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Assessing the robustness of adaptation decisions to climate change uncertainties: A case study on water resources management in the East of England

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Abstract

Projections of future climate change are plagued with uncertainties, causing difficulties for planners taking decisions on adaptation measures. This paper presents an assessment framework that allows the identification of adaptation strategies that are robust (i.e. insensitive) to climate change uncertainties. The framework is applied to a case study of water resources management in the East of England, more specifically to the Anglian Water Services' 25 year Water Resource Plan (WRP). The paper presents a local sensitivity analysis (a 'one-at-a-time' experiment) of the various elements of the modelling framework (e.g., emissions of greenhouse gases, climate sensitivity and global climate models) in order to determine whether or not a decision to adapt to climate change is sensitive to uncertainty in those elements.

Water resources are found to be sensitive to uncertainties in regional climate response (from general circulation models and dynamical downscaling), in climate sensitivity and in climate impacts. Aerosol forcing and greenhouse gas emissions uncertainties are also important, whereas uncertainties from ocean mixing and the carbon cycle are not. Despite these large uncertainties, Anglian Water Services' WRP remains robust to the climate change uncertainties sampled because of the adaptation options being considered (e.g. extension of water treatment works), because the climate model used for their planning (HadCM3) predicts drier conditions than other models, and because 'one-at-a-time' experiments do not sample the combination of different extremes in the uncertainty range of parameters. This research raises the question of how much certainty is required in climate change projections to justify investment in adaptation measures, and whether such certainty can be delivered.

Keywords: Climate change; Adaptation; Uncertainty; Robustness; Sensitivity analysis; Water resources; East of England

1. Introduction

Decisions about managing the environment are plagued with uncertainty. There is uncertainty about the past state of the environment, uncertainty about the current state of the environment and further uncertainty about the future state of the environment. It is therefore surprising that in the field of global environmental change little attention has been given to the sensitivity of management decisions to uncertainties in environmental predictions.

There are some exceptions though. For example, Lempert et al. (2003, 2006) demonstrated the application of robust decision methods to the problem of global

Abbreviations: AWS, Anglian Water Services; EA, Environment Agency; ES&E, East Suffolk and Essex; GCM, General Circulation Model (or also Global Climate Model); GHG, Greenhouse gases; IPCC, Intergovernmental Panel on Climate Change; PDF, Probability distribution function; MAGICC, Model for the Assessment of Greenhouse-gas Induced Climate Change; RCM, Regional Climate Model; SRES, Special Report on Emissions Scenarios; UKCIP, United Kingdom Climate Impacts Programme; UKWIR: United Kingdom Water Industry Research; WRP, Water Resource Plan; WRZ, Water Resource Zone; WTW, Water Treatment Works

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Fig. 1. The area supplied by Anglian Water in the East of England. In the ellipse is the East Suffolk and Essex Water Resource Zone. Source: Anglian Water.

sustainable development, while Regan et al. (2005) used information-gap theory to propagate uncertainty and to rank conservation management decisions about an endangered species.

In climate change some attention has been given to the issue of robust decisions,[1] but this has mainly focused on the mitigation side of the problem (e.g., Lempert et al., 1996; van Lenthe et al., 1997; Lempert and Schlesinger, 2000; Caldeira et al., 2003; Yohe et al., 2004).[2] Trying to identify robust decisions to climate change uncertainties in the context of adaptation has been even less researched. This is mainly due to the lack of consistent treatment of uncertainties in climate change scenario construction (Carter et al., 2001). There have been some attempts to examine robust adaptation decisions against climate change uncertainties (Yohe, 1991; Hobbs, 1997; Hobbs et al., 1997; Risbey, 1998), but these have only sampled a fraction of the known range in future climates.

This paper uses current knowledge of climate change uncertainties to test the robustness of proposed adaptation options against these uncertainties. The decision-making context is water resources planning in the Water Resource Zone (WRZ) of East Suffolk & Essex (ES&E) in the East of England (Fig. 1). The emphasis of the paper is on demonstrating how a robust decision-making methodology that explicitly includes uncertainties can be applied to real world decisions about adaptation to climate change. While this paper focuses on the local implications of global environmental change, it brings to bear knowledge from earth system science that include global climate models (GCMs), scenarios of future world development and estimates of climate sensitivity.

Section 2 describes the decision-making context where adaptation to climate change occurs in water resources management in the East of England. Section 3 explains the modelling framework used, while Section 4 elaborates how climate change uncertainties were managed. Section 5 performs a local sensitivity analysis to determine the sensitivity of water resources to various climate change uncertainties as well as the robustness of the Water Resource Plan (WRP) to these uncertainties. Section 6 discusses the results and provides some conclusions.

2. Adaptation to climate change and water resources planning

The Intergovernmental Panel on Climate Change (IPCC, 2001) defines adaptation as an "adjustment in ecological, social, or economic systems in response to actual or expected climatic stimuli and their effects or impacts". Since the focus of this paper is exclusively on human systems, the central unit of analysis becomes the adaptation decision(s). Defining adaptation to climate change is complicated because agents adapt to a number of different pressures at the same time, not just to climate change. Defining successful adaptation is even more complicated because criteria for success are generally contested and context specific. Adger et al. (2005) suggest that elements of effectiveness, efficiency, equity and legitimacy are important in judging successful adaptation. This paper focuses exclusively on one of the key indicators of the effectiveness of an adaptation action: robustness to uncertainty.[3] The next sub-sections contextualise adaptation to climate change by briefly describing water resource planning, how climate change has been incorporated into this process and the adaptation options available in the East of England.

2.1. Water resources planning

Every 5 years, UK water companies produce a WRP where they lay out what actions they will take in order to

[1]In this paper, "robust decisions" are defined as decisions that work well (that achieve their goals) even with the inclusion of various uncertainties. In other words, "robust decisions" are decisions that are insensitive to uncertainties known at the time.

[2]Some of these studies, mostly using integrated assessment models, include an extremely simplified conception of adaptation (e.g., on or off) based on damage costs and functions.

[3]According to Adger et al. (2005) the other important indicator is flexibility, i.e., the ability to change in response to altered circumstances. Sometimes called "adaptive responses" in the literature.

maintain security of supply over the next 25 years (EA, 2003). The unit the WRP is compiled in is the resource zone which is defined as: "The largest possible zone in which all resources, including external transfers, can be shared and hence the zone in which all customers experience the same risk of supply failure from a resource shortfall" (EA, 2003, p. 18). For example, Anglian Water has 12 WRZs. The basic framework of a WRP follows a structure that considers all of the components of a company's water balance for each year until the planning horizon of 2030. In broad terms this involves evaluating the amount of water available for supply as well as all of the demands on this water. This is done for "dry year" annual average unrestricted daily demand as the norm, but "normal year" and dry year "critical period" are also explored to test sensitivities. This is first carried out for "baseline" conditions (2002/03) and then for final planning scenarios.

