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Setting an environmental flow regime under climate change in a data-limited Mediterranean basin with temporary river

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ABSTRACT

Study region: Catchment in Southern Italy.
Study focus: Mediterranean waterways are commonly non-perennial; they are vulnerable to climate change (CC). Their management is particularly complex due to limited data availability. This work aims to develop a methodology for setting an Environmental Flow regime (E-Flows) for a temporary river (Locone, Italy) under limited data availability and under CC. As observed long-term time series of streamflow under natural conditions were not available, the Soil and Water Assessment Tool model (SWAT+) was applied to simulate the daily streamflow for the baseline period (1980–2010) and future (2020–2050) based on observed and model climate projections, respectively. A specific workflow was developed for model calibration focusing on the low flows. The hydrological regime was characterized by means of Indicators of Hydrological Alteration (IHAs), whereas the Range of Variability Approach (RVA) was applied to define the E-Flows.
New hydrological insights for the region: The basin is experiencing a statistically significant increase in the air temperatures observed from 1971 to 2020, which is also predicted to continue in the future. Consequently, the average annual streamflow and monthly streamflow in winter and spring is expected to decrease. The calibration, based on a multi-objective model evaluation, improved the low-flow simulation. The detected differences in IHAs for the predicted periods should be considered in future water management when setting E-Flows for temporary rivers.

1. Introduction

River flow regulations and ongoing climate change (CC) alter the natural hydrological regime of rivers (Arthington, 2012; Schneider et al., 2013). All components of the flow regime play a decisive role in the health of aquatic ecosystems and in the physical condition of the habitats (Rolls and Arthington, 2014). Hence, deviations from the natural flow condition may lead to river ecosystem degradation (Poff et al., 1997). Based on this awareness, the principle of "Environmental flow regime" (E-Flow), which is the flow regime necessary to maintain river ecosystems, was introduced (Arthington, 2012). Many methods have been developed to set the E-Flow regime (Tharme, 2003). The main limitation for most of them is the data requirement (i.e., hydrological, hydraulic, and biological data) (Dyson et al., 2003; Tharme, 2003). The hydrological methods are simple and easy to apply; the input is a time series of

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streamflow (monthly or daily) of at least 20 years under un-impacted conditions or for which the alterations induced by anthropic activities are negligible (Pastor et al., 2014). In areas where streamflow time series are not available, due to poor monitoring or because measuring instruments are in highly impacted locations, hydrological models can be used to generate data under un-impacted conditions (De Girolamo et al., 2017b; Senent-Aparicio et al., 2021b; Castellanos-Osorio et al., 2023). Richter et al., (1996, 1997, 1998) developed the Indicators of Hydrological Alterations (IHAs), which can describe the hydrological regime components, and the "Range of Variability Approach (RVA)" for assessing the hydrological alterations of a river by comparing the IHAs computed before and after the impacts. The E-Flows may be set by defining a range of values for each IHA within its natural variability (i.e., 25th-75th percentile). The latter is computed over a long period in natural conditions (Stewardson and Gippel, 2003). Like all hydrological methods, the RVA should be considered a first phase of E-Flows design that should be revised after assessing the ecological status (Arthington, 2012). Indeed, setting an E-Flow regime should always be considered an iterative process that should include the evolution of the ecology over time and the quantitative variations due to CC (Arthington, 2012), balancing human and ecosystem water needs (Derepasko et al., 2021a; Ćosić-Flajsig et al., 2021).

At the European level, the need to restore and protect aquatic ecosystems is regulated by the Water Framework Directive (WFD; EC, 2000), which requires Member States to address river degradation by improving or maintaining a good ecological status. The Guidance document no. 31 - "Ecological flows in implementation of the Water Framework Directive" (CIS n. 31; EC, 2015) suggests evaluating all the components of the hydrological regime and adopting measures to improve the ecological status associated with the flow regime. Leone et al. (2023a) pointed out that with the implementation of the WFD and, in particular, with the adoption of CIS no. 31 (EC, 2015), the definition of E-Flows also includes ecological aspects in most of the EU Member States. However, neither European nor national legislation of the EU Mediterranean countries provides specific guidelines for setting up E-Flows in non-perennial rivers (Leone et al., 2023a). In Italy, with the Decree D.D. STA 30/2017 (MATTM, 2017), some methodologies have been defined to set up the E-Flow regime, i.e., hydrological methods, habitat simulation methods, and biological methods. It is up to the river basin districts to define the method in the River Basin Management Plans based on the availability of data, environmental needs and water requirements for human activities, and hydraulic conditions.

The Mediterranean region suffers from water shortage due to a number of both anthropogenic and natural factors. Waterways, which are mainly non-perennial, are particularly sensitive to the impacts of CC and human pressures (Borg Galea et al., 2019). Non-perennial rivers are characterized by naturally specific aquatic habitats of a temporary character with different biogeochemical processes and biological communities compared to perennial rivers and, therefore, deserve specific studies (Datry et al., 2014). However, the poor monitoring network and the measuring instruments' difficulty in recognizing zero or extremely low flows (Tramblay et al., 2021; van Meerveld et al., 2020; Zimmer et al., 2020) make the eco-hydrological study of these rivers very complex. In addition, although these river ecosystems are of scientific interest, they are often neglected in eco-hydrological studies, and the lack of guidelines and legislation specific for non-perennial rivers (Leone et al., 2023a) is a challenge for sustainable water resource planning and management (Prat et al., 2014).

The Mediterranean basin is a hotspot for CC (Mereu et al., 2021; Noto et al., 2023). Most of the future climate projections show an increase in temperatures (increase in evapotranspiration) and a decrease in precipitation right from the first half of the 21st century (García-Ruiz et al., 2011; Molina-Navarro et al., 2014; Noto et al., 2023; Noto et al., 2022; Senent-Aparicio et al., 2021a). Furthermore, in the Mediterranean area, the increased demand for water to support agricultural, urban, and industrial development (Bradford, 2000; Iglesias et al., 2007) will probably lead to excessive exploitation of water resources, which entails a consequent qualitative degradation of fresh water. Southern Italy, and in particular the Apulia region (S-E Italy), reflects the climatic conditions of the Mediterranean area, being geographically and geomorphologically subject to hydroclimatic risks. Several extreme climatic events occurred in Apulia in recent decades: droughts (Marini et al., 2019), floods, and fast fluctuations of droughts/floods (Polemio and Lonigro, 2015). Recent studies showed a clear trend toward warmer temperatures and drier conditions during the second half of the 20th century that has several implications for water resource availability (De Girolamo et al., 2017a; De Girolamo et al., 2022a; Lionello et al., 2014). The Apulia region has the largest agricultural production in Southern Italy, which could be at risk due to water shortage and CC impacts (D'Agostino et al., 2014; Ronco et al., 2017). Indeed, the water requirement for irrigation is continuously increasing together with other water uses related to domestic supply and industrial processes (SEETCP, 2012–, 2014). In this context, water resource management is central to a sustainable supply of water for human uses and ecological functions and must consider the impacts of CC on water resources. Furthermore, due to its hydromorphological characteristics that prevent the storage of large volumes of surface water, Apulia is forced to import water from neighboring regions (i.e., Campania, Calabria) to meet its water demands (SEETCP, 2012–, 2014). For this reason, many reservoirs were built in the last century. A challenge for the next few decades will be to determine water storage and release to rivers for the reservoirs that is efficient enough to balance human and ecosystem needs.

Very few papers have been published analysing E-Flows in basin with limited data available, including the potential impact of CC on the flow regime (Senent-Aparicio et al., 2021b). To the best of our knowledge, there are no articles focused on a temporary river. In this context, this paper aims to set E-Flows under CC in a data-limited basin with a temporary river. The specific aims are: i) simulating the possible alterations induced by CC on the hydrological regime of the Locone River, and ii) evaluating the impact of these alterations on the E-Flows. For the future scenario (2020–2050), climatic data from two combinations of General Circulation Models (GCMs) and Regional Circulation Models (RCMs) were used. Due to the lack of hydrological data, the E-Flow was set up applying the RVA using simulated daily streamflow in un-impacted conditions. The new version of the Soil and Water Assessment Tool (SWAT) model was used. SWAT is one of the most widely used hydrological and water quality models (Bieger et al., 2017) in the world with different applications even in contexts of data scarcity (De Girolamo et al. (2022b); Ricci et al. (2018); Nyeko (2015)). The new version, SWAT+ , is the result of improvements, overcoming some limitations of the previous versions. In SWAT+ , the algorithms and the type of input data required have not changed, while the structure and organization of the code and the input files have undergone significant changes. There are still a few applications of SWAT+ in the Mediterranean environment (SWATLiteratureDatabase; last view August 2023), especially in basins with limited data availability (Leone et al., 2023b). This is both because the SWAT+ model is still relatively new and because modeling streamflow in a data scarcity context is very complex (Shanafield et al., 2021), especially in basins with temporary rivers. Leone et al. (2023b) applied SWAT+ to simulate the streamflows of the temporary Locone River (S-E Italy), processing the calibration and validation with the Toolbox (v.0.7.6). The authors highlighted that the model underestimated the low flows. Based on that study, this paper attempts to identify specific strategies to improve the low-flow and zero-flow simulations that are generally recognized as critical phases in modeling hydrology in temporary rivers (De Girolamo et al., 2022a; Kirkby et al., 2011). This study contributes to the SWAT+ community by showcasing a model calibration procedure adapted to conditions of extended low-flow periods. Furthermore, it provides valuable information to water resource managers for setting an E-Flow regime for temporary rivers under CC.

