# IMPLEMENTATION PLAN FOR LIBRARY OF TOOLS FOR UNCERTAINTY EVALUATION


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## Summary
This report sets out the framework for including risk and uncertainty analysis within the Flood Risk Management Research Consortium (FRMRC). Risk and Uncertainty is a cross-cutting theme for FRMRC and needs to address a wide variety of needs and applications in the other themes of the project. The report discusses why risk and uncertainty needs to be considered as a normal part of any flood analysis and decision making process; sources of uncertainty in analysis, modelling and decision making; methods for assessing model predictions; and the implementation of a risk and uncertainty framework in software.

At this stage, the report concentrates on uncertainty estimation methods, which are a fundamental input to the evaluation of risk. A review of available uncertainty estimation methods is provided in Chapter 4. This will form the basis for the Catalogue of Uncertainty methods that will be a deliverable of this FRMRC Research Priority Area. Applications within the context of the other RPA areas will form the basis of a final summary of guidance to the use of these tools. A glossary of common terms is also provided.

# Document Details

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## Acronyms

| | |
|---|---|
| Defra | Department for Environment, Food and Rural Affairs (UK) |
| EA | Environment Agency (UK) |
| FEH | Flood Estimation Handbook |
| FRMRC | Flood Risk Management Research Consortium |
| KF | Kalman Filter |
| EnKF | Ensemble Kalman Filter |
| EKF | Extended Kalman Filter |
| RPA | Research Priority Area |
| SA | Sensitivity Analysis |

| | |
|---|---|
| WP | Work Package |
| NUSAP | Numeral, Unit, Spread, Assessment, Pedigree |

# 1. Introduction

## 1.1 BACKGROUND

Risk and Uncertainty analysis is a cross-cutting and overarching theme in the Flood Risk Management Research project and thus has been identified as one important scientific objective. The purpose of this report is to convince the hydrological and hydraulic modelling community of the advantages of using risk and uncertainty tools and to give an initial guideline on available tools. It will also discuss how such tools could be implemented within the Flood Risk Management Consortium framework. At this stage, the report concentrates on uncertainty estimation methods, which are a fundamental input to the evaluation of risk.

**Risk analysis** has always formed a central part of the science of hydrology and hydraulics. For example, in Frontius' legacy (translated from Latin by Herschel [1]), which describes the water supply system of ancient Rome, the necessity of adding additional aqueducts was justified by the risk of water shortage. Although, the concepts of what constitutes risk may have since evolved to a more detailed level, the basic understanding is rooted deeply in our civilisation. A common (but not universal) definition of risk is probability times consequence i.e. it involves two quantities subject to uncertainty and for which uncertainty analysis might be required.

**Uncertainty analysis,** on the contrary, is a very recent development in the modelling community. Most papers in the beginning of the last century did acknowledge the existence of uncertainty, but did not deal with it in an explicit way. For instance, the first research papers on the computation of discharge in pipes, point out that there is a considerable uncertainty in computing exact values and suggest that any engineer will have to expect a range of values, which could be equally likely[2]. However, the solution has been to take an average and ignore any distribution around this average. This long standing tradition has survived the last century and it is not surprising that modelling results are still very rarely presented with uncertainty bounds to decision makers or even at scientific conferences.

**Risk-based decision analysis** is a logical consequence of estimation of risk and uncertainty. In simple terms in the flooding context, an increase in the magnitude of an event (smaller exceedence probability) will have a greater consequence (increased flood damage. A decision about infrastructure development for flood protection must take the risk (probability*consequence) into account as well as the infrastructure costs. As noted already, the scientific estimation of risk involves uncertainty, therefore the estimation of uncertainty should be embedded into the decision making framework. As well as being based on a comparison of risk and cost, risk-based decision-making in general includes attitude to risk in the form of utility functions. Whether or not this is formally included, some reflection on the decision-makers attitudes and preferences is essential. There are a number of methodologies for risk-based decision making (see, for example, Bedford and Cooke [3]).

Today there is a greater appreciation of the uncertainty of model predictions and the effect that such uncertainties might have on decision making. However, there has still been relatively little use of uncertainty analysis by hydrologic and hydraulic practitioners. This may be because their contractor did not desire them to use such tools or perhaps that they could not see any advantage. It has been also suggested, that there may be is no trust in the credibility of the tools available and that the methodologies may be over complex [4]. An alternative reason for the lack of use of these software tools may be a lack of communications skills of the hydrological risk and uncertainty community. This report seeks to provide a convincing case for the use of risk and uncertainty tools.

## 1.2 JUSTIFICATION FOR RISK AND UNCERTAINTY ANALYSIS

Current practice in flood risk management has not taken much account of risk and uncertainty in decision making. Flood frequencies are generally estimated statistically, but even when extrapolating to the 100 year or 200 year flood from short records, the uncertainty in those estimates is rarely considered. Flood risk maps, based on those 100 year or 200 year flood discharge estimates are usually modelled deterministically, without consideration of the uncertainties associated with model implementations, choice of parameter values, or the uncertain discharge estimates. Real-time flood forecasts are still being made deterministically, despite the real uncertainties in knowledge of the rainfall inputs to a catchment and in the prediction of runoff generation (there is, as yet, little consideration of uncertainty in the National Flood Forecasting System commissioned by the Environment Agency).

Public discussions, policy decisions and scientific discourses, results and decisions are frequently based on such deterministic model results. We proceed as if our models are true and every prediction can be made with certainty even though, most modellers would, after a cursory reflection, acknowledge the existence of uncertainties. This reflection does not necessarily translate into the application of uncertainty methodologies and, in setting the context for risk and uncertainty analysis, it interesting to reflect on why this should be the case. Some of the arguments for why there has been some resistance to the routine use of risk and uncertainty analysis in the past are discussed in Appendix 1.

Certainly, uncertainty analysis is an additional complication that can only be incorporated at the cost of additional expense, understanding and training but to ignore uncertainties in any form of flood risk prediction carries an associated risk for the analyst of being wrong, and does not allow the decision maker to take account of different risks of potential outcomes.

Risk and Uncertainty analysis is currently recognized as an important area of research and development. Its significance has been acknowledged by National Agencies such as Defra and the Environment Agency (EA). This chapter will set the context and definitions of risk and uncertainty used within this report. It will highlight the connection between risk and uncertainty and discuss the implications for flood inundation modelling and forecasting.

The current interest in risk and uncertainty analysis can be illustrated by two examples:
A scientific program of the International Association of Hydrological Science, called the **Prediction of Ungauged Basins** [5] initiative, has uncertainty analysis as the main focus for a ten year science program. Working groups of specialists have been formed to compare, evaluate and develop uncertainty methodologies specifically for environmental modelling [6].

Moreover, Defra and the EA have initiated **reports in risk, performance and uncertainty in flood and coastal defence** [4]. Reviews, as well as a forward R&D Plan, have been published providing a detailed discussion on the risk and uncertainty issue and is a starting point for work in RPA9.

This implementation report builds on these previous efforts and expands the topic to be suited for the research conducted in the Flood Risk Management Research Consortium. We will especially draw from the Glossary and definitions in Sayers et al. [4].

## 1.3 CONTRACTUAL BACKGROUND

This report is part of a deliverable of the Research Priority Area (RPA) 9 (Risk & Uncertainty) of the Flood Risk Management Research Consortium (FRMRC). The FRMRC is an interdisciplinary research consortium jointly funded by ESPRC, DEFRA/EA Joint R&D programme on Flood and Coastal Defence, UKWIR, NERC and ESRC to investigate the prediction, prevention and mitigation of flooding. It aims to combine the strength of academic research and near-market needs within a truly interdisciplinary setting.
Key aims of the FRMRC are:

- short-term delivery of tools and techniques to support more accurate flood forecasting and warning, improvements to the flood management infrastructure and the reduction of flood risk to people, property and the environment;
- Establishment of a programme of high quality science that will enhance our understanding of flooding and improve our ability to reduce flood risk through the development of sustainable flood prevention, management and mitigation strategies.

The objectives are to increase our understanding of flooding, generate new and original science and support improved flood management. The consortium consists of eligible academic institutions working alongside appropriate stakeholders and users in the public and private sectors [7]. The consortium focuses on nine research priority areas (see figure 1):

**RPA1** Programme Management (Dr Stephen Huntington)
**RPA2** Land Use Management (Prof Howard Wheater)
**RPA3** Real Time Forecasting (Prof Ian Cluckie)
**RPA4** Infrastructure Management (Paul Sayers)
**RPA5** Towards Whole Systems Modelling (Prof Gareth Pender)
**RPA6** Urban Flood Management (Prof Adrian Saul)
**RPA7** Stakeholders and Policy (Dr Joe Howe)
**RPA8** Geomorphology, Sediment and Habitats (Prof Colin Thorne)
**RPA9** Risk and Uncertainty (Prof Keith Beven)

Within each of the RPAs there are up to 5 Work Packages. More details are available on the Consortium website: *www.floodrisk.org.uk*.

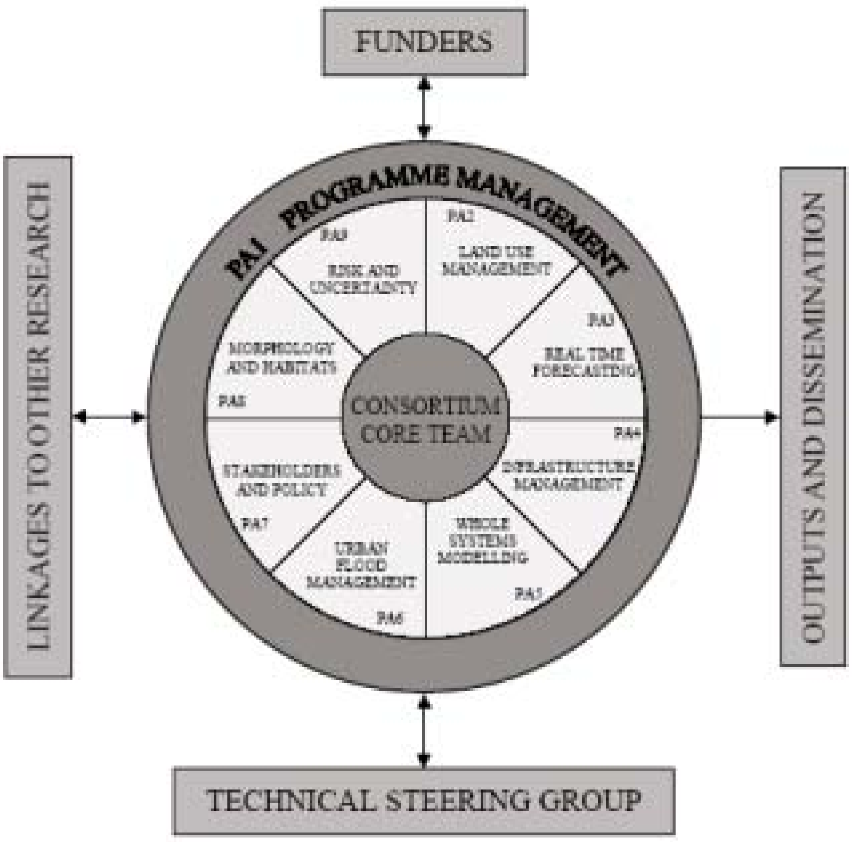


**Figure 1 Organigram illustrating the overall structure of the FRMRC Consortium and its principal linkages [8]**

This report is a deliverable of RPA 9 (Risk and Uncertainty), which is a cross-cutting theme that touches upon all of the specific research domains but merits some additional generic research in its own right. The proposed aims of this research are three-fold:

- to make uncertainty analysis a routine aspect of flood risk modelling activities, so that decision-makers are always provided with information on uncertainties in model predictions in a standard format;
- to resolve the uncertainty-handling and software issues associated with the construction of composite risk models of flooding systems, including issues of model choice in view of model scale, complexity, credibility and uncertainty;
- to support the implementation of methods for robust, risk-based decision-making for flood management.

## 1.4 REPORT OBJECTIVES

This report is based on the commitment of RPA9 to be a cross-cutting theme and advance science by interdisciplinary research. All project partners and RPA areas have committed themselves to cooperate with each other and interlink with individual stake-holder advisory groups (for the stake holder groups, please see www.floodrisk.org.uk).

***Target audience***
This report is aimed at the broad flood modelling community of researchers and practitioner users of software within this area. It further aims to give decision makers an insight into state-of-the-art uncertainty and risk analysis tools and the context in which these have been developed.

Especially targeted are all project partners within the FRMRC project and therefore this report builds the basis for further cooperation. The tools are aimed at models with a wide range of scientific disciplines such as rainfall-runoff, urban flooding, geomorphology, infrastructures and many others. This list is not exclusive and most tools and concepts presented in this document can be applied to other areas.

***Objectives***
The key objectives of this report are to:

- raise the awareness of the risk and uncertainty issue
- define the context of Risk & Uncertainty within RPA9
- argue for the necessity of risk & uncertainty analysis
- provide detailed background to uncertainty in the modelling process
- propose an initial catalogue of uncertainty estimation methods and highlight advantages and disadvantages
- discuss the implementation of risk and uncertainty tools

## 1.5 OUTLINE OF REPORT

**Chapter 1** Introduction
Provides the background to this project and this report and its setting within the FRMRC framework. The project objectives including the target audience are also defined in this chapter.

**Chapter 2** Context
Defines the terms risk and uncertainty as used within this report and RPA9. Definitions for risk and uncertainty will be given and the concepts explained on examples

**Chapter 3** Implementation
Discusses approaches to implementing uncertainty and risk analysis tools and frameworks, highlighting some limitations of current modelling frameworks as a platform upon which to build.

**Chapter 4** Methods and techniques
Provides an initial catalogue of methodologies and gives a guidance on their usage.

**Appendix 1** Justification of Risk and Uncertainty Analysis
Resistance to risk and uncertainty analysis has been expressed in number of different ways. This appendix explores some of the most common arguments against the use of risk and uncertainty analysis as normal component of any flood analysis.

**Appendix 2** Glossary
A glossary of terms modified from Goulsby and Samuels, 2004, Language of risk – project definitions. FLOODsite report T34/04/01, at www.floodsite.net

# 2. Context of Risk and Uncertainty analysis

## 2.1 THE CONCEPT OF RISK

The terms risk and uncertainty have been in circulation for a very long time and are used in a number of different contexts and show how adaptive any concept of risk can be [4]. For example in the area of natural hazard studies, several interpretations can be found (modified from Kelman[9]):

Total risk = Impact of hazard x Elements at risk x Vulnerability of elements at risk [10]

"Risk is the actual exposure of something of human value to a hazard and is often regarded as the combination of probability and loss" [11]

Risk is "Expected losses (of lives, persons injured, property damaged, and economic activity disrupted) due to a particular hazard for a given area and reference period. Based on mathematical calculations, risk is the product of hazard and vulnerability" Hazard is "a threatening event, or the probability of occurrence of a potentially damaging phenomenon within a given time period and area". Vulnerability is "Degree of loss resulting from a potentially damaging phenomenon" [12]

The Defra/EA report [4] determines Risk broadly as "a combination of the chance of a particular event (probability), with the impact that the event would cause (consequence) if it occurred. Helm [13] warned that a simple product of probability and consequence will never be sufficient to describe risk fully, but claims that it provides an adequate basis for comparison and decision making. The units in which risk is measured depend on the definition of probability and consequence and enforces the argument that risk is a flexible concept. The following two

### 2.1.1 Definition of consequences

Consequences can be defined in many units or terms such as loss of life, stress, material damage, environmental degradation and so on. Moreover, it is possible to measure this consequence qualitatively (such as "an area of high flood risk"), quantitatively (such as "value of a damaged house") and an infinite number of shades and combinations of both. Thus it is inevitable that the usage of the term risk is always defined according to the task; each participant of the FRMRC project should be encouraged to state an explicit definition within the framework of their particular application, which can be openly challenged or endorsed.

Fundamentally, it is difficult to adapt a unique definition for consequences, which includes a restricted group of variables or outcomes. Thus the consequence is perhaps best defined and redefined by the problem at hand (e.g. justifying flood defences by risk of damage argument). Therefore, it is justified to adopt any definition as long as it can be justified. For example, the Environmental Agency publishes flood *risk* maps on the internet. The detailed description on the web page does explain that it is the 100a or 200a return period – thus in this case risk is defined as a hazard parameter. Arguing along this line, risk could be defined with a particular predicted outcome of such as discharge, erosion, dam failure, inundation extent etc. Any such definition bears similarity to the definition of hazard parameters, which have been summarized in figure 2 for flood risk in coastal areas [9]. This simple example illustrates how important it is to offer a definition of the terms used in each Research Priority Area.

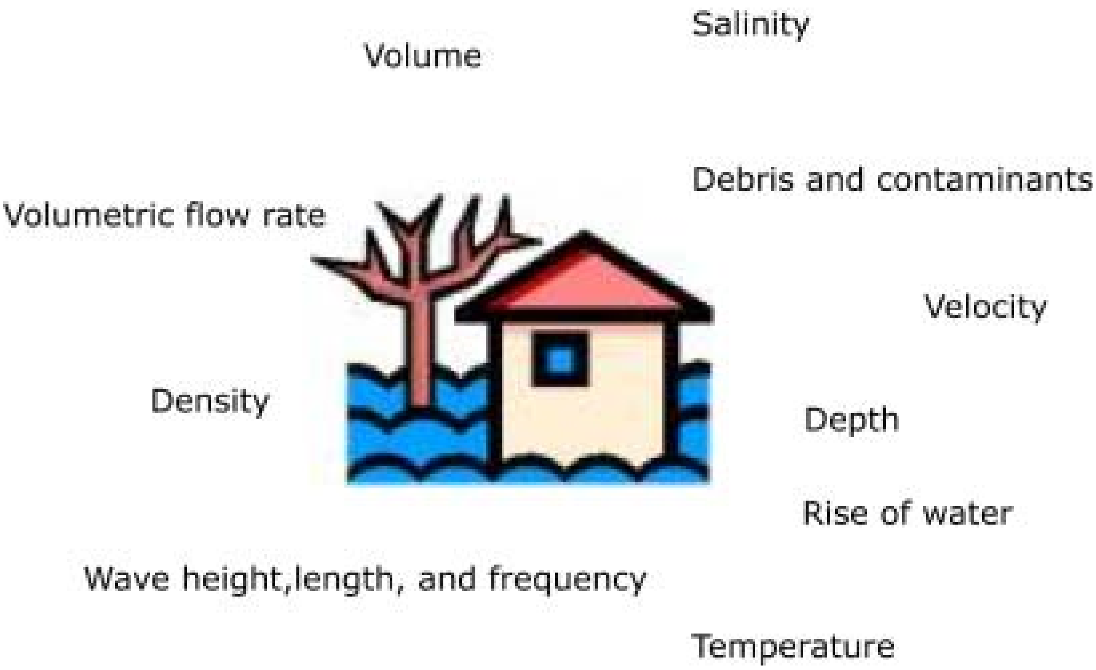


**Figure 2 Examples of flood hazard parameters for a coastal zone (modified from Kelman, 2002[9])**

However, if the problem is extended these hazard parameters can be transformed, by the use of an additional impact model, into a quantitative consequence e.g. damage costs or actuarial costs of loss of life. Any individual definition of consequences will be conditional on the underlying assumptions of the impact model, which may have its own uncertainties. The assignment of a single cost to the impact of a water level or velocity is very difficult as it requires a strict definition (such as what is the value of human life or stress). Even very simple costs cannot be assigned without uncertainty. For example, several methods exist to assign a cost to the damage of an inundated housing estate, but they have to be based on generalizing assumptions such as the average value of house content. Although, it might be possible to quantify an average value from past insurance payments and model projections of future costs, it is also obvious that the value of individual properties will differ. Therefore, a distribution of the uncertainty around the integral of cost distribution is required.

It has to be noted that there is a social construct to the subjectivity of risk. For example, how individuals perceive risk is an important factor in determining how they will respond to warnings of an impending natural hazard. Wilson[14] indicates that perception can be viewed as a process of transforming input (e.g., a warning) to output (e.g. a mitigation response). Slovic[15] has identified features of risks that make them more or less acceptable. According to his criteria flooding is apparently one of the more acceptable risks in society. Research in this area will be conduced by RPA7 (Stakeholders and Policy) and is therefore not discussed extensively in this report.

Overall, it has to be concluded that the definition of consequences and its quantification is subject to uncertainty which should be considered in any planning or prediction process.

### *2.1.2 Definition of probability*

Probability is the chance of occurrence of one event compared to the population of all possible events. The probability is normally computed for a particular event or outcome. Therefore, probability is subject to the definition of an event as well as the methodology of computing a probability. It is quite important to note here that the probability of flooding may be quite different to the probability of some stage or discharge being exceeded in a river. Flooding is modified by the effects of flood defence and drainage systems.

It is important to recognise that even in well defined statistical system the estimation of a probability of an event will itself be uncertain. In poorly defined environmental systems, with many and various sources of uncertainty, this uncertainty might be significant. This is best illustrated here in the context of flood frequency. Risk maps require the definition of a discharge with a particular probability (0.01 in any year or 100 year return period for fluvial flooding). There are very few sites with discharge records of a length of 100 years in the UK. For a good statistical estimate of the 100 year event, even longer records would be required, with the additional assumption that the climatic forcing and the catchment characteristics are stationary. Thus, especially for sites with shorter record lengths, the estimation of the 100 year event will require a model (generally a fitted distribution for this type of problem) but there will be uncertainty as a result of choosing the form of distribution and extrapolating the data to longer return periods on the basis of a small sample. Current practice generally requires the estimation of only a best estimate of the discharge for a given return period. Best practice would require that the uncertainty due to both model choice and extrapolation be estimated. Well-established statistical, and continuous simulation, methods of flood frequency estimation allow this.

The Flood Estimation Handbook (FEH) [16] gives guidance on how to apply both peaks over threshold and annual maximum methodologies of frequency estimation (but the FEH software does not estimate uncertainty in, for example, the T year flood as a standard procedure). For further definitions of probability and flood frequency analysis the reader is referred to Sayers et al. [4], p 7 and 10, box 2.1 and 2.2 respectively.

The previous two sections demonstrate that the computation of risk is in fact a combination of two probability distributions. The consequence as well as the probability are uncertain and are combined to a risk prediction. There are many different sources of uncertainty and estimating the net effect on predictions will depend on the assumptions made. Thus a more detailed understanding of the sources and propagation of uncertainties through prediction systems is required.

## 2.2 UNCERTAINTY

This section will give a brief introduction to uncertainty. It will list various sources of uncertainty in hydrological and hydraulic models and explain them with examples. Moreover, the issue of model performance will be discussed within this context.

