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A hydrologically-driven approach to climate change adaptation for multipurpose multireservoir systems

Caio Sant'Anna [a,*], Amaury Tilmant [a], Manuel Pulido-Velazquez [b]

[a] Laval University, Quebec, Canada
[b] Polytechnic University of Valencia, Spain

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A B S T R A C T

Climate change can significantly affect water systems with negative impacts on many facets of society and ecosystems. Therefore, significant attention must be devoted to the development of efficient adaptation strategies. More specifically, the reoperation of water resources systems to keep the overall performance within acceptable limits should be prioritized to avoid, or at least delay as much as possible, costly infrastructural investments. This manuscript presents a hydrologically-driven approach to support the reoperation of multipurpose multireservoir systems. The approach is organized around 1) the use of a large ensemble of GCM hydro-climate projections to drive a climate stress test; 2) the bottom-up clustering of those hydrologic projections based on hydrologic attributes that are both relevant to the region of interest and interpretable by the operators; and finally, 3) the identification of adaptation measures for each cluster after developing a one-way coupling of an optimization model with a simulation model. The climate impact assessment is illustrated with the multipurpose multireservoir system of the Lievre River basin in Quebec (Canada). Results show that cluster-specific, adapted, operating rules can improve the performance of the system and reveal its operational flexibility with respect to the different operating objectives.

1. Introduction

1.1. Background and context

The pivotal role played by water in mitigating climate change impacts in the other sectors such as food, energy or health, implies that significant attention must be devoted to the development of adaptation strategies for our water resources systems (Rogers, 2011). More specifically, the reoperation of water resources systems to keep the overall performance within acceptable limits should be prioritized in order to avoid, or at least delay as much as possible, costly infrastructural investments (Gleick, 2018). When dealing with multireservoir systems, the question of when and how to reoperate the system has been studied, for example, by Giuliani et al. (2016) and Quinn et al., 2019. Climate impact studies have also been used for infrastructural investment planning (Gersonius et al., 2013; Beh et al., 2017), flood management (Poff et al., 2016), urban water supply (Brown et al., 2012; Turner et al., 2014; Mukundan et al., 2019), and irrigation (Jones, 2001; Rajagopalan et al., 2018).

Climate impact assessments in water resources initially attempted to use a limited number of scenarios derived from global or regional climate models through a top-down approach. Those climatic scenarios were downscaled to match the scale of the

* Corresponding author.

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hydrological model, whose output would then be processed by an impact model (e.g. river basin management model.) (Fortin et al., 2007; Brekke et al., 2009; Vicuna et al., 2010). The rationale was to assess the impacts on the most likely futures, an approach consistent with the *predict-then-act* decision-making paradigm for which a prior characterization of the problem's uncertainty is a prerequisite (Weaver et al., 2013).

However, uncertainties related to climate change lie in the realm of deep uncertainty since scientists or decision-makers do not know or cannot agree on (i) society's social and technological developments that will drive future greenhouse gas emissions; (ii) the best climatic model describing the underlying phenomena behind the chaotic nature of global climate and (iii) the prior probability distributions of climatic variables and their interdependencies. This makes the traditional decision-making framework based on predictions ill-suited to deal with climate change (Lempert et al., 2004).

To address the challenges posed by the difficulty in providing climate predictions with well-characterized probability distributions, one may seek robust solutions; that is, solutions that hedge effectively against the risks associated with the various sources of uncertainty. The idea is to exhaustively explore the climate-related exposure space and assess the corresponding performances of the water resources system by considering the different sources of uncertainty in the climate change problem (Brown et al., 2019). This is equivalent to a climate stress test to support the construction of a climate response function linking climate information to performance indicators. The rationale is to identify all combinations of hydroclimatic stressors, typically changes in temperature and precipitation, that cause the water system to fail, and then propose potential interventions to these vulnerabilities (Brown et al., 2012). One advantage of those bottom-up, vulnerability assessment approaches is that they also directly involve stakeholders in the development of a shared vision of the system performance and the definition of critical thresholds to identify system failures, so that we can evalute the impact of climate change and assess different adaptation strategies. This involvement is key to facilitate the uptake of climate information and to engage stakeholders in climate-related decision-making (Kuang and Liao, 2020; Poff et al., 2016; Pahl-Wostl, 2007).

To construct the climate response function, bottom-up vulnerability stress tests require hundreds to thousands of synthetically-generated hydro-climatic scenarios to exhaustively explore the exposure space. One of the techniques consists in modifying statistical properties of historical data to capture the envelopes of natural, GCM climate or paleoclimate variability. Prudhomme et al. (2010) and Culley et al., 2016 generate the exposure space by making incremental changes to attributes (e.g. mean, 7-day maximum, etc.) of resampled historic series of hydrological variables. Keylock (2012) makes use of a wavelet-based method to generate synthetic flow series that preserve the non-linear properties of the original data. Borgomeo et al. (2015) rather generate streamflow sequences through a nonparametric and data driven method, which uses a simulated annealing algorithm to impose desired statistical properties.

1.2. *Objective and motivations*

As an alternative to synthetically-generated scenarios, we propose a hydrologically-driven approach to support decision-making based on climate information. This approach is motivated by the fact that the availability and number of hydro-climate projections keep increasing (Hayhoe et al., 2017; Fournier et al., 2020) up to a point where they could directly be used in a vulnerability assessment framework. Our working hypothesis is that the explicit representation of the underlying physical processes associated with GCM projections, combined with the diversity captured by those projections, makes them as suitable candidates as synthetically-generated hydrologic sequences based on arbitrarily-chosen combinations of climate stressors. In this study, 828 thirty-year hydrologic projections for a water resources system in Canada were generated considering uncertainties related to future emissions, as well as climate and hydrologic models.

The second motivation for this hydrologically-driven approach comes from the fact that water operators are more familiar with the hydrologic characteristics of their system and less with the regional climate. To take advantage of this experiential knowledge, interpretable hydro-climatic descriptions are built after clustering the hydrologic projections based on a set of agreed-upon hydrologic attributes that are relevant for the region of interest. In other words, hydrologic projections are grouped based on their hydrologic properties, regardless of the combination of climate stressors or climate/hydrologic models. This clustering is a way to further involve water operators in the modeling exercise, a clear advantage shared by bottom-up approaches. The proposed approach therefore also contributes to a growing body of work on how to communicate climate information to policy makers, water managers and the public. As pointed by Marx et al. (2007), the communication of most climate-related information usually assumes that people process information analytically, largely ignoring that they also rely heavily on an experiential processing system. For example, Karpudewan and Mohd Ali Khan (2017) show that experiential-based climate change activities was key to improve students' knowledge on climate change and increase motivation towards caring for the environment. In fact, experiential learning tends to be more powerful than statistical results when the underlying process is both hard to perceive via everyday experience and is not the main concern in your daily life, which is typically the case with climate change (Myers et al., 2013). In their study, Kaufmann et al. (2017) demonstrate that public's willingness to believe that global warming is happening in the US depends, to a certain extent, on the degree to which they personally experience a warmer or cooler climate. When it comes of reservoir operators, we argue that they can more easily relate to hydrologic than to climate projections, especially when the former are clustered using a set of familiar attributes that are used to characterize the flow regime in his/her region. For example, in our case study, operators immediately seek to associate the five clusters to past hydrologic conditions that resemble to their description, and how they coped with those conditions. Ultimately, the hydrologically-based clustering facilitates the uptake of climate information for the management of water resources systems because it triggers experiential processing therefore making the information more comprehensible and apprehensible.

The third motivation for the proposed approach based on the clustering of GCM-based projections is more closely related to the internal processes of the water agency and preferences formulated by the staff; it is therefore highly dependent on the case study. Some operators, and more generally some stakeholders, might not be comfortable with the use of arbitrarily generated hydrologic sequences to identify the conditions leading to adverse outcomes. Various reasons might explain this reluctance. First, some stakeholders are getting more and more acquainted with GCM-based projections, their strengths and weaknesses, and are therefore keen to fully exploit them. Second, institutional reasons may favor the use of GCM-based projections when, for example, they are already available and generated by another group within the same organization or by a trusted partner organization.

The fourth motivation for the proposed approach is related to the limitations of response surfaces built exclusively from coarsely defined stressors such as mean annual precipitation and temperature. Since such stressors can only partially explain hydro-climatic uncertainties, they may lead to imprecise performance estimates (Lachaut and Tilmant, 2021). This paper proposes an alternative to response surfaces by presenting the impacts of climate change in the system's performance using clusters built with multiple hydrological stressors, better reflecting potential alterations of the flow regimes. The transcription of those clusters into linguistic descriptors allows to indirectly grasp the effects of multiple hydroclimatic stressors simultaneously by looking at overall patterns instead of assessing the combination of only two to three stressors at a time. As shown by Casale et al. (2021), applying a bottom-up approach that explores only changes in annual precipitation and temperature yields response surfaces that are not able to capture the mutual interactions between temperature and precipitation as well as changing seasonal patterns.

