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Using response surfaces to estimate impacts of climate change on flood peaks: assessment of uncertainty

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Abstract

The potential impacts of climate change are an increasing focus of research and ever-larger climate projection ensembles are available, making standard impact assessments more onerous. An alternative way of estimating impacts involves response surfaces, which present the change in a given indicator for a large number of plausible climatic changes defined on a regular sensitivity domain. Sets of climate change projections can then be overlaid on the response surface and impacts estimated from the nearest corresponding points of the sensitivity domain, providing a powerful method for fast impact estimation for multiple projections and locations. However, the effect of assumptions necessary for initial response surface development must be assessed. This paper assesses the uncertainty introduced by use of a sensitivity framework for estimating changes in 20-year return period flood peaks in Britain. This sensitivity domain involves mean annual and seasonal precipitation changes, and a number of simplifications were necessary for consistency and to reduce dimensionality. The effect of these is investigated for nine catchments across Britain, representing nine typical response surfaces (response types), using three sets of climate projections. The results show that catchments can have different causes of uncertainty, and some catchments have an overall higher level of uncertainty than others. These differences are compatible with the underlying climatological and hydrological differences between the response types, giving confidence in generalisation of the results. This enables the development of uncertainty allowances by response type, to be used alongside the response surfaces to provide more robust impact estimates.

Keywords

Climate change; probabilistic projections; hydrological impacts; uncertainty; sensitivity.

1. Introduction

The hydrological cycle is already being affected by anthropogenic climate change, both globally (IPCC 2007) and locally (e.g. Kay et al. 2011). Hydrological models, driven by plausible climate time-series for future periods, are often used to assess potential impacts on the frequency of floods and droughts. Such climate projections are typically derived from Global Climate

Models (GCMs), usually with some form of downscaling as the resolution of GCMs is generally considered too low to drive most hydrological models directly. Downscaling can be statistical (e.g. Wilby et al. 2002), dynamic — nesting a finer-scale Regional Climate Model (RCM) within the GCM (e.g. Bell et al. 2012), or simply involve applying delta-changes derived from climate models to baseline observed time-series (e.g. Kay et al. 2009b). Each approach has advantages and disadvantages.

Increasingly large ensembles of climate projections are being produced (e.g. PRUDENCE, Christensen et al. 2007; ENSEMBLES, van der Linden and Mitchell 2009; UKCP09, Murphy et al. 2009), using multiple runs of multiple climate models, for multiple emissions scenarios and time-slices, with the aim of enabling assessment of uncertainty from various sources (e.g. Kay et al. 2009b, Wilby and Harris 2006). In addition, probabilistic ensembles, like UKCP09 and those presented by Harris et al. (2010) for Europe, allow a risk-based approach to decision-making (Kay and Jones 2012, Christierson et al. 2012). The impact assessment process is thus becoming less straightforward, with a greater number of projections to consider, and each time new projections are released numerous impact assessments potentially have to be redone and any differences investigated.

Recently a new way of modelling the impacts of climate change has been developed, which makes the process of re-assessing impacts under alternative projections less onerous. This involves the production of ‘response surfaces’, which present the change in a given indicator for a large number of plausible climatic changes defined on a regular sensitivity domain. For example, the domain could simply involve changes in mean annual precipitation (P) and temperature (T), each in fixed increments between a minimum and maximum, with change in mean annual runoff (the impact indicator) calculated for each combination of P and T changes. Sets of climate change projections can then be overlaid on the response surface, and impacts estimated from the nearest corresponding points of the sensitivity domain. Response surface approaches have been used for seasonal flows in 18 catchments across Europe (Weiss 2011), lake levels/outflows in Sweden (Wetterhall et al. 2011), flood warning level exceedance in the Upper Severn, UK (Cloke et al. 2013) and the change in area suitable for palsa mires in Fennoscandia (Fronzek et al. 2010).

Prudhomme et al. (2010) applied a sensitivity-based method to estimate the impacts of climate change on flood peaks in Britain. Their sensitivity domain involved changes in mean annual P and seasonality of P, as well as T and corresponding potential evaporation (PE) changes. Bastola et al (2011) applied a similar domain for four catchments in Ireland. Prudhomme et al. (2013a) went further by producing response surfaces for 154 catchments across Britain and grouping them by similarity, giving nine ‘response types’. They then characterised families of response types by catchment properties (Prudhomme et al. 2013b), enabling estimation of catchment sensitivity where-ever the necessary properties are available. This provides a powerful method for easily estimating the impacts of multiple climate change projections at multiple locations, but requires an assessment of the uncertainty introduced by the assumptions necessary to make the approach tractable. This paper uses example catchments of each response type to assess the additional error derived from use of response surfaces rather than direct impacts modelling. In particular, do response surfaces consistently over- or under-estimate changes in flood peaks in comparison to direct modelling? Section 2 describes the existing sensitivity framework in more detail, and presents the catchments and climate change projections used for the uncertainty assessment. Section 3 describes the factors included in the assessment, with results (Section 4), discussion (Section 5) and conclusions (Section 6).

2. Background, catchments and data

2.1 Sensitivity framework, flood response surfaces and response types

The sensitivity framework developed and used by Prudhomme et al. (2010, 2013a,b) relies on two key methods/assumptions:

1. Delta-change downscaling; monthly (percentage or absolute) changes in a climate variable (P, T, PE) are applied to a baseline time-series of that variable, to produce modified time-series.
2. A single-harmonic (cosine) function representing the monthly pattern of P and T changes.

The former allowed the consistent application of a large set of climatic changes to a large number of catchments. The latter allowed the dimensionality of the sensitivity domain to be greatly reduced.

The single-harmonic function of Prudhomme et al. (2010) is given by

$$X(t) = X_{mean} + A \cos [\, 2\pi \,(t - \Phi) / 12 \,] \qquad (1)$$

with $X(t)$ the change for month t (1=January, 12=December), X_{mean} the mean monthly change (harmonic mean), and A and Φ the harmonic amplitude and phase (timing of maximum X) respectively. For P, the phase Φ was set to 1 (January). Thus the number of dimensions of P change was reduced from 12 (months) to two (X_{mean} and A), each of which was varied in 5% increments between minimum and maximum values (-40% to +60% for X_{mean} and 0% to +120% for A) to give 525 scenarios of P change (Table 1). As floods are much less sensitive to T than P, only eight T-change scenarios were selected, each of which has a corresponding PE-change scenario (Table 1). Each of the eight T/PE scenarios was thus combined with each of the 525 P scenarios, to give a sensitivity domain consisting of 4,200 scenarios. The sensitivity framework thus consisted of the sensitivity domain applied using delta-change downscaling.

Using this sensitivity framework, Prudhomme et al. (2013a) modelled 154 British catchments using two hydrological models: 120 with the Probability Distributed Model (PDM; Moore 1985) (74 daily and 46 hourly time-step) and 35 with the Climate and LAnd-use Scenario Simulation In Catchments model (CLASSIC; Crooks and Naden 2007) (daily time-step). PDM is a lumped conceptual model, suitable for smaller catchments, while CLASSIC is a semi-distributed model, generally used for larger catchments. One catchment was modelled with both hydrological models. A simple T-dependent snowmelt module (Bell and Moore 1999) was used with each model. See Crooks et al. (2009) for further details on models and calibration. The baseline period for catchments modelled at a daily time-step was 1961-2001.

For each scenario of the sensitivity domain, a flood frequency curve was fitted to peaks-over-threshold (POT) from the modelled flow series. Each scenario flood frequency curve was then compared to a baseline curve (fitted to POT from the modelled baseline flow series), to assess changes in four flood indicators: 2-, 10-, 20- and 50-year return period flood peaks. The response of each catchment, for each indicator and each T/PE scenario, was presented as a 2-dimensional flood response surface, with the P harmonic amplitude (A) on the x-axis and the P harmonic mean (X_{mean}) on the y-axis. The colour of the square at each point represents the modelled change in the given flood indicator for that scenario of change in P, T and PE (Figure 1a).