There are at least as many definitions for uncertainty as have been quoted for risk. The Defra report [4] defines it as “a general concept that reflects the lack of sureness about something, ranging from just a sort of complete sureness to an almost complete lack of conviction about an outcome”. This definition can be narrowed for *uncertainty analysis*, which aims to quantify the overall uncertainty associated with the response as a result of uncertainties in the model input/parameters/structure/etc.

Traditionally, uncertainty is divided into *natural (or aleatory) variability* which refers to the randomness observed in nature and *knowledge (or epistemic) uncertainty* which refers to the state of knowledge of a physical system and our ability to measure and model it (an in depth discussion has been presented by Hall[17]). It has been argued that only knowledge uncertainty can be used to reduce the overall uncertainty. Moreover, it has been stated that natural uncertainty is a property of the system, whereas epistemic uncertainty is a property of the analyst. This distinction is a valuable theoretical concept, however, it can be questioned if it is in most cases possible to distinguish between these two fundamental uncertainties. When (as commonly in science) knowledge is captured though an imperfect model or theory, the boundary between natural and knowledge uncertainties will be blurred and will change over time. Lack of understanding of a process, for example, might initially appear as natural variability; inclusion of that process into a formal model might then appear to shift some of the uncertainty into knowldege uncertainty.

Continuing with the flood frequency example, it is common to fit a single statistical distribution to all the flood peak data that are available. This is despite the fact that different peaks might come from quite different physical mechanisms, each of which might have its own distribution (synoptic rainfall events, convective rainfall events, combined rain on snow events) and might not be easily represented as a single distribution. The dilemma then is that including such knowledge also makes the knowledge model more complex and consequently more difficult to calibrate with small data samples. The multiple sources of uncertainty involved in flood modelling processes for different applications will necessarily make it difficult to separate between these types of uncertainty in practice.

Nevertheless, any attempt to characterize knowledge uncertainty highlights the three key parts of any uncertainty analysis:

1. Define what is uncertain in the modelling process (Sources of Uncertainty)
   The various sources of uncertainty have to be identified and quantified. A methodology has to be chosen accordingly.
2. Define how to quantify output uncertainty consequent on the sources of uncertainty
   The various sources of uncertainty have to be propagated through the modelling system
3. Define how to condition the uncertainty estimate as data on model predicted variables become available.
   Many uncertainty methods require a definition of model performance (e.g. how well does a model predicted variable compare to measurements, which may themselves be associated with uncertainty). Measures of model performance should lead to uncertainty constraint and refinement of risk estimates through model conditioning or rejection.

In the following these key points will be explored in more detail with explicit examples to models used within the FRMRC framework.

### *2.2.1 Sources of Uncertainty*

A model is built up from the very instant a natural phenomena is explained. Such a model manifests itself initially only in the mind (perceptual model) [18] which is based on education, field and work experience. Thus it comes as no surprise that a well educated engineer will propose or explain a process in a different manner to a statistician. This understanding will then be formalized into a conceptual model in the form of equations, and finally a procedural model that will run on a computer and provide quantitative predictions[19]. The procedural model will be a combination of numerical implementations of hypotheses that can or cannot be tested individually[20] and that will be different from original conceptual hypothesis because of implementation approximations. Every model will be an incomplete representation of reality as a result of multiple sources of uncertainty.

We may distinguish the primary sources of uncertainty as follows:

- Choice of model structure as a simplification of reality (including models of both events and consequences)
- Numerical approximations in solution of equations defined in model structure
- Definition of the flow domain considered, particularly in the subsurface
- Definition of boundary conditions, including input forcing data
- Choice of effective parameter values, including scaling and incommensurability effects

#### Choice of Model Structure

A fundamental source of model uncertainty is the definition of model structure, including models of both flood occurrence and of the consequences of a given flood magnitude). Most flood risk estimation problems (particularly those involving rainfall-runoff modelling) allow a choice between a number of different perceptual models of the processes involved. Different implementations of these perceptual models as equations and code will produce a larger number of conceptual and procedural models. This plethora of different models and approaches proves that the transformation process from a 'mind model' to a material model is not straightforward. Therefore, it is not surprising that models may have slightly different structures and that these different structures may give different results (see e.g. Smart et al. [21]). In recent years an increasing amount of computer power has resulted in an increase in complexity in models from simple lumped models to highly distributed ones. The aim of increasing complexity has been to increase the realism of the resulting models, but the same dilemma noted above arises. An increase in complexity will introduce more model data and parameter requirements, where both data and parameters may be uncertain.

The model structure has to be chosen according to the circumstances, the task and the data available. For example, it may well be that many rivers can be approximated by a transfer function for certain tasks and do not require more complicated solutions e.g. the simpler solution may perform equally well in terms of model data in comparison to a more complicated one [22-26], or a 3 dimensional representation may not be necessary for relatively shallow flow [27]. However, a physically based model representation may be chosen over a simpler structure in order to resolve the effects of different flood risk management options. The problem is complicated by the fact that it might be sometimes difficult to determine if a certain model structure has failed or is in error [28]. This is currently seen as more problematic for rainfall-runoff models than for flood routing models, because flow dynamics and subsurface boundary conditions are much more difficult to specify from physical considerations.

## Numerical approximation of model equations

Distributed physically based models may be subject to additional uncertainty because the partial differential equation systems of these models often cannot be solved analytically (unless very simple boundary conditions are assumed). They rely on approximate numerical solutions and therefore, numerical diffusion and other inaccuracies may occur, depending on the numerical implementation used. For example Bates at al. [29] investigated different numerical techniques for flood inundation models and show a clear impact on model predictions. Other studies find only a minor impact due to numerical solution [30, 31]. This indicates a complex interaction between numerical solutions and other model parameters as well as boundary conditions. For example, many cell based flood inundation models use a flow limiter, which restricts the amount of water that can flow from one cell to another within a time-step, to damp numerical oscillation and allow the model to remain stable. However, this flow limiter directly affects the uncertainty and sensitivity of the floodplain surface roughness (in this particular case it made the parameter insensitive). In fact, the number of parameters which have to be chosen for a numerical scheme can be so large that they have to be investigated in a 'stand-alone' uncertainty or sensitivity analysis (see e.g. Claxton [32]). Similar numerical approximations can also arise in other types of models, such the predictions obtained may not be an accurate solution of the original conceptual model equations (e.g. Kavetski et al.[33]), depending on the scale and resolution of the numerical approximations. The choice of scale and resolution may also be expected to interact with the effective values of the parameters and boundary conditions required by the model.

Thus, in general, the procedural models that provide quantitative predictions will only be an approximation of the real processes (and, in some cases, of the equations of the conceptual model). There will therefore always be some uncertainty associated with the choice of a particular model structure and implementation. Given the other sources of uncertainty in the modelling process, however, it has proven very difficult to separate out the model structural and implementation uncertainty or even to give guidance about what procedural model (model structure and implementation method) to use in different circumstances. The use of model calibration or conditioning on observations allows (to some extent) the effects of model structural and implementation error and input error to be compensated by change in effective parameter values.

**Table 1 Examples of model structure choices in flood prediction and damage estimation**

| Model type | Example |
|---|---|
| Flood inundation | 0D, 1D, 2D, 3D flow modelling |
| Rainfall-Runoff | 0D, 1D, 2D, 3D Representations of surface and subsurface flow |
| Flood Frequency Analysis | Distribution function and underlying assumptions (e.g. GEV/GLD/GPD & independence of samples)<br>Rainfall and rainfall-runoff models for continuous simulation flood frequency estimation |
| Infrastructure failure | - to be added - |
| Flood Damages | - to be added - |

## Definition of the Flow Domain

Scale and resolution problems can also arise in defining the flow domain for both surface and subsurface flow processes. Surface processes will normally require only the definition of topography of the domain, but subsurface processes require the geometry of the various soil and geological layers in the system and the subsurface boundaries of the domain.

Surface topography is often derived by utilizing remote sensing [34] and although one of the most important inputs into most distributed models, topography is often seen as the factor with the least uncertainty. Various studies have shown that small errors in flood plain topography can have significant effects on flood inundation model results (see e.g. [29, 34-37]). Such errors can be especially significant if they are related to embankment height or channel depth. Additional models have to be developed to determine e.g. flow paths for rainfall runoff.

Obtaining information on subsurface structure is much more difficult and is likely to be associated with much greater uncertainties in both geometry and characteristics. The sensitivity of groundwater flow predictions, for example, to the conceptual geological model of the flow domain has been demonstrated[38].

## Definition of Boundary Conditions including forcing input data

Boundary conditions are the physical conditions at the boundaries of a system. Two of the most common boundary conditions are rainfall and stage/flow hydrographs.

Many flood runoff generation models are extremely vulnerable to uncertainty in precipitation. The impact of uncertainty in precipitation can be most clearly seen when weather forecasts [39] are applied to drive a model. For example, wind can be responsible for errors of up to 20% in gauged rain measurements which has to be corrected for [40]. Moreover, for the most physically based distributed models, a rainfall field has to be interpolated. This is done by a variety of methods (= models) of different complexity. The quality of these interpolations and corrections will most probably not be consistent with real rainfall patterns and will depend largely on the characteristics of the storm event, which is very rarely included in any interpolation routine. Measuring rainfall by radar an alternative to rain gauges. Rainfall measured by radar is effectively a continuously updated measurement ([19], p. 256 et sqq.) but is based on spatial correction techniques [41]. Furthermore, radar measurements suffer from wind attenuation and depend heavily on the type of rainfall (drop size distribution –rain near the radar sometimes effects signal from rain further away) [41]. Also ice clouds (bright band) and snow fall will affect a radar measurement and further complicate the estimation of precipitation intensities at ground level by introducing an additional source of uncertainty e.g. quantification of melting and refreezing processes [42].

Another boundary condition regularly used in flood inundation modelling is upstream discharge. The flow of water in a channel is normally estimated from stage-discharge curves. The relationship can be significantly distorted by uncertainties [43]. Even when it is determined with more advanced technologies e.g. by ultrasonic gauges large uncertainties remain in the estimation of discharges for flood stages [44]. Lateral and tributary inflows to a stream channel, and their dependence on conditions in and below the flood plain, will be even more uncertain.

In coastal and estuarine flooding, which is often the result of combined tidal, wind, storm surge and river discharge forcing, there may also be similar uncertainties in boundary conditions at any particular application site. The local downscaling of atmospheric model predictions to give local storm surge and wave heights will result in uncertain in water levels.

### Choice of effective parameter values

The choices made in effecting the procedural model will normally involve the choice of scale and resolution at which the calculations will be made. For the nonlinear equations common in environmental modelling problems, the sensitivity of solutions to space and time resolution can generally only be estimated locally, but it can be expected that there will be an interaction between scale and resolution and the effective values of the parameters required by a model.

The effects of spatial resolution on models have been explored by various authors [45-47]. For example Hardy et al. [48] and Yu and Lane [49] found that spatial resolution has a major effect on inundation extent and flow predictions. Different processes will be dominant on different scales and it can be argued that, in the nonlinear case, a model which is applicable at a small scale may require a different formulation to be used on a larger scale [50, 51]. In particular, the effects of sub-grid heterogeneity are expected to be more important with increasing scale and mesh size [50].

Thus, the values of model parameters required in a model formulation might also change with changing scale or resolution. This creates difficulties in estimating parameters that it is actually possible to measure in the field. For example, a roughness coefficient for flow over a flood plain or in a river channel, might be inferred from velocity profiles at a point on the flood plain or a cross-section of a channel. This will not, however, be the value required in a discretised model of the flow domain that will need to reflect changing geometry and surface characteristics (e.g. pool-riffle structures in a channel, effects of vegetation, hedges and walls on the flood plain).

Similar arguments can be made about many other "measureable" parameters. For example the hydraulic conductivity, which can be determined by measurements at the point scale [52], but is often difficult to reconcile on a grid cell [53]. The parameter values required by the model will be '<u>effective</u>' rather than 'real' and the values required by the model might be incommensurate with values that are measured at a different scale in the field. Many other model parameters are ill-defined or have no basis for estimation at all.

Even where parameter measurements can be made, there will also always be uncertainty in extrapolating from points where there are measurements to other points in the flow domain. Thus, it may never be possible to determine such a parameter everywhere in a distributed model without uncertainty, considering not only the scaling issue above, but also the uniqueness of place argument by Beven [54]. Even when a perfect model structure is assumed, it will be difficult to determine the parameters from one place to another, because of the specific characteristics of each site and the problems in scaling.

Recent progress in remote sensing increases the possibilities to determine spatial patterns of parameters. In this way it might be possible to estimate parameters such as the Manning surface roughness and apply them within flood inundation models [34, 55], though, as noted above in Section 2.2.1.1, the <u>effective</u> values of parameters required by a model may still be dependent on model implementation and boundary conditions. Some uncertainty in estimating effective values will therefore necessarily remain. Remote sensing offers considerable opportunities to acquire information about a large number of distributed input parameters [56], although it should not be forgotten that additional models (with additional parameters) have to be applied to process the remotely sensed information. Such a sub-model will also be liable to uncertainty (see e.g. [57]).

### Additional sources of uncertainty

This list of sources of uncertainty is far from being complete and depending on the modelling task, several additional sources of uncertainty will have to be considered. Some of the examples given may not always fit into the same category of uncertainty source. For example, is a hydrograph a boundary condition for a dam break model but not for a rainfall-runoff model in which it is used for model evaluation.

Despite this incomplete list it is hoped that problems due to model uncertainties have now been highlighted for the user community. . Of further importance to uncertainty analysis is the way models are evaluated and what data are used.

## 2.3 EVALUATING MODEL PERFORMANCE AND CONDITIONING OF UNCERTAINTIES AS DATA ARE MADE AVAILABLE

Most problems in flood risk management require the identification of appropriate model structures or parameter values. This is usually carried out in a model calibration exercise by comparing observed and predicted responses and attempting to improve some measure of model performance. Since all models are in error, if only because of observation measurement error, then the model calibration problem is intrinsically linked to the estimation of model uncertainties. In some problems that can be formulated in a statistical framework (such as fitting a particular flood frequency distribution or a water level / damage cost curve by regression analysis), there is a strong and clear relationship between error and uncertainty.

As noted above, however, it is often difficult to formulate a statistical model of the errors in calibrating a complex environmental model. There is, in hydrology and hydraulics, a very extensive literature on methods of model calibration (see Gupta et al.[58], and a wide variety of performance measures have been used in model calibration and evaluation or confirmation. The importance of uncertainties in model calibration and confirmation has been recognised for a long time. Early in the history of distributed rainfall-runoff modelling (1976), for example, Stephenson and Freeze [59] recognised that complete validation or verification of a model will always be impossible because of uncertainties about the inputs, initial conditions, and observations against which model performance will be compared. This question has also been discussed as a problem in modelling philosophy by Oreskes et al. [60] and Beven[61] .

All models and calibrated parameter values are sensitive to the data used in calibration and evaluation [62, 63]. Gupta and others [64-66] showed that the quality of data is sometimes more important than the length of the record. ‘Quality’ includes not only the accuracy of the input and output data available, but also the variety of hydrological and hydraulic behaviour. If a model is supposed to work not only for a restricted range of conditions, but also more globally, it is important that e.g. wet as well as dry periods are included in the record used for calibration and evaluation [67, 68].

This raises the question if a model, which is designed to predict floods should also performing well under low flow conditions. Ideally, a physically based model should perform under all conditions otherwise the adequacy of the physically based model can be questioned. However, this requires that the effective observational errors allowed are also physically consistent and that the effective parameters are stationary over time. This argument will be briefly explored for a flood inundation model (for a more detailed discussion please see Pappenberger et al[69]). It is for example often the case that when images of inundation are projected back onto the available geometry, then the interpolated inundation heights are not physically consistent, even allowing for the difficulties in finding the inundation boundary. In this case it may be very difficult to find a model that provides simulation results that are globally consistent with the observations. There are then four possible responses: investigate those regions of the flow domain where there are consistent anomalies between model predictions and range of observations; avoid using data we don't believe or that is doubtful; introduce local parameters if there are particular local anomalies; make error bounds wider in some way where data is doubtful; and if none of the above can be done (because, for example, there is no reason to doubt anomalous data) then resort to local evaluations in assessing local uncertainties.

### 2.3.1 Model Performance Measures

Evaluating the performance of complex nonlinear models, often given limited observational data that may not exactly match model predicted variables, remains a fundamental problem. As noted earlier, methods for model evaluation and uncertainty analysis are well established in statistics, where formal assumptions can be made about the nature of the errors. In principle, these methods can also be applied to evaluate model structural error (sometimes called model inadequacy) where that error can also be represented by a statistical model (e.g. [70, 71]). Bayesian statistical methods also allow prior information about model structures and parameters to be incorporated into the process. Where the necessary assumptions can be justified, these methods allow strong inference about the probabilities of predicting observations conditional on the model. These types of methods have been increasingly used in rainfall-runoff modelling (e.g [33, 72-78]).

When considered in the context of linear statistical inference, assumptions about the structure of the errors allow the interpretation of modelling uncertainty as a probability of predicting an observation conditional on the model. Thus, for example, in linear statistics use of the standard least square objective function in estimating prediction confidence limits implies an assumption of an uncorrelated Gaussian noise. If this assumption is not correct (as is normally the case in rainfall-runoff modelling, for example, where model residuals are often heteroscedastic and invariably correlated in time; or in hydraulics where errors may exhibit bias and be correlated in both time and space) statistical theory shows that for a linear system the resulting parameter estimates will be biased. By analogy, we should expect a similar bias with a nonlinear model (e.g. [33]). Different (more complete) assumptions can be made about the residuals to formulate more complex statistical likelihood functions (e.g.[73, 79-81]), and, in principle, the validity of the error assumptions can be checked. However, with the multiple interacting sources of uncertainty common to environmental systems, it seems that it will be difficult to formulate a consistent statistical representation of the modelling error [82].

There is a very real difficulty of whether for the type of nonlinear modelling commonly applied in flood hydrology and hydraulics there is adequate justification for making the strong statistical error assumptions required by these models (see the discussion of Beven and Young[83]). This is particularly true for the evaluation of distributed model predictions where observational data are available for model evaluation. This has led to the development of alternative formal frameworks for model evaluation and rejection [63, 84]. In that these methodologies are not based on formal statistical assumptions they will not provide estimates of the probability of predicting a measured value conditioned on the model. They can provide an estimate of the range of predictions consistent with the observational data available for conditioning of the model (see for example the GLUE methodology below which can use informal or fuzzy performance measures to condition belief in a model).

There has been a tradition in rainfall-runoff modelling, for example, of using, Nash-Sutcliffe efficiency [85] to evaluate predicted flow hydrographs. Efficiency is based on the sum of squared errors between observed and predicted values and therefore, in statistical inference, could result in biased parameter estimates where the errors do not have a Gaussian independent structure. There are many other informal evaluation measures in the literature[84, 86-88]

**Table 2 Examples of performance measures for flow hydrographs**

| Name | Formula | Reference |
|---|---|---|
| Cumulative Absolute Error | $\sum_{i=1}^{n_t} \lvert x_i - y_i \rvert$ | -- |
| Nash-Sutcliffe | $1 - \frac{\sum_{i=1}^{n_t} (x_i - y_i)^2}{\sum_{i=1}^{n_t} (x_i - \bar{x})^2}$ | 85 |
| Cumulative Error | $\sum_{i=1}^{n_t} x_i - y_i$ | -- |
| Willmot Index of agreement | $1 - \frac{\sum_{i=1}^{n_t} (x_i - y_i)^2}{\sum_{i=1}^{n_t} (\lvert y_i - \bar{x} \rvert + \lvert x_i - \bar{x} \rvert)^2}$ | 89, 90 |
| Chiew and McMahon | $1 - \frac{\sum_{i=1}^{n_t} (\sqrt{x_i} - \sqrt{y_i})^2}{\sum_{i=1}^{n_t} (\sqrt{x_i} - \sqrt{\bar{x}})^2}$ | 91 |
| Fuzzy Performance Measures | $\max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$ | e.g. [84, 92] |

It appears that no particular objective function is superior to others under all circumstances and that no unambiguous way of evaluating a model with complex error structures in space and time may exist [62, 64, 65, 74, 92-94]. It has been argued that in a decision-theoretic setting there would be an objective solution that minimises loss or risk. However, if there is uncertainty in both predicted outcomes and possible consequences, and different ways to compute costs or benefits, a decision maker may want to allow for such uncertainties in taking a more or less precautionary position to risk.

In summary, model evaluation criteria should be chosen to be fit for purpose. For example, if flood peaks are of interest than a performance measure which gives greater weight to the simulation errors for the flood peaks should be used. One rational method to choose a measure of model performance is derived from the risk-based decisions which the model is intended to inform: In the long run does the model improve decision-making (in the sense of long run net gain/loss of utility) compared with competing models?

An additional way to counter this problem is by using multi-objective or multi-criteria model calibration [62, 94-98]. In this work a distinction is made between multi-criteria and multi-objective (sometimes termed multi-signal). Multi-criteria are used when different evaluation criteria are used on the same set of data [93, 99-103] whereas multi-objective are applied when different data sets are used for model evaluation [104-109]. It has been recognised that global indices on their own are not distinctive enough to discriminate between several models [95, 110-120].

In other words, equal performance may result from fundamentally different model responses [121]. An analogy would be if one tries to classify animals. When one looks only at one property for example colour. A grey elephant would be the same as a grey hippo. However, if additional measures are included it might be possible to distinguish these two. Therefore, it is necessary to apply various objective functions which reflect different features of the evaluation data to test the model hypothesis

[122]. For example, it is possible to combine the Nash-Sutcliffe [85] criterion, which is more sensitive to errors in simulating the peak values of variables, with a volumetric measure and thus extract more information on model performance out of the same data series. Another recent example is the subdivision of a hydrograph into three local criteria, which match the rising limb, the early recession and the late recession of a flow hydrograph [95, 123]. Other methods include the analysis of seasonal responses [98, 124]. The seasonal response is closely linked to the second way forward to tackle the problem of computing 'correct' responses based on the 'correct' reasons. The analysis of several model results (multi-objective) can give valuable insight into model behaviour. For example, an inundation model should not only be able to predict the outflow hydrograph, but also water levels within the reach.

However, mixed results have been achieved employing the multi-objective framework. In some studies the uncertainty range in parameter estimates and responses could not be reduced [125, 126] whereas in others significant improvements could be achieved [93, 101-103, 109, 114, 127-133]. This discrepancy can be simplified by our previous animal analogy: No improvement of our evaluation would be given by an evaluation criteria based on the number of legs. However, if the length of a trunk would have been chosen, a classification might have been possible. This shows that a multi-criteria approach does not necessarily increase the information content for model evaluation.

