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Coping with climate change uncertainty for adaptation planning: An improved criterion for decision making under uncertainty using UKCP09 ☆

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ABSTRACT

Despite information on the benefits of climate change adaptation planning being widely available and well documented, in the UK at least relatively few real-world cases of scenario led adaptation have been documented. This limited uptake has been attributed to a variety of factors including the vast uncertainties faced, a lack of resources and potentially the absence of probabilities assigned to current climate change projections, thereby hampering conventional approaches to decision making under risk. Decision criteria for problems of uncertainty have been criticised for being too restrictive, crude, overly pessimistic, and data intensive. Furthermore, many cannot be reproduced reliably from sub-samples of the UKCP09 probabilistic dataset.

This study critically compares current decision criteria for problems of uncertainty and subsequently outlines an improved criterion which overcomes some of their limitations and criticisms. This criterion, termed the Green *Z*-score, is then applied to a simplified real-world problem of designing an irrigation reservoir in the UK under climate change. The criterion is designed to be simple to implement, support robust decision making and provide reproducible results from sub-samples of the UKCP09 probabilistic dataset. It is designed to accommodate a wide range of risk appetites and attitudes and thereby encourage its use by decision makers who are presently struggling to determine whether and how to adapt to future climate change and its potential impacts.

Analyses using sub-samples of the complete probabilistic dataset showed that the Green *Z*-score had comparable reproducibility to Laplace and improved reproducibility compared to other current decision criteria, and unlike Laplace is able to accommodate different risk attitudes.

Introduction

Despite information on the benefits of climate change adaptation planning being widely available and well documented, in the UK at least relatively few real-world cases of climate change adaptation planning have been recorded outside of government led initiatives (Tompkins et al., 2010). Elsewhere in the world, while adaptation has been recorded, it is generally limited to high income (developed) nations, has been viewed as inadequate and is seldom undertaken in response to climate change alone (Adger et al., 2009; Berrang-Ford et al., 2011; Chen et al., 2004). This limited uptake has been attributed to a

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variety of factors including the availability, accessibility and willingness to use information, availability of resources, leadership, legal and procedural feasibility and many more, see Moser and Ekstrom (2010) for a more comprehensive discussion.

Adaptation, like any decision problem, may be represented as a series of options, with different outcomes for each possible future state, amongst which a decision maker must choose the option which provides the "best" outcome (Tversky and Kahneman, 1986). Options can refer to both soft and hard solutions such as promoting education or building new infrastructure, outcomes refer to the payoff associated with these options and states refer to potential futures which may occur. Two distinct fields of decision theory are widely acknowledged (French, 1986), namely decision making under risk and decision making under uncertainty.

In the field of adaptation planning, decision makers often find themselves in situations of decision making under uncertainty "in which analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system's variables, (2) the probability distributions to represent uncertainty about key parameters in the models, and/or (3) how to value the desirability of alternative outcomes" (Walker et al., 2013), p. 958. A variety of decision criteria have been developed to address problems of decision making under uncertainty, discussions of which can be found here and in Chisholm and Clarke (1993), Bouglet and Vergnaud (2000) and more recently Ranger et al. (2010). In addition to several well-known decision criteria including Laplace (Laplace, 1951), Maximin (Wald, 1945), Maximax, Hurwicz's criterion (Hurwicz, 1951) and Minimax regret (Savage, 1951), decision makers can generate problem-specific criteria using Multi-attribute utility theory (MAUT) or Multi-criteria analysis (MCA) Dyer et al., 1992. MAUT and MCA consist of a wide range of methods, but in general the principle remains the same, options are compared using several criteria that are weighted to produce a single criterion. Alternatively, the criteria can be assigned a score and an aggregated score is then calculated. Any of these criteria can be used with existing decision methods for managing uncertainty, well-known examples of which include Info-gap theory (Ben-Haim, 2001, 2006) Real option analyses (Amram and Kulatilaka, 1999) and Robust decision making (Lempert and Grooves, 2000). Here, criteria refer to the metrics used to compare options and identify the optimum decision outcome (typically by maximizing an objective function or satisficing constraints), whereas decision methods describe the steps by which these decision criteria are applied.

For the purpose of climate change adaptation planning, the vast majority of decision criteria rely on the decision maker having access to future climate change projections. One of the key sources of climate change projections in the UK is UKCP09 which provides probabilistic projections of future climate change (Murphy et al., 2011). The move from deterministic to probabilistic methods of communicating climate change information observed in recent years, driven by improvements in uncertainty quantification (Rougier and Sexton, 2007; Stainforth et al., 2007; Tebaldi and Knutti, 2007) has further complicated the process of adaptation planning given that it communicates extra uncertainty within the projections that was previously not available to decision makers, who may have limited experience working with uncertainty (Green and Weatherhead, 2013a).

The scenarios used in this study are the SRES A1F1, A1B and B1 scenarios, referred to as the low medium and high greenhouse gas emission scenario within the current suite of national UK climate change projections (Nakicenovic et al., 2000). They represent different 'story lines', interweaving complex social, economic and environmental factors (Polasky et al., 2011). All three scenarios, rather controversially, are often regarded as equi-probable (Harris et al., 2012). It has been argued that the vast uncertainties surrounding future climate change, more so in the distant future, make the prescription of probabilities unrealistic and an arguably subjective affair. Others have argued that the choice to not assign probabilities to either the original scenarios or the probabilistic projections provided by UKCP09 make the projections of limited value for decision making (Schneider, 2001, 2006).

The large number of projections available within the UKCP09 probabilistic dataset, some 10,000 per emission scenario, may in some cases present a 'barrier to entry' for some decisions makers. A previous study by Green and Weatherhead (Green and Weatherhead, 2013c) found that a number of decision criteria that are applied in situations of uncertainty have been shown to be incompatible with sub-samples of the probabilistic dataset. Decision criteria using a single projection to inform the decision outcome such as Maximin and Maximax have proved very difficult to obtain from small samples that are consistent with the complete probabilistic dataset (Green and Weatherhead, 2013c).

