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Report on an initial exploration of effects of sources of uncertainty in projected future climate change on changes in flood frequency in the UK

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Key outcomes/non-technical summary

This report looks at model quality and uncertainty issues for climate change impact studies, with particular reference to the impact of climate change on flood frequency in the UK. It is a preliminary study in the sense that there is only limited sampling of the sources of uncertainty and there is no attempt to provide wide spatial coverage. It is intended to serve as a useful demonstration of how these issues may be tackled and to provide some initial indication of how to formulate a more comprehensive study to provide a demonstration of these issues for UKCIP08.

Seven different sources of uncertainty are discussed:

- Future greenhouse gas emissions,
- Global Climate Model (GCM) structure,
- GCM parameters and initial conditions,
- Downscaling from GCMs (including Regional Climate Model structure),
- Hydrological model structure,
- Hydrological model parameters, and
- Impact definition.

Each of these sources of uncertainty is demonstrated for two example catchments in England, by propagation through to flood frequency impact. Multi-propagation (that is, propagation of more than one source of uncertainty at once) is not attempted.

The results from single-propagation of each of the sources of uncertainty suggest that uncertainty from GCM structure is by far the largest source of uncertainty. However, this is due to the extremely large increases in winter rainfall predicted by one of the 5 GCMs used (CCSR). Omitting the results for this GCM means other sources of uncertainty become more significant, although uncertainty from sources relating to modelling of the future climate is generally still larger than that relating to emissions or hydrological modelling. It is also shown that natural variability can play a significant role.

The results presented here are certainly not conclusive as there is only limited representation of some of the sources of uncertainty. Additions may, but would not necessarily, increase the range of uncertainty from any source, though they would make the results more robust. In addition, more catchments need to be assessed to decide whether some sources of uncertainty are consistently more or less important, or are more/less important for certain types of catchment or for certain areas of the country.

Associated publications

None

Press interest

None

1 INTRODUCTION

There is uncertainty in the results of any modelling, of different types and from different sources. It is possible that some of this uncertainty can be reduced, through research or modelling improvements, but some cannot be reduced and it is unlikely that uncertainty can ever be completely removed. However, any individual source of uncertainty, if quantified in some way, can be propagated through to give an uncertainty in the end result. This propagation could be done individually, for each different source of uncertainty, (termed here “single-propagation”) or in combination with other sources (termed here “multi-propagation”, or known as a “cascade of uncertainty”). The sources of uncertainty in a climate change impact study are represented schematically in Figure 1.1.

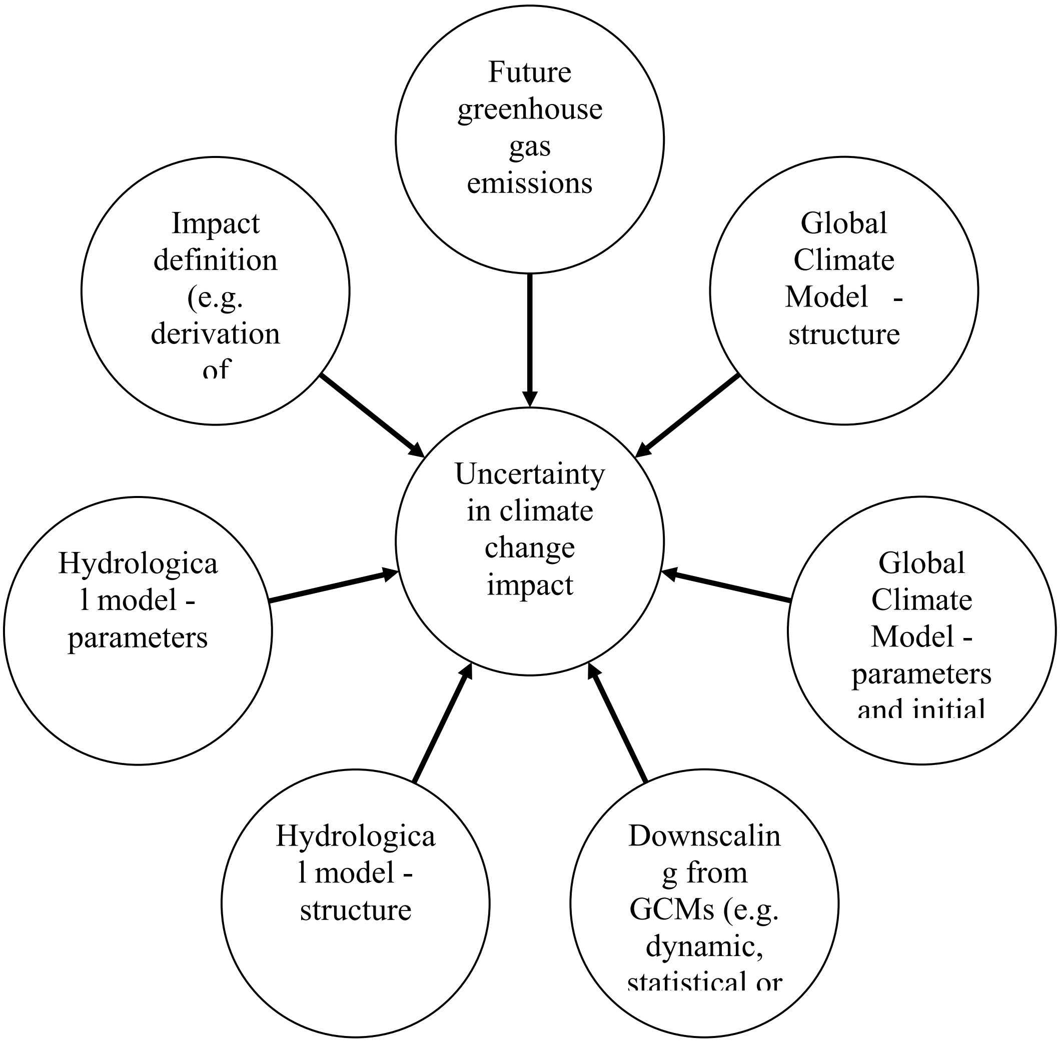


Figure 1.1 Some of the sources of uncertainty in a climate change impact study.

Quantification and propagation of uncertainty could allow research to be targeted at specific areas where uncertainty is currently large but potentially reducible. In the case where modelling results are presented with some quantification of (currently irreducible) uncertainty included, it is then up to the user of the results to decide how best to take account of that uncertainty when planning or making decisions.

Section 2 of this report considers the various sources of uncertainty which apply in the hydrological modelling of this project and discusses how some of them are being tackled (either within the project or elsewhere). Section 3 presents examples of the single-propagation of a number of these sources through to the impact of climate change on flood frequency, for two catchments in England. Multi-propagation is not attempted. Conclusions are given in Section 4.

2 SOURCES OF UNCERTAINTY

Two different hydrological models are currently being applied within this project. These are

- a grid-based model, the Grid-to-Grid (or G2G) (Bell *et al.* 2003, 2004, 2005, 2006), which is being developed for use within the Hadley Centre Regional Climate Model (RCM), as well as for offline work covering Europe (25 km grid) or the UK (1 km grid), and
- the catchment PDM (Moore 1985, 1999, Kay 2003, Kay *et al.* 2003, 2006a,b), which is being used solely offline and helping to validate the G2G model (Bell *et al.* 2004). Within this project, the PDM was usually run with parameter values generalised from catchment properties, rather than specifically calibrated to the catchment, so that the model could be run for any catchment in the UK.

Some of the uncertainty in results from these two models will be the same (e.g. that due to emissions, the Global Climate Model (GCM) etc) whilst some will be different (e.g. that due to hydrological model parameterisation). In this section, different sources of uncertainty will be discussed in more detail, with particular reference to how they relate to either hydrological model, where appropriate. The length of the discussion on each source is in no way indicative of their importance. The relative sizes of different sources of uncertainty are also discussed, as well as the applicability of model features or assumptions under future climates.

2.1 Future greenhouse gas emissions

Clearly, the future course of greenhouse gas emissions cannot be known. For this reason the IPCC produced a Special Report on Emissions Scenarios (SRES; IPCC 2000) describing four alternative ‘storylines’ for future emissions (referred to as A1, A2, B1 and B2), based on four different sets of assumptions on global development over the next century. Within each of these storylines a number of specific emissions scenarios were described (40 in all), each representing a specific quantification of greenhouse gas emissions.

The UK Climate Impacts Programme (UKCIP) selected one emissions scenario from each of the four SRES storylines, for their latest set of climate change scenarios for the UK (UKCIP02, Hulme *et al.* 2002). The selection was made so as to span the range of SRES scenarios well; for the A1 storyline, the highest emissions scenario was selected (A1F1). The emissions scenarios termed High, Medium-High, Medium-Low and Low in UKCIP02 correspond, respectively, to the SRES A1F1, A2, B2 and B1 emissions scenarios. However, the impact of these emissions on UK climate was only specifically modelled for a single scenario, that of A2 (Medium-High), using a three member ensemble of the Hadley Centre RCM HadRM3; the impact under the other three emissions scenarios was scaled from the A2 HadRM3 ensemble mean using the global temperature from the corresponding runs of the GCM, HadCM3. (Note that Murphy *et al.* (2004) question the effectiveness of this form of scaling to represent the range of potential impacts).

The climate change work within this project has only used data from HadRM3H under the A2 emissions scenario, but recent work by CEH Wallingford for the Environment

Agency looked at the impact of all four UKCIP02 scenarios on flood frequency for a number of catchments in Great Britain (Reynard *et al.* 2004).

2.2 GCM – structure

There are a number of GCMs, developed and run in various countries across the globe, and these produce different impacts of given emissions scenarios. Not only do they have different climate sensitivities (the change in global mean temperature under a doubling of CO_2) but they show different patterns of change in temperature and precipitation. See Figures 24-27 of UKCIP02, for patterns of change in winter and summer temperature and precipitation across the UK, under 9 different GCMs. Information on changes in various climate variables under future emissions scenarios, from a number of GCMs, can be obtained from the IPCC data distribution centre (ipcc-ddc.cru.uea.ac.uk).

Another potential source of uncertainty in GCM results, which can be defined as structural, is the effect of grid resolution (both horizontal and vertical). Increasing model resolution is likely to lead to more reliable results, due to less spatial averaging, but has a consequent increase in computing requirements.

2.3 GCM – parameters and initial conditions

GCMs require initial conditions, and patterns of change vary somewhat dependent on these. UKCIP02 used an ensemble of three runs with different initial conditions (see Figures 24-27 of UKCIP02), and presented results based upon the mean of these, to reduce the effect of initial condition uncertainty. Initial condition uncertainty is essentially a demonstration of natural climate variability.

GCMs also use parameterisations, to deal with processes that occur on scales smaller than the grid resolution of the GCM (e.g. schemes to estimate the amount of cloud). Some of these schemes are well-constrained (by observations) but others are less well understood, hence the uncertainty due to parameterisation could be important. Murphy *et al.* (2004) investigate the effect of parameterisations on climate sensitivity through the use of a so-called ‘perturbed physics ensemble’ (with 53 members), for a version of the Hadley Centre GCM. They present two pdfs of resulting climate sensitivity; one which assumes each parameterisation is equally likely (5-95% range of 1.9-5.3°C, median 2.9°C), and one which weights the parameter sets according to a measure of how well they reproduce features of the climate in the recent past (5-95% range of 2.4-5.4°C, median 3.4°C).

ClimatePrediction.net is a large distributed computing experiment aiming to investigate the full range of potential climate change, by using the spare capacity of participants’ PCs throughout the world to produce very large initial condition and parameter ensembles. At present this experiment has produced over 150000 runs of a GCM with a simplified (slab) ocean component (HadSM3), and results (Stainforth *et al.* 2005) show a range of climate sensitivities more than twice that used in the IPCC TAR (IPCC, 2001). Moreover, the regional patterns of change differ, not just for versions with different sensitivities but for versions with similar sensitivities (Stainforth *et al.* 2005). Climateprediction.net will move to the use of a fully coupled GCM in 2006, aiming eventually to produce the most complete probabilistic climate forecast for the next century.

The climate change work within this project has only used data from an RCM nested within one current and one future run of the HadCM3 GCM. The above suggests that the use of ensemble runs would be desirable, to obtain a fuller range of possible impacts.

2.4 Downscaling from GCMs

The coarse spatial resolution of GCMs, and the greater uncertainty in their outputs at fine temporal resolution (especially for precipitation), means that they are generally not appropriate for finer scale impacts modelling, like flooding. This is particularly true of flood modelling in the UK, where even the largest catchments are smaller than a GCM grid box, and where local topography is vital in determining rainfall patterns. Spatial interpolation can be used to represent the outputs on a finer grid (Hulme and Jenkins 1998), but this does not incorporate any extra information.

The standard method used as an alternative to the direct use of GCM data is to derive proportional or absolute changes in mean rainfall from the GCM data and to apply these changes to baseline observed climate; sometimes called the delta change method. Such methods have been used to examine the potential impacts of future climate change on flooding (Crooks *et al.* 1996, Prudhomme *et al.* 2002, Reynard *et al.* 2001, Schreider *et al.* 2000). The changes are usually derived from monthly GCM time-series, so methods of applying the changes to daily (or even sub-daily) data are required. The method chosen affects the outcome of the subsequent hydrological modelling quite significantly, and there is no right or wrong answer to how it should be done. The straightforward application of monthly percentage changes to all observed daily or sub-daily rainfall totals in the month means that no account is taken of changes in variability, which could mean that future changes are underestimated (Arnell *et al.* 2003). A variation on applying the delta change method to baseline observed rainfall is its application to stochastic rainfall series, generated for the current climate using a stochastic rainfall model (Cameron *et al.* 2000).

As well as rainfall, the hydrological models also require input time-series of potential evaporation (PE). As this is not a direct output of GCMs, these data need to be estimated from other variables output by the GCM. A frequently used form of PE is Penman-Monteith (Monteith 1965), which requires temperature, wind speed, net radiation and humidity data, but these are not always available (although they are from the Hadley Centre GCM), so substitutes may have to be used. Even when the required variables are available, the calculated monthly PE may not seem realistic (e.g. very negative values), possibly due to errors resulting from the coarse resolution of the GCMs.

