

Climate change and its effects on the streamflow of an Andean river basin with volcanic activity

Hernán D. Salas ^{a,b,*}, Carolina Florian ^a, Alejandro Builes-Jaramillo ^a, Juliana Valencia ^a, Darwin Mena ^c, Juan Camilo Parra ^d and Juan Carlos Valdés ^d

^a Facultad de Arquitectura e Ingeniería, Institución Universitaria Colegio Mayor de Antioquia, Carrera 78 65–46 Bloque Fundacional – Piso 2, Medellín 050034, Antioquia, Colombia

^b Facultad de Ciencias Exactas y Aplicadas, Instituto Tecnológico Metropolitano, Calle 73 No. 76A – 354, Medellín 050034, Antioquia, Colombia

^c Faculty of Environmental Engineering, Universidad Santo Tomás, Carrera 9 51–11, Bogotá 050021, Cundinamarca, Colombia

^d Faculty of Civil Engineering, Politécnico Colombiano Jaime Isaza Cadavid, Carrera 48 7–151, Medellín 11021, Antioquia, Colombia

*Corresponding author. E-mail: hernan.salas@colmayor.edu.co; hernansalas@itm.edu.co

 HDS, 0000-0002-6182-237X; CF, 0000-0003-1807-1379; AB, 0000-0002-3474-6922; JV, 0000-0002-8590-8821; DM, 0000-0002-7265-5722; JCP, 0000-0003-2450-584X; JCV, 0000-0002-6378-1559

ABSTRACT

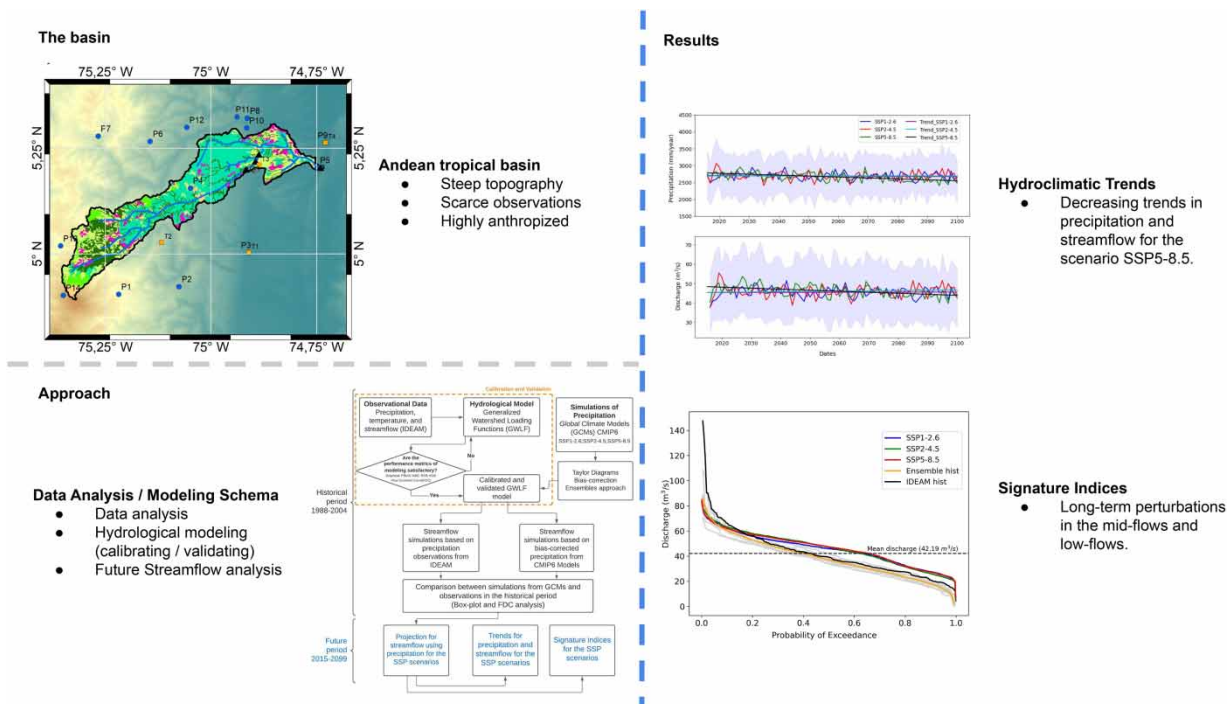
We use a Generalized Watershed Loading Function (GWLF) model to simulate streamflow in the Gualí River Basin. The model's performance is assessed using metrics such as percentage of bias (PBIAS), Nash–Sutcliffe efficiency (NSE), RMSE–observations standard deviation ratio (RSR), and Kling–Gupta efficiency (KGE) to indicate good performance. Furthermore, we analyze projections of precipitation and streamflow using several global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 6 (CMIP6) and three shared socioeconomic pathways (SSP1-2.6, SSP2-4.5, SSP5-8.5). Despite the uncertainties and coarse resolution, our results show that increases in the mean streamflow and significantly decreasing trends in projected precipitation and streamflow are observed from 2015 to 2099 under the SSP5-8.5 scenario. Furthermore, our findings suggest an increase in long-term mid-flow and low-flow. Moreover, this work provides a methodological framework for hydrological modeling in small tropical river basins, by incorporating data from GCMs while raising concerns and caveats. This study offers valuable insights into the potential effects of climate change on streamflow in an Andean river basin characterized by volcanic activity and significant human impacts. The findings reported here provide useful information for future decisions related to water supply for the social, environmental, and productive sectors in the seven towns within the catchment.

Key words: climate models, hydrological alterations, precipitation, projections, rainfall–runoff, river flows

HIGHLIGHTS

- There are few studies of streamflow projections for tropical river basins with volcanic activity.
- We provide new information about streamflow modeling using data from CMIP6 models.
- The Gualí River Basin has a high population with different economic activities, so this research is important to water resources management there.
- This work sheds light on challenges in hydrological processes in complex river basins.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Economic development in Colombia has favored the Andean territory ever since the 16th century. This is why more than 70% of its economy and population (more than 30 million) is located in the Andes. Therefore, Andean river basins in Colombia are under a lot of pressure to attend to the needs of a growing population, in terms of water for irrigation, industry, agroindustry, public utilities, and so on. With more than 80,000 inhabitants, the Gualí River Basin meets the fresh water supply requirements for the residential population, distributed in seven towns and undertaking different economic activities. The main direct and indirect pressures on the water resources across the basin are related to the expansion of agricultural activities, as well as commercial and illegal logging (CORTOLIMA *et al.* 2014a). These activities generate consequences, such as decreased soil productivity, increased water source sedimentation, reduced water quality and quantity, and diminished representative vegetation, and the fauna related to these ecosystems.

Furthermore, the Gualí River poses great modeling challenges because it lies in the central Andes at the foothills of the Nevado del Ruiz volcano (known as 'Cumanday' in the pre-Hispanic era). The volcano erupted in 1985, altering the river channel due to the mudflow produced by the lahar of the eruption, which reached more than 100 km and transported more than 5–10 hm³ of melted water and soil components (Huggel *et al.* 2007; Marulanda Aguirre *et al.* 2016). In particular, river basins on the slope of active explosive volcanoes undergo geomorphic transformations in their valleys, which may alter the main channel depth or even generate new channels. The deposition of volcanoclastic material (tephra) may affect future infiltration and underwater storage and the changes induced in the vegetation cover may change the evapotranspiration patterns of the basin (Pierson & Major 2014; Martini *et al.* 2019; Malawani *et al.* 2021). The review by Pierson & Major (2014) mentioned that river basins within 10–20 km of a volcanic eruption may experience disruptions to their equilibrium state.

The hydrology of the Gualí River Basin is defined by the complex, interdependent, and delayed interaction between its climate, vegetation, and geology. Climatologically, the river basin is mostly influenced by the intertropical convergence zone (ITCZ) migration, at a seasonal timescale, and the El Niño–Southern Oscillation (ENSO), at an inter-annual timescale; as much as the Tropical Andes basins (Espinoza *et al.* 2020). These climatic drivers, mixed with an altitudinal range from 600 to 4,100 m above sea level (m.a.s.l), configure wind currents derived from temperature and pressure gradients. These facilitate orographic precipitation over the mountain's foothills (CORTOLIMA *et al.* 2014a), therefore configuring a diverse range of climatic zones, including super humid high *Páramo*, humid high *Páramo*, super humid cold, and humid temperate,

among others. The vegetation in this area mainly comprises *páramos*, barren lands, and rocky outcrops, with natural pastures also present (CORTOLIMA *et al.* 2012; Mena *et al.* 2021).

