The application of probabilistic climate change projections: a comparison of methods of handling uncertainty applied to UK irrigation reservoir design
Michael Green and Edward Keith Weatherhead

ABSTRACT
Climate projections are increasingly being presented in terms of uncertainties and probability distributions rather than median or ‘most-likely’ values. The current national UK climate change projections, UKCP09, provide 10,000 probabilistic projections (PP) and 11 spatially coherent projections (11SCP) for three future emission scenarios. In contrast, previous iterations such as UKCIP02 provided only a single ‘most-likely’ (deterministic) projection for each. This move from deterministic to probabilistic methods of communicating climate change information, whilst increasing the wealth of the data, complicates the process of adaptation planning by communicating extra uncertainty to the public and decision-makers. This paper examines the application of probabilistic climate change projections and explores the impact of uncertainty on decision-making, using a case study of irrigation reservoir design at three sites in the UK. The implications of sub-sampling the PP using both simple random and Latin-hypercube sampling are also explored. The study found that the choice of dataset has a much larger impact on irrigation reservoir design than emission uncertainty. The study confirmed the dangers of inadequate sample size, particularly when applying decision criteria based on extreme events, and found that more advanced stratified sampling techniques did not noticeably improve the reproducibility of decision outcomes.

Key words | adaptation planning, decision-making under uncertainty, deterministic, probabilistic, UKCP09, WaSim

INTRODUCTION
In the UK, approximately 150,000 ha of agricultural land are irrigated (Knox et al. 2010). In parts of the UK during a dry year, supplemental irrigation is essential for growing high-quality produce, most notably potatoes. However, increasing demand, climate change and the need to balance environmental demands are now adversely affecting the availability of water for irrigation (Weatherhead et al. 2008). Farmers with access to a winter-filled reservoir can ensure that the environmental impacts of irrigation abstraction during summer months, when water resources are most constrained, are reduced (Weatherhead et al. 2008).

Irrigation reservoirs, like much of the UK’s water infrastructure, were originally designed on the assumption that the climate in which it was built would endure for its lifetime; due to climate change this is no longer the case (Gleick 2001). As a result, climate change projections are increasingly being used to test the performance of existing assets as well as support the design of new assets which will be robust to climate change (Anderson & Bows 2011; Fung et al. 2011; Sanderson et al. 2011; Harris et al. 2014; Green & Weatherhead 2014a, b, c). This approach is commonly referred to as scenario-led adaptation and is the focus of this research; readers should be aware there are other approaches to adaptation including vulnerability (or bottom-up) and hybrids thereof, the merits of which are discussed elsewhere and in greater detail (e.g. Wilby & Dessai

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Scenario-led adaptation uses downscaled regional-scale climate projections to inform adaptation plans designed to maximise potential benefits and/or minimise potential risks (Wilby & Dessai 2010). Scenario-led adaptation is gradually gaining more traction within the scientific community, although practical uptake is limited to some extent by the financial and technical capacity of the individuals undertaking adaptation, their risk appetite, the availability of high-quality downscaled climate change information and the type of adaptation options being considered (Adger et al. 2005; Dessai et al. 2005).

Decision-makers are increasingly looking to scientists for information about the likelihood of future climate change. Traditionally, science has proved invaluable to decision-makers, either by providing accurate predictions or by enabling technological advancements which have enabled decision-makers to ‘steer’ the future toward desired outcomes (Dessai et al. 2009). Unfortunately, there are many examples, of which climate change is an example, where the science has not been as forthcoming as decision-makers had hoped (Millner 2012). Scientists, correctly, emphasise the uncertainties, while decision-makers seek a clear picture. As a result, a large disparity has begun to emerge between what decision-makers want and what scientists can reasonably provide.

Recent advances in computational power have allowed for partial quantification of model uncertainty including perturbed physics ensembles (Stainforth et al. 2005), multi-model ensembles (Tebaldi & Knutti 2007) and advanced statistical techniques (Rougier & Sexton 2007) on which the current generation of national UK climate change projections, termed UKCP09, are founded.

In recent years, a change from deterministic to probabilistic methods of communicating climate change information and uncertainty has been observed, though how the latter should be interpreted is an area of continuing debate (Stainforth et al. 2007). Expressing climate change as a range of potential outcomes as opposed to a single value in itself increases the complexity. The move from deterministic methods of communicating climate change information (e.g. UKCIP02) to probabilistic methods (e.g. UKCP09) may be viewed as a ‘conceptual leap’ and has forced many decision-makers to reassess how they use climate change information to inform policy (Weaver et al. 2013; Harris et al. 2014).

In the UK, the current suite of national climate change projections is UKCP09 (Murphy et al. 2009). UKCP09 used advanced statistical methods to generate probabilistic projections (PP) of future climate change and thereby explore the wider uncertainties in climate system processes. Probabilistic climate projections are provided at a 25 km scale resolution generated from a perturbed ensemble experiment using the HadSM3 Global climate model (Murphy et al. 2009). Some 10,000 probabilistic monthly change factors are available for a 25 km grid covering the whole of the UK, for three different greenhouse gases emission scenarios (low, medium and high) for seven 30-year time-slices (2020s, 2030s, 2040s, 2050s, 2060s, 2070s and 2080s). Future climate change is thus expressed as a large range of potential outcomes as opposed to a single ‘most likely’ projection (Dessai et al. 2009).