Central to the WRP is the concept of headroom that combines numerically the forecasts of supply and demand. Carnell et al. (1999) developed a pragmatic methodology for converting uncertainty in the supply/demand balance into headroom. The following concepts are important to understand headroom:

Target headroom: the minimum buffer that a prudent water company should allow between supply (including raw-water imports and excluding raw-water exports) and demand to cater for specified uncertainties in supply and demand (except for those due to outages).

Available headroom: the difference between water available for use (including raw-water imports less raw-water exports) and demand.

Supply: water available for use.

Demand: dry year annual average unrestricted demand (or critical period demand) (Carnell et al., 1999).

There is a range of uncertainties that affect headroom, climate change being one of them both on the supply and demand side. The headroom methodology provides a "risk envelope" against which companies should derive a balanced portfolio of supply and demand management options for each resource zone.

2.2. Climate change and water resources planning

Over the last periodic review of WRPs, water companies took climate change into account by using climate change scenarios produced for the UK Climate Impacts Programme (UKCIP02, Hulme et al., 2002). These scenarios were constructed using the ensemble mean of three simulations (using different initial conditions) of one regional climate model (RCM; HadRM3) driven by one high-resolution atmospheric GCM (HadAM3H), conditioned by a global coupled ocean-atmosphere model (HadCM3) under one specific emission scenario (SRES A2; medium-high). Simulations were run for a reference period (1961–90) and a future period (2071–2100, also known as the 2080s). Results for different time horizons (2020s and 2050s) and different emission scenarios (SRES A1FI, B1 and B2; respectively high, low and medium-low) were obtained using the pattern-scaling technique, which assumes a linear relationship between global warming and local climate response.

The UKCIP02 scenarios were translated into streamflow and groundwater recharge changes for the 2020s for several regions and catchments (Arnell, 2003; UKWIR, 2003; Arnell, 2004). These results included three scenarios—low, medium[4] and high—and extra two scenarios to represent climate model uncertainty: "warm and dry" and "cool and wet".[5]

Using the UKWIR/Arnell streamflow and recharge changes, water companies in England and Wales calculated the impact of climate change on their water supplies with hydrological models (sometimes in-house models were used, sometimes external models). Once the loss of deployable output was estimated it was included in 'target headroom' or directly into supply and demand estimates in the WRP. For more on adaptation to climate change in the UK water supply sector, see Arnell et al. (2004), Dessai (2005) or Arnell and Delaney (2006).

2.3. Water resources in the East of England: context and local adaptation options

The decision context where the framework was applied is that of water resources planning in the East of England. The East of England is the driest region of the UK with annual average rainfall around 595 mm, compared with a national average for England and Wales of 897 mm. Effective rainfall (precipitation minus evaporation) is only a quarter of average rainfall at 147 mm. Long dry summers during which evaporation exceeds rainfall are a normal part of the climate in the region (EA, 2001). Climate change is expected to exacerbate drought-like conditions because of increasing temperatures and dryer summers (EERA and SDRT, 2004).

The water company that supplies most of the East of England is Anglian Water Services (AWS), who provide water to four million people. AWS prepared a WRP for the period 2005–30 that includes climate change impacts (on supply, but not on demand) and various other risks (e.g., borehole deterioration) and uncertainties (e.g., future demand). Here the WRZ of ES&E[6] is examined in more detail (Fig. 1) because AWS found it to be particularly vulnerable to climate change and because this WRZ has a deficit of average available headroom against target headroom from the start of the planning period. Without planned intervention (i.e., increases in supply or decreases in demand) this WRZ grows in deficit as the target headroom increases over the 25 year planning

[4]Because medium-low and medium-high UKCIP02 scenarios are virtually identical for the 2020s.

[5]There were also two extra scenarios representing natural multi-decadal climate variability (without any climate change).

[6]The description of the ES&E WRZ is largely based on Anglian Water Services' Water Resource Plan.

horizon. Fig. 2 shows how AWS plans to manage the ES&E WRZ by increasing supply and by reducing demand and leakage, given a background of rising target headroom. Also shown is the overall supply/demand balance.

ES&E WRZ is predominantly supplied by groundwater with some contribution from surface water. Surface water is developed through raw water storage reservoirs at Alton and at Ardleigh. Total domestic demand for the zone for the base year (2002/3) is assessed at 75.6 Ml/d and the commercial demand is assessed at 25.6 Ml/d. AWS expects the total domestic demand to decline to 70.5 Ml/d by the year 2029/30 because of increased metering penetration, expected overall fall in household occupancy size and the net effect of water efficiency and demand management initiatives on the domestic demand. Commercial demand is expected to remain steady over the planning period at 25 Ml/d for the year 2029/30. See full grey line in Fig. 2 for overall demand changes.

The target headroom in this WRZ is affected by the risk of climate change on Alton Water reservoir. There are also fairly large risks associated with the anticipated deterioration of borehole condition and loss of supply due to groundwater pollution. To this is added the uncertainty over forecast demand and leakage. These risks and uncertainties combine to give this WRZ the highest target headroom in the region (see full black line in Fig. 2).

The cornerstone for the investment plans is the development of the trunk main system by linking the Ipswich and Colchester storage reservoirs (this does not actually increase water supply, but makes it more secure). In the short term, AWS has identified the need for increase supplies to the Colchester Planning Zone. This can be achieved by upgrading Lexden sourceworks to utilise the current licence by improved blending for fluoride and by a temporary re-allocation of the proportion of the deployable output of Ardleigh Water Treatment Works (WTW). This, together with the construction of a new treated water storage reservoir at Ardleigh WTW, forms the optimal solution for the Colchester Planning Zone, according to AWS (this is shown as the first increase in supply in Fig. 2).

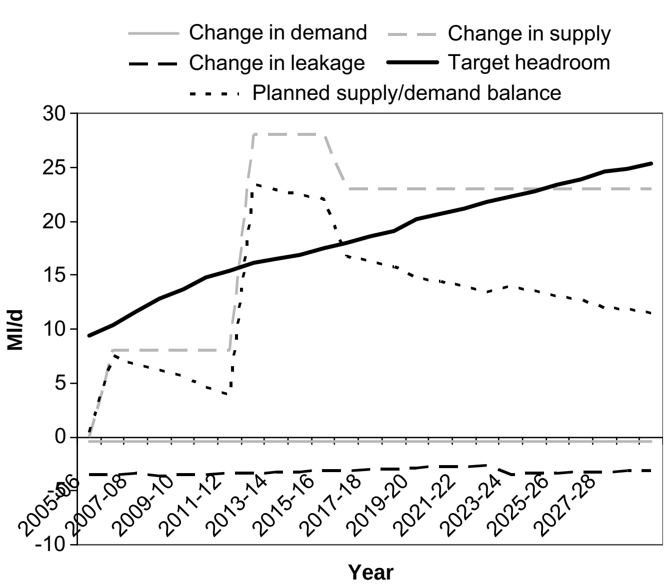

Fig. 2. Changes in water demand, leakage, supply (Water Available For Use) from 2005–06 to 2029–30 (compared to the base year of 2002–03) for the East Suffolk and Essex WRZ. Also shown is target headroom and the planned supply/demand balance.

