Supplementary Materials: Hydropower Future: Between Climate Change, Renewable Deployment, Carbon and Fuel Prices

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Introduction

This supplementary material provides a more detailed description of the results found in the study. Firstly, results found in the calibration and validation of both the hydrological and the management model and the procedure followed in the assessment of their accuracy was described. Finally, the results of climatic and price scenarios for the case study are illustrated.

S1.1 Calibration and Validation of the Hydrological model

To define all the input parameters, it was necessary a phase of calibration and validation, to obtain the Nash variables. So that the simulated discharge is similar to the real one. As the available years of real runoff are from 2012 to 2016 and are available in hourly scale but the hydrological model works at daily scale, it is necessary to convert. Observed data were converted to daily scale, computing a daily average from the hourly discharge available.

The year of calibration chosen was 2012, while the period 2013–2016, was used for the validation. The accuracy of the model was evaluated considering 3 error indices:

- *Root Mean Square Error (RMSE)*, which represents the sample standard deviation of the differences between predicted values and observed values. It indicates the order of magnitude of the error and the perfect correspondence is when RMSE = 0;
- *Nash Sutcliffe Efficiency (NSE)* [1], which represents the relative magnitude of the residual variance ("noise") associated to the measured data variance ("information"). It varies in the range of $-\infty$ to 1. Where an efficiency of 1 symbolizes perfect match between the simulated and observed data, while efficiency of 0 (E = 0) denotes the simulated values being precise as the mean of the observed data. Closer is the efficiency value to 1, precise is the model;
- *Volumetric Deviation Coefficient* (ΔV) [2] is an indicator that shows if the annual simulated volume, overestimates or underestimates the observed one.

The process of calibration was made by varying the values of n_{LIQ} and k_{LIQ} and taking the minimized *RMSE* and ΔV and maximized *NSE*, searching a compromise between the expected behaviours of all the indices and a good representation of the whole behaviour of the incoming discharge.

As explained the model was firstly calibrated on the first year of available data, 2012. To check the efficiency of the model to describe the hydrological transformations that take place in the basin, the discharge computed at daily scale were considered. Since, the final aim of this study is to compute the variations in the hydroelectric production, from these discharges the cumulated volumes were computed. The comparative analysis of the volumes is important because it allows the possibility not only to detect differences, but also to understand what the causes of this difference are, and which component is not simulated properly in the model. To make the results as comparable as possible, the outlet of the catchment modelled was taken in correspondence with the point where the real measurements are taken. The discharge simulated were compared to the actual observed data collected, and the cumulated volumes computed from these were also compared. As in past studies [3], the model behaved better at a monthly scale, so the discharge at this scale were also simulated and indices of errors were computed.

A detailed analysis over the calibration year and the other validation years are shown in Figures S1–S3**.** For 2012 the behaviour of the volumes is very good and the general trend is well represented, with the final volume that is equal to the observed one. Some errors can be found in spring, where the incoming volume tend to be anticipated. This could be for errors in liquid precipitations. About the other years, it can be observed that, in the July of the year 2013 and 2015, the two curves start to diverge, and the error propagates in the following months. This is something attributable probably to errors in the phase of accumulation and ablation of snow, that cause an overestimation of snow runoff in that period. For 2014 and 2016 the two curves are quite similar. The situation becomes better if the monthly scale is considered (Figure S3), where the curves are better in phase and the general behaviour is very well represented. In order to give a more detailed explanation of the results, error indices have to be considered. Table S1 reports the error indices computed both in the daily and monthly scale of discharge. In addition to the RMSE, the NSE and the ΔV, the average discharges were computed, and the indices were also computed at monthly scale. Furthermore, the performances of the model deeply improve if a monthly resolution is considered, this is something evident in the precedent works [3] and is attributable to the fact that working in a wider scale would reduce the uncertainty and the variability associated to the hydrological processes that take place in the catchment.

Firstly, if the average discharge is considered, it can be seen that the values predicted by the model are very similar to the one measured in almost all the years. There is an overestimation in 2013 and underestimations in 2015 and 2016, but if the average values are considered the it remains constant. This is a confirmation of the observations done considering the daily discharge, where the general behaviour is very well represented, even with local differences due to both errors in the modelling of the processes at a so reduced scale and in the observed data.

S1.2 Calibration and Validation of the Management Model

The present work aims to compare the past incomes with the expected incomes for the future years, to check the impacts of both climate changes and future prices of electricity. We first calibrated the parameter of the algorithm with the observed data. Beside validating the model, it provides comparable incomes. Therefore, the values and the parameters involved are not necessarily the best ones and the corresponding income is not the absolute optimum, it represents what can be defined as an “observed optimum”. The management model was calibrated considering the available data of generated power and daily volumes in the reservoir for the year 2012, and from the corresponding prices of electricity, an estimation of the real annual income was calculated.

The calibration was done in 2 steps:

- First, we tested jointly the results of all the possible combinations (continuous/binary schedule and strategy for reservoir limits) in the objective function and of an increase in the number of steps to do the simulation.
- Second, the effect of an increase in the number of restarts was tested.

For evaluating the results, the model was forced to predict initial and final volume equal to the ones observed for the year 2012 and the followings available years, by introducing a penalty function that would penalize every difference simulated. This was done to enhance the possibility of comparing the incomes simulated and to check the capability of the model to work in the similar conditions that were observed. In the future projections, this issue will be solved using a method based on the future data of run-off and prices of electricity, that will be explained more in detail in the section about the results. The second feature that has been introduced is link to the price and so on the optimization. In the simulation, prices are known in advance, that means that the model will understand easily when to produce, knowing in advance the prices and when there will be the highest values. In fact, in *spot electricity market*, the one simulated in the present work of thesis, prices are known at least 1 day before. This could explain some differences between what is simulated and what is observed.

S1.2.1 The Effect of Parameters of Threshold Algorithm

The three parameters of the Threshold algorithm are *steps*, *rounds* and *restarts*. Where rounds act on the number of times the threshold is reduced, while steps act on the computations introduced and the resources spent. We explored steps ranging from 10^2 to 10^6, and values of rounds increasing from 3 to 7. Therefore, the whole number of steps considered, that is a sort of representation of the computational weight of the simulation, as the product of these two parameters and which lies in the range between 300 and 7,000,000. It wasn't considered the effect of number of restarts higher than 1 in a first phase. The aim of this part of the work was to check which of the possible combinations is the best one. In the present work, the term "best" can be thought to have two main meanings. Best means faster in reaching the observed income, so low computational weight requested, but it also means ability to reach higher values of income in long-term, so with a higher number of steps. So that the choice of a particular setting in the model is mainly linked to the fact that it will permit to reach easily and with low computational weight the observed income.

We evaluate the model with four combinations, namely 1,2,3 and 4. The combinations 1 and 2 are characterized by the fact that the schedule is characterized by values among 0 and 1, so the algorithm predicts them not only to work or not to work but also at which percentage of their maximum power they have to work. While the, combination 3 and 4 both rely on the "0 or 1 method", so the schedule of the turbines may only be put 0 or 1. This means that the by defining the scheduled, predicts the turbines only to work (when there is 1) or not to work (when there is 0), but they will work at their maximum power.

