

Quantifying variations in reservoir projections: Uncertainty assessment in reservoir indices under RCP8.5 scenario

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Abstract

Use of various tools such as multiple general circulation models (GCMs), hydrological models (HMs), downscaling techniques, etc. may induce variations in climate change projections. Featuring this uncertainty issue becomes important for relevant authorities who are involved in climate change impact studies, adaptation, and mitigation. Thus, the uncertainty analysis in climate change projections for water resources such as dams has importance in reservoir operations as well. Hence, in this study, an uncertainty analysis with respect to climate change was tried to be carried out for reservoir performance indices of a prominent dam which is located in Turkey. Eleven GCMs of CMIP5 datasets for the RCP8.5 scenario and five hydrological models were performed to get the future projections of precipitation, temperature, and streamflow. In the upshot, reservoir projections were made and the sources of uncertainty in reservoir performance indices were quantified. According to the results, the negative effects of climate change for the RCP8.5 scenario are estimated as a decrease of precipitation and streamflow and an increase of temperature. In uncertainty analysis of reservoir performance indices, it was obtained that in several indices depending on high streamflow conditions such as time-based reliability or resiliency, most of the uncertainty was originated in GCMs, however, in indices such as vulnerability, which is based on the severity of water deficit in related time, the HMs uncertainty has the major fraction.

Keywords: downscaling, hydrological modelling, reservoir operation, uncertainty analysis

1. Introduction

In climate change studies, it can be estimated different future projections with different approaches and modelling schemes. In this respect, general circulation models (GCMs) have become beneficial tools in order to get future predictions for the atmospheric variables of interest and so they enable people and relevant authorities to adapt and mitigate climate change. However, when the GCMs are taken into consideration, it can be obviously seen that they are generated under different methodological pipelines by various research centers. Hence, they estimate spatially and time-varied future projections from each other. Sure, the difference between GCMs is not a single uncertainty source in climate change projections such that there are other fractions that give rise to uncertainty as well. For instance, Hawkins and Sutton (2009, 2011) state that there are two other major uncertainty sources besides GCM uncertainty (sometimes referred to as model uncertainty) such that they are originated from different emission scenarios and internal variability. In the related work, the scenario uncertainty is determined as the uncertainty in future emissions and radiative forcing which affect the climate. Of the three, the latter stands for the natural fluctuation of the climate with no consideration of anthropogenic effects. Besides Hawkins and Sutton (2009, 2011), there are various studies in which the related uncertainty sources are considered major ones. For instance, Yip et al. (2011) used an ANOVA-based model to decompose the total variance in the future projections and evaluated the three major uncertainty and interactions between them. Knutti and Sedláček (2013) made a comprehensive study in which they show the variations in the results between different Coupled Model Intercomparison Phase (CMIP) models and different emission scenarios. In these works, it can be seen how the ratio of uncertainty sources changes with respect to GCMs, and emission scenarios.

In the climate change literature, the researches have been done for not only atmospheric variables such as precipitation, temperature and etc. but also variables related to hydrometeorology, biodiversity, human health, and so on. In this study, the analysis was made only for hydrometeorological cases. The studies made about the climate change effects on hydrometeorological variables generally covers a few main topics such as downscaling (Kirdemir et al, 2022; Okkan and Kirdemir, 2018; Fistikoglu and Okkan, 2011; Sachindra et al, 2018), bias correction (Okkan and Kirdemir, 2016; Maraun, 2013), streamflow modelling (Najafi et al., 2011), reservoir operations (Okkan and Kirdemir, 2018), extreme events (Kirdemir and Okkan, 2019; Mesbahzadeh et al., 2019; Skougaard Kaspersen et al., 2017) and etc. When the studies analyzing the climate change effects on hydrometeorological variables are evaluated, it can be realized that the calculation of future projections demands different models each of which has varying modelling algorithms, parameterization, data usage and etc. Thus the combinatorial strategies take out additional uncertainty sources in future projections. In this context, it is possible to encounter studies that address different uncertainty sources in the literature. For instance, Lehner et al. (2020) dealt with the uncertainty sources originating from bias calculations in future precipitation and temperature

