Reservoir Storage–Yield Analysis under the Uncertainty of Climate Change

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Abstract

According to the Sixth Assessment Report by The Intergovernmental Panel on Climate Change, the negative effect on global climate systems by human activities is unequivocal and has led to the gradual warming of the atmosphere, oceans and surface of the Earth. Climate change has a significant effect on nature, population and water resources. Its effect is particularly pronounced in the water cycle, which represents a delicate balance between precipitation, runoff, evaporation and other interactions between the atmosphere and surface of the Earth. Consequently, hydrological conditions in the landscape have changed. Although it is known that climate will change in the future, it is impossible to predict the exact rate at which this will happen. Therefore, it is important to consider uncertainties in the information provided regarding future changes. It is necessary to note that uncertainties are inherent in all of the supporting data needed for any decision. The correct determination of uncertainties as part of data assessment will provide a better understanding of the information and can increase its usefulness in decision-making processes. Hence, the adaptation of water resource management to uncertain climate change is crucial. But how can one assess the active storage of a reservoir under the uncertain conditions of climate change and ensure its operational sustainability?

This paper will present a lumped water balance rainfall-runoff hydrological model within a monthly time step. The model is based on mean monthly soil moisture and runoff in a river catchment. During the computation of the total runoff from the catchment of surface flow, groundwater discharge and potential evapotranspiration are considered. The estimate of potential evapotranspiration is computed using the Thornthwaite method. The model is calibrated for 37 parameters that are optimised by the generalised reduced gradient algorithm. The calibrated model is then used to process climatological data containing uncertainty of climate change, which is represented by an ensemble of future climatological scenarios generated for the period between 2021 and 2060. These scenarios were generated by LARS WG software. The ensemble contains nine climatological scenarios based on combinations of four global climate models and three representative concentration pathways (RCP). Specifically, these are EC EARTH, HadGEM2-ES, MIROC5 and MPI-ESM-MR models and RCP2.6, RCP4.5 and RCP8.5 emission scenarios.

As a tool for long-term water management planning, a reservoir simulation model, Unce Clima Change, is used. In the simulation, time-based reliability is determined, which is a percentage of the duration that the reservoir operates without failure. In this case, failure means any reduction in the quantity of water delivered to the consumer without altering the draft from the reservoir. The assessment of maximum values of active storage volumes for determining drafts/yields is based on results from the Unce Clima Change software. For each scenario, time-based reliability is evaluated with the minimum threshold value of 99.50% as an average value across the ensemble. The assessment of the magnitude of climate change impacts on the reservoir's active storage capacity is presented using a robustness method. In the paper, the aforementioned approaches are applied to the Vranov reservoir in the Thaya river catchment, which is located in the Czech Republic in Central Europe.

Annotation:
This paper aims to assess the Vranov reservoir's active storage for predetermined time-based reliability under the conditions of uncertain climate change. Uncertainty is embedded into the input data in the form of an ensemble of climatological scenarios generated by LARS WG software. The lumped water balance hydrological model has been developed to process the climatological scenarios and analyse storage–yield using the Unce Clima Change software. The impact of climate change on the reservoir's active storage is assessed using a robustness approach.

Keywords:
Climate change, robustness, lumped model, reliability, uncertainty, Thaya river, Vranov reservoir

Abstrakt

Dle šesté hodnotící zprávy Mezivládního panelu pro změnu klimatu je jednoznačné, že antropogenní činnost negativně ovlivňuje globální klimatický systém, jímž důsledkem je změna klimatu způsobená postupným oteplením atmosféry, oceánů a povrchu Země. Klimatická změna má velký vliv na přírodu, lidskou populaci i vodní zdroje. Její efekt se výrazně projevuje především v koloběhu vody, který představuje delikátní rovnováhu mezi srážkami, odtokem, evaporací, a veškerými interakcemi mezi atmosférou a povrchem Země. Důsledkem toho je pak ovlivnění a změna hydrologických podmínek v krajině. Přestože je známo, že se klima bude v budoucnosti měnit, není možné předpovědět přesnou úroveň projevu této změny. Proto je důležité uvažovat i s nejistotami a neurčitostmi doložených informací ohledně budoucích změn. Je třeba si uvědomit, že nejistoty jsou vlastní všem podpůrným datům potřebným k jakémukoliv rozhodnutí. Správné určení nejistot jako součástí vyhodnocení dat poskytne lepší porozumění těmto podkladům a může zvýšit jejich užitečnost v rozhodovacích procesech. Z toho důvodu je adaptace hospodaření s vodními zdroji na nejistou klimatickou změnu zásadní. Otázkou je, jakým způsobem vyhodnotit zásobní objem vodní nádrže v podmínkách nejistot klimatické změny a zajistit tak její provozní udržitelnost?