Another alternative is to use the GCM-derived changes to infer changes in the parameters of a weather generator, which can then be used to simulate rainfall time-series under current and future climates for use as input to continuous hydrological models (Schreider *et al*. 2000, Tung 2001). However, such methods rely on the ability of the random element of the weather generator to simulate a wider range of conditions than may be available in the observed record used for model development. These methods can also be overly-influenced by any problems in the historical record, such as missing data. Another option is provided by statistical downscaling, in which relationships are developed between large-scale, GCM-generated atmospheric variables and observed rainfall series (e.g. Wilby *et al.* 2002). These regression relationships are then applied, using current- and future-climate GCM data, to generate long time-series of rainfall under current and future conditions, assuming the relationships remain valid under future conditions. Muller-Wohlfeil *et al.* (2000) use a combination of statistical downscaling and a weather generator, which they term 'expanded downscaling', to generate input for a spatially distributed hydrological model for a catchment in northern Germany. The combined method is developed to overcome the low variability seen in generated time-series, particularly for rainfall, when using statistical downscaling alone, but still relies on current relationships being applicable in the future.

The recent advent of Regional Climate Models (RCMs) nested within GCMs (dynamic downscaling) has greatly improved matters, by providing more regional detail without an unreasonable increase in computing time. In 2002 UKCIP released a new set of climate scenarios for the UK, based on the ~50 km grid of HadRM3 (UKCIP02). These scenarios are now widely used in the UK for climate change impact studies, although they generally apply monthly proportional changes in the climate variables (delta change method, as for GCMs), to investigate impacts (e.g. Reynard *et al.* 2004, Cameron 2006).

To date there has been little direct use of RCM data for impact studies, despite the fact that RCM rainfall is significantly better than that simulated by the GCM (Durman *et al.* 2001, Huntingford *et al.* 2003). The work for this project was, as far as we know, the first of its kind (Kay 2003, Kay *et al.* 2003, 2006a,b). The RCM used in this project is the same as that for UKCIP02, but with a further improvement in the temporal and spatial resolution (hourly precipitation data on a ~25 km grid). The PE calculated from this RCM data was realistic when compared with PE from MORECS (Meteorological Office Rainfall and Evaporation Calculation System; Thompson *et al.* 1982, Hough *et al.* 1997), which also uses Penman-Monteith (Figure 2.1).

An advantage of downscaling using either delta change or statistical methods over dynamic downscaling is the ease with which alternative emissions scenarios, or those based on alternative GCMs, can be applied: RCMs are relatively expensive in terms of computer power and data storage. Statistical methods also allow the easy use of longer time-series, to cover rarer events (higher flood frequency return periods), or multiple realisations (to cover natural variability).

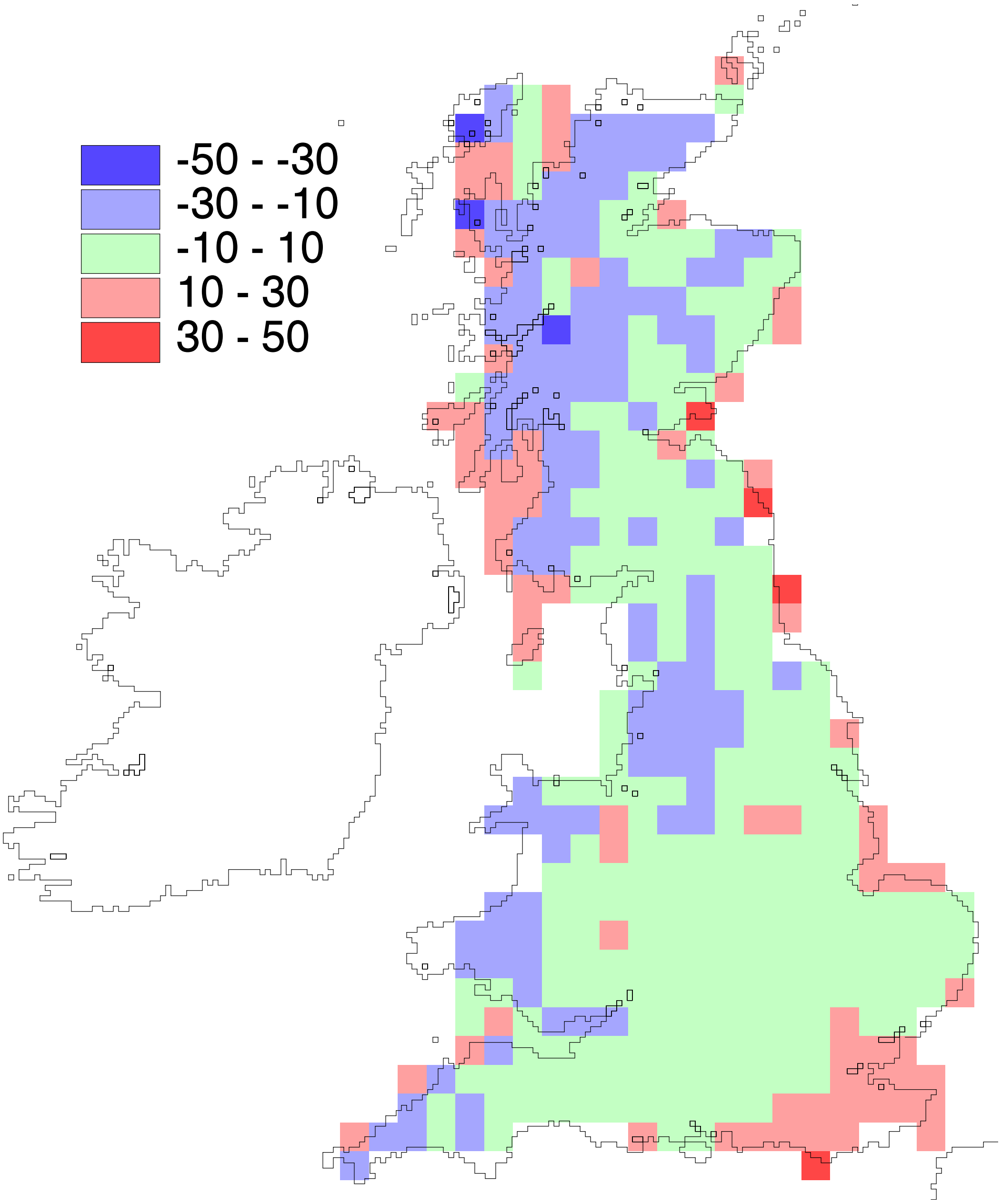


Figure 2.1 Percentage error in mean annual PE derived from RCM data (25km RCM driven with European re-analysis boundary conditions for 1979-1993), compared to MORECS PE averaged over the same period (with interpolation from 40km MORECS grid to 25km RCM grid).

The EU-funded PRUDENCE project (http://prudence.dmi.dk) produced high-resolution climate change scenarios for Europe (for 2071-2100) based on the use of 9 different RCMs nested within a Hadley Centre GCM (HadAM3H). Some of these data have been obtained, in order to investigate the effect of RCM uncertainty on the impact of climate change on flooding. PRUDENCE also used the ECHAM GCM with some RCMs, and applied two different emissions scenarios in some cases, meaning that GCM and emissions uncertainty could also be investigated to some extent.

In this project, further downscaling is required from the RCM grid resolution, either down to the catchment scale (for the PDM) or down to the 1km UK national grid (for the UK G2G). This is straightforward for the required PE inputs, but precipitation is much more affected by topography. A method was thereby devised which made use of Standard Annual Average Rainfall (SAAR) data, available on a 1km grid for the UK. This SAAR data indicates areas which receive consistently more rainfall than others, so is used to distribute the rainfall from the 25km RCM grid. Any errors in the gridded SAAR data will then affect the downscaled RCM data.

2.5 Hydrological model – structure

There are numerous hydrological models, each of which could be used to assess the effect of climate change on flows. No model is perfect in its representation of reality, and the choice of model must be based on, for instance, study aims, performance under current conditions for required catchments/areas, data requirements etc.

The G2G model has been developed, within this project, specifically to be a grid-based model that can be used within the RCM, 'online'. As such, it must be able to be run on the grid of the RCM (possibly with some sub-grid scale processing). The definition of the flow network on the appropriate grid is therefore a vital component of the model. Initial development of the model was based on a hand-corrected flow network for Europe and the UK, but such hand correction is very time-consuming. Recently, methods have been investigated to automatically define flow networks at the required grid scale, based on Digital Terrain Model (DTM) or river data on a finer grid, and these are proving to be a great improvement. However, they require careful definition of an appropriate land-sea mask beforehand, paying particular attention to estuaries and their inflow points.

The PDM itself has a number of variations, but spatial generalisation (relating model parameters to catchment properties) was improved in parameter-sparse models (Lamb *et al.* 2000), so the parameter-generalised PDM used within this project is a simplified version with just five catchment-specific parameters; other parameters have fixed values. This will sacrifice some catchment-specific performance.

2.6 Hydrological model – parameters

Hydrological model parameters that require calibration (that is, adjustment until a satisfactory or best fit to flow observations is achieved) will be uncertain. A different method of fitting (manual, semi- or fully-automatic) or using a different measure of fit (objective function), that concentrates on different observed features (e.g paying particular attention to high or low flows), will likely result in different calibrated parameter values. This is particularly true where a number of parameters require concurrent calibration, if there is any sort of interdependence between them; often, a number of parameters sets will provide almost equally good fits to observations (equifinality). Performance may even appear to be insensitive to the value of a particular parameter (non-identifiability), at least with respect to a given objective function.

An additional factor which could affect calibration performance is data quality, for both input data (rainfall and potential evaporation) and calibration data (observed flows). Data quantity is also important, as there must be a sufficient length of data, covering a range of flow regimes, for calibration to be effective. The calibrated parameters will thus differ to some extent according to the data used for calibration.

The catchment PDM used in this project runs at an hourly internal time-step, and has hourly observed flow and rainfall data for calibration (although some missing hourly rainfall was infilled using daily totals with average hourly profiles). However, the G2G requires gridded rainfall inputs, and so only has observed rainfall data at a daily time-step for the UK. These data are available on a 5km grid, and are downscaled to the 1km model grid for the UK using SAAR data, in the same way as for downscaling from the 25km grid of the RCM. These data are used for calibration against daily mean flows for specific catchments, but first have to be disaggregated in time to go into the model at the 15 minute internal time-step (required for numerical stability). The simulated flows are then averaged up to a daily time-step to fit to observed flows. This disaggregation and averaging means that the calibration process is less able to model flows at smaller time-step lengths, such as hourly, although the effect will be more pronounced on some catchments (i.e. smaller or quicker-responding catchments) than others (i.e. catchments which are larger or more baseflow-dominated).

A further complication with calibration of the G2G model is that, when run as an area-wide model, its parameters either have to be identical over the region of interest (often the RCM domain), or derived via other data that are available over the region (e.g. topography, soils, land use, geology etc.). The latter development, of ways to fully parameterise the G2G using other data sets, is ongoing. Consequently, the model currently does not work as well in some areas as others: it performs better in regions where flows are very much driven by topography (e.g. Wales) and worse in regions of high baseflow (e.g. the South East of England). The G2G's requirement for area-wide parameter values can be relaxed when it is run over smaller areas, with specific calibration to flows of individual catchments in those areas. This results in improved simulations, but generally, at the present level of model development, these are still not as good as the simulations using the parameter-generalised PDM (Bell *et al.* 2004).

There are various ways in which calibration uncertainty can be systematically investigated, although the application of these in a grid-based model such as the G2G would be very difficult. For the catchment PDM, with its catchment-average inputs, such methods are more straightforward. One method, which has been applied on the form of model used here, is a variation on the statistical technique of jack-knifing. This involves the generation of a number of different calibrated parameter sets, each based on slightly different data: one whole year of observed flow data is ignored in the generation of each set (all input data are retained, to preserve the year-to-year water balance). Thus N years of data leads to N+1 calibrated parameter sets (one based on the use of all the data). The model can then be run with each of these parameter sets, and the spread of the results used to assess calibration uncertainty (note that the calculation of variance is slightly altered when jack-knifing is used, with a multiplier of (N-1)/N rather than 1/N (Shao and Tu, 1995)).

When model parameters are estimated in some way from catchment properties, rather than through direct calibration, there is additional uncertainty from this generalisation. The latest work on spatial generalisation of the PDM, for flood frequency estimation at ungauged sites in the UK, also looked at uncertainty from this process, to provide uncertainty bounds on the generalised flood frequency curves (Calver *et al*. 2005).

2.7 Impact definition

When a flood frequency curve is fitted to point data (whether annual maxima or peaks-over-threshold), there is uncertainty in the fit. This is particularly true where there are 'outlier' events in the point series, or where a catchment's flood events can be generated by very different processes (e.g. flash floods from heavy summer storms, groundwater floods from sustained autumn/winter rainfall, floods from snow melt). Also, the shorter the data series the flood frequency curve is based on, the more likely it is to diverge from average conditions, and instead over- or under-estimate flood frequency due to flood-rich or flood-poor groupings of years that occur due to natural climate variability. This could be a particular problem with the delta change method of downscaling, which is highly dependant on the variability and ordering of events within the (relatively short) baseline period. In particular, the sequencing of wet and dry seasons and years could have a significant effect on the flood frequency. The 30-year time-slices of the RCM are less prone to the latter effect, but the use of data from single RCM runs, rather than ensembles, means that the potential presence of outliers in simulations from either the current or future time-slice is more problematic.

In the derivation of flood frequency, peaks-over-threshold (POT) are generally preferred over annual maxima, as they make more use of the data. However, the use of POT within the G2G model is difficult, as it is not straightforward to extract these data when the model is being run. This is because the threshold is defined implicitly through the extraction of an average number of peaks per year (often three, so 3T peaks would be extracted from T years of flows, but not necessarily three peaks from each year), and also because of the application of independence criteria for peaks. As annual maxima are much simpler to extract, this method has been employed within the G2G. Note that, whichever way the peaks are extracted, the flood frequency curve fitted to them is not intended for extrapolation to higher return periods, but simply to interpolate and smooth the point data; for T years of data the limit is a return period of approximately 2T years.

The impact of climate change on flood frequency is often defined by the percentage change in a flood peak of a given return period, or sometimes by the change in the return period of a given flood magnitude. Whichever way it is defined, there is no single figure for the impact at any location as this is likely to differ by return period (or magnitude).