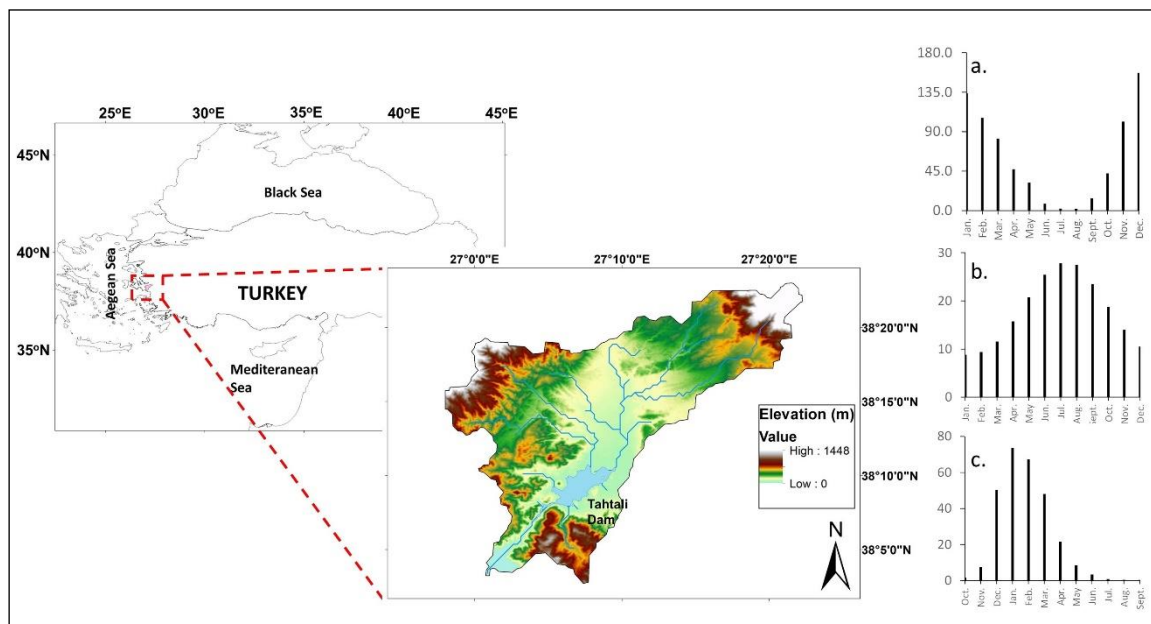
projections. Wang et al. (2020) tried to decompose uncertainty sources in streamflow projections and they addressed the variations originating from selected downscaling methods, hydrological models, and hydrological model parameterization. Orłowsky and Seneviratne (2013) made drought projections in different parts of the world and quantified uncertainties in these projections.

In this study, a reservoir projection study was conducted for a dam basin of Turkey by integrating divergent combinations of GCMs and hydrological models (HMs) under a pessimistic representative concentration pathway (RCP8.5) scenario. Eleven CMIP5 datasets which were generated under the Fifth Assessment Report (AR5) of Intergovernmental Panel on Climate Change (IPCC) were utilized and a statistical downscaling strategy was carried out to obtain precipitation and temperature projections for the term 2020-2050. Then, by developing a regionalized evaporation model, five HMs were established for the study area and future streamflow projections were obtained. Subsequently, reservoir operations were fulfilled for each GCM-HM combination and the predicted reservoir performance metrics were evaluated. In the upshot, uncertainty sources in projected reservoir metrics under the RCP8.5 scenario were tried to be decomposed from the total uncertainty originated from different model pairs. The study mainly has 3 parts: a) precipitation and temperature downscaling, b) hydrological modeling and streamflow projections and c) decomposing uncertainty sources in reservoir operations. The detailed information about the study area and the utilized data are given in the next section.

2. Study Area and Data

The study area covers Tahtali Dam basin with a 546 km² drainage area in the western part of Turkey. Tahtali dam, which has a lake volume of 306 hm³, is one of the major water resources for Izmir city and is operated for supplying drinking water. The Mediterranean climate characteristics prevail in the study region. In the study region, the observed data, which represent the term 1948-2008, for monthly total precipitation and monthly average temperature were obtained from the Turkish Meteorological Service (TMS), and monthly total streamflow data of Tahtali Dam for the term 1970-1988 was obtained from General Directorate of State Hydraulic Works. According to the utilized data, mean areal precipitation is about 727 mm per year, and the mean annual temperature is observed as 17.8 °C. Annual mean streamflow observed at the inlet of Tahtali Dam is about 155 hm³ per year (Fig 1).