V tomto příspěvku je představen bilanční srážko-odtokový hydrologický model pracující v měsíčním kroku výpočtu. Model je založený na průměrném měsíčním nasycení půdy v povodí a průměrném měsíčním odtoku vody z povodí. Při výpočtu odtoku vody z povodí je uvažováno s povrchovým i podzemním odtokem a potenciální evapotranspirací, jejíž odhad je počítán metodou dle Thornthwaitea. Model je kalibrován na 37 parametrů, které jsou optimalizovány metodou redukovaných gradientů. Kalibrovaný model je následně využit pro zpracování klimatologických dat zatížených nejistotou klimatické změny. Nejistota klimatické změny je reprezentována ansámblem budoucích klimatologických scénářů vygenerovaných pro období let 2021–2060. Tyto scénáře byly vygenerovány pomocí softwaru LARS WG. Ansámble tvoří 9 klimatologických scénářů založených na kombinaci 4 globálních klimatických modelů a 3 scénářů představující reprezentativní směry vývoje koncentrací (RCP). Konkrétně se jedná o modely EC EARTH, HadGEM2-ES, MIROC5 a MPI-ESM-MR a scénáře RCP2.6, RCP4.5 a RCP8.5.

Jako nástroj pro dlouhodobé vodohospodářské plánování je využit simulační model vodní nádrže Unce Clima Change. V rámci simulace provozu vodní nádrže je stanovena zabezpečenost dle doby trvání, která představuje procentuální vyjádření doby trvání, po kterou vodní nádrž pracuje bez poruchy. Poruchou se rozumí jakékoli omezení množství vody dodané spotřebiteli beze změny nalepšeného odtoku. Na základě výsledků ze softwaru Unce Clima Change jsou následně vyhodnoceny maximální hodnoty získaných zásobních objemů pro zvolené nalepšené odtoky z nádrže. Pro jednotlivé scénáře v ansámblu je rovněž stanovena zabezpečenost dle doby trvání, jejíž minimální limitní hodnota byla stanovena na 99.50 % jako průměr za celý ansámbl. Vyhodnocení míry dopadů klimatické změny na zásobní objem vodní nádrže je prezentováno pomocí metody robustnosti. V příspěvku jsou zmíněné postupy aplikovány na vodní nádrž Vranov v povodí řeky Dyje, nacházející se v České republice, ve střední Evropě.

Anotace:

Cílem tohoto příspěvku je vyhodnotit zásobní objem nádrže Vranov pro předem stanovenou zabezpečenost dle trvání v podmínkách nejistot v rámci klimatické změny. Nejistoty jsou zahrnuty ve vstupních datech ve formě ansámblu klimatologických scénářů, vygenerovaných pomocí softwaru LARS WG. Pro zpracování klimatologických scénářů byl vytvořen bilanční srážko-odtokový model a pro analýzu velikosti zásobního prostoru vodní nádrže byl použit software Unce Clima Change. Vyhodnocení dopadu klimatické změny na zásobní objem nádrže bylo provedeno metodou robustnosti.

Klíčová slova:

Klimatická změna, robustnost, bilanční model, zabezpečenost, nejistota, řeka Dyje, vodní nádrž Vranov

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1 Introduction

Nowadays, climate change is a very serious topic of discussion as it has a major impact on nature, population and water resources. Based on the Sixth Assessment Report by the Intergovernmental Panel for Climate Change (IPCC, 2021), each of the last four decades has been successively warmer than any decade that preceded it since 1850. This global warming is caused by a gradual increase of well-mixed greenhouse gas concentrations that are unequivocally caused by human activities. The negative effect of climate change on the global climate system appears mainly in the water cycle. Consequently, hydrological conditions in the landscape have changed. Although it is known that hydrological and climatological conditions will change, it is impossible to predict the degree of change in the future. Thus, it is important to evaluate predictions that are afflicted by uncertainty and be prepared for each future scenario that may occur. The evaluation of uncertain predictions is especially important in water resource management, where sustainability during future uncertain conditions is crucial. Foley (2010) and Refsgaard et al. (2013) highlighted that the emission scenarios, climate models and uncertainty that stem from statistical downscaling methods are sources of aleatory and epistemic uncertainty in climate change modelling processes for water management. To assess uncertain future climate projections, an ensemble of plausible scenarios has been created, which includes the uncertainty of climate change. The ensemble has then been evaluated using a robustness approach (Groves et al., 2008).

This paper presents an analysis of the storage–yield capacity of a reservoir under the uncertainty of climate change in the near future. Runoff analysis will be performed using a lumped water balance hydrological model within a monthly time step. The input data for the model will be generated using LARS WG software (Racsko et al., 1991) in the form of an ensemble of nine climate scenarios. To create the ensemble, four global climate models and three representative concentration pathways (RCPs) will be used. Afterwards, the reservoir's performance will be analysed and assessed using time-based reliability and a robustness approach.