As a result of the large data requirements of decision methods under risk and the apparent limitations of some criteria for decision making under uncertainty, alternative decision criteria which are more compatible with the UKCP09 probabilistic climate change projections should be sought.

Aim

The aim of this study is to critically compare five current decision criteria and in turn develop a novel improved decision criterion, which supports robust decision making in situations of deep uncertainty. All five decision current criteria are evaluated using the full UKCP09 probabilistic ensemble and sub-samples of it to ensure the decision outcome associated with each could be reliably reproduced from sub-sampling. The novel decision criterion is initially described, it was designed to be simple to implement, support sensitivity analysis and be compatible with the UKCP09 probabilistic dataset and samples of it, to ensure it is suitable for real world decision making. The UKCP09 probabilistic dataset was chosen owing to its legitimacy and credibility within the UK (Tang and Dessai, 2012), though the criterion presented in theory is applicable to all situations (and other countries) where multiple competing, though equally plausible, projections are available. If their probabilities are different but available, the decision maker can calculate an outcome for each state (by multiplying the probability of the state by the payoff), the best course of action can then be determined using any of the criteria shown here.

Material and methods

The methodology is presented in three stages; firstly five current decision criteria are described and their criticisms discussed. Secondly, an improved decision criterion is outlined. Thirdly, all of the decision criteria are applied to a simplified real-world problem of designing an irrigation reservoir to meet the water demands of a potato crop for the 2050s using climate change projections taken from UKCP09.

Current decision criteria

This study considered five decision criteria that are typically employed in situations of uncertainty, they include Laplace (Laplace, 1951), Maximax, Maximin, Hurwicz's criterion and Minimax regret. Laplace is based on the principle of insufficient reason which assumes that all potential states are equi-probable in the absence of knowledge of event probability i.e. it assumes that there is no reason to favour one state over another. It identifies the best option as the option which yields the largest average expected outcome based on all the potential states. 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 α, 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. Readers are directed to Ranger et al. (2010) for practical examples of applying these criteria.

A general criticism levelled against all of these criteria is that all are "rationalised on some notion of ignorance" (Froyn, 2005), p. 204. It has previously been suggested that none of the current decision criteria are as 'good' as one might wish (French, 1986). It seems highly unlikely that all five criteria (Laplace, Maximin, Maximax, Hurwicz and Minimax regret) are equal, and there must exist some way to evaluate which is best. This view led to the development of a set of axioms, which reflect 'good' properties of decision making criteria, and which may be used to formally assess which is optimal (French, 1986). If we accept the axiom basis of a criterion we should in theory accept its implications. However, none of the popular criteria are validated by all the axioms of decision theory and in fact it is not possible for any criterion to satisfy all of the axioms; see French (1986) for formal proof. As opposed to assessing our criterion against French's original axioms of decision theory (French, 1986), we therefore explore the wider criticisms surrounding these criteria and examine whether or not they are suitable for use with the UKCP09 probabilistic climate change projections.

With regards to Laplace, two fundamental criticisms have emerged, namely that it is too restrictive in its design and that the principle of insufficient reason which states that all states are equally likely is "by no means as innocuous as it might appear" (French, 1986), p. 218. It has previously been suggested that it is rare (though not impossible) for no information to exist regarding the likelihood of states occurring, thus the premise of scenario symmetry (i.e. all scenarios are equally likely) is arguably flawed and with it the principle itself (French, 1986). Laplace was further criticised by Knight (2012) who suggested that blind use of this approach can lead to absurd conclusions. Maximin and by extension Hurwicz's criterion have been criticised for being too crude; Maximin in particular is considered to be overly pessimistic as an approach and not suitable for real world decision making (Etner et al., 2012). Minimax regret can be similarly criticised, the values of regret used to determine the optimal decision are not absolute but strictly relative, and as a result the decision outcome can be altered easily by introducing irrelevant or flippant options.

However, since we do not know the probability of the occurring event, it is reasonable to assume in situations of deep uncertainty that any projection is just as likely as any other. As a result, a core assumption of this study is that the probability distribution is considered to be uniform, akin to the 'Laplacian' view of decision making under uncertainty which is consistent with emerging guidelines (EA, 2013). While this may remain a point of contention for some individuals, the alternatives which would require us to generate subjective probabilities for each of the UKCP09 projections or omit projections that we perceive as unlikely is not advisable.

Current decision criteria, such as Maximax and Maximin, typically fit the decision maker to a specific rational model. In the case of Maximin, this rational model describes an individual that is particular pessimistic, while Maximax describes an individual that is very optimistic. Laplace, in theory, represents a "neutral" viewpoint. A hypothetical problem, comparing three irrigation solutions, termed option A–C, across a discrete number of states is shown for demonstration. These options may represent entirely different solutions such as installing a new water delivery system or building an on-site reservoir. Alternatively, they may represent options which are subtly different such as building a lined or unlined reservoir. Fig. 1 was generated by ranking the outcome of three options from smallest to largest across a discrete number of states. In this (hypothetical) example, the average outcomes of options A–C happen to be equal. As such, Laplace would view these options as equal. Whilst there is nothing intrinsically wrong with this, real decision makers can and regularly do depart from this idealised sense of the rational decision maker. For example some optimistic decision makers may perceive option A to be the best because it could provide the largest outcome. Pessimistic decision makers may perceive option C to be the best

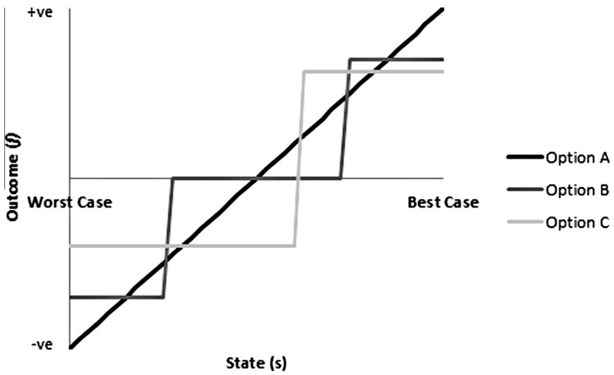

Fig. 1. Hypothetical problem comparing three options against a discrete number of states. Average outcome of option A–C are equal (not actual data).

because it has the smallest negative outcome. Other decision makers may prefer option B because it has a smaller number of states with a negative outcome.

