

# A look at new and existing hydropower projects on the Zambezi under climatic uncertainty

**J.P. Matos**

École Polytechnique Fédérale de Lausanne  
Laboratory of Hydraulic Constructions  
EPFL-ENAC-IIC-LCH  
GC A3 504, Station 18  
CH-1015 Lausanne, Switzerland

**A.J. Schleiss**

École Polytechnique Fédérale de Lausanne  
Laboratory of Hydraulic Constructions  
EPFL-ENAC-IIC-LCH  
GC A3 504, Station 18  
CH-1015 Lausanne, Switzerland

## Introduction

Dams have a prominent role in the Zambezi River Basin (ZRB). Affecting local economies, ecosystems and society, they are vital for electricity generation, flood management, and seasonal transfers of water for irrigation. In spite of its already relevant regional impact, hydropower in the ZRB still has a large potential for expansion.

While holding great development opportunities to be seized, Africa has been identified as particularly vulnerable to climate changes, and the ZRB is no exception to that. With increasing demands to the Zambezi system in terms of water and energy, and rising challenges in the form of less runoff due to climate change, it is paramount to plan ahead. In particular, it must be understood how major hydropower schemes will interact with large and ecologically invaluable wetlands in order to support balanced decisions for the future of the basin.

The present contribution constitutes an attempt to quantify how future climate developments can affect the system while accounting for modelling uncertainty and, more relevantly, while taking into account adaptation through optimizations to the operation of major dams. A data-driven approach was adopted to model the runoff produced by Regional Climate Models (RCM) and, based on its results, predictive uncertainty was estimated. In order to run the optimization model, runoffs at input locations were artificially generated as to allow them to 1) incorporate climate changes stemming from the chosen scenario and RCM, and 2) reflect modelling uncertainty.

Results show that, using a data-driven approach, modelling errors and uncertainty do not allow for a clear quantification of how the water resources in the ZRB are going to be affected. Despite this, in the case of a high rise in mean temperatures there will be a substantial loss of water due to increased evaporation. Under more moderate changes impacts on energy production and ecosystems are difficult to distinguish from the climate variations that are characteristic of the region.

## 1. Background

This work focuses on the upper and middle regions of the ZRB (Fig. 1). In these regions, the river flows from its headwaters in Northwestern Zambia past the vast Barotse Floodplain, down the world-renowned Victoria Falls, along the border with Zimbabwe, and through the massive Kariba reservoir to the edge of the Cahora Bassa lake, on the Mozambican border. The main stem of the Zambezi is joined by several tributaries flowing from the south and, relevantly, the Kafue river, from the North. A detailed description of the ZRB can be found in Schleiss and Matos [2016].

The largest impoundment in the area is Kariba hydropower system, with 1450 MW installed capacity which can be increased. Also, Kariba lake is the largest reservoir in the world by volume with approximately 180 km<sup>3</sup>. About 80% of its inflows are runoff from the upper Zambezi that pass over Victoria Falls, while the remaining 20% come from tributaries mainly to the South. A new hydropower project, the Batoka Gorge dam, is planned for the reach between Victoria Falls and Kariba (1600 MW). To the north, the Kafue hydropower system relies on the Itezhi-Tezhi reservoir (6 km<sup>3</sup>) for flow regularization. While the Itezhi-Tezhi dam is not a large producer of electricity, its releases flow through approximately 250 km of wetland – the Kafue Flats – before being turbined at the Kafue Gorge dam (900 MW), downstream of which the Kafue Gorge Lower dam is under development (750 MW). These five dams and the Kafue Flats comprise the system studied here (Fig. 2).

Aiming to quantify how future scenarios may affect water resources in the basin, this work builds on a previous publication dedicated to studying how, through the optimization of dam operations, existing and future hydropower schemes can best interact with ecologically valuable wetland areas [Matos *et al.*, 2016]. There, a multi-objective algorithm was used to find the Pareto set of operation strategies that span between the cases of highest energy production and lowest impact on historical ecological indicators. In this contribution that work is extended to analyze the behavior of the system under climate changes. In order to do so, future runoff is computed from RCM outputs resorting to data-driven models (feedforward artificial neural networks) [Haykin, 1994; ASCE Task Committee on Application of Artificial Neural Networks in Hydrology - Rao S. Govindaraju, 2000a, 2000b] and a model to compute predictive uncertainty [Matos and Schleiss, 2017].