The Intergovernmental Panel on Climate Change's Sixth Assessment Report (AR6) emphasized the crucial role of human activities in understanding the impacts of climate change, as well as adaptation and vulnerability (IPCC 2022). All over the world, there has been evidence of increasing temperatures and changes in precipitation and streamflow in recent decades (Tabari 2020; Shah *et al.* 2021; Mann & Gupta 2022; Brêda *et al.* 2023). Central and South America, having already been exposed to and impacted by climate change, face exacerbated challenges because of factors such as inequality, poverty, and deforestation. This situation intensifies the risks to ecosystems, water, agriculture, and migration. Significant impacts on ecosystems, water, and food are anticipated, particularly in the northwest South American region, including the Andes and the Gualí River Basin. Effective adaptation strategies require cross-scale policies, participatory approaches, and the integration of ecosystem-based and community-based adaptation. A lack of sufficient data and analysis of adaptation experiences remains a key obstacle to addressing water challenges in the region, highlighting the need for improved knowledge.

A previous study by Mena *et al.* (2021) investigated the unmet water demand under climate change scenarios in the Gualí River Basin. To this end, they integrated two modeling tools, as well as precipitation and temperature data from three general circulation models from the coupled model intercomparison project (in its fifth phase – CMIP5), for the climate change scenarios associated with the representative concentration pathways (RCP) denoted as RCP2.6 and RCP8.5. They found that, for the period covering 2011–2100, flow decreased between 5.80% and 9.56%, for RCP2.6, and between 2.18% and 6.86% for RCP8.5. Furthermore, they mentioned that the period 2013–2040 will be the one with the greatest reduction in flow.

The latter study requires further research, considering the fact that the IPCC's sixth assessment report provided several new GCMs from the sixth phase (CMIP6), that included shared socioeconomic pathway (SSP) scenarios. In this sense, the findings by Mena *et al.* (2021) required: (i) verification using the new generation of CMIP6 GCMs; (ii) acknowledgement of the limitations of hydrological simulations of climate change projections due to climate and hydrological modeling uncertainties (Banda *et al.* 2022); (iii) understanding the need to downscale techniques like dynamic (Giorgi 2019; Brêda *et al.* 2020) or statistical downscaling (Ebrahim *et al.* 2013) to tackle the limitations of GCMs when simulating climate at a regional level; and, finally, (iv) facing up to the uncertainties associated with data from GCMs when implementing techniques such as bias correction (Christensen *et al.* 2008; Teutschbein & Seibert 2012; Muerth *et al.* 2013) and/or ensemble approaches (Hagedorn *et al.* 2005; Semenov & Stratonovitch 2010; Díaz *et al.* 2021).

We analyzed the projected precipitation and streamflow in the Gualí River Basin by addressing the following questions:

- 1) Does precipitation and simulated streamflow over the basin exhibit changes in trends and/or exceedance probabilities for the future scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5?
- 2) What are the possible impacts on streamflow according to the projected precipitation by different SSP scenarios?
- 3) What are the shortcomings associated with using CMIP6 data in small tropical basins?

Trying to answer these questions will provide further evidence on how to assess the use of future CMIP projections for hydrological modeling in small tropical mountainous basins vulnerable to climate change, acknowledging the limitations given by scaling and modeling uncertainties.

This work is organized as follows: Section 2 describes the region of study. Section 3 describes the observational and simulated datasets for precipitation. Section 4 presents the general methodology. The results and discussion are presented in Section 5. Conclusions are drawn and future work is suggested in Section 6.

2. STUDY REGION

The Gualí River Basin is located in Tolima (Colombia), near the coordinates 5°12'0"N and 74°43'60"W, in the central Andes mountain range (Figure 1). This catchment has an area of 821.48 km² and is home to a population of approximately 83,500 inhabitants in seven towns: Mariquita, Fresno, Herveo, Honda, Palocabildo, Casabianca, and Falan. This catchment exhibits elevation ranges between 4,150 and 600 m.a.s.l, temperatures between 6 °C (at the head of the basin) and 20 °C (at its lowest zone), precipitation ranges between 1,278 and 3,565 mm/year, and the average discharge is about 42.8 m³/s. Regarding the land cover in the river basin, 62.63% of its total area corresponds to agricultural uses, 35.81% of its area contains

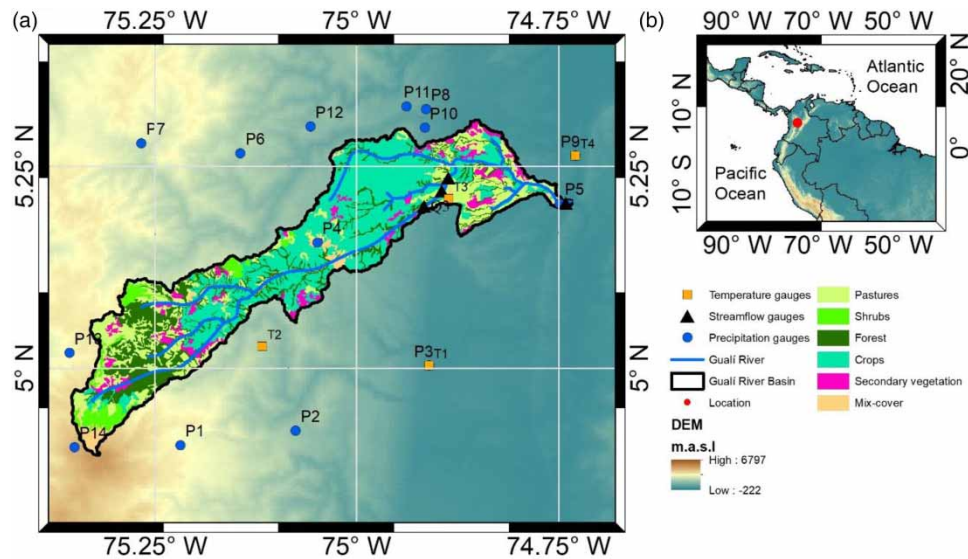


Figure 1 | (a) Location of the Gualí River Basin within the slopes and the lowlands of the Andes mountain range, (b) regional context of the basin location. Blue dots show the locations of precipitation gauges, yellow squares indicate the locations of temperature record stations, and black triangles are the locations of streamflow gauges.

forests and rural zones, 0.88% of its territory comprises urban and industrial areas, and 0.68% is covered by water bodies such as lakes, swamps, and rivers (CORTOLIMA *et al.* 2014b).

3. DATA

3.1. Observational data

We used time series data, at a daily temporal resolution, for precipitation and streamflow. This was provided by the *Institute of Hydrology, Meteorology, and Environmental Studies* (IDEAM is its acronym in Spanish). In particular, we used 14 time series of precipitation records, two time series of temperature, and four time series of streamflow records for the common period 1988–2021 (41 years record length). These time series of streamflow and precipitation were used in the semi-distributed rainfall–runoff model (see Section 4.1). In this work, we only provide results for the Honda streamflow gauge, which is located at the output of the basin. Moreover, we used time series for both variables, considering less than 10% of missing data in the time series due to the lack of data in this river basin. In particular, to replace the missing data, we used the long-term monthly average of available historic data for the streamflow gauge station. The data are freely available at <http://dhime.ideam.gov.co/webgis/home/>. We also used a gridded precipitation product from the Global Precipitation Climatology Centre (GPCC) for the period 1988–2014, at a monthly temporal scale and a $0.25^\circ \times 0.25^\circ$ spatial grid size. This dataset is available at <https://psl.noaa.gov/data/gridded/data.gpcc.html>.

3.2. Global climate models

We used precipitation data provided by the Global Climate Models (GCMs) from CMIP6 experiments (Eyring *et al.* 2016), which are available from the Earth System Grid Federation web page ESFG (<https://esgf-node.llnl.gov/projects/esgf-llnl>) for the period 1988–2014 and for the 2015–2099 period, in each of the three SSP scenarios selected for this study, denoted as SSP1-2.6, SSP2-4.5, and SSP5-8.5 (<https://www.ipcc.ch/report/ar6/syr/>). SSP1-2.6 represents a very low greenhouse gas (GHG) emission declining to net zero by about 2070. SSP2-4.5 has an intermediate GHG emission, maintaining current levels until the middle of the century, and pathway SSP5-8.5 represents very high GHG emissions, doubling the current levels by 2050. Table 1 provides some general information about climate models that provide precipitation projections for the region of study and that exhibit a good performance, according to Almazroui *et al.* (2021), Arias *et al.* (2021) and Dias & Simões Reboita (2021). For further comparison among the datasets, they were interpolated to a $0.25^\circ \times 0.25^\circ$ common grid using bilinear interpolation (Accadia *et al.* 2003).

