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Re: Adaptation of water resource systems to an uncertain future

22 January 2016

Dear Editor

On behalf of my co-authors, please find below responses to reviewer's comments. The reviewers made a number of suggestions to the paper for which we are very grateful as we agree that addressing these have improved the paper. These have been addressed as follows (reviewers' comment in italics; our response in plain text):

Response to interactive comments by H Maier

This paper addresses an important problem and presents a nice application of a reasonably standard approach to a case study. While the results are interesting, I believe that the value of the paper to the community working in this field could be improved considerably if this research was tied into other work in this area. This should be done both in the Introduction so that it is clear where this work fits in with other recent efforts tackling the same problem, as well as the discussion to highlight similarities and differences between the findings of this and other studies. In addition, it would be useful to discuss potential limitations of the approach used in light of recent papers that have introduced more advanced methods for tackling the problem being addressed. Some of the papers that have dealt with issues similar to those addressed in this paper but that have not been referred.

We would like to thank the referee for their positive comments and their suggestion of recent papers that will better frame this work in a wider context. The papers listed are based around the use of robustness analysis for water systems to enable better decision making. Whereas we do make reference to some example literature in this field e.g. Groves et al. 2008, Lempert & Groves 2010, Matrosov et al. 2013, Borgomeo, we do feel that referring to some of these more recent papers in this arena such as Whateley et al. 2014 and Steinschneider et al 2015 in the introduction would be valuable. In particular those studies by Beh et al, 2015a, 2015b and Paton et al 2013, 2014; Zeff et al. 2014 and Haasnoot et al 2014 would contribute to and strengthen the penultimate paragraph of the discussion section that debates costs, benefits and trade-offs of adaptation measures. The following text has been added to the manuscript:

Page 3, line 32: 'More recently the decision-scaling method (Brown et al., 2012) or climate stress testing (Brown and Wilby, 2012) has been applied to water resources systems. Multiple sources of climate information, climate projections and stochastic assessments are used to evaluate risks

(Brown et al., 2012) and subsequently applied to determine robust adaptation strategies (e.g. Whateley et al., 2014; Steinscheider et al. 2015).'

Page 15, line 27: 'In their case study on Adelaide's southern water supply system, Beh et al., 2015a,b and Paton et al., 2014 demonstrate a multi-objective evolutionary algorithm framework to consider the trade-offs between reducing greenhouse house emissions while planning sustainable urban water supply systems. Applied to North Carolina Zeff et al. 2014 investigated how more flexible and adaptable water supply portfolios can be implemented alongside financial mitigation tools to reduce trade-offs between fluctuations of revenues and costs of implementing new solutions. Haasnoot et al 2014 demonstrate the development of adaptation pathways whereby environment and policy responses are analysed through time to develop an ensemble of plausible futures to support decision making under uncertainty.'

The following references have been included in the reference list from page 19:

Beh, E. H. Y., Maier, H. R. and Dandy, G. C.: Scenario driven optimal sequencing under deep uncertainty, Environ. Modell. Softw., 68, 181-195, doi:10.1016/j.envsoft.2015.02.006, 2015a.

Beh, E. H. Y., Maier, H. R. and Dandy, G. C.: Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty, Water Resour. Res., 51, 1529-1551, doi:10.1002/2014WR016254, 2015b.

Brown, C. and Wilby, R. L.: An alternate approach to assessing climate risks, Eos, Trans. Am. Geophys. Union, 93, 41, 401–402, doi: 10.1029/2012EO410001**,** 2012.

Brown, C., Ghile, Y., Laverty, M. and Li, K.: Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. Water Resour. Res., 48(9): W09537, doi:10.1029/2011WR011212, 2012.

Haasnoot, M., van Deursen, M. P. A., Guillaume, J. H. A., Kwakkel, J. H., van Beek, E. and Middelkoop, H.: Fit for purpose? Building and evaluating a fast, integrated model for exploring water policy pathways, Environ. Modell. Softw, 60, 99-120, doi:10.1016/j.envsoft.2014.05.020, 2014.

Paton, F. L., Maier, H. R. and Dandy, G. C.: Including adaptation and mitigation responses to climate change in a multi-objective evolutionary algorithm framework for urban water supply systems incorporating GHG emissions, Water Resour. Res., 50, 8, 6285-6304, doi: 10.1002/2013WR015195, 2014.

Steinschneider, S., McCrary, R., Wi, S., Mulligan, K., Mearns, L., and Brown, C.: Expanded Decision-Scaling Framework to Select Robust Long-Term Water-System Plans under Hydroclimatic Uncertainties, Journal Water Res. Pl-ASCE, 141, 11, 04015023, 10.1061/(ASCE)WR.1943-5452.0000536, 2015.

Whateley, S., Steinschneider, S., Brown, C.: A climate change range based method for estimating robustness for water resources supply. Water Resour. Res., 50(11): 8944-8961.

Zeff, H. B., Kasprzyk, J. R., Herman, J. D., Reed, P. M. and Characklis, G. W.: Navigating financial and supply reliability tradeoffs in regional drought management portfolios, Water Resour. Res., 50, 4906-4923, 2014.

Response to referee comments by R Wilby

Reviewer's comments in *italics*; authors' response in plain text.

This is an interesting manuscript that contributes to a growing body of research that applies probabilistic climate information and resource system analysis to determine efficacy of adaptation options. The Thames Basin, UK has been the subject of numerous climate risk assessments. However, the paper adds new insights on the significance of future water demand relative to other key uncertainties. The authors have also applied end-user relevant water resource indicators, and introduced technical advances in the form of a new spatial weather generator. Some methodological details require further elaboration (e.g. treatment of change factors, groundwater exploitation, return flows) and the assumptions behind the water demand estimates could be more transparent.

The plausibility of some adaptation options (e.g. 35% demand reduction by 2020) is highly questionable and, arguably the most serious threat to the system – multi-season droughts – warrants further consideration.

On this basis, publication is recommended subject to the following modest revisions, minor corrections and clarifications.

We thank R Wilby for his overall positive comments on this manuscript and for the valuable comments and challenges that would strengthen and improve this paper. We respond to the comments below, indicating what changes or additions we would make if invited to prepare a final manuscript.

Main comments
[Abstract] Please incorporate a few more headline statistics and link any projected impacts to the specified time horizon. Presumably, the cited five-fold increase in drought order occurrences pertain to the 2050s?

Yes, the five-fold increase mentioned in the abstract refers to results from the 2050s. We could also include some results for the 2020s for example a decrease in per capita demand of 3.75% reduces the median frequency of DS4 measures by 50%.

Page 1, Line 29: 'by the 2050s' added for clarification.
Page 2, Line 2: The following statistic has been included: 'A decrease in per capita demand of 3.75% reduces the median frequency of drought order measures by 50%.'

[Methodology/Results] The UKCP09 projections suggest an average 18% reduction in summer precipitation and 15% increase in winter for the Thames Basin. However, a fundamental limitation of the change factor methodology is that it does not readily produce hitherto unseen sequences of exceptionally dry periods that would truly stress the water supply system (such as two or more dry winters and summers in a row). It would be helpful to know what the longest below average sequence was generated by the method of adjusting observed rainfall and refitting the STNSRP to the perturbed series.

We agree with the reviewer in that sequences of dry periods are important and potentially critical to water supply systems. Mean seasonal precipitation was calculated for spring, summer, autumn and winter and then each season was expressed as an anomaly from the means. The figures for the longest sequences of negative seasonal anomalies are 10 for the control and 18 for SCN50, a significant increase. This result has been added to the paper, see below for added text and appropriate reference'.

Page 9, line 30: 'Mean seasonal precipitation was also calculated for each season and expressed as an anomaly from the long-term mean to determine the longest sequence of negative seasonal anomaly. This suggested the potential lengthening of periods with below average rainfall - for BSL the longest sequence was 10, whereas for SCN50 it was 18. However, we note that a limitation of applying change factors through a Weather Generator to assess future projections in rainfall is that it does not readily produce the longer sequences of dry periods (Wilby et al. 2014) that may produce multi-seasonal droughts and hence stress the water supply system.'

Page 24, line 4: the following reference has been added: Wilby, R. L., Charles, S. P., Zorita, E., Timbal, B., Whetton, P. and Mearns, L. O.: *Guidelines for Use of Climate Scenarios Developed from Statistical Downscaling Methods. IPCC Task Group on Scenarios for Climate Impact Assessment (TGCIA), Geneva, Switzerland.* http://www.narccap.ucar.edu/doc/tgica-guidance-2004.pdf, *2004.*

[Methodology] Given the heterogeneity of land cover in the Thames basin, the decision to apply a single Potential Evapotranspiration (PET) record at the centroid of the basin should be further justified. For instance, how representative is this of the moisture loss from the urban sub-catchment?

We recognise that the calculation of PET is essential in calculating future water resource availability and that different downscaling methods yield different PET change predictions. The Thames basin was divided into three sub-catchments to conduct the hydrological modelling as shown in Figure 2. Within each of the catchments there are a variety of land uses which would in turn affect moisture losses, as the reviewer highlights. Given the similarity in the three catchments in terms of elevation and heterogeneity of land cover, and that CATCHMOD is a lumped model, only one PET series for each sub-catchment could be used as input, it was decided to use the same PET record for the three areas. Unfortunately with applying a lumped model it is not possible to investigate how representative this is for the urban sub-catchment. However, in a publication forthcoming we use a physically-based spatially distributed hydrological model which uses spatially correlated precipitation and PET input data from the UKCP09-WG on a 5km grid. Thereby giving a better representation of input data across the Thames basin.

Page 7, line 37: the following justification has been added: ‘It is recognised that within each of the catchments the variety of land cover would in turn affect moisture losses. However, given the similarity of the catchments in terms of elevation and heterogeneity of land cover, and that the rainfall-runoff model is lumped, a single PET record generated at the centroid of the whole Thames basin was used; the representative 5km grid cell is highlighted in Fig 2. A forthcoming paper will present the application of a spatial weather generator which will feed a physically based, spatially distributed hydrological model which will allow better representation of both the climatological and land cover heterogeneity of the catchment. Furthermore, it will enable changes in land cover i.e. increasing urban areas to be considered’

[Methodology] Explain how groundwater abstraction was handled by the catchment/ water resource modelling. What input data were used for the groundwater source node shown in Figure 4? Likewise, what values were applied for return flows to the Thames from the water treatment works node?

Groundwater is included as an aggregate inflow of 467.4 Ml/d directly to meet London's demand. A proportion of the inflow to the water treatment works is leakage, this is equivalent to 12% of demand and is returned back to the river and modelled as a contribution to the minimum environmental flow. This information has been included in the caption for Figure 4.

Page 25, line 12: Figure 4 (NB: groundwater is include as an aggregate inflow of 467.4 Ml/d to meet London’s demand. A proportion of the inflow to the water treatment works is leakage, this is equivalent to 12% of demand and is returned back to the river and modelled as a contribution to the minimum environmental flow.)

Page 31, line 4: Figure 4 (NB: groundwater is include as an aggregate inflow of 467.4 Ml/d to meet London’s demand. A proportion of the inflow to the water treatment works is leakage, this is equivalent to 12% of demand and is returned back to the river and modelled as a contribution to the minimum environmental flow.)

[Methodology/Results] How well does the LARaWaRM replicate the historic frequency of demand saving days when given observed climate and water use profiles?

As far as we are aware there is no data indicating the historical frequency of demand saving days for the catchment. Furthermore there is also no account of the vast changes that have taken place in the catchment around usage data, given the shift from industrial use to predominantly residential or of the supply infrastructure changes over time. We have run the observed flow record (1883-2005) through LARaWaRM which gives a single value that falls within the range of those produced using control climate simulated flows.

[Methodology] Provide a summary table of all the demand measures that were factored into the analysis whether implicitly or explicitly. Explain how demand per capita was altered to reflect technological advances and efficiency measures. State the assumed consumptive water demand (i.e. fraction of used water that is not returned to the Thames as treated effluent).

The paper does not implicitly or explicitly consider specific demand measures or technological advances of efficiencies. We present a sensitivity analysis of demand changes which may reflect behaviour or technological efficiencies we refer to this part of the analysis as a sensitivity test and on P8869, L18 highlight that such reductions may be unrealistic.