The development of Alton WTW will require the augmentation of the reservoir yield to cater for increased output and the potential decline in yield identified through the analysis of climate change impact. The main options for augmentation are effluent re-use, transfer through the Ely Ouse to Essex Transfer Scheme or augmentation from the confined chalk aquifer. Analysis shows that augmentation is required during the period 2005–10 to avoid a deficit of target headroom in a dry year (this is shown as the second increase in supply in Fig. 2). However, the risk will be mitigated by the connection of the Ipswich and Colchester systems.

We conducted elite interviews with water managers at AWS and it was acknowledged that no strategy was developed in detail beyond 2030. However, any such strategy is likely to involve transfer from the River Trent, development of pumped-storage reservoir in Lower Witham catchment and adjacent to the Cut-Off Channel with a new transfer link. It is estimated that such a strategy would need implementation just prior to 2030. An older version of this strategy is further described by Sheriff et al. (1996) who estimated additional potential yield and indicative capital cost (shown in Table 1). A few other options suggested by the Environment Agency (2001) are included in Table 1 including: Aquifer Storage Recovery, raising Abberton Reservoir and a desalination plant.

Climate change is a significant driver of target headroom in this WRZ because it has an impact on surface water, which affects the yield of Alton and Ardleigh reservoirs. Based on hydrological modelling and human judgement, AWS decided to include climate change risk in the calculation of target headroom using a triangular probability distribution function (PDF). This distribution has a minimum (0 Ml/d), a maximum (17.2 Ml/d) and a most likely (9.6 Ml/d) value for the loss of deployable output due to climate change. In our subsequent analysis, several comparisons will be made with this distribution, since this is what AWS has planned for in terms of climate change impacts.

3. The modelling framework

This section describes the modelling framework applied in this paper. A number of methods were used to elicit adaptation options. These included extensive literature reviews (based on peer-reviewed and grey literature), elite interviews with water managers and in-depth examination of planning documents. Once a list of adaptation options was compiled for the East Suffolk and Essex WRZ (see Table 1) the next stage was to link options (with changes in a climate variable or variables (e.g., temperature or

Table 1
Adaptation options for the East Suffolk and Essex Water Resource Zone

Adaptation decisions	Planned gains in supply or savings in demand by 2029–30 (Ml/d)	Planned implementation date	Total net present cost (£M)
Ardleigh Reservoir increased take	0.00[a]	2006–07	4.71–1.98[b]
Uprating Lexden sourceworks	3.00	2006–07	3.32–3.15[b]
Alton water treatment works extension and effluent re-use resource scheme at Cliff Quay	20.00	2012–13	42.85–33.87[b]
Aquifer storage recovery in the confined chalk aquifer under the Felixstowe Peninsula[c]	10–20	5–10 years to implement	High
Abberton Reservoir raising	50	10 years to implement	Medium
Desalination plant (Brackish Suffolk)	5–10	2–5 years to implement	High
Trent-Anglian transfer (to Essex reservoirs via Fossdyke Navigation, R Witham and existing Ely Ouse-Essex transfer)	Capacity 200[d]	Medium time to promote	108
East Anglian reservoir—figures only available for Great Bradley reservoir	174[d]	Long time to promote	69

In italic are the decisions already included in Anglian Water Services' current Water Resources Plan.
[a]Temporary increased take of 5 Ml/d between 2006–07 and 2013–14.
[b]Based on figures from the WRP and supply-demand worksheet.
[c]Based on Environment Agency figure for Essex Chalk.
[d]Only a portion of this water would reach the ES&S WRZ.

precipitation). This is one of the most difficult tasks of the assessment because agents adapt to a number of different pressures simultaneously, not just to climate change.[7] Nevertheless, an attempt was made to link adaptation options exclusively to climate change. This was done through expert judgement (based on a questionnaire sent to AWS water managers) and using planning documents that have already incorporated climate change (and that had performed sensitivity analysis). Usually, climate change is incorporated into planning by combining climate change scenarios with observed climate records which serve as input to an impact model, which outputs changes in the variable of interest (e.g., water yield change). Using these results it is possible to link changes in climate variables (e.g., summer temperature or precipitation change) with impacts and subsequently with adaptation options required to maintain a certain level of service for example. Fig. 3 shows the relationship used between changes in summer precipitation[8] and additional water required for the ES&E WRZ. In the absence of the hydrological and yield models used by AWS, the relationship in Fig. 3 was used as a simple hydrological-yield model to estimate the additional water required in this WRZ given possible future climates.

Ideally, one would run a number of impact models and different parameterisations to sample uncertainty in the models (see, e.g., Wilby, 2005). Because this was not performed, the transfer function from Fig. 3 was assumed to be uncertain by changing the gradient $\pm 25\%$. This uncertainty range is partially informed by the uncertainty analysis performed by Wilby (2005) on water resources projections, which focused on uncertainties arising from the choice of model calibration period, model structure and non-uniqueness of model parameter sets (also known as equifinality).

We now describe the climate scenario construction exercise. There is a plethora of different methods to estimate future change in seasonal temperature, precipitation and potential evaporatranspiration. The approach applied here tries to quantify as much of the uncertainty as possible given our current knowledge. The analysis can be neatly divided into a global and regional scale. At the global scale a simple energy-balance model developed by Wigley and Raper (1992, 1995, 2001) was used. This model, known as Model for the Assessment of Greenhouse-gas Induced Climate Change (MAGICC), allows uncertainty analysis to be performed on certain key parameters such as emissions of greenhouse gases (GHGs), climate sensitivity, carbon cycle, ocean diffusivity and aerosol forcing in the calculation of global temperature change. A combination of literature review and expert advice was used to define uncertainty ranges for these parameters. For example, for the emissions of GHGs, scenarios from the IPCC Special Report on Emissions Scenarios (SRES, Nakicenovic et al., 2000) were used, whereas for climate sensitivity PDFs available in the literature (Andronova and Schlesinger, 2001; Wigley and Raper, 2001; Forest et al., 2002; Knutti et al., 2002; Murphy et al., 2004; Stainforth et al., 2005) were used. The connection between the simple climate model and regional climate change is completed using the pattern-scaling technique (originally developed by Santer

[7]Adger et al. (2005) note that it is difficult to separate climate change adaptation decisions or actions from actions triggered by other social or economic events.

[8]Through the questionnaire used, summer precipitation was identified by AWS water managers as the most important climatic driver for water resources in the region. This simplification was necessary because the hydrological model used in planning was not available.