Developing a novel decision criterion

Given the acknowledged limitations with the criteria discussed, an attempt has been made to develop a novel discussion criterion, hereby termed the Green *Z*-score, which considers all the potential options, outcomes and states, and hence is amenable to sub-sampling of the complete probabilistic dataset.

Unlike Laplace, which uses a single rational model to describe all decision makers, the Green *Z*-score uses three parameters to generate a simplified rational model that can be personalised to the individual decision maker, in many ways similar to MCA. MCA was selected as the basis for the Green *Z*-score as it places the focus on choice behaviour, enabling decision makers to resolve trade-offs in a transparent, audible and analytically robust manner (Hajkowicz, 2008). The parameters underpinning the Green *Z*-score consist of the coefficient of optimism (α), the coefficient of robustness (β), and a user defined threshold of acceptability (t), defining the boundary between acceptable and unacceptable outcomes. The coefficient of optimism is used to describe how optimistic the decision maker is about the future, specifically whether they are more concerned about the negative or positive outcomes associated with a particular decision. The coefficient of robustness (β) is used to quantify how "robust" the decision maker wants their option to be, specifically whether they are more concerned about the overall performance of option across all states or merely those states where the option performs exceptionally better than all other options.

The Green *Z*-score for each option is calculated using a weighted difference between its overall performance, calculated across all states, and its negative performance, calculated across those states where the outcome falls below the threshold of acceptability. The weighting is determined by the coefficient of optimism α. The optimal decision outcome is then the option with the highest Green *Z*-score.

This concept of a coefficient of optimism (α) can be traced back to Hurwicz's criterion which uses a similar criterion to describe how optimistic an individual is about the future. In Hurwicz's weighted criterion model, the decision outcome is obtained using a weighted average of Maximin and Maximax, and hence only considers the payoffs from extreme states, which may not be considered in sub-samples of the complete probabilistic dataset. To calculate the Green *Z*-score, Maximin and Maximax in Hurwicz's original model have been substituted with two alternative parameters. These parameters, termed the overall performance and negative performance respectively, are summed across all states, providing a value for each option.

The mathematical definition of the Green *Z*-score is given in Eqs. (1.1)–(1.3).

$$z_d = \max_{d \in D}((\alpha \cdot A) - ((1-\alpha) \cdot B)) \tag{1.1}$$

where z_d is the decision outcome, d is the option, D is the options, α is the coefficient of optimism (where $0 < \alpha \geqslant 1$), A is the overall performance (see Eq. (1.2)), B is the negative performance (see Eq. (1.3))

$$A = \sum_{s=1}^{s=n}\left(\frac{(f_d - \chi)}{\left(\max\limits_{d \in D} f_d - \chi\right)}\right) \tag{1.2}$$

where f_d is the option outcome, s is the state, $\chi = \left(\max_{d\in D} f_d - \left((\max_{d\in D} f_d - \min_{d\in D} f_d) \cdot \left(\frac{\beta}{100}\right)\right)\right)$, β = coefficient of robustness

$$B = \sum_{s=1}^{s=n} \left(\frac{(f_d - t)}{\left(\min\limits_{d \in D} f_d - t \right)} \right) \tag{1.3}$$

where f_d os the option outcome, s is the state, t is the threshold of acceptability (e.g. 0)

Calculating the Green Z-score

The overall performance of each option is calculated first as follows. The effective outcome range of all options is calculated for each state. This is the difference between the maximum outcome and minimum outcome across all options, multiplied by the coefficient of robustness, $\beta/100$ (where $0 \leqslant \beta \geqslant 100$). This value is then deducted from the maximum outcome to calculate the minimum bound of the effective range. If absolute robustness is sought a β value of 100 is used, in which case the effective outcome range is the full 0–100% outcome range (i.e. max-min outcome for each state). If a β value of 50, say, is used, the effective outcome range is the 50–100% effective outcome range (i.e. max–median outcome for each state). The outcome of each option is then normalised against the effective outcome range for each state. If the outcome of an option is equal to the maximum bound of the effective range for that state (i.e. it has the best outcome) it assigned a value of 1. If the outcome of an option is equal to the minimum bound of the effective range for that state (i.e. it has the worst outcome), it is assigned a value of 0. Options in between are assigned a value of 0–1 depending on their position relative to the maximum outcome and minimum bound of the effective range. If the outcome of an option is less than the minimum bound (which can occur if β <100) it is assigned a value of 0. The overall performance of each option in then obtained by summation across all states.

The negative performance of each option is then calculated for each state. The user defined threshold of acceptability (t) can be any value between the max and minimum outcome. Decision makers who are particularly risk adverse may use a high threshold, while those that are particularly risk seeking may use a low threshold. The acceptability range considering all available options is then calculated; this represents the difference between the threshold and the minimum outcome across all options. If the outcome of an option is less than this threshold then it is counted against the option's Green Z-score i.e. it is considered undesirable. The payoff of each option is then normalised against the acceptability range. If the outcome of an option is equal to the minimum bound of the acceptability range for that state (i.e. it has the worst outcome) it is assigned a value of 1. If the outcome of an option is equal to the maximum bound of the acceptability range for that state (i.e. it equals the threshold value), it is assigned a value of 0. Options in between are assigned a value of 0–1 depending on their position relative to the minimum bound and the maximum bound of the acceptability range. If the outcome of an option is greater than the maximum bound (which can occur if $t < \max f$) it is not counted towards the negative performance of that option. The negative performance of each option in then obtained by summation across all states.

The Green Z-score is then calculated by multiplying the overall performance by α (representing the coefficient of optimism) and deducting the negative performance multiplied by $1 - \alpha$. The option yielding the largest Green Z-score is then selected as optimal.