Table 1 | Description of global climate models (GCMs) from the CMIP6 experiment

Model	Long × Lat resolution	Institute	Reference
FGOALS-g3	2.00° × 2.25°	Institute of Atmospheric Physics, Chinese Academy of Sciences	Arias <i>et al.</i> (2021) and Li (2019)
EC-Earth3	0.70° × 0.70°	EC-EARTH Consortium	Arias <i>et al.</i> (2021) and EC-Earth Consortium (2019b)
EC-Earth3-Veg	0.70° × 0.70°	EC-EARTH Consortium	Arias <i>et al.</i> (2021) and EC-Earth Consortium (2019a)
MPI-ESM1-2-HR	0.93° × 0.93°	Max Planck Institute for Meteorology	Arias <i>et al.</i> (2021) and Jungclaus <i>et al.</i> (2019)
CESM2-WACCM	1.25° × 0.93°	National Center for Atmospheric Research, Climate and Global Dynamics Laboratory	Almazroui <i>et al.</i> (2021) and Danabasoglu (2019)
MRI-ESM2-0	1.18° × 1.12°	Meteorological Research Institute	Almazroui <i>et al.</i> (2021) and Yukimoto <i>et al.</i> (2019)
CanESM5	2.81° × 2.81°	Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada	Dias & Simões Reboita (2021) and Swart <i>et al.</i> (2019)
CMCC-CM2-SR5	1.25° × 0.93°	Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	Dias & Simões Reboita (2021) and Lovato & Peano (2020)
INM-CM4-8	2.00° × 1.50°	Institute for Numerical Mathematics	Dias & Simões Reboita (2021) and Volodin <i>et al.</i> (2019a)
INM-CM5-0	2.00° × 1.50°	Institute for Numerical Mathematics	Dias & Simões Reboita (2021) and Volodin <i>et al.</i> (2019b)

4. METHODS

Figure 2 presents a schematic of the methodological approach of the present study. First, the observed hydrological data and CMIP6 datasets were selected (as presented in Section 3), as well as the calibration of the GWLF hydrological model. Once a satisfactory performance of the hydrological model was achieved for the basin, we simulated streamflow with observations and bias-corrected precipitation from GCMs, over the historical period. After comparing the results for the historical period, in terms of box plots and flow duration curves (FDCs), we simulated projected streamflow for each of the future SSP scenarios for the period 2015–2099. This framework can be adapted for lumped, semi-distributed, and distributed hydrological modeling approaches, different bias-correction techniques, and streamflow alteration analysis. In our case, we quantified trends in future projections of precipitation and streamflow, as well as the signature indices, as a measure of hydrologic alteration. Each step in the framework is presented in the following.

4.1. Hydrological model

Hydro-BID includes the Generalized Watershed Loading Function (GWLF) model, which is used to simulate the rainfall-runoff process in basins over a wide spatial range, using the attributes of soil type and land use (Wu & Lin 2015; Qi *et al.* 2019). GWLF takes into account snow melt, potential evapotranspiration, runoff, percolation, flow, and routing (Haith & Shoemaker 1987; Moreda & Miralles-Wilhelm Raúl Muñoz Castillo 2014). The summary equations of the GWLF models are shown in Table 2. Details about Hydro-BID are available on the web page (<https://hydrobidlac.org/>).

Wu & Lin (2015) recommended a set range of values for the calibration process of the GWLF model (Table 3).

4.2. Bias correction for the GCMs' precipitation and performance criteria for the rainfall-runoff model

We used Taylor diagrams (Taylor 2001) to compare the historical observations of precipitation with the one simulated by the GCMs over the Gualí River Basin, for the different SSP scenarios over the period 1988–2014. In this sense, Taylor diagrams were used to quantify the degree of correspondence between the observations and simulations, in terms of the Pearson correlation coefficient, the root-mean-square error (RMSE), and the standard deviation. This analysis was used to determine whether it was necessary to implement a bias correction for the simulated precipitation provided by the GCMs. From this perspective, bias correction is a common procedure that is intended to correct systematic biases in climate models (Teutschbein & Seibert 2012; Chathuranika *et al.* 2022).

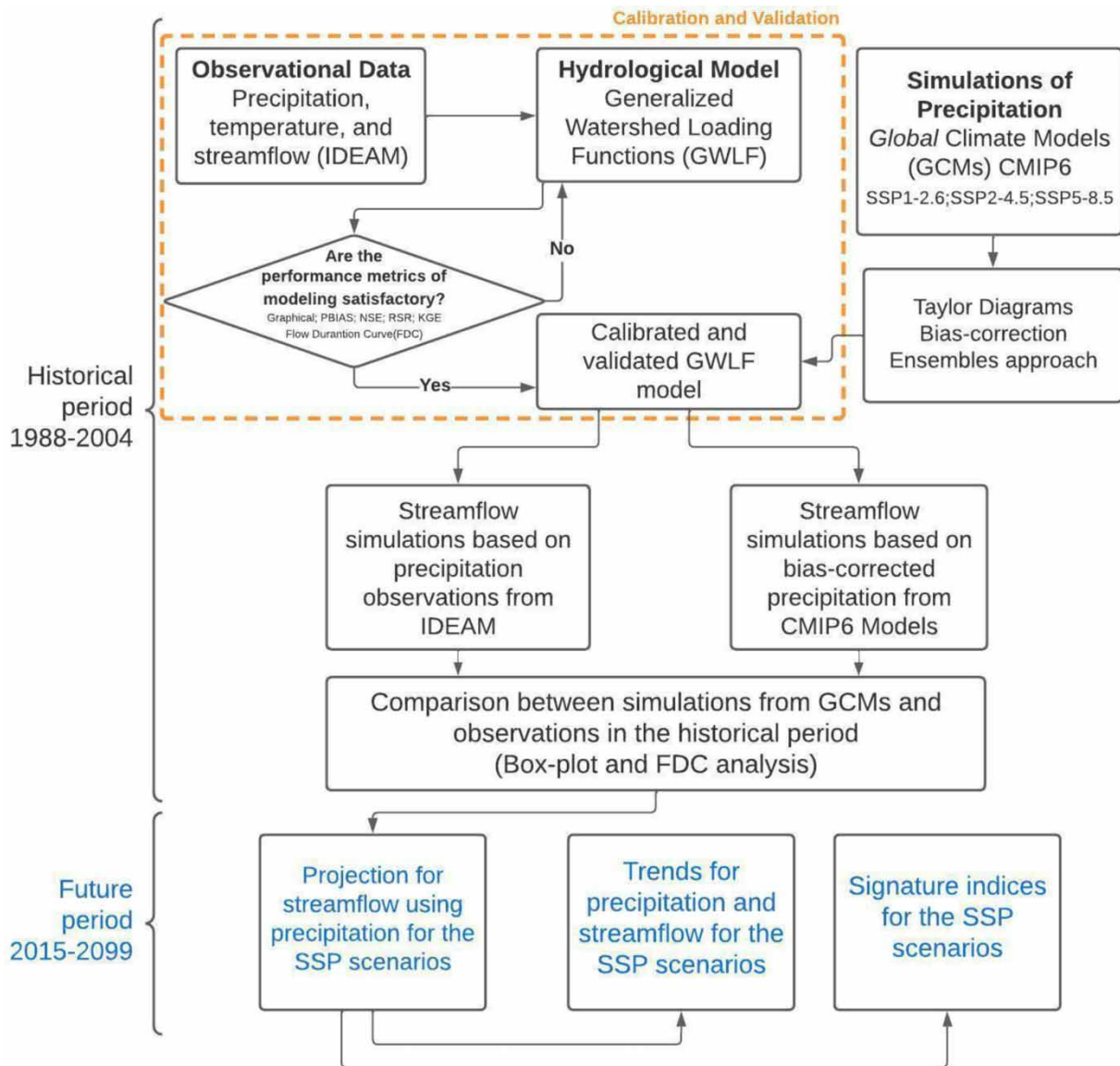


Figure 2 | Schema of the methodological framework for going from observations and simulations to the hydrological simulation and evaluation of different scenarios.

For hydrological modeling considering climate change scenarios, in particular, bias correction is used to reduce the uncertainty before the use of the GCM data for hydrological simulations (Hagedorn *et al.* 2005). When bias correction was required, we used simple empirical quantile mapping between observed and simulated precipitation by the GCMs. In general, quantile mapping is a technique for correcting extreme values and modifying the shape of distributions by finding a statistical relationship between the quantiles of the two distributions; this method provides comparable results to others based on the probability distribution functions (Maraun 2013; Dekens *et al.* 2017; Prasanna 2018).

Regarding the performance criteria for the rainfall–runoff model, we used the percentage bias (PBIAS), the Nash–Sutcliffe efficiency (NSE), and the ratio of the RMSE to the standard deviation of measured data (RSR), as recommended by Moriasi *et al.* (2007), which stated that, for streamflow, a model simulation can be judged as satisfactory if $NSE > 0.50$, $RSR < 0.70$, and $PBIAS \pm 25\%$. Moreover, we used the Kling–Gupta efficiency (KGE) (Gupta *et al.* 2009), for which other studies suggested that $KGE > 0.5$ is high enough to indicate a suitable and favorable performance of a hydrological model (Wu *et al.* 2022).