Prudhomme et al. (2013a) analysed the similarity of the response surfaces of the 154 modelled catchments, and grouped them into nine response types. Each response type was represented, for each indicator, by a composite (average) response surface (the mean change in the indicator at each position on the sensitivity domain, over all T/PE scenarios and all catchments of that type). The response types were approximately ordered and named by the sensitivity shown in their composite response surfaces: Damped-Extreme, Damped-High, Damped-Low, Neutral, Mixed, Enhanced-Low, Enhanced-Medium, Enhanced-High and Sensitive. Damped response types show percentage changes in flood peaks that are generally smaller than the maximum monthly P percentage change prescribed by the sensitivity domain, whereas Enhanced types show changes in flood peaks generally larger than for P, and the Neutral type shows changes in flood peaks similar to those for P. Mixed or Sensitive types show more variable changes in flood peaks, depending on the magnitude and seasonality of P change (see Prudhomme et al. 2013a Table 1). Prudhomme et al. (2013b) then characterised families of response types using decision trees. This enables estimation of response type from catchment properties, so allows impact estimation for un-modelled catchments via composite response surfaces.

2.2 Catchments

From the 154 catchments modelled by Prudhomme et al. (2013a), a small number were selected (Table 2 and Figure 2) to represent the nine response types. A catchment modelled with PDM at a daily time-step was selected for each response type, after consideration of calibration results and catchment location. Response surfaces for these nine catchments (Figure 1b) clearly show their differing sensitivity. In particular, they show the difference between Damped and Enhanced/Sensitive response types; the former have a relatively gradual increase in the impact on flood peaks as both the P harmonic mean and amplitude increase (i.e. moving from bottom-left to top-right of the response surface), while the latter have a much steeper increase in impact.

In addition to the full uncertainty assessment using nine catchments modelled with PDM, a partial assessment is made for four larger catchments, modelled with CLASSIC (Table 2 and Figure 2); a full assessment is not possible as there are not catchments of each response type modelled with CLASSIC.

2.3 Climate change projections

Uncertainty associated with use of response surfaces is assessed using three sets of climate change projections, each using the 1970s (1961-1990) baseline time-slice and 2080s (2070-2099) future time-slice under SRES A1B emissions (IPCC 2000):

1. **GCM projections:** 16 projections from AR4 (IPCC 2007) (see Prudhomme et al. (2010) Table 2). Available as monthly time-series of various climate variables, on relatively low-resolution grids, from which monthly delta-changes are calculated.
2. **RCM projections:** 11 projections from a perturbed-physics ensemble (PPE) of HadRM3 nested in HadCM3; part of UK Climate Projections 2009 (UKCP09; Murphy et al. 2009 Section 5). Available as daily time-series of various climate variables, on an approximately 25km x 25km grid over the UK, from which monthly delta-changes are calculated. The time-series are also used directly (Section 3.4).
3. **UKCP09 projections:** 10,000 probabilistic projections (Murphy et al. 2009). Available as monthly delta-changes for various climate variables, on the same grid as the RCM projections or for 23 river-basin regions covering Britain.

These three sets of projections cover a variety of climate change ensemble methods (GCM, PPE and statistically emulated) and sizes. For each catchment, GCM and RCM projections are taken from the grid-box containing the catchment centroid, while UKCP09 projections are taken from the river-basin region containing the catchment (Table 2).

3. Investigation of factors contributing to uncertainty

The sensitivity framework provides a potentially powerful method for fast estimation of the impacts of multiple climate change projections at multiple locations (Prudhomme et al. 2013b); the projections are simply overlaid on an appropriate response surface. However, there is clearly uncertainty in such estimates, due to necessary simplifications. Here, the uncertainty assessed is that from use of catchment response surfaces instead of directly modelling the impact of climate change projections on a catchment. In particular, does use of catchment response surfaces consistently over- or under-estimate changes in flood peaks in comparison to directly modelled impacts? The assessment focuses on 20-year return period flood peaks (RP20). If composite response surfaces are being used (i.e. for un-modelled catchments, where the response type has been estimated from catchment properties) then there is additional uncertainty which can be included through use of standard deviation surfaces (representing the range of catchment response surfaces within a given response type, Prudhomme et al. 2013a).

For each of the example catchments, the three sets of climate change projections (Section 2.3) are overlaid on the response surface and the impacts extracted. Then, the influence of various simplifications on these response surface impacts is investigated by directly modelling the impacts under the same projections, using alternative methods designed to address simplifications grouped into three main factors:

- **Factor 1:** Harmonic function simplifications;
- **Factor 2:** Use of harmonic function instead of actual monthly changes;
- **Factor 3:** Use of simple delta-change downscaling.

Section 3.1 describes the overlay of projections on response surfaces, while Sections 3.2-3.4 describe the alternative methods addressing each factor. Table 3 provides a summary and the notation for each method and set of projections.

3.1 Overlaying projections on response surfaces

In order to use a response surface to estimate the impact of a given climate change projection, a single-harmonic function (Section 2.1) is first fitted to a set of monthly P changes. Two harmonic function parameters (mean and amplitude) are then used to overlay the projection on a response surface, to estimate the impact from that of the nearest point of the sensitivity domain (Table 1). A single-harmonic function could also be fitted to a corresponding set of monthly T changes, to select the closest T/PE scenario of the sensitivity domain. Here though, the modelled response surfaces for just one T/PE scenario (Medium-Aug; Table 1) are used for each catchment (Figure 1b), as the variability of catchment response surfaces for different T/PE scenarios is much smaller than that between catchments (Prudhomme et al. 2013a).

For GCM and RCM projections, harmonic functions are fitted using the method of Prudhomme et al (2010), which involves deriving multiple sets of monthly changes by using all combinations of 20-year sub-periods within the baseline and future time-slices, and fitting the harmonic function to the monthly medians. This method acknowledges natural variability in climate model data and allows a better harmonic fit. For UKCP09 projections, harmonic functions are fitted to each of the 10,000 sets of monthly P changes based directly on 30-year baseline and future time-slices (data are not available to allow application of the sub-period method; Section 2.3). Figure 1a shows an example of the three sets of climate change projections overlaid on a catchment response surface.

3.2 Factor 1: Harmonic function simplifications

The use of a single-harmonic function, to reduce dimensionality, included a number of simplifications:

- The maximum increase in P occurs in January.
- There is symmetry between summer and winter variance from the mean.

The phase of the fitted harmonic is ignored, as are the exact harmonic mean and amplitude, since the response surface harmonics all correspond to a January peak P change and have means and amplitudes in multiples of 5% (Table 1). To demonstrate the effect of this assumption, the monthly P changes given by each fitted single-harmonic are applied directly to the baseline P series and run through the catchment hydrological model. Similarly, the effect of the symmetry implicit in the single-harmonic is explored through use of a double-harmonic fitted to the same set of monthly P changes, thus allowing asymmetry and possibly giving two P harmonic peaks in a year (Prudhomme et al. 2010). The monthly P changes given by the fitted double-harmonic are applied to the baseline P series and run through the catchment hydrological model. For GCM and RCM projections both the single- and double-harmonic are applied, but only the single-harmonic is applied for UKCP09 as the ensemble is so large.

To further investigate the potential influence of the fixed January phase of the sensitivity domain, alternative response surfaces are produced for the example catchments modelled with PDM, with the phase set in each alternative month.

3.3 Factor 2: Use of harmonic function instead of actual monthly changes

As well as not taking account of the month in which the fitted harmonic peak occurs, extracting an impact estimate from the response surface takes no account of how well the single-harmonic fits the 12 monthly P changes from a climate projection, or of the corresponding monthly T changes from that projection. Thus sets of monthly P and T changes are applied directly to baseline time-series, without fitting a harmonic. For GCM and RCM projections, a number of alternative sets of monthly P changes are applied, each with corresponding monthly T changes:

- Median monthly P changes (to which the P harmonic was fitted).
- Each set of monthly P changes (121, from 20-year sub-periods within the 30-year baseline and future time-slices).
- Alternative monthly P changes (from standard 30-year time-slices).

Only the last combination is applied for UKCP09 as data are not available to derive the others (Section 2.3).

3.4 Factor 3: Use of simple delta-change downscaling

The simple delta-change method of downscaling involves the perturbation of a fixed baseline of observed data. The perturbed series is inevitably similar to the baseline in terms of the relative size and ordering of events, which limits its variability, and other changes in P, like intensity, are ignored (Cloke et al. 2013). This issue is addressed by using the time-series data from the RCM projections to drive the hydrological model for each catchment; the RCM PPE addresses uncertainty in climate projections due to many important physical processes not being explicitly resolved by climate models, but also includes natural climate variability as each member is driven by different boundary conditions (from the HadCM3 GCM PPE). Each of the 11 PPE ensemble members is a plausible realisation (no weights are attached). Bias-correction of RCM time-series is not attempted, as there is relatively good agreement between flood frequency curves simulated with baseline RCM data and observed data for these catchments (Kay and Jones 2012) and any correction requires strong assumptions on error stationarity etc. (Cloke et al. 2013).

