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

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

18 **Green, M. and Weatherhead, E.K**

19 **Abstract:**

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

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

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

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

37 **Key Words:**

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

## 39 **Background**

40 Water is integral to the UK's ability to grow high quality horticultural produce. In the UK,  
41 approximately 150,000 ha are irrigated during a dry year (Knox et al, 2010). The sustainability of  
42 irrigated production is however under threat from competition for water from other sectors, new  
43 legislation designed to enhance environmental protection, and climate change (Weatherhead et al,  
44 2008).

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

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

56 Two responses have emerged in reaction to the risks posed by future climate change, namely  
57 mitigation and adaptation (Füssel, 2007). Mitigation refers to “an anthropogenic intervention to  
58 reduce the sources or enhance the sinks of greenhouse gases” (IPCC, 2001). In contrast, adaptation,  
59 studied in this paper, refers to “the adjustment in natural or human systems in response to actual or  
60 expected climatic stimuli or their effects which moderates harm or exploits beneficial opportunities”  
61 (Parry et al, 2007, p.6). In the UK, adaptation planning emerged as a policy issue in 1997 in response  
62 to the formulation of the UK Climate Impacts Programme (UKCIP) (Hedger et al, 2006), receiving

63 renewed interest with the passing of the Climate Change Act 2008 (Tang and Dessai, 2012). The  
64 apparent 'failure' of high profile climate change protocols (e.g. the Kyoto protocol) has undermined  
65 confidence in the success of mitigation efforts, making adaptation a more attractive surrogate  
66 (Anderson and Bows, 2011; Fung et al, 2011 and Sanderson et al, 2011; Harris et al, 2012).

67 A number of approaches to adaptation have been identified. Vulnerability-led adaptation includes  
68 methods aimed at identifying and reducing present community/system vulnerability; thereby  
69 reducing future exposure to potentially damaging impacts. Scenario-led adaptation, studied here,  
70 uses future climate change projections to assess future climate change impacts. Downscaled  
71 regional-scale climate scenario data can be fed into impact models; the outputs are then used to  
72 inform adaptation, to maximise potential benefits and/or minimise potential risks (Wilby and Dessai,  
73 2010). A hybrid approach, combining elements of vulnerability-led and scenario-led approaches has  
74 recently emerged, though is not the focus of this paper (Brown and Wilby, 2012).

75 Scenario-led adaptation is limited by the financial and technical capacity of the individuals  
76 undertaking the adaptation; their risk appetite, the availability of high quality downscaled climate  
77 change information and the type of adaptation options being considered (Adger et al, 2005; Dessai  
78 et al, 2005). Despite greater awareness of its benefits (Füssel, 2007; Ranger et al, 2010), few real-  
79 world cases of scenario-led adaptation decisions have been realised (Tompkins et al, 2012), with  
80 large sector and regional differences in the type of adaptation considered. This limited uptake has  
81 been attributed to a variety of factors; see Moser and Ekstrom (2010) for an extensive discussion.

82 Scenario-led adaptation is used here to model irrigation demand and inform farm reservoir design in  
83 a semi-humid climate. A sufficiently long daily weather record is essential to adequately gauge the  
84 amount of water required. For the baseline period (1961-1990), irrigation demand calculations are  
85 often based on the observed record, though this may be substituted with a synthetic series from a  
86 weather generator provided it has been suitably calibrated (Green and Weatherhead, 2013).  
87 Similarly, a sufficiently long record of future daily weather data is required to model irrigation

