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Robustness-based evaluation of hydropower infrastructure design under climate change

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ABSTRACT

The conventional tools of decision-making in water resources infrastructure planning have been developed for problems with well-characterized uncertainties and are ill-suited for problems involving climate nonstationarity. In the past 20 years, a predict-then-act-based approach to the incorporation of climate nonstationarity has been widely adopted in which the outputs of bias-corrected climate model projections are used to evaluate planning options. However, the ambiguous nature of results has often proved unsatisfying to decision makers. This paper presents the use of a bottom-up, decision scaling framework for the evaluation of water resources infrastructure design alternatives regarding their robustness to climate change and expected value of performance. The analysis begins with an assessment of the vulnerability of the alternative designs under a wide domain of systematically-generated plausible future climates and utilizes downscaled climate projections *ex post* to inform likelihoods within a risk-based evaluation. The outcomes under different project designs are compared by way of a set of decision criteria, including the performance under the most likely future, expected value of performance across all evaluated futures and robustness. The method is demonstrated for the design of a hydropower system in sub-Saharan Africa and is compared to the results that would be found using a GCM-based, scenario-led analysis. The results indicate that recommendations from the decision scaling analysis can be substantially different from the scenario-led approach, alleviate common shortcomings related to the use of climate projections in water resources planning, and produce recommendations that are more robust to future climate uncertainty.

1. Introduction

Investments in water infrastructure typically involve tradeoffs between large capital costs and difficult-to-quantify delayed benefits ranked by current societal values, all subject to large uncertainties regarding future climatic, demographic, technological, and socio-economic conditions (Fankhauser et al., 1999; Pahl-Wostl, 2007; Jeuland, 2010; Furlong, et al. 2016). The design process for new water projects can be lengthy and highly complex, as such projects may often cause societal and environmental impacts, both positive and negative, that go well beyond the lifetime of the investment (Bednarek, 2001; Hallegatte, 2009; Hall et al., 2015). And though the complexities and uncertainties inherent in the design of new water infrastructure often warrant lengthy cautious discussion that delays investment, the world's poor living in conditions of high climate variability (e.g., in sub-Saharan Africa) suffer

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through the delays (Brown and Lall, 2006; Hall and Murphy, 2012; Strzepek et al., 2013; Groves et al., 2015). The primary purpose of this work is to improve the process of water infrastructure planning such that cost-effective, sustainable design alternatives can be more confidently identified and implemented considering climate variability and change.

The conventional modeling paradigms in water systems planning have assumed stationarity in long-term natural processes and estimated decision-relevant climate or hydrological statistics, for example, annual mean flow or 100-year flood from historical data (Hirsch, 2011; Jeuland and Whittington, 2014). This statistical information allowed planners to define generally few number of possible future states with known occurrence probabilities, and subsequently identify optimal or near-optimal project designs through expected utility maximization (Maas et al., 1962; Loucks et al., 1981; Wurbs, 1993; McInerney et al., 2012). However, recent evidence of climate change, including unprecedented changes in the precipitation patterns, and the frequency and intensity of storms, the timing and magnitude of surface runoffs has raised questions regarding whether water system planners shall continue to use stationarity-based methods, when making long-term, costly investment decisions (Milly et al., 2008, 2015; IPCC, 2013; Arnell and Lloyd-Hughes, 2014; Koutsoyiannis, 2014). There is now a general agreement that climate-related uncertainties in water planning are deep due to unknowable trajectories of future greenhouse gas emissions (O'Neill et al., 2014), natural variability dominating at decision-relevant time scales (Deser et al., 2012; Enserink et al., 2013), and our understanding of the how the biophysical systems would respond to climate change, particularly at finer scales needed for decision-making (Hawkins and Sutton, 2011; Forster et al., 2013; Hall, 2014).

Over the past few decades, growing concerns on the use of conventional planning methods have resulted in interest in new, risk-based planning approaches for better consideration of climate uncertainty in decision-making (Lempert et al., 2004; Brekke et al., 2009; Hall and Borgomeo, 2013; Kwakkel et al., 2016). As an initial response, many water system planners have focused on climate information from the coupled Atmosphere-Ocean General Circulation Models (AOGCMs, hereafter GCMs) to understand and assess the possible range of outcomes under climate change. This predict-then-act approach typically begins with selecting a subset of scenarios describing the state of future global development and demographic conditions, such as the Intergovernmental Panel on Climate Change (IPCC)'s "representative concentration pathways" (RCPs) (Moss et al., 2010). The selected set of scenarios is then evaluated through a subset of GCMs to assess the global climate response to greenhouse gas concentrations and then downscaled to a finer temporal and spatial resolution needed by the decision-makers. The downscaled climate projections are then evaluated through linked simulation models, e.g., hydrology, water quality, and reservoir operations to assess the outcomes of climate change. As a result, the findings of the predict-then-act analyses rely heavily on the probability distribution of climate or hydrologic variables that are affected by the subjective assumptions and the source of information defining the scenarios and modeling procedures (Dessai and Sluijs, 2007; Dessai and Hulme, 2009).

Decision-centric frameworks attempt to address the shortcomings of predict-then-act approach by shifting the emphasis from climate science modeling to climate vulnerability at the local level (Walker et al., 2013; Singh et al., 2014; Wise et al., 2014; Herman et al., 2015). These approaches use exploratory modeling to examine a broad range of outcomes under future climate uncertainty, then identify decision alternatives or management actions to reduce vulnerability to climate change. Vulnerability reduction can be expressed in various ways, for example by increasing the system's ability to perform adequately or acceptability under uncertainty (robustness), to adapt to changing conditions (flexibility), or to recover quickly from undesired states or failures (resiliency). Decision-centric frameworks typically apply structured sensitivity analyses to identify critical outcomes across a broad range possible futures, and commonly aim to cover extreme or surprise futures often described as 'black swans' (Taleb 2007). The decision rules employed in decision-centric frameworks are typically non-probabilistic and show a departure from the conventional, expected utility based decision rules to accommodate for greater risk-aversion. For example, they rank choices based on the worst possible outcome, *maximin* (Wald, 1950), a weighted score from the worst and best possible outcomes, *optimism-pessimism* (Hurwicz, 1951), or based on acceptable performance on a specified performance benchmark, *satisficing* (Simon, 1955).The most prominent decision-centric frameworks are Robust Decision Making (Groves and Lempert, 2007; Lempert and Collins, 2007; Bryant and Lempert, 2010), vulnerability-based or scenario-neutral planning (Prudhomme et al., 2010; Nazemi et al., 2013; Nazemi and Wheater, 2014), Info-Gap Decision Theory (Ben-Haim, 2006; Korteling et al., 2013), and decision scaling (Brown et al., 2011; Whateley et al., 2014).

It is common in both decision-centric frameworks and predict-then-act analyses that the scenarios defining the domain of plausible future climates are derived from GCM-based climate change projections. However, this *ex ante* use of climate projections presents potentially biased inputs, which potentially bias the evaluation of design or planning alternatives. The use of an ensemble of projections reveals the performance of designs for the futures those models happen to produce, which is not an unbiased representation of possible climate change (Stainforth et al., 2007; Weigel et al., 2010; Knutti et al., 2013), notwithstanding bias correction techniques, which map projections to historical conditions but do not address biases in projections of the future or sampling bias in the selection of GCMs used. The emission or concentration scenarios used in climate models incorporate numerous assumptions and subjective choices about how the future would unfold that cannot be verified. For example, all RCP scenarios from the IPCC's 5th Assessment Report assume a large reduction in the atmospheric aerosol emissions by the end of the 21st Century, which is argued to be too narrow (Stouffer et al., 2017). Also, many GCMs share basic structural assumptions, numerical schemes, and data sources, and consequently respond quite similarly to related models (Weigel et al., 2010; Knutti et al., 2013) leading to biases when viewed as independent realizations of possible future climate (Steinschneider et al., 2015a). They perform poorly in simulating interannual variability in precipitation (Brown and Wilby, 2012; Rocheta et al., 2014), the frequency and intensity of extreme events (Sillmann et al., 2013; Crétat et al., 2014), especially at fine scales relevant for the water system planners (Schiermeier, 2007). The choice of downscaling method (Pielke et al., 2012) and methodological challenges related to model calibration, e.g., model overfitting (Rougier and Goldstein, 2014) introduces additional concerns in the use of GCM projections in decision-making. Consequently, careful consideration is warranted in the sampling of future climate conditions in scenarios used for infrastructure design, whether

using a decision-analytical or climate-science based approach.

