Journal of Water and Climate Change, 2013, Vol 5, No 1, pp 13–24

A critical comparison of using a probabilistic weather generator versus a change factor approach; irrigation reservoir planning under climate change

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Abstract:

In the UK, there is a growing interest in constructing on-farm irrigation reservoirs, however deciding the optimum reservoir capacity is not simple. There are two distinct approaches to generating the future daily weather datasets needed to calculate future irrigation need.

The change factor approach perturbs the observed record using monthly change factors derived from downscaled climate models. This assumes that whilst the climate changes, the day-to-day climate variability itself is stationary. Problems may arise where the instrumental record is insufficient or particularly suspect. Alternatively, probabilistic weather generators can be used to identify options which are considered more robust to climate change uncertainty because they consider non-stationary climate variability.

This paper explores the difference between using the change factor approach and a probabilistic weather generator for informing farm reservoir design at three sites in the UK. Decision outcomes obtained using the current normal practice of 80% probability of non-exceedance rule and simple economic optimisations are also compared.

Decision outcomes obtained using the change factor approach and probabilistic weather generators are significantly different; whether these differences translate to real-world differences is discussed. This study also found that using the 80% probability of non-exceedance rule could potentially result in maladaptation.

Key Words:

Irrigation demand, Adaptation, UKCP09, Weather generator, Change factor, WaSim

Background

Water is integral to the UK's ability to grow high quality horticultural produce. In the UK, approximately 150,000 ha are irrigated during a dry year (Knox et al, 2010). The sustainability of irrigated production is however under threat from competition for water from other sectors, new legislation designed to enhance environmental protection, and climate change (Weatherhead et al, 2008).

Water resources in many catchments are already strained. During summer, many existing water sources become increasingly unreliable and new licenses for summer abstractions are now widely unobtainable or are issued with tight minimum flow or minimum level constraints. Increasingly farmers, agribusiness and water resource managers are being encouraged to build on-farm irrigation reservoirs as part of their water resource strategy to avoid the restrictions and environmental impact of abstraction during summer months (Weatherhead et al, 2008). Climate change is expected to simultaneously increase water demand and reduce water availability (Kang et al, 2009).

The unpredictability of the future climate is perhaps the greatest challenge facing the water industry (Harris et al, 2012). In the UK at least, much of the current infrastructure including irrigation reservoirs were built on the assumption that the climate in which it was built would endure for its entire lifetime – this is no longer the case (Harris et al, 2012).

Two responses have emerged in reaction to the risks posed by future climate change, namely mitigation and adaptation (Füssel, 2007). Mitigation refers to "an anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases" (IPCC, 2001). In contrast, adaptation, studied in this paper, refers to "the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects which moderates harm or exploits beneficial opportunities" (Parry et al, 2007, p.6). In the UK, adaptation planning emerged as a policy issue in 1997 in response to the formulation of the UK Climate Impacts Programme (UKCIP) (Hedger et al, 2006), receiving renewed interest with the passing of the Climate Change Act 2008 (Tang and Dessai, 2012). The apparent 'failure' of high profile climate change protocols (e.g. the Kyoto protocol) has undermined confidence in the success of mitigation efforts, making adaptation a more attractive surrogate (Anderson and Bows, 2011; Fung et al, 2011 and Sanderson et al, 2011; Harris et al, 2012).

A number of approaches to adaptation have been identified. Vulnerability-led adaptation includes methods aimed at identifying and reducing present community/system vulnerability; thereby reducing future exposure to potentially damaging impacts. Scenario-led adaptation, studied here, uses future climate change projections to assess future climate change impacts. Downscaled regional-scale climate scenario data can be fed into impact models; the outputs are then used to inform adaptation, to maximise potential benefits and/or minimise potential risks (Wilby and Dessai, 2010). A hybrid approach, combining elements of vulnerability-led and scenario-led approaches has recently emerged, though is not the focus of this paper (Brown and Wilby, 2012).

Scenario-led adaptation is limited by the financial and technical capacity of the individuals undertaking the adaptation; their risk appetite, the availability of high quality downscaled climate change information and the type of adaptation options being considered (Adger et al, 2005; Dessai et al, 2005). Despite greater awareness of its benefits (Füssel, 2007; Ranger et al, 2010), few real-world cases of scenario-led adaptation decisions have been realised (Tompkins et al, 20120), with large sector and regional differences in the type of adaptation considered. This limited uptake has been attributed to a variety of factors; see Moser and Ekstrom (2010) for an extensive discussion.