88 demand under the effects of climate change. Future weather data is typically generated from  
89 downscaled global climate models (GCM). GCM outputs are often only available as monthly values  
90 (Holman et al, 2009), which are generally insufficient for modelling dry year supplemental irrigation  
91 demand and many hydrological processes. They can however be used to perturb an observed or  
92 synthetic daily series using the 'change factor' approach (Loaiciga et al, 2000), elsewhere referred to  
93 as perturbation or the "delta-change" method (Prudhomme et al, 2002). A change factor is obtained  
94 for each month in the future series, these figures are then used to perturb an observed baseline  
95 daily series to produce a future series i.e. applying a January monthly change factor of 10% to an  
96 observed series would make all of the daily values in the future series for the month of January +10%  
97 larger (Holman et al, 2009). A criticism of the change factor approach is that it assumes that the  
98 climate variability is stationary, e.g. the same patterns of wet and dry days will occur in the future  
99 dataset as in the original baseline (Harris et al, 2012). Despite this, it remains a popular approach,  
100 given its relative simplicity and low computation demands (e.g. Dacacche et al, 2012). Alternatively,  
101 a probabilistic weather generator can be used to generate multiple future time series using  
102 perturbed synthetic baselines. Unlike the conventional change factor approach, weather generators  
103 are not dependant on the individual having access to a suitably long observed record (Green and  
104 Weatherhead, 2013) nor do they assume that the future climate variability is stationary, making  
105 them an attractive tool for supporting robust decision making (Groves and Lempert, 2007; Dessai et  
106 al, 2009; Lempert and Groves, 2010; Harris et al, 2012). The change factor approach and UKCP09  
107 weather generator (Semenov 2007; Wilks and Wilby, 2009) are both examples of statistical  
108 downscaling (Wilby et al, 2004), while they are not utilised here, alternative methods collectively  
109 referred to as dynamical downscaling techniques also exist (Mearns et al, 2003). An extensive  
110 discussion of the merits and weaknesses of these and other downscaling techniques can be found  
111 elsewhere and in greater detail (Prudhomme et al, 2002; Fowler et al, 2007)

112 The primary source of future climate projections in the UK is the UKCP09 dataset (Murphy, 2009).  
113 UKCP09 provides 10,000 probabilistic climate projections at a 25km scale resolution generated from

114 a perturbed ensemble experiment using the HadCM3 Global climate model (GCM). These are  
115 provided in the format of monthly change factors. Alternatively, daily (and even hourly) projections,  
116 and at a finer spatial resolution of 5km<sup>2</sup>, are readily available as outputs from UKCP09's weather  
117 generator (Jones et al, 2009). The weather generator provides baseline ("control") and future  
118 scenario sequences for three different greenhouse gases emission scenarios (low, medium and high)  
119 and for selected 30 year time-slices (centred around the 2020s, 2030s, 2040s, 2050s, 2060s, 2070s  
120 and 2080s respectively).