Once the GCM-based projections are grouped according to their hydrologic characteristics, adaptation measures can be found for each cluster. First, an adapted operating policy is determined for a representative scenario within each cluster using a stochastic optimization model of the water resources system that captures the natural uncertainty of inflows. Then, the new policy is simulated across all scenarios belonging to the same cluster in order to assess its robustness vis-à-vis hydrologically similar projections. Since the clusters are mutually exclusive - there is no reason to suspect that the hydrological regime could switch from one cluster to another so rapidly that the operators would have no time to adapt - the robustness is determined locally. Performance indicators that have been interactively defined with the operators are then assessed from the simulation results. This exercise provides an indication of the flexibility of the water resources system, i.e. its operational adaptive capacity (Culley et al., 2016) to climate change, while focusing on the hydrologic properties that are meaningful to the operators instead of a small set of broad climate attributes, e.g. temperature and precipitation, or radiative forcings.

The paper is organized as follows. It starts with a general presentation of the methodology, which is followed by a brief description of Lievre's system. Section 2.2 introduces the climate information used for the case study and discusses its suitability for a stress test. Section 2.3 is devoted to the clustering of the scenario ensemble. Then, Section 2.4 presents the impact model formed by the combined use of optimization and simulation models. Next, Section 3 presents the simulation results for the current operating policy (3.1) and the portfolio of adapted operating policies (3.2). Finally, concluding remarks are given in Section 4.

2. Material and method

Fig. 2 provides an overview of the proposed approach to analyze the reoperation of multireservoir systems based on climate information.

The approach begins with acquiring a large ensemble of GCM-based hydrologic projections, simulating reference (REF) and future (FUT) climates. The availability and number of hydro-climate projections keeps increasing, and so does our understanding of the underlying physical and biogeochemical processes at work in the climate system (Hayhoe et al., 2017; Fournier et al., 2020).

Next, using the K-means clustering approach, those hydrologic projections are grouped based on their hydrologic properties. This clustering has two purposes: (i) it helps bridge the gap between the operators' experience and the hydrologic projections and (ii) it reduces computational efforts related to the search of alternative operating policies through optimization, which appears to be the bottleneck in the impact modelling chain since it may require hundreds of thousands of runs (Giuliani et al., 2016; Quinn et al., 2019).

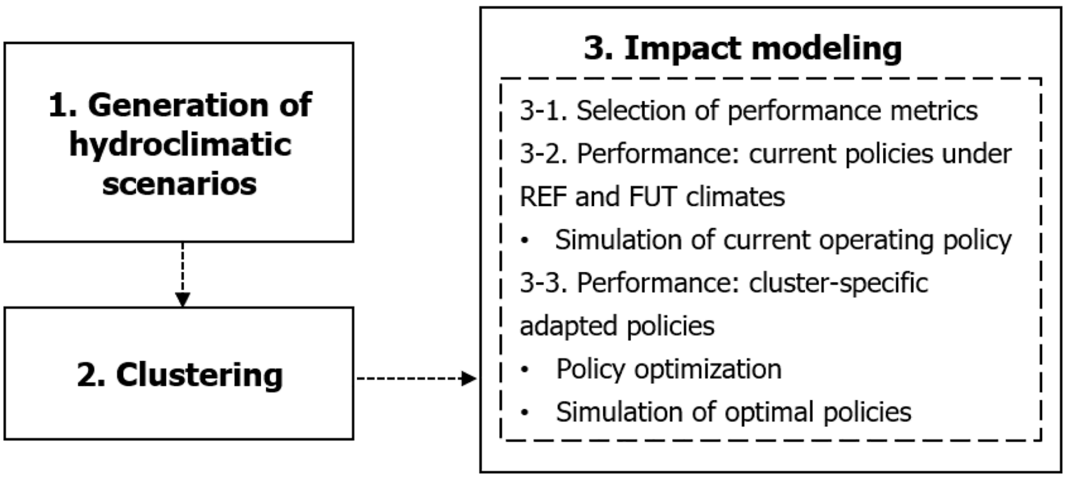

Fig. 1. Overview with the main steps of the hydrologically-driven approach.

Then, the current reservoir operating policy is simulated over all hydrologic projections, and the performance indicators of the system are assessed. Depending on the operating objective, assessing the performance might require the input of relevant stakeholders to provide, for example, thresholds making the distinction between satisfactory and failure states (Poff et al., 2016; Lachaut and Tilmant, 2021), or their utility with respect to state/decision variables (Herman and Giuliani, 2018).

Finally, a stochastic optimization model determines cluster-specific adapted operating policies, which are then used in simulation to update the performance indicators. More specifically, for each cluster, the optimization model generates new guide curves that are then used as inputs to the simulations model for more detailed simulations of the water resources system across all projections belonging to that cluster. The coupling of simulation and optimization models has already been widely applied in water resources management (Loucks et al., 2005; Lee et al., 2009).

An ensemble of five adaptation scenarios (corresponding to the number of clusters) forms the portfolio of adapted operating policies, giving an indication of the adaptive capacity of the multireservoir system; that is, its ability to adapt to altered flow regimes identified from the statistical analysis of a large ensemble of GCM-based hydrologic projections. Fig. 1.

The overall approach, summarized in Fig. 2, is implemented in the Lievre River Basin.

2.1. *Multipurpose multireservoir system of the Lievre River Basin*

The water system of the Lievre River includes three high-capacity reservoirs, Mitchinamecus, Kiamika, and Poisson Blanc (Fig. 2). The first two are located upstream and have a storage capacity of 533 and 435 hm^3, respectively. Further downstream, we find Poisson Blanc, a 910 hm^3 reservoir that controls a cascade of 5 hydropower plants with a combined capacity of 238 MW. Other critical operating objectives are flood control, recreation, and environmental flows.

2.2. *Generation of hydroclimatic scenarios*

For this case study, we have exploited an ensemble of 828 thirty-year GCM-derived hydrologic projections provided by the Quebec Water Agency (CEHQ, 2015) based on the Hydrotel model (Direction de l'expertise hydrique, 2018; Lachance-Cloutier et al., 2017).

The projections consider four time horizons, 1970–2000, 2011–2040, 2041–2070 and 2071–2100. The first horizon is the reference period characterized by a stationary climate and a corresponding flow regime representative of the hydrologic conditions that prevailed during much of the XXth century. The water resources system was designed and the operating rules were developed for this reference flow regime. For the next three horizons, projections take four different social and technological trajectories called

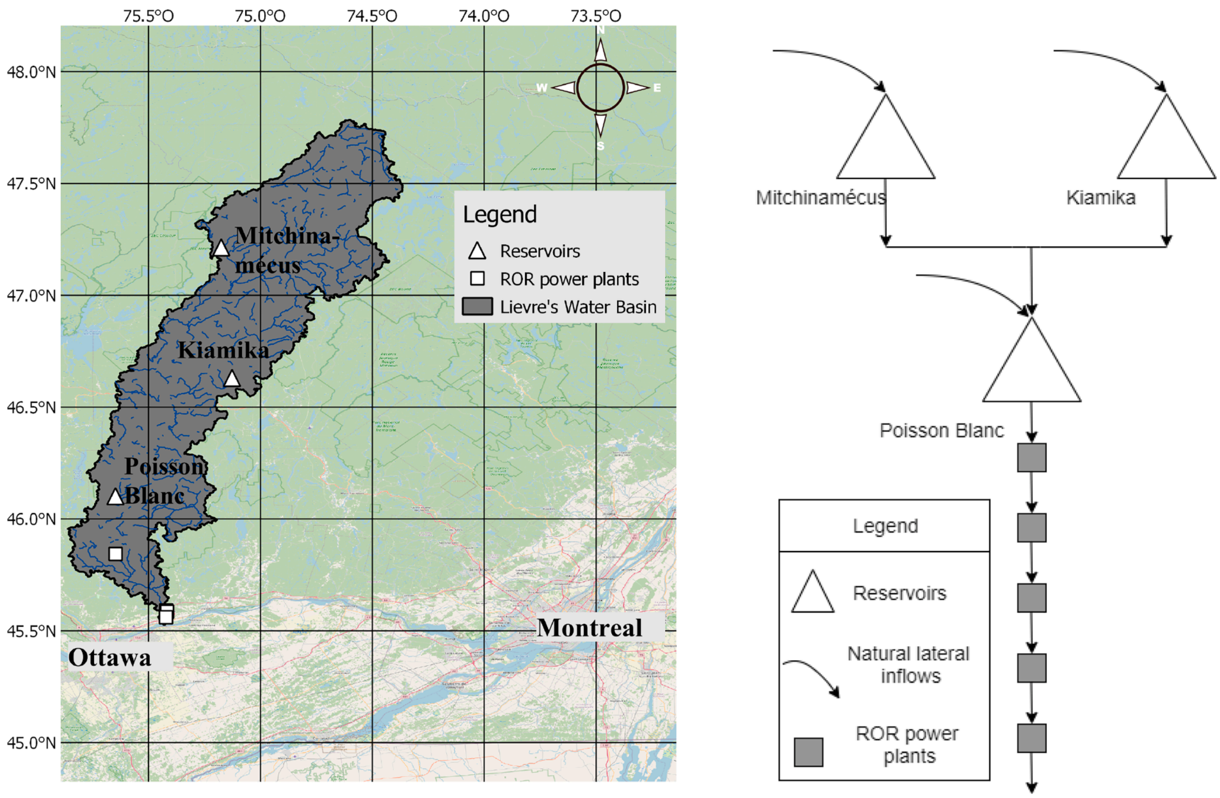

Fig. 2. Lievre River Basin [map produced in Qgis with data from ©OpenStreetMap (2020)].