The values found for these four combinations were normalized by the observed income for the year 2012, and the results obtained are plotted in Figure S4. All the possible combinations show a more or less good behaviour, that is embodied by the fact that all of them reach the observed income, even with a different number of steps. Obviously, it would have been a trouble if the optimization model wasn't able to reach the observed income, even at a higher number of steps, because it meant that the model was working in a sub-optimal configuration. From a first look at the general trend, it can be stated that the general behaviour of combination 4 and 3 are very similar, and the same can be told if combinations 1 and 2 are considered. Table S2 clearly shows how combinations 3-4 and 1-2 are similar to each other. In an absolute way, combination 4 appears to be the best one in all the two meanings explained above:

- It reaches the observed optimum with a number of steps equal to 3×10^5, very lower than the ones needed by the other combinations, for which it is reached for 7×10^5 steps;
- At a higher number of steps, the value of optimum obtained is higher, even if the differences among all the combinations tend to thin.

The results obtained aligned to what could have been expected at the beginning of the simulation. The differences between combination 3 and 4 are only linked to the penalties on the volume, in fact, the results show that constraints put may enhance the possibility to faster reach the observed income than not putting. Therefore, it becomes clear that combination 3 and 4 will be faster and will have a very fast increase in the objective function, while the other two combinations will show a slower trend, even if always a positive one. According to what appears from the behavior of the combinations, the 4 is the best one, even if it has also to be checked its capability in representing the volumes. Due to reason linked the policy of the utility company, is not possible to plot directly the annual volumes, for this reason, were considered the volumes normalized over the maximum volume possible in the reservoir.

The volumes simulated by the optimization model are at hourly scale, which was transformed in daily scale, taking as reference value the volume in the reservoir at midnight of every day. This was done to compare with the observed data which is in daily scale. The comparison of the two curves in Figure S5 shows a good fitting, with the curves being in phase even with local differences. Except for initial and final volumes that, as told before, were forced to be equal to the real ones, the general trend is very similar to the observed one. The model prescribes the emptying of the reservoir in the first 4 months of the year, then filling up to October and then the subsequent emptying.

As outlined above slight differences are present, at the beginning of the year the model tends to keep water inside the reservoir for more days and then at the end of the year tends to empty it faster. The reasons of this behavior can be explained by the fact that the model knows prices in advance, so that it knows exactly when to empty the reservoir and to fill it according to the yearly trend of electricity prices for 2012 (see Figure S6). Figure S6 clearly shows a peak corresponding to the maximum absolute of the prices in correspondence on the beginning of February, and in particular the 36th day of the year. Having known in advance that the prices would be higher on that particular day, the model has kept the water in the reservoir, releasing it when the price was higher and so maximizing the income. Therefore, an overall view of the volumes, states that the model behaves well also in predicting the trend in the volumes, not only avoiding it to go beyond the minimum and above the maximum but also behaving exactly in the same way as the reality. This means that the constraints put in the model, so the penalty function added, are very efficient.

With all the features explained above, it can be accepted as reference configuration the one guaranteed by combination 4, justifying it only in terms of time to reach observed income. In this way Tremorgio is managed using the objective function with a schedule of the turbine given by a sequence of 0 or 1 (even if no substantial difference is found with the sequence of values comprised between 0 and 1) and with a number of rounds equal to 3 and that of steps equal to 10^5. The number of restarts has been put equal to 1 and is necessary to investigate if any improvement is guaranteed by a higher number.

In order to check the influence of the *restarts,* the model was launched with an increasing number of restarts and in particular according to what is stated in Gilli and Winker [4] a range between 2 and 20 were chosen so 3,5,10,15 and 20 restarts. So, the income was computed and then normalized as per the observed one and along the time necessary for doing the simulation was computed. It this section the interest was in understanding if and how restarts would impact the simulation and especially if they permit to reach the observed income with a lower number of steps. In this horizon the necessity of computing the time needed is linked to the possibility of evaluating the effectiveness of the restarts, so to evaluate the trade-off between the time to do the simulation (that increases as the number of restarts increases) and the number of steps requested.

From the analysis of normalized income i.e., the ratio between the simulated and observed income, as seen in Table S3 no significant improvement is gained increasing the number of restarts. The general trend is very similar, even if local and negligible differences appear. This aspect is confirmed by the values in the Table S4, that is barely above the 2%, and in many cases are in the order of the 1%, that represents an improvement negligible. On the other hand, what appears clear is that an increase in a number of restarts determines an increase in the time needed for the simulation. However, for all the results found previously, it was decided not to increase the number of restarts in the simulation, as no substantial improvement is found in the results and substantial time is consumed to perform it.

The best configuration found is the one with 1 restart, 3 rounds and 10^5 steps. The validation was done considering the other years for which data of production were available, i.e., 2013, 2014 and 2015. The aim of this part was to check the behavior of the model using the best configuration found in the calibration phase, i.e., combination 4. The idea was to check how the objective function evolved and if the number of steps and restarts requested to reach the observed income was comparable.

Finally, as done in the case of 2012 the annual volumes were plotted for the three years of validation in Figures S7–S9. The analysis done on the volumes shows a non-perfect fitting among the two curves, the observed and the simulated, even if the general trend seems to be the same and the curves with an upward shift, are in phase for all the three years. This can be explained with the fact that, as shown previously also in the results for 2012, the model doesn't know the real management philosophy used and on the other hand knows the prices in advance. Note, the real volume in the available years of data, never goes above 5 Mm^3, so the volume available in the reservoir is not used completely. The model doesn't know this aspect, and, according to the inflows, tends to accumulate water reaching values of volume higher than the observed one and then releasing it to maximize the income.

For all the aspects outlined above, and according to the previous tables, the decision was to run the optimization model with 7 rounds and 10^5 steps and with a maximum volume equal to the observed maximum. This decision was taken in order to guarantee as much as possible the reliability of the model, avoiding possible underestimations and reducing overestimations. It would have been a nonsense to consider the optimal configuration found in the calibration phase because as shown in Table S5, two years out of three of validation were characterized by an underestimation. In opposition, the configuration chosen is the one according to which the observed income is reached, with an acceptable computational cost, for the 75% of the years considered both in the calibration and in the validation.

S1.4 Hydrological Model Outputs: Tremorgio

By the analysis of Figure S10, it can be inferred that the effects of the climate variations at short-term are not so relevant. An anticipation in the spring peaks for scenarios 2–4 is observed, since increase in the temperature would be translated in an anticipation of the period of the year in which there will be the peak in the ablation of seasonal snow. This effect is not so relevant for 2020, as we are considering a short-term future and in fact can be easily seen that the yellow, orange and red curves are in phase with the dotted one, even if for scenario 4 a higher inflow is seen in April and May and an anticipation in the phase of decrement of the discharge is present. The results don't change for 2025, even if an increment in the spring inflows and the consequent anticipation in the reduction phase is more emphasized. This can be partially explained by the fact that the analysis is focused on a very short term, with a whole increase that is equal to 0.8 °C up to 2025. Also, for climatic scenarios 5–8 the effects of increasing temperatures are negligible.

Figure S11 shows the simulated discharge for 2045 (farther horizon). Considering scenarios 2–4, the curves are no more in phase with each other and their behavior is different. For liquid-only precipitation scenarios, the behavior is almost similar to the previous years (2020 and 2025) but an evident reduction in the annual volume is observed. Hence, at 2045, the effects will be more severe, affecting the inflow to the reservoir. Table S6 presents the reduction of the volumes for 2045, expressed in relative terms with respect to base scenario (scenario 1). Increase in temperature will have a profound impact on the volumes incoming in the reservoir. In fact, even for scenario 2 that is the "softer" one, the reduction of volumes is in the order of the 7.4%, while for scenario 4 the reduction of volumes is in the order of the 11.5%. The results obtained clearly show that if a longer time interval is considered, the temperature increase will result in a reduction of the volumes available for the hydroelectric purpose because the rate of increase in temperatures becomes relevant (2.6 °C in the case of scenario 5). All the considerations done above, is presented in terms of evolution of cumulated volumes for all the scenarios is presented in Figure S12. A progressively lowering of the curves is observed with respect to base scenario along the simulated horizon from 2017 to 2045, underlying an ever-increasing impact of the climate changes.

