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RESEARCH ARTICLE

Assessment of climate change effects on dam reservoir management

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Abstract

Climate change will alter the inflows into the dam in the future; thus, the balance between water supply and water availability will directly impact the water levels and indirectly affects dam safety. Therefore, estimating the future inflows and reservoir water content can help the operators. In this study, a machine learning Wavelet-MultiLayer Perceptron (W-MLP) method is applied to estimate monthly future projections (2016-2100) of the inflows into the reservoir. The methodology is tested for one of the main water supply reservoirs in Ankara, which distributes annual 142 hm^3 water. The EURO-CORDEX database is used to obtain Regional Climate Model (RCM) simulations of RCA4 (12.5 km) from two different Global Circulation Models (GCMs), MPI-ESM-LR and IPSL-CM5A-MR, under two Representative Concentration Pathways (RCPs) (RCP 4.5 and RCP 8.5) scenarios. The monthly W-MLP models are independently trained and tested for each data set (observed data and GCM outputs). The GCM scenario results indicate a shift in monthly hydrographs for both RCPs projections with a reduction in inflows which will directly change the operation of the reservoir. The daily HEC-ResSim model mimics future water content and releases. According to the results, the annual reduction expected in the future inflows scenarios varies between -3 % to -13% under the RCPs, and the effects on annual reservoir water content are much higher (between -21 % and -37 %). These findings can be used in different risk assessment metrics (reliability, resilience, and vulnerability) to estimate the future effects of dam safety.

1. Introduction

Water supply systems consist of many decision variables, natural and regulated flows, interconnected water elements, independent variables, etc. Decision makers such as analysts/operators at water structure utilities apply operational simulation/optimization tools to derive rational decisions from available information. However, climate change exacerbates the precipitation intensity and temperature [1], directly affecting these structures' operation and decision. The capacities of these structures are calculated with present criteria and historical data sets. From one aspect, some research mainly focused on the change in extremes like droughts and flood conditions [2-7]. On the other hand, spatial and temporal variation of the hydrograph and its effects on the existing water structures due to climate change is still a research question. Climate change is expected to alter the streamflow pattern, so the operation of the current water structures will be modified [8-9]. Therefore, their assessment for future changes is an essential issue to increase preparedness for water availability, disaster management, and dam safety [10-11].

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The most widely used approach is conducting the daily or sub-daily simulation of hydrological processes via a validated hydrological model (physical, conceptual or data-driven) using Global Circulation Model (GCM) based climate projections. The accuracy of GCMs directly affects the hydrological model results, but their uncertainty is massive, especially due to the low accuracy of precipitation. Despite their significant uncertainties, GCMs are still the most reliable technique [12]. In most cases, GCM projections cannot be used directly because their spatial resolution is too coarse to model hydrological processes at the required regional or local scale. Thus, they must be downscaled and eventually bias-corrected [13].

Rainfall-runoff models are used to estimate the rainfall-runoff relationship for future hydrological projections. Machine learning methods provide valuable alternatives to setting up nonlinear mapping. Hybrid systems are gaining popularity by merging advantageous parts of different approaches. For example, Humphrey et al. [14] apply a hybrid monthly streamflow simulation model by taking the Bayesian Artificial Neural Network (ANN) for producing 1-month ahead streamflow forecasts at three key locations in the South East of South Australia into account. Tongal and Booij [15] separate streamflow into different components like baseflow and surface flow and apply different machine learning techniques. Fan et al. [16] employ a machine learning method based on climate reconstruction to generate runoff for the data-scarce mountainous basin. Yazdandoost and Moradian [17] use CMIP5 (Coupled Model Intercomparison Project Phase5) data sets and downscaled them with the Artificial Neural Network (ANN) technique.

The assessment of the performances of water systems under climate change is an urgent issue for better adaptation studies. There is still limited study in the literature about this problem. For example; Ehsani et al. [10] emphasize that existing reservoirs in the Northeastern United State will be inadequate in forming drought/flood resiliency. Ehteram et al. [18] investigate reservoir operation using different heuristic optimization approaches under climate change using various climate change models for irrigation demand for the Dez basin in Iran. Sharifinejad et al. [19] evaluate water system vulnerability under changing climate from the outputs of 19 climate models under two RCPs by coupling the four hydrological models with HEC-ResSim (Hydrologic Engineering Centre-Reservoir Simulation Model) model on a headwater water resources system in Alberta, Canada.

The consequences of climate change are also depending on the selected region. This study aims to integrate a machine learning-based Wavelet-Multi-Layer Perceptron (W-MLP) rainfall-runoff model that employs two different GCM outputs of precipitation and temperature. Two RCPs mimic future monthly inflows into the dam reservoir, with a daily reservoir simulation model which estimates the effects on dam operations using USACE HEC-ResSim. The application reservoir is selected from one of the main water supply recourses of the capital city of Turkey, Ankara that distributes the annual 142 hm^3/year of water. The future inflow projections are generated using EURO-CORDEX (Coordinated Regional Climate Downscaling Experiment) of RCA4 (Rossby Centre Regional Atmospheric Model) regional outputs (12.5 km). They are derived from two different GCMs i.e. MPI-ESM-LR and IPSL-CM5A-MR under two Representative Concentration Pathways (RCPs) (RCP 4.5 and RCP 8.5) scenarios. The simulation model results are also compared with a benchmark model having no change in inflows into the dam reservoir.

