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Investigating the Role of Bias Correction Methods and Climate Models on Water Budget of Büyük Menderes Basin

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Abstract

Büyük Menderes Basin is one of the largest basins in Turkey, with almost half of the basin area utilized for agricultural purposes. The amount of water allocated to the agricultural areas in the basin corresponds to 80% of water use in the watershed. Hence, the impact of climate change on the water supply in the Büyük Menderes Basin will be significant for the basin. In this study, we model the effects of climate change on the water budget (water supply and demand balance) of the Büyük Menderes Basin using the Water and Evaluation and Planning (WEAP) tool. Future precipitation, temperature, and evaporation data for the basin are attained from outputs of the HadGEM2-ES global circulation model (GCM), along with CNRM-CM5.1 and GFDL-ESM2M regional circulation models (RCM) for RCP 4.5 and RCP 8.5 scenarios. Subsequently, the study applies different statistical bias correction methods (Linear Scaling (LS), Distribution Mapping (DM), Local Precipitation Scaling (PLIS), and Power Transformation of Precipitation (PTP) for raw outputs of GCMs and RCMs and analyzes the changes in outcomes of projected climate data and the impact of changes on the hydrology of the basin using the WEAP model. For this analysis, calibrated and validated WEAP model for the 12 reservoirs of Büyük Menderes Basin is used to understand the impact of different bias correction methods on reservoir levels.

Keywords: Büyük Menderes Basin, climate models, WEAP, bias correction methods, water budget

1. INTRODUCTION

Due to climate change, extreme events like floods, droughts, and heat waves have increased. Therefore, modeling these impacts on surface water become more vital as we observe the ecosystem impacts of climate change more vividly. The success in modeling the climate change impacts also depends on the reliability of climate change projection data. For climate projection data, Global Circulation Models (GCMs) and Regional Circulation Models (RCMs) are used to quantitatively assess changes in climate conditions [1].

The resolution of GCMs varies from 12 km to 100 km, and they are at global or regional scales [2]. The coarse resolutions of GCMs do not match the fine-scale resolution of the

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hydrological models, which are built at the basin scale [3-4]. To overcome this challenge, RCMs with higher spatial resolution have been developed. The resolution of RCMs rises proportionately with increasing computational power. Currently, RCMs with 5 km resolution are more in use. However, datasets with this highest resolution are not available for regions such as the Middle East and North Africa (MENA) [5-8]. Therefore, for studying climate change impacts at finer scales, such as at the watershed scale, it is necessary to perform downscaling methods to produce local-scale, bias-corrected, and finer-resolution climate datasets based on the outputs of GCMs and RCMs [9].

Aside from the relatively coarse resolution of GCMs and RCMs, the constraints of climate models, such as simplification of real-world physics (as an inevitable feature of all models), incomplete knowledge of the Earth's climate system, and impact of model bias on climate assessments make downscaling indispensable for climate change impact studies [10]. In this study we use outputs of HadGEM2-ES (GCM), along with CNRM-CM5.1 and GFDL-ESM2M (RCMs). HadGEM2-ES is developed by the UK Met Office and combines an atmosphere-ocean-land-sea ice model, providing a comprehensive understanding of the climate system. CNRM-CM5.1 is a model developed by France's National Centre for Meteorological Research (CNRM) that simulates the interactions between the atmosphere, oceans, land surface, and sea ice. GFDL-ESM2M, developed by the Geophysical Fluid Dynamics Laboratory (GFDL) in the United States, is renowned for its ability to capture complex climate processes, making it a valuable tool in climate change studies.

In terms of climate scenarios, our models considered two climate projections, namely RCP 4.5 and RCP 8.5. These scenarios are developed by the Intergovernmental Panel on Climate Change (IPCC) to explore potential future trajectories of greenhouse gas emissions and their impact on the Earth's climate. RCP 4.5 addresses a more safe discharge pathway, expecting that global greenhouse gas emissions peak around the year 2040 and afterward decline. The implementation of significant mitigation measures and a shift toward cleaner energy sources are assumed in this scenario. RCP 8.5, on the other hand, is a high-emission pathway whose greenhouse gas emissions will continue to rise throughout the 21st century, causing significant effects on climate change. This situation expects a future with restricted climate policies and heavy dependence on fossil fuels. Higher temperatures, rising sea levels, and widespread disruptions to ecosystems are all depicted in RCP 8.5 as future climate conditions become more severe.