We have amended the following text to clarify that we are performing a sensitivity test rather than testing specific individual technologies:

Page 10, line 1: 'Demand reduction: sensitivity analysis considering reduction in per capita demand between 0- 35%, at 5% intervals which represent a range of behavioural and technical efficiencies;'

[*Results] The 10th percentile change in precipitation shown in Figure 5 is based on the ensemble uncertainty. However, what proportion of weather generator runs produced a decrease in precipitation in all months? This is no doubt a much rarer likelihood than 10% of ensemble members. In other words, 10th percentile scenario (and attendant adaptations) is actually much rarer than implied for a continuous simulation.*

We calculated that the monthly means for the control and 2050s to determine whether the monthly mean increased or decreased relative to the control. The data showed that none of the 100 runs show a decrease in every month - so the likelihood is much rarer than 10% as the reviewer suggests.

[Discussion] As noted before, further comment is needed on the treatment and effectiveness of the adaptation measures under conditions of multi-season drought. For instance, ***how more/less frequent*** *are 24-month periods with below average precipitation under SCN20 and SCN50? Would the preferred mix of adaptation measures differ if these particular climate threats are considered?*

We have calculated the number of spells of below average rainfall that last at least 24 months (i.e. at least 8 seasons of negative anomalies) for one grid cell. In the control period you typically get one such spell (ranging from 1-2 occurrences). In SCN50, we start to see evidence of more frequent occurrences up to 5 (ranging from 1-5 occurrences). Multi-season droughts are important and a very brief analysis suggests that these could occur more often but a full assessment is needed In the UK groundwater and reservoir recharge typically occurs over the winter from November to April. Successive dry winters cause significant water resource issues particularly in the east and south of England due to the importance of groundwater in providing base flows in rivers. As the reviewer suggests this may have implications for the mix of adaptations, with a greater emphasis needing to be applied to for example, demand-saving measures, leakage reduction and desalination. Considering multi-season drought alongside sequencing of adaptation options as proposed by e.g. Beh et al. 2015 or adaptation pathways e.g. Haasnoot et al. 2014 would be a valuable extension of this work. This has been reflected in the conclusions and appropriate references added.

Page 17, line 30: 'This alongside a third research priority looking more generally about the sequencing of choice of adaptation options over indicative planning horizons taking account of trade-offs with reducing greenhouse gas emissions or investment portfolios could make use of more robust decision making frameworks under uncertainty such as those proposed by for example Beh et al. 2015 or Haasnoot et al. 2014.'

Page 19, line 2: Beh, E. H. Y., Maier, H. R. and Dandy, G. C.: Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty, Water Resour. Res., 51, 1529-1551, doi:10.1002/2014WR016254, 2015.

Page 22, line 6: Haasnoot, M., van Deursen, M. P. A., Guillaume, J. H. A., Kwakkel, J. H., van Beek, E. and Middelkoop, H.: Fit for purpose? Building and evaluating a fast, integrated model for exploring water policy pathways, Environ. Modell. Softw, 60, 99-120, doi:10.1016/j.envsoft.2014.05.020, 2014.

[Conclusion] Please add a paragraph spelling out the priorities for further research.

Page 17, line 21: The following paragraph would be added to the end of the paper highlighting priorities for further research.

This study of the Thames catchment and subsequent analysis has highlighted the following priorities for future research. Firstly, which will be addressed in a forthcoming paper, is an extension of the climate scenarios to include the 2080s time period, coupled with the application of a spatial weather generator feeding a physically based, spatially distributed hydrological model which will allow better representation of both the climatological and land cover heterogeneity of the catchment. Furthermore, it will enable changes in land cover i.e. increasing urban areas to be considered. Secondly, recognising the importance of groundwater in the Thames catchment and hence the potential impact that multi-season droughts may have on the area, further research is needed to understand how trends in such phenomena may affect or influence the choice of adaptation options. This, alongside a third research priority looking more generally about the sequencing of implementation of adaptation options over indicative planning horizons taking account of trade-offs with reducing greenhouse gas emissions or investment portfolios could make use of more robust decision making frameworks under uncertainty such as those proposed by for example Beh et al., 2015b or Haasnoot et al., 2014.

Minor corrections and clarifications

[P8856, L10] Exactly what "changes" in upland river catchments were analysed?

Changes in precipitation and PET; this has be made clear.

Page 3, line 12: 'precipitation and PET in' has been added to address the above point

[P8856, L17] ": : :greater proportion of uncertainty: : :" by when? Note that the relative importance of different uncertainty components varies with time in the future i.e. climate variability (near-term), climate model (medium-term), emissions scenario (longterm). Hence, it is critical to attach the time-stamp to any such impact or uncertainty statement.

The work referred to here was considering scenarios in the 2080s – the time stamp has been added, taking note of the reviewer's comment about the importance of uncertainty components varying over time.

Page 3, line 20: 'for the 2080s' included to clarify the date stamp.

[P8857, L25] In what ways are the PET data "consistent"?

The phrase 'consistent' refers to the relationship with the rainfall scenario. 'Corresponding' is perhaps a better term and will be used instead.

Page 4, line 21 'consistent' replaced with 'corresponding'.

[P8858, L1] Ditto for "consistent river flows"?

Here the term 'consistent' refers to the relationship of flows to the rainfall and PET series. We have rewritten these three sentences to make this clearer.

Page 4, line 25: 'Fig 1 outlines the methodological approach taken and the associated sequence of models used to simulate the Thames Valley water resource system. Starting from the climate model outputs provided by UKCP09, spatially consistent downscaled rainfall scenarios are generated using a spatial rainfall model of the Thames and Lee river basins. These, alongside corresponding downscaled Potential Evapotranspiration (PET) data produced with a weather generator, are used to drive catchment rainfall-runoff models, which output corresponding river flows. These, in turn, are input to a model of the water resource system which enables a range of supply and demand management options to be tested which incorporate projections of demographic change.'

[P8858, L20 and P8871, L26] Given the large uncertainties, better to use "could" rather than "will".

These changes have been made.

Page 5, line 17: 'will' replaced with 'could'.
Page 16, line 16: 'will' replaced with 'could'.

[P8859, L19 and P8870, L29] Comment: Given that the longest time horizon investigated was the 2050s, uncertainty due to emissions scenario can be largely discounted.

[P8860, L7] At what time-scale were the change factors produced? Was it annual, seasonal, or monthly? Please specify.

Change factors were monthly. This has been clarified.

Page 6, line 24: 'monthly' has been added to clarify the time-scale of the change factors used.

[P8861, L5] Please cite the Nash-Sutcliffe efficiency (and other performance metrics) for the validation period.

Both Nash-Sutcliffe efficiency and time periods for calibration and validation of the CATCHMOD model have been added as described below.

Page 7, line 18: Nash-Sutcliffe efficiencies have been included: 'The following Nash-Sutcliffe efficiencies were achieved for each catchment: Teddington Weir: calibration: 0.88; validation 0.86; Feildes Weir: calibration: 0.68; validation 0.69; Days Weir: calibration: 0.86; validation 0.90.'

Page 25, line 7: The following statement has been added to Figure 3's caption to clarify the calibration and validation periods. 'The calibration period against historical flows was 1/1/1961 - 31/12/1978 for Teddington and Days Weir, and 1/1/1961 - 31/12/1975 for Fields Weir. The validation period for all catchments was 1/1/1979 - 31/12/2002.'

[P8865, L23] Justify the assumption that per capita demand remains the same as present in SCN20 and SCN50.

In the scenarios presented in Figure 8 we are concerned with determining the individual impact of climate projections and population projections, therefore per capita demand is kept constant. The scenarios presented in Figure 9 go on to consider per capita demand.

[P8865, L25] The existing level of service for severe water rationing (DS4) is set at zero frequency (Table 1). What criteria were used to determine when the DS4 measure is invoked under SCN20 and SCN50?

The criteria remains the same as the present day. As suggested in the reviewer's comment on Table 1 below, it would be useful to display the reservoir trigger thresholds. However, given these thresholds are dynamic and vary monthly, and that it would not be helpful to include an average value we have therefore included the table below as Supplementary Material and added the following to the main manuscript caption for Table 1.

Page 24, line 2: 'See Supplementary Material Table 1 for reservoir total storage capacity trigger levels for the different levels of restrictions.'

Supplementary Material Table 1: Percentage of total storage capacity that invokes the different levels of restrictions (Source: Thames Water, 2014).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Level 1	69.5	82.0	89.5	92.1	92.1	90.9	86.0	74.9	64.8	61.0	59.8	61.0
Level 2	42.2	47.8	55.3	65.2	74.0	76.5	74.7	67.7	55.7	46.2	41.1	39.8
Level 3	33.6	37.3	43.4	52.1	60.9	65.9	67.2	62.4	51.2	41.2	34.9	32.4
Level 4	17.4	19.8	24.8	29.8	34.8	38.6	39.8	39.8	37.4	31.2	25.0	20.0

[P8866, L22-24 and P8872] Please explain how a 100% reduction in the mean number of DS4 days can be achieved twice over (first by leakage reduction and a new reservoir, second by adding a desalination plant to the portfolio).

This figure has been incorrectly reported. It should read 37.5% and has been changed.

Page 12, line 12: ‘100%’ replaced with ‘37.5%’.
Page 16, line 20: ‘100%’ replaced with ‘37.5%’.

[P8868, L22] Should Fig.10c be Fig.8c?

Yes. This would be amended.
Page 13, line 13 ‘Fig 10a’ replaced with ‘Fig 8a’.
Page 13, line 31 ‘Fig 10c replaced with ‘Fig 8c’.

[P8868, L29] Comment: Water use for industry and mining may have declined, but fracking of natural gas reserves in southeast England could add to future water demand.

Future pressures on water demand could be wide ranging; an initial search of proposed fracking sites in the UK has not revealed any in the Thames catchment.

[P8869, L10] How sustainable is the expected 10-15% water saving in metered households? Some studies suggest that demand creeps up in the long run.

It is difficult to comment on how sustainable the expected 10-15% reduction in water usage would be. However, this could be monitored and analysed from meter data over time. Technological advances in water appliances may indeed offset any increases.

[P8869, L18] Note that a 35% reduction in per capita demand by 2020 is unrealistic. It is much better to reframe these results as a sensitivity analysis that demonstrates the scale of the challenge ahead.

We agree and on P8862, L28 we refer to this part of the analysis as a sensitivity test and on P8869, L18 highlight that such a reduction is unrealistic.

[P8869-P8870] Note that the water supply-demand outlook could be even more finely balanced if more stringent treatment of environmental flow requirements are taken into account. This factor might be particularly problematic under the multi-season drought episodes noted above.

This note relates to earlier points made by the reviewer, which have been addressed in the main text and conclusions.

[P8871, L23] Note that climate change impacts on water balance risks might exceed those due to population growth beyond 2050.

[P8872, L19] Please clarify the sentence "Given the typical time: : :"

This refers to the investment time scale of water resource planning; this has been clarified.

Page 17, line 4: 'investment timescale' has been added.

[Table 1] Add a column of the precise triggers/thresholds used by Thames Water to invoke the different levels of restriction.

The reviewer suggests adding a column to indicate the thresholds for demand saving measure. Given these thresholds are dynamic and vary monthly, and that it would not be helpful to include an average value we suggest that the table below is included as Supplementary Material. See also comment above.

Supplementary Material Table 1: Percentage of total storage capacity that invokes the different levels of restrictions (Source: Thames Water, 2014).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Level 1	69.5	82.0	89.5	92.1	92.1	90.9	86.0	74.9	64.8	61.0	59.8	61.0
Level 2	42.2	47.8	55.3	65.2	74.0	76.5	74.7	67.7	55.7	46.2	41.1	39.8
Level 3	33.6	37.3	43.4	52.1	60.9	65.9	67.2	62.4	51.2	41.2	34.9	32.4
Level 4	17.4	19.8	24.8	29.8	34.8	38.6	39.8	39.8	37.4	31.2	25.0	20.0

[Figure 1] Please add boxes/arrows for "Observed data" and "Performance metrics" to complete the picture of the whole analytical framework.

Thank you for this suggestion; these boxes and relevant arrows have been added to Figure 1.

Page 28: updated Figure 1.

[Figure 3] Add the Nash-Sutcliffe scores to each panel.
The Nash-Sutcliffe scores for calibration and validation have been included in the text as the Figure becomes too crowded.

Page 7, line 18: Nash-Sutcliffe efficiencies have been included: 'The following Nash-Sutcliffe efficiencies were achieved for each catchment: Teddington Weir: calibration: 0.88; validation 0.86; Feildes Weir: calibration: 0.68; validation 0.69; Days Weir: calibration: 0.86; validation 0.90.'

[Figure 10] For clarity, replace "No" with "No supply measures", and spell out "D", etc. on the x-axis.

