Accounting for climate change uncertainty in long-term dam risk management

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Abstract:

This paper presents a practical approach for adaptive management of dam risk based on robust decision-making strategies coupled with estimation of climate scenario probabilities. The proposed methodology, called Multi-Prior Weighted Scenarios Ranking, consists of a series of steps from risk estimation for current and future situations through the definition of the consensus sequence of risk reduction measures to be implemented. This represents a supporting tool for dam owners and safety practitioners to help make decisions for managing dams or prioritizing long-term investments using a cost-benefit approach. This methodology is applied to the case study of a Spanish dam under the effects of climate change. Several risk reduction measures are proposed and their impacts are analyzed. The application of the methodology allows identifying the optimal sequence of implementation measures that overcomes the uncertainty from the diversity of available climate scenarios by prioritizing measures that reduce future accumulated risks at lower costs. This work proves that such a methodology helps address uncertainty that arises from the existence of multiple climate scenarios while adopting a cost-benefit approach that optimizes economic resources in dam risk management.

Keywords: Climate change; Uncertainty; Dam safety management; Decision making; Risk reduction.

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1 INTRODUCTION

Risk assessment techniques help implement dam safety management as a comprehensive approach. Such techniques are applied worldwide in the dam sector (ANCOLD 2003; ICOLD 2005; SPANCOLD 2012; USACE 2011) to support informed safety governance when adopting risk-reduction measures and their prioritization. Moreover, these approaches are often based on quantitative methods and models, which depend strongly on the quality and precision of the input data.

Climate change imposes new challenges to the application of risk analysis techniques. Dam risk management can no longer be envisioned by assuming risk stationarity over long-term operations (Fluixá-Sanmartín et al. 2019, 2020; USACE 2016). Updating the risk components becomes imperative to consider new climate scenarios under a more robust approach. Efforts are currently focused on defining, analyzing, and managing climate change impacts on risks (Chernet et al. 2014; International Hydropower Association 2019; USACE 2016; USBR 2014, 2016; Willows and Connell 2003).

However, one issue remains challenging: climate-related uncertainties come on top of other uncertainty sources, which affects the results of risk analysis models and their effectiveness (Morales-Torres et al. 2019). This represents a major roadblock for adaptive decision-making and requires organizations and individuals to adapt their standard practices and decision procedures (National Research Council (U.S.) 2009). Under uncertain future climate conditions, response strategies that explicitly recognize these uncertainties are an essential element of decision-making (Khatri and Vairavamoorthy 2011; Street and Nilsson 2014).

The first aspect to consider is the incorporation of climate (and other) uncertainties into the dam safety assessment. That is, evaluating their effect on each component of risk, taking into account their interdependencies. This can be achieved using quantitative risk models, which are useful tools for the identification and structuration of climate change impacts and uncertainties for each dam risk component. These models have been recently applied in several studies (Fluixá-Sanmartín et al. 2019, 2020; Morales-Torres et al. 2019).

Secondly, it is important to establish how to incorporate these uncertainties into the process of dam governance by defining so-called robust adaptation strategies and prioritizing risk reduction investments. Such strategies seek options to satisfy their purpose across a variety of futures by integrating a wide range of climate scenarios or model results (Haasnoot et al. 2013; Wilby and Dessai 2010). Recent efforts have been put in applying decision-making approaches to cope with uncertainty effects in water resources systems (Miao et al. 2014; Minville et al. 2010; Roach et al. 2016; Spence and Brown 2018), although more work needs to be done in the context of dam safety.

A common economic approach when modeling uncertainty is the use of the expected utility framework defined by von Neumann and Morgenstern (1944). This technique has been applied in different fields to make decisions without knowing what outcomes will result from a given decision (Chamberlain 2000; Danthine and Donaldson 2015; Levitan and Thomson 2009). The goal is to capture such uncertainty by characterizing the outcome likelihood with a given probability distribution and act accordingly. Knowing climate change probabilities would allow determining the plausibility of risk conditions, which leads to more informed decision-making (Dessai and Hulme 2004; Jones 2000).

Nevertheless, the struggle to assign probabilities makes it difficult to support informed decisions (New and Hulme 2000) since no probabilities have been attached to the future climate scenarios (IPCC 2013). Even though probabilities are needed for risk and adaptation studies (Pittock et al. 2001), the application of methods to assign these probabilities remains a controversial topic and require further development (Knutti et al. 2010a). In addition, the expected utility is highly dependent on the selected configuration of probabilities and there is a risk of overweighing a particular climate scenario, leading to suboptimal decisions.

Since our knowledge about the climate system is not (yet) of enough quality to assign a unique probability distribution over states, an alternative to the expected utility framework is the application of a multiple priors approach. The idea is to use different distributions and assign a weight to each of them (Garlappi et al. 2004; Heal and Millner 2014). These distributions are then used to evaluate the convenience of a decision. This approach would help lessen the sensitivity of the expected utility evaluation to the probability configuration used.

This paper presents a practical approach to support robust decision-makings adapted to dam safety in the context of climate uncertainty. The goal is to define a complete procedure that allows defining and prioritizing risk reduction measures based on their short- and long-term efficiency while establishing the consensus implementation sequence. The usefulness of the approach consists of aggregating multiple scenarios by applying and adapting the expected utility theory and the multiple priors approach, providing different results than simply considering a compilation of states. First, the primary uncertainty sources related to future climate change scenarios are presented. Secondly, a probabilistic approach is given as focused on evaluating the robustness of measures and on their prioritization strategy. Finally, the procedure is applied to a real case study of a Spanish dam based on previous risk results (Fluixá-Sanmartín et al. 2019).

2 CLIMATE CHANGE UNCERTAINTY IN DAM RISK MANAGEMENT

When evaluating the risk of dams as well as other complex structures, two types of uncertainty are generally distinguished as (Ferson and Ginzburg 1996; Hartford and Baecher 2004):

- Natural uncertainty: Arising from inherent variability in natural processes.
- Epistemic uncertainty: Resulting from not having complete knowledge or information about the analyzed system.

When studying dam risk management, natural uncertainties can arise from variability in potential flood magnitudes that occur. Epistemic uncertainties are related to the estimation of fragility curves, which represent a relationship between the conditional failure probabilities and the magnitude of loads that produce such failures. Fluixá-Sanmartín et al. (2019) applied a sensitivity analysis to assess how uncertainty in meteorological modelling affects dam risks. An extract of these results is shown in **Figure 1**.

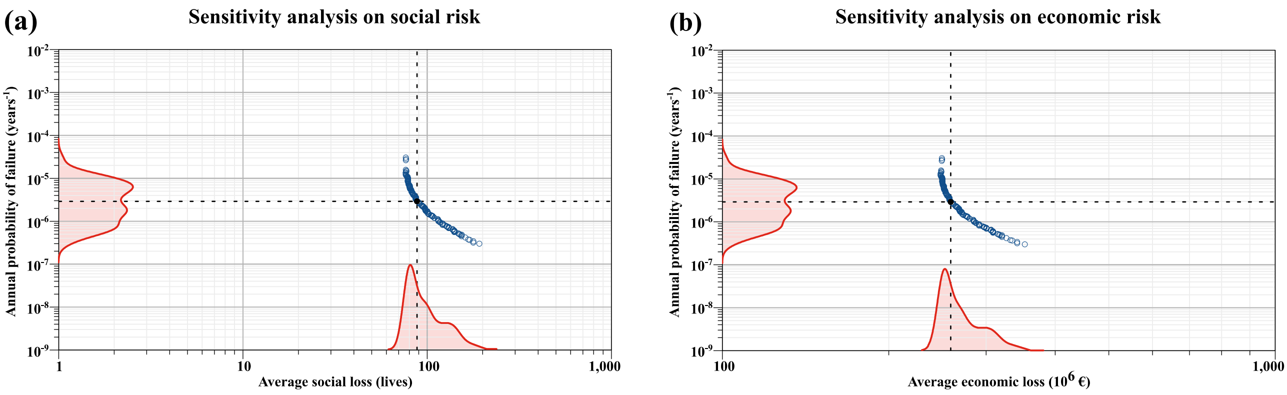

Figure 1. Effects of precipitation sampling uncertainty on (a) social and (b) economic risks, where the kernel density plot for each variable is displayed in red on the x and y axes (adapted from Fluixá-Sanmartín et al. (2019)).