Representative Concentration Pathways (RCPs). Tables 1,2 in the appendix lists all the herein used climatic models from the CMIP5 experiment.

A stress test must involve exploring a wide range of stressors to effectively capture the vulnerability domain, something challenging to achieve with a limited number of GCM-based projections. For instance, Brown and Wilby (2012) shows that GCM simulations of the historical period underestimate the diversity of hydrological states compared with resampled observed data. However, as the availability and diversity of GCM-based projections increase (Hayhoe et al., 2017; Fournier et al., 2020), they explore a larger region of the hydrological conditions that may drive the future water resources systems' performance. Moreover, the explicit representation of the underlying physical processes associated with GCM projections, combined with the diversity captured by those projections, makes them as suitable candidates as synthetically-generated hydrologic sequences based on arbitrarily chosen combinations of climate stressors.

This assumption is tested after comparing the natural variability of relevant hydrological attributes with that associated with GCM-based hydrological projections. Fig. 3 shows 30-year averages of spring and annual inflow to Poisson Blanc to illustrate the extent of hydrologic states covered by the ensemble of 828 GCM-based projections. In Quebec, spring flow affects the reservoir systems' overall performance, especially those refilled during spring. Each grey point corresponds to a different GCM projection, and the dashed line delineates the region defined by the natural variability of the reference, GCM-derived, climate. Black triangles represent stochastic simulations of natural variability, generated by the Kirsch-Nowak method (Quinn et al., 2017), made available online as a Matlab code by Quinn (2017). First, the region covered by the dashed line is similar to the one covered by the stochastic variability, indicating that GCMs can reproduce well current natural variability. Moreover, future GCM data covers a broader region of the space, illustrating the growing uncertainties related to future hydroclimatic conditions.

2.3. Clustering of hydrologic projections

Clustering allows one to group objects sharing features within the group but have dissimilarities with other groups. In this study, the clustering of all hydrologic projections based on their hydrologic properties aims at facilitating the intake of climate information by the operators and reduce the computational burden associated with the search for adapted operating policies. For the Lievre River Basin, the hydrological attributes are five hydrologic statistics commonly used by the Quebec Water Agency: winter, spring, summer, autumn, and annual flow averages taken over a 30-year period (CEHQ, 2015). The volume of the spring snowmelt is particularly important as it drives the refill phase of the reservoirs, and thus the satisfaction of the operating objectives during the rest of the year. As shown in CEHQ (2015), the spring snowmelt is likely to be affected by climate change, through changes in the snowmelt volume and/or timing with an onset taking place up to 3–4 weeks earlier than in the reference climate.

The K-means clustering method is chosen for its simplicity and demonstrated ability to keep the inherent diversity of scenario ensembles (Houle et al., 2012; Lee and Kim, 2017). Initially, the Algorithm 1 randomly places the n centroids in the space defined by the objects to be clustered. Then, it 2) calculates the distances from each object to each centroid and assigns each object to the closest centroid. Finally, it 3) recalculates and replaces the previous centroids. Steps 2 and 3 are repeated until the objects no longer move (Breinl et al., 2015). In this method, the number of cluster n must be previously determined.

A key issue with clustering is the number n of clusters needed to ensure the maximization of both the internal cohesion within each of the clusters and the dissociation between them. Various validation criteria are available in the literature to help identify the right number of clusters (see e.g. Hennig et al., 2015 for a review). Many criteria typically seek to find a balance between within-cluster homogeneity and cluster separation. However, for the same data set, the use of different criteria will likely yield different recommendations in terms of the number of clusters, so that the ultimate decision is left to the analyst/operator. In this study, the most common criteria give an optimal number of clusters between two (Calinski and Harabasz index) and ten (nearest neighbours index), with most of the values around 4 (average silhouette width, Pearson correlation, Dunn index). Here, the number of clusters ($n = 5$) was chosen because it was found to be a good compromise between the number of future hydrologic scenarios to be explored and their diversity in terms of altered flow regimes so that cluster-specific policies are clearly distinct to those of neighboring clusters.

Fig. 4 shows the altered flow regime associated with each cluster by boxplots of seasonal and annual flows for intermediate inflow at Poisson Blanc, the same hydrological attributes used to cluster the scenarios. Each point in the graphs represents a flow average for a single scenario over a 30-year period. The reference lines were calculated by taking the average of all GCM reference simulations of historical observations, and thus represent current conditions. Cluster 1 is the closest to the reference values during all seasons, indicating that those scenarios are comparable to current conditions. For cluster 2, there is larger inflows during winter, spring and autumn, which explains the largest annual inflow among all clusters. Cluster 3 presents a wetter winter (like cluster 2), but the summer is drier, so that the total annual volume remains close to current conditions. Cluster 4 behaves similarly to current conditions for total

Table 1
Easily interpretable linguistic descriptions of the five clusters and analogous years.

Clusters	Descriptor	Analogous years
1	*No change*	like every "normal" year
2	*Large annual volume*	2006 and 2008
3	*Moderate seasonality*	2002 and 2004
4	*Low annual volume*	2000, 2007, 2010, and 2012
5	*Strong seasonality*	

Table 2
Annual energy loss in GWh/yr and percentage values relative to mean annual production for each cluster under current operating policy.

Cluster	Lost energy (GWh/yr)	Relative loss (%)
1	313	20
2	475	30
3	403	30
4	223	20
5	529	40

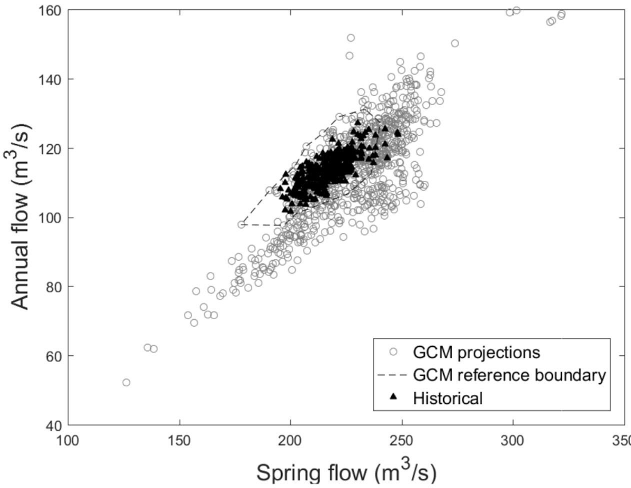

Fig. 3. Spring and annual daily averages of intermediate inflow at Poisson Blanc reservoir.

volume during winter but shows lower flows for the rest of the year. Cluster 5 shows the highest shift in the seasonality pattern, with the largest increase of winter flows and more severe low flows during the summer. Relatively to cluster 1, clusters 2, 3 and 5 present larger volumes during winter, which, for the study region, points to an earlier snowmelt.

The clusters can also be transcribed into hydroclimatic descriptors (Table 1) to help water operators interpret those changes. In our case study, operators immediately seek to associate the five clusters to similar past hydrologic conditions. For example, *large annual volume* scenarios (cluster 2) can be related to the atypical years of 2006 and 2008, marked by significant flood events in Southern Quebec, while *low annual volume* scenarios (cluster 4) could be associated with the 2012 drought in this region (Mayer-Jouanjean and Bleau, 2018). The years mentioned above provide guidelines for future adaptation since the operators had to modify their usual operating rules to cope with the hydrological anomalies. Some future hydrological states, like *strong seasonality* scenarios (cluster 5), cannot be related to past hydrologic conditions. Far from being a problem, it further motivates the determination of adapted operating policies and the understanding of the operational flexibility of the water resources system.