2. Methods and data

The study consists of two parts. First, inflows into the dam reservoir that is operated for only water supply purposes, the meteorological observations (precipitation and temperature) provided from a nearby station together with climate projection data are obtained. These data are used in developing of the rainfall-runoff model to produce reference and future projections. Compared to the reference period, the changes in the future years have been determined, and a synthetic future hydrograph is derived. In the second part of the study, a reservoir simulation model is set to simulate the effects of future inflows on operational conditions. To that end, physical and operational data sets are provided and integrated with the synthetic future hydrograph and expected water demand. The study flow chart is presented in Fig. 1.

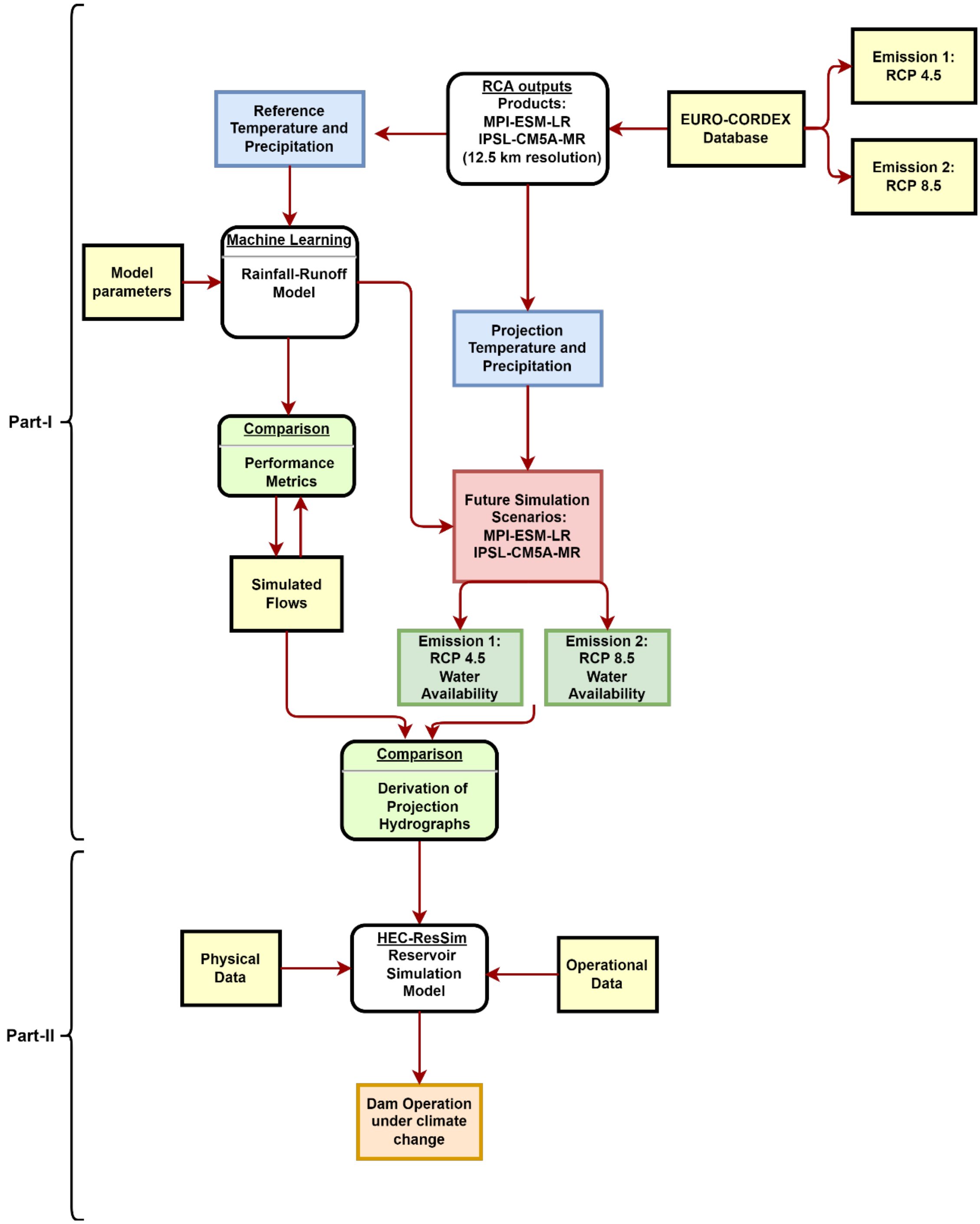


Fig. 1. The flowchart of the study

2.1. Machine learning inflow simulation model

Physical and conceptual models may necessitate a complex and rich data network to properly calibrate various model parameters. Machine learning methods provide powerful nonlinear relationship capabilities to relate meteorological variables and hydrological responses [20-22]. The MLP model is a feedforward network with linked neurons systematized into three layers: an input layer, a hidden layer, and an output layer [23]. The model is feedforward and the number of input and output nodes varies according to the problem type and data sets. Eq. (1) demonstrates the output of node j, Q_j.

$$Q_j = f\left(X.W_j - b_j\right) \quad (1)$$

$$X = (X_1, \dots, X_i, \dots, X_n)$$

$$W_j = \left(W_{1j}, \dots, W_{ij}, \dots, W_{nj}\right)$$

where X is information from previous nodes, w_{ij} represents the connection weight from the i^{th} node in the preceding layer to this node, where b_j is bias, and f is the activation function.

