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Streamflow Projections in Valgrosina Valley: Climate Change Calls for Adaptation in the Alpine Region

Andrea Citrini^{1,2}  | Adriana Bruggeman³  | Ioannis Sofokleous³  | George Zittis⁴  | Georgia Lazoglou⁴  | Giovanni P. Beretta¹  | Corrado A. S. Camera¹ 

¹Dipartimento di Scienze della Terra “Ardito Desio”, Università degli Studi di Milano, Milan, Italy | ²Biosphere Sciences & Engineering, Carnegie Institution for Science, Stanford, California, USA | ³The Cyprus Institute, Energy, Environment and Water Research Center (EEWRC), Nicosia, Cyprus | ⁴The Cyprus Institute, Climate and Atmosphere Research Center (CARE-C), Nicosia, Cyprus

Correspondence: Corrado A. S. Camera (corrado.camera@unimi.it)

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ABSTRACT

Climate change is increasingly impacting mountainous regions, emphasising the need for reliable streamflow projections to support adaptive hydropower management. This study focuses on the Valgrosina Valley (Northern Italy) with two main objectives: (i) to project impacts on streamflow under four global warming levels (+1.5°C, +2.0°C, +3.0°C, and +4.0°C relative to pre-industrial conditions) and to evaluate their effects on gross hydropower potential (GHP); and (ii) to compare the performance of two bias-correction approaches—yearly vs. monthly quantile delta mapping (QDM-y and QDM-mo, respectively)—on hydrological projections. Daily precipitation and temperature timeseries from 21 regional climate models (approximately 12.5 km² resolution) were bias-corrected and downscaled using observed data from the 2005–2020 reference period and then used to drive reference and future simulations that reveal pronounced intra-annual shifts relative to the reference period. Under the most severe warming scenario (+4.0°C), winter flows are projected to increase by approximately +0.5 m³ s⁻¹ (around +300%), while summer flows decline by about -0.7 m³ s⁻¹ (-19% to -20.5%), indicating a strong seasonal redistribution of runoff. Correspondingly, the GHP indicated a summer potential decline of up to 20% in energy production. The QDM-mo bias correction approach performed better than QDM-y in preserving intra-annual variability with 14% and 3% less bias than the observed series for precipitation and temperature, respectively. The results underline the vulnerability of hydropower systems to future climatic changes and emphasise the need for adaptive strategies to ensure sustainable use of water and energy in Alpine environments.

1 | Introduction

Water resources management and hydropower play a pivotal role in the energy sector for both mitigating and adapting to climate change, particularly in mountainous regions (Gaudard et al. 2014). Globally, hydropower generates 14% of electricity and represents the largest source of renewable power generation, accounting for a 47% share in global production (International

Energy Agency 2024). Even though the environmental impacts of hydropower on sediment and nutrient transport, water quality, aquatic species, biodiversity and society have been well recognised (e.g., Almeida et al. 2022; Botelho et al. 2017; Winemiller et al. 2016; Zarfl et al. 2019), hydropower remains a widely adopted renewable energy option. This resilience in popularity is largely due to its limited quantitative impact on the global hydrological cycle compared to other energy production methods.

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Most of the water used in hydropower generation is returned to the river downstream of the power plant, either passing through the turbines or flowing over the spillway when the reservoir is full (UN Water 2020).

Climate change is already altering hydrological regimes across Europe, with notable consequences for hydropower production (European Commission Joint Research Centre 2020; Zittis et al. 2021). Alpine regions, where many hydropower systems rely on snowmelt and seasonal runoff, are particularly vulnerable to shifts in precipitation patterns and temperature increases (Calvin et al. 2023; Finger et al. 2012; Intergovernmental Panel on Climate Change 2023; Laghari et al. 2012). These impacts are expected to intensify under high-emission scenarios, with projected hydropower potential reductions between -20% and -25% in Southern Europe by the end of the century (Lehner et al. 2005; Mima and Criqui 2015; Tobin et al. 2018). Italy provides a tangible example of this trend: during the summer of 2022, the country experienced one of the worst droughts in recent decades, with cascading effects on hydropower generation due to prolonged water shortages (Bonaldo et al. 2023).

While future projections of streamflow and hydropower potential are widely used to support adaptation planning, their accuracy depends strongly on the methods used to preprocess climate model outputs (Maraun 2016; Teutschbein and Seibert 2012). In particular, bias correction techniques play a crucial role in adjusting raw regional climate model (RCM) data to local hydrological conditions (Hempel et al. 2013; Themeßl et al. 2011). However, most existing studies rely on a single bias correction implementation, often without evaluating how different approaches might influence the resulting hydrological simulations (Addor and Seibert 2014; Ehret et al. 2012). This gap is especially problematic in alpine catchments, where small differences in corrected temperature or precipitation can produce amplified changes in runoff and storage dynamics due to elevation-dependent processes (Kuhn and Olefs 2020; Mountain Research Initiative EDW Working Group 2015).

To address this methodological gap, the present study aims (i) to assess projected changes in streamflow dynamics under four global warming levels (GWLs) ($+1.5^{\circ}\text{C}$, $+2.0^{\circ}\text{C}$, $+3.0^{\circ}\text{C}$ and $+4.0^{\circ}\text{C}$ above pre-industrial temperatures) and evaluate their implications for gross hydropower potential (GHP) in an Alpine watershed and (ii) to critically examine how different implementations of the quantile delta mapping (QDM) bias correction technique (yearly vs. monthly) affect both the correction and downscaling of climate projections. Together, these results are used to inform a broader discussion on the need for adaptive hydropower management strategies under future climate conditions.

To achieve these goals, the study applies a high-resolution hydrological modelling framework to the Valgrosina Valley in Northern Italy (Central Alps) as a case study. Daily outputs from 21 RCMs were bias-corrected using two distinctly different QDM approaches: a yearly-based and a monthly-based approach. The corrected datasets were then used to force a calibrated and validated hydrological model to assess future streamflow dynamics and associated changes in GHP. While the localised application provides detailed insights into the challenges faced by Alpine

hydropower systems, the methodological advances proposed are intended to be applicable to a broader range of mountainous catchments worldwide.

2 | Data and Methods

2.1 | Study Area

The study area is located in the Valgrosina catchment (130 km^2) in the Lombardy region (Italian Central Alps). Valgrosina is an accessory valley of Valtellina, which is an east–west-oriented structure on the border between Italy and Switzerland (Figure 1a). The main watercourse of Valgrosina is the Roasco stream, which branches into two secondary valleys: the eastern Eita valley (62 km^2 , from 1200 to 3370 m a.s.l.) and the western Sacco valley (71 km^2 , from 1200 to 3260 m a.s.l.). A dam built in 1960 at the Eita valley's closing section facilitates water resource management throughout Valgrosina, connecting it to the Upper Valtellina hydropower park and the Sacco valley via bypass channels (Figure 1b,c). The Valgrosina reservoir, located at about 1200 m a.s.l. and with a capacity of $1.3 \times 10^6\text{ m}^3$, is fed by the Roasco d'Eita and Roasco di Sacco streams and can be regulated by hydraulic structures. All water volume is operated by the Grosio hydropower plant (run by the A2A company), located in the downstream village. The area is characterised by metamorphic rocks with medium to very low permeability, which can vary locally depending on the degree of fracturing (Mohn et al. 2011). Similarly, the superficial deposits are mostly gravelly sandy moraines and landslide deposits with medium to very low permeability (Pozzi et al. 1990).

The entire Upper Valtellina area exhibits considerable spatial variability for precipitation and temperature due to its complex topography and elevation gradients. The valley's microclimate is influenced by its unique geomorphology and steep slopes, affecting local weather patterns. The lower valley areas are generally characterised by a supratemperate climate (mean annual temperature around 8°C – 13°C , Rivas-Martinez et al. 2004), allowing for agricultural activities like viticulture, while the upper regions are colder and more suited to forestry and pastureland (De Pasquale and Spinelli 2022). Precipitation is high throughout the year.

The average annual totals are around 1200 mm (Luino et al. 2019), with peaks during late spring and summer, often taking the form of thunderstorms. However, there has been increased variability in weather patterns, including more frequent droughts, sudden heavy rainfall events and earlier snowmelt flow (Casale and Bocchiola 2022).

According to the Köppen–Geiger classification (Geiger 1954, 1961; Köppen 1900), Valgrosina predominantly features Alpine Tundra (ET) and Boreal Subarctic (Dfc) climates, along with various microclimates (Figure 1c). In the valley's lower sections, Temperate Oceanic Climate (Cfb) and Subpolar Oceanic Climate (Cfc) microclimates are observed (Rubel et al. 2017). The Grosio–Fusino weather station (Figure 1d), situated near the dam, serves as a reference for climate data. It reports an average annual precipitation of 970 mm, with temperatures ranging from -0.2°C in January to 16.0°C in July based on a 30-year

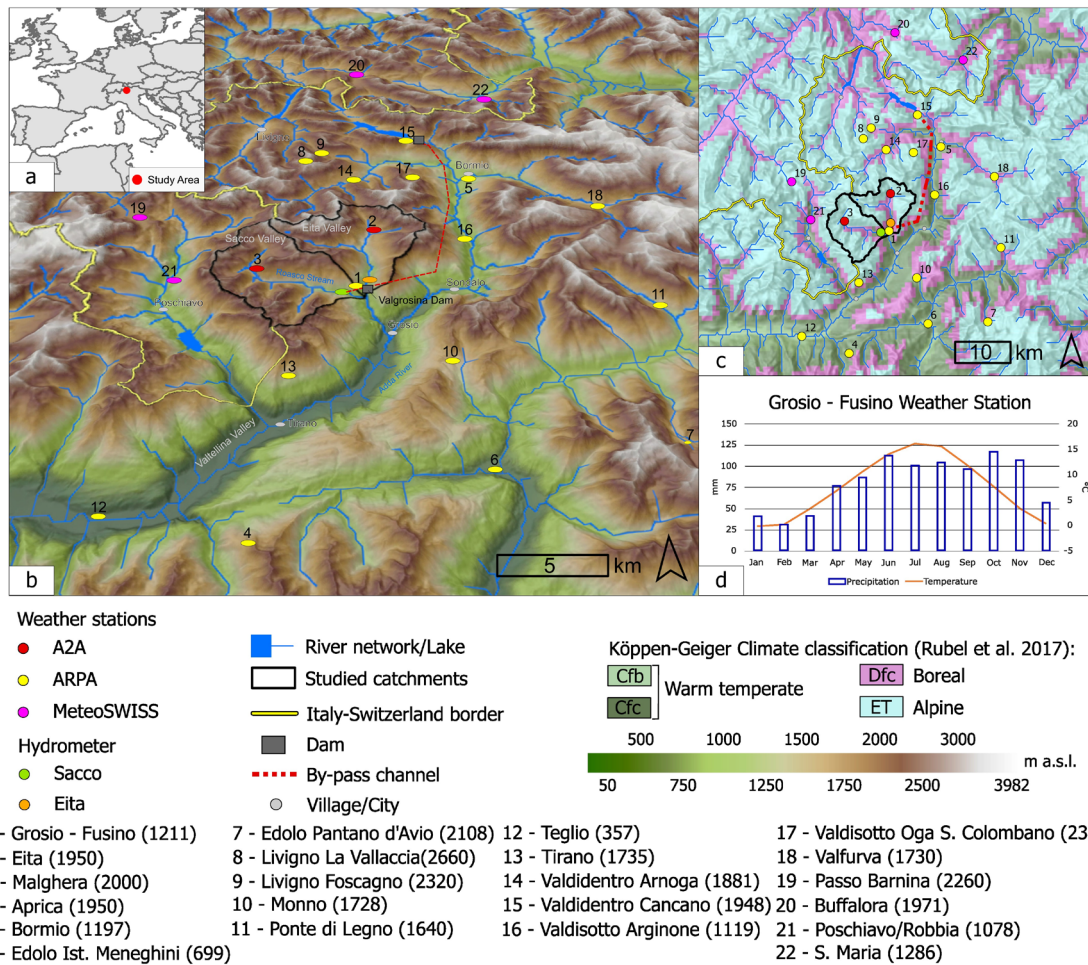


FIGURE 1 | Overview of the study area, showing the locations of weather stations (elevations in m a.s.l.), hydrometers, river networks and major dams. (a) The study area location. (b) 3D digital elevation model map highlights the geographic features of the area. (c) Köppen–Geiger climate zones classification of the area from Rubel et al. 2017. (d) Climograph of the Grosio–Fusino Weather Station, illustrating average monthly precipitation (mm) and temperature (°C) for the region, with distinct patterns in seasonal climate variation.

period from 1991 to 2020. Annual snowfall varies between 8.1 and 21.2 cm, with peaks occurring in February.