Figure 1. The location of the Tahtali Dam basin. The bar charts on the right stand for the monthly total precipitation (a), average temperature (b), and total streamflow for months



The reanalysis data which represent the atmospheric, oceanic, and land surface characteristics of the past time are utilized in the climate-related assessments frequently (Kirdemir et al., 2022). In this work, NCEP/NCAR reanalysis datasets accessed in monthly time scale for the 37.5°N-27 5°E coordinates were selected as large-scale predictors such that they were operated in order to train downscaling models. The large-scale output databases from eleven GCMs which include both historical scenario outputs representing 20th-century climate (1980-2005) and 21st-century climate simulations under RCP8.5 scenario (2020-2050), were selected for the downscaling exercise. The information about the selected GCMs was given in Table 1.

In this study, twelve ERA-Interim variables, which were common to data involved in eleven GCMs for the RCP8.5 scenario, were extracted so as to perform statistical downscaling models in order to transform GCM outputs to the monthly total precipitation and monthly mean temperature. The content of the data set consists of several variables including mean air temperature (ta), geo-potential height (zg), and relative humidity (hur) at different atmospheric levels (200, 500, and 850 hPa), large-scale precipitation (pr) and sea level pressure (psl) at surface, which are the potential predictor variables. The least Absolute Shrinkage and Selection Operator (Lasso) method was performed in order to sort out the predictor variables of precipitation and temperature Tahtali dam basin. To avoid the computational cost in downscaling model deployment, a subsample with pr , $hur850$, and $ta850$ for precipitation and tas and psl for temperature was selected with Lasso to use as model inputs

Table 1. The information about GCMs utilized in the study.

GCM	Institution	Resolution
		Lat (°) x Lon (°)
CCSM4	National Center for Atmospheric Research, USA	0.942 x 1.25
CESM1(CAM5)	National Center for Atmospheric Research, USA	0.942 x 1.25
CSIRO-Mk3.6	Commonwealth Scientific and Industrial Research Organisation, Australia	1.865 x 1.875
GFDL-CM3	Geophysical Fluid Dynamics Laboratory, USA	2 x 2.5
GFDL-ESM2M	Geophysical Fluid Dynamics Laboratory, USA	2.022 x 2.5
GISS-E2-H	NASA Goddard Institute for Space Studies, USA	2 x 2.5
GISS-E2-R	NASA Goddard Institute for Space Studies, USA	2 x 2.5
HadGEM2-ES	Met Office Hadley Centre, UK	1.25 x 1.875
IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	1.895 x 3.75
MIROC-ESM	Atmosphere and Ocean Research Institute, Japan	2.791 x 2.813
MRI-CGCM3	Meteorological Research Institute, Japan	1.12 x 1.125

3. Statistical Downscaling

Due to the coarse pattern of GCM data, it turns out to be troublesome to carry out climate change analysis at a regional scale. In this respect, the application of a downscaling procedure, that is, projection of coarse GCM data to a local scale, becomes advantageous to overcome the results with systematic biases at the regional scale. Thus, in this study, statistical downscaling models were established for precipitation and temperature variables to use future projections later on. A machine learning technique namely Artificial Neural Networks (ANN) was utilized to downscale the coarse-resolution GCM data to the local scale. In this respect, the predictor variables sorted out for each of precipitation and temperature were presented as inputs to downscaling models. The models were evaluated by means of several statistical performance criteria such as determination of coefficient (R^2), Nash-Sutcliffe (NS), proportion of root mean square error (RMSE) to standard deviation of observed data (RSR), and percent of bias (PBIAS). The detailed information about the ANN and utilized performance metrics for model assessments are given in Fistikoglu and Okkan (2011).

Besides GCMs have a coarse-resolution structure, the complicated pattern of the atmosphere induces systematic errors in GCM generation (Kirdemir et al., 2022; Li et al., 2010). Thus, postprocessing of downscaling results may produce more robust projections which return climate characteristics of the study region. For postprocessing, a distribution-based method, Quantile Delta Mapping (QDM), was used to transform the downscaled data and reduce biases. QDM was developed by Cannon et al. (2015) in that the GCM-based relative changes in quantiles are preserved and the reduction of biases in quantiles is determined with respect to observed time series. This method was carried out for reference (REF), in other words, historical data and extrapolated scenario data for each GCM.

4. Streamflow Modelling

In reservoir operation studies, one of the main variables to use is streamflow such that it is possible to achieve its mathematical model through different techniques. In the study, lumped hydrological modeling methods were exploited in order to get predictive models for Tahtali Dam flows. Five different hydrological models were utilized such that they were commonly conceptual, deterministic, and parametric models and operated in monthly time scale. The input variables for all of the models are monthly total precipitation and monthly total potential evapotranspiration. The hydrological models which were performed in this study were namely Thornthwaite Water Balance Model (TWWBM; Thornthwaite, 1948; Thornthwaite and Mather, 1955), abcde model (Thomas, 1981), GR2M model (Mouelhi et al., 2006), Dynamic Water Budget Model (DYNWBM; Zhang et al., 2008) and Temez model (Temez, 1977).