Table 2 | Components of the GWLF model (USAID 2018)

Component	Equation
Snow melt	$SNO_t = SNO_{t-1} + R_t - SNO_{melt}$ SNO_t : Water content of the snowpack on a given day R_t : Amount of precipitation in a day SNO_{melt} : Amount of snow melt estimated
Potential evapotranspiration	$PET_t = \frac{0.021 H_t^2 e_t}{T_t + 273}$ PET_t : Potential evapotranspiration. H_t : Number of daylight hours per day. e_t : Saturated water vapor pressure in millibars on day t T_t : Temperature on day t (°C)
Potential evapotranspiration adjusted to land use and cover	$PET_{Adj}(t) = CV \times PET_t$ PET_{Adj} : Land use and cover adjusted PET CV : Cover factor PET_t : Potential evapotranspiration
Runoff	$Q_t = \left(\frac{R_t - 0.2D_t}{R_t + 0.2D_t} \right)^2$ $D_t = \frac{2,540}{CN_t} - 25.4$ Q_t : Runoff (cm) R_t : Sum of rain and melt D_t : Detention parameter CN_t : Curve number assigned by land use
Percolation	$U_{t+1} = U_t + R_t + M_t - Q_t - E_t - P_t$ $S_{t+1} = S_t + P_t - G_t - L_t$ U_t : Unsaturated zone soil moistures at the beginning of day t R_t : Rain on day t M_t : Melt on day t Q_t : Runoff on day t E_t : Actual evapotranspiration on day t P_t : Percolation in the shallow saturated zone on day t S_t : Shallow saturated zone soil moistures at the beginning of day t G_t : Groundwater discharge to the stream (i.e. base flow) on day t L_t : Seepage flow to the deep saturated zone on day t
Flow	$F_t = Q_t + G_t$ F_t : Total flow generated from the catchment Q_t : Runoff G_t : Ground flow

4.3. Signature indices for streamflow projection analysis

Once we achieved a calibrated rainfall–runoff model, we simulated runoff using the precipitation from GCMs for historic and future periods, using the scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5. Furthermore, we quantified trends using Kendall's non-parametric test (Kendall 1975) for a monotonic trend, using the Theil–Sen method (Sen 1968) to estimate the slope, confidence intervals, and significance test at a significance level of 0.05. To simulate streamflow, we quantified changes in the FDC for simulations with historical observations and simulations with GCM runs, for the periods 2015–2047, 2048–2073, and 2074–2099, as established by Chathuranika *et al.* (2022).

We used the signature indices defined by Casper *et al.* (2012) to analyze different characteristics of the FDCs and assess future changes in surface runoff. We calculated percentage bias in the mean values (BiasRR) (Equation (1)), mid-range flow levels (BiasFMM) (Equation (2)), the slope of the mid-segment (BiasFDCmidslope) (Equation (3)), high-segment volumes (BiasFHV) (Equation (4)), differences in long-term baseflow (BiasFLV) (Equation (5)), and the flow duration curve at the 95% percentile (DiffQ95) (Equation (6)), as defined by Pimentel *et al.* (2021). Each signature index was defined by the equations below, with $FDC_{o,p}$ and $FDC_{s,p}$ being the observed and simulated FDCs of the streamflow and p being the probability of

Table 3 | Recommended ranges for the GWLF model parameters

Parameter	Recommended ranges of values
Curve number (CN)	0.8–1.2
Available water content (AWC)	0.2–1.2
Recession coefficient (<i>r</i>)	0.001–0.750
Seepage coefficient (<i>S</i>)	0.005–0.100
Growth season ET factor	0.5–1.5
Dormant season ET factor	0.5–1.5
Impervious cover percentage	1
Temperature threshold	1
Melt factor	1

exceedance.

$$\text{BiasRR} = \frac{\text{mean}(\text{FDC}_s) - \text{mean}(\text{FDC}_o)}{\text{mean}(\text{FDC}_o)} \times 100 \quad (1)$$

$$\text{BiasFMM} = \frac{\text{median}(\text{FDC}_s) - \text{median}(\text{FDC}_o)}{\text{median}(\text{FDC}_o)} \quad (2)$$

$$\text{BiasFDCmidslope} = \frac{(\log(\text{FDC}_{s,0.20}) - \log(\text{FDC}_{s,0.70})) - (\log(\text{FDC}_{o,0.20}) - \log(\text{FDC}_{o,0.70}))}{(\log(\text{FDC}_{o,0.20}) - \log(\text{FDC}_{o,0.70}))} \times 100 \quad (3)$$

$$\text{BiasFHV} = \frac{\int_0^{0.10} \text{FDC}_{s,p} dp - \int_0^{0.10} \text{FDC}_{o,p} dp}{\left(\int_0^{0.10} \text{FDC}_{s,p} dp \right)} \quad (4)$$

$$\text{BiasFLV} = \frac{\int_{0.7}^{1.0} (\log(\text{FDC}_{s,p}) - \log(Q_{\min s})) dp - \int_{0.7}^{1.0} (\log(\text{FDC}_{o,p}) - \log(Q_{\min o})) dp}{\int_{0.7}^{1.0} (\log(\text{FDC}_{o,p}) - \log(Q_{\min o})) dp} \times 100 \quad (5)$$

where $Q_{\min s}$ and $Q_{\min o}$ are the minimum value of FDC_s and FDC_o .

$$\text{DiffQ95} = \frac{\text{mean}(\text{FDC}_{s,95}) - \text{mean}(\text{FDC}_{o,95})}{\text{mean}(\text{FDC}_{o,95})} \times 100 \quad (6)$$

5. RESULTS AND DISCUSSION

5.1. Performance of the rainfall–runoff model

Figure 3 shows the observed precipitation for the period 1988–2004 (17 years) as an ensemble of the four nearest to or within the basin precipitation gauges (P4, P5, P10, and P14, as named in Figure 1), as well as the observed and simulated streamflow for the same period in the output of the basin. The observations show a precipitation (streamflow) maximum of around 400 mm/month (150 m³/s). Hereafter, we illustrate the results of our analysis of streamflow on this site, at the output of the basin (see Figure 1(a)). Figure 3 shows that streamflow simulations for 1988 are lower than the observed streamflow because this is the first year of simulation. In terms of the performance metrics, for the calibration period (1988–1999), the Soil Moisture Method (SMM) model yields: PBIAS = −1.39%, NSE = 0.51, RSR = 0.69, and KGE = 0.66. For the validation period (2000–2004), the rainfall–runoff model yields: PBIAS = 4.50%, NSE = 0.50, RSR = 0.72, and KGE = 0.72.

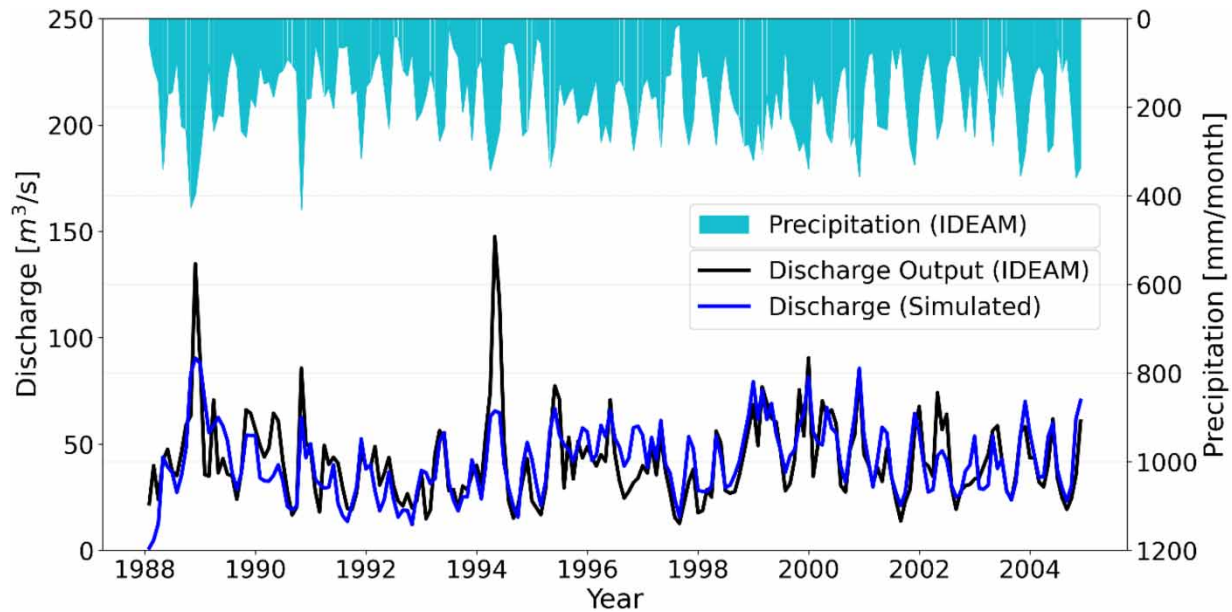


Figure 3 | Precipitation and discharge for the period 1988–2004. The precipitation ensembled with the time series within the river basin is shown in cyan; observed discharge in the output station is shown in black; and the discharge simulation with satisfactory performance, according to *Moriasi et al. (2007)*, is shown in blue.