Fundamentally, there is an unresolved problem of linking field measurements to catchment responses [134]. For example, many variables predicted by models are not the same quantity as their measured 'equivalents' despite being termed in the same way. Such discrepancy can be due to heterogeneity, scale effects, nonlinearities or measurement techniques. A soil moisture variable, for example, might be predicted as an average over a model grid element several metres in spatial extent and over a certain time step; the same variable might be measured at a point in space and time by a small gravimetric sample, or by time domain reflectrometry integrating over a few tens of cm, or by a cross-borehole radar or resistivity technique, integrating over several metres. Only the latter might be considered to approach the same variable as predicted by the model, but may itself be subject to a model inversion that involves additional parameters in deriving an estimate of soil moisture [63].

### 2.3.2 Conditioning uncertainty as data are made available

Despite these difficulties of comparing model predicted variables and observational data, we generally expect that as more data are made available it should be possible to refine our model representations and reduce the uncertainties in model parameters and predictions. Model calibration is, itself, a form of conditioning of model parameters and uncertainties. This will be self-evidently true if a model is a true representation of the system, and the major sources of uncertainties are those associated with the input and boundary condition data, together with observation measurement error. It is less clear that this will be case if the representation of the system is subject to model structure and incommensurability effects. What might still hold in the latter case is that more data will tend to either confirm that the model representation (or, possibly, different model representations) is still acceptable, or alternatively can be rejected.

In either case, the availability of additional data will allow further conditioning of the modelling process that may, hopefully (but not necessarily), result in a reduction in the uncertainty in predictions. Since such prediction uncertainties enter directly into the estimation of risk, there is also the possibility of conditioning risk estimates. In the case where formal statistical likelihood measures can be assumed to be acceptable, this conditioning process can be carried out using either analytically or within a Bayesian likelihood framework. In the case where informal or fuzzy model evaluation measures are used, it will still be possible to combine prior likelihood measures with those arising from an evaluation against the new data in some way (using Bayes equation, Fuzzy Union, or other combination method) to produce a posterior likelihood or ranking of different models. In this informal framework, however, the result cannot be considered as a statistical probability of estimating an observation conditional on the model. Different approaches to conditioning model predictions and parameters on available data are outlined in Section 4.3 and 4.4.

## 2.4 RANKING OF UNCERTAINTIES

It will be impractical and not possible to consider all uncertainties in every modelling process. This requires an informed advanced decision about which uncertainties are most important to the problem at hand, which will be specific to the circumstances and the model used. Most modellers will have an intuitive feeling on the processes and parameters which need to be considered, as dependent on understanding of the system and the accuracy and availability of data. Sensitivity analysis and screening methods[135] can be used to give some guidance. However, such methods are best developed for linear systems. In addition, no sensitivity analysis method can take account of processes and parameters that have not been included in the analysis, except through the identification of errors that appear to be the result of model structural error.

Thus, guidance through demonstrator applications may be the best way to communicate uncertainties in different settings. Such a catalogue of examples, carried out in collaboration with other RPA areas, will be part of the final report of RPA9 at the end of the FRMRC project.

## 2.5 CASCADING OF RISK AND UNCERTAINTY

Many modelling exercises focus on only one specific model component and evaluate only partially a full modelling cascade. However, in many applications several models are linked with each other. In this section, we will present three examples, which can be easily expanded to other model cascades, which will be part of the software framework described in chapter 3 which aims to make this type of uncertainty propagation through multi-component model cascades much simpler for the user. The first example will be explained in more detail to highlight the difficulties and problems.

### 2.5.1 Example 1: From weather forecast to inundation, the Glue-cascade (from Pappenberger et al. [136])

This example attempts to predict inundation hazard through a modelling cascade from weather-forecast over rainfall-runoff to an inundation model. Each of the model components have their own source of uncertainties and therefore uncertainty cascades from rainfall forecasts, through the runoff generation prediction to the flood wave forecasts. At each stage of the cascade we are dealing with nonlinear transformations, from atmospheric conditions to rainfall forecasts, from rainfalls to runoff forecasts, and from runoff to flood wave and inundation forecasts. Thus, it is difficult to use traditional linear statistical methods for cascading the uncertainties through the forecasting system. Uncertainties in nonlinear systems can often be estimated simply using some form of Monte Carlo simulation technique. However, in such a complex modelling system it is still computationally infeasible to perform such an analysis fully and thus first estimates of the magnitude of the uncertainty can be only achieved by some approximate methods. Uncertainty in the forecasts should then be assessed over all combinations of rainfall inputs, runoff predictions and flood routing models (the GLUE-cascade, see Figure 3).

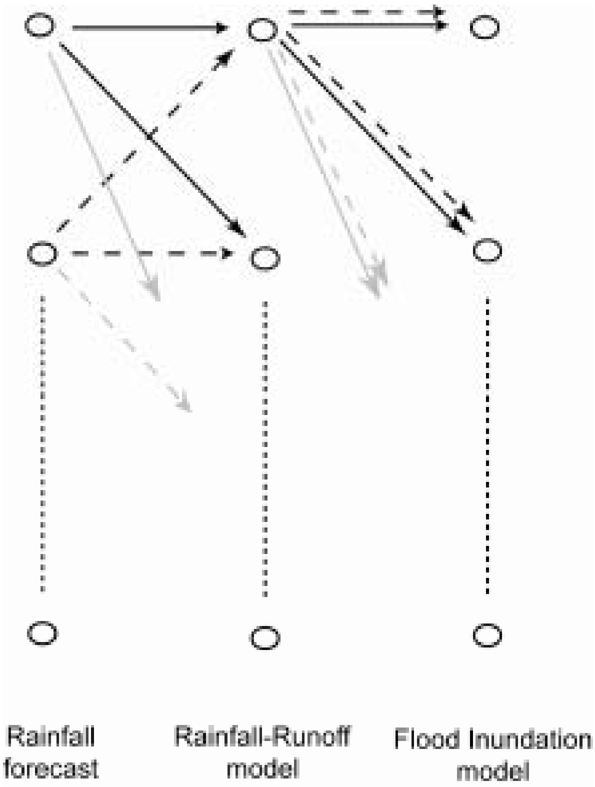


**Figure 3 Sketch which illustrates the uncertainty propagation and the implementation**
*Each empty circle presents one single model, with defined parameters/structure/etc. For example one rainfall forecast is fed into several implementations of rainfall-runoff models and all the results are the input for several defined flood inundation models.*

Assuming that the rainfall forecasts can be provided on a continuous basis, this may be computationally feasible given, say, a large parallel PC system. However, using distributed models in such a task does demand very significant computational resources even when the analysis is run off-line (so that time is not critical) rather than in real time. There are two ways of resolving this computational problem. One would be to simplify the runoff generation and flood wave routing models for example using the type of transfer function models explored in [137, 138]. The other is to reduce the number of runs required. The latter approach has been taken in the Pappenberger et al. application to the River Meuse by using the concept of functional similarity of parameter sets.

In the Meuse study 52 ECMWF ensemble rainfall forecasts are used as inputs into the rainfall-runoff model, which is represented by a large number of parameter set realisations. The ensemble forecasts are of unknown probability (assumed to be of equal prior probability) but likelihood weights can be determined for the combined rainfall and flow forecasts by comparing observed and predicted discharges at the different flow gauging stations.

The idea implemented in this study is to classify those simulations that are retained as behavioural into different functional types, and use only representative parameter sets for each functional type in the forecasting. To implement this procedure, the behavioural hydrographs predicted for a calibration data set by the rainfall-runoff model at a given point on the river network (here the head of the reach for which hydraulic modelling is undertaken) have been classified by cluster analysis. The classification method is described in more detail in Pappenberger and Beven[84]. Each class of behavioural hydrographs can then be represented in prediction by a single (or small number of) models, weighted by the sum of likelihood weights of all the behavioural parameter sets in that class.

It was found that 6 classes could be used to represent the rainfall-runoff model responses. The likelihood weighted outflow hydrographs of the 52*6 realisations builds the upstream boundary condition for the inundation model, which is again represented by a certain number of parameter sets. It is possible to construct predictive percentiles from these realisations (Figure 4).

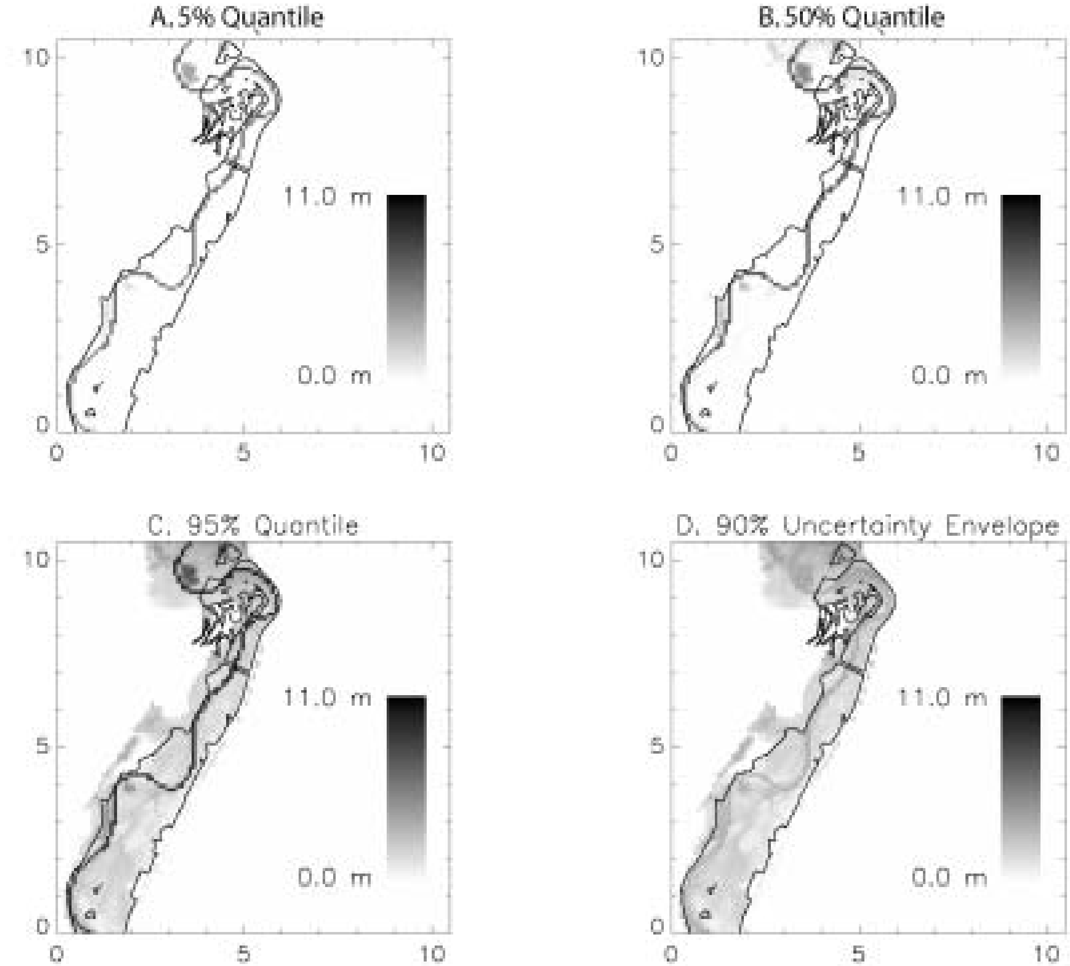


**Figure 4 Predicted water levels (grey scale)**
*The 5%, 50% and 95% prediction quantiles are shown as well as the envelope between the 5 and 95% quantiles. The mapped inundation is indicated by a dark black line.*

### *2.5.2 Example 2: From flood frequency to damage estimation (from Apel et al. [139])*

Other examples of model cascades and uncertainty routing have been presented. For example Apel et al.[139] developed a stochastic flood risk model which cascades uncertainties through a flood process chain from precipitation, runoff generation and concentration in the catchment, flood routing in the river network, possible failure of flood protection measures to economic damage. All these models provide descriptions of the processes at different scales and complexity. As at the first example, it has been not possible to compute the uncertainty fully due to the high CPU demand of each component. Therefore, the model components have been simplified and the simplified model chain calibrated and parameterized on results of the complex deterministic one (Figure 5). This allows the occurrence for events of different magnitude to be computed and linked to economic damage estimates. Moreover, the contributions of each component to the overall uncertainty has been traced.

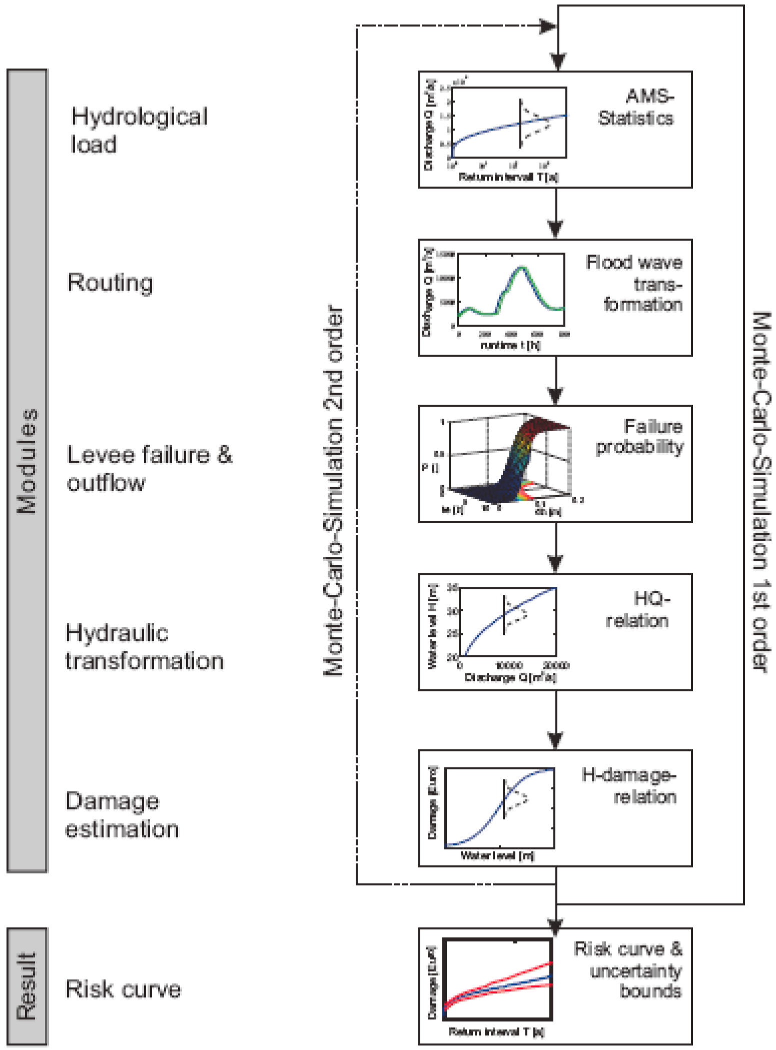


**Figure 5 Schematic of the risk and uncertainty calculations (by Apel et al [139])**

### *2.5.3 Example 3: From weather forecast to river stage (in realtime, the Bayesian Forecasting system – from Krzysztofowicz [140])*

Of further interest is the Bayesian forecasting system (BFS) by Krzysztofowicz which produces a short- term probabilistic river stage forecast. It is based on a probabilistic quantitative precipitation forecast and has three structural components: the precipitation uncertainty processor, the hydrologic uncertainty processor, and the integrator. A series of articles[140-144] described the Bayesian forecasting theory and detailed each component. The concept can be easily extended to other model cascades (e.g. similar to example 2).

The precipitation uncertainty is based on the total basin average precipitation and quantified in a probability distribution. The hydrologic uncertainty processor aggregates all uncertainties from sources other than the basin average precipitation. The system is structured in two components of the hydrologic model. One component maps precipitation uncertainty into output uncertainty under the hypothesis that there is no hydrologic uncertainty. The other components quantifies hydrologic uncertainty under the hypothesis that there is no precipitation uncertainty (the latter step is not done in real time). The distributions for both steps are combined in an integrator. Figure 6 presents a simplified version of that process (after fig 1 in [141]).

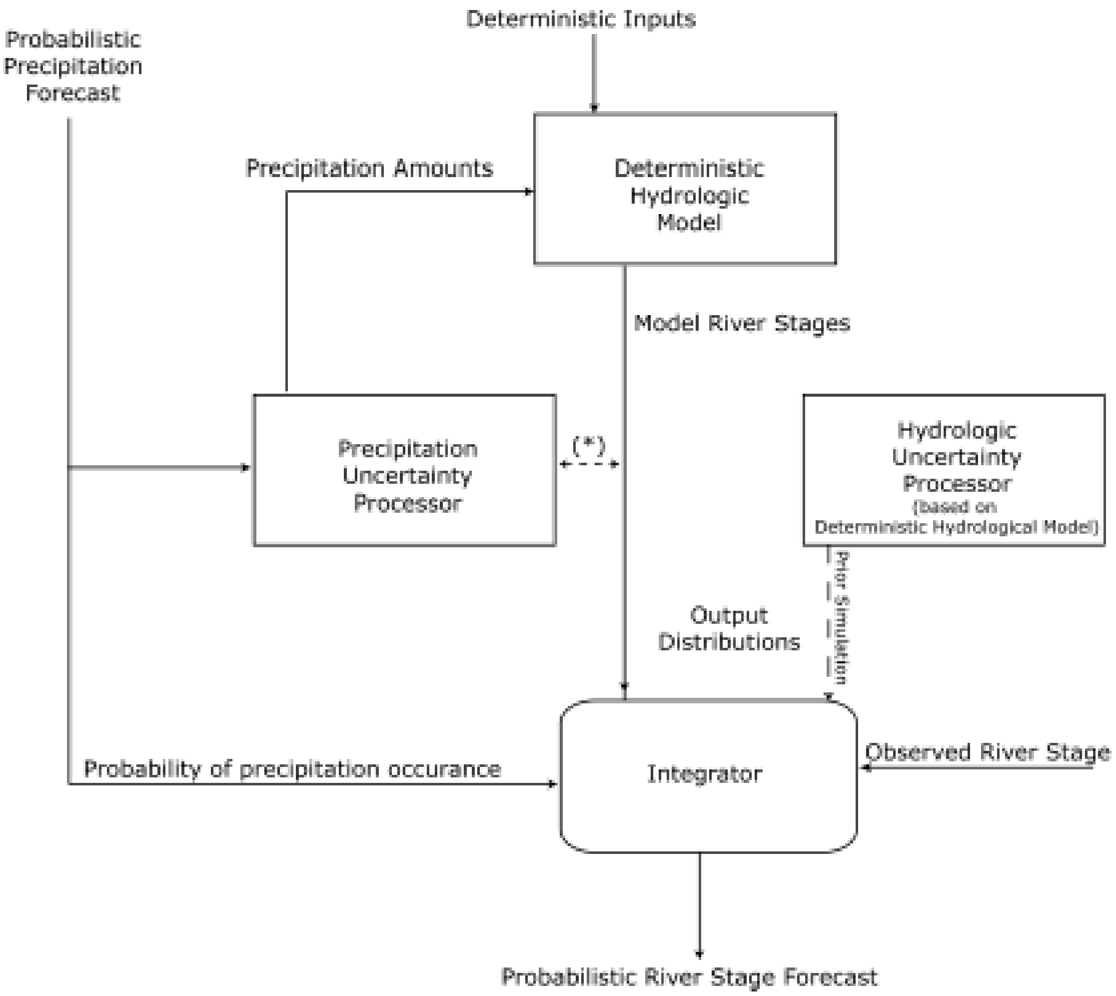


**Figure 6 Simplified sketch of the Bayesian Forecasting system after [141]. For a more detailed version including explanations for (*) the reader is referred to figure 1 in [141]**

This system is in several ways different from example 1 and 2:

- Only one deterministic model is driven by the probabilistic forecast, whereas the system in example 1 used several functional classes. Therefore BFS assumes that the uncertainty in the non-linear interaction between rainfall and runoff model is not dominant.
- Rainfall (predicted or measured) is the dominant source of uncertainty. The importance of rainfall uncertainty may vary with the lead time. Long term forecasts are more likely to be influenced by rainfall uncertainty than short lead times.
- Strict distributions for the different processors have to be assumed beforehand. These assumptions can be modified if necessary. In contrast the GLUE-cascade assumes the stationary of functional classes, but has less strict assumptions of the distributions.

## *2.6 SUMMARY OF CHAPTER 2*

Risk and uncertainty analysis is one of the main topics in current research. This chapter outlines the context of risk and uncertainty analysis used in this report.

### *2.6.1 Risk*

Some of the many definitions of risk appropriate to flood risk management have been listed. For this report we will define risk broadly as a combination of a particular event (probability or possibility) with the impact the event would cause (consequence). Risk estimation requires quantification of both he probability or possibility of an outcome and the estimation of the consequences of that outcome. Both will be subject to uncertainty.

In many cases of interest to flood risk management the concept of probability can be contested. It is shown on the example of event probability, that several assumptions are necessary to derive return periods and that each of these assumptions can be questioned. The quantification of consequences is also difficult and has to include consideration of uncertainty. For example is it impossible to assign a single cost to likely flood damage a housing estate based on the estimations of an average household and some uncertainty will be inherent in quantification of consequences of a flood of a given magnitude in a model of damage based on the limited data available. This leads to the discussion of uncertainties.

### *2.6.2 Uncertainty*

Various sources of uncertainty are listed and illustrated with examples. Uncertainty sources are broadly divided into uncertainties through model structure, scaling / resolution, parameters, topography and boundary conditions. Another important factor in any uncertainty analysis is how the model performance is evaluated. The quality and quantity of available data are at least as important as the subjective choice of a performance measure. Examples of evaluation measures in the literature range from measures including traditional statistical assumptions about the error structure to more unconventional fuzzy-like representations. It is argued that no objective function is superior to another *a priori* and that any model evaluation should be done depending on the modelling goal. Fundamentally, there is an unresolved problem of linking field measurements to catchment responses. For example, many variables predicted by models are not the same quantity as their measured ‘equivalents’ despite being termed in the same way. Such discrepancy can be due to heterogeneity, scale effects, nonlinearities or measurement techniques. A soil moisture variable, for example, might be predicted as an average over a model grid element several metres in spatial extent and over a certain time step; the same variable might be measured at a point in space and time by a small gravimetric sample, or by time domain reflectrometry integrating over a few tens of cm, or by a cross-borehole radar or resistivity technique, integrating over several metres. Only the latter might be considered to approach the same variable as predicted by the model, but may itself be subject to a model inversion that involves additional parameters in deriving an estimate of soil moisture

The following steps are suggested as essential to modelling risk and uncertainty:

1. *Define what is uncertain in your model (Sources of Uncertainty)*
   The various sources of uncertainty have to be identified and quantified, including uncertainties in quantifying the consequences of an outcome for risk estimation. A methodology has to be chosen according to which sources of uncertainty are considered.

2. *Define how to quantify output uncertainty (Model performance) including, as often necessary, the propagation of uncertainty through a cascade of predictive models*
   Many uncertainty methods require a definition of model performance (e.g. how well does a model compare to measurements). Such performance can be evaluated in different ways, which will have impact on the outcome of the uncertainty analysis.