The impact is also dependent on the time-horizon under consideration, as would be expected. However, not only is the dependence not necessarily linear, but the direction of change may not be consistent between time-horizons: Under a given emissions scenario, downscaling method, hydrological model etc., some catchments can show an increase in flood frequency to the 2050s but a decrease by the 2080s, or vice-versa (Reynard *et al.* 2004). This is likely to be due to the balance between increased winter rainfall and decreased summer rainfall, with higher temperatures, meaning higher soil moisture deficits which have to be refilled before flooding can occur.

A further complication in the definition of the impact is the time-step or averaging period used to extract POT or AM: the flood frequency curve based on hourly instantaneous flows will differ from that based on daily or monthly mean flows, and so too might the percentage changes in these curves from current to future times-slices.

2.8 Relative sizes of uncertainties

No studies so far have propagated the full range of sources through to climate change impacts on flooding and compared the relative sizes. The work of Reynard *et al.* (2004) includes emissions uncertainty (4 UKCIP02 scenarios) and downscaling uncertainty (delta change, statistical and RCM), and finds that emissions uncertainty is less important than downscaling uncertainty. However, several studies have looked at the effect of different sources of uncertainty on precipitation, and greater uncertainties in precipitation might be expected to lead to greater uncertainties in flows. In addition, several studies have looked at the effect of some sources of uncertainty on the impact of climate change on water resources (monthly mean flows).

Rowell (2004) used PRUDENCE data to compare the effect of different sources of uncertainty (emissions scenario, GCM, RCM, and initial condition ensemble) on changes in seasonal surface air temperature (SAT) and precipitation over the UK. For seasonal SATs it was found that uncertainty from GCM formulation was always the largest, followed by emissions, then RCM formulation. For precipitation it was found that the relative contribution of the four sources was more equal; although that from the emissions scenario was generally the lowest, the ordering of the uncertainties from the other three sources varied from season to season. It is reassuring that all the experiments consistently predict increased winter rainfall and decreased summer rainfall, but there is less change, and less consistency in direction of change, for spring and autumn rainfall. The changes in autumn rainfall, in particular, could be crucial for determining changes in (winter-dominated) flooding in the UK.

However, it should be noted that uncertainty from GCM formulation is unlikely to represent the full range of possibilities in the latter work, as data from only two different GCMs (with the same nested RCM) was available for analysis. Similarly, emissions uncertainty will be underestimated as only data from the A2 and B2 scenarios was available. Studies of changes in global mean rainfall from different GCMs and emissions scenarios suggest that GCM-uncertainty dominates emissions uncertainty (Jenkins and Lowe 2003).

Recent work looking at the uncertainty in the impact of climate change on water resources (monthly mean flows) in the UK suggested that GCM uncertainty (from 3

GCMs) was the largest source of uncertainty, with downscaling uncertainty also significant. Hydrological uncertainty was found to vary significantly between catchments, so could be more significant for some than others. Emissions uncertainty was not found to be significant, but only two emissions scenarios (A2 and B2) were used and the time-slice under consideration was the 2020s; emissions uncertainty will be higher for later time-slices, such as the 2080s used in this project. The research was based on 13 catchments spread across Great Britain, modelled using a version of the PDM slightly different to that used in this project (Prudhomme *et al.* 2005).

Wilby (2005) also investigated the impact of climate change on water resources (monthly mean flows), using a conceptual water balance model for the Thames catchment, particularly looking at the effect of model uncertainty. He found that calibration uncertainty was comparable in size to emissions uncertainty (even for the 2080s), although only two emissions scenarios (A2 and B2) were used, which do not span the full range. GCM uncertainty was not assessed.

2.9 Validity of 'Current to Future' assumptions

Listed below are some aspects which are assumed to be the same, when using future scenarios, as for the current climate.

- GCM parameterisations.
- Downscaling from GCMs:
    - statistical downscaling model (fit of GCM features to rainfall),
    - RCM parameterisations,
    - SAAR downscaling, for hydrological model rainfall inputs.
- Hydrological model:
    - Parameter values,
    - Generalisation relationships.

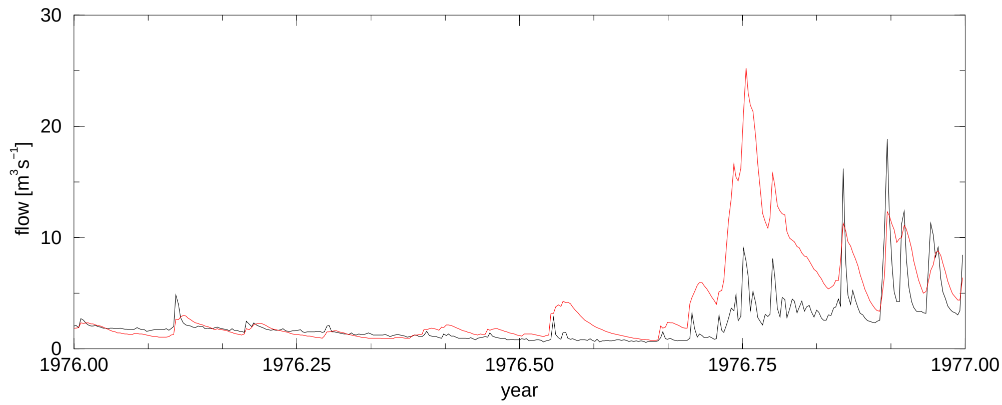
Some of these it may seem reasonable to assume are constant, as they are based on physical responses (e.g. those due to soil type, geology etc) that should not change significantly. However, some things may change because of the change in climate. For example, if climate change means a change in the tracking of weather fronts then the relative SAARs of different areas may change. However, this should have a relatively minor affect on the SAAR downscaling given the grid scale, unless many weather fronts were to come from a very different direction.

Another example is that land cover may change, due to the dieback of certain plants that cannot cope with the increased temperatures and/or changed rainfall patterns or the need to grow more resilient crops. This could lead to changes in runoff, and so hydrological model parameters may need to be changed. However, the fitting of relationships between catchment properties such as land-use and model parameters does not necessarily provide a straightforward way of making such an adjustment. This is because some properties could be acting as surrogates for other features affecting the hydrological regime. For instance, in the UK there is a high (negative) correlation between proportion of arable land and mean catchment altitude, which is in turn correlated with average rainfall and mean catchment slope.

2.10 Model performance under future conditions

One relatively consistent feature of the predictions of different GCMs is the increased seasonality of rainfall, with wetter winters and drier summers particularly over southern England. This means that the models must be able to cope with quick recovery from high soil moisture deficits. Checking this recovery on a historical period of similar strong seasonal differences thus provides reassurance about response under future climates. Similarly, response could be specifically assessed during historical periods of other extremes that may be predicted to occur more frequently in the future.

a)



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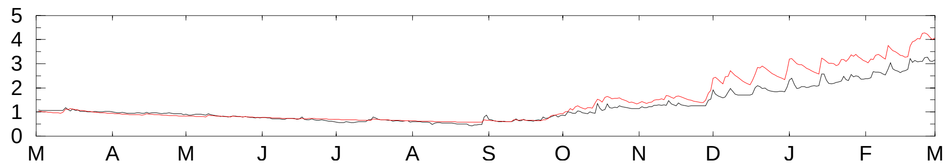


Figure 2.2 Examples of simulated recovery (during late 1976) from the 1975/76 drought (red), compared to observed flows (black), for two catchments: a) 39007 (the Blackwater at Swallowfield) modelled with the G2G model, and b) 42012 (the Anton at Fullerton) modelled with the PDM.

The driest conditions for much of the UK during the standard baseline period of 1961 to 1990 occurred in the summer of 1976, following on from the low rainfalls during the winter of 1975/76. The drought period ended very rapidly in the autumn of 1976. Inspection of model response during periods such as this is thus recommended. Examples of simulated recovery from drought during late 1976 are shown in Figure 2.2 for the G2G and PDM models. The performance for each model suggests that simulations of flood events following droughts under future climates (where conditions may not be more extreme than in 1976, but such events may occur more frequently) are more likely to over- rather than under-estimate subsequent runoff. This is consistent with the performance of a further model used by the group for modelling climate change impacts, the semi-distributed model CLASSIC (Reynard *et al.* 2004).

If the future change in hydrological regime for a catchment is beyond that available in its historical data, it may be possible to find a so-called analogue catchment to investigate. That is, a catchment which is relatively similar (in terms of physical catchment properties) to the catchment of interest, and whose historical record does contain events of the type that that catchment may experience in future. Investigating model performance during particular events for the analogue catchment may then give confidence in performance for the catchment of interest under future conditions.

3 EXAMPLES OF THE EFFECT OF UNCERTAINTY ON FLOOD FREQUENCY ESTIMATION

This section presents examples of each of the sources of uncertainty, for two catchments in England. These catchment are 40005 (the Beult at Stile Bridge, in the South East) and 74001 (the Duddon at Duddon Hall, in the North West), and they are shown on the map in Figure 3.1. Some details of the catchment are given in Table 3.1. Both catchments are essentially rural, but are very different in terms of area, rainfall regime and topography (Figure 3.2). These factors, as well as location (amongst other things), are likely to mean a differing impact of climate change.

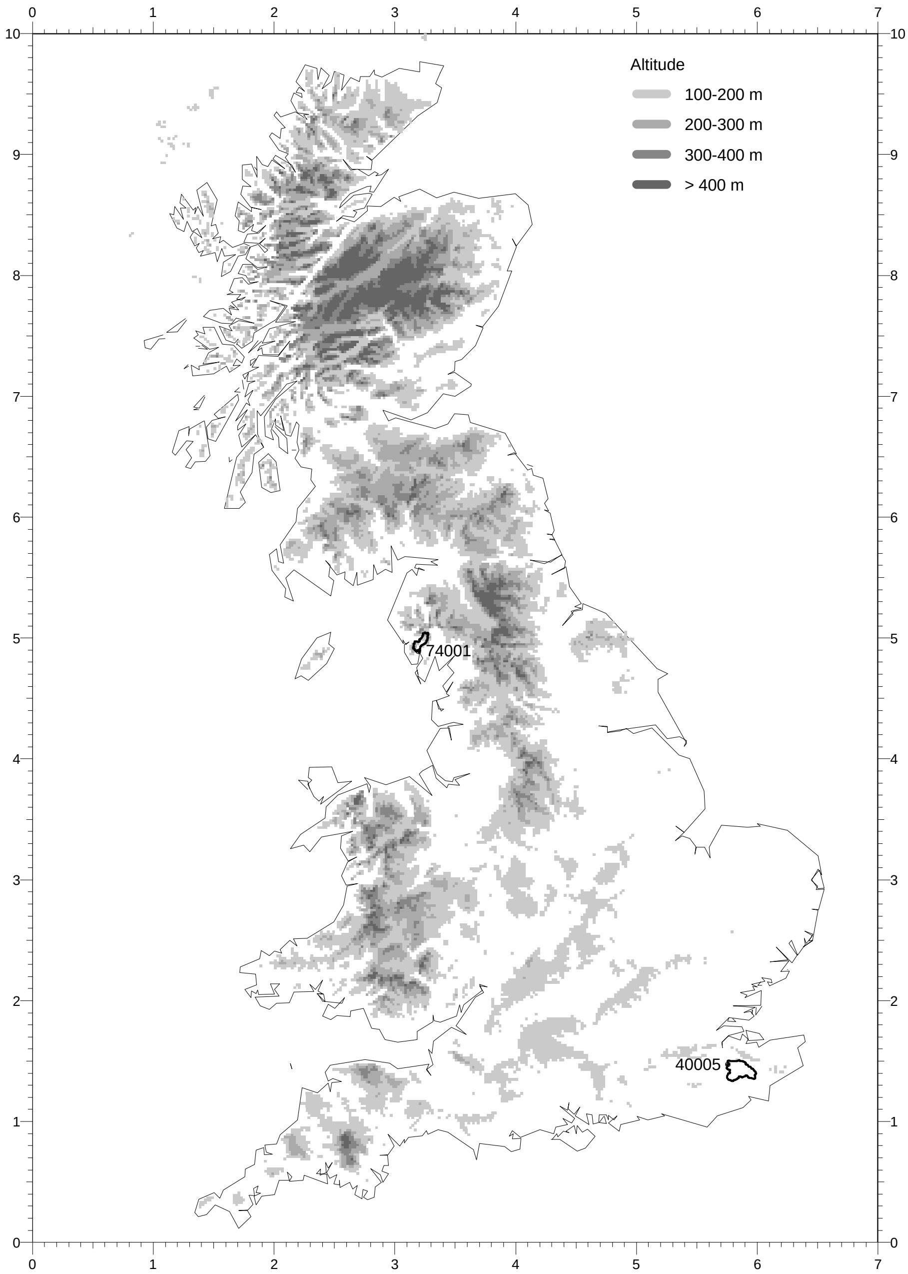


Figure 3.1 Map showing the locations of the two example catchments.

Table 3.1 Details of the two example catchments.

Catchment number	Catchment area (km^2)	Altitude range (m)	Mean altitude (m)	Baseflow index	Mean flow (m^{3}s^{-1})	SAAR$_{61-90}$ (mm)	R
40005	277	13 – 161	45	0.24	2.1	690	0.34
74001	86	17 – 799	315	0.28	4.8	2265	0.81

SAAR$_{61-90}$ = standard annual average rainfall for 1961-1990, R = mean annual runoff / mean annual rainfall.