Most of the studies are conducted using lagged observed discharge in their model inputs [24]. However, this is not possible in climate change assessment studies, since the future projections are mainly obtained using meteorological outputs. Moreover, wavelet-based seasonal models outperform only Autoregressive models (i.e., ANN and Adaptive Neuro-Fuzzy Inference System, ANFIS) in order to increase their performances [25]. Hence, in this study, previous flow values are not provided in the model setup and the Wavelet-based MLP (W-MLP) model is configured with the best performance combination inputs as shown in Eq. (2).

$$I_n = f(P_n^A, P_n^D, P_n, P_{n-1}, P_{n-2}, P_{n-3}, T_{n-1}, T_{n-2}) \quad (2)$$

where f, P, T, and n represent the neural network model, total precipitation, average air temperature, and time step. A and D represent components of 1-D wavelet decomposition, so they are decomposed into two sub-signals. The target time series are provided as monthly total observed inflows in hm^3/month. The model is coded using MATLAB version 2022a software (License number: 40994073).

The model parameters (weights and biases) are optimized with Levenberg-Marquardt (LM) backpropagation algorithm, since it provides fast and robust solutions. This is a second order quasi-Newton method which updates the weights with Jacobian matrix for finding an optimal solution as shown in Eq. (3):

$$w_{k+1} = w_k - [\mathcal{J}^T \mathcal{J} + \mu I]^{-1} \mathcal{J}^T \varepsilon \quad (3)$$

where w_{k+1} and w_k are weights during $(k+1)^{th}$ & k^{th} epoch, $\mathcal{J}$ is the Jacobian matrix that contains the first derivatives of the network errors with respect to the weights and biases, μ is the learning rate and ε is a vector of network errors.

2.2. Reservoir operation simulation model

HEC-ResSim developed by USACE (United States Army Corps of Engineers Hydrologic Engineering Center) is selected to accomplish the reservoir simulations. HEC-ResSim 3.1 version is used in the study [26]. The computer program applies hydrologic and hydraulics of reservoir system simulation models. It is used in water resources management studies to simulate water systems and test various operational alternatives [27-30]. Software and documents are free and can be downloaded from the developer's internet page [31]. Multi-purpose and multi-reservoir systems are simulated by employing unique algorithms developed for particular purposes. So that, alternative operations can be generated and simulated.

Simulation of the water resource system is based on water accounting procedures associated with mass conservation. Since water is a constant density fluid for most reservoir/river system analysis applications, conservation of mass implies conservation of volume as well. In a general form, the mass balance or quantity equation for reservoirs can be formulated in Eq. (4) as:

$$S_t = S_{t-1} + I_t - R_t^1 - R_t^2 - R_t^3 - E \quad (4)$$

where; S is the reservoir storage, I is the total volume of inflow into the dam reservoir; R^1 is the total volume of water supply flow, R^2 is the total volume of spillway release, R^3 is the total volume of environmental flow through downstream, E is the volume of evaporation and t is the time index.

The model is configured daily in this study using monthly inflows. HEC-ResSim applies a simple linear interpolation to convert monthly data into daily. The decisions are taken according to the Guide Curve (GC) definition. Operations, rules, and alternatives are defined to simulate the operation of the system. The rules are prioritized depending on their descriptions. In this study, the HEC-ResSim model simulation model is conducted on a daily time period.

2.3. Data sets

2.3.1. Study area and hydro-meteorological data

The developed model is applied to the Çamlıdere Dam Basin (753.4 km^2), which supplies most of the municipal water to Ankara, the capital of Turkey (Fig. 2). Çamlıdere dam which is a rock-filled dam has been operating since 1987. The annual water withdrawal was planned for about 142 hm^3/year considering annual water availability of 161 hm^3. The reservoir volume was designed to accumulate a more significant flow considering further water diversions from other basins. However, in this study we only focus on the water availability of the Çamlıdere Basin, and the water transfers from other systems are not considered within the scope.

The data used in the study are total monthly precipitation (P), average monthly air temperature (T), monthly total net evaporation (E) and monthly inflow volumes into the reservoir (Q). The inflows into the dam reservoir are calculated between 1960 and 2016 by the State Hydraulic Works (DSI). The 1970 – 2005 period is selected as the application range considering the reference period data range of the EURO-CORDEX database [32]. There are 6 rain gauges called Kızılcahamam, Nallıhan, Beypazarı, Esenboğa, Keçiören and Polatlı in Ankara and around the basin. The highest correlation with observed inflows is detected with precipitation data of Kızılcahamam station, the nearest station to the dam lake. Hence, we use Kızılcahamam gauge station data and the climate data is also extracted from the closest node to the station. For the W-MLP model configuration, the first 252 months (between January 1970 and December 1990) are used for the training period, while the remaining data (177 months) that are not used in any part of the training (between January 1991 and September 2005) are split for testing the model.