As mentioned above, the HMs demand the monthly total precipitation and potential evapotranspiration data so as to predict the streamflow for the given study region. For potential evapotranspiration, FAO-56 suggests the use of the Penman-Monteith method (Allen et al., 1998) as the reference method to calculate potential evapotranspiration which is the summation of water amount that can evaporate to the atmosphere from the saturated soil with the amount of water released to the atmosphere by plants through transpiration. The related method which relies on the combination of mass transfer and radiation-based methods demands atmospheric data which are difficult to observe such as wind speed, solar radiation, surface pressure, etc. Hence, this method has constraints to perform in the regions where limited data observation exists. Moreover, in climate change studies, if it is desired to have future projections of potential evapotranspiration obtained through the Penman-Monteith method, the inputs of this method (wind speed, radiation, etc.) should be downscaled as well. In this regard, this is another drawback of Penman-Monteith for potential evapotranspiration calculation. To overcome this issue, it was decided to use pan evaporation data as input which were observed in the study region. For the future projections of evaporation under the RCP8.5 scenario, a temperature-based evaporation model was developed. This model was called as regionalized Kharrufa (Reg-Kharrufa) model such that it was derived with respect to the Kharrufa formula (Kharrufa, 1985) with a similar strategy which was mentioned in Kirdemir et al. (2022).

5. Reservoir Operation and Performance Indices

The reservoir volume that Tahtali Dam stores in each month is calculated with behaviour analysis method based on the water budget model as in Equation 1.

$$V_{t+1} = V_t + Q_t - D_t - E_{net,t} \quad C_{min} \leq V_{t+1} \leq C_{max} \quad (1)$$

where V_{t+1} is the water volume in the beginning of the month $t+1$, V_t is the water volume in the beginning of the month t , Q_t is the monthly total inflow rate stored in reservoir in month t , D_t is the amount of water demanded in month t and $E_{net,t}$ is the net evaporation of month t . According to the reservoir operation rule, the reservoir returns a supply deficit in month t (Def_t) if the lake volume reaches under minimum volume (C_{min}), that is, this amount is difference between C_{min} and V_{t+1} . The reservoir performance indices evaluated in the study are time-based reliability (Rel_t), resiliency (Res), vulnerability (Vul) and sustainability (SI) indices. These indices mainly depend on frequency of deficit occurrence and deficit volume in a given time period. The formulas of the related reservoir performance indices are given in Table 2. The detailed information about the related indices can be accessed in Okkan and Kirdemir (2018).

Table 2. The reservoir performance indices utilized in the study.

Reservoir Performance Indices				
	Time-based reliability (Rel_t)	Resiliency (Res)	Vulnerability (Vul)	Sustainability (SI)
Formula	$Rel_t = \frac{Fr(Def_t = 0)}{n}$	$Res_t = \frac{Fr(Def_t = 0 Def_{t-1} > 0)}{Fr(Def_t > 0)}$	$Vul_t = \frac{\sum_{t=0}^{t=n} Def_t}{\sum_{t=0}^{t=n'} (D_t Def_t > 0)}$	$SI = \left[\prod_{m=1}^M PI_m \right]^{1/M}$
Description	Fr(.) = The frequency of an event in the given time interval		n'= The number of months in which deficit occurs D _t = The demand in the month in which deficit occurs	m= The performance indice M= The total number of performance indices

6. Uncertainty Analysis

Different global circulation models used in climate change studies produce coarse-resolution estimations about atmospheric variables for the past and future periods with different approaches by different research centers, and these models have become useful tools in studies prepared for climate projections. For different atmospheric variables, each climate model predicts statistically varying scenarios for different radiative forcing scenarios, and this causes variation in the derived climate change projections for different variables. A similar situation is encountered in the outputs obtained with different HMs. For example, while some HMs better model dry season flows, some models can better model wet season flows, and similar situations cause variability in the derived flow simulations.

For this reason, the uncertainty caused by the different GCMs, and HMs used in the prepared study in the reservoir performance projections has been tried to be determined quantitatively. For this, the variance decomposition method (VDM) will be used in the study and the ratio of each factor in the uncertainty will be tried to be obtained.

