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Evaluating the sensitivity of robust water resource interventions to climate change scenarios

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A R T I C L E I N F O

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A B S T R A C T

Water resource system planning is complicated by uncertainty on the magnitude and direction of climate change. Therefore, developments such as new infrastructure or changed management rules that would work acceptably well under a diverse set of future conditions (i.e., robust solutions) are preferred. Robust multi-objective optimisation can help identify advantageous system designs which include existing infrastructure plus a selected subset of new interventions. The method evaluates options using simulated water resource performance metrics statistically aggregated to summarise performance over the climate scenario ensemble. In most cases such 'robustness metrics' are sensitive to scenarios under which the system performs poorly and so results may be strongly influenced by a minority of unfavorable climate scenarios. Understanding the influence of specific climate scenarios on robust optimised decision alternatives can help better interpret their results. We propose an automated multi-criteria design-under-uncertainty sensitivity analysis formulation that uses multi-objective evolutionary algorithms to reveal robust and efficient designs under different samples of a climate scenario ensemble. The method is applied to a reservoir management problem in the Rufiji River basin, Tanzania, which involves the second largest dam in Africa. We find that solutions optimised for robustness under alternative groups of climate scenarios exhibit important differences. This becomes particularly decision-relevant if analysts and/or decision-makers have differing confidence levels in the relevance of certain climate scenarios. The proposed approach motivates continued research on how climate model credibility should inform climate scenario selection because it demonstrates the influence scenario selection has on recommendations arising from robust optimisation design processes.

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1. Introduction

Water resources systems planning confronts high levels of uncertainty, including from the largely unknown impact of climate change on the future local hydrology. Climate projections used to assess individual infrastructure investments or overall system-scale designs are generated with imperfect numerical models limited in their representation of complex climate processes. Because of this, the climate models themselves contribute significantly to uncertainties in climate projections (Hawkins & Sutton, 2009, 2011; Rockström et al., 2009; Siderius et al., 2021), notably for precipitation (Lehner et al., 2020).

Given the uncertainty of future climate and its importance when planning for the future, 'decision-making under deep uncertianty' (DMDU) approaches aim to identify and select 'robust' strategies that meet decision-makers' criteria without initially presuming whether any one scenario is more likely than another (Lempert et al., 2006). Several analytical decision-making approaches have been developed to try and identify designs that perform acceptably well (e.g., are sufficiently cost-effective, resilient, reliable, etc.) under a range of 'plausible' future conditions (Walker et al., 2013; Marchau et al., 2019). Examples from the developing world are limited (Bhave et al., 2016), however, programmes such as Future Climate for Africa have promoted such approaches within a broader understanding of the roles of climate services and the institutional and resource constraints they face in sub-Saharan Africa (Vogel et al., 2019; Conway & Vincent, 2021).

Climate modelling uncertainties propagate into water resources planning, and if future climate scenarios used in climate change studies are inappropriate (not representative of what may actually happen), this could lead to either excessively costly or risky solutions being suggested for implementation. If a system design is particularly influenced by one or more scenario members in an ensemble of climate scenarios, this paper suggests analysts, stakeholders and decision-makers should be aware of this. We therefore explore the dependence of the recommendations of an automated computer design process, in our case using a method called robust optimisation, on the climate scenarios used in a planning exercise.

Climate change impact decision support should acknowledge the fact that just as climate models have different levels of performance in modelling present climate, model-generated future climate scenarios are likely to differ in their representativeness of the future (Hall et al., 2012; Hulme & Dessai, 2008; Kolusu et al., 2021). Decision-makers will typically have differing opinions on the relevance of future scenarios and how limited resources should be spent (Guy et al., 2014; Nissan et al., 2019; Roelich & Giesekam, 2019). Several researchers have recently advocated attention to the selection of climate scenarios for environmental system option analysis and their impact on assessments. 'Scenario-neutral' or 'bottom-up' approaches (Prudhomme et al., 2010; Moody & Brown, 2012) to climate change design identify system performance thresholds (Brown et al., 2012; Weaver et al., 2013) and show how individual climate scenarios compare to the thresholds. Brown et al. (2012) represented the uncertainty space using changes to climate variables, dividing a scenario climate space into regions for which different decisions would be preferable. The results reveal the preferred adaptation options to specific changes in climate. Culley et al. (2016) built on Brown et al. (2012) to design optimal feedback control policies for a water system. Their approach describes operational policies for a range of potential futures but also enables an assessment of a system's upper limit of operational adaptive capacity, beyond which upgrades to infrastructure become unavoidable. Lamontagne et al. (2018) developed an analytic scenario generation framework that combines visual and statistical techniques to facilitate the selection of scenarios most tied to user-specified measures for policy-relevant outcomes of interest. Giuliani et al. (2016) mapped the percentage of scenarios satisfying predefined performance criteria, enabling the consideration of their robustness and acceptability under different thresholds. McPhail et al. (2020) demonstrated a quantitative method for exploring the influence of scenario selection on the robustness and the ranking of decision alternatives.

Optimisation algorithms allow efficient searching through large sets of alternative interdependent design options (such as new infrastructure, management rules or both) and are increasingly used in DMDU approaches. The advent of global search (heuristic optimisation algorithms) (Deb & Goel, 2001; Hadka & Reed, 2013; Hadka, 2018) enables robust optimisation of real world non-linear systems over future scenario ensembles, where each scenario represents a different 'state of the world'. In this case robust optimisation works by simulating the performance of different alternative system designs and systematically evaluating them by aggregating performance across the scenario ensemble using robustness metrics (Kwakkel et al., 2016a; Kwakkel et al., 2016b; Maier et al., 2016; McPhail et al., 2018). In water resource systems, optimisation has been used to identify system-scale designs robust to a set of plausible climate futures (e.g., Hamarat et al., 2014; Beh et al., 2015; Huskova et al., 2016).

Bartholomew and Kwakkel (2020) review recent scenario-based robust optimisation methods. The two bookend approaches vary by the extent to which robustness is achieved through post-search analysis, or sought for directly within the search. In the first, each different scenario is optimised separately, then the resulting vulnerability of each optimised design is assessed (Watson and Kasprzyk, 2017). This approach is less computationally demanding as each search considers only one future scenario at a time, and shows how to best respond to those specific future conditions. Recommended designs however will tend to be brittle, i.e., they might fail under a scenario other than the one optimised for. A variation is proposed by Culley et al. (2016) who find the optimal operational policies to reach a system's upper operational adaptive limit for any individual climate scenario, beyond which upgrades to infrastructure become unavoidable. Bertoni et al. (2019) use a similar approach to assess water infrastructure to adapt to individual hydro-climatic and demand scenarios. The second approach is to put all scenarios into a single large multi-scenario optimisation problem (e.g., Huskova et al. 2016). This results in robust designs that perform acceptably across the whole uncertainty envelope, but typically recommends conservative system designs that may be maladapted (e.g., over or under-designed) to any single future scenario. The method proposed in this paper builds on this second approach, investigating the influence of individual scenarios with the scenario ensemble used in the robust optimisation.