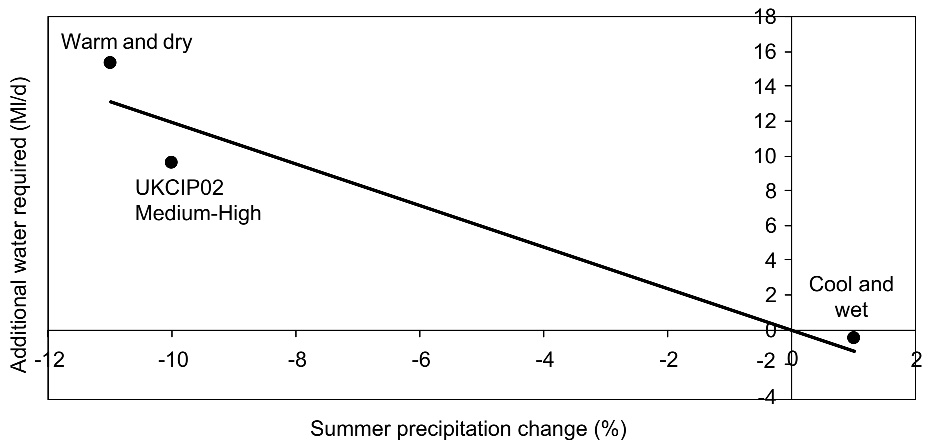

Fig. 3. Relationship between changes in summer (JJA) precipitation and additional water required (or loss of deployable output; in Ml/d) for the ES&E WRZ. The positive precipitation change (1%) relates to the "cool and wet" UKWIR03 scenario, the middle precipitation change (−10%) relates to the medium UKWIR03 scenario (equivalent to the UKCIP02 Medium-High scenario) and maximum precipitation change (−11%) relates to the "warm and dry" UKWIR03 scenario. The black line represents a linear transfer function with an R^2 of 0.92.

et al., 1990) and results from global and RCMs. The GCM results originated from the IPCC-Data Distribution Centre.[9] The RCM results, also known as dynamical downscaling, originated from the PRUDENCE project.[10] For the RCMs, there were a number of different forcings (either from different emissions scenarios or different driving GCMs) and resolutions. We have kept GCM and RCM results separate because RCMs only represent one approach of downscaling GCM results and because the majority of RCMs were only driven by one GCM. Fig. 4 summarises some of the main features of the framework described.

4. Managing climate change uncertainties

"Uncertainty management is the raison d'etre of risk assessment, extreme care must be exercised through out an assessment, so that uncertainties are **identified**, the nature of their propagation throughout the assessment is **understood** and that they are **communicated** as part of the results" (Jones, 2001) (bold emphasis our own).

Jones (2000) reminded the climate change community of the importance of managing uncertainties for impact assessment. However, he also noted that there is little evidence to show which methods are best for managing uncertainty, so a number need to be tested under a range of conditions and for different purposes. This is partially what this paper tries to achieve.

Much has been written about uncertainty management (we include uncertainty assessment and communication in this definition). The uncertainty literature is large and growing (Knight, 1922; Kahneman et al., 1982; Funtowicz and Ravetz, 1990; Morgan and Henrion, 1990; Helton and Burmaster, 1996; Winkler, 1996; Casman et al., 1999; Stewart, 2000; van Asselt, 2000; Goodman, 2002; Helton and Davis, 2002; van der Sluijs et al., 2003; Walker et al., 2003; van der Sluijs et al., 2004). For each proposed taxonomy, there is probably an equal number of different methodologies to handle uncertainties. The basic premise for this paper, which comes out of exploratory modelling (see Bankes, 1993) and risk assessment (see Jones, 2001) is that there is uncertainty (sometimes deep uncertainty[11]) about almost every aspect of a climate change risk assessment. There is uncertainty about what values various parameters should have, uncertainty about the structure of the models, uncertainty about the options available to decision-makers, uncertainty about the methodology, etc.

The approach presented here tries to quantify as much of the climate change uncertainty as possible using knowledge from the literature and expert judgement in the framework explained in the previous section. We do this using a combination of methods including: scenario analysis where there is deep uncertainty (e.g., in emissions of GHGs), exhaustive fractile sampling in MAGICC, Monte Carlo analysis using Latin Hypercube sampling for the pattern-scaling and a simple but uncertain impact transfer function for the hydrological-yield modelling. Each facet of the framework presented in Fig. 4 has a different uncertainty treatment because they are representing different types of uncertainties (but also sometimes for pragmatic reasons).

[9] http://ipcc-ddc.cru.uea.ac.uk/.

[10] Prediction of regional scenarios and uncertainties for defining European climate change risks and effects: http://prudence.dmi.dk/.

[11] Deep uncertainty is sometimes called Knightian uncertainty, after Knight (1922), who distinguished risk from uncertainty. For Knight (1922) risk is a realm where factors can be quantified whereas uncertainty denotes unknown factors poorly-described by quantifiable probabilities. Lempert et al. (2003, 2006) have defined deep uncertainty as the condition where 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, or (3) how to value the desirability of alternative outcomes.

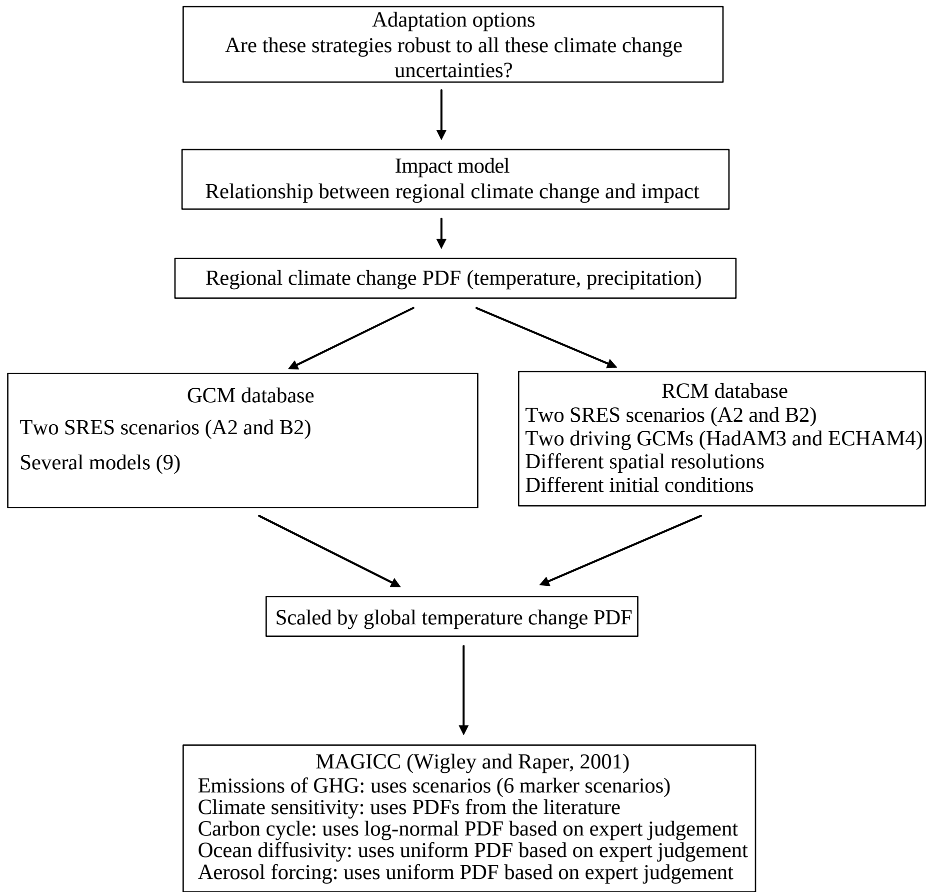

Fig. 4. Schematic of the overall methodological framework used.