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

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

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

148 **Method:**

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

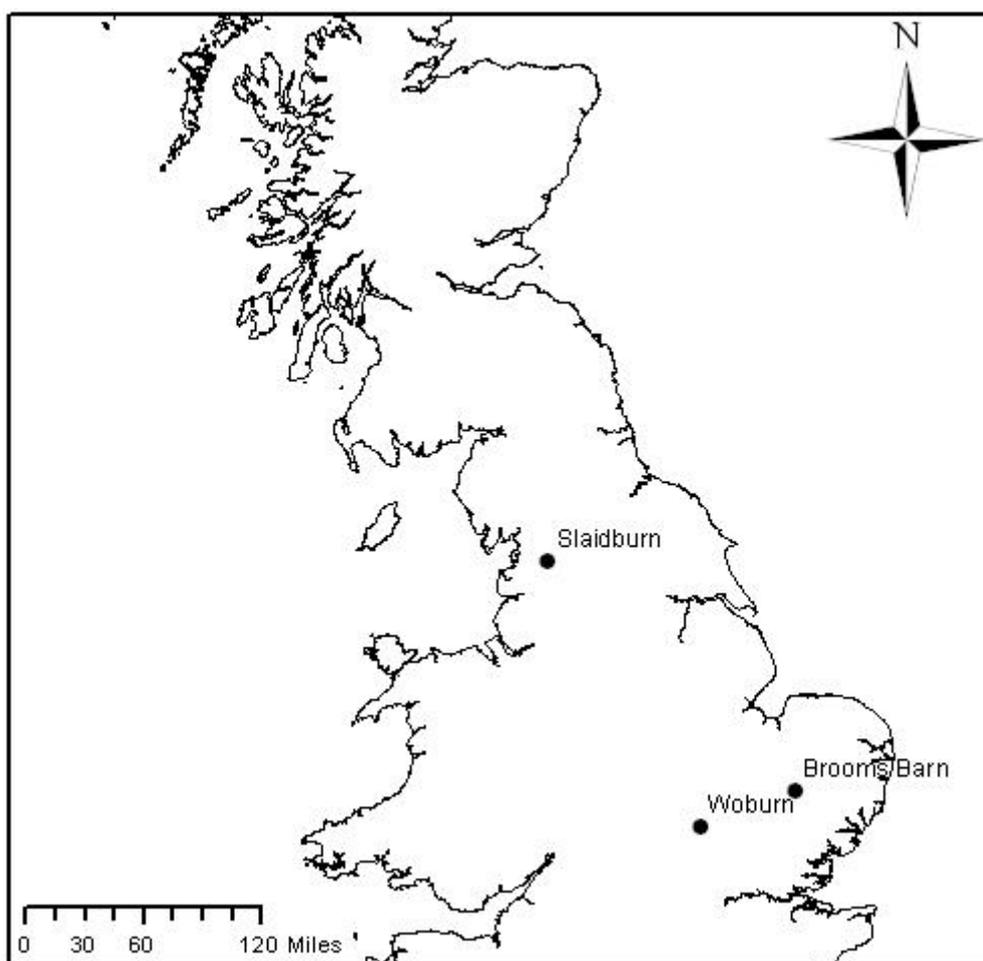
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**Table 1 Weather station sites and records used**

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

162



163

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

168 Monteith (Monteith, 1965); wind speed was assumed to be the same as the observed baseline  
169 (1969-1990) due to the lack of earlier baseline data and future projections of wind speed.

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

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

182 Next, WaSim was used to model irrigation demand at each site. In its basic format WaSim is not  
183 capable of processing multiple climate files succinctly, so a modified version was developed and  
184 employed for this study to read-in multiple climate files and output a single results file containing  
185 the daily irrigation demand for each of the 10000 climate files. A potato crop was simulated with a  
186 planting depth of 0.15m, max root depth of 0.7m and planting date of 1<sup>st</sup> April. A rule based  
187 irrigation schedule was modelled based on best practice guidelines including scab control (Defra,  
188 2005). This schedule consisted of 4 periods (1 non-irrigation followed by 2 irrigation and 1-non  
189 irrigation), applying 15mm of water early in the growing season whenever the root zone deficit  
190 exceeded 18mm during period 2 (15<sup>th</sup> May-30<sup>th</sup> June) and applying 25mm of water whenever the  
191 root zone deficit exceeded 30mm during period 3 (30<sup>th</sup> June-31<sup>st</sup> Aug). Irrigation early in the growing  
192 season is essential for some varieties for minimising the chance of potato scab, a common bacterial

193 blight which can severely reduce the market value of produce (Liu et al 1996). Irrigation is also  
194 important for promoting higher tuber numbers, accelerating crop canopy growth, reducing the  
195 chance of uneven growth and thumbnail cracking and reducing crop damage during harvesting  
196 (Defra, 2005). The soil type was set as sandy loam, which is the dominant soil type for potato crops  
197 in England, with an assumed saturation of 43.3% and field capacity of 24.5%.