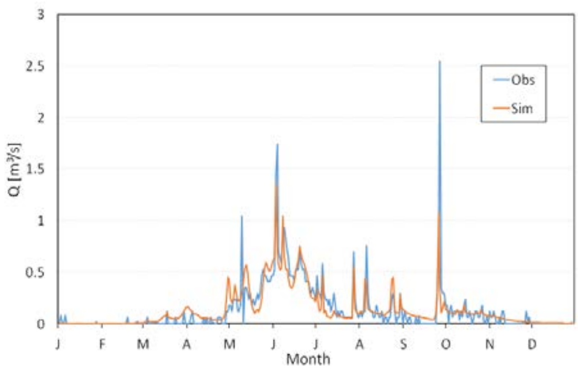
S1.5. Tremorgio Results from Management Model: Impacts of Climate Changes

One important thing that can be outlined from the analysis of the behavior of volumes is that there isn't an evident influence of them on temperature scenarios at a near horizon. For further analysis, the reservoir volume for 2030 and 2045 were compared for the worst scenario (scenario 4) are plotted in Figure S13, considering an increment of temperature that will reach 2.6 °C in 2045, double that for 2030. In fact, the comparison of blue and red lines permits to point out that there is a sensible anticipation in the minimum emptying peak and there will be the tendency to keep higher volumes and higher heads to minimize these losses.

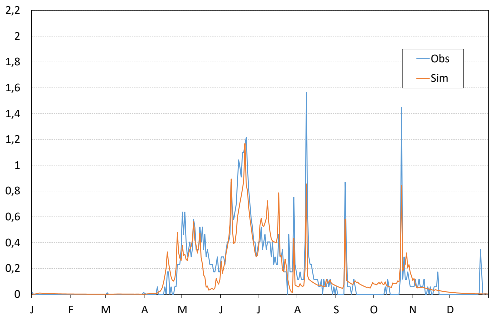
Since, the real maximum volume of Tremorgio basin reservoir is 5.54 Mm^3 instead of the theoretical one of 8.25 Mm^3, because of losses that occur over a certain volume. So, it is also important to analyze, what would be the effect on the management of the reservoir and on the income if the volume can be entirely used. For this analysis, the worst scenario in terms of increase of temperature i.e., scenario 4 at 2045 was calculated, in order to see if fixing of the reservoir losses and consequently an increase of the available volume and net head, could mitigate the effects of the climate change. Figure S14 shows the volumes of the two cases with different maximum volume and the base scenario. The shape of the two curves, as we expected, is the same, in fact, the discharge doesn't change. The initial and final volume found for the case with higher capacity is higher, this is because of the increase in the volume available, in order to maximize the income, the management is done keeping the head as higher as possible. To better understand this in terms of revenue, the income from both cases are shown in Figure S15. With the Increase in capacity the reduction in terms of revenue becomes 7%, so there is a gain of 1% compared to the case with the real volume. The effects of an increase in the maximum capacity aren't so relevant but there is only a small improvement.

S1.6. Tremorgio Results from Management Model: Impacts of Price Scenarios

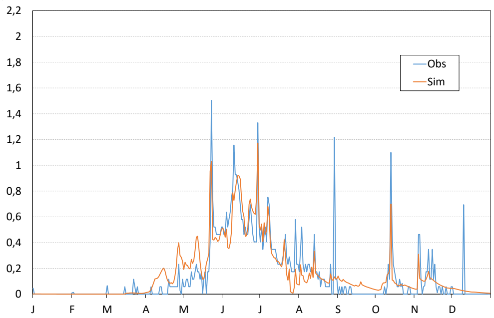
The incomes variation of all scenarios is represented in descending order in Table S7. As already explained, the reduction of the income is found for only three scenarios. In these three scenarios, the prices of fuel and carbon remain at a current level and only increase in renewable resources determines the reduction of electricity price in 2030.



(a)



(b)



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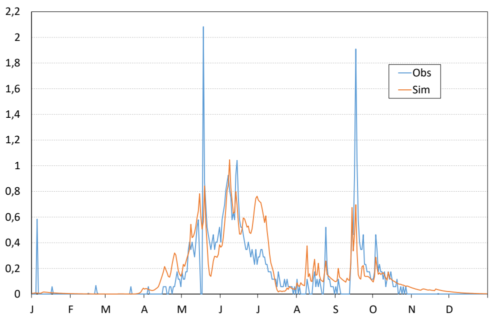

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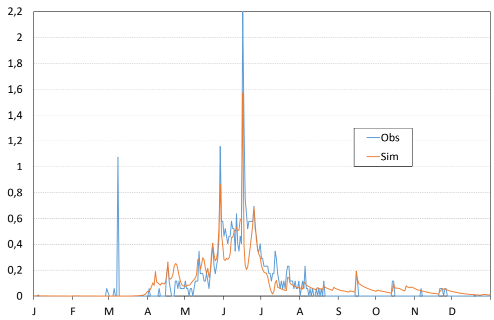


(e)

Figure S1. Comparison of observed and simulated daily discharge of the year (**a**) 2012; (**b**) 2013; (**c**) 2014; (**d**) 2015; (**e**) 2016.