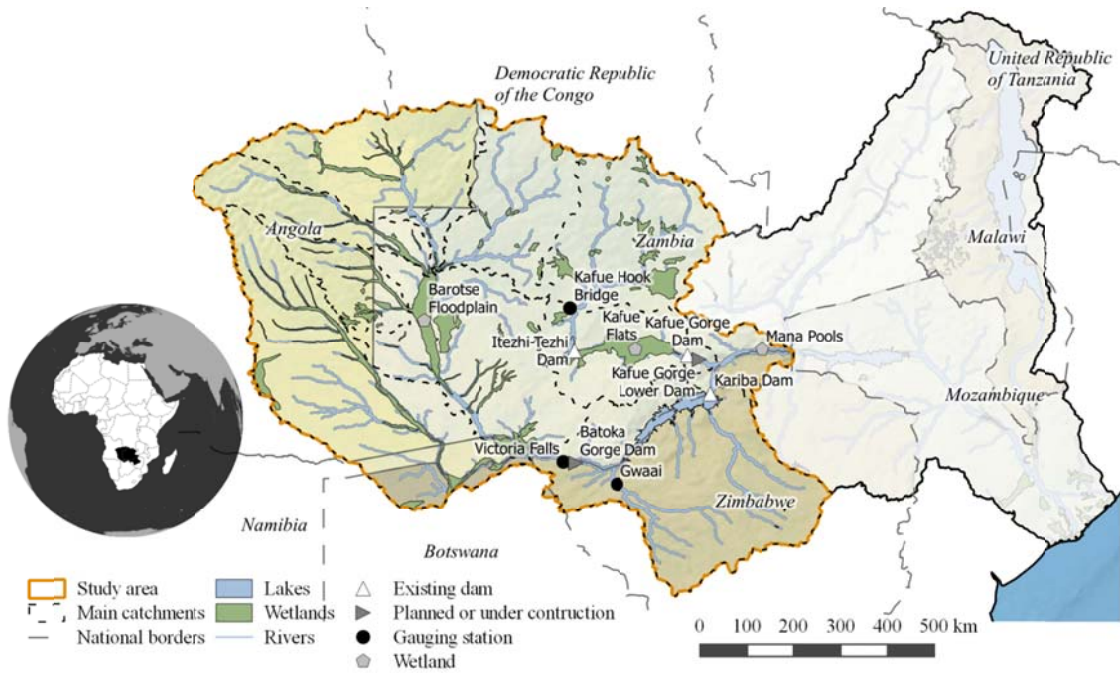


Fig. 1. Region under analysis with main features highlighted.

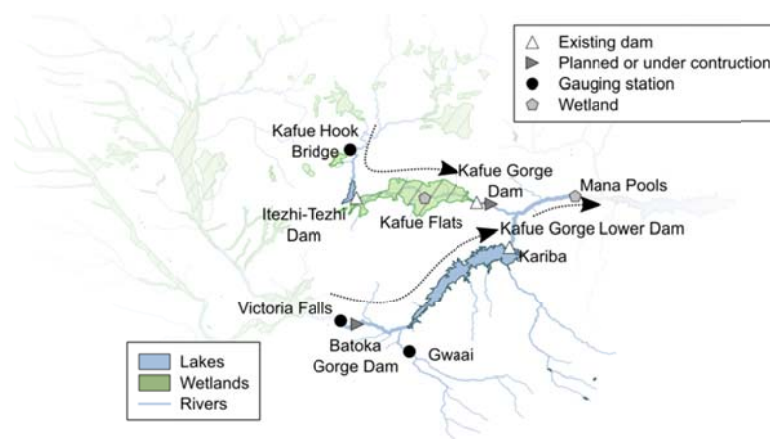


Fig. 2. System under study. Adapted from Matos *et al.* [2016].