Scenario-led adaptation is used here to model irrigation demand and inform farm reservoir design in a semi-humid climate. A sufficiently long daily weather record is essential to adequately gauge the amount of water required. For the baseline period (1961-1990), irrigation demand calculations are often based on the observed record, though this may be substituted with a synthetic series from a weather generator provided it has been suitably calibrated (Green and Weatherhead, 2013). Similarly, a sufficiently long record of future daily weather data is required to model irrigation demand under the effects of climate change. Future weather data is typically generated from downscaled global climate models (GCM). GCM outputs are often only available as monthly values (Holman et al, 2009), which are generally insufficient for modelling dry year supplemental irrigation demand and many hydrological processes. They can however be used to perturb an observed or synthetic daily series using the 'change factor' approach (Loaiciga et al, 2000), elsewhere referred to as perturbation or the "delta-change" method (Prudhomme et al, 2002). A change factor is obtained for each month in the future series, these figures are then used to perturb an observed baseline daily series to produce a future series i.e. applying a January monthly change factor of 10% to an observed series would make all of the daily values in the future series for the month of January +10% larger (Holman et al, 2009). A criticism of the change factor approach is that it assumes that the climate variability is stationary, e.g. the same patterns of wet and dry days will occur in the future dataset as in the original baseline (Harris et al, 2012). Despite this, it remains a popular approach, given its relative simplicity and low computation demands (e.g. Dacacche et al, 2012). Alternatively, a probabilistic weather generator can be used to generate multiple future time series using perturbed synthetic baselines. Unlike the conventional change factor approach, weather generators are not dependant on the individual having access to a suitably long observed record (Green and Weatherhead, 2013) nor do they assume that the future climate variability is stationary, making them an attractive tool for supporting robust decision making (Groves and Lempert, 2007; Dessai et al, 2009; Lempert and Groves, 2010; Harris et al, 2012). The change factor approach and UKCP09 weather generator (Semenov 2007; Wilks and Wilby, 2009) are both examples of statistical downscaling (Wilby et al, 2004), while they are not utilised here, alternative methods collectively referred to as dynamical downscaling techniques also exist (Mearns et al, 2003). An extensive discussion of the merits and weaknesses of these and other downscaling techniques can be found elsewhere and in greater detail (Prudhomme et al, 2002; Fowler et al, 2007)

The primary source of future climate projections in the UK is the UKCP09 dataset (Murphy, 2009). UKCP09 provides 10,000 probabilistic climate projections at a 25km scale resolution generated from a perturbed ensemble experiment using the HadCM3 Global climate model (GCM). These are provided in the format of monthly change factors. Alternatively, daily (and even hourly) projections, and at a finer spatial resolution of $5km^2$, are readily available as outputs from UKCP09's weather generator (Jones et al, 2009). The weather generator provides baseline ("control") and future scenario sequences for three different greenhouse gases emission scenarios (low, medium and high) and for selected 30 year time-slices (centred around the 2020s, 2030s, 2040s, 2050s, 2060s, 2070s and 2080s respectively).

These daily weather datasets can be imported into soil water balance models such as WaSim, freely available via the Cranfield University website, to model the irrigation demand of various crops (Hess and Counsell, 2000). WaSim simulates inflow (infiltration) and outflow (evapotranspiration and drainage) and storage of soil water in response to climate, irrigation and drainage (Depeweg and Fabiola Otero, 2004). WaSim has proven invaluable across a range of previous studies including determining irrigation requirements, optimising water management, assessing the performance of sub-surface drainage systems and studying the effects of climate change on water resources (Depeweg and Fabiola Otero, 2004; Hirekhan et al, 2007, Warren and Holman, 2011). WaSim divides the soil profile into five layers, water moves from upper layers to lower layers when the water content of the respective layer exceeds field capacity. The first three layers are comprised of the surface layer (0-0.15m), the active root zone layer (0.15-root depth) and the unsaturated layer below the root zone (root depth-water table). The remaining 2 layers are comprised of the saturated layer above drain depth (water table – drain depth) and the saturated layer below drain depth (depth drain – impermeable layer). The boundary between the second and third layers changes in response to root growth (e.g. in the case of potatoes, layer 2 has zero thickness when root depth is less than 0.15m, and then increases as the potato develops). Guidance values covering crop development and root depths are provided for selected crops within WaSim, and up to three crops can be combined in a cropping pattern (Hess and Counsell, 2000).

In the field of irrigated agriculture, decision makers have typically relied on the design dry year rule for estimating the volume of irrigation required. A design dry year is defined in the UK as a year with an 80% probability of non-exceedance (roughly equivalent to the older "fourth driest year of five" rule of thumb). This rule of thumb is generally considered the 'best practice approach' and forms the basis of most water allocation for UK irrigated agriculture (Weatherhead and Knox, 2000).