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

204 For the economic evaluation, typical costs and benefits for clay agricultural reservoirs were obtained  
205 from a concurrent study (Weatherhead et al, 2008). The economic benefit of the water contained  
206 within each reservoir was calculated on the basis of average water use, assuming an average net  
207 benefit (for potatoes) of £1.56/m<sup>3</sup> of water used (Morris et al, 1997). Earthwork costs were assumed  
208 to be £1.125 per m<sup>3</sup> of earth moved, plus an additional 15% reflecting site investigation costs. A  
209 further £20k was added, representing the assumed connection costs of 3-phase electricity. Annual  
210 OPEX was assumed to be 1% of CAPEX, representing the low maintenance cost of clay reservoirs  
211 (Weatherhead et al, 2010). Each of the 10,000 sequences was then used to calculate the net present  
212 value (NPV) of a range of reservoir sizes, with usable storage capacities equivalent to 0 to  
213 1000mm.year<sup>-1</sup> for the area irrigated. NPV provides a measure of the present value of the difference  
214 between the assumed costs and benefits of a decision. NPV was calculated by discounting the  
215 annual net benefit of the reservoir less OPEX costs with a lumped (non-discounted) CAPEX in year 0,  
216 assuming current government discount rate guidelines of 3.5% on investments of up to 30 years  
217 (Treasury HM, 2011). Each reservoir was assumed to last 30 years, representing their typical life

218 cycle. The optimum reservoir capacity, defined as the size providing the highest NPV was calculated  
219 for each of the 10,000 sequences. The median, mean, quartile and extreme values for each site,  
220 emission scenario and dataset were identified as before.

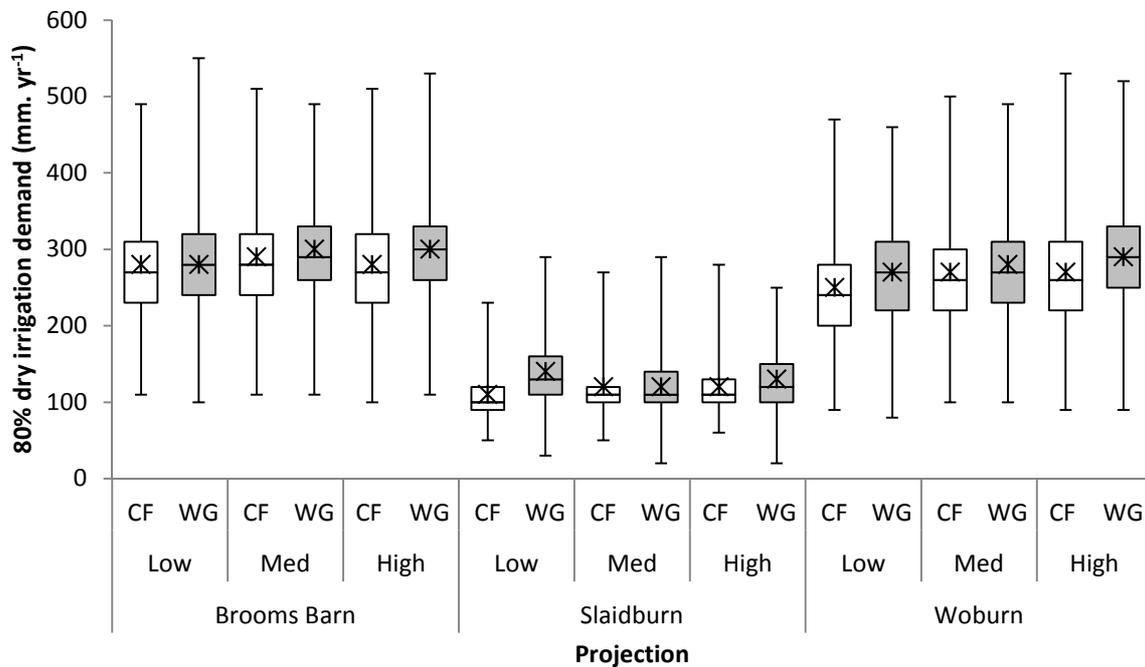
221 The Mann-Whitney U-test (Mann and Whitney, 1947) was used to establish whether there was  
222 significant differences between the change factor and weather generator datasets in terms of both  
223 the 80% dry year irrigation demands and the optimum reservoir capacities. The Mann-Whitney U  
224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