2.2 | Data Resources

Precipitation and temperature data were obtained from the dam managing company (A2A S.p.A.), the Regional Environmental Agency of Lombardy (ARPA Lombardia) and MeteoSwiss at an hourly resolution, for a total of 22 weather stations and the period 2005–2020 (Figure 1). Details on the specific periods of data availability at the 22 meteorological stations are shown in Table A1. For the same period, the hourly Combi-precip weather radar product was made available by MeteoSwiss (Sideris et al. 2014). The hourly data were used to compute daily precipitation totals and daily mean temperature values. To create a daily precipitation spatial blended product, the method proposed by Citrini et al. (2024) for hourly data was adopted. The method consists of combining the MeteoSwiss weather radar trend with Ordinary Kriging (OK), applied on the rain-gauge/radar cell residuals (Radar+OK). For temperature data, Detrended Kriging was applied to spatialise observations across the catchment. These processed meteorological datasets were

subsequently used to run the hydrological model for the reference period (2005–2020).

The climate projections are provided by the European Hub of the Coordinated Regional Downscaling Experiment EURO-CORDEX (Jacob et al. 2020). Specifically, to provide policy-relevant climate information, GWLs of +1.5°C, +2.0°C, +3.0°C and +4.0°C since the pre-industrial era were considered. These are based on a high-forcing representative concentration pathway (RCP8.5) and were retrieved by the IPCC-WGI Atlas repository (Iturbide et al. 2021). To clarify, a future climate projection achieves a specific GWL when its global near-surface air temperature anomaly, averaged over successive 20-year periods, reaches that level of warming relative to its 1851–1900 climate simulation (namely the period taken as the industrial baseline) (Intergovernmental Panel on Climate Change 2021) (Table 1). Many recent climate change impact studies use GWLs as a reference because of the 2015 Paris Agreement (UNFCCC 2016), instead of using fixed periods (typically near, middle and far future) for the different scenarios (Diez-Sierra et al. 2023).

Within this study, the GWLs are referred to as scenarios S1 for +1.5°C, S2 for +2°C, S3 for +3°C, and S4 for +4°C. These

TABLE 1 | List of the 21 EURO-CORDEX regional projections used in the present study, with their time intervals according to the global warming levels (GWLs) for the investigated climate scenarios.

Model ID	Global model	Regional model	1.5° GWL (S1)	2° GWL (S2)	3° GWL (S3)	4° GWL (S4)
mod1	CNRM-CERFACS-CNRM	CLMcom-CCLM4	2020–2039	2035–2054	2057–2076	2077–2096
mod2	CNRM-CERFACS-CNRM	ETH-COSMO				
mod3	CNRM-CERFACS-CNRM	DMI-HIRHAM5				
mod4	CNRM-CERFACS-CNRM	GERICS-REMO2015				
mod5	ICHEC-EC-EARTH	CLMcom-CCLM4	2008–2027	2024–2043	2050–2069	2072–2091
mod6	ICHEC-EC-EARTH	ETH-COSMO				
mod7	ICHEC-EC-EARTH	DMI-HIRHAM5				
mod8	ICHEC-EC-EARTH	KNMI-RACMO22E				
mod9	IPSL-CM5A-MR	KNMI-RACMO22E	2005–2024	2020–2039	2040–2059	2056–2075
mod10	IPSL-CM5A-MR	DMI-HIRHAM5				
mod11	IPSL-CM5A-MR	GERICS-REMO2015				
mod12	MOHC-HadGEM2	CLMcom-CCLM4	2013–2032	2025–2044	2044–2063	2061–2080
mod13	MOHC-HadGEM2	ETH-COSMO				
mod14	MOHC-HadGEM2	DMI-HIRHAM5				
mod15	MOHC-HadGEM2	KNMI-RACMO22E				
mod16	MPI-M-MPI-ESM-LR	CLMcom-CCLM4	2007–2026	2027–2046	2051–2070	2071–2090
mod17	MPI-M-MPI-ESM-LR	DMI-HIRHAM5				
mod18	MPI-M-MPI-ESM-LR	ICTP-RegCM4				
mod19	MPI-M-MPI-ESM-LR	KNMI-RACMO22E				
mod20	NCC-NorESM1-M	ICTP-RegCM4	2001–2020	2022–2041	2038–2057	2062–2081
mod21	NCC-NorESM1-M	KNMI-RACMO22E				

scenarios offer a simple dimension of climate change to examine regional responses of climate variables and indices as a function of global warming. For each RCM, we selected a 20-year window centred around when the global circulation model that drives the RCM reaches these thresholds. Although shorter than the standard 30-year climatological baseline, this duration allows consistent use of all 21 models while preserving inter-model variability (Dawkins et al. 2023; Nordling et al. 2025). The use of GWLs focuses on climate states rather than fixed time periods and supports more relevant adaptation assessments. Precipitation, minimum and maximum temperature data were extracted for nine cells of the Western and Central Europe (WCE) sub-domain of the EURO-CORDEX region, to ensure that the whole study area was covered, considering 21 RCMs at a spatial resolution of about $12.5\text{ km} \times 12.5\text{ km}$ (Table 1).

The study relies on the digital elevation model (DEM) with a resolution of $20\text{ m} \times 20\text{ m}$, sourced from the Lombardy Region geoportal, alongside the daily measured discharges (m^3s^{-1}) entering the artificial reservoir. The discharge data, provided by the A2A company, span the period from October 2010 to September 2020 and cover measurements from Eita and the bypass channels at Sacco. Additionally, in accordance with regional environmental

regulations, the minimum environmental flow (MEF) values for the Roasco stream (Sacco valley side) were incorporated into the hydrological modelling framework, ensuring that flows of at least $0.244\text{ m}^3\text{s}^{-1}$ during the winter months and $0.406\text{ m}^3\text{s}^{-1}$ during the summer months are maintained downstream of the bypass channel. For model calibration, the combination of discharge data from the Sacco intake and the corresponding MEF serves as a reliable benchmark. In the Eita valley, however, streamflow is recorded by a hydrometer prior to its entry into the reservoir, eliminating the need to consider MEF adjustments.

2.3 | Methods

The applied procedure consisted of four steps. First, the hydrological model was calibrated and validated for the reference period (2005–2020) using observed meteorological inputs (Section 2.3.1). Second, the RCM outputs were bias-corrected and spatially downscaled using the QDM technique under two different application approaches (QDM-y and QDM-mo) (Section 2.3.2). Third, the quality of the bias-corrected data was evaluated by comparing corrected and observed series using several climatic indices and bias metrics (Section 2.3.3). Fourth,

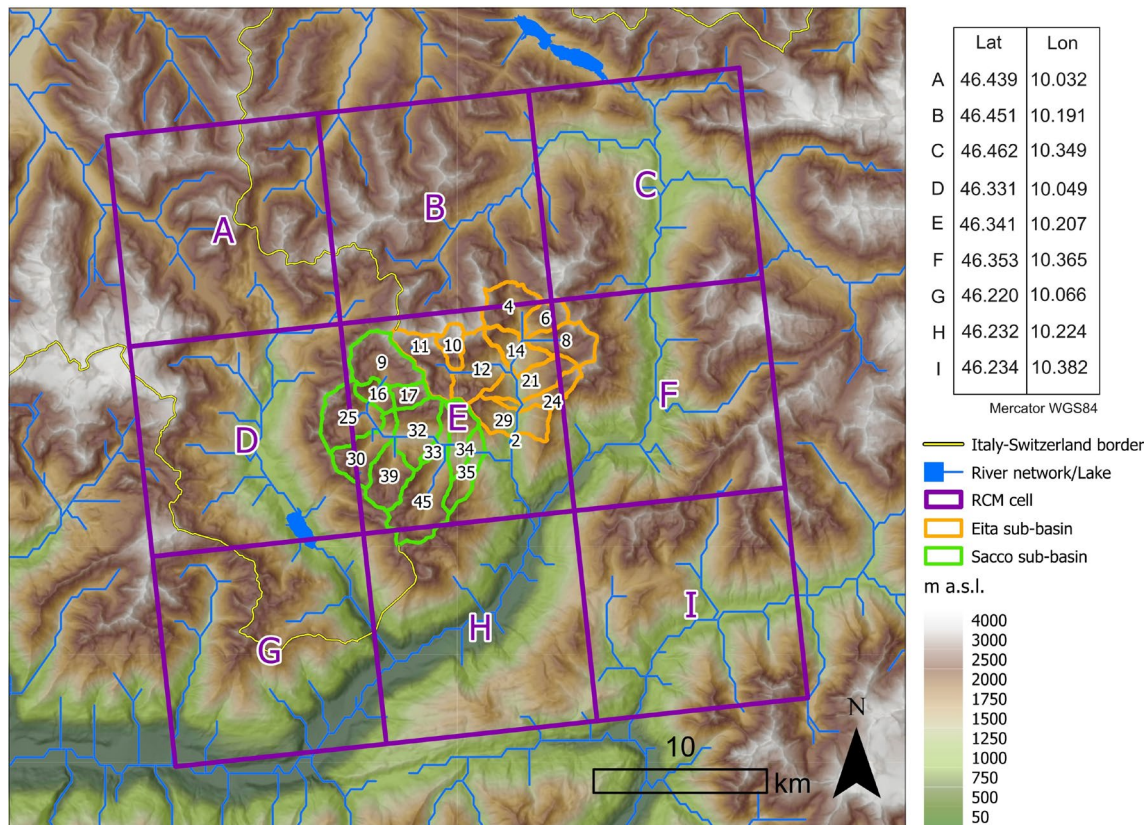


FIGURE 2 | Cell position of the RCMs with respect to the centroids of the Valgrosina sub-basins according to the model configuration of Citrini et al. (2024).

future streamflow and GHP were simulated by forcing the hydrological model with the corrected climate timeseries, and the results were statistically analysed to assess seasonal and annual impacts (Section 2.3.4).

2.3.1 | Hydrological Model

The daily streamflow simulation was carried out exploiting the GEOframe model (Formetta, Antonello, et al. 2014; Bancheri 2017; Bancheri et al. 2020). This model is a semi-distributed, modular hydrological framework that integrates multiple components to represent individual processes within the hydrological cycle. By assembling these components sequentially, GEOframe simulates surface runoff and the hydrological behaviour of a catchment using meteorological, rainfall and hydrometric data. The catchment is divided into sub-basins, and the model resolves the hydrological budget for each, linking these units to generate the cumulative response for the entire catchment.