If GCM projections are not to be used as possible futures, how can this uncertain but potentially useful information be incorporated into climate risk analysis? An alternative is to use GCM projections *ex post*, i.e., after a broad range of future climate changes are explored for making posterior inference about the future. The ex post use of climate science information in water systems planning is presented by decision scaling (DS) applications (Moody and Brown, 2013; Whateley et al., 2014; Steinschneider et al., 2015b; Culley et al., 2016). In DS, a *climate stress test* is first applied to reveal vulnerable outcomes across a wide range of climate uncertainties using climate/weather simulator and stochastic simulation analyses. The results of the stress test identify sensitivity to climate change, rather than sensitivity to the climate change projections and their associated and often untested biases that happen to be available from the current generation of GCM runs. Summary statistics from GCM projections, such as long-term trends in mean conditions are then considered to make a subjective judgment on whether identified problematic outcomes are likely to occur in the future. Finally, the system robustness is quantified by decision rules by considering both vulnerabilities as well as the probabilistic information derived from climate projections.

This manuscript demonstrates the first application of the DS framework to the design of water facilities, specifically related to hydroelectricity. In doing this, we present a detailed comparison of the proposed framework to a conventional top-down analysis on two key aspects: the use of climate information in the decision analysis process and the choice of the decision rule for the preference ranking of the design alternatives respectively. For the former aspect, we compare and discuss using GCM projections at the initial phase of the process to describe the possible states of the world (which we refer to as the *ex ante* use) versus later in the process following the vulnerability analysis for making a probabilistic inference (which we refer as the *ex post* use). In the latter case, we compare infrastructure design preference under robustness criterion to more conventional criteria based on expected value of performance and performance under the expected future. Although numerous studies discuss the use of climate information from a methodological point of view (Dessai and Hulme, 2004, 2007; Prudhomme et al., 2010), and the choice of decision rule in decision-making processes (Lempert and McKay, 2011; Budescu et al., 2014; Giuliani and Castelletti, 2016), we are not aware of any studies that evaluate both aspects together and demonstrate the practical implications quantitatively.

This manuscript is organized as follows: Section 2 introduces the adapted DS framework for water infrastructure design; Section 3 provides a comparative analysis of the proposed framework for a hydropower design case study in Lower Fufu River in Malawi; Section 4 provides a further discussion of the key findings, limitations, and conclusions.

2. Methods

The proposed water infrastructure design framework consists of three steps: [1] a project framing to identify the essential processes and components of the analysis, [2] a climate stress test for exploring system performance under different design alternatives and plausible futures, and [3] an *ex post* decision analysis for ranking the alternatives using robustness-based decision rules and climate science information (Fig. 1).

The first step of process is the stakeholder-driven decision framing to describe the essential features of the analysis, including the design alternatives d to be evaluated through the process; the performance metrics M for expressing the performance of the alternatives, and the system model(s) $y_M = f(d,x)$ to relate design alternatives d to the consequences y_M contingent on the climate conditions x. Prior to the analysis, a set of discrete design alternatives can be specified jointly with the stakeholders, e.g., associated local organizations, project partners, funding agencies. It is also possible to specify the options through a computational search based on Monte Carlo methods (Korteling et al., 2013) or evolutionary algorithms (Kasprzyk et al., 2013; Reed et al., 2013). The system models(s) are built based on the principal hydroclimatic, economic and operational processes, and the relevant temporal-spatial scales of the infrastructure design problem. As mentioned, although the framework presented here focuses on climate uncertainties, the same approach can be extended to include non-climatic factors, including uncertainties associated with price, population, or water demand change, although achieving unbiased sampling of those uncertainties has yet to be explored.

The second step is the climate stress test, a procedure to systematically explore how the infrastructure design may perform across a wide range of plausible future climate conditions, including changes in mean climate as well as climate variability. Typically, climate change studies use time-series of projections from GCMs to evaluate future performance. However, GCM projections do not systematically explore plausible climate changes, especially variability changes. They offer a glimpse based on what the projection happens to produce. The results indicate the performance relative to the projection that happens to be used. Finally, climate change projections are contingent on the emissions scenario used, downscaling and bias correction used, and a host of other subjective choices that obfuscate the final results of the analysis. In contrast, the climate stress test is specifically designed to systematically evaluate response to alternative climate futures that are represented unbiasedly and precisely. Climate stress test is implemented by first systematically sampling new realizations of the past climate using a stochastic weather generator (Steinschneider and Brown, 2013). In this process, the weather generator is conditioned on the s historical climate statistics such as its mean and variance to produce an unbiased sample. The weather generation process yields n realizations x_i: $i = 1...n$ each consisting of a set of time-series of climate variables at the desired temporal scale and spatial resolution. Long-term changes in the climate system, such as trends or shifts in mean temperature and/or precipitation conditions are represented through m delta factors c_j: $j = 1...m$. The variability realizations and the delta factors are then combined, resulting in a matrix of $n\,x\,m$ climate traces $X = \{x_t = x_i \cdot c_j\text{: } t = 1...,n\,x\,m\}$, where $(\cdot)$ is the operator used for modifying a given climate variable time-series. The system model $y_M = f(d,x)$ is then simulated for each climate trace $x \in X$ and design alternative $d \in D$ to evaluate the consequences under each case. The climate stress test thereby explores performance across systematically generated samples of climate variability and change, going beyond a conventional scenario-led analysis, in which the vulnerabilities are only estimated for the climate changes and variability that happen to be sampled

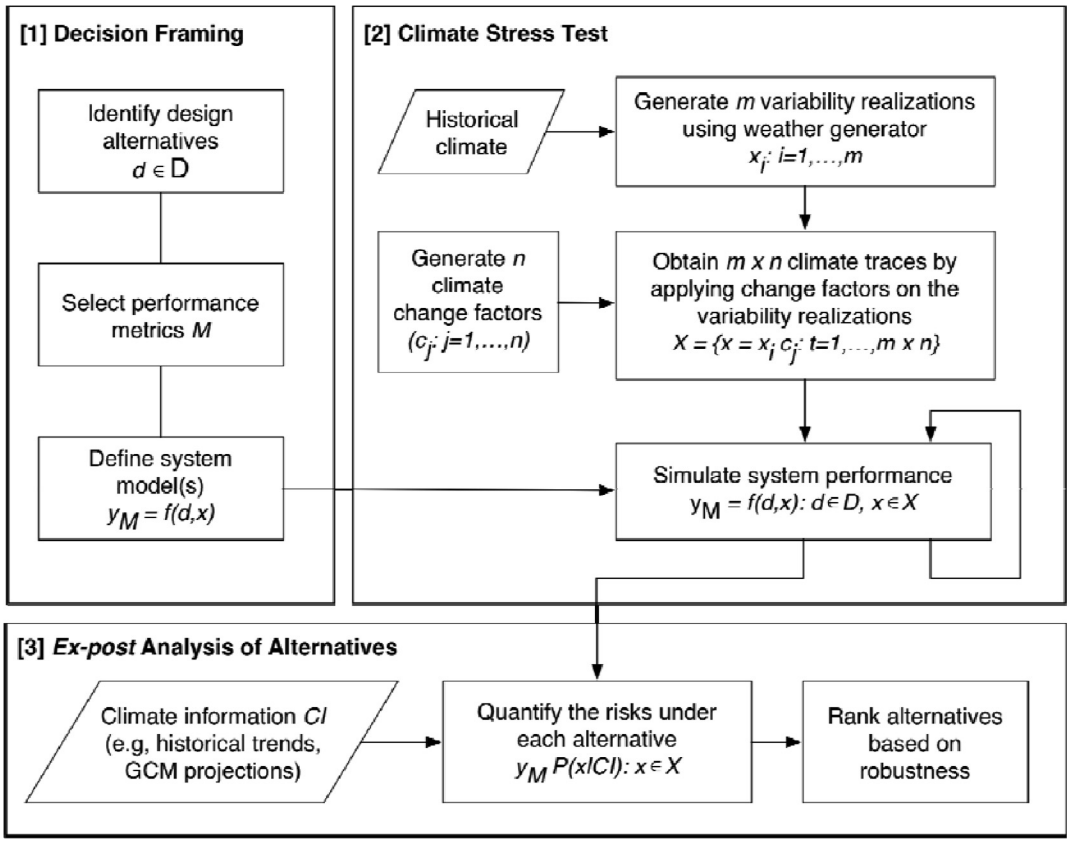

Fig. 1. The proposed decision scaling framework for water infrastructure design under climate uncertainty. The rectangles and the parallelograms mark major model processes and information inputs respectively.

by the available climate projections.