Unfortunately given space it is not possible to spell out the abbreviations the x-axis on Figure 10. The abbreviations are explained in the figure caption; 'no adaptations available' has been replaced with 'no supply measures' to distinguish between demand and supply adaptation measures.

Page 26, line 6: 'adaptations available' replaced with 'supply measures'.
Page 37, line 4: 'adaptations available' replaced with 'supply measures'.

Response to referee comments by Y Xuan
Reviewer's comments in *italics*; authors' response in plain text.
Thanks to the authors for sharing the research findings with the community.

I like the points made by presented on pg 8857 as to the differences between this manuscript and other studies utilising similar approaches. However, while I appreciate the new weather generator, the way of predicting future water demand as well as population growth which for sure are interesting to the other researchers in the community; I do think that the paper can be improved considerably by addressing the following questions:

We thank Y Xuan for his comments and questions which we address below.

1. The paper mentions that a new weather generator that can captures the spatial variability of rainfall; and later it also indicates a lumped hydrological model was used. What are the main benefits of such combination?
The application of the spatial weather generator captures the non-linear impacts of climate change on the water resources of the Thames. Although as the referee points out this is then aggregated as input to the hydrological model, the approach does ensure correlated weather events between the three sub-catchments modelled. We feel this is adequately explained on page 6 lines 13-20. As described below in a publication forthcoming we use a physically-based spatially distributed

hydrological model which uses spatially correlated precipitation and PET input data from the UKCP09-WG on a 5km grid. Thereby giving a better representation of input data across the Thames basin. The following additional text has been added.

Page 17, line 22: 'Firstly, which will be addressed in a forthcoming paper, is an extension of the climate scenarios to include the 2080s time period, coupled with the application of a spatial weather generator feeding a physically based, spatially distributed hydrological model which will allow better representation of both the climatological and land cover heterogeneity of the catchment. Furthermore, it will enable changes in land cover i.e. increasing urban areas to be considered.'

2. It seems that the paper focus mainly on the climate uncertainties. I am under the impression that the uncertainties due to the models (structures/parameterisations) can be ignored. However, this is yet to be justified. It would be interesting to see how decisions can be affected due to over/under-estimate of those models – in particular the catchment and the water resources models used by the study.

This is an interesting question but one which we believe is beyond the scope of this paper. Others such as Wilby and Harris, 2006 have looked at two hydrological model structures, and two sets of hydrological model parameters for the Thames. As mentioned below in a publication forthcoming we use a physically-based spatially distributed hydrological model to drive LARaWaRM which if returns different flows may give an indication of the issue raised.

3. For catchment models, the paper does not give an account of how well the model has performed. It is very hard to tell this by looking only at Fig 3. As the catchment model is the first node of the model chain, it is very important to know: 3.1) how the model was calibrated, against which dataset; 3.2) whether the model has been tested using the baseline climate data+ weather generator. These questions need to be addressed to make the paper more convincing.

The calibration period against historical flows was 1/1/1961 - 31/12/1978 except for the Lee at Feildes Weir which was 1/1/1961 - 31/12/1975, as the gauge was out of commission for 2 years during 1976-8. The validation period was 1/1/1979 - 31/12/2002. This information has been added to the caption if Figure 3, alongside the Nash-Sutcliffe scores in the text as also suggested by referee, Wilby.

Page 7, line 18: Nash-Sutcliffe efficiencies have been included: 'The following Nash-Sutcliffe efficiencies were achieved for each catchment: Teddington Weir: calibration: 0.88; validation 0.86; Feildes Weir: calibration: 0.68; validation 0.69; Days Weir: calibration: 0.86; validation 0.90.'

Page 25, line 7: The following statement has been added to Figure 3's caption to clarify the calibration and validation periods. 'The calibration period against historical flows was 1/1/1961 - 31/12/1978 for Teddington and Days Weir, and 1/1/1961 - 31/12/1975 for Fields Weir. The validation period for all catchments was 1/1/1979 - 31/12/2002.'

4. The limitation of the methodology needs to be presented clearly and properly. As an example, the catchment is calibrated using a fixed PET whereas projected PET's are fed to study the climate changing impact - would a large change in PET change the rainfall-runoff relation at all?

This question raised is similar to a point made by referee, Wilby. We recognise that the calculation of PET is essential in calculating future water resource availability and that different downscaling methods yield different PET change predictions. The Thames basin was divided into three sub-catchments to conduct the hydrological modelling as shown in Figure 2. Within each of the catchments there are a variety of land uses which would in turn affect moisture losses, as the reviewer highlights. Given the similarity in the three catchments in terms of elevation and heterogeneity of land cover, and that CATCHMOD is a lumped model, only one PET series for each sub-catchment could be used as input, it was decided to use the same PET record for the three areas. Unfortunately with applying a lumped model it is not possible to investigate how representative this is for the urban sub-catchment. However, in a publication forthcoming we use a physically-based spatially distributed hydrological model which uses spatially correlated precipitation and PET input data from the UKCP09-WG on a 5km grid. Thereby giving a better representation of input data across the Thames basin.

The following text has been amended for clarity:

Page 7, line 37: ‘It is recognised that within each of the catchments the variety of land cover would in turn affect moisture losses. However, given the similarity of the catchments in terms of elevation and heterogeneity of land cover, and that the rainfall-runoff model is lumped, a single PET record generated at the centroid of the whole Thames basin was used; the representative 5km grid cell is highlighted in Fig 2. A forthcoming paper will present the application of a spatial weather generator which will feed a physically based, spatially distributed hydrological model which will allow better representation of both the climatological and land cover heterogeneity of the catchment. Furthermore, it will enable changes in land cover i.e. increasing urban areas to be considered’

In addition, more details/references are needed about the LARaWaRM.

The paper presents the first published application of LARaWaRM which as referenced in the text is based upon the Environment Agency’s representation of the water resource zone in AQUATOR. The model is a bulk demand supply model run on a daily timestep. There are five phases to the water movements: river flows are input at the start of each day via a time series of values; river regulators then augment river flows to satisfy river flow constraints; demand centres then try to satisfy their demands by drawing water from any or all available supplies, such as river abstractions, groundwater abstractions, reservoirs, etc.; reservoirs refill as necessary from their available supplies according to built-in rules; finally at the end of the day any reservoir which has had excess water pushed into it will spill into its attached river spillway. This information is provided in the referenced document and after addressing the comments by referee, Wilby, we would argue that no further details would add value.

Once again we would like to thank the three reviewers whose comments, which have led us to including additional supporting references, have substantially improved the manuscript; we acknowledge them in the paper.

Yours faithfully,

Claire Walsh (on behalf of all co-authors)

Adaptation of water resource systems to an uncertain future

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Abstract

Globally, water resources management faces significant challenges from changing climate and growing populations. At local scales, the information provided by climate models is insufficient to support the water sector in making future adaptation decisions. Furthermore, projections of change in local water resources are wrought with uncertainties surrounding natural variability, future greenhouse gas emissions, model structure, population growth and water consumption habits. To analyse the magnitude of these uncertainties, and their implications for local scale water resource planning, we present a top-down approach for testing climate change adaptation options using probabilistic climate scenarios and demand projections. An integrated modelling framework is developed which implements a new, gridded spatial weather generator, coupled with a rainfall-runoff model and water resource management simulation model. We use this to provide projections of the number of days, and associated uncertainty that will require implementation of demand saving measures such as hose pipe bans and drought orders. Results, which are demonstrated for the Thames basin, UK, indicate existing water supplies are sensitive to a changing climate and an increasing population, and that the frequency of severe demand saving measures are projected to increase. Considering both climate projections and population growth the median number of drought order occurrences may increase five-fold by the 2050s. The effectiveness of a range

of demand management and supply options have been tested and shown to provide significant benefits in terms of reducing the number of demand saving days. A decrease in per capita demand of 3.75% reduces the median frequency of drought order measures by 50% by the 2020s. We found that increased supply arising from various adaptation options may compensate for increasingly variable flows; however, without reductions in overall demand for water resources such options will be insufficient on their own to adapt to uncertainties in the projected changes in climate and population. For example, a 30% reduction in overall demand by 2050 has a greater impact on reducing the frequency of drought orders than any of the individual or combinations of supply options; hence a portfolio of measures are required.

1 Introduction

Climate change projections point to longer or more frequent (or both) meteorological droughts in some regions by 2100 but there remain substantial uncertainties as to how rainfall and soil moisture deficits might translate into prolonged periods of reduced streamflow and groundwater levels (IPCC, 2014). This, and other pressures, affect and will continue to affect UK water availability into the future. Climate change could cause a decline in the amount of water available for supply, particularly in summer months if lower average rainfall coincides with increased temperatures (e.g. Murphy et al., 2009). Water demand may also be sensitive to climate variability, although few studies have examined this aspect (e.g. Parker and Wilby, 2013). Population growth, alongside a greater number of single occupancy households will greatly affect water demand and this stresses the need for greater water efficiency. Water resources may therefore increasingly need to be enhanced and managed through new supply or demand management options. Supply options may include storage reservoirs, inter-basin transfers, desalination plants, effluent reuse, groundwater and river abstractions whilst demand management options may include water meters, water saving devices, efficient appliances, rainwater collection systems and grey-water recycling.

A number of studies have investigated the impact of climate change on water resources, addressing the associated uncertainties, using both deterministic and probabilistic projections of climate change. For example, in the UK these include Wilby and Harris (2006), New et al. (2007), Dessai and Hulme (2007), Christensen and Lettenmaier (2007), Vidal & Wade (2009), Manning et al. (2009) and Lopez et al. (2009). Burke et al. (2010) indicated that an 11 member HadRM3 perturbed physics ensemble showed uncertainty as to whether drought occurrence will decrease or increase across the UK by the end of the 21st century (consistent with earlier results from a multi-model ensemble (Blenkinsop & Fowler, 2007)) although they identify a predominant tendency to the latter. Burke & Brown (2010) demonstrate similar results, with relatively little spatial variation across the UK. Such studies show the ~~disagreement between results from different climate models~~sensitivity of projections to climate model structure and parameterization and suggest that methods to downscale climate information can result in large sources of uncertainty in future river flows. However, a 'cascade' of uncertainties arise when considering climate change impact assessments for decision making (Jones, 2000). Wilby (2005) showed that uncertainties associated with impact studies arise from model structure, choice of model calibration period, choice of parameter sets, as well as climate scenarios and downscaling methods.

In this study we use the UK Climate Projections (UKCP09) which provides an ensemble of climate model outputs that capture a number of important uncertainties in climate model parameterisation and structure (Murphy et al., 2009). The UKCP09 outputs have been used to consider: flood risk (Cloke et al., 2013; Kay and Jones, 2012), changes in precipitation and PET in upland river catchments (Thompson, 2012), sediment yield in catchments (Coulthard et al., 2014), urban heat island effects (Lee and Levermore, 2013) and overheating in buildings (Patidar et al., 2014; Jenkins et al., 2014). Their release and availability has also enabled better assessment of uncertainties in projections of water availability in a changing climate (e.g. Christierson et al. 2012; Harris et al. 2013; Warren and Holman, 2012). Using the UKCP09 projections, Harris et al. (2013) found that for the North Staffordshire Water Resource Zone uncertainty in climate model parameterisation causes a greater proportion of uncertainty in estimates for the 2080s of change in overall flow and water shortage per year than emission scenario choice. Whitehead et al. (2006), Wilby and Harris (2006), Dessai and Hulme (2007), New et al. (2007) have all conducted end-to-end assessments of propagation of uncertainties in adaptation assessments. Understanding the range of uncertainties when assessing future water shortages in the face of climate change will enable policies and strategies to be designed that are robust to the full range of plausible futures. Methods such as Robust Decision Making (RDM) provide a quantitative approach to facilitate decision-making under a range of assumptions and uncertainties. RDM has been used to develop long-range water management plans in the US (Groves et al., 2008; Lempert and Groves, 2010). Matrosov et al. (2013) applied both RDM and Info-Gap Decision Theory to consider uncertainties to proposed water supply portfolios for the Thames Basin. ~~More recently~~ Borgomeo et al. (2014) demonstrated a methodology based on UKCP09 that used nonstationary probabilistic climate scenarios to aid risk-based water resource management. More recently the decision-scaling method (Brown et al., 2012) or climate stress testing (Brown and Wilby, 2012) has been applied to water resources systems. Multiple sources of climate information, climate projections and stochastic assessments are used to evaluate risks (Brown et al., 2012) and subsequently applied to determine robust adaptation strategies (e.g. Whateley et al., 2014; Steinscheider et al. 2015).