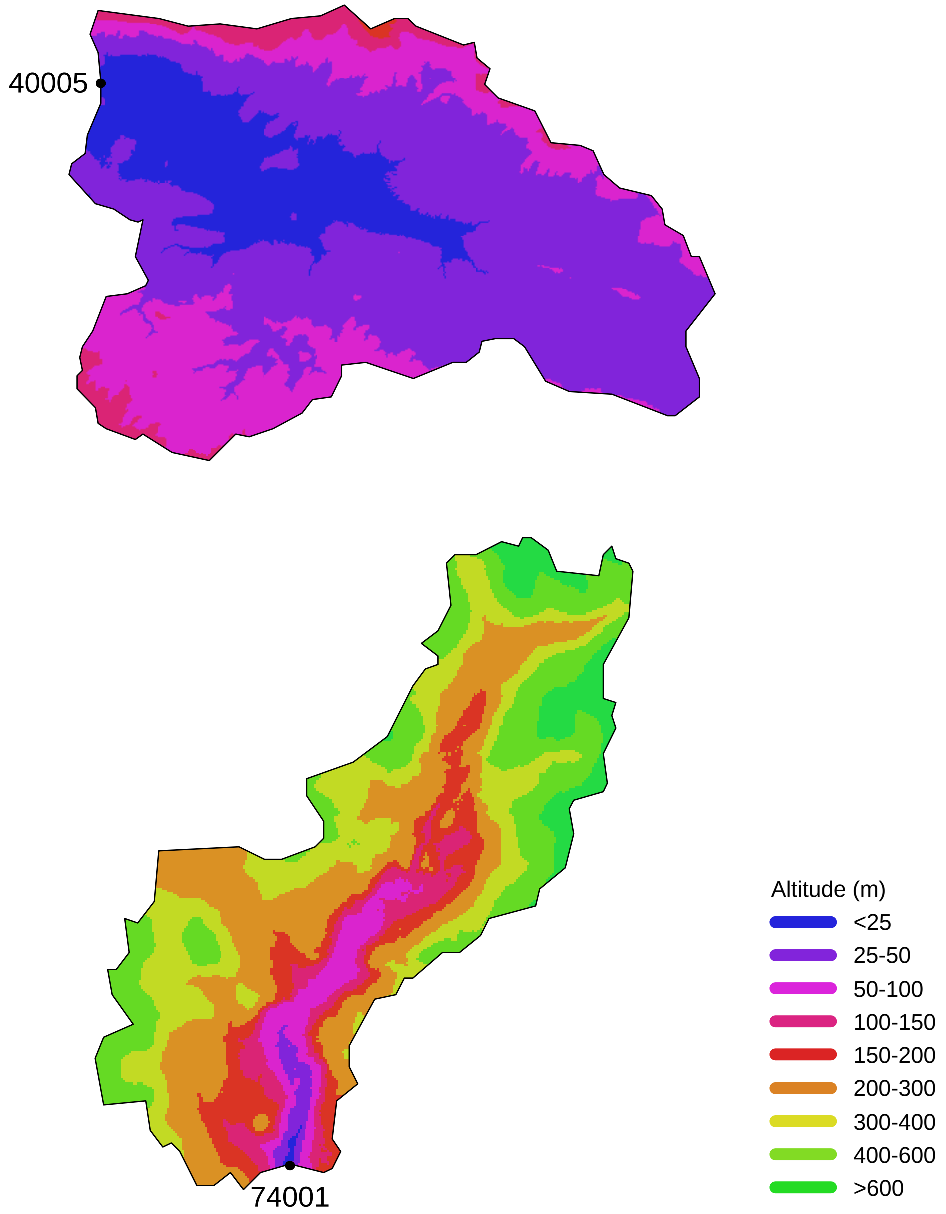
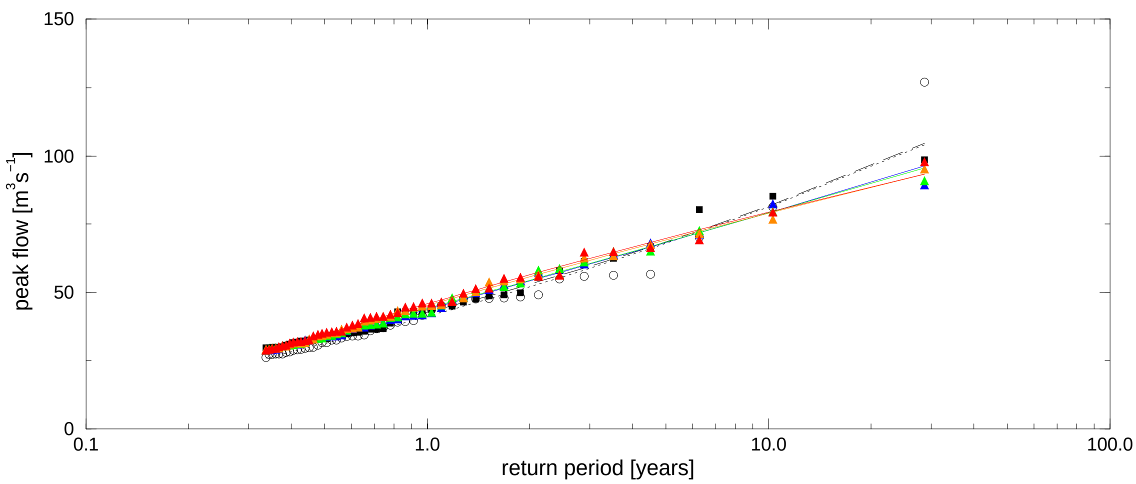


Figure 3.2 Topography of the two example catchments.

3.1 Future greenhouse gas emissions

Figure 3.3 shows examples of the effect of emissions uncertainty on flood frequency estimation, using the four UKCIP02 emissions scenarios for the 2080s (see Section 2.1). The scenarios are applied by adjusting baseline (hourly) rainfall and PE data using mean monthly percentage changes derived from each of the UKCIP scenarios (see Section 2.4). The results show that uncertainty due to emissions is very low for catchment 40005, but more important for catchment 74001. However, it should be recalled that three of the UKCIP02 scenarios are pattern-scaled from the ensemble mean of the medium-high scenario, and that even these four scenarios do not cover the full IPCC range.

a) 40005



b) 74001

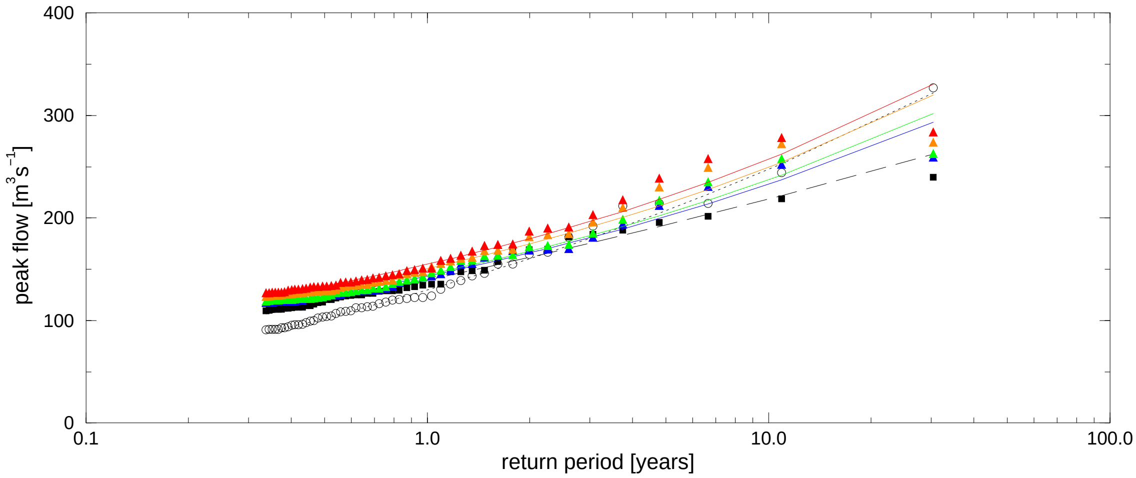
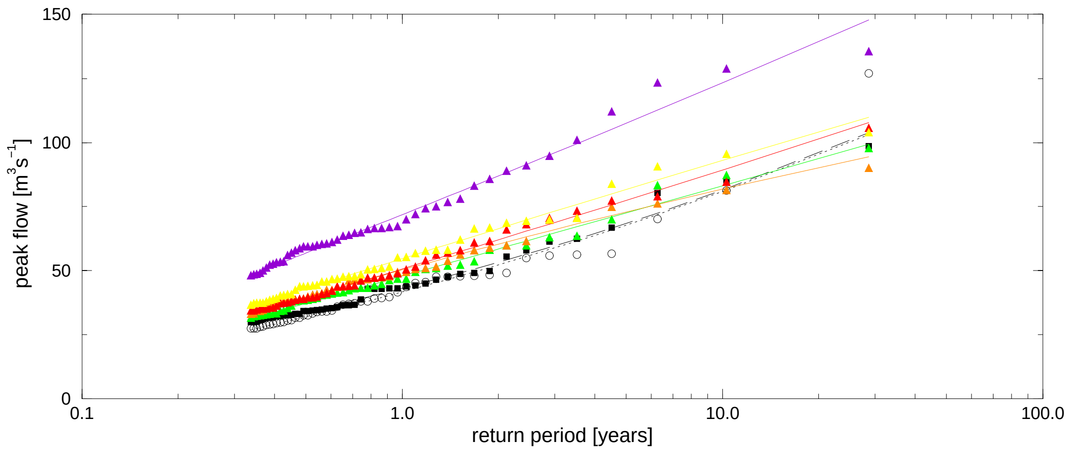


Figure 3.3 Examples of flood frequency uncertainty from emissions uncertainty, showing results for the UKCIP02 High (red), Medium-high (orange), Medium-low (green) and Low (blue) scenarios for the 2080s. The current flood frequencies from observed flows (black dotted line) and simulated with observed rain (black dashed line) are also shown.

3.2 GCM – structure

Figure 3.4 shows examples of the effect of GCM uncertainty on flood frequency estimation, under the A2 emissions scenario for the 2080s. The 5 GCMs represented here are HadCM3 (UK Hadley Centre), CSIRO-Mk2 (Australia), CGCM2 (Canada), ECHAM4 (Germany) and CCSR (Japan) (but there are others). The delta change method is used to apply monthly percentage changes in rainfall and PE, derived from each of the GCMs, to the baseline hourly data for the catchments. The results show that GCM uncertainty could be quite important for both catchments, although the GCM resulting in the highest increase in flood frequency for both catchments, CCSR, is generally considered to be quite extreme in terms of the increase in winter rainfall that it predicts. The ordering of the effect of other GCMs differs between the two catchments.

a) 40005



b) 74001

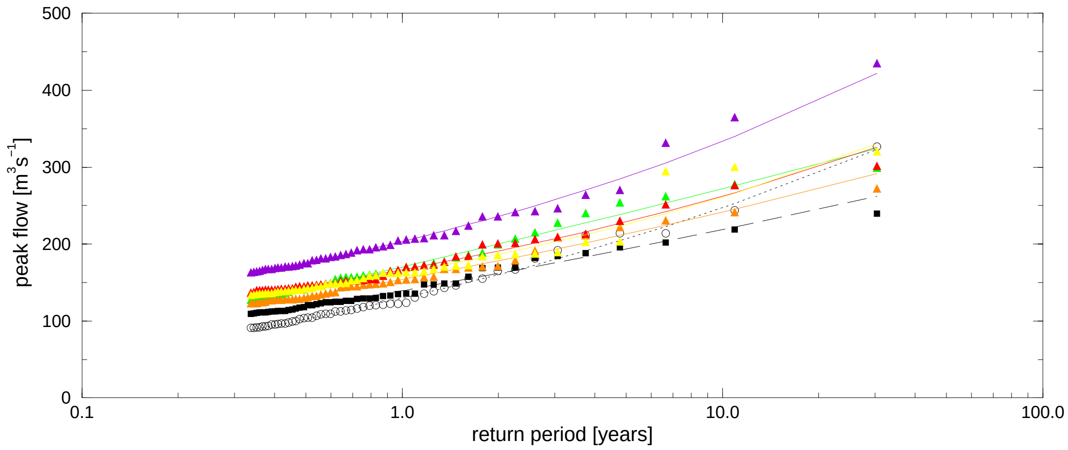


Figure 3.4 Examples of flood frequency uncertainty from GCM structure uncertainty, showing results for 5 GCMs (2080s, A2 emissions scenario); HadCM3 (green), CSIRO-Mk2 (yellow), CGCM2 (orange), ECHAM4 (red) and CCSR (purple). The current flood frequencies from observed flows (black, open circles/dotted line) and simulated with observed rain (black, filled squares/dashed line) are also shown.

3.3 GCM – initial conditions

Figure 3.5 shows examples of the effect of GCM initial condition uncertainty on flood frequency estimation, under the A2 emissions scenario for the 2080s. Results are shown for the HadRM3P RCM nested within a three-member initial condition ensemble of the HadAM3P GCM (data from PRUDENCE project). The delta change method is used to apply monthly percentage changes in rainfall and PE, derived from each of the RCM runs, to the baseline hourly data for the catchments. The results suggest a greater effect of GCM initial condition uncertainty for catchment 40005 than for catchment 74001. The ordering of the effect of the three ensemble members differs between the two catchments, although the third ensemble member generally has the greatest effect on both (at least at lower return periods). GCM initial condition uncertainty is essentially a demonstration of natural climate variability, which is discussed further in Section 3.7.1.

3.4 Downscaling from GCMs

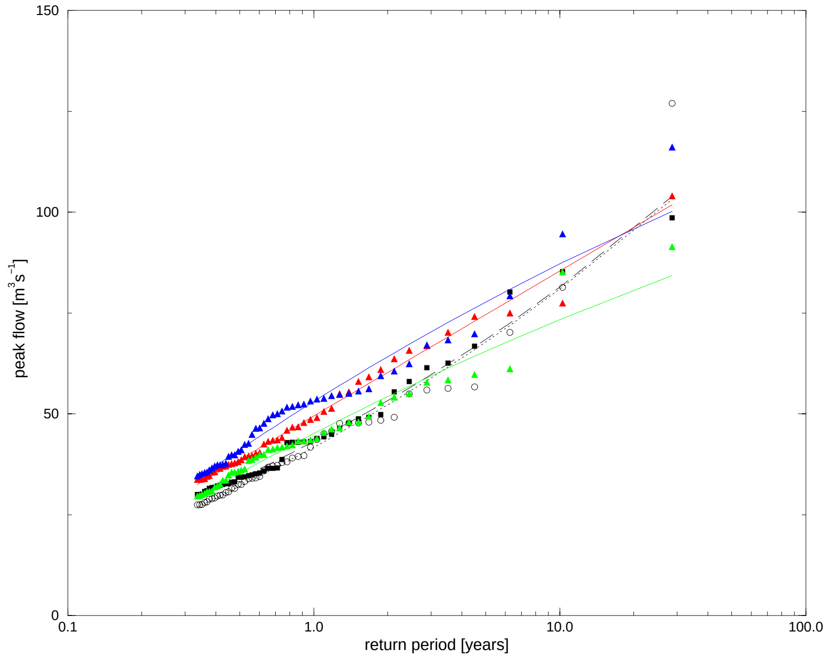
3.4.1 Delta change vs. direct use of RCM data

Figure 3.6 shows examples of the effect of downscaling uncertainty on flood frequency estimation, under the A2 emissions scenario for the 2080s. Results are shown for four different downscaling methods, the first three of which are based on the delta change method and the last of which uses data directly from an RCM.