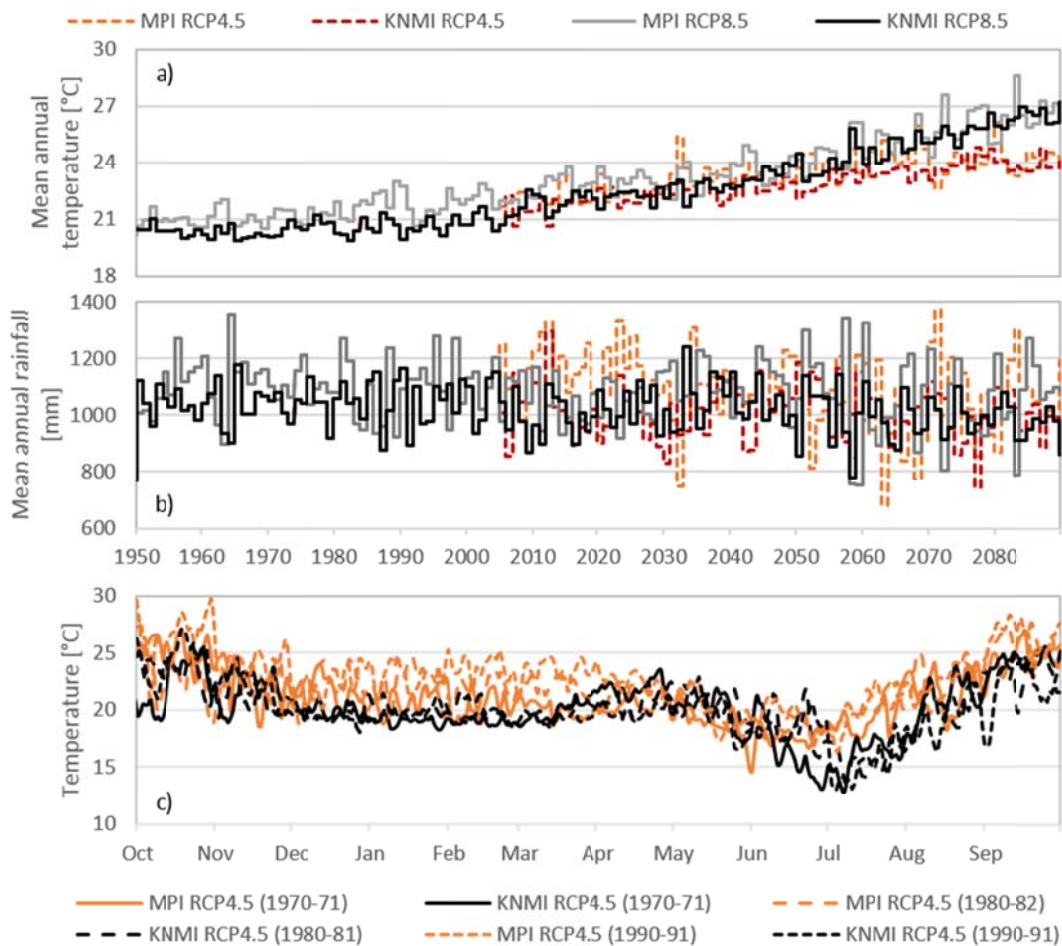
## 2. Methodology and data

### 2.1 Generation of synthetic flows affected by climate change

The base data used to characterize inflows to the system were precipitations and temperatures retrieved from a Regional Climate Model (RCM). In the scope of this work RCM data from the Coordinated Regional Climate

Downscaling Experiment (CORDEX) were used. The REMO2009 RCM model (Max Planck Institute for Dynamics of Complex Technical Systems Magdeburg) was employed with forcing by the MPI-ESM-LR Global Circulation Model (GCM; Max Planck Institute for Meteorology). Initially, another CORDEX regional data set, by the Royal Netherlands Meteorological Institute (KNMI), was also considered (RCM: RACMO22T, GCM: HadGEM2-ES), but due to difficulties in reproducing historical Zambezi and Kafue flows from the data, that analysis was not pursued. Several studies look into the precipitations simulated by RCM over Africa [e.g. *Endris et al.*, 2013; *Kalognomou et al.*, 2013; *Gbobaniyi et al.*, 2014].

The impacts of two Representative Concentration Pathways (RCP) were tested over the ZRB: RCP4.5 and RCP8.5. A description of both pathways can be found in Wayne [2013]: RCP 4.5 was developed by the Global Change Assessment Model modeling team at the Pacific Northwest National Laboratory's Joint Global Change Research Institute, USA. It is a stabilization scenario in which total radiative forcing is stabilized shortly after 2100, without overshooting the long-run radiative forcing target level. RCP 8.5 was developed using the MESSAGE model and the Integrated Assessment Framework by the International Institute for Applied Systems Analysis, Austria. RCP 8.5 is characterized by increasing greenhouse gas emissions over time, representative of scenarios in the literature that lead to high greenhouse gas concentration levels.