To subdivide the study area, the geomorphological analysis tool within GEOframe was applied, using the 20 m×20 m DEM as input. Streams were defined by setting a minimum upstream area of 2.5 km². Next, using the interpolated temperature and precipitation values (Section 2.2), the model calculates rain and snow partition (Formetta, Kampf, et al. 2014; Hock 1999), short and longwave radiation (Formetta et al. 2013, 2016) and evapotranspiration (Priestley and Taylor 1972) at the centroids of each sub-basin, through internal routines, although it can

also incorporate externally processed spatial datasets. Once the inputs are prepared, the hydrological processes within each sub-basin are simulated. The model components interact to represent processes such as snow accumulation and melt, interception by vegetation, soil infiltration and groundwater storage. These interactions determine the timing and amount of water discharged from each sub-basin outlet. Finally, the sub-basin outputs are connected according to a topology scheme, which reflects the upstream and downstream relationships, enabling the simulation of the overall streamflow at the catchment's closure section. The sub-basin outlets were aligned with hydrometers located at the dam inflow point (Eita) and the bypass channel intake (Sacco) (Figure 2). The model was calibrated using an automated, stepwise multi-objective procedure employing the Shuffled Complex Evolution algorithm (Duan et al. 1993) in the period October 2011 to March 2016 and validated in the interval April 2016 to September 2020, with a spin-up period of 1 year (October 2010 to September 2011). Through calibration, a set of 17 parameters was optimised within predefined ranges, using the Kling–Gupta Efficiency (KGE; Gupta et al. 2009; Kling et al. 2012) on daily streamflow as the performance metric. Separate parameter sets were determined for each section (Sacco and Eita).

2.3.2 | Bias-Correction and Spatial Downscaling Procedure

The spatial downscaling approach followed the one proposed by Mendes and Maia (2020). In their work, 3-h rainfall data derived

TABLE 2 | List and description of the modified ETCCDI indices considered.

Index	Description	Index	Description
FA20	Relative frequency of days with $T_{\text{mean}} > 20^{\circ}\text{C}$	PRCTOT_mean	Mean annual precipitation (mm)
FB0	Relative frequency of days with $T_{\text{mean}} < 0^{\circ}\text{C}$	PRCTOT_sd	Annual precipitation, standard deviation (mm)
MEAN_Tmean	Mean annual temperature ($^{\circ}\text{C}$)	R01mm	Annual number of days ≥ 0.1 mm
MIN_Tmean	Annual minimum daily mean temperature ($^{\circ}\text{C}$)	R1mm	Annual number of days ≥ 1.0 mm
MAX_Tmean	Annual maximum daily mean temperature ($^{\circ}\text{C}$)	R10mm	Annual number of days ≥ 10.0 mm
		RX1day	Annual maximum 1-day precipitation (mm)

from the ERA-Interim reanalysis product (which combines atmospheric model outputs with observational data, at a 0.75° grid resolution) were bias-corrected and spatially distributed on a 0.125° grid. Similarly, in this study, the RCM cell value (approximately $12.5\text{ km} \times 12.5\text{ km}$) was linked to the Radar+OK daily precipitation product by associating the sub-basin centroids with the corresponding RCM cell. For instance, referring to Figure 2, the temperature and precipitation time series of centroid no. 21 were associated with the series of the central cell E, and those of centroid no. 8 with those of cell F.

The 2005–2020 interval was defined as the reference period. The downscaling was performed using the QDM technique proposed by Cannon et al. (2015), improved by Cannon (2018) and implemented in the R environment in the package ‘MBC: Multivariate Bias Correction of Climate Model Outputs’ (Cannon 2023). The QDM approach allows the comparison of reference and projected periods of different lengths (Cannon et al. 2015), and it requires three sets of data for calculation: the observed series, the control series (reference period 2005–2020), and the projected series (intervals of 20 years varying according to Table 1), which will be bias-corrected and downscaled. The daily mean temperature (T_{mean}) from RCM output required by the hydrological model was computed as the arithmetic average of the daily maximum and minimum temperatures, a standard approximation when only daily extremes are available (Allen 1998; Demaria et al. 2013; Vásquez et al. 2024; World Meteorological Organization 2011). The procedure was carried out following two approaches: (i) considering the entire reference series (October 2005 to September 2020, QDM-y approach) and (ii) applying it month by month (QDM-mo approach). This was done to evaluate the differences between the two approaches.

2.3.3 | Bias-Correction Evaluation

The evaluation of the bias-correction procedure was carried out by comparing the observed temperature and precipitation series with the bias-corrected series of the 21 RCMs. Five indices for temperature and six for precipitation were adopted for the evaluation. In detail, these indices were selected from the Climate Change Indices–Expert Team on Climate Change Detection and Indices (ETCCDI) (Gutiérrez et al. 2019). The selected indices are shown in Table 2. Some indices were modified, given the

choice to operate with the daily mean temperature. For example, the FA20 index, which is aimed at counting the number of days above 20°C in the mean temperature series, is a modification of FA30 (count of the days with maximum temperature $> 30^{\circ}\text{C}$). For each model and each climatic index, the relevant metric was computed annually at each centroid. The annual values were then spatially averaged across the study area and temporally averaged over the historical period (2005–2020). The same procedure was applied to the observed data, and the relative bias was quantified using the Percent Bias (PBIAS) metric by comparing modelled and observed multi-year means. In addition, the number of rainy days above the 99th percentile (extreme events) and maximum length of consecutive days of no precipitation (consecutive dry days, < 0.1 mm, CDD) were calculated for the two approaches with respect to the precipitation series used for hydrologic model calibration.

2.3.4 | Future Discharge Assessment and GHP

The discharge rates obtained from the calibrated hydrologic model fed by the downscaled and bias-adjusted output of the 21 RCMs were evaluated at the monthly level. The results of the various scenarios are presented using ensemble monthly hydrographs of streamflow and precipitation, where the ensemble is represented by the median across the RCMs and the interquartile range (25th–75th percentiles) to indicate uncertainty. In addition, the monthly Percent Bias (PBIAS) of modelled discharge relative to observed discharge, as well as the number of days exceeding the 99th percentile (extreme flow events) and the number of days falling below the MEF (only for the Sacco stream), were computed to identify inter-annual underestimations and overestimations.

The monthly GHP (GHPm) (W/month) was estimated by combining the formulations proposed by Hoes (2014), Liu et al. (2016) and Zhou et al. (2015) in order to analyse its changes for each scenario considered.

$$GHPm = \rho \cdot g \cdot Q_{\text{ave}} \cdot h_{\text{ave}} \quad (1)$$

where ρ is the density of water (1000 kg/m^3); g is gravitational acceleration (9.81 m/s^2); Q_{ave} is the monthly average streamflow ($\text{m}^3\text{ s}^{-1}$); and h_{ave} is the hydraulic head (m). According to Lehner et al. (2005), this potential can be intended either as absolute

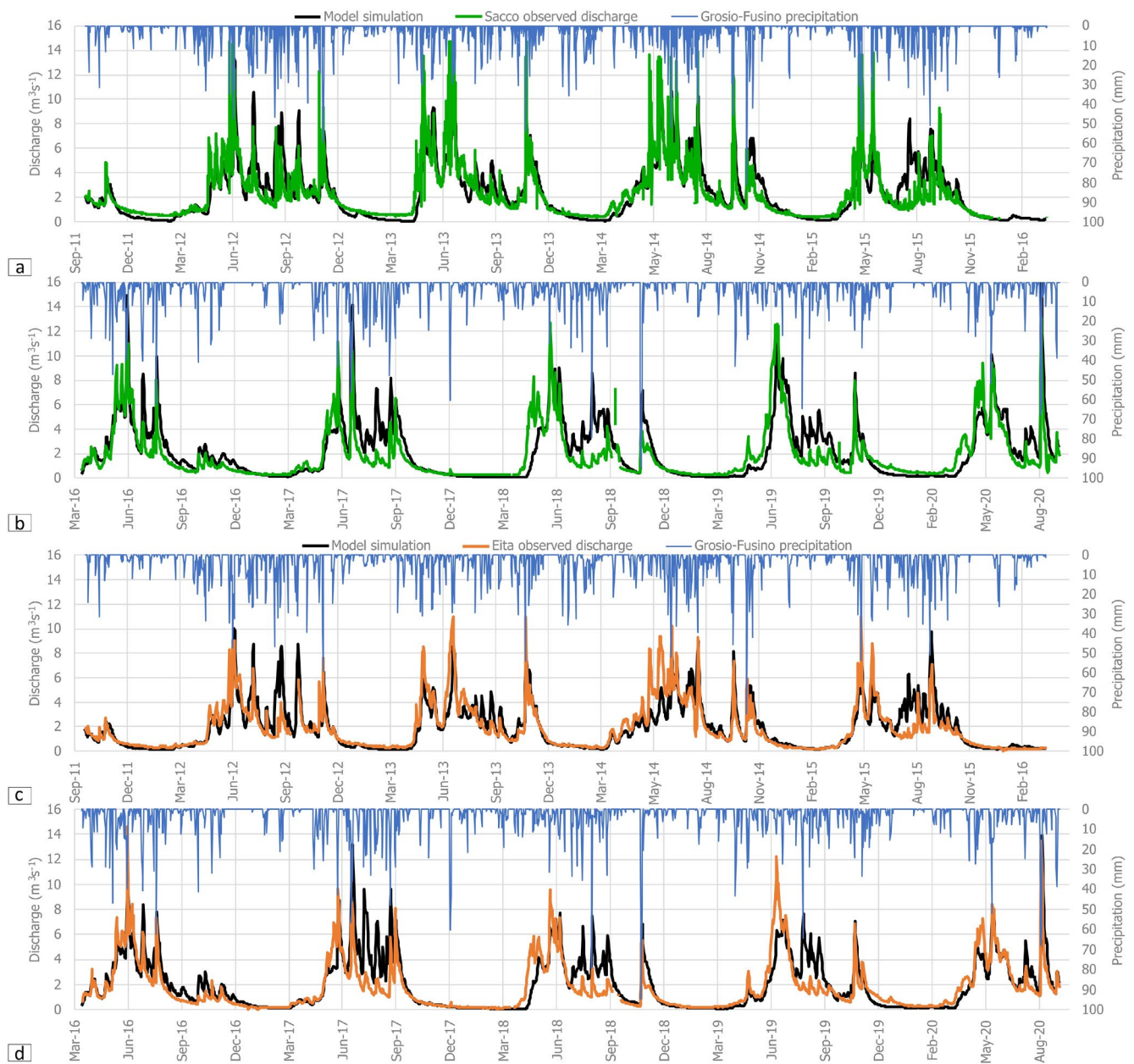


FIGURE 3 | Comparison between observed and simulated daily discharge rates ($\text{m}^3 \text{s}^{-1}$) for the Sacco (a, b) and Eita (c, d) sections during the calibration period (October 2011 to March 2016) and validation period (April 2016 to September 2020).

potential, namely by assuming the average elevation value of the entire basin, or as potential to be exploited locally at the plant, by considering the elevation difference between upstream (lake reservoir) and downstream (hydropower plant turbines). In the hydrologic and hydroelectric setting of the Valgrosina, it is interesting to focus on the second approach, considering the elevation difference between the level of the dam lake and the Grosio plant. The average reservoir level was derived from the mean of the minimum and maximum regulation stages according to the IAR-HP database (Galletti et al. 2025). In addition, to assess the sensitivity of the results to the reservoir level assumption, the percentage variation in GHP potential was also calculated when using the minimum and maximum regulation stages instead of the average. Furthermore, in order to have a conservative economic estimate of the change in GHP, the highest levelised cost of electricity (LCOE) in the 5-year period 2019–2023, equal to

\$0.061/kWh, was taken as the reference value for hydropower generation (IRENA 2024).

3 | Results

3.1 | Hydrologic Model Calibration-Validation

The results of the hydrologic model calibration and validation, fed by the daily Radar+OK precipitation series, are presented for the Sacco (Figure 3a,b) and Eita (Figure 3c,d) sections. The performance indices for calibration and validation in Eita and Sacco sections highlight a robust parametrisation of the model. In detail, daily KGE values of 0.80 (0.73) and 0.84 (0.77) were calculated for calibration (validation) of Sacco and Eita sections, respectively.