Specific sources of uncertainty can be identified when considering climate change projections. For example, Hawkins and Sutton (2009) grouped the uncertainties into three major categories: (i) scenario, (ii) internal climate, and (iii) model uncertainties. Further detailed descriptions of the uncertainty sources can be found in other references (Eggleston et al. 2006; European Environment Agency 2017; Knutti et al. 2010a; Wilby and Dessai 2010). The ensemble of uncertainties is propagated through input data and models, which inherit prior uncertainties and expand at each step of the process. To address such uncertainties, it is typical to work with ensemble simulations that combine different regional climate models (RCMs), scenarios, and models.

Dam risk is subjected to the impact of climate change uncertainties in different ways. The primary component that is affected by climatic drivers is the hydrology of river basins. Precipitation regimes play a key role in this component, as do other factors that are highly dependent on temperature, such as snowmelt and soil moistening/drying. Uncertainties related to these natural aspects will inevitably affect the evaluation of flood occurrence through its magnitude and frequency. The other component subjected to the uncertainty of meteorological scenarios is the distribution of water storage in reservoirs. This determines the loads a dam is subjected to at the moment of flood arrival, which influences its safety level (SPANCOLD 2012). Surface water availability is expected to fluctuate primarily from variability in precipitation (IPCC 2014) and evapotranspiration (Kingston et al. 2009; Seneviratne et al. 2010), which directly impacts reservoir water levels.

Besides natural uncertainty, the socio-economic dimension of climate change impacts must also be considered. For example, the evaluation of dam risks also includes the potential consequences downstream from the dam, which are directly related to the exposure and vulnerability of people, livelihoods, infrastructure, or assets in at-risk areas. The evolution of exposure is subjected to global socio-economic trends that are attributed to climatic drivers (Choi and Fischer 2003; Neumayer and Barthel 2011). Moreover, changes in freshwater needs, agricultural land use, water resource management strategies, and population growth are likely to modify the balance between water availability and supply, which then directly impact the reservoir water levels. However, such processes are still poorly known, and the unpredictability of future socio-economic scenarios also accentuates the uncertainty on the final consequences (Burke et al. 2011).

The aforementioned uncertainties influence the reliability of the results and the adopted adaptation strategies. This affects how decisions are made and the planning of long-term investments when future climatic conditions are only conjectured. However, while it is a challenging task, the incorporation of uncertainties must not prevent decisions from being made. Uncertainty should actually boost strategies that prevent the considered actions from being inadequate, inappropriate, or increase the vulnerability (Street and Nilsson 2014). When uncertainty cannot be reduced through data collection, research, or improved modeling, the incorporation of uncertainty into the decision-making process represents a suitable option (Schneider 2003).

In the context of climate adaptation in policy making, relevant approaches include adaptive policy making (Walker et al. 2013, 2001), adaptation pathways (Haasnoot et al. 2012), or real options analysis (Gersonius et al. 2012; Park et al. 2014). In addition, there are several other methodologies, tools, and techniques to handle uncertainties in general. A few examples are scenario planning (Swart et al. 2004), Monte Carlo analysis (Zhang and Babovic 2012), multi-layer decision analysis (Harvey et al. 2012), and safety margin strategies (Hallegatte 2009).

In this work, the treatment of climate uncertainty in adaptation decision-making relies on a combination of expected utility theory and a multi-prior approach, based on Cost-benefit analysis (CBA) techniques.

3 A DECISION-MAKING APPROACH INCORPORATING CLIMATE CHANGE UNCERTAINTY

The approach proposed in this paper is called *Multi-Prior Weighted Scenarios Ranking* (MPWSR). It allows overcoming the above-mentioned limitations in the assignation of scenario probabilities by simultaneously using multiple probability configurations, which leads to lessen the sensitivity and increase the robustness of the results. The methodology is based on robust decision-making strategies coupled with climate scenario likelihoods where each climate projection is associated with a probability, even if it is only subjective. The ultimate results or recommendations are expressed in the form of a ranking of measures associated with a certain degree of confidence (or uncertainty). Thus, a 6-step iterative strategy is proposed in this paper to apply robust decision-making for dam risk management under climate change uncertainty (see **Figure 2**). When repeated, this approach ultimately allows identifying the most favorable sequence of implementable risk reduction measures.

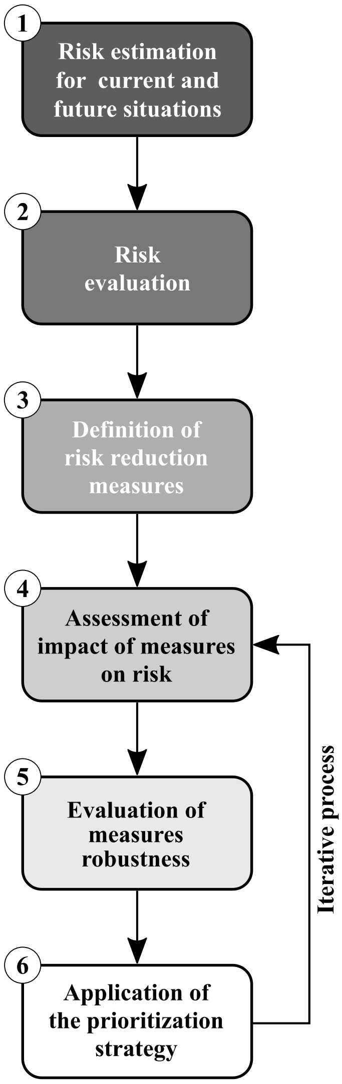

Figure 2. Flow diagram of the decision-making strategy.

3.1 Risk estimation for current and future situations

The first step of the proposed decision-making approach is to estimate risk for the current situation and its evolution with time. In this context, risk can be defined as the combination of three concepts: what can happen (dam failure), how likely it is to happen (failure probability), and what its consequences are (failure consequences including but not limited to economic damage and loss of life) (Kaplan 1997). Therefore, risk can be obtained through the following formula:

$$Risk = \sum_e p(e) \cdot p(f|e) \cdot C(f|e) \quad (1)$$

where the summation is defined over all events *e* under the study, risk is expressed in consequences per year (social or economic), *p(e)* is the probability of an event that causes failure, *p(f|e)* is the probability of failure due to event *e*, and *C(f|e)* are the consequences produced as a result of each failure *f* and event *e*. For simplicity, it is suggested to calculate future risks for a select number of time horizons and then interpolate between them for arbitrary times within the analysis period.

Risk models are the basic tool to quantitatively assess risk and integrate and connect most variables concerning dam safety (Ardiles et al. 2011; Bowles et al. 2013; Serrano-Lombillo et al. 2012). By applying such techniques, Fluixá-Sanmartín et al. (2018, 2019) confirmed that changes in climate, such as variations in extreme temperatures or the frequency of heavy precipitation events (IPCC 2012; Walsh et al. 2014), are likely to affect the different components that drive dam risks. These works provide theoretical and practical guidance on the use of risk models to calculate dam risk evolution under this approach.

3.2 Risk evaluation

Risks must be evaluated after they are calculated for current and future scenarios. That allows assessing whether a risk is tolerable and eventually justifies the proposal and implementation of the risk reduction measures. Judgments and tolerable risk thresholds are introduced in the process (ICOLD 2005), and risk is generally classified as either unacceptable, tolerable, or broadly acceptable (HSE 2001). Different organizations have proposed risk tolerability recommendations to evaluate whether dam risk levels are tolerable or not (ANCOLD 2003; SPANCOLD 2012; USACE 2011; USBR 2011).