Two methods of downscaling for bias correction (BC) purposes are statistical and dynamic downscaling [11]. For both methods, the goal is to transform or map outputs of the future simulated models into the observation domain, with the help of utilizing the relationship between the observations and the model value for the base/historical period [12].

Given the importance of the operation of downscaling in climate change impact studies, this study focuses on the effects of downscaling methods on the water budget of BMB under different climate scenarios and models. At this point, Water and Evaluation and Planning (WEAP) is advantageous because the WEAP model comprehensively takes into account both the water supplies (inflows) computed through watershed-scale hydrologic processes along with water demands (outflows) coming from various water users and environmental requirements. The watershed and the physical network of reservoirs govern the hydrological modeling process. In doing so, WEAP calculates the water budget at the watershed scale and is widely used to assess the impacts of climate change on water resources at the watershed scale [13-15]. In addition, WEAP can operate on watersheds of large geographic scales and spatially scattered water demand sites [16]. Considering that BMB occupies an area of around 25,000 km^2 and that there are scattered demand sites across the basin, WEAP is a suitable hydrological modeling tool [17].

2. STUDY AREA

Büyük Menderes Basin is the 8th largest basin in Turkey and occupies an area of about 25,000 km^2 [17]. The drainage area of BMB corresponds to approximately 3% of the country [18]. The Büyük Menderes River originates near the Dinar district of Afyon and flows into the Aegean Sea, flowing through Uşak, Denizli, and Aydın (Figure 1). While almost half of the basin area is currently utilized for agricultural purposes, the amount of water allocated to the agricultural areas in the basin corresponds to 80% of the water use in the basin [19]. During 1975 and 2009, the average summer temperature in the basin was around 23-26 ℃, and the average winter temperature was around 5-7 ℃. During the same period, the annual precipitation rate was approximately 600 mm. Both temperature and precipitation rates are relatively higher in Aydın and Muğla compared to Uşak and Denizli, situated upstream of the basin [20]. The cities Aydın, Denizli, Muğla, and Uşak located inside BMB consist of around 90% of the total basin area [18]. Among the cities occupying most of BMB, Aydın, Denizli, and Muğla accommodate the major reservoirs in the watershed. There are currently 12 reservoirs in the basin whose storage capacities, initial storage values, and size of irrigation areas are given in Table 1 [21].

3. METHOD

3.1. WEAP

WEAP is a physical modeling tool for estimating the water budget of watersheds under changing hydrological conditions and policy scenarios [22]. WEAP simulates the water budget of the watershed by incorporating both climatic conditions and water use behaviors [23-24].

Table 1 Capacities and establishment years of reservoirs in BMB, Source: Adapted from [21]

	Reservoir Capacity (million m^3)	Initial Storage at the year of establishment (million m^3)	Planned Irrigation Area (ha)	Establishment Year
Kemer	419,17	123.847	58.930	1958
Yaylakavak	31,42	3.294	3.348	1997
Topçam	97,74	25.986	4.983	1985
Çine	350,00	221.814	22.358	2010
Karacasu	17,2	9.342	2.814	2012
İkizdere	194,96	83.131	3.625	2009
Adıgüzel	1.076,00	477.526	78.060	1990
Işıklı	237,8	72.335	50.486	1953
Gökpınar	27,72	12.219	5.824	2002
Cindere	84,27	59.249	78.060	2008
Tavas	65,00	51.135	3.304	2010
Bayır	7,17	1.919	1.050	2008
Total	2.608,45	1.141.197	312.842	

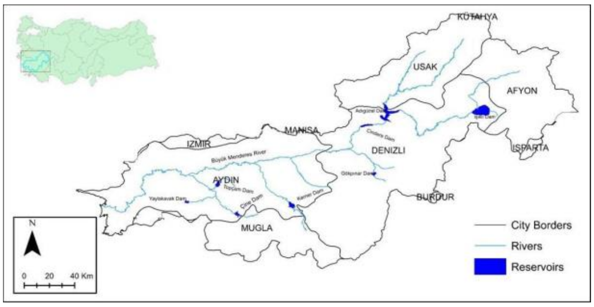

Figure 1 Map of BMB with water supplies and city borders, Source: Adapted from [21]