3.2 | Bias-Correction and Downscaling Results

The results of the two bias-correction approaches are presented in Figure 4a and Table A2 and Figure 4b and Table A3 for QDM-y and QDM-mo approaches, respectively. Figure 4c represents the percentage differences between the observed monthly value and the corresponding value of the reference period (2005–2020) for precipitation and temperature, and for the two approaches. Results show that the QDM-mo approach performs better than the QDM-y approach with mean differences of precipitation (temperature) of -0.38% ($+0.20\%$) and $+14.56\%$ ($+3.31\%$), respectively. The QDM-mo approach proved to be better than the QDM-y approach, both visually by comparing the bars and lines for the observed and reference period precipitation and temperature values (Figure 4a,b) and by considering the monthly PBIAS values (Figure 4c). During the winter months, the spread among models tends to narrow, indicating greater agreement between the RCMs regardless of the bias-correction method. In contrast, during the summer months, while the inter-model variability remains similar, the QDM-mo correction effectively shifts the ensemble median closer to the observed values—particularly for precipitation—compared to the QDM-y approach, which underestimates summer precipitation. The downscaling results revealed an average temperature increase up to 5°C in July for the most severe scenario (with respect to the 2005–2020 reference period). No robust signal was observed for the annual precipitation pattern, with differences ranging from $+4\%$ to $+7\%$ compared to the observed data.

In addition, the results of the modified ETCCDI indices are expressed as percentage differences, based on the comparison between observed data and bias-corrected model outputs over the common reference period 2005–2020 (Figure 5). The presented indices show only minor differences between methods for temperature and precipitation. However, these small residual errors are propagated into the hydrological model through the forcing, and their effects on streamflow simulations are examined for the two bias-correction methods in Section 3.3. The percentage differences are maintained between -6% and $+10\%$, and between -5% and $+14\%$ for the QDM-y and QDM-mo approaches, respectively. Only the percentage differences between days above 20°C (FA20 index) show higher fluctuations between -16% and $+50\%$ for the QDM-y approach and between $+14\%$ and $+23\%$ for the QDM-mo approach. Figure 6 represents the number of days above the 99th percentile of the observed series (58 days above 30.9 mm/day) and the maximum CDD (32 days for the observed series) for both approaches. Focusing on the green box of the reference period (Figure 6), it is evident that the bias-correction procedures effectively reduced biases for both extreme precipitation events and maximum CDD relative to observations, although the two indices respond differently. For the maximum CDD, improvements are likely linked to the correction of small rainfall amounts and to the nature of the QDM-mo approach, which can adjust monthly totals while affecting sequences across months. For the number of extreme events, bias correction aligns the corrected reference period well with observations, as expected due to direct distribution correction. Overall, extreme events increase in the various scenarios in both approaches, while dry periods tend to decrease compared to the observed value.

3.3 | Future Discharges

The discharge projections were obtained using the model calibrated with the Radar+OK precipitation series and forced with the bias-corrected and downscaled precipitation and temperature outputs using the QDM-y and QDM-mo approaches. The results for the reference period and the four scenarios are presented in Figure 7 as ensemble median in terms of monthly hydrographs (hydrological year, from October to September) for the Sacco and Eita sections, respectively. Figure 7 also shows the monthly solid precipitation values in millimetres of snow water equivalent for the benchmark simulation (Radar+OK, 2010–2020) and for the scenarios considered. In addition, the percentage differences obtained by comparing the streamflow values for the reference period and climate scenarios are shown monthly in Tables A4 and A5 (and seasonally in Tables A6 and A7) for QDM-y and QDM-mo approaches, respectively. While both approaches show similar qualitative trends (i.e., increased winter discharge and decreased summer discharge with warming), significant differences emerge in the magnitude and timing of the hydrological response. Under the QDM-y approach (Figure 7a,b), the streamflow peaks are systematically anticipated with respect to the reference simulation, and the seasonal hydrograph is more distorted, particularly in the Sacco section. The runoff peak, which typically occurs in late spring or early summer due to snowmelt, is shifted earlier and appears sharper under QDM-y, suggesting premature snowmelt driven by an unrealistic phase partitioning. In contrast, QDM-mo (Figure 7c,d) better preserves the timing and shape of the seasonal hydrograph, maintaining a smoother transition into the snowmelt season and a more consistent summer recession. This difference is especially notable in the Sacco section, where the QDM-mo approach reproduces a more physically realistic snowmelt-driven response across scenarios. Overall, these results confirm that QDM-mo preserves the seasonal coherence between temperature and precipitation more effectively, leading to more robust hydrological projections, particularly in snow-dominated basins.

In Figure 7a,b, under QDM-y, simulated snow values are largely decoupled from the expected seasonal signal, especially in late spring and summer. Conversely, QDM-mo (Figure 7c,d) better preserves the seasonal pattern of snowfall, maintaining a more coherent snow accumulation signal across months and scenarios. However, simulated QDM-mo snow values of the reference period underestimate benchmark values by an average of 41% (-82 mm/year) for Sacco and 39% (-77 mm/year) for Eita, with the largest relative monthly underestimation occurring in May (-72% and -71% , corresponding to approximately -3.5 mm/year , respectively). From the analysis of the scenarios, a decrease in snowfall is observed as the severity of the scenario increases. Average decreases of -50% (-52%) with a maximum of -72% (-65%) in April are found when comparing the results of the reference period and the S4 scenario for the Sacco (Eita) section. However, given that GEOframe does not fully resolve the snowpack mass and energy balance, these results should be interpreted as indicative of trends rather than precise estimates (Essery et al. 2013; Magnusson et al. 2011).

Regarding the days characterised by extraordinary discharge, Figure 8 shows that neither the QDM-y nor the QDM-mo

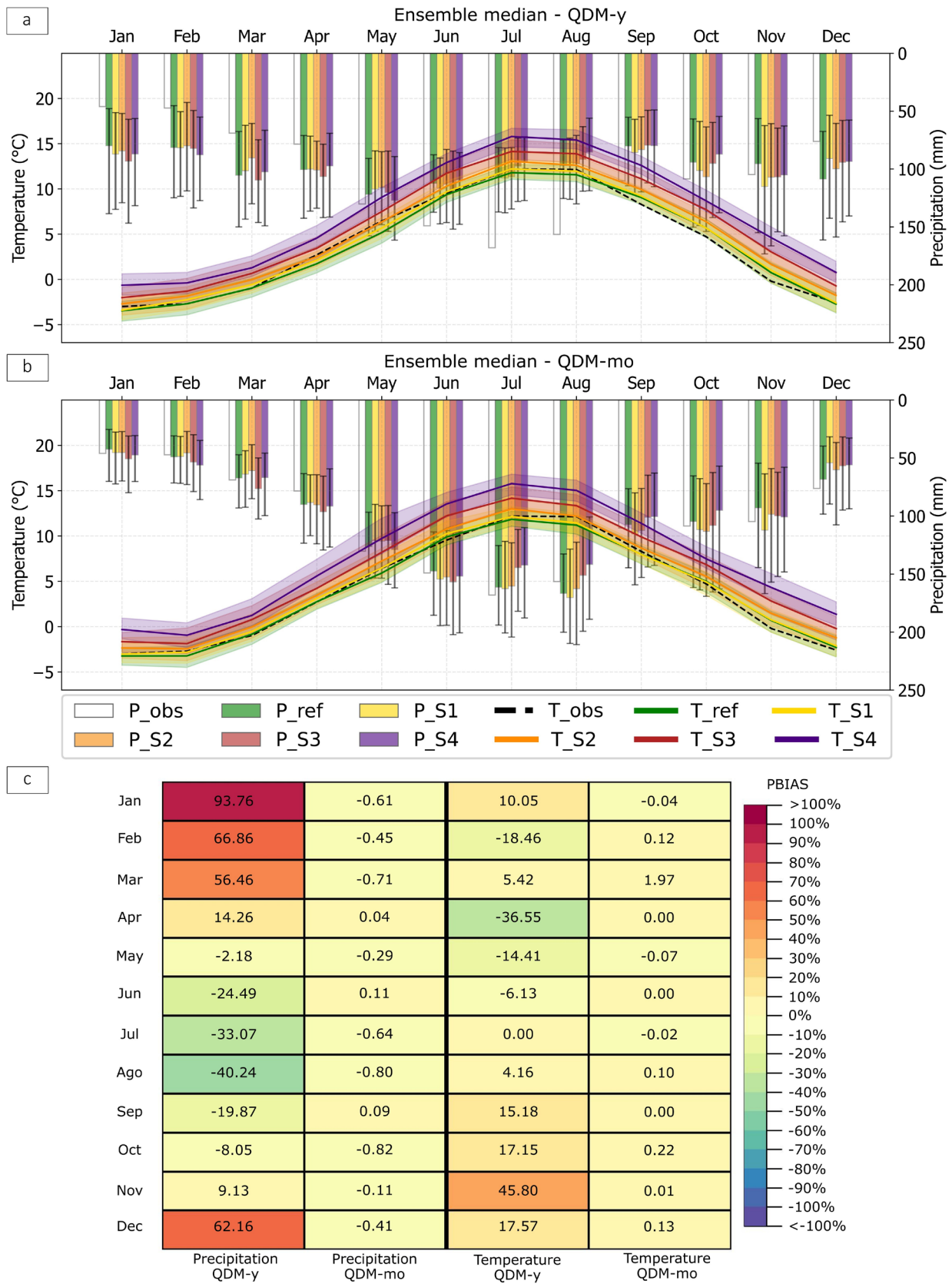


FIGURE 4 | Ensemble-median downscaling results for (a) the QDM-y approach and (b) the QDM-mo approach, showing monthly cumulative precipitation (mm) and mean monthly temperature (°C) for the observed and reference period (ref, 2005–2020) and for climate change scenarios (S1–S4). In each case, the ensemble is represented by the median value across the regional climate models (RCMs) and hydrological model centroids, with shaded bands indicating the interquartile range (25th–75th percentiles). (c) Percentage Bias (PBIAS) illustrating the differences between observed monthly values and the corresponding reference period values for cumulative precipitation and mean monthly temperature, comparing both downscaling approaches.

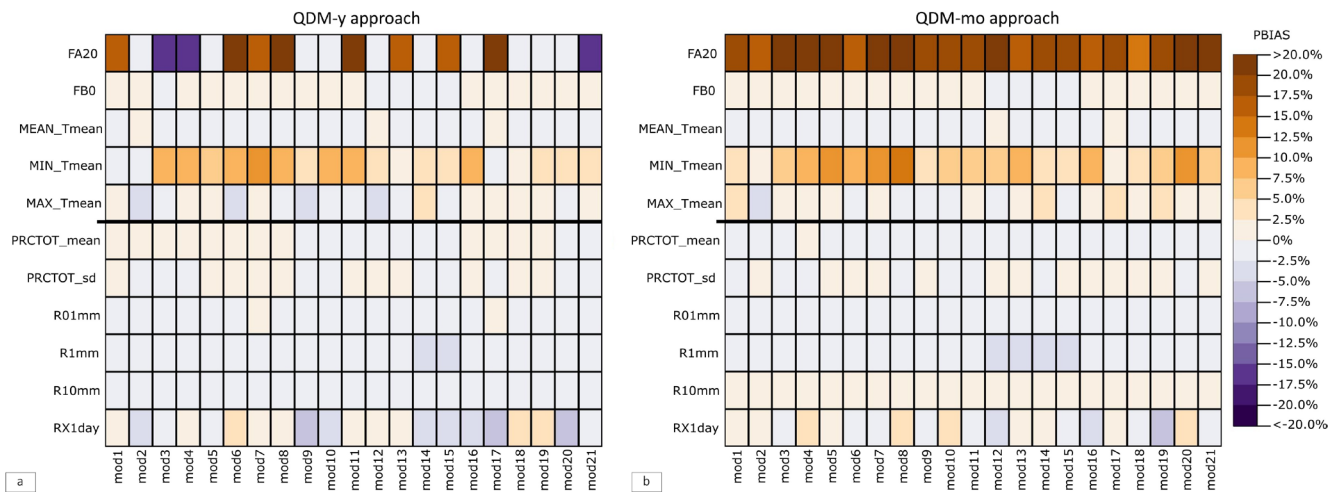


FIGURE 5 | Heat diagrams showing the percentage differences (PBIAS) between the observed series and the reference period for ETCCDI-modified indices (refer to Table 2 for acronym definitions) for each RCM. Results are presented for the (a) QDM-y approach and the (b) QDM-mo approach, highlighting differences between the two methodologies.

approaches fully reproduce the number of extreme streamflow days observed or simulated under benchmark (Radar+OK) conditions during the reference period, at both the Eita and Sacco sections. In all cases, the ensemble median lies between the observed and simulated data series, indicating a systematic underestimation of extremes. An overall increasing trend in the number of days exceeding the 99th percentile is evident as scenario severity intensifies, particularly for the Eita section and more consistently under the QDM-mo correction (Figure 8b). In contrast, the Sacco section under QDM-y (Figure 8c) shows no clear relationship with scenario severity: the number of extreme days tends to decrease slightly, with median values consistently ranging between 3 and 10 days and interquartile ranges remaining within 15 days. This limited response suggests a reduced sensitivity to climate forcing when using the QDM-y method at this model section and clearly reflects the muted changes in streamflow observed in the hydrographs shown in Figure 7. This situation may also be attributed to uncertainties in the streamflow observations of the Sacco section, which were obtained by summing the measurements recorded in the bypass channel to the dam and the MEF requirement that is maintained for downstream flow. As a result, uncertainties in the observed data could have propagated into the calibration process, suggesting that results for this section should be interpreted with some caution.