For each ensemble member, changes are assessed between two 30-water-year time-slices, 1 October 1960-30 September 1990 (Baseline) and 1 October 2069-30 September 2099 (Future), with a 9 month run-in (from 1 January) for each time-slice [note that an RCM year is only 360 days]. For each grid box, daily P and T are available directly. Daily PE from the land-surface is derived from daily RCM open-water PE using the method of Bell et al. (2011). The required PDM catchment-average or CLASSIC grid-average P and PE are produced using area-weighting, with additional weighting for P using standard average annual rainfall information (Kay et al. 2006), with T from the grid box containing the catchment centroid (and altitude from the RCM orography file).

3.5 Comparison of P changes and derivation of PE changes

Figure 3 presents an example comparison of sets of monthly P changes: A response surface harmonic (Figure 3a) is contrasted with corresponding P changes from Factors 1 and 2 (Figure 3b-d; Table 3). Comparing Figure 3b and 3a, a shift in phase between an actual single-harmonic and its response surface harmonic can be seen, along with a small difference in harmonic mean and amplitude, as these are rounded to the nearest 5% for the response surface harmonic. The asymmetry of the actual double-harmonic compared to the single-harmonic is also shown (Figure 3b). Figure 3c shows the wide range of monthly P changes derived from 20-year sub-periods within time-slices, while Figure 3d shows corresponding P changes using fixed 30-year time-slices.

For RCM projections, the PE delta-changes are derived from RCM PE time-series data (Section 3.4). For GCM or UKCP09 projections, PE is not directly available so for simplicity a T-based PE formula (Oudin et al. 2005) is applied, as for the PE scenarios of the sensitivity domain (Table 1). For each catchment and each projection, monthly PE changes are calculated as the difference between baseline and scenario T-based PE time-series (derived respectively from baseline T, and baseline T adjusted using projected T changes). Note that there are a number of issues and uncertainties involved in PE estimation under climate change (Kay et al. 2013), but Oudin PE is preferred here over other simple formulae as it includes extra-terrestrial radiation (Shaw and Riha 2011).

4. Results

Figure 4 shows the impacts on RP20 for each of the nine example catchments modelled with PDM, using each set of projections and each alternative method of application (Table 3). For each catchment, the results using GCM projections are first (six methods, gcm_*), then RCM projections (seven methods, rcm_*), then UKCP09 (three methods, ukcp_*). For each projection set, the results using the catchment response surface are first (*_rs), then the alternative methods (in order from Table 3). The differing sensitivity of the catchments is immediately clear from Figure 4, as the Damped catchments show a much narrower range of impacts than the Enhanced/Sensitive catchments. The results are discussed below in terms of how the impacts from different methods compare, for the three factors addressed.

4.1 Factor 1: Harmonic function simplifications

For GCM and RCM projections, Figure 4 shows that the impacts estimated from the response surfaces (gcm_rs, rcm_rs) are generally similar to or larger than those when the actual P single-harmonics are applied (gcm_harm, rcm_harm), in terms of mean and/or maximum impacts on RP20. Only for catchment 07002 are the mean and maximum impacts from the response surfaces clearly lower than those from use of P single-harmonics. For UKCP09 projections though, most catchments have lower mean and maximum impacts using response surfaces (ukcp_rs) than using P single-harmonics (ukcp_harm). This suggests that the response surface assumption of a January phase is more consequential for the estimation of impacts for some catchments and using UKCP09 projections than GCM or RCM projections.

To further investigate the potential influence of the fixed January phase of the sensitivity domain, Figure 5 shows 11 alternative response surfaces for the nine example catchments, with the phase set to each month from February to December. These surfaces show that, if the phase is between February and mid-summer the impact on RP20 is generally less than that for a January phase, whereas if the phase occurs in autumn or earlier in winter then the impact can be greater (the exception is 07002, where the impact is greater if the phase is April onwards). Some catchments show a clearly increased sensitivity in their response surfaces for some alternative phases when compared to their January response surface. For example, the September response surface for 07002 and the November surface for 02001 look more similar to the January surface for 14001 (Damped-Low) than they do to their own January surfaces (Damped-Extreme and Damped-High respectively). Similarly, October for 34003 (January Mixed) looks like January for 21023 (Enhanced-Medium) and November for 21023 looks like January for 43005 (Enhanced-High). The other catchments have most sensitive surfaces which are still more similar to their own January response surface than to any of the other January surfaces, so use of their January surfaces should not significantly under-estimate impacts. [Note that these differences with phase were taken into account to some extent by Prudhomme et al. (2013b), by grouping response types into families and characterising those families by catchment properties.] It must be recalled when looking at alternative response surfaces (Figure 5) that not all P harmonic phases are equally likely under existing projections. Histograms (Figure 6) show that phases in spring, summer or (early) autumn are quite unlikely, especially for the RCM and UKCP09 projections, and that January is the predominant phase for most catchments, for all three sets of projections. Exceptions are 07002 and 02001 for UKCP09 projections (and 02001 for RCM projections), where December becomes the predominant phase, so using the January rather than December response surface for all projections will lead to some under-estimation of impacts in these cases (Figure 5). Similarly, for 14001 and 21023 for UKCP09 projections, although January is the predominant phase there is also a high proportion in December. Any bias in impacts extracted from the January response surface for a catchment is thus a consequence of both the true phases of the projections (Figure 6), and the differing responses for different phases (Figure 5), and each should be borne in mind.

For the P double-harmonics, Figure 4 shows that there are minimal differences in impacts using actual double-harmonics for GCM and RCM projections (gcm_harm2, rcm_harm2) compared to corresponding single-harmonics (gcm_harm, rcm_harm). This suggests that use of a more complex harmonic function is unnecessary, at least for these sets of projections over Britain.

4.2 Factor 2: Use of harmonic function instead of actual monthly changes

For GCM and RCM projections, Figure 4 shows that the mean, minimum and maximum impacts on RP20 are generally greater when the median monthly changes are used directly (gcm_20med, rcm_20med) rather than being smoothed out by a single-harmonic function (gcm_harm, rcm_harm). The main exception is 54008 for RCM projections. The largest difference in the maximum (mean) impact between the two methods, of around 35% (25%), occurs for 38003 under GCM projections. The differences in mean impacts are often smaller using RCM than GCM projections (6 out of 9 catchments).

When the sets of monthly changes in P, T and PE are used (gcm_20, rcm_20), rather than the median monthly changes calculated from these (gcm_20med, rcm_20med), Figure 4 shows that the median impact of the former is within 6% of the mean impact of the latter. In addition, the 10^{th}-90^{th} percentile range of the former mostly encompasses the latter; there are just a small number of projections with impacts which fall slightly below (above) the corresponding 10th (90th) percentile. The maximum (minimum) impacts using the sets of monthly changes (gcm_20, rcm_20) are generally greater (less) than all impacts using delta-change methods with corresponding sets of projections, particularly for GCM projections (where the maxima are often outside the +85% plot limit).

The 10th-90th percentile range from the use of the sets of monthly changes (gcm_20, rcm_20) also mostly encompasses the range of impacts when the monthly changes from the fixed 30-year time-slices are applied (gcm_30, rcm_30). Interestingly though, the mean of the latter is similar to or less than the median for the former: The difference is within 5%, except for 34003, 43005 and 38003 for GCM projections where it is 10-17%. This shows that the way in which monthly P changes are derived could affect the results considerably, and suggests that the use of multiple sub-periods within a time-slice may be preferable to take some account of uncertainty due to natural variability, not just to improve the range of impacts but also the average impact.

For UKCP09 projections, Figure 4 shows that the median impact when the monthly changes from the fixed 30-year time-slices are applied (ukcp_30) is generally within 5% of that using the fitted P single-harmonic (ukcp_harm). Exceptions are 47007, where the former is 9% greater than the latter, and 38003, where it is 14% less.