3. *Define how to condition uncertainties on available data*

# 3. Implementing software for uncertainty and risk analysis

In this chapter we discuss the implemention of risk and uncertainty analysis techniques in software. We consider what is needed of such software and highlight the shortcomings of existing tools and software frameworks. We find that while it is possible and valuable to retrofit existing software with uncertainty analysis facilities, such an approach necessarily limits the types of analysis which can be conducted. Providing full software support for a risk-based approach to decision making requires the development of a new class of tools.

Following some preliminary comments, in section 3.4 we set out a set of basic requirements for an uncertainty and risk analysis framework. Two existing frameworks are then compared against this reference in section 3.5. Neither of these was explicitly designed to support general uncertainty analysis, and both have shortcomings in this regard.

Much of this chapter is derived from Harvey et al. [145]. That report should be consulted (available at the FRMRC web site http://www.floodrisk.org.uk/ for a more complete analysis of the issues discussed here. It also presents a preliminary design for a computational engine capable of meeting the requirements set out below.

## 3.1 TAKING A BROAD VIEW

We must recognise that it is support for *risk-based decision making as a process* rather than simply the implementation of computational uncertainty and risk analysis techniques which is our ultimate goal. This sets the boundaries of our analysis very wide, and necessarily so. Software implementing the computational aspects of these processes will ultimately be but one part – albeit a very significant one – of a much larger overall system. In designing such a system we must acknowledge the fact that risk-based decision making is a fundamentally human, social process, and support it as such.

Such support, for example, could be provided by the deployment of tools for distributed collaboration in the context of shared virtual workspaces. The data- and knowledge-intensive nature of risk-based decision making will often require the participation of individuals from several organisations, making traditional centralised approaches to data and knowledge management inappropriate. Instead dynamic synchronisation of information (using secure protocols, and subject to access rules) will become increasingly essential.
The details of such future needs would be impossible to predict, and the task of meeting them does not fall entirely to the flood risk management community. It is possible to make predictions in general terms, however, and such predictions provide important constraints on the design of a more narrowly defined framework for uncertainty and risk analysis. Indeed the simple recognition that any framework should be able to operate as a component within a very wide range of systems introduces a set of design constraints. It would be unfortunate to create now a framework which, by failing to meet these constraints, was unfit to act as a platform for development even in the near future.

## 3.2 SOME COMMENTS ON CONCEPTS OF OPEN ARCHITECTURE

The Environment Agency has established a software strategy which defines "open architecture" as a desirable property of software systems. The goal of this strategy is to avoid vendor lock-in and to protect the Agency's investment in software from loss of value through premature obsolescence. The meaning of "open" in this context is "open to change", particularly "open to change by parties other than the original software developer".

Software can only be said to have open architecture *with respect to* some particular set of changes or types of change. Perhaps the most ubiquitous example of open architecture is the use of web browser plug-ins in Netscape (and now Mozilla and Firefox) and Internet Explorer to allow these browsers to display an open-ended range of document types. This plug-in facility renders web browsers open to extension in one or more of the following respects:

- Rendering of a block of data downloaded from the network can be devolved to a plug-in. Most commonly this involves drawing to the screen, although audio, for example, can also be "rendered" using plug-ins. The browser provides the plug-in an area of the screen to draw into and hands the data to be rendered to the plug-in as an unstructured stream of bytes.
- Keyboard and mouse activity within an area of the screen for which control has been passed to the plug-in can be forwarded to the plug-in.
- Plug-ins can trigger a range of browser actions such as loading a new web page.

With respect to the rendering of types of document which can be downloaded from a network, this facility provides infinite extensibility. With respect to anything else, it provides zero extensibility. In the context of the web browser, the role of which is to render downloaded data into a form accessible to a human user, this is very powerful, but it is nonetheless very limited. Multiple plug-ins can be active at one time, even multiple instances of a single plug-in (e.g. to provide multiple adverts on a web page), but no facility is available for multiple plug-ins to collaborate to generate extended behaviour.

In just the same way, every extensibility mechanism will support a very specific set of extensions. The fact that a system has the extensibility mechanisms which allow it to lay claim to the title "open architecture", then, offers no information as to whether any particular type of modification is supported. The corollary of this is that in order for any particular modification or extension to be supported by some software, it must be designed to support that modification or a class of modifications which includes it.
The web browser plug-in mechanism is a simple solution to a simple problem. The demands of software to support decision making using simulation and quantitative uncertainty and risk analysis lie at the opposite end of the complexity scale. The simple mechanism illustrates the basic elements of open architecture: independently developed pieces of code communicating via well defined interfaces. In more complex situations, such as that we face here, the design of these interfaces is a very difficult problem. "Open architecture" then becomes not so much a solution as the essence of the problem.

## 3.3 SOME COMMENTS ON CONCEPTS OF OPEN SOURCE SOFTWARE

Open source software (see Harvey[145] for an extended discussion of open source and its significance to hydroinformatics) is software which is released, with source code, under a license which meets a minimum specification laid down by the Open Source Initiative. These terms include the right of the recipient of the software to modify it and to distribute modified versions. In practice modifications are most commonly contributed back for inclusion in a future release of the original software rather than "branching" (starting an independent development branch from a common basis). Although the term "open source" was coined to carry this rather precise meaning, it is sometimes used more loosely to refer to software for which source code is available, regardless of the terms under which that code is made available. The term used increasingly widely in the flood risk management community for this more general concept is "open code".

If a piece of software is supplied with source code, it is possible, at least in theory, to modify it to any degree. This form of modification is neither the same as, nor in conflict with that supported by open architecture. Open architecture demands well defined, stable interfaces in order that independently developed components implementing those interfaces can be relied upon to interoperate. These components may be developed using open or closed source development practices, and may be supplied with or without source code.

## 3.4 FUNCTIONAL REQUIREMENTS OF A GENERIC SOFTWARE FRAMEWORK FOR RISK AND UNCERTAINTY ANALYSIS

### 3.4.1 Support all of the computations involved in uncertainty and risk analysis

By definition a generic framework should not only support the implementation of one or a small number of analysis techniques. It is therefore necessary to establish a general model of the calculations involved in a wide range of analysis techniques. Particular techniques can then be expressed in terms of these primitives.

### 3.4.2 Support extension with new uncertainty and risk analysis techniques

The framework must be open to the addition of new uncertainty and risk analysis techniques as modules. It is essential that these can be independently developed, and thus this is one aspect in which the framework must an “open architecture”.

### 3.4.3 Support the definition and execution of simulators

The primary purpose of this framework is to support the application of uncertainty and risk analysis techniques to simulators. The design of this framework must therefore allow for the definition and execution of simulators. Particular simulators may be implemented within the framework by “wrapping” legacy code.

### 3.4.4 Support extension with new simulators

The purpose of the framework is to allow generic analysis tools to be applied to any simulator, so as with analysis tools the framework must be open to independently developed simulator components.

### 3.4.5 Provide a standard interface to all inputs, outputs, and states of simulators

These simulators must expose their inputs, states, and outputs to analysis tools in a standard way. Any inputs, states, or outputs not thus exposed will be unavailable for analysis. The purpose of wrapping an externally defined simulator (see 3.4.2) is to expose the inputs, states, and outputs of the wrapped simulator in the standard form expected by the framework.

### 3.4.6 Support the generic implementation of updating algorithms

Algorithms which involve ongoing updates of some combination of inputs, states, parameters, and outputs, which are common in real time flood forecasting where incoming measurements of forecast variables are used to continually adjust forecasts and forecasting models. One example is the Kalman filter, which assimilates data and updates the states of simulators every time step. While a framework for uncertainty and risk analysis cannot be expected to enable the updating of states in simulators which are not defined using the facilities of the framework, it should do so for those defined within it.

In the context of traditional approaches to the implementation of simulators, this amounts to the splicing of additional processing into the time loop, processing which can make updates to variables in ways which are not well localised. This has the potential to raise many of the problems, such as reduced transparency and maintainability and increased susceptibility to bugs, which have led to the deprecation of the practice of using global variables. The requirement is then not just for a mechanism to make the implementation of such algorithms possible in a generic form, but for a mechanism which makes such generic implementations safe.

### 3.4.7 Support the nesting of analyses

Analysis tools will often need to be nested. Risk-based optimisation, for example, requires that optimisation tools are applied to a computation which already embeds simulation within a risk analysis. This implies that the inputs and outputs of analysis tools should be treated identically to those of simulators in order that other analysis tools can be applied to them. This together with 3.4.8

suggests that a single, uniform mechanism should support the composition of simulators and the definition of more general computations.

### 3.4.8 Support the definition of new computations as hierarchical combinations of simpler definitions

The computations involved in risk analysis can become extremely complex. Tools to manage this complexity will become increasingly important. Hierarchical composition is a key complexity management tool. At the same time rigidly hierarchical structures can be constraining; balance must be struck.

### 3.4.9 Support for use of legacy code

The legacy of existing code in use in flood risk management is large and represents an enormous investment. It is crucial that the value of this investment is maximised. This means that maximum opportunity should be ensured for the reuse of existing code.
Two comments should be made to this requirement. Firstly, the legacy code issue is one among many, and should not be allowed to dominate the design. The future must take precedence over the past. Secondly, the issue at stake is the maximisation of the value of an investment, *not* the blind reuse of as much code as possible. The decision regarding whether to reuse or rewrite may be difficult, and will come down to a cost/benefit analysis where both the costs and benefits may be difficult to assess.

### 3.4.10 Support use of legacy code with minimum intrusion

Different uses of code will require different levels of integration with a new framework. It should not be necessary to undertake an expensive, deep integration just to perform a sensitivity analysis against inputs and outputs which a legacy code already exposes. A range of levels of integration should therefore be supported. In the context of the comments to 3.4.9, the level of integration to be undertaken would be chosen to minimise cost/benefit.

### 3.4.11 Code reuse

Apart from the reuse of legacy code, the framework should be designed to encourage maximum reuse of code for components implemented within the framework.

### 3.4.12 Embeddability within other systems

The computations supported by this framework will be of great importance in a wide range of tools of different types. To maximise the value of investment in this framework, it should be designed as an embeddable component which can be built in to many different systems. Care must be taken to avoid assumptions which make it less suitable for use in particular situations (such as an assumption of batch operation, which may not be appropriate in a real time forecasting context).

### 3.4.13 Ability to treat computation definitions as data

Computation definitions, which may include simulators and analysis tools, should be available for manipulation as data to the degree possible and practical. Just as a human user may define a computation (equivalent to programming language source code), it should be possible for the system to “compute” code and compile and use it on the fly.  One restriction on this is likely to be commercial interests in hiding the structure of code, but restrictions should be the exception rather than the norm.

This facility has a range of uses, and is important in expressing some advanced forms of computation succinctly. Techniques such as Genetic Programming, for example, which can be used to search model spaces as well as the parameter spaces of specific models, require some form of support for the dynamic generation and use of computation definitions (roughly speaking, source code).

Model management systems, which will become increasingly important as the number of independently developed modules available grows, require at least course grained support for treating computation definitions as data in order that modules can be stored in a database and retrieved when desired.

### 3.4.14 Support for parameterised computation

Parameterised computation here refers to the ability to partially define a computation, the remaining part being provided as a parameter at run time. Generic support for treating model structure uncertainty by including a range of model structures in an analysis will build on this facility. Optimisation techniques such as GP require the ability to run simulations using simulators generated on the fly.

### 3.4.15 Support for creation and use of emulators

Even with easy access to high performance computing resources, the computational demands of some simulators may be prohibitive. In this situation a number of techniques exist which allow the full complexity simulator to be *emulated* by a reduced complexity component.

These emulators are emulators of specific full complexity simulators over particular parameter ranges. The relationship between emulator and emulated simulator, and to the simulator runs against which the emulator was established, are crucial information in understanding the meaning and limitations of the emulator. They should be automatically recorded when an emulator is established, otherwise the user is being left with the mundane task of expressing the same information twice (once to the software and once in documentation). In reality this is highly unlikely to happen reliably, leading to potentially dangerous misapplication of emulators.

If the information is automatically recorded, and further recorded in a formal way, then it can be used in user interfaces to provide advice to users about valid uses of an emulator, or warnings if uses are regarded as invalid.

### 3.4.16 Accommodate use in interactive, batch, and long-running modes

While much risk analysis work involves use of computational tools in interactive and batch modes, other systems, most notably flood forecasting systems, operate on a continuously updated basis. This latter “long-running” mode is also important to accommodate arrangements such as that of having continuously updated graphical displays while a time consuming computation is under way.

All of these styles of operation should be equally well supported.

### 3.4.17 Maintain appropriate independence between computational engine and user interface

Much work remains to be done in develop effective graphical representations; it is to be expected therefore that new representations of the same underlying data structures will be developed over time. Many representations of one data set are possible and useful, even simultaneously, so some level of decoupling between computation and display is essential. Different facilities for graphical display (and indeed for interaction) will be needed in the many larger systems within which this framework will be a component; in some, such as real time control systems, it may be that no such facilities are required. It will be increasingly common for computation to take place on quite separate computer systems from user interaction.

Computation and representation are in principle linked only through the data sets generated by one and displayed by the other. There is no reason why this separation cannot also be manifested in practice. Integration between user interface and computational engine in the experience of the user can be achieved while maintaining architectural separation.

### 3.4.18 Ability to connect with other tools and frameworks

It is important that any future uncertainty and risk analysis framework is able to make use of facilities provided by other software and be made use of in turn by that software. This means that consideration should be given to the ability to expose framework functionality in different ways, and to the ability to express the semantics of external systems in framework terms. The external software in question might include Geographical Information Systems and simulation frameworks such as the OpenMI (see section 3.7).

The extent to which this is possible is the extent to which the framework has a structure which is flexible enough to accommodate the more limited flexibility of the external tools of interest. Ideally it should be possible to express the limitations of such links with external tools in a formal manner.

### 3.4.19 Enable parallel and distributed programming

The computational demands of uncertainty and risk analysis can become very high. Parallel and distributed computing resources, including “grid” computing in its many guises, are becoming more widely available, but remain too difficult to use. It should be possible to deploy computations to a range of computing resources as appropriate “at the push of a button”.

## 3.5 AVAILABLE SOFTWARE FRAMEWORKS

A wide range of software exists which must be taken into account when considering developing future tools for uncertainty and risk analysis. Much of this is in the form of modelling systems or more rudimentary model implementations (simulators). A range of tools exist which implement uncertainty analysis methods. In general these two sets of tools are developed quite independently. Using them together will generally require some level of data file format conversion. Their implementation as separate tools with data input and output facilities and separate user interface and visualisations facilities limit the scope for bringing them together within a coherent integrated environment.

In recent years a number of software frameworks have emerged which aim to provide some level of modularity for process simulation. Of these the most relevant in the present context are the DELFT-FEWS framework, which provdes the basis of the UK National Flood Forecasting System, and the Open Modelling Interface (OpenMI) created by the EU FP5 project HarmonIT. In this section we discuss briefly the nature of these frameworks and their limitations with regard to uncertainty and risk analysis.

The conclusion to be reached from this analysis is that these frameworks are not an adequate basis upon which to implement generic uncertainty and risk analysis tools. This is not to say that an uncertainty and risk analysis framework developed within the FRMRC project should not integrate well with them, as it should with as much existing software as possible.

## 3.6 DELFT-FEWS/NFFS

### 3.6.1 Description

DELFT-FEWS is a flood forecasting system framework. It avoids committing to the use of particular types of model by implementing a novel architecture which allows the coordination of unmodified external simulation programs (here referred to as “modules”) to generate forecasts. A FEWS-based system will consist of a core, a set of simulator modules, and a set of configuration scripts. Among these scripts are “workflow” definitions which define the sequence in which the core should trigger external modules and what data should be passed to and retrieved from those modules.

FEWS provides a relatively high level of functionality in its core, but this functionality does not include any specific process simulators. In particular it implements a data store, and all data exchange between modules takes place through the core. Data exchange is via an adaptor, with each external module requiring a unique adaptor to convert back and forth between the published data encoding used by FEWS and the native encodings used by the module.

### 3.6.2 Limitations

There are a number of commendable features of the DELFT-FEWS approach, of which perhaps the most significant is the shift relative to traditional modelling systems from a model-centric to a data-centric design [146]. This might be regarded as the first step on the path which leads to the treatment of models as data mentioned in section 3.4.13.

On the other hand, FEWS was designed under a particular set of constraints which differ from those appropriate to the design of a longer term, more general solution to the problem of providing tightly integrated support for simulation and uncertainty and risk analysis. Its use of course grained integration of external modules and its lack of a “theory” of data limit the types of uncertainty analysis which can be implemented within it. FEWS would not be an appropriate place to implement a risk analysis framework.

FEWS is a flood forecasting framework, not a general modelling framework. As such, its strategy for enabling the use of external simulation tools is highly effective, but does not transfer well to the more general case, where it will often be necessary to integrate modules more intricately than at the scale of the whole time series.
The use of XML as an intermediate data format is entirely appropriate, and a similar approach could be devised in a more general framework for the purpose of loosely integrating external simulators. Again the use of XML is not universally appropriate however. The overheads involved in generating and parsing XML may become prohibitive. More importantly, the use of XML is only appropriate where data exchange through an external representation is otherwise already necessary. The use of file based data transfer of any time restricts a framework to course grained integration of components.

Certain types of uncertainty projection could be implemented within FEWS, though the question of the extent to which the core of FEWS would need to be modified to accommodate this remains open. Even with modification the architecture of FEWS would limit the range of techniques which could be implemented. It is unclear at present how FEWS would be extended to handle uncertain values natively. The XML format for time series data accommodate only time series of floating numbers. Grid data are stored in external (non-XML) formats with an XML description. Some external raster formats may be “repurposable” to carry uncertainty information (support for multiple spectral bands in the USGS BIL format could possibly be used for this purpose, for example) but they do not provide specific, general support for this.

Inputs and parameters the uncertainty in which might need to be taken account of are transferred in different documents formats. Some of these share an XML foundation, but not all. No uniform access to input and output values is available, so it is hard to envisage how truly generic uncertainty analysis components could be written which communicate using the current published interface of FEWS.

## 3.7 HARMONIT OPENMI

### 3.7.1 Description

The Open Modelling Interface (OpenMI) defined by the EU FP5 project HarmonIT is a mechanism for coupling simulators. The justification for this development, and in particular for its part funding by the European Union, lay in the needs of water managers faced with the implementation of the Water Framework Directive. The logic is that integrated catchment management requires integrated catchment simulators to enable the simulation of complex interactions between subsystems.

OpenMI differs from DELFT-FEWS in a number of significant respects. These differences derive from the goals of the two systems. The OpenMI core consists of little more than the definition of a set of interfaces. A number of support libraries are provided which are not regarded as part of the OpenMI itself. The OpenMI interfaces are defined as Microsoft C#/.NET object interfaces. Data exchange at run time takes place directly through these interfaces and does not involve exchange of data in an external encoding such as an XML vocabulary. External software can be "wrapped" to operate as an OpenMI module, but such software must be capable of support the OpenMI interface semantics or provide the facilities which allow the wrapper to do so.

This model of simulator coupling arose from the need to support exchange of boundary conditions during simulation. OpenMI modules are connected directly with each other and do not exchange data through a central framework. Feedback loops can be present, allowing some forms of implicit solution across module boundaries to be implemented.

### 3.7.2 Limitations

OpenMI is a significant development and support for it is likely to provide access to a wide range of modules, but it is not itself adequate as the basis for an uncertainty and risk analysis framework. As with DELFT-FEWS, a number of types of uncertainty handling can no doubt be implemented within OpenMI, but because OpenMI was not designed with this in mind it will be difficult to do so. Seyoum [147] for example has demonstrated that it is possible to implement an Ensemble Kalman Filter within the OpenMI, but doing so required writing considerable code where a full uncertainty and risk analysis framework should support simple configuration of components.

The most significant limitation of OpenMI with respect to uncertainty analysis is the lack of a theory of data which allows access to all inputs, outputs, and state variables for the purposes of the implementation of analysis or updating algorithms. The assumptions about the ways in which simulators will be used change substantially when uncertainty analysis is considered; it is highly unlikely that any framework not explicitly designed to support these uses will provide adequate support for them.

Section 3.4.7 draws attention to the need to nest analyses. If an uncertainty and risk analysis framework were designed which targeted the OpenMI interfaces, supporting this would require that the analysis tools themselves could be used via those interfaces. OpenMI interfaces are not sufficiently general for this. The core of the OpenMI data exchange interface is a function call, "GetValues".

A call to this function must provide as a parameter a time instant or time span for which the receiving module should generate and return values. The assumption embedded in this is that simulation time is the outermost computation loop which a module will implement. The corresponding return value type, the "value set" also embeds assumptions about the structure of the data being passed which eliminate the possibility of passing the multi-dimensional data structures which occur in uncertainty and risk analysis.

The requirement of using OpenMI that all modules should be integrated to quite a deep level supporting exchange of data at the time step level raises a significant barrier to entry. An uncertainty analysis framework which requires OpenMI compliance from simulators is therefore unlikely to stimulate the uptake of sensitivity and uncertainty analysis techniques which is required.

## 3.8 SOFTWARE IMPLEMENTATION STRATEGIES

### 3.8.1 Continue as at present

Many will continue to author self contained simulators and analysis tools as at present, achieving integration by exchange of files. Considerable software of this type is expected to emerge from the Flood Risk Management Research Consortium itself. Until an alternative is available, this strategy is the only one available.

### 3.8.2 Retrofit of existing frameworks for uncertainty and risk analysis

As discussed above in the cases of DELFT-FEWS and OpenMI, existing frameworks not designed to support general uncertainty analysis will at best be able to support some forms of analysis. The needs of risk analysis, particularly at the level aspired to in the PAMS project [148] go far beyond what is possible based solely on these tools. The complexity of constructing a framework capable of supporting risk analysis at this level in a modular ("open architecture") way is such that amounts to ab initio framework development even if integration with existing frameworks is a requirement.

The evidence from the development work reported in Harvey et al. [145] is that a sufficiently flexible risk analysis framework provides a superset of the capabilities needed for uncertainty analysis and simulation frameworks. As a result it should be possible to design bridges between any new framework and existing ones to allow the use of modules for those frameworks.

### 3.8.3 Refine the current approach of file-based data exchange

A range of external data encodings exist for environmental data. Few if any of these accommodate uncertain values. File exchange based integration would be greatly eased if this situation were rectified.

Unfortunately a full solution would require data encodings which were extensible to support different representations of uncertainty. Furthermore the ability to pass data sets of high dimensionality complete with machine-readable descriptions of the meanings of dimensions would be required for a full solution. Reaching this point would require much of the work involved in developing an uncertainty and risk analysis framework "ab initio", including getting to grips with the semantics of the data and ensuring sufficient flexibility and extensibility to enable future development.