These results indicate that the rainfall–runoff has a satisfactory performance, according to the recommendations provided by *Moriasi et al. (2007)* and *Wu et al. (2022)*. The selected calibration values for satisfactory performance are: curve number (CN) = 1.28; available water content (AWC) = 0.21; recession coefficient (r) = 0.013; and seepage coefficient (S) = 0.00055. For the growth season ET factor and dormant season ET factor, a constant value of 1.0 was considered.

Figure 4 shows the annual cycles and duration curves for the calibration (Figure 4(a) and Figure 4(c)) and validation periods (Figure 4(b) and Figure 4(d)), from 1989 to 1999 and from 2000 to 2004, respectively. This figure indicates that, during the dry

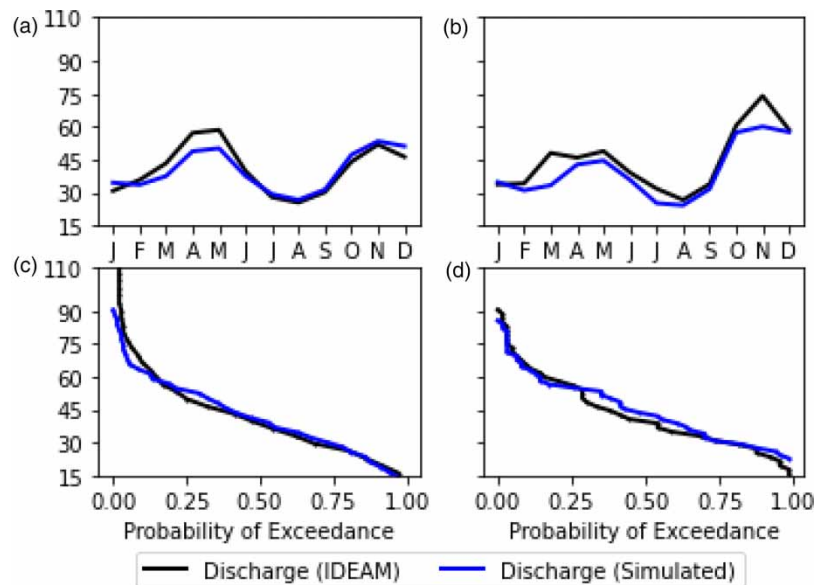


Figure 4 | Annual cycle and flow duration curves for the observed (black) and simulated (blue) discharges. (a) Annual cycle for the calibration period 1989–1999. (b) Annual cycle for the validation period 2000–2004. (c) Curve of probability of exceedance for the calibration period 1989–1999. (d) Curve of probability of exceedance for the validation period 2000–2004.

seasons (June–July–August and December–January–February), streamflow is well represented by the model. In addition, during the wet seasons (March–April–May and October–November), streamflow simulations are lower than the observations. Furthermore, Figure 4(c) and 4(d) confirm that, for the calibration period, the simulated discharges are well represented by the model, with a probability of exceedance of more than 5%, whereas discharges with a probability of exceedance of less than 5% are not well represented by the model.

5.2. On the need for bias correction in the precipitation provided by GCMs for streamflow simulations

Figure 5 shows the Taylor diagram of monthly precipitation in the Gualí River Basin for the period 1988–2014; this is common to the selected CMIP6 models with bias correction (blue markers) and without bias correction (red markers). The GPCC dataset (black dots) is compared with the basin average of the precipitation gauges from IDEAM (black stars). In general, the GCMs without bias correction exhibit higher dispersion in their standard deviations, ranging from 90 to 240 mm/month. All models show standard deviations higher than the reference value, which can be explained in terms of the difference between time series of the observations (ensemble based on rain gauge stations) and time series from the gridded GCMs. Furthermore, the correlation coefficient for all models is below 0.40, indicating that GCMs do not exhibit higher correlations with the reference values. In this sense, the coarse spatial resolution of the models for a small basin may explain this low correlation. Furthermore, the centered root-mean-square (RMS) errors range between 100 and 250. These results from the Taylor diagrams do not show clustering among GCM models, which suggests that a bias correction process is necessary for precipitation projections from GCMs before they can be used for rainfall–runoff modeling.

For this reason, Figure 5 shows the Taylor diagram for precipitation over the historic period (1988–2014), after bias correction (blue markers), using simple empirical quantile mapping (Maraun 2013). In general, after bias correction, precipitation exhibits clustering among GCM models with standard deviations ranging from 80 to 120 mm/month, showing a reduction compared with the non-bias-corrected data. The correlation coefficients for all models remain below 0.40, indicating that

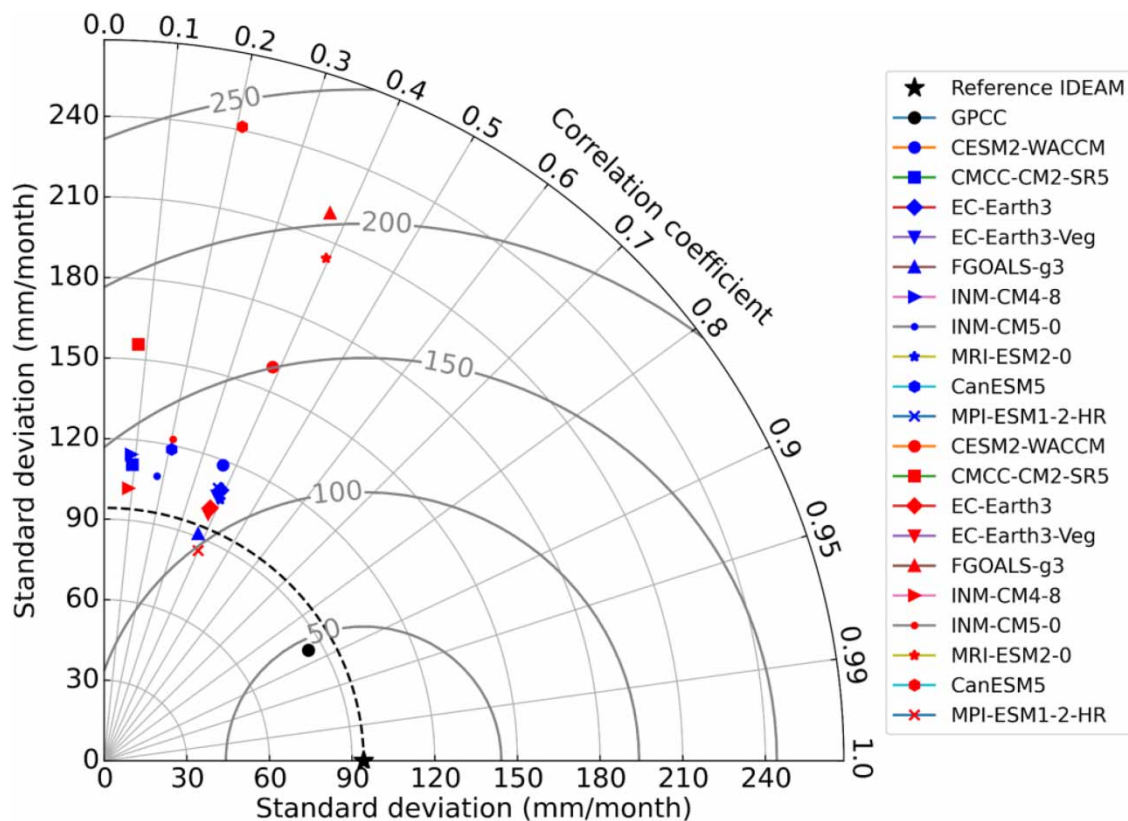


Figure 5 | Taylor diagram for monthly precipitation in the Gualí River Basin, according to different GCMs in the period 1988–2014. Data without bias correction are in red. Data with bias correction are in blue. The GPCC dataset is represented as a black dot.

GCMs do not exhibit a notable improvement, in terms of correlations between models and the reference. Correlations between observations and CMIP6 simulations were reported in the range 0.3–0.4, for the tropical Andes, in the work by [Arias et al. \(2021\)](#). Furthermore, the centered root-mean-square (RMS) errors after bias correction decrease to a range between 100 and 150. It is important to note that, despite the low correlations between bias-corrected data and the observations, the hydrological impact assessment of CMIP6 projections has been carried out in other regions ([Thalli Mani et al. 2022](#); [Acharki et al. 2023](#); [Rudraswamy et al. 2023](#)).