Figure 9 represents the simulated days below MEF only for Sacco, since no downstream releases occur for the Eita section. The MEF ranges from 0.244 to 0.406 m³ s⁻¹ for the winter (Figure 9a,b, November to April) and summer (Figure 9c,d, May to October) seasons, respectively. The observed value is not reported because the MEF is always guaranteed in the observed record. Instead, the reference used for comparison is the hydrological simulation forced with observed meteorological data (Radar+OK), which provides a consistent baseline for evaluating the climate model scenarios. In winter, both QDM-y and QDM-mo (Figure 9a,b) show a consistent decrease in the number of days below MEF with increasing scenario severity. However, the decrease in median values is more progressive and regular under QDM-y, while under QDM-mo the decline tends to flatten after scenario S2, suggesting a threshold-like behaviour

in the hydrological response. In the most severe scenario (S4), both methods show a substantial reduction in MEF violations, though with greater variability under QDM-y. In contrast, in summer (Figure 9c,d), both approaches indicate an increasing number of days below MEF as the climate scenarios become more extreme. The rise is particularly marked under QDM-y, where median values nearly double from the reference period to S4. Under QDM-mo, the increase is more gradual and contained, with a smaller spread of values, pointing to greater stability and potentially more realistic behaviour of the hydrological model under this correction method. Looking at the QDM-mo results under the scenarios S3 and S4, the median number of days above the 99th percentile (Figure 8) and below MEF (Figure 9) tends to stabilise compared to S1 and S2. This apparent plateau may suggest that hydrological responses to warming begin to saturate at higher GWLs, where further temperature increases yield diminishing marginal impacts on threshold exceedance frequencies.

3.4 | GHP Projections

A hydraulic head of 540.5 m was considered for the GHP calculation, computed as the difference between the average reservoir level (1196.5 m a.s.l.) and the Grosio hydropower plant elevation (656.0 m a.s.l.). The average reservoir level was derived from the mean of the minimum and maximum regulation stages (1183.0 and 1210.0 m a.s.l., respectively), as reported in the IAR-HP database (Galletti et al. 2025). Monthly GHP projections for the entire Valgrosina valley are presented as ensemble distributions in Figure 10, based solely on streamflow simulations derived from the QDM-mo method, which demonstrated superior preservation of seasonal hydroclimatic dynamics.

GHP projections follow the trend of projected discharge, being the result of a product (Equation 1). The simulated data (black square) are far from being represented by the values of the reference period (green dot). However, a positive trend is visible from November to April, considering all four scenarios. The spring–summer period shows a decreasing trend, which becomes more acute for the most severe scenario (+4.0°C). This behaviour is

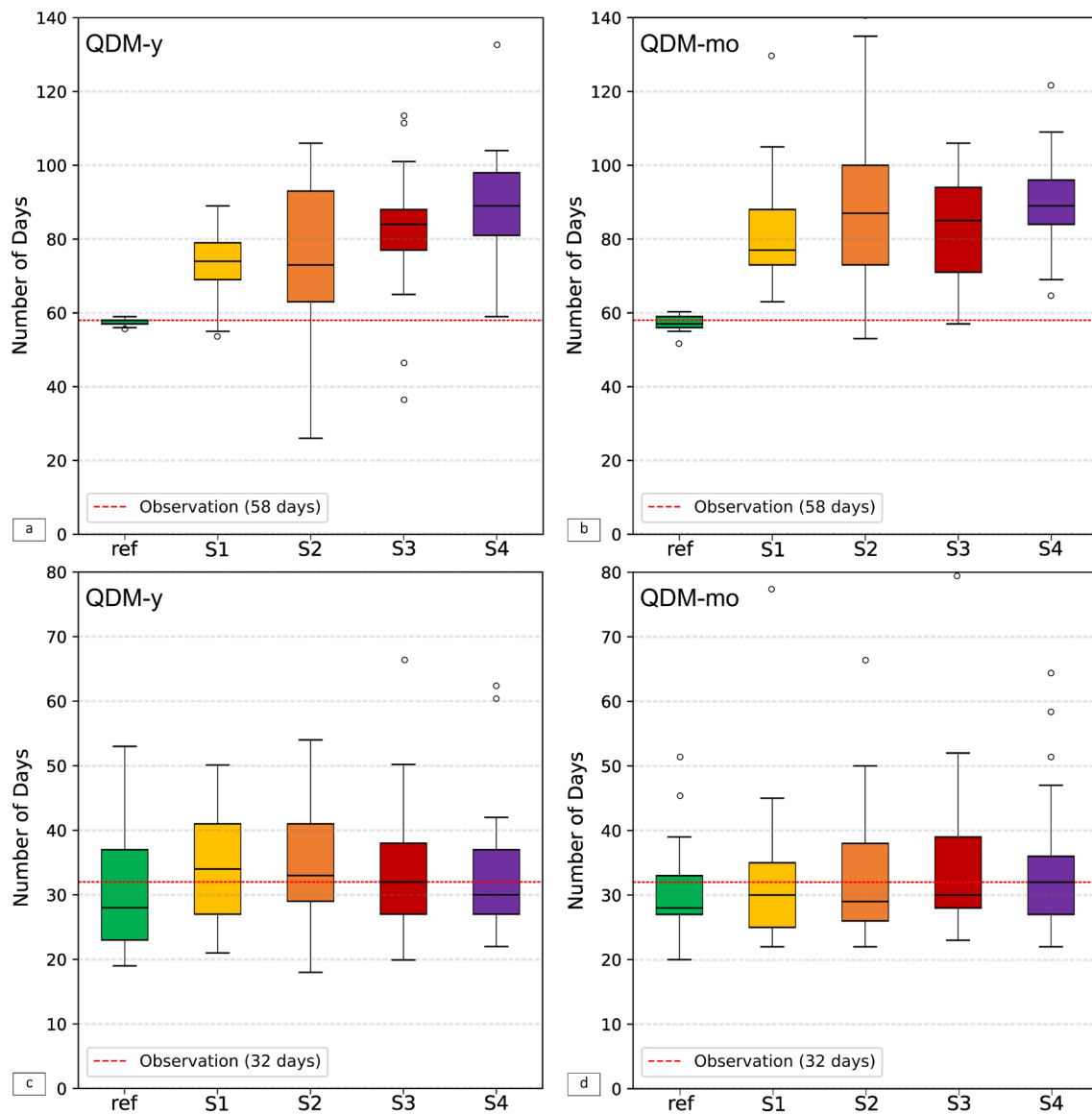


FIGURE 6 | Number of days exceeding the observed 99th percentile (58 days, 30.9 mm/day) for the (a) QDM-y and (b) QDM-mo approaches; maximum CDD (32 days) for the (c) QDM-y and (d) QDM-mo approaches. Boxplots summarise results from 21 RCMs: The box spans the 25th–75th percentiles, whiskers extend to the 5th and 95th percentiles, and outliers are plotted individually. Observed values are shown as dashed red lines.

consistent with a seasonal shift in precipitation phase under warming conditions: higher winter temperatures lead to a greater proportion of precipitation falling as rain rather than snow, resulting in increased immediate runoff and hydropower production. Consequently, reduced snow accumulation in winter contributes to lower GHP values during the spring months due to diminished snowmelt-driven flow. However, these results should be interpreted with caution, as simulated GHP estimates are compared with observed values derived from discharge measurements at the by-pass channel (Sacco) and at the dam inlet (Eita), assuming a constant reservoir level equal to the average between the minimum and maximum regulation stages. Given the linear nature of the GHP formulation, using the minimum or maximum reservoir regulation stage instead of the average results in a variation of approximately $\pm 2.5\%$ in the final GHP estimates, which remains consistent across all scenarios. In the summer period, in contrast to the other seasons, there are negative variations in the order of $-19\% \div -20.5\%$ for the S4 scenario

compared to the reference scenario. Adding also that the S4 June discharge peak is projected to be 14%–25% lower than the reference scenario, these results suggest that strategic storage from April to May may be increasingly important to mitigate summer shortages. In the Valgrosina system, reservoir levels are generally maintained near maximum throughout the year, including spring months, as confirmed by communications with the plant operator. However, under future climate conditions, current release strategies may need to be revised to account for earlier snowmelt and avoid suboptimal storage management. In addition, considering the value of the highest LCOE for the 2019–2022 period, equal to 0.061 US Dollar per kWh, monthly estimations of gross revenue were obtained for both model sections and for all scenarios (Table A8). These values give an idea of the weight of hydropower production fluctuations from the economic point of view. Obviously, they follow the trend of the GHP projections, but it is interesting to observe that, for the critical month of June for the most severe scenario, a potential