2. Material and methods

2.1. Study area

The study area is the Locone River basin (228 km^2), located in S-E Italy in the border region between the Basilicata and Apulia regions (Fig. 1). The Locone River is one of the major tributaries of the Ofanto, the most important river in Apulia. The total length of the main course is 33 km. The elevation of the study area varies between 616 m a.s.l. and 128 m a.s.l. (average value 341 m a.s.l.). The mountainous part of the basin is mainly formed by calcareous and dolomitic formations of the Murgia, which rest on the clastic deposits of the Bradanic cycle. The hilly and plain areas are characterized by the clastic sediments of the Fossa Bradanica, mainly clays and sands and, secondarily, conglomerates and calcarenites, lying on the Mesozoic calcareous-dolomitic basement. The small thickness of these sediments means that the tributary hydrographic network is very scarce, discontinuous, and not very engraved. The main soil types are classified as Typic Calcixerept of fine loamy, Mixed, and Thermic Calcaric Regosol, according to the USDA Soil Taxonomy (Soil Survey Staff, 2022). The soil texture is predominantly sandy-clay-loam, and clay-loam.

In the study area, there are four weather stations (WSs): WS1, WS2, WS3, and WS4 respectively in the N-E, N-W, S-W, and S-E of the basin. The stations have been in operation since 1971. All stations are recording precipitation. In addition, WS1 and WS4 measure minimum and maximum air temperatures. The mean annual rainfall is 584 mm, with most of it falling in the period from September to May; the mean annual temperature ranges from 7.6 °C (January) to 24.3 °C (August) (reference period 1971–2020). The Mediterranean climate is characterized by a wet winter season and a dry summer season. Consequently, the Locone has the typical characteristics of the torrents of Southern Italy with very scarce summer outflows and flash floods and a wet season (winter, spring). The Basin Authority classifies the Locone River as a “temporary” river (river with dry conditions on the entire body of water or parts of it, recorded annually or at least 2 out of 5 years) (Legislative Decree no. 131/2008; Apulia Region, 2010). The only streamflow gauge was located at the Ponte Brandi (PB, 41° 06’ 35’’ N; 16° 00’ 03’’ E), upstream of the Locone dam, operating from 1971 to 1983. However, data from 1973 to 1983 were excluded from this study because they were inconsistent with precipitation and affected by errors and

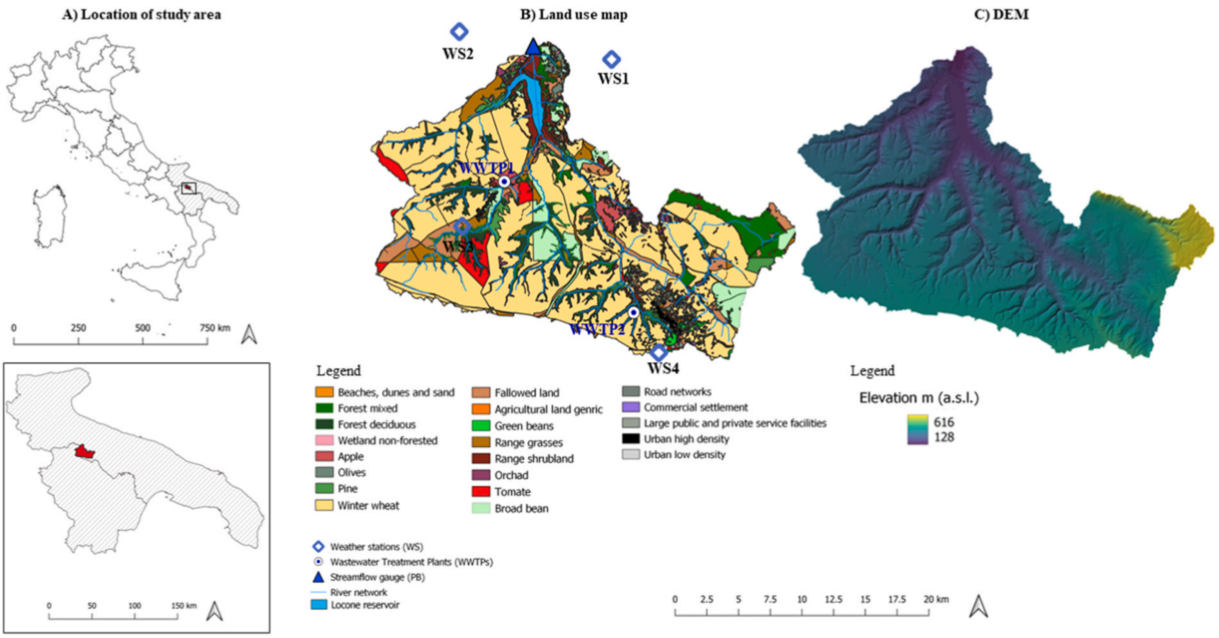

Fig. 1. Study area: Locone River Basin (S-E Italy). A) Apulia and Basilicata regions (S-E Italy); B) Land use map and Weather Stations (WS1, WS2, WS3, WS4), Wastewater Treatment Plants (WWTP1, WWTP2), Ponte Brandi (PB) gauge station locations; C) DEM.

missing data.

The Locone dam (41° 05' 06'' N; 16° 00' 00'' E), which was built from 1982 to1986, has a maximum capacity of 108 million m^3 (irrigation, provision of a hydroelectric power plant, and supply of drinking water). The main land use in the catchment is agriculture with winter wheat the predominant crop (64%), followed by deciduous forests (6.6%), extending mostly along the coasts of the reservoir, and broad beans (5.4%). Agriculture, mainly rainfed, is the main economic activity of the area, but CC threatens its sustainable production (Daccache et al., 2016). D'Agostino et al. (2014) pointed out that future CC will correspond to a significant increase in the water requirement of the most cultivated crops, which could lead to a global reduction of the irrigated surface due to the decreased water resource availability. Polemio and Lonigro (2015), who analysed the trend of flood events in Apulia from 1918 to 2006, highlighted the urgency of further studies to understand the dynamics of damaging hydrogeological events and climatic variables. In recent decades several dry years (e.g., 2012; 2022) and several floods were recorded producing damage to crop production (e.g., 2011; 2016). Hence, on the one hand, an increase in competition for water is expected in the near future and on the other hand, the reduction of the current water inflow into the reservoirs will require a periodic revision of the E-Flows.

The two main urban areas are located to the southwest and southeast of the basin with a total population of approximately 8500 inhabitants. Additional pressures in the study area include two urban wastewater treatment plants (WWTPs) discharging into the river, a quarry above a landfill to be reclaimed, and agricultural land runoff. These are the main threats to the Locone River water quality.

2.2. *Future climate*

Several studies reported a reduction of water resource availability in Apulia in recent decades, mainly due to an increase in air temperature that has caused an increase in potential evapotranspiration (PET) and a reduction in snowfall (De Girolamo et al., 2022a; Marini et al., 2019). Those studies also reported a similar trend for future decades underlining the urgency of using future climate projections to understand how CC will affect the water resources to better manage the competition for water uses, balancing human and ecosystem needs.

2.2.1. *Description of future climate projections*

Future climate projections are based on numerical models, which are presented by GCMs and RCMs. The first ones, with low resolution (between 100 and 300 km), describe processes on a global, continental, or national scale and the second ones, with higher resolution (between 1 km and 50 km), describe the processes at a regional scale.

The climate projections used in this study are derived from two models: the MPI-ESM 1.2-LR (Max-Planck-Institute Earth System Model, Low Resolution) climate model (MPI hereinafter) (Wieners et al., 2019); and the CMCC-CM-COSMO-CLM model (CMCC hereinafter), which was developed for Italy (Bucchignani et al., 2016; Scoccimarro et al., 2011; Zollo et al., 2016). The CMCC model is widely used by the Italian scientific community because it has shown it can represent the Italian climate – both in terms of average and extreme values, even at a local scale (Bucchignani et al., 2016; Zollo et al., 2016) – well. However, the CMCC underestimated the climatic variables of the study area, therefore, a second climate model, the MPI model, was considered that, on the contrary, overestimated the climatic variables. Both climate models provide daily time series for precipitation and minimum and maximum daily air temperatures. The data provided by MPI covers the historical period from 1850 to 2014, while historical data from CMCC are available from 1979 to 2005. Future climate projections representing the Shared Socioeconomic Pathways (SSPs) SSP1–2.6, SSP2–4.5, SSP3–7.0, and SSP5–8.5 are available from MPI for the period 2015 to 2099. Future projections from CMCC were simulated assuming the IPCC CMIP5 Representative Concentration Pathways (RCPs) scenarios RCP4.5 and RCP8.5 for the time period 2006 to 2100.