Another challenge to design under climate change uncertainty, including using optimised design processes, is that decision-makers may have different thresholds for what constitutes acceptable robustness (Herman et al., 2015; Maier et al., 2016; McPhail et al., 2018). In the second approach outlined above, which provides a single robust optimisation multiple climate change-impacted scenarios, a justified concern is that search results could be sensitive to or unduly impacted by one or a few scenarios (Giuliani & Castelletti, 2016; McPhail et al., 2018, McPhail et al., 2020), which climate experts might not even consider to be very likely. Therefore, being able to reveal the dependence of robust optimised design recommendations on scenario sampling, i.e., which climate scenarios are included in the automated robust search-based design exercise, is relevant. It helps to identify the role individual climate scenarios have in driving results (system design recommendations) of the robust search process. This task is challenging however, as robust optimisations would need to be carried out with many different scenario samples. For example, testing the impact of excluding one, two, and three climate scenarios from a group of 30 would require 30, 450 and 4060 different robust optimisations, respectively. This is computationally impractical., which is why we propose a single robust search formulation which achieves a similar result, i.e., to reveal how design recommendations are impacted by different climate ensemble samples.

We demonstrate the approach on a multi-objective problem relating to the planned Julius Nyerere Hydropower Project (JNHPP) in the Rufiji River basin in Tanzania. For ease of interpretation only management options (in this case reservoir operating rules) are optimised. Section 2 presents the proposed problem formulation and describes the simulation and optimisation methods used. Section 3 describes the Rufiji River basin system and Section 4 describes the results of the proposed method's application. A discussion of results, assumptions and limitations of the study is presented in Section 5, followed by conclusions in Section 6.

2. Methods

In its simplest form, sensitivity analysis of robust multi-scenario optimised decision options to an ensemble of climate scenarios would require re-optimizing the system with each of the scenarios being removed from the ensemble, one at a time. Because more than one scenario could be disproportionately affecting the system design - this analysis would also need to consider removing more scenarios, and their unique combinations. This would be computationally prohibitive for anything but small ensembles. Here we describe a robust search problem formulation that achieves a similar sensitivity analysis using existing search algorithms in a novel way.

Multi-objective Evolutionary Algorithms (MOEAs) identify through an iterative process the best possible outcomes for real world systems (Goldberg, 1989). In the case of water resource systems, the search tool works by connecting to a system simulator to iteratively discover the best possible ('efficient', 'optimised') intervention bundles and the trade-offs in performance they imply (Karamouz et al., 2009; Reed et al., 2013; Kasprzyk et al., 2013; Maier et al., 2014; Geressu & Harou, 2015). In the case of a system design study under climate change using robust optimisation, a MOEA typically will be used to search for acceptably robust designs using a fixed number of climate scenarios (e.g., Huskova et al., 2016).

In the method proposed here, for various sizes of climate scenario ensembles (ranging from one scenario to the full ensemble) we let the search algorithm select the scenarios (ensemble members) that optimise metric performance. This is achieved by adding a performance metric representing the number of scenarios in the ensemble. For each number of scenarios, the other performance metrics enable identification of both the best system design and the climate scenario selections that lead to highest performance. Plots of performance with increasingly fewer climate scenarios will then reveal how performance improves by dropping one, then two, three, etc. climate scenarios; this reveals by how much one or more climate scenarios in the ensemble can act to lower performance estimates under uncertainty.

Reservoir operating policies guide the day to day operation of reservoirs and balance short- and long-term water system performance goals. The search algorithm can help to seek the best parameterisation of reservoir operating policies for reservoirs in the system. We apply direct policy search (Giuliani et al., 2014), where the operating policy is first parameterised within a given family of functions and then the parameters optimised with respect to the operating objectives. We parameterise the control policies using piece-wise-linear forms of release rules from each of the reservoirs based on available storage relative to the storage capacity (Geressu & Harou, 2015). Each piece-wise-linear curve is expressed with eight parameters (four for the fraction of storage and four for the release amount corresponding to those). At each time step the simulator computes the storage in a reservoir and then releases corresponding to the storage fraction. An interpolated amount is released where the storage fraction falls inbetween the four storage fraction parameters.

The method results in a Pareto-optimal set of reservoir operating rules where the trade-off between larger ensemble size and performance is revealed along with the trade-offs between conventional performance metrics themselves (e.g. between energy generation, water supply reliability, etc). So, in a study considering, say ten climate change scenarios, we optimise the system under ten scenarios, then nine scenarios, etc. down to one, each time letting the search identify which scenarios to include, i.e., those that achieve best performance.

In addition to the performance estimates, each water system design in the Pareto optimal solution will have information on the climate models it is tested with. The approach considers the number of scenarios as an objective that should be maximised (f_{EnSize} in eq. (1) below). It is anticipated that designs could underperform in scenarios for which they have not been optimised for. To visualise performance regrets in the event of an omitted climate scenario being realised and assess the risk of overestimating performance by ignoring individual climate scenarios, we then evaluate the optimised designs in all climate scenarios for verification.

3. Application

The Rufiji River basin, Tanzania's largest, supplies water for around 4.5 million people and generates 80% of Tanzania's hydropower and covers roughly 20% of the country (177,420 km^2 (Geressu et al. 2020). The river basin's topology (disposition and connectivity of water supply and demand locations) is displayed in Fig. 1; there are 11 established irrigation demand areas and four reservoirs, three of which are currently in use (Kidatu, Mtera and Kihansi). This set up draws from basin planning reports including the latest river basin management plan WREM International (2015) and is explained in (Geressu et al., 2020). The JNHPP is currently under construction and is the largest hydropower project among all the existing and planned projects. The environmental disruption due to regulation of the naturally variable flow is a concern. Because of these factors, and to simplify the communication of results, this study assesses only the JNHPP by optimising robust reservoir operating policies under different samples of available climate scenarios.

A water resources management simulator built with the generalised Python Water resources (Pywr) model (Tomlinson et al., 2020) represents the Rufiji River basin including all the existing and government planned irrigation sites and large dams. Operating rules are storage release curves, which instruct dam operators how much to release as a function of current reservoir storage.

Performance measures tracked by the river basin simulation model allow evaluation of performance under various climate scenarios represented by simulated hydrological time series. These performance measures are used as the objectives of the multi-criteria robustly optimised design process. The objectives were identified through a literature review and stakeholder consultations. Performance metrics are evaluated by simulating the system on a monthly time step using 30 years of historical and climate forced flow data (see Section 3 for a description the climate forcing).