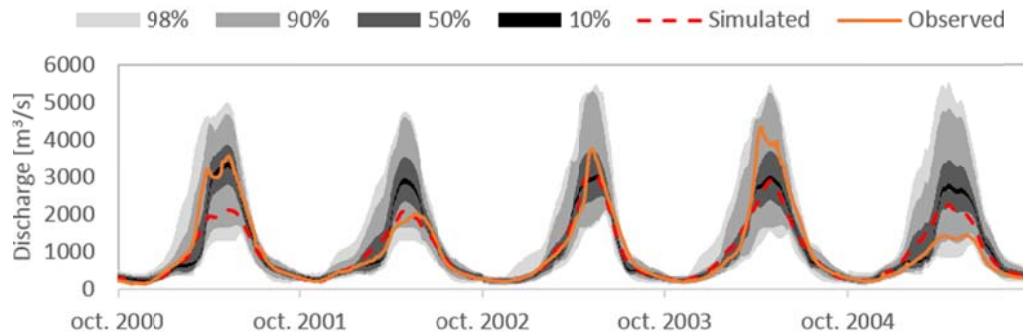


*Fig. 3. Illustration of MPI and KNMI regionalized climate simulation models for historical (1950-2005) and prediction (2006-2090) periods over the study area using data from experiment RCP 4.5. a) mean annual temperature; b) mean annual rainfall; and c) comparison of three years of daily temperature data (1970-71, 1980-81, and 1990-91).*

Temperature and precipitation evolutions for both RCPs are depicted in Fig. 3. As can be seen in the figure, there is a substantial disagreement in terms of both precipitation and temperature among MPI and KNMI RCMs, and this only considering annually averaged values. The future scenarios characterized by RCP4.5 and RCP8.5 lead to clearly observable trends regarding rising temperatures (Fig. 3a). This is not the case for precipitation (Fig. 3b). It is

interesting to remark that, even focusing on temperature, the change of RCM is much more important than the inter-annual variations (Fig. 3c).

The data from the CORDEX MPI RCM dataset was then used to predict daily flows in Victoria Falls and Kafue Hook Bridge – the main water inlets to the analyzed system (Fig. 1). As previously mentioned, a feedforward Artificial Neural Network (ANN) was used to accomplish this. As can be guessed from the disagreement between MPI and KNMI data, the RCM outputs do not approximate with a great level of detail precipitation distributions over the study area, even when the validation period is considered (1950 to 2005). Naturally, this has a significant impact on the simulated flows – which stray significantly away from the historically observed values (Fig. 4).



*Fig. 4. Depiction of simulated discharges at Victoria Falls using the MPI RCM model precipitation and temperature as inputs. Illustration of predictive uncertainty bands around the simulations.*

Being considered that the ANN simulations have too much uncertainty over the historical period to provide sufficiently accurate predictions of future responses, the predictive uncertainty bounds of the simulations were computed (Fig. 4). Based on these predictive uncertainty bounds and accounting for the autocorrelation of the hydrological series, synthetic datasets were created for two periods: near future (2010-30) and far future (2060-80). The models for simulation and creation of synthetic series accounting for predictive uncertainty being the same for both future scenarios (RCP4.5 and RCP8.5) and periods (2010-30 and 2060-80), differences between series are exclusively due to the RCM inputs and the stochasticity of the creation process.

The resulting synthetic series, presented in Fig. 5, were then used as the basis upon which the dam operations in the analyzed system were optimized. That optimization is described below.

## 2.2 Multi-objective optimization of reservoir operations

As previously mentioned, the multi-objective optimization approach used here was introduced in Matos et al. [2016] and most of this subsection originates from that contribution. In short, the optimization relies on a mass-balance routing system and allows for variations in base outflows and characteristics of environmental flow pulses in the dams with relevant storage within the system. The environmental pulses are defined by their duration, timing, and peak discharge. When reservoir levels fall significantly below the rule curve, the environmental flow is reduced as a means to spare water. An illustration of an environmental flow setting on Kariba dam is given in Fig. 6.