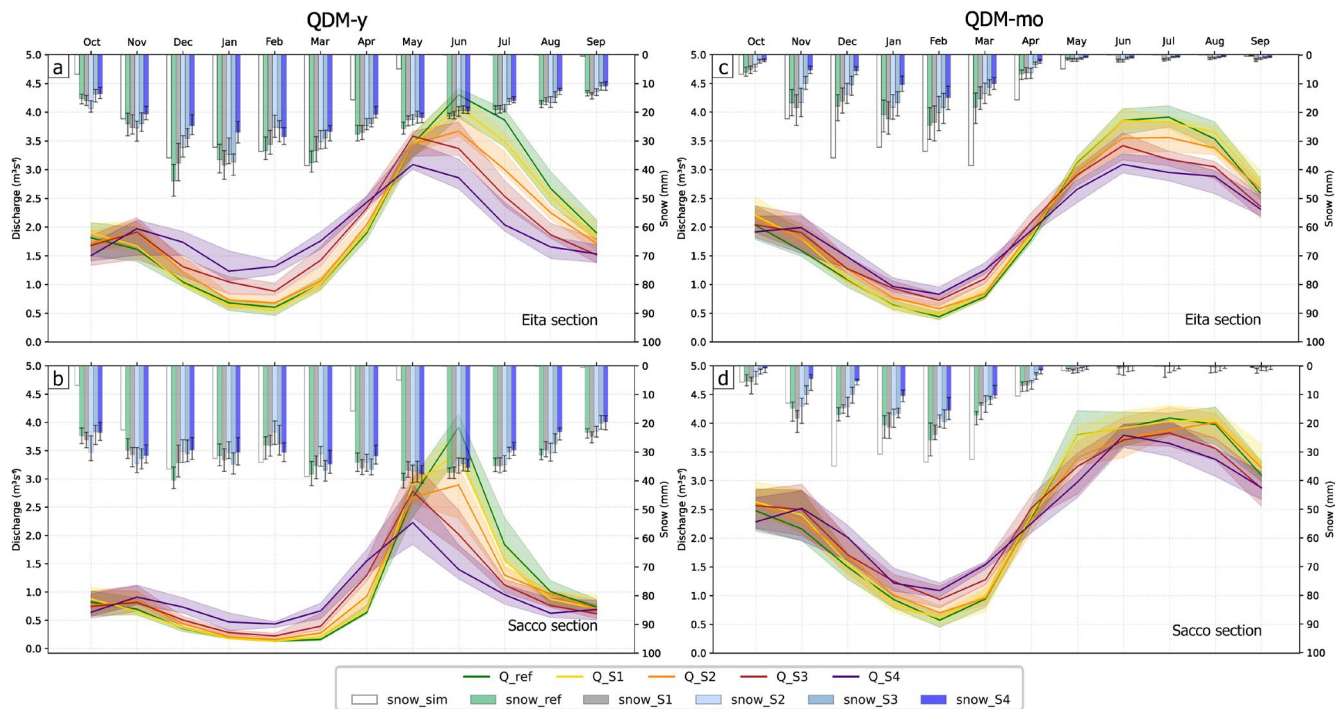


FIGURE 7 | Comparison of projected streamflow ($\text{m}^3 \text{s}^{-1}$) and solid precipitation (mm) under the (a, b) QDM-y and (c, d) QDM-mo bias correction approaches for the (a, c) Eita and (b, d) Sacco sections. For comparison, the corresponding snow simulation results (snow_sim) obtained from the model using the Radar+OK dataset are also included. The interquartile range is plotted for each scenario as shading for the discharge and whiskers for snow.

economic loss of around \$360 000 compared to the 2005–2020 reference scenario could occur.

4 | Discussion

As climate change reshapes water availability in mountainous regions (Brosse et al. 2022; Kotlarski et al. 2023), selecting appropriate methods for bias correction becomes a critical step in ensuring reliable hydrological projections. This study demonstrates how the choice of bias correction method can substantially influence hydrological simulations and impact assessments in Alpine catchments. Among the tested approaches, the QDM-mo outperformed the annual-based version (QDM-y) in preserving seasonal patterns of temperature and precipitation, which are critical in snow-driven systems where phase partitioning strongly affects runoff timing and magnitude (Marx et al. 2018; Vormoor et al. 2015).

QDM-y, while preserving annual quantile distributions, introduces inconsistencies in the seasonal structure. In particular, it distorts the intra-monthly coherence between daily temperature and precipitation, which is critical when precipitation occurs near the freezing point. This leads to incorrect phase partitioning, underestimation of snow accumulation and a premature shift in runoff. These issues are evident in the Sacco basin, where the snow signal is lost, and the runoff timing is strongly affected (Figure 7). Conversely, QDM-mo corrects each calendar month independently, preserving the seasonal cycle and maintaining a more physically realistic relationship between snow processes and streamflow. Given these advantages and the subsequent improvements in hydrological realism (Figures 7–9),

the QDM-mo approach was selected for the GHP assessment. While both methods yield similar performance on broad statistical indicators (e.g., Figure 5), only QDM-mo retains the climatic and hydrological signatures that are essential to assessing future streamflow and hydropower potential in snow-dominated basins. Given the focus on hydropower potential, both seasonal water volumes and the timing of threshold-exceeding flow events are relevant, as they directly influence energy yield and reservoir operation. This further supports a goal-oriented evaluation of bias correction performance.

Despite its improved performance, QDM-mo is not without limitations. Monthly corrections do not ensure temporal coherence at the daily scale, and they may introduce artificial discontinuities at month boundaries. Moreover, residual errors in reproducing extreme events or high-frequency variability persist, particularly during transitional periods (e.g., late winter or early spring). Additionally, one source of uncertainty lies in the structure of the hydrological model itself, which employs a temperature-based snowmelt routine. While the applied formulation (Formetta, Kampf, et al. 2014; Hock 1999) is an enhanced temperature-index model that accounts for radiation inputs, it does not include a full energy balance representation. This may limit the model's ability to simulate melt processes accurately under changing climate conditions where multiple energy fluxes (e.g., humidity and wind) interact nonlinearly. Therefore, future work should consider implementing full energy-balance-based snow models, which account for a broader set of physical drivers and may be more robust under conditions of temporal mismatch between climate drivers. Alternatively, future model developments could combine trend-preserving QDM with a multivariate bias-correction approach to jointly adjust downscaled

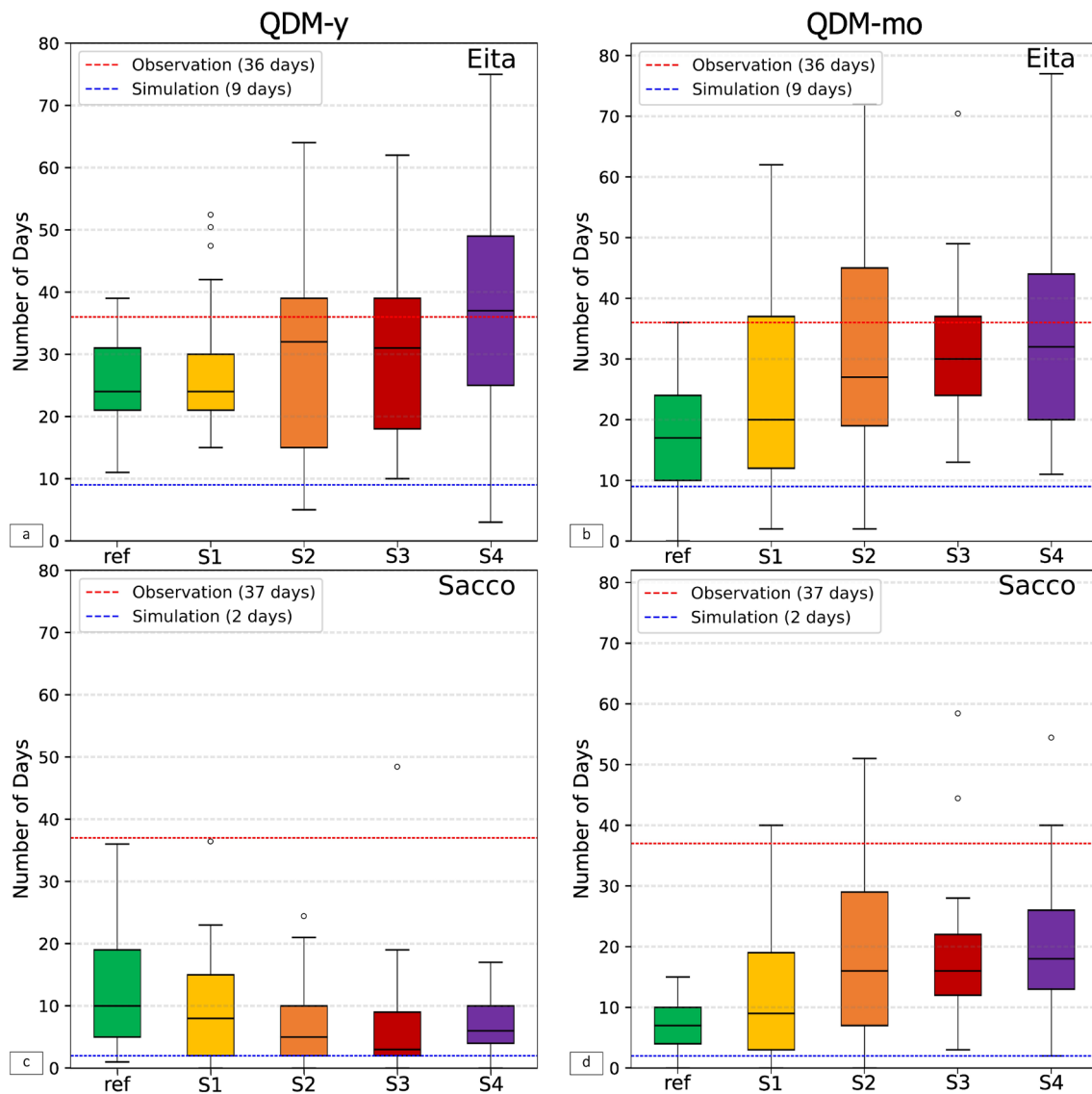


FIGURE 8 | Boxplots of the 21 RCMs with the number of days characterised by streamflow above the 99th percentile for the simulations of (a, b) Eita ($8.37 \text{ m}^3 \text{ s}^{-1}$) and for (c, d) Sacco ($10.46 \text{ m}^3 \text{ s}^{-1}$) sections obtained for QDM-y (left column) and QDM-mo (right column) correction methods. The red line indicates the number of days calculated from observations (2005–2020), while the blue line indicates those from the simulation forced with Radar+OK data.

temperature and precipitation while preserving their inter-variable dependence (Cannon 2018, 2023).

As anticipated, directly comparing the QDM-y and QDM-mo streamflow simulations (Figure 7) reveals that QDM-y introduces significant distortions in snow accumulation and run-off timing, particularly in the Sacco basin, due to its failure to preserve the seasonal coherence between temperature and precipitation. In contrast, QDM-mo maintains the expected snowmelt-driven hydrological cycle, resulting in more realistic discharge dynamics and improved consistency across scenarios than QDM-y. Focusing on the future streamflow projections forced by QDM-mo, the two main branches of the valley—Sacco and Eita—show a similar response to climate change scenarios. Under the most severe warming scenario ($+4.0^\circ\text{C}$) for QDM-mo, both the Sacco and Eita branches are projected to experience similar absolute changes in streamflow compared to the reference period, with an increase of approximately $+0.5 \text{ m}^3 \text{ s}^{-1}$ in

winter (from 0.2 to $0.7 \text{ m}^3 \text{ s}^{-1}$, about $+300\%$) and a decrease of about $-0.7 \text{ m}^3 \text{ s}^{-1}$ in summer (from 3.6 to $2.9 \text{ m}^3 \text{ s}^{-1}$ in Sacco and from 3.5 to $2.8 \text{ m}^3 \text{ s}^{-1}$ in Eita). However, these similar absolute changes translate into markedly different seasonal impacts in relative terms: the winter increase represents a tripling of streamflow, while the summer reduction, although comparable in volume, amounts to only about -19.0% to -20.5% . This contrast highlights the strong seasonal redistribution of water availability under warming conditions, a well-established feature in snow-dominated Alpine basins (Table A7) (Citirini et al. 2020; Hanus et al. 2021; Wagner et al. 2017). These projected trends are consistent with previous studies in Alpine catchments of northern Italy, where similar summer decreases (up to -30%) have been reported by Patro et al. (2018). The slightly different relative decrease can be explained by the fact that the hydrologic behaviour of Valgrosina is certainly snow-driven, but the valley is not fed by a glacier. Similar annual-scale streamflow decreases were reported by Gaudard et al. (2014) for the Aosta