Two of the delta change methods use different data sources to determine the monthly percentage changes that are applied; the first uses GCM data while the second uses RCM (UKCIP02) data. These changes are applied to the baseline hourly rainfall and PE through the simple application of the monthly percentage changes to each hour of baseline data according to month. However, this does not allow for more complex changes in rainfall distributions. Reynard *et al.* (2004) developed a version of the delta change method which aims to match changes in daily rainfall intensity as well as percentage changes in monthly means (PE is still adjusted simply through changes in monthly means), and it is this which is applied in the third version of the delta change method, again using changes derived from UKCIP02 RCM data. The final of the four methods uses data directly from an RCM (25km HadRM3H) to derive rainfall and PE inputs for the hydrological model (Kay *et al*. 2003).

For the two catchments used here, the three delta change methods show very similar results, with a decrease in flood frequency at higher return periods for catchment 40005, and an increase in flood frequency at all return periods for catchment 74001 (Figure 3.6a-c). It is more difficult to compare these to the results using RCM data directly, as bias means that it is necessary to use both current (1961-1990) and future (2071-2100) time-slices of RCM data, and look at changes between these rather than changes from an observed flood frequency curve (Figure 3.6d). However, the pairs of curves for the two catchments show similar decreases for 40005 and increases for 74001.

a) 40005



b) 74001

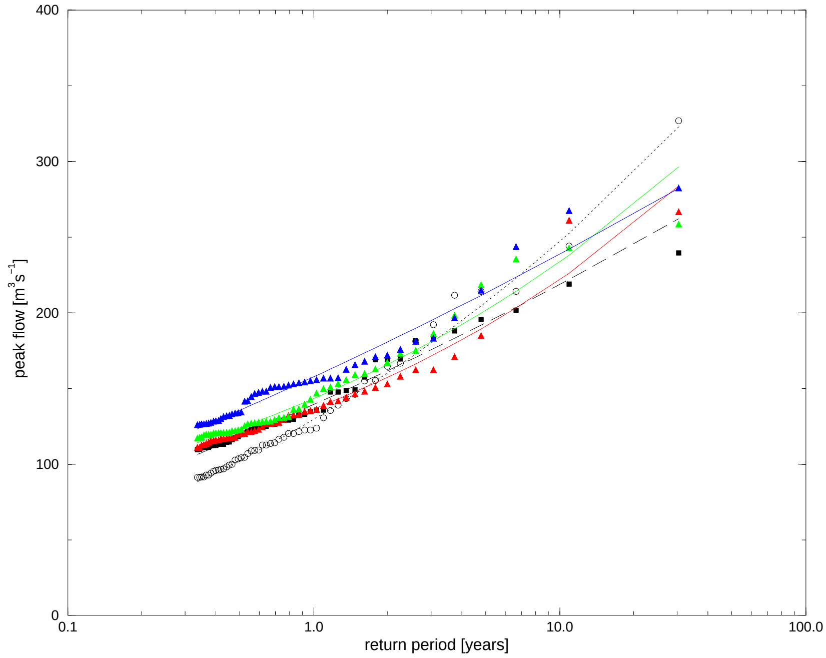


Figure 3.5 Examples of flood frequency uncertainty from GCM initial condition uncertainty (2080s, A2 emissions scenario), showing results for the HadRM3P RCM nested within three ensemble members of the HadAM3P GCM (red, green and blue). The current flood frequencies from observed flows (black, open circles/dotted line) and simulated with observed rain (black, filled squares/dashed line) are also shown.

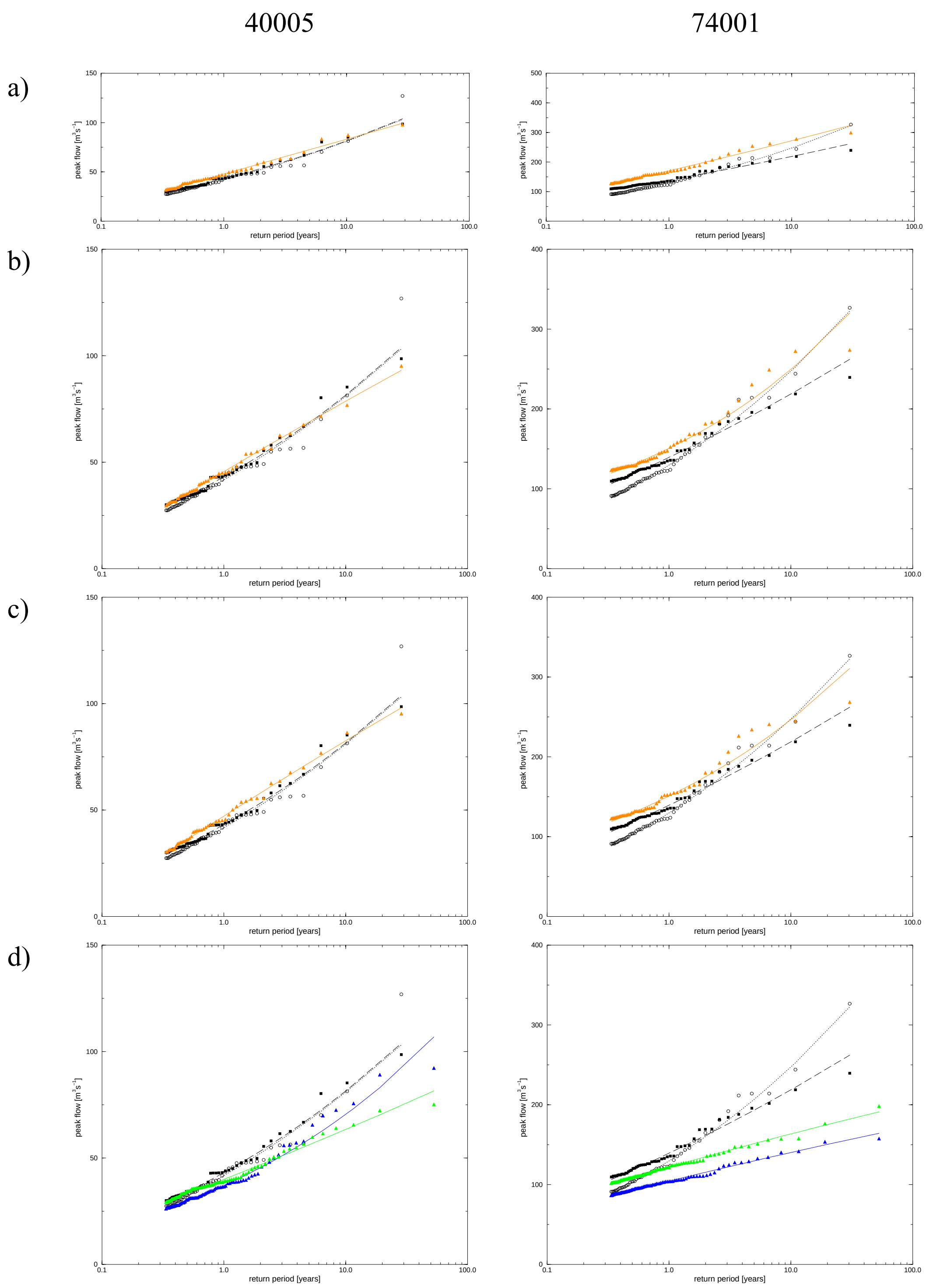


Figure 3.6 Examples of flood frequency uncertainty from downscaling uncertainty (2080s, A2 emissions): a) delta change from HADCM3 GCM (orange), b) delta change from UKCIP02 RCM (orange), c) extended delta change from RCM (orange), and d) direct use of hourly RCM (25km HadRM3H) data (1970s – blue, 2080s – green). The current flood frequencies from observed flows (black, open circles/dotted line) and simulated with observed rain (black, filled squares/dashed line) are also shown.

3.4.2 RCM structure

Figure 3.7 shows examples of the effect of RCM uncertainty on flood frequency estimation, using PRUDENCE data for 5 different RCMs nested within the same GCM (HadAM3H). The 5 RCMs represented here are from the Hadley Centre (UK), ICTP (Italy), DMI (Denmark), ETH (Switzerland) and KNMI (Netherlands). [Note that only 5 of the 9 PRUDENCE RCMs are included here as data from the others are not available, at the time of writing, due to PRUDENCE disc problems.]

The results shown are based on the use of the simple delta change method, with monthly percentage changes in rainfall derived from the RCMs (2080s, A2 emissions scenario) and applied to the baseline catchment rainfall. Due to difficulties in deriving PE in a consistent way for different RCMs (because of the high data requirements, in terms of variables needed for the Penman-Monteith method used for observed PE), the same change in PE has been applied for all RCMs: that derived from the UKCIP02 Medium-High emissions scenario.

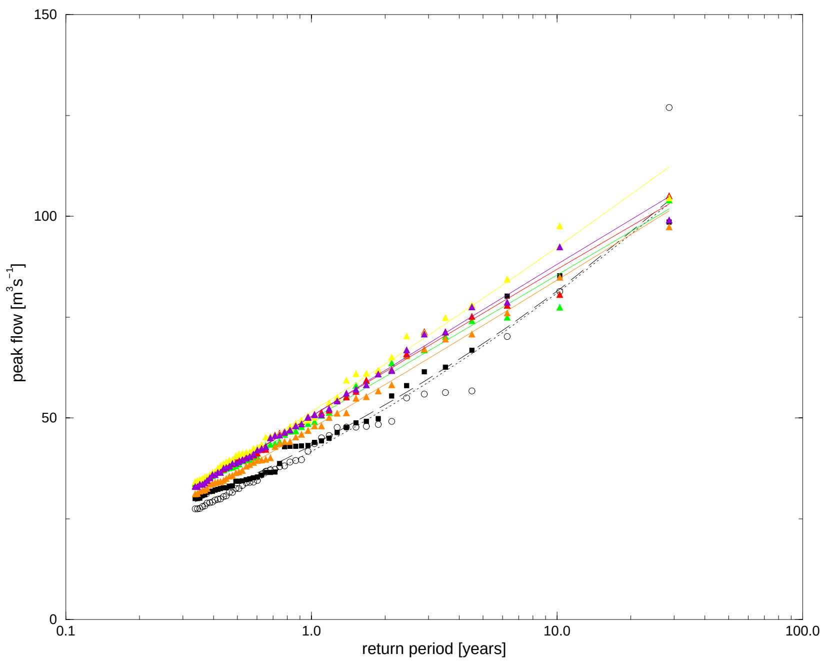
For each of the two catchments, the results for the 5 RCMs show a similar pattern of change, with an increase at lower return periods and a decrease at higher return periods for catchment 40005, whilst for catchment 74001 there is an increase at most return periods which is larger for higher return periods. However, the ordering of the impacts from the 5 RCMs is different for each catchment; the ICTP RCM shows the greatest effect for catchment 40005 but the ETH and KNMI RCMs shows the greatest effect for catchment 74001. Similarly, the DMI RCM shows the least effect for catchment 40005 while the Hadley RCM shows the least effect for catchment 74001.

3.5 Hydrological model – structure

Figure 3.8 compares the results for the two example catchments from the two models being used within this project, G2G and PDM, at three return periods. Results are from the direct use of hourly RCM (25km HadRM3H) data for current (1970s) and future (2080s, A2 emissions scenario) timeslices.

The impact on flood frequency is shown for the G2G model as the change at each river point on the 1km flow network, and the change for the catchment PDM is overlaid as a box, with the catchment boundary also shown. The two models compare very well, and show the same pattern of a decrease in flood frequency change with return period for catchment 40005, and a more uniform flood frequency change with return period for catchment 74001.

a) 40005



b) 74001

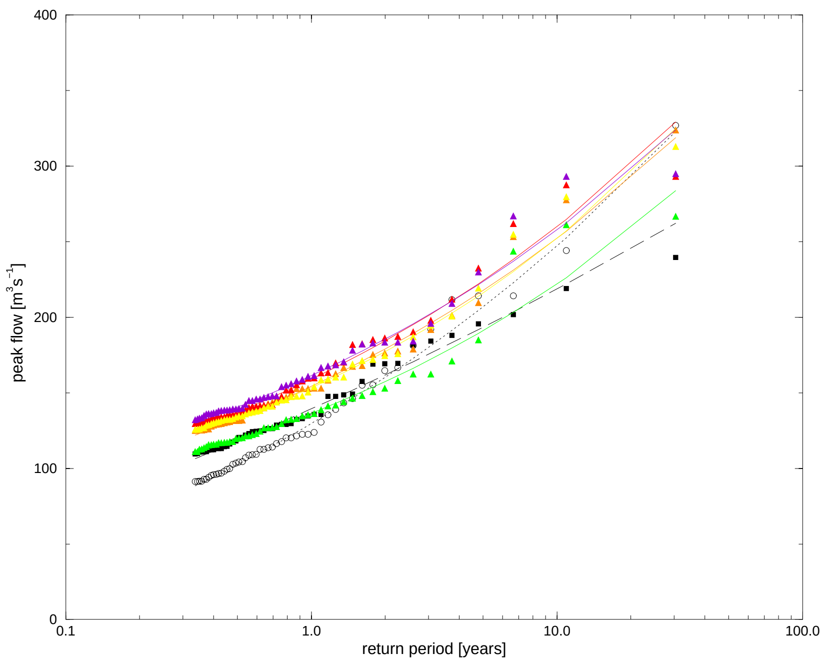


Figure 3.7 Examples of flood frequency uncertainty from RCM uncertainty, showing results for 5 RCMs (2080s, A2 emissions); Hadley Centre (green), ICTP (yellow), DMI (orange), ETH (red) and KNMI (purple). The current flood frequencies from observed flows (black, open circles/dotted line) and simulated with observed rain (black, filled squares/dashed line) are also shown.