As a water budget model tool, WEAP requires datasets of water supply and demand for the area of interest. With these datasets, WEAP creates a water account that consists of water supply from different resources (i.e. aquifers, groundwater resources, and reservoirs) and water demand of various agents/users such as industry, municipalities, households, and agricultural production [25]. An advantage of WEAP is to rank the priority level of each demand node [22], giving the modelers the flexibility to predetermine a rule that dictates meeting a particular demand (i.e., household water need) over other water demand types. In doing so, WEAP allows its users to represent the study areas' characteristics and enables them to create a wide range of scenarios where users can test the impacts of various priority-driven policies in the watershed of interest. Once the basin's water budget is calibrated and validated, these models are also used for forecasting purposes [22].

3.2. Downscaling Methods

Downscaling aims to transform or map outputs of the future simulated model into the observation domain with the help of utilizing the relationship between the observations and the model value for the base/historical period [26]. Dynamic downscaling (DD) reanalyzes the outputs of GCMs or RCMs to produce localized climate datasets through models, such as Limited Area Models [27]. Carrying out dynamical downscaling involves interactions between different elements of climate systems, such as precipitation and temperature. Therefore, it is computationally intensive and time demanding [28].

Statistical downscaling is a method of establishing statistical relationships between historical and current large-scale atmospheric and local climate variables. Subsequently, future climate variables that GCMs/RCMs project are used to forecast future local climate data [29]. In the literature, the prevalently utilized SD methods are quantile mapping (QM), delta change/correction (DC) approach, statistical downscaling method (SDSM), linear scaling (LS), distribution mapping (DM), local intensity scaling (LOCI), and power transformation of precipitation (PTP) [30-34]. This study will compare the performances of LS, PTP, LOCI, and DM methods in terms of their improvements in climate projection data.

Linear Scaling (LS) is a statistical method to match the mean of downscaled data with the observed data [35] and has been used in various climate change impact studies [36-39]. Using the differences between the observed and simulated data obtained directly from GCMs and RCMs, LS operates with monthly downscaling values. Precipitation is corrected with a multiplier term and temperature with an additive term on a monthly basis. In Equations 1 and 2, $P_{down,m,d}$ and $T_{down,m,d}$ represent corrected precipitation and temperature values respectively on the d^{th} day of the m^{th} month. Besides, $P_{raw,m}$, and $T_{raw,m}$ denote raw simulated precipitation and temperature values sequentially on the month's dth. Lastly, $\mu()$ indicates the expectation function. For instance, $\mu(T_{obs,m})$ represents the mean value of observed temperature at month m [40].

$$P_{down,m,d} = P_{raw,m} * \mu(P_{obs,m}) / \mu(P_{raw,m}) \quad (1)$$

$$T_{down,m,d} = T_{raw,m} + \mu(T_{obs,m}) - \mu(T_{raw,m}) \quad (2)$$

Power transformation of precipitation (PTP) can be carried through several software packages available in the literature, such as CMhyd and Powertransformation v2.0 [41-43]. The main advantage of this method is that, unlike LS (correcting the biases solely in the mean), PTP also corrects the coefficient of variation defined as the ratio between sample standard deviation and sample mean [44]. The algorithm through which PTP carries out the correction operations is based on a non-linear transformation. In Equation 3, the power "b" is predicted monthly with a 90-day window centered on the interval with a root-finding algorithm. Consequently, P^b is multiplied by the coefficient obtained by dividing the monthly mean observed precipitation by the monthly mean powered projected precipitation [45].

$$P^* = a * P^b \quad (3)$$

The Local Intensity Scaling (LOCI) Method for Precipitation amends frequencies and intensities of wet days and thus improves the raw data with drizzle days [46]. This method validates the precipitation intensity threshold ($P_{thres,m}$) for each month. This way, it is assured that the number of days exceeding a threshold for the simulation model matches the wet-day frequency of the observation data. Consequently, a scaling factor (s_m) is computed, so that the mean of the corrected rainfall equals the mean of the observed rainfall (Equations 4 and 5) [40].

$$S_m = \frac{\mu(P_{obs,m,d} \mid P_{obs,m,d} > 0)}{\mu(P_{raw,m,d} \mid P_{raw,m,d} > P_{thres,m})} \quad (4)$$

$$P_{cor,m,d} = \begin{cases} 0 & \text{if } P_{raw,m,d} < P_{raw,m,d} \\ P_{raw,m,d} * S_m, & \text{otherwise} \end{cases} \quad (5)$$