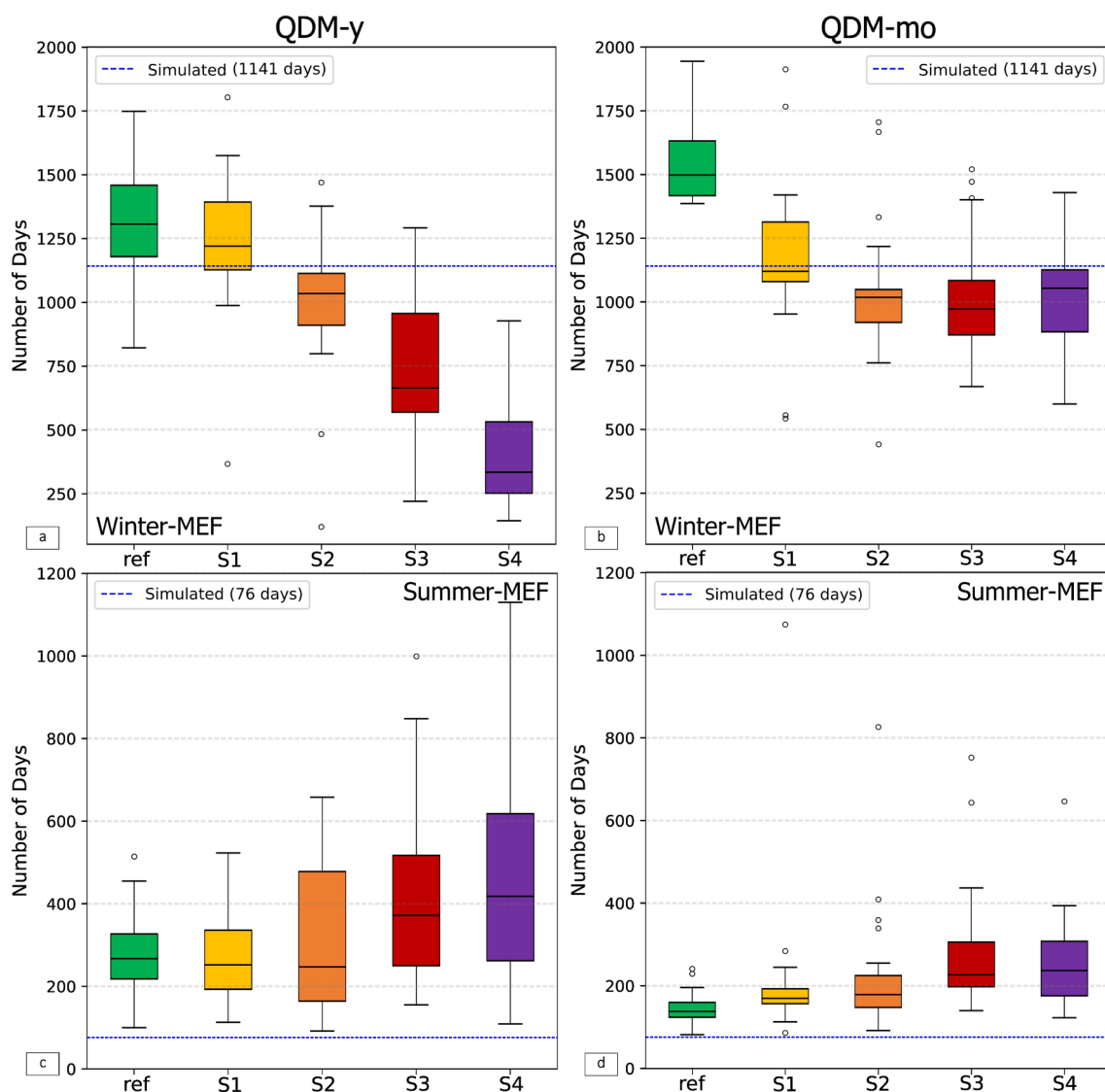


FIGURE 9 | Boxplots of the 21 RCMs with the number of days below Minimum Environmental Flow (MEF) for the Sacco section in (a, b) the winter ($0.244 \text{ m}^3 \text{ s}^{-1}$) and (c, d) summer seasons ($0.406 \text{ m}^3 \text{ s}^{-1}$) obtained for QDM-y (left column) and QDM-mo (right column) correction methods. The blue line indicates the days below the threshold for the simulation forced with Radar+OK data (1141 and 76 for winter and summer, respectively).

Valley under the SRES A1B scenario, which approximately corresponds to a $+2.5^\circ\text{C}$ to $+3.0^\circ\text{C}$ GWL by the end of the 21st century (2070–2100). However, projections of this type are strongly influenced by the location of the study area and its hydrologic setting. Despite the resulting opposing trends in this type of study, both on annual and seasonal scales, there is a need to reconsider the management of water resources to contrast and mitigate the effects of climate change, leading to the definition of a new adaptive management.

The climate uncertainties, along with the environmental impact of hydropower plants, raise significant questions about the long-term sustainability of this energy source. Kumar et al. (2011) pointed out an average reduction in European hydropower potential of 6% by 2070, with southern Europe facing a more substantial impact than northern Europe. Tobin et al. (2018) reported a decrease of up to 30% in hydropower potential for Greece, Spain and Portugal by the end of the century. Koch et al. (2011) projected moderate to severe reductions in hydropower production

in the Danube Basin for the period 2051–2060, estimating decreases ranging from -2.2% to -15.0% . This trend is further supported by the findings of Koch et al. (2015), Pašičko et al. (2012) and Totschnig et al. (2017), which confirmed similar declines in Germany, Austria and Croatia, respectively. The climate projections for the alpine region indicate a marked rise in average temperatures and a shift in precipitation patterns, with an expected decrease in snowfall and an increase in rain during winter months (Kotlarski et al. 2023). These projections align with the findings of this study, which indicated reductions in simulated snow accumulation and corresponding increases in winter streamflow in the Valgrosina catchment. Additionally, extreme weather events, such as intense storms and heatwaves, are anticipated to occur more frequently, further stressing the valley's ecosystems (Barbagallo et al. 2024). Adapting to climate change requires a thorough reassessment of existing hydropower infrastructure, with a focus on maintaining performance under evolving hydroclimatic regimes (Schmitt and Rosa 2024). In this study, although summer streamflow remains the highest in

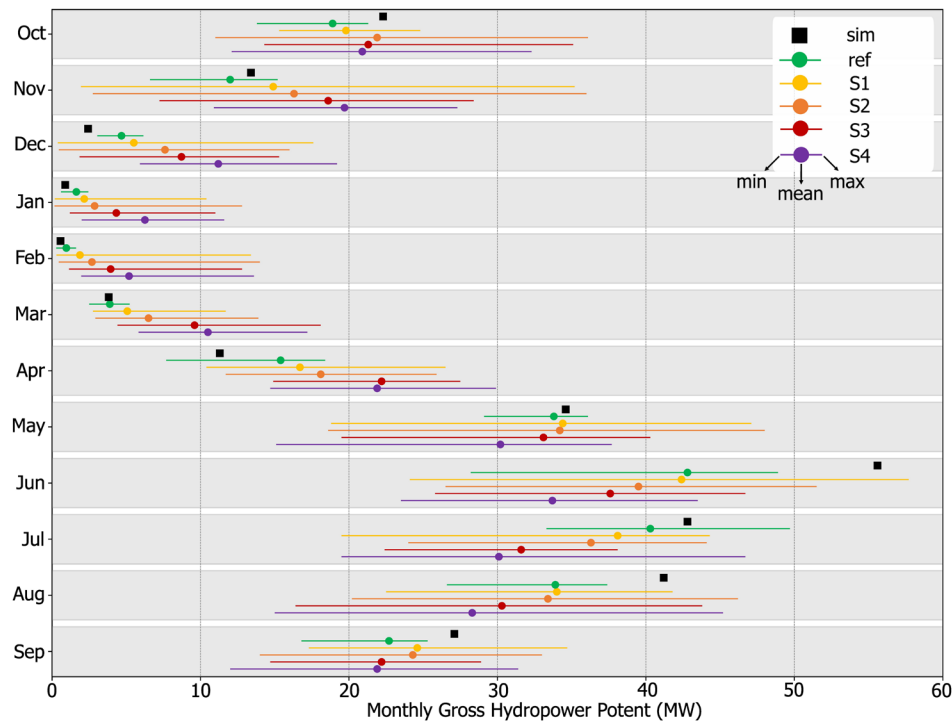


FIGURE 10 | Monthly variations in total gross hydropower potential (GHP) for Valgosina, aggregated across the Sacco and Eita sections. The plot shows the monthly average GHP (MW) for the simulation (sim), reference period (ref) and four climate change scenarios (S1–S4). Each dot represents the ensemble mean, with horizontal lines indicating the minimum and maximum range across the 21 RCM projections.

absolute terms, it is projected to decline compared to the reference period. This may challenge hydropower operations, particularly during dry years, when demand is high and inflows become less predictable (Naumann et al. 2021). On the other hand, increased winter flows (driven by reduced snow accumulation and more rain-fed runoff) could offer new opportunities for energy production. However, fully leveraging these changes calls for an adaptation of reservoir operation practices, as conventional rules based on snowmelt timing may no longer be optimal (Tobias et al. 2023; Wagner et al. 2017; Zhao and Boll 2022). To quantify GHP, a simplified assumption of average reservoir level and constant head was used, providing a first-order estimate without dynamic simulation of storage and operational constraints. In practice, however, prolonged low-flow conditions in summer may reduce storage flexibility and limit generation capacity, especially when competing water uses must be prioritised (Kapica et al. 2024; Wan et al. 2021). For instance, the ‘forced’ releases observed during the 2022 drought (primarily driven by agricultural and downstream water supply needs) reduced the ability to retain water for hydropower purposes (Bonaldo et al. 2023). Balancing energy production with environmental conservation is a complex challenge that demands a holistic approach and innovative strategies (Batra 2023). Companies operating hydropower plants must take concrete actions to adapt to these changing conditions. To ensure stable power production, they need to review operational planning, maintenance and potential engineering interventions (Kougias et al. 2019). Producing accurate scenarios requires more than statistical agreement with historical observations; it involves selecting and validating correction strategies that yield physically meaningful hydrological responses under future conditions. This includes the preservation of seasonal dynamics, consistency in threshold-based

indicators and alignment with operational constraints relevant for energy production.

5 | Conclusions

In this study, streamflow and hydropower potential projections were computed by forcing hydrologic simulations with climate change scenarios that consider global temperature increases of +1.5°C, +2.0°C, +3.0°C, and +4.0°C relative to the pre-industrial period. Daily precipitation and temperature outputs from 21 RCMs (approximately 12.5 km² resolution) were bias-corrected and downscaled using observed data for the 2005–2020 reference period, and the corrected datasets were then used as input for both the reference period simulations and the future projections. The streamflow and hydropower potential projections developed here indicate substantial intra-annual shifts in streamflow regimes, with winter increases (+48% ÷ +37% comparing the S1 and S4 scenarios with respect to the reference period, respectively) and summer decreases (–2% ÷ –9% under scenarios S1–S4 relative to the reference period, respectively) becoming more pronounced under higher GWLs.

Crucially, the adoption of two different bias-correction and downscaling approaches highlighted the importance of methodological choices in climate impact studies: the QDM-mo bias-correction approach outperformed the QDM-y method, especially in preserving seasonal variability. This demonstrates that the selection and application of bias-correction methods must be considered a critical component of hydrological projections, particularly in mountainous regions where snow- and rain-driven processes are highly sensitive to temperature

changes. While QDM-mo preserved seasonal variability more effectively than QDM-y, particularly in snow-dominated hydrology, its application is not without limitations. Temporal inconsistencies at the daily scale and the simplifications inherent in the hydrological model structure remain sources of uncertainty. Nevertheless, given the objective of assessing future hydropower potential, the QDM-mo approach was better suited than QDM-y to preserve the physical signals critical to this goal. These considerations support the notion that bias correction should be evaluated within a goal-oriented framework, where the method's adequacy is judged based on its ability to reproduce the dynamics most relevant to the intended application.

Although summer remains the period with the highest absolute streamflow, the projected decline compared to historical conditions may still constrain hydropower production, especially in dry years when inflows are less reliable and demand is elevated. Conversely, the anticipated increase in winter discharge could support additional energy generation during typically underutilised periods. Yet, capitalising on this seasonal shift requires revisiting reservoir operation strategies, as traditional rules optimised for snowmelt-driven regimes may become increasingly inadequate under future climate conditions. Explicit simulation of reservoir dynamics would further improve the accuracy of hydropower production estimates. In this study, the GHP was used as a first-order indicator, providing an initial approximation of production potential based on available streamflow and assumed reservoir conditions. Future work could integrate dynamic reservoir operation models to refine these projections and better support adaptation planning.