It is assumed that risks are likely to evolve with time primarily due to climate change impacts; thus, the results from risk evaluation evolve as well. Under such circumstances, it is convenient to compare the present and future situations of a dam in terms of its risk evaluation. The different combinations of dam evaluation cases based on present and future risks are proposed as presented in **Table 1**. This may help identify the sensitivity of dam risk to climate change. The more the dam risk tolerability changes between present and future conditions, the more the dam is susceptible to climate change impacts.

Table 1. Different dam evaluation cases based on present and future risks.

		Present risk		
		Broadly acceptable	Tolerable	Unacceptable
Future risk	Broadly acceptable	I	II	III
	Tolerable	IV	V	VI
	Unacceptable	VII	VIII	IX

3.3 Definition of potential risk reduction measures

The previous step defines the convenience of adopting a certain risk reduction strategy. A set of potential risk reduction measures is proposed based on the tolerability scenarios for the computed present and future risks. However, depending on the resulting classification of the dam from Section 3.2, measures that are justifiable in the present may not be necessary in the future (e.g., class III in **Table 1**) and vice versa (e.g., class VII). This greatly affects not only the type of measures to be applied but also the decision time horizon. This horizon is the upper limit of the time interval during which the investment is to be justifiably financed (Lind 2007). This implies that some measures will only be justifiable for long-term operations.

Moreover, under the uncertainties imposed by climate change scenarios, envisioned risk adaptation measures must fit the so-called robust approaches. This may help design more robust measures (i.e., no/low regret options) and discard those that do not perform well for different climate scenarios (Noble et al. 2014). The design of adopted measures depends on different factors, which include: risk conditions

in the present/future situations; decision time horizon; implementation and operation costs of each measure; availability of funds; expected lifetime of the dam; technical feasibility of the measure in the long term; socio-environmental factors; or impact of measures on risk.
Risk analysis techniques rely on the efficiency of measures to optimally reduce dam risks, which creates options that reduce risk at the lowest cost. To assess such an efficiency, the effects of implementing these measures on the risks must be evaluated, not only in the short term but also for the future. This is usually performed by applying the principles of cost-benefit analyses where the total expected cost of each measure is compared with their total expected benefit (Baecher et al. 1980; Palmieri et al. 2001), which is in terms of risk reduction here. Different indicators can be used to evaluate dam risk reduction measures, including social and/or economic terms for the risks (ANCOLD 2003; Bowles 2001, 2004; Serrano-Lombillo et al. 2013). In general, the measure that reduces the risk with the lowest cost consequently presents the highest efficiency will be prioritized, which is the measure with the lowest indicator value.

Fluixá-Sanmartín et al. (2020) presented a methodology to assess the effects of risk reduction measures in the long term using a proposed risk reduction indicator called the aggregated adjusted cost per statistical life saved (AACSLS). The AACSLS indicator is used to calculate the total cost of a statistical life saved over a given period to evaluate the long-term efficiency of the risk reduction strategy. The prioritization of risk reduction measures can then be defined using this indicator.

3.4 Evaluation of measure robustness

3.4.1 Considerations

In contrast with traditional decision analyses seeking strategies that perform best for a fixed set of assumptions about the future, under robust decision-making approaches the prioritized measures must perform well under a wide range of scenarios (Lempert et al. 2003). This work proposes applying the expected utility theory (von Neumann and Morgenstern 1944; Ramsey 1926; Savage 1972) combined with multi-prior approach to assess the robustness of measures and apply it to dam safety management.

Based on the expected utility theory, preference for a set of alternatives can be established using a quantitative valuation of their utility, which can be estimated as the sum of the utility of outcomes multiplied by their respective probabilities (Davis et al. 1998). The alternative with the highest expected utility should then be selected. In this case, each outcome measures the efficiency of a risk reduction measure under an expected climate scenario, and the respective probability designates the likelihood of such a scenario. Therefore, applying this method requires quantifying the outcome that results from implementing a specific measure and to assign probabilities to each climate scenario. Despite the difficulty of finding quantitative methods to assess the preferences among different adaptive strategies (Lempert et al. 2006), risk reduction indicators in the context of dam safety can be used as they quantify the efficiency of each alternative (measure) envisioned. This paper proposes using the AACSLS to quantify the utility of each risk reduction measure under a certain future climate scenario; the core of the proposed methodology will therefore rely on a Cost-benefit analysis (CBA) approach.

It is necessary to determine which configuration(s) of probabilities are used to evaluate the adaptation measure suitability while also defining the likelihood of each projection. A practical methodology based on multi-prior approach is proposed in this work to lessen the sensitivity and increase the robustness of the process by performing simulations under different configurations. Such a methodology includes two levels.

First is the generation of a scheme of weighted probabilities configurations, each one describing the plausibility of the climate future, defined in a prior level or hyperprior. For each configuration, the different future states (in our case, the climate projections) are assumed having different probabilities of occurrence. The definition of these configurations thus depends on the knowledge of the climate system and the modelled projections.

Second is to generate the probabilities assigned to each projection and for each configuration. The resulting ensemble of configurations are presented in the form of modulated probabilities, as shown in **Figure 3**.

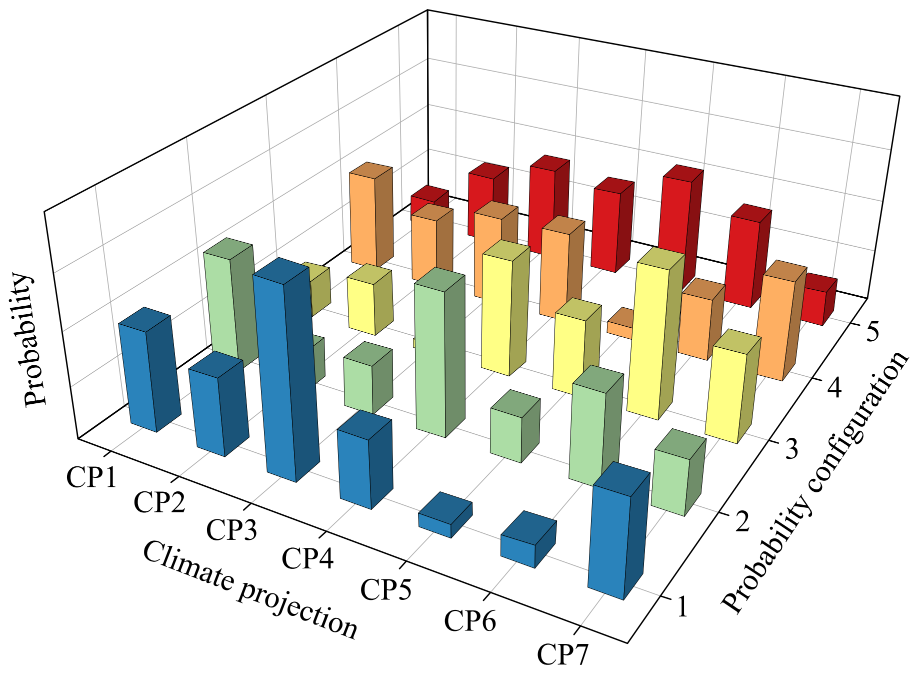

Figure 3. Example of probability configurations (1 to 5) for different climate projections (CP1 to CP7).