In addition to 10,000 PP, 11 spatially coherent projections (11SCP) are available via the UKCP09 user interface. The 11SCP were created by applying scaling factors to the 11-member regional climate models (11RCM) with the aim of incorporating the wider uncertainties considered by UKCP09. Unlike the 10,000 PP, the 11SCP are spatially and temporally consistent across the grid. The 11SCP should be used wherever the decision-maker is considering impacts derived from more than one grid square in a spatially coherent way, e.g. catchment runoff, or wants to explore some of the uncertainty associated with UKCP09 (the 11SCP consider a much wider range of uncertainty compared to the 11RCM, although not as much as the 10,000 PP). However, while the 11SCP are considered to be equi-probable, the projections are not probabilistic in nature, e.g. they do not consider the structural uncertainty in the atmospheric processes, uncertainty arising from the carbon and sulphur cycle or ocean physics. UKCIP have been clear to stress that the 11SCP are not a replacement for the PP; despite this, some users may purposely use them, even for single grid squares, because the resources required to process and interpret the outputs from the 11SCP are much smaller.

As previously suggested, one of the key challenges facing users of UKCP09 is the sheer number of climate change projections that are provided. UK Climate Impacts Programme (UKCIP) recommends decision-makers use a minimum of 100 climate change projections in order to preserve the probabilistic characteristics of the underlying projections...
(Christierson et al. 2012). Of course a sample this large may still be beyond the capabilities of many complex models, in particularly national scale models (Christierson et al. 2012) and computationally demanding models such as DSSAT (Daccache et al. 2011). As a result, it is often necessary to sub-sample the 10,000 projections (alternatively, a rapid assessment model can be used, although these are discussed elsewhere and in greater detail, e.g. see Haasnoot et al. 2012; Kwakkel et al. 2012). The design and complexity of these sampling methods will depend on both the availability of resources and technical expertise to the decision-maker in question.

The size of these sub-samples and choice of sampling methodology are particularly important. Basing decisions on a single or small subset of projections can result in maladaptation, if events occur which are outside the range described by that subset of projections. Using a wide range of projections can lead to increased adaptive capacity, although it is not guaranteed to be more successful, especially if the ‘real’ future climate is not expressed by any single projection within the available projections (Dessai & Hulme 2007). Furthermore, if the potential climate change impacts are diverse and the projections too numerous or difficult to interpret, the identification of suitable adaptation measures may become too complex and no action may be taken, with potentially serious consequences.

Latin hypercube sampling (LHS) (Mckay et al. 1979) has previously been shown to be an effective tool for sub-sampling the UKCP09 dataset (Christierson et al. 2012). In two dimensions, a Latin hypercube can be represented by a simple grid, with one climate variable represented by a row and the other climate variable a column. A Latin hypercube with more dimensions can be considered the generalisation of this concept. This study utilises two types of LHS, specifically optimum and Maximin. Optimum LHS uses a columnwise–pairwise (CP) algorithm to generate an optimal design using an S optimality criterion (Liefvendahl & Stocki 2006). An S optimality criterion seeks to maximise the average distance between design points (or projections) to all other points in the state space (Stocki 2005). In contrast, Maximin LHS maximizes the minimum distance between design points, this ensures the points out are spread out across the state space (Stein 1987).

Climate projections from UKCP09 can be directly imported into soil water balance models such as WaSim (Hess & Counsell 2000), freely available via the Cranfield University website (www.cranfield.ac.uk/about/people-and-resources/schools-and-departments/school-of-applied-sciences/groups-institutes-and-centres/cws-software/cswi-wasim-download.html), to model the irrigation demand of various crops. These data, combined with cost and benefit information, have been used for example to inform the optimum capacity of a reservoir required to meet future irrigation demands. WaSim simulates inflow (i.e. infiltration) and outflow (i.e. evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage (Depeweg & Fabiola Otero 2004). WaSim has proven invaluable in a range of previous studies including determining irrigation requirements; optimising water management, assessing the performance of sub-surface drainage systems and studying the effects of climate change on water resources (Depeweg & Fabiola Otero 2004; Hirekhan et al. 2007; Warren & Holman 2012).

WaSim requires rainfall and evapotranspiration data, the latter can be estimated using Penman–Monteith (used here), FAO Modified-Penman or Penman methods (Monteith 1965). Guidance values covering crop development and root depths are provided for several crops within WaSim, enabling up to three crops to be combined in a cropping pattern (Hess & Counsell 2000). Irrigation schedules may be set up as either calendar or rule based. Calendar schedules assume a fixed irrigation date, whereas rule-based scheduling, used here, divides the cropping season into a series of irrigation and non-irrigation periods governing the frequency and volume of irrigation required.