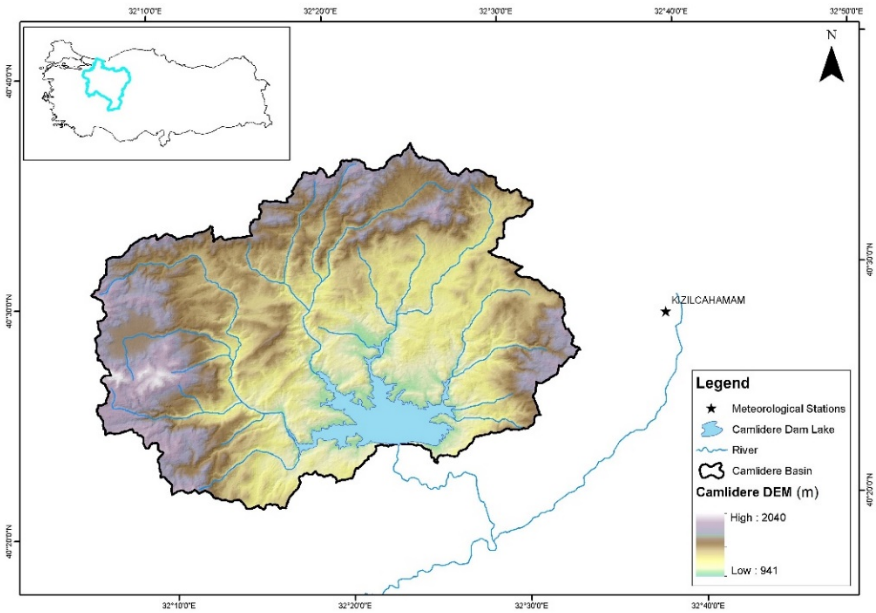


Fig. 2. Location and topography of the study area with station network

The physical characteristics of the dam reservoir (elevation-storage-area curve), and the elements of the dam such as spillways, intake structures, sluiceways, etc. with their capacity curves are defined in the HEC-ResSim model. The main characteristics of the dam and the reservoir are briefly given in Table 1. The delivered amount for water supply purposes is assumed as 163.3 hm^3/year (15% increased amount of the planned demand) according to the expected increase in demands due to the population growth [33]. The discharged amounts of environmental and additional purposes to the downstream regions are taken as 19 hm^3/year, and 6 hm^3/year, respectively [33]. The dam reservoir is designed to handle a larger capacity than its total volume considering further inter-basin water transfers; thus, the initial reservoir content in the reservoir simulations is assumed to be 1/3 of the total conservation pool which equals 356.7 hm^3 (almost double the annual total inflows). Evaporation data is assumed to be constant in the reference and future periods. The reservoir is divided into three zones: dead (inactive) volume, conservation volume, and flood control volume. The top of each pool elevation is defined as different zone partitioning with information in Table 1. Water withdrawals are defined as constant rules from intakes. Since there are no flood control purposes, the conservation volume (maximum operation level of the dam) is defined as the GC.

2.3.2. Climate projections

GCM is run for the reference (historical) period and projection period. In this study, the reference and future projections of precipitation and temperature are provided from the EURO-CORDEX data of CMIP5 which is freely available to all users [32]. There are different GCM and RCA in the system, and we select two GCMs that are appropriate for the Turkey region in the literature. MPI-ESM-LR and IPSL-CM5A-MR under two RCPs (RCP 4.5 and RCP 8.5) recommended by the IPCC (Intergovernmental Panel on Climate Change). We use downscaled versions of GCM data derived from the RCA4 Regional Climate Model to provide a range of high-resolution inputs (12.5 km resolution). Due to data-driven modeling, no further error correction is performed for precipitation and temperature datasets. The reference period has a range of 1970–2005 whilst the future projection has a range of 2016–2100. RCP 4.5 is a radiative forcing path equivalent to 4.5 Wm−2 (equivalent to 650 ppm CO_2 concentration) and RCP 8.5 is equivalent to 8.5 Wm−2 (equivalent to 1370 ppm CO_2 concentration). It is a radiative forcing path that rises up until 2010 [34]. Therefore, RCP8.5 represents a future worst-case scenario compared to the RCP4.5 scenario.

2.4. Performance metrics

The performance of the inflow simulations is tested with observed inflows using the square of correlation coefficient (R) called the coefficient of determination (R^2), Nash-Sutcliffe Model Efficiency (NSE) and Percent-Bias (P-Bias) in Eqs. 5 - 7.

Table 1. Physical characteristics of Çamlıdere Dam

	Elevation, AMSL* (m)	Reservoir Storage (hm^3)
Flood control	999.70	1337.06
Maximum operation	995.00	1220.38
Minimum operation	942.14	150.06
Spillway crest	995.00	-
Sluiceway	897.75	-
Minimum intake	942.14	150.06

* Above mean sea level

$$R = \frac{\sum_{t=1}^{n}(X_m^t - \overline{X}_m)(X_o^t - \overline{X}_o)}{\sqrt{\sum_{t=1}^{n}(X_m^t - \overline{X}_m)^2}\sqrt{\sum_{t=1}^{n}(X_o^t - \overline{X}_o)^2}} \quad (5)$$

$$NSE = 1 - \frac{\sum_{t=1}^{n}(X_o^t - X_m^t)^2}{\sum_{t=1}^{n}\left(X_o^t - \overline{X}_o\right)^2} \quad (6)$$

$$P - Bias = \frac{\sum_{t=1}^{n}(X_m^t - X_o^t)}{\sum_{t=1}^{n} X_o^t} \quad (7)$$

where X_m^t is modeled flow, X_o^t is observed flow, $\overline{X}_m$ is the average of the modeled inflows, $\overline{X}_o$ is average observed flows, n is the number of data sets and t is the time index.