This paper builds on and extends this previous research to assess current and future water resources risk by developing and integrating:

- simulation models of precipitation, catchment hydrology and water resource systems within an uncertainty analysis framework;
- a new spatial weather generator, that unlike previous work in this area, e.g. Borgomeo et al. (2014), captures the spatial variability of rainfall in large catchments, to produce high-resolution catchment-wide precipitation simulations for the Thames Basin in the UK;
- consideration of climate uncertainties as a driver of water resource availability, as in e.g. Harris et al. (2013), but also evaluating other uncertainties such as changes in future demand;
- analysis and testing of the effectiveness of a number of adaptation options to manage both the demand and supply of water resources; and,
- provision of end-user relevant water resource indicators increasingly referred to as 'climate services' (Hewitt et al., 2012) such as the frequency of triggering reservoir storage control levels, or triggering of Demand Saving Measures, that are used by water companies (e.g. Thames Water, 2014) and promoted by the UK Government (DEFRA, 2008) and the Environment Agency.

Fig 1 outlines the methodological approach taken and the associated sequence of models used to simulate the Thames Valley water resource system. Starting from the climate model outputs provided by UKCP09, spatially consistent downscaled rainfall scenarios are generated using a spatial rainfall model of the Thames and Lee river basins. These, alongside corresponding downscaled Potential Evapotranspiration (PET) data produced with a weather generator, are used to drive catchment rainfall-runoff models, which output corresponding river flows. These, in turn, are input to a model of the water resource system which enables a range of supply and demand management options to be tested which incorporate projections of demographic change. ~~Fig 1 outlines the methodological approach taken and the associated sequence of models used to simulate the Thames Valley water resource system. Starting from the climate model outputs provided by UKCP09, spatially consistent downscaled rainfall scenarios are generated using a spatial rainfall model of the Thames and Lee river basins. These, alongside consistent downscaled Potential Evapotranspiration (PET) data produced with a weather generator, are used to drive catchment rainfall-runoff models, which output consistent river flows. These, in turn, are input to a model of the water resource system which enables a range of supply and demand management options to be tested which incorporate projections of demographic change.~~

2 Methodology

2.1 Case study: Thames Basin, UK

The Thames basin (Fig 2) is 10,000km^2 in area, mainly underlain by permeable chalk, the basin is predominantly rural, yet densely urbanised downstream. The southeast of England is the most water scarce region in the UK, having lower than average rainfall and a very large water demand (Environment Agency, 2007a) i.e. 'seriously' water stressed. The basin receives an average of 690mm of rainfall each year (250mm only is effective rainfall (Environment Agency, 2014)) compared to a national average for England and Wales of 897mm. The River Thames and River Lee supply most of the water for London and southeast England, with 70% of all water being taken from upstream of Teddington Weir; the remainder is abstracted from aquifers (GLA, 2011). Per capita, Londoners consume more water per day (167 litres) than the UK average (146 litres). Much of the water resource system's infrastructure is more than 150 years old and leakage is a major issue which is currently being addressed. The GLA (2011) expect London's population to rise from 7.56 million at present to between 8.79 and 9.11 million by 2031. UKCP09 probabilistic projections (Murphy et al. 2009) identify potential future climatic pressures in this region (50th percentile figures), suggesting that average summer temperatures could~~will~~ increase by 2.7°C and winter temperatures by 2.2°C. Average summer rainfall are projected to decrease by 18% and winter rainfall to increase by 15% (GLA, 2011).

2.2 Probabilistic climate scenarios

Uncertainties in projections of future climate originate from a number of sources, including modelling uncertainty, and it is not meaningful to use only one ~~climate scenario~~model realisation in climate change assessments. UKCP09 provides a perturbed physics ensemble (PPE) of simulations, downscaled using the regional climate model (RCM) HadRM3 at a resolution of 25km where each ensemble member uses different parameter values within expert-specified bounds. UKCP09 also incorporates projections from 12 other climate models possessing different structures, allowing the sampling of structural modelling errors from a multi-model ensemble. These two ensembles are combined within a Bayesian statistical framework to produce the UKCP09 probabilistic projections (Murphy et al., 2009). Additional downscaling onto a 5km grid through a combined change factor (CF) and weather generator approach, provides a spatial resolution more appropriate for considering catchment response.

Here we use an extended version of UKCP09 stochastic weather generator (Jones et al., 2009) (referred to hereafter as UKCP09-WG), which provides simulations of daily and hourly weather variables for both a “baseline” (1961-1990) and a selected future climate (emissions scenario and time horizon) for each member of a probabilistic projection. Projections for two 30-year periods centred on the 2020s (SCN20) and 2050s (SCN50) were identified as most relevant to stakeholders who expressed the greatest need for near- to medium-term future scenarios (Hallett, 2013). The analysis was restricted to the A1B (medium) emissions scenario, although a complete consideration of future uncertainties would need to examine alternative scenarios. These future projections were assessed against the 1961-1990 baseline (BSL) which also served to provide information on current hazard.

The standard UKCP09-WG framework is extended here by replacing the single-site rainfall model with a spatial rainfall model, the stochastic Spatial-Temporal Neyman-Scott Rectangular Pulses model (STNSRP; Cowpertwait, 1995, Burton et al., 2008). This models spatial rainfall variability and so helps to capture non-linear impacts of climate change on water resources - in particular correlated weather events between sub-basins. Whilst this is not necessary for small catchments (e.g. Harris et al. (2013) use a simple scaling relationship) such an approach is required here due to the larger scale of the Thames basin. The spatially continuous nature of the STNSRP process is therefore advantageous as it may be sampled at any location (Burton et al., 2010a) or even on a regular grid (e.g. Blanc et al., 2012; Burton et al., 2013). Here, we present one of the first published applications to generate, and assess the impact of, future climate gridded rainfall datasets using the STNSRP model.

Ten, 100-year gridded daily rainfall simulations were generated using the BSL climatology (Perry and Hollis, 2005a,b). Following the UKCP09 approach (Jones et al., 2009) 100 sets of monthly change factors for each time-slice for the A1B emissions scenario were randomly sampled and applied to the observed daily rainfall statistics. The rainfall model was refitted to these perturbed statistics and used to generate 100-year gridded daily simulations for each of the randomly sampled 100 sets of CFs for both SCN20 and SCN50. Batch processing of these scenarios was facilitated through the use of the efficient STNSRP simulation scheme described in Burton et al. (2010a). The CRU Daily Weather Generator was used to generate long time series of synthetic daily weather variables, conditioned by the synthetic daily rainfall generated with the ~~better a~~ NSRP process (Kilsby et al., 2007). For simulation, input rainfall series were derived for each sub-catchment from the weather generator output by averaging simulated point rainfall records generated over the 5km grid cells covering the sub-catchment. Here, only the PET output variable was required as input to the rainfall-runoff model. ~~A single PET record generated at the centroid of the whole Thames basin was used; the representative 5km grid cell is highlighted in Fig 2~~. Since the region under study concerns only 10,000km2, with a maximum elevation of 330m, PET is not very variable, so a single PET record has been used for all catchments, representative of the point rainfall record generated at the centroid of the whole Thames basin. It is recognised that within each of the catchments the variety of land cover uses would in turn affect moisture losses. However, given the similarity of the catchments in terms of elevation and heterogeneity of land cover, and that the rainfall-runoff model is lumped, a single PET record generated at the centroid of the whole Thames basin was used; the representative 5km grid cell is highlighted in Fig 2. A forthcoming paper will present the application of a spatial weather generator which will feed a physically based, spatially distributed hydrological model which will allow better representation of both the climatological and land cover heterogeneity of the catchment. Furthermore, it will enable changes in land cover i.e. increasing urban areas to be considered.

Supplementary resources present further details about the validation of the UKCP09-WG and presents a brief assessment of the robustness of the random sample of CFs used in this study.

2.3 Catchment models

Flow time-series were generated using the CATCHMOD rainfall-runoff model, which is a water balance model used for water resource planning by the UK Environment Agency, and has been described in detail elsewhere (Wilby et al., 1994; Davis, 2001). CATCHMOD is a lumped parameter conceptual model, which allows for the subdivision of the catchment into a number of zones, according to its geological and surface runoff characteristics. Input to the model is in the form of time series of daily rainfall and potential evapotranspiration representative of the entire catchment and the output is a time series of the daily flow at the catchment output. Three parameterisations of this model were used, to produce flow series for each of the three input sub-catchments locations of the water resource model. Each of these involves three zones, representing clay, limestone and urban regions. Parameters were chosen by optimisation of the Nash-Sutcliffe efficiency in reproducing historically observed flow, and validated by comparison with flows in a different historical period (see Manning et al., 2009 and Fig. 3). The following Nash-Sutcliffe efficiencies were achieved for each catchment: Teddington Weir: calibration: 0.88; validation 0.86; Feildes Weir: calibration: 0.68; validation 0.69; Days Weir: calibration: 0.86; validation 0.90.

~~For simulation, input rainfall series were derived for each sub-catchment from the weather generator output by averaging simulated point rainfall records generated over the 5km grid cells covering the sub-catchment. Since the region under study concerns only 10,000km^2, with a maximum elevation of 330m, PET is not very variable, so a single PET record has been used for all catchments, representative of the point rainfall record generated at the centroid of the whole Thames basin.~~

The ensemble of 100 future 100-year scenarios of rainfall and PET generated by UKCP09-WG for both the SCN20 and SCN50, alongside the 10 BSL scenarios were used to drive CATCHMOD to produce synthetic river flow data for use as input into the water resource model.

2.4 Water resource modelling

To enable assessment of London's Water Resource Zone scenarios a rule-based water resource management simulation program was developed for this study in the MatLab© programming language. This was parameterised with the same operational rules, flow, demand and capacity data as the Environment Agency's implementation of the AQUATOR software (Oxford Scientific Software Ltd., 2004) for the Thames basin but is orders of magnitude faster and able to simulate 100 years' conditions in ~1s. The London Area Rapid Water Resource Model (LARaWaRM) is a network model comprising nodes and links representing various water resource components and interactions. Nodes can represent diversions, natural lakes, reservoirs, aquifers, wetlands, gauge sites with a defined time-series flow, and demand consumption sites. At each (daily) time step, water is moved according to the input data, with rules defining the behaviour of each node and link, and connectivity between components.

Fig 4 presents a schematic of LARaWaRM which was used to investigate the potential impacts of climate change, socio-economic change and supply/demand options on the resource system. Synthetic river flows~~,~~ generated by CATCHMOD were input into LARaWaRM to evaluate the impacts of the downscaled climate change UKCP09 probabilistic projections.

Drought risk is estimated by the frequency, in terms of the number of days, that a demand saving (DS) measure is imposed. In water resources planning, demand saving measures or Levels of Service describe the average frequency that a company will apply restrictions on water use, triggered by reservoir control curves. In robust analysis of water resource systems, failure to meet a particular Level of Service can act as a suitable metric of risk and one against which the effectiveness of interventions to a system can be judged (Hall et al., 2012; Groves and Lempert, 2007). Table 1 describes these Levels of Service, restrictions and their target frequencies for the Thames basin.

To explore the impact of population growth on drought risk, population and employment growth estimates were also used to scale current demand. Population estimates were taken from the Greater London Authority's strategic plan for London (GLA, 2011) for up to 2031 and then extrapolated at the same average annual growth rate of 51,000 to provide an estimate of population for 2050. Employment growth estimates were calculated using the Tyndall Centre for Climate Change's methodology derived for the Urban Integrated Assessment Facility (see Hall et al., 2009; Walsh et al., 2011). In addition, demand per capita was altered to reflect technological advances such as improved water efficiency measures. By altering the properties of existing links and nodes or introducing new links and nodes into the model domain, a number of supply adaptation options were also investigated.

Adaptation options considered included:

- Demand reduction: sensitivity analysis considering reduction in per capita demand between 0- 35%, at 5% intervals which represent a range of behavioural and technical efficiencies;
- Desalination plant: capacity providing 150ML/day, which represents the Thames Water site at Beckton;
- Leakage reduction: in 2010/11, Thames Water reported leakage losses of 26%; the UK water company average is 18.5% (GLA, 2011), a linear reduction in leakage to 18.5% by 2050 is applied;
- New reservoir: storage capacity of 100 million m^3 added to the 2050 runs, as realistically such infrastructure is planned over a 30 year timeframe;
- Combinations of the above: the model's computational efficiency enables a range of different combinations of adaptation options to be tested.