Applying the Green Z-score in practice

The Green Z-score is used to identify the optimal reservoir capacity at a number of sites distributed around the UK under climate change. Three sites representing different agro-climatic conditions are selected as case studies. 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 located in the district of Lancashire, approximately 60 km north-west of Leeds and is the wettest site with an average annual rainfall of 1515 mm for the baseline period (1961–1990). 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. Irrigation water requirements are calculated and used to inform the design of on-farm irrigation reservoirs using sequences derived from the full UKCP09 2050s 10,000 projection sample ensemble and sub-samples of it.

Green and Weatherhead (2013b) provide a detailed methodology covering the exact methods used to generate the future weather sequences used in this study. In summary, baseline observed climate data is extracted from a weather station at

Table 1
Weather station sites and records used.

Station	Lat.	Long.	Elevation (m AOD)	Average annual (1961–1990)		Data	
				Rain (mm)	ETo (mm)	From	To
Brooms Barn	52.260	0.567	75	588	585	1964	1990
Slaidburn	53.987	−2.433	192	1515	487	1961	1990
Woburn	52.014	−0.595	89	632	564	1961	1990

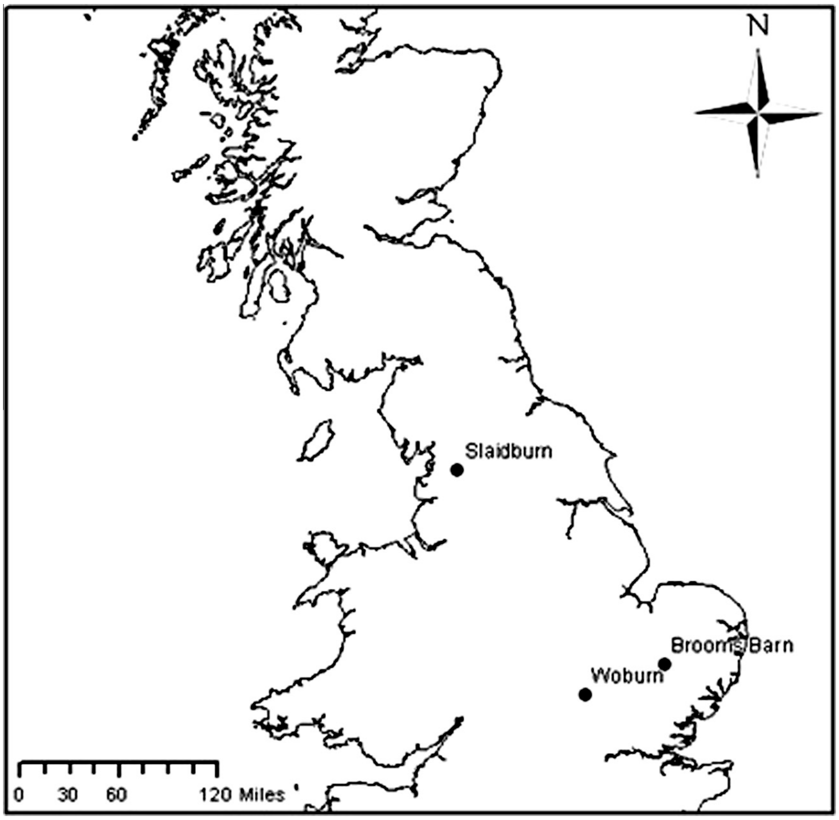

Fig. 2. Weather station sites.

each site (Table 1). All 10,000 monthly change factor climate change factors are extracted from the UKCP09 25 km member ensemble for the 2050s time slice for a 25 km grid square overlying each weather station (Fig. 2). Each set of monthly change factor is then used to perturb an observed baseline period daily weather series at each weather station to generate 10,000 future sequences for each site. This is repeated for all three emission scenarios, producing 90,000 climate projections in total (30,000 for each site, split across three emission scenarios).

WaSim is used to model the annual water use at each site. It simulates inflow (infiltration) and outflow (evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage. The annual water use of a potato crop is calculated for each year in the 10,000 × 30 year generated sequences for each site and emission scenario. Typical costs and benefits for clay agricultural reservoirs are obtained from a concurrent study (Green and Weatherhead, 2013b). Each of the future 10,000 projections is then used to calculate the net present value (NPV) of a range of reservoir sizes, with usable storage capacities equivalent to applying from 0 to 1000 mm to the area irrigated (i.e. 0–10,000 m^3 ha^{-1}). The Green *Z*-score is calculated for all reservoir capacities for all three sites and all three emission scenarios and the optimal reservoir capacity compared to those obtained using current decision criteria (Green and Weatherhead, 2013c).

Table 2
Optimum reservoir capacity (mm) obtained using a selection of current decision criteria for the three sites and three emission scenarios. Results obtained from 10,000 future projections for each emission scenario for each site. Each sequence generated from a perturbed observed series using monthly change factors taken from UKC09 10,000 member ensemble 2050s time slice. Hurwicz calculated using $\alpha = 0.5$. Green *Z*-score calculated using coefficient of robustness $\beta = 100$, threshold of acceptability $t = 0$, coefficient of optimism $\alpha = 0.5$.

Site	Brooms Barn			Slaidburn			Woburn		
Emission scenario	L	M	H	L	M	H	L	M	H
Laplace	390	410	400	0	0	0	360	380	390
Maximin	0	0	0	0	0	0	0	0	0
Maximax	600	620	650	280	310	330	530	580	620
Minimax regret	420	450	430	100	120	140	380	420	440
Hurwicz	560	590	600	270	300	300	510	540	570
Green	370	390	380	0	0	0	340	360	370

Results

With standard (neutral) parameter values, the optimal reservoir capacities from the Green Z-score and Laplace are largely similar. At all three sites the optimal reservoir capacity based on Green Z-score is within 25 mm of Laplace, with the Green Z-score generally suggesting a slightly smaller capacity (Table 2). Maximin typically results in no reservoir being built. Maximax results in much larger reservoir capacities compared to all other decision criteria. The range within each decision outcome (Table 2) highlights the considerable uncertainty in the probabilistic dataset while the difference between the criteria reflects the fundamental differences between them (Table 2).