In this work, daily data of precipitation and maximum and minimum air temperatures from 1971 to 2005 (MPI) and from 1979 to 2005 (CMCC) were used as the historical periods to carry out the bias correction. For the near-future scenario (2020 to 2049), the RCP 4.5 scenario of CMCC and SSP2 4.5 scenario of MPI were used. The RCP4.5 emission scenario shows an increase in greenhouse gas emissions, which causes an increase in radiative forcing of approximately 4.5 Wm^{-2}. The climate scenario SSP2–4.5 represents "intermediate" levels of greenhouse gas emissions, which is reflected in an intermediate probability that global surface temperatures will increase by 1.5 °C (relative to 1850–1900) in the short term (2021–2040). Trends in observed maximum and minimum temperatures and observed precipitation on a daily scale from 1971 to 2020 were analysed with the Mann-Kendall test using the R package 'Kendall' (McLeod, 2022; see 2.2.1). Information about the models and periods analysed is given in Table 1.

Table 1
Climate model Projections: GCMs, RCMs, spatial resolution, historical and near-future period, climatic variables (PCP = precipitation, TMP max and TMP min = maximum and minimum temperature, respectively), sources of each dataset.

GCMs	RCMs	Spatial resolution	Historical	Near future	Climate variable	Source
CMCC-CM	COSMO-CLM	8 km	1979-2005	2020-2049 (RCP 4.5)	TMP max TMP min PCP	https://dds.cmcc.it/#/dataset/climate-projections-8km-over-italy
ECHAM6.3	MPI-ESM1-2-LR	40 km	1971-2005	2020-2049 (SSP2 4.5)	TMP max TMP min PCP	https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6?tab=form

2.2.2. Downscaling precipitation and temperatures: bias correction

The statistical methods of downscaling (bias correction) provide local-scale projections of the GCMs-RCMs outputs by using the observed climatic variables and empirical-statistical relationships. RCM outputs are often subject to random and systematic errors (Teutschbein and Seibert, 2013). Therefore, bias corrections are particularly needed (Glavan et al., 2015), especially in the Mediterranean environment where the climatic variables are strongly influenced by the position of the measuring stations and by the orography (De Girolamo et al., 2017b; Bonada and Resh, 2013).

The CMCC and MPI models mean annual rainfall and mean annual maximum and minimum temperatures of the historical period (1979 to 2005 and 1971 to 2005, respectively) were compared with observed data in the same periods for the four WSs (Figs. 3 and 5). To ensure that the near-future scenario simulated by the models reflects the peculiarities of the local climate, two different procedures of bias correction were performed for precipitation and maximum and minimum temperatures, respectively, based on the models' historical climatic data and the measuring station data of climatic variables in the same period. For precipitation, a simple ratio method proposed by De Girolamo et al. (2017a) (Eq. 1) was applied, where the observed average data (AVGmon(i)Hist_OBS) for each month was divided by the corresponding average data simulated by the models (AVGmon(i)Hist_SIM), obtaining a monthly correction factor which was then multiplied with the daily data of the models (daily PCP SIM) (2020–2049).

$$\frac{AVGmon(i)Hist\_OBS}{AVGmon(i)Hist\_SIM} \bullet daily \quad PCP \quad SIM$$

For the correction of daily temperatures, the quantile mapping (QM) method was applied, which adjusts the quantiles through a univariate transfer function independently of each variable to relate the cumulative distribution function of a simulated variable to the observed one. The QM method corrects for the mean value of each simulated series and the overall variability and is potentially more effective for correcting for extreme values (Wetterhall et al., 2012). This method proved to be valid for the correction of the bias of climatic variables (Dumitrescu et al., 2023), especially for temperatures (Maraun, 2013), and was performed in the R environment with the 'qmap' package 1.0–4 (Gudmundsson, 2016; Gudmundsson et al., 2012). In this work, the monotonic tri-cubic spline type interpolation was found to be the best performing for the transformation of the variable x.

Once the biases were determined based on the observed and historical climatic variables, the correction factors were applied to the climatic variables of the future scenarios to adjust them according to the local characteristics.

2.3. Simulation of daily streamflow

Due to the lack of observed streamflow over a long period in natural or near-natural conditions, the SWAT+ model, a new release of the hydrological and water quality SWAT model (Arnold et al., 1998), was applied at the Locone River basin to generate a long series of daily data at the outlet (PB gauging station, Fig. 1). The model was run from 1980 to 2010 using measured climatic data as the baseline period and from 2020 to 2050 for the near future using downscaled climatic data, without considering other factors such as WWTPs emissions and water abstractions.

Table 2
Input data: data type, source, time and spatial scale, information.

Data	Source	Scale / Resolution	Information
Precipitation	Civil Protection Service implemented with Regional Agency for Irrigation and Forestry Activities (ARIF)	Daily	WS1, WS2, WS3, WS4 (1971-2020)
Temperature	Civil Protection Service implemented with ARIF	Daily	WS2, WS4 (1971-2020)
Corine Land use map	European Environment Agency, 2020 and statistical information (ISTAT, 2010) for agricultural areas	10 m·10 m	22 different types of land use
Digital Elevation Map (DEM)	Regional geoportal of Basilicata; Regional geoportal of Apulia.	10 m·10 m	
Soil type Map	ACLA 2- FEOGA EU Project for Puglia and Land Use Cover Area frame Survey (LUCAS) project for Basilicata	10 m·10 m	12 soil profiles
Management Practices	Interviews with farmers and agricultural advisors (D'Ambrosio et al., 2020)		Planting, irrigation, fertilizing, tillage operations, and grazing operations for pastures are detailed for each crop.
Streamflow gauging station	Civil Protection Service	Daily	PB streamflow measurement station (1971-1972)
River network	Regional geoportal of Basilicata and Regional geoportal of Apulia.	1:250000	
Point source WWTP1	Regional Agency for Environmental Protection for Apulia	Monthly	Volume = 1265 $m^3 day^{-1}$ Qualitative data: total sediments; Biochemical Oxygen Demand (BOD); total phosphorus; total nitrogen. (2012-2021)
Point source WWTP2	Regional Agency for Environmental Protection for Basilicata Wastewater – emission limit values – Annex 5, Legislative Decree 152/ (2006)		Volume = 510 $m^3 day^{-1}$ No qualitative data is available. The limit values of the legislation have been used.

2.3.1. The eco-hydrological model SWAT+

The SWAT+ model is an open-source, process-based, semi-distributed watershed model, which is widely used for different purposes (e.g., hydrological cycle simulation, water quality) and at different spatial and temporal scales (Bieger et al., 2019).

As input data, SWAT+ requires the daily weather input data (at least precipitation and maximum and minimum temperatures), a digital elevation model (DEM), spatially distributed soil data (soil hydraulic and chemical parameters), information on crop management operations, and the land cover. In SWAT+ , the code and input files have been modified (Bieger et al., 2017). The catchment area is subdivided into separate spatial units, such as aquifers, reservoirs, channels, ponds, hydrological response units (HRUs), and Landscape Units (LSUs). SWAT+ is more flexible in terms of spatial representation (Bieger et al., 2019) than the previous versions, emphasizing the connectivity between spatial objects (Barresi Armoa et al., 2023). The HRUs are the smallest spatial unit representative of a single combination of land use, slope, and land within each LSU. The major innovation is the introduction of LSUs, i.e., portions of subbasins that are delimited based on channel thresholds to separate mountain processes and alluvial plains (Bieger et al., 2017).

2.3.2. Model input data SWAT+ model setup

The QSWAT+ plug-in for QGIS3 (Dile et al., 2023) was used for defining the spatial objects of the SWAT+ model (delineation of HRUs, LSUs, and sub-basins and definition of the river network). In this work, the SWAT+ executable revision 60.5.5 was used. All input data for setting up the model are summarized in Table 2. A DEM with 10 m spatial resolution was extracted from the databases of the reference regions. Observed daily precipitation and the maximum and minimum air temperatures were available for the period 1971 to 2020 for the WSs present in the area. The land use map is based on the Corine Land Cover classification (CLC2006 version 2020_20u1; EEA, 2019) and a reclassification based on the National Agricultural Census (ISTAT, 2010) data was carried out on a municipal scale to provide more details. The hydrological parameters of the soils such as saturated hydraulic conductivity (K) and available water capacity (AWC) were obtained from the soil texture using the SPAW Hydrology and Water Budgeting tool (Keith et al., 2019).

The volumetric instream contribution of the WWTPs was set to a constant value, due to the lack of data. The potential of WWTPs (expressed in equivalent inhabitants) is provided by the Regional Agency for Environmental Protection of Basilicata and Apulia. The volume was obtained by multiplying the equivalent inhabitants by the daily water supply from the literature. The qualitative data (nutrient loads in treated wastewater) were available on a monthly scale for WWTP1, while no data was available for WWTP2, which is why we used the limits imposed by legislation (Wastewater – emission limit values – Annex 5, Legislative Decree 152/, 2006) as reference values. For further details concerning input data, the reader is referred to Leone et al. (2023b). The Locone basin was divided into 31 sub-basins, 183 channels, 183 LSUs, and 739 HRUs, the latter defined by setting the land use, soil, and slope thresholds as 15%, 15%, and 25%, respectively. The Hargreaves-Samani formula was used to calculate PET (Hargreaves and Samani, 1985), and the SCS Curve Number method (USDA-SCS, 1972) was applied to calculate the surface runoff. The equation of Williams (1995) was used to calculate the USLE K (the soil erodibility factor) as a function of the percentage content of sand, clay, and carbon in the soil layers.

2.3.3. Model calibration and validation

The hydrological calibration and validation of the SWAT+ model were performed based on the observed streamflow data that are available at the PB gauging station for the years 1971 and 1972. Other years were excluded from the observation data set either because they were affected by measurement errors or because there was no correspondence between rainfall and streamflow.