The final step is the *ex post* analysis of alternatives to identify one or few low-risk options for the project of interest. First, the risk associated with each option is quantified by weighting the set of consequences $\{y_M(d,x)\}$ based on available sources of climate information *CI*, such as including historical trends, paleoclimate data, GCM projections or expert views. The conditional probability weights assigned to future climate states $P(x|CI)$ $x \in X$ can be obtained from the most credible information or decision-relevant statistics extracted from the information source. For example, in recognition that the climate model projections are most credible at reproducing mean climate conditions (versus higher order moments, i.e., variability and extremes) at broader spatial scales (versus a single grid cell), only long term mean precipitation and temperature are used from the climate model outputs. Extracted climate information can be treated within a formal probabilistic framework to set the conditional probability weights of the conditions evaluated in the stress test (Moody and Brown, 2013). Finally, the quantified risks are summarized by a choice of robustness criteria, including stakeholder-defined robustness index (Whateley et al., 2014), satisficing metrics (Lempert and Collins, 2007) or conditional-value-at-risk (Webby et al., 2007). The choice of decision criteria in robustness-based performance assessments allows creating a spectrum of attitudes reflecting the decision-maker's behavior, from full optimism, e.g., maximax, to extreme pessimism, e.g., minimax regret (Giuliani and Castelletti, 2016).

3. Case Study: Hydropower facility design

The case study used to demonstrate the approach is the design and analysis of a hydropower facility currently in the planning phase. The results of the analysis are compared to the results of a scenario-led evaluation of the same project. The implications of the use of climate information and alternative decision criteria are discussed for both methods.

3.1. Project description

A planned investment in northern Malawi combines water resources from the North Rumphi and South Rukuru rivers for generating hydropower through a run-of-the-river plant (Fig. 2). The required flow is diverted via two equally sized intake weirs and underground supply tunnels. The design problem consists of the choice of an economically viable hydropower facility size among the twelve prespecified design alternatives from 84 to 148 MW, which were defined by the project stakeholders prior to the analysis. The

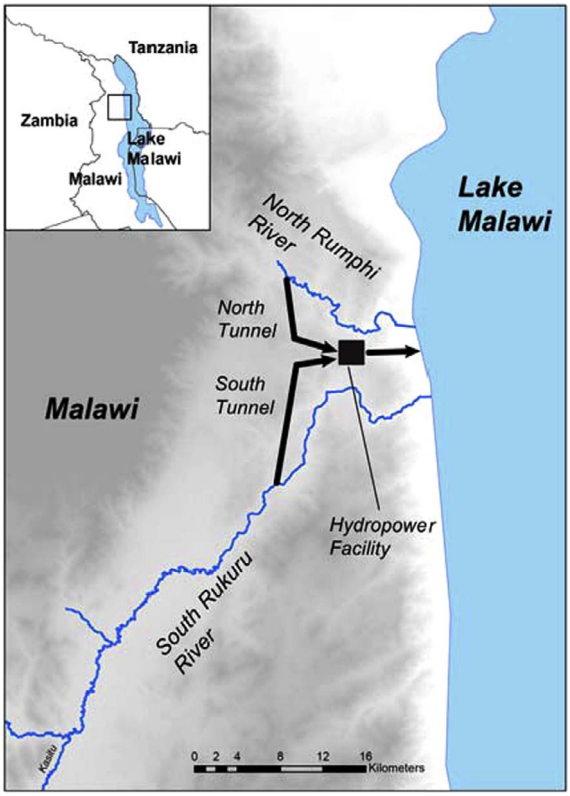

Fig. 2. Illustration of the planned hydropower development project. Arrows indicate the direction of the diverted streamflow for hydropower generation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

present value life cycle costs of these twelve options increase linearly from $223 to $342 million with increasing plant size. The design variable of the analysis is the combined maximum flow allowed through the supply tunnels (design flow) that range from 29 to 51 m^3/s, depending on the selected hydropower plant size (Table 1).

The climate of northern Malawi is mild tropical with Austral rainy summers from December to April, and very dry winters from July to October. The primary driver for precipitation is the migration of the Inter-Tropical Convergence Zone (ITCZ) that separates the southeast trade winds and the north-east monsoon of the Indian Ocean (Jury and Mwafulirwa, 2002). The historical climate conditions of the study region were evaluated for the period 1974–2008 using the combined reanalysis with observation data from the Terrestrial Hydrology Research Group at Princeton University (Sheffield et al., 2006). According to the available data, precipitation ranges from 700 to 1350 mm/yr, with a mean of 1001 mm/yr. The marked variability in the annual precipitation can be attributed to large-scale teleconnection effects, such as El Niño–Southern Oscillation (ENSO) and the stratospheric Quasi-Biennial Oscillation (QBO) (Nicholson, 2000). Historical mean temperature over the same period shows a linear increase of about 0.9 °C, with

Table 1
Design alternatives for the proposed hydropower facility. Design flow indicates the combined maximum flow allowed through the supply tunnels. The project cost shows the summation of the project capital costs and the estimated operations and maintenance costs over the project lifetime.

Design capacity (MW)	Design flow (m^3/s)	Project cost ($ million)
84	29	223.0
90	31	231.0
96	33	238.8
102	35	246.4
107	37	253.9
113	39	261.2
119	41	268.4
125	43	275.4
131	45	282.3
137	47	289.1
142	49	295.8
148	51	302.4

a mean of 20.6 °C.

3.2. Modeling of system performance

The hydropower generation from the run-of-the-river facility is simulated using an application of Water Evaluation and Modeling System (WEAP), a decision support tool for integrated water resources management. For this particular case study, the WEAP model was developed by Cervigni et al. (2015).The WEAP schematic of the study area includes two source nodes that simulate monthly surface flow from time-series of rainfall (mm) and temperature (°C); and two withdrawal nodes that divert simulated flow to the hydropower plant. Since the planned hydropower facility do not dam the river to create a reservoir, the hydropower output is approximated as a linear function of combined diverted flow (m^3/s) with a fixed hydraulic head of 336 m and a plant efficiency factor of 88% based on the project feasibility study (Norconsult, 1996).

The economic performance of the project is assessed by the Levelized Cost of Energy (LCE) based on the stakeholder preference. The LCE metric gives the price at which the electricity must be sold to break even financially over the lifetime of the project (in $/GWh):

$$LCE(d,x) = C(d)*\left(\sum_{t=1}^{T} P_t(d,x)*(1+r)^{-t}\right)^{-1} \tag{1}$$

where C is the present value cost of the project under design d ($), $P_t(d,x)$ is simulated hydropower output in year t (GWh) under design d and climate condition x, T is the project lifetime (assumed as 35 years), and r is the economic discount rate (set as 5%, based on the stakeholder preference).

3.3. Assessing design alternatives under climate uncertainty

The twelve designs are subjected to a climate stress test to explore the performance of each under a large domain of future climate conditions. The input data for the climate stress test is obtained through the procedure described in Section 2, by first generating a set of new climate variability realizations, and then applying a set of change factors to the climate realizations to reflect gradual climate changes.

The new climate realizations are generated by a first-order wavelet autoregressive model (WARM) (Kwon et al., 2007; Steinschneider and Brown, 2013). For this process, the historical precipitation record (from 1974 to 2008) for the two upstream catchments are area-averaged and aggregated to annual values. Next, ten annual, thirty-five-year precipitation realizations are sampled from the WARM, with approximate means and standard deviations of 1001 mm and 150 mm respectively, and with power spectrum similar to the observed record. The generated annual precipitation realizations are then disaggregated to multi-site monthly time-series using a K-Nearest Neighbor (K-NN) resampling scheme (Lall and Sharma, 1996). The outcome of the weather generation process is a relatively unbiased sample of the observed climate record with matching mean, standard deviation, and low-frequency variability. Next, delta factors are applied to the climate realizations to simulate long-term trends in the precipitation and temperature. For temperature, six additive factors applied from -1 to 4 °C, with increments of 1 °C. For precipitation, thirteen multiplicative factors are applied ranging from 0.4 to 1.6 with increments of 0.1. These climate change factors increase linearly by starting from zero-change at year one and ending at the specified level (e.g., 3 °C). The choice of delta factors is made to span a broad range of climate changes for the study area, exceeding the range of projected temperature increases (up to 2.5 °C) and precipitation changes (up to 30%) in 2060's relative to 20th Century means (Cervigni et al., 2015).