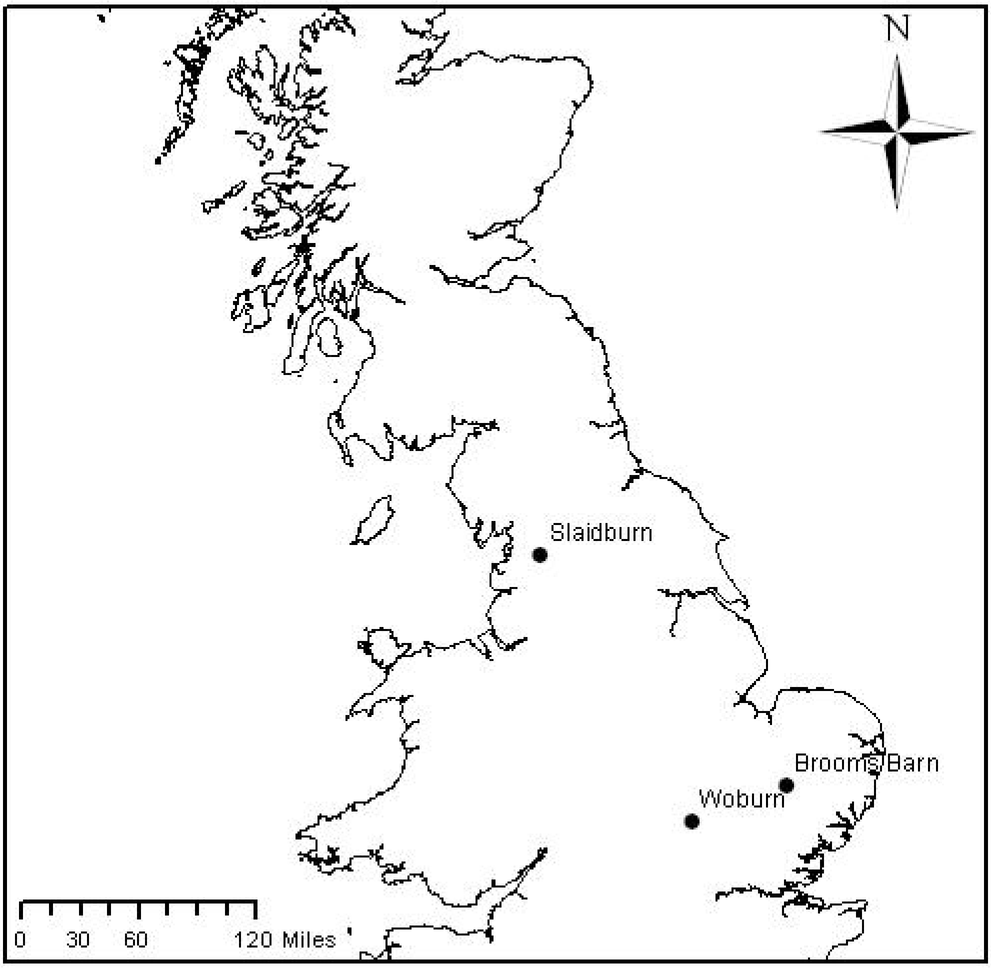
This study explores the difference between using the change factor approach and the UKCP09 weather generator for modelling future irrigation demand and informing reservoir design at three sites in the UK. Decision outcomes are obtained using the 80% probability of non-exceedance rule and an economic optimisation and compared.

Method:

A previous study by Green and Weatherhead (2013) found that the weather generator was reasonably calibrated at a number of UK sites. Three sites representing different agro-climatic conditions distributed around the UK were selected as case studies. These particular sites were chosen because they had the most complete record for the baseline period. Brooms Barn is located in the county of Suffolk, near Bury St Edmunds, approximately 30km east of Cambridge and is the driest of the investigated sites. Slaidburn is located in the district of Lancashire, approximately 60km north-west of Leeds and is the wettest site with an average annual rainfall of 1515 mm.year^{-1} for the baseline period. Lastly, Woburn is situated in the county of Bedfordshire, 50km north-west of London and is marginally wetter than Brooms barn but with slightly lower annual evapotranspiration. Observed climate data was extracted for the baseline period from the weather station at each site. Additional hydroclimatology data for the baseline period is shown in Table 1.

Table 1 Weather station sites and records used

Station	Lat.	Long.	Elevation	Average annual (1961-1990)		Data	
			(m AOD)	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



All 10,000 monthly change factor climate projections were extracted from the UKCP09 sample ensemble for the single 25km^2 grid square overlying each weather station, for each emission scenario (i.e. low, medium and high) for the 2050s time slice (i.e. 2040-2069). Baseline evapotranspiration and monthly evapotranspiration change factors were estimated using Penman-

Monteith (Monteith, 1965); wind speed was assumed to be the same as the observed baseline (1969-1990) due to the lack of earlier baseline data and future projections of wind speed.

Ten thousand climate projections were simultaneously generated using the UKCP09 weather generator, using the same ID codes to allow direct comparison, again for each weather station and each emissions scenario. The UKCP09 weather generator was previously found to be reasonably calibrated at these sites with the exception of some extreme events (which are beyond the scope of our analysis and do not impact the reservoir design) (Green and Weatherhead, 2013).

As the weather generator offers a much greater spatial resolution of $5km^2$, data was generated for a grouping of 25 individual grid squares (i.e. a combined area of $25km^2$) overlying each weather station, to be directly comparable with the 10,000 member ensemble $25km^2$ grid square. It should be noted that the weather generator and 10,000 member sample ensemble spatial grids differ slightly in their orientation which may create subtle differences in the projected climate, though because of the large areas used, the impact is considered somewhat negligible. Despite this, the potential impacts on the outcomes of this study are an acknowledged limitation.