The streamflow was simulated using only the bias-corrected precipitation from GCMs. [Figure 6](#) shows the Taylor diagram for streamflow in the period 1988–2005 (for which observations of streamflow are available). Our results suggest clustering among streamflow simulations, using data from bias-corrected GCM precipitation, with standard deviations ranging from 12 to 20 m³/s. The correlation coefficients for all simulations remain below 0.30. Furthermore, the centered root-mean-square (RMS) errors are in the range 20–30.

5.3. Changes in projected precipitation and streamflow for different climate change scenarios

[Figure 7](#) shows box plots corresponding to precipitation and simulated streamflow for the GCM ensembles, compared with the reference data (IDEAM). [Figure 7\(a\)](#) shows that precipitation in each of the scenarios for the period 2015–2099 is about 2,500 mm/year. Furthermore, high variability is observed in the first and third quartiles for all scenarios, with similarities in the first quartile, between the SSP1-2.6 and SSP5-8.5 scenarios, compared with the mean. All three scenarios show an increase in the range (from 8% to 12%) compared with the reference mean, but the SSP1-2.6 and SSP2-4.5 scenarios exhibit atypical values of approximately 6,000 mm/year, while the SSP5-8.5 scenario does not show atypical values, though its maximum values are close to 6,000 mm/year. [Figure 7\(b\)](#) shows precipitation for each climate scenario in three different periods (2015–2047, 2048–2073, and 2074–2099), with an increase in relation to the reference mean of between 8% and 12% during all periods. However, greater variability is observed between the minimum and maximum values during the 2015–2047 and

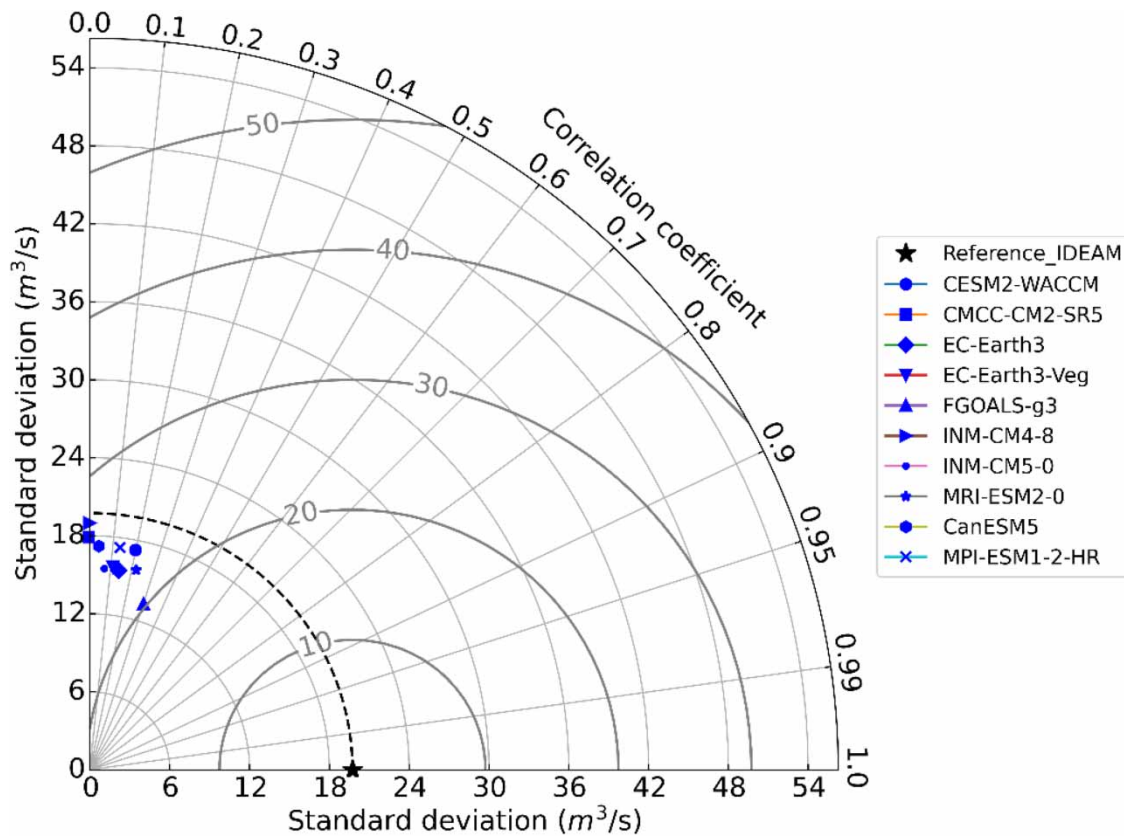


Figure 6 | Taylor diagram for monthly streamflow in the Gualí River Basin, for the historic period 1988–2005, according to different GCMs, from simulations using precipitation with bias correction.

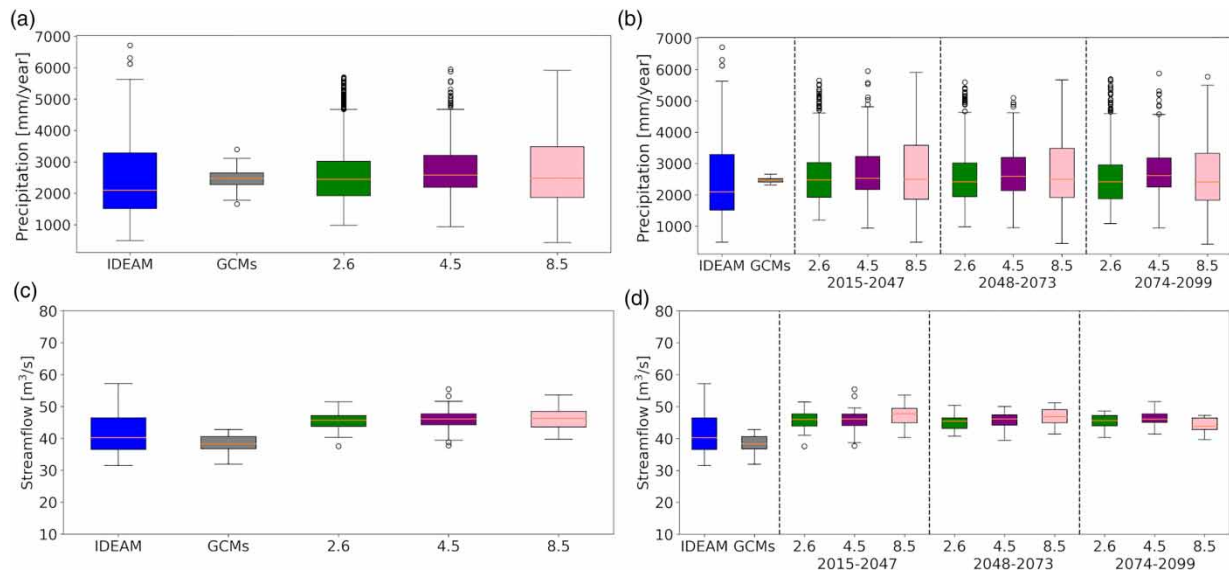


Figure 7 | Boxplots of precipitation and flow. (a) Boxplot of precipitation for each climate scenario for the full period 2015–2099. (b) Boxplot of precipitation for each climate scenario in three different periods: 2015–2047, 2048–2073, and 2074–2099. (c) Boxplot of streamflow for each climate scenario for the full period 2015–2099. (d) Boxplot of streamflow for each climate scenario in three different periods: 2015–2047, 2048–2073, and 2074–2099. Axis labels 2.6, 4.5, and 8.5 correspond to the SSP1-2.6, SSP2-4.5, and SSP5-8.5 scenarios, respectively.

2074–2099 periods, while maximum values show variability during all periods, with atypical values for the SSP5-8.5 scenario in the 2074–2099 period and atypical values for the SSP1-2.6 and SSP2-4.5 scenarios during all periods.

Figure 7(c) shows that the simulated streamflow in each of the scenarios, for the period 2015–2099, is approximately $46 \text{ m}^3/\text{s}$, and this overestimates the mean reference value, with greater variability in the data distribution for all scenarios. In addition, the SSP2-4.5 scenario shows higher atypical values, while the SSP5-8.5 scenario shows none. Figure 7(d) shows the simulated streamflow for each climate scenario in three different periods (2015–2047, 2048–2073, and 2074–2099). The periods 2015–2047 and 2048–2073 show an increase in the mean simulated streamflow, in relation to the reference, ranging from 8% to 10%, whereas the period 2074–2099 exhibits a 5% decrease in the mean streamflow for the SSP5-8.5 scenario, in relation to SSP1-2.6 and SSP2-4.5.