### 3.8.4 Ab initio framework design and development

It can be argued that it is only by developing a full framework that the issues involved can be properly understood. The requirements for an external data encoding will not be entirely clear until this is done, for example. *No such software exists at present*. The problem of providing generic support for uncertainty and risk analysis, of allowing analysis tools as well as simulators to be constructed by combining components, is much more difficult than that of providing for the coupling of simulators alone.

As with any complex software there will be many possible designs for a framework for uncertainty and risk analysis, each with differing pros and cons. Harvey et al. [145] outlines one which promises to meet all of the requirements identified in section 3.4. Although early prototyping supports this promise, considerable further development will be needed to show the extent to which it can be realised. This will be pursued in the context of the Consortium and the EU FP6 FLOODsite project.

## 3.9 SUMMARY OF CHAPTER 3

Those implementing risk and uncertainty tools cannot at present take advantage of any supporting frameworks above the level of the programming language and libraries available to them. As a result, such tools are often implemented as self-contained applications which must be linked with the simulators which are to be analysed by means of data file exchange.

Some candidate frameworks exist for the modular construction of simulators. In general these do not treat values sufficiently uniformly for truly generic uncertainty analysis tools to be constructed. The requirements for risk analysis tools are even more severe, as the inputs and outputs of these tools must themselves be available for analysis; this means that a single unified framework is needed covering simulation as well as uncertainty and risk analysis.

The implementation of analysis tools for any particular existing framework would render them unusable with any other. Until such time as a framework exists which can act as a bridge between these various frameworks, there is no obvious way in which the implementation of analysis tools can be improved. An experimental framework which aspires to this goal is being further developed in FRMRC Work Package 9.2; in the meantime, it is expected that selected uncertainty and risk analysis methods will be implemented in ways consistent with software developments within the FRMRC community as required by the cross-cutting nature of this theme.

A review of available risk and uncertainty methods follows in Chapter 4. This will form the basis for the Catalogue of Risk and Uncertainty methods that will be a deliverable of this FRMRC Research Priority Area. Applications within the context of the other RPA areas will form the basis of a final summary of guidance to the use of the these tools.

# 4. Methods of Uncertainty Analysis

Any implementation report for risk and uncertainty methodologies has to consider which type of methodologies should be implemented. A vast number of different methodology exists and clear guidance is necessary to understand and apply the different methodologies.

This chapter will first list forward uncertainty propagation methods, which evaluate uncertainty and risk without evaluation data at hand. Evaluation data are all types of data which can be used to test the model performance. These methodologies will be extremely valuable in situations in which no data are available to evaluate the model performance. This is followed by a list of methods which can be applied if evaluation data are available. The third category which is considered, are real-time data assimilation methods. Finally, some comments about the qualitative assessment of the uncertainty associated with model predictions is provided, based on the recent implementation of such a system at RIVM in the Netherlands.

## *4.1 METHODS FOR SENSITIVITY ANALYSIS*

The problems encountered in Flood Risk Management often involve many sources of uncertainty and the propagation of uncertainty through a cascade of models. This then results in a problem of deciding how to reduce the dimensions of the problem to a manageable computational requirement. One way of doing so is to carry out a sensitivity analysis (SA) of the various components in the modelling problem with a view to deciding where effort in defining and reducing uncertainty should be concentrated.

SA tries to understand how the variations in the outcome are based on variations of inputs, whereas uncertainty analysis is supposed to concentrate only on the model output. This seems to be an unrealistic reduction of uncertainty analysis. Many uncertainty analysis tools deal with parameter identifiability, ambiguity or uniqueness (e.g.[128, 149]). Thus parameter understanding is important and sensitivity is inherit in most uncertainty algorithms. For example, every optimization algorithm optimizes on local sensitivities. On the other hand, plots which show model parameters *vs* model results in the form of a dotty plot do already include parameter sensitivity[135]. Depending on the form of sensitivity, one is interested it is either the top marginal distribution (is the surface flat or does it show an optimum) or the variation of an interpolated average. Therefore, one could argue that sensitivity analysis is a sister discipline to uncertainty analysis and thus should be included in risk and uncertainty tools.

### Further reading

**Saltelli, A., A. Tarantola, F. Campolongo, and M. Ratto**, *Sensitivity Analysis in Practice - A Guide to Assessing Scientific Models*. 2004, Chichester: John Wiley & Sons. [135]

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**Hall, J.W., S. Tarantola, P.D. Bates, and M.S. Horritt**, *Distributed sensitivity analysis of flood inundation model calibration.* Journal Of Hydraulic Engineering-Asce, 2005. **131**(2): p. 117-126. [151]

**Pappenberger, F., I. Iorgulescu, and K.J. Beven**, *Sensitivity Analysis based on Regional Splits (SARS - RT).* Environmental Modelling & Software, in press. [152]

**Oakley, J.E. and A. O'Hagan**, *Probabilistic sensitivity analysis of complex models: a Bayesian approach.* Journal Of The Royal Statistical Society Series B-Statistical Methodology, 2004. **66**: p. 751-769. [153]

## 4.2 METHODS FOR FORWARD UNCERTAINTY PROPAGATION

Forward Uncertainty Propagation methods propagate uncertainty using prior assumptions about the different sources of uncertainty without the use of additional evaluation data. The assumptions that need to be made normally include prior distributions for parameters and other inputs. No model evaluation is necessary to apply forward uncertainty propagation although forward uncertainty propagation is often applied to an optimal model after a calibration exercise or some "best estimate" model. It is evident that for nonlinear models the results of a forward uncertainty propagation will depend on the model assumed, as well as the prior assumptions about the parameter and input uncertainties.

### 4.2.1 Error propagation equations

**Description**

Error propagation equations combine two or more random errors together and propagate uncertainty according to a standard set of rules. For example, in the Manning equation:

$$V = \tfrac{1}{n}\left(\frac{A}{P}\right)^{\frac{2}{3}} S^{1/2} \qquad \textbf{Equation 1}$$

N: Manning Roughness
A: Area
P: Wetted Perimenter
S: Slope
V: Velocity

With the assumption that the Manning surface roughness, the area and the wetted perimeter are uncertain, the error could be quantified as:

$$\frac{\sigma_V}{V} = S^{1/2}\sqrt{\left(\frac{\sigma_n}{n}\right)^2 + \left(\frac{\frac{2}{3}\sigma_A}{A}\right)^2 + \left(\frac{\frac{2}{3}\sigma_P}{P}\right)^2} \qquad \textbf{Equation 2}$$

Standard rules for the error propagation equations can be found in many standard handbooks on statistics and measurement error analysis.

**Advantages**

- *Requires very little resources*
  Most computation can be performed on a piece of paper and requires only minimal computations.

- *Very Quick*
  There is no major additional computational burden involved besides the derivation of the error equation

**Disadvantages**

- *Assumes Gaussian and independent errors*
  In the basic version it is assumed that the error around the measurements is normal, which is not always the case in nature. For example, many thermostats measure temperature more accurately at room temperature than at low temperatures. In such a case the distribution would be skewed and non-gaussian. However, the method can be extended to allow for non-Gaussian distributions and covariance [154, 155].
- *Difficult to apply in complex calculations*

The more complex and non-linear the equations are the more difficult is it to apply all the rules for error propagation.

- *Assumes correct model structure*
  The error equations are based on the assumption that the underlying model is correct. However, for example, there is a large variety of alternatives to the Manning equation, for which this methodology could not take account for.

### Further reading

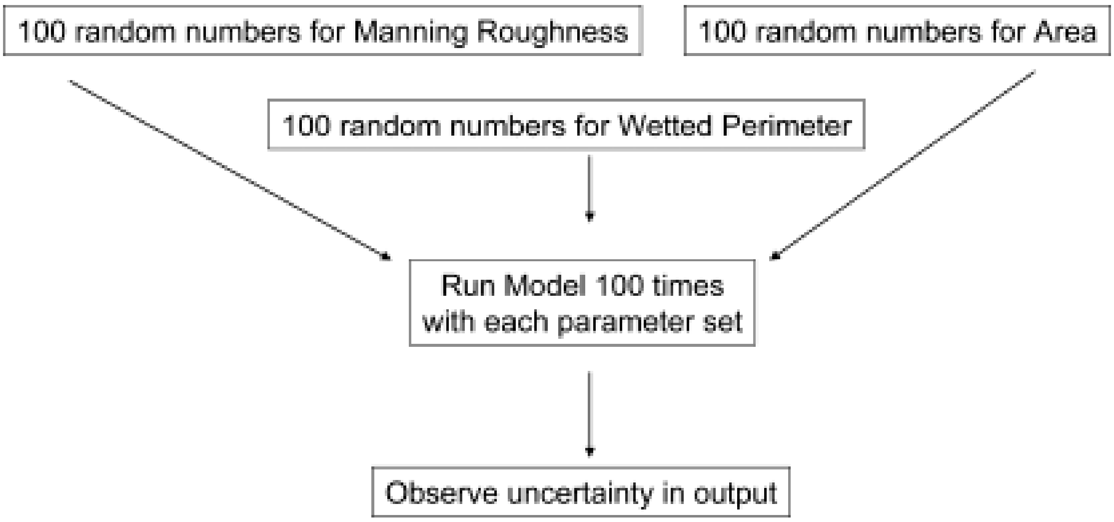
van der Sluijs, J., J. Risbey, P. Kloprogge, J. Ravetz, S. Funtowicz, S. Quintana, A. Pereira, B. De Marchi, A. Petersen, P. Janssen, R. Hoppe, and S. Huijs, *RIVM/MNP Guidance for Uncertainty Assessment and Communication*. 2003, University of Utrecht & RIVM: Utrecht. (download from http://www.nusap.net/)[156]

Benjamin, J.R. and C.A. Cornell, *Probability, Statistics, and Decision for Civil Engineers*. 1993, New York: McGraw. Hill. [157]

### *4.2.2 Monte Carlo propagation*

**Description**

A methodology which investigates a model by generating random numbers and observing the changes in the output. It is usually applied when a problem cannot be solved analytically. For our previous example, a research design could be:




There is a large number of packages available to perform such an analysis, including stand-alone packages and Excel add-ins, such as @RISK (www.palisade.com/), Crystal Ball (www.decisioneering.com/), SimLab (sensitivity-analysis.jrc.cec.eu.int ) and many others. It can be easily performed from any statistical software package such as Matlab or R. Many of these packages also allow for a more effective sampling design to for example distribute the random numbers evenly and avoid clusters.

### Advantages

- *Forces explicit acknowledgement of all sources of uncertainty*
  All sources of uncertainty have to be stated.
- *Can take account of any distribution and correlation*
  The method is not restricted to a specific set of distributions and can deal with all forms of correlation
- *Can include other sources of error*
  The methodology can virtually include all sources of uncertainty

- *Can be applied to complex models*
  Model complexity is not a limiting factor as in so many other methodologies.

## Disadvantagess

- *Computational intensive*
  The methodology is computational intensive and become infeasible with models which have a long run time or too many sources of uncertainty.

## Further reading

**EPA**, *Risk Assessment Forum, Guiding Principles for Monte Carlo Analysis, EPA/630/97/001, 1997.* 1997. [158]

**Morgan, B.J.**, *Elements of simulation*. 1984: Chapman & Hall. [159]

**Ripley, B.D.**, *Stochastic simulation*. 1978: Wiley[160]

### *4.2.3 Reliability methods*

Reliability theory deals with estimating the probability of failure of engineering systems. Reliability methods are conventionally divided into three levels [161]:

- Level 1 methods use specified quantiles of distributions and applying 'partial safety factors' to ensure that the probability of failure is sufficiently low. Level 1 methods are based on probabilistic principles but do not in practice require probabilistic calculations.
- Level 2 methods estimate the probability of failure analytically, based on first (FORM) or second order (SORM) approximations to the limit state function (the function separating 'failed' from 'non-failed' system states) and transformation of the basic variables of the limit state function to standard Normal space.
- Level 3 methods use Monte Carlo sampling methods to estimate the probability of failure. Because the probability of failure is small and its location in basic variable space can usually be approximated, importance sampling methods can greatly improve the sampling efficiency [162].

**Advantages**

- Application of reliability methods is essential in any flooding situation where the probability of flooding is modified by an engineering system which may fail under some circumstances.
- Reliability methods are well established and widely used in other engineering disciplines.
- Reliability methods explicitly deal with *systems* of engineering components and how they interact with each other.

**Disadvantages**

- Reliability methods calculate the probability of system failure. For flood risk analysis the probability of system failure may not be the main quantity of interest and it will often be necessary to estimate the probability of different combinations of failure modes [163]. Reliability methods can be adapted for this purpose.
- Because systems are usually designed to have low probabilities of failure and because failures are usually destructive unrepeatable events, there is no direct mechanism for validation of failure probability estimates.

**Further reading for reliability theory**

**Melchers, R. E.**, *Structural reliability analysis and prediction*. 2nd Edition, John Wiley & Sons, New York, 1999[162]

**Benjamin, J. R. and C. A. Cornell**, Probability, *Statistics and Decision for Civil Engineers*, McGraw-Hill, 1970[164]

**Ang, A. H-S. and Tang, W.H.**, *Probability Concepts in Engineering Planning and Design*, Vol. 2 - Decision, Risk and Reliability, John Wiley & Sons, New York, 1984[165]

### 4.2.4 Fuzzy and imprecise methods

One feature of uncertainty is the degree of precision with which a statement is made. Statements that are less precise contain less information. This notion of uncertainty is quite different to probabilistic uncertainty, which (according to the frequentist interpretation) expresses the relative frequency with which specified events will occur. Imprecision can be represented in mathematical terms using set-theoretic methods. For example, an imprecise statement about the outcome of the next throw of a six-sided dice would be that it will result on one of the outcomes in the set {1,2,3}. Fuzzy set theory extends this type of approach to the situation where it is not precisely defined whether a given outcome is in the set of interest or not. For example an assessment of the outcome of a given computer experiment being in the set of "behavioural runs" can be expressed with a fuzzy membership function between 0 and 1.

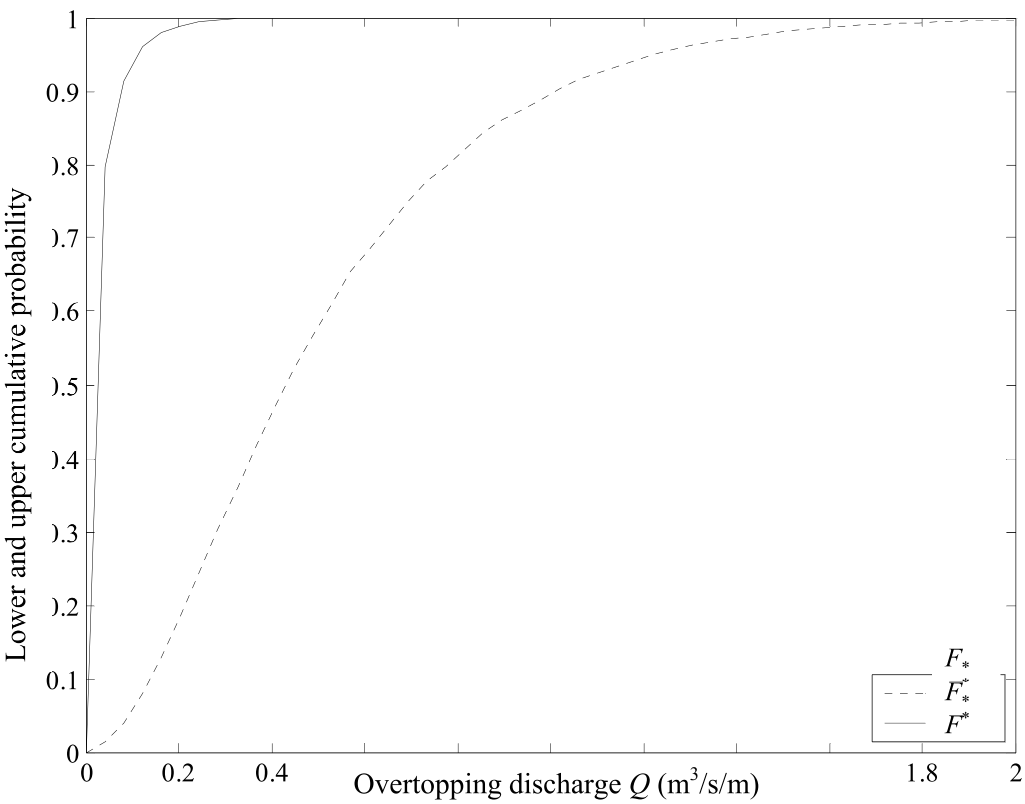



**Figure 7 Typical lower ($F_*$) and upper ($F^*$) cumulative probability distributions on overtopping discharge $Q$ from fuzzy and imprecise probability analysis (after Hall, 2002)**

A further extension of this approach is to deal with the situation where probabilities are not precisely known, which in practice is almost universally the case. The theory of imprecise probabilities [166] deals with sets of probability measures, or, more generally, sets of gambles. Indeed, Klir and Smith [167] illustrate how the theory of imprecise probabilities generalises classical probability theory and some interpretations of fuzzy set theory. A well justified theory of decision-making forms the basis of this approach.

In practice using fuzzy and imprecise methods in flood modelling involve propagating sets of intervals through a numerical model. A practical approach is described by Hall[168] and the references therein. The computational expense of this approach can be greatly reduced if there is some prior knowledge about the behaviour of the numerical model (whether, for example, its response is monotonic with given variables).

**Advantages**
- Able to represent the imprecision that is inherent in some (arguably most) information.
- Enables the exploration of robustness of decision options to imprecision in available knowledge.

**Disadvantages**
- A proliferation of alternative approaches and interpretations (particularly for fuzzy methods) some of which lack sound theoretical basis.

**Further Reading**
**Klir, G.J. and Folger, T.A**. *Fuzzy Sets, Uncertainty and Information*, Prentice Hall , New Jersey, 1988[169]

**Ross, T**, *Fuzzy Logic with Engineering Applications*, Wiley, 2004[170]

### *4.2.5 Info-gap methods*
Information-gap decision theory was initiated and developed by Prof Yakov Ben-Haim[171] and has its origins in the early 1980s in convex modelling of materials, mechanical and dynamical problems. A system model is parameterised so that system response to loading is represented by nested sets containing excursions of system behaviour. Of particular interest is the level at which system behaviour exceeds some failure criterion. In work with Isaac Elishakoff[172], Ben-Haim demonstrated how diligently applied probabilistic methods can result in disturbingly inaccurate estimates of the probability of failure of safety-critical systems, whilst convex analysis identified more reliable bounds on system behaviour [172]. This work was cultivated into a theory of non-probabilistic robust reliability [171] and subsequently into a complete theory of decision-making under severe uncertainty [173].

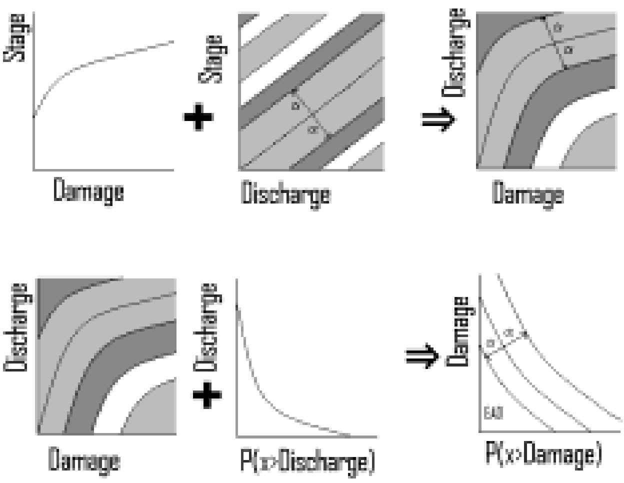



**Figure 8 Schematic of Info-gap expected annual damage calculation procedure (after Hine and Hall, 2005)**

An info-gap analysis has three components: a system model, an info-gap uncertainty model and performance requirements. The system model describes the structure and behaviour of the system in question, using as much information as is reasonably available. The system model may, for example, be in the form of a set of partial differential equations, a network model, or indeed a probabilistic model such as a Poisson process. The uncertainty in the system model is parameterised with an uncertainty parameter $\alpha$ (a positive real number), which defines a family of nested sets that bound regions or clusters of system behaviour. When $\alpha = 0$ the prediction from the system model converges to a point, which is the anticipated system behaviour, given current available information. However, it is recognised that the system model is incomplete so there will be a range of variation around the nominal behaviour. Uncertainty, as defined by the parameter $\alpha$, is therefore a range of variation of the actual around the nominal. No further commitment is made to the structure of uncertainty. $\alpha$ is not normalised and has no betting interpretation, so is clearly distinct from a probability.

Next, two contrasting consequences of uncertainty are introduced: 'catastrophic failure' and 'windfall success'. Two immunity functions, a robustness function and an opportunity function, describe the variation of $\alpha$ with the magnitude of the unfavourable and favourable consequences. Info gap theory therefore seeks to gain from favourable excursions in uncertain system behaviour as well as developing robust strategies that guard against the effects of unfavourable excursions. Excessive emphasis on failure can result in a loss of opportunity, but the two are not always mutually exclusive.

**Advantages**

- Provides a quantitative measure of the robustness of decision options to severe uncertainty.

**Disadvantages**

- Is not practical for dealing with multi-dimensional uncertainties where these cannot be reduced to one or two dimensions.
- No consistent scale or metric for comparing robustness from different info-gap models.

**Further Reading**

**Ben-Haim, Y**. *Information-Gap Decision Theory: Decisions Under Severe Uncertainty*. Academic Press, San Diego, 2001[173]

### 4.2.6 Questioning Forward Uncertainty Analysis

Forward feeding uncertainty analysis is based on no comparison against any measured data. It has to assume that all the approximations made are correct or negligible and that the methodology and model are a valid/reasonable representative of the real physical system. This assumption may be based on past performance within different set-ups or the hypothesis that the system is physically correctly represented. The arguments made earlier do question the fundamental possibility of such assumptions. Therefore, such analyses should be associated with a caveat that the results are conditional on the uncertainties assumed a priori. However, the methodology is vital in the model development phase as well as in conditions in which no or not enough measurements can be acquired. Moreover, in situation in reliability problems of unobserved or unrepeatable events it is the only alternative (see discussion in Hall and Anderson [174]. However, model evaluation and conditioning should be carried out whenever observations to check model predictions are available.