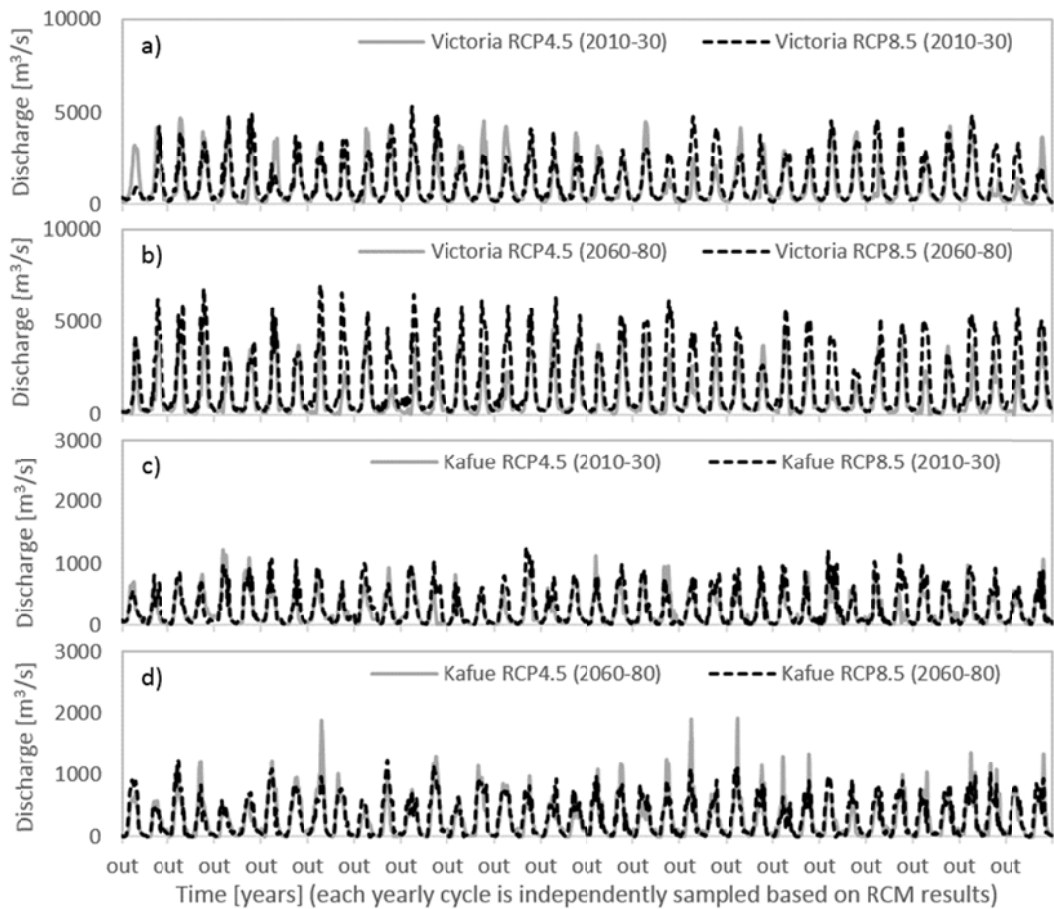


Fig. 5. Synthetic series generated at Victoria Falls and Kafue Flats for both RCPs (4.5 and 8.5) and analysis periods (2010-30 and 2060-80). The series are characteristic of each period and RCP. They are annually independent, which means they can span more than the 20 years of each reference period.

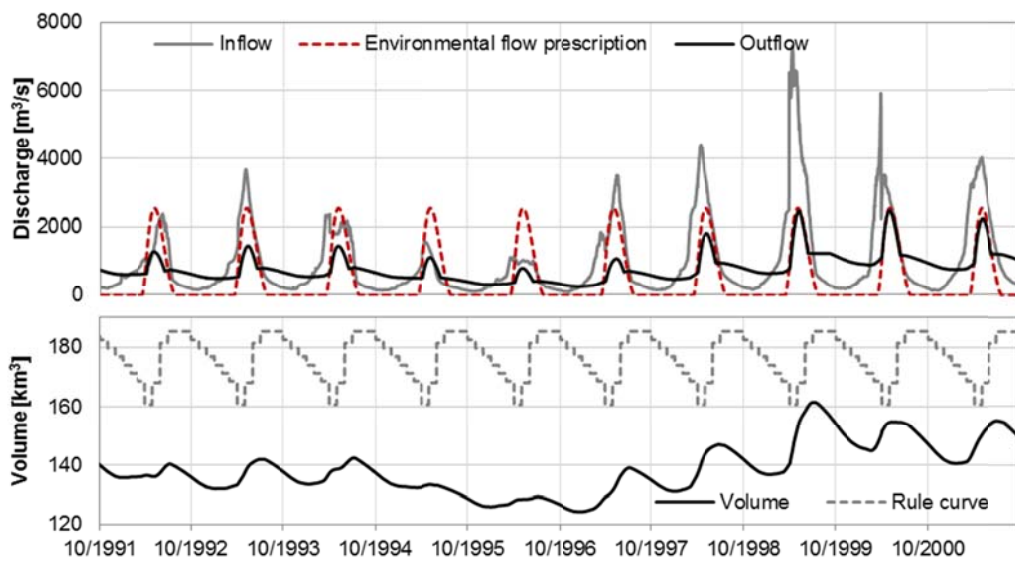


Fig. 6. Region under analysis with main features highlighted [Matos et al., 2016].