5. Local sensitivity analysis

This section performs a local sensitivity analysis on the various elements of the modelling framework in order to determine whether or not a decision to adapt to climate change is sensitive to uncertainty in those elements. Elements that can easily change a decision (high sensitivity) should be included in an uncertainty analysis (which this paper does not perform), while elements that do not change a decision (low sensitivity) need not.

The modelling framework used here is a sequential one. Therefore, in order to examine the sensitivity of adaptation decisions to the various elements of this sequence, each element is examined in turn to keep uncertainties manageable. This allows the examination of how much uncertainty each parameter contributes while the other parameters are kept constant. This methodology is consistent with Visser et al. (2000) and Jones and Page (2001) and is known in the sensitivity analysis literature (see, e.g., Campolongo et al., 2000) as 'one-at-a-time' experiments, where the impact of changing the values of each factor is evaluated in turn. The experiment that uses the 'standard' values is here called the 'default scheme'[12] and is shown in Table 2.

[12]Other authors call this the control experiment or control scenario (Campolongo et al., 2000).

In the various sections that follow much attention is given to the 95th percentile. This happens because AWS associates the 95th percentile with a specific level of service defined as

- Restriction on the use of hosepipes not more than 1 in 10 years.
- Use of Drought Orders to enforce restriction on non-essential uses and secure raw water resources not more than 1 in 40 years.
- Imposition of the use of standpipes not more than 1 in 100 years (AWS, 2004).

That means AWS can be 95% confident that it has sufficient supply provision over the 25 year planning horizon to ensure that it can meet the stated level of service. Results are presented as uncertainty ranges between the maximum and minimum values that a particular parameter yields at the 95th percentile. The shortfall between AWS's triangular distribution (see Section 2.2), assumed to represent climate change impacts, and the maximum value for the parameter being sampled here is also reported at the 95th percentile (named AWS shortfall). The WRP is robust if the shortfall is smaller than the supply/demand balance in 2030 and weak if the shortfall is larger than the supply/demand balance in

Table 2
Scenarios, PDFs or transfer functions used in the default scheme for the local sensitivity analysis

Uncertain parameter	Default combination
GHG emissions	SRES A2-ASF scenario
Climate sensitivity	Log-normal PDF (W&R, 2001)
Carbon cycle	Log-normal PDF (W&R, 2001)
Ocean diffusivity	Uniform PDF (W&R, 2001)
Aerosol forcing	Uniform PDF (W&R, 2001)
Regional climate response	Uniform distribution (for GCMs)[a] and equally likely frequency distribution (for RCMs)
Climate impacts	Transfer function estimated from AWS hydrological modelling

[a]A uniform distribution is used for GCMs because summer precipitation changes for the East of England show a wide range of results, depending on which GCM is used, including different sign changes.

2030. Therefore, it is important to keep in mind the estimated supply/demand balance value from the current WRP for the ES&E WRZ: **11 Ml/d** in 2030 (see Fig. 2). Also shown in the subsequent results is the additional water required solely due to natural multi-decadal climate variability. This allows the comparison of the ''noise'' caused by internal variability with the climate change ''signal'' caused by anthropogenic forcing in order to determine the significance of the model-simulated response to anthropogenic forcing. Natural multi-decadal climate variability was estimated for the region using the England and Wales Precipitation series (Alexander and Jones, 2001) from 1766 to 1950.[13]

5.1. Greenhouse gas emissions

Future GHG emissions are an important source of uncertainty in any climate risk assessment. Fig. 5 shows the impact of different emissions scenarios on the cumulative probability of additional water required by the 2030s for the ES&E WRZ due to climate change (under the default scheme and using only RCMs). Also shown is the additional water required solely due to natural multi-decadal variability (in triangles) and the assumed distribution by the water company (in diamonds). The shape of the AWS strategy is very similar to the RCM curves. In fact, the AWS strategy matches very well the A2-ASF scenario, which is essentially equivalent to the medium UKWIR03 scenario (derived from UKCIP02 medium-high). This confirms that the modelling framework used here can mimic results from UKCIP02. If one is concerned with drought, which water managers are, then it is promising to observe that AWS strategy can deal with the entire range of natural climatic variability.[14] It is interesting to note that one of the 'greenest' scenarios (A1-T; a rapid globalising world with a technological emphasis on non-fossil energy sources) produces the worst results from a water resources perspective. This is mainly due to the impact of sulphur emissions, which have a negative forcing (i.e., cooling effect) on global temperature change. The A1-T scenario has some of the lowest emissions of sulphur dioxide (therefore net warming) compared to other scenarios. The uncertainty introduced by emissions scenarios at the 95th percentile is 4.57 Ml/d and the AWS strategy is short of 6.73 Ml/d compared to A1T-MES.

If one uses GCMs instead of RCMs, as in Fig. 6, then the total uncertainty range is much larger, ranging from less water being required to more water being required. This occurs because a minority of GCMs show a increase in summer rainfall while the majority shows a decrease. At the 95th percentile, the range of uncertainty due to emissions scenarios using GCMs is 5.55 Ml/d, rather larger than when RCMs were used.

In summary, the uncertainty introduced by the six illustrative SRES emissions scenarios to water resources planning for the 2030s is significant (in the order of 4.5–5.55 Ml/d), but does not represent a threat to the ES&E WRZ because of positive supply/demand balance in 2030 (11 Ml/d). However, this element of uncertainty will grow in significance the further into the future the planning horizon is.

5.1.1. Mitigation/stabilisation scenarios

Mitigation and stabilisation scenarios are important for a number of reasons. In the 'real' world, climate policies are being enacted (e.g., Kyoto Protocol, EU Emissions Trading Scheme, UK Climate Change Programme, etc.) and are expected to be reinforced in the future. However, this is extremely uncertain because it depends on human choice, in particular how much mitigation (GHG emissions reduction) is going to happen over the next decades. The SRES scenarios do not include explicit climate policies (although they do include environmental policies), so one could argue that they are 'unrealistic'. Including climate mitigation policies in the SRES scenarios is, therefore, important and for this reason the Post-SRES mitigation/stabilisation scenarios are used here (Morita and Robinson, 2001). The inclusion of mitigation adds further uncertainty to the risk assessment since it is impossible to know at which level atmospheric concentrations of GHGs will be stabilised over the next 100 years. Hence, different stabilisation levels were examined for a few SRES scenarios.