These differences in impacts are partly due to the use of the actual monthly P changes instead of the changes smoothed through the year via the fitted single-harmonic function. However, they are also due to the use of the actual monthly T/PE changes for the catchment, rather than the Medium-Aug T/PE scenario (from T changes smoothed through the year via a harmonic function; Table 1).

4.3 Factor 3: Use of simple delta-change downscaling

When baseline and future climate time-series derived from the 11-member RCM ensemble (Section 3.4) are used as direct inputs to the PDM for each catchment (rcm_tseries), the mean impact is generally within (or just outside) the range of average impacts obtained from the alternative delta-change methods using RCM projections (Figure 4). The exception is 38003 (Sensitive), where the mean from direct use of RCM data is around 12% larger than the highest average from any of the alternatives methods (rcm_20 in this case).

Although the mean impacts from direct use of RCM data are generally similar to the means from one or more of the delta-change methods using RCM projections, the full range of impacts is often much wider (Figure 4). However, it is not always the same ensemble member that results in the increased range at either end (not shown), suggesting that the particular parameter settings of individual members are less important and that natural variability (on a range of timescales) is the more dominant factor. In particular, both baseline and future RCM time-slices are affected by natural variability: the RCM baselines are not meant to exactly reproduce the climate in the baseline period but are simply one representation of what could have occurred, just as the Future time-slice is one representation of what might occur (under given assumptions on emissions etc). Also, for a given RCM ensemble member and future period, longer timescale natural variability could act in the same (opposite) direction as climate change, reinforcing (reducing) its apparent effect (Murphy et al. 2009 Section 2.2). The inclusion of natural variability in RCM time-series thus helps explain their expanded range relative to that from delta-change methods, although it is difficult to separate this from possible differences in the underlying spatial patterns in RCM data. The UKCP09 projections also include natural climate variability (to some extent) in their range (Murphy et al. 2009 Section 2.2), perhaps contributing (along with the much larger sample size) to their expanded range relative to GCM and RCM projections.

4.4 Summary

When compared to values extracted from the response surfaces, some catchments show greater differences under alternative methods than other catchments. To compare the potential levels of uncertainty between the nine example catchments modelled with PDM, the differences between the mean (or median) impacts for each of the alternative methods and the mean impacts from the response surfaces are calculated. The three sets of projections are kept separate (e.g. the mean of gcm_harm is compared to that of gcm_rs whereas the mean of rcm_harm is compared to that of rcm_rs). Table 4 gives the maximum of these differences for each catchment and set of projections. This shows that 14001 (Damped-Low), 47007 (Neutral), 54008 (Enhanced-Low) and 43005 (Enhanced-High) have relatively low potential uncertainty, while 38003 (Sensitive) shows by far the highest potential uncertainty for all three sets of projections. The other four catchments, representing Damped-Extreme, Damped-High, Mixed and Enhanced-Medium response types, have intermediate uncertainty. A second set of nine catchments modelled with PDM gave similar relative differences in uncertainty by response type (not shown).

For larger catchments a partial uncertainty assessment was performed using four catchments modelled with CLASSIC (Table 2). This compared the impacts using RCM time-series (rcm_tseries) to the corresponding impacts extracted from response surfaces (rcm_rs). The results (Table 5) show similar relations between catchments as those for the PDM catchments (Table 4); 76007 (Neutral) and 39001 (Damped-Low) show a lower level of uncertainty (cf. 47007 and 14001), with greater uncertainty for 27009 (Damped-High) and 33026 (Mixed) (cf. 02001 and 34003). Table 5 and Table 4 also show that each CLASSIC catchment has a higher level of uncertainty than the corresponding (same response type) PDM catchment. It is possible that this apparent increased response of catchments modelled with CLASSIC compared to those modelled with PDM, when using RCM time-series as input, is due to the larger area of the CLASSIC catchments (Table 2); a larger area means an increased possibility of large accumulations of water reaching the river, and the RCM data could be suggesting greater spatial coherence in future rainfall (due to wetter winters and drier summers meaning more large-scale, frontal rainfall and less convective rainfall) (Buonomo, pers. comm.).

5. Discussion

Comparison of the impacts on RP20 extracted from the response surfaces with those using alternatives methods shows that different catchments can have different causes of uncertainty (that is, the differences in comparison to the response surface results occur for different factors in the uncertainty assessment). Perhaps more importantly, some catchments have a higher potential level of uncertainty than other catchments. Some catchments have a similar level of uncertainty across the four return periods (2-, 10-, 20- and 50-years), whereas others have a level of uncertainty which increases/decreases with return period (not shown).

Assuming the differences in average impacts for the example catchments also apply to catchments of the same response type, it is possible to say something about the potential level of uncertainty for different response types. For instance, Neutral catchments will have quite a low level of uncertainty, as will Damped-Low or Enhanced-Low catchments, while Damped-High or Mixed catchments are likely to have a higher level of uncertainty, and Sensitive catchments are likely to have the greatest uncertainty. These results are compatible with the underlying climatological and hydrological differences between the response types (Prudhomme et al. 2013a). The characteristics selected in the decision trees, which can be used to estimate catchment response type, demonstrate that change in the water balance is the dominant factor determining change in flood potential (Prudhomme et al. 2013b). For Neutral catchments, where the response surfaces show a near-linear response to P changes, the water balance throughout the year is not unduly affected by changes in P and PE, so uncertainty in flood change is small. In contrast, for Sensitive catchments the response surfaces have a very narrow band where the change in flood peak can be anywhere between 0 and 90%, so seasonal changes to P and PE can easily alter the balance between these two factors and consequent flood potential. Thus precisely how and when climatic changes occur through the year causes differences in impact on the water balance, resulting in comparatively high uncertainty. Mixed, Enhanced-Medium and Enhanced-High catchments are also susceptible to seasonal changes in the water balance, so have fairly high uncertainty. Uncertainty for Damped-High catchments is probably less affected by potential water balance changes than by the causes and month of extreme event occurrence, for example changes in T or P which affect the incidence of snowmelt floods or summer storms.

Despite the small number of catchments investigated here, the fact that the results are physically reasonable, and the relative similarity of the results for comparable PDM and CLASSIC catchments, gives confidence in the extension of the results to response type. That is, the analysis in Section 4.4 can be used to develop uncertainty allowances by response type, to be used alongside the response surfaces to provide more robust impact estimates. For example, it might be decided to add 8% to a set of impacts derived by overlaying a large ensemble on a response surface for a Damped-High catchment, as this is the difference in the mean impacts modelled for the example Damped-High catchment (Table 4). For a larger catchment (Area > 2000km^2 say), the differences in Table 5 might be taken into account.

It should be noted that the analysis presented in Section 4.4 concentrates on differences in average impacts, but the full results (Figure 4) also indicate differences in the impact ranges between the different methods. In particular, the range is larger when natural variability and its projected changes are considered, either through use of delta-changes derived from multiple sub-periods within time-slices, or use of simulated time-series. This feature was also shown by Kay and Jones (2012), who compared flood impacts using alternative UKCP09 products for the same nine catchments as here. This possible expansion of the uncertainty range is not included in the example above but could potentially be incorporated into modified impact distributions.

6. Conclusions

Sensitivity frameworks and response surfaces provide a useful way of estimating the potential impacts of climate change. The great strength of the approach is that alternative large sets of projections (for different emissions or time-slices, or entirely new projections) can be readily applied without the need for a significant new impact modelling study. However, a number of simplifications are necessary to construct response surfaces, particularly for indicators like flood flows where the seasonal pattern of climate change is important. The sensitivity framework developed by Prudhomme et al. (2010) facilitated the production of flood response surfaces, representing the sensitivity of a given flood indicator for a catchment to a particular set of changes in precipitation (P), temperature (T) and potential evaporation (PE). Here, the uncertainty introduced by some of the simplifications has been assessed for a small number of catchments.

The analyses suggest that the results can be extended from catchments to response types, enabling the development of uncertainty allowances by response type. This means that the methodology of Prudhomme et al. (2013a,b) can be used with greater confidence for impact estimation for un-modelled catchments. That is, for such a catchment, first the response type is estimated via the decision trees then the composite response surface of that type is combined with a set of climate projections (Prudhomme et al. 2013b). This provides an initial estimate of the set of impacts, to which the uncertainty allowance would be added to correct for potential bias in the average impact (and possibly a range correction too). Then the standard deviation surface of the same type is also combined with the set of climate projections, to allow for the range of responses within the type (Prudhomme et al. 2013b). Whilst this provides a useful first level of assessment it is recommended that further hydrological modelling is carried out in certain cases (e.g. for very vulnerable situations or where significant investment is planned), where the chance of greater impacts than estimated using the sensitivity framework may be critical.