The aim of the calibration process was to improve the model performance of the SWAT+ model setup that was presented in Leone et al. (2023b) and was carried out with the SWAT+ toolbox (v.0.7.6). This tool, which is independent from the SWAT+ model, performs both automatic and manual calibration of the parameters, choosing the objective function. In previous work, the automatic calibration of the sensitive parameters was performed with 500 iterations, maximizing the Nash-Sutcliffe efficiency (NSE) as objective function. Even with good statistical results, the authors highlighted the underestimation of low flows. The model calibration in this work was performed in the R environment. For the hydrological model calibration, 15 parameters were selected that are relevant for the simulation of hydrological processes. Some of these parameters were already identified as sensitive in previous work in the Mediterranean environment (De Girolamo et al., 2022a; Brouziyne et al., 2021; Leone et al., 2023b). The parameters, with their selected ranges and the types of applied changes, are listed in Table 4. The sampling of the parameter combinations was performed with Latin Hypercube Sampling (McKay et al., 1979) using the 'lhs' R package (Carnell, 2022). In total, 5000 parameter combinations, with one iteration, were included in model simulations. The simulation runs were performed in parallel on 50 cores using the R package 'SWATplusR' (version 0.6.7., Schürz, 2022).

The model evaluation was based on a multi-objective analysis. For the calculation of model performance criteria, the Rpackage

Table 3
Comparison of the average maximum and minimum temperatures observed in the baseline period (1980–2010) and of the average maximum and minimum temperatures in the near future (2020–2049).

	Baseline (1980- 2010)		CMCC (2020-2049)		MPI (2020-2049)	
	T max (°C)	T min (°C)	T max (°C)	T min (°C)	T max (°C)	T min (°C)
WS1	22.19	12.57	23.23	13.64	23.13	13.26
WS4	19.87	10.67	21.12	11.97	21.30	11.90

Table 4
Calibrated parameters; description; range of variability; type of change [replacement of the initial value with a new value in absolute value (absval); addition of an absolute value to the initial value (abschg); multiplication of the initial value by 1 + given value (relchg)]; best value.

Parameter	Description	Range of variability	Type of change	Value
ESCO.hru	Soil evaporation compensation factor	0.15 - 0.35	Absval	0.302
PERCO.hru	Percolation coefficient	-0.3 - 0.3	Abschg	0.195
CN3_SFW.hru	Soil water factor for CNIII	-0.3 - 0.3	Abschg	0.0599
LATQ_CO.hru	Lateral flow coefficient	-0.3 - 0.3	Abschg	-0.12
AWC.sol	Available Water Capacity of the soil layer (mm H2O/mm soil)	-0.5 - 0.5	Relchg	-0.483
BD.sol	Moist Bulk Density (Mg/m^3)	-0.5 - 0.5	Relchg	-0.115
K.sol	Saturated hydraulic conductivity (mm/hr)	-0.5 - 2	Relchg	1.91
SURLAG.bsn	Surface runoff coefficient	0.01 - 2	Absval	0.0249
CN2.hru	Initial SCS runoff CNII	-0.15 - 0.10	Relchg	20 [A] ÷ 91[B]
LAT_TTIME.hru	Lateral flow travel time (days)	0.1 - 100	Absval	89.5
LAT_LEN.hru	Slope length for lateral subsurface flow (m)	1 - 100	Absval	17.3
ALPHA.aqu	Baseflow alpha factor, Index of groundwater flow response to changes in recharge (day^{-1})	0 - 0.2	Abschg	0.163
DEEP_SEEP.aqu	Deep aquifer percolation fraction	-0.9 - 1	Relchg	-0.373
SP_YLD.aqu	Specific yield of the shallow aquifer (m^3/m^3)	-0.9 - 1	Relchg	0.587
REVAP_CO.aqu	Groundwater "revap" coefficient.	0 - 10	Relchg	1.38

[A] dense vegetation cover and good infiltration conditions (hydrological soil group A).
[B] non-perennial crops (e.g., durum wheat) and poor infiltration conditions (hydrological soil group D).

'hydroGOF' (Mauricio Zambrano-Bigiarini, 2020) was used. Several studies underline the urgency of improving the performance of hydrological models in simulating low flows (Rivas-Tabares et al., 2019; Staudinger et al., 2011). Therefore, the selected performance criteria that were employed in the multi-objective model evaluation put a specific focus on low flows. To consider a model parameterization as acceptable, the following criteria were defined: (i) the simulation of daily discharge compared to the observations must exceed a Kling-Gupta-Efficiency of KGE_cal > 0.75; (ii) the absolute value of the percentage bias in the low-flow period must not exceed 5% (abs(PBIAS_lf) < 5%); and (iii) the mean absolute error of the daily simulated discharges in the low-flow period must be lower than the standard deviation in this period (MAE_lf < sd(qobs_lf)). The low-flow period (lf) was defined as the period between 1971–05-01 and 1971–12-31 (Fig. 6A). For model validation, the KGE was calculated for those simulations that were considered as acceptable in the calibration phase; finally, the simulation that returned the highest KGE value was chosen as the best. For additional model evaluation, the coefficient of determination for goodness of fit (R^2), the NSE, and the Root Mean Square Error (RMSE) were calculated. The KGE is increasingly used because it compensates for some deficiencies of the NSE, which is not suitable for evaluating the seasonal simulation performances (Knoben et al., 2019). Furthermore, as demonstrated by Althoff and Rodrigues (2021), the use of several performance criteria enables the consideration of several characteristics of the hydrograph: for example, a KGE greater than a certain value for the entire period guarantees a minor bias even in low-flow conditions (Althoff and Rodrigues, 2021); limiting the absolute value of the PBIAS controls the over/underestimation of the low flow; and limiting the MAE in the low-flow period to the standard deviation (sd) in this period guarantees a realistic overall variability of low-flow values.

Three years of warm-up have been included in the simulation to initialize internal storage. The qualitative and quantitative contribution of the WWTPs was included in the model setup. Once the model was calibrated and validated, this contribution was removed to characterize the natural flow regime and the daily streamflow was simulated for the baseline period (1980–2010) and for the near-future period (2020–2050).

2.3.4. Zero-flow threshold

Hydrological modeling often fails to fully represent the entire flow regime (De Girolamo et al., 2015a). This is particularly the case for temporary rivers, since in summer, both continuous flow and dry conditions may occur along the river network. Previous studies in Southern Italy (De Girolamo et al., 2017b; Leone et al., 2023b) have highlighted a discrepancy between the simulated and measured flow especially for the extremely low flow and the zero flow. De Girolamo et al. (2015a) pointed out that the zero-flow condition is extremely important in classifying the river type and characterizing the flow regime. Therefore, the authors suggested correcting the best simulation in a river section by introducing the Zero-Flow threshold (ZF), which is the value of simulated streamflow corresponding to the absence of flow. To consider the "temporary" nature of the Locone River, we applied the ZF threshold, which was estimated by comparing the flow duration curve (FDC) of observed daily streamflow from 1971 to 1972 and simulated streamflow (Fig. 6C). The ZF value was subtracted from the daily values of both baseline and near-future streamflow; therefore, values lower than ZF threshold were considered null.

2.4. Hydrological method for setting up an E-Flow regime

Based on the Natural Flow Paradigm (Poff et al., 1997), E-Flows should mimic the natural flow regime. The Range of Variability Approach (RVA), which is based on this principle (Richter et al., 1996), relates the natural variability of hydrological regimes, expressed in terms of the following flow regime components: timing, duration, frequency, and rate of change, to the sustenance of native biodiversity and integrity of aquatic ecosystems (Richter et al., 1997). The simulated flow in un-impacted conditions was used to calculate a number of IHAs that characterize the flow regime. The IHAs are classified into 5 groups representing the components of the flow regime (Poff et al., 1997). Groups include: magnitude of monthly water conditions, extent and duration of annual water extremes, timing of annual water extremes, frequency and duration of high and low pulses, as well as the rate and frequency of change in water conditions (The Nature Conservancy, 2009). The open-source software "Indicators of Hydrological Alteration" Version 7.1.0.10 developed by The Nature Conservancy (2009) was used to calculate the IHAs, their inter-annual variability, and statistics by non-parametric analysis for the baseline period and for the future scenarios. Each indicator represents a specific ecological function. It is assumed that each indicator can vary within a range of its natural variability without compromising river ecology and the health of aquatic ecosystems (Richter et al., 2003). In this work, the range of variability for each indicator was set between the 25th percentile and the 75th percentile. All hydrological methods (Arthington, 2012) are based on streamflow data in pristine condition recorded over the past 20 or 30 years. However, several studies (De Girolamo et al., 2022a; Brouziyne et al., 2021) reported that the flow regime is changing due to CC with a general reduction in streamflow. Therefore, when setting an E-Flow regime, the hydrological alterations due to CC should be considered. The IHAs selected in this study are the magnitude and duration of monthly streamflow as well as the IHAs representing the magnitude and duration of annual extreme conditions of different duration (1-, 3-, 7-, 30-, 90- days). In this work, an analysis of the IHAs computed over the past decades (1980–2010, baseline) and those predicted for the near future (2020–2050) was carried out. The methodology is schematized in Fig. 2.