Next, WaSim was used to model irrigation demand at each site. In its basic format WaSim is not capable of processing multiple climate files succinctly, so a modified version was developed and employed for this study to read-in multiple climate files and output a single results file containing the daily irrigation demand for each of the 10000 climate files. A potato crop was simulated with a planting depth of 0.15m, max root depth of 0.7m and planting date of 1^{st} April. A rule based irrigation schedule was modelled based on best practice guidelines including scab control (Defra, 2005). This schedule consisted of 4 periods (1 non-irrigation followed by 2 irrigation and 1-non irrigation), applying 15mm of water early in the growing season whenever the root zone deficit exceeded 18mm during period 2 (15^{th} May-30^{th} June) and applying 25mm of water whenever the root zone deficit exceeded 30mm during period 3 (30^{th} June-31^{st} Aug). Irrigation early in the growing season is essential for some varieties for minimising the chance of potato scab, a common bacterial blight which can severely reduce the market value of produce (Liu et al 1996). Irrigation is also important for promoting higher tuber numbers, accelerating crop canopy growth, reducing the chance of uneven growth and thumbnail cracking and reducing crop damage during harvesting (Defra, 2005). The soil type was set as sandy loam, which is the dominant soil type for potato crops in England, with an assumed saturation of 43.3% and field capacity of 24.5%.

The irrigation demand was calculated for each year in the 10,000 x 30 year sequences for each site and emission scenario, using both the change factor and weather generator datasets. The values within each sequence were then ranked from smallest to largest. The irrigation demand during the design dry year, (referred to hereafter as 80% dry year irrigation demand) was calculated for each of the 10,000 sequences, using the 80% probability of non-exceedance rule. The median, mean, quartile and extreme values for each site, emission scenario and dataset were identified.

For the economic evaluation, typical costs and benefits for clay agricultural reservoirs were obtained from a concurrent study (Weatherhead et al, 2008). The economic benefit of the water contained within each reservoir was calculated on the basis of average water use, assuming an average net benefit (for potatoes) of £1.56/m^3 of water used (Morris et al, 1997). Earthwork costs were assumed to be £1.125 per m^3 of earth moved, plus an additional 15% reflecting site investigation costs. A further £20k was added, representing the assumed connection costs of 3-phase electricity. Annual OPEX was assumed to be 1% of CAPEX, representing the low maintenance cost of clay reservoirs (Weatherhead et al, 2010). Each of the 10,000 sequences was then used to calculate the net present value (NPV) of a range of reservoir sizes, with usable storage capacities equivalent to 0 to 1000mm.year^{-1} for the area irrigated. NPV provides a measure of the present value of the difference between the assumed costs and benefits of a decision. NPV was calculated by discounting the annual net benefit of the reservoir loss OPEX costs with a lumped (non-discounted) CAPEX in year 0, assuming current government discount rate guidelines of 3.5% on investments of up to 30 years (Treasury HM, 2011). Each reservoir was assumed to last 30 years, representing their typical life cycle. The optimum reservoir capacity, defined as the size providing the highest NPV was calculated for each of the 10,000 sequences. The median, mean, quartile and extreme values for each site, emission scenario and dataset were identified as before.

The Mann-Whitney U-test (Mann and Whitney, 1947) was used to establish whether there was significant differences between the change factor and weather generator datasets in terms of both the 80% dry year irrigation demands and the optimum reservoir capacities. The Mann-Whitney U test was chosen due to the non-parametric nature of the data even after applying transformations. The Mann-Whitney U test is used to test the equality of two population medians. It is considered the non-parametric alternative to the 2-sample t-test, it assumes that the populations are independent and have a similar distribution shape. Unlike the 2-sample t-test it does not require the two populations to be normally distributed.

In addition, a sensitivity analysis was undertaken to establish how sensitive the decision outcome was to the choice of discount rate, benefit of the water and earthwork costs. Each parameter was varied in turn, keeping the other parameters fixed, and the median optimum reservoir capacity identified, calculating the percentage difference before and after varying each parameter. The discount rate was initially fixed at 3.5%, water benefit at £1.56/m^3 and earthworks at £1.1.25/m^3, and subsequently scaled up and down using a linear coefficient.

Results and Discussion:

The 80% dry year irrigation demands were compared between the change factor and weather generator sequences for each sites and emission scenario (Figure 1). The median 80% dry year irrigation demand was similar across both datasets. Both also had a similar interquartile and extreme range. These results support the assumption that the weather generator was reasonably calibrated with the observed record (Green and Weatherhead, 2013) and suggest that using the UKCP09 weather generator instead of the conventional change factor approach may not necessarily lead to more robust decision making.