3 Results

3.1 Changes in rainfall and potential evapotranspiration

For each sub-catchment, mean monthly precipitation was calculated for each of the 100 simulated series for SCN20 and SCN50 and changes were examined relative to the median monthly precipitation derived from the 10 BSL simulations. There is relative uniformity across the 3 sub-catchments with a greater range in projections in summer months - the median estimate of change indicates a pattern of wetter winters and drier summers. For SCN20 projected changes in mean precipitation are relatively small, <+10% in winter and >-10% in summer but increase in magnitude to ~+15% to +20% and ~-10% to -30% respectively for SCN50 (see Fig 5). The ensemble uncertainty shows that there could be substantially greater pressure on water resources - the 10th percentile indicating decreases projected for all seasons; for SCN50 this represents a typical decrease of ~45% during summer with a small (<~-5%) decrease in winter. However, the 90th percentile suggests less stress with an increase in precipitation throughout the year. Mean seasonal precipitation was also calculated for each season and expressed as an anomaly from the long-term mean to determine the longest sequence of negative seasonal anomaly. This suggested the potential lengthening of periods with below average rainfall - for BSL the longest sequence was 10, whereas for SCN50 it was 18. However, we note that a limitation of applying change factors through a Weather Generator to assess future projections in rainfall is that it does not readily produce the longer sequences of dry periods (Wilby et al. 2014) that may produce multi-seasonal droughts and hence stress the water supply system.

The projected change in occurrence of precipitation was also assessed through the examination of dry day probabilities (PDD). Fig 6a demonstrates that for SCN20 the central estimate shows relatively little change in PDD relative to the BSL during winter and spring but that PDD is projected to increase in summer. For SCN50 (Fig 6b) there remains little change in PDD during winter but there is a further increase between May and October with the median estimate of up to ~0.8 in August.

Mean daily PET is projected to increase throughout the year (Fig 6c and 6d). For SCN20 the largest increase occurs in summer, the central estimate indicating an absolute increase of ~+0.3 mm d^{-1} relative to a BSL value of ~3.0 mm d^{-1}. For winter the change is smaller, ~+0.1 mm d^{-1} relative to a BSL value of ~0.4 mm d^{-1}. However, these figures represent a larger relative increase in PET in winter. For SCN50 the increase in summer is ~+0.6 mm d^{-1} with an additional increase in winter ~+0.1 mm d^{-1}. These combined changes demonstrate potential future pressure on water resources arising from climate change which is investigated further through the application of these ensemble projections to a rainfall runoff model and water resource model for the Thames.

3.2 Changes in river flows

Precipitation and PET series for the two 100 member future scenario ensembles are used to generate river flows for the three sub-catchments using the CATCHMOD rainfall-runoff model. Fig 7 shows the percentage change in monthly and seasonal flows for each sub-catchment for SCN20 and SCN50 compared to the 10 BSL simulations. The bars show the median changes in flows, with the upper and lower horizontal bars showing the 10^{th} and 90^{th} percentiles, indicating the degree of uncertainty in the climate projections. Generally there is a large spread in the projections. For SCN20, from February to June there is a small increase in median flows for the Upper Thames, and an even smaller increase in the Lower Thames, with the Lee showing a decrease during these months. All other months, for each catchment show decreases in median flows, with substantial decreases from July to December in SCN50. Plotted seasonally, the greatest decreases are evident in the autumn months (September, October and November). Mean estimates for flow quantiles (not shown) at Kingston, the outlet of the catchment, when compared with BSL, indicate a decrease for SCN20 across the entire flow duration curve, with greater decreases in Q90 and Q95 ~~quantiles~~ of 14% and 15%

respectively. For SCN50 the ~~scenarios~~ simulations also show a decrease in mean flow quantiles across the entire flow duration curve, with the exception of higher flows i.e. Q5 and above. Decreases in lower flows are more substantial, with mean decreases of 33% and 37% in Q90 and Q95 ~~quantiles~~respectively.

3.3 Water resource availability

Initial analysis determined the relative impacts of climate change and population growth on drought risk, in terms of change in frequency of demand saving measures derived from LARaWaRM. Fig 8 presents the number of days that each of the DS measures are implemented for the baseline and SCN20 and SCN50 runs for i) the climate projections only; ii) changes in population growth only (where per capita allocation remains the same); iii) climate and population growth signals combined. Both climate projections (i) and population growth scenarios (ii) increase the frequency of all DS measures. The climate scenarios introduce a greater degree of variability and uncertainty into the frequency estimations which increases as the severity of the DS measure worsens. Considering the population signal alone, there is a smaller increase in SCN20 frequencies compared to the BSL scenarios. However, there is a greater shift in median values from SCN20 to SCN50. The relative contribution to drought risk from population growth is greater than that from the climate projections. However, these simulations assume that per capita demand remains the same as present in SCN20 and SCN50.

Fig 9 demonstrates the effectiveness of reducing demand, i.e. per capita allocation, on the frequency of DS4 measures for BSL, SCN20 and SCN50. Although probably unrealistic, a reduction in per capita allocation of 35% would eliminate the need for drought orders in the 2020s. Even a small decrease of 3.75% in SCN20 reduces the median frequency by 50%. However, by the 2050s the growing population and intensification of the climate change signal means that the 35% reduction in per capita allocation is no longer effective, suggesting that new supply options may be required to complement demand management strategies by the 2050s.

Therefore, we also investigated a number of supply options to supplement the currently available water. Fig 10 presents the frequency of DS4 days for a number of supply adaptation options for the 2020s and 2050s: i) a desalination plant: capacity of providing 150ML/day, which represents the Thames Water site at Beckton; ii) a linear reduction in leakage to 18.5% by 2050 is applied to the simulations; iii) reservoir: storage capacity of 100 million m^3 is added to the 2050 runs as realistically such infrastructure is planned over a 30 year timeframe; iv) various combinations of i, ii and iii. In addition, results are shown for all cases with no reduction in per capita demand and for a reduction in per capita demand of 15% by 2020 and 30% by 2050. Per capita demand is reduced by 15% in 2020 to bring this in line with the UK's average per capita usage. By 2050 it is reduced by a further 15% to 30% to reflect the potential impact of demand saving measures e.g. water meters alone can create water savings of 10-15% per household (Environment Agency, 2007b).

Individually, all options considered have a positive effect in reducing the frequency of DS4 measures. The availability of 150ML/day from the desalination plant in 2020 reduces the median frequency value by around 100%; however, its effectiveness is diluted by 2050. ~~In the~~For SCN50~~ scenarios~~, reducing leakage has a greater impact than the desalination plant itself. Combinations of adaptation options improve the situation further. To obtain a 100% reduction in the median number of DS4 days by 2050, a combined contribution from leakage reduction and a new storage reservoir is necessary. An additional 37.5~~100~~% improvement can be obtained by adding the contribution of the desalination plant to this portfolio. A 15% reduction in overall demand in 2020 and 30% in 2050 has a greater impact on reducing the frequency of DS4 days than any of the individual or ~~combinations of~~combined supply options. Introducing demand reduction also reduces the variability significantly.

4 Discussion

Between 2003 and 2006, England and Wales reported the third lowest rainfall since 1932-1934; the Thames and the South East experienced exceptional regional rainfall deficits. Of particular importance was the disproportionate concentration of overall rainfall deficit in the winter and spring, when typically modest evaporation losses allow the bulk of reservoir replenishment and aquifer recharge (Marsh, 2007). Drought Severity Index analysis for the Thames catchment, as for other water resource regions in the south, shows an historical increase in drought intensity, and frequency of drought months in both wet and dry seasons, as well as frequency of drought events with persistence of at least 3 and 6 months (Rahiz and New, 2013). In this study, the combined projection of increased PDD and PET during summer months and lasting further into autumn, highlight the potential for increased frequency of such climate-driven water resource pressures in the future.

The largest decreases in river flows are projected for September to November; with the greatest effects being decreases in low flows. At the outlet of the catchment projected mean change in Q90 is a 14% decrease, with a similar value, 15% for Q95 (SCN20). However, the changes are much greater for SCN50 – 33% for Q90 and 37% for Q95. Manning et al. (2009), found mean decreases in Q95 of 45% using the HadRM3H model and 37% using the HadRM3P model for the 2080s, using the medium-high scenario for the Thames. In their UK-wide study, Christierson et al. (2012) highlight that the largest flow decrease was found in the Thames, Anglian and Severn river-basin regions, with a high probability assigned to decline in summer flows. They also conclude that the dispersion of distributions in projected monthly flows for the Thames catchment to be larger than the range of natural variability.

There have been five major water resource droughts in the Thames catchment over the last 90 years (Thames Water, 2014): 1920-21; 1933-34; 1943-44; 1975-76; 2010-2012. Most recently, the 24-month period from April 2010 to March 2012 was the driest in the 128 year record for the Thames catchment. During this period intensive media campaigns highlighted the drought and promoted water efficiency; in 2012 both a Temporary Use Ban and Non-Essential Use ban restrictions were implemented (i.e. Level of Service 3 restrictions). Our results (see Fig 8~~10~~a) clearly show that existing water supplies are sensitive to changing climate. In particular, the requirement for DS3 and DS4 measures is projected to increase by the 2020s and more so by the 2050s. Similarly, Darch et al. (2011) found their central estimates of supply-demand deficiency for the London Water Resource Zone may increase from 51 ML/day under the 2020s medium emissions scenario to 516 ML/day under the 2080s high emissions scenario, albeit with large uncertainties. Although they considered a wider range of climate projections, they did not consider how such impacts may be compounded by population growth; resulting in increasing demand for resources.

Population growth, especially in London and the south-east will inevitably place increased pressure on already limited water resources. By 2031, the GLA (2011) expect London's population to increase by 16-21%. Our analysis demonstrates the potential impacts of both climate change and population growth on water availability. Population projections are available up to 2031, beyond which we have extrapolated the average growth rate to 2050. It could be argued that this may be a conservative estimate as London continues to regenerate, expand and invest in major infrastructure projects to attract increased investment and agglomerations of organisations, and hence ultimately population. However, both climate changes and population growth will occur simultaneously, therefore the starting point for assessing the benefit of any supply and demand adaptation measures needs to be based upon the projections shown in Fig 8~~10~~c. When comparing the expected frequency of level of service/demand saving measures from Thames Water (see Table 1), results show that targets are increasingly less likely to be met. For example, currently the target is to never implement DS4 measures, but our analysis indicates that these may be required once every two years by the 2020s and once every year by the 2050s.

Globally, the greatest demand for water is driven by agriculture and industry; however, in the UK, given reduced industrial and mining demand for water, more emphasis has been placed on the demand management of potable water (McDonald, 2007). Supply-side solutions have dominated water management, with little attention given to long-term demand forecasting. Parker and Wilby (2013) reviewed approaches to water demand estimation and forecasting for daily-season and years-decade timescales for household water use. They concluded that little consideration has been given to UK household water demand estimation and forecasting under a changing climate. However, water demand management is increasingly recognised as a ‘low regret’ adaptation from both a financial and environmental point of view, which can be implemented at a range of scales from individuals and~~,~~ households ~~and~~ to communities. Water meters have been shown to decrease water use by 10-15% per household (GLA, 2011), as well as improve energy efficiency, given the substantial proportion of energy used to heat water within a household. The GLA have ambitious targets for the installation of water meters in London properties (all houses and blocks of flats by 2020 and all individual flats by 2025 (GLA, 2011)). There are no guarantees on the uptake of demand saving measures such as water meters, grey water recycling or water efficient appliances; however, our analysis (see Fig 10) has demonstrated that even small reductions in per capita demand can reduce the median frequency of DS4 measures, for e.g. by 50% by the 2020s. A 35% reduction in per capita demand by 2020, which is perhaps unrealistic, would eliminate the risk of drought orders. The Future Water Strategy (DEFRA, 2008) suggests a target of reducing per capita usage from 150l to 130l per day, a 13% reduction, by 2030. By 2050, even a 35% reduction in per capita demand is no longer effective and new supply options need to be considered.