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

## 235 **Results and Discussion:**

236 The 80% dry year irrigation demands were compared between the change factor and weather  
237 generator sequences for each sites and emission scenario (Figure 1). The median 80% dry year  
238 irrigation demand was similar across both datasets. Both also had a similar interquartile and extreme  
239 range. These results support the assumption that the weather generator was reasonably calibrated  
240 with the observed record (Green and Weatherhead, 2013) and suggest that using the UKCP09

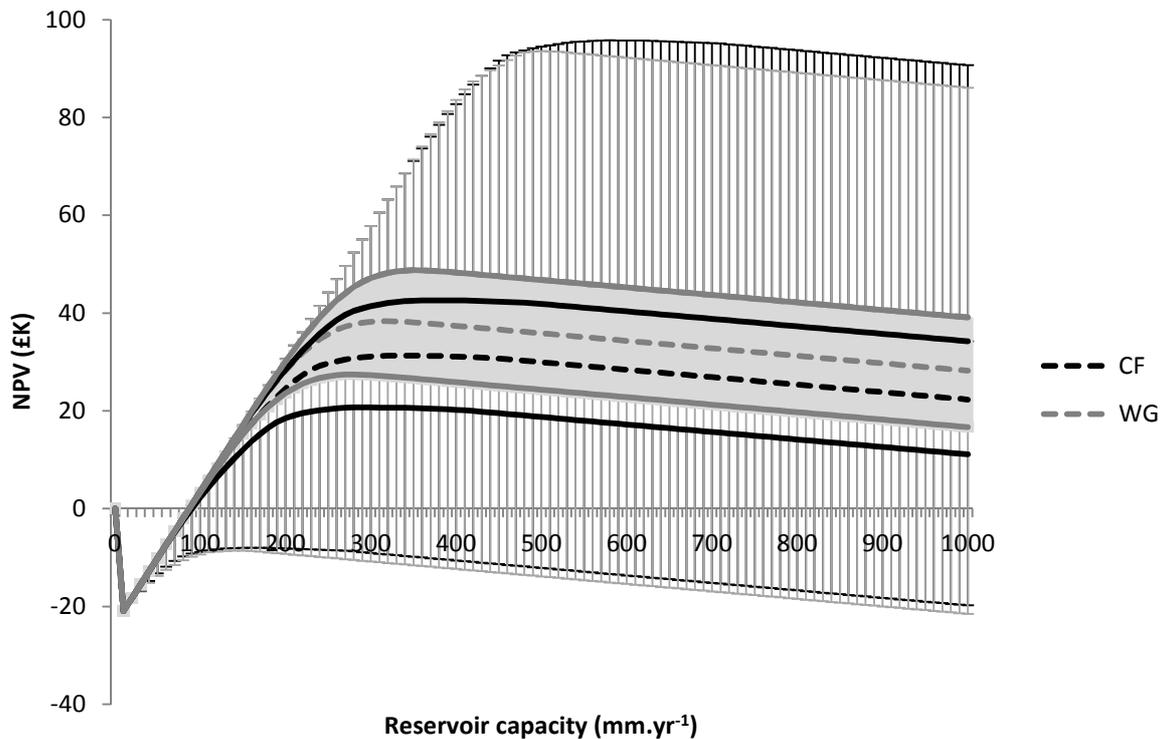
241 weather generator instead of the conventional change factor approach may not necessarily lead to  
 242 more robust decision making.