3.4.2 Procedure

Suppose we have *N* risk reduction measures and *P* climate scenarios. The process to define the robustness of this set of measures is repeated *M* times using the following steps:

a) Calculate the AACSLS indicator (noted $x_{j,k}$) for each risk reduction measure *j* and for each climate scenario *k*.

b) Generate a configuration of probabilities p_k associated with each climate scenario *k*, verifying that:

$$\sum_{k=1}^{P} p_k = 1 \quad (2)$$

The ensemble of probabilities can be generated or modulated based on one of the scenario weighting schemes presented in Section 3.4.3.

c) Calculate the expected utility $E[u(x_j)]$ of each measure *j* as the weighted average of all possible outcomes of such a measure under the different envisioned scenarios. This is expressed as the sum of the products of probabilities (weights) and utilities (AACSLS values) over all possible scenarios as:

$$E[u(x_j)] = \sum_{k=1}^{P} (p_k \cdot x_{j,k}) \quad (3)$$

d) Rank the measures according to their expected utility. In expected utility theory, preferred actions are those that present a higher utility; however, the AACSLS presents lower values for more efficient options. Therefore, when applying this approach, the criterion to be followed in the expected utility formula is applied inversely and the measure with the lowest $E[u(x_j)]$ is prioritized. Thus, for each configuration, the *M* measures have the expected utilities $E[u(x_1)]$, $E[u(x_2)]$, …, $E[u(x_N)]$ and associated prioritization orders (*PO*).

e) Repeat M times steps b) to d), where the probabilities p_k are redefined. At each repetition of the process, we assume a different plausibility of the climate futures projected.

The results are expressed in the form of a matrix with M rows and N columns, which define the ranking or priority order $PO_{i,j}$ of the N measures for each probability configuration (**Table 2**). Once the matrix is built, a prioritization strategy must be performed to define the most suitable measure.

Table 2. Priority orders of the *N* risk reduction measures for each probability configuration.

Probability configuration	Measure			
	1	2	…	N
1	$PO_{1,1}$	$PO_{1,2}$	…	$PO_{1,N}$
2	$PO_{2,1}$	$PO_{2,2}$	…	$PO_{2,N}$
…	…	…	…	…
M	$PO_{M,1}$	$PO_{M,2}$	…	$PO_{M,N}$

3.4.3 Scenario weighting scheme

As defined in step b) of Section 3.4.2, each considered climate scenario k must be weighted according to its relative importance through an associated probability p_k. This step is repeated M times.

According to IPCC (2013), no probabilities have been attached to the alternative RCP scenarios (as was the case for SRES scenarios) and each of them should be considered plausible, as no study has questioned their technical feasibility. However, in some cases evidences might show that one or several models are not performing adequately (e.g., unrealistic models for mountain regions in Switzerland detected in CH2018 (2018)) or that a given ranking of such models is of application. In order to pertinently apply this information to the analysis, a weighting scheme can be envisaged, although some critical aspects must be taken into account when assessing climate change model results for such purposes (Knutti et al. 2010a).

The different weighting schemes proposed in this work to apply the multi-model combination approach are presented here as:

a) Equal weights. This is the simplest way to construct the multi-model, and it is assumed that all models and climate scenarios perform similarly. The projections are then considered as equiprobable (i.e., $p_1=p_2=\ldots=p_P=1/P$ in Eq.(3)). It has been demonstrated that on average, an equally weighted multi-model consistently outperforms single models (Knutti et al. 2010b; Weigel et al. 2010). In this case, unless the subset of projections varies among each probability configuration, the procedure described in Section 3.4.2 consists of a unique configuration, and **Table 2** would contain only a single row. This option may be adequate when all climate scenarios are considered equally plausible, as suggested by IPCC (2013).
b) Pure random weights. In this case, probabilities are randomly generated while verifying that their sum is always equal to 1 (Eq. (2)).
c) Based on subjective criteria. Weights can also be established based on subjective criteria to give preference to cases that better suit the objectives or conditions of the study. Such weighting can be performed at the global/regional climate model level (GCMs/RCMs) and/or of the representative concentration pathways (RCPs).
d) Based on climate model performance. There are different available techniques for model weighting based on multiple performance metrics. For example, Christensen et al. (2010) explored the applicability of combining a set of six performance metrics to produce one aggregated model weight. Giorgi and Mearns (2002) weighted the results from an ensemble of

GCMs based on two criteria: 1) the skill with which an individual model reproduces historic climate change, and 2) the extent to which the projections of an individual model converge to the ensemble mean. However, as stated in Weigel et al. (2010), if the weights do not appropriately represent the true underlying uncertainties, weighted multi-models may perform worse than equally weighted approaches.

Such schemes can be applied to the entire ensemble of available climate projections or to a subset of them. This is true when one of the several projections are not reliable or when they are ill-suited for the study case. The subset of projections itself may even vary between each repetition (step (**e**) in Section 3.4.2).

A particular case of ensemble subsetting is presented when a single climate projection is used, although this does not correspond *stricto sensu* with a robust decision-making approach. This may be true when only one climate projection is available, or when the objective is to plan risk adaptation based on the worst-case scenario, i.e., choosing the projection that presents the highest risk. However, this approach is not recommended because it may lead to an unrealistic scenario. In addition, it is not always simple or automatic to identify the worst-case climatic model, and the concept of highest risk varies because the risk can evolve with time (Fluixá-Sanmartín et al. 2019).

3.5 Definition of prioritization strategy

When applying the expected utility theory to a specific probability configuration, the alternatives with the highest utility value (or lowest AACSLS, in this case) should be prioritized. However, the results from previous steps are given in the form of a table with multiple probability configurations and multiple classifications of alternatives or rankings (**Table 2**). A prioritization strategy that considers such diverse results is therefore needed. Four approaches are proposed in this paper: (i) average ranking, (ii) likelihood of rankings, (iii) index of ranking coincidence, and (iv) consensus ranking.

3.5.1 Average ranking

The simplest approach is to assess the preferences of each measure based on its average priority order from the corresponding row in **Table 2**. That is, the final priority order PO_j of each measure j among the M probability configurations is defined as:

$$PO_j = \sum_{i=1}^{M}\left(PO_{i,j}\right) \Big/ M \tag{4}$$

The measure with the lowest final PO value is then prioritized, which is equivalent to averaging the rankings and then ranking the averages. Although simple in application, this approach may underestimate the possible non-linearities due to the sequential application of risk reduction measures. To increase its robustness, this methodology should be complemented with the use of additional descriptive statistics (e.g., median, mode, and standard deviation of the $PO_{i,j}$) as well as with descriptive graphics (e.g., boxplots) to detect possible dispersion in the results.

3.5.2 Likelihood of rankings

This technique consists of assigning a probability to a certain ranking depending on how many times the ranking is repeated across the columns of **Table 2**. First, all plausible rankings of the measures are identified by removing duplicates from **Table 2**. Then, the frequency of coincidences for each ranking is calculated as the number of times it is repeated divided by the total number M of tested probability configurations. Finally, the scale proposed by Mastrandrea et al. (2010) is used to sort the rankings by their rate of recurrence and to classify them by their probability or likelihood of suitability (**Table 3**). The ranking with highest preference is selected.

By considering each ranking independently, this method cannot capture the similarity of ranking pairs. For example, among the following prioritization rankings, A and B (where alternatives 2 and 1 are the most suitable) are much more similar than ranking C. However, each ranking is treated as a separate entity without correlation with the others. This ineffectiveness is reduced when testing more probability configurations.

- **Ranking A**: 2, 1, 4, 5, 3
- **Ranking B**: 2, 1, 5, 4, 3
- **Ranking C**: 5, 4, 3, 1, 2

Table 3. Classification of the ranking preference according to their frequency (adapted from Mastrandrea et al. (2010)).