The London Water Resource Zone supply-demand deficit is currently finely balanced and it is recognised that a new supply resource will be required by the end of the 2020s (Thames Water, 2014). The UK’s first desalination plant built in the Thames Gateway became operational in 2010. Our results show that this new resource increases the reliability of supply through the 2020s; however, by the 2050s, consistent with Borgomeo et al (2014), our analysis shows that further new resource may be required. Here, we go further to consider additional supply options. A new reservoir with a storage capacity of 100 million m^3 is a beneficial new resource in the 2050s; however, in addition to the socio-economic costs of new schemes, climate sensitivity of both supply and demand reduction options also need to be considered. For instance leakage reduction and artificial recharge are not as sensitive to externalities as new storage options which require adequate precipitation or personal usage reductions given a warmer climate. In their 2011 study, Darch et al. found that the cost effectiveness of new reservoir options for the Thames catchment are sensitive to assumptions about climate change. Compulsory metering and leakage reduction schemes were selected under all of the scenarios, with a new reservoir option becoming plausible by the 2050s under medium emissions scenarios. By the 2080s it was found that a strategic transfer e.g. Severn-Thames would also be necessary; alternatives such as indirect reuse and further desalination capacity were also considered but are much more expensive and carbon intensive (Darch et al. 2011).

Results from this study advocate the twin-track approach of demand reductions and new supply options to minimise the risk of severe imposed restrictions on water resources. Considering a plausible representation of future climate, demand scenarios and potential adaptation strategies will aid water managers' assessment of where vulnerabilities occur. Hall and Borgomeo (2013) proposed a framework to test strategies for adapting to risks that enables testing large numbers of synthetic hydrological sequences and allows exploration of different sources of uncertainty including climate, catchment responses and demands. In their case study on Adelaide's southern water supply system, Beh et al., 2015a,b and Paton et al., 2014 demonstrate a multi-objective evolutionary algorithm framework to consider the trade-offs between reducing greenhouse gas emissions while planning sustainable urban water supply systems. Applied to North Carolina, Zeff et al., 2014 investigated how more flexible and adaptable water supply portfolios can be implemented alongside financial mitigation tools to reduce trade-offs between fluctuations of revenues and costs of implementing new solutions. Haasnoot et al. 2014 demonstrate the development of adaptation pathways whereby environment and policy responses are analysed through time to develop an ensemble of plausible futures to support decision making under uncertainty. Applying the approach and outcomes from this research in such ~~a~~ risk frameworks would be valuable in considering costs, benefits and trade-offs of adaptation measures. This would facilitate adaptive strategies that are able to evolve as new information becomes available; this is particularly useful given climate model, demographic and supply uncertainty.

This study has advanced understanding of the potential future water resource risk and possible adaptation options for managing these risks for the Thames catchment. However, the study has a number of limitations. We used the UKCP09 probabilistic climate scenarios only for the medium emission scenario, for two time periods; although Harris et al. (2013) indicate that for the 2080s the uncertainty in the UKCP09 PPE is the cause of a greater proportion of uncertainty in flow and water shortage probability than is caused by emissions scenario. We used only one hydrological model, CATCHMOD, and one parameter set although this has been extensively tested for the Thames catchment (e.g. Davies, 2001; Wilby, 2005; Wilby and Harris, 2006; Manning et al., 2009). Wilby and Harris (2006) showed how both choice of hydrological model and choice of model parameters can affect the outcome of the modelling study. We have only considered the impacts of climate change and demand change on water resource availability at defined points in the future i.e. 2020s and 2050s; however, there is a growing practical interest on how changes play-out throughout a planning horizon such as an Asset Management Plan period. For this a transient implementation of the single-site NSRP model and Climatic Research Unit (CRU) weather generator (Burton et al., 2010a; Blenkinsop et al., 2013) could be implemented (e.g. Goderniaux et al., 2011).

5 Conclusions

The application of a sequence of models, including an extension of the UKCP09 weather generator that generates downscaled, probabilistic projections of rainfall on a grid over the Thames catchment, indicates that the hazard of inadequate water supply is expected to increase as a function of both climatic and socio-economic drivers. Here we show that these hazards can be managed most effectively through a portfolio of adaptation measures.

Population growth exhibits a greater contribution to drought risk than climate projections. An extreme reduction of 35% in daily per capita allocation would be necessary to offset application of drought orders by 2020. However, a relatively small decrease would have a significant impact, yet moving towards 2050 the need for new supply options could~~will~~ intensify. We found that increased supply from various adaptation options may compensate for increasingly variable flows; however, without reductions in overall demand for water resources such options will not be sufficient to adapt to both climate change projections and a growing population. For example, a 100% reduction in the median number of DS4 days by 2050 can be achieved through leakage reduction and a new storage reservoir. An additional 37.5~~100~~% improvement can be obtained by adding the contribution of the desalination plant to this portfolio. A 15% reduction in overall demand in 2020 and 30% in 2050 has a greater impact on reducing the frequency of DS4 days than any of the individual or combinations of supply options. Water demand reductions are clearly important in reducing water resource deficits; however, given projected population growth these will need to be significant to offset demand increases alongside climate change.

Like other cities, London is at risk from and needs to adapt to a range of climate-related hazards e.g. flooding, urban heat, subsidence (Hallett, 2013) that need to be managed synergistically to avoid any potential conflicts (Dawson, 2007). Many urban areas have set greenhouse gas emission reduction targets (Heidrich et al., 2013), reducing water demand can reduce energy consumption as water use in the home accounts for 89% of all carbon emissions resulting from water use (EA, 2008), conversely the introduction of energy intensive adaptation options such as desalination plants or inter-basin transfers may conflict emission reduction targets.

Given the typical investment timescale to plan for, get approved and implement changes, decisions for water management infrastructure development can have consequences over long timescales (Hallegatte, 2009); when considering any major infrastructure investment and development such as a new reservoir a range of environmental, economic and social consequences need to be critically analysed. The approach demonstrated here can be used to assess a range demand and supply adaptations that can be implemented and be effective on short and long timescales to make robust decisions about water resource management.

This study of the Thames catchment and subsequent analysis has highlighted the following priorities for future research. Firstly, which will be addressed in a forthcoming paper, is an extension of the climate scenarios to include the 2080s time period, coupled with the application of a spatial weather generator feeding a physically based, spatially distributed hydrological model which will allow better representation of both the climatological and land cover heterogeneity of the catchment. Furthermore, it will enable changes in land cover i.e. increasing urban areas to be considered. Secondly, recognising the importance of groundwater in the Thames catchment and hence the potential impact that multi-season droughts may have on the area, further research is needed to understand how trends in such phenomena may affect or influence the choice of adaptation options. This, alongside a third research priority looking more generally about the sequencing of implementation of adaptation options over indicative planning horizons taking account of trade-offs with reducing greenhouse gas emissions or investment portfolios could make use of more robust decision making frameworks under uncertainty such as those proposed by for example Beh et al., 2015b or Haasnoot et al., 2014.

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Figure 1. Methodological approach for the study of current and future water resources for the Thames.

Figure 2. Map of the Thames basin showing the gauging stations at the outlet of the three sub-basins: Upper Thames, Lower Thames and Lee. The grid cells correspond to the 5km spatially correlated gridded rainfall; the black grid cell indicates the catchment's centroid cell for which PET was generated.

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Figure 4. A schematic of LARaWaRM indicating the various water resource system components and interactions. (NB: groundwater is include as an aggregate inflow of 467.4 Ml/d to meet London's demand. A proportion of the inflow to the water treatment works is leakage, this is equivalent to 12% of demand and is returned back to the river and modelled as a contribution to the minimum environmental flow.)

Figure 5. Percentage change in precipitation for a) SCN20 and b) SCN50. The bars denote the median change from the 100 member ensemble, the upper and lower horizontal lines indicate the ensemble 90th and 10th monthly percentiles respectively.

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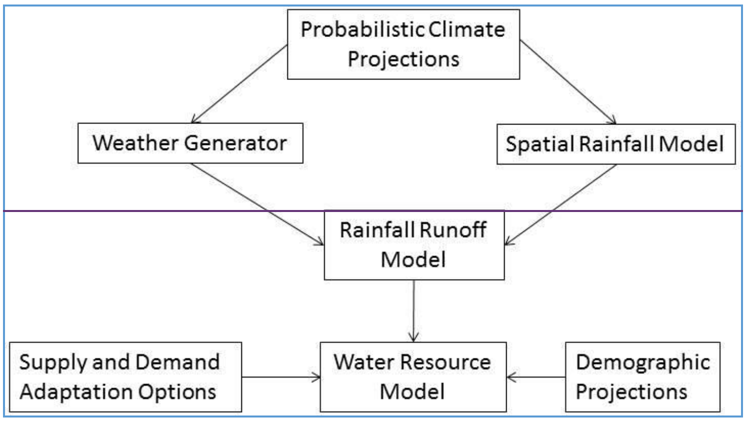
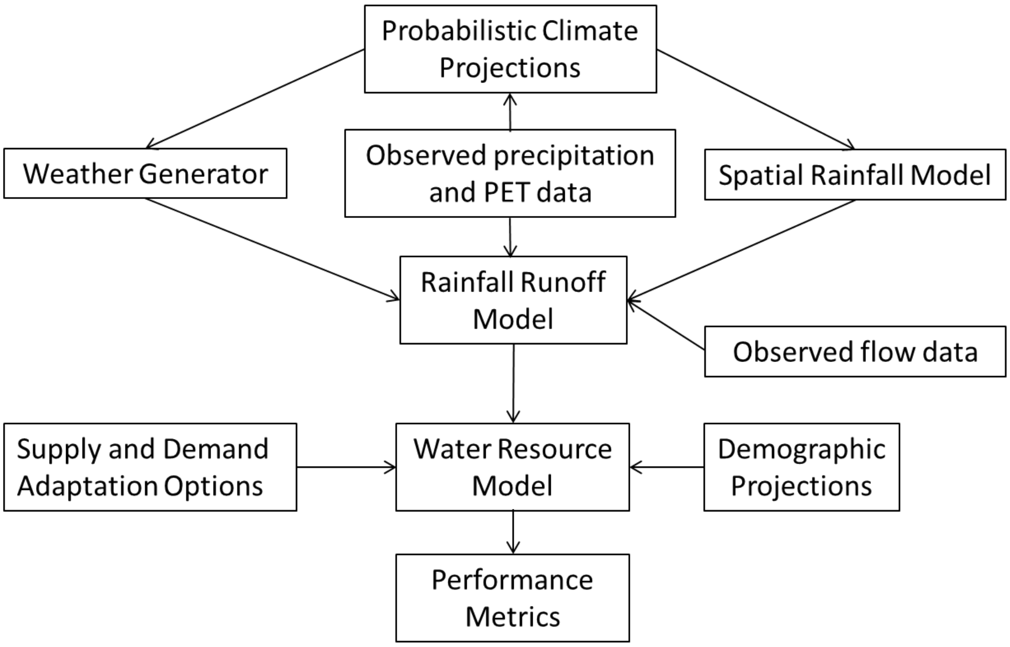
Table 1. Levels of service: restrictions and frequency of restrictions (Source: GLA, 2011; Thames Water, 2014). See Supplementary Material Table 1 for reservoir total storage capacity trigger levels for the different levels of restrictions.