243  
 244 **Figure 1. Median (-), mean (X), quartile and extreme values of the 80% dry year irrigation demand**  
 245 **for the change factor (CF) and weather generator (WG) sequences for each site and emission**  
 246 **scenario.**

247 Next, the economic performance of various reservoir capacities generated using the full 10000  
 248 change factor and weather generator sequences were compared against each other for each site  
 249 and emission scenario. Figure 2 shows the results obtained for the site of Woburn using the medium  
 250 emission scenario. Despite subtle differences in the projected NPV, both datasets showed a similar  
 251 trend in NPV against reservoir capacity. The weather generator projected a higher NPV for most  
 252 reservoir capacities, based on the median projection, with the exception of small reservoirs with a  
 253 capacity of less than 100mm.yr<sup>-1</sup>. The NPV range (i.e. the difference between the max payoff and  
 254 minimum payoff for each reservoir size) is initially quite narrow and increases with reservoir  
 255 capacity. The NPV range is larger for the weather generator dataset than for the change factor

256 dataset for all the reservoir capacities considered. For the change factor dataset, the median  
257 optimum reservoir capacity was 340mm.year<sup>-1</sup>. In contrast, the weather generator estimated the  
258 median optimum reservoir capacity to be marginally smaller at 320mm.year<sup>-1</sup> but with a 20% larger  
259 NPV. Similar results were recorded for all three emission scenarios for all three sites.



260

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

264 Statistical analysis was undertaken to establish whether there was significant difference between  
265 using the weather generator and change factor datasets in terms of 1) the 80% dry year irrigation  
266 demand and 2) the optimum reservoir capacity. The 80% dry year irrigation demand values obtained  
267 using the weather generator dataset were significantly greater than those from using the change  
268 factor dataset. In contrast, the optimum reservoir capacities from the weather generator dataset  
269 were significantly lower than from the change factor dataset. However, while the differences were

270 statistically significant at the 95CI (Table 2), the difference in the 80% dry year irrigation demand was  
 271 generally less than 25mm.year<sup>-1</sup>, which is only the depth of a typical single application of water. The  
 272 difference in the optimum reservoir capacities was similarly small (though generally >25mm.year<sup>-1</sup>),  
 273 with the exception of the Brooms Barn site. These results again suggest that using the weather  
 274 generator in place of the conventional change factor, while theoretically leading to more robust  
 275 decision making, in reality is unlikely to greatly affect the decision outcome.

276 **Table 2. Results of Mann-Whitney U-test statistical analysis comparing 80% dry year irrigation**  
 277 **demand and optimum reservoir capacity obtained using economic optimisation with change factor**  
 278 **(CF) and weather generator (WG) datasets, showing median reservoir capacity, whether they are**  
 279 **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		0.00		0.00		0.00		0.00	