Frequency of ranking	Preference of ranking
>99%	Exceptionally high
90% - 99%	Very high
60% - 90%	High
33% - 66%	About as preferable as not
10% - 33%	Low
1% - 10%	Very low
0% - 1%	Exceptionally low

3.5.3 *Index of ranking coincidence*

Morales-Torres et al. (2019) proposed a methodology to consider epistemic uncertainty for risk-informed management. They developed an index of coincidence to measure the effects of uncertainty when calculating the prioritization sequences. The index quantifies differences in the order of measures between each sequence issued from the results of a second-order probabilistic risk analysis and the reference sequence obtained from the averages of the first-order risk analysis.

Therefore, a new index is proposed in this work to obtain the likelihood of an ensemble of rankings for measures with respect to a series of reference rankings. The index of ranking coincidence (IRC) is expressed as:

$$IRC = \frac{\sum_{i=1}^{M}\left(\sum_{j=1}^{N}\left(1-\frac{\left|PO_j^{(r)}-PO_{i,j}\right|}{max\left(PO_j^{(r)}-1,N-PO_j^{(r)}\right)}\right)\right)}{M\cdot N} \qquad (5)$$

where M is the number of probability configurations tested, N is the number of proposed measures, $PO_j^{(r)}$ is the priority order of measure j in the reference ranking, and $PO_{i,j}$ is the priority order of measure j in the ranking from probability configuration i. It is noted that the expression $max(PO_j^{(r)}-1,N-PO_j^{(r)})$ represents the maximum possible distance between the priority orders of the reference and the compared rankings.

The proposed procedure based on this index is as follows:

- Extract the $N!$ permutations without repetition of the N envisioned measures
- Consider each permutation as a reference ranking to calculate the *IRC* compared with the rest of the M rankings
- The ranking representing the highest *IRC* is adopted

3.5.4 Consensus ranking

A more complex approach consists of applying consensus ranking analyses. The resulting prioritization matrix given in **Table 2** represents a set of *M* ordinal rankings of *N* risk reduction measures. The goal is to define a consensus ranking that presents the maximum degree of consensus within the *M* rankings. This technique has received growing consideration over the past few years and has been widely used in a variety of domains (Leyva López and Alvarez Carrillo 2015; Luo et al. 2018; Meila et al. 2012; Plaia et al. 2019).

The procedure consists primarily of two stages. First, the agreement between rankings needs to be quantified, which can be achieved through dissimilarity or distance measures between the rankings. The most common measures are those related to distances or correlations. The measures related to distances evaluate the distance between any two elements in the set of *N* ordered objects (Farnoud Hassanzadeh and Milenkovic 2014). Rank correlation coefficients measure the degree of similarity between two rankings by associating a value of +1 to those in full agreement and -1 to those in full disagreement (and all others in between). A large assortment of methods can be used to accomplish this (Kendall and Gibbons 1990). Typical examples of metrics in this framework are Spearman's ρ and Kendall's τ (Kendall 1938). Spearman's ρ is the sum of square differences in the ranks at which items appear, while Kendall's τ is based on the concept of measuring the minimum number of interchanges for adjacent ranked objects as required to transform one ranking into the other. However, other metrics, such as the Kemeny distance (Kemeny and Snell 1962) or the τ_x of Emond and Mason (Emond and Mason 2002), have been developed to solve different limitations of common methods.

Second, the agreements among rankings must then be combined to identify a compromise or a consensus. The objective is to select the ranking that maximizes the average correlation with (or, equivalently, minimizes the average distance to) the *M* rankings. Different strategies and algorithms can be used for complex problems (Amodio et al. 2016; Emond and Mason 2002).

In the context of the proposed prioritization strategy and similar to the previous strategy, the suggested approach includes:

- Extract the *N!* permutations without repetition of the *N* envisioned measures
- For each permutation, measure the agreement with the remaining *M* rankings using one of the available metrics
- Choose the combination that verifies the defined consensus criteria

3.6 Identification of sequence of implementation

The proposed approach is an iterative process that must be repeated (steps 2 to 6 in **Figure 2**) until the sequence of implementation for all measures is obtained. In its first iteration, the entire set of risk reduction measures is ranked from best- to worst-suited, and the best measure is selected as the first to be implemented. At each new iteration, the new base state is defined from the previous implemented measures and the effects of the remaining proposed measures are analyzed. The process is applied again, but to the set of measures not including the ones selected from the previous iterations. A sequence of measures is finally obtained after this process is consecutively followed. Hence, the procedure does not intend to choose between different alternatives but prioritizes them by assuming that sufficient time and resources would allow all of them to be implemented. Although the final sequence may not be systematically the optimal option, it is intended to be the most agreed not only among all the climate projections but across the different probability configurations.

For each iteration, the decision time horizon and the time of implementation of the measures must be re-assessed based on the efficiency of the previous measures and on other factors such as the remaining funding capacity or the program of scheduled maintenance works.

4 CASE STUDY

The proposed methodology was applied to the case study of a Spanish dam from the Duero River Basin Authority. The Santa Teresa dam is a concrete gravity dam built in 1960 with a height of 60 m and a length of 517 m. The reservoir has a capacity of 496 hm^3 at its normal operating level and is bound by the Santa Teresa dam and a smaller auxiliary dike. The dam is equipped with a spillway regulated by five gates capable of relieving a total of 2,017 m^3/s with two bottom outlets each having a release capacity of 88 m^3/s.

The effects of climate change on the failure risk of this dam through the end of the 21st century were assessed by Fluixá-Sanmartín et al. (2019). It is worth mentioning that, although there may be other sources of uncertainty embodied in other risk components, in this assessment a first-order probabilistic analysis (Pate-Cornell 2002) for the structural response was carried out. This assumes a mean conditional failure probability for each loading state ($p(f|e)$ from Eq. (1)), which allows us to focus on the influence of climate-related uncertainties.

An overall risk increase is expected based on most scenarios, which indicates significant risk uncertainty as given by the dispersion in the climate projection inputs. This highlights the difficulty of unequivocally defining recommendations for dam owners and managers on how to develop and implement risk reduction strategies. Such issues impose a need to address the associated uncertainty of climate modeling under a decision-making approach. Therefore, this approach was used to define a robust decision-making strategy for risk reduction under climate uncertainty based on the procedure displayed in **Figure 2**.

4.1 Risk estimation

The authors used in Fluixá-Sanmartín et al. (2019) a risk model for the dam with the iPresas software (iPresas 2019) to compute the associated failure risks for current conditions and for future climate scenarios. This study integrated the various projected effects acting on each component of the risk, and was based on existing data and models from different sources such as climate projections, historical hydro-meteorological data or the water resource management model. It is worth mentioning that the reservoir's exploitation rules were extracted from the current Hydrological Plan of the Duero River Basin (Confederación Hidrográfica del Duero 2015) and were adapted based on the the expected population evolution in the study area. A complete description of the model and the methodology followed to obtain future risks can be found in Fluixá-Sanmartín et al. (2019).

The analysis was applied using 21 climate projections (CPs) extracted from the World Climate Research Programme (WCRP) Coordinated Regional Downscaling Experiment (CORDEX) project (Giorgi et al. 2009) that encompassed three RCPs (RCP2.6, RCP4.5 and RCP8.5). This gave a total of 47 combinations of CPs and RCPs (**Table 4**).

The results were obtained over four periods (1970-2005; 2010-2039; 2040-2069; and 2070-2099), which were used as reference points (years 2005, 2039, 2069, and 2099, respectively) to interpolate the risk and failure probability for any given year. Accordingly, the evolution of risk for each CP–RCP combination through the end of the 21st century was calculated.

4.2 Risk evaluation

The USBR tolerability criteria (USBR 2011) was applied to determine the convenience of implementing mitigation measures. These tolerability guidelines were represented on an f-N graph where the vertical axis represents the failure probability and the horizontal axis represents the average life loss, which can be obtained by dividing the social risk by the failure probability.

Table 4. List of climatic projections (CP) used in the case study showing the driving GCM, ensemble member, institute, and RCM for each where the RCP is available.