3. Results

3.1. Bias correction

3.1.1. Rainfall data

At the basin scale, for the historical period (1980–2010), the CMCC model underestimated the average annual rainfall by about 100 mm. In contrast, the MPI model overestimated precipitation by about 100 mm. The boxplots of the mean annual observed precipitation (OBS), uncorrected (hist) and bias corrected (downscaled) model outputs of the historical period (1979–2005 CMCC; 1971–2005 MPI) are presented in Fig. 3. The median annual precipitation of WS1 (NE; 116 m a.s.l.) was significantly overestimated by the MPI model (563 mm) and underestimated by the CMCC model by 143 mm. The median annual precipitation of WS2 (NW; 0 m a.s.l.) and WS3 (SW; 350 m a.s.l.) were both underestimated by the CMCC model by 216 mm and 134 mm, respectively. The MPI model instead underestimated the median annual precipitation of WS2 by about 30 mm and overestimated that of WS3 by 30 mm. For WS4 (SE; 458 m a.s.l.), the median was overestimated with the MPI model (158 mm) while the CMCC model underestimated the median value by 55 mm.

The ratio method applied to remove bias errors in rainfall data provided good results (Fig. 3). After the bias correction, the

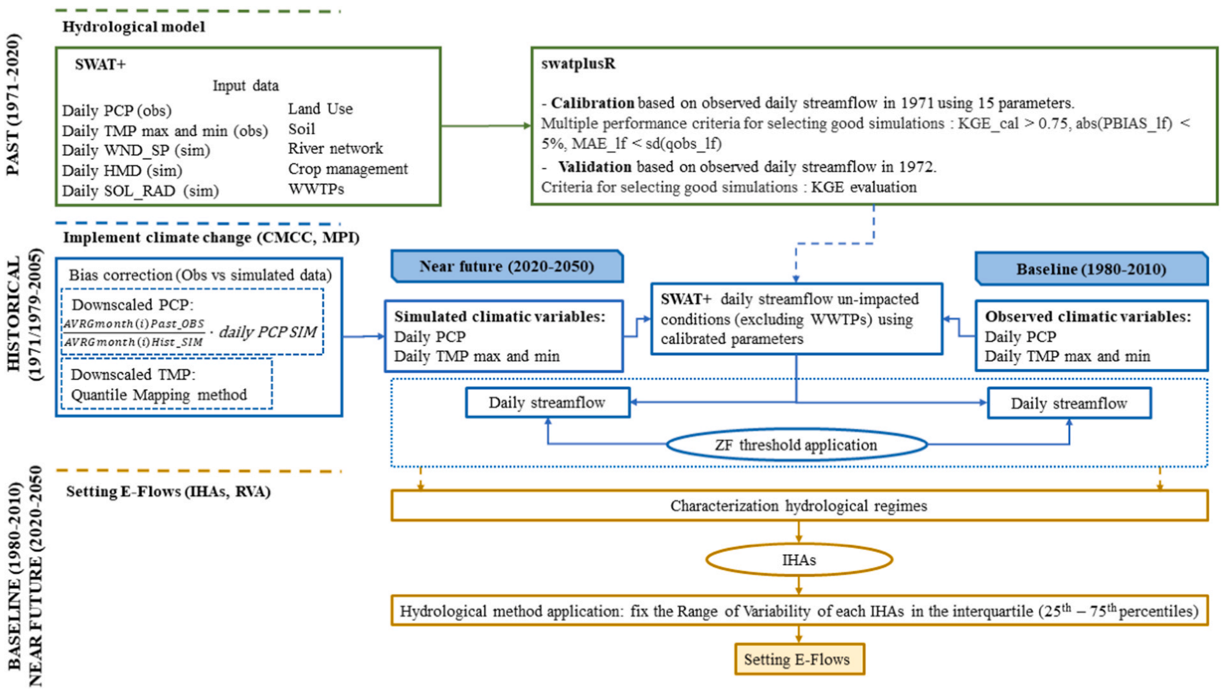

Fig. 2. Flowchart of the applied methodology.

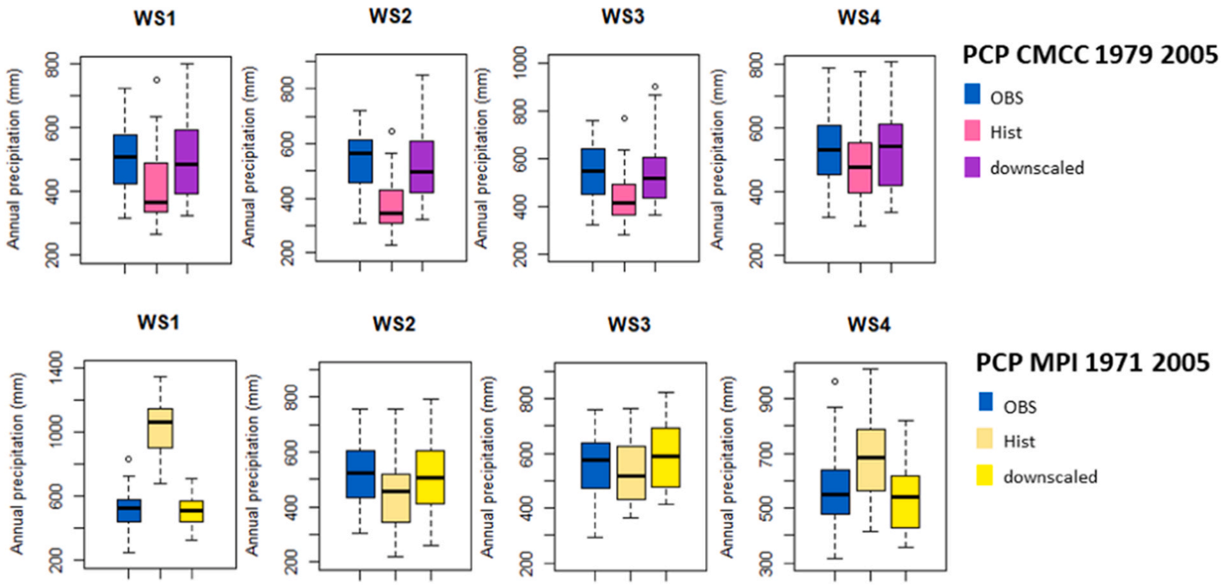

Fig. 3. Comparison of observed, historical, and downscaled mean annual precipitation (1979–2005) for the CMCC model and the MPI model (1971–2005). The upper whiskers represent the 90th percentile, the lower the 10th percentile; the major quartile the 75th percentile, the minor the 25th percentile, and the central black line the median.

forecasted average monthly rainfall for the baseline period (1980–2010) and for the near future (2020–2049) were compared (Fig. 4) and the future trends were investigated.

In line with other studies carried out in the Apulia region (De Girolamo et al., 2022a; Lionello et al., 2014), for the historical period, a statistically significant positive trend emerged for the maximum and minimum temperatures (p-value < 0.002), while a non-statistically significant trend was detected for rainfall. A similar situation occurred in the near-future scenario: both models showed a statistically significant positive trend (p-value < 0.0035) of the minimum and maximum temperatures for both stations, while no trends for precipitation appeared. The climate models provide slightly different projections for each station when compared on a monthly scale, probably due to their different spatial resolutions (Fig. 4). It should be emphasized that rainfall can substantially vary within a short distance because it is strongly conditioned by orography (Ricci et al., 2018; De Girolamo et al., 2017b). In the winter months (Dec, Jan, Feb), a reduction in rainfall is expected for all WSs. In the spring months (Mar, Apr, May), a reduction in rainfall at the basin scale is predicted for both models (-25% CMCC model and -11% MPI model) (Fig. 4). The greatest reduction in precipitation from 1800 to 2000 in Italy occurred in the spring months (Brunetti et al., 2006). Both models predict an increase in summer rainfall (Jun, Jul, Aug) at the basin scale, especially the CMCC (+24%), due to an increase in rainfall in August (Fig. 4). For the autumn season (Sep, Oct, Nov), a reduction (-8%) at the basin scale is envisaged for both models (Fig. 4).

3.1.2. Temperature data

The quantile mapping (QM) has proven to be a valid method to remove the bias for temperatures simulated by climate models

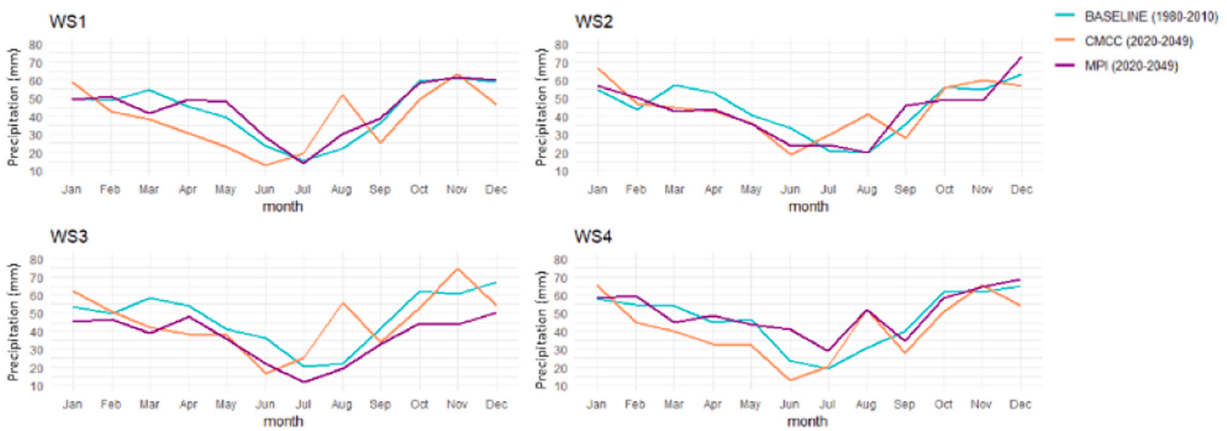

Fig. 4. Comparison of baseline (1980–2010) and near-future (2020–2049) average monthly rainfall.