3.1. Robust optimisation formulation

Relevant performance objectives (Geressu et al., 2020) include maximising the average annual energy generation, maximising the firm annual energy generation, maximising firm monthly energy from existing dams and the JNHPP, maximising irrigation water supply reliability and minimising a flow alteration metric at specific points in the catchment. Various metrics have been used in the past to track the impact of flow regulation on environmental flow regimes. We use a flow alteration metric which assesses the deviation of the statistical distribution of the regulated flow from the unregulated (Gao et al., 2009), the 'Eco deficit and Eco surplus' metric, to provide an overall representation of the degree of alteration of a streamflow time series. This metric is a measure of the statistical

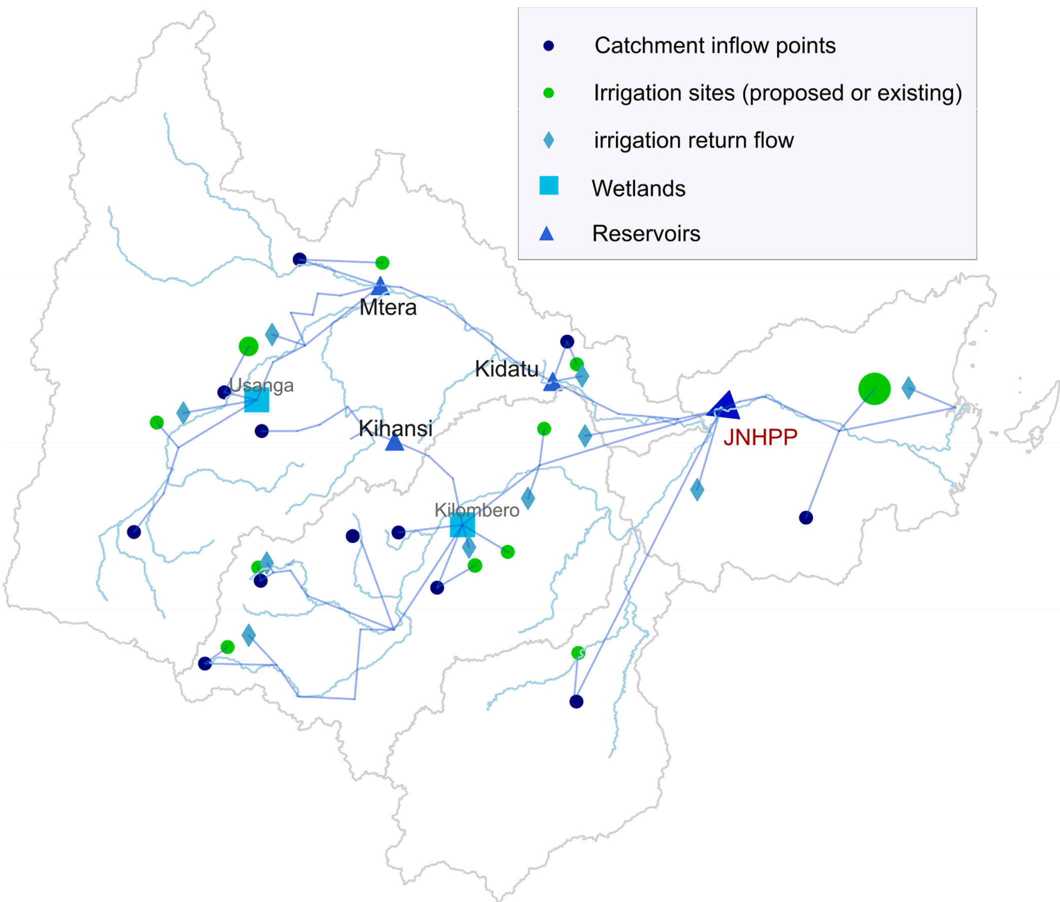

Fig. 1. Water resources management model schematic showing main existing Rufiji River basin reservoirs (blue triangles), planned and informal irrigation expansion areas (green circles) and wetlands (cyan squares). The JNHPP is under construction. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

resemblance of altered flow to that of the natural flow. The flow alteration is used as a general indicator of downstream environmental conditions (e.g., less alteration is associated with improved environmental performance). This is in recognition that flow variability is recognised as the primary driver of riverine ecosystem function and structure.

The multi-objective problem is formulated as:

$$\text{Minimise}\, F_x = (-f_{FE}, -f_{AAE}, -f_{FAE}, f_{IRel}, f_{Env}, f_{EnSize}) \tag{1}$$

$$\forall x \in \Omega$$

$$X = (Op_i, Climate_c) \tag{2}$$

i Represents individual reservoirs

$$Climate_c = \{0, 1\} \forall c \in intheavailableclimateensemble$$

Where.

F_x	=	Objective function
$F_{FmEu} = quantile_{j\in(1,..,m)}\{f_{fee}, 0.99\}$	=	Reliability of the monthly energy output measured as the monthly energy generation exceeded 99% of the time. The objective is to maximise the minimum monthly energy generation from all time steps (months) in the simulation period modelled. The performance metric represents the dry period (both dry season and low flow years) energy outputs.
$F_{AAEu} = quantile_{j\in(1,..,ts)}\{f_{fee}, 0.5\}$	=	The average annual energy generation from the combined Rufiji dams
$F_{FAEu} = quantile_{j\in(1,..,ys)}\{f_{fee}, 0.99\}$	=	The firm annual energy generation from the combined Rufiji dams
$F_{IRu} = Max_{j\in(1,..,m)}\{Sum(f_{ID}, IS)\}$	=	Reliability of irrigation water supply
$F_{Envu} = \sum_{p=1}^{100} Abs[quantie\{Obs, p\} - quantie\{Sim, p\}]$	=	Environmental flow metrics downstream of the JNHPP dam
f_u		A measure of the climate change uncertainty (fraction of ensembles that decisions are tested under)

A robustness metric is used to aggregate the information of each performance metric evaluated in the different climate scenarios. For performance metrics that are desired to be high (e.g., energy), we use a metric that quantifies minimum performance across a group of scenarios. For metrics that are desired to be low (i.e., the water supply deficit and the environmental flow metric) we use the maximum value in the group of climate scenarios. Different robustness metrics reflect different aspects of what makes a choice robust (Drouet et al., 2015; Herman et al., 2015; Kwakkel et al., 2016a; Kwakkel et al., 2016b; Lempert & Collins, 2007; McPhail et al., 2018; Roach et al., 2016). Given the choice of robustness metric will influence the trade-offs ultimately presented to decision-makers, selecting an appropriate metric is important to appropriately characterise system performance (Giuliani & Castelletti, 2016).

For this study we selected robustness metrics based on several considerations. The first ones are the lack of equivalent infrastructural decision alternatives relative to the large dam planned for the Rufiji (the JNHPP) and the lack of input from decision-makers on what is acceptable performance. These factors put some metrics out of scope, including Starr's domain criterion and minimax regret which transform performance based on satisfaction of constraints and regret from best decision alternative respectively. Hurwicz optimism–pessimism rule (Hurwicz, 1951) and Laplace's principle of insufficient reason (Brookes et al., 1953) are excluded because their performance transformation is associated with the mean of values in different climate scenarios. We select maximin (Wald, 1949) robustness criteria for performance measures that are desired to be minimised because it reflects risk averse decision making (McPhail et al., 2018). The decision context involves a large investment cost (the JNHPP project) and the risks to hydropower investments in regions likely to be affected by climate change. We choose the minimax robustness criteria for energy metrics and the maximax criteria for water supply deficit and environmental metric where lower values are desired. Five decision variables of the multi-objective

Table 1
List of performance metrics to be either maximised or minimised as part of the multi-scenario multi-objective robust optimisation process.

