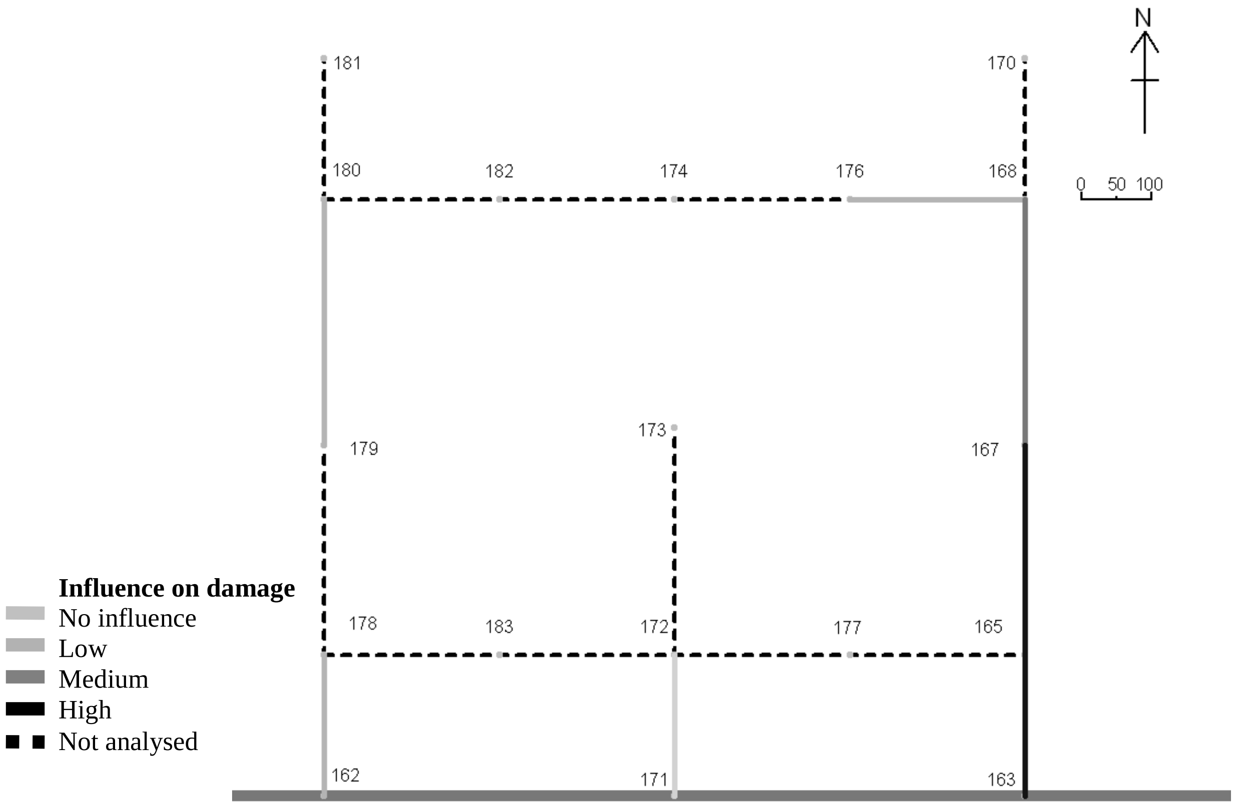


Figure 7 Pipes that, when blocked, have the greatest influence on flood damages (shaded, based on the total sensitivity indices given in Table 6)

6 Conclusions

The core principles of a systems-based flood risk analysis in urban areas have been presented and illustrated in the context of a simplified synthetic case study. Central to urban flood risk analysis is the notion of risk attribution, and several approaches to attribution have been discussed and presented. The results from the synthetic study have demonstrated how risk can be attributed to individual loading variables or infrastructure components. This information can be used to prioritise asset improvement or monitoring strategies.

Standards-based attribution, whilst being computationally inexpensive, is limited to situations where standards are well defined. Whilst standards based attribution provides an indication of risk ownership, unlike a sensitivity-based approach it does not identify those variables that have the most influence upon flood risk. Moreover, a standard's based approach provides little guidance about the management of residual flood damage that occurs above the design standard.

Whilst linear regression is less computationally demanding than variance based techniques, the low coefficients of determination in the analysis reported here indicate that linear regression models are not a good representation of the response of urban flood damage to input variables so are of limited use as a basis for sensitivity analysis. The low first order indices in the variance-based methods applied here indicate the importance of interactions between the input variables. Replicated Latin Hypercube Sampling was used to generate first order variance-based sensitivity indices for correlated input variables, but it has the deficiency that it is not possible to compute higher order indices. The variance-based methods provide detailed information regarding the behaviour of the urban drainage system and can be used to prioritise investment decisions by identifying the contribution towards risk from different loadings, infrastructure components and stakeholders. Results of the variance-based sensitivity analysis attribution should be interpreted carefully, and using more traditional methods, such as plots of damage response surfaces over pairs of variables can help to interpret system behaviour.

When considering asset management decisions, it is important to recognise that parameters such as pipe size (*i.e.* not parameters such as rainfall statistics which an urban flood risk manager has no control over) are essentially decision variables. Sensitivity to these decision variables indicates that the urban flood engineer is (at a cost) able to modify the system in able to reduce risk. However, the approach relies on appropriate specification of the potential range of variation of decision variables, and that range will be influenced by cost considerations.

Only 50% of sewer floods in the UK are attributable only to exceedance of sewer capacity: approximately 40% of are associated with a blockage, and the remainder associated with some other type of failure (CIRIA, 1997; NAO, 2004). This paper has demonstrated a method for blockages analysis that identifies those components that contribute most to flood risk when blocked, therein providing a rational method for prioritising asset improvement schemes. This type of analysis can be combined with methods to identify those pipes most likely to block or fail.

The computational expense of the methods proposed are considerable, even for the rather small system reported here. In practice, urban flooding systems involve tens of thousands of variables. The only feasible approach to tackling this problem is therefore by hierarchical simplification of the system, with the attribution analysis being applied at several levels, with initial screening to identify the most important variables. The approach demonstrated here for analysing blockages is an example of how this could be achieved.

7 Acknowledgements

This research was funded through the Infrastructure Management and Urban Flood Management Research Priority Areas of the Flood Risk Management Research Consortium (FRMRC). The Consortium is funded by the *UK Engineering and Physical Sciences Research Council* under grant GR/S76304/01, jointly with the *UK Natural Environment Research Council*, the *Department of the Environment Food and Rural Affairs*, the *Environment Agency of England and Wales*, the *Scottish Executive*, the *Rivers Agency (Northern Ireland)* and *UK Water Industry Research*.

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