While the computation of the produced energy is straightforward given the hydraulic system's characteristics, evaluating hydrological impacts is more complex. In line with the work by Cohen Liechti et al. [2015], environmental criteria were based on the Range of Variability Approach (RVA) proposed by Richter et al. [1997]. The flow was analysed according to magnitude, volume, timing, and duration:

- $D_{Q30}$  – Discharge matched or exceeded 30 days during the year. Characterizes the annual flood peak;
- $D_{Q335}$  – Discharge matched or exceeded 335 days during the year. Characterizes the low flow period;
- $D_{VolQ30}$  – Volume of the discharge matched or exceeded 30 days during the year. Characterizes the annual volume;
- $D_{DateQ1}$  – Date of the maximum discharge. Characterizes the timing of the annual flood peak;
- $D_{Dur\hat{Q}30}$  – Duration of the flood peak. Characterizes the duration of the annual flood peak, taken as the number of days in the year in which the flow is higher than a certain threshold. This threshold was taken as the 0.92 quantile of the observed discharge.

For each chosen indicator, the degree of alteration is a function of the simulated years which fall within the band delimited by the 25<sup>th</sup> and 75<sup>th</sup> “unaltered or natural” percentiles. It is computed according to Eq. (1):

$$D_k = \frac{|N_k^o - N_k^e|}{N_k^e} \quad (1)$$

where  $D_k$  is the degree of alteration for indicator  $k$ ,  $N_k^o$  is the number of years in which the indicator falls within the specified “natural” band, and  $N_k^e$  represents the expected number of years to be in the same range (in this case 50%).

The aggregation of the results for the various indicators and selected locations of environmental interest is done resorting to Eq. (2):

$$D = \frac{1}{N \cdot K} \sum_{i=1}^N \sum_{k=1}^K D_{k,i} \quad (2)$$

Where  $D$  stands for the total degree of alteration,  $N$  represents the number of locations,  $K$  is the number of indicators, and  $D_{k,i}$  is the indicator  $D_k$  computed at location  $i$ .

### 3. Results and discussion

The results of the optimization procedure are presented in Fig. 7. In it the Pareto sets spanned between maximal energy production and minimum degree of alteration are depicted. Before interpreting results, however, some aspects should be emphasized:

- The RCM data that was used does not necessarily lead to good flow predictions in the ZRB. Of course, it presents series of precipitation and temperature that can be converted into runoff, but whether that runoff is truly characteristic of the ZRB is a matter of debate. In fact, the historical predictions based on MPI RCM data could be considered poor (Fig. 4). If it is difficult to reproduce observations at Victoria Falls and Kafue Hook Bridge from 1950 to 2005, there is a high chance that future predictions will be equally, if not more, affected by errors.
- A data-driven approach such as an ANN relies on training data to “learn” a certain functional relationship. In this case, that functional relationship translates precipitation and temperature into runoff. Training is, however, bound to historical observations (1950 to 2005). This poses a problem when evaluating the effects

of rising temperatures (Fig. 3a) as their annual averages should go up significantly towards the end of the 21<sup>st</sup> century in both RCP4.5 and 8.5 scenarios, well beyond the range observed from 1950 to 2005. It is very likely that the model, calibrated using historical observations, does not “know” how to cope with increased temperatures.

- The ZRB is marked by a very significant climate variability, with strong decadal cycles that can be clearly seen in historical records. Climate changes are now adding to this climate variability but, concerning runoff, their impact is still arguably within the variability bounds. In terms of dam operations and energy production – and particularly at Kariba – inter-annual cycles are extremely important. In fact, while the reservoir can withstand well one or two unusually dry years amidst a series of wet ones, it’s active volume will not suffice to guarantee power production at full capacity during a decadal series of dry years. These decadal cycles do not seem to be captured in the RCM precipitation simulations, and they are not accounted for in the procedure that was followed to produce synthetic discharges at Victoria Falls and Kafue Hook Bridge. As such, it is expected that energy production is overestimated.