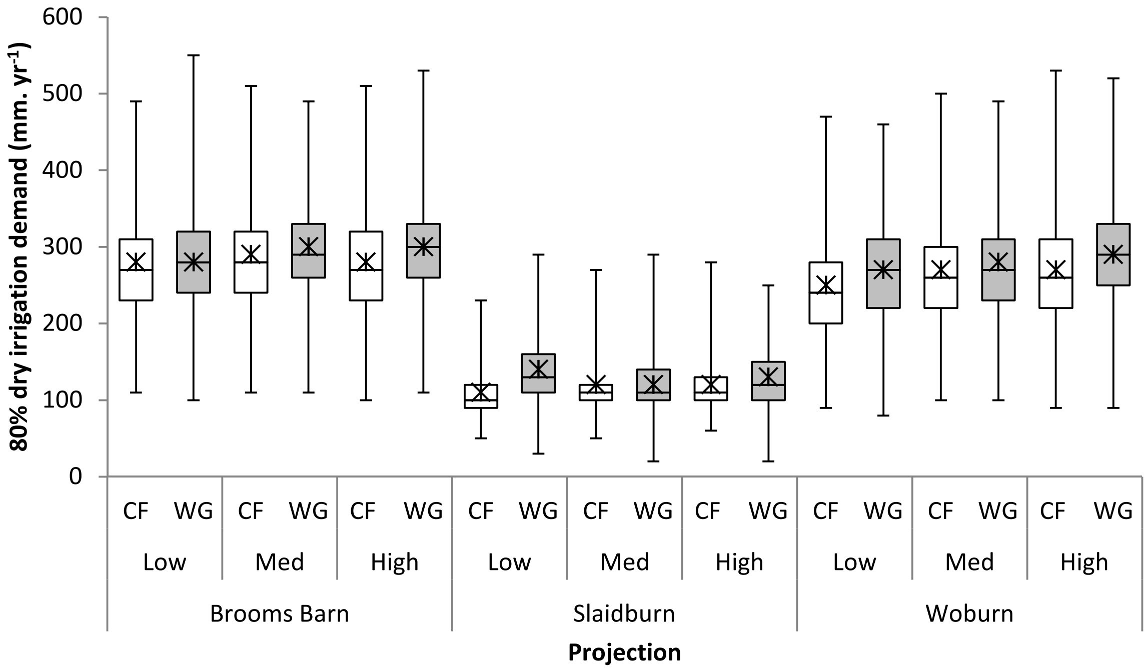


Figure 1. Median (-), mean (X), quartile and extreme values of the 80% dry year irrigation demand for the change factor (CF) and weather generator (WG) sequences for each site and emission scenario.

Next, the economic performance of various reservoir capacities generated using the full 10000 change factor and weather generator sequences were compared against each other for each site and emission scenario. Figure 2 shows the results obtained for the site of Woburn using the medium emission scenario. Despite subtle differences in the projected NPV, both datasets showed a similar trend in NPV against reservoir capacity. The weather generator projected a higher NPV for most reservoir capacities, based on the median projection, with the exception of small reservoirs with a capacity of less than $100 mm.yr^{-1}$. The NPV range (i.e. the difference between the max payoff and minimum payoff for each reservoir size) is initially quite narrow and increases with reservoir capacity. The NPV range is larger for the weather generator dataset than for the change factor dataset for all the reservoir capacities considered. For the change factor dataset, the median optimum reservoir capacity was 340mm.year^{-1}. In contrast, the weather generator estimated the median optimum reservoir capacity to be marginally smaller at 320mm.year^{-1} but with a 20% larger NPV. Similar results were recorded for all three emission scenarios for all three sites.