Performance metrics	Robustness metric used to aggregate performance across different scenarios	Rationale
Total average annual energy from all dams in giga watt hour per year (Gwh/year)	Minimum	Indicates potential energy generated from existing dams and the JNHPP in a typical year.
Firm annual energy (Gwh/year)	Minimum	Calculated from the statistical distribution of the annual energy generation in a simulated period and indicates what can be reliably generated (i.e., the level exceeded 99% of the time).
Firm monthly energy (Gwh/month)	Minimum	The monthly energy that is exceeded 99% of the time. It is an indicator of how the energy generation is distributed seasonally and the reliability of energy supply
Irrigation water supply demand deficit (MCM/day)	Maximum	The sum of the unmet water demands of irrigation sites. It indicates the extent to which the combination of assets leads to water supply deficits.
Lower Rufiji flow disruption (unitless metric)	Maximum	Change in hydrological variability due to upstream regulations just downstream of the planned location of the JNHPP.

optimisation include the release rule parameters of the JNHPP reservoir and existing dams (Table 1).

3.2. Climate models and hydrological driving data

Using the water resources management simulator and optimisation described above, we assess multiple performance metrics describing the existing dams in the Rufiji River basin and the JNHPP under hydrological time series generated using multiple climate change projections for the region. We use hydrologic realizations generated by driving a basin hydrological model with future climate scenarios from a selection of 29 climate models from the CMIP5 multi model ensemble (Taylor et al., 2012, drawing on models from 18 different research institutes given in Table S1). Climate data from each climate model are bias corrected based on a full quantile mapping (QM) approach (data sourced from Famien et al, 2018) such that the future climate scenarios incorporate the model's projected changes in both mean climate and variability. The hydrological model is a basin-scale implementation of the LPJml for the Rufiji River basin calibrated using historical data (Siderius et al., 2018) and then forced with 29 future climate scenarios for the period indicative of 2020–50 as well as a baseline realization with observed climate (1981–2010).

4. Result

We begin this section by showing optimisation results that are robust over subsets (of different sizes) of the 29 hydrological time series representing future climate scenarios and one representing the recent past hydrology. Fig. 2 Panels A and B show the trade-offs between the size of the scenario ensemble and robustness performance metrics showing only one of the energy performance metrics at a time. Each marker represents different system designs (i.e., in this case reservoir operating rule parameters) that are best (robust) for the associated climate scenarios; labels next to markers show the climate scenarios that are omitted from the available set (i.e., the 30 scenarios).

Fig. 2 shows the sensitivity of the optimised estimated performance for different climate scenario sample sizes. The climate scenario HADGEM2-A0 is the most impactful to performance evaluation for both the average and firm annual energy metrics; its exclusion results in an increase of the minimum average and firm annual performance estimate by 1000 Gwh/year (compare designs 'a' and 'b' in panel A, and designs 'e' and' f' in Panel B). The robust average annual energy estimate would be higher by a further 500 gwh/year if there were sufficient evidence to exclude the climate scenarios INMCM4, HADGEM2-A0, and GFDL-ESM2G together. The firm annual energy estimate remains relatively stable after eight climate scenarios (see label 'h'), and is affected by up to ten of the climate scenarios (label 'i'). The average annual energy is relatively insensitive to climate ensemble size once more than five of the 30 climate scenarios are excluded (label 'd').

Different performance metrics for energy generation are sensitive to different groups of climate projections (e.g., designs labelled 'c' and 'f' exclude different scenarios). Based on the climate scenario sampling, the robust performance could be overestimated by 15% in average annual energy, 20% in firm annual and 75% in firm monthly energy generation. Results show the HadGEM2-AO is the most unfavourable climate scenario for the two energy performance metrics and it is always omitted as more climate scenarios are ignored. Note this is consistent with the results reported in (Kolusu et al., 2021) and (Siderius et al., 2021) as it is one of the three climate projections with the largest average reduction in precipitation and runoff. The GFDL_ESM2G climate scenario (omitted as part of the climate scenarios shown with label 'c' in Panel A) is not excluded in the solutions where more climate scenarios are ignored (shown to the right on Panel A of Fig. 2 such as label 'd'). This shows that the sensitivity of performance to climate scenarios also depends on which of the climate scenarios are bundled together to optimise designs.

Performance of designs represented with markers in Fig. 2 differ not only by the exclusion of climate scenarios but also because of differences in their optimised reservoir operating rules. Fig. 3 shows for the JNHPP (the basin's largest hydropower dam) the water storage-release rules of the system designs optimised under the different climate ensembles ('e-f', shown in Fig. 2 panel B). As more

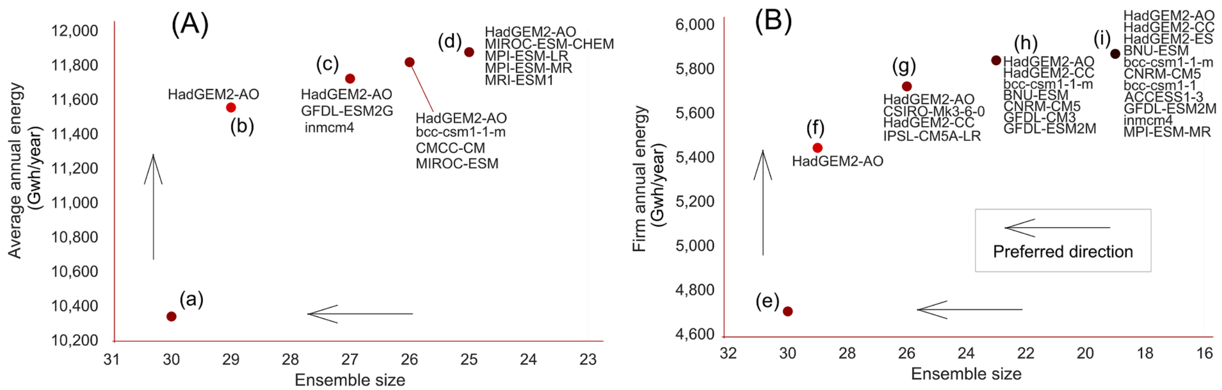

Fig. 2. Variations in energy performance (Gwh/year) as designs are robust optimised with climate ensembles of different sizes. The majority of climate scenarios indicate the minimum average annual (panel A) and firm annual energy (Panel B) to be above 11.4 and 5.4 Gwh/year, respectively. They are reduced by 1000 Gwh/year if the HADGEM-AO climate scenario is included. Excluded scenarios in each case (a to i) are listed.

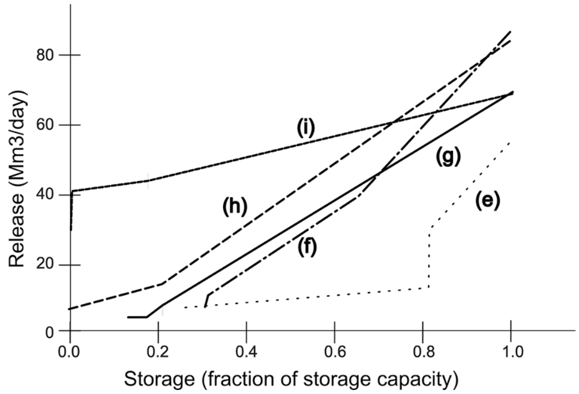

Fig. 3. Differences in storage-release operating rule parameters for the JNHPP reservoir optimised under different climate scenario ensembles. The labels ('e' to 'i') show the performance of the designs with scenario combinations shown in Fig. 2 Panel B. The Y-axis shows the amount of daily release in Mm3/day for the corresponding storage value on the X-axis (given as percentage of the maximum storage capacity).

climate scenarios are considered (from 'i' to 'h', 'g', 'f' and 'e'), operating rules that release less water for a given fraction of the storage capacity in the JNHPP will lead to higher reliability of the annual enegy generation. This is because the most unfavourable climate scenarios are those with drier conditions and, hence, operating rules that maintain water in storage provide more reliable water releases during dry periods.