In the field of irrigated agriculture, decision-makers have typically relied on the design dry year approach for estimating the volume of irrigation required. A design dry year is defined in the UK as a year with an 80% probability of non-exceedance (roughly equivalent to the older ‘fourth driest year in five’). This industry ‘rule-of-thumb’ forms the basis of many asset design and water allocation decisions in the field of irrigated agriculture (Weatherhead & Knox 2000). However, recent studies suggest that the simple 80% probability of non-exceedance approach may risk maladaptation, depending on the crop value and the cost of the water (Green & Weatherhead 2014b).

Alternative decision criteria may be sought which dispense with probability altogether (Ranger et al. 2010).
These criteria are commonly used to support decision-making under uncertainty (i.e. in situations where no information of event likelihood exists) (Dessai et al. 2009; Ranger et al. 2010). These criteria include Laplace’s criterion (Laplace 1825), Wald’s Maximin criterion (Wald 1945), Maximax criterion, Hurwicz’s realism criterion (Hurwicz 1951), and Savage’s Minimax regret criterion (Savage 1951). For the purpose of this study, it was assumed that the decision-maker would use Laplace (in line with emerging guidelines, e.g. see EA 2013), although the other decision criteria (i.e. Maximin, Maximin, Minimax regret and Hurwicz’s criteria) are presented for completeness. Laplace’s criterion is based on the premise of symmetry (Ranger et al. 2010); each potential environmental state (i.e. each climate change projection) is considered to be equi-probable in the absence of prior knowledge. The average expected payoff for each option (i.e. reservoir capacity) is calculated using all the states (i.e. climate projections); for Laplace, the option providing the largest average payoff is considered the design capacity. Maximin identifies the best option as the option which provides the largest expected outcome from the worst possible state. In contrast, Maximax identifies the best option as the option providing the largest outcome from the best possible state. The best option under Hurwicz’s criterion is calculated using a weighted average of Maximin and Maximax (with the weighting defined by $\alpha$, representing the optimism of the decision-maker). Minimax regret identifies the option with the smallest regret, representing the difference between the best and worst possible outcomes across all states. For a detailed explanation covering the methods used to generate all of the criteria readers are directed to Sniedovich (2007), Ranger et al. (2010) or more recently Green & Weatherhead (2014b).

**AIM**

The aim of this study was to examine the implications of different ways of using probabilistic climate change projections and explore the impact of uncertainty on decision-making, using a case study of irrigation reservoir design at three sites in the UK on the basis of the 2050s low, medium and high emission scenarios. It critically compares the optimum reservoir sizes obtained using the median or ‘most likely’ projection and design reservoir capacities using the 11SCP projections and the 10,000 PP, under various decision-making criteria. It then critically compares applying simple random, Optimal and Maximin Latin hyper cube methods of sub-sampling the 10,000 PP.

**METHODOLOGY**

In summary, a series of irrigation reservoirs were designed using projections derived from the UKCP09 probabilistic dataset using high, medium and low emission scenarios for the 2050s for three sites in the UK. The emissions scenarios used in this study are commonly referred to as the SRES A1F1, A1B and B1 scenarios respectively (Nakicenovic & Swart 2000), although the terms high, medium and low will be more familiar to users of UKCP09 data and decision-makers in the UK. These emission scenarios do not consider planned mitigation policies but do enable different demographic and socio-economic development pathways to be simulated in a limited capacity (e.g. switching from fossil fuels to renewable sources of energy). Unlike the UKCP09 PP, the emission scenarios underpinning them are not probabilistic in nature; rather they are strictly deterministic, although the generation of probabilistic emission scenarios might be possible in the future.

Design reservoir capacities were identified by applying popular decision criteria typically employed in situations of deep uncertainty, including Laplace, Maximin, Maximax, Minimax regret and Hurwicz’s criteria, to the outputs (net present values – NPVs) obtained using the complete probabilistic dataset (i.e. all 10,000 projections), the 11SCP and finally various sub-samples of the complete probabilistic dataset using different sampling techniques.

A summary diagram is provided in Figure 1 detailing the main steps taken; further details of each stage and additional comparisons made are given below.

**Case study sites**

A previous study by Hess (2010) identified 11 meteorological stations, representing a range of agroclimatic
conditions distributed around England. Three of these sites, providing the most complete baseline (1961–1990) records, were selected as case studies (Green & Weatherhead 2014a, b, c) (Figure 2). Brooms Barn is located in the county of Suffolk, near Bury St Edmunds, approximately 30 km east of Cambridge and is the driest...
of the investigated sites. Slaidburn is in the county of Lancashire, approximately 60 km north-west of Leeds and is the wettest site. Lastly, Woburn is situated in the county of Bedfordshire, 50 km north-west of London and is marginally wetter than Brooms Barn but with slightly lower annual evapotranspiration. Observed daily climate data were extracted for the baseline period from the weather station at each site. Summary climatological data for the baseline period (1961–1990) are shown in Table 1.