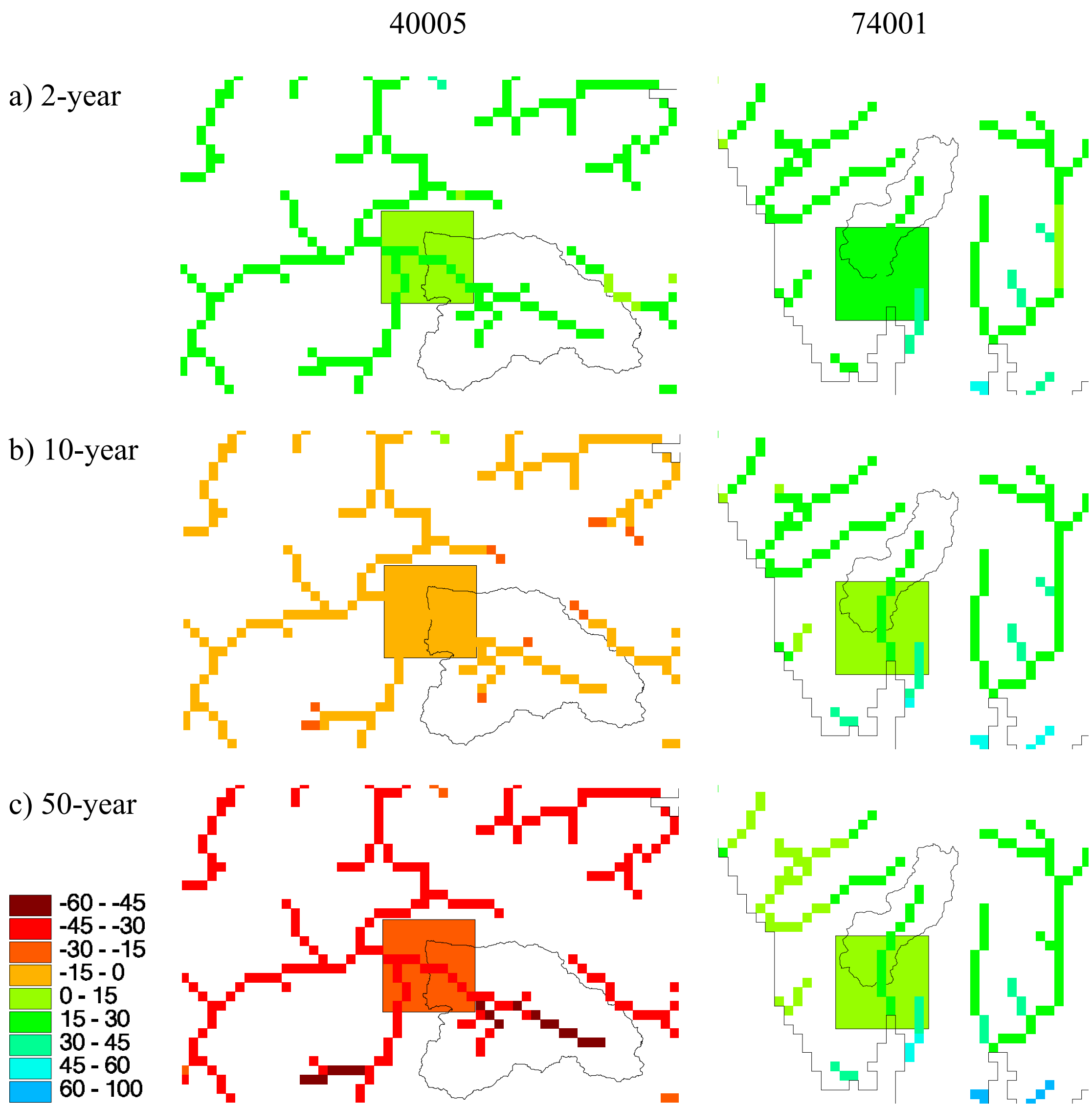


Figure 3.8 Examples of flood frequency uncertainty from hydrological model structure uncertainty, showing results for the G2G model (coloured lines) compared to those of the catchment PDM (coloured squares) at three return periods. Both models have been driven directly with RCM data for current (1970s) and future (2080s, A2 emissions) time-slices, and the percentage change in flood frequency calculated at three return periods.

3.6 Hydrological model – parameters

Figure 3.9 shows examples of the effect of parameter uncertainty, in the catchment PDM, on flood frequency estimation, under the A2 emissions scenario for the 2080s. Jack-knifing has been used to obtain a number of (automatically) calibrated parameter sets for each catchment, with each new parameter set obtained by leaving out one year of flow data (all input data are retained, to maintain the water balance). Thus there are 17 jack-knifed parameter sets for each catchment, plus the original (manually) calibrated parameter set. Each set has then been used with the baseline input data and with inputs adjusted by the delta change method (UKCIP02 Medium-High 2080s).

For both the baseline and future period, error bars are constructed for the flood frequency curves at specific return periods by estimating the variance (σ^2) from the values of the 17 jack-knifed flood frequency curves at that return period. The 95% error bars can then be plotted as $\mu \pm 2\sigma$, where μ is the mean of the jack-knifed values. However, jack-knife theory requires that the variance be calculated slightly differently to a usual sample, and this inflates the size of the error bars. Figure 3.9 shows the jack-knifed flood frequency curves, with error bars at specific return periods determined by both the standard variance (solid lines) and jack-knife variance (dotted lines). The same principle is used to construct the error bars for the percentage change in flood frequency at different return periods, after calculating changes between each pair of jack-knifed flood frequency curves (i.e. those using the same jack-knifed parameter set).

Note that the jack-knifed parameter sets are produced using an automatic method of calibration, and only include the calibration uncertainty due to data availability, not that due to equifinality for example. This is why the range of results from the jack-knifed parameter sets does not always include the flood frequency curve resulting from the original calibrated parameter set, as this was derived through manual calibration. Thus the full effect of parameter uncertainty on flood frequency estimation is larger than that represented here. In particular, for catchment 40005 the jack-knifed parameter sets all show a small increase in flood frequency at higher return periods and a small decrease at lower return periods (Figure 3.9a), whereas the original calibrated parameter set (with the same emissions scenario, downscaling method etc.) gave a small decrease in flood frequency at higher return periods and a small increase at lower return periods (Figure 3.6b). The flood frequency for catchment 74001 shows a very consistent increase at all return periods, for all calibrated parameter sets.

a) 40005

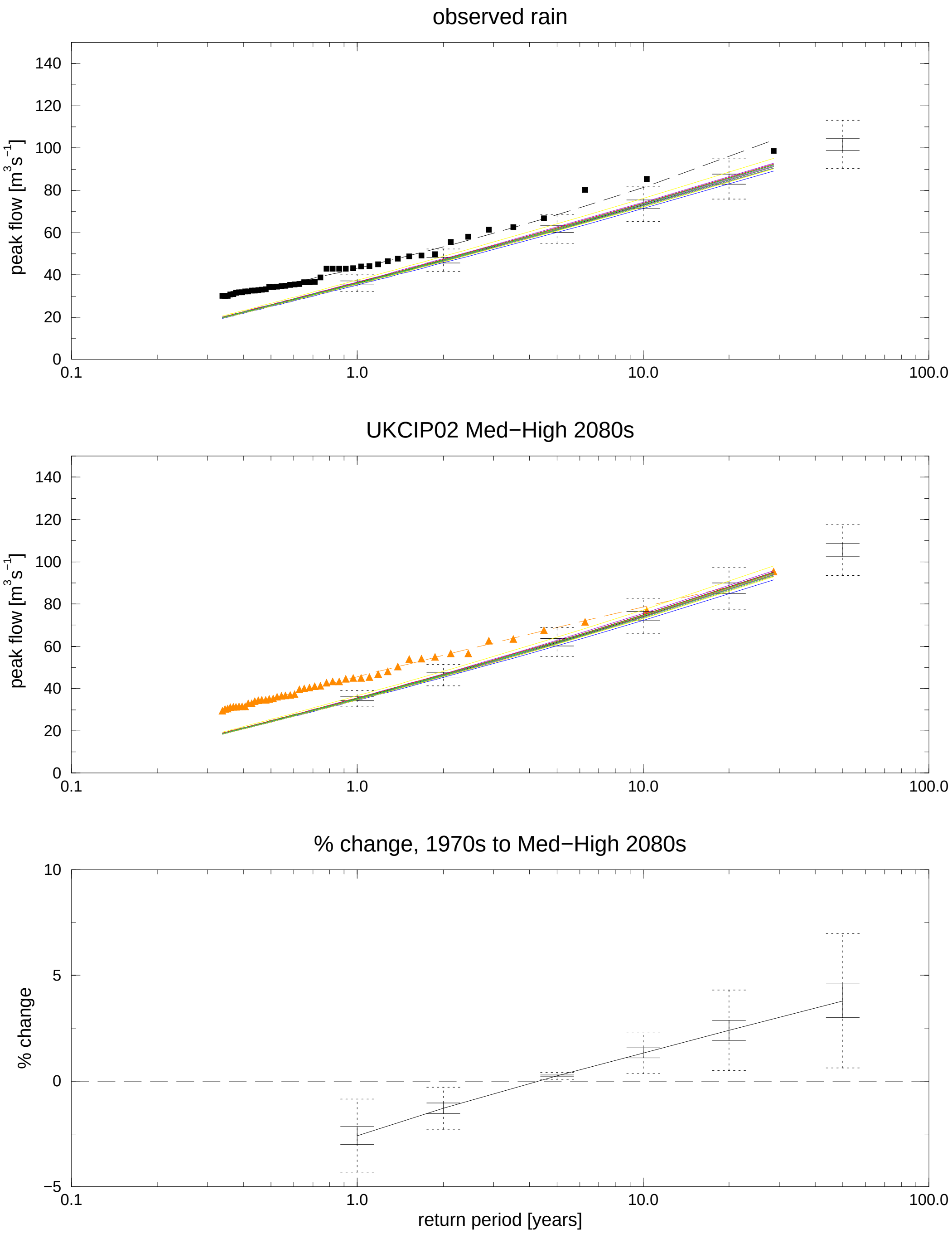


Figure 3.9 Examples of flood frequency uncertainty from calibration uncertainty. The solid coloured lines show results for each jack-knifed parameter set for the baseline period (top graph of each three) and the future period (middle graph of each three; UKCIP02, 2080s, Medium-High emissions). Also shown for each period are the curves using the original calibrated parameter sets (dashed lines and points). (Continued on next page.)

b) 74001

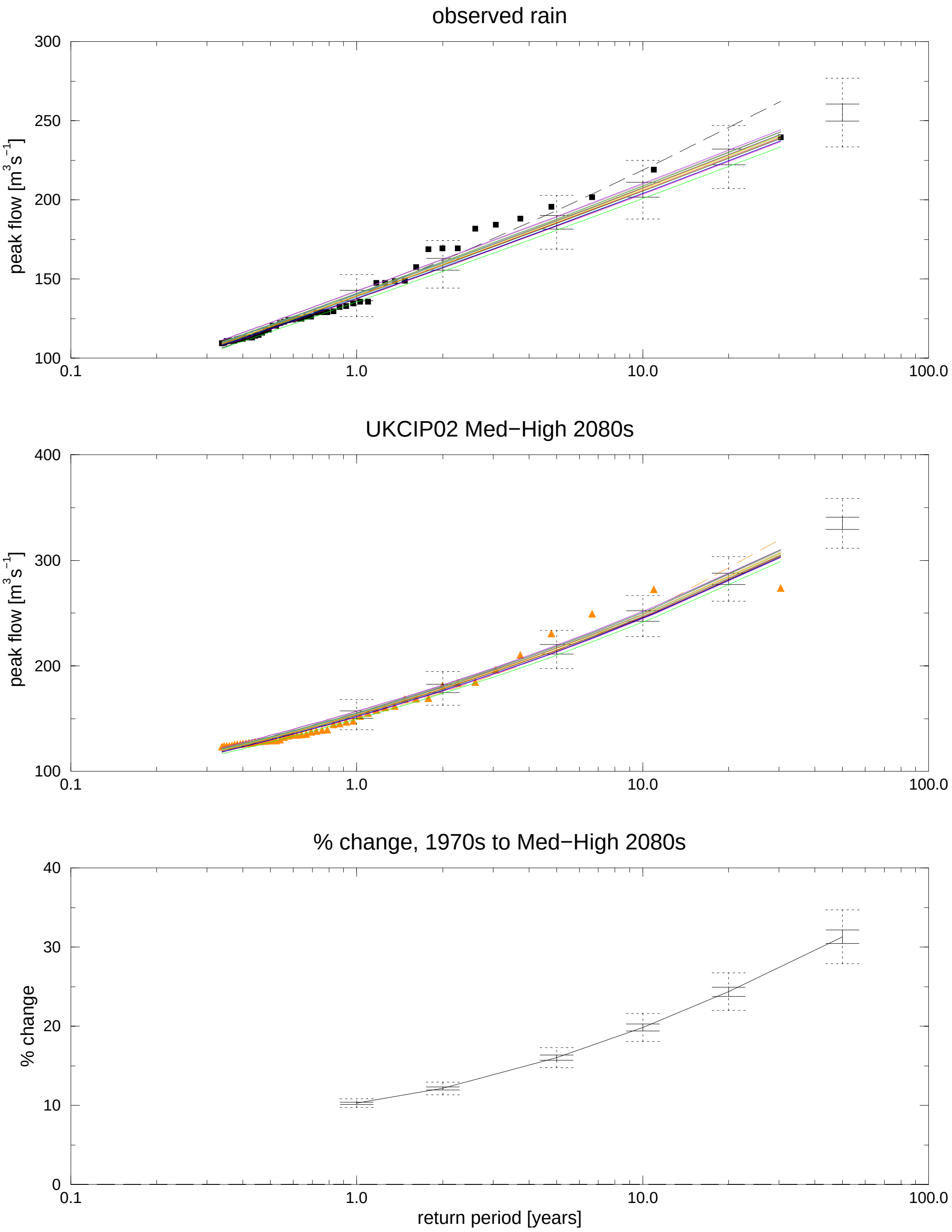


Figure 3.8 (continued.) The bottom graph of each three shows the range of percentage changes between each current/future pair (i.e. from the same model parameter set). Two sets of error bars are shown on each graph, at return periods of 1, 2, 5, 10, 20 and 50 years. The inner error bars use the standard estimate of variance, whilst the outer ones (dotted lines) use the jack-knife estimate of variance.