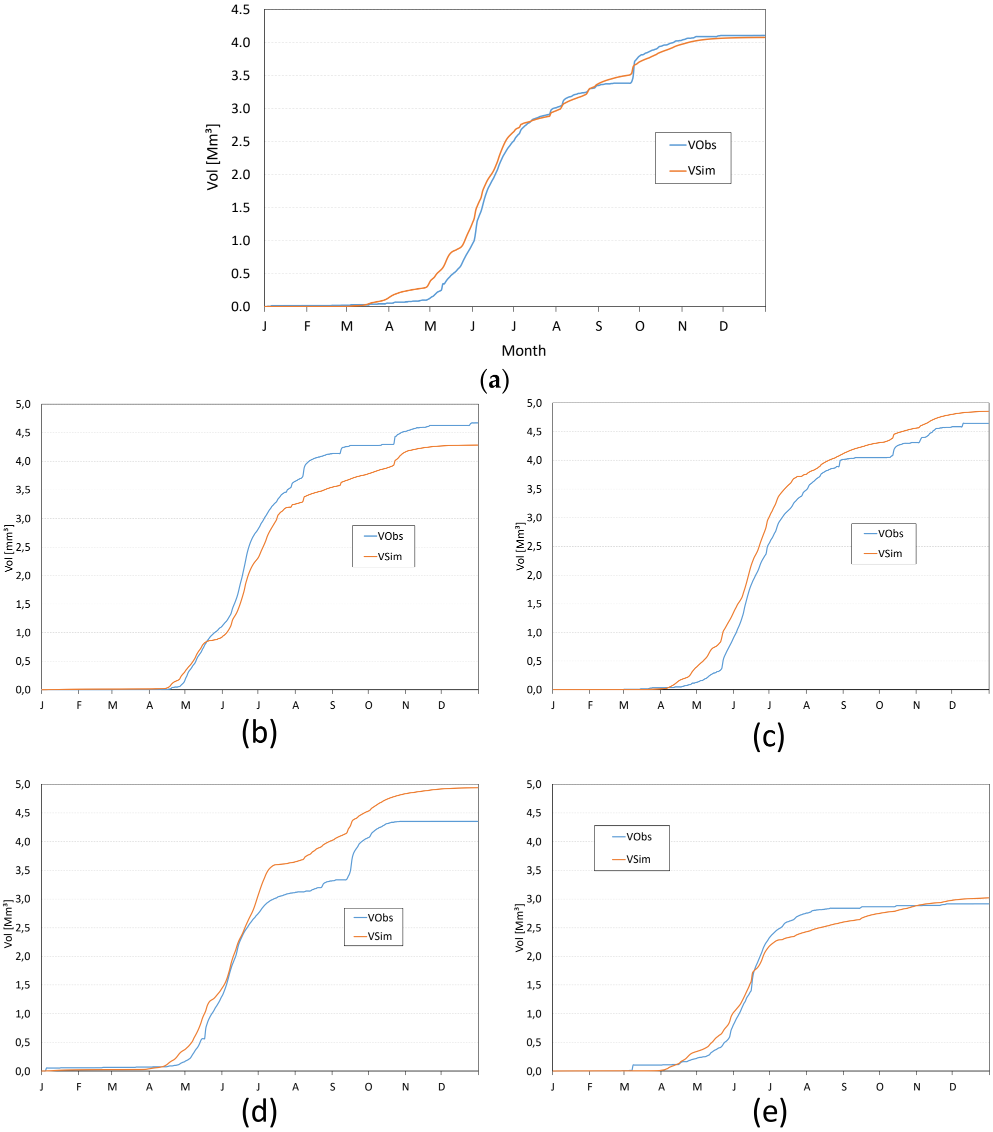
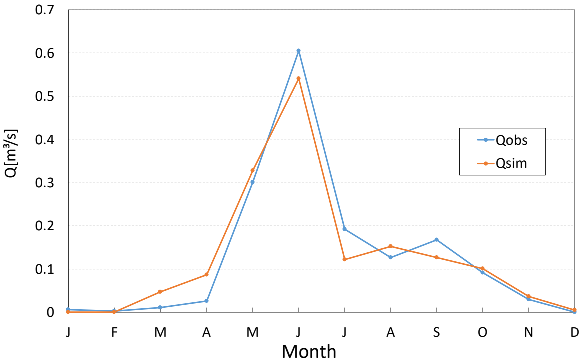


Figure S2. Comparison of observed and simulated daily cumulated volumes of the year (**a**) 2012; (**b**) 2013; (**c**) 2014; (**d**) 2015; (**e**) 2016.



(**a**)

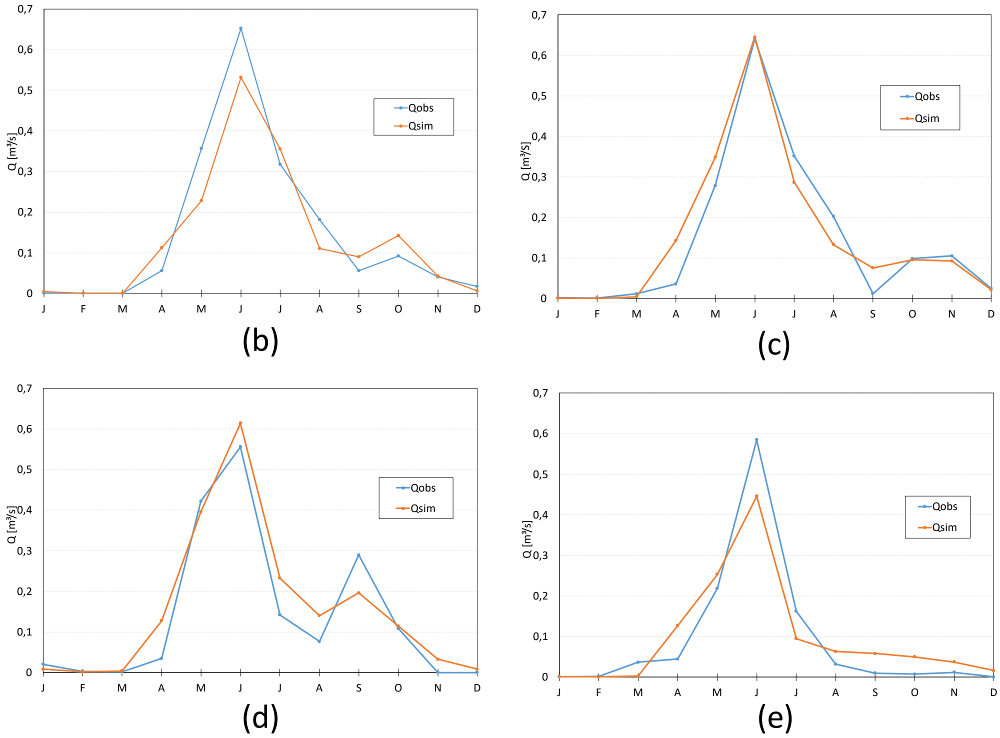


Figure S3. Comparison of observed and simulated monthly discharge of the year (**a**) 2012; (**b**) 2013; (**c**) 2014; (**d**) 2015; (**e**) 2016.

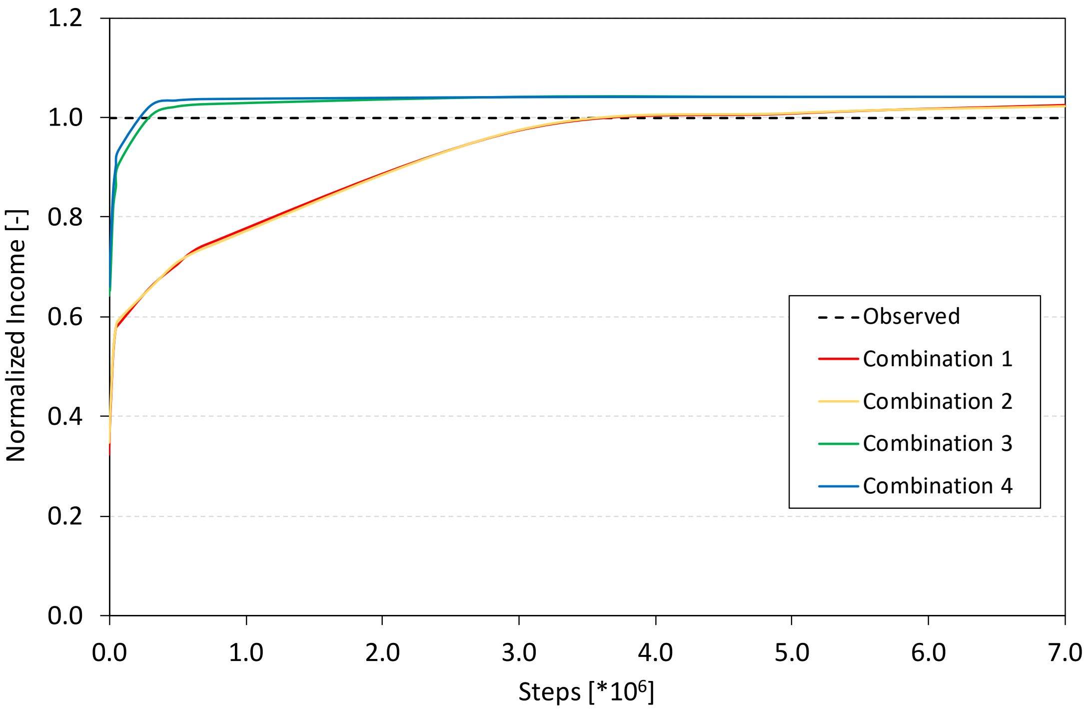


Figure S4. Comparison of the results obtained in terms of income with the four performances analysed, considering a progressively increasing number of steps. The results are normalized over the value obtained for the 2012.