The analysis shows that by the 2030s mitigation policies will have a small influence on water resources planning in

[13]A series of 30-year overlapping means (with a total of 156 values) were calculated for summer for the period 1766–1950 (by not including the last 50 years this excludes any possible anthropogenic influence). All these values were normalised by the tri-decadal mean over the entire period and a frequency distribution was constructed.

[14]Although perhaps one should expect water companies to be already well adapted to natural climatic variability. This would imply having a surplus of roughly 7.5 Ml/d in the supply/demand balance at any point in time.

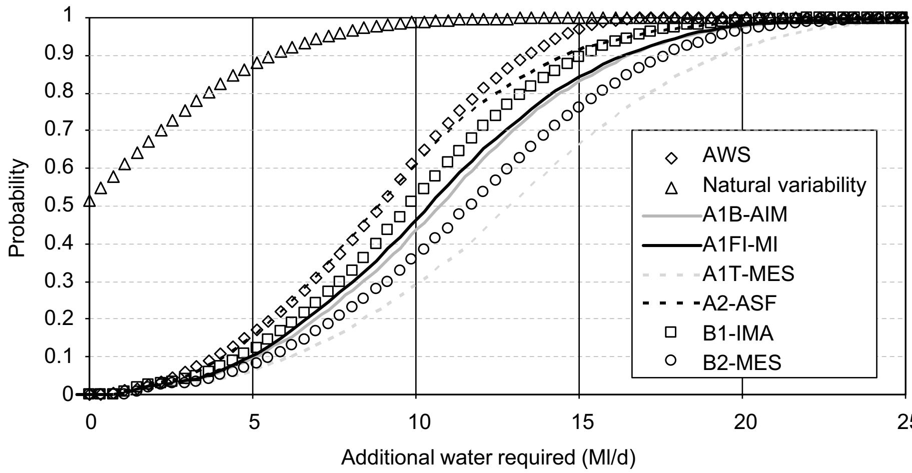

Fig. 5. Cumulative probability of additional water required (in Ml/d) for the ES&E WRZ by the 2030s using the default scheme with regional climate model (RCM) results, and comparing different marker emission scenarios (A1B-AIM, A1FI-MI, A1T-MES, A2-ASF, B1-IMA and B2-MES). Also shown is the AWS strategy (in diamonds) and the additional water required solely due to natural multi-decadal climate variability (in triangles).

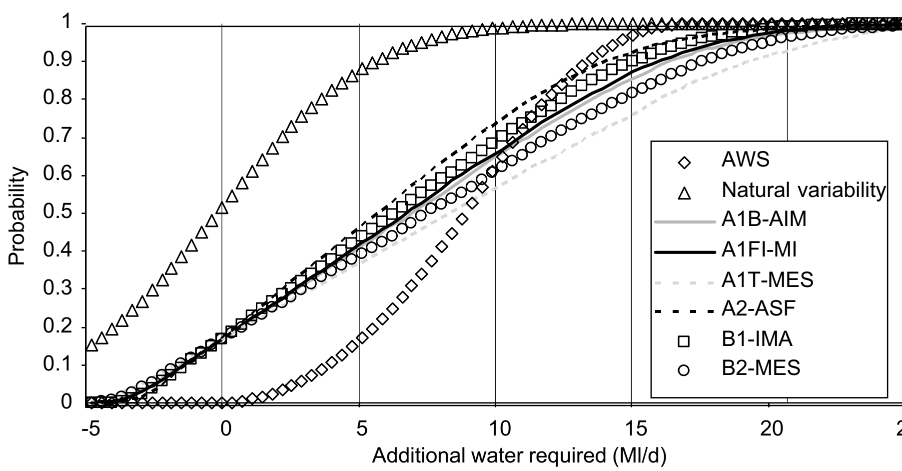

Fig. 6. As Fig. 5, but for global rather than regional climate models.

the ES&E WRZ under the A2-ASF scenario. Thus, stabilising GHG concentrations at 550 ppm (which is essentially the EU/UK position/vision, see Comission, 2005) would lead to a reduction in water required by 2030 of between 1.63 and 1.93 Ml/d (GCM-RCM range) at the 95th percentile. Table 3 shows that greater reductions in water required are possible under the A1FI-MI scenario, reaching a maximum of between 3.34 and 3.57 Ml/d (GCM–RCM range) with a 450 ppm stabilisation scenario. In this scenario, mitigation policies are not entirely negligible for adaptation purposes. The higher the emissions in the baseline scenario, the greater the impact of mitigation policies will be on reducing the amount of additional water required.

5.2. Climate sensitivity

Climate sensitivity is an important parameter to be incorporated in any climate change risk assessment. Climate sensitivity is the equilibrium change in global surface temperature resulting from a doubling of atmospheric equivalent CO_2 concentration. Uncertainty about climate sensitivity has been shown to influence important mitigation decisions (see, e.g., Caldeira et al., 2003). How important is it for adaptation decisions?

Table 4 shows the impact of using different climate sensitivity PDFs for the risk that climate change poses for water resources in our region. Under the default scheme, uncertainty about the shape of the climate sensitivity PDF introduces large uncertainties into water resources planning. At the 95th percentile, the range of uncertainty for the ES&E WRZ is 8.27 Ml/d. AWS WRP remains robust to climate sensitivity uncertainty, but using the Uniform cp.net PDF only leaves 1.61 Ml/d in the supply/demand balance by 2030. It is worth noting that in the case of the Forest et al. (2002) PDF, expert judgement reduces the range of uncertainty and the amount of additional water required at the 95th percentile. In the Murphy et al. (2004)

Table 3
Percentiles of additional water required (in Ml/d) by the 2030s for the ES&E WRZ under the A1FI-MI baseline scenario and different stabilisation scenarios (750, 650, 550 and 450 parts per million) for the default scheme using GCM and RCM results

	Percentiles (%)	Baseline	750	650	550	450
GCM	2.5	−2.96	−2.67	−2.62	−2.58	−2.31
	5.0	−2.25	−2.06	−2.03	−1.99	−1.77
	50.0	6.84	6.41	6.29	6.10	5.32
	95.0	18.27	17.19	17.21	16.41	14.70
	97.5	20.06	18.93	18.91	18.29	16.42
RCM	2.5	2.18	2.03	1.98	1.94	1.74
	5.0	3.76	3.48	3.44	3.28	2.87
	50.0	10.58	9.82	9.68	9.28	8.23
	95.0	18.09	17.00	16.81	16.24	14.76
	97.5	19.43	18.58	18.36	17.69	16.15