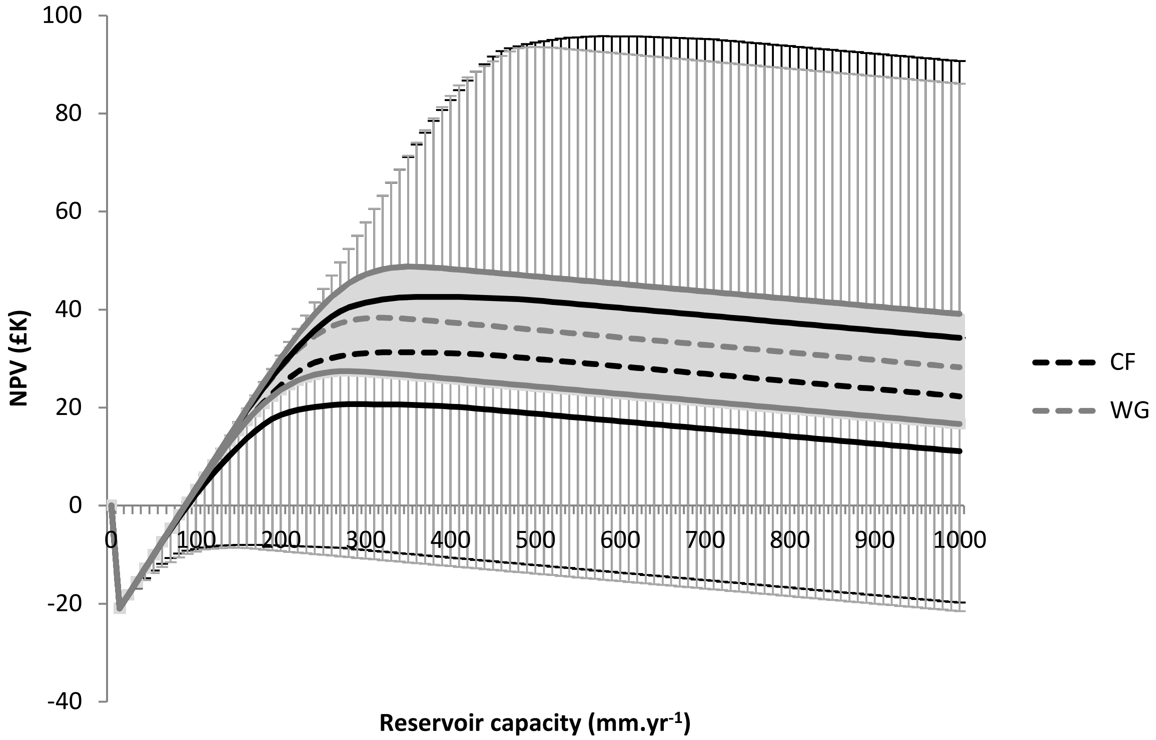


Figure 2. Median, quartile and extreme values of NPV against reservoir capacity for the change factor (CF) and UKCP09 weather generator (WG) sequences for the Woburn site and medium emission scenario.

Statistical analysis was undertaken to establish whether there was significant difference between using the weather generator and change factor datasets in terms of 1) the 80% dry year irrigation demand and 2) the optimum reservoir capacity. The 80% dry year irrigation demand values obtained using the weather generator dataset were significantly greater than those from using the change factor dataset. In contrast, the optimum reservoir capacities from the weather generator dataset were significantly lower than from the change factor dataset. However, while the differences were statistically significant at the 95CI (Table 2), the difference in the 80% dry year irrigation demand was generally less than 25mm.year^{-1}, which is only the depth of a typical single application of water. The difference in the optimum reservoir capacities was similarly small (though generally >25mm.year^{-1}), with the exception of the Brooms Barn site. These results again suggest that using the weather generator in place of the conventional change factor, while theoretically leading to more robust decision making, in reality is unlikely to greatly affect the decision outcome.

Table 2. Results of Mann-Whitney U-test statistical analysis comparing 80% dry year irrigation demand and optimum reservoir capacity obtained using economic optimisation with change factor (CF) and weather generator (WG) datasets, showing median reservoir capacity, whether they are significantly different and using 95 confidence interval (95CI).

Site	Brooms Barn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	270	280	280	290	270	300	360	310	370	320	370	330
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		000		0.00		0.00		0.00	

Site	Slaidburn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	L		M		H		L		M		H	
Data	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	100	130	110	110	110	120	0	0	0	0	0	0
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Site	Woburn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	Low		Med		High		Low		Med		High	
Data source	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	240	270	260	270	260	290	320	300	340	320	340	320
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00		0.00		0.00		0.00		0.00	

Finally, the optimum reservoir capacity was directly compared with the dry year irrigation demand calculated using a range on probability of non-exceedance values (80%, 85%, 90%, 95% and 100%). Based on these initial findings, the 80% probability of exceedance rule appears to underestimate the optimum reservoir capacity at Brooms Barn and Woburn and overestimate the optimum reservoir capacity at Slaidburn (the wettest site), with a difference of between -120 to +100mm.ha^{-1} (Figure 3). The 95% probability of non-exceedance rule had a smaller difference of between 0 to + 170mm.year^{-1}. Visual comparison would suggest that the 95% probability of non-exceedance rule is much closer to the optimum reservoir capacity at the sites of Brooms Barn and Woburn. However at the site of Slaidburn, all five probability of non-exceedance rules tested appear to considerably overestimate the optimum reservoir capacity (see Figure 3). This result should serve as a warning to those stakeholders who do not consider the underlying economics of their decision; blind use of probability of non-exceedance rules can lead to maladaptation with stakeholders either over-designing or under-designing their assets.