There is no consensus on how to rank the credibility of climate projections from different climate models (Stainforth et al., 2007; Chen et al., 2017; Kolusu et al., 2021). It is therefore of interest to examine how scenario subsets used in robust optimisation affect system performance, to understand the performance regret that would occur if certain climate scenarios were ignored. We do this by evaluating robust optimised designs under all climate scenarios and comparing them to performance when one or more scenarios are excluded. Fig. 4 shows that ignoring up to five climate scenarios leads to relatively low performance estimate bias in firm annual

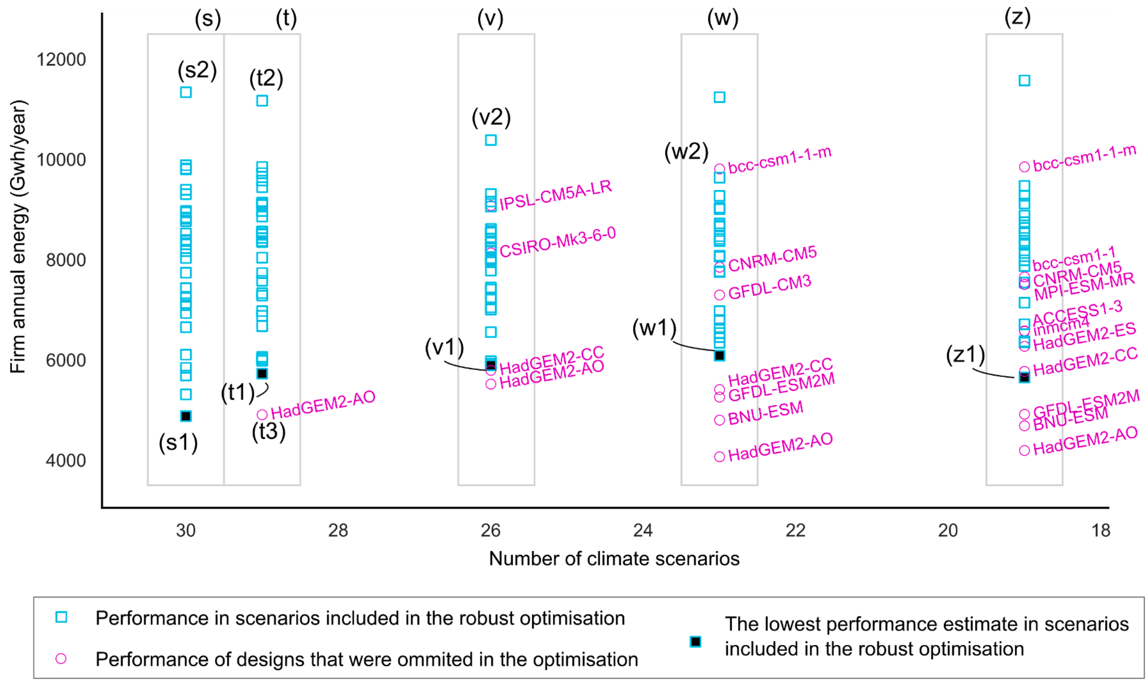

Fig. 4. Performance of robust optimised designs considering progressively fewer climate scenarios (from left to right; s = 30, t = 29, v = 26, w = 23, and z = 19). Each column shows performance of a design in different climate scenarios. Cyan markers show simulated performance of the individual scenarios included in the robust optimisation. Magenta markers show performance under simulated climate scenarios excluded from the robust optimisation. Labels 's1′, 't1′, 'v1′, 'w1′ and 'z1′ show worst case performance for each subset of climate scenarios considered in the optimisation with progressively fewer scenarios ('s' designs are optimised considering all available climate scenarios, designs labelled 't' ignore one of the scenarios, 'v' 2, etc.). Markers at the top in each column such as 's2′, 't2′, etc. are performance estimates for the most favourable climate scenarios. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

energy but that the bias increases with designs optimised with less than 25 climate scenarios (e.g., comparing labels ’v’ and ’w’). Bias here refers to performance being lower for some scenarios not included in the robust optimisation than what would have been considered a ‘worst case’ performance (i.e., when the pink circular rings are below the lowest cyan square in Fig. 4). Ignoring climate scenarios also leads to a decrease in performance in opportune (more favourable than expected) conditions (e.g., compare labels ’s2′, ’t3′ and ’v2′).

Relatively low estimate bias occurs if a scenario ignored in the robust optimisation materialises (e.g., comparing labels ’t1′ and ’t3′ in Fig. 4) in optimised designs where less than four scenarios were omitted. The performance of the optimised design under the ignored scenarios is not necessarily at the lower end of the range (e.g., ’w2′). The performance estimate of designs in the worst case scenarios increases as more climate scenarios are ignored up to ’w’ (compare ’s1′ and ’t1′,’v1′,’w1′, and ’z1′). A more dramatic change to the performance regret is seen at a cut-off point of around 23 scenarios (e.g., ’w’). For this example, design ’v’ is attractive as it maximises lower performance by ignoring few of the climate scenarios but does not result in high regret if the ignored scenarios are realised. The results for the 28, 27 and 25 climate scenario ensemble sizes are not shown because they are not significantly different from neighbouring ensemble sizes. For example, removing any more (one or two) climate scenarios from the ensemble corresponding to design labelled ’t’ will not raise performance, but when four climate scenarios are removed, it does. Less robustness to the minimum performance is also associated with decreased performance in the most favourable scenarios (e.g., label ’s1′). The fact that performance in opportune scenarios decreases as designs are trained with less of the unfavourable scenarios (cyan squares are lower on the y-axis for the 23 and 19 member ensembles) points to the value of optimising system designs for as diverse conditions as possible.