Generating baseline and future climatology

Future daily weather datasets were generated using the change factor approach (elsewhere referred to as the delta change method) (Loaiciga et al. 2000; Prudhomme et al. 2002). In summary, the observed daily weather dataset was extracted from a weather station at each site (Table 1). All 10,000 sets of monthly change factors were downloaded from the UKCP09 probabilistic dataset for the 25 km grid square overlying each weather station for the 2050s time slice (i.e. 2040–2069).

Table 1: Weather station sites and records used

<table>
<thead>
<tr>
<th>Station</th>
<th>Lat.</th>
<th>Long.</th>
<th>Elevation (m AOD)</th>
<th>Rain (mm)</th>
<th>ETo (mm)</th>
<th>From</th>
<th>To</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brooms Barn</td>
<td>52.260</td>
<td>0.567</td>
<td>75</td>
<td>588</td>
<td>585</td>
<td>1964</td>
<td>1990</td>
</tr>
<tr>
<td>Woburn</td>
<td>52.014</td>
<td>–0.595</td>
<td>89</td>
<td>632</td>
<td>564</td>
<td>1961</td>
<td>1990</td>
</tr>
</tbody>
</table>

*Altitude above ordnance datum.
Evapotranspiration.
These were used to generate evapotranspiration change factors using the Penman–Monteith equation (Monteith 1965). Wind speed was assumed to be the same as the observed baseline (1969–1990) due to the lack of earlier baseline data and future projections of wind speed. The monthly precipitation and evapotranspiration change factors were then used to perturb the observed daily weather series, producing 10,000 future daily projections based on the UKCP09 probabilistic dataset for each site. Readers are directed to Green & Weatherhead (2014b) for a more detailed explanation of the methods used to generate the future climate projections used in this study.

Calculating future irrigation demand

WaSim (described earlier) was used to model the annual irrigation water use at each site. In its basic format WaSim is not capable of processing multiple climate files succinctly, so a modified version was developed and employed for this study to speed up data processing. This modified version was designed to read in multiple climate files and output a single .csv file containing the daily irrigation demand for each of the 10,000 projections from the probabilistic dataset. The annual water use of a potato crop was calculated for each year in the 10,000 × 30 year sequences from the PP for each site and emission scenario using a rule-based irrigation schedule based on typical UK practice (DEFRA 2005). This irrigation schedule consisted of four periods (one non-irrigation followed by two irrigation and one non-irrigation), applying 15 mm of water early in the growing season whenever the root zone deficit exceeded 18 mm during period 2 (15 May–30 June) and applying 25 mm of water whenever the root zone deficit exceeded 30 mm during period 3 (30 June–31 August).

Calculating NPV using cost-benefit analysis

Typical costs and benefits for clay (unlined) agricultural reservoirs were obtained from a concurrent study (Green & Weatherhead 2014b). The NPVs of a range of reservoir sizes, with usable storage capacities equivalent from 0 to 1000 mm depth over the area irrigated (i.e. 0 to 10,000 m³ ha⁻¹), were then calculated for each of the 10,000 projections (see Figure 1 for an overview of the methodology). The benefit of the water contained within each reservoir was calculated on the basis of average water use modelled over the 50-year sequence for each reservoir capacity (in some years not all the water may have been used, in other years use may have been constrained by the given capacity). An average net benefit (for potatoes) of £1.56/m³ of water used was assumed (Morris et al. 1997). Earthwork costs were assumed to be £1.125/m³ of earth moved, plus an additional 15% reflecting site investigation costs. A further £20,000 was added, representing the assumed connection costs of three-phase electricity. Annual operating expenditure was assumed to be 1% of capital expenditure, representing the low maintenance cost of clay reservoirs (Weatherhead et al. 2008). NPV was calculated by discounting the annual net benefit of the reservoir loss operating expenditure costs with a lumped (non-discounted) capital expenditure in year 0, assuming current government discount rate guidelines of 3.5% on investments of up to 30 years (HM Treasury 2003). Each reservoir was assumed to last 30 years, representing their typical life cycle.

Using decision criteria to calculate the irrigation reservoir capacity

Laplace and the other decision criteria were then used to select the design reservoir capacities using the complete probabilistic dataset (i.e. S1 to S10,000); the method is demonstrated for four states only in Table 2. For example, for the Laplace criterion, this was the capacity providing the maximum NPV averaged across all of the 10,000 PP, whereas for Maximin this was the capacity providing the maximum NPV based on the worst case of all the 10,000 PP. Where the result was found to be negative, the capacity was set at zero, i.e. it was assumed no reservoir would be built.

Comparing the impact of using a single deterministic projection instead of the complete probabilistic dataset

To examine the implications of different ways of using the UKCP09 probabilistic dataset and explore the impact of uncertainty on decision-making associated with moving from a single deterministic projection to using the complete probabilistic dataset, it is of course necessary to know the single projection that would have been used if
only one projection was provided. However, in the case of UKCP09, no such single ‘most-likely’ projection exists when dealing with multiple climate parameters; each of the 10,000 projections is considered to be equally likely (UKCIP 2013). It would be tempting, but potentially misleading, to try to select one with median temperature, median rainfall, etc.; however, such a combination could actually be unlikely. Selecting the most-likely projection within a single metric would require a (partly) arbitrary choice; using a different metric would probably lead to a different projection.