A similar sensitivity framework method could be developed for other impact sectors (e.g. water availability) and include factors other than climate change (e.g. land-use change) if appropriate models are available. However, the design of the framework has to be carefully tailored to the sector and the factors of importance. Choices potentially influencing response surface results include:

- Climate variables: For flood peak changes it was assumed that P change was more important than T or PE change, thus only eight T-change scenarios were applied here, with corresponding PE-changes derived from T (Table 1). However, T changes are likely to be more important in regions more strongly influenced by snow (e.g. Wetterhall et al. 2011) and PE changes are likely to be more influential for changes in low flows than floods (Kay and Davies 2008). Changes in other meteorological variables than T affecting PE, such as radiation and wind, may then be

important, as might changes in plant physiology (Kay et al. 2013, Bell et al. 2011).
- Seasonality: A single-harmonic function was used to represent seasonality here (Section 2.1). Alternatives include use of a fixed monthly pattern to distribute annual changes (e.g. Wetterhall et al. 2011, Cloke et al. 2013). If seasonality is not important for the indicator under consideration then only mean annual changes need be considered (e.g. Fronzek et al. 2010 for P).
- Increment: Increments of 5% were used here (Table 1). Use of finer increments would result in more continuous response surfaces but require many more simulations, and is unlikely to make a substantial difference to the impact distribution extracted for a large projection ensemble; interpolation could be used instead. However, if any sharp change/discontinuity is shown by a response surface, some refinement may be advisable to better resolve this.
- Downscaling: Delta-change downscaling was used here (Section 2.1), but this method is limited in terms of variability. A possible alternative is applying a weather generator (Bastola et al. 2011), although ideally multiple runs would be required at each position of the sensitivity domain to reduce the noise that could be introduced by single runs; significantly increasing the computational burden.
- Impact model structure and parameterisation: Hydrological modelling uncertainty was not considered here, but the response surfaces for a catchment modelled with both hydrological models are very similar (not shown), and other research has suggested that hydrological modelling uncertainty is smaller than GCM uncertainty (e.g. Kay et al. 2009b, Wilby and Harris 2006). However, such uncertainty could be included in response surfaces; e.g. Cloke et al. (2013) use 100 parameter sets with their hydrological model, Bastola et al. (2011) apply four hydrological models each with 50 parameter sets, and Fronzek et al. (2011) include uncertainty in their palsa mire models.

However, the balance between uncertainty in the results and complexity of the framework has to be carefully considered. Increasing the number of dimensions in the sensitivity domain will not only increase the number of runs necessary, but also make presentation and analysis (e.g. grouping and characterisation, Prudhomme et al. (2013a,b)) more difficult, so will not necessarily decrease the overall potential for uncertainty. It is recommended that, when designing a framework, some initial testing is carried out to facilitate an assessment of the relative importance of different factors and suitability of simplifications.

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Tables

Table 1 Sensitivity domain for change in precipitation (P), temperature (T) and potential evaporation (PE) relative to the baseline, for construction of response surfaces.

Climate variable	Harmonic phase (Φ)	Harmonic mean (X_{mean})	Harmonic amplitude (A)	Scenarios
Change in P	January	-40% to 60%	0 to +120%	All combinations by increments of 5% Total: 525 scenarios
Change in T	January and August	1.5℃ 2.5℃ 4.5℃	1.2℃ 0.8℃ 1.6℃	Low-Jan and Low-Aug Medium-Jan and Medium-Aug High-Jan and High-Aug
	None	0.5℃; 4.5℃	0℃	Low-/High-Non-Seasonal (NS) Total: 8 scenarios
Change in PE	One scenario corresponding to each of the T scenarios (based on the Central-England T series and T-based PE formula of Oudin et al. 2005). Resulting monthly percentage changes range from less than 2% (in July under Low-Jan) to over 100% (in February under High-Jan) but average around 22% (see Kay et al. 2009a Figure 1.3).			Total: 8 scenarios

Table 2 Details of the nine example catchments modelled with PDM (one for each response type) and the additional four example catchments modelled with CLASSIC.

Response type (short-hand)	Catchment number	River name@ Location	Area (km^2)	$SAAR_{61-90}$ (mm)	BFI (-)	UKCP09 river-basin region (see Section 2.3)
PDM catchments:						
Damped-Extreme (DpE)	07002	Findhorn@ Forres	781.9	1064	0.41	North Highland
Damped-High (DpH)	02001	Helmsdale@ Kilphedir	551.4	1117	0.48	North Highland
Damped-Low (DpL)	14001	Eden@ Kemback	307.4	799	0.62	Tay
Neutral (Neu)	47007	Yealm@ Puslinch	54.9	1410	0.56	Southwest England
Mixed (Mix)	34003	Bure@ Ingworth	164.7	669	0.83	Anglian
Enhanced-Low (EnL)	54008	Teme@ Tenbury	1134.4	841	0.57	Severn
Enhanced-Medium (EnM)	21023	Leet Water@ Coldstream	113.0	671	0.35	Tweed
Enhanced-High (EnH)	43005	Avon@ Amesbury	323.7	745	0.91	Southwest England
Sensitive (Sen)	38003	Mimram@ Panshanger Park	133.9	656	0.94	Thames
CLASSIC catchments:						
Damped-High (DpH)	27009	Ouse@ Skelton	3315	914	0.46	N/A
Damped-Low (DpL)	39001	Thames@ Kingston	9948	719	0.64	N/A
Neutral (Neu)	76007	Eden@ Sheepmount	2287	1214	0.49	N/A
Mixed (Mix)	33026	Bedford Ouse@ Offord	2570	609	0.47	N/A

$SAAR_{61-90}$ = Standard Average Annual Rainfall (1961-1990);
BFI = baseflow index, a measure of the proportion of flow coming from stored sources like groundwater

Table 3 Summary of the methods applied to investigate each factor leading to uncertainty from use of catchment response surfaces (Section 3), with the notation used for the results from each set of projections (GCM, RCM, UKCP09; Section 2.3).

Factor	Precipitation (P)	Temperature (T) and Potential Evaporation (PE)	Notation for sets of climate change projections (2080s, A1B emissions)		
			16 GCMs	11 RCMs	10,000 UKCP09
-	Response surface P harmonic (multiple of 5% for mean and amplitude, January phase; Table 1)	Medium-Aug T harmonic and corresponding monthly PE delta-changes (Table 1)	gcm_rs	rcm_rs	ukcp_rs
1	Actual P single-harmonic (fitted to median monthly P changes below)	As above	gcm_harm	rcm_harm	ukcp_harm
1	Actual P double-harmonic (fitted to median monthly P changes below)	As above	gcm_harm2	rcm_harm2	N/A
2	Median monthly P delta-changes (median of range below)	Corresponding monthly T and PE delta-changes	gcm_20med	rcm_20med	N/A
2	Range of monthly P delta-changes (20-year sub-periods in baseline and future time-slices)	As above	gcm_20	rcm_20	N/A
2	Alternative monthly P delta-changes (fixed 30-year baseline and future time-slices)	As above	gcm_30	rcm_30	ukcp_30
3	P time-series (daily)	T and PE time-series (daily)	N/A	rcm_tseries	N/A

Table 4 The maximum difference (%) between the average impacts from each of the alternative methods (*_harm/harm2/20med/20/30/tseries where * is gcm, rcm or ukcp; Table 3) and those extracted from response surfaces (*_rs), for each example catchment modelled with PDM and each set of projections.

PDM catchment (response type)	Projection set GCM	RCM	UKCP09	Mean	Maximum
07002 (Damped-Extreme)	7	11	9	9	11
02001 (Damped-High)	3	14	8	8	14
14001 (Damped-Low)	5	6	5	5	6
47007 (Neutral)	3	1	6	3	6
34003 (Mixed)	11	10	6	9	11
54008 (Enhanced-Low)	5	0	-1	1	5
21023 (Enhanced-Medium)	4	13	7	8	13
43005 (Enhanced-High)	8	1	0	3	8
38003 (Sensitive)	16	20	11	16	20
Mean	7	8	6	7	10
Mean over four types (Damped-High to Mixed)	5	8	6	6	9

Table 5 The difference (%) between the mean impact from use of RCM time-series (rcm_tseries) and that extracted from response surfaces (rcm_rs), for each example catchment modelled with CLASSIC.