The Thaya river basin in the cross-border area of Austria and the Czech Republic was chosen to analyse the impact of climate change. The river basin has an area of 13,419 km^2, of which the area of interest covers 2,124 km^2. The runoff from the study area that will be analysed contributes to inflows to the Vranov reservoir, which was chosen because it is one of the largest reservoirs in the Czech Republic, and its main purpose is to cover water supply demands and ensure the ecological streamflow under the reservoir. The total Vranov volume is 132.7 mil m^3, from which the active storage volume is 79.7 mil m^3 and flood volume is 21.2 mil m^3. The total uniform outflow/yield from the reservoir is 4 m^3/s for 100% time-based reliability and 4.3 m^3/s for 99.50% time-based reliability (estimated values from the handling regulations of the Vranov reservoir). Methods and tools will be applied to the Vranov reservoir's active storage.

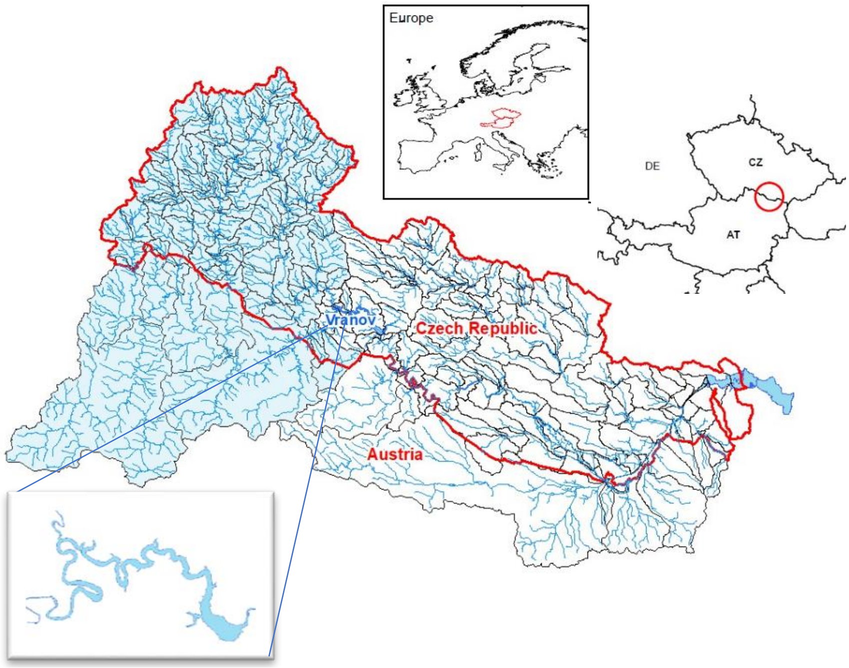

Figure 1: General location of the Thaya river basin with marked river network and Vranov reservoir: blue area – study area that contributes to inflows to the Vranov reservoir; red line area – the Czech part of the basin

2 Methodology

2.1 Lumped water balance model

The lumped water balance model forms the basis of the method adopted in this paper. The model is based on control formulae that specify the total monthly flow and monthly soil moisture. The balance model computes three main components, which are mean monthly surface flow q_s, mean monthly groundwater discharge q_g and mean monthly evapotranspiration E. The equations defining the rainfall-runoff process were published by Wang et al. (2014) and Wang et al. (2016) and were adapted to the conditions of Central European hydrology and climate by Marton and Knoppová (2019). The main formulae that define the rainfall-runoff process are described as follows:

$$q_{s,i} = k_s \cdot \frac{S_{i-1}}{S_{max}} \cdot h_{m,i} \tag{1}$$

where $q_{s,i}$ is the mean monthly surface flow [mm], k_s is the model parameter of the surface flow [-], S_{i-1} is the mean soil moisture in the previous time step [mm], S_{max} is the maximum soil moisture storage [mm] and $h_{m,i}$ is the mean monthly precipitation [mm]. Equation (2) describes the computation of the groundwater discharge:

$$q_{g,i} = k_g \cdot S_{i-1} \tag{2}$$

where $q_{g,i}$ is the mean monthly groundwater discharge [mm], k_g is the model parameter of the groundwater discharge [-] and S_{i-1} is the mean soil moisture in the previous time step [mm]. Furthermore, the monthly mean evapotranspiration E is evaluated using Eq. (3):