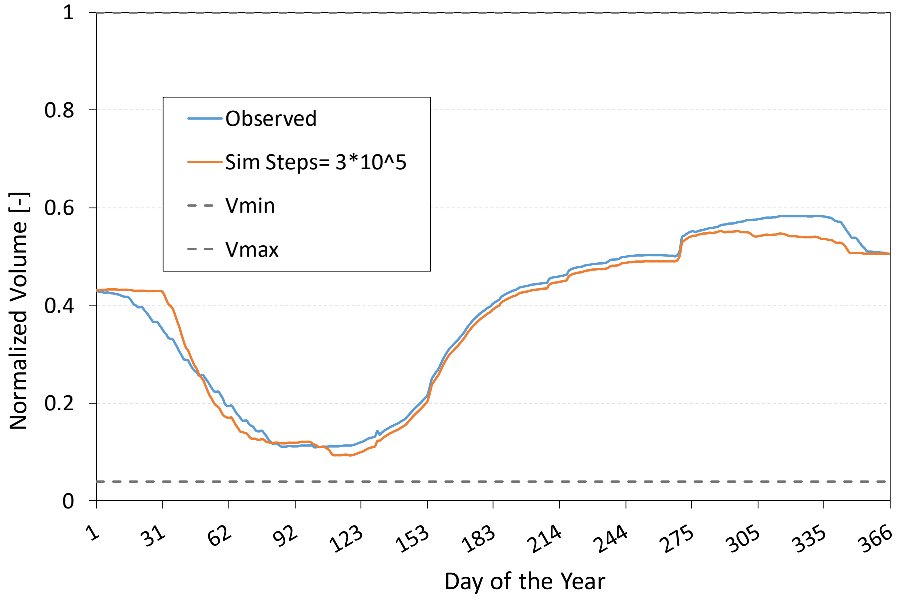


Figure S5. Comparison of the annual volumes simulated with the optimal configuration of parameters and the observed ones. Differences can be found due to the "perfect foresight" condition.

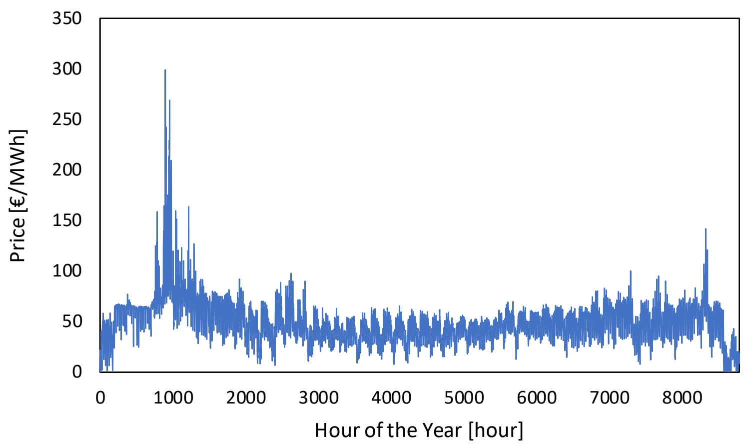


Figure S6. Electricity spot prices for Switzerland in 2012, according to http://www.epexspot.com/.

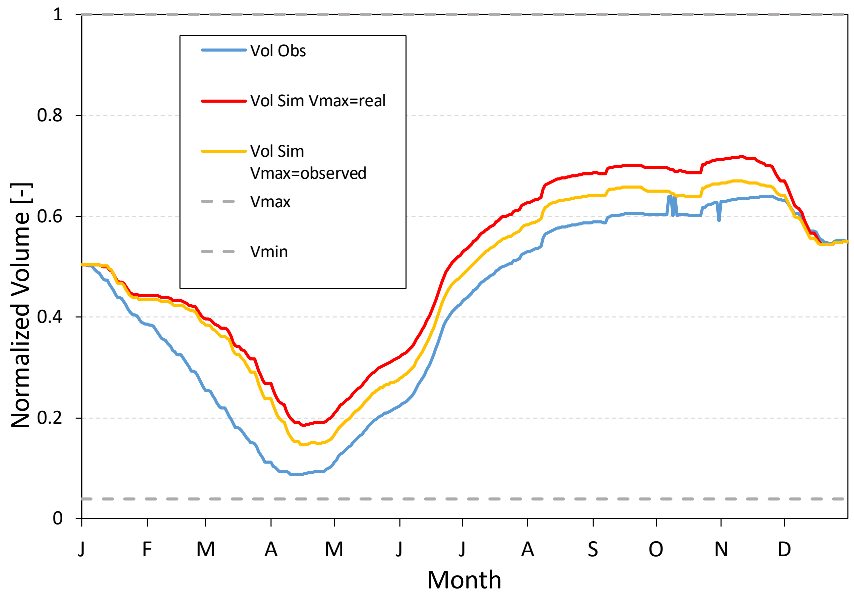


Figure S7. The behaviour of annual volumes for 2013 with the two values of maximum volume, where red is the maximum capacity of the reservoir, while orange is the maximum value observed from the real data available.

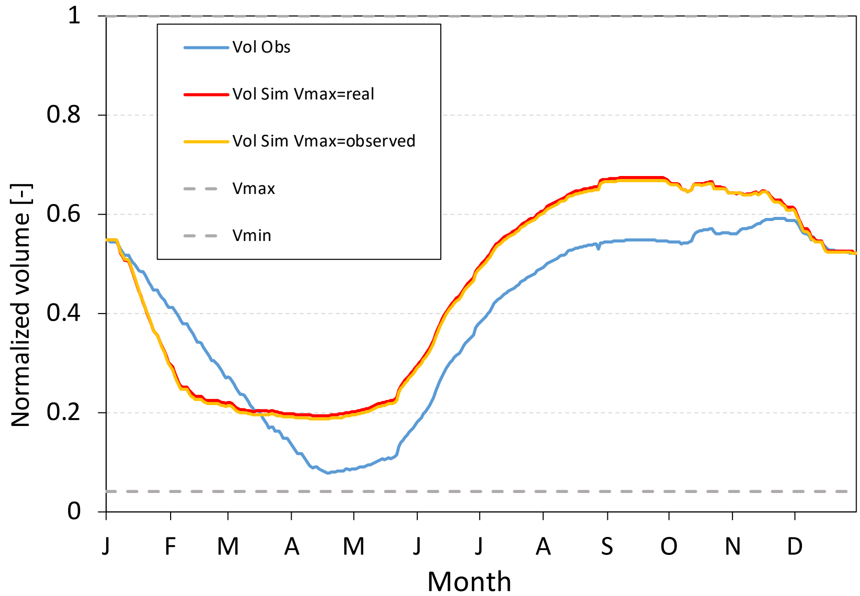


Figure S8. Behaviour of annual volumes for 2014 with the two values of maximum volume, where red is the maximum capacity of the reservoir, while orange is the maximum value observed from the real data available.