A larger number of atypical values are observed for the SSP2-4.5 scenario in the 2015–2047 period, while the SSP1-2.6 scenario shows atypical values in the 2015–2047 and 2074–2099 periods, being the only scenario with atypical values for this latter period. The SSP5-8.5 scenario does not show any atypical values in any of the periods, and greater variability is also observed between the maximum values of the scenarios for all periods, with values between 46 and $56 \text{ m}^3/\text{s}$, showing greater difference in the first quartile between the SSP1-2.6 and SSP5-8.5 scenarios in the 2015–2047 and 2074–2099 periods. Our results contrast with the findings of Mena *et al.* (2021), who used three CMIP5 models and concluded that, for the period covering 2011–2100, the available flow is expected to decrease by 6%–10% for RCP 2.6, and by 2%–7% for RCP 8.5, with the greatest reduction in flow occurring during 2013–2040.

5.4. Trends in precipitation and streamflow for different climate change scenarios

Figure 8 shows the trends of GCM precipitation and simulated streamflow for the GCM ensembles for each scenario. We found that, for the SSP5-8.5 scenario, there is a significant decrease in the trend for both variables. For precipitation, the slope in the SSP1-2.6 scenario ($c = -3.371 \text{ mm/dec}$) is not significant. The slope for the scenario SSP2-4.5 ($c = 0.940 \text{ mm/dec}$) is also not significant. The slope for the scenario SSP5-8.5 ($c = -29.023 \text{ mm/dec}$), however, is significant. For streamflow, the slope of the scenario SSP1-2.6 ($c = 0.029 \text{ m}^3/\text{dec}$) is not significant but the slopes for scenario SSP2-4.5 ($c = 0.135 \text{ m}^3/\text{dec}$) and scenario SSP5-8.5 ($c = -0.572 \text{ m}^3/\text{dec}$) are significant.

5.5. Signature indices for different climate change scenarios

Figure 9 shows the FDC for observations by IDEAM, as well as the ensemble of simulated streamflow using precipitation from GCMs for the historic period (1988–2015). These results indicate that the historic streamflow GCM's ensemble

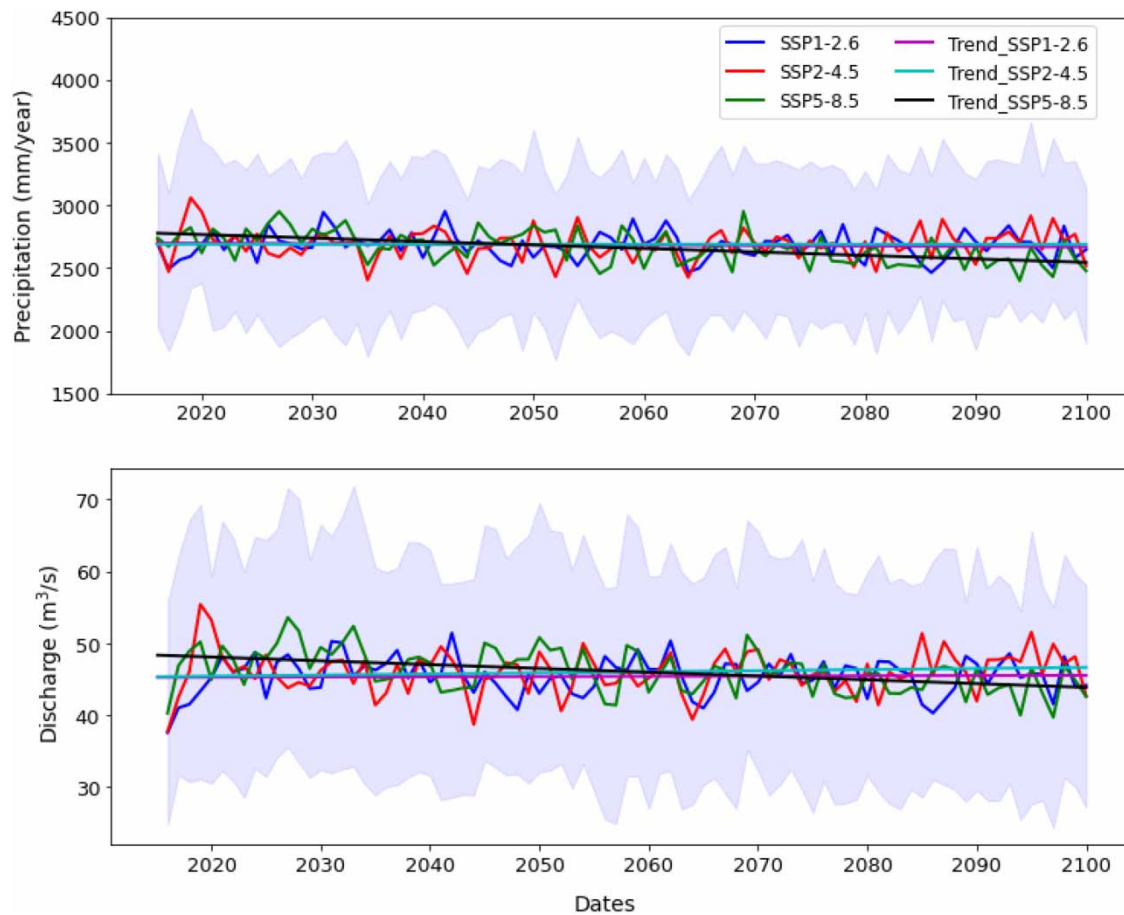


Figure 8 | Future projection of mean annual precipitation (upper) and discharges (lower) in the Gualí River Basin for the period 2020–2099. The trend is drawn from the ensemble for all the CMIP6 models used. The blue area in the background is the intermember spread of the ensemble.

simulation adequately represents the observed FDC for probabilities of exceedance above 0.10. However, for high streamflow (probabilities of exceedance in the range 0.00–0.10), the GCM's ensemble simulation does not adequately represent the observations. Notwithstanding this, in general, the model has a good performance in simulating the historic period using bias-corrected precipitation from the GCMs. On the other hand, for the future projections of streamflow (2015–2099), Figure 9 shows that FDCs notoriously deviate from the reference value, with a 20% exceedance percentage for the three SSP scenarios.

Table 4 shows six signature indices to quantify the change in the runoff for three climate change scenarios (SSP1-2.6, SSP2-4.5, and SSP5-8.5) for the 2015–2099 period. The percentage bias in the mean values (BiasRR) indicates that the mean streamflow for future periods is higher than observed, with a range of 7.6%–9.3%. Moreover, BiasRR tends to increase in each SSP scenario, being higher for the SSP5-8.5 scenario (9.31%). Furthermore, the percentage bias in mid-range flow levels (BiasFMM) shows that simulated runoff is higher than the reference for the analyzed period, in the range 17.1%–20.5%, the highest value being for SSP5-8.5 (20.58%).

The percentage bias in the slope of the mid-segment (BiasFDCmidslope) shows that, for all SSP scenarios, the streamflow projections exhibit lower values than the reference value. BiasFDCmidslope reduction ranges between 41.5% and 31.9%, with the highest values being for SSP2 and SSP5. Furthermore, for all SSP scenarios, the differences in long-term baseflow (BiasFLV) suggest that simulations are higher than observations (ranging between 60% and 122%). The percentage bias in high-segment volumes (BiasFHV) shows a bias higher than 330%, for all scenarios during the period. Lastly, the difference of FDC at the 95% percentile (DiffQ95) shows an increase for all scenarios (higher than 20%), the highest increases being for SSP1-2.6 and SSP5-8.5 (30% and 27.9%, respectively).