Lastly, distribution mapping (DM) is another widely utilized downscaling method for processing projected climate change data [44] to align the distribution function of observation data with the raw data [45]. DM matches the standard deviation, mean, and quantiles of both datasets, raw/unprocessed, and observation [40]. For precipitation, a gamma distribution with parameter α and scale parameter β is used (Equation 6).

$$f(x \mid \alpha, \beta) = x^{\alpha-1} * 1/\beta^{\alpha} * e^{-x/\beta} \; ; \; x \geq 0, \alpha, \beta > 0 \quad (6)$$

Consequently, the threshold for a wet day in the LOCI method comes into play before applying DM so that the effects of the days with little precipitation (drizzle effects) are minimized. After applying the threshold used for the LOCI method, the corrected precipitation values are removed from the drizzle effect (Equation 7). In the formulation, $F\gamma$ and $F\gamma^{-1}$ represent Gamma cumulative distribution functions and their inverse, respectively [29].

$$P_{cor,m,d} = F\gamma^{-1} (F\gamma (P_{LOCI,m,d} \mid \alpha_{LOCI,m}, \beta_{LOCI,m}) \mid \alpha_{obs,m} \; \beta_{obs,m} \quad (7)$$

For water budget calculations, the WEAP model requires climate (temperature and precipitation) data at the local scale. The downscaling methods provide local-scale, bias-corrected, and finer resolution climate datasets based on the outputs of GCMs and RCMs.

This study uses the precipitation dataset obtained from the Turkish State Meteorological Service. The study area covers three cities in BMB, namely Aydın, Denizli, and Muğla (Table 2). The future climate data are spatially averaged for each city within given coordinates (Table 2)

Table 2 Meteorological stations for data collection in the historical/observed period and the coordinates for future climate data

City	Station Code	Turkish State Meteorological Service Station Coordinates	Coordinates for GCM and RCM climate data
Aydın	17234	37.84 N, 27.83 E	27.28-28.6E, 37.5-38N
Denizli	17237	37.76 N, 29.09 E	28.6-29.9E, 37.15-38.3N
Mugla	17292	37.2 N, 28.36 E	27.6-28.7E, 37-37.5N

4. RESULTS

The climatic parameters such as temperature, precipitation, and evapotranspiration are significant determinants of the water budget at the watershxed scale. Understanding the impacts of climate change on the water budget requires precise prediction of these parameters. Hence different downscaling methods and their particular effects on climatic variables need to be studied. In doing so, we use the already calibrated and validated WEAP model developed for the Büyük Menderes Basin and its 12 reservoirs [21]. The existing model has satisfactory model evaluation and can be used to understand the impacts of future climate change projections for RCP 4.5 and RCP 8.5 scenarios of various GCM (HADGEM2-ES) and RCMs (CNRM-CM5.1 and GFDL-ESM2M). Our study reports future precipitation values for the cities that lie within the Büyük Menderes Basin (Aydın, Denizli, Muğla, Uşak) using different downscaling methods. As a representative case, in Figures 2-5 we demonstrate future precipitation values for Aydın using DM downscaling method for the CNRM-CM5.1 model (RCP 4.5 scenario) dataset. The Appendix section demonstrates the precipitation data of Aydın and Denizli downscaled using the downscaling methods for 3 GCM/RCM and for two scenarios (RCP 4.5 and RCP 8.5).

For this analysis, the impacts of different downscaling methods using different GCMs and RCMs outputs are measured by investigating the changes in reservoir volumes. In the BMB, 12 reservoirs have different storage capacities and average annual total volumes (Table 1). The average of 12 reservoirs' total volume in BMB from 2005 to 2018 was 1.49 billion cubic meters per year with annual fluctuations. Figure 6 shows the historical change in the overall reservoir storage volume in BMB for 2005 to 2018 [21].