A comparison against the projection with the median ‘optimum’ outcome was used here, although of course identifying that state required all the projections to be modelled first. In order to calculate the median optimum outcome, the reservoir capacity providing the maximum NPV was identified for each projection and the median value (i.e. the ‘most likely’ outcome from processing all 10,000 PP individually) selected. However it is important to stress that the projection underpinning this median optimum outcome or reservoir capacity is not necessarily the median climate projection; in a non-linear system using the average or median values of the individual climate parameters does not necessarily give the average or median impact.

The differences in reservoir capacities between using the complete probabilistic dataset and all of the 11SCP, using Laplace and other decision criteria, and the median optimum reservoir capacity, represented the ‘most likely’ outcome, were then compared.

### Comparing the impact of different sources of uncertainty

This study considered two sources of uncertainty: (1) uncertainty attributed to differences between the 11SCP and 10,000 PP and (2) emission scenario uncertainty. The chosen methodology enabled both sources of uncertainty to be simultaneously compared whilst providing an insight into the impact of uncertainty on decision-making for irrigation reservoir design. Uncertainty associated with the 11SCP and 10,000 PP was assessed by comparing differences between the median optimum reservoir capacities (i.e. the ‘most likely’ outcomes) and the range of outcomes of both datasets (represented by box and whisker plots). The impact of emission scenario uncertainty was assessed by comparing the differences in reservoir capacities between the low, medium and high emission scenarios. The impact of the choice of decision criteria was also assessed by comparing the reservoir capacities based on different decision criteria with the median optimum reservoir capacity representing the ‘most likely’ outcome.

### Sub-sampling the complete probabilistic dataset

To compare the success of alternative sampling methods, simple random sampling and two variants of LHS (optimum and Maximin) were used to sub-sample the complete probabilistic dataset. Sub-samples created using these methods were compared to each other and the complete probabilistic

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Table 2 | Simplified example of calculations using the decision criteria and median reservoir capacity (not actual data)

<table>
<thead>
<tr>
<th>Option (reservoir capacity)</th>
<th>State</th>
<th>Outcome (decision criteria)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Average (Laplace)</td>
</tr>
<tr>
<td>A 10 20 50 100</td>
<td>10 20 50 100</td>
<td>45 10</td>
</tr>
<tr>
<td>B 2 3 3 1000</td>
<td>1000</td>
<td>2</td>
</tr>
<tr>
<td>C 200 200 202 202</td>
<td>201</td>
<td>200</td>
</tr>
<tr>
<td>D 100 110 120 410</td>
<td>185</td>
<td>100</td>
</tr>
<tr>
<td>Highest NPV 200 200 202 1000</td>
<td>Decision design outcome (✓)</td>
<td></td>
</tr>
<tr>
<td>‘Optimum’ option</td>
<td>C C C B</td>
<td>B C B B B</td>
</tr>
<tr>
<td>Median</td>
<td>C</td>
<td></td>
</tr>
</tbody>
</table>
dataset in terms of the design reservoir capacity calculated using Laplace and the other decision criteria. The Latin hypercube method presented here sampled 30 future projections from the 10,000 available for the 2050s using six dimensions to stratify the probabilistic dataset. These six dimensions were the monthly precipitation and evapotranspiration change factors for June, July and August (the three main irrigation months). All six dimensions were tested for inter-correlation prior to undertaking LHS. Thirty climate projections were used, as this provided a balance between sampling accuracy and efficiency and was considered to be representative of real world practice. Each 30-projection Latin hypercube sample was then compared to the complete dataset as well as the simple random sample (also consisting of 30 projections) by identifying the design reservoir capacity on the basis of each decision criteria. Each of the projections within the simple random sample was randomly selected using only the projection number.

RESULTS

The design reservoir capacities calculated using the complete probabilistic dataset and the 11SCP were compared first, using each of the decision criteria in turn. Design reservoir capacities calculated using the Laplace criterion (summarised in Table 3) show small differences (<8%) between the emission scenarios, but much larger differences between using the probabilistic dataset and the 11SCP (10 to 25%, depending on the site and emission scenario). This suggests that the uncertainty considered by the PP (and that is absent from the 11SCP) has a much larger impact on irrigation reservoir design compared to the choice of emission scenario. This agrees with studies by Harris et al. (2014) who found that the choice of emission scenarios had a comparable small impact on future water shortages in the public water supply sector. In addition, the results show that using the PP consistently resulted in building a bigger reservoir compared to using the 11SCP, regardless of the site and emission scenario used. In contrast, a previous study by Kay & Jones (2012) found that the median of the PP and 11SCP were generally in agreement regarding changes in flood frequency. Similar results were obtained using the other decision criteria, with the exception of Maximin which suggested building a much smaller reservoir when using the probabilistic dataset.