Clustering also helps reduce the computational effort associated with the search of adapted operating policies, a computationally demanding task typically carried out with optimization models. Instead of identifying an optimal operating policy for each of the 828 projections, we implement the optimization on each cluster's representative projection, i.e. the projection closest to each cluster's centroid.

2.4. Performance assessment under current (REF) and future climates (FUT)

Fig. 5 The performance of a water resource system can be synthesized by relating climate conditions to system behaviour for a set of attributes and specified thresholds. The current policy can be stress-tested using the ensemble of projections to identify the hydro-climatic conditions that may yield unsatisfactory results. Once the current operating policy vulnerabilities are revealed, the optimization model determines an adapted operating policy for each cluster. The idea is to improve the system's performance for those clusters where the current operating policy does not perform well (Fig. 2).

2.4.1. Simulating the multireservoir system

Reservoir simulation models provide a realistic description of the operations of reservoir systems. They can test the current operating rules and the optimal, adapted ones across reference and future hydrologic projections. For the present case study, we have applied the simulation model HEC-ResSim, which is used by the Quebec Water Agency to manage the Lievre multireservoir system. In HEC-ResSim, the decisions (e.g. reservoir releases) are determined by the guide curve and other operating constraints. The guide curve

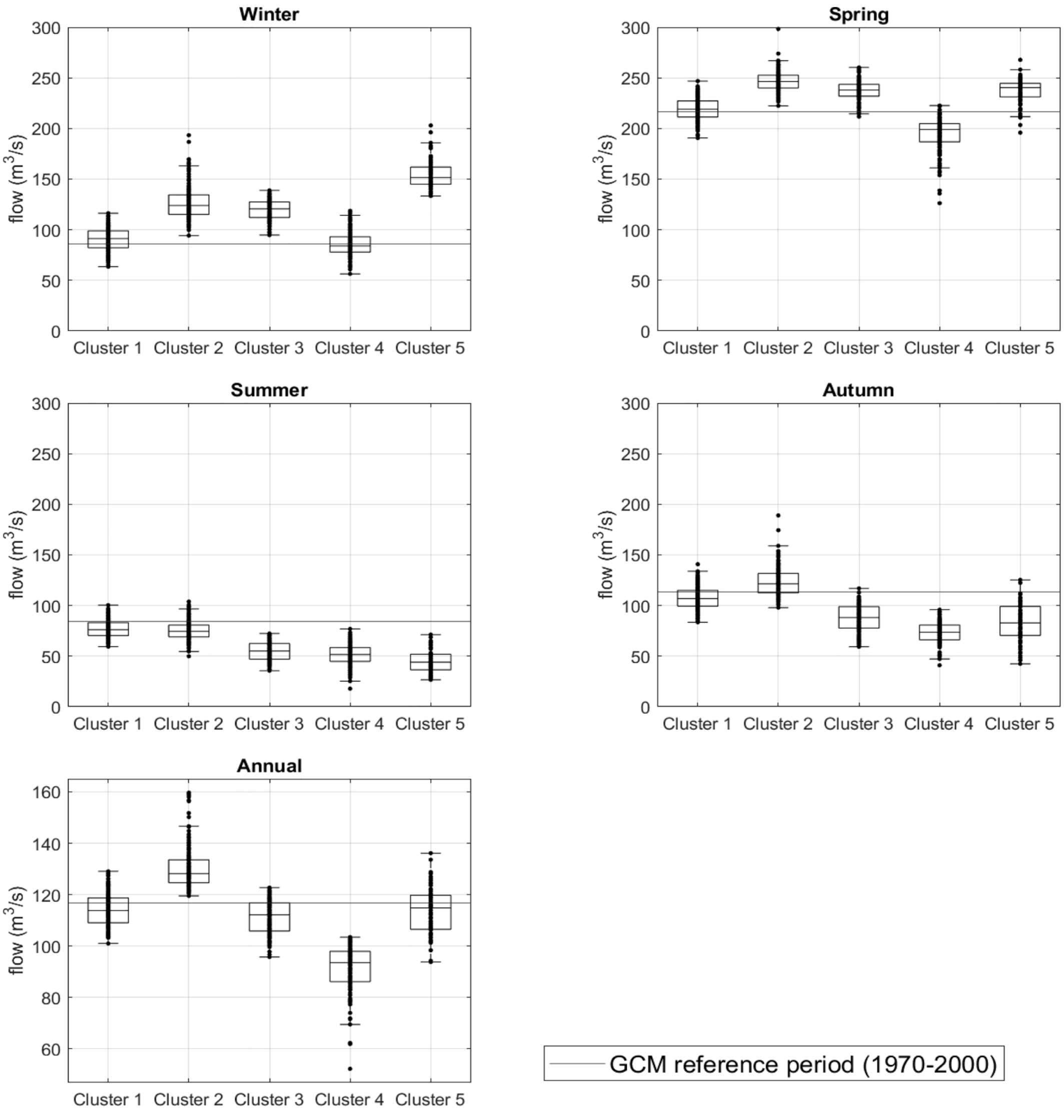

Fig. 4. Boxplots of seasonal and annual flows for intermediate inflow at Poisson Blanc. The reference lines were calculated by taking the average of all GCM simulations of the historical, reference period (1970–2000).

corresponds to the desired reservoir level at each time step under normal conditions. As an example, Fig. 6 depicts the guide curve for the Kiamika reservoir. HEC-ResSim will follow the guide curve as long as the physical and operational constraints are met. Those operating rules depend on several factors such as the season, the inflow, and the reservoirs' water level. The guide curve typically subdivides the reservoir into at least three horizontal zones:

- the dead storage, for which no operational rule can be applied;
- the conservation zone, which is below the guide curve;
- the flood control zone above the guide curve.

Once the guide curve is defined and operation rules are developed for each zone, and for a specific time series of daily inflows, the model simulates daily releases, storages, withdrawals, spills and hydroelectric power generation (Alvarez, 2014).

The performance indicators can be then assessed from the time series of daily water levels and flows throughout the system. For the Lievre system, we measure the performance in terms of the annual number of failures for flood control, recreational use and ecological flow, and in terms of annual energy production. A failure in one objective corresponds to a situation whereby the system crosses at least one of the relevant thresholds in the entire system. For example, a failure concerning the recreational objective occurs when the daily water level in at least one of the three reservoirs falls below the corresponding minimum acceptable level.