ID	Driving GCM	Ensemble	Institute	RCM	RCP2.6	RCP4.5	RCP8.5
CP1	CNRM-CERFACS-CNRM-CM5	r1i1p1	CLMcom	CCLM4-8-17		x	x
CP2	CNRM-CERFACS-CNRM-CM5	r1i1p1	SMHI	RCA4		x	x
CP3	ICHEC-EC-EARTH	r12i1p1	CLMcom	CCLM4-8-17	x	x	x
CP4	ICHEC-EC-EARTH	r12i1p1	KNMI	RACMO22E	x	x	x
CP5	ICHEC-EC-EARTH	r12i1p1	SMHI	RCA4	x	x	x
CP6	ICHEC-EC-EARTH	r1i1p1	KNMI	RACMO22E		x	x
CP7	ICHEC-EC-EARTH	r3i1p1	DMI	HIRHAM5	x	x	x
CP8	IPSL-IPSL-CM5A-LR	r1i1p1	GERICS	REMO2015	x		
CP9	IPSL-IPSL-CM5A-MR	r1i1p1	IPSL-INERIS	WRF331F		x	x
CP10	IPSL-IPSL-CM5A-MR	r1i1p1	SMHI	RCA4		x	x
CP11	MOHC-HadGEM2-ES	r1i1p1	CLMcom	CCLM4-8-17		x	x
CP12	MOHC-HadGEM2-ES	r1i1p1	DMI	HIRHAM5			x
CP13	MOHC-HadGEM2-ES	r1i1p1	KNMI	RACMO22E	x	x	x
CP14	MOHC-HadGEM2-ES	r1i1p1	SMHI	RCA4	x	x	x
CP15	MPI-M-MPI-ESM-LR	r1i1p1	CLMcom	CCLM4-8-17		x	x
CP16	MPI-M-MPI-ESM-LR	r1i1p1	MPI-CSC	REMO2009	x	x	x
CP17	MPI-M-MPI-ESM-LR	r1i1p1	SMHI	RCA4	x	x	x
CP18	MPI-M-MPI-ESM-LR	r2i1p1	MPI-CSC	REMO2009	x	x	x
CP19	NCC-NorESM1-M	r1i1p1	DMI	HIRHAM5		x	x
CP20	NCC-NorESM1-M	r1i1p1	SMHI	RCA4			x
CP21	NOAA-GFDL-GFDL-ESM2G	r1i1p1	GERICS	REMO2015	x		

An initial limit was set at a failure probability of 10^{-4} years^{-1}, which is related to individual risk, public responsibility of the dam owner, and protecting the image of the organization. A second limit was set for social risk, suggesting a maximum of 10^{-3} lives/year. These limits define two areas. The upper (lower) area indicates that the risk reduction measures are more (less) justified when further from the limit lines. Moreover, a limit on consequences is placed on the value of 1,000 lives. If the risk is to the right of this line, risks should be evaluated carefully, ensuring the as-low-as-reasonably-practicable (ALARP) considerations are addressed. The ALARP suggest that tolerable risks should only be assumed if their reduction is impracticable or the cost of such reductions is disproportional to its safety gain.

Figure 4 presents the results corresponding to the year 2019, which were calculated using linear interpolation of the risks for the four different periods described before. Each point represents the 2019 projected dam risk situation based on a certain CP-RCP combination. The USBR recommendations suggest that none of the cases indicate an urgent need for risk reduction measures.

However, the results show a progressive deterioration of the dam risk conditions for most of the projections. For example, **Figure 5** shows the risk in 2059 is confronted with the USBR tolerability criteria. As risk progresses with time, more cases are found to be above the tolerability limits. Therefore, the need for risk mitigation becomes progressively more important.

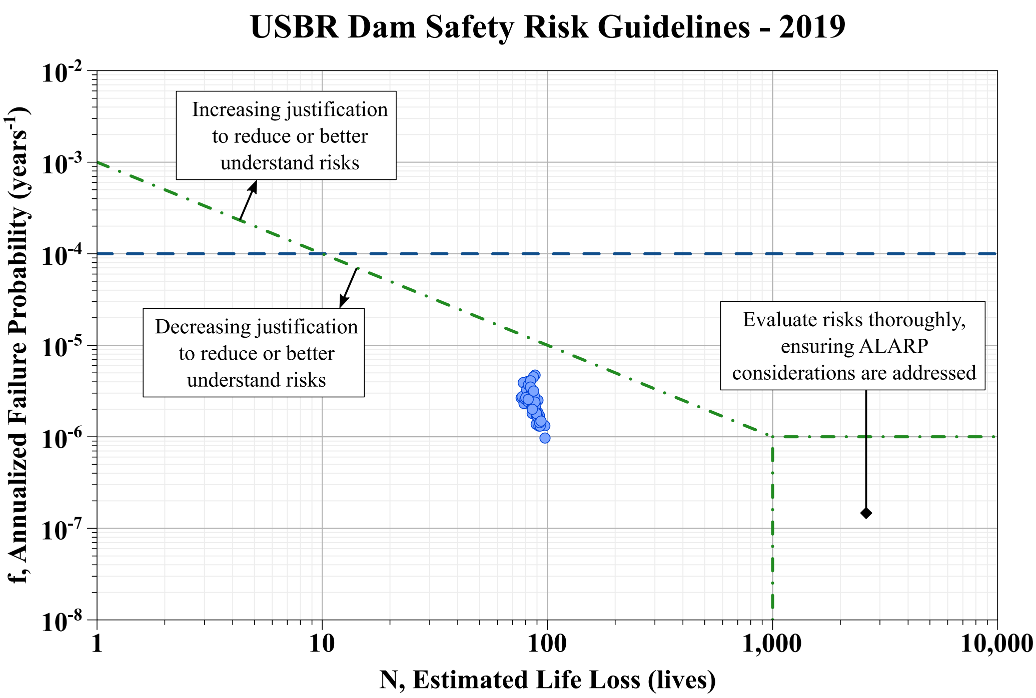

Figure 4. USBR tolerability criteria and f-N points representing the estimated failure probability and loss of life based on the risk results for 2019.

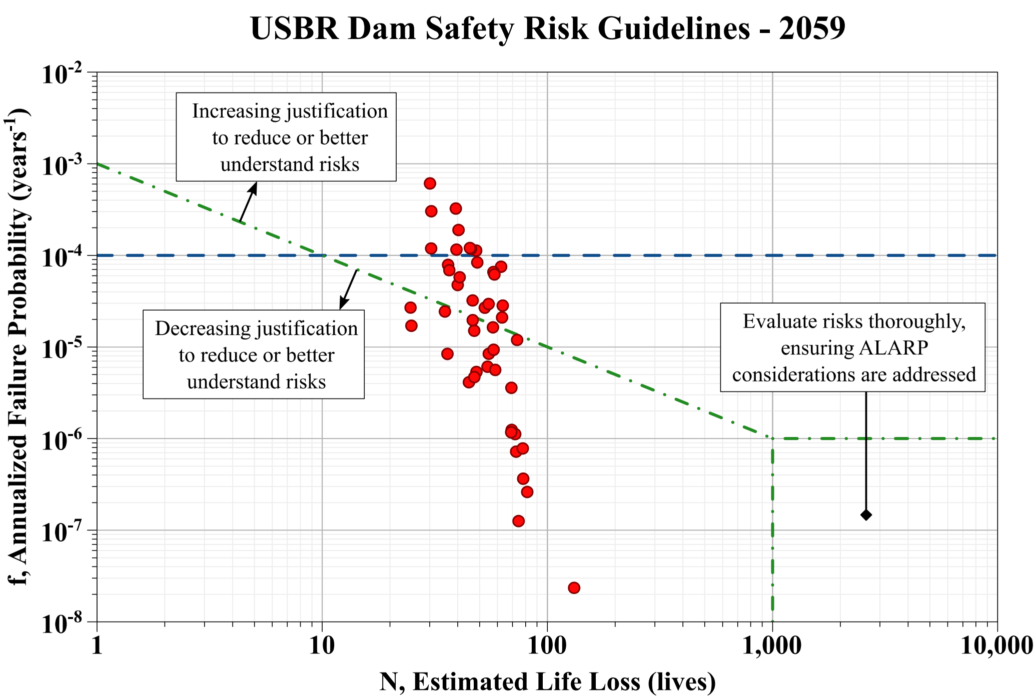

Figure 5. USBR tolerability criteria and f-N points representing the estimated failure probability and loss of life based on the risk results for 2059.