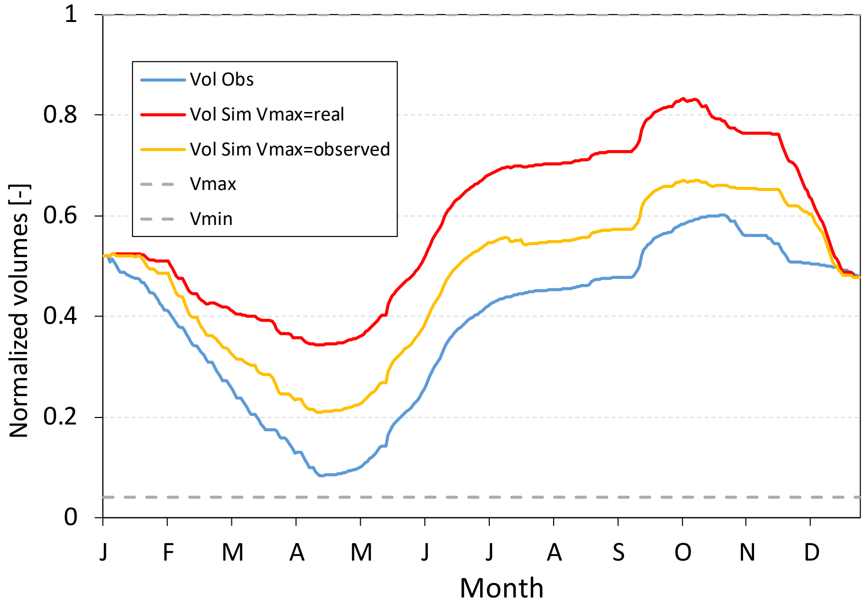
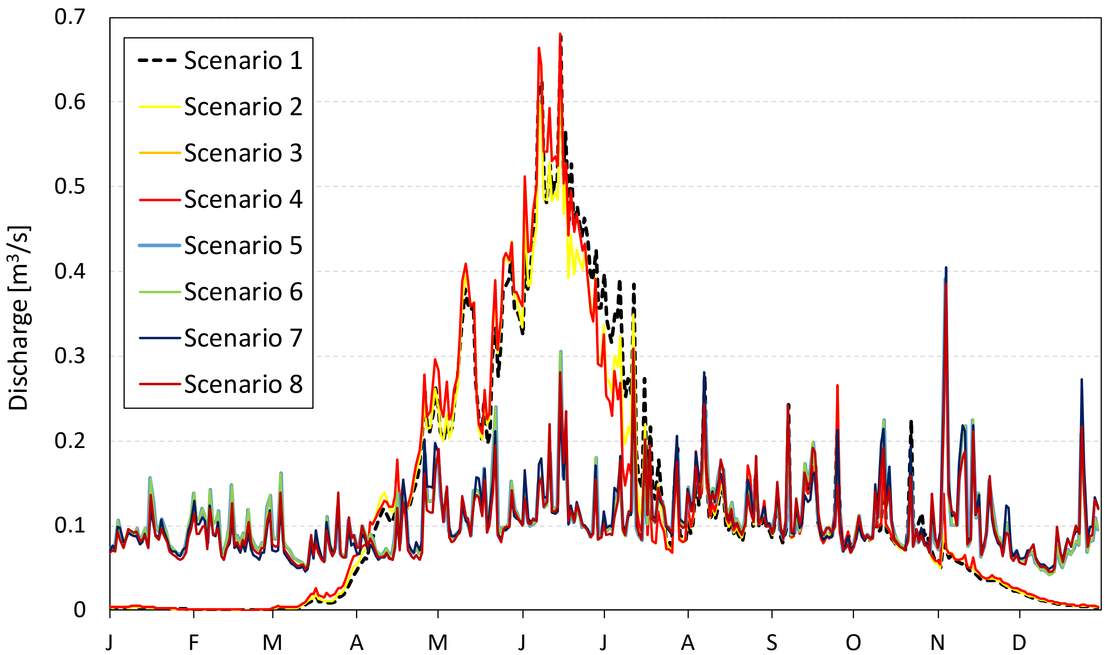
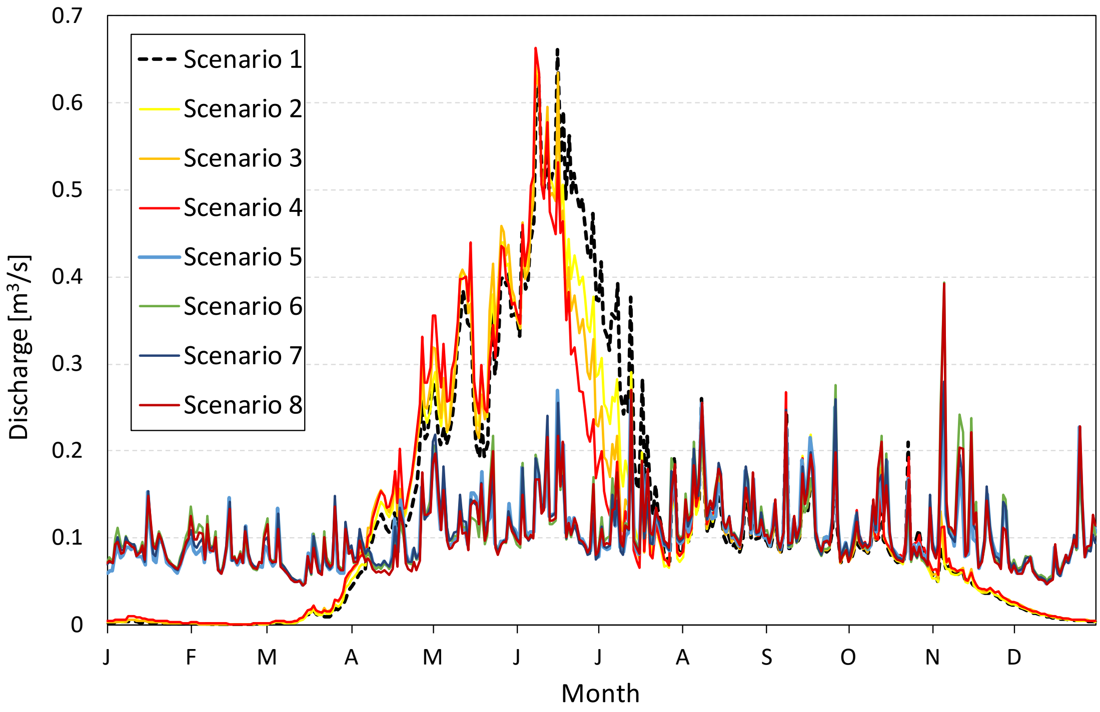


Figure S9. Behaviour of annual volumes for 2015 with the two values of maximum volume, where red is the maximum capacity of the reservoir, while orange is the maximum value observed from the real data.



(**a**)



(**b**)

Figure S10. Average daily discharge for all the scenarios at (**a**) 2020; (**b**) 2025.