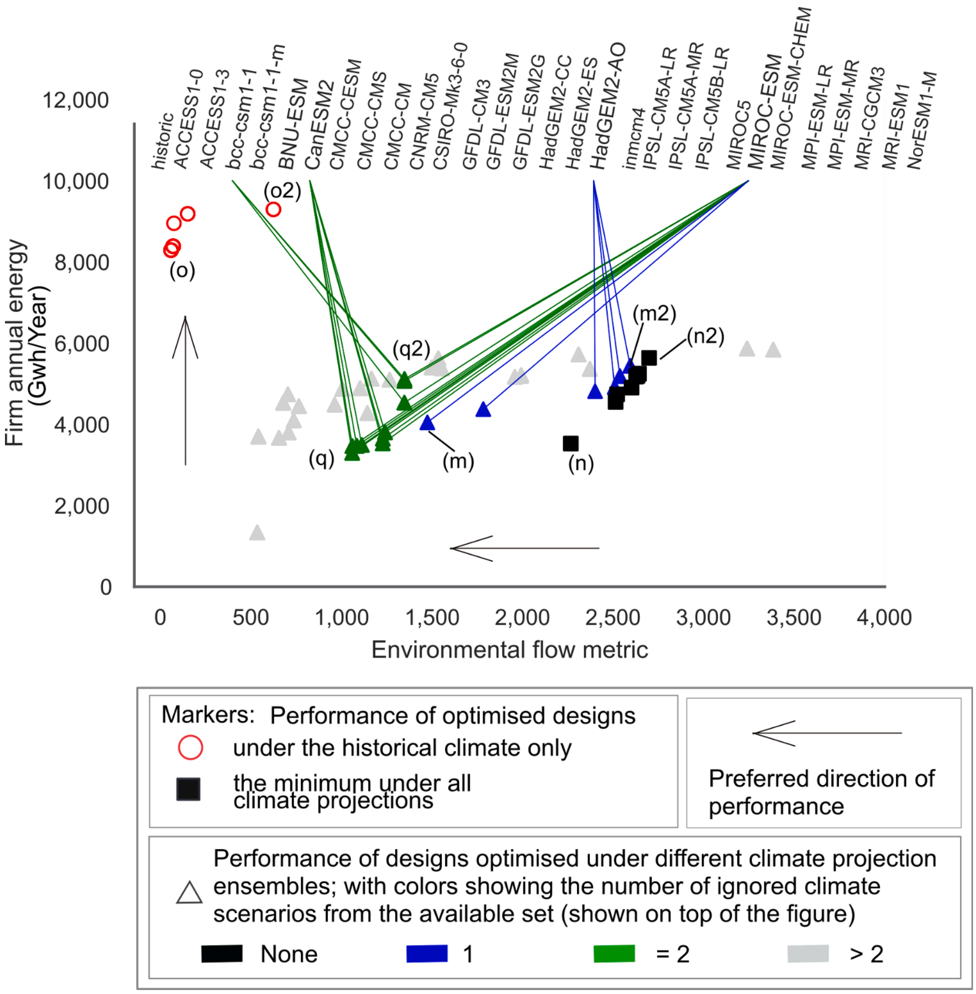

Fig. 5. Performance of designs that are Pareto optimal for firm annual energy, environmental flow and number of climate scenarios. Red markers show performance under the observed (historic) climate; the balance between environmental and energy metrics differs based on reservoir operating rules. Black markers show the minimum performance considering all 30 scenarios. Blue, green and grey markers show performance of designs optimised ommiting one, two, and more than two climate scenarios, respectively. Lines show scenarios ignored in the design and performance estimates. Among designs that omit the same number of climate scenarios, performance estimates differ both on the preferred balance of performance and the climate scenarios that are omitted (e.g., Points ‘m’ and ‘m2′ and Points ‘q’ and ‘q2′) due to differing operating procedures. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

We now consider the environmental flow performance objective alongside energy (Fig. 5). Comparing 'o2′ and 'n2′ in Fig. 5 shows the possible overestimate in the reliable (firm) annual energy from existing dams and the JNHPP that would result if all the climate change scenarios (in our sample of 30) for the region are ignored (i.e. where no climate change assessment/adaptation is done, and the most unfavourable climate scenario actually occurs). The firm annual energy performance can be impacted more by climate change than by measures to improve environmental performance under the observed climate or the worst case conditions (compare labels 'o2′ and 'o', 'o2′ and 'n2′, 'n' and 'n2′). Detailed analysis of the climate scenarios shows that most of the climate models project an increase in intra- and interannual precipitation variability over the region, that becomes amplified in runoff (Siderius et al., 2021). This reduces the firm annual energy that can be generated. The trade-offs between firm annual energy and the environmental flow metric are accentuated in some climate scenarios. Hence, excluding one or more scenarios could give the impression that the trade-off between firm annual energy and this specific environmental flow metric is lower than it could be in a future climate.

Fig. 6 Panel A shows performance relationships when multiple optimised metrics are shown together. The values at the top of the