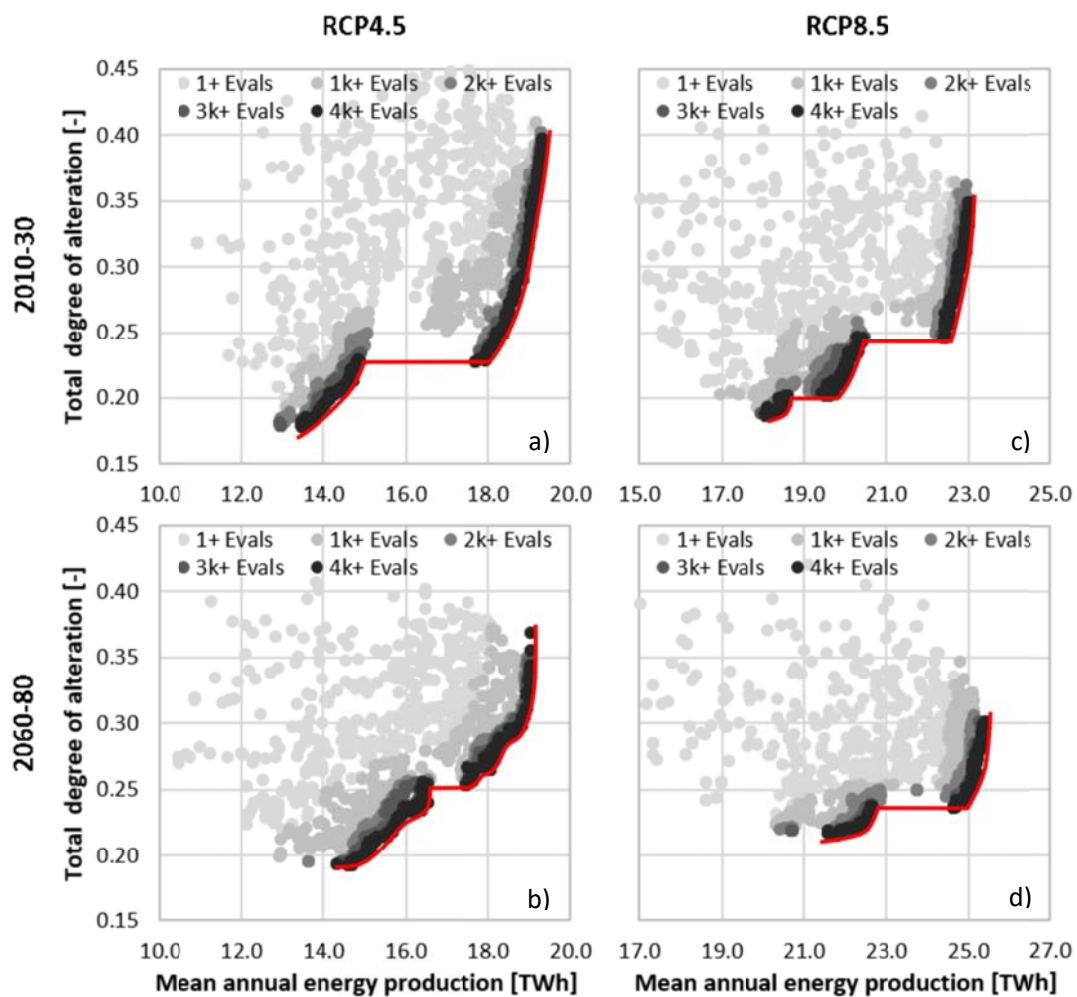


Fig. 7. Pareto sets of optimal solutions for each analysis period and RCP scenario. Top row: period of 2010-30. Bottom row: period of 2060-80. Left column: RCP4.5. Right column: RCP8.5.