Level of Service	Restrictions	Frequency of restrictions (Thames Water, 2014)
DS1	Media campaigns, additional water efficiency activities, enhanced activity and restrictions to reduce risk to water supply	1 in 5 years on average
DS2	Enhanced media campaign, customer choice/voluntary constraint, sprinkler ban.	1 in 10 years on average
DS3	Temporary Use Ban (formerly hosepipe ban), Drought Direction 2011 (formerly non-essential use bans) requiring the granting of an Ordinary Drought Order.	1 in 20 years on average
DS4	Severe water rationing e.g. rota cuts, stand pipes i.e. Emergency Drought Order.	Never





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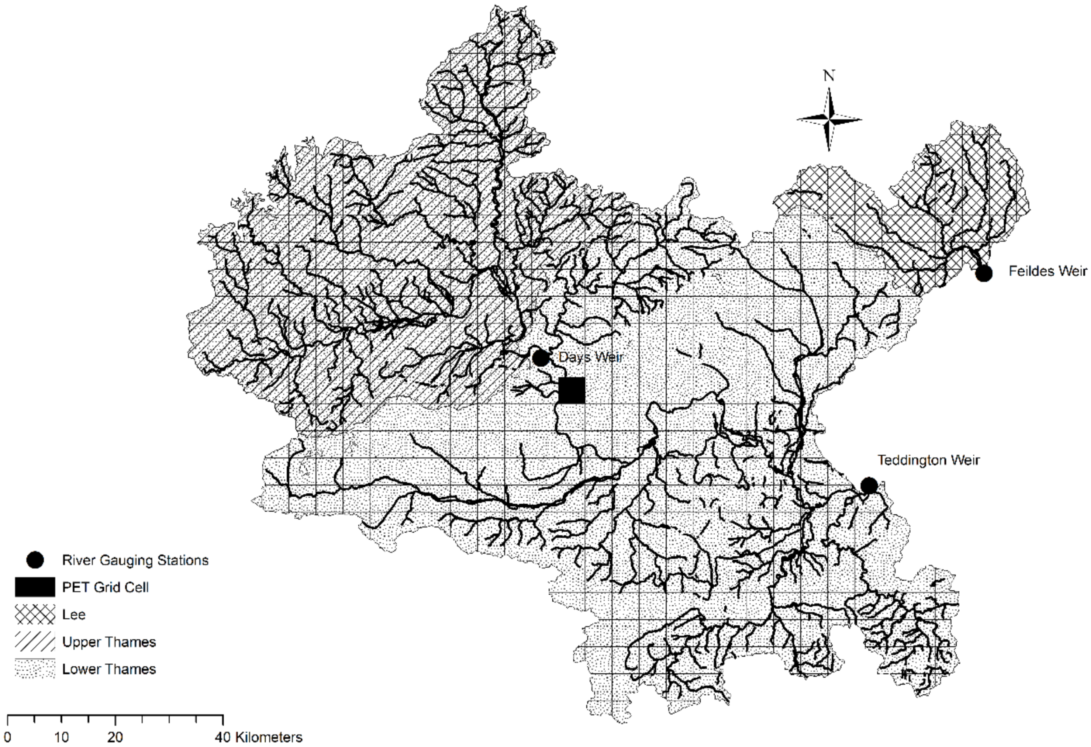

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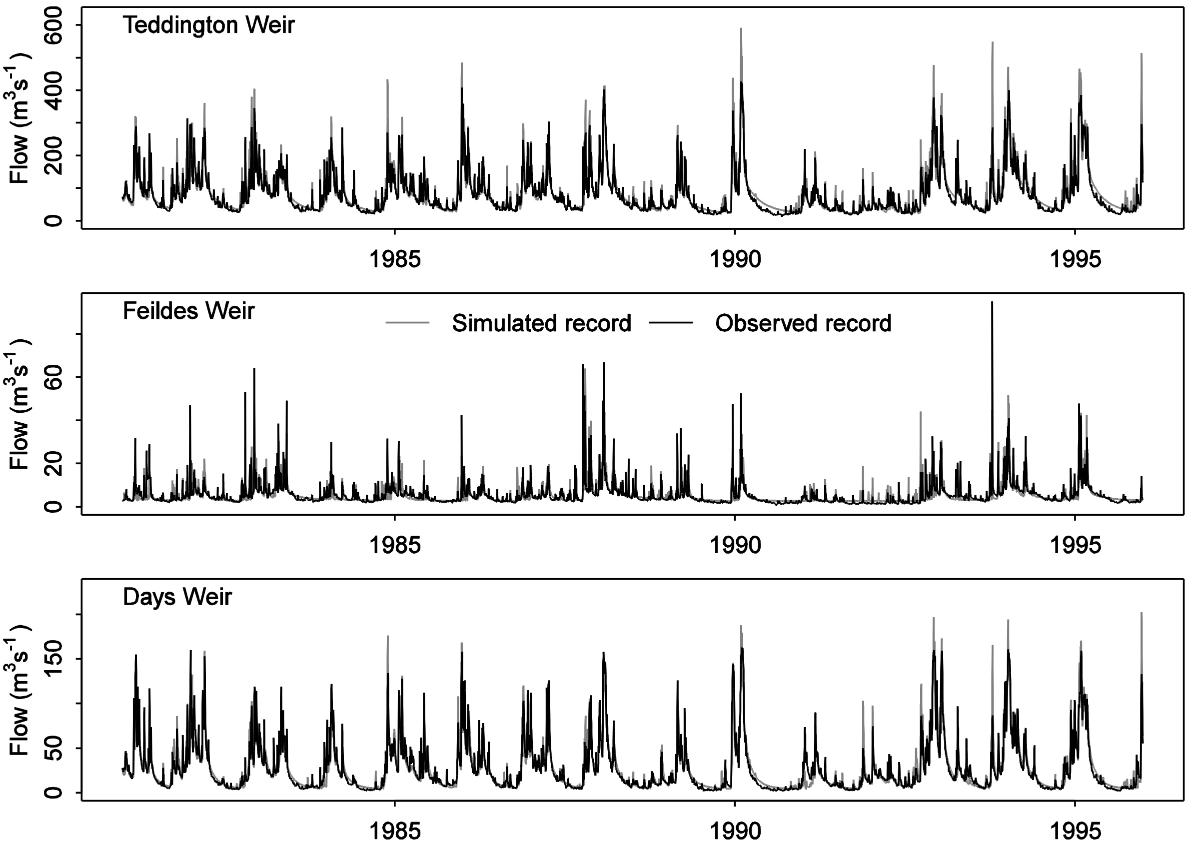

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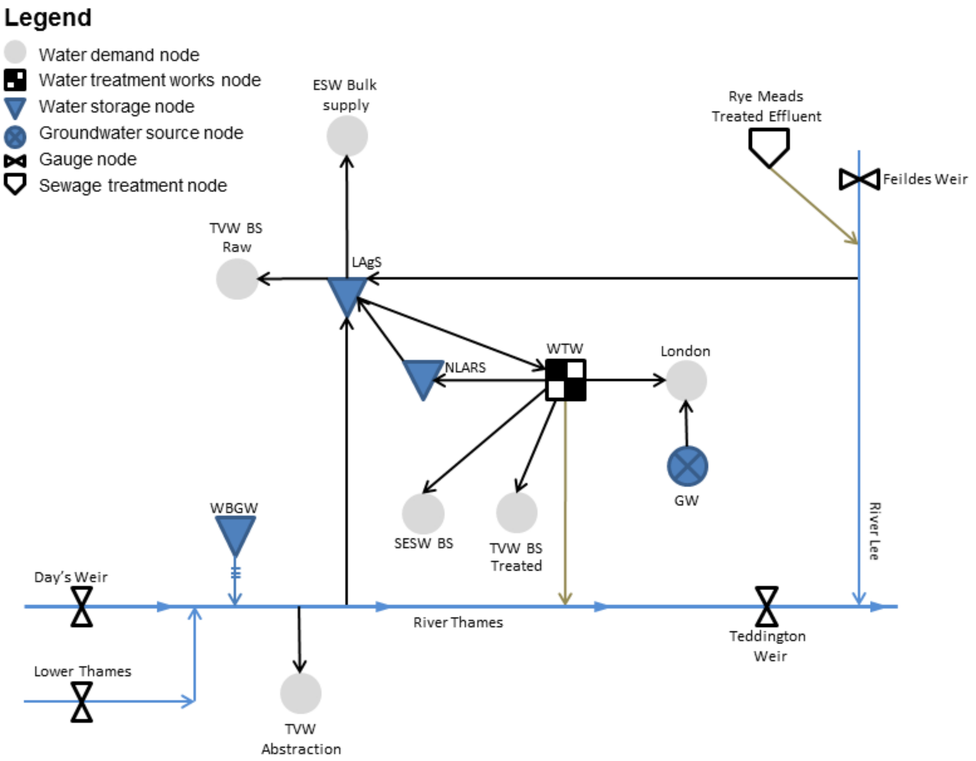

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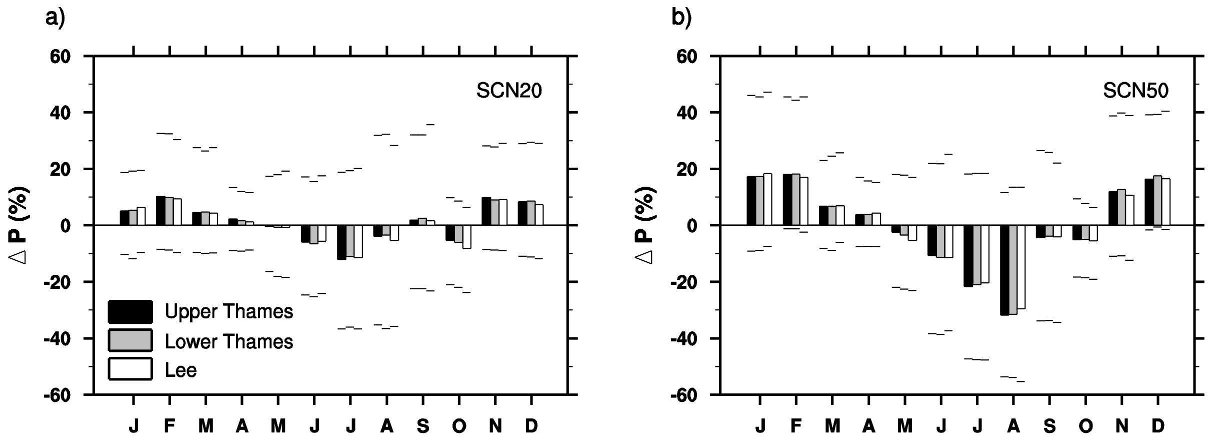

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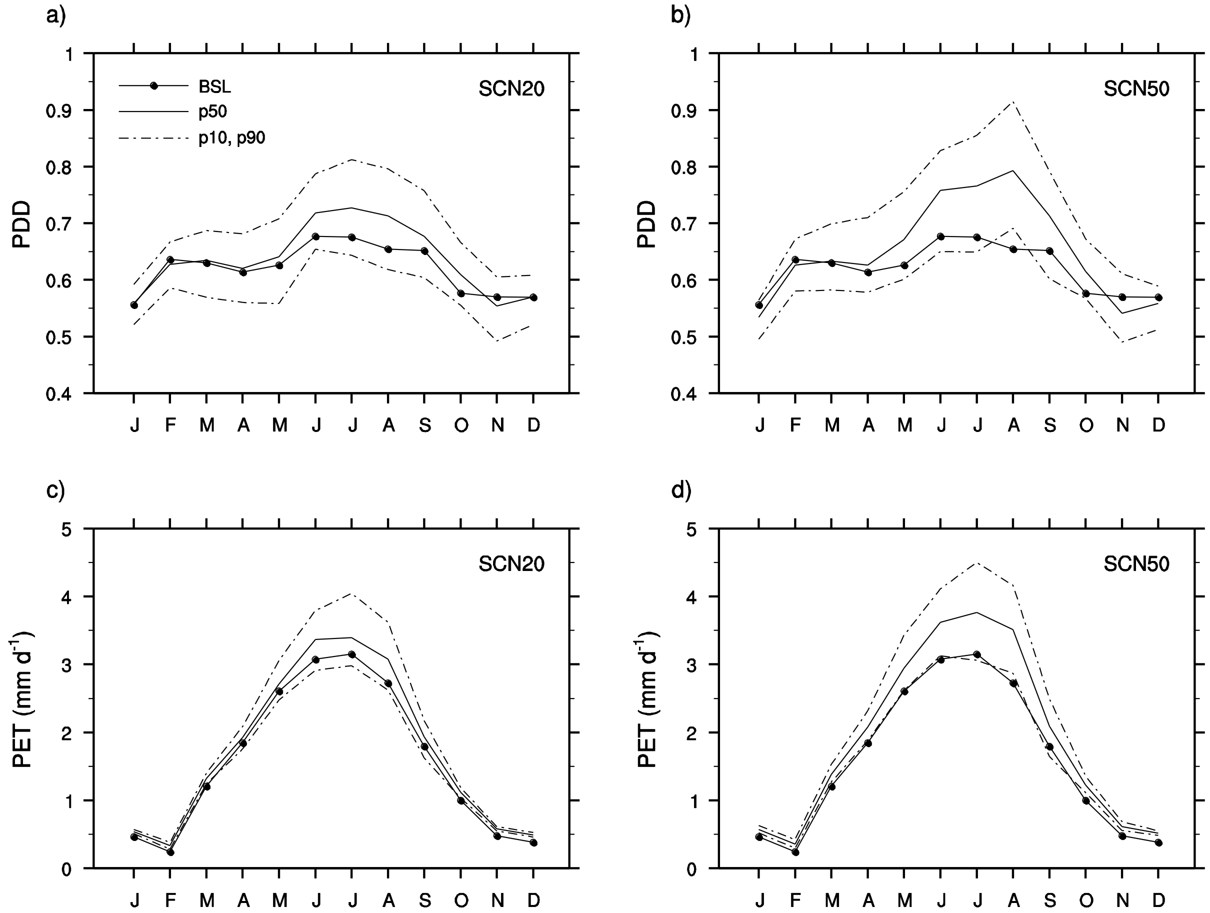