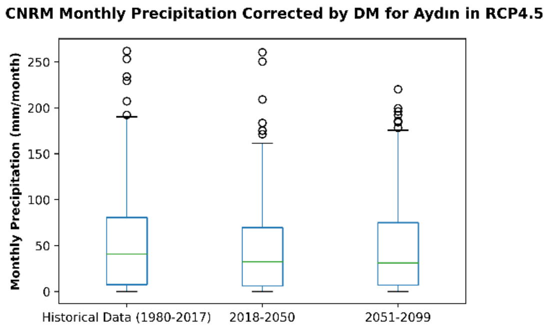

Figure 2 Average precipitation change by 2100 in Aydın with CNRM data under RCP4.5 scenario, using DM correction method

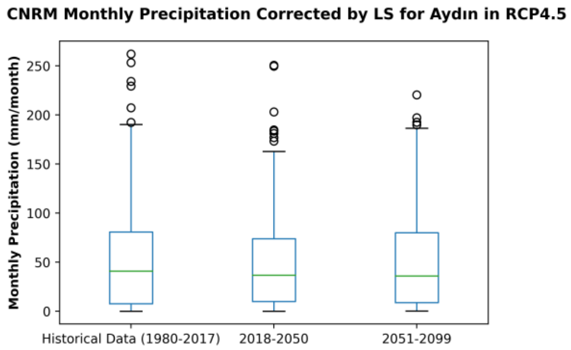

Figure 3 Average precipitation change by 2100 in Aydın with CNRM data under RCP4.5 scenario, using LS correction method

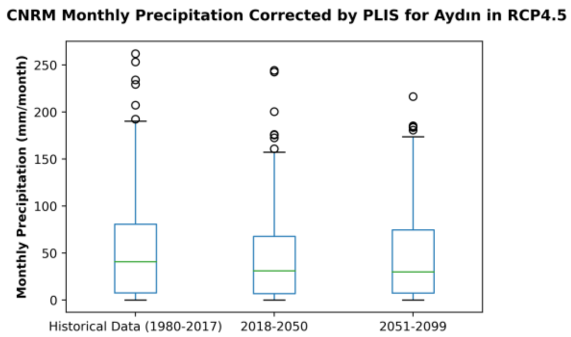

Figure 4 Average precipitation change by 2100 in Aydın with CNRM data under RCP4.5 scenario, using PLIS correction method

For the simulation period of 2019-2099 with all three circulation models, the WEAP model takes downscaled and bias corrected precipitation data from GCM (HADGEM2-ES) and RCMs (CNRM-CM5.1 and GFDL-ESM2M) as input and projects changes in the total amount of water in the reservoirs (compared to the historical total average).

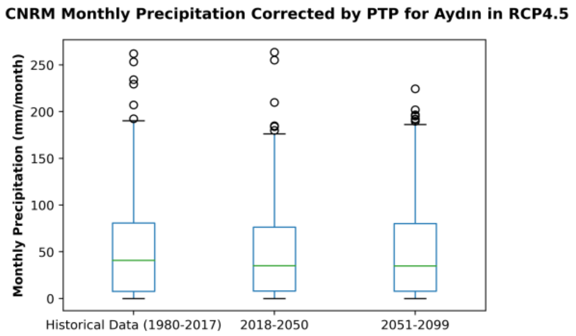

Figure 5 Average precipitation change by 2100 in Aydın with CNRM data under RCP4.5 scenario, using PTP correction method

The most significant reduction among the three models is observed with the HADGEM2-ES model dataset. Under the RCP4.5 and RCP 8.5 scenarios, the results with the HADGEM2-ES indicate a 6%-7% decrease from the historical average when downscaled with DM method.

Table 3 Average changes in total reservoir volume when different downscaling methods were applied to GCM and RCM models under RCP4.5 scenario

	DM RCP4.5	LS RCP4.5	PLIS RCP4.5	PTP RCP4.5
CNRM-CM5.1	-5.43%	-5.22%	-5.80%	-5.05%
GFDL-ESM2M	-5.17%	-4.57%	-5.43%	-4.54%
HADGEM 2-ES	-6.83%	-3.34%	-5.36%	-3.45%

However, different statistical downscaling methods yield highly different results, especially for the HADGEM2-ES model. The results obtained with HADGEM2-ES show that, under the RCP4.5 scenario, a reduction of 3% and 7% - with respect to average baseline volume is observed during the simulation period range depending on the downscaling method applied. The downscaled CNRM-CM5.1 dataset demonstrate a 5% lower reservoir water volume than the historical average volume rates. Additionally, for CNRM-CM5.1 and GFDL-ESM2M datasets, different bias methods does not indicate significant differences. Under the RCP4.5 scenario, the total reservoir volume decrease around 5% with all downscaling methods (Table 3).