$$E_i = k_e \cdot \frac{S_{i-1}}{S_{max}} \cdot E_{p,i} \tag{3}$$

where E_i is the estimated mean monthly evapotranspiration from the river catchment [mm], k_e is the model parameter of the estimated evapotranspiration [-] and $E_{p,i}$ is the potential mean monthly evapotranspiration [mm]. The potential evapotranspiration (PET) must be provided for the model's computing process; therefore, it is computed in advance. The Thornthwaite empirical temperature-based method (Thornthwaite, 1948) was used to calculate the PET. This method estimates the PET for a standard month of 30 days, each day having a 12-hour photoperiod as a function of the monthly average temperature. The main PET formula is as follows:

$$E_{p,i} = 16 \cdot \left(10 \cdot \frac{T_{mean,i}}{I_j}\right)^{a_j} \cdot \frac{L_i}{12} \cdot \frac{d_i}{30} \tag{4}$$

where $E_{p,i}$ is the mean monthly PET [mm.mon^{-1}], $T_{mean,i}$ is the mean monthly air temperature in the i-th month [°C], L_i is the average day length of the i-th month [hours] and d_i is the number of days in the i-th month being calculated [-]. Parameter a_j is dependent on the heat index I_j of the j-th year and is evaluated by the following equations:

$$I_j = \sum_{m=1}^{12} \left(\frac{T_{mean,i}}{5}\right)^{1.5} \tag{5}$$

$$a_j = \left(0.0675 \cdot I_j^3 - 7.71 \cdot I_j^2 + 1792 \cdot I_j + 47239\right) \cdot 10^{-5} \tag{6}$$

The total monthly runoff q_a from the river catchment is estimated by the sum of the mean monthly surface flow q_s and the mean monthly groundwater discharge q_g (Eq. (7)).

$$q_{a,i} = q_{s,i} \cdot q_{g,i} \tag{7}$$

Finally, the soil moisture content S_i is calculated by Eq. (8):

$$S_i = S_{i-1} + h_{d,i} - q_{a,i} - E_i \tag{8}$$

where S_i is the soil moisture at the end of the i-th month [mm], S_{i-1} is the mean soil moisture in the previous time step [mm], $h_{d,i}$ is the mean monthly precipitation [mm], $q_{a,i}$ is the estimated monthly total runoff from the catchment and E_i is the mean monthly evapotranspiration [mm]. Equations (1) to (8) are for i=1, 2, …, N, where N is the length of the data time series.

2.2 Optimisation method

The optimisation problem is defined by establishing the system of equations and selecting several decision variables. In this case, the decision variables are model parameters. The Nash–Sutcliffe model efficiency coefficient (NSE, Nash and Sutcliffe, 1970) was used as the objective function to optimise the model parameters during the calibration process. The NSE acquires values in the interval from −∞ to 1 (inclusive). The value of NSE is calculated by Eq. (9):

$$NSE = 1 - \frac{\sum_{i=1}^{N}(Q_{o,i} - Q_{p,i})^2}{\sum_{i=1}^{N}(Q_{o,i} - \overline{Q_o})^2} \tag{9}$$

where $Q_{o,i}$ is the observed value of monthly flow [m^3.s^{-1}], $O_{p,i}$ is the predicted/modelled value of monthly flow [m^3.s^{-1}] for i=1, 2, …, N, where N is the length of the data time series, and $\overline{Q_o}$ is the mean value of the flow from the whole period observed [m^3.s^{-1}].

Moriasi et al. (2007) highlighted that values between 0 and 1 are generally considered an acceptable level of model performance, whereas values less than 0 indicate that the mean observed value is a better predictor than the simulated values, which denotes unacceptable performance.

Moriasi et al. (2015) established general performance ratings for recommended statistics for the monthly temporal scale of watershed-scale models: unsatisfactory ($NSE \leq 0.50$), satisfactory ($0.50 < NSE \leq 0.70$), good ($0.70 < NSE \leq 0.80$) and very good ($0.80 < NSE \leq 1.00$).

2.3 Statistical downscaling

To obtain the necessary weather data, LARS WG (version 6) software was used (Racsko et al., 1991), which is a common statistical downscaling tool for climate change projections. A detailed description of the climate model and downscaling procedures can be found in the user manual for LARS WG, version 3.0 by Semenov and Barrow (2002).

Using LARS WG, an ensemble of nine climate scenarios was created. Climate scenarios were set by coupling the downscaling method with four global climate models (GMCs) using representative concentration pathway (RCP) emission scenarios (Moss et al., 2010) as the boundary conditions for the future projections. RCP2.6, RCP4.5 and RCP8.5 emission scenarios were used for this paper. The peak-and-decline mitigation scenario, RCP2.6 (van Vuuren et al., 2011), is an optimistic progression scenario that leads to a low forcing level at the end of the twenty-first century (2.6 $W.m^{-2}$). The RCP4.5 scenario is a medium stabilisation scenario in which radiative forcing peaks at about 4.5 $W.m^{-2}$ in 2100 and then slowly decreases (Thomson et al., 2011). The RCP8.5 scenario assumes a high rate of emissions, leading to high radiative forcing in the twenty-first century where it reaches 8.5 W.m-2 in 2100 and continues to increase (Riahi et al., 2011).