3. Results

3.1. W-MLP model results for the reference period

The reference period of the climate data sets (1970-2005) is configured as the hydrological model configuration period. The W-MLP-based monthly inflow model results are presented in terms of water volume (hm^3/month) in Figs. 3-5 for the whole period (the training period from 1970 to 1990 and the testing period from 1991 to 2005). Each model is trained and tested separately. The final model parameters (the weights and the biases) of each W-MLPs are selected from the best run of various independent trials applying the trial-and-error procedure. The station data-based W-MLP model experiment demonstrates the best capability of the machine learning W-MLP technique applied in this study under perfect input (forcings) conditions. The findings indicate that the developed W-MLP configuration gives satisfactory performance metrics (R^2 and NSE>0.65 and >0.50 for the training and testing, respectively). The R^2 and NSE performances of both climate data set-based W-MLP models are lower than station-based modeling. However, monthly P-Biases show satisfactory values with less than 12% overestimations which shows the convenience of the model performances (Table 2).

3.2. W-MLP model results for future projections under GCM scenarios

The future inflow projections under RCP4.5 and RCP8.5 concentration scenarios are conducted between 2016 to 2100 using two monthly different climate data sets through previously developed and tested W-MLP models. The monthly average future simulation inflows are presented in comparison with the monthly average reference model inflows from October to September. The water year concept is used in the Northern hemisphere (Fig. 6). The peak of the monthly inflows into the dam reservoir during the spring seasons is expected to drastically decrease while early inflows during fall and winter slightly increase. The worst-case scenario (RCP 8.5) based inflows are lower than RCP 4.5 scenario-based inflows. The total percent reduction in mean future annual total inflows (2016-2100) with respect to their annual reference mean total values are approximately -7 % and -3 % in RCP4.5 and -14% and -5% in RCP 8.5 for MPI and IPSL, respectively.

The projection inflows cannot be directly used in the reservoir operation study, hence the percent changes of the future projections with respect to the reference period are calculated for each month and climate change-based inflow hydrographs are derived by multiplying with observed values. The final form of the one annual water year cycle hydrograph is shown in Fig. 7.

Table 2. Comparative performances of the W-MLP model for simulating inflows into the dam reservoir

	R^2			NSE			P-Bias (%)		
	Station	MPI	IPSL	Station	MPI	IPSL	Station	MPI	IPSL
Training Period	0.66	0.65	0.67	0.65	0.65	0.67	7.2	5.7	6.0
Testing Period	0.51	0.33	0.12	0.50	0.30	0.12	11.1	5.8	11.9