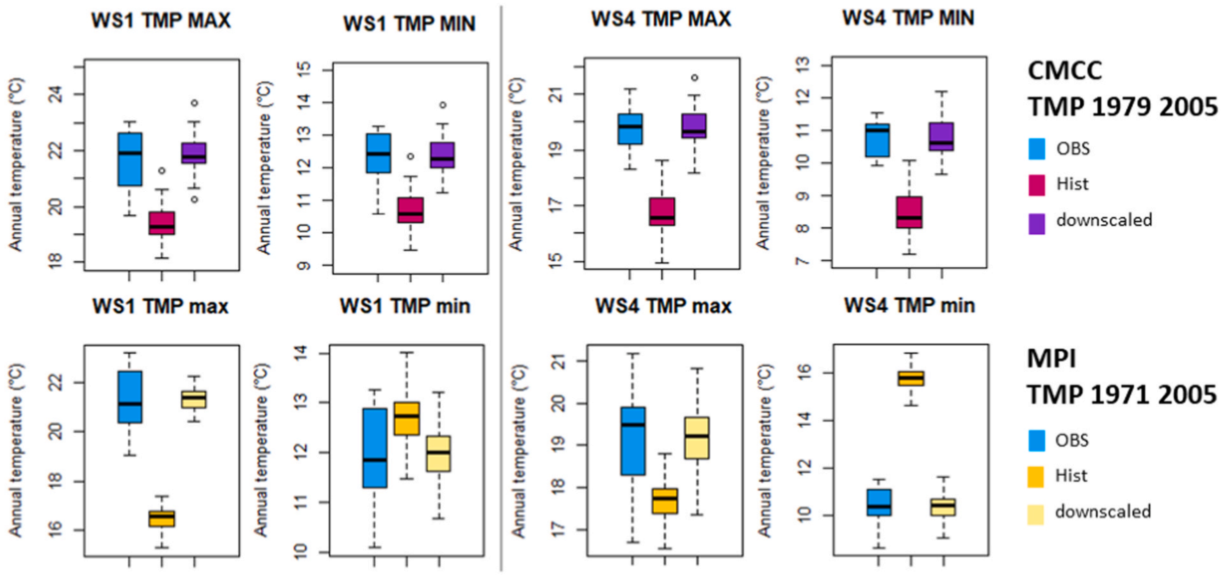

Fig. 5. Comparison of observed, historical, and downscaled (1979–2005) annual mean maximum and minimum temperatures for the CMCC model and the MPI model (1971–2005). The upper whiskers represent the 90th percentile, the lower the 10th percentile, the major quartile the 75th percentile, the minor the 25th percentile, the central black line the median, and the dots are the outliers.

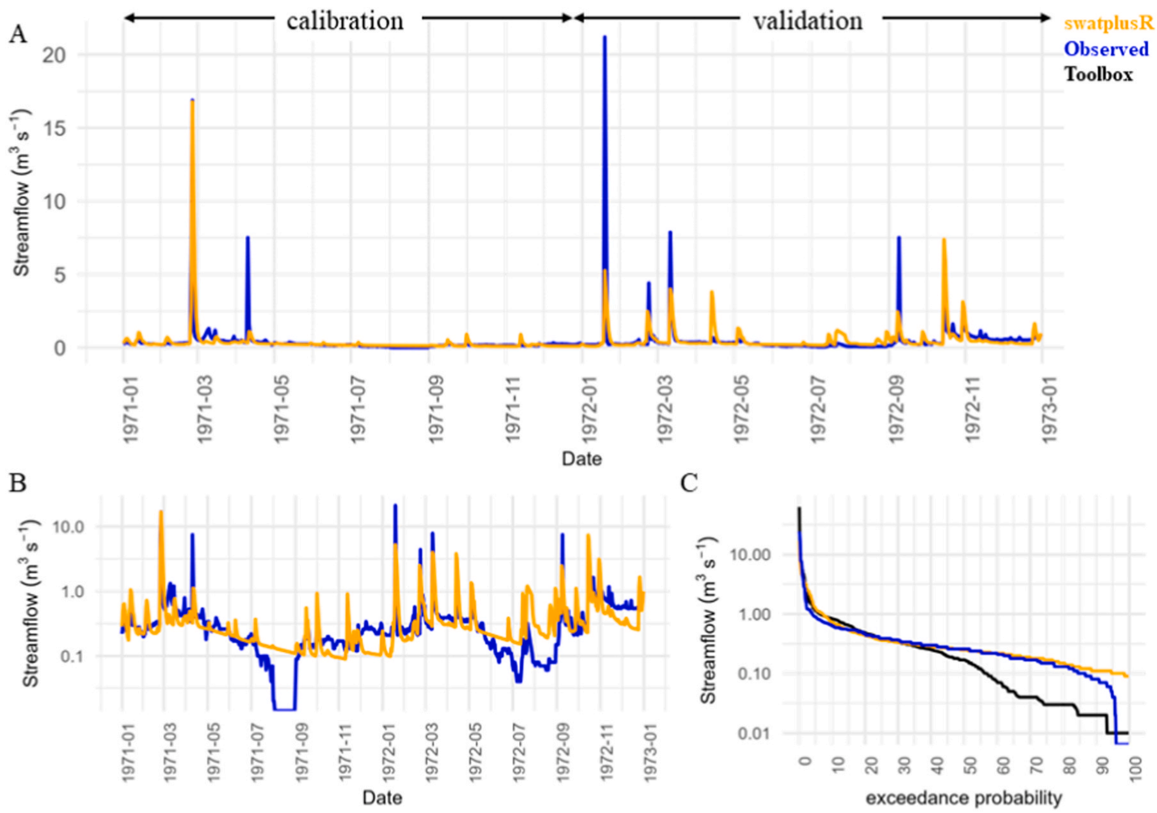

Fig. 6. A) Calibration (1971) and validation (1972) results; observed and simulated streamflow comparison; B) observed streamflow and simulated streamflow in logarithmic scale; C) comparison of FDCs observed streamflow, simulated with SWATplusR and simulated with the SWAT+Toolbox (v0.7.6) in logarithmic scale.

(Fig. 5). The CMCC model underestimated the median annual maximum temperatures by about 3 °C for both stations. The median annual minimum temperatures were underestimated by about 2 °C (WS1) and by 2.7 °C (WS4). The MPI model underestimated the medians of the annual maximum temperatures by 4.5 °C (WS1) and 1.7 °C (WS4) and overestimated the medians of the annual minimum temperatures by about 1 °C (WS1) and about 5 °C (WS4) (Fig. 5).

In the Locone basin, a global increase in average annual temperatures is expected for the near future (2020–2049) compared to the baseline period (1980–2010) (Table 3). The expected increase for the maximum temperatures is + 1.04 °C (CMCC) and + 0.94 °C (MPI) for WS1 and + 1.25 °C (CMCC) and + 1.47 °C (MPI) for WS2. An increase of + 0.7 °C and + 1.23 °C is expected for the minimum temperatures (Table 3). Both models predict an increase in average summer temperatures of more than 1 °C. The greatest increase is expected for the average maximum temperatures in August, which vary between + 6 °C and + 3 °C respectively for the CMCC and MPI model for WS1 and + 3 °C according to the MPI model for WS2.