The ranges of reservoir capacities providing the maximum NPV for each of the projections for each dataset were then compared. Box and whisker plots showing the minimum, 25th percentile, median, 75th percentile and maximum reservoir capacities for all three sites are shown in Figure 3. The probabilistic dataset gave a much wider interquartile range compared to the 11SCP, and at Brooms Barn and Woburn the median optimum reservoir capacities were larger compared to the 11SCP. This result, consistent with the previous findings, suggest that the choice of dataset (and the range of uncertainty it considers) has a much larger impact on the decision outcome compared to the choice of emission scenario.

Next, the median optimum capacities of both datasets, representing the ‘most-likely’ decision outcomes, were compared to the design reservoir capacities calculated using each of the decision criteria with the complete probabilistic dataset and using all of the 11SCP (Table 4).

It is clear (Table 4) that decision outcomes resulting from an individual who considers themselves risk neutral (i.e. someone who would typically use Laplace) would not be very substantially different regardless of whether the ‘most likely’ projection was used instead of the complete dataset, given the comparably small differences (0–15%) between the reservoir capacities obtained using Laplace and the median optimum reservoir capacities at all the sites investigated. Where reservoirs were indicated, the

| Table 3 | Design reservoir capacities (mm) calculated using the Laplace criterion with the complete probabilistic dataset (i.e. all 10,000 projections) (PP) versus the 11SCPs, for Brooms Barn, Slaidburn and Woburn, for the 2050s low, medium and high emission scenario |
|--------|-------------|-------------|-------------|-------------|-------------|-------------|
| Site   | Decision criterion | Emission | Site  | Decision criterion | Emission | Site  | Decision criterion | Emission |
|        |               | L | M | H | L | M | H | L | M | H |
| Laplace | PP | 350 | 350 | 390 | 0 | 0 | 0 | 560 | 560 | 590 |
|        | 11SCP | 350 | 350 | 360 | 0 | 0 | 0 | 280 | 280 | 290 |
design capacities calculated using Laplace across the datasets were higher than using the median values, and the capacities from using the complete probabilistic dataset were higher than using the 11SCP dataset.

In contrast, the differences between datasets when using the other decision criteria were much larger and far more variable. The difference between the complete probabilistic dataset and median optimum reservoir capacity were also generally larger than the difference between the 11SCP and the median optimum reservoir capacity. This result can be largely attributed to the wider range of projections (and uncertainty) considered by the PP which differ substantially in their decision outcomes. At Slaidburn, the low annual irrigation demand typically favoured taking no action meaning the differences between the PP and median optimum reservoir capacity tended to be large regardless of the decision criteria or dataset used. When used with the complete probabilistic dataset certain decision criteria such as Maximax and Maximin resulted in very extreme decision outcomes such as taking no action or building very large reservoirs.

Table 4 | Reservoir capacities (mm) calculated using median ‘most likely’ decision outcome and compared to the design reservoir capacities calculated using Laplace and other decision criteria using the complete probabilistic dataset (PP) and 11SCP for all three sites. Hurwicz’s criterion calculated using coefficient of optimism \( \alpha = 0.5 \).

<table>
<thead>
<tr>
<th>Decision criteria</th>
<th>Site</th>
<th>Emission</th>
<th>Brooms Barn</th>
<th>Slaidburn Low</th>
<th>Slaidburn Medium</th>
<th>Slaidburn High</th>
<th>Woburn Low</th>
<th>Woburn Medium</th>
<th>Woburn High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median optimum reservoir capacity</td>
<td>PP</td>
<td>Low</td>
<td>360</td>
<td>370</td>
<td>0</td>
<td>0</td>
<td>310</td>
<td>320</td>
<td>330</td>
</tr>
<tr>
<td></td>
<td>11SCP</td>
<td>Low</td>
<td>340</td>
<td>340</td>
<td>0</td>
<td>0</td>
<td>280</td>
<td>280</td>
<td>270</td>
</tr>
<tr>
<td>Laplace</td>
<td>PP</td>
<td>Medium</td>
<td>390</td>
<td>410</td>
<td>0</td>
<td>0</td>
<td>360</td>
<td>380</td>
<td>390</td>
</tr>
<tr>
<td></td>
<td>11SCP</td>
<td>Medium</td>
<td>350</td>
<td>350</td>
<td>0</td>
<td>0</td>
<td>280</td>
<td>280</td>
<td>290</td>
</tr>
<tr>
<td>Maximin</td>
<td>PP</td>
<td>High</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>11SCP</td>
<td>High</td>
<td>300</td>
<td>300</td>
<td>0</td>
<td>0</td>
<td>250</td>
<td>250</td>
<td>250</td>
</tr>
<tr>
<td>Maximax</td>
<td>PP</td>
<td>Low</td>
<td>600</td>
<td>620</td>
<td>0</td>
<td>0</td>
<td>350</td>
<td>380</td>
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</tr>
<tr>
<td></td>
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<td>Low</td>
<td>370</td>
<td>370</td>
<td>190</td>
<td>0</td>
<td>200</td>
<td>200</td>
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</tr>
<tr>
<td>Minimax regret</td>
<td>PP</td>
<td>Medium</td>
<td>420</td>
<td>450</td>
<td>0</td>
<td>0</td>
<td>350</td>
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</tr>
<tr>
<td></td>
<td>11SCP</td>
<td>Medium</td>
<td>350</td>
<td>350</td>
<td>0</td>
<td>0</td>
<td>280</td>
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<td>280</td>
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<tr>
<td>Hurwicz</td>
<td>PP</td>
<td>Medium</td>
<td>560</td>
<td>590</td>
<td>270</td>
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<td>Medium</td>
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<td>0</td>
<td>0</td>
<td>290</td>
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Sub-samples of the PP were taken and the design reservoir capacities obtained using different decision criteria were compared with the results obtained using the complete probabilistic dataset. Certain decision criteria and their associated outcomes were successfully reproduced from sub-sampling while others including Maximin and Maximax were not. The percentage difference between the design reservoir capacities calculated using the complete probabilistic dataset and the average of 30 sub-samples (each consisting of 30 projections) for each decision criteria are shown in Figure 4.