CLASSIC catchment (response type)	RCM projections
27009 (Damped-High)	18
39001 (Damped-Low)	12
76007 (Neutral)	7
33026 (Mixed)	20
Mean	14

Figures

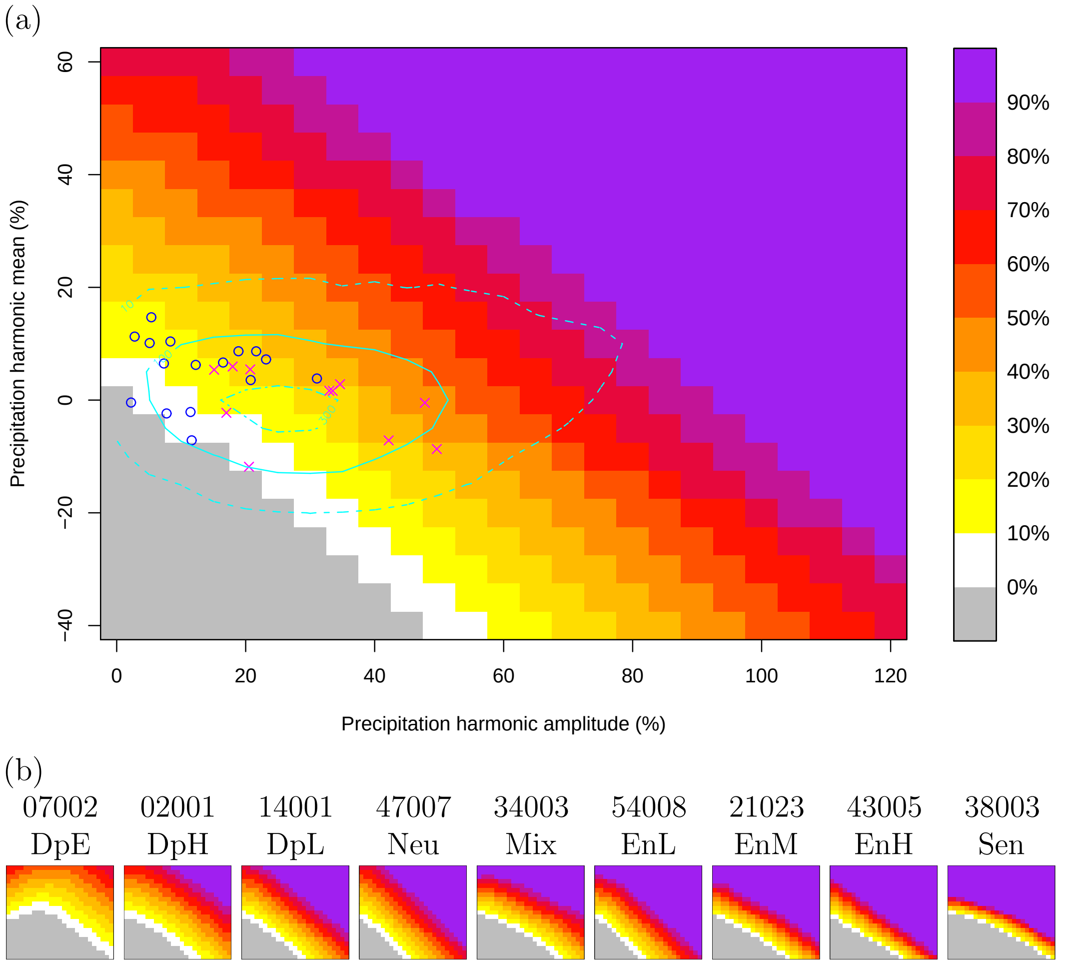

Figure 1 Response surfaces for changes in 20-year return period flood peaks under the Medium-Aug T/PE scenario (Table 1): (a) catchment 47007 with axis labels and colour key, (b) the nine example catchments modelled with PDM (Table 2). Overlaid on the response surface in (a) are three sets of climate change projections, from GCMs (16 circles), RCMs (11 crosses) and UKCP09 (contours delineating densities of 10, 100 and 300 projections per 5%x5% sensitivity domain square) (see Section 2.3).

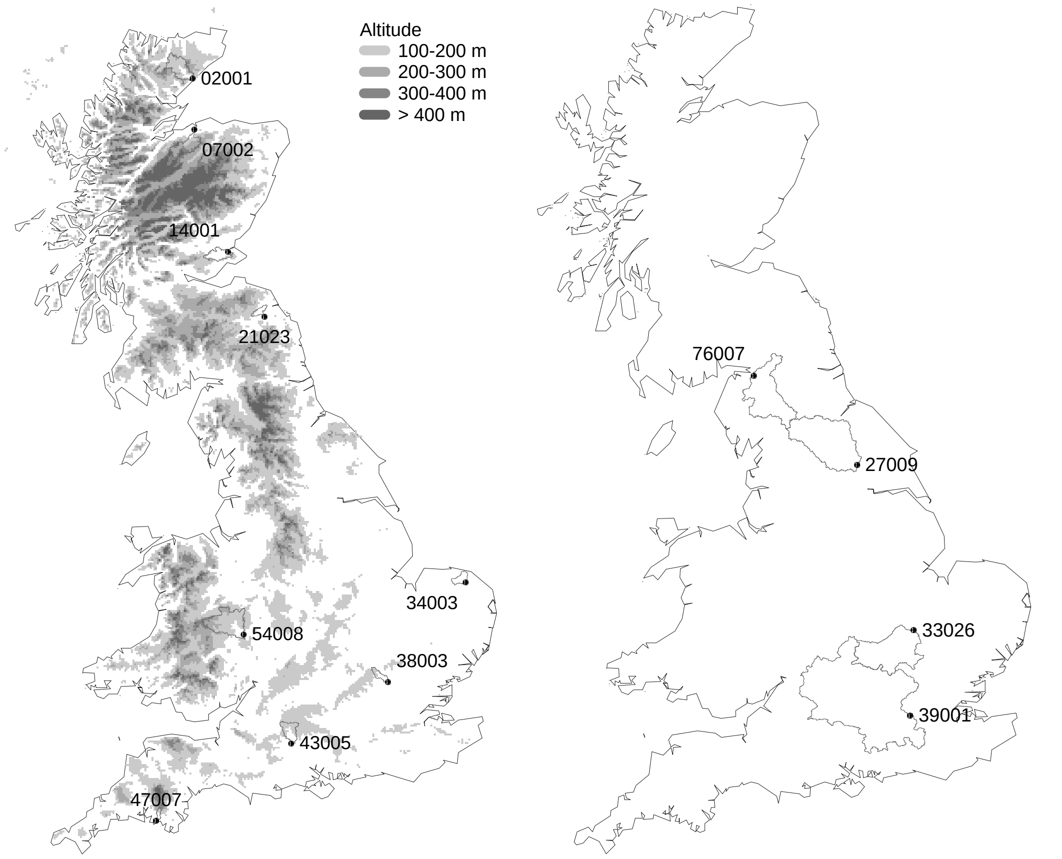

Figure 2 Boundaries and outlet locations of the nine example catchments modelled with PDM (left) and the four example catchments modelled with CLASSIC (right).