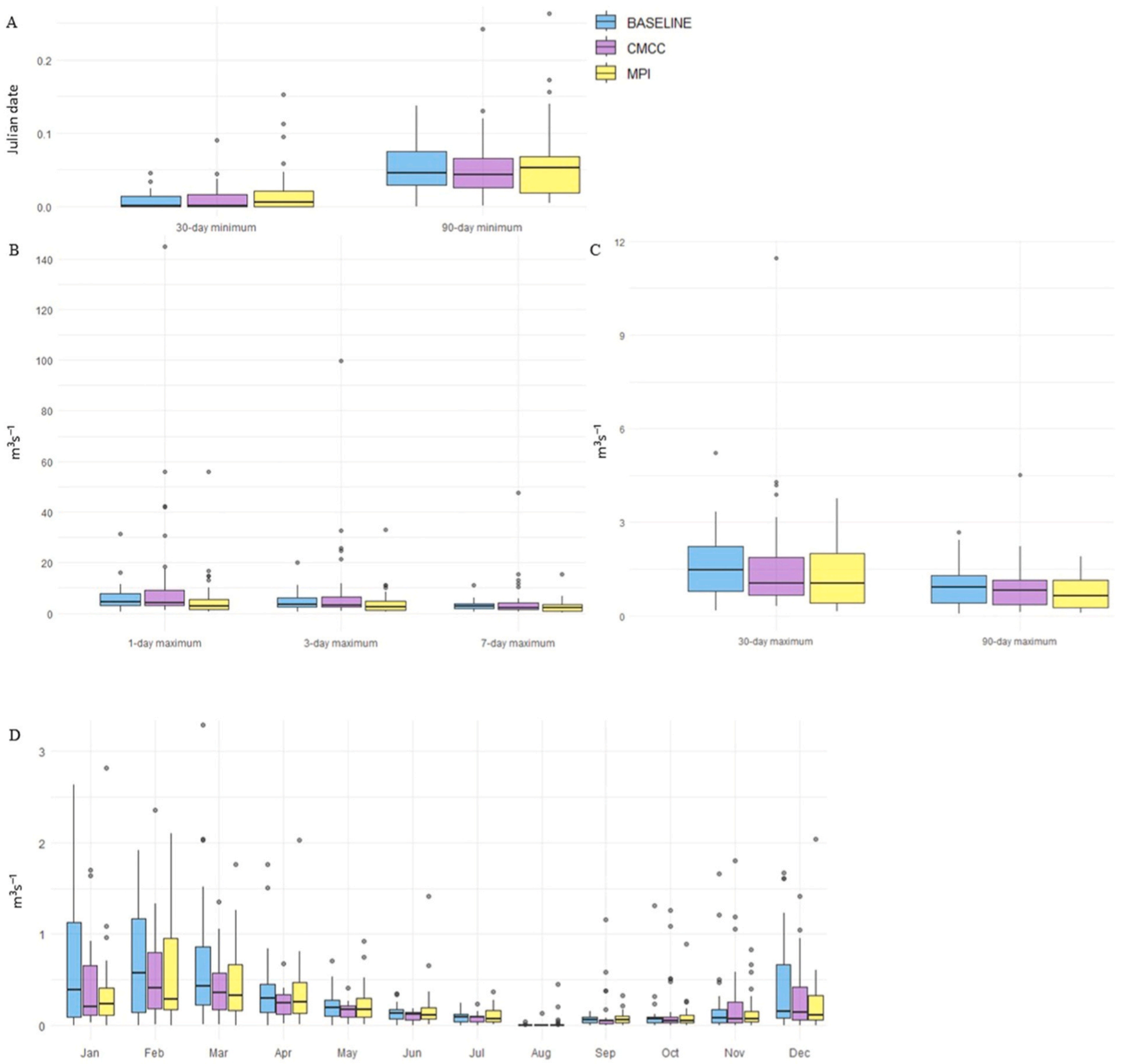

Fig. 7. A) Annual minimum, average: 30-day minimum, 90-day minimum. B) Annual maximum, average: 1-day maximum, 3-day maximum, 7-day maximum. C) Annual maximum, average: 30-day maximum,90-day maximum. D) Monthly mean flow. The upper whiskers represent the 90th percentile, the lower the 10th percentile, the major quartile is the 75th percentile, the minor is the 25th percentile, the central black line is the median, and the dots are the outliers.

3.2. Modeling daily streamflow

Table 4 lists the 15 model parameters that were included in the model calibration. The right column shows the final parameter change value that was selected in the calibration. The type of change may consist of: replacing the initial value of the parameter with a new value in absolute value (absval); adding an absolute value to the initial value of the parameter (abschg); multiplying the initial value of the parameter by 1 + given value (relchg). Some parameters have been added compared to the previous work (Leone et al., 2023b): SURLAG, PERCO, CN3_SWF and LATQ_CO. In particular, CN3_SWF allows for a delay in the onset of runoff after dry spells while LATQ_CO is a linear coefficient controlling lateral flow (Wagner et al., 2022).(Table 4).

The defined objective criteria identified 16 acceptable simulations. The single selected model parameterization resulted in model performance values of r = 0.80, MAE = 0.16, RMSE = 0.6, R^2 = 0.63, PBIAS = 0.29, NSE = 0.65, and KGE = 0.75. For the low-flow period the values were MAE = 0.08 and PBIAS = -4.53. For validation they are r = 0.60, R^2 = 0.4, PBIAS = -1.05, KGE = 0.40 and NSE = 0.40. These values were considered good for calibration and acceptable for validation based on other work in the Mediterranean environment (De Girolamo et al., 2015; De Girolamo et al., 2017b) and considering that the calibration was carried out on a daily scale that leads to greater difficulties in dry climates (Castellanos-Osorio et al., 2023). The recession of both peaks of the calibration period is well simulated although one of the two peaks is underestimated (Fig. 6A, B). The recession phase in the validation period was also well simulated by the model; however, the peaks are not well simulated since both overestimation and underestimation were predicted (Fig. 6A, B). This is justifiable considering that climate data are affected by errors and missing data and because rainfall events are frequently localized in small areas. The mean annual PET estimated by the model at basin scale was 1057 mm. This value was comparable with similar studies in neighboring watersheds (De Girolamo et al., 2022c; Gentilucci et al., 2021).

The changes made in this work compared to the previous one (Leone et al., 2023b) have led to a better simulation of the low flows at the PB measurement station (Fig. 6C). In Leone et al. (2023b), albeit with good statistical results, the authors highlighted the underestimation of the low flows. In this work, therefore, efforts have been made to improve the simulation of the low flow (exc. freq. 50–80% in FDC, Fig. 6C) and the extremely low flow (exc. freq. 80–90% in FDC, Fig. 6C). However, the zero-flow condition remains a critical point in the simulation, therefore the ZF threshold was defined based on the FDC. Specifically, the minimum simulated streamflow was compared with minimum measured streamflow and a value of 0.070 m^3s^{-1} was assumed as ZF threshold.

3.3. Setting an E-Flow regime under climate change impact

The boxplots (Fig. 7) provide quantitative information on the variability of the flow regime components, useful to water resource managers to define the near-future releases from the dam. The IHAs were evaluated based on daily streamflow simulated by the model with observed climatic data (1980–2010 baseline, Supplementary material S1) and based on simulated daily streamflow with the projected climate for the near-future scenario (2020–2050; Supplementary material S2 and S4) of the two models. Globally, a reduction in flows is expected in the near-future scenario: the average flow calculated over 30 years is equal to 0.40 m^3s^{-1} for the baseline, 0.38 m^3s^{-1} and 0.32 m^3s^{-1}, respectively, for the CMCC model and the MPI model.

The number of outliers detected for the IHAs showing the magnitude and duration of the low flow (i.e., minimum flow recorded over consecutive days, 30-day minimum and 90-day minimum flow) (Fig. 7A) tends to increase according to the MPI model, due to an increase in extreme events of minimum magnitude as identified by IHA findings (e.g., small floods recorded in summer; Supplementary material, S4). No changes are foreseen for the IHAs, such as annual minimum flows over 1-, 3- and 7- consecutive days (1-, 3-, 7-days minimum), because their values were zero both for the baseline and for the near future. The outliers of the IHAs, representing the magnitude and duration of high flow (1-, 3-, 7- day maximum), increased for future scenarios due to an increase in small floods (Fig. 7B) (Supplementary material, S4). The CMCC model resulted in greater variability with respect to the baseline while the MPI model predicted a reduction in the interquartile range. Globally, a reduction of the 30- and 90-day maximum flow according to both models is expected.

The magnitude of monthly flow is shown in Fig. 7D; these IHAs are part of the first group and represent the extent of the monthly water condition. In the baseline, the low-flow condition in the Locone river occurs from the end of May to the end of December. The median streamflow in these months varies from 0.20 m^3s^{-1} to 0.15 m^3s^{-1} with the zero-flow condition in August. In future scenarios, the largest CC impact was predicted in the winter months (Dec-Jan-Feb). Indeed, the reduction of the 75th percentiles of the streamflow was 30% and 53% (Dec), 36% and 63% (Jan), 36% and 21% (Feb), for the CMCC and the MPI models, respectively. A reduction in the average monthly flow is also expected in the spring months (Mar-Apr-May). The E-Flows should be set in spring between 0.16 m^3s^{-1} and 0.54 m^3s^{-1} (interquartile range) based on the baseline streamflow data, while E-Flows would vary between 0.12 m^3s^{-1} and 0.44 m^3s^{-1} based on the near-future data. In summer (Jun-Jul), the models provided different results: the CMCC model predicted a reduction of the 75th percentile of the flows (-35% and -15%) and the MPI model an increase (+47% and +38%), probably due to an increase in the incidence of small floods. Furthermore, it is important to underline the presence of outliers in the streamflow in August (MPI model) and in the autumn months (Sept-Oct-Nov) according to both models. The outliers are due to an increase in small floods (Fig. 7D) (Supplementary material, S4). For the IHAs representing the frequency and duration of high and low pulses (group 4), the E-Flow regime should consider that low-pulse counts vary between 2 and 8 and high-pulse counts between 4 and 8. There is a slight reduction in low-pulse duration and a slight increase in high-pulse duration for the two models. The E-Flow regime should be set with respect to the duration of the low pulses between 8 and 19 days and between 3 and 6 days for the high pulses.