Using LARS WG, the nine climate scenarios were created based on the aforementioned GCMs and RCPs for two time periods: P1 (2021–2040), P2 (2041–2060) and their combination P1+P2 (2021–2060). The downscaled weather datasets are presented as monthly temperature (mean, minimum and maximum) and precipitation for each of the determined climate scenarios. The final combination of GCMs and RCPs used to obtain the ensemble of nine climate scenarios is shown in Table 1.

Table 1: Combinations of GCMs and RCPs used (ensemble of nine climate scenarios)

Global climate models	Representative concentration pathways
EC EARTH	RCP4.5, RCP8.5
HadGEM2-ES	RCP2.6, RCP4.5, RCP8.5
MIROC5	RCP4.5, RCP8.5
MPI-ESM-MR	RCP4.5, RCP8.5

2.4 Unce Clima Change

The Unce Clima Change software is based on a simulation model of a reservoir that uses the mass balance equation described by Starý (2005) to simulate reservoir filling and emptying. Two procedures are applied during the simulation. The first procedure consists of evaluating reservoir active storage for 100% time-based reliability, R_T. Subsequently, when we know the active storage for non-failure time-based reliability, the second procedure is then based on evaluating time-based reliability for an increased draft (more than 100% of a long-term mean flow). The base concept of water resource system performance evaluation by reliability is described by Hashimoto (1982).

The software analyses the ensemble of climate scenarios under the uncertainty of climate change and evaluates both abovementioned procedures for each scenario.

2.5 Robustness

A robustness method was used to assess the results for the climate scenario ensemble that contains the uncertainty of climate change. It is commonly described as the degree to which a water supply system performs at a satisfactory level across a broad range of plausible future conditions (Groves et al., 2008). The robustness of the ensemble for determined drafts is evaluated as the fraction of scenarios that satisfy the water supply demand at time-based reliability higher than or equal to 99.50% and the total number of scenarios in the ensemble. This approach is adopted from Roach et al. (2016). Robustness is then estimated by Eq. (10):

$$ROB = \frac{S}{T} \quad (10)$$

where ROB is the robustness of the ensemble, S is the number of scenarios in which system performance is considered satisfactory and T is the total number of scenarios in the ensemble.

3 Results and discussion

To process the climatological scenarios generated by the LARS WG software, the lumped water balance model had to be calibrated first. For this purpose, a time series of the observed values for temperature and precipitation were available for the period between 1991 and 2018. The percentage ratio of the calibration/validation datasets was 70/30; thus, calibration data were taken from 1991 to 2009 and validation data from 2010 to 2018. NSE was used as the objective function for optimisation. As the highest value of NSE is 1, the optimisation was set up as a maximising problem. A generalised reduced gradient algorithm (Lasdon et al., 1978) implemented in Microsoft Excel was applied to solve the optimisation problem. As mentioned above, the decision variables were model parameters. The model is based on the monthly computational time step; hence, the number of decision variables was 37 (three parameters per month in a year plus one parameter as an initial condition of soil moisture in the catchment). The objective function for the calibration period was evaluated as NSE_{cal}=0.758, which is within an interval between 0.70 and 0.80. Thus, model performance is considered good. The visual comparison of observed and simulated datasets with linear trends for calibration and validation periods is shown in Figures 1 and 2, respectively.