Table 4 Average changes in total reservoir volume when different downscaling methods were applied to GCM and RCM models under RCP8.5 scenario

	DM RCP8.5	LS RCP8.5	PLIS RCP8.5	PTP RCP8.5
CNRM-CM5.1	-5.06%	-4.80%	-5.10%	-4.86%
GFDL-ESM2M	-6.51%	-5.48%	-6.09%	-5.71%
HADGEM 2-ES	-6.95%	-4.09%	-5.87%	-4.19%

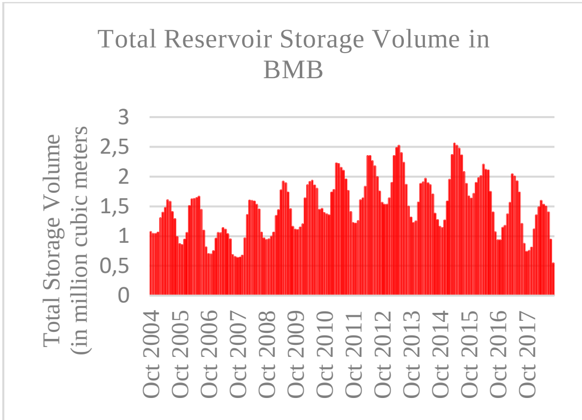

Figure 6 Total reservoir storage volume during 2005-2018 observation period, Source: Adapted from [21]

Similarly, under the RCP8.5 scenario, the results indicate an approximately 6% decline for all downscaling methods (Table 4). In other words, the RCM-based (CNRM-CM5.1 and GFDL-ESM2M) results are not significantly impacted by the choice of downscaling methods. However, for GCM-based (HADGEM2-ES) results, the choice of downscaling methods significantly impact the total reservoir volume (Tables 3 and 4).

Taylor diagrams in the Appendix section (Figures 45 and 46) demonstrate the improvement rates by applying different downscaling methods for GCM/RCMs. These figures demonstrate that the downscaling method is evidently influential in the outputs of HADGEM2-ES. While the Pearson coefficient between the raw data of the HADGEM2-ES model and the observed historical precipitation data was 0.1, the value of this coefficient increases to almost 0.5 with the application of different bias correction methods. The most remarkable improvement for the Pearson coefficient is with the Power Transformation of Precipitation (PTP) method. However, the outputs of the CNRM-CM5.1 along with GFDL-ESM2M models are not influenced by the statistical bias correction processes as much as the outputs of HADGEM2-ES. Pearson coefficients of both models are approximately 0.4 with raw (not processed) RCM outputs and increase to 0.50 – 0.55 in the post-correction period.

5. CONCLUSION

Climate change has been threatening the existing freshwater resources, complicating the management issues and requiring adaptation measures to be devised. Increased frequency of extreme events (floods, droughts) augments the need for precise future projections. However, one of the most critical factors influential in the reliability and robustness of a model is the accuracy of climate change projection data. Compared to the scale of climate change impact studies on freshwater systems, the resolution of climate change data are still relatively coarser despite advancements in the last decades. Therefore, downscaling climate change data is vital in determining the success of modeling studies. This study reveals the impact of the downscaling method chosen on simulation results. The outputs of projection data are from GCM HADGEM2-ES, along with RCMs CNRM-CM5.1 and GFDL-ESM2M. Besides, this study investigates DM, LS, PLIS, and PTP as downscaling methods and shows that the downscaling method has an impact on the outputs of HADGEM2-ES dataset the most. Outputs of HADGEM2-ES indicate significant differences depending on the different downscaling methods. Under the RCP4.5 and RCP8.5 scenarios, average reservoir volume during the simulation period show a difference between 3% and 7% with respect to the average observed volume. On the other hand, the results obtained with outputs of CNRM-CM5.1 and GFDL-ESM2M indicate a 5% lower reservoir water volume compared to the historical average volume rates. For the RCM models (CNRM-CM5.1 and GFDL-ESM2M), the downscaling methods are less influential.

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Authors' Contribution
The authors’ contribution is as follows: ZIE: Methodology, Validation, Visualization, Writing, and IDC: Conceptualisation, Methodology, Writing, Supervision

The Declaration of Conflict of Interest/ Common Interest
No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval
This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics
The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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