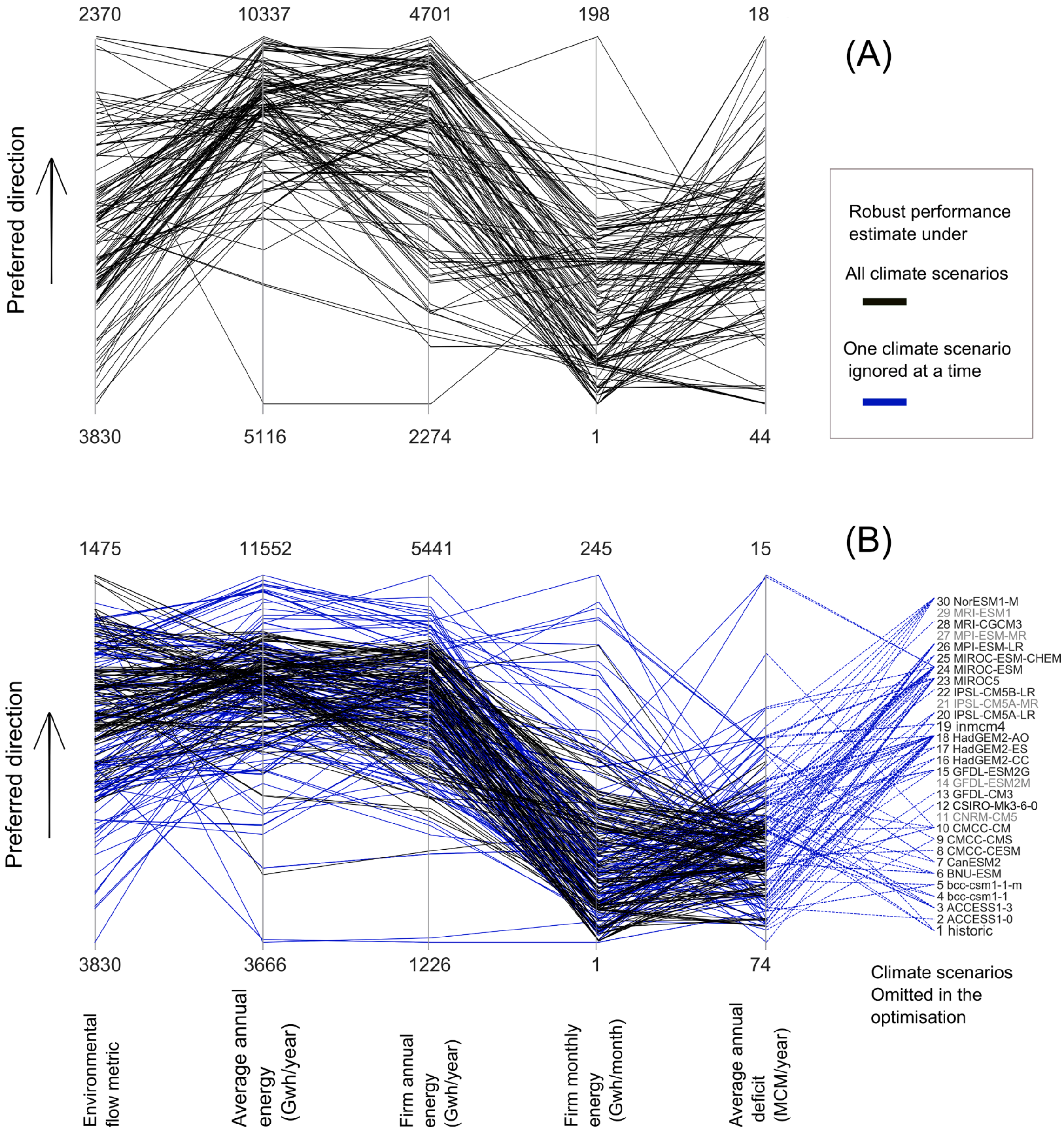

Fig. 6. Sensitivity of multi objective performance to different ensemble sizes (Performance objectives explained in Table 1). Black and blue lines show performance in 30 and 29 climate scenario ensemble sizes, respectively. Numbers at top and bottom of y-axes represent maximum and minimum performance levels achieved, respectively (Units given in Table 1; preferred direction is up). Average annual deficit is relative to total irrigation water demands. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

five parallel axes (from the left) show the maximum minimum (Maximin) performance achievable if that particular objective were to be prioritized above all others. The lines between the axes represent efficient (Pareto-optimal) designs; they are the reservoir operating policies achieving all feasible combinations of human preferences between the five objectives in the plot.

The minimum performance values shown for each axis (at the bottom of the axes) indicate the threshold value after which any further increase in that performance leads to a reduction in at least one other performance objective. Lines that cross between two adjacent axes signal a trade-off between those measures; the steeper the angle the stronger the trade-off between the two performance indicators.

The black lines shown in Fig. 6 Panel A (also repeated in Panel B) show the maximum minimum (maximin) performance of designs considering all climate scenarios. Panel B shows the maximin performances with a blue line if one of the climate scenarios were to be omitted; with the omitted climate scenarios being the most critical to an increase in the maximin performance. The sixth column in Panel B shows the climate scenario omitted in the optimisation and the calculation of the minimum performance.

In Fig. 6, the difference in the desirable performance (at the top of each axes) on Panel A and Panel B shows the impact of excluding climate scenarios in the performance estimate where multiple performance objectives are considered. If one performance objective were to be maximised and if the critical climate scenario were to be found less likely, the performance estimate could change by 11 to 61% for the different performance objectives compared to the baseline approach where all climate scenarios are considered.. The conservative estimate for average annual energy is less sensitive to climate scenario sampling than the firm energy indicators. Both firm monthly and firm annual energy are sensitive to designs being optimised with certain scenarios omitted with the firm monthly estimate varying by 14% and firm anual energy estimate by 19% while the average annual energy varies by 11%. The relative difference in these high scores of performance objectives shows how the omision of climate scenarios may affect performance estimates. The sensitivity of performance indicators to the climate scenarios changes as different balances of performance are sought.

For the Rufiji River basin these results show how projections of climate change system performance are sensitive to the ensemble of climate models used and whether certain influential scenarios are included. The implication is that given the uncertainity of climate change direction and magnitude, even where the conservative estimate of average annual energy justifies hydropower development, the firm energy generation from hydropower dams might turn out lower than expected.

5. Discussion

Here Pareto-optimal designs that are robust under different sample sizes of the uncertainty space (the climate scenario ensemble) are generated to allow decision-makers to form a view on the influence of specific climate scenarios when evaluating robust optimised system scale intervention portfolio recommendations. The proposed approach builds on the generate-first-choose-later approach (Cohon & Marks, 1975; Herman et al., 2014), where there is no need to prioritise climate model scenarios or objectives a priori. This allows decision-makers to see after the optimisation (a posteriori) how individual climate scenarios and objectives impact optimised designs, in a sensitivity analysis type approach, rather than being presented with ready-made best solutions (Herman et al., 2015; Quinn et al., 2017).

5.1. Implications for decision-making under climate change uncertainty

In selecting water resource system interventions, identifying less favourable future climate conditions is not straightforward because multiple system performance metrics need to be considered simultaneously and they may have differing responses to climate change scenarios. Here we develop earlier work by McPhail et al. (2020) who studied the impact of scenario selection on a the ranking of decision alternatives: we propose an approach which identifies decisions that are Pareto-optimal for different sets of scenario ensembles and we present a computationally efficient approach to do so. Our results show the sensitivity of robust optimised system performance trade-offs to climate scenario sampling. Fig. 2 shows how operating rules maximise performance under the most unfavourable of an increasingly small subset of climate-driven hydrological scenarios. The implications of these results for actual decisions in practice (a situation that is still quite rare) will vary based on the preferred approach in dealing with uncertainty due to climate scenarios. For example, should the HadGEM2-AO model scenario, which causes the most difference in performance in the optimised designs, be considered an outlier and excluded? Some argue that climate models are not equally good (Brunner et al., 2019; Knutti et al., 2010; Sanderson et al., 2017) and consider whether climate models can be ranked based on their past performance in predicting various weather variables (Chen et al., 2017; Eyring et al., 2019; Kolusu et al., 2021). The relevance of a system performance estimate to decision-making (e.g., 'a' and 'b' or 'e' and 'f' in Fig. 2) depends on how climate scenarios are evaluated or perceived by scientists and stakeholders. For example, if HadGEM2-AO is considered a relatively poorly performing model by climate scientists according to some agreed criteria, then decisions could be based on scenario sampling that excludes it. However, complementary analysis of climate model performance in this region finds HadGEM2-AO is ranked sixth highest out of 29 scenarios, based on eight climate model performance metrics applied to the wider south eastern Africa region (Kolusu et al., 2021), which suggests it should be included. Fig. 4 shows that performance regret does occur when a climate scenario is simulated with a design that was optimised without considering it. The results reinforce the importance of giving careful consideration to the selection of climate scenarios in robust optimised designs.

The actual decision about whether specific climate scenarios can be considered less likely than others is beyond the scope of this study. Even when there is a desire to consider climate change impacts, the full range of climate change scenarios available through programmes such as CMIP3 and CMIP5 are rarely included in climate impact assessments of water resources projects. This may be due to lack of access, the selection of sub-samples that span ranges of outcomes such as change in rainfall, or because of the large computational effort needed to process the information into decision relevant form (e.g., Meehl et al., 2007). One lesson from our results is that performance estimates can be sensitive to different climate projections. Given that many water resources problems are multi-objective, pre-emptive omission of climate scenarios before the water impact modelling and multi-objective analysis could bias decision-making. The proposed approach having shown how climate scenario selection affects recommendations from robust optimisation motivates further investigation of climate model credibility ranking or selection.