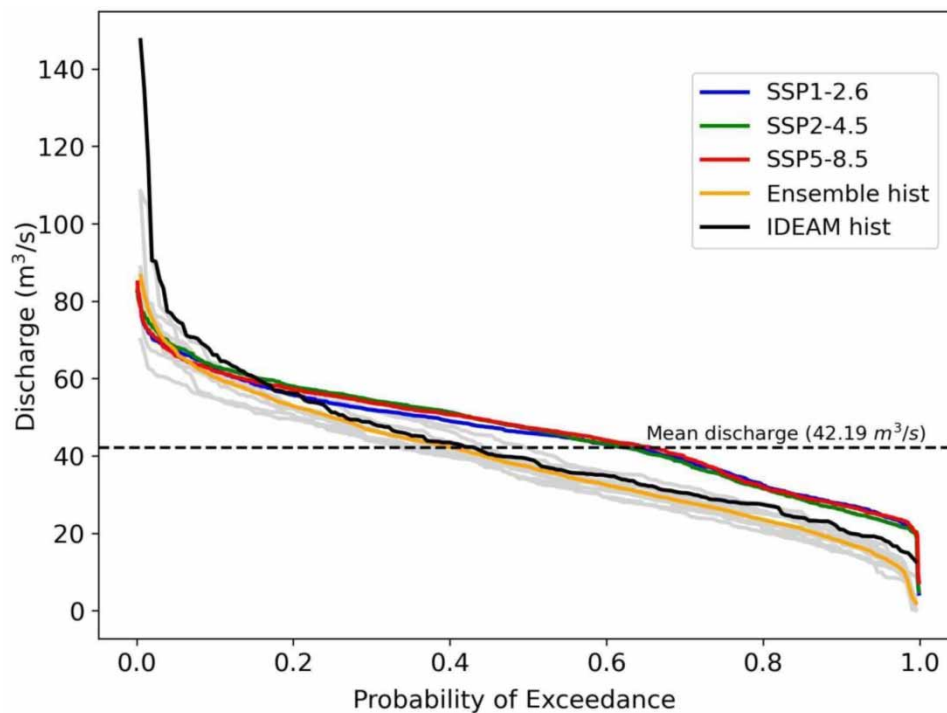


Figure 9 | Flow duration curves for streamflow. The reference curve from IDEAM for the historic period (1988–2015) is shown in black. The ensemble of simulated streamflow using precipitation from GCMs for the historic period (1988–2015) is shown in orange. The simulated streamflow for each GCM for the historic period (1988–2015) is shown in gray. The ensemble of projected streamflow (2015–2099), using projected precipitation from GCMs for the scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5, is shown in blue, green, and red, respectively. The mean discharge for the IDEAM reference, over the historic period, is shown as a dashed line.

Table 4 | Signature indices for monthly streamflow for the climate change scenarios SSP1-2.6, SSP2-4.5, and SSP5-8.5 for the period 2015–2099

	SSP1-2.6	SSP2-4.5	SSP5-8.5
BiasRR	7.64	9.06	9.31
BiasFMM	17.10	20.16	20.58
BiasFDCmidslope	–41.55	–31.89	–40.18
BiasFLV	122.26	99.31	59.98
BiasFHV	337.89	345.41	334.28
DiffQ95	30.07	22.86	27.93

6. DISCUSSION

For the projections under climate change scenarios, we found contrasting results, indicating that although the magnitude of the mean streamflow of the Gualí River is higher for the simulations than for the observations, the variability is greatly reduced (mainly due to the ensemble and bias correction approaches). For scenarios SSP1-2.6 and SSP2-4.5, there is an increased streamflow but no significant trends for precipitation or streamflow. For SSP5-8.5, although the mean streamflow increases compared with the observations, there is a reduction of streamflow of around 5% when compared with SSP1-2.6 and SSP2-4.5, for the 2074–2099 period. These results coincide with those provided by [Mena et al. \(2021\)](#), who, through CMIP5 models, reported reductions in streamflow of around 2% and 7%. Also for SSP5-8.5 in terms of trends, there is a coherent significantly decreasing trend for precipitation and streamflow (–29.023 mm/dec and –0.572 m³/dec, respectively).

Furthermore, our findings indicate that, if GCMs deviate from a good simulation for precipitation, these deviations can induce discrepancies in the simulated streamflow magnitude, notwithstanding that signals of a decreasing trend are observed for both precipitation and streamflow. In that sense, our results introduce the quantification of trends with CMIP6 data to support the panorama of climate change shown by [Mena et al. \(2021\)](#). The results have helped us to address the first question posed in this study. Despite the uncertainties and the lack of confidence in future projections derived from GCMs, for this particular geographical scale, our study reveals a consistent increase in mean streamflow for the basin.

To address the second research question in this study, in terms of signature indices, the streamflow projections exhibit an increase in the mean-, high-, and low-flow features. Moreover, it is remarkable that the projections suggest an increase in mid-flow and low-flow features (BiasFDCmidslope, BiasFMM, BiasFLV, BiasFHV), as well as an increase in the percentage bias in the mean values and the 95th quantile of the flows (BiasRR and DiffQ95). These findings provide useful information about the long-term mean streamflow and baseflow, which provides a continuous supply of water for human consumption, irrigation, and other human uses. In addition, it helps to maintain the health of aquatic and terrestrial ecosystems.

There are still some challenges regarding the calibration and validation of the rainfall–runoff modeling for the Gualí River Basin, which could be useful to know for similar applications in the region. In this sense, we found acceptable (but not high) performance metrics for the hydrological model, which can be explained because: (1) the Gualí River Basin is located in the Andes mountain range and processes such as orographic forcing, vegetation diversity, and tropical climates induce particularities, as stated by other authors ([Canchala et al. 2020](#); [Yeditha et al. 2022](#); [Ghaderpour et al. 2023](#)); (2) we hypothesize that the difficulties in the model representing the higher streamflow values can be related to the alterations in the infiltration regime across the basin, induced by the most recent explosive eruption of the Nevado del Ruíz in 1985. The eruption deposited volcanoclastic materials during the explosion and then lahar, which affected the Gualí River Basin due to its proximity to the volcano (within 10–20 km); (3) we lack data for the melt water and soil from the Nevado del Ruiz, to be able to improve model representation; and (4) the performance of GCMs at finer scales is not optimal ([Banda et al. 2022](#)); therefore, regional modeling, downscaling or bias correction (in our particular case, the basin size) and the coarse resolution of the GCMs may be sources of uncertainty that must not be disregarded.

7. CONCLUSIONS AND FUTURE WORK

We simulated monthly streamflow in the Gualí River Basin (Colombia) using the GWLF model included with Hydro-BID software. To this end, we used a calibrated and validated hydrological model that met the literature's satisfactory performance criteria. Furthermore, we used precipitation simulations from ten GCMs and three shared socioeconomic pathways (SSPs) (denoted as SSP1-2.6, SSP2-4.5, and SSP5-8.5) and quantified the trends and signature indices for projected precipitation and streamflow in the period 2020–2099. The rainfall–runoff modeling process for this river basin is evidence that it is necessary to verify the coherence between observed precipitation and simulated precipitation by GCMs, over the historic period, before incorporating these data into future streamflow projections. In general, we found disagreement in the Taylor diagrams between the precipitation reference and precipitation provided by GCMs for the historic period. This disagreement could be explained in terms of the limitations of the GCMs, such as systematic biases, coarse spatial resolution, and lack of representation of climatic processes at regional scales ([Falco et al. 2019](#); [Llopert et al. 2020](#); [Ciarlò et al. 2021](#)).

Moreover, our results show the necessity of bias correction or ensemble approaches ([Hagedorn et al. 2005](#); [Muerth et al. 2013](#)) in order to face up to the uncertainties of GCM projections and streamflow simulations. After the bias correction of precipitation from GCMs, we obtain streamflow simulation results that agree with the observations, in terms of magnitude and FDC for the historic period, which provide confidence in the streamflow simulation for future projections, especially for probabilities of exceedance above 0.20. For probabilities of exceedance below 0.20, the FDCs exhibit higher dispersion and an underestimation of simulations, in relation to the observed streamflow.

We would caution practitioners when using GCM datasets, even with the bias correction proposed by [Meresa et al. \(2022\)](#), when assessing precipitation extremes and flood risk with the CMIP dataset. These issues about geographical scale and the uncertainties when resolving convection in GCMs are common in hydrological analysis involving CMIP6 datasets, as stated by [Martel et al. \(2022\)](#), for catchments in the USA, and by [Guo et al. \(2022\)](#), for basins in the northern hemisphere where GCMs provide higher performances than in the tropics. Notwithstanding this, we note that our case study in South America provides valuable information to improve climate models which, in the absence of historical datasets of sufficient length from systematic and reliable observations, are suitable for certain purposes, such as risk management at a regional scale, the

evaluation of environmental determinants, and supporting processes immersed in the structure of integrated water resources management (IWRM).

Further research is needed in light of these contrasting results. We propose some aspects that should be focused on: (1) explore the basin size/model resolution sensitivity in the Andean basin context; (2) generate a hydrological multi-model ensemble that, like the approach with GCMs, allows enhanced confidence intervals after the inclusion of climate change scenarios in water planning; (3) studying the infiltration variations over the basin due to continuous changes in the soil, as a result of explosive eruptions of the Nevado del Ruíz, is of utmost importance for the improvement of this variable in hydrological modeling; and (4) carry out hydrological modeling experiments considering land use and land cover changes in the river basin (Nama *et al.* 2022), in order to incorporate alterations that help policy makers and management support decision-making around water resources.

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AUTHOR CONTRIBUTIONS

H.D.S., A.B.J., C.F., and J.V. conceptualized the whole article, developed the methodology, and wrote the first version of the manuscript. H.D.S. and A.B.J. administered the project and supervised the work. C.F. and J.V. processed climate and hydrological data. D.M. and J.C.P. reviewed the first version of the manuscript. H.D.S., C.F., A.B.J., and J.V. analyzed data and edited the final version of the manuscript.

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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