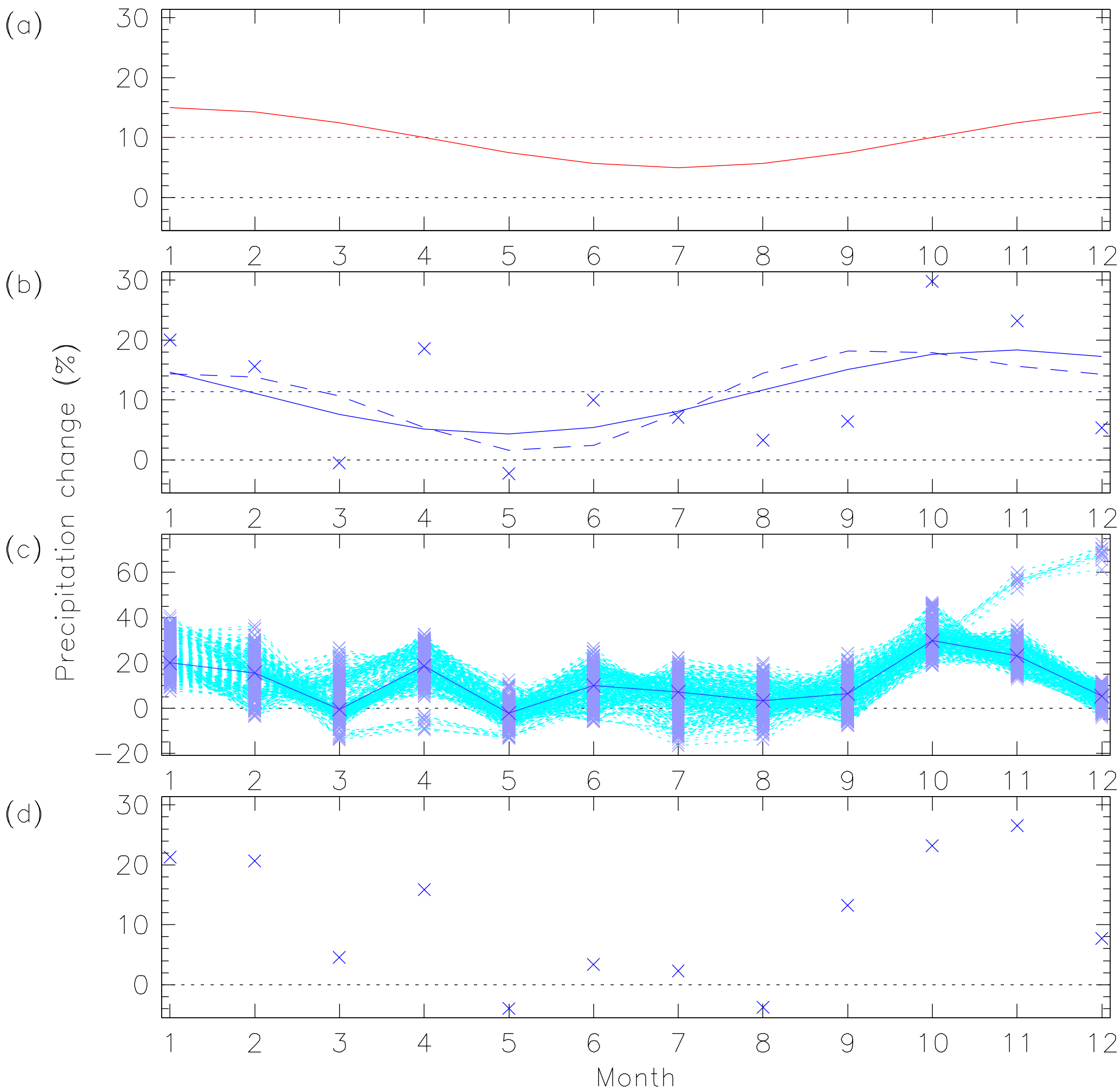

Figure 3 Example of how alternative sets of monthly P changes (Table 3) compare, for one GCM projection and one grid box (over catchment 02001): (a) response surface harmonic (gcm_rs, solid line; X_{mean}=10%, A=5%, Φ=January); (b) actual single-harmonic (gcm_harm, solid line; X_{mean}=11.4%, A=7%, Φ=November), actual double-harmonic (gcm_harm2, dashed line), and the median monthly P changes to which the harmonics are fitted (gcm_20med, crosses; medians from c); (c) range of monthly P changes derived from 20-year sub-periods within baseline and future time-slices (gcm_20, crosses/dotted lines, with medians as darker crosses/lines); (d) alternative monthly P changes derived directly from fixed 30-year time-slices (gcm_30, crosses). The zero line is also shown on each plot (to highlight any decreases in P), with additional horizontal dotted lines in (a) and (b) showing X_{mean}.

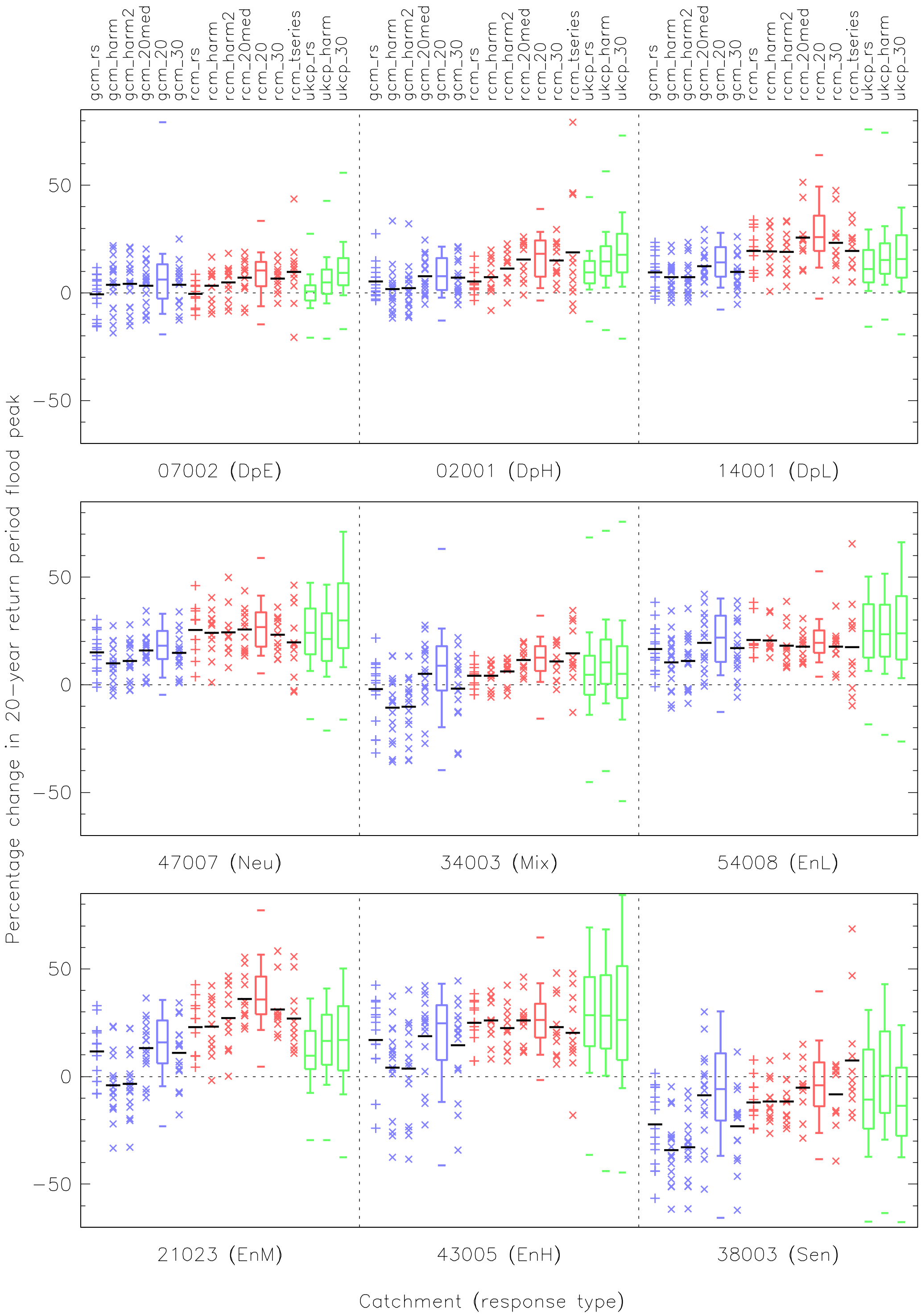

Figure 4 Modelled changes in 20-year return period flood peaks for the nine example catchments modelled with PDM, using GCM (blue), RCM (red) and UKCP09 (green) projections. Impacts are shown for each application method of Table 3 (labelled along top). Boxes-and-whiskers are used for large sets (gcm_20, rcm_20, ukcp_rs, ukcp_30, ukcp_harm): boxes show the 25th-50th-75th percentile range, whiskers the 10th-90th percentile range, additional markers the minima and maxima (if in the plotted range -70%-+85%). Smaller sets are plotted as separate points (16 for GCMs, 11 for RCMs), using plus signs if from response surfaces (gcm_rs and rcm_rs) and crosses otherwise, with means shown by horizontal bars (black).