## 4.3 METHODS FOR MODEL CALIBRATION AND CONDITIONING UNCERTAINTY ON AVAILABLE DATA

There are two fundamentally different approaches to model calibration and conditioning given observational data. The first is based on treating model error as an additive term to the model prediction:

$$Y(\underline{x},t) = M(\underline{\theta}, \underline{x}, t) + \varepsilon(\underline{x}, t)$$

Where Y is an observed values, the function M represents a model variable predicted using parameter set $\underline{\theta}$, ε is an error, $\underline{x}$ is space and t is time. Formal statistical assumptions about modelling errors are of this type and may involve additional parameters (such as bias and variance) in the error model ε(). Multiplicative errors can be treated in the same way by using log values of the observations and model predicted variables. The error model is normally evaluated using predictions based on some "optimal" parameter set. This is the basis of the regression (Section 4.3.1) and Bayesian (Section 4.3.2) methodologies described below. In some studies, the evaluation of uncertainties around an optimal model is carried out after optimisation, rather than as an intrinsic part of the model calibration process.

The second approach rejects the concept of an optimal model in favour of the equifinality concept of allowing for multiple acceptable models. It is a rejectionist approach, in that only those models considered to give acceptable predictions in calibration will be retained for use in prediction. The errors associated with the predictions of a particular parameter set are treated implicitly in that it is assumed that the structure of the errors found in calibration (in all their complexity) will be "similar" when that model is used in prediction. This is the basis of the GLUE approach (see section 4.3.3 below). In this approach, informal model performance measures can be used to decide whether a model is retained (but can use formal error assumptions as a special case, treating the parameters of the error model as additional parameter dimensions).

### 4.3.1 Linear/Nonlinear Regression

**Description**

Non-linear regression techniques stem from the consideration of the hydrological model as a regression function and need for improved computation techniques due to the bias introduced by Standard Least Squares (SLS) parameter estimation [175] caused both by input uncertainty and the non-linearity in the model. In general the techniques works by specifying a likelihood function relating the model output and observed data series. The likelihood function selected is often based on time-series analysis [176]. Two schools of computational techniques exist. The first school implements Bayesian inference schemes to derive posterior parameter distributions from which samples are generated [76, 78, 177, 178]. In some cases the sampling algorithm is deigned to highlight aspects of the data set, for example the information content of the data [179]. The second school aims to find the Maximum Likelihood Estimator (MLE), often through the use of a Gauss-Marquard-Levenberg methodology [180]. The parameter uncertainty around this MLE can be approximated by linearization techniques or regularisation [180]. It ahs also been shown [105] that with a carefully chosen likelihood function that the posterior distribution can be calculated in close form for little computational cost.

**Advantages**

- Many tools available for analysis;
- Computational complexity can be tailored by the selection of the likelihood function (error model);
- Potential for the representation of the uncertainties in a posterior distribution.

**Disadvantages**

- Without strong assumptions as to the likelihood function computation may be expensive, especially for large numbers of unknowns;
- Different sources of error are not explicitly represented;
- Assumptions about the likelihood function are hard to justify in terms of beliefs about the sources of error.

**Further reading**

**Doherty, J.**, 2002. *PEST Model-Independent Parameter Estimation*, http://www.sspa.com/pest/download.html[181]

**Poeter, E.P. and Hill, M.C.**, 1999. UCODE, *A computer code for universal inverse modeling*. Computers in Geosciences, 25(4): 457-462[182]

**Clarke, R.T.**, 1994. *Statistical modelling in hydrology*. Wiley & Sons, Chichester, xii,412p. [183]

**Thiemann, M., et al.**, *Bayesian recursive parameter estimation for hydrologic models.* Water Resources Research, 2001. **37**(10): p. 2521-2535

**Box, G.E.P. and G.C. Tiao**, *Bayesian inference in statistical analysis*. 1973, Reading, Massachusetts: Addison-Wesley.

### *4.3.2 Bayesian Methods*

**Description**

Bayesian Methods cover a very broad class of methods based on Bayes equation in which the posterior probability of an outcome is proportional to the product of a prior probability and a likelihood measure evaluated with respect to some observation. Bayesian Statistics is now the dominant paradigm in statistical inference, even for cases where prior probability distributions are poorly known and subjectively chosen. Bayes equation also provides a method of sequential updating as more observational data become available (see Section 4.4.4 Sequential Monte Carlo methods). The GLUE methodology (Section 4.3.3) can also be interpreted as a Bayesian method when used with a formal likelihood measure (noting that Bayes equation does not preclude the use of subjective likelihood measures, though the resulting posterior will then not provide a formal estimate of the probability of predicting an observed value conditional on the model). For simple cases (e.g. Gaussian prior distributions and a likelihood based on a Gaussian error model) Bayes equation can be applied analytically: for more complex cases, particularly where prior distributions about model inputs and parameters are processed by a nonlinear model function, approximate numerical methods must be used to calculate the posterior distribution. This is essentially a problem of estimating the shape of the likelihood surface in the multiple dimensions of the uncertain variables (model structures and parameters and/or inputs). Much current work on evaluating such likelihood surfaces is based on Monte Carlo Markov Chain (REF) or Importance Sampling (REF) techniques. To speed up this process for models that have very large numbers of parameters or long run times, there is research on model emulation techniques under development (e.g.[153, 184, 185])

The two critical components of a Bayesian method are the choice of the prior distributions and the choice of a likelihood function or measure. The likelihood function is usually based on a model of the error structure, which might include a component to allow for model structural error (e.g. Kennedy and O'Hagan[186]). Given valid assumptions about the nature of the errors, application of Bayes equation will then provide an estimate of the probability of predicting an observation conditional on the model, which can be presented as prediction quantiles for an predicted variable. As more data become available, continued application of Bayes equation should refine these estimates.

**Advantages**

The method results in an estimate of the probability of predicting an observation conditional on the model, if the error assumptions are correct. Given a residual error series, these assumptions can be tested. Integrating over the likelihood surface can also give marginal distributions for particular parameter values. Multiple model structures can be included within the Bayesian framework.

**Disadvantages**

The method requires prior distributions to be specified for all uncertain quantities, which are often poorly known (especially for "effective" parameter values required by a particular model structure). The method is often applied as if the input data and model were correct or with unrealistic assumptions about the nature of the residual errors. This can lead to overconfidence in the estimates of parameter values, or to model errors being compensated by large residual variances (see, for example, the application of a sequential Bayesian methodology to the calibration of a hydrological model in the paper of Thiemann et al.[76] and the resulting discussion by Beven and Young[83]). In some circumstances it may be difficult to define an appropriate likelihood function, because the nature of the errors is complex (e.g. showing non-Gaussian behaviour, changing form of distribution, or non-stationary variances). Some of these problems might be overcome by suitable transformations, where, for example, non-stationarity can be related to some other variable.

**Further reading**

**Bernardo, J.M. and Smith, A.F.M.**, *Bayesian Theory*, Wiley: Chichester, 1996.[187]

**Congdon, P**, *Applied Bayesian Modelling*, Wiley, Chichester, 2003[188]

**Howson, C. and Urbach, P.**, *Scientific Reasoning: the Bayesian Approach*, Open Court: LaSalle, IL. 2nd edn 1994[189]

**Lee, P.M.**, *Bayesian Statistics, An Introduction*, Arnold:London, 3rd Edition, 2004.[190]

**O'Hagan, A.**, *Bayesian methods in Asset Management* in V Barnett and K F Turkman, Statistics for the Environment 2: Water Related Issues, Wiley: Chichester 1994, 235-248[191]

**Romanowicz, R, Beven, K and Tawn, J**, *Evaluation of predictive uncertainty in nonlinear hydrological models using a Bayesian approach*, in V Barnett and K F Turkman, Statistics for the Environment 2: Water Related Issues, Wiley: Chichester 1994, 297-318.[192]

### *4.3.3 GLUE methods and Extended GLUE (rejectionist) methods*

**Description**

The original development of the Generalised Likelihood Uncertainty Estimation (GLUE) methodology [193] arose out of a dissatisfaction with an optimisation approach to model calibration and with the assumptions of statistical models of "measurement error" in representing model uncertainties. Arguments in favour of the GLUE approach have been rehearsed elsewhere [61, 63, 83, 194].

As noted above, GLUE allows that multiple models may provide acceptable simulations of the response of the system of interest. A search for acceptable models is generally made by uniform random sampling of the parameter space, assuming that upper and low limits for each parameter can be specified. For models with significant run times, this is only generally possible for a small number of parameter dimensions.

In GLUE, modelling errors associated with each acceptable model are treated implicitly, under the assumption that error series associated with a particular model (such as over- or under-prediction of flood peaks) will be similar in prediction to those found in evaluation or calibration. Each model can be given a likelihood weight to express relative belief in that particular model, based on the evaluation of the model performance for a calibration data set. Informal likelihood measures can be used in deciding on model acceptability, and in determining likelihood weights. Models that are rejected during calibration will have a likelihood of zero and need not be used in prediction. Different model structures, as well as different parameter sets in a particular model structure, are easily combined within this framework.

As more data become available, a variety of methods can be used to combine likelihood measures, including Bayes equation, fuzzy operations, averaging and other methods. Recently [63] the method has been extended to be more rejectionist in approach by allowing that, to be retained for use in prediction, a model must provide predictions that lie within the range of some "effective observational error" defined prior to making any model runs (rather than by a measure based on a residual series).

Approaches based on formal statistical error model structures can be considered to be special cases of GLUE in which the modeller is prepared to make strong assumptions about the nature of the errors and for which additional parameter dimensions for the error structure are added (e.g. Romanowicz et al., [72]). In this case, however, if there is a well-defined likelihood surface, uniform Monte Carlo sampling may not be an efficient way of sampling for behavioural models and other approaches (such as Bayesian Monte Carlo Markov Chain methods) should be considered.

The application of GLUE requires a number of choices as follows:

- Choice of one or more model structures to be considered
- Choice of ranges for each parameter values (including error model parameters if included)
- Choice of sampling strategy for searching the parameter space (e.g. discrete interval sampling, uniform random sampling, latin hypercube sampling, importance sampling)
- Choice of likelihood measure or measures for model evaluation, including criteria for model rejection

**Advantages**
- Allows for equifinality in model structures and parameter sets, which may mitigate against an optimised model being overparameterised when used in prediction.
- Many different types of performance measure
- Subjective assumptions in applying the method must be made explicit and can be assessed.
- May result in all models being rejected as nonbehavioural, leading to review model structures or data sets.

**Disadvantages**
- The method has been criticised for its lack of formal assumptions in assessing the likelihood of different models, leading to subjectivity in its approach.
- May require high performance or parallel computing resources to obtain sufficient samples of acceptable models from the full range of potential models
- Whether a model produces acceptable simulations or not may depend on (unknown) error in input and boundary conditions.
- May result in all models being rejected as nonbehavioural (unless an explicit error model is added to compensate for other sources of error).

**Further reading**
A summary of the GLUE approach is given in Beven [19] (see also www.es.lancs.ac.uk/hfdg/glue.html). There have been a variety of applications to rainfall runoff modelling (e.g. [111, 193, 195]); flood inundation modelling (e.g. [87, 196, 197]); and flood frequency analysis (e.g. [86, 198, 199]). The extended GLUE methodology is described in Beven [63].

## 4.4 METHODS FOR REAL TIME DATA ASSIMILATION

The most important issue in real time flood forecasting is to allow for the fact that in any prediction event there will be departures between observations of water levels or discharges and predicted values. Any real time forecasting system should therefore allow for an updating or data assimilation strategy, with a view to minimising the uncertainties in the updated predictions. This will be possible in real applications as long as real time observations can be made available to the forecasting system, e.g. by telemetry. A number of data assimilation strategies are available, depending on the assumptions that the modeller is prepared to make.

### 4.4.1 Kalman Filter

**Description**
The Kalman Filter (KF) was introduced by Kalman [200] as a new approach to discrete data linear filtering using state space methods, in other words, the estimation of the state of the system on the basis of noisy measurements considered as a linear combination of state variables. The solution is in the form of a recursive algorithm that, given the state space model of the system, provides an estimate of the state at each sampling instant that is optimal in a least square sense. The KF estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains

feedback in the form of (noisy) measurements [201]. The equations for KF form two groups: time update equations, called also *predictor* equations, and measurement equations, called *analysis* or *corrector* equations. The time update equations project forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations perform the feedback – i.e. incorporate a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

**Advantages**
The advantages of KF are: it is powerful, fast, supports estimation of past, present and future states, its disadvantage is that it is applicable only to linear or nearly linear problems. It is interesting to note that the derivation provided by Kalman applies to arbitrary random signals, described by up to a second order average statistical properties and does not assume Gaussian properties of the states.

**Disadvantages**
The process and/or the measurement relationships must be linear.

**Further reading**
Extensive information about KF can be found on a web page http://www.cs.unc.edu/~welch/kalman/. There are many books written and applications are numerous in many different subjects, from engineering, computing to biological and environmental sciences. Apart from the literature cited above, Young [202], Harvey [203] and Brown and Hwang[204] are recommended for general reading on KF and methods of recursive estimation.

### *4.4.2 Extended Kalman Filter*

**Description**
In the extended Kalman filter (EKF) for nonlinear systems [205], approximate expressions are found for the propagation of the conditional mean and its associated covariance matrix. The structure of the propagation equations is similar to those of the classic Kalman filter for a linear system, as they are linearized about the conditional mean. In high-dimensional problems (such as storm surge forecasting or coastal models) the EKF often has to be simplified by a suboptimal scheme for reduction of the computational burden.

**Advantages**
EKF may be applied to estimation of nonlinear multidimensional systems with small non-linearities. This method handles well small non-linearities. It has been successfully applied to the land data assimilation problem[206, 207]; as well as in 2D hydrodynamics and oceanography[208, 209].

**Disadvantages**
EKF is rather inefficient in case of very nonlinear systems as explained in Julier and Uhlman[210]. Moreover the method is not suited for large dimension systems, as the calculation of the derivatives, using a finite difference method, demands n + 1 model evaluations for each time step (n is the dimension of the state vector), and q + 1 evaluations of the observation operator (q is dimension of the observation space). The other possibility is to write a tangent linear model, but it is generally difficult for complex models or impossible for highly non-linear models. The derivation of a tangent linear model to approximate a complex system may be very tedious, as well as techniques to treat the instabilities which might arise from such an approximation. [211]

**Further reading**
The basic discussion and derivation of the EKF is given by Jazwinski [205] and Gelb[212]. A very good discussion on data assimilation techniques and their applications in environmental problems is given by Bertino et al. [213]. General introduction to EKF is given by Decourt [214].

### 4.4.3 Ensemble Kalman Filter

**Description**

The Ensemble Kalman Filter (EnKF) was developed by Evensen [215] as an alternative to the Extended Kalman Filter (EKF) approach. The EnKF is the adaptation of the Kalman Filter (KF) model to non-linear systems using Monte Carlo sampling (in the propagation step) and linear updating (correction or analysis step). In the ensemble Kalman filter (EnKF) an ensemble of model states is integrated forward in time using the nonlinear forward model with replicates of system noise. At update times, the error covariance is calculated from the ensemble. The traditional update equation from the classical Kalman filter is used, with the Kalman gain calculated from the error covariances provided by the ensemble. It has been applied to rainfall-flow modelling by Vrugt et al. [216] and Moradkhani et al.[80].

**Advantages**

The advantages of the EnKF are as follows: any model can be used; model does not need to be differentiable; noise can be placed anywhere, for example, on uncertain parameters and forcing; noise can be non-Gaussian and non-additive; uses all data in a batch window to estimate the state.

**Disadvantages**

Estimates are conditioned on past measurements only and it uses a linear analysis step. This may lead to physically non-feasible solutions of the propagation step (e.g. negative flow). Another problem – is that it is computationally intensive, requiring many Monte Carlo realizations at each propagation step. Moreover, due to the high complexity of these approaches, there may be questions about the identifiability of parameters involved in the different aspects of the applied routines (e.g. the choice of the variance during the state and parameter estimation processes).

**Further reading**

A good description of the method may be found in Bertino et al [213] and Evensen [215].

### 4.4.4 Sequential Monte Carlo Methods

**Description**

Sequential Monte Carlo (SMC) Methods fall into two groups, those aimed at sequential data assimilation (commonly referred to as particle filters) and those designed for generating samples from stationary distributions[217]. In general SMC methods aim to approximate the distribution of interest by a properly weighted set of particles generated by importance sampling. Particle filters [218, 219] overcome the two main limitations of Kalman filter based techniques, that is the approximation by second order moments and assumption of normal distributions. Particle filters allow any probability distribution to be used to represent the error on the observed data series or, if required, the state corrections and parameter evolution. Also by generating a sample of particles from the full distribution they capture the full moments of the distribution. This additional theoretical completeness comes at the cost of computational efficiency due to the large amount of sampling involved in generating and evolving the particles. With certain sampling strategies the computational scheme may require monitoring to confirm that particle sample does not become highly correlated. There are several published applications of particle filters in environmental settings [220, 221]. SMC techniques for the generation of samples from stationary distributions[222] are less well known in environmental modelling, though they over an interesting alternative to Markov Chain Monte Carlo samplers [217]. These techniques are generally based upon sequential importance sampling from the distribution of interest, or from a series of artificial distribution that move slowly from an initial (easily sampled distribution) to the complex distribution of interest.

**Advantages**

- Filter algorithms that allow a free choice of probability distribution for the observational errors;
- Sampling within the filtering algorithm that is dependant upon the whole distribution of interest, not just it's first two moments;
- Computationally simple and robust

**Disadvantages**

- Computationally expensive in terms of model evaluations;
- Computational scheme may need careful monitoring;
- Additional thought has to given to the selection of error distributions used.

**Further reading**

**Andrieu C., Doucet A., Robert C.P.**; *Computational advances for and from Bayesian Analysis*. Statistical science 19(1) 2004. [217]

**Moradkhani, H., Hsu, K.L., Gupta, H. and Sorooshian, S.**, 2005. U*ncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter*. Water Resources Research, 41(5): art. no.-W05012. [221]

## 4.5 QUALITATIVE METHODS FOR ASSESSING UNCERTAINTY IN MODEL PREDICTIONS

Many of qualitative methods for assessing uncertainty incorporate methods of uncertainty analysis described earlier. They build the overarching building block in deriving decisions based on uncertainty analysis. These methodologies present the connection between RPA9 (Risk and Uncertainty) and RPA7 (Policy and Stakeholders). This will be illustrated by the example of NUSAP

### 4.5.1 NUSAP (Numeral, Unit, Spread, Assessment, Pedigree)

**Description**

NUSAP is designed as a diagnostic and analysis tool of uncertainty in science and policy. It incorporates the quantitative and qualitative dimensions of uncertainty and promotes an extended review process.

It is based on the idea to quantify five qualifiers (Numerical, Unit, Spread, Assessment and Pedigree) and display them in a standardized and self-explanatory way. The *Numerical* qualifier is usually expressed by an ordinary number, but can also be presented as a general quantity. The second qualifier (*Unit*) can be defined conventional or with additional information. *Spread* conveys the spread or uncertainty and thus can be usually computed by one of the methods described above. These quantitative measures are supplemented by qualitative quantifiers in *Assessment*, which provides a qualitative judgement about the information involved. It could be the systematic error of an analysis or it might be the qualifier “optimistic” or “pessimistic”. Finally, the qualifier *Pedigree* has to be defined. This conveys an evaluation process of information. A set of pedigree criteria is used to assess different aspects. The subjectivity and arbitrariness has been limited by coding the qualitative judgement for each criterion into a scale linked to linguistic descriptors. An example of such a matrix is given in Risbey et al. [223]. It contains criteria such as “Proxy Representation” to express how good or close a measure of quantity that we measure or model is to the actual quantity we seek or represent; “Empirical Basis”, which refers to the degree which direct observations, measurements and statistics are used to estimate parameters; “Methodological Quality”, which refers to the norms for methodological rigour in this process applied by peers in the relevant disciplines; and Validation, which refers to which degree one has been able to crosscheck the data and assumptions used. It has to be noted that some of the criteria of pedigree mentioned are in fact also part of methods to evaluate model uncertainty (e.g. extended GLUE approach, section 4.3.3). The pedigree scheme has also been extended to incorporate the socio-political context (see references in [156]).

**Advantages**

Identifies and displays different sorts of uncertainty in quantitative information and allows a clear and transparent assessment of uncertainties. It explicitly acknowledges the issue of quality of information, which is not part of many traditional risk and uncertainty methodologies. Therefore, the open discourse is enhanced and the communication between expert and lay improved.

**Disadvantages**
Pedigree scores might be misinterpreted. Moreover, motivational bias towards good pedigree scores in elicitation, especially when they concern specific 'pet' methods have been reported[156]. Many different ways of computing scores could be proposed and a socio-political agreement is required to set standards.

**Further reading**
The NUSAP approach was introduced by Funtowicz and Ravetz [224]. The website http://www.nusap.net disseminates NUSAP tools including tutorials and papers. Further references can be found in the RIVM/MNP Guidance for Uncertainty Assessment and Communication[156].

## 4.6 GUIDANCE IN CHOOSING A METHODOLOGY

It is impossible to suggest a universal uncertainty methodology, only to make clear the different assumptions and choices that are necessary in the application of any of the methods presented above. Discussion about what might be the 'right' methodology continues (e.g. Gupta et al., [225]; Beven and Young, [83]). Therefore, any attempt to produce guidance in choosing a methodology for a particular application will necessarily reflect the view of the author. The following decision tree is such an initial (non-objective) attempt to provide guidance on the choice of methods. This tree will be refined within the FRMRC project. It has to be noted that NO guidance is given with respect to the type of model (physically-based, data-based), which should be used. This has to be decided on different criteria.