By applying all possible combinations of change factors over the ten realizations, a total of 780 climate traces is obtained. The climate stress test is then executed for each design alternative by simulating the WEAP model of the system under each climate trace to obtain monthly hydropower outputs. LCE metric is calculated for each simulation run (1), and then are transformed to regret to identify the design(s) that would give a relatively low level of regret over the range of climate conditions assessed:

$$regret_M(d,x) = |LCE(d^*,x) - LCE(d,x)| \tag{2}$$

where the regret $regret_M(d,x)$ is the absolute difference between the LCE of design d in some future condition x, $LCE(d,x)$, and the levelized cost of the best-performing design, d^*, under the same future condition, $LCE(d^*,x)$. Note that the presented approach of comparing the design alternatives, i.e., by assessing the range of low regret outcomes in each option, does not make use of climate information. To aid the decision-making process, downscaled GCM projections is used to set the likelihood of future climate conditions (see the following section).

3.4. Robustness analysis of the alternatives

In the final phase, the twelve alternatives are evaluated in terms of their ability to perform acceptably under the future climate conditions evaluated. This is done by calculating the robustness of each alternative from the set of LCE regret values calculated through the climate stress test (Section 3.3). Climate science information is incorporated at this phase to assign relative weights to alternative futures.

The robustness of the options is expressed using a modified version of the Robustness Index (*RI*) (Whateley et al., 2014). The first step of RI calculation is parsing the stress test results into regions of acceptable and unacceptable outcomes with respect to a pre-

defined performance threshold I^T:

$$\Lambda(d,x) = \begin{Bmatrix} 1, & if\ regret_M(d,x) \leqslant I^T \\ 0, & if\ regret_M(d,x) > I^T \end{Bmatrix} \tag{3}$$

where, I^T is the performance threshold that is set to a LCE regret of 200 \$/GWh, and $\Lambda(d,x)$ is a binary variable that takes a value of one when the computed regret value is less than or equal to the threshold value and zero when the regret is higher than the threshold. The threshold value is set based on the stakeholder opinion among a range of alternatives. Next, a *RI* value is computed from the weighted sum of the binary variable $\Lambda(d,x)$ conditional on the climate information *CI*:

$$RI_{d^*} = \text{argmax}_d[\sum_x \Lambda(d,x).\ Px|CI)] \tag{4}$$

where, $P(x|CI)$ is the relative weight assigned to each climate state x conditional on the climate information. For this study, the climate information is obtained from the World Climate Research Programme Coupled Model Intercomparison Project Phase 5 (CMIP5) multi-model ensemble (Taylor et al., 2012). The ensemble has a total twenty GCM models that consists of twenty model runs forced with the historical conditions (the atmospheric composition of the 20th century), and a total of fifty-four model runs forced with the IPCC's representative concentration pathways (RCPs) 4.5 and 8.5 respectively (IPCC, 2013). The GCM outputs from all model runs are statistically downscaled to a monthly temporal resolution and a 0.5° spatial resolution according to the Bias Correction Spatial Disaggregation (BCSD) method (Cervigni et al., 2015).

Using the CMIP5 ensemble, the relative weights assigned to the climate states are obtained in four steps. First, the vector of mean annual precipitation and temperature changes are calculated from all future climate projections. Second, the computed mean changes from twenty GCMs are then reduced to eight data points to account for the potential sampling biases due to the structural similarities in GCMs (Knutti et al., (2013). In doing this, we treated all model runs equally, and by simple averaging within each model group. Third, the computed eight data points are used to define a probability distribution function (PDF) for the domain of climate changes. In this work, we used a bivariate Cauchy distribution:

$$g(x,y) = \frac{1}{2\pi}[\gamma((x-x_0)^2 + (y-y_0)^2 + \gamma^2)^{-1.5}] \tag{5}$$

where, x_o and y_o are the location parameters that are set to the mean temperature and precipitation value of the eight data points; and γ is the scale parameter that is set to the covariance matrix obtained from the eight data points. The reason for using a heavy-tailed Cauchy distribution over a more common Gaussian (Whateley et al., 2014) is assign higher relative weights to extreme changes for greater risk-averseness. Finally, we use (5) to obtain the contingent normalized probability weights of the 78-plausible mean temperature and precipitation changes. The RI calculation is repeated for each climate variability realization and then averaged over with an assumption that each variability realization is equally likely to occur.

In addition to the RI criterion, we also show design preference under two more commonly applied decision rules for comparison. The first additional criterion is the design choice based on the most likely (ML) future state:

$$ML_d = LCE(d,x):\ \max_X P(x|CI) \tag{6}$$

where, $\max_X P(x|CI)$ is the 'most likely' climate future conditional on the imperfect climate information; $LCE(d,x)$ is the LCE value under that most-likely climate state. The latter criterion of EV is the weighted sum of the computed LCE values contingent on relative probability weights obtained from the climate information CI:

$$EV_d = \sum_x LCE(d,x)P(x|CI)] \tag{7}$$

3.5. Design evaluation based on scenario-led analysis

The twelve design alternatives are also evaluated under the historical climate conditions, and by way of a conventional top-down, GCM-based analysis to demonstrate differences on the proposed framework. In this case, climate information is used *ex ante* to describe the domain of climate scenarios and the evaluation process is carried out based on the results obtained from those scenarios.

For the analysis under historical climate, the WEAP system model is simulated under a single forcing scenario representing the historical climate of the 1974–2008 period. For the latter case of GCM-based analysis, the model is forced with all downscaled GCM outputs over the 2016–2050 period. In both cases, the simulated hydropower output and the present value costs are used to calculate the LCE (1). The results are then summarized using the same decision criteria of RI, ML, and EV respectively. For the RI and EV criteria, it is assumed that each GCM-based climate scenario is independent and equally likely to occur. For the ML criterion, the most likely climate scenario is determined based on the empirical density of the projected climate changes in the multi-model ensemble.

4. Results and discussion

4.1. Design preferences under decision scaling (DS) application

The LCE values obtained from the stress test range from 18,400 to 32,800 \$/GWh for the smallest design (29 m^3/s) and from