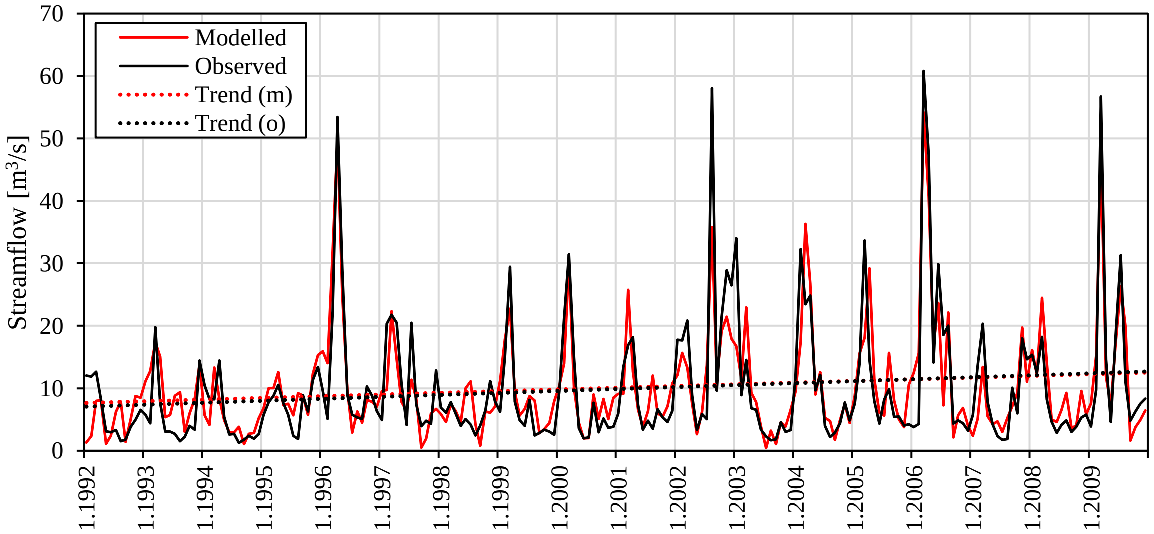

Figure 2: Comparison of the monthly mean flow values of the observed data and simulated data obtained from the calibration process

Figure 2 shows that the calibration results correspond to the criterion value, and the simulated flows are well fitted to the observed values. The gradients of the linear trends of observed and simulated datasets are almost the same. Optimised parameters were then used to simulate the rainfall-runoff process during the validation period where the optimisation criterion reached a value of NSE_{val}=0.309. This value is quite low in comparison to the calibration results. The main reason for this is that there was an unusually extreme drought in the river catchment from 2015 to 2018, during the validation period (NOAA, 2019). The calibration/validation ratio changed to 80/20 when these years were discarded from the validation period (2010–2014). By removing these extremely inconsistent years, the value of the validation criterion increased by almost 25% to NSE_{val}=0.385.

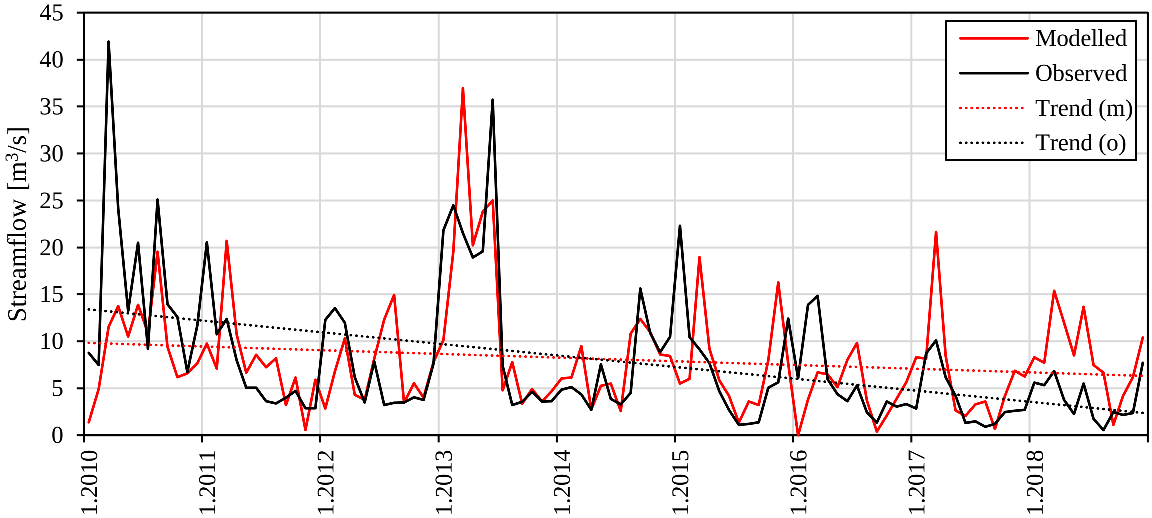

Figure 3: Comparison of the monthly mean flow values of the observed data and simulated data obtained from the validation process

Figure 3 shows that the observed time series has a much steeper downward linear trend than the simulated data, which is caused by unusually dry years from 2015 to 2018. Therefore, these unusual years influenced the final value of the criterion. Hence, the model was considered successfully calibrated and validated. The calibrated model was then used with the data from the ensemble of climatological scenarios and baseline data. The long-term mean streamflow for the historical observed data was evaluated at 9.068 m^3/s for the period between 1991 and 2018. The long-term mean streamflow for the baseline was overvalued at 10.872 m^3/s. Thus, the 'bias' of the generated scenarios' data had to be corrected. The output ensemble data were linearly scaled by the ratio between the mean long-term streamflow values of observed and baseline output data (Lenderink et al., 2007).

The long-term mean streamflow was then computed for each of the climate scenarios. Table 2 shows the comparison of these values.