Sensitivity to extreme projections

The optimal reservoir capacity associated with each decision criteria is subsequently compared using progressively fewer climate change projections, sequentially excluding the extreme outcomes. This is undertaken to establish how sensitive the optimal reservoir capacity associated with each decision criteria is to extreme projections within the probabilistic dataset and provide the basis for further analysis of sub-samples of the complete probabilistic dataset. This is achieved by first identifying the optimal reservoir capacity calculated using the complete probabilistic dataset i.e. all 10,000 projections, for each of the decision criteria. For each reservoir capacity, all 10,000 projections are then ranked in terms of NPV from smallest to largest. Projections are then systematically removed from the tail ends of the NPV distribution, re-calculating the optimal reservoir capacity after removing each projection, eventually leaving only the median projection.

The results for Woburn 2050s medium emission scenario are shown in Fig. 3. Similar results are obtained from the other sites and emission scenarios.

As a result of the complexity of many models, e.g. crop growth simulations, it is often not feasible to use all 10,000 projections, and therefore sampling is frequently used (Green and Weatherhead, 2013c) (alternatively, a rapid assessment model may be used, though readers are directed elsewhere for further details (Haasnoot et al., 2012; Kwakkel et al., 2012). These sampling methods should be carefully designed to ensure they capture extreme projections so as not to bias the decision outcome should certain decision criteria be used. Combining a poorly designed sampling method with a decision criterion that is very sensitive to the inclusion of extreme projections such as Maximin or Maximax can result in very different decision outcomes compared to using the complete probabilistic dataset (Green and Weatherhead, 2013c). Certain decision criteria are particular sensitive, with clear trends emerging. Interestingly, Hurwicz tended to favour Maximax despite using a coefficient of optimism of 0.5. This result is the result of the number of "good" and "bad" projections contained with the complete probabilistic dataset, they are not equal and as such Hurwicz does not appear halfway between Maximax and Maximin. Beginning within the median projection from the probabilistic dataset and gradually introducing additional projections (Fig. 3), all six decision criteria are relatively stable up until 30%, beyond which they begin to diverge. Maximax and Maximin follow an exponential type curve, confirming that just a few extreme projections exert a substantial pull on the

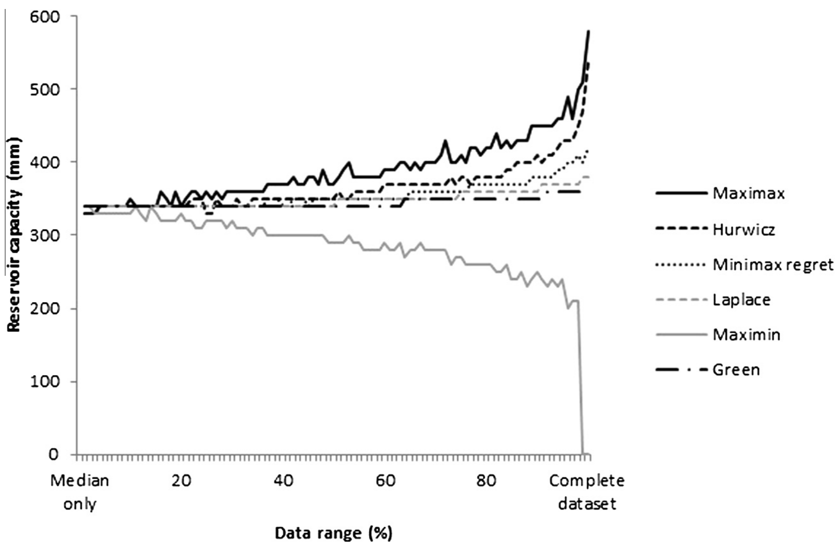

Fig. 3. Optimal reservoir capacities for various decision criteria generated excluding extreme climate change projections, for the 2050s medium emission scenario. Projections systematically removed in an iterative manner (right to left) starting with the most extreme (min and max NPV respectively), calculating the optimal reservoir capacity at each step. Hurwicz calculated using coefficient of optimism $\alpha = 0.5$. Green Z-score calculated using coefficient of robustness $\beta = 100$, threshold of acceptability $t = 0$, coefficient of optimism $\alpha = 0.5$. Adapted from Green and Weatherhead (2013c).

decision outcome. Maximax and Maximin each use a single extreme projection, best or worst, to inform the decision outcome and so this result is not unexpected. Laplace and Green *Z*-score are much less sensitive.

Due to the sensitive nature of Maximax and Maximin, and to a lesser extent Hurwicz and Minimax regret, use of these criteria with sub-samples of the complete UKCP09 probabilistic dataset can lead to misleading conclusions (Green and