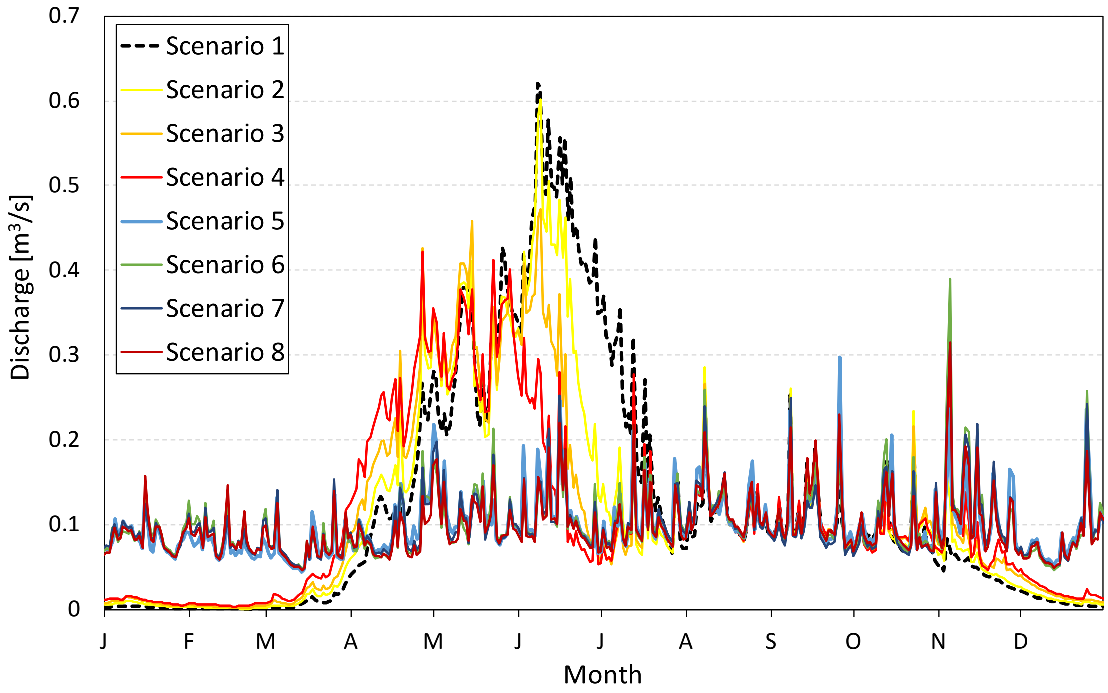


Figure S11. Average daily discharge of all the scenarios at 2045.

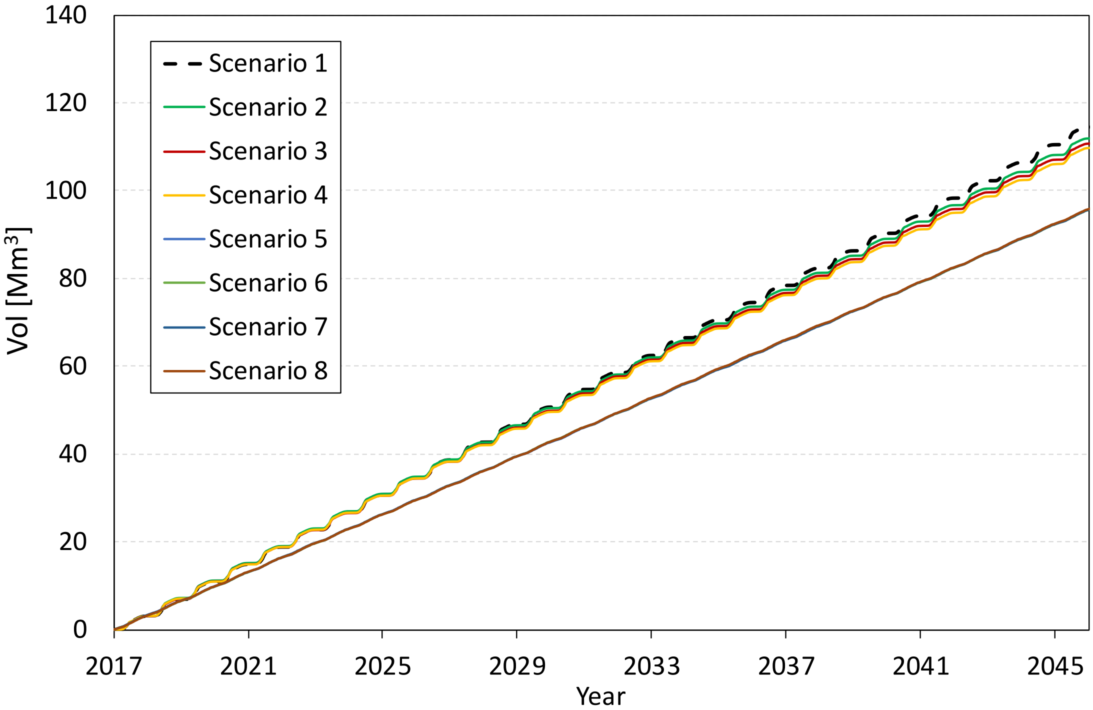


Figure S12. Cumulated volumes of all the scenarios, for the considered period of simulation.

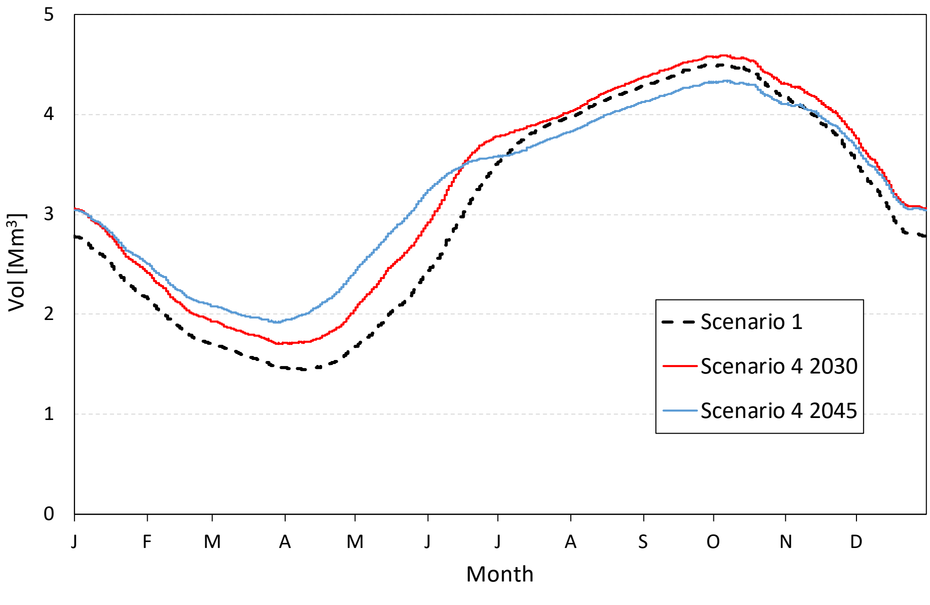


Figure S13. Comparison of hourly reservoir's volumes for scenario 4 at 2030 and 2045, in terms of the average values with a 95% confidence interval.

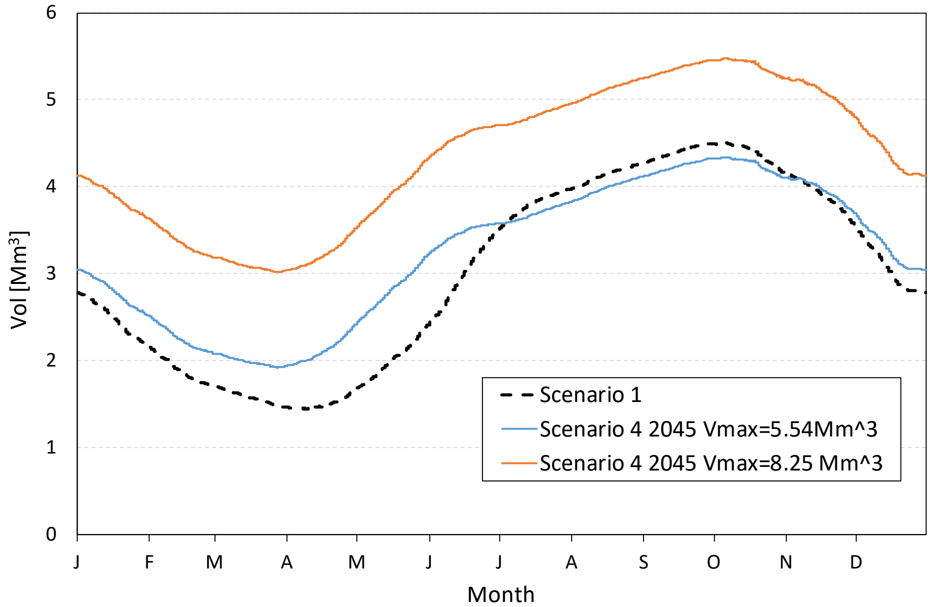


Figure S14. Comparison of hourly reservoir's volumes for scenario 4 with different maximum volume, at 2045, in terms of the average values with a 95% confidence interval.