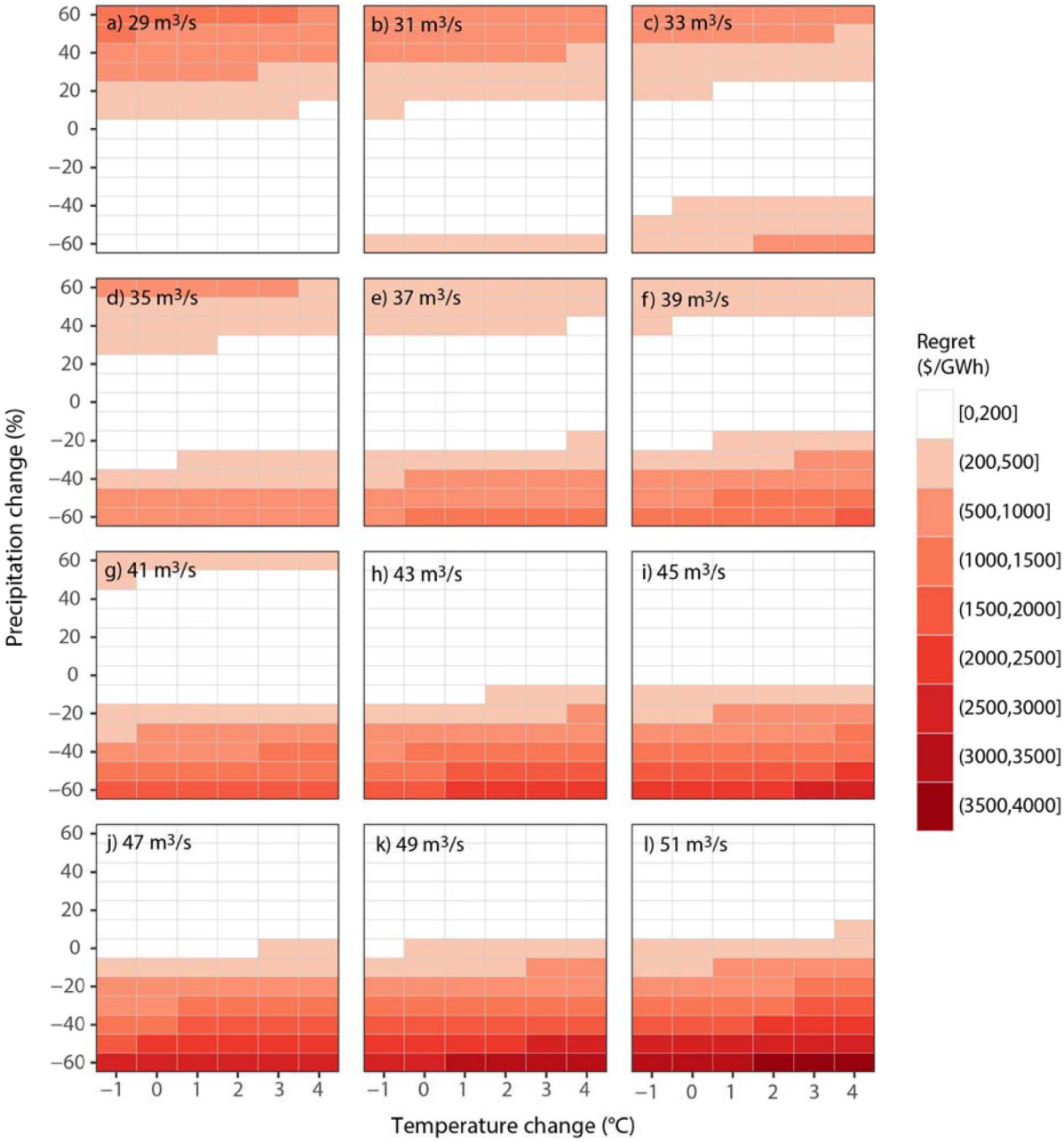

Fig. 3. Computed range of LCE regret across the domain of climate changes ($/GWh) under each design alternative. The cells shaded with white color mark the climate conditions that lead to a low (acceptable) level of regret.

17,000 to 37,000 $/GWh for the largest design (51 m^3/s), respectively. We note that the order of magnitude of differences among the LCE values may be relatively small for real-world decisions; however, the results illustrate the application of the evaluation process despite the small magnitude of the economic values. The differences in results become more noticeable in regret terms, as the computed regret for the smallest and largest design sizes are up to 1400 and 4300 $/GWh, respectively.

Fig. 3 shows the regret for each alternative under evaluated climate changes. The relatively sharp changes over the y-axis (precipitation change) indicate that the results are more sensitive to precipitation than to temperature. Among the twelve alternatives, the smallest (29 m^3/s) results in a regret of less than 200 $/GWh, and therefore performs acceptably when the mean annual precipitation is less than the historical mean. However, for the smallest option, the regret increases to 1500 $/GWh under wetter futures. In contrast, larger options, i.e., 45 m^3/s or greater, are vulnerable to drier futures, with a maximum regret of 2000 $/GWh or greater. As no single option dominates, and the choice varies whether the future would be drier or wetter, climate likelihood information is useful at this stage for making a judgment on the relative risks presented.

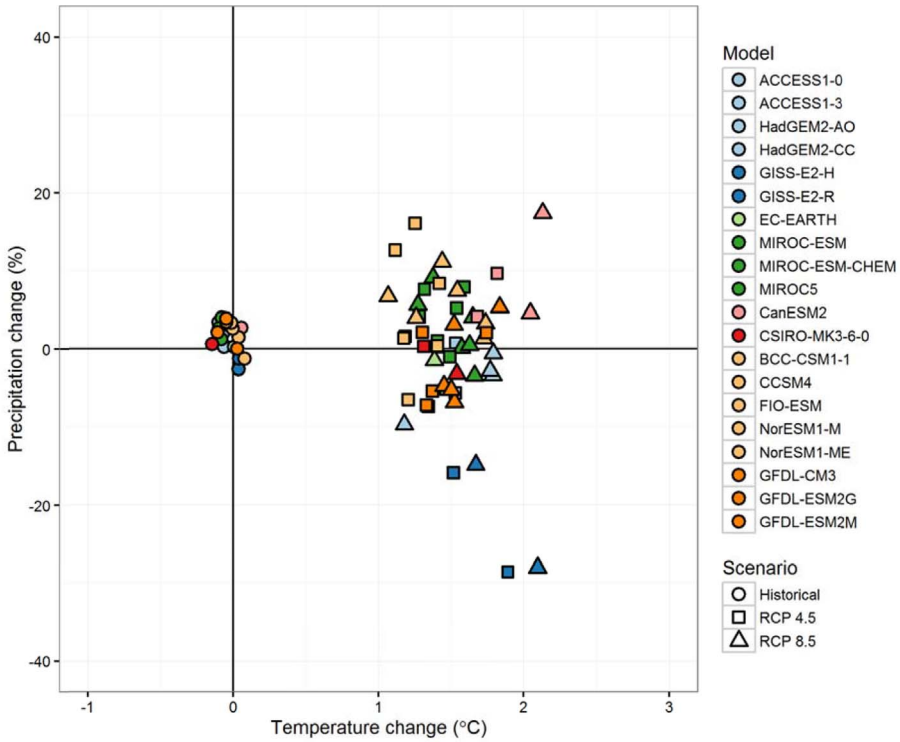

Fig. 4. Projected mean changes in annual temperature (°C) and precipitation (%) in the seventy-four GCM runs relative to the historical period 1974–2008. GCMs sharing similar model code are shown in the same color. Shapes represent a model response to different climate forcing scenarios. The intersection of the vertical and horizontal line marks the value of mean observed temperature (20.6 °C) and precipitation (1001 mm). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 4 shows the scatter plot of annual mean climate changes from the CMIP5 ensemble of GCM output. The multi-model ensemble shows a large range of outcomes for both the direction and the magnitude of change in mean annual precipitation (−30% to +20%) and a relatively small range of outcomes in the magnitude of increases in mean annual temperature (1 °C to 2.2 °C) relative to the historical averages.

The results from the vulnerability analysis (Fig. 3) and the climate information derived from the CMIP5 ensemble (Fig. 4) can be combined to for the risk analysis of alternatives. Fig. 5 depicts the climate conditions under which each design is the no-regret choice or the best performing alternative. In Fig. 5, eight data points representing the mean climate changes from each GCM group (see Fig. 4) are superimposed to provide a graphical indication of the GCM-based likelihood of evaluated climate changes. It is seen that most designs are optimal for a narrow band of plausible climate changes, while the smallest and largest design flows, 29 and 51 m^3/s respectively, outperform the others over a relatively larger domain of climate changes. However, these represent extreme climate changes that are less likely to occur according to the mean changes from the model groups. As Fig. 5 shows, most model groups indicate little change in mean precipitation and a temperature increase between 1 and 2 degrees, although there is one warmer-and-wetter and one dryer.

The computed decision criteria applied to the design question reveals a single best design of each evaluation criteria. For the ML criterion, the 35 m^3/s design gives the lowest LCE, with a value of 23,400 $/GWh under the most likely conditions of a mean temperature increase of 2 °C and historical precipitation means (no-change). Fig. 6 shows the results under the EV and RI criteria for each climate realization, as well as for the conditions averaged over their means. The EV criterion indicates design 35 m^3/s as the best choice. Note that the role of variability, however, as the design preferences vary from the 33 to 37 m^3/s based on the choice of climate realization (Fig. 6-a). The RI criterion also indicates design 35 m^3/s as the best choice, with results ranging from 31 to 39 m^3/s over the ten individual variability realizations (Fig. 6-b).

4.2. Comparison to results under scenario-led analysis

The simulated LCE values under the historical climate period (1974–2008) across the twelve alternatives show 39 m^3/s as the optimal design option. Under the scenario-led analysis, the LCE metric ranges from 19,300 to 31,500 $/GWh for the smallest size (29 m^3/s), and from 18,400 to 35,400 $/GWh for the largest size (51 m^3/s). The design preference is found to be highly dependent on the choice of criterion, as the choices were 39 m^3/s for the ML, 31 m^3/s for the EV, and 29 m^3/s for the RI respectively.