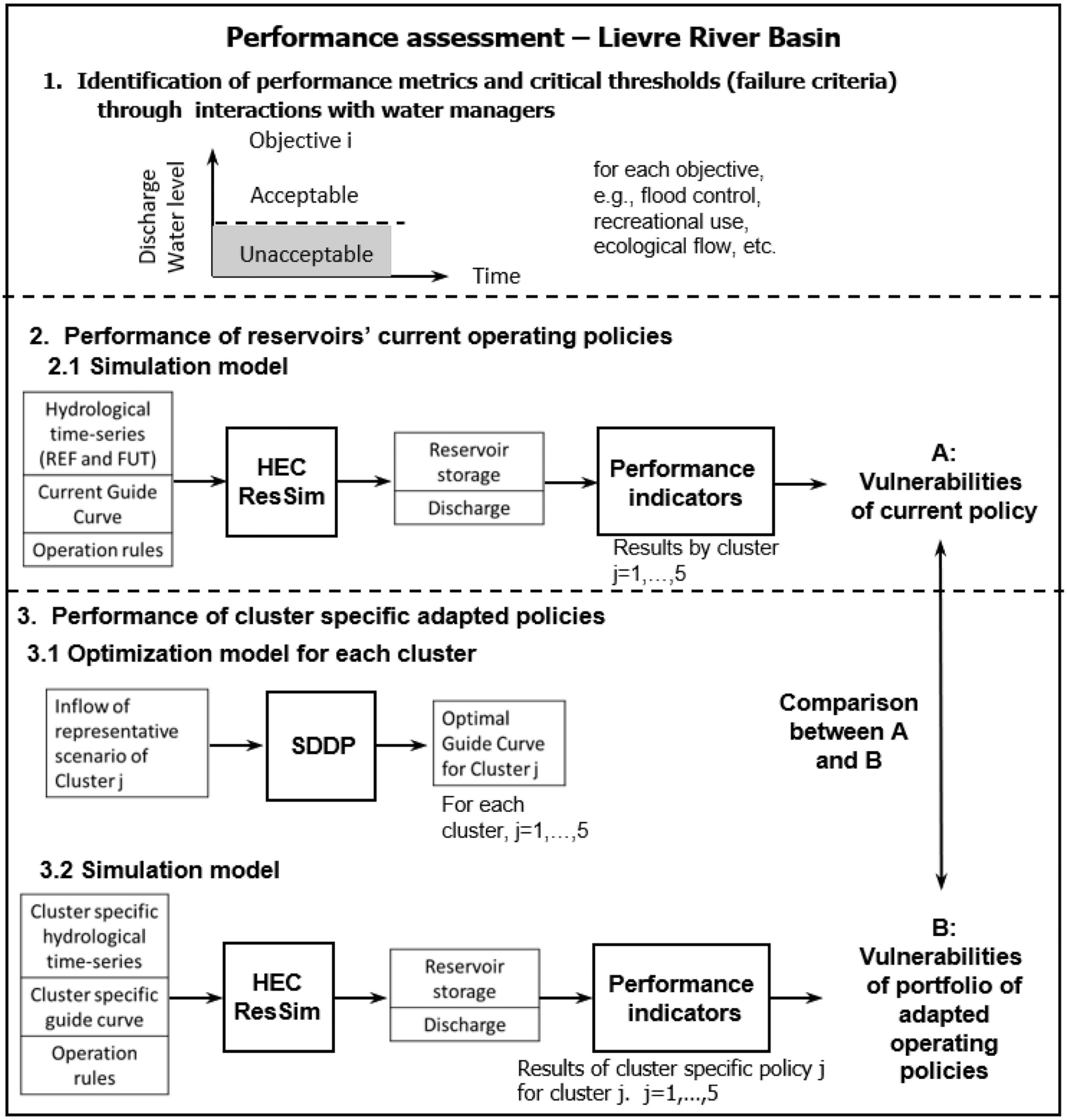

Fig. 5. Performance assessment for the Lievre River Basin.

2.4.2. Determining adapted operating policies

The reoperation of a multireservoir system is a non structural adaptation measure designed to keep the overall performance within acceptable limits. In the case of the Lievre's system, reoperating the system implies modifying the guide curves in the three reservoirs. Prescriptive methods like optimization are best suited to determine adapted operating policies and have been extensively used in climate change adaptation studies (Vicuna et al., 2010; Tariku et al., 2021). Various optimization models are available to solve reservoir operation problems and state-of-the-art reviews can be found in Labadie (2004) and in Rani and Moreira (2010).

When dealing with water systems characterized by multiple, conflicting, objectives, trade-offs are inevitable. In that case, the main outcome of the optimization is an adapted, Pareto optimal, operating policy. In the objective space, the set of Pareto optimal solutions is a frontier - also called the Pareto front - between dominated and unfeasible solutions. Various approaches are available to trace out this Pareto front (Loucks et al., 2005). Here, the original multi-objective problem is transformed into many single objective problems that are solved independently using mathematical programming. Once the optimal, adapted, operating policy is identified, it must be translated into modified guide curves and rules to be processed by the simulation model HEC-ResSim.

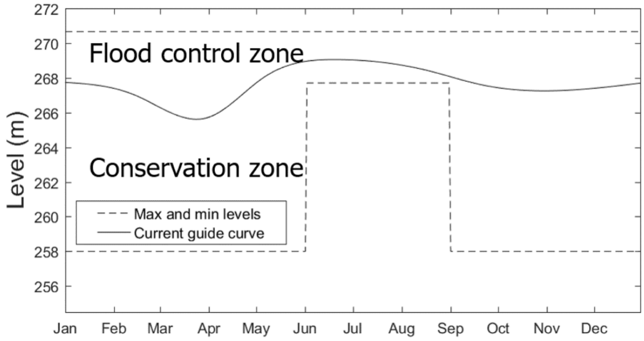

Fig. 6. Guide curve of the Kiamika Reservoir.

The operation of the multireservoir system is optimized using stochastic dual dynamic programming (SDDP). The SDDP algorithm was first proposed by Pereira and Pinto (1991) to solve the hydro-thermal scheduling problem in Brazil. To achieve this, SDDP decomposes the original sequential decision-making problem into a sequence of one-stage problems that are solved recursively. Prior to moving from one stage to the next, a benefit-to-go function must be constructed, indicating how the aggregated future benefits change over the state-space domain. In SDDP, that benefit-to-go function is progressively constructed as the algorithm iterates between a backward optimization and a forward simulation phase. Due to space limitation, this section only provides an overview of the SDDP model; the reader should refer to (Tilmant and Kelman, 2007 and Goor et al., 2011) for a comprehensive description.

Assuming that the state variables are the volumes in storage $\mathbf{s}_t$ at the beginning of stage t and the inflows $\mathbf{q}_{t-1}$ observed during the previous stage, the one-stage SDDP optimization problem can be written as:

$$F_t(\mathbf{s}_t, \mathbf{q}_{t-1}) = \max_{\mathbf{x}_t}\{b_t(\mathbf{s}_t, \mathbf{q}_t, \mathbf{x}_{t+1}) + \alpha_{t+1}F_{t+1}\} \tag{1}$$

where F_t is the benefit-to-go function at stage t, $\mathbf{s}_t$ is the vector of storage volumes at the beginning of stage t, $\mathbf{x}_t$ is the vector of allocation decisions at stage t (here reservoir releases, spillage losses, end-of-period storages), $\mathbf{q}_t$ is the vector of inflows at stage t, $b_t(.)$ is the net benefit function at stage t, α_{t+1} is a discount factor and F_{t+1} is a variable representing future benefits.

The immediate benefit function $b_t(.)$ of Eq. 1 aggregates in a single objective function the four operating objectives using a variant of the constraint method (Loucks et al., 2005) in which all objectives but one are treated as flexible constraints, that is, $b_t(.)$ is penalized when these constraints are not met. The immediate benefit function is, therefore, the sum of the benefits associated with hydropower generation (*HP*) minus penalties for not meeting target storage levels for recreation purposes, minimum flow requirement for ecological purposes and penalties for exceeding maximum water discharge to prevent flooding:

$$b_t(.) = HP_t - \rho_t^T z_t \tag{2}$$

Where z_t is a vector of slack variables (unit surplus or deficit), and ρ_t^T is a vector of penalty coefficients.

The main constraints are:

- Water balance equations:

$$\mathbf{s}_{t+1} - \mathbf{C}(\mathbf{r}_t + \mathbf{l}_t) + \mathbf{e}_t(\mathbf{s}_t) = \mathbf{s}_t + \mathbf{q}_t(\mathbf{q}_{t-1}, \xi_t) \tag{3}$$

  where $\mathbf{C}$ is the connectivity matrix representing the topology of the system, and $\mathbf{e}_t$ is the vector of evaporation losses, $\mathbf{l}_t$ is the vector of spillage losses, and $\mathbf{q}_t(\mathbf{q}_{t-1}, \xi_t)$ denotes the built-in autoregressive model of order one (AR(1)) with the stage-wise independent random vector ξ_t.
- The outer approximation of the future benefits is given by the following inequalities:

$$F_{t+1} - \boldsymbol{\varphi}_{t+1,l}^{\tau}\mathbf{s}_{t+1} \leqslant \boldsymbol{\gamma}_{t+1,l}^{\tau}\mathbf{q}_t + \beta_{t+1,l}(l = 1, 2, \ldots, L-1) \tag{4}$$

  where $\boldsymbol{\varphi}_{t+1,l}$ and $\boldsymbol{\gamma}_{t+1,l}$ are the gradients of F_{t+1} with respect to the state variables $(\mathbf{s}_{t+1}, \mathbf{q}_t)$, $\beta_{t+1,l}$ is the intercept, and L-1 is the number of iterations that have already been completed. More details on the procedure used to derive the gradients and the intercepts can be found in (Tilmant et al., 2008).
- The other constraints are upper and lower bounds on storages, allocation decisions, as well as the convex hulls approximating the nonlinear hydropower production functions (Goor et al., 2011).

Here, the planning horizon T is 5 years and the optimization problem is solved on a weekly time step ($t = 1 \ldots 260$). The main results are the 52 piecewise linear value functions extracted from the intermediate year (here year #3), i.e. $(\boldsymbol{\varphi}_{t+1,l}, \boldsymbol{\gamma}_{t+1,l}, \beta_{t+1,l})$, $t = (105, 106, \ldots, 156)$ and $l = (1, 2, \ldots, L)$. The results for the first and last two years are ignored because they are influenced by the boundary conditions (initial and final storage volumes). Since these value functions indicate how the optimal benefits from system operation would change with respect to the storage level and the inflows, they encapsulate the operating policies adapted to the selected hydrologic projection/cluster processed by the algorithm.