3.7 Impact definition

3.7.1 Natural variability

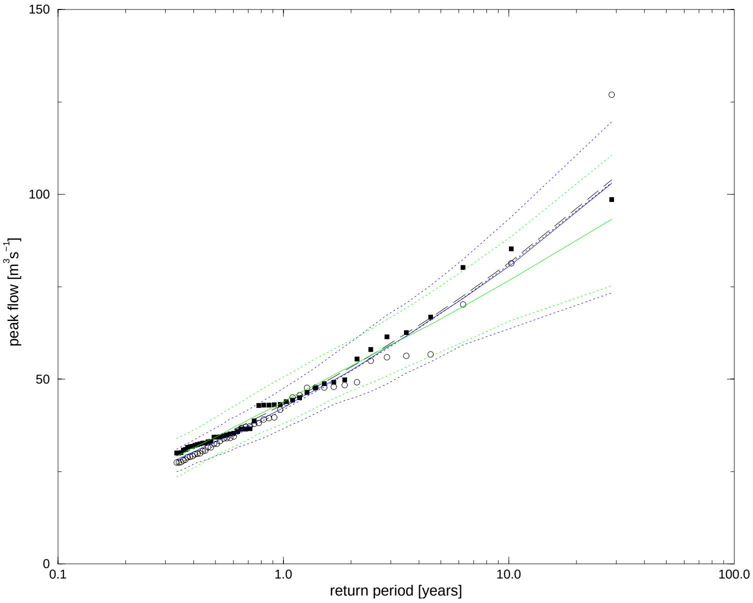
A simple way of demonstrating the potential effect of natural climate variability on flood frequency is to resample rainfall series, to produce a large number of new rainfall series. Monthly resampling involves the formation of new time-series through the random selection of rainfall, month by month, from the original series. For example, from a baseline series for January 1985 - December 2000, a new series would be created by first selecting a January from any of those in the baseline period, to represent January 1985, then selecting any February to represent February 1985, and so on until a series of the same length as the original is created. The months are selected with replacement, so that the rainfall for the same month could be repeated in any one of the resampled series, and some months may not be used at all.

Resampling by month or season (3-month blocks) limits the effect of time-correlations in rainfall series. It does not allow for variation in the short term extremes (e.g. hourly/daily maxima etc.), but does allow variation in longer term accumulations by, for instance, meaning that a wet winter can potentially follow a wet autumn. Resampling under the current climate allows the representativeness of the original baseline series to be assessed, by comparison against the median and bounds from the set of resampled series. Resampling under the current and future climates allows the potential range due to natural variability under the current climate to be compared to the range of changes that might be expected under climate change.

Some form of stochastic rainfall model could be used to generate a large number of rainfall time-series for the current or future climates, which would allow for variation in shorter-term extremes. However, such use would require significant checking of the performance of the rainfall model under current conditions, in terms of its ability to simulate extremes as well as its replication of the seasonal cycle etc. Initial condition ensembles of GCMs (Section 3.3) also give a demonstration of natural variability, including the possibility of variation in shorter term extremes, but it is too computationally expensive to run large GCM ensembles. Resampling thus represents a simple proxy for the effect of natural variability.

Figure 3.10 shows the potential effect of natural variability in the current and future climates, for the two example catchments. The future climate uses the simple delta change method to adjust the baseline rainfall and PE according to the UKCIP02 medium-high emissions scenario for the 2080s. A set of 100 resampled rainfall series have been produced for both the current and future climate, with resampling in 3-month blocks, and the model run with each new rainfall series. The median flood frequency curve and its upper and lower 90% bounds have then been calculated for each period. The results suggest that natural variability could be significant for both catchments, but larger for catchment 40005, particularly at higher return periods (Table 3.2).

a) 40005



b) 74001

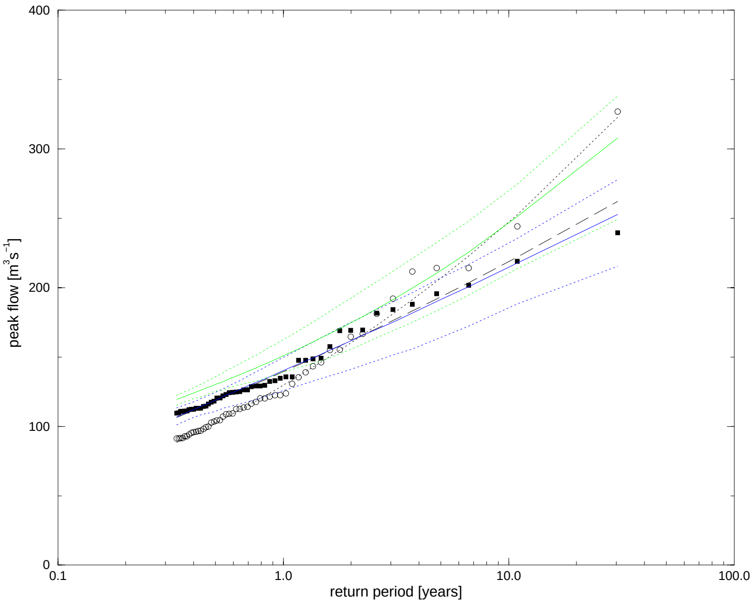


Figure 3.10 Examples of flood frequency uncertainty from natural variability, showing results from resampled baseline (blue) and future (green; 2080s, UKCIP02 medium-high emission scenario) rainfall. The median flood frequency (solid line) and the upper and lower 90% bounds (dotted lines) are shown for each period, from 100 resampled series (3-month blocks). The simple delta change method is applied for the future scenario. The current flood frequencies from observed flows (black, open circles/dotted line) and simulated with observed rain (black, filled squares/dashed line) are also shown.

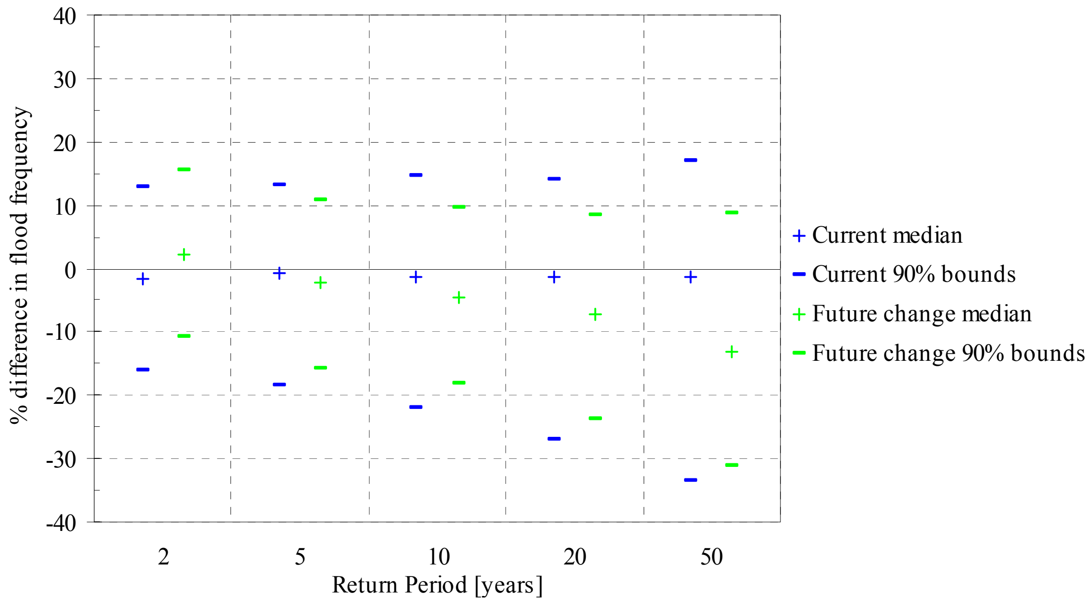
Table 3.2 Description of the resampling results for the current and future periods, for the median flood frequency curve and the upper and lower 90% bounds. For the 'Current' period the percentage differences are shown from the flood frequency simulated with the original baseline rainfall. For the 'Future' period the percentage differences are shown from the median current flood frequency.

Catchment	Period (change from…)	Change (%) to…	Return Period				
			2	5	10	20	50
40005	Current (from simulated baseline)	90% lower	-16.0	-18.4	-21.9	-27.1	-33.5
		median	-1.7	-0.8	-1.3	-1.3	-1.2
		90% upper	12.9	13.2	14.5	14.0	16.9
		size of range (upper-lower)	28.9	31.6	36.4	41.1	50.4
	Future (from median current)	90% lower	-10.7	-15.7	-18.3	-23.7	-31.1
		median	2.1	-2.1	-4.7	-7.3	-13.2
		90% upper	15.5	10.7	9.6	8.5	8.8
		size of range (upper-lower)	26.1	26.4	27.9	32.2	39.9
74001	Current (from simulated baseline)	90% lower	-12.7	-15.2	-15.3	-16.5	-19.5
		median	0.0	-1.0	-1.9	-2.4	-4.3
		90% upper	8.2	7.1	6.3	6.1	7.3
		size of range (upper-lower)	20.9	22.3	21.5	22.6	26.7
	Future (from median current)	90% lower	-3.9	-3.5	-2.4	-0.4	1.1
		median	8.0	11.0	14.9	18.4	25.8
		90% upper	19.0	22.5	25.4	29.0	40.8
		size of range (upper-lower)	22.9	25.9	27.8	29.4	39.7

The smaller effect for catchment 74001 could be due to the fact that the resampling method only allows variation in longer term extremes, as the longer memory of larger, flatter catchments, like 40005, means that variation in longer term extremes has a greater effect on them than on more responsive (small, steep) catchments, like 74001. In contrast, variation of shorter term extremes would have a greater effect on more responsive catchments.

The effect of climate change could be much more significant, in comparison with natural variability, for catchment 74001 as its 'Future' bounds are consistently shifted upwards compared to the 'Current' bounds, whereas the 'Future' bounds for catchment 40005 are almost completely contained within its 'Current' bounds (Figure 3.11). For both catchments though, natural variability could be a significant factor in the future experience of flooding (the *potential*, versus the *actual*).

a) 40005



b) 74001

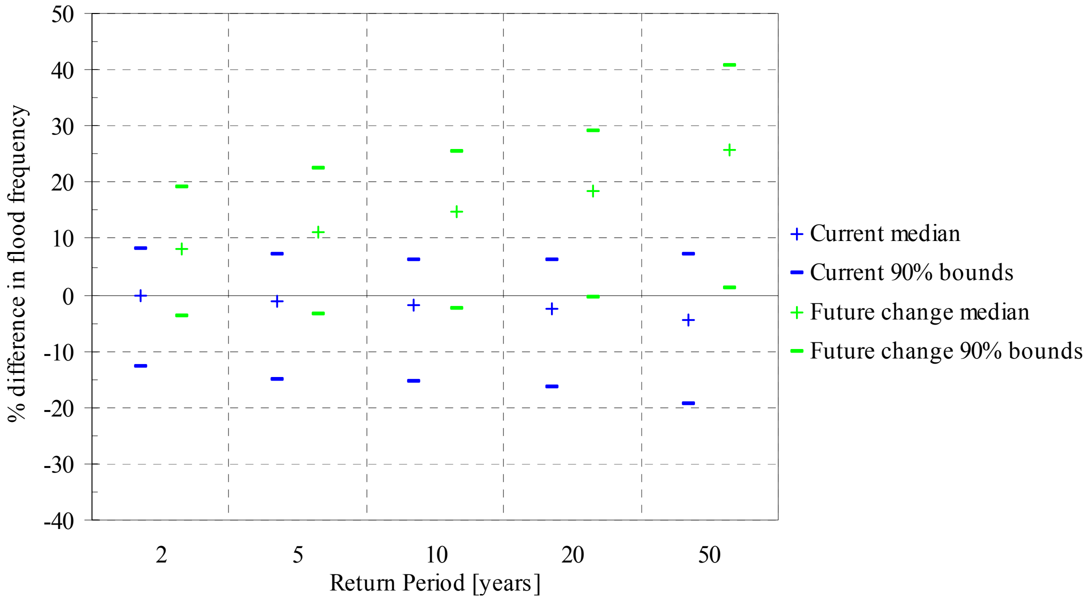


Figure 3.11 Graphs illustrating the range of natural variability in the current climate (blue) and in potential future changes (green), for five return periods (2, 5, 10, 20 and 50 years). The median (plus signs) and the 90% upper and lower bounds (bars) are shown for each (from Table 3.2). Resampling in 3-month blocks has been used as a proxy for natural variability, with the future climate produced using the simple delta change method and the UKCIP02 medium-high scenario for the 2080s, and the future change is calculated from the median current flood frequency.

The natural variability in future changes as represented by the 3-member initial condition ensemble of the Hadley Centre GCM/RCM (Section 3.3) is generally well-contained within that represented by resampling in 3-month blocks. The exception is lower return periods (< 10 years) for catchment 40005, where the impact from one of the three runs from the initial condition ensemble is slightly above the upper 90% bound from the resampling.

3.7.2 Return period and time-scale

The variation of impact on flood frequency according to return period, for the two example catchments, is illustrated in Figure 3.12 for the range of scenarios and methods presented in Sections 3.1-3.6. For catchment 40005 there is a consistent reduction in the flood frequency percentage change with increasing return period, with an increase in flood frequency at lower return periods turning into a general decrease at higher return periods. For catchment 74001 the majority of the percentage changes are positive, and increase with increasing return period.