4.3 Definition of risk reduction measures

The results justify the implementation of risk reduction measures to address risk in the medium and long term. Four measures are proposed based on prior risk analyses performed on a set of dams from the Duero River Basin Authority (Ardiles et al. 2011; Morales-Torres et al. 2016) combining the recommendations of failure mode identification working sessions and the actions foreseen by the dam manager. Quantitative risk results were used to select the most efficient options for further analysis and prioritization. In addition, two measures (C and D) were designed selecting the most efficient configuration of wall height and spillway crest level by comparing its costs with the risk reduction achieved. A description of each measure is presented below, and the corresponding implementation and operation costs are provided in **Table 5**.

- **Measure A**: Implementation of an emergency action plan. This measure reduces the potential societal consequences of dam failure by applying adequate protocols and systems for warning and evacuating the downstream population. Measure A does not impact the failure probability or economic risk, but only affects social risk as it only addresses the exposure of at-risk populations.
- **Measure B**: Construction of a continuous concrete parapet wall with height of 1.5 m along the dam and the auxiliary saddle dam. The direct effect is an increased dam freeboard, which reduces the probability of overtopping.
- **Measure C**: Lowering the spillway crest level by 1.5 m and replacing the Tainter gates that regulate the outflows. This increases the discharge capacity through each gate from 403 m^3/s at its nominal operating level up to 588 m^3/s.
- **Measure D**: Implementation of an enhanced maintenance program for spillway gates. The gate reliability is assumed to progressively deteriorate with time. Under this measure, the individual reliabilities are conserved, which reduces future dam failure risks.

Table 5. Implementation and maintenance costs for each risk reduction measure.

Measure	Implementation cost	Operation cost
A	601,528 €	30,076 €/year
B	479,413 €	0 €/year
C	2,817,365 €	0 €/year
D	0 €	82,750 €/year

4.4 Estimation of the efficiency in risk reduction for each measure

The risk model was used to compute the evolution of social and economic risks through the end of the 21st century by considering the effects of each measure on the different dam safety components. This assesses the efficiency of each measure and for each future scenario by applying the AACSLS indicator (Fluixá-Sanmartín et al. 2020). One of the key factors in assessing the efficiency of each measure using the AACSLS is the definition of the decision time horizon, which is the upper limit of the time interval during which the investment is justifiably financed (Lind 2007). Given the age of the Santa Teresa dam and the functionality of the proposed risk reduction measures, the decision time horizon was set to 40 years. Thus, the study period is from 2019 to 2059.

Once the indicator was computed, the four proposed risk reduction measures were ranked for each of the 47 CP-RCP combinations using only the AACSLS indicator (lower AACSLS values indicate more efficient options). **Figure 6** shows the uncertainty behind the analysis as the number of combinations that lead to a specific priority order for each measure. As a result, it appears that Measure A is ranked primarily in the 2nd position and Measure D is in last position. However, it remains unclear what positions (1st and 3rd) occupy Measures B and C. This highlights the need for a more robust approach to define the sequence of measures to implement.

4.5 Multi-model combination

Next, the Multi-Prior Weighted Scenarios Ranking method was applied. The robustness of the four measures were first evaluated, and a total of 100 probability configurations were established. For each configuration, a set of 47 probabilities were generated and associated with each CP and RCP combination. The scenario weighting scheme was then used to produce purely random probabilities. Next, the expected utility of each measure *j* was calculated following Eq. (3) to establish the measure ranking based on the increasing expected utility. For each probability configuration, the measures were prioritized and a table analogous to **Table 2** was obtained from their prioritization orders.

4.6 Prioritization strategy

Once the rankings were obtained for the 100 tested probability configurations, the four prioritization strategies were applied. These measures are the average ranking, likelihood of rankings, index of ranking coincidence, and consensus ranking (in this case, using the Spearman's ρ rank correlation coefficient to quantify the agreement between rankings).

4.7 Identification of the implementation sequence

The procedure from steps 2 to 6 of **Figure 2** has been sequentially applied to identify the optimal sequence of risk reduction measures. The procedure was repeated at each implementation step (i.e., considering each step as the case with the previous measures already implemented to analyze the effects of the remaining proposed measures) until the sequence of measures was finally obtained.

At each step of the implementation, the same prioritization ranking of measures was consistently obtained with all the tested methods, which highlights the robustness and high confidence of the choices made. It is noted that a waiting period of 2 years was fixed between each measure implementation to account for budget limitations and the completion of measures. Subsequent application of this procedure led to the following sequence of measure implementation (**Table 6**):

- 1st step: Measure B
- 2nd step: Measure A
- 3rd step: Measure C
- 4th step: Measure D

The homogeneity of the obtained results is in contrast with the uncertainty shown in **Figure 6**, which emphasizes the convenience of the proposed approach.

Moreover, the risks in 2059 (after the 40-years decision time horizon) resulting from the sequential implementation of the four measures were computed and are presented in **Figure 7**. Starting with the base case situation in 2059 (**Figure 5**), a progressive reduction in both the failure probability and life loss is observed as the measures are implemented. It is noted that some measures, such as B or C, reduce both the failure probability and the average consequences. However, as mentioned above, Measure A only reduces the societal consequences and does not impact the failure probability.

Table 6. Order of implementation in the sequence of risk reduction measures based on each of the proposed prioritization strategies.

Strategy	Measure			
	A	B	C	D
Average ranking	2	1	3	4
Likelihood of rankings	2	1	3	4
Index of ranking coincidence	2	1	3	4
Consensus ranking	2	1	3	4

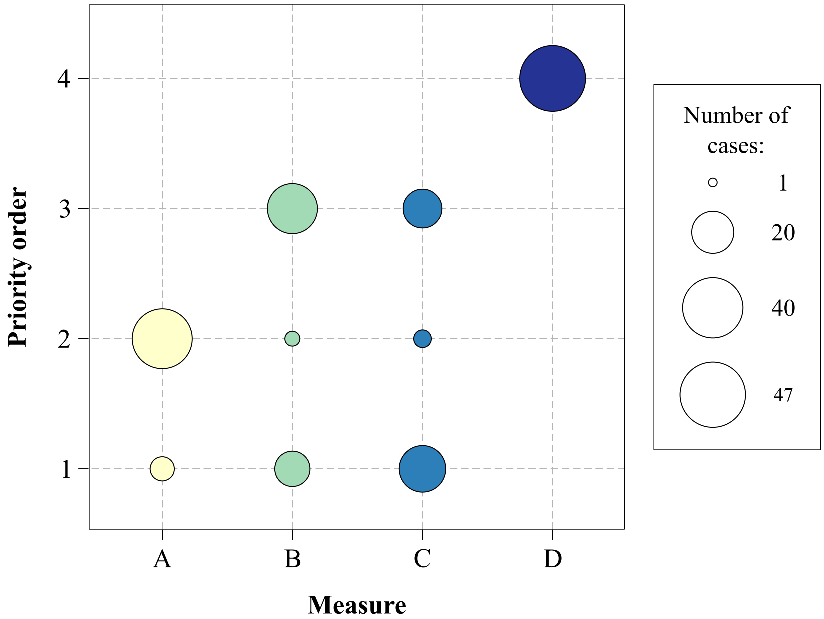

Figure 6. Number of cases (CP-RCP combinations) leading to the priority order for each risk reduction measure.