In conclusion, this work highlights how projected changes in streamflow and GHP strongly call for adaptive management of hydropower systems in response to climate change. While no explicit adaptation strategies were simulated, the emerging seasonal imbalances and reduced flexibility during low-flow periods emphasise the need for rethinking operational practices. Future studies should integrate dynamic reservoir operations and multi-objective management frameworks to quantify and evaluate specific adaptation options. Utilising site-specific projections based on calibrated hydrologic models forced by bias-corrected climate change scenarios is essential for adaptive management. While such modelling efforts do not affect hydraulic efficiency per se, they provide essential insights into future water availability, timing of flows and potential low-flow risks. This information can inform strategic decisions regarding reservoir operations, seasonal scheduling and long-term infrastructure investments. In this context, integrating dynamic and forward-looking strategies becomes a key investment to enhance the resilience of hydropower systems and safeguard both water and energy security under evolving climate conditions.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Appendix A

TABLE A1 | Elevation in metres a.s.l. and year of automation of weather stations used in this research. For the spatial distribution, refer to Figure 1.

ID	Name	Elevation (m a.s.l.)	Year of automatisisation
2	Eita	1950	2008
3	Malghera	2000	2008
1	Grosio	1211	2002
4	Aprica	1950	1992
5	Bormio	1197	1987
6	Edolo, Ist. Meneghini	699	1993
7	Edolo, Pantano d'Avio	2108	1998
8	Livigno, La Vallaccia	2660	1998
9	Livigno, Foscagno	2320	2002
10	Monno	1728	2004
11	Ponte di Legno	1640	2004
12	Teglio	357	2012
13	Tirano	1755	2011
14	Valdidentro, Arnoga	1881	1988
15	Valdidentro, Cancano	1948	2012
16	Valdisotto, Arginone	1119	2007
17	Valdisotto, Oga S. Colombano	2300	2012
18	Valfurva	1730	2012
19	Passo Bernina	2260	2014
20	Buffalora	1971	1998
21	Poschiavo/Robbia	1078	1981
22	S.Maria	1286	2012

TABLE A2 | QDM-y downscaling results in terms of monthly cumulative precipitation (P, mm) and monthly mean temperature (T, °C) for the reference period (ref) and climate change scenarios (S1–S4) in comparison with observations (obs).

	P_obs	P_ref	P_S1	P_S2	P_S3	P_S4	T_obs	T_ref	T_S1	T_S2	T_S3	T_S4
Jan	52.3	101.4	99.4	98.0	111.0	100.9	−3.2	−3.6	−3.4	−2.8	−2.1	−0.6
Feb	53.8	89.8	89.7	87.4	95.2	98.5	−3.3	−2.7	−2.3	−2.0	−1.2	−0.3
Mar	72.0	112.6	108.4	100.0	117.0	113.9	−0.9	−0.9	−0.5	−0.1	0.8	1.5
Apr	96.8	110.6	108.3	109.1	112.6	109.7	2.8	1.8	2.2	2.6	3.6	4.9
May	128.9	126.1	121.6	120.8	122.9	126.6	6.0	5.1	5.7	6.3	7.5	9.0
Jun	153.8	116.2	121.5	117.4	122.2	118.0	9.9	9.3	9.8	10.4	11.8	13.0
Jul	165.5	110.7	110.2	109.0	101.8	100.6	11.9	11.9	12.4	13.1	14.3	15.8
Aug	171.3	102.4	103.2	101.7	94.6	89.2	11.3	11.7	12.1	12.7	13.9	15.5
Sep	112.2	89.9	97.7	93.9	89.3	87.3	7.9	9.1	9.3	9.9	11.1	12.6
Oct	123.2	113.3	113.3	117.4	107.7	105.0	4.8	5.6	5.7	6.3	7.5	8.7
Nov	106.2	115.9	130.6	121.7	118.9	120.1	0.5	0.8	0.8	1.7	3.1	4.6
Dec	73.0	118.4	104.2	115.2	107.4	106.0	−2.2	−2.5	−2.5	−1.8	−0.7	0.9

Note: All values represent spatial averages over the hydrological model centroids.

TABLE A3 | QDM-mo downscaling results in terms of monthly cumulative precipitation (P, mm) and monthly mean temperature (T, °C) for the reference period (ref) and climate change scenarios (S1–S4) in comparison with observations (obs).

	P_obs	P_ref	P_S1	P_S2	P_S3	P_S4	T_obs	T_ref	T_S1	T_S2	T_S3	T_S4
Jan	52.3	52.0	52.6	52.2	59.5	53.3	−3.2	−3.2	−2.7	−2.1	−1.5	0.0
Feb	53.8	53.6	55.5	55.0	58.9	62.8	−3.3	−3.3	−2.5	−2.3	−1.5	−0.6
Mar	72.0	71.5	70.0	65.5	79.4	76.1	−0.9	−0.9	−0.3	0.1	1.1	1.7
Apr	96.8	96.9	95.4	99.4	102.9	99.1	2.8	2.8	3.3	3.8	4.7	6.1
May	128.9	128.5	123.2	125.3	127.1	131.4	6.0	6.0	6.6	7.2	8.4	9.9
Jun	153.8	154.0	162.2	158.4	162.5	162.0	9.9	9.9	10.2	10.8	12.2	13.4
Jul	165.5	164.4	166.5	167.1	151.0	152.8	11.9	11.9	11.9	12.7	14.0	15.4
Aug	171.3	169.9	174.0	171.1	158.9	147.9	11.3	11.3	11.3	12.0	13.1	14.7
Sep	112.2	112.3	125.6	120.8	111.6	109.4	7.9	7.9	7.8	8.5	9.7	11.2
Oct	123.2	122.2	126.3	133.1	121.8	118.7	4.8	4.8	4.7	5.3	6.6	7.6
Nov	106.2	106.1	127.5	118.8	116.2	113.2	0.5	0.5	0.6	1.6	2.9	4.5
Dec	73.0	72.7	63.7	73.2	68.2	66.2	−2.2	−2.2	−1.9	−1.1	0.0	1.6

Note: All values represent spatial averages over the hydrological model centroids.

TABLE A4 | QDM-y monthly percentage differences in projected streamflow (Q) between the reference period and the various scenarios (S1–S4) considered for the two model sections of the Valgrosina.

QDM-y %	Sacco				Eita			
	Q_S1	Q_S2	Q_S3	Q_S4	Q_S1	Q_S2	Q_S3	Q_S4
Oct	9.32	2.67	−3.35	−11.20	3.33	−5.08	−9.30	−12.20
Nov	1.22	25.23	22.58	24.81	4.66	17.85	9.37	15.46
Dec	5.87	30.02	38.24	111.46	0.05	21.44	22.50	54.88
Jan	0.46	19.00	47.61	147.31	2.90	15.66	58.51	111.28
Feb	0.40	20.25	62.81	219.84	1.84	19.57	65.66	138.69
Mar	18.13	51.69	148.37	296.62	3.96	7.10	47.90	74.58
Apr	20.50	52.94	123.58	177.66	−2.48	6.89	24.98	32.79
May	3.92	6.12	3.15	−9.34	1.33	0.62	1.90	−7.08
Jun	−5.90	−27.92	−48.97	−60.81	−1.34	−11.41	−17.35	−30.79
Jul	−13.43	−27.41	−37.27	−44.69	−7.16	−19.39	−29.70	−44.15
Aug	−6.28	−8.29	−16.82	−30.21	−4.41	−14.99	−27.52	−36.87
Sep	−0.34	−0.21	−14.17	−5.77	−2.52	−10.64	−21.63	−22.67

TABLE A5 | QDM-mo monthly percentage differences in projected streamflow (Q) between the reference period and the various scenarios (S1–S4) considered for the two model sections of the Valgrosina.

QDM-mo %	Sacco				Eita			
	Q_S1	Q_S2	Q_S3	Q_S4	Q_S1	Q_S2	Q_S3	Q_S4
Oct	4.27	15.12	10.89	9.65	5.04	15.59	15.04	14.12
Nov	24.48	34.42	52.09	63.34	23.02	33.97	53.12	64.32
Dec	18.82	61.37	80.97	135.00	15.84	58.63	80.09	131.80
Jan	37.83	71.07	157.95	293.72	28.97	66.81	144.31	252.37
Feb	111.01	195.66	316.18	473.87	74.66	140.71	232.04	332.74
Mar	35.65	80.75	176.41	205.88	28.80	58.56	122.27	138.45
Apr	7.81	18.07	45.77	43.38	9.34	17.76	45.44	46.16
May	0.79	−0.77	−7.25	−18.33	3.60	6.07	8.16	2.09
Jun	−1.79	−9.45	−17.16	−24.83	0.60	−3.73	−4.04	−13.88
Jul	−5.42	−10.46	−21.72	−22.89	−3.78	−7.16	−18.17	−24.77
Aug	1.15	0.33	−7.84	−13.76	−0.51	−3.37	−11.29	−18.21
Sep	8.45	7.10	−1.82	−2.78	8.46	5.99	−0.52	−2.56

TABLE A6 | QDM-y seasonal percentage differences in projected streamflow ensemble mean between the reference period and the various scenarios considered for the two model sections of the Valgrosina.

QDM-y %	Sacco				Eita			
	Q_S1	Q_S2	Q_S3	Q_S4	Q_S1	Q_S2	Q_S3	Q_S4
D-J-F	2.2	23.1	49.6	159.5	1.6	18.9	48.9	101.6
M-A-M	14.2	36.9	91.7	155.0	0.9	4.9	24.9	33.4
J-J-A	−8.5	−21.2	−34.4	−45.2	−4.3	−15.3	−24.9	−37.3
S-O-N	3.4	9.2	1.7	2.6	1.8	0.7	−7.2	−6.5
Year	2.8	12.0	27.1	68.0	0.0	2.3	10.4	22.8

TABLE A7 | QDM-mo seasonal percentage differences in projected streamflow ensemble mean between the reference period and the various scenarios considered for the two model sections of the Valgrosina.

QDM-mo	Sacco				Eita			
%	Q_S1	Q_S2	Q_S3	Q_S4	Q_S1	Q_S2	Q_S3	Q_S4
D-J-F	55.9	109.4	185.0	300.9	39.8	88.7	152.1	239.0
M-A-M	14.8	32.7	71.6	77.0	13.9	27.5	58.6	62.2
J-J-A	−2.0	−6.5	−15.6	−20.5	−1.2	−4.8	−11.2	−19.0
S-O-N	12.4	18.9	20.4	23.4	12.2	18.5	22.5	25.3
Year	20.3	38.6	65.4	95.2	16.2	32.5	55.5	76.9

TABLE A8 | Monthly US dollar values of hydropower gross revenue in accordance with projected gross hydropower potential (GHP) values and the highest levelised cost of electricity (LCOE) for the period 2019–2023.

\$	GHP_ref	GHP_S1	GHP_S2	GHP_S3	GHP_S4
Oct	802587	839743	925676	905521	896807
Nov	510203	631761	684791	778313	835604
Dec	199176	233883	318860	359625	465084
Jan	69139	92284	116829	173710	258168
Feb	41720	79692	110739	154322	207034
Mar	163029	215227	275515	403876	440443
Apr	652120	707426	769067	949658	942924
May	1432083	1460373	1462287	1421088	1292677
Jun	1811020	1798735	1688101	1611081	1453810
Jul	1695550	1617529	1546152	1357364	1291491
Aug	1439857	1444324	1417615	1301870	1209293
Sep	961962	1043269	1025060	950522	936228