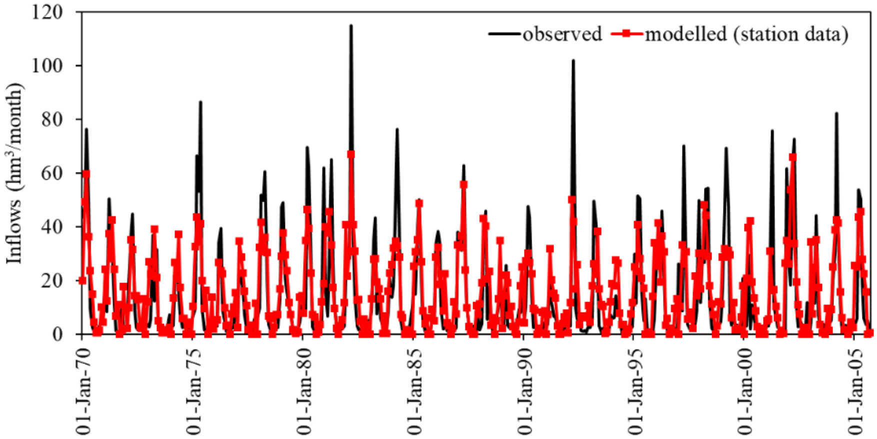


Fig. 3. W-MLP modeling results using observed station data sets

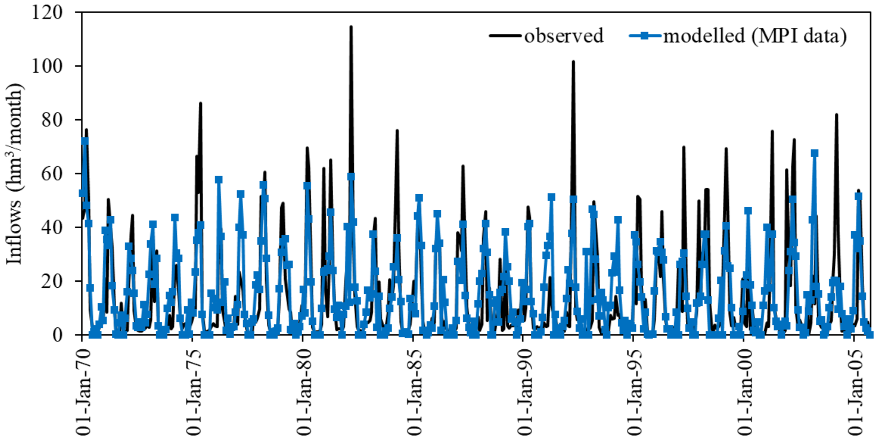


Fig. 4 W-MLP modeling results using MPI-ESM-LR reference climate data sets

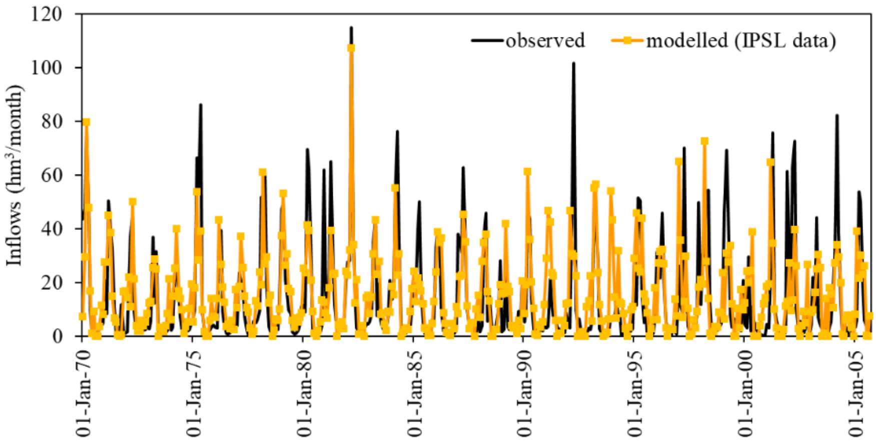


Fig. 5. W-MLP modeling results using IPSL-CM5A-MR reference climate data sets

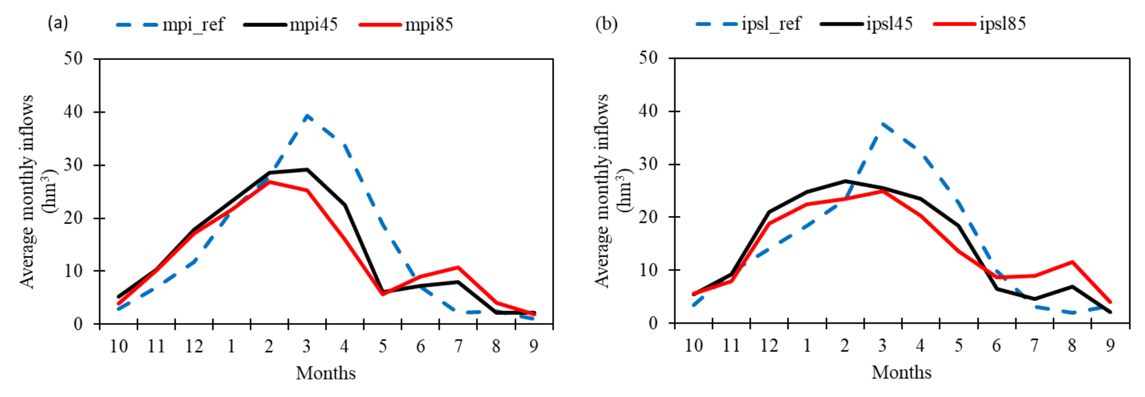


Fig. 6. Variation of monthly inflows in comparison with reference period (a) MPI (b) IPSL

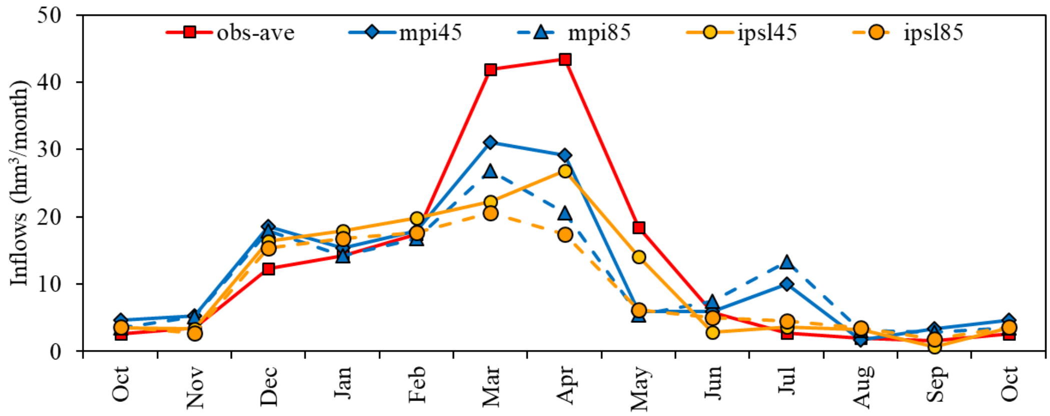
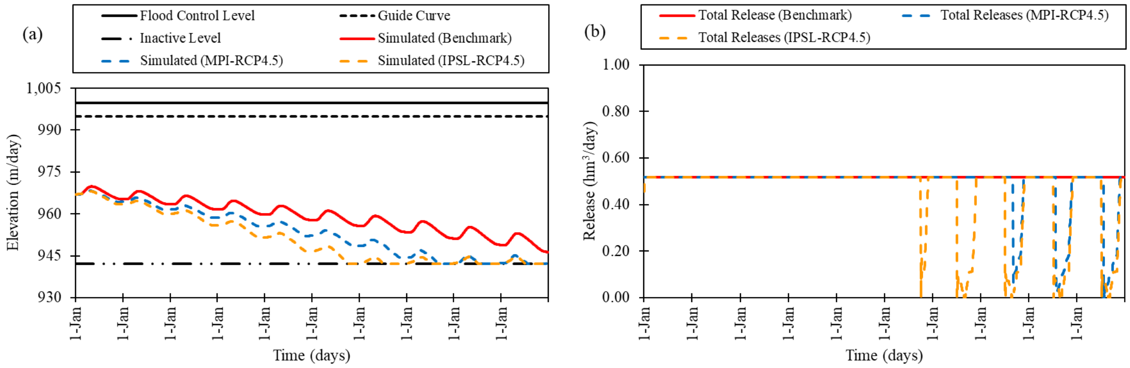