When the previous information is considered, it is evident that the results in Fig. 7 should not be interpreted in absolute terms. Something can, however, be learned from near- and far-future scenario comparisons, which should be more reliable for the less extreme RCP4.5. From Fig. 7a and Fig. 7b, it can be seen that under RCP4.5 the best-case scenario of hydrological alteration marginally worsens from 2060-80. Despite this, hydropower production is not significantly affected and high ecological concerns on the part of dam operators may be rewarded with more energy production. According to the trained data-driven model, RCP8.5 scenarios would actually lead to more

energy production, and this in spite of increased evaporation in the Kariba reservoir due to the higher temperatures. These results are counter-intuitive and, in light of the expected difficulty of the ANN models to cope with high temperatures, they are considered unreliable. It is hard to tell whether regional precipitation will increase or decrease in the far-future (Fig. 3b). If it remains within historical bounds, though the effect of added evaporation alone (in the Kariba reservoir, the Barotse Floodplain, the Itzhi-Tezhi reservoir, and the Kafue Flats) the available runoff should be significantly reduced.

It is believed that the use of a conceptual or physically based hydrological model to characterize future runoff scenarios [e.g. *Kling et al.*, 2014] should be preferred to a data-driven one. Despite that, it remains unclear whether the RCM models are sufficiently detailed and accurate to depict the true hydrological responses of the ZRB. Due to this, accounting for predictive uncertainty is paramount.

#### 4. Conclusions

The present contribution constituted an attempt to quantify how future climate developments can affect the ZRB while accounting for modelling uncertainty and, more relevantly, while taking into account adaptation through optimizations to the operation of major dams.

Overall, it appears that ecological flow pulses (artificial floods) that are beneficial to the maintenance of historical hydrological regimes can be introduced in the system with relatively small impacts on energy production. Despite this, given the data-driven modelling strategy that was used, it is hard to draw reliable conclusions for high temperature increase scenarios such as RCP8.5. Under the RCP4.5, which is arguably more likely to take place than RCP8.5 due to the increasing societal awareness towards climate change and the mounting political will to engage the problem, modeling uncertainty does not allow for clear-cut results regarding whether the Upper and Middle ZRB's hydropower systems will be significantly affected by climate change. At least using the methodology employed in this work, it appears the regional hydropower systems may be capable of coping with future hydrological changes without major impacts on energy production or strongly augmented hydrological alterations.

#### Acknowledgments

The authors would like to acknowledge the Zambezi River Authority, ZESCO, and the Department of Water Affairs of Zambia, who collected and provided the data needed to undertake this study. Also, the authors thank the Swiss Competence Center Environment and Sustainability (CCES) for having provided the funding needed to accomplish this project.

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## The Authors

**J.P. Matos** is a Postdoctoral Researcher at the Laboratory of Hydraulic Constructions of the École Polytechnique Fédérale de Lausanne (EPFL). His PhD focused on the development of a hydrologic model for the Zambezi River basin using satellite data and artificial intelligence techniques. He holds an MSc in Civil Engineering from the Technical University of Lisbon and has worked as a consultant in hydrology, water supply, and sanitation. He is interested in the fields of risk assessment, machine learning, remote sensing, and optimization of complex non-linear systems.

**Prof Dr A.J. Schleiss** graduated in Civil Engineering from the Swiss Federal Institute of Technology (ETH) in Zurich, Switzerland, in 1978. After joining the Laboratory of Hydraulic, Hydrology and Glaciology at ETH as a research associate and senior assistant, he obtained a Doctorate of Technical Sciences on the topic of pressure tunnel design in 1986. He then worked for 11 years for Electrowatt Engineering Ltd in Zurich, and was involved in the design of many hydro projects around the world as an expert on hydraulic engineering and underground waterways. In 1997 he was nominated full professor and became Director of the Laboratory of Hydraulic Constructions (LCH) at the Swiss Federal Institute of Technology Lausanne (EPFL). LCH’s activities comprise education, research and services in the field of both fundamental and applied hydraulics and design of hydraulic structures and schemes. The research focuses on the interaction between water, sediment-rock, air and hydraulic structures as well as associated environmental issues and involves both numerical and physical modeling. Prof. Schleiss is also involved as an international expert on several dam and hydropower projects throughout the world. From 2006 to 2012 he was Director of the Civil Engineering program of EPFL and Chairman of the Swiss Committee on Dams. In 2006 he obtained the ASCE Karl Emil Hilgard Hydraulic Prize as well as the J. C. Stevens Award. He was listed in 2011 among the 20 international personalities that “have made the biggest difference to the sector of Water Power & Dam Construction over the last 10 years”. For his outstanding contributions to advance the art and science of hydraulic structures engineering he obtained in 2015 the ASCE-EWRI Hydraulic Structures Medal. After having served as vice-president between 2012 and 2015 he was elected president of the International Commission on Large Dams (ICOLD) in 2015.