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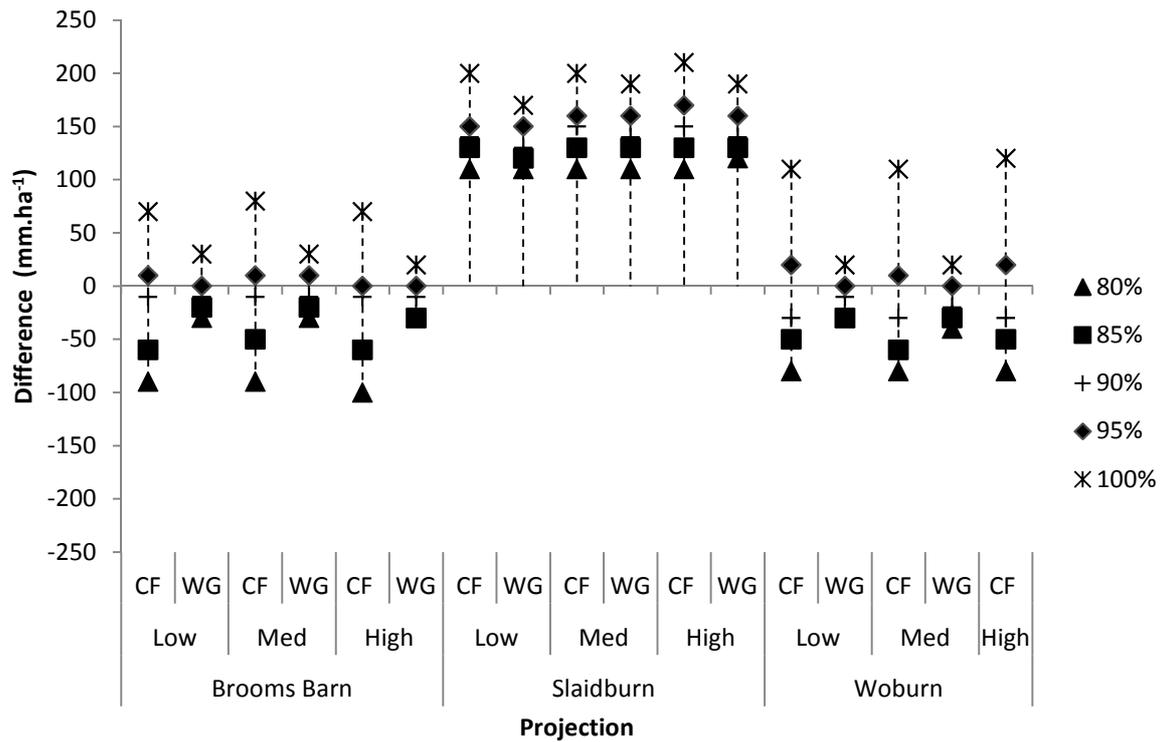
Site	Slaidburn											
Criteria	80% Dry year irrigation demand						Optimum reservoir capacity					
Emission scen.	L		M		H		L		M		H	
Data	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG	CF	WG
Res. capacity	100	130	110	110	110	120	0	0	0	0	0	0
Sig. difference?	Yes		Yes		Yes		Yes		Yes		Yes	
P-value (95CI)	0.00		0.00	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

281

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	

282

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



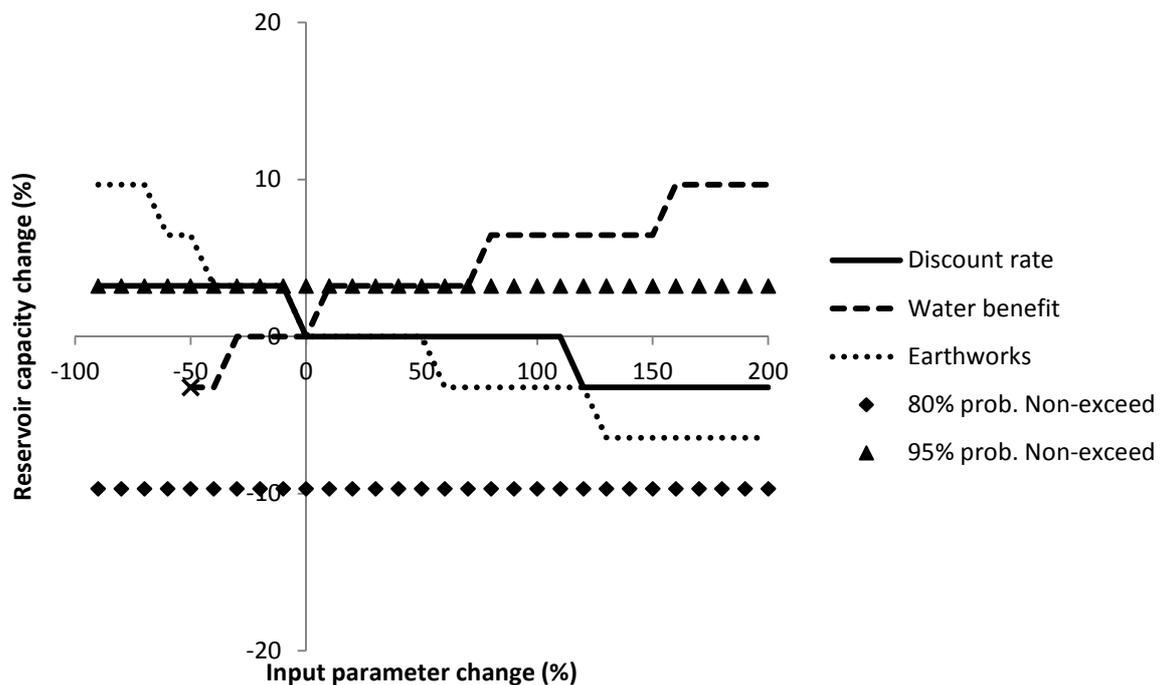
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297 **Figure 3. Differences between the median dry year irrigation demands using 80% to 95%**  
 298 **exceedance rules and the median optimum reservoir capacity, for the change factor (CF) and**  
 299 **weather generator (WG) sequences for each site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