The ratio of the variances obtained for each factor in the VDM method shows how much uncertainty the related factor yields on the estimations. In the study, a total of $N_{GCM} \times N_{HM}$ ($11 \times 5 = 55$) predictions were made for each of the reservoir projections and the uncertainties of the obtained results on the factors were tried to be examined. Detailed information on the VDM method can be obtained from Yip et al. (2011).

7. Results

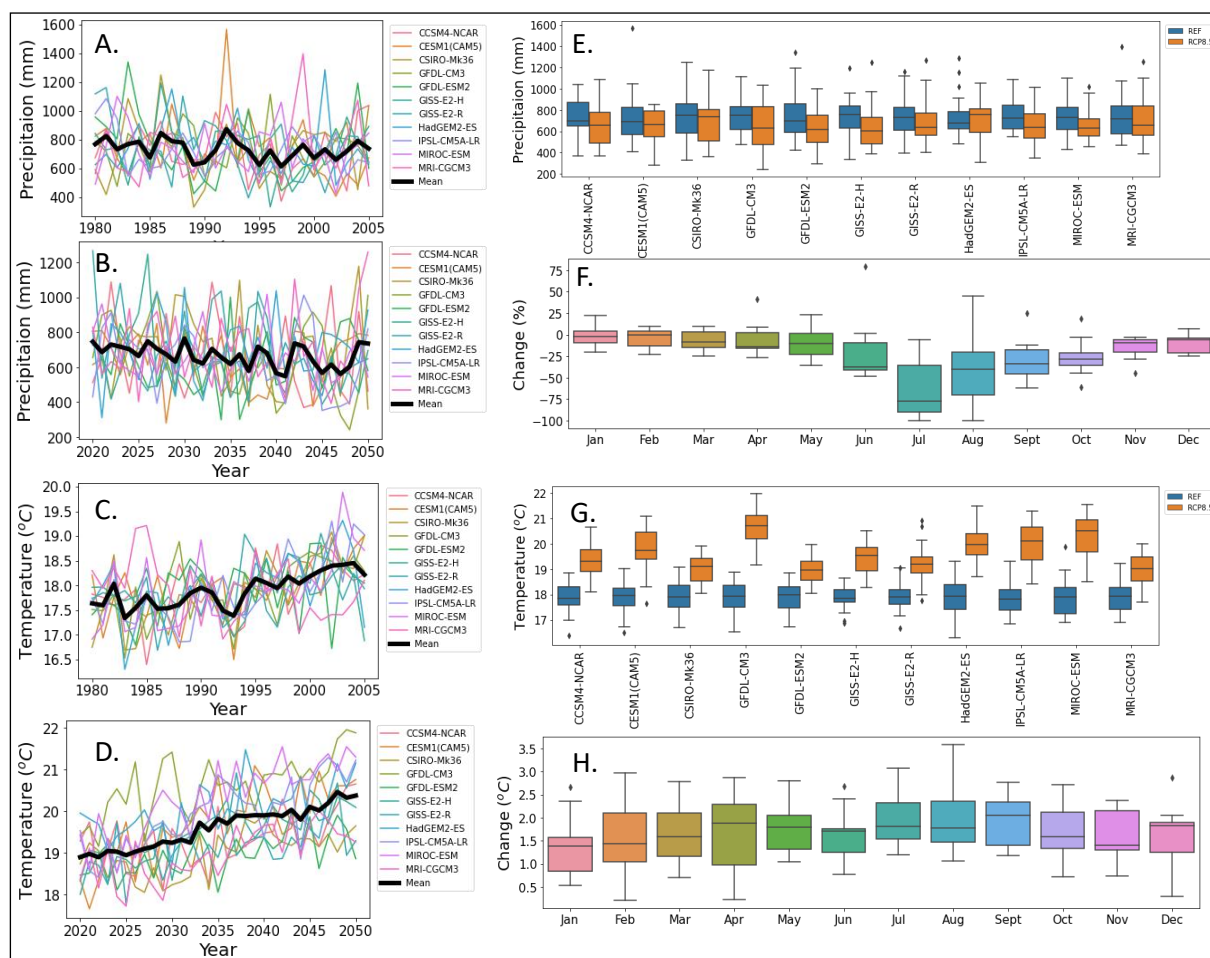
In the study, the ANN method was performed in order to carry out the downscaling implementations for both precipitation and temperature variables. The filtered reanalysis datasets with Lasso were given as inputs to the model and the results were integrated with the QDM. At the end of this process, the precipitation and temperature projections under RCP8.5 scenario were obtained for the term 2020-2050. According to the results, the ANN model has generally shown ‘*very good*’ and ‘*good*’ results in terms of statistical performance criteria which were utilized in the study for both precipitation and temperature downscaling. At this stage, the projections with respect to 11 GCMs were evaluated and according to the estimations, it is estimated that decreases in the precipitation in the future term for RCP8.5 scenario. These decreases are expected to be between 2.5% (HadGEM2-ES) and 14.3% (GFDL-ESM2) in the future. When the temperature projections of the study area are examined, it is revealed that more stable results are derived from climate models, unlike precipitation projections. In temperature projections, increases in temperatures are expected for each climate model in all statistical values. When the annual average values are examined, it is estimated that there will be increases of 1.1-2.7 °C for the RCP8.5 scenario in the future (Fig 2). As mentioned in the previous sections, different GCMs have varying statistical patterns, and this causes variability between the estimations. In Fig. 2 the variability in distributional patterns in the REF and RCP8.5 results throughout the GCMs can be realized for both precipitation and temperature. Moreover, when the effects of radiative forcing are taken into consideration, the estimated physical effects of radiative forcing simulated under the RCP8.5 scenario yield different results for each GCM in each month. The changes in precipitation have larger variability in the dry months (May, June, July, and August) while these changes in temperature have larger variability in wetter months such as February, March, and April (Fig 2, F, H).