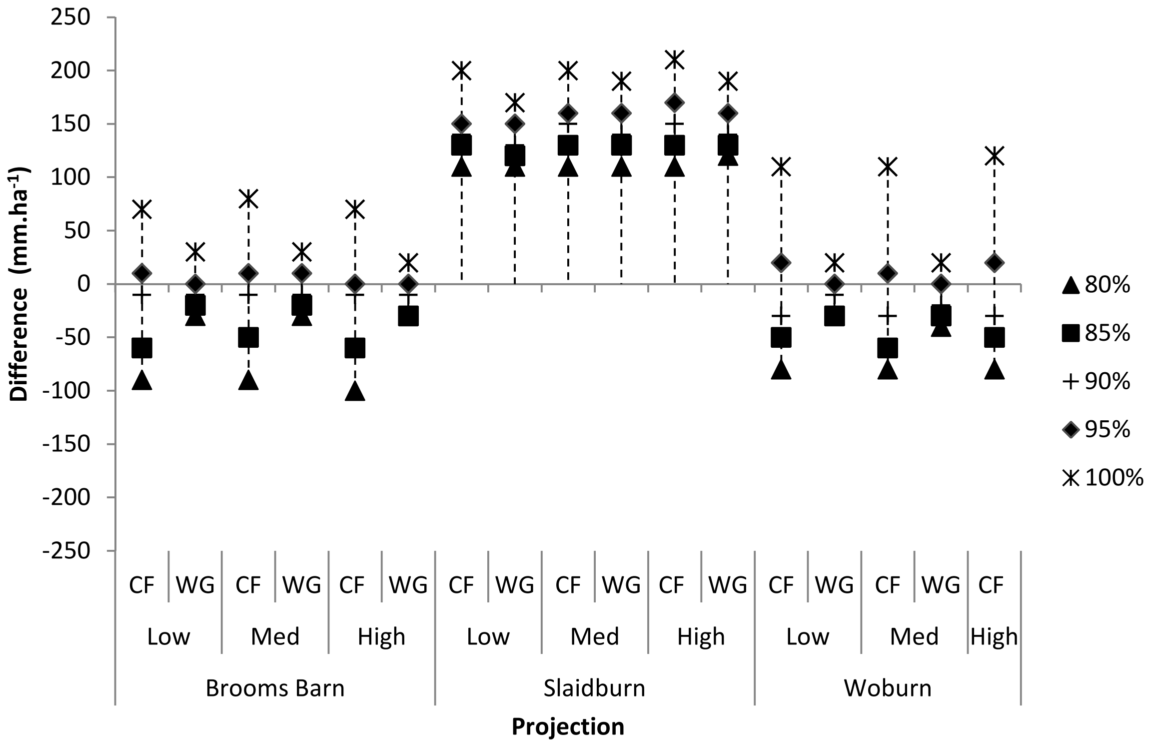


Figure 3. Differences between the median dry year irrigation demands using 80% to 95% exceedance rules and the median optimum reservoir capacity, for the change factor (CF) and weather generator (WG) sequences for each site and emission scenario.

The results of this study are dependent on several assumptions including 1) discount rate, 2) earth work costs and 3) monetary benefit of the water. Each of these variables is a potential source of uncertainty and may potentially affect the optimum reservoir capacity. As a result, a sensitivity analysis was undertaken to establish whether altering these parameters changed the perceived optimum reservoir capacity.

The sensitivity analysis is presented here for the site of Woburn, for the medium emission scenario and the weather generator dataset. Similar results were obtained for the other sites and emission scenarios and for the change factor dataset. The optimum reservoir capacity was largely insensitive to the discount rate, evident from the near horizontal line, with larger discount rates slightly favouring smaller reservoirs (**Figure 4**). The reservoir capacity was more sensitive to earthworks costs, with larger earthworks costs favouring smaller reservoirs, again as expected. The value of the water in the reservoir had the largest effect on the optimum reservoir capacity; below £0.78.m^{-3} the reservoir produced a negative NPV and was no longer economically viable at this site. Increasing the value of water above £1.56.m^{-3} had surprisingly little effect on the optimum reservoir capacity, increasing it by only 9.7% even up to a value of £4.68.m^{-3}; this reflects the point that useful capacity is limited by demand, with decreasing returns to additional capacity.

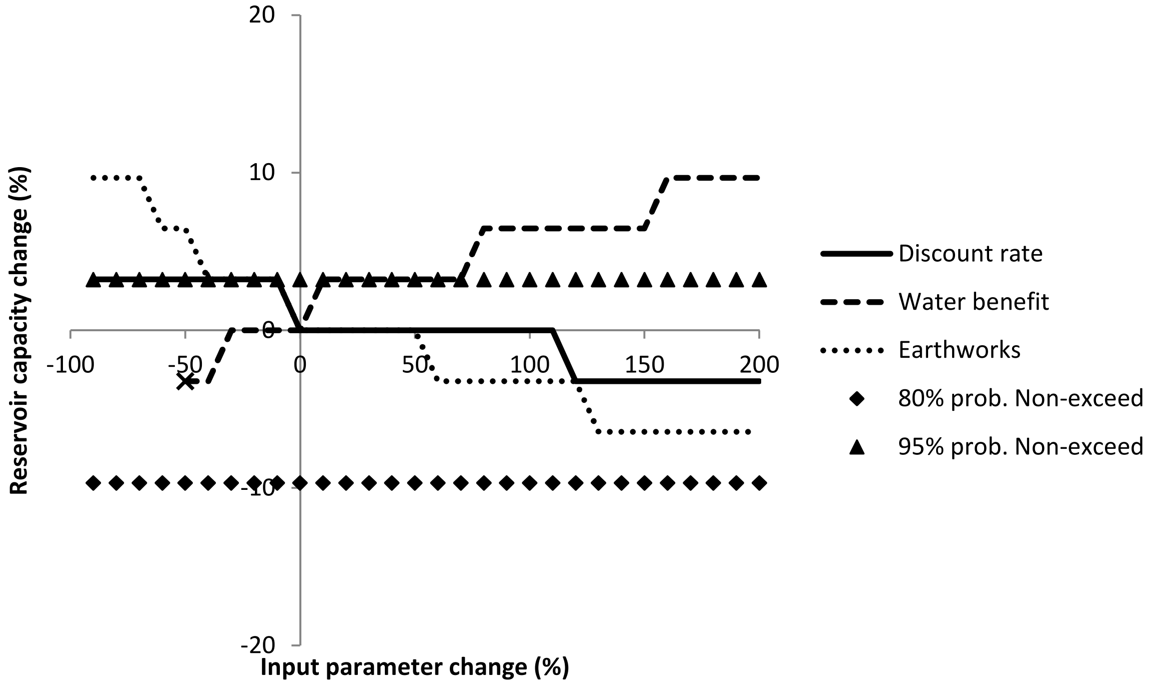


Figure 4. Sensitivity analysis comparing optimum reservoir capacity against discount rate, water benefit and earthworks cost, showing changes relative to base parameter values, for the Woburn site and medium emission scenario. The 80% and 95% dry year irrigation demands are also shown for comparison.