To determine the best values for the penalty coefficients ξ in Eq. 2, thousands of optimization instances were run, exhaustively exploring the penalty space $\rho \in \mathbb{R}^{p-1}$, where p is the number of operating objectives. For each run, the values of the p objectives Z_j ($j = 1, 2 \ldots, p$) are stored: net revenues from hydropower generation ($/year); the risk of not meeting the desired storage volume for recreational activities during the summer (–); the risk of not meeting the minimum ecological flows (–); and the risk of exceeding the maximum flow to prevent flooding (–). To select the best vector of penalty coefficients, a geometric notion of best was chosen; the vector must minimize the Euclidean distance d_2 between the Zj and their corresponding ideal values Z_j^* (Cohon, 1978):

$$d_2 = \sqrt{\sum_{j=1}^{p} \left(Z_j^* - Z_j\right)^2} \tag{5}$$

2.4.3. Simulating optimal allocation policies

Once the optimization model prescribes adapted operating policies for each cluster, the next step is to transcribe the adapted rules for application in the water management simulation model. To build the adapted guide curves required by HEC-ResSim, we must first reoptimize the operation of the system over the entire hydrologic projection, that is, over a 30-year period (as seen in Section 2.2), to obtain, for each reservoir and each week, a (30 × 1) vector of simulated storage volumes. Assuming that the desired storage volume in a given week and for a given reservoir is the expected value, the guide curve can be constructed after interpolating between the 52 average storage volumes and finally disaggregating those volumes into daily values to fulfil the requirements of the simulation model.

The reoptimization procedure employs the 52 piecewise linear value functions extracted from the intermediate year (here year #3) once the SDDP algorithm has converged. Mathematically, the benefit-to-go function at week w (F_{w+1}) is defined by the triplets ($\boldsymbol{\varphi}_{w+1,l}$, $\boldsymbol{\gamma}_{w+1,l}$, $\beta_{w+1,l}$).

At time t (year y, week w), the reoptimization problem is:

$$Z = \max_{\mathbf{x}_t} \left\{ b_t(\mathbf{s}_t, \mathbf{q}_{y,w}, \mathbf{x}_t) + F_{w+1} \right\} \tag{6}$$

Subject to

$$\mathbf{s}_{t+1} - \mathbf{C}^R(\mathbf{r}_t + \mathbf{l}_t) + \mathbf{e}_t(\mathbf{s}_t, \mathbf{s}_{t+1}) = \mathbf{s}_t + \mathbf{q}_{y,w} \tag{7}$$

$$F_{w+1} - \boldsymbol{\varphi}_{w+1,l}^{\tau} \mathbf{s}_{t+1} \leqslant \boldsymbol{\gamma}_{w+1,l}^{\tau} \mathbf{q}_{y,w} + \beta_{w+1,l} (l = 1, 2, \ldots, L-1) \tag{8}$$

Note that the other constraints found in one-stage SDDP optimization problem are also applicable here. Once we have the solution to the reoptimization problem, the system moves to time $t + 1$ using the mass balance Eq. (7 and a new reoptimization problem is solved, and so on until we reach the end of the hydrologic projection.

At the end of the reoptimization procedure, one of the main results are the simulated reservoir storages s_t, which can then processed to derive the desired storages s_t^o, i.e. the guide curve. Here, the desired storage in a given reservoir j at a given week w is the expected storage $s_w^o(j) = \frac{1}{30} \sum s_w(j)$. The corresponding guide curve associated with reservoir j is obtained after interpolating between consecutive $s_w^o(j), w = 1 \ldots 52$.

HEC-ResSim can then process the adapted guide curves to simulate the daily operation of the multireservoir system under the hydrologic conditions that prevailed in the cluster. The same performance indicators are again assessed and compared to those obtained with the current operating policy. This optimization-simulation procedure is repeated for all clusters. As an example, Fig. 7 exemplifies the adapted guide curve for Kiamika's reservoir for cluster 5 (*strong seasonality scenarios*), prescribed by the optimization model. We can see that the adaptation adjusts the drawdown-refill cycle to account for a stronger seasonality and earlier spring snowmelt.

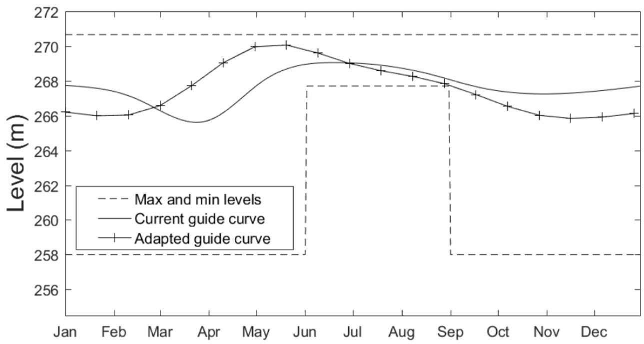

Fig. 7. Comparison of official and adapted guide curves at Kiamika Reservoir.

3. Results and discussion

3.1. Current operating policy

Fig. 8 shows the performances associated with the current operating policy for each cluster identified by its linguistic descriptor as listed in Table 1: *no-change*, *large annual volume*, *moderate seasonality*, *low annual volume* and *strong seasonality*. Each point corresponds to the performance achieved for each one of the 828 30-year future hydrologic projections. Since the hydrologic projections in the *no-change* cluster are characterized by a flow regime close to current conditions, the corresponding performances are the benchmark against which the other clusters are compared.

The performance regarding flood control is assessed in terms of an annual number of global failures. A global failure in flood control occurs when the maximum water level in one or more reservoirs is not respected or when the flow downstream reaches a critical level causing significant damages. We observe a slight increase of the flood risk for the clusters *large annual volume* and *strong seasonality* due to larger volumes of water during winter and spring. However, the median and the interquartile range of the boxplots remain close to zero, which indicates that the three main reservoirs are able to provide similar performances despite the potential alterations of the flow regime in the future. In other words, the large storage capacity can handle the projected increase in winter and spring flows.

A failure in recreational use occurs when one or more reservoirs cannot provide the minimum level for recreational activities during summer. For the *no change* cluster, 75% of the scenarios present less than 20 failures/year. *Large annual volume* and *moderate seasonality* scenarios can keep the performance close to current conditions. However, *low annual volume* and *strong seasonality* scenarios present a risk increase of 300% and 100%, relatively to the median performance of the *no change* cluster. For *low annual volume* and *strong seasonality* scenarios, the early onset of the high flows season, together with lower flows during the summer, makes it difficult for the system to attain the expected level during summer when following the current guide curve which recommends the start of refilling the reservoir Poisson Blanc by the end of April. Fig. 9 illustrates the impact of the driest states of three plausible future hydrological regimes, *no change*, *low annual volume*, and *strong seasonality* scenarios, in Poisson Blanc reservoir, if there is no adjustment in the drawdown-refill cycle. The driest states are represented here by the first quartile of the interannual level and incremental inflow. For the current operating rule, the Poisson Blanc reservoir starts to be refilled by the end of April, which takes place at the end of the high-flows period induced by the seasonal ice melt for clusters *low annual volume* and *strong seasonality*. As a result, less water is available to refill the reservoir for these clusters. Besides, the low summer flow often lies below the minimum required ecological flow downstream, which means that the reservoir must be depleted even further.

Failure in meeting minimum ecological flows occurs when one or more reservoirs do not release the minimum flow required to sustain ecosystems. The minimum flow is a top-priority constraint for the Lievre system, so the non-satisfaction of this operating objective only occurs when the reservoirs are depleted. The median is zero failure per year for all clusters, which points to the robustness of the multireservoir system regarding ecological flows. *Strong seasonality* scenarios present a slightly higher risk of failure since they have the lowest summer inflows and the most pronounced time shift for the snowmelt season among the clusters, as

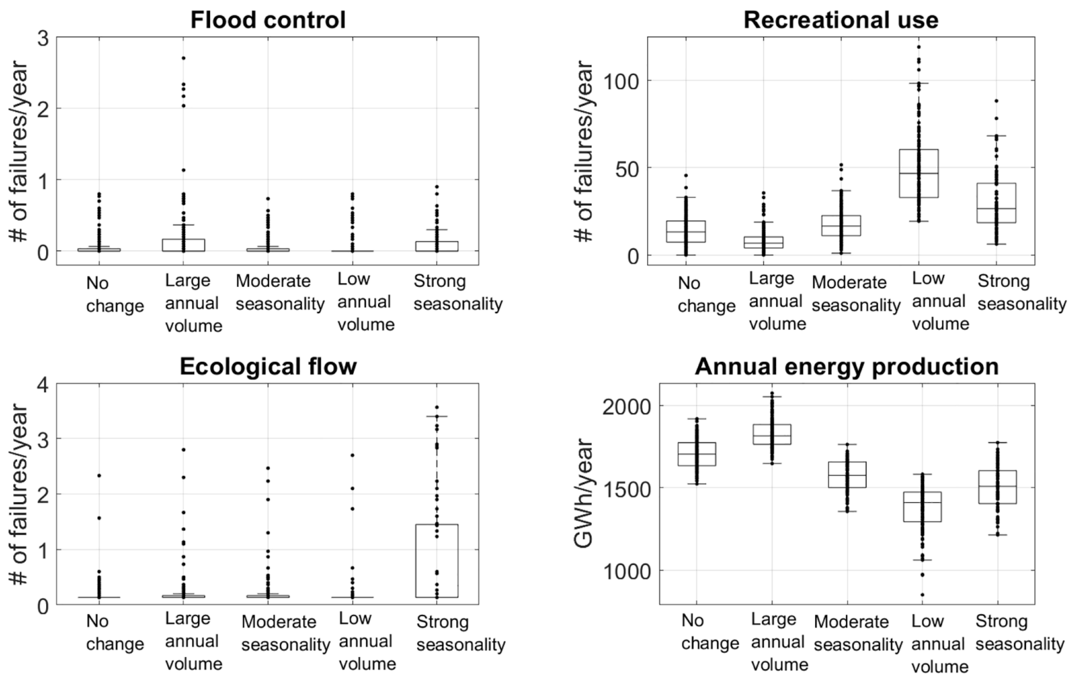

Fig. 8. Global performance for all clusters, represented here by their linguistic descriptors (Table 1), and considering four performance criteria, annual number of failures regarding flood control, recreational use and ecological flow, and annual en.ergy production.