Subsequent to obtaining the precipitation and temperature projections, it becomes possible to derive streamflow estimations by performing HMs which were trained by means of observed data previously. The precipitation and temperature projections were integrated to the trained HMs and extrapolations for the RCP8.5 scenario were obtained. When the derived streamflow values for the REF period are considered, it has been observed that approximate values are derived for HMs in the RCP8.5 scenario, and it has been determined that these values vary between 275 mm and 300 mm on the basis of the average annual total streamflow. In the RCP8.5 scenario, future streamflow is expected to decrease. In the related

scenario, the average annual total streamflow varies between 175 mm and 300 mm on average. Considering the changes according to the REF period, a decrease in flows is predicted in all climate models in the RCP8.5 scenario, and these decreases are estimated to be between 2% and 35%. The absolute highest decrease is predicted for GFDL-ESM2 in the future term. Due to the fact that the hydrological models are sensitive to precipitation data, the lowest decrease is predicted in GFDL-ESM2 climate model as in precipitation projections. (Fig 3). The streamflow projections can be evaluated with respect to HM alongside the GCMs. When the boxplots in Fig 3a and Fig 3b are examined, it can be seen that the variations between HMs are less than those of GCMs and have more consistent patterns. It is obvious in the boxplots that the inter-quartile ranges of GCMs are higher than those of HMs. In Fig 3b, it can be deduced that streamflow decreases are expected in the near future for all of HMs and maximum decreases are expected in Temez and TWWBM models, respectively.

In the study, the operation studies of Tahtali Dam and the future reservoir operation projections will be made through the hydrometeorological projections obtained in the previous phases of the study. The hydrometeorological projections obtained were presented as input to the water budget model, and then the reservoir performances were tested. In the study, it is assumed that water is demanded from the reservoir with a constant draft with predetermined regulation rates of 0.9. According to the reservoir projections derived under different GCM-HM pairs, 55 different reservoir projections were simulated and the uncertainty sources in reservoir performance indices under the RCP8.5 scenario were investigated. The uncertainty analysis on the projections of performance indices for the RCP8.5 scenario shows that the GCM uncertainty is significantly higher for the Rel index. It is seen that the GCM uncertainty is more dominant in the Rel index and Res index due to high streamflow conditions. Here, the GCM uncertainty for the RCP8.5 scenario is 93% and 86%, respectively. In the Vul index, on the other hand, it is seen that the variation in the HM outputs is more dominant. Here, at the same time, it is seen that the amount of uncertainty due to internal variability is relatively more dominant than GCM. In the SI index, it is seen that both GCM and HM uncertainty cause variations in future performance projections and the ratio of variances of these factors is 63% and 31%, respectively, for the RCP8.5 scenario. In the within-group variances of the GCMs, it is seen that the GFDL-CM3 and HadGEM2-ES climate model outputs have the maximum variance for the Rel index. When the within-group variances of the HMs are examined, it is seen that the Temez model reaches the maximum variance values in Rel and SI indices, and the minimum variance values of the abcde model. In the RCP8.5 scenario, it is seen that the GR2M model predicts results with a low variance ratio by deriving consistent results for all performance criteria. It is seen that the TWWBM