Fig. 7. Climate change-based scenario hydrographs

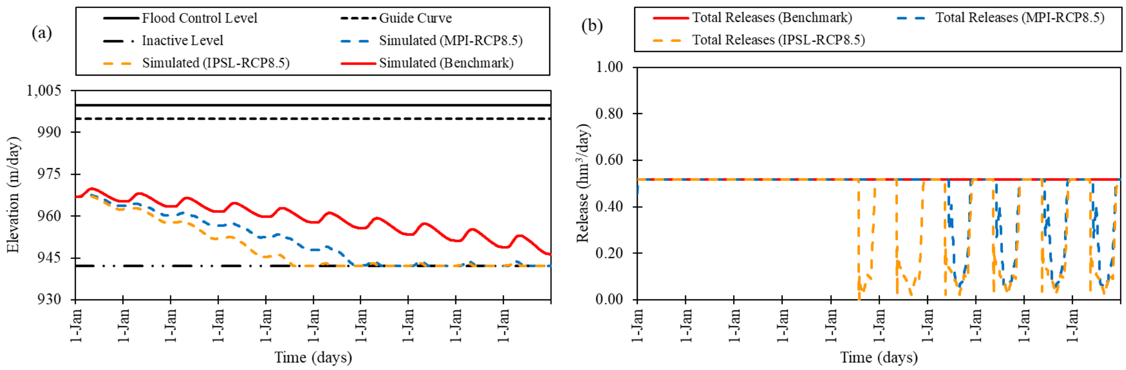
3.3. Reservoir simulation-based dam operation model results under climate change

The daily simulation models are accomplished with different expected inflow scenarios under the HEC-ResSim model with derived hydrographs under the same physical, operational, and demand data. Water demands are increased in the simulation model with the expected values in the future. Since the hydrograph is derived for one annual cycle, the simulation period is extended to discard the initial water level by sequentially providing the same scenario hydrograph. In order to make a comparison, a benchmark reservoir simulation model is also employed with monthly average observed inflow values. The benchmark model also enables the determination of the time horizon of the simulation. According to the benchmark model findings a sequential ten-year time horizon is sufficient without any water shortage. The results (reservoir water level and total releases from the reservoir for different purposes) are presented for RCP 4.5 and RCP 8.5 concentration scenarios of two climate data in Fig. 8 and Fig. 9, respectively. HEC-ResSim model allows conducting the simulation time step in daily or lower (hourly) time resolution. Since the study is based on assessing the performance of a water-supply reservoir regardless of the flood control purpose, thus the extreme cases in inflows are not reflected in a monthly model. However, monthly extremes (such as March and April) are properly reflected in the HEC-ResSim model through the filling of the reservoir. Considering the reservoir capacity, there are no spillway discharges in the simulations. RCP4.5-based simulations provide less water shortage compared to RCP8.5 simulation results.



a) Reservoir lake elevation b) Release from the dam reservoir

Fig. 8. Reservoir simulation results under RCP 4.5 scenario (arbitrary 10 years)



a) Reservoir lake elevation b) Release from the dam reservoir

Fig. 9. Reservoir simulation results under RCP 8.5 scenario (arbitrary 10 years)

The durations for reaching the inactive zone for the first time that also shows the alarm situation due to water shortage are 7.8 years, 6.9 years, 6.8 years, 4.8 years for MPI-RCP4.5, IPSL-RCP4.5, MPI-RCP8.5, and IPSL-RCP8.5, respectively. Although the change in total annual water availability is less in W-MLP-based future flows in IPSL, however, it shows the worst case in the reservoir simulation model in terms of operation. This is mainly due to the change in the shape of the inflow hydrograph timing and the effects of the total reduction in inflows for the IPSL scenario, thus they have direct effect on water availability in the reservoir.