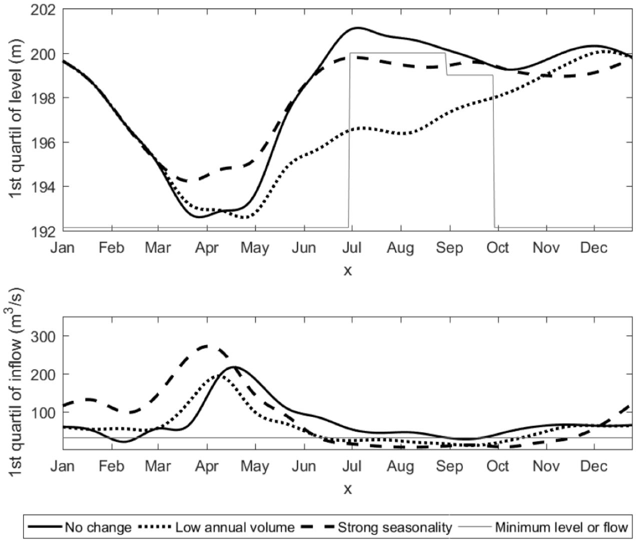

Fig. 9. First quartile of interannual level (top) and intermediate basin inflow (bottom) of Poisson Blanc reservoir for the representative scenarios of *no change*, *low annual volume* and *strong seasonality* clusters.

illustrated in Figs. 4 and 9.

Finally, regarding annual energy production, clusters *moderate seasonality*, *strong seasonality* and *low annual volume* scenarios present the lowest annual values, with a reduction of 8, 17 and 11% compared to the median of the *no change* cluster. For the *large annual volume*, we observe an increase of 7% compared to the same reference. Then, the *large* and *low annual volume* scenarios present the best and worst performances regarding energy production, which is expected since the annual flow is strongly correlated to energy

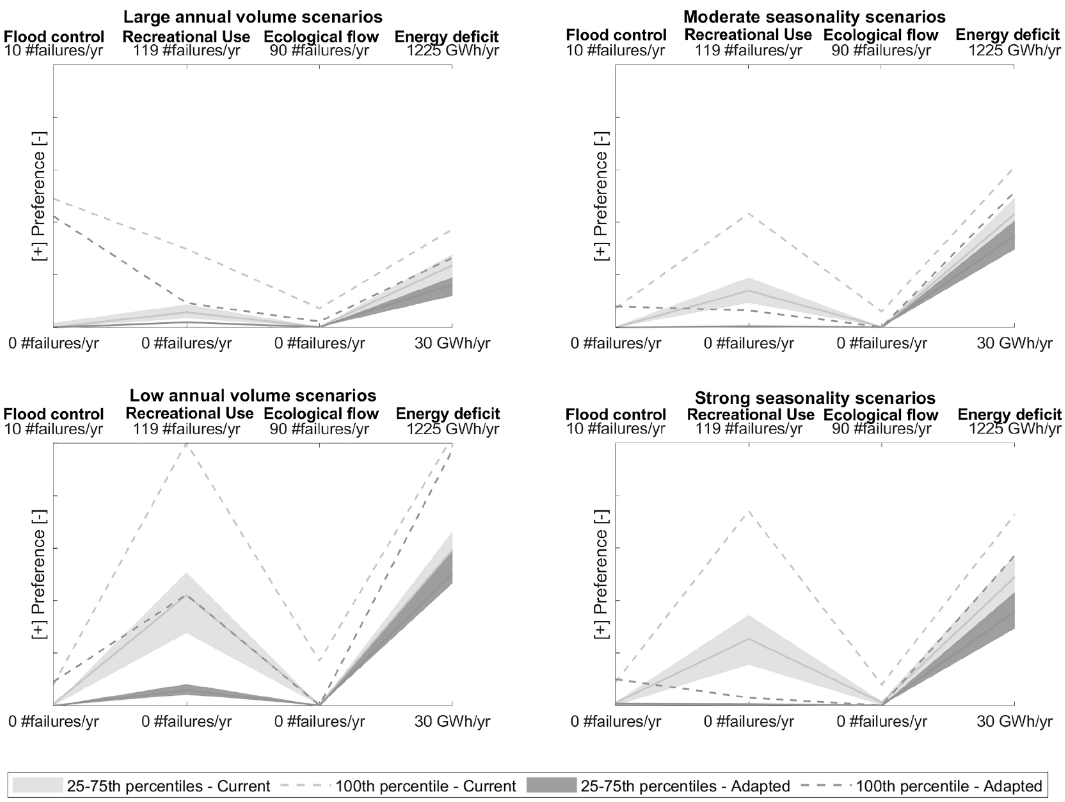

Fig. 10. Comparison of the current and adapted operating policies for large annual volume, moderate seasonality, low annual volume and strong seasonality scenarios. The graphs show the performance ranges between the 25th and 75th percentile, and the 100th percentile (worst scenarios).

production for regulated reservoirs. Also, Table 2 shows an increase in spillages losses, described here in terms of energy losses, for *large annual volume*, *moderate seasonality*, and *strong seasonality* scenarios, which suggests that the current operating policy might be sub-optimal for those clusters. Such increase is mostly explained by a shift in the seasonality patterns, i.e., earlier snowmelt.

3.2. Portfolio of adaptation operating policies

The last step of the proposed methodology yields a portfolio of cluster-specific, adapted, operating policies tailored to the hydrologic characteristics shared by all the projections in the same cluster. Those adapted policies are determined by an optimization model and are then translated into new guide curves for the simulation model. From the simulation results, the performance indicators can be calculated and compared to those obtained with the current operating policy.

For the *no change* scenarios, there is no need for adaptation measures since the current operating policy is already robust for current conditions. Besides, no alternative dominating the current operating policy could be found, indicating that the latter is already on the Pareto front regarding the four operating objectives.

For the remaining clusters, Fig. 10 shows parallel-coordinate plots comparing the current and cluster-specific operating policies found with the help of the optimization model SDDP. To make sure that all the indicators point in the same direction (minimization), the performance of the energy sector is measured in terms of energy deficit, which is the difference between the energy generated by the most productive scenario and that corresponding to the cluster of interest. The performance indicators are listed on the X-axis, while the Y-axis indicates the direction of increasing preference. Here, the ideal – but infeasible – solution corresponds to the bottom horizontal axis. The average performances are represented by the interquartile range 25%–75%, and the 100th percentile represents the worst performances. The comparison between current policy and cluster-specific operating policies shows that the latter dominates the former considering the four operating objectives.

Concerning flood control, the adapted policy for *large annual volume* scenarios slightly reduces the risk of flooding. For the other clusters, the flood risk remains as low as for the current operating policy.

The cluster-specific adapted operating policies for *moderate seasonality*, *low annual volume* and *strong seasonality* scenarios improve the performance regarding recreational use by 97, 85, and 98%, respectively and relatively to the median performance. For ecological flow, the risk of failure is virtually absent with the operating policies of the portfolio. Moreover, the adaptation significantly reduces the performance variability for recreational use and ecological flow. The robustness of the cluster-specific policies is also highlighted by Fig. 11, which compares the driest states for the *low annual volume* (left) and *strong seasonality* (right) scenarios, under current and adapted operating policies. We observe that the cluster-specific operating policies manage to keep the reservoir level above the minimum level during summer, even for the driest states. Relatively to the current operating policy, the adapted operating policies for *low annual volume* and *strong seasonality* start refilling the reservoir earlier to take advantage of the anticipated snowmelt.