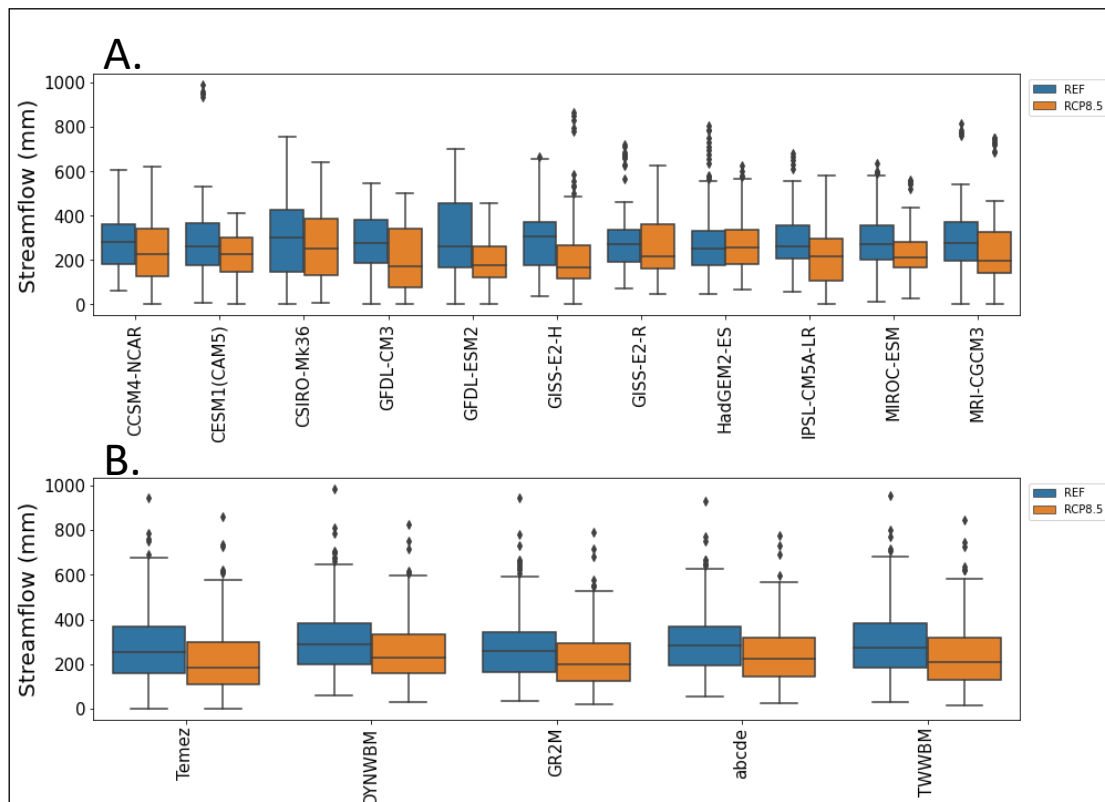
Figure 2: The precipitation and temperature results obtained after downscaling and bias correction. A: Annual sum of precipitation plot for REF, B: Annual sum of precipitation plot for RCP8.5, C: Annual average temperature plot for REF, D: Annual average temperature for RCP8.5, E: Boxplots for REF (blue) and RCP8.5 (orange) for each GCM, F: Boxplots for precipitation changes w.r.t. REF, G: Boxplots for temperature (same as precipitation), H: Boxplots for temperature changes w.r.t. REF.