Table 2: Mean long-term streamflow of the predicted climate change data

Combination of GCMs and RCPs	Long-term mean streamflow of the ensemble data [m^3/s]				Relative difference to the baseline [%]		
	Baseline	P1	P2	P1+P2	P1	P2	P1+P2
EC EARTH 4.5	9.068	8.79	7.40	8.093	-3.1	-18.4	-10.8
EC EARTH 8.5	9.068	9.06	6.30	7.683	-0.1	-30.5	-15.3
HadGEM2-ES 2.6	9.068	6.02	6.35	6.183	-33.7	-30.0	-31.8
HadGEM2-ES 4.5	9.068	6.80	5.45	6.129	-25.0	-39.9	-32.4
HadGEM2-ES 8.5	9.068	6.50	5.30	5.896	-28.4	-41.6	-35.0
MIROC5 4.5	9.068	8.08	7.59	7.838	-10.9	-16.3	-13.6
MIROC5 8.5	9.068	7.70	6.78	7.239	-15.1	-25.2	-20.2
MPI-ESM-MR 4.5	9.068	7.34	7.01	7.175	-19.1	-22.7	-20.9
MPI-ESM-MR 8.5	9.068	7.75	7.67	7.707	-14.6	-15.4	-15.0

Table 2 shows that during each period, the long-term mean streamflow decreased without exceptions. In comparison to the baseline value, the long-term mean streamflow will decrease by -10.7% to -35.0% until 2060. Considering the change in streamflow values, the reservoir's active storage may not be sufficient in the future. To evaluate the predicted ensemble data on reservoir storage–yield capacity, a robustness method and temporal-based reliability were applied.

First, the actual active storage volume had to be found for the non-failure reliability of the baseline data. The Vranov reservoir active storage volume is 79,668,000 m^3, which is the original value from the reservoir's handling regulations. For this volume, the firm yield was evaluated at 4 m^3/s. These two values were sought using Unce Clima Change software on the historical dataset to check the functionality of the software and the correctness of the dataset. The computed active storage volume was 79,670,424 m^3, which was paired with a firm yield of 4.412 m^3/s. The difference between the computed and real values can be explained by the different lengths of historical datasets used for the computation of each, but the accuracy is sufficient. Similar values were expected for the baseline data. The closest active storage volume to the real one was for the baseline data computed at 79,695,800 m^3 for a firm yield of 5.196 m^3/s. This firm yield value is larger than expected by about 15% because the LARS WG software overvalued the peak values of data, which then led to a higher value of long-term mean streamflow. Hence, the results for the ensemble will be compared only to the baseline data because there is a possibility that predicted datasets from LARS WG are biased because of overvaluing peak values. However, there is a possible assumption that the predicted value of yields will be also higher by about 15%.

As the ensemble covers a large range of future climate progressions, there is a large difference between the minimum and maximum active storage volumes needed for the determined yields. It was difficult to satisfy average volumes across the ensemble because the maximum values of volume for some scenarios were absurdly high. Therefore, only the maximum values of active storage volumes for determining yields were sought within the ensemble for each period. Firm yields for maximum volumes within the ensemble are shown in Table 3.

Table 3: Firm yields for maximum volumes within the ensemble for each period

Periods	Firm yield [m^3/s]	Minimum active storage [m^3]	Maximum active storage [m^3]
P1	4.678	35,538,508	79,648,312
P2	4.759	35,021,892	79,650,424
P1+P2	4.677	35,537,832	79,682,440

The yields for 100% time-based reliability shown in Table 3 were found for maximum volumes of storage needed within the ensemble. The active storage needed was as close to the real active storage volume as possible with a yield precision of 0.001 m^3/s (1 litre per second). Compared to the firm yield for baseline data, the ensemble for the whole period (P1+P2) shows a decrease in firm yield by 0.519 m^3/s, which is almost a difference of 10%.

Next, firm yields were used as initial conditions for computing yields for time-based reliability lower than 100%. To find the highest possible yields for computed 100% active storage volumes, the stopping threshold value of time-based reliability was determined at 99.50%. By sequentially increasing the yield, the average time-based reliability of the ensemble was evaluated for each increase until the threshold value was reached. When the average reliability of the ensemble was as close to the threshold value as possible, robustness was evaluated for the ensemble. The robustness results for the ensemble are shown in Table 4.