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

305 The sensitivity analysis is presented here for the site of Woburn, for the medium emission scenario  
 306 and the weather generator dataset. Similar results were obtained for the other sites and emission  
 307 scenarios and for the change factor dataset. The optimum reservoir capacity was largely insensitive  
 308 to the discount rate, evident from the near horizontal line, with larger discount rates slightly  
 309 favouring smaller reservoirs (**Figure 4**). The reservoir capacity was more sensitive to earthworks

310 costs, with larger earthworks costs favouring smaller reservoirs, again as expected. The value of the  
 311 water in the reservoir had the largest effect on the optimum reservoir capacity; below  $\text{£}0.78.\text{m}^{-3}$  the  
 312 reservoir produced a negative NPV and was no longer economically viable at this site. Increasing the  
 313 value of water above  $\text{£}1.56.\text{m}^{-3}$  had surprisingly little effect on the optimum reservoir capacity,  
 314 increasing it by only 9.7% even up to a value of  $\text{£}4.68.\text{m}^{-3}$ ; this reflects the point that useful capacity  
 315 is limited by demand, with decreasing returns to additional capacity.



316  
 317 **Figure 4. Sensitivity analysis comparing optimum reservoir capacity against discount rate, water**  
 318 **benefit and earthworks cost, showing changes relative to base parameter values, for the Woburn**  
 319 **site and medium emission scenario. The 80% and 95% dry year irrigation demands are also shown**  
 320 **for comparison.**

321 These variations in median optimum reservoir capacity were subsequently compared to the  
 322 capacities given by the simpler % exceedance rules, in this case the 80% and 95% dry year irrigation  
 323 demand. For the Woburn site and the base variable values, the 95% probability of non-exceedance  
 324 rule out performs the 80% probability of non-exceedance rule (Figure 4). At larger discount rates  
 325 ( $>7\%$ ) the 80% rule works better, and for lower earthwork costs (less than  $\text{£}1.80.\text{m}^{-3}$ ) the two rules

326 are equally close. For all water values, the 95% probability of non-exceedance rule was nearer the  
327 optimum value, but both rules failed to show that the reservoir was no longer economically viable  
328 when the water value was less than £0.78.m<sup>-3</sup>. More case studies would be needed to confirm  
329 these are general results, but they suggest that the 80% rule may be misleading.

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

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

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

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

362 A criticism of the change factor method, as previously noted, is that it assumes that the temporal  
363 and spatial structure of future precipitation and evapotranspiration remains unchanged (Diaz-Nieto  
364 and Wilby, 2005; Fowler et al, 2005; Minville et al, 2008; Harris et al, 2012). In some situations, it is  
365 necessary to evaluate changes in climate variability and not just changes in means (Semenov et al,  
366 1998). Despite this, the change factor approach remains popular because of its simplicity and is  
367 useful for converting monthly change factors into daily projections needed to model most  
368 hydrological processes without incurring excessive expense (Minville et al, 2008).

## 369 **Conclusions**

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

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

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