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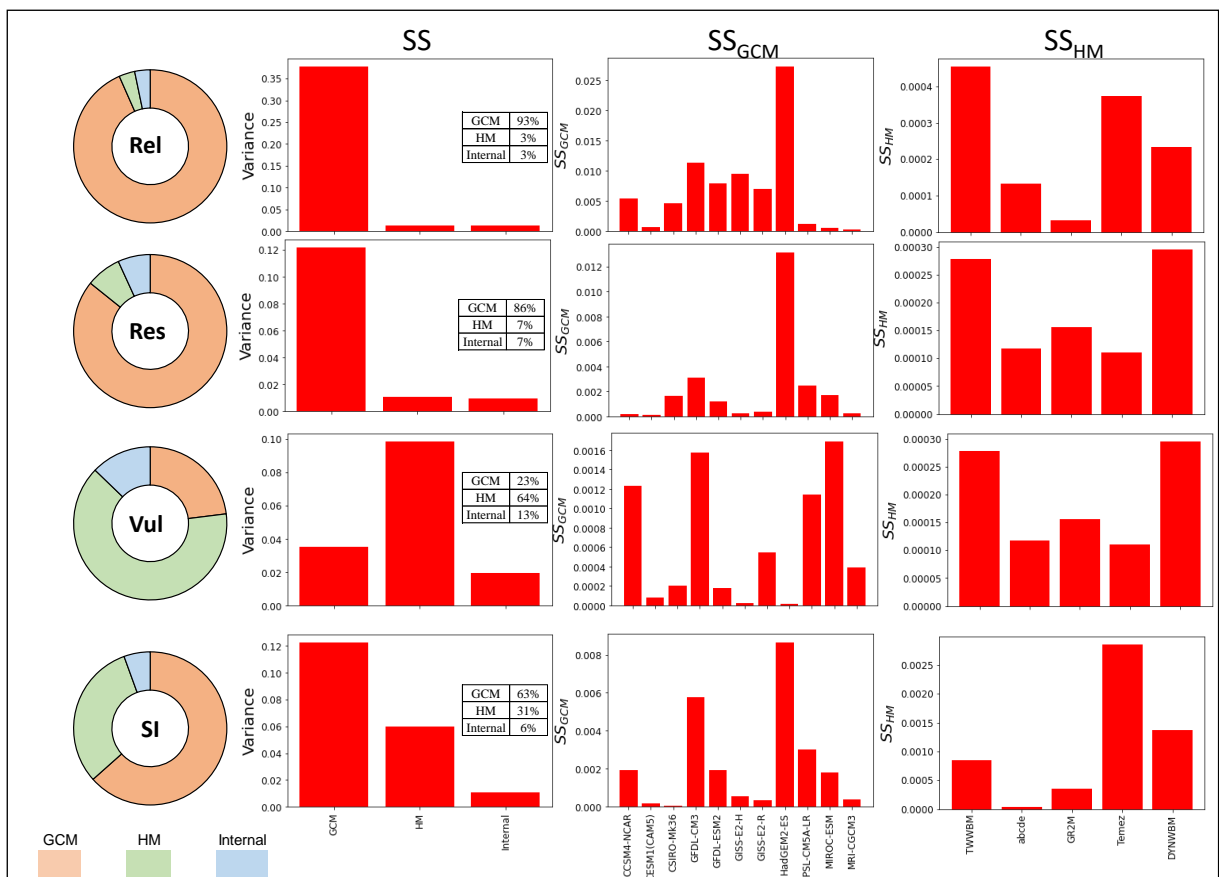
Figure 3: The streamflow changes in terms of RCP scenarios. The upper figure (A) demonstrates the streamflow changes for each GCM and the lower figure (B) demonstrates obtained streamflow changes w.r.t HMs.



8. Conclusion

In climate change studies, use of different tools such as multiple number of GCMs, HMs etc. accompany the uncertainty issue in projections. In order to evaluate the uncertainty, quantitative analysis can be made by decomposing uncertainty sources in the experiments. The stages of analysis such as the use of divergent downscaling strategies, bias correction methods, hydrological models, optimization techniques, or even spatial properties, etc can be the sources of uncertainty to reveal. In this study, only two factors, GCMs and HMs were taken into account in reservoir performance indices, such that the internal variability was evaluated, as well. First, the ANN model was performed to downscale the precipitation and temperature data extracted from 11 different GCMs and then systematic errors were corrected with QDM. In this respect, the use of single downscaling and postprocessing methods is one of the limitations in the evaluation of uncertainty sources in reservoir performance indices. Subsequently, the 5 lumped HMs were calibrated using observed precipitation and evaporation data. The trained models were integrated with the precipitation and temperature projections to obtain the streamflow estimations under the RCP8.5 scenario for the term 2020-2050.

Figure 4: Donut plots for total variance partitions and bar plots of within-group variances for each of the reservoir performance indices



According to the estimated hydrometeorological changes, decreases in precipitation and streamflow and increases in temperature are foreseen in the mid-21st century. However, as expected, these estimations have variability throughout GCMs and HMs. When the reservoir indices are evaluated, the major uncertainty source of the Rel and Res indices is GCMs. Hence, it is thought that if an analysis is desired to be carried out for these indices, the issues such as GCM elimination, or use of combinatorial GCMs come into prominence. If the amount of deficit water relative to the demanded water is taken into account, as in Vul indice, the results can be more dependent on HM selection. Thus, it can be deduced that both factors have relative importance in different cases. In further studies, it is thought by the authors that the additional sources in climate change projections will be investigated and quantified by decomposing uncertainty sources with different techniques.

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