These variations in median optimum reservoir capacity were subsequently compared to the capacities given by the simpler % exceedance rules, in this case the 80% and 95% dry year irrigation demand. For the Woburn site and the base variable values, the 95% probability of non-exceedance rule out performs the 80% probability of non-exceedance rule (Figure 4). At larger discount rates (>7%) the 80% rule works better, and for lower earthwork costs (less than £1.80.m^{-3}) the two rules are equally close. For all water values, the 95% probability of non-exceedance rule was nearer the optimum value, but both rules failed to show that the reservoir was no longer economically viable when the water value was less than £0.78.m^{-3}. More case studies would be needed to confirm theses are general results, but they suggest that the 80% rule may be misleading.

It should be noted that these findings are conditional on the view that the median optimum reservoir capacity of the 10,000 sequences represents the most appropriate course of action (akin to the 'Laplacian' view of investment appraisal) (French, 1986). Decision makers who are particularly risk averse or risk seeking may disagree with this assumption and may instead use the quartile or even best/worst case projections, though for the vast majority of stakeholders our stated assumptions should suffice.

Global climate models (GCM) providing "high" resolution daily projections are few in number and those which do are considered less accurate (Paluktikof et al, 1997; Huth et al, 2001). As a result, GCM climate change projections often need to be downscaled both spatially and temporally before they can be of any use for decision makers. Numerous downscaling approaches are available, including but not limited to the change factor approach and UKCP09 weather generator considered here. Different downscaling techniques come with their own advantages and disadvantages; see Wilby et al (2004) and Fowler et al (2007) for extensive reviews. The UKCP09 weather generator is theoretically better than the conventional change factor approach, given that it allows for non-stationary variability to be simulated and thus incorporated into climate change risk assessments and adaptation planning (Harris et al, 2012). The UKCP09 weather is however not without its flaws, a previous study by Tham et al (2011) found that the weather generator initially released with UKCP09 was unable to reproduce observations of key climate variables including sunshine duration and solar irradiation.

In later versions of the UKCP09 weather generator, modifications were made to the weather generator to improve its predictive capabilities, which were later verified by Eames et al, (2012).

They found that the weather generator was capable of producing weather data that was consistent with historical monthly observations of wind, speed, direct irradiation, diffuse irradiation, global irradiation, maximum temperature, minimum temperature and mean temperature. This result is consistent with previous findings by Green and Weatherhead (2013) which showed that the UKCP09 was capable of reproducing observed precipitation and evapotranspiration and annual irrigation demand reasonably well. Eames et al (2012) also noted that subsequent iterations of the UKCP09 weather generator had issues reproducing a realistic distribution of sunshine hours and direct and diffuse irradiation which can lead to absurd conclusions. We expect that the UKCP09 weather generator will be gradually improved over time to reduce or remove these concerns; while they did not affect the findings of this study they may have implications for other applications where hourly data is of high importance.

A criticism of the change factor method, as previously noted, is that it assumes that the temporal and spatial structure of future precipitation and evapotranspiration remains unchanged (Diaz-Nieto and Wilby, 2005; Fowler et al, 2005; Minvlle et al, 2008; Harris et al, 2012). In some situations, it is necessary to evaluate changes in climate variability and not just changes in means (Semenov et al, 1998). Despite this, the change factor approach remains popular because of its simplicity and is useful for converting monthly change factors into daily projections needed to model most hydrological processes without incurring excessive expense (Minville et al, 2008).

Conclusions

This study found that use of a weather generator not greatly alter the decision outcome compared to using the conventional and relative crude change factor approach, suggesting that the changes in day-to-day climate variability that is simulated by the weather generator are not significant enough to warrant action when informing irrigation reservoir design. This result is contrary to the expectation that the UKCP09 weather generator lends itself to more robust decision making; in reality the difference between the two approaches is negligible.

The core benefits of the weather generator may continue to make it an attractive tool to use, those being that it provides hourly climate data and readily available evapotranspiration data. Whether these benefits outweigh its fundamental limitations including the poor simulation of extreme meteorological events, is subject to the sensitivity of each application and the user's requirements. The study also found that the "best-practice" approach of using the 80% probability of non-exceedance rule is inadequate and designers should instead investigate the fundamental economics (e.g. NPV) that underpin the decision making process.

Acknowledgements

We would like to thank the Engineering and Physical Sciences Research Council (EPSRC) and HR Wallingford for funding this research.

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