Table 4
Percentiles of additional water required (in Ml/d) by the 2030s for the ES&E WRZ under the default scheme using GCMs and different published climate sensitivity PDFs. Also shown is AWS plan and the additional water required solely due to natural multi-decadal climate variability

Percentiles (%)	Wigley and Raper (2001)	Andronova and Schlesinger (2001)	Uniform Forest et al. (2002)	Expert Forest et al. (2002)	Knutti et al. (2002)	Unweighted Murphy et al. (2004)	Weighted Murphy et al. (2004)	Uniform cp.net (2005)[a]	AWS	Natural variability
2.5	−2.54	−2.49	−2.94	−2.40	−3.40	−2.67	−2.94	−3.54	2.04	−8.81
5.0	−1.98	−1.74	−2.11	−1.88	−2.61	−2.11	−2.37	−2.67	2.87	−7.40
50.0	5.81	5.05	6.15	5.53	8.07	6.42	7.17	7.83	9.09	0.00
95.0	16.56	18.36	20.83	15.76	22.43	17.56	18.89	24.03	14.64	7.39
97.5	18.66	21.90	24.81	17.64	25.03	19.70	20.86	27.08	15.39	8.78

[a]The results from Stainforth et al. (2005) are here interpreted as a uniform distribution from 1 to 11 degrees C (called Uniform cp.net) because these results had not been constrained by any sort of observed data at the time; it is only the raw data from the uncertainty analysis.

PDFs, the weighted PDF (which uses a Climate Prediction Index to judge the agreement of simulations with observations) increases the uncertainty range and the additional water required at the 95th percentile compared to the unweighted PDF.

5.3. Other climate parameters

With the modelling framework applied here it is possible to determine whether the climate parameters defined in the simple climate model have an impact on adaptation decisions. The parameters examined included: aerosol forcing, ocean diffusivity and carbon cycle. One by one, the highest and lowest values of one parameter were investigated, with the default uniform distribution (or log-normal in the case of carbon cycle) applied to the other two parameters. Table 5 shows the impact of these three parameters on water resources of the ES&E WRZ. Ocean diffusivity and carbon cycle uncertainties have a small influence on water resources (between 2.69 and 2.91 Ml/d at the 95th percentile), but aerosol forcing introduces a larger uncertainty for planning (7.53 Ml/d). This latter uncertainty is large because in the A2-ASF scenario there are large emissions of sulphur dioxide in the first couple of decades of the century. Under low aerosol forcing much more water is required than under high aerosol forcing. This uncertainty is much more scenario dependent than for ocean diffusivity and the carbon cycle; i.e., in a scenario with lower sulphur dioxide emissions than A2-ASF, aerosol-forcing uncertainty will be smaller than in A2-ASF. In conclusion, these three sources of uncertainty are not entirely negligible parameters when it comes to adapting to climate change, especially the magnitude of aerosol forcing.

5.4. Regional climate response

The regional climate response is represented in this modelling framework by a database of results from GCMs and RCMs. If one does not combine the GCM/RCM results into a single PDF as was done in the previous figures (and there are some good reasons why this should not be done), then the largest uncertainty from a decision point of view comes from inter-GCM uncertainty, in the order of 23 Ml/d (Table 6). This large uncertainty arises because certain GCMs show an increase in summer precipitation (e.g., CSIRO), while others show decreases. If RCMs are used instead of GCMs, the uncertainty range at the 95th percentile is still in the order of 15 Ml/d (not shown), which means the uncertainty of how one derives

Table 5
Percentiles of additional water required (in Ml/d) by the 2030s for the ES&E WRZ under the default scheme using GCMs and under changing climate parameters (low and high aerosol forcing, ocean diffusivity and carbon cycle). Also shown is AWS plan and the additional water required solely due to natural multi-decadal climate variability

Percentiles (%)	Default scheme	Low aerosol forcing	High aerosol forcing	Low ocean diffusivity	High ocean diffusivity	Low carbon cycle	High carbon cycle	AWS	Natural variability
2.5	−2.54	−3.27	−2.01	−2.92	−2.56	−2.55	−2.95	2.04	−8.81
5.0	−1.98	−2.52	−1.61	−2.27	−2.01	−2.00	−2.31	2.87	−7.40
50.0	5.81	7.71	4.82	6.93	6.13	5.98	7.12	9.09	0.00
95.0	16.56	20.28	12.75	18.38	15.69	15.82	18.74	14.64	7.39
97.5	18.66	22.02	13.91	20.02	16.97	17.31	20.22	15.39	8.78

Table 6
Percentiles of additional water required (in Ml/d) by the 2030s for the ES&E WRZ under the default scheme using GCMs (uniform distribution) and using different GCMs forced by SRES A2. Also shown is AWS plan and the additional water required solely due to natural multi-decadal climate variability

Percentiles (%)	CGCM2	CSIRO Mk2	CSM 1.3	ECHAM4/ OPYC3	GFDL_ R15_b	MRI2	CCSR/ NIES2	DOE PCM	HadCM3	Default scheme	AWS	Natural variability
2.5	1.23	−1.95	1.22	4.49	3.30	8.23	2.88	0.81	4.59	−2.56	2.03	−8.82
5.0	1.35	−1.81	1.34	4.91	3.61	9.00	3.16	0.89	5.02	−1.98	2.87	−7.40
50.0	2.15	−1.18	2.13	7.81	5.74	14.31	5.02	1.41	7.98	5.82	9.09	0.00
95.0	3.29	−0.74	3.26	11.96	8.79	21.91	7.68	2.17	12.22	16.50	14.64	7.39
97.5	3.55	−0.68	3.52	12.92	9.49	23.67	8.29	2.34	13.20	18.56	15.40	8.82

regional climate information from global models has considerable significance for adaptation planning.

5.5. Climate impacts

The relationship between changes in climate and additional water required in the WRZ is based on hydrological and yield modelling performed by AWS (see Fig. 3). No uncertainty analysis was performed on these models so we assume the gradient of the transfer function to be is uncertain by $\pm 25\%$, based on other uncertainty analysis of water resource projections (see, e.g., Wilby, 2005). The uncertainty range introduced by this variable at the 95th percentile for both GCMs and RCMs is almost the same at around 8.3 Ml/d (not shown). AWS' WRP remains robust nonetheless.

5.6. Summary of the sensitivity analysis

This section summarises the sensitivity experiments/simulations conducted in the previous sections. Table 7 shows the sensitivity of adaptation decisions (measured as additional water required) to the various parameters analysed. The largest uncertainty introduced into adaptation planning comes from the regional climate response, mainly from differences between GCMs, but closely followed by how regional information is derived from GCMs (i.e., RCMs). Both hydrological modelling (climate impacts) and climate sensitivity uncertainties are of equal significance at third place in the sensitivity ranking. Next comes aerosol forcing followed by GHG emissions scenario uncertainty. Ocean diffusivity and carbon cycle uncertainties are amongst the parameters to which the water adaptation decision is least sensitive. It is important to note that uncertainties about aerosol forcing and mitigation policies are largely scenario dependent.