Table 4: Results of active storage reliability and robustness

Periods	**Yield [m^3/s]**	**Min(R_T) [%]**	**Max(R_T) [%]**	**μ(R_T) [%]**	**σ(R_T) [%]**	**ROB [%]**	**Number of unsatisfactory scenarios in the ensemble**
P1	4.967	98.04	100.00	99.532	0.726	66.67	3
P2	4.883	96.80	100.00	99.520	1.023	77.78	2
P1+P2	4.932	98.40	100.00	99.519	0.576	55.56	4

The decrease in long-term mean streamflow (Table 2) indicates that there will be less water in the river basin, which was confirmed by a decrease in yield for the periods compared to the baseline firm yield. Table 4 shows that in P1, the maximum outflow from the reservoir is 4.967 m^3/s, for which the average time-based reliability R_T fell below the determined threshold of 99.50%. For this yield value, robustness was evaluated at 66.67%; thus, six out of nine scenarios will satisfy water supply demands with $R_T \geq 99.50\%$. In this case, the yield will fall by 4.41% compared to the baseline firm yield. In P2, the yield will decrease by 6.02% with a ROB value of 77.78%; thus, seven out of nine scenarios will satisfy the water demand. The combination of P1 and P2 shows a decrease of 5.08% with a robustness of 55.56%. Thus, during the whole predicted future period, only five out of nine scenarios will satisfy water supply demands, with time-based reliability higher than or equal to the threshold value $R_T \geq 99.50\%$.

The assessment of the climate change ensemble shows a falling trend for streamflow and reservoir outflows in the river basin. The results show that the combination of EC EARTH and RCP4.5 give the most optimistic results for future projections, in which the long-term mean streamflow will decrease by 3.1% until 2040 and then by another 15.3% until 2060 compared with the baseline period. However, the RCP2.6 scenario is a mitigation scenario, and the results for HadGEM2-ES and RCP2.6 show the highest decrease in long-term mean streamflow until 2040. In this case, the streamflow decreased by 33.6% in P1, and then the decrease in value of long-term mean streamflow slightly increased to 30.0% in P2 compared to the baseline period. Within the ensemble across both periods, the combination of MPI-ESM-MR and the stabilisation scenario RCP4.5 can be identified as the average scenario. This combination gave a decrease of 19.1% in the value of long-term mean streamflow in P1 and a decrease of 22.7% in P2 compared to the baseline period.
The reservoir outflow results indicate that for the threshold R_T=99.50% and maximum active storage volumes required, the outflow will decrease compared to the baseline firm yield. The results show that robustness increased during P2 compared to P1, which was caused by a lower long-term mean streamflow that led to decreased outflow from the reservoir, for which more scenarios could satisfy the water supply demand. However, the robustness values for P1 and P2 are higher than 65%, and the whole period, P1+P2, is evaluated with a robustness of 55.56%. This quite low value is a consequence of different unsatisfactory scenarios within P1 and P2. Thus, the number of unsatisfactory scenarios for P1+P2 is four, P1 is three and P2 is two. The yield value for P1+P2 is not that robust even though the average time-based reliability of the ensemble is over the threshold value of 99.50%.

4 Conclusion

The computational algorithm was set up in a general way and can be quickly used in other catchments with a reservoir. The lumped water balance model setup used for the simulation works with a set of 37 decision variables and used the Thornthwaite method to evaluate the PET. With this model setup, optimisation criterion NSE_{cal}=0.758 in the calibration process and NSE_{val}=0.309 (NSE_{val}=0.385 without considering extreme droughts from 2015 to 2018) in the validation process were achieved for the study area. According to the established recommended general model performance ratings, NSE values between 0.70 and 0.80 are considered good model performance. Therefore, the lumped water balance model used in this study is considered suitable for the climate in the Czech Republic. However, it will need to enhance the performance and precision of the simulated data because the model did not consider water from snowmelt, which can have a significant effect on the catchment runoff during the spring season in the region.
The results showed a decreasing trend in values of long-term mean streamflow in the river basin. The decrease varied from 0.10% to 33.7% between 2021 and 2040 and 15.4% to 41.6% between 2041 and 2060. Considering the combination of both periods, the long-term mean streamflow will decrease by 10.8% to 35.0% compared with the baseline period. Storage–yield analysis under the uncertainty of climate change showed that the outflow from the reservoir will decrease to satisfy water supply demands within a boundary condition of time-based reliability higher than 99.50% in comparison to the baseline period. For the given reliability threshold, the yield for P1 decreased by 4.41% with robustness of 66.67%, which means that three out of nine scenarios will not satisfy water supply demands in climate conditions during P1. During P2, the yield decreased even more by 6.02% with robustness of 77.78%, where only two out of nine scenarios will not satisfy water supply demands. With a uniform yield value of 4.932 m^3/s during both periods, the reliability threshold of 99.50% will not be exceeded but with robustness at only 55.56%, four out of nine scenarios will not meet the requirements of water supply demands. However, the overall yield value is not that robust as it is a value for the worst-case scenario because the whole assessment was evaluated for the maximum active storage needed within the ensemble. Therefore, the scenario with the highest deficit of water in the

basin was considered as an initial scenario for analysis. Hence, these results represent the maximum yields available for a given active storage capacity that satisfy the condition of minimum time-based reliability of 99.50% across the whole ensemble of climate scenarios to cover the uncertainty of climate change.

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