The results of the portfolio of adapted policies with regards to energy production show a gain of 90, 102, 78 and 166 GWh (or 5, 7, 6 and 11%), for clusters *large annual volume*, *moderate seasonality*, *low annual volume* and *strong seasonality*, respectively. To better understand how the adapted policies increase energy production, Fig. 12 compares monthly energy production and energy loss through spillage for the clusters *low annual volume* and *strong seasonality* when applying the current and cluster-specific adapted policies. Additionally, it shows values for the *no change* cluster (dashed lines), serving as a reference for the expected outcome. For both cluster-

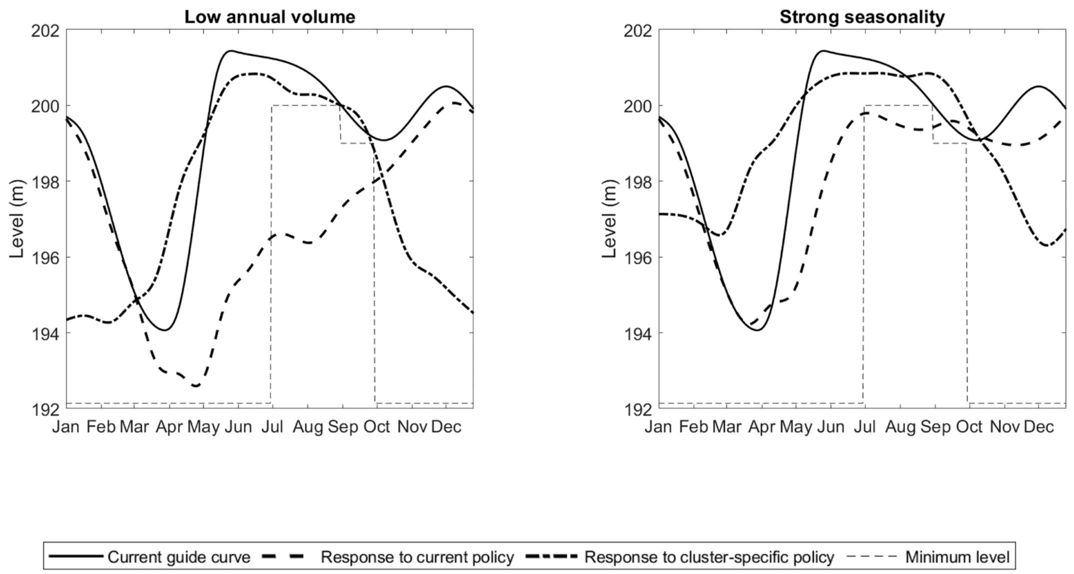

Fig. 11. First quartile of interannual level of Poisson Blanc's reservoir for the representative scenarios of *low annual volume* and *strong seasonality* clusters as a response of current policy (dashed lines) or cluster specific policies (dash-dotted lines).

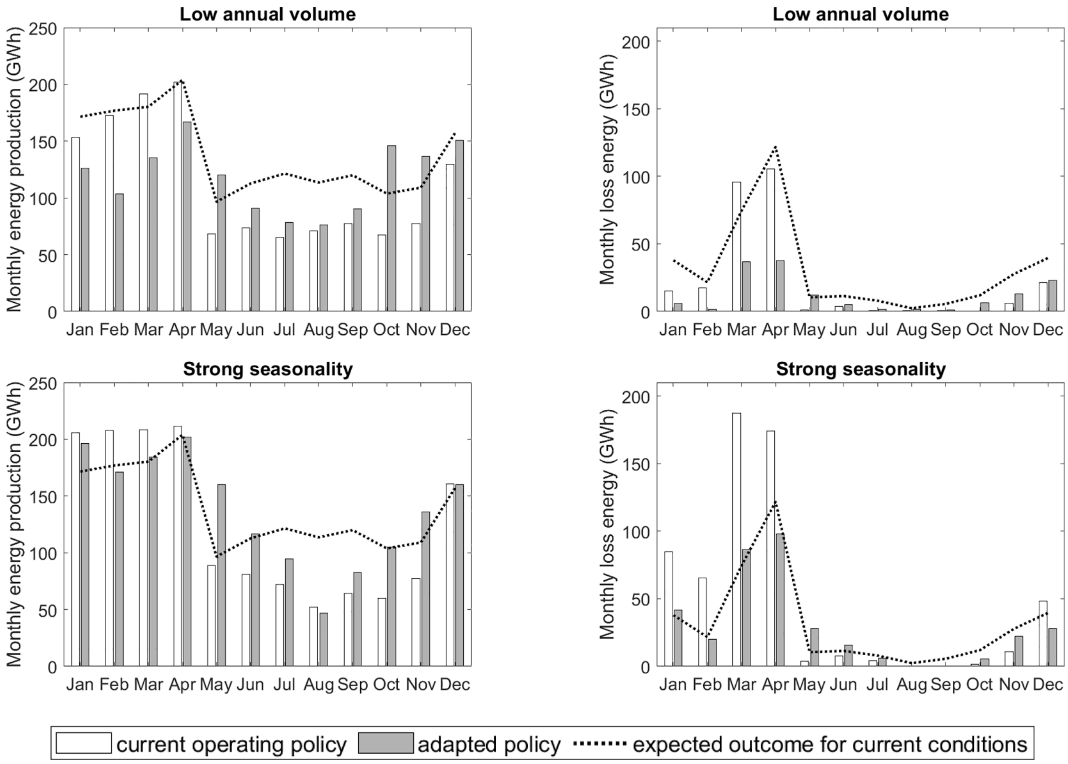

Fig. 12. Annual averages of energy production and lost energy for *low annual volume* and *strong seasonality* scenarios, current (white bars) and adapted operating policies (grey bars). The dotted lines represent the average performance for *no change* scenarios to represent the expected outcome for current conditions.

specific operating policies shown in Fig. 12, we notice a reduction of the lost energy during the snowmelt season, and an increase in energy production for the rest of the year. However, the adapted rules reduce the energy production during winter for both clusters, relatively to the current policy. The reduction of energy production during winter is not problematic for *strong seasonality* scenarios since their adapted policy allows the same production levels during winter as current conditions. For the *low annual volume cluster*, the energy deficit during winter is a clear trade-off that has to be considered if applying the adapted operating policy.

4. Conclusions

Because of the expected impact of climate change on water availability and increase in drought episodes, and also considering the pivotal role of water in mitigating climate change impacts in the other sectors such as food, energy, or health, significant attention must be devoted to developing adaptation strategies for our water resources systems (Rogers, 2011). More specifically, the reoperation of water resources systems to keep the overall performance within acceptable limits should be prioritized to avoid, or at least delay as much as possible, costly infrastructural investments (Gleick, 2018). We propose an approach to support the reoperation of reservoirs based on the clustering of a large ensemble of hydrological projections, which is followed by the development of reservoir operating policies tailored to flow regime changes. The robustness of the identified adapted policies are then locally assessed after simulating the policies across all hydrologically-similar projections.

The proposed approach is scenario neutral (Prudhomme et al., 2010) since the projections are grouped into clusters regardless of the climatic model or emission trajectories. The clustering of hydrologic projections is also compatible with a decision-scaling framework, which states that the climate information should be tailored to the best interest of their users (Brown et al., 2011). Here, the clusters are formed based on hydrologic attributes well known to the operators. This hydrologic-based clustering also helps triggering the experiential knowledge of the operators, which could be exploited to derive the adaptation measure while further involving them into the modelling exercise. Clearly, this clustering involves a loss of information which must be weighed against the benefits of more easily interpretable results since the adaptation policies are directly related to changes in the flow regime rather than changes in climate variables. Assessing that loss of information was beyond the scope of the present study; it would involve comparing the intrinsic variability of performance indicators within and across clusters.

The proposed hydrologically driven approach to climate change adaptation does not replace well-established scenario discovery approaches. Instead, it addresses situations whereby a large ensemble of GCM-based projections is available, covering a range of uncertainty large enough so that the operators are comfortable using them in the stress test. Provided that condition is met, the proposed approach relies on a multi-dimensional stress test driven by changes in hydrologic attributes directly relevant to characterize the flow regime instead of a limited number of relatively broad climate variables.

The final step of this approach produces a portfolio of operating policies tailored to potential alterations of the flow regime, revealing the operational flexibility of the multireservoir system; that is, its capacity to adapt to likely hydrological changes. The approach proposed in the manuscript does not intend to inform water operators on detecting hydrological regime shifts to support real-time operations. Instead, it provides an ex-ante assessment of a water resources system's operational flexibility and should be regularly updated as new climate information becomes available. Those regular updates will also allow the operators to "continuously" adjust the operating rules while the uncertainty regarding the direction of the hydrologic alteration gradually vanishes.

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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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.crm.2022.100427.

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