Table 7
Quantification of the uncertainty introduced by the parameters sampled in the assessment using the default scheme (with GCMs) in terms of additional water required (Ml/d) for the East Suffolk & Essex WRZ (at the 95th percentile)

Parameter	Uncertainty range (Ml/d)	AWS shortfall (Ml/d)
GHG emissions scenario	5.55	7.35
Climate sensitivity	8.27	9.39
Aerosol forcing	7.53	5.63
Ocean diffusivity	2.69	3.74
Carbon cycle	2.91	4.01
Regional climate response GCMs (RCMs)	22.66 (14.88)	7.28 (9.10)
Climate impacts	8.28	6.06

Also shown is AWS's WRP shortfall, i.e., the difference between the most extreme PDF, scenario or value sampled for each parameter and the triangular PDF AWS used in its planning at the 95th percentile.

6. Discussion

This paper has demonstrated the application of a framework to identify robust adaptation decisions under conditions of climate change uncertainty. To our knowledge, no adaptation assessment has ever considered this many climate change uncertainties in such a systematic approach. Water resources were found to be highly sensitive to a number of uncertainties such as regional climate response (in particular to GCMs, but also to RCMs), climate sensitivity and climate impacts. Aerosol forcing and GHG emissions uncertainties were also found to be moderately important, whereas uncertainties from ocean mixing and the carbon cycle were not.

Under the 'one-at-a-time' sensitivity experiments, Anglian Water's WRP remained robust to the uncertainties examined. There are three major explanations for this. One is that the WRP was put together using, by chance not design, one of the driest models (HadCM3) in the range (see Table 6). Their strategy, therefore, happens to be robust to enhanced drought conditions for this fortuitous reason. The second explanation is due to the size of the adaptation options being considered, for example large supply side increases such as WTWs or reservoir extensions, which leaves a positive supply/demand balance by the end of the period. The third reason is that 'one-at-a-time' experiments do not combine extremes: for example, a high carbon emissions scenarios with low sulphur forcing, with high climate sensitivity and a strong drying regional response. If one combines the extremes of each uncertainty sampled here in order to quantify the bounds of possibilities then the additional water required by 2030s for the ES&E WRZ ranges from −5.12 to 62.16 Ml/d. If water managers at AWS wanted to be immune to all these combinations of uncertainties and maintain levels of service during the next 25 years then further investment (beyond that anticipated in the WRP) is required.

Perhaps not surprisingly regional climate change is the largest source of uncertainty in the assessment conducted here. It is important to note that the RCM results (and its uncertainty range) are only a subset of the GCM results since they were driven by only two GCMs (HadCM3 and ECHAM4). This implies that the regional climate change uncertainty is in fact larger than the results presented here. Various efforts are underway at exploring this facet (see Hewitt and Griggs, 2004; Stainforth et al., 2005). Even though it was scenario dependent, aerosol-forcing uncertainty introduced some uncertainty into water resources planning, larger than that introduced by emission scenario and climate sensitivity uncertainties. The WRP was largely insensitive to uncertainties in the carbon cycle and ocean mixing, as applied in this modelling framework and assuming the WRP is fully implemented. For a less-stringent WRP even these uncertainties could matter.

The modelling framework applied in this paper can be characterised as mostly linear. This emanates from using a simple energy balance model, the pattern-scaling technique and linear transfer functions for climate impacts. There are various advantages and disadvantages to such a modelling framework. Perhaps the most obvious and pertinent advantage of this approach, compared to more complex approaches, is the ability to perform sensitivity analysis. It is impossible as yet to perform global sensitivity analysis in complex non-linear GCMs in order to determine which parameters dominate the model's response to external forcing. The fact that the modelling framework is linear and simple is also the source of its major limitations. For example, the energy balance model MAGICC can emulate the behaviour of more complex GCMs, but it cannot mimic the variability and other non-linearities that GCMs display. Pattern scaling assumes there is a linear relationship between global mean temperature and local climate variables. This relationship has been shown to hold with one climate model (HadCM2, see Mitchell et al., 1999; Mitchell, 2003) but it is unknown whether it holds throughout the uncertainty spectrum explored here. Instead of using a simple transfer function to represent climate impacts and its uncertainty an actual hydrological model could be used (see, e.g., Wilby, 2005). Due to computational power restrictions a pragmatic trade off between being able to perform sensitivity analysis and model complexity is required.

Another limitation of this study is that only changes in average seasonal summer precipitation for a 30-year period centred on the 2030s was examined. This was a limitation brought about by using the pattern-scaling technique and the desire to manage uncertainties consistently. This means this paper is silent about changes in inter-annual variability and extremes. It essentially assumes that the transfer function for climate impacts provides this information. If the variance of extremes changed significantly, for example with a substantial increase in dry spells, then the results of this paper would represent an underestimation of risk for AWS.

One of the major challenges of this work was to link climate change uncertainties to real world decision-making. However, it is important to acknowledge that the decisions being contemplated (in particular those beyond 2015) are not actually being implemented or perused yet (e.g., Alton WTW extension or a new East Anglian reservoir) because, according to the water regulators, there is currently not enough certainty or evidence to justify investment in water resources if climate change is the main driver (see EA, 2004). This is not surprising given that water companies have put together their WRPs using only one RCM driven by one GCM (see UKCIP02), thus sampling only a very small fraction of the plausible uncertainty space.

The approach developed here opens up a large array of new questions, in particular to the decision-makers. How much climate change uncertainty do we want to adapt to? How can we trade-off robustness with increasing cost? Are robust adaptation options socially, environmentally and economically acceptable? How do climate change uncertainties compare with other uncertainties (e.g., changes in demand)? How much public money should be invested to research the largest scientific (tractable) uncertainty to try to reduce it?

Are the conclusions from this paper valid in other adaptation settings, for example in other sectors? From the experience of conducting this research it is possible to speculate that: (1) robustness to climate change uncertainties usually means higher costs (and therefore lower aspirations); (2) different impact sectors will be sensitive to different uncertainties in climate change assessments; (3) the robustness of adaptation strategies to climate change uncertainties will likely depend on the pressure exerted on the decision process by drivers other than climate. This implies that context is crucial and that it is difficult to generalise any lessons from this case study to wider adaptation planning. Further case studies need to be investigated to illuminate these speculations.

Clearly robust adaptation decisions are desirable, but these have to be negotiated between the decision-makers and stakeholders involved in the adaptation process. This will put greater emphasis on communicating uncertainties, using a transparent modelling and assessment framework and embracing participatory approaches. Robust adaptation to climate change is not easy.

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