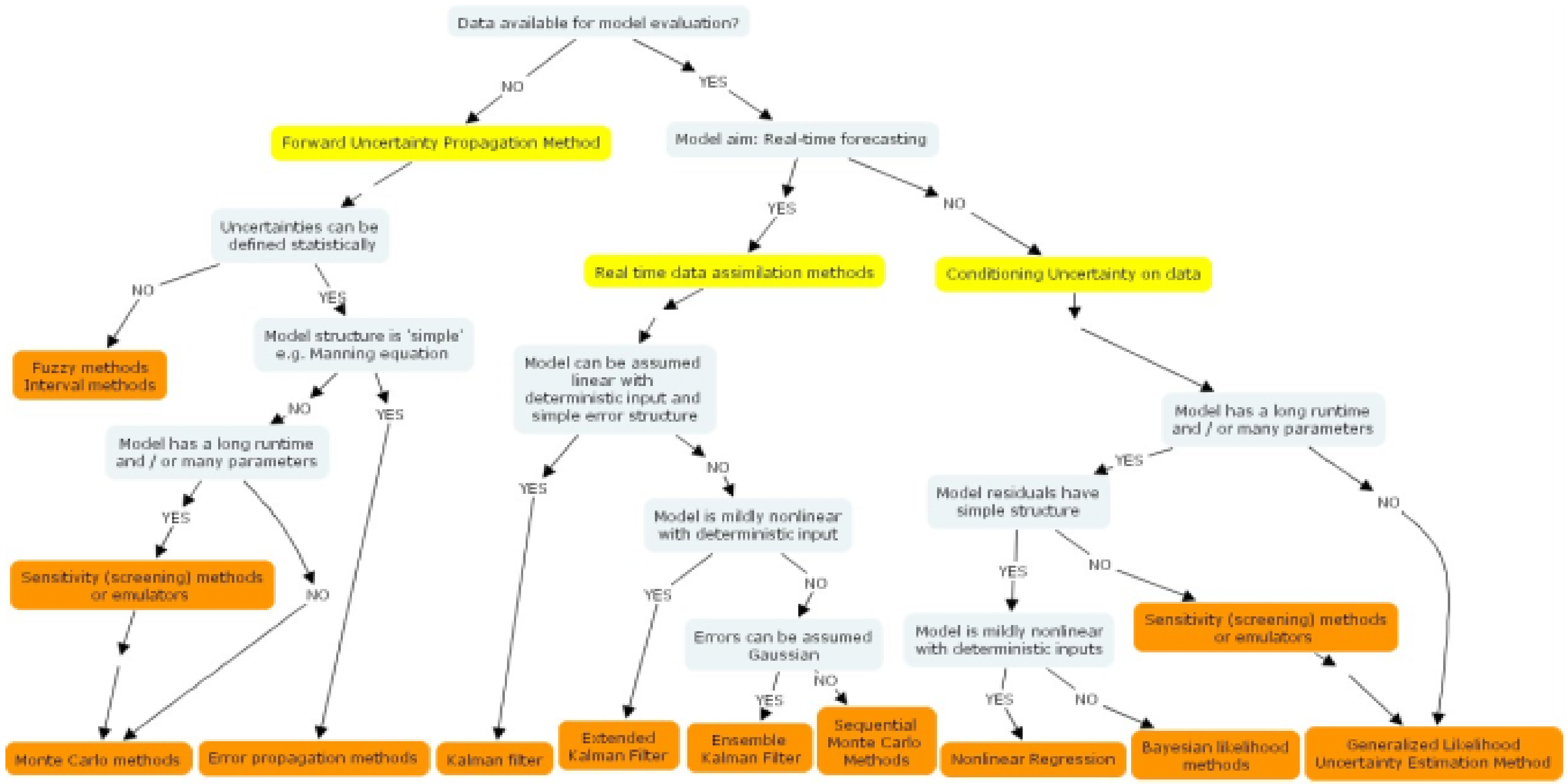



**Figure 9 Decision tree for uncertainty analysis tools (blue boxes represent the questions to derive a decision for an uncertainty method, yellow boxes show the major classifications of several uncertainty methods and orange boxes stand for individual methods or small sub-groups of those)**

The orange and yellow boxes in figure 9 are explained in the previous chapter. The blue boxes are decisions or assumptions which have to be made in order to derive one specific uncertainty method. The boxes can be explained as following:

***Data available for model evaluation?***
The question is if data are available which have not been used in creating the model and allow a comparison to the model results.

***Uncertainties can be defined statistically***
Distribution functions can be assumed or approximated for all uncertainties. If this question is answered with yes, then it is for example possible to define a range of possible floodplain roughness based on a Gaussian/normal distribution (see explanation below).

***Model structure is 'simple' e.g. Manning equation***
No numerical analysis or complex direct solution schemes are required to compute these equations.

***Model has a long runtime and / or many parameters***
The more parameters a model has the more runs are necessary to describe the response surface adequately. In this particular figure, parameters are taken as example and synonym for sources of uncertainty (see chapter 2).
For example, a two parameter model would need four simulations to sample a two by two grid. 100 simulations would be already necessary to sample a 10 by 10 grid. The amount of subdivision needed for each parameter would depend on the non-linearity of the response surface. The sampling increases with the number of parameters. For our example it could be computed by

$$N_S = D^{N_p}$$ **Equation 3**

$N_S$: Number of samples
D: Number of subdivisions in the parameter space
$N_p$: Number of parameters.

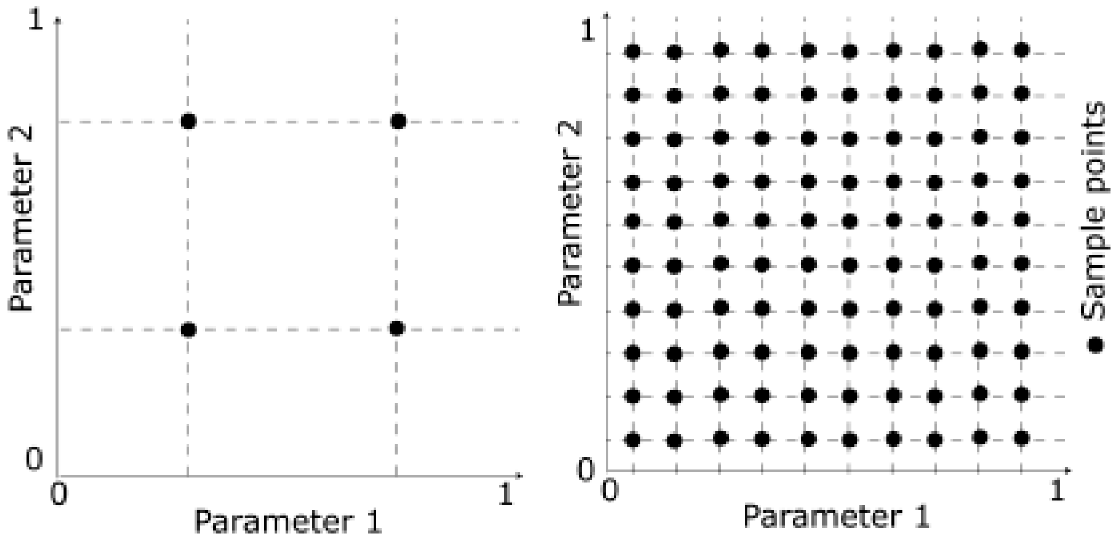



**Figure 10 Example of sampling the parameter space**

In this particular set-up the total processor run-time required would be the number of samples multiplied by the execution time of one model realisation. It has to be noted, that this is just a crude example as most uncertainty techniques have more efficient techniques to quantify the response surface.

In summary, this question depends highly on the type of model or model cascade used and should be based on previous experience. As a bold statement, we argue that a model with more than 8 parameters and an execution time of more than 2 minutes should be considered as computer intensive (if executed on a single CPU).

***Model aim: Real-time forecasting***
This question is based on practical considerations. A forecast is called a real-time if the combined reaction- and execution-time of the forecast is *shorter* than the maximum delay that is allowed, in view of circumstances outside the forecast. In other words, a flood forecast including uncertainty analysis is computed as soon as all input data are available.

The two branches arising at this node could be combined, as **all** methods under this heading are examples of conditioning on data and could be applied for real-time forecasting or off-line analysis. The main difference is that methods which are quoted in the left leave usually treat data sequentially time step by time step, whereas methods in the right leave usually work on *en bloc* data set. However, even this distinction is blurred. Therefore the question is reasoned by preference based on extensive experience of the authors.

***Model can be assumed linear with deterministic input and simple error structure***
*Linear*
A system is linear if its response is directly proportional to changes in the quantities of the system, for every part of the system.

*Deterministic input*
Model input does not vary randomly in time. In contrast stochastic input varies randomly in time. A simple example, would be the difference between one rainfall prediction (deterministic) and an ensemble of rainfall predictions (stochastic).

*Simple error structure*
The model errors can be explained by for example simple distributions such as the normal distribution. Most error structures are more complicated and cannot be easily approximated.

***Model is mildly nonlinear with deterministic input***
*Mildly nonlinear*
A relationship between numerical quantities is called nonlinear if there is not a constant proportion relating changes in one quantity to changes in the other. Nonlinear systems are probably easiest understood as "everything except the relatively few systems which prove to be linear"[226]. Mildly nonlinear are all systems which could be approximated by linear systems subject to a small model error.

*Deterministic input*
(see above)

***Errors can be assumed Gaussian***
This assumption is mathematically convenient in that it means that advantage can be taken of a body of statistical theory.  It is not always verified that the actual errors in an application are indeed Gaussian.

*Model Error*
The difference between a quantity and its estimated or measured quantity. The latter being based on the whole population.

*Gaussian / Normal Distribution*
A normal distribution I a variate X and a mean μ and the variance $\sigma^2$ is a statistic distribution with probability function

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/(2\sigma^2)}$$ **Equation 4**

On the domain $x \in (-\infty, \infty)$ .

***Model residuals have simple structure***
*Model residual (after* [227])
A residual is an observable *estimate* of the unobservable error. The simplest case involves a random sample of *n* men whose heights are measured. The sample average is used as an estimate of the population average. Then we have:

- The difference between the height of each man in the sample and the unobservable population average is an error, and
- The difference between the height of each man in the sample and the observable sample average is a residual.

Residuals are observable; errors are not (see [227]).

*Simple structure*
The model residuals can be explained by for example simple distributions such as the normal distribution. Most residual structures are more complicated and cannot be easily approximated.

In general we would argue that most environmental models have a complicated residual structure which can rarely be approximated in advance or indeed after the analysis.

## 4.7 SUMMARY OF CHAPTER 4

s chapter has reviewed a wide variety of uncertainty estimation methods that can be used with different models in a range of FRMRC applications, together with some guidance on the advantages and disadvantages of each method. Methods for forward uncertainty propagation; model calibration and conditioning; real-time data assimilation and model updating; and qualitative assessment of model uncertainties, have been reviewed.

A preliminary decision tree for choosing an uncertainty estimation method has been presented.

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# Appendix 1: Justification for Risk and uncertainty analysis

It appears, however, that some resistance to the routine use of uncertainty analysis methods remains, whether for reasons of expense, understanding of methods, or training in the requisite skills. This resistance has been expressed in a number of ways and in what follows in this appendix, we explore the following commonly expressed arguments against the use of risk and uncertainty analysis as a normal component of any flood analysis.

- Uncertainty analysis is not necessary given physically realistic models
- Uncertainty distributions cannot be understood by policy makers and the public
- Uncertainty analysis cannot be incorporated into the decision making process (e.g. evacuate an area at risk of flooding)
- Uncertainty analysis is too difficult to perform
- Uncertainty analysis does not matter, as current praxis has been proven sufficient

### A1. Uncertainty analysis is not necessary given physically realistic models

There are fundamentally different philosophical positions within the modelling community, which influence particular views on uncertainty analysis and indeed, whether an uncertainty analysis would be performed at all.

There are some physically based modellers who believe that their models are (or at least will be in the future) physically correct and thus these models can be used in a deterministic framework (*modeller type 0*). This means that all parameters, structures and boundary conditions can be quantified a priori and do not need to be adjusted under any circumstances. Such modellers would argue that parameter calibration or uncertainty analysis should not be necessary if predictions are based on a true understanding of the physics of the system simulated.

Others take a less strongly realist position, but believe that models should be only calibrated within a very strictly-known range (*modeller type 1*). This type of modeller would argue that any calibration beyond such ranges cannot be physically justified.

There are also modellers who have a less firm belief in the correctness of the implementation physical equations and laws used within any modelling framework, and who will happily adjust parameters even beyond their established ranges (*modeller type 2*)

Fundamentally, only modeller type 0 would reject any calibration on the basis of physical correctness. This position seems difficult to justify considering developments and publications in all scientific fields of flood risk prediction and management in respect to uncertainties (see Oreskes et al. [60]; Beven[61]). Thus readers with this point of view are referred to section 2.2.1 which highlights, and gives examples of, different sources of uncertainty. We argue that any critical observer will find uncertainties in any modelling process and a total denial of uncertainty is impossible.

Both modellers of type 1 and 2 would fundamentally not oppose calibration or uncertainty analysis. However, the uncertainty analysis approach taken by the two types of modeller would differ in extent and magnitude. This discussion is illustrated in the argument between Beven and Pappenberger (type 2) [228] *vs* Abbott et al. (type 1) [229]. Abbott et al. [229] have argued that uncertainty analysis should not be necessary given an adequate understanding of the system and its boundary conditions – whereas modellers of type 2 would argue that modellers of type 1 have too much faith in the model representation of physical laws.

In summary, if you consider yourself as a type 1, 2 or intermediate modeller some uncertainty (and consequent risk) analysis should always be considered as necessary. A fourth group of modellers has not yet been acknowledged in this section: data-based and data-based mechanistic modellers (*modeller type 3*). These types of modellers build their model from data (simplest cases: a regression line or linear transfer function) and inherently accept uncertainties to different degrees as a result of errors and natural variability in time series.

## A2. Uncertainty (probability) distributions cannot be understood by policy makers and the public

One goal of modelling, beside simple curiosity, is to provide knowledge in a form that is accessible and useful to decision makers. Many modellers argue that policy makers and the public are not capable of understanding uncertainty or even the simplest form of any probability. In a particular case quoted in Patt and Dessai [230], people were asked to estimate the chances that a person had a rare disease, given a positive result from a test that sometimes generates false positives. If the problem was framed for a single patient receiving the test result, and the probability of the disease (e.g. 0.001) together with the reliability of the test (e.g. 0.95), most people significantly overestimated the chance. However when the problem was framed in the form of a thousand patients, they resorted to counting the people and usually arrived at the correct result. Thus errors in logic as well as a misunderstanding of probabilities can lead to wrong conclusions[10].

This example is comparable to misunderstood definitions of flood frequency and the probability of occurrence, which is at the centre of debate in many recent articles (see Sayers et al.[4]). However, Sayers et al. suggest that it may be effective communication that is the major problem, in addition to a lack of understanding. The concepts of 'uncertainty' and 'risk' are based on opinions and perceptions and have different meanings for different individuals. However, it can be shown that when both parties (scientists and public) work together this gap can be bridged. For example, several studies have shown that probabilistic weather forecasts can be understood [231-233].

Other studies suggest that decision makers actually want to get a feeling for the range of uncertainty and thus distributions. This is demonstrated, for example, in the case of possible signal errors in the US command and control system in the case of a nuclear attack[234]. Moreover, examples can be presented in which a loss of credibility in the model and the modelling process has occurred due to forecasting errors and the lack of communicating the uncertainties [235, 236]. A loss of credibility is extremely important for systems such as any flood forecasting system where it is necessary to communicate risk to the public.

Work has already been carried out elsewhere on the communication of uncertainty to decision makes and the public. The detailed guidance for uncertainty assessment and communication published by RIVM provides[156] a detailed questionnaire, which makes the modeller aware of many problems. By answering a set of questions about the problem framing, context and process assessment the danger of miscommunication is reduced, although more detailed guidelines on how exactly to present uncertainty and risk within the flood risk management context will have to be the focus point of future investigations.

In summary, it is possible to communicate uncertainty and risk, but much more research and education for scientists as well as the public and decision makers are needed to achieve this goal. Thus it comes to no surprise that Morin[18] argued for uncertainty to be one of the types of knowledge necessary for future education.

## A3. Uncertainty analysis cannot be incorporated into the decision making process (e.g. evacuate an area at risk of flooding)

This statement is supported by two arguments: Firstly, many decisions are binary and secondly uncertainty bounds can be so large that it is impossible to derive a decision between various scenarios.

*A3.1 Decisions are binary*

Decisions are not uncertain, many of them are either black or white. There is no middle ground between the decision to evacuate a floodplain, warn residents or leave them sleeping in peace. Some modellers argue that therefore uncertainty analysis has no value, and deterministic model results should be used. This stand point seems to be based on a misplaced faith in deterministic modelling in the light of existing uncertainty. Any deterministic model simulation, will present only one possibility, of unknown likelihood, in an uncertainty framework. For example, it could well be that the parameters chosen present the medium or indeed an extreme. There is no real need to ignore uncertainty, as literature as well as decision support systems do provide a wealth of methods to make decisions under uncertainty.

Most of these methods have been applied under different circumstances e.g. for investment [237], in the mining industry[238], in transport planning[239] and many others. Moreover, one should not forget that many of our every day decisions are based on uncertainties, although we rarely scrutinise our wrong decisions in the light of uncertainty[7]. Admittedly, a concentrated effort is needed to implement industry standards for flood inundation forecasting, which will be part of a workshop within the FRMRC project. Several open questions will have to be resolved, such as under which circumstances a risk & uncertainty averse or risk & uncertainty neutral approach should be adopted (e.g. accept a low probability or high probability of flood inundation risk). Which levels of confidence can be seen as acceptable (e.g. would we raise the alarm if the probability of overtopping is a dam is 50%)? It is well known that people making decisions under conditions of uncertainty may violate many normative axioms of choice and are at times inconsistent and counter productive[240, 241], thus a scientific-political discussion is needed to agree on certain norms and language (e.g. see **Table A1.**, Definitions of the probabilistic words and phrases used in the IPCC Third Assessment Report).

**Table A1. Definitions of the probability words and phrases used in the IPCC Third Assessment Report**

| Probability Range | Descriptive term |
|---|---|
| <1% | Extremely unlikely |
| 1-10% | Very unlikely |
| 10-33% | Unlikely |
| 33-66% | Medium likelihood |
| 66-90% | Likely |
| 90-99% | Very likely |
| >99% | Virtually certain |

*A3.2 Uncertainty bounds are too wide*

There is no question that many uncertainty studies lead to uncertainty bounds which are so wide that decisions are difficult to make. For example, they may show predicted flow hydrographs with a bandwidth which is up to 30% of the total discharge [242]. In other cases the predictive probability distribution for outcomes of different scenarios are significantly larger than the differences between the expected values of different policy alternatives[17]. Reichert and Borusk[17] have shown that the uncertainty bounds for different scenarios of a phosphorus model were significantly larger than a choice between these scenarios. Thus in the first instance it looked like that it did not make any difference which policy scenario was implemented. It is an interesting notion not to report the uncertainty bandwidth, when faced with such a situation. Rather than an approach based on ignorance, we instead suggest the problem should be tackled pro-actively[243]. For example Reichert and Borsuk[243] offer a solution to this dilemma, by finding that the knowledge about the difference of the uncertainty of single scenarios can be included in the decision process.

In summary, uncertainty analysis can be incorporated into any decision making process. However, guidelines have to be agreed beforehand and communicated to the scientists and the decision makers.

Thus it is perhaps this uncertainty about the guidelines, which results in the wrong assumption of many flood forecasters and engineers that uncertainty cannot be part of a decision process.

## A4. Uncertainty analysis is too difficult to perform

Uncertainty analysis is NOT too difficult to perform! Most uncertainty analysis hides behind a difficult mathematical notation, but is simple if explained step-by-step. Example applications and programs (if their basics are well explained to the user) can help to perform most types of uncertainty analysis. The problem is fundamentally which methodology to choose under different circumstances and model environments[244]. Undoubtedly, there are neither enough software tools nor enough guidance published to justify the claim that everyone can perform uncertainty and risk analysis. However, the RPA9 project will provide guidance and example applications to show that uncertainty analysis is not difficult and could be performed by everyone.

## A5. Does uncertainty really matter?

In many past decision-making processes uncertainty analysis has been ignored and it can be argued that under many circumstances it did simply not matter. Morgan[245] stated that uncertainty is currently a fashionable discipline but that it cannot be denied that civilisation has advanced with simply muddling along and not explicitly acknowledging uncertainty. However, his arguments for uncertainty analysis are compelling as he stresses that:

- it makes one think about the processes involved and the decisions based on our model results
- it makes predictions of different experts more comparable and leads to a transparent science
- it allows a more fundamental retrospective analysis and allows new or revised decisions to be based on the full understanding of the problem and not only a partial snap-shot
- decision-makers and the public have the right to know all limitations in order to make their own minds up and lobby for their individual causes

It cannot be ignored that the open scientific discourse on risk and uncertainty will have important implications for the environmental decision process as a whole. Decisions based on an open communication of the uncertainties involved can be easily disputed as science is not (and never has been) a source of verifiable facts and theories about reality. In this context Sarewitz[246] argues that it is desirable to “de-scientize” the decision process and decisions have to come from a political process.
The presentation of uncertainty and its use in decision making will be the subject of an interaction between RPA9 and RPA7 (Stakeholders and Policy). The aim of RPA9 will be to provide realistic estimates of uncertainty, based on good scientific practise[247, 248], for model predictions in different contexts and applications of the FRMRC programme that can then be embedded into a risk-based, socially aware, decision making process.

## Summary of Appendix 1

This appendix has explored the five most common misconceptions about risk and uncertainty analysis.

1. Uncertainty analysis undermines physical models
   *Argument*: Physically based models are built on build on equations and uncertainty analysis introduces a ‘non-physical’ component into the modelling process.

   *Counter-argument*: All models are approximations, neither parameters, structures or boundary conditions can claim to represent ‘true’ nature. Therefore, uncertainty analysis is inevitable – although the extend will depend on your modelling philosophy.

2. Uncertainty distributions cannot be understood by policy makers and the public

*Argument*: Policy makers and the public are not capable of understanding uncertainty or even the simplest form of any probability

*Counter-argument*: Already an initial literature review reveals many areas in which policy makers and the public could understand uncertainty. It is rather an educational/communication problem.

3. Uncertainty analysis cannot be incorporated into the decision making process (e.g. evacuate an area at risk of flooding)

*Argument*: Many decisions are binary and not probabilistic. Moreover, uncertainty bounds are very often too wide to base decisions on them.

*Counter-argument*: It is common practise in many disciplines to deal with uncertain information (e.g. nuclear safety, financial models) and can be easily incorporated into decision-making processes. Examples in the literature show that even too wide uncertainty bounds have value.

4. Uncertainty analysis is too difficult to perform

*Argument*: Modelling in itself is a laborious process and uncertainty analysis is a complicated and complex addition based on equations, which cannot be understood.

*Counter-argument*: Most modeller will not be able to derive the complicated equations in the model they are currently using. Uncertainty analysis is very often wrapped up in complicated equations which can be understood if properly explained. Tools or Toolboxes can assist to perform these analysis.

5. Uncertainty analysis does not matter, as current praxis has been proven sufficient

*Argument:* Modelling and decision making has been successfully used and applied without uncertainty analysis in the background.

*Counter-argument:* Stating all assumptions and problems is simply good scientific practise. There are many examples, in which decisions without uncertainty analysis have been proven wrong (e.g. the challenger space shuttle mission).

Many more arguments for and against uncertainty analysis can be presented. Beven[61] has presented the case for including uncertainty estimation into a coherent pragmatic realist philosophy of environmental modelling. Experience suggests that trying to predict the response of environmental systems, particularly with limited data on system characteristics, is very often associated with an element of surprise. Uncertainty estimation, from both the modellers' and decision makers' perspectives has the advantage of at least reducing the potential for surprise in the future. It should form the basis of any serious scientific study that involves prediction of future outcomes.