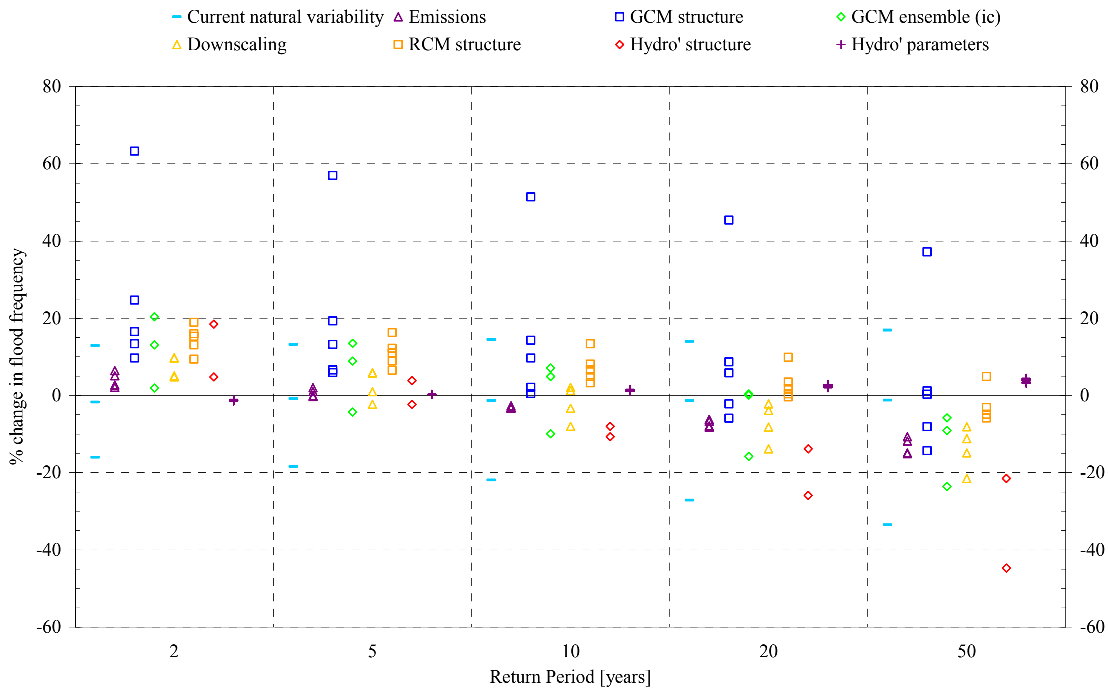
Table 3.3 shows the percentage change in flood frequency based on hourly flows (used for all of the previous results) compared to those from daily mean flows, based on the direct use of hourly RCM data (1970s to 2080s under the A2 emissions scenario) in the catchment PDM. For each catchment, the hourly and daily changes have slightly different magnitudes, but show the same pattern of decrease with increasing return period.

Table 3.3 Percentage change in flood frequency (1970s to 2080s, A2 emissions scenario) from hourly flows and from daily mean flows, using RCM data directly in the catchment PDM.

Catchment	Timescale	Return Period				
		2	5	10	20	50
40005	hourly	6.8	-0.6	-6.7	-13	-21.2
	daily	5.8	3.1	-0.2	-3.8	-8.7
74001	hourly	18.4	15.3	12.4	9.3	4.9
	daily	15.3	12.0	8.6	4.7	-0.9

An analysis of the impact of climate change on flows at a variety of time-scales could be important, as it could be that there is little discernible effect at one time-scale but a significant effect at another (Kay *et al.* 2004). For instance, the flood events of Autumn 2000 were more notable in terms of flows averaged over longer durations than in terms of maximum (instantaneous) flows.

a) 40005



b) 74001

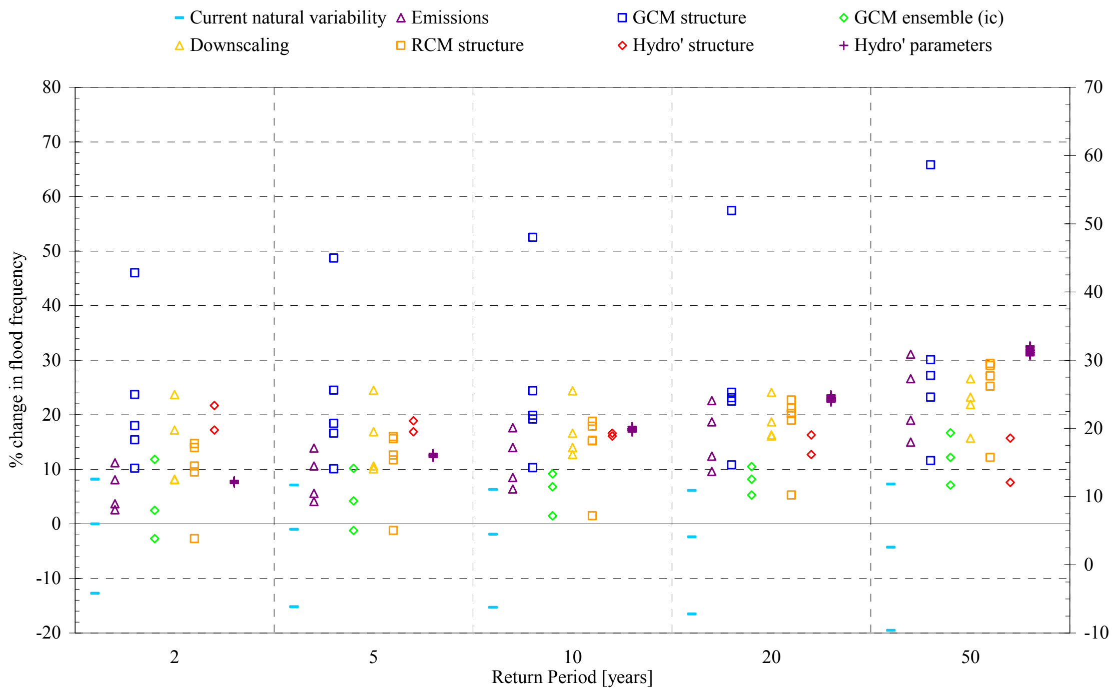


Figure 3.12 Graphs of the variation in the impact of climate change on flood frequency, from various sources (‘ic’ is ‘initial condition’), for five return periods (2, 5, 10, 20 and 50 years). The impact is shown as the percentage change in flood frequency from the current period to the 2080s. The potential range of current natural variability is also shown for comparison (from Table 3.2), by bars at the median and at the 90% upper and lower bounds.

3.8 Relative sizes of uncertainties

Figure 3.12 also illustrates the range of impacts due to uncertainty from the various sources. The ranges overlap to a good extent, but the sizes vary quite considerably. This is illustrated in Figure 3.13, which shows bar charts of the impact range sizes based on the data points plotted in Figure 3.12.

When all of the data points are included, GCM structure is by far the dominant source of uncertainty (Figure 3.13a). However, when the data points for the most extreme GCM (CCSR) are excluded, the uncertainty due to GCM structure becomes more similar in size to that from other sources of uncertainty (Figure 3.13b). Although the uncertainty from hydrological model parameters is seemingly the smallest in all cases, the ordering of the other sources varies by return period and between the two catchments.

Table 3.4 shows the ordering of the sources when the size of the impact range is averaged over the 5 illustrated return periods (when the CCSR GCM is excluded, Figure 3.13b; 'GCM structure' is promoted to number 1 in the list if this GCM is included). The more dominant sources of uncertainty in this case appear to be those related to the GCM or to the method of downscaling from the GCM (including RCM structure). The uncertainty from hydrological model structure is higher for catchment 40005 than for catchment 74001 probably because of the G2G's lower performance for catchments with a less topographically-driven flow regime, particularly with the area-wide parameters used here (rather than catchment-calibrated parameters).

Section 3.7.1 showed, through the application of a simple resampling technique, that natural variability could be important for both of the example catchments, although potentially more important for catchment 40005. The size of the potential range of natural variability under current conditions is actually comparable with the larger ranges from the various sources of climate change uncertainty: natural variability would appear at the top of the lists in Table 3.4, although the full range of uncertainty from GCM structure exceeds that of natural variability. The positioning of the future changes relative to the bounds from current natural variability is the crucial factor though, as is illustrated in Figure 3.11 and Figure 3.12.

Table 3.4 The ordering of the sources of uncertainty for the example catchments, based on the size of their impact ranges averaged over the 5 return periods (excluding the CCSR GCM).

	40005	74001
1	GCM ensemble (ic)	RCM structure
2	GCM structure	GCM structure
3	Hydro' structure	Downscaling
4	RCM structure	Emissions
5	Downscaling	GCM ensemble (ic)
6	Emissions	Hydro' structure
7	Hydro' parameters	Hydro' parameters

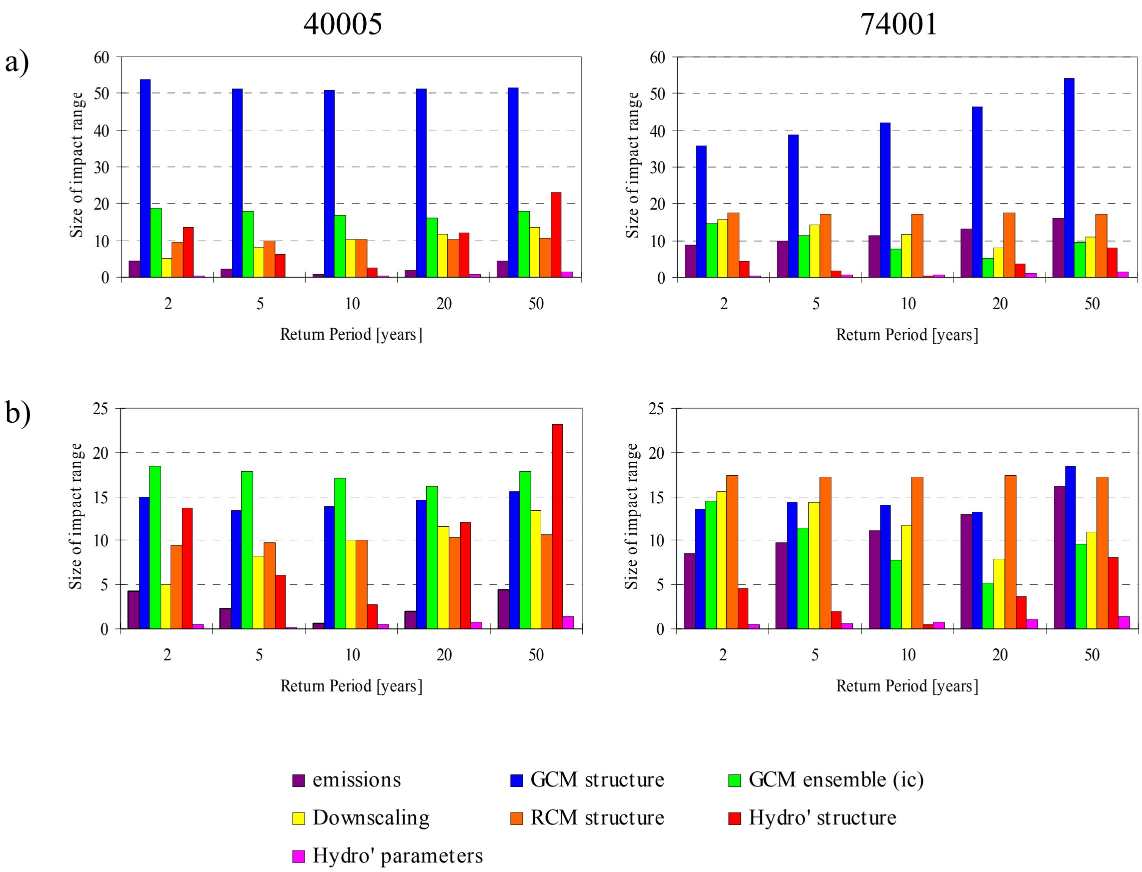


Figure 3.13 Bar charts showing the relative size of the impact range from the various scenarios and methods, for five return periods, a) for all the possibilities presented previously, and b) after excluding the results for the most extreme GCM (CCSR).

It should be noted that the results presented here are preliminary, in that they do not cover the full range of possibilities:

- The range of emissions scenarios used (from UKCIP02) is not the full IPCC range (and the A1F1, B1 and B2 scenarios are scaled from the ensemble results for the A2 scenario).
- Only 5 GCMs are used to represent GCM structure uncertainty. More are available, but there are difficulties in the consistent calculation of Penman-Monteith PE for these. We hope to investigate the use of simpler PE formulae soon.
- Only 5 RCMs are used to represent RCM structure uncertainty. More are available from PRUDENCE, but at the time of preparation of this report there are difficulties downloading data due to PRUDENCE disc problems.
- The PRUDENCE RCM rainfall changes have been used with UKCIP02 PE changes, due to the aforementioned difficulty of calculation of Penman-Monteith PE.

- Only two models are used to represent hydrological model structure uncertainty, one of which (the G2G) has particular difficulty in flatter regions. Ongoing development of the G2G should improve its performance in such regions.
- The uncertainty from hydrological model parameters is being represented through the use of jack-knifed calibrated parameter sets, which cover the uncertainty from data but not from equifinality etc.
- Resampling in 3-month blocks is used as a simple proxy for natural variability. Use of methods which allow for variation in shorter term extremes could lead to wider ranges of natural variability, particularly for more responsive catchments (like 74001).

The inclusion of more possibilities would lead to more robust conclusions, but not necessarily to wider ranges of impacts.

In addition, more catchments would need to be studied to determine anything conclusive about the importance of different sources of uncertainty; overall, for different types of catchment, or for different locations in the country. However, the ordering here is consistent with the conclusions of Prudhomme *et al.* (2005) for the uncertainty in the impact of climate change on water resources (based on investigations for 13 catchments in Britain).

4 DISCUSSION AND CONCLUSIONS

This report discussed sources of uncertainty in climate change impact studies, with particular reference to the impact of climate change on flood frequency in Britain. Various assumptions made when modelling future time-horizons, and checks that could be made on model performance for such applications, were also briefly discussed. Examples were then given of the single-propagation of the sources of uncertainty through to their range of impacts on flood frequency, for two catchments in England. Multi-propagation (that is, propagation of more than one source of uncertainty at once) was not attempted.

The results from single-propagation of each of the sources of uncertainty suggested that uncertainty from GCM structure was by far the largest source of uncertainty. However, this is due to the extremely large increases in winter rainfall predicted by one of the 5 GCMs used (CCSR). Omitting the results for this GCM led to other sources of uncertainty becoming more significant, although uncertainty from sources relating to modelling of the future climate was generally still larger than that relating to emissions or hydrological modelling. Natural variability could also play a significant role.

The results presented here are not conclusive as some of the sources of uncertainty are not fully represented. Additions would not necessarily increase the range of uncertainty from any source, but would make the results more robust. In addition, more catchments would need to be assessed to decide whether some sources of uncertainty are consistently more or less important, or are more/less important for certain types of catchment or for certain areas of the country.

Comparison of the uncertainty from different sources can help to suggest where more research effort should be placed, in order to try to reduce uncertainty. However, such a reduction will not always be possible. For example, we cannot know *at this point in time* how emissions will evolve over the next century. Knowledge on the potential path of emissions could improve with time though.

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