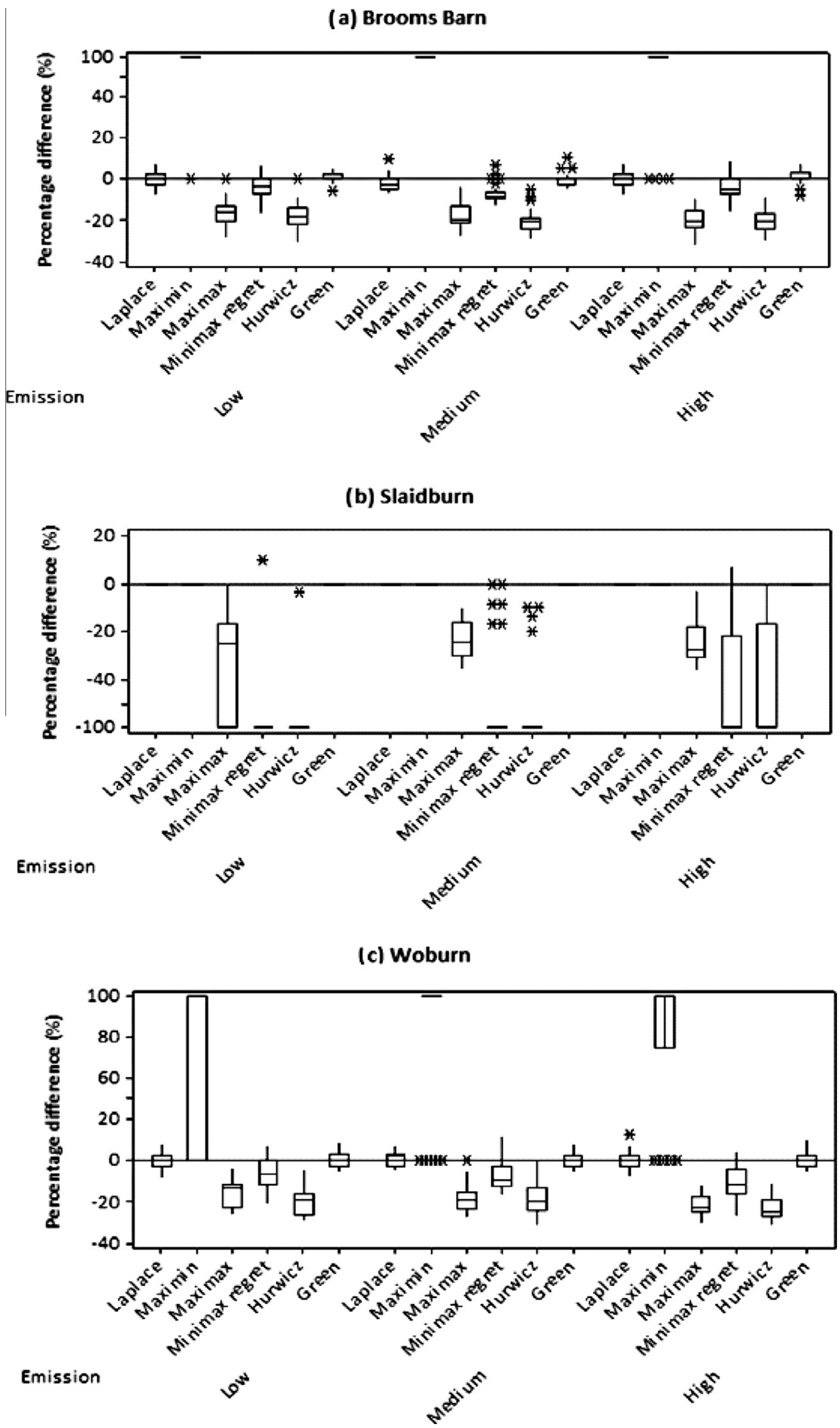

Fig. 4. Percentage difference in optimal reservoir capacity for each decision criteria using sub-samples of the probabilistic dataset in place of the complete probabilistic dataset (i.e. all 10,000 projections) for Brooms barn (a), Slaidburn (b) and Woburn (c), for the 2050s and three emission scenarios. Results calculated using 30 sub-samples consisting of 30 projections each. Hurwicz calculated using coefficient of robustness $\alpha = 0.5$. Green *Z*-score calculated using coefficient of robustness $\beta = 100$, threshold of acceptability $t = 0$, coefficient of optimism $\alpha = 0.5$. Outliers included (*).

Weatherhead, 2013c). If, for example, the extreme projection is not sampled and thus excluded from the analysis, the result can be a very different sized reservoir.

Using sampled data with the Green Z-score

In order to establish whether the optimum reservoir capacity could be estimated from samples of the complete probabilistic dataset more reliably using the Green *Z*-score than using the current decision criteria, 30 simple random samples of 30 projections are extracted from the complete probabilistic dataset. The percentage difference between the optimum reservoir capacities obtained using each of the decision criteria with the complete probabilistic dataset and with each sample is calculated (Fig. 4). Simple random sampling was chosen both for convenience and on the basis of previous findings which suggest it provides similarly rich sub-samples compared to more advance stratified methods (Moser and Ekstrom, 2010).

Comparing the three sites overall, all but Laplace and Green show poor reproducibility from sub-samples of the complete probabilistic dataset, evident from the large range of percentage differences shown (Fig. 4). Laplace and Green exhibit the smallest percentage differences, both in terms of median and range, at all three sites. Maximin exhibit the largest maximum percentage difference at Brooms Barn and Woburn, though at Slaidburn it appears to perform as favourably as Green and Laplace; however, this result can be attributed to the low irrigation demand combined with the worst case rational model underpinning Maximin, which in this example always favoured building no reservoir.

On the basis of these initial results, the Green *Z*-score produces comparable results to Laplace with sampling. This can be largely attributed to the similar methods used by each approach. Both criteria utilise multiple projections to inform the decision outcome. However, the advantage of the Green *Z*-score compared to Laplace is that it allows different risk appetites to be accommodated. The parameters underpinning the Green *Z*-score i.e. coefficient of optimism, coefficient of robustness and threshold of acceptability, can be varied to be representative of decision makers expressing differing degrees of optimism and pessimism. To establish whether variations of Green *Z*-score could produce more consistent results than current decision criteria from sub-samples, the optimal reservoir capacity is calculated for the Green *Z*-score using parameters representative of individuals who would typically prefer Laplace, Maximin, Maximax or Hurwicz's criterion, (Table 3), and for each of the decision criteria, using the complete dataset and each of the 30 samples of 30 projections. It is not possible to compare

Table 3
Green *Z*-score parameter setup, showing four decision criteria regularly employed in situations of uncertainty along with four variations of Green *Z*-score representative of different types of decision maker including the neutral, pessimist, optimist and optimist–pessimist.