Our conclusion differs from earlier work by McPhail et al., (2020) when it comes to the ranking of decision alternatives. They report that despite the robust performance estimates drastically varying as different scenarios are added or removed from a scenario ensemble, the recommended system designs tend to remain similar. The reservoir operating rules (Fig. 3) optimised for different scenario ensembles, which refer to designs with performance reported in Fig. 2, vary substantially. The difference in the conclusions is the result of the decision alternatives in our study being optimised along with the scenario ensemble selection and because we specifically deselect (sets of) scenarios with the largest impact on the decision outcome. However, it could also be the result of us dealing with a more complex/different problem design.

Although reservoir operating rules could be more easily adapted later on than say the size of a dam or the combination of dams implemented, flexibility to change operating rules is often limited by agreements and regulatory constraints (Fernandez et al., 2013; Giuliani et al., 2014; Sheer, 2010). For example, power contracts are often required to meet certain levels of firm, and peak power which makes the later changing of operating rules difficult. Environmental requirements and downstream regulations may also complicate changing operating rules. Some large reservoirs such as the Rufiji dam project threaten fragile ecosystems downstream because they change the natural hydrological variability. This can be exacerbated by climate change and re-operating the dams to adapt might not be done sufficiently quickly before irreversible damage is sustained. For these reasons, although operating rules can be changed, there is a significant water management incentive to get them as well designed as possible when the dam is being planned.

5.2. Computational efficiency

Applications of multi-objective evolutionary algorithms on real systems can generate prohibitive computational needs (Beh et al., 2017; R. T. Geressu & Harou, 2019; Reed et al., 2013), especially when including multiple scenarios within a single search. In robust optimisation using a maximin robustness aggregation metric, each simulation considers multiple scenarios; but for each of the performance metrics, only the performance under the least desirable scenario is reported back to the optimiser. In an MOEA evaluation using the proposed formulation, designs are compared based on their aggregated performance under different sets of the climate scenarios. This allows for designs that would have been rejected in the evolutionary process to survive. The suggested method takes advantage of the evolutionary algorithm's search process where candidate solutions evolve as a population, with the best design parameters (in our case release rules) being shared regularly in the evolution process. Because of this, designs that are evaluated under different climate ensembles are able to share their best traits (parameters), accelerating convergence.

The computational feasibility of the proposed method emanates from the fact that it identifies how climate scenario sampling impacts design recommendations without requiring repeated independent optimisations. The number of optimisations needed to test the possible combination of climate scenarios separately (if not for the suggested formulation) would be too high to be computationally tractable. The method could not generate the super set of all Pareto optimal solutions that would be computed if separate optimisations were conducted under each possible combination of climate scenarios.

5.3. Limitations and future work

This study investigates optimisation with only one of many possible robustness metrics (i.e., maximising the minimum performance). Previous work (Herman et al., 2015; McPhail et al., 2018) shows that the robustness of options varies with the choice of robustness metric (i.e., maximin, regrets, domain criteria, satisficing criteria, etc.). Robust optimisation with the maximin metric in our case tracks the performance with the worst climate scenario and provides a conservative estimate of performance (McPhail et al., 2018). Future work could investigate the use of other robustness metrics.

6. Conclusion

Algorithmic screening of portfolios of intervention options via robust optimisation techniques can help identify appropriate portfolios of interventions under climate change uncertainty. But individual projections in an ensemble of scenarios can have strong influence on estimated system performance and therefore on the recommended robust strategy. Because of this, solutions optimised for robustness under alternative groups of climate scenarios may exhibit significant differences. This becomes decision relevant if analysts and/or decision-makers have differing levels of confidence in the scenarios. The method we suggest reveals the impact of inclusion/exclusion of the different climate scenarios individually and as a group without presumption of which climate scenario/s may be outliers. The extent to which a robust optimised design is the result of one or a few climate scenarios should ideally be known to analysts when presenting results to decision-makers; without this type of scrutiny recommended designs could be excessively costly or conservative.

Revealing the dependence of robust optimised design recommendations on scenario sampling is relevant to climate uncertainty informed decision-making. Such sensitivity analysis helps explore the impact of climate scenario sampling on design recommendations, performance estimates and their trade-offs. Where there are differing confidence levels in the plausibility of the various climate scenarios, the number of scenario combinations (and hence separate optimisations) to be tested runs quickly runs into the hundreds.

This is especially true in multi-objective problems because different performance metrics are likely to be influenced differently by individuals climate scenarios. We proposed and demonstrated a computationally feasible approach for optimizing alternative system-scale intervention portfolios under different samples of a given climate scenario ensemble in a single implementation of robust multi-objective optimisation. The results are Pareto-optimal solutions which include information on trade-offs between robustness performance metrics, Pareto optimal decision options and the climate scenarios subsets. Results reveal the association between performance, recommended system designs and the number and combination of climate scenarios. The method identifies the multi-dimensional opportunity cost of the most taxing climate scenario(s) to the ensemble, or the benefit (in terms of increased performance) of removing one or more scenarios which cause most stress to the robust optimised design.

Results in our case study application show the different performance objectives considered in the Rufiji River basin are sensitive to different climate scenarios. Energy, environmental and agricultural water supply performance metrics are sensitive to different subsets of a 30 climate scenario ensemble when alternative balances of performance objectives are prioritised. In contrast to earlier studies (McPhail et al., 2020), the sensitivity of robust estimates (in our case the conservative performance), and variation of designs (in our case reservoir operating rule parameters) is high when specific energy metrics were prioritised in the Rufiji River basin case study.

At present there is no widely accepted process for including or excluding climate model scenarios. As more become available (CMIP6, new climate models and new versions of established climate models, new experimental designs/forcing scenarios, regional models, etc.), it is becoming increasingly pressing that the climate modelling community develop best practices on this issue. As the numbers of climate projections increases it becomes increasingly difficult to consider them all in impact simulations aiming at informing decision-making. While resolving this issue is beyond the scope of this study, our method provides a rigorous way of highlighting the performance implications of different scenario combinations and our case-study results show that the scenarios used in robust optimisation matter; reinforcing the value of guidance on climate scenario selection.

7. Key points

- The selection of development options in robust optimisation studies can be sensitive to individual climate scenarios
- Planners should be aware if one or more climate scenarios are strongly influencing recommended designs and their estimated performance
- The proposed sensitivity analysis approach optimises infrastructure systems under different climate scenario ensembles
- The method helps analysts assess and communicate how optimised designs are impacted by individual climate scenarios within an ensemble

8. Plain language summary

Climate models differ in how they represent complex climate processes. Because of this there is uncertainty as to the projected impacts of climate change. Robust designs of future coupled human-natural systems, such as water supply infrastructure systems, that perform acceptably well in all or most plausible future climate scenarios are desired. With automated computer-assisted design processes, that optimise designs over a range of climate scenarios, a few potentially unrealistic climate scenarios might disproportionately influence recommended designs. This could lead to costly or risky design recommendations and may not be acceptable to some decision-makers, especially if it can be demonstrated that some climate models make poor predictions. In this case, being able to inform decision-makers about how climate-robust designs are being influenced by particular climate scenarios within an ensemble, can help inform decisions. This article proposes an approach to help undertake such a sensitivity analysis, applied to the Rufiji River basin in Tanzania.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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We obtained the bias corrected climate model data from the Future Climate for Africa project (data sourced from Famien et al., 2018).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2022.100442.

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