Table 2 summarizes the preferred choices under the past climate, and the scenario-led and decision-scaling analyses on the three decision criteria applied. Considering the RI criterion, the best alternatives are identified as the 39 m^3/s for the historical climate,

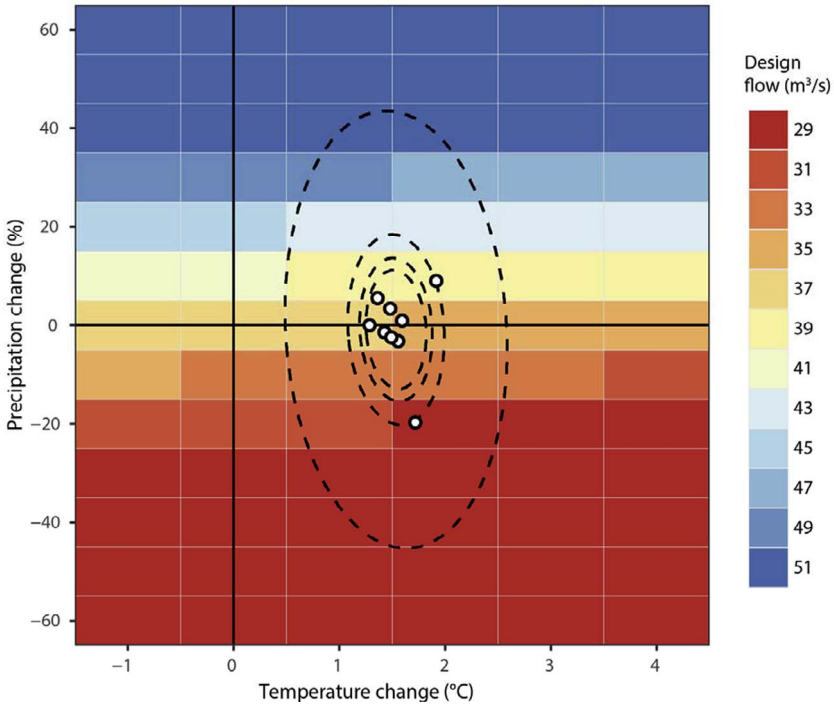

Fig. 5. No-regret domains of the designs under the evaluated range of climate changes. Each color region marks a design's zero-regret performance domain regarding LCE. The intersection of the vertical and horizontal line marks historical mean temperature and precipitation (1974–2008 period). The circles mark projected means from 11 GCM groups in the CMIP5 ensemble for the period of 2016–2050. The contours indicate the levels (1×10^{-3}, 3×10^{-3}, 5×10^{-3}, 7×10^{-3} and 9×10^{-3} respectively) of the bivariate Cauchy distribution derived from the GCM data. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

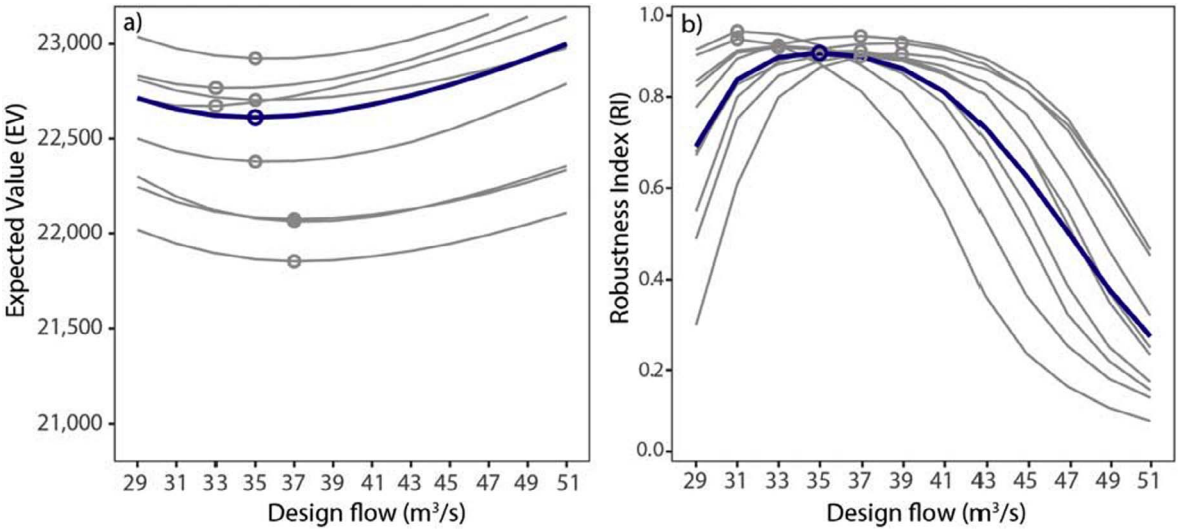

Fig. 6. a) Variation in EV criterion, in US/GWh. b) Variation in RI criterion. The gray lines show the variation of results across the ten stochastic climate variability realizations. The blue lines show the mean results averaged over the individual variability realizations. The gray and blue circles mark the preferred design choices for each condition. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

29 m^3/s for the scenario-led analysis, and 35 m^3/s for the decision-scaling analysis respectively. To illustrate the differences between these three optimal choices, we focus on their relative performances under future climate. Fig. 7 depicts the regret from the options of 29, 35, and 39 m^3/s versus the potential future mean streamflow based on 780 stochastic climate traces used in the stress test analysis. If the mean streamflow were to decline in the future, the historical choice performs very poorly, while the two alternatives that accommodate climate change perform better. Therefore, it remains helpful to bring in a representation of the information from both climate projections as well as the historical mean value to assess alternative designs. Shown as pdfs of climate change in parallel

Table 2
The summary of findings from each decision criteria under the historical climate conditions, and based on the scenario-led and the decision scaling analyses. The values in bold show the final preference in each case.

Decision criteria	Historical climate	Scenario-led analysis	Decision scaling analysis
ML	**39 m^3/s**	37 m^3/s	35 m^3/s
EV	–	31 m^3/s	35 m^3/s
RI	–	**29 m^3/s**	**35 m^3/s**

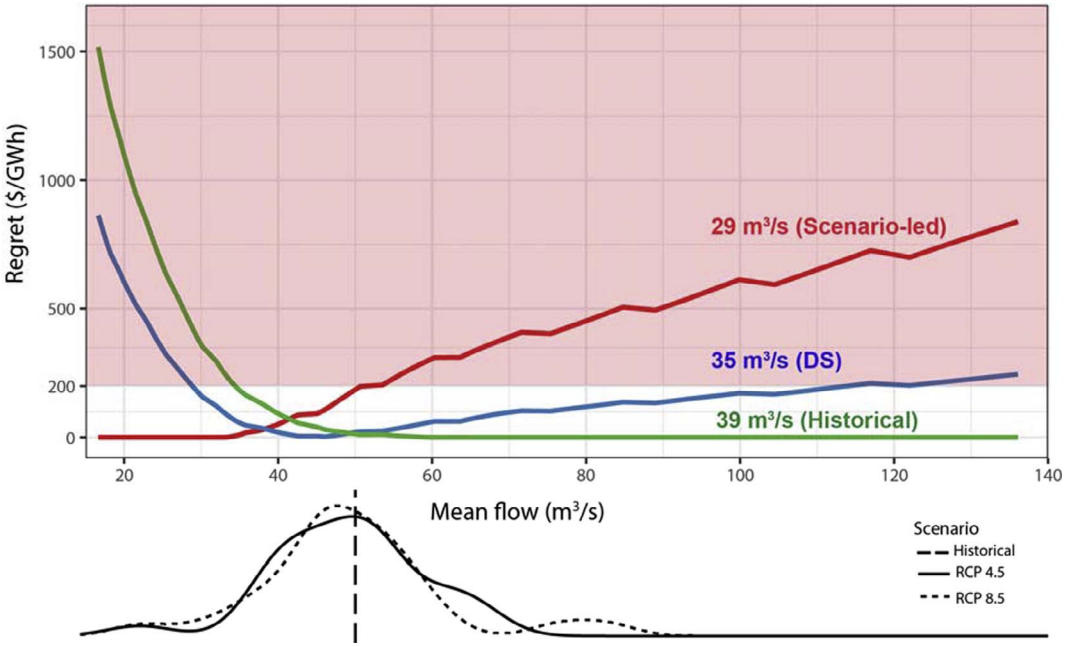

Fig. 7. LCE regret (in $/GWh) versus mean flow at the upstream the project site (m^3/s) for the best performing designs under the historical climate, and under future climate with the scenario-led and decision-scaling approaches. The region shaded in light red shows the unacceptable performance when regret is above 200 $/GWh. The lower panel shows the historical mean, and the density distribution of mean streamflow from the GCM runs with the RCP 4.5 and 8.5 forcings respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

coordinates (lower panel), the 35 m^3/s (based on DS) and 39 m^3/s (based on historical conditions) perform better over the conditions indicated to be probable by the available climate evidence.