Decision maker	Decision criterion	Green *Z*-score parameters		
		Coefficient of optimism (α)	Coefficient of robustness (β)	Threshold of acceptability (t)
Neutral	Laplace	0.5	100	0
Pessimist	Maximin	0.01	100	0
Optimist	Maximax	1	0.01	0
Optimist–pessimist	Hurwicz	0.5	0.01	0

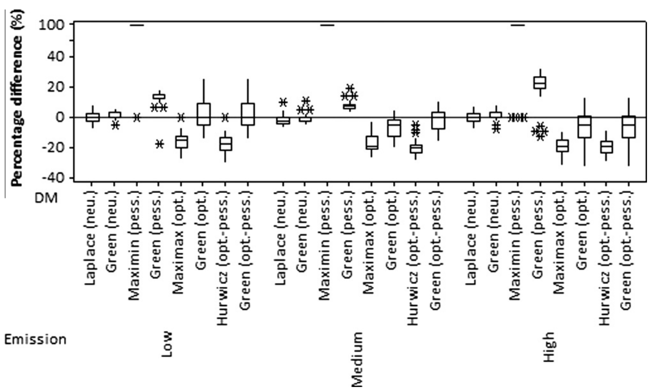

Fig. 5. Percentage difference in optimal reservoir capacity for each of the decision criteria using sub-samples of the probabilistic dataset in place of the complete probabilistic dataset (i.e. all 10,000 projections) for Brooms Barn for the 2050s and three emission scenarios. Results calculated using 30 sub-samples consisting of 30 projections each. Hurwicz calculated using coefficient of robustness $\alpha = 0.5$. Green *Z*-score calculated using coefficient of robustness $\beta = 100$, threshold of acceptability $t = 0$, coefficient of optimism $\alpha = 0.5$. Outliers included (*) Four different categories of decision maker (DM) assumed; neutral, pessimist, optimist and optimist–pessimist, each category containing two decision criteria; a current decision criterion and a variation of Green *Z*-score.

decision outcomes from the Green Z-score against Minimax regret due to the fundamental differences between these two decision criteria.

The percentage differences in the optimum reservoir capacity between the complete dataset and the sub-samples is then calculated, showing the difference in terms of the decision outcome associated with each of the decision criteria and each variation of the Green Z-score. The results for Brooms Barn are shown in Fig. 5.

At all three sites and all three emission scenarios, the optimum reservoir capacity from the full dataset is reproduced better under sampling using the Green Z-score than using any of the other decision criteria. At Brooms Barn, while the percentage difference ranges are comparable, each variation of Green Z-score has a smaller median percentage difference compared to current decision criteria. At Slaidburn, the percentage difference between the complete probabilistic dataset and each sub-sample, in terms of the optimal reservoir capacity is zero for every variation of Green Z-score. In contrast, the percentage difference for Hurwicz and Maximax is greater and has a much larger range, suggesting that that they would be poorly reproduced from sub-sampling. At Woburn, Green Z-score largely out performed current decision criteria, while the percentage difference ranges are comparable, the median percentage difference is smaller for Green Z-score compared to current decision criteria.

Discussion

Numerous decision methods and criteria have been developed to assist with decision making under risk and under uncertainty (Ranger et al., 2010). Methods of decision making under risk are not suitable for adaptation planning as the climate change projections on which adaptation is based are not provided with a probability of occurrence (Polasky et al., 2011). In the UK, advances in modelling capabilities and a greater appreciation of uncertainty (Stainforth et al., 2007; Tebaldi and Knutti, 2007) have provided decision makers with a "legitimate and credible" suite of climate change projections in the form of UKCP09 (Tang and Dessai, 2012). However, these advances have come at the expense of saliency. It has previously been suggested that over time climate science may become too complex and thus inhibit decision makers from making sensible decisions, reflected in the perceived saliency gap associated with UKCP09 (McNie, 2007; Sarewitz and Pielke, 2007; Tribbia and Moser, 2008). The diversity of users and lack of specific guidance on how to use UKCP09 may have diminished its usability. Modelling can result in misleading conclusions if projections are not used correctly. As a result, it has been suggested that the value of UKCP09 for real world decision making is limited (Tang and Dessai, 2012).

UKCP09's saliency gap can be attributed in part to the move from deterministic to probabilistic methods of communicating climate change information. Unfortunately, this move, aimed at quantifying at least part of the underlying uncertainty in the climate change projections and discussed elsewhere (Green and Weatherhead, 2013c) has not yet been accompanied by the development of supporting tools and techniques. A large number of criteria which were previously developed to support decision making have shown to be not appropriate for climate change adaptation because they require more information that can be realistically obtained (Froyn, 2005; Polasky et al., 2011) are crude, overly complex (Ranger et al., 2010) or not reproducible from sub-samples of the probabilistic dataset (Green and Weatherhead, 2013c).

As a result, a novel decision criterion, the Green Z-sore, is developed and applied to a simplified real-world decision problem of designing an on-farm irrigation reservoir. This method is purposely designed to be simple to implement and thereby encourage its use among decision makers that until now were largely reliant on proponents of classical decision theory (French, 1986), some of which are shown here for comparison purposes, to help inform adaptation. Since the Green Z-score is based on MCA it is subject to similar limitations. These limitations are consistent with the general criticisms levelled against MCA and its incorrect application, cost-benefit analysis (CBA) and economic valuation techniques as opposed to an issue with the criterion itself. MCA is subject to a host a potential pitfalls, stemming from incorrectly defining the problem structure, poor performance data, inappropriate capturing of decision-maker preferences, incorrect application of additive utility and duplication or overlapping criteria (Hajkowicz, 2008). The majority of criticisms levelled against MCA are generally associated with the incorrect application of the method as opposed to issues with the method itself.

CBA, which forms the basis of the analysis underpinning the Green Z-score has previously been criticised because it does not generally account for interactions between impacts. Certain individuals may feel more strongly about a project if it imposes both environmental and social costs, regardless of whether these effects are valued independently (Dodgson et al., 2009). Non-monetary elements can also present their own challenges for CBA which may make Green Z-score less suitable, however these elements can sometimes be valued using hedonic pricing (Pearson et al., 2002), travel cost methods (Chen et al., 2004) or other non-market value methods. A further limitation of CBA and by extension the Green Z-score is the time and resources it takes to estimate the financial benefits of an action. However, it can be argued that the time the effort required to estimate financial benefits is proportional to the relative costs of taken said action. "For example, where a tidal barrier is protecting hundreds or thousands of properties, a proportionate amount of effort in estimating monetised benefits would be justified" (EA, 2013), p. 3. However, while Green Z-score does suffer from some of the limitations of CBA it also borrows a number of positive elements from MCA, specifically its greater flexibility and its ability to resolve trade-offs in a transparent, audible and analytically robust manner. Similarly, Green Z-score can be combined with Monte-Carlo simulation to explore the wider uncertainties and ensure decision outcomes are robust (Dorini et al., 2011). Further work, testing the real-world application of the Green Z-score and whether or not it is preferred to conventional decision criteria with actual decision makers is however recommended.