4. Discussion of the results

Generally, the W-MLP monthly rainfall-runoff model performances of each data set (station and climate) are satisfactory, especially in terms of monthly P-Bias values. The lower relationships for the climate-based models are expected considering the lower spatial resolution of climate data and uncertainties associated with global atmosphere models. Compared to daily modeling, the application of monthly modeling is more challenging in the literature. However, in this study, the lower NSE values compared to R^2 and the mismatches of the peak values might be attributed to no lagged inflow data set in the modeling scheme. Considering two climate models and RCP scenarios, the total reduction in future inflows (2016-2100) is expected to be between -13 % and -3 %. However, a large variation in months and seasons affects the reservoir simulation results. This also shows the importance of accounting for future inflows in a water-budget-based reservoir simulation model. Finally, a summary chart (Fig.

10) depicts the annual average water availability in the reservoir and the annual average total releases obtained from the reservoir simulation model under the effects of climate change. The worst and the best cases are detected for IPSL-RCP 8.5 and MPI-RCP 4.5, respectively. Percent changes are given in Table 3 compared to the benchmark model which assumes no change in the historical inflows in the future. According to the study results, it is remarkable to notice that climate change affects the operation of the Çamlıdere dam by decreasing -37 % of the total reservoir storage in the future which is a much more significant impact compared to the worst-case -13 % reduction in annual inflows into the dam reservoir.

5. Conclusions and outlook

The hydrological processes are complex, and various factors affect the performances (i.e. the uncertainties of the model structure, forcing variables, initial conditions, etc.). However, hydrological models provide valuable information about the responses of the atmospheric variations within a catchment. One of the biggest challenges of the current era is human-induced climate change. New approaches [35-37] and their integration with management of water structures are still needed for better adaptation to these challenges. This study proposes an application scheme to operate the existing water structures under changing climates. Even though the GCM model includes larger uncertainties, they still offer advantageous information about future conditions. The study demonstrates a useful scheme for integrating reservoir simulation models with inflow estimation, which might reveal valuable results for the dam operators, modelers, and decision-makers. The conclusions and future recommendations are briefly defined as:

- The developed W-MLP models are capable of simulating monthly rainfall-runoff nonlinear relationships. Training GCMs-based forcings (precipitation and temperature) separately in the modeling scheme provides to estimate future projections.

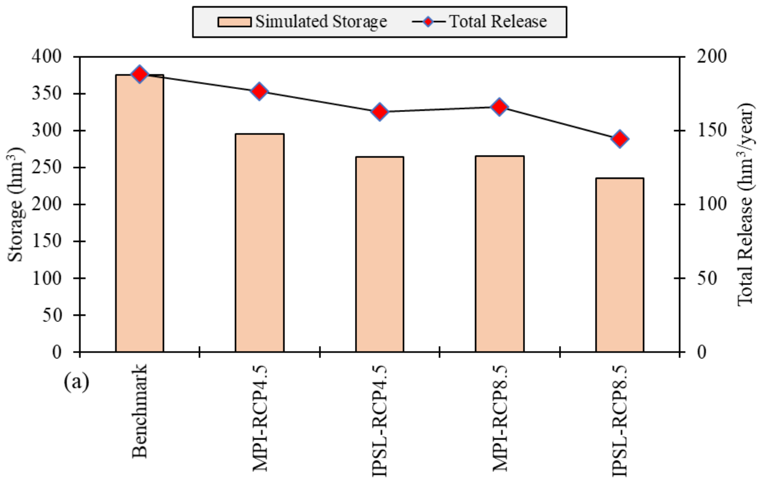


Fig. 10. Summary of the reservoir performance under the future projection in comparison with the benchmark model

Table 3. Changes in inflows and dam storage due to climate change

	Change in the inflows (%)		Change in the dam storage (%)	
GCM	RCP4.5	RCP8.5	RCP4.5	RCP8.5
MPI-ESM-LR	-7 %	- 13 %	-21 %	-29 %
IPSL-CM5A-MR	-3 %	-5 %	-30%	-37 %

- Considering two GCMs (MPI-ESM-LR and IPSL-CM5A-MR) under RCP4.5 and RCP8.5 concentration scenarios, the total reduction in future inflows (2016-2100) is expected to be between -14 % and -3 %.
- The impact of the future variability expected in inflows is much higher since the reservoir storage content varies between -37 % and -21 % indicating water shortages in the future conditions according to the reservoir simulation model. This might be attributed to the change in the inflow hydrograph timing, the effects of the total reduction in inflows for a longer time horizon, and the relative effects of the increments in water demand amounts in the future.
- In further studies, rather than a single synthetic hydrograph for the future variability, the monthly scenario inflows can be also generated by updating with monthly correction factors obtained between observed inflows and the reference climate inflows and provided to reservoir simulation. This can help to reveal variations in reservoir water content and releases for various time horizons (e.g. 2016-2049, 2050-2075, 2076-2100).
- The obtained results might be engaged with different risk assessment metrics (reliability, resilience, and vulnerability) to determine the future condition of dam safety. The developed scheme can be applied to other reservoirs and regions, also accounting for other multi-purpose targets such as flood control and energy production. The precautions for future cases such as adaptation are vital for secure water management and dam safety.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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