4.3. Implications of ex ante and ex post uses of GCM projections on the design preference

The differences in the results of the two methods presented (Table 2) can be explained by the underlying methodological choices, and mainly by how climate uncertainty is sampled in each case. The DS approach provides a fuller and more systematic exploration of the climate change uncertainties through a stress test, in this case, with a full factorial design consisting of six additive factors of mean temperature increases up to 4 °C and thirteen multiplicative factors of mean precipitation changes from −40% to 40%. In contrast, the scenario-led approach explores system sensitivity to the downscaled range of CMIP5 projections, consisting of twenty GCM models and two RCP scenarios. These GCM projections represent a relatively narrow range of climate changes (e.g., for precipitation from about −30% to 20%) and a clustered sample set of mean climate changes based on the underlying assumptions such as the forcing scenarios used, the downscaling method or the structural similarities among the climate models. The clustering of model estimates in the given multi-model ensemble (e.g., the clustering of mean annual precipitation around the historical mean of 1000 mm/year in Fig. 4) imposed an *ex ante* probability distribution over the evaluated range of uncertainties. The preference for relatively smaller project design capacities in the scenario-led analysis can be attributed to this implicit probability distribution, with a higher density on the lower range of potential precipitation changes.

Second, the DS and scenario-led analyses represent historical climate variability differently. In DS, historical climate variability is represented by ten stochastic realizations from a wavelet auto-regressive model. The statistical properties of these ten realizations match well with the historical record. For example, the differences in standard deviation are less than 3%, and the correlation between the power spectra of each realization and the historical data ranges from 0.5 to 0.7 (Fig. 8). In contrast, the GCM time-series used in the scenario-led analysis are biased in the representation of historical climate variability. The downscaled GCM runs over-estimate the historical standard deviation by 14%, on average, with particular runs deviating from the true standard deviation by

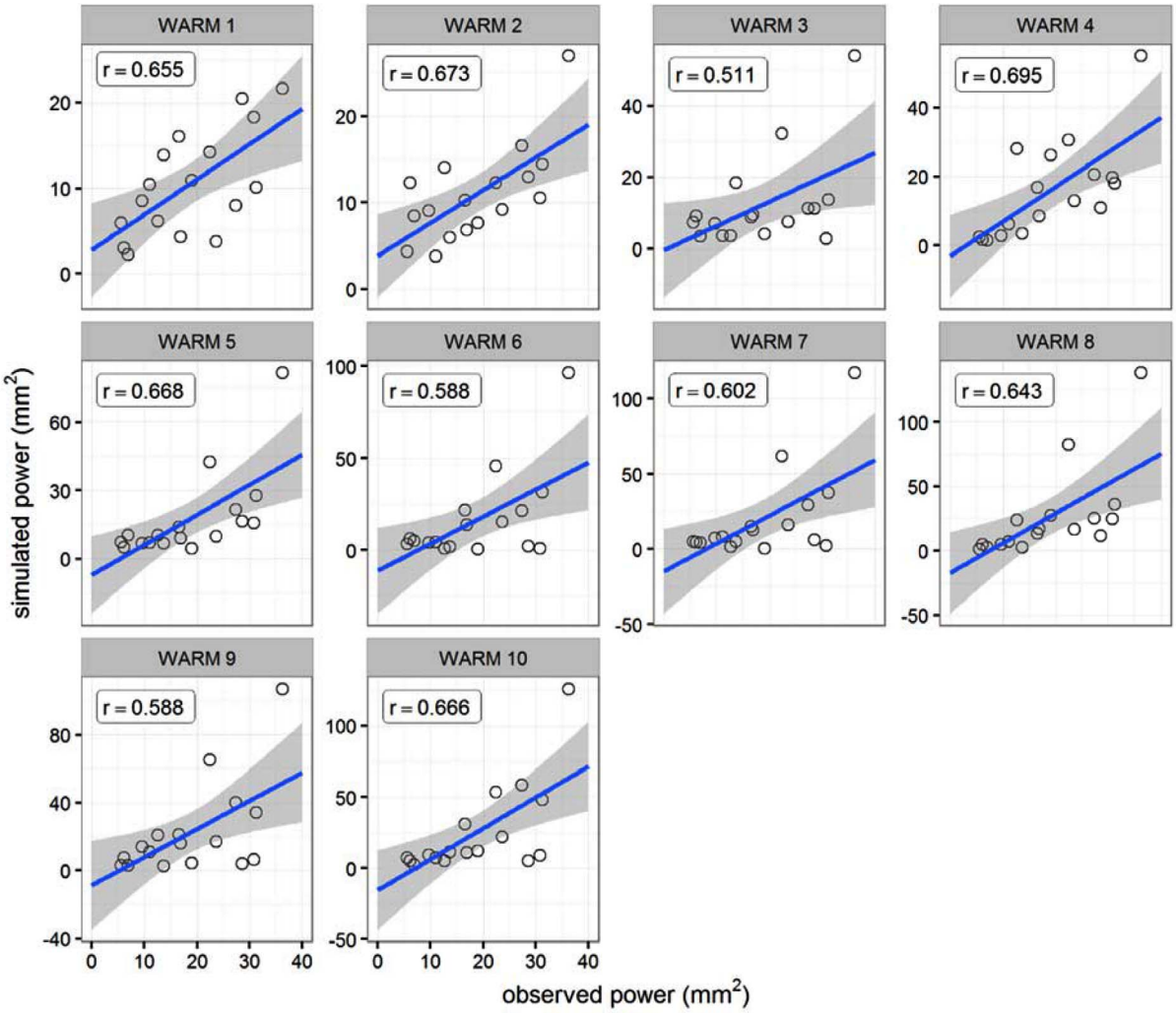

Fig. 8. Power correlations between the observed precipitation (1974–2008) and the precipitation realizations generated by WARM. In each panel, the blue line shows the linear regression line and the gray ribbon represents the 95% confidence interval of the regression.

−20% to +63%. The downscaled GCM runs perform particularly poorly with regard to precipitation persistence. Half of the models carry a negative correlation with the observed power spectrum (with values ranging from −0.6 to 0.7) (Fig. 9).

In addition to the biases associated with the historical GCM runs, the sensitivity of results to climate variability could not be observed in the scenario-led approach, as no GCM model had more than a few realizations of the possible future climate under the given concentration forcing assumption. Moreover, no data were available to indicate the degree to which the inherent climate noise influenced the downscaled GCM runs, or if the design preferences from the scenario-led analysis would change in a repeated analysis with different climate time series obtained from the same GCM projections and concentration scenarios. We are aware that the sampling of climate variability can be improved by making use of GCM data from large perturbed physics experiments such as the UKCIP scenarios (Murphy et al., 2007), but such were not available for this study.

4.4. Implications of decision criteria on the design preference

Faced with a deeply uncertain climate, the water systems planning community has commonly agreed that long-term, costly investment decisions would do well to emphasize robustness, the ability of the system to perform satisfactorily across a broad range of futures. This marks a departure from the conventional decision theory, by which analysts commonly prescribe uncertainties *ex ante*, commonly through a single, well-defined PDF, and then model the system using a “most likely” future, or run the model for a number of scenarios and make a recommendation to decision makers based on the single expected value of outcomes. The limitations of conventional criteria in contrast to robustness-based based approaches have been discussed in detail, particularly on results sensitivity to underlying probabilities (McInerney et al., 2012; Walker et al., 2013; Heal and Millner, 2014) and underestimation of risks from low-probability-high-impact events (Weitzman, 2009). However, the implications of their use in planning problems in