One of the greatest challenges associated with UKCP09 and its uptake is the sheer number of climate change projections provided. Many impact models are limited by the number of projections they can realistically handle. Some organisations do not have the available resources to utilise these projections, notably in instances where climate change impacts tend to be wide ranging and the potential solutions very diverse. As a result, sample analysis is undertaken to ensure Green Z-score can be reliably reproduced from small sub-samples of the UKCP09 probabilistic dataset and as such is suitable for real-world practice.

Conclusion

Consistent with previous findings, this study found that a number of current decision criteria should be not be used with sub-samples of the UKCP09 probabilistic dataset on account that the decision outcomes obtained from them tend to differ substantially to the complete dataset. Certain methods, including Laplace, whose outcomes are successfully reproduced from small samples, are subject to their own criticisms and limitations, both in their assumptions and rational model. Other criteria give different results depending on the sample. Many of the current decision criteria including Laplace and Maximin assume a fixed rational model; such models are rarely accommodating of all decision makers attitudes, particularly when working in the realms of climate change where uncertainty abounds. The apparent lack of flexibility in current decision criteria may account for their limited uptake. While their use has been previously advocated for adaptation planning, it is much harder to develop a real world case for using them with the current suite of probabilistic climate projections owing to their practical limitations. The Green Z-score, unlike many of the current decision criteria considered here, provides reproducible decision outcomes from sub-samples of the UKCP09 dataset and can accommodate a host of differing risk appetites.

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Appendix A. – practical example

A practical example of Green Z-score is provided to guide readers through its calculation. The following decision problem compares three options (option A–C) with different outcomes (f_d) across 11 discrete states (s). The minimum ($\min_{d\in D} f_d$) and maximum payoff ($max_{d\in D} f_d$) of all three options for each state is also shown.

State (s)	Option A	Option B	Option C	$\min_{d\in D} f_d$	$\max_{d\in D} f_d$
1	−10	−15	−3	−15	−3
2	−8	−15	−3	−15	−3
3	−6	−15	−3	−15	−3
4	−4	0	−3	−4	0
5	−2	0	−3	−3	0
6	0	0	−3	−3	0
7	2	0	3.6	0	3.6
8	4	0	3.6	0	4
9	6	15	3.6	3.6	15
10	8	15	3.6	3.6	15
11	10	15	3.6	3.6	15

The following parameters are used:

Coefficient of optimism (α)	Coefficient of robustness (β)	Threshold of acceptability (t)
0.5	80	0

All workings are provided for option A only, all options are summarised at the end of the appendix along with the decision outcome.

The negative performance (B) is initially calculated

$$B = \sum_{s=1}^{s=n} \left(\frac{(f_d - t)}{(\min\limits_{d \in D} f_d - t)} \right)$$

where f_d is the option outcome, s is the state, t = threshold of acceptability (i.e. 0)

State	f_d	t	$(f_d - t)$	$\min_{d\epsilon D} f_d$	$\min_{d\epsilon D} f_d - \mathrm{t}$	$\left(\frac{(f_d-t)}{(\min_{d\in D} f_d - t)}\right)$
1	−10	0	−10	−15	−15	0.67
2	−8	0	−8	−15	−15	0.53
3	−6	0	−6	−15	−15	0.40
4	−4	0	−4	−4	−4	1.00
5	−2	0	−2	−3	−3	0.67
6	0	0	*	−3	*	*
7	2	0	*	0	*	*
8	4	0	*	0	*	*
9	6	0	*	3.6	*	*
10	8	0	*	3.6	*	*
11	10	0	*	3.6	*	*
Total						3.27

* This value is not calculated because $f_d > t$.

The overall performance (A) is then calculated

$$A = \sum_{s=1}^{s=n} \left(\frac{(f_d - \chi)}{\left(\max_{d \in D} f_d - \chi \right)} \right)$$

where f_d is the option outcome, s is the state

$$\chi = \left(\max_{d \in D} f_d - \left(\left(\max_{d \in D} f_d - \min_{d \in D} f_d \right) \cdot \left(\frac{\beta}{100} \right) \right) \right)$$

β = coefficient of robustness

State	f_d	$\max_{d\epsilon D} f_d$	$\min_{d\epsilon D} f_d$	χ	$(f_d - \chi)$	$(\max_{d\epsilon D} f_d - \chi)$	$\left(\frac{(f_d-\chi)}{(\max_{d\in D} f_d - \chi)}\right)$
1	−10	−3	−15	−12.60	2.60	9.60	0.27
2	−8	−3	−15	−12.60	4.60	9.60	0.48
3	−6	−3	−15	−12.60	6.60	9.60	0.69
4	−4	0	−4	−3.20	*	*	*
5	−2	0	−3	−2.40	0.40	2.40	0.17
6	0	0	−3	−2.40	2.40	2.40	1.00
7	2	3.6	0	0.72	1.28	2.88	0.44
8	4	4	0	0.80	3.20	3.20	1.00
9	6	15	3.6	5.88	0.12	9.12	0.01
10	8	15	3.6	5.88	2.12	9.12	0.23
11	10	15	3.6	5.88	4.12	9.12	0.45
Total							4.75

* This value is not calculated because $f_d < \chi$.

$$z_d = \max_{d \in D}((\alpha \cdot A) - ((1 - \alpha) \cdot B)) \tag{1.1}$$

where z_d is the decision outcome, d is the option, D is the options, α is the coefficient of optimism (where $0 < \alpha \geqslant 1$), A is the overall performance (see Eq. (1.2)), B is the negative performance (see Eq. (1.3))

Option	A	B	$(\alpha{\cdot}A)$	$((1 - \alpha){\cdot}B)$	Green Z-score
A	4.75	3.27	2.37	1.63	0.74
B	6.00	3.00	3.00	1.50	1.50
C	4.94	3.35	2.47	1.68	0.79

The decision outcome (z_d) is option B because it has the highest Green Z-score.

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