Simple random sampling, optimum LHS and Maximin LHS performed comparably. Christierson et al. (2012) previously suggested that LHS is an appropriate sampling approach for use with the probabilistic dataset. However, on the basis of these results it did not noticeably improve the ‘reproducibility’ of the design reservoir capacities from the sub-samples (i.e. the percentage differences between the sub-samples and the complete probabilistic dataset did not vary greatly between sampling methods). All three sampling approaches yielded similar decision outcomes to each other, regardless of the decision criteria and site used. The number of projections contained within each sample (i.e. 30) was purposely designed to be representative of real-world practice; further work using much larger sample sizes is recommended, although whether this would be representative of practical real-world applications is open to debate.

Sub-sampling highlighted the shortcomings of some of the decision methods. Design reservoir capacities calculated using Maximin, Maximax and Hurwicz’s criterion were poorly reproduced from sub-sampling (Figure 4). Minimax regret was poorly reproduced at Slaidburn; however, at Brooms Barn and Woburn, the design reservoir capacity was reproduced reasonably well from sub-sampling, evident from the small percentage differences (Figure 4). The decision outcome associated with Laplace, consistent with previous findings, was reproduced well from sub-sampling. In addition, unlike the other decision criteria, the difference between Laplace’s design reservoir capacities using the complete probabilistic dataset and sub-samples was not affected by the site or emission scenario.

**DISCUSSION**

Climate change uncertainty abounds as a result of epistemic and aleatory uncertainty. Uncertainties stemming from a lack of knowledge (e.g. cloud physics), randomness (e.g. chaotic nature of the climate system) and the result of...
future anthropogenic activity, whose effects may be far reaching and span many decades, but which are very much uncertain (e.g. greenhouse gas emissions, economic development, population growth) (Dessai et al. 2009). It has long been argued that effective adaptation necessitates an understanding of the uncertainty and is dependent on the availability of and access to ‘accurate’ and ‘precise’ climate change information (Cooper 1978; Kelly 1979; Hickox & Nichols 2003; Murphy et al. 2004). Partial quantification of uncertainty has been attempted in recent years, although is an area of continual debate and development (Stainforth et al. 2005; Rougier & Sexton 2007; Tebaldi & Knutti 2007).

Despite the seemingly irreducible uncertainty, decision-makers still need to, and regularly do, make decisions without having access to accurate predictions. Various criteria and methods are available to assist them in doing so, the majority of which provide very acceptable results despite the absence of probabilities of expected outcomes (Dessai et al. 2009; Polasky et al. 2011). These criteria and methods typically work by identifying strategies that perform reasonably well over a wide range of future states at the expense of some loss of optimum performance.

It has previously been suggested that current decision criteria are applicable to adaptation planning (Dessai et al. 2009; Ranger et al. 2010; Polasky et al. 2011). At the time of writing, climate change impact assessments using UKCP09 are beginning to emerge, particularly within the building sector (Hanby & Smith 2012; Williams et al. 2012). Despite growing awareness on the need for adaptation, practical examples of adaptation using current decision criteria appear lacking despite receiving renewed interest in recent years (Polasky et al. 2011).

This study observed variable differences between the 11SCP and the 10,000 PP depending on the decision criteria and projection used to evaluate options. This result was attributed to differences between the 11SCP and the 10,000 PP, specifically the additional uncertainty considered by the latter. The interquartile and minimum-maximum range of optimum outcomes suggested by the PP were much larger compared to the 11SCP, although the difference between the median optimum reservoir capacity using the 11SCP and PP was comparably small compared to the difference between the maximum and minimum reservoir capacities respectively.