# Appendix 2: Glossary

(modified from Gouldby and Samuels, 2004, Language of risk – project definitions. FLOODsite Report T34/04/01, at www.floodsite.net)

**Accuracy** - closeness to reality.
**Adaptive capacity -** Is the ability to plan, prepare for, facilitate, and implement adaptation options. Factors that determine a community adaptive capacity include its economic wealth, its technology and infrastructure, the information, knowledge and skills that it possesses, the nature of its institutions, its commitment to equity, and its social capital.
**Aims** - The objectives of groups/individuals/organisations involved with a project. The aims are taken to include ethical and aesthetic considerations.
**Attenuation (flood peak) -** lowering a flood peak (and lengthening its base).
**Basin (river)** ***(see catchment area) -*** the area from which water runs off to a given river.
**Catchment area -** the area from which water runs off to a river
**Bias** - The disposition to distort the significance of the various pieces of information that have to be used.
**Characterisation** - The process of expressing the observed/predicted behaviour of a system and it's components for optimal use in decision making.
**Cognition** - The conscious or unconscious process of deriving meaning from sensory data. So 'perceived risk' might be more correctly termed "cognated" risk.
**Conditional probability** - The likelihood of some event given the prior occurrence of some other event.
**Confidence interval -** A measure of the degree of (un)certainty of an estimate. Usually presented as a percentage. For example, a confidence level of 95% applied to an upper and lower bound of an estimate indicates there is a 95% chance the estimate lies between the specified bounds. Confidence limits can be calculated for some forms of uncertainty (see knowledge uncertainty), or estimated by an expert (see judgement).
**Consequence** - An impact such as economic, social or environmental damage/improvement that may result from a flood. May be expressed quantitatively (e.g. monetary value), by category (e.g. High, Medium, Low) or descriptively.
**Coping capacity —** The means by which people or organisations use available resources and abilities to face adverse consequences that could lead to a disaster.
**Correlation** - Between two random variables, the correlation is a measure of the extent to which a change in one tends to correspond to a change in the other. One measure of linear dependence is the correlation coefficient p. If variables are independent random variables then p = 0. Values of +1 and -1 correspond to full positive and negative dependence respectively. Note: the existence of some correlation need not imply that the link is one of cause and effect.
**Critical element** – A system element, the failure of which will lead to the failure of the system.
**Damage potential —** A description of the value of social, economic and ecological impacts (harm) that would be caused in the event of a flood.
**Decision uncertainty –** The rational inability to choose between alternative options.
**Defence system** - Two or more defences acting to achieve common goals (e.g. maintaining flood protection to a floodplain area/ community).
**Design objective** - The objective (put forward by a stakeholder), describing the desired performance of an intervention, once implemented.
**Design discharge** - See Design standard and Design flood
**Design standard** - A performance indicator that is specific to the engineering of a particular defence to meet a particular objective under a given loading condition. Note: the design standard will vary with load, for example there may be different performance requirements under different loading conditions.
**Dependence** - The extent to which one variable depends on another variable. Dependence affects the likelihood of two or more thresholds being exceeded simultaneously. When it is not known whether dependence exists between two variables or parameters, guidance on the importance of any assumption can be provided by assessing the fully dependent and independent cases (see also correlation).
**Deterministic process / method** - A method or process that adopts precise, single-values for all variables and input values, giving a single value output.
**Discharge (stream, river) -** as measured by volume per unit of time.
**Efficiency** - In everyday language, the ratio of outputs to inputs; in economics, optimality.
**Element** - A component part of a system
**Element life** - The period of time over which a certain element will provide sufficient strength to the structure with or without maintenance.

**Emergency management -** The ensemble of the activities covering emergency planning, emergency control and post-event assessment.

**Epistemology** - A theory of what we can know and why or how we can know it.

**Ergonomics** - The study of human performance as a function of the difficulty of the task and environmental conditions.

**Error -** Mistaken calculations or measurements with quantifiable and predictable differences.

**Evacuation scheme -** plan for the combination of actions needed for evacuation (warning, communication, transport etc.).

**Event (in flood context)** – Conditions which may lead to flooding. An event is, for example, the occurrence in *Source* terms of one or more variables such as a particular wave height threshold being exceeded at the same time a specific sea level, or in *Receptor* terms a particular flood depth**.** When defining an event it can be important to define the spatial extent and the associated duration. Appendix 1 expands upon this definition.

**Exposure** - Quantification of the receptors that may be influenced by a hazard (flood), for example, number of people and their demographics, number and type of properties etc.

**Expectation -** Expectation, or "expected value" of a variable, refers to the mean value the variable takes. For example, in a 100 year period, a 1 in 100 year event is expected to be equalled or exceeded once. This can be defined mathematically (Appendix 1).

**Expected annual frequency -** Expected number of occurrences per year (reciprocal of the return period of a given event).

**Expected value** — see Expectation

**Extrapolation** - The inference of unknown data from known data, for instance future data from past data, by analysing trends and making assumptions.

**Failure** - Inability to achieve a defined performance threshold (response given loading). "Catastrophic" failure describes the situation where the consequences are immediate and severe, whereas "prognostic" failure describes the situation where the consequences only grow to a significant level when additional loading has been applied and/or time has elapsed.

**Failure mode** - Description of one of any number of ways in which a defence or system may fail to meet a particular performance indicator.

**Flood: -** A temporary covering of land by water outside its normal confines.

**Flood control (measure) —** A structural intervention to limit flooding and so an example of a risk management measure.

**Flood damage -** damage to receptors (buildings, infrastructure, goods), production and intangibles (life, cultural and ecological assets) caused by a flood.

**Flood forecasting system—** A system designed to forecast flood levels before they occur:

**Flood hazard map -** map with the predicted or documented extent of flooding, with or without an indication of the flood probability.

**Flood level -** water level during a flood.

**Flood management measures -** Actions that are taken to reduce either the probability of flooding or the consequences of flooding or some combination of the two.

**Flood peak -** highest water level recorded in the river during a flood.

**Floodplain -** part of alluvial plain that would be naturally flooded in the absence of engineered interventions.

**Flood prevention -** actions to prevent the occurrence of an extreme discharge peak.

**Flood protection (measure) -** to protect a certain area from inundation (using dikes etc).

**Flood risk zoning -** delineation of areas with different possibilities and limitations for investments, based on flood hazard maps.

**Flood risk management** - Continuous and holistic societal analysis, assessment and mitigation of flood risk.

**Flood warning system (FWS) —** A system designed to warn members of the public of the potential of imminent flooding. Typically linked to a flood forecasting system.

**Flooding System** (in context) - In the broadest terms, *a system* may be described as the social and physical domain within which risks arise and are managed. An understanding of the way a system behaves and, in particular, the mechanisms by which it may fail, is an essential aspect of understanding risk. This is true for an organisational system like flood warning, as well as for a more physical system, such as a series of flood defences protecting a flood plain.

**Fragility** - The propensity of a particular defence or system to fail under a given load condition. Typically expressed as a *fragility function curve* relating load to probability of failure. Combined with descriptors of decay/deterioration, fragility functions enable future performance to be described.

**Functional design** - The design of an intervention with a clear understanding of the performance required of the intervention.

**Governance** - The processes of decision making and implementation

**Harm -** Disadvantageous consequences — economic, social or environmental. (See *Consequence).*

**Hazard -** A physical event, phenomenon or human activity with the *potential* to result in harm. A hazard does not necessarily lead to harm.

**Hazard mapping -** The process of establishing the spatial extents of hazardous phenomena.

**Hierarchy** - A process where information cascades from a greater spatial or temporal scale to lesser scale and vice versa.

**Human reliability** - Probability that a person correctly performs a specified task.

**Ignorance** – Lack of knowledge

**Institutional uncertainty** - inadequate collaboration and/or trust among institutions, potentially due to poor communication, lack of understanding, overall bureaucratic culture, conflicting sub-cultures, traditions and missions.

**Integrated risk management-** An approach to risk management that embraces all sources, pathways and receptors of risk and considers combinations of structural and non-structural solutions.

**Integrated Water Resource Management** - IWRM is a process which promotes the co-ordinated management and development of water, land and related resources, in order to maximise the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems.

**Intervention -** A planned activity designed to effect an improvement in an existing natural or engineered system (including social, organisation/defence systems).

**Inundation -** Flooding of land with water. (NB: In certain European languages this can refer to deliberate flooding, to reduce the consequences of flooding on nearby areas, for example. The general definition is preferred here.)

**Joint probability** - The probability of specific values of one or more variables occurring simultaneously. For example, extreme water levels in estuaries may occur at times of high river flow, times of high sea level or times when both river flow and sea level are above average levels. When assessing the likelihood of occurrence of high estuarine water levels it is therefore necessary to consider the joint probability of high river flows and high sea levels.

**Judgement** - Decisions taken arising from the critical assessment of the relevant knowledge.

**Knowledge** - Spectrum of known relevant information.

**Knowledge uncertainty -** Uncertainty due to lack of knowledge of all the causes and effects in a physical or social system. For example, a numerical model of wave transformation may not include an accurate mathematical description of all the relevant physical processes. Wave breaking aspects may be parameterised to compensate for the lack of knowledge regarding the physics. The model is thus subject to a form of knowledge uncertainty. Various forms of knowledge uncertainty exist, including:

*Process model uncertainty* – All models are an abstraction of reality and can never be considered true. They are thus subject to process model uncertainty. Measured data versus modelled data comparisons give an insight into the extent of model uncertainty but do not produce a complete picture.

*Statistical inference uncertainty* - Formal quantification of the uncertainty of estimating the population from a sample. The uncertainty is related to the extent of data and variability of the data that make up the sample.

*Statistical model uncertainty* - Uncertainty associated with the fitting of a statistical model. The statistical model is usually assumed to be correct. However, if two different models fit a set of data equally well but have different extrapolations/interpolations then this assumption is not valid and there is statistical model uncertainty.

**Legal uncertainty** - the possibility of future liability for actions or inaction. The absence of undisputed legal norms strongly affects the relevant actors' decisions.

**Likelihood** - A general concept relating to the chance of an event occurring. Likelihood is generally expressed as a probability or a frequency.

**Limit state** - The boundary between safety and failure.

**Load** - Refers to environmental factors such as high river flows, water levels and wave heights, to which the flooding and erosion system is subjected.

**Mitigation** – *see Flood management measures*

**Model -** An abstract construct to represent a system for the purposes of reproducing, simplifying, analyzing, or understanding it. The definition of a model can be broadly divided into perceptual, conceptual and procedural models. (see [19])

**Model, Perceptual -** Summary of our (personal) perceptions on how a system responds. Perceptual models are frameworks representing how a given theorist views the phenomena of concern to a discipline. People receive information, process this information, and respond accordingly many times each day. This sort of processing of information is essentially a perceptual model of how things in our surrounding environment work. The perceptual understanding of systems is far greater than most material model implementations. (see [19])

**Model, Conceptual -** The mathematical description of a perceptual model is a conceptual model. It is a construct of mathematical and logical statements that describe a complex system in quantitative terms; a carefully constructed, but sharply limited simulation of nature. It includes hypotheses and assumptions to simplify the processes. (see [19])

**Model, Procedural -** Converts a conceptual model essentially to a computer code for example the replacement of differentials of the original equation by finite-difference or finite-volume equivalents. (see [19])

**Natural variability -** Uncertainties that stem from the assumed inherent randomness and basic unpredictability in the natural world and are characterised by the variability in known or observable populations.

**Parameters** - The parameters in a model are the "constants", chosen to represent the chosen context and scenario. In general the following types of parameters can be recognised:

*Exact parameters* - which are universal constants, such as the mathematical constant: Pi (3.14259...).

*Fixed parameters* - which are well determined by experiment and may be considered exact, such as the acceleration of gravity, g (approximately 9.81 m/s).

*A-priori chosen parameters* - which are parameters that may be difficult to identify by calibration and so are assigned certain values. However, the values of such parameters are associated with uncertainty that must be estimated on the basis of a-priori experience, for example detailed experimental or field measurements

*Calibration parameters* - which must be established to represent particular circumstances. They must be determined by calibration of model results for historical data on both input and outcome. The parameters are generally chosen to minimise the difference between model outcomes and measured data on the same outcomes. It is unlikely that the set of parameters required to achieve a "satisfactory" calibration is unique.

**Pathway** – Route that a hazard takes to reach Receptors. A pathway must exist for a Hazard to be realised.

**Performance -** The degree to which a process or activity succeeds when evaluated against some stated aim or objective.

**Performance indicator -** The well-articulated and measurable objectives of a particular project or policy. These may be detailed engineering performance indicators, such as acceptable wave overtopping rates, rock stability, or conveyance capacity or more generic indicators such as public satisfaction.

**Post-flood mitigation -** Measures and instruments after flood events to remedy flood damages and to avoid further damages.

**Precautionary Principle** - Where there are threats of serious or irreversible damage, lack of full scientific certainty shall not be used as a reason for postponing cost-effective measures to prevent environmental degradation.

**Precision —** degree of exactness regardless of accuracy.

**Pre-flood mitigation -** Measures and instruments in advance to a flood event to provide prevention (reducing flood hazards and flood risks by e.g. planning) and preparedness (enhancing organisational coping capacities).

**Preparedness –** The ability to ensure effective response to the impact of hazards, including the issuance of timely and effective early warnings and the temporary evacuation of people and property from threatened locations.

**Preparedness Strategy** - Within the context of flood risk management a preparedness strategy aims at ensuring effective responses to the impact of hazards, including timely and effective early warnings and the evacuation of people and property from threatened locations.

**Probability** (see also Appendix 1) — A measure of our strength of belief that an event will occur. For events that occur repeatedly the probability of an event is estimated from the relative frequency of occurrence of that event, out of all possible events. In all cases the event in question has to be precisely defined, so, for example, for events that occur through time reference has to be made to the time period, for example, annual exceedance probability. Probability can be expressed as a fraction, % or decimal. For example the probability of obtaining a six with a shake of four dice is 1/6, 16.7% or 0.167.

**Probabilistic method -** Method in which the variability of input values and the sensitivity of the results are taken into account to give results in the form of a range of probabilities for different outcomes.

**Probability density function (distribution) -** Function which describes the probability of different values across the whole range of a variable (for example flood damage, extreme loads, particular storm conditions etc).

**Probabilistic reliability methods -** These methods attempt to define the proximity of a structure to fail through assessment of a response function. They are categorised as Level III, II or I, based on the degree of complexity and the simplifying assumptions made (Level III being the most complex).

**Process model uncertainty -** See *Knowledge uncertainty.*

**Project Appraisal** - The comparison of the identified courses of action in terms of their performance against some desired ends.

**Progressive failure -** Failure where, once a threshold is exceeded, significant (residual) resistance remains enabling the defence to maintain restricted performance. The immediate consequences of failure are not necessarily dramatic but further, progressive, failures may result eventually leading to a complete loss of function.

**Proportionate methods -** Provide a level of assessment and analysis appropriate to the importance of the decision being made.

**Proprietary uncertainty** - indicates contested rights to know, to warn or to secrete. In both risk assessment and management, there are often considerations about the rights of different people to know, to warn or to conceal

**Random events** – Events which have no discernible pattern..

**Receptor -** Receptor refers to the entity that may be harmed (a person, property, habitat etc.). For example, in the event of heavy rainfall *(the source)* flood water may propagate across the flood plain *(the pathway)* and inundate housing *(the receptor)* that may suffer material damage *(the harm or consequence).* The vulnerability of a receptor can be modified by increasing its resilience to flooding.

**Record (in context) -** Not distinguished from event (see *Event)*

**Recovery time** – The time taken for an element or system to return to its prior state after a perturbation or applied stress.

**Reliability index -** A probabilistic measure of the structural reliability with regard to any limit state.

**Residual life -** The residual life of a defence is the time to when the defence is no longer able to achieve minimum acceptable values of defined performance indicators (see below) in terms of its serviceability function or structural strength.

**Residual risk -** The risk that remains after risk management and mitigation measures have been implemented. May include, for example, damage predicted to continue to occur during flood events of greater severity that the 100 to 1 annual probability event.

**Resilience -** The ability of a system/community/society/defence to react to and recover from the damaging effect of realised hazards.

**Resistance** – The ability of a system to remain unchanged by external events.

**Response (in context) -** The reaction of a defence or system to environmental loading or changed policy.

**Response function -** Equation linking the reaction of a defence or system to the environmental loading conditions (e.g. overtopping formula) or changed policy.

**Return period -** The expected (mean) time (usually in years) between the exceedence of a particular extreme threshold. Return period is traditionally used to express the frequency of occurrence of an event, although it is often misunderstood as being a probability of occurrence.

**Risk -** Risk is a function of probability, exposure and vulnerability. Often, in practice, exposure is incorporated in the assessment of consequences, therefore risk can be considered as having two components — the probability that an event will occur and the impact (or *consequence)* associated with that event. See Section 4.3 above. Risk = Probability multiplied by consequence

**Risk analysis -** A methodology to objectively determine risk by analysing and combining probabilities and consequences.

**Risk assessment -** Comprises understanding, evaluating and interpreting the perceptions of risk and societal tolerances of risk to inform decisions and actions in the flood risk management process.

**Risk communication (in context)** – Any intentional exchange of information on environmental and/or health risks between interested parties.

**Risk management -** The complete process of risk analysis, risk assessment, options appraisal and implementation of risk management measures

**Risk management measure** - An action that is taken to reduce either the probability of flooding or the consequences of flooding or some combination of the two

**Risk mapping -** The process of establishing the spatial extent of risk (combining information on probability and consequences). Risk mapping requires combining maps of hazards and vulnerabilities. The results of these analyses are usually presented in the form of maps that show the magnitude and nature of the risk.

**Risk mitigation -** See *Risk reduction.*

**Risk perception -** Risk perception is the view of risk held by a person or group and reflects cultural and personal values, as well as experience.

**Risk reduction -** The reduction of the likelihood of harm, by either reduction in the probability of a flood occurring or a reduction in the exposure or vulnerability of the receptors.

**Risk profile -** The change in performance, and significance of the resulting consequences, under a range of loading conditions. In particular the sensitivity to extreme loads and degree of uncertainty about future performance.

**Risk register -** An auditable record of the project risks, their consequences and significance, and proposed mitigation and management measures.

**Risk significance** (in context) — The separate consideration of the magnitude of consequences and the frequency of occurrence.

**Robustness** – Capability to cope with external stress. A decision is robust if the choice between the alternatives is unaffected by a wide range of possible future states of nature.
Robust statistics are those whose validity does not depend on close approximation to a particular distribution function and/or the level of measurement achieved.

**Scale** - Difference in spatial extent or over time or in magnitude; critical determinant of vulnerability, resilience etc.

**Scenario –** A plausible description of a situation, based on a coherent and internally consistent set of assumptions. Scenarios are neither predictions nor forecasts. The results of scenarios (unlike forecasts) depend on the boundary conditions of the scenario.

**Sensitivity -** Refers to either: the resilience of a particular receptor to a given hazard. For example, frequent sea water flooding may have considerably greater impact on a fresh water habitat, than a brackish lagoon; or: the change in a result or conclusion arising from a specific perturbation in input values or assumptions.

**Sensitivity Analysis** - is the study of how the variation in the output of a model can be apportioned, qualitatively or quantitatively, to different sources of variation

**Social learning** - Processes through which the stakeholders learn from each other and, as a result, how to better manage the system in question.

**Social resilience** - The capacity of a community or society potentially exposed to hazards to adapt, by resisting or changing in order to reach and maintain an acceptable level of functioning and structure. This is determined by the degree to which the social system is capable of organising itself to increase its capacity for learning from past disasters for better future protection and to improve risk reduction measures.

**Spatial planning** - Public policy and actions intended to influence the distribution of activities in space and the linkages between them. It will operate at EU, national and local levels and embraces land use planning and regional policy.

**Standard of service -** The measured performance of a defined performance indicator.

**Severity —** The degree of harm caused by a given flood event.

**Source —** The origin of a hazard (for example, heavy rainfall, strong winds, surge etc).

**Stakeholders —** Parties/persons with a direct interest (stake) in an issue — also Stakeowners.

**Stakeholder Engagement** - Process through which the stakeholders have power to influence the outcome of the decision. Critically, the extent and nature of the power given to the stakeholders varies between different forms of stakeholder engagement.

**Statistic** - A measurement of a variable of interest which is subject to random variation.

Strategy **(flood risk management-) – A strategy is a combination of long-term goals, aims, specific targets, technical measures, policy instruments, and process which are continuously aligned with the societal context.**

**Strategic spatial planning -** Process for developing plans explicitly containing strategic intentions referring to spatial development. Strategic plans typically exist at different spatial levels (local, regional etc).

**Statistical inference uncertainty -** *See Knowledge uncertainty*

**Statistical model uncertainty -** *See Knowledge uncertainty*

**Sustainable Development** - is development that meets the needs of the present without compromising the ability of future generations to meet their own needs

**Sustainable flood risk management -** involves:

- ensuring quality of life by reducing flood damages but being prepared for floods
- mitigating the impact of risk management measures on ecological systems at a variety of spatial and temporal scales
- the wise use of resources in providing, maintaining and operating infrastructure and risk management measures
- maintaining appropriate economic activity (agricultural, industrial, commercial, residential) on the flood plain

**Sustainable flood risk management strategy —** An approach which

- aims to be effective in the long term, and
- can be combined (`integrated') with other international, national and regional activities (transport, environment, conservation etc.)

**Susceptibility** – The propensity of a particular receptor to experience harm.

**System** - An assembly of elements, and the interconnections between them, constituting a whole and generally characterised by its behaviour. Applied also for social and human systems.

**System state -** The condition of a system at a point in time.

**Tolerability -.** Refers to willingness to live with a risk to secure certain benefits and in the confidence that it is being properly controlled. To tolerate a risk means that we do not regard it as negligible, or something we might ignore, but rather as something we need to keep under review, and reduce still further if and as we can. Tolerability does not mean acceptability.

**Ultimate limit state -** Limiting condition beyond which a structure or element no longer fulfils any measurable function in reducing flooding.

**Uncertainty -** A general concept that reflects our lack of sureness about someone or something, ranging from just short of complete sureness to an almost complete lack of conviction about an outcome.

**Uncertainty Analysis (Model) -** Assesses the uncertainty in model outputs that derives from uncertainty in structure, parameters, boundary conditions and evaluation data.

**Validation** - is the process of comparing model output with observations of the 'real world'.

**Variability** - The change over time of the value or state of some parameter or system or element where this change may be systemic, cyclical or exhibit no apparent pattern.

**Variable** – A quantity which can be measured, predicted or forecast which is relevant to describing the state of the flooding system e.g. water level, discharge, velocity, wave height, distance, or time. A prediction or forecast of a variable will often rely on a simulation model which incorporates a set of parameters.

**Voluntariness -** The degree to which an individual understands and knowingly accepts the risk to which they are exposed in return for experiencing a perceived benefit. For an individual may preferentially choose to live in the flood plain to experience its beauty and tranquillity.

**Vulnerability –** Characteristic of a system that describes its potential to be harmed. This can be considered as a combination of susceptibility and value.