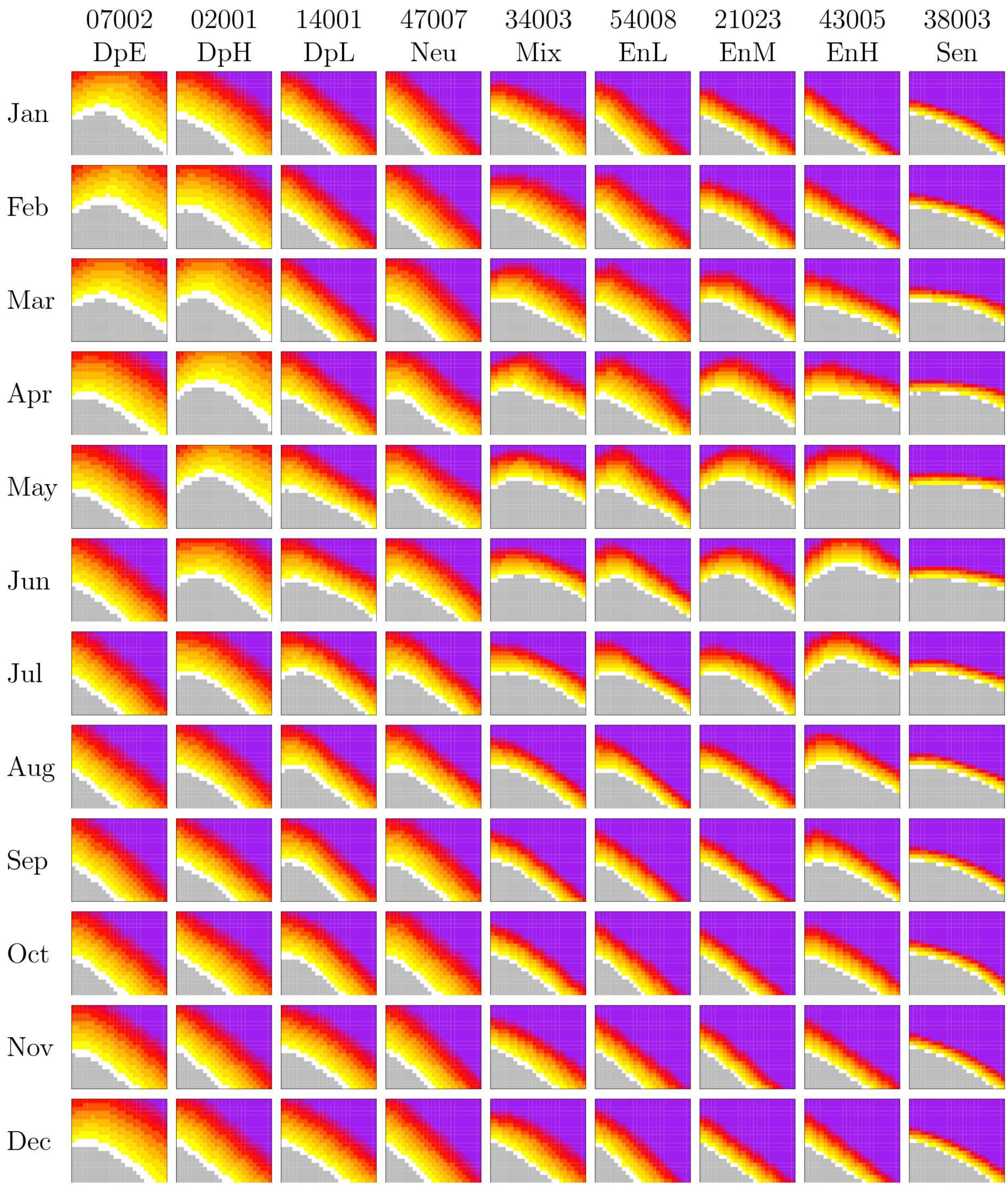

Figure 5 Modelled response surfaces for each of the nine example catchments modelled with PDM, showing the percentage change in 20-year return period flood peaks under the Medium-Aug T/PE scenario (Table 1) but with the harmonic phase (month of peak P change) occurring in each alternative month of the year (top to bottom). See Figure 1a for axis information and colour key.

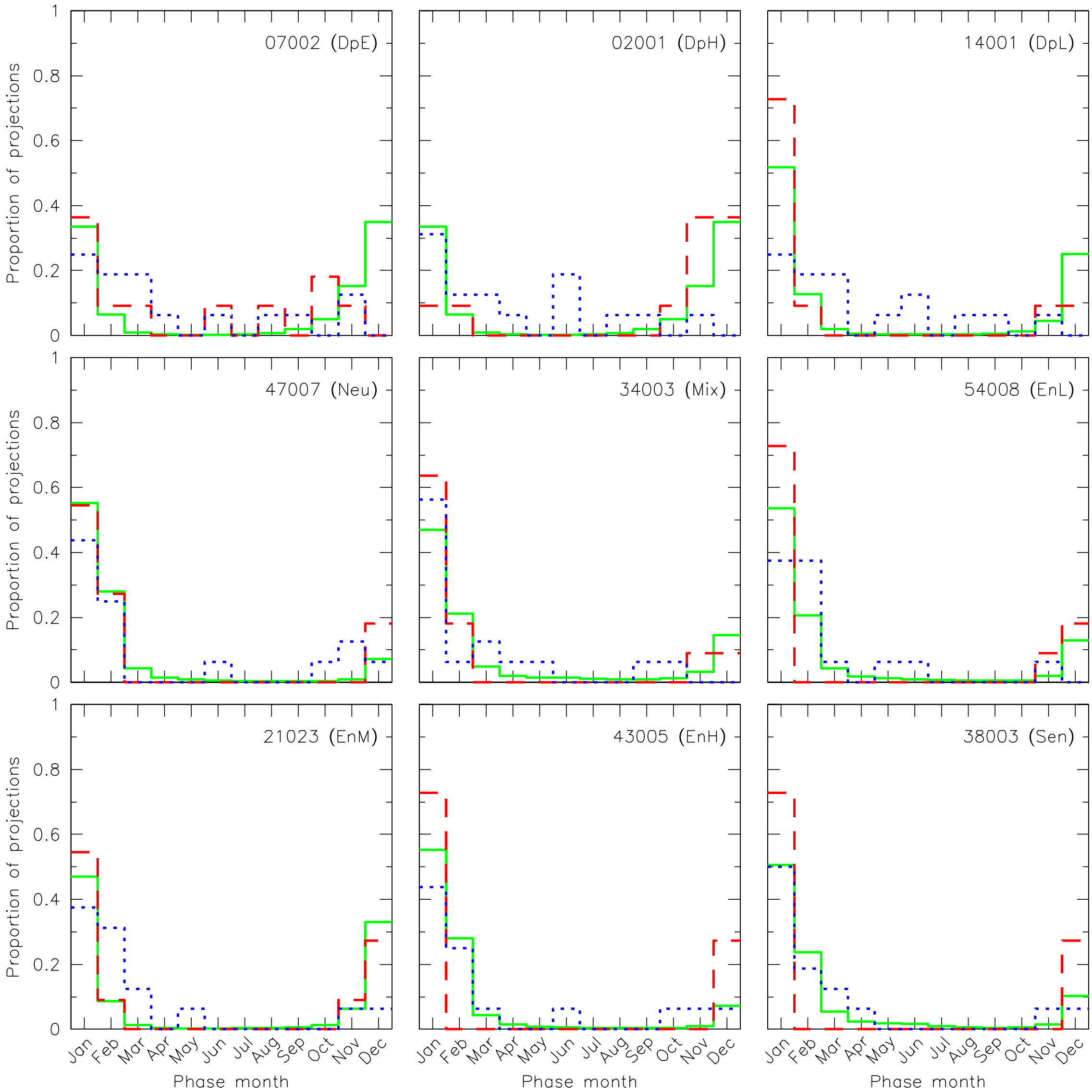

Figure 6 Histograms of P harmonic phase (month of peak P change in the fitted single-harmonic) for each of the nine example catchments modelled with PDM, for GCM (blue dotted), RCM (red dashed) and UKCP09 (green solid) projections.