Furthermore, as the implementation of the measures progresses, progressively fewer cases are above the tolerability criteria. For example, after implementing Measure A, all cases are below the social risk limit of 10^{-3} lives/year. While this would imply that the implementation of further measures is no longer justified, risk is expected to continue to rise through the end of the 21st century. Therefore, the measures that may not be entirely justified for a specific period could be necessary when considering a wider time horizon.

It is noted that current USBR guidelines do not include the temporal dimension in their criteria, indicating they do not account for the influence of climate change. Therefore, a re-definition of such recommendations is worthwhile. After revising these criteria, the proposed methodology is re-defined or techniques to update its application are established.

Moreover, in order to assess the sensitivity of the results to the weighting scheme selected, the analysis has been repeated using the “Equal weights” scheme instead of purely random probabilities. In this case, the procedure consists of a unique configuration where all climate projections have equal probabilities. According to the results, the same sequence of measure implementation as in **Table 6** has been obtained for the four proposed prioritization strategies.

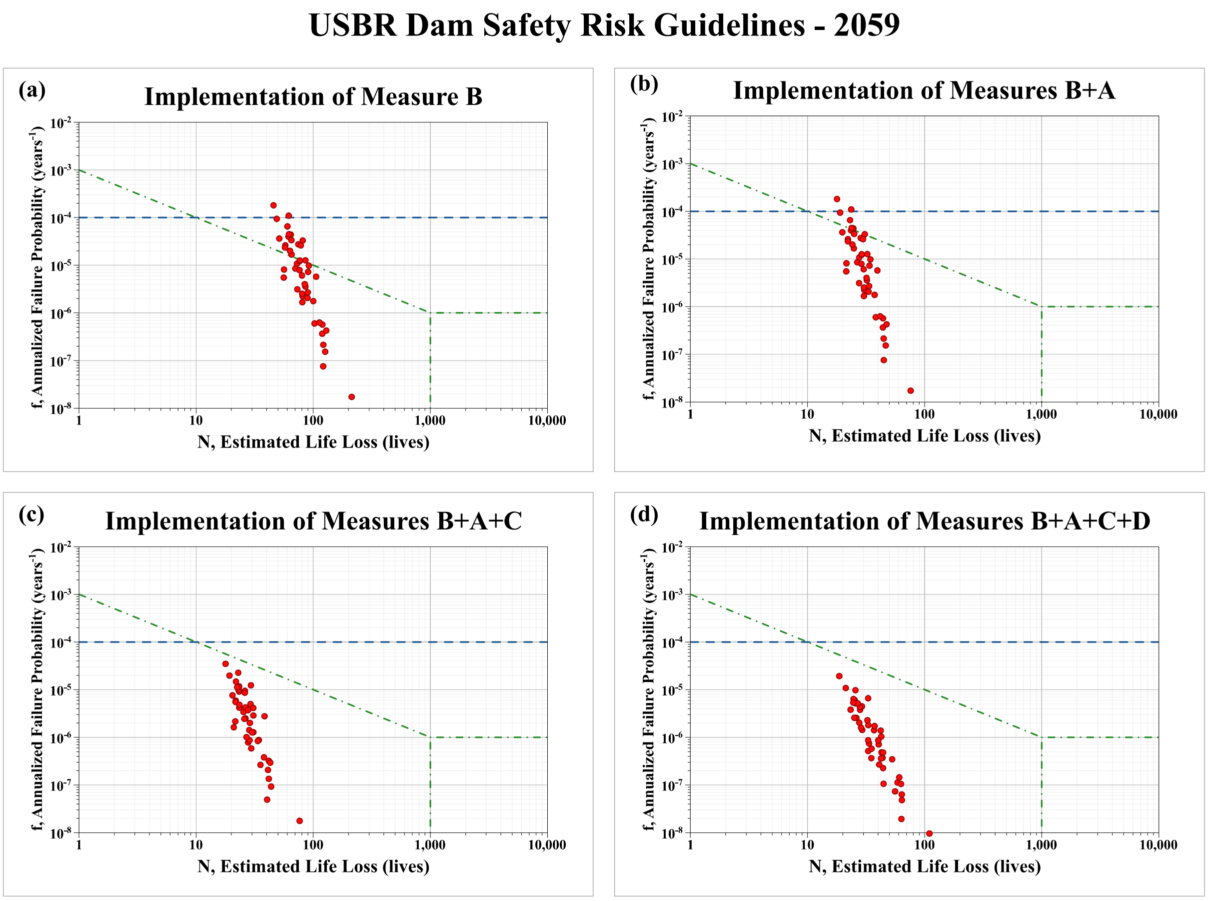

Figure 7. Representation of the f-N points for the estimated failure probability and loss of life in 2059 after sequentially implementing (a) Measure B, (b) Measures B and A, (c) Measures B, A and C, and (d) Measures B, A, C and D.

5 CONCLUSIONS

Advances are being made towards adaptation approaches for dam risk management under the influence of climate change to help dam owners and safety practitioners in their decision-making processes. However, some factors remain a challenge and must be comprehensively integrated in such a process. In particular, further efforts that address the intrinsic uncertainties related to climate change are needed. This work presents an innovative approach on dealing with climate uncertainty applied to dam risk management based on robust decision-making strategies coupled with climate scenario probabilities assignation.

The proposed Multi-Prior Weighted Scenarios Ranking approach encompasses a complete procedure that allows defining and ranking risk reduction measures based on their efficiency on short- to long-term operations. The methodology helps to establish the consensus sequence of risk reduction measures to be implemented by integrating the uncertainty of future scenarios. It guides the dam practitioner in selecting the scenario weighting scheme as well as in defining the alternatives prioritization strategy, while introducing a new index (IRC) to obtain the likelihood of an ensemble of rankings for measures. The usefulness of the approach consists of aggregating multiple scenarios by applying and adapting the expected utility theory and the multiple priors approach, providing different results than simply considering a compilation of states. The final result will be expressed as the most agreed sequence of measures, not only among all the climate projections considered, but across the different probability configurations.

The developed methodology was applied to the case study of a Spanish dam for which the risks were quantified for present and future states using a quantitative risk model. The results revealed the need for mitigation measures to reduce risks in the medium and long term. Four risk reduction measures were proposed and their effects analyzed. Different prioritization strategies were tested and the resulting measure rankings were compared for each implementation step using the AACSLS indicator and a multi-model combination procedure. Finally, the most favorable sequence of measure implementations was obtained, which prioritizes those that reduce future accumulated risk at lower costs. The results indicate a homogeneous portrayal of the most convenient and agreed courses of action for risk adaptation. It was demonstrated that such a methodology helps cope with uncertainty that arises from the existence of multiple climate scenarios while adopting a cost-benefit approach to help optimize economic resources in dam risk management.

Although climate change-related uncertainty was addressed in this work, other sources of uncertainty remain highly influential in dam risk assessment and should be integrated in a comprehensive approach for decision-making. Some of these include incomplete knowledge of the dam behavior (e.g., fragility curves) while others are affected by the intrinsic variability of climatic and environmental systems, or the effect of socioeconomic scenarios on the exploitation rules of the dam-reservoir system. Moreover, the assessment of climate change impacts on dam safety incorporates a series of limitations that remain a challenge, as raised in previous references of the authors (Fluixá-Sanmartín et al. 2018, 2019, 2020). This type of strategies would therefore benefit from complete analyses combining all sources of uncertainty, thus allowing to support decisions based on all of them altogether. Under this perspective, the advantage of using the risk modelling approach is that the impact of all types of uncertainties on each component of the risk can be easily identified and analysed, taking into account their potential interrelations.

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