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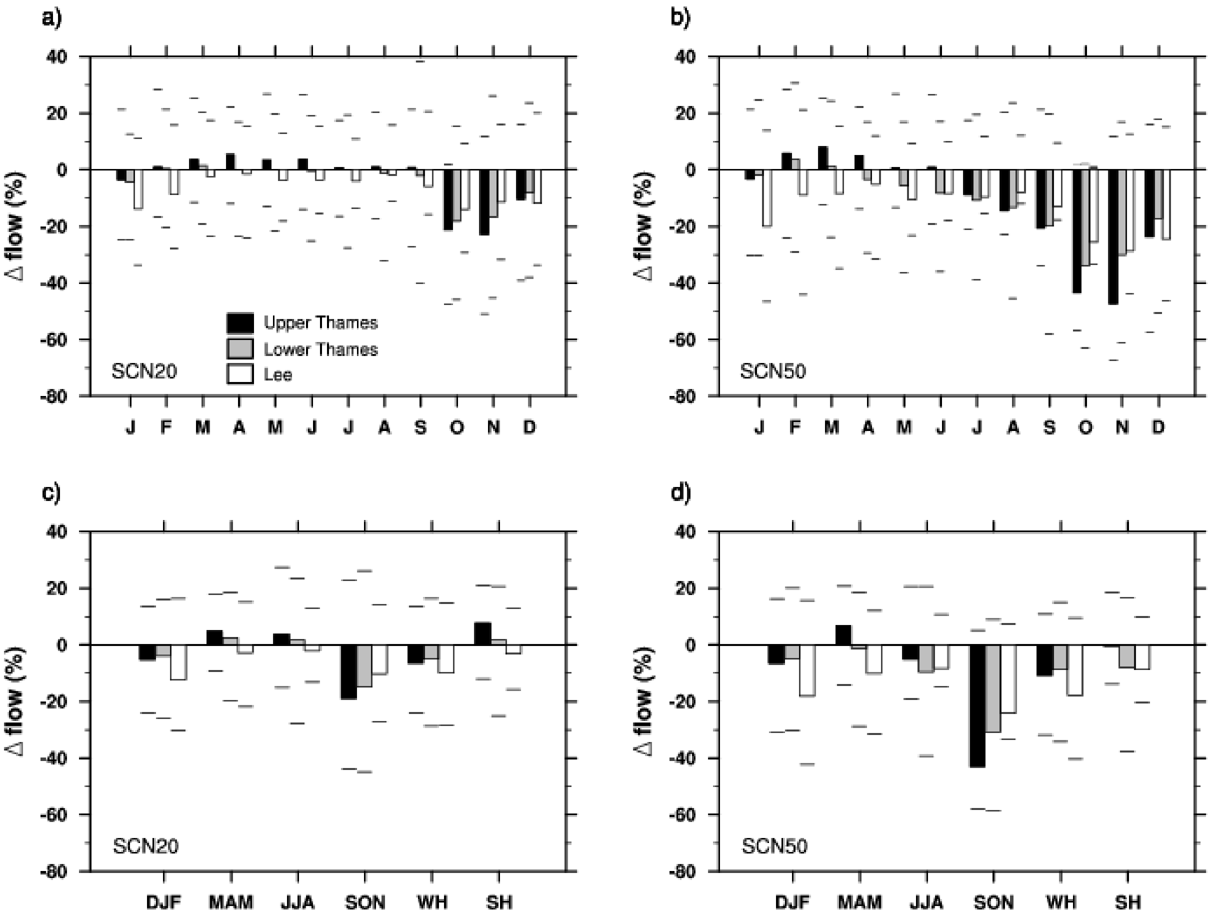

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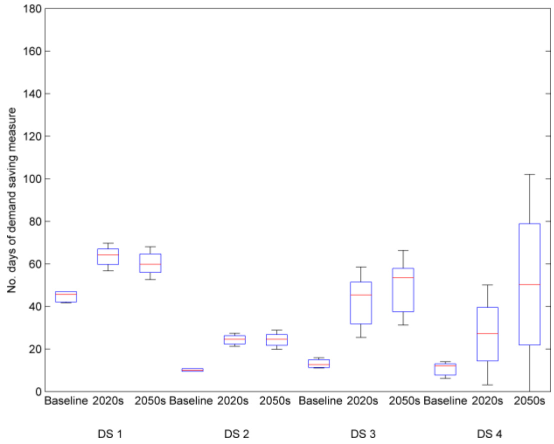
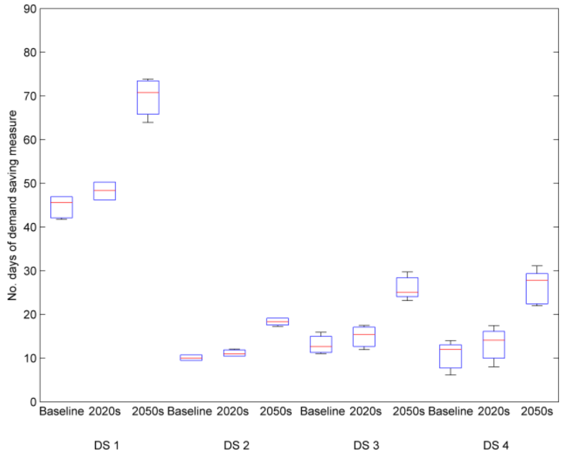
a



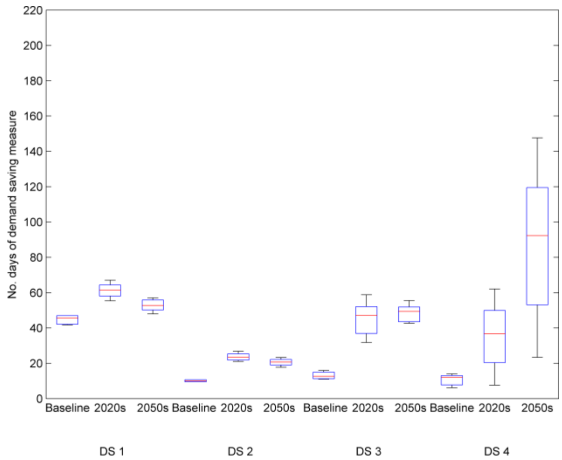
No. days of demand saving measure
Baseline 2020s 2050s Baseline 2020s 2050s Baseline 2020s 2050s Baseline 2020s 2050s
DS 1
DS 2
DS 3
DS 4

b



No. days of demand saving measure
Baseline 2020s 2050s Baseline 2020s 2050s Baseline 2020s 2050s Baseline 2020s 2050s
DS 1
DS 2
DS 3
DS 4

c



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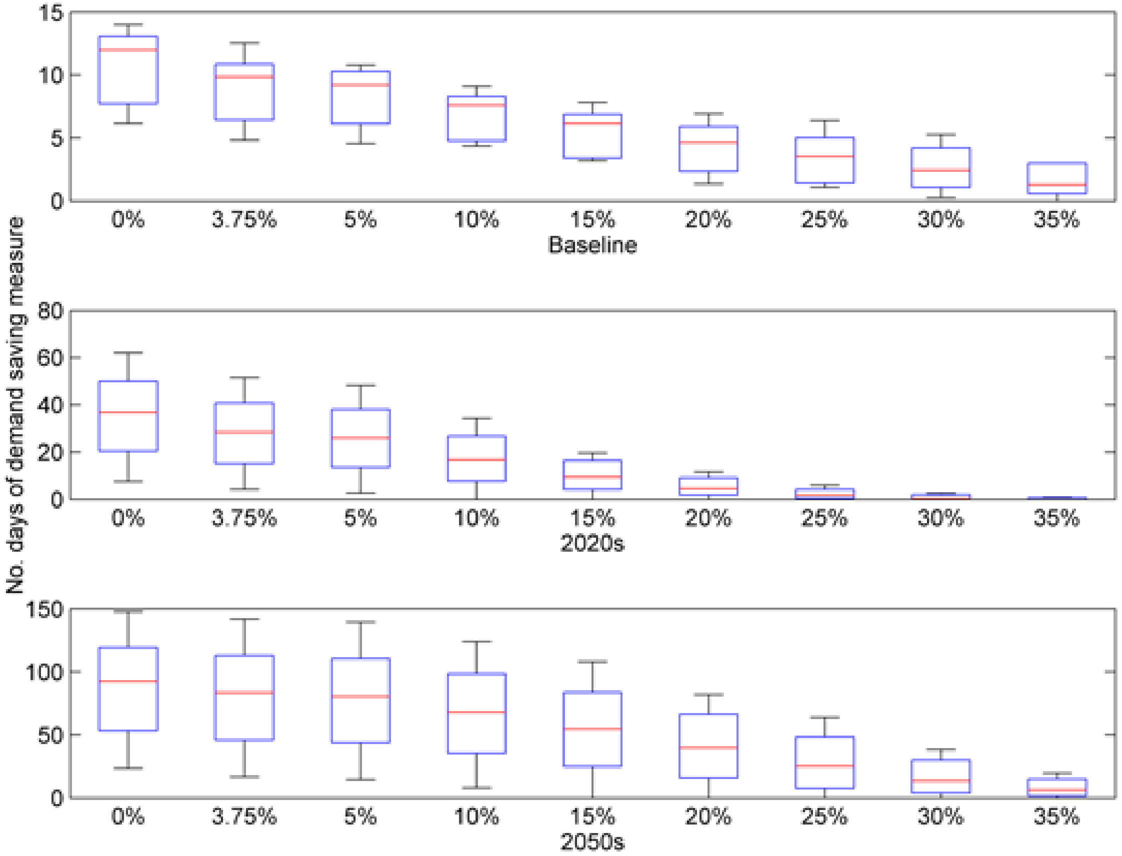

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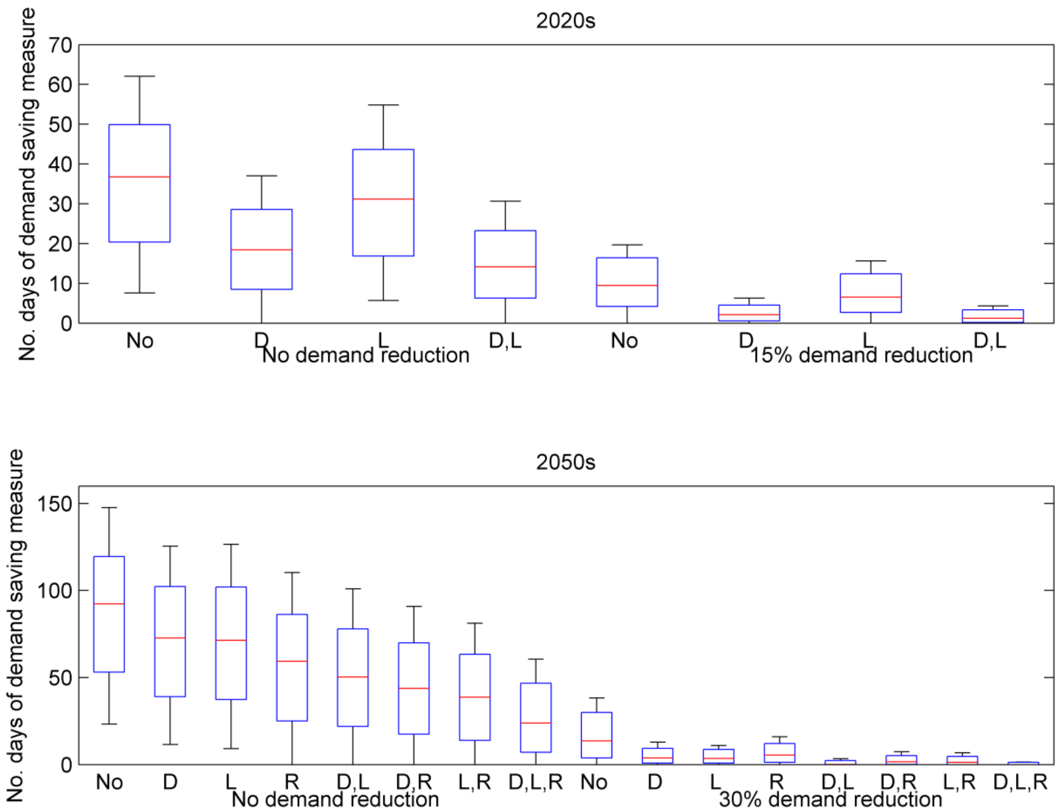

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