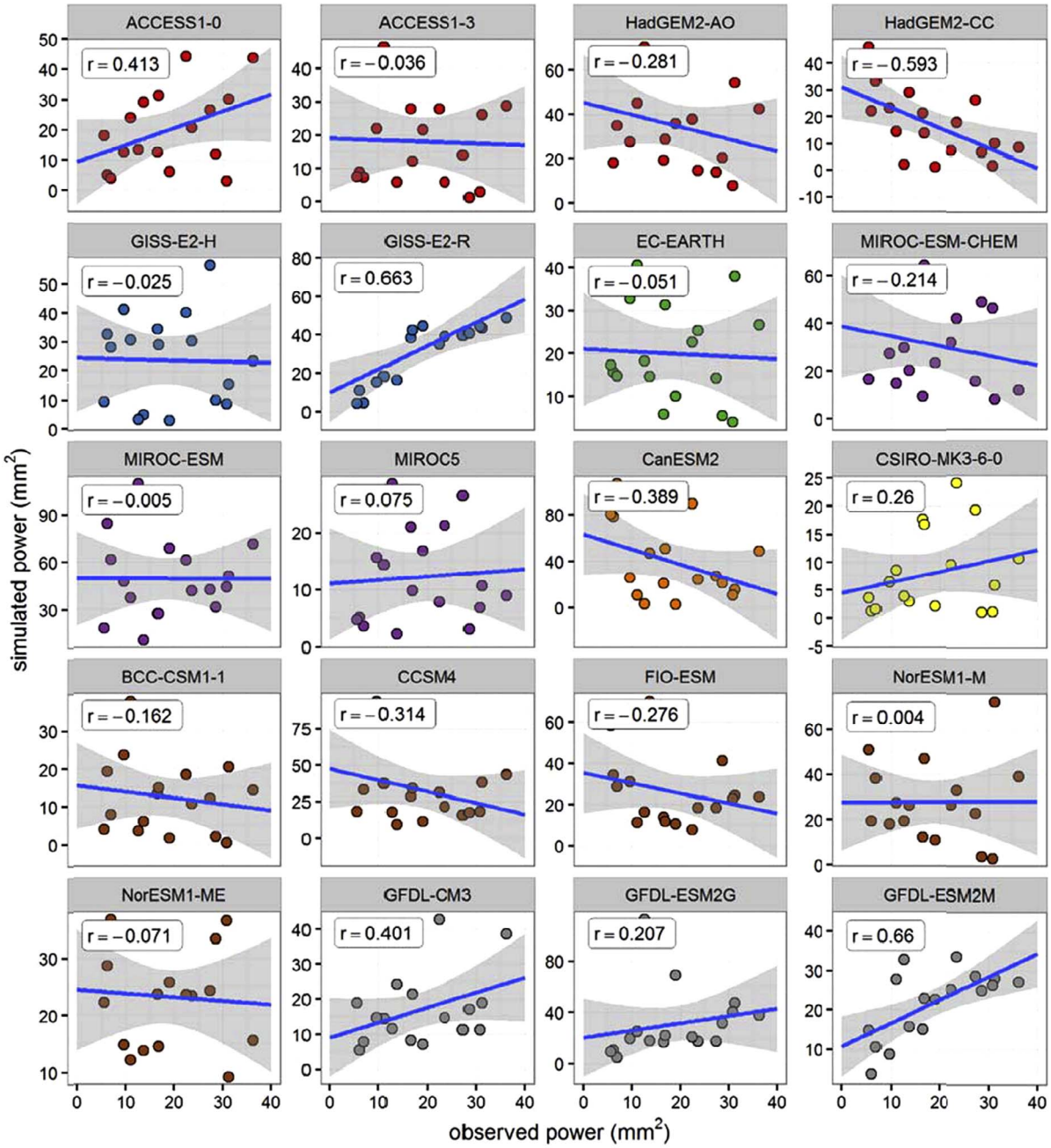

Fig. 9. Power correlations between the observed annual precipitation of the 1974–2008 period (x-axis) and the historical GCM runs (y-axis). In each panel, the blue line shows the linear regression line, and the gray ribbon shows the 95% confidence interval of the regression line. Colors indicate GCM family scheme.

comparison to robustness-based criterion have not been demonstrated. To address this point, we have shown a comparative analysis for a hydropower design problem.

The preferences under the decision criteria of RI, ML, and EV (Table 2) show high sensitivity to underlying experimental design, in this case, how the domain of future changes is defined and weighted. In the scenario-led case, the RI criterion results in the most 'conservative' choice of 29 m^3/s (i.e., the alternative with the lowest capital cost) to maintain a low regret regarding economic efficiency across all projected climate changes. However, under the decision-scaling analysis, both RI and the conventional criteria of ML and EV resulted in the same mid-sized design choice (35 m^3/s). This result is not necessarily generalizable, but is indicative in its demonstration for this case.

4.5. Limitations of the analysis presented

The case study explored the future vulnerabilities across a broad domain of climate states considering both natural variability and long-term climate change. We represented future climate changes through simple change factors applied to annual mean temperature and precipitation. However, the changes in extremes (e.g., future monthly maximum precipitation) or in intra-annual variability (e.g., seasonality of precipitation) remains as an important concern in long-term planning (IPCC, 2013) and could also be explored. For this purpose, Steinschneider and Brown (2013) describe a quantile mapping method to alter frequency distributions of precipitation time-series (e.g., monsoon arrival time and duration) that could be integrated into the presented framework.

We represent climate information for the area of interest based on a set of fifty-four downscaled GCM projections. Although the multi-model GCM ensembles are standard inputs to many top-down climate risk assessment studies, it is possible to improve the sampling of uncertainty in model projections using more rigorous approaches. For example, Borgomeo et al., (2014) present a risk-based approach to water systems planning, where they define the probability distribution of future climate states using a large perturbed physics ensemble (PPE). In their work, Borgomeo et al. (2014) couple data from UKCP09 PPE with a transient stochastic weather generator for better sampling of natural climate variability and model parameterization. Various other decision-centric analyses show similar ways of using GCM projections using large model experiments and stochastic sampling or downscaling algorithms (Groves et al., 2008; Lopez et al., 2009; Bussi et al., 2016; Turner et al., 2016). However, these more rigorous frameworks still lack proper treatment of uncertainties due to model structures or underlying emission scenarios.

Another important point related to the use of climate information in decision-making is the approach to account for the sampling bias due to the similarities among the climate models. In this work, we address the bias due to model similarity using a single representative value (the mean) from each GCM family based on the model genealogy scheme given by Knutti et al., (2013). We are aware that this is a coarse approximation of the probabilistic information that can be extracted from a multi-model climate projections ensemble. More sophisticated methods can be used to maintain model diversity without replication, for example through a performance-based weighting scheme (Haughton et al., 2015), k-means clustering (Cannon, 2015), or by assessing the correlations in the error structure of the model projections (Arnell and Lloyd-Hughes, 2014; Evans et al., 2013).

5. Conclusions

This paper has applied DS concepts to the design of the turbine capacity for a run of the river hydropower facility. Previous applications of DS have been *risk assessment* applications: assessments of the impact of possible climate changes on a water resources system. Here, the approach is used for *risk management*, to identify a specific design under climate change. Design outcomes were explored under multiple dimensions of climate uncertainty, on natural climate variability, long-term climate change, and climate projections. Design alternatives were compared and ranked by way of a formal decision analysis procedure, using optimality and robustness-based decision criteria. In this framework, subjective information regarding the future, such as climate projections, was applied *ex post* (following the process of stress test analysis) and indirectly (to set the conditional likelihoods of the stress test outcomes). The approach was compared to a conventional scenario-led framework through a hydropower project design study, and the decision outcomes under both frameworks were discussed.

The framework provides a systematic procedure to incorporate the effects of natural climate variability, through a stochastic weather generator conditioned on the historical climate record. In contrast, scenario-led analyses provide limited means to explore these kind of climate variability effects, for example through the use of perturbed physic ensembles (Lopez et al., 2009; Fung et al., 2013), or by the use of stochastic downscaling methods (Groves et al., 2008; Fatichi et al., 2014). We note that the uncertainty effects of natural climate variability are likely to outweigh the uncertainty effects of global climate change in the next couple of decades (Deser et al., 2012; Ledbetter et al., 2012; Fatichi et al., 2014); hence need to properly be addressed in the frameworks of infrastructure planning and design.

Given the biases and structural problems in GCM projections, an important issue for the decision-makers is to what extent they should trust these model results, and how to use these (often conflicting) model outputs in their analysis frameworks. Through the *ex post* application of appropriate information from GCM projections (e.g., long-term changes in mean climate conditions), the analyst can *explicitly* set the statistical properties of the valuable information, for instance, the choice of probability distribution used to fit the climate statistics. In contrast, the *ex ante* use of information in the scenario-led framework provides no flexibility, as the analysis is entirely dependent on the time-series data from the GCMs. An important implication of this *ex ante* use of GCM projections is the bias due to the empirical distribution of the parameters, e.g., the repeated sampling of certain projected conditions due to model similarities.

Under deep uncertainty regarding future climate conditions, irreversible and costly infrastructure planning decisions need to be made with risk-aversion. However, the level of acceptable risk, and the trade-offs between performance and robustness are highly subjective and dependent on the decision maker's (stakeholder's) perspective. Examples of the ramifications of such risk aversion perspectives (ML, EV, RI) have been quantitatively demonstrated here. The influence of the decision criterion applied was found to be higher under the scenario-led analysis in comparison to decision scaling.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.crm.2017.08.002.

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