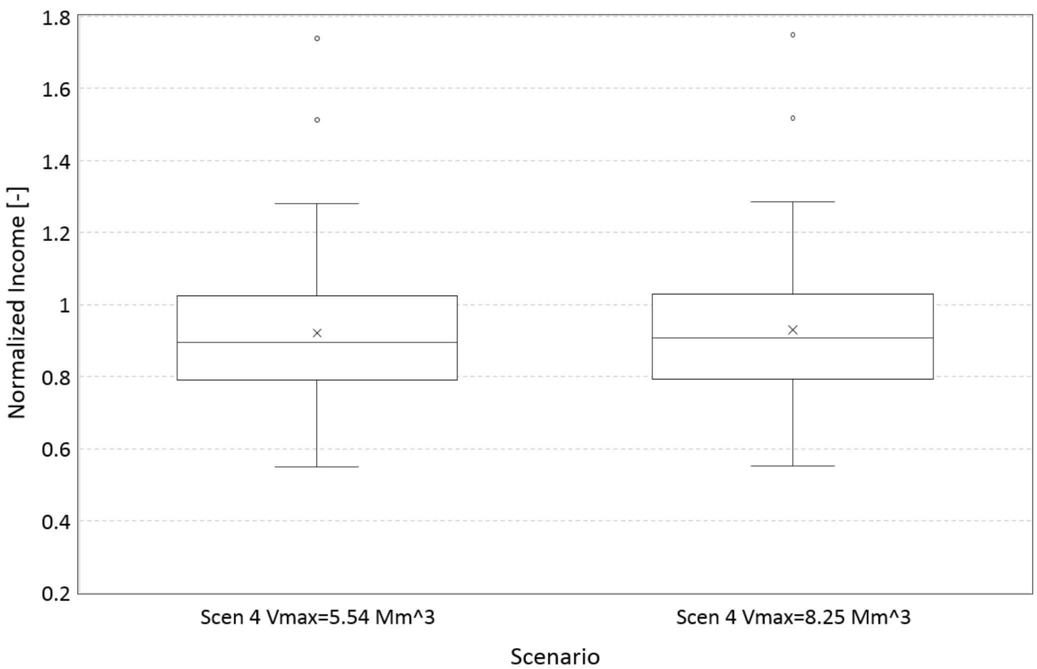


Figure S15. Box plots comparison for scenario 4 with different V max at 2045. They are normalized with respect to base scenario.

Table S1. Performance of the model in reproducing the observed discharge at reservoir outlet section. The analysis is made at daily and at monthly scale and is provided in terms of three performance indexes, RMSE (m^3/s), NSE (-) and ΔV (-). Where Qobs and Vobs is the observed discharge and volume respectively, while Qsim and Vsim is the simulated discharge and volume respectively.

Year	Qobs (m^3/s)	Qsim (m^3/s)	Vobs (Mm^3)	Vsim (Mm^3)	ΔV (%)	NSE (-)	NSE (-) Month	RMSE (m^3/s)	RMSE (m^3/s) month
2012	0.13	0.13	4.11	4.08	−0.74%	0.6	0.95	0.16	0.04

2013	0.15	0.14	4.67	4.28	−9.08%	0.79	0.90	0.12	0.06
2014	0.15	0.15	4.64	4.85	4.32%	0.73	0.93	0.13	0.05
2015	0.14	0.16	4.35	4.94	11.81%	0.56	0.91	0.17	0.05
2016	0.09	0.10	2.91	3.02	3.40%	0.72	0.88	0.11	0.06
Avg	0.13	0.13	4.14	4.23	1.94%	0.68	0.91	0.14	0.05

Table S2. The behaviour of the different combinations. The steps needed to reach the observed income, and the income normalized over the observed income for 2012 at the highest number of steps is reported.

Combination	Steps to reach observed income	Normalized income at 7×10^6 steps
I	5,000,000	1.024
II	5,000,000	1.022
III	300,000	1.042
IV	300,000	1.042

Table S3. Normalized income over the observed income for the different simulations with increasing number of restarts.

Steps	1 Restart	3 Restarts	5 Restarts	10 Restarts	15 Restarts	20 Restarts
3×10^4	0.851	0.862	0.860	0.863	0.862	0.862
5×10^4	0.903	0.901	0.907	0.912	0.913	0.913
7×10^4	0.935	0.940	0.941	0.943	0.946	0.946
3×10^5	1.024	1.027	1.026	1.028	1.029	1.029
5×10^5	1.035	1.036	1.037	1.036	1.036	1.036
7×10^5	1.038	1.039	1.038	1.038	1.039	1.039

Table S4. Difference between the income found in the different simulations and the one found with only 1 restart, normalized over it. It allows to monitor the improvement in the objective function gained by increasing the restarts.

Steps	3 Restarts	5 Restarts	10 Restarts	15 Restarts	20 Restarts
3×10^4	1.32%	3.0%	0.9%	−1.4%	1.8%
5×10^4	−0.26%	0.7%	−3.5%	−5.2%	−0.9%
7×10^4	0.55%	−2.9%	−2.1%	0.1%	−4.0%
3×10^5	0.36%	1.1%	1.5%	1.3%	1.8%
5×10^5	0.05%	0.4%	1.0%	1.0%	1.3%
7×10^5	0.11%	0.6%	0.9%	1.2%	1.1%

Table S5. Overall results from calibration and validation years according to combination 4. The observed income for each step is reported along with the the average of percentages found for validation years.

Steps	2012	2013	2014	2015	Average on Validation Years
3×10^4	85%	85%	88%	89%	87%
5×10^4	90%	90%	92%	93%	92%
7×10^4	94%	92%	94%	95%	94%
3×10^5	102%	97%	99%	100%	99%
5×10^5	104%	98%	99%	101%	101%
7×10^5	104%	98%	100%	101%	101%

Table S6. Annual volumes of all scenarios at 2045 for Tremorgio, along with the variation in volumes with respect to the base scenario i.e., scenario 1.

Scenario	Annual Volume (Mm^3)	ΔV (%)

1	3.9	-
2	3.6	−7.4%
3	3.5	−9.2%
4	3.4	−11.5%
5	3.1	−19.2%
6	3.1	−19.0%
7	3.1	−19.5%
8	3.0	−21.1%

Table S7. Variation income of all scenarios with respect to base scenario (2015). The results are arranged in descending order.

Scenario	Income Variation (-)
C++F++R−	71%
C++F++	64%
C++F++R+	59%
C+F++R−	53%
C++F+R−	52%
C+F++	49%
C+F++R+	47%
C++F+	45%
EU Trend	41%
C++F+R+	39%
C+F+R−	36%
C+F+	33%
F++R−	32%
C++R−	31%
F++	30%
C+F+R+	27%
C++	26%
F++R+	26%
C++R+	21%
C+R-	18%
F+R−	16%
C+	14%
F+	13%
C+R+	11%
F+R+	10%
R−	−8%
Base Price 2015	−11%
R+	−12%

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