In addition, this study recorded variable differences between the PP and 11SCP design reservoir capacities using different decision criteria and the median optimum reservoir capacity, considered here to be the ‘most likely’ decision outcome. Design reservoir capacities calculated using certain decision criteria were more closely related to the median optimum reservoir capacity, specifically Laplace and to a lesser extent Minimax regret. Though it should be stressed that use of a single ‘most likely’ projection in the manner described here should be avoided. Probabilistic projections present their own challenges and some of the current decision criteria are not ideal. However despite associated challenges, they remain popular because they are simple to implement and are founded on rational models which can be reasonably justified.

Certain decision criteria are calculated using a single projection; it is these methods that were generally poorly reproduced from sub-samples of the complete probabilistic dataset. Given the sensitive nature of the design reservoir capacities to extreme projections it is not surprising that some sampling approaches appear inadequate when used in combination with these decision criteria. This result should serve as a warning for users of certain decision criteria with sub-samples of the probabilistic dataset (as opposed to a reason for inaction). None of the sampling approaches considered here, performed ideally. However, the alternative would require each of the 10,000 projections to be modelled and the sampling strategy constructed in such a way as to ensure reasonable coverage of the samples in the state space. Unfortunately, such an approach is rarely feasible in practice due to the non-linear nature of climate variables and impacts and the complex nature and potentially long run times of models capable of simulating hydrological processes (Christierson et al. 2012).

**CONCLUSION**

With regard to the sources of uncertainty considered by this study, the results would suggest that the largest source of uncertainty and the factor that has the greatest impact on irrigation reservoir design is the dataset used to evaluate options. Traditionally, decision-makers have focused their attention on emission scenario uncertainty. While differences between emission scenarios did contribute to the decision outcome, their impact was relatively small when compared with moving from the 11SCP to the 10,000 PP.
(and the additional uncertainty considered) on irrigation reservoir design. These differences were most apparent where the decision-maker exhibited a polarised risk appetite, as the extra uncertainty considered by the latter had a much larger impact where the maximum and minimum pay-offs were used to compute design reservoir capacities.

Clearly this reflects the origin and nature of the SRES future emission scenarios which underpin the UKCP09 datasets. If we assume their range of future emissions is reasonable, then the results obtained above, using decision criterion such as Laplace, suggest that the impact of emission scenario uncertainty on irrigation reservoir design (up to the 2050s at least), are less significant than the impact of uncertainties caused by the models themselves, supporting other results (Harris et al. 2014). However, the scenarios are not probabilistic in nature and only three are considered by UKCP09; if more emissions scenarios were provided (and covering more extreme scenarios) then decision criteria such as Maximin and Maximax may show much greater variability, although it is likely that outcomes obtained using Laplace would remain fairly static. At this stage, it is not clear whether the same is true for other assets in the field of water management and as a result this is recommended for further work. This study did not consider the impact of other sources of uncertainties including irrigation model structure and technical uncertainty, evapotranspiration uncertainty and statistical post-processing uncertainty associated with downscaling projections. The impacts of these sources of uncertainty has, however, been considered elsewhere and in greater detail and were generally found to contribute less uncertainty than the PP themselves (Kay & Davies 2008; Kay et al. 2009; Prudhomme & Davies 2009; Boshard et al. 2013; Green & Weatherhead 2014b).

With regard to sampling, it should be noted that sampling methods are ultimately confined by the available data. For the purpose of this study, as with most real-world applications, sampling is used to characterise the climate parameters using a small number projections to ease impact modelling. Sub-samples of the complete probabilistic dataset can then be fed into impact models to inform the decision outcome. However, in a non-linear system using the average or median values of the individual climate parameters does not necessarily give the average or median impact. The decision outcomes resulting from any sampling method, however complex, will likely differ from that using the complete dataset. At which point the decision outcome becomes a function of the choice of sampling method and not the underlying dataset, with obvious implications.

Decision outcomes associated with certain methods, specifically Maximin and Maximax could not be effectively reproduced from sub-samples of the probabilistic dataset. This was despite trialling a number of different sampling methods, simple to complex, including LHS. LHS has previously been shown to be a suitable method for sub-sampling the UKCP09 probabilistic dataset. However, this study found that it did not improve the reproducibility of decision outcomes compared to using simplified sampling methods. Maximin and Maximax, and by extension Hurwicz should be strictly avoided when working with sub-samples of the complete probabilistic dataset given the limitations of the sampling methods. Laplace emerged as a viable decision criterion for use with sampling of the probabilistic dataset, showing strong reproducibility from different sub-samples. However, as with any decision criterion, Laplace may not appeal to decision-maker’s rational model and risk appetite and as a result other decision criteria should be sought. One such example is the Green Z-score (Green & Weatherhead 2014a, b, c) which was designed with the sole purpose of resolving trade-offs in a transparent, audible and analytically robust manner. It was designed with the intent of ‘bridging the gap between the science of UKCP09 and its user basis’, which despite having access to its full technical capabilities which from the perspective of the knowledge producers is very impressive, continue to use solely the summary reports and figures (Tang & Dessai 2012).

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