4. Discussion

4.1. Bias correction

The two climate models used in this work differ in terms of spatial resolution (8 km CMCC and 40 km MPI) and in terms of climate outputs. The daily precipitation provided by the CMCC model in the historical period (1979–2005) was underestimated compared to the observed data; the same applies to the maximum and minimum temperatures. The daily precipitation of the MPI model was overestimated (in the historical period 1971–2005), while the daily maximum temperatures were overestimated, and the minimum temperatures were underestimated. The outputs of climate models are often affected by systematic errors. For this reason, it is extremely important to resort to bias correction procedures (De Girolamo et al., 2017a) so that the outputs of climate models are modified based on local conditions. The downscaling is particularly important in the Mediterranean environment where rainfall is subject to spatial variability (Peres et al., 2020; Senatore et al., 2022). There are many bias correction methods with different advantages and disadvantages, and the debate about the "best method" is still heated (Maraun et al., 2017; Teutschbein and Seibert, 2012). Ngai et al. (2017) and Dumitrescu et al. (2023) pointed out that the QM is the method that provides more accurate results for the temperatures. The QM is not limited to a simple correction of the mean value of each simulated series but also corrects the overall variability. This aspect makes it potentially more effective for correcting extreme values (Wetterhall et al., 2012). After the bias correction, both models represented the rainfall and temperature for the historical period well; therefore, both models are reliable for future predictions. However, since rainfall is strongly influenced by the orography of the study area, the higher spatial resolution of the CMCC compared to the MPI could be an advantage in mountainous areas.

A limitation of this work may derive from the limited number of climate models used for future climate projections (CMCC and MPI). Our choice was based on the necessity of making the results easily readable. The E-Flow regime was set through many IHAs; therefore, using more climatic models would have made it difficult to summarize and represent the results. Indeed, a high variability can be found among climate models resulting in different predicted flow-regime alterations (Kakouei et al., 2020). On the other hand, our goal was to evaluate whether climate change needs to be considered when setting E-Flows or if it is negligible. To include the variability due to climate models, we selected two models: the CMCC and MPI, which underestimated and overestimated climatic variables in past decades, respectively. However, a large uncertainty could affect the results of the IHAs estimated for the near future.

4.2. Hydrological modeling

The limited data availability (hydrological and ecological) is the main problem that complicates eco-hydrological studies in the Mediterranean environment, despite the expansion of the monitoring networks being one of the cornerstones of the WFD (EC, 2000) and of the Guide document no. 31 (CIS n. 31; EC, 2015). As reported by Leone et al. (2023a), there are only a few studies in the literature in which a specific methodology is applied to set an E-Flow regime to non-perennial rivers. Most of the authors (e.g., Papadaki et al., 2017; Godinho et al., 2014; Senent-Aparicio et al., 2021; Theodoropoulos et al., 2018) used hydrological methods because these approaches require only daily or monthly streamflow in un-impacted conditions.

In case of limited data availability, hydrological models are valid tools to generate un-impacted streamflow (De Girolamo et al., 2017b). For instance, the SWAT model is a flexible tool also widely used in the Mediterranean environment (Aloui et al., 2023). However, hydrological modeling is more reliable the better and denser the input database is. The main difficulties of this work are caused by the limited available quantitative and qualitative input data (i.e., limited number of weather stations, gaps in the time series, WWTP data). Since there are only a few measurements available throughout the year concerning the WWTPs, we forced the discharge to be constant and the qualitative values to be equal to the threshold limits required by the law. These assumptions may have strongly influenced the simulation results, especially the low flow. In addition, the Mediterranean region is often subject to convective precipitation, which is strongly dependent on the orography and often localized in very small areas. This characteristic has a huge influence on the modeling results, especially in catchments where the rainfall gauges are sparse (Ricci et al., 2018). The PET calculated with the Hargreaves and Samani equation was found to be coherent with the data reported in the literature in the same climatic area, but it depends on extraterrestrial solar radiation for which there are no observed data in the basin resulting in a further element of uncertainty. The availability of only two years of daily streamflow certainly makes calibration and validation even more uncertain since floods with very high return periods could not be accurately simulated. Despite the above-mentioned limitations, this work allows us to demonstrate the enormous potential of the new version of the SWAT+ model by testing new parameters. For example, a good simulation of the recession after the peak was obtained due to the new CN3_SWF parameter. Indeed, this parameter allows the user to have more control over the runoff according to Wagner et al. (2022).

There can be different calibration strategies for hydrological models to simulate flows in non-impacted conditions in an arid environment. For example, Castellanos-Osorio et al., (2023) have demonstrated this by applying SWAT+ at a monthly scale and then obtaining the daily flow rate with monthly-daily disaggregation techniques. Senant-Aparicio et al., (2021) evaluated the performance of the SWAT+ model in simulating low flow using the logarithmic NSE.

This paper had the twofold objective of improving the low-flow simulation and showing a different calibration strategy, given the common difficulties reported in the literature (Staudinger et al., 2011; Pfannerstill et al., 2014). In the previous work by Leone et al. (2023b), the calibration of SWAT+ for the same study area was conducted using 11 parameters with the SWAT+ Toolbox and NSE maximization as an objective function. Although considered good from a statistical point of view following the criteria proposed by Moriasi et al. (2007), the result revealed a substantial underestimation of low flow (from 50% to 95% of exc. frequency in the FDC, Fig. 6C). This is in contrast with the results obtained by other authors (De Girolamo et al., 2022b; Ricci et al., 2022) who used the

SWAT2012 version in a Mediterranean environment and who obtained an overestimation of the low flow.

According to Wagner et al. (2022), a definitive improvement in the simulation of low flow could be obtained by making changes to the groundwater parameters by reactivating, for example, the GW_DELAY parameter (the time in which the water remains in the vadose zone before recharging the aquifer) included in the SWAT2012 version. In this work, the SEEP_DEEP parameter proved sensitive to reducing the amount of water that recharges the deep aquifer and which the model reads as "water lost from the catchment area" (Neitsch et al., 2005). The model calibration performed in the R environment allowed different criteria to be set to determine 'good' simulations following the parameter calibration. Each performance criterion has its advantages and disadvantages: the KGE tends to underestimate the peaks and overestimate the low water flows, but compared to the calibration based on the NSE, it improves the bias and the measure of variability (Gupta et al., 2009). The results clearly showed an improvement in simulating the low flow (Fig. 6C) compared to the previous version of the SWAT+ (v2.0.4 revision 60.5.3) (Leone et al., 2023b). However, the zero flow was never simulated by the model, even in the latest version. To improve the simulation of zero flows, observed in August, we introduced the ZF threshold as reported in previous studies (De Girolamo et al., 2015; De Girolamo et al., 2017b; De Girolamo et al., 2022b). Identified through a simple comparison of the annual FDCs (measured and simulated), this threshold was subtracted from the simulated daily streamflow time series before computing the IHAs. However, in this work, the introduction of the ZF threshold is an additional source of uncertainty, which is difficult to quantify since the same measurements of the extremely low flow are affected by large uncertainty (van Meerveld et al., 2020).

4.3. E-Flow regime and hydrological regime alterations due to CC

The Mediterranean regions will be among the most vulnerable areas on the planet to CC (IPCC, 2014). The extreme climatic events that have occurred in Apulia due to CC and the vulnerabilities of the region make it extremely important to develop cross-sectoral approaches and methodologies that can be integrated into decision-making processes (SEETCP, 2012–, 2014). In line with other studies in the Mediterranean environment (De Girolamo et al., 2022a; De Girolamo et al., 2017a; Mereu et al., 2021; Nerantzaki et al., 2015; Skoulikidis et al., 2011), this study highlighted that an increase in dry conditions (lower average precipitation and increase in temperatures) may occur at the basin scale in the near future. The main effects in terms of precipitation will occur in spring, as this season is subject to more variations induced by CC than the others (Gordo and Sanz, 2010). Indeed, both models predicted drier springs (Mar- Apr- May) (rain reduction by -24% CMCC model and -11% MPI model). The greatest temperature variations are expected in the summer (between +1 °C and +3 °C respectively for the CMCC and MPI model). These changes in climate will produce alterations of the hydrological regime, aggravating the condition of water stress, which are recorded in the region and in large parts of the Mediterranean Basin (Skoulikidis et al., 2011; Iglesias et al., 2007). In their studies, several authors reported a shift from perennial to non-perennial rivers and an intensification of the low-flow condition towards extreme low flow (De Girolamo et al., 2022a; Döll and Schmied, 2012). In this study, to characterize the hydrological regime, daily streamflows under un-impacted conditions were simulated for the baseline period 1980–2010, based on the observed precipitation and temperatures, and for the near future (2020–2050), based on two scenarios RCP 4.5 and SSP2 4.5 using bias-corrected climatic variables. The IHAs were calculated and compared with those of the baseline to evaluate the alterations induced to the hydrological regime by the CC.

The studies conducted by De Girolamo et al. (2017a), (2022a) in a basin near the Locone River reveal a reduction in the average annual flow of approximately 20% according to the MPI model in the period 2030–2059. Senant-Aparicio et al., (2021) evaluated the impact of climate change in a basin in northern Spain. The results that emerged for the near future (2021–2050) included a reduction in the average flows of the series between 5% and 7%. In this paper, similar results showed that a reduction of the mean annual streamflow is expected for the near future (5% and 20% for CMCC model and the MPI model, respectively) and a different intra-annual variability compared to the baseline. For this reason, the alterations induced by CC should be considered in the definition of the E-Flow regime to balance the human and river ecosystem needs. The monthly flows represent a crucial indicator for characterizing the hydrological regime of temporary rivers. In this work, both models envisage a reduction in the winter and spring streamflow; the CMCC model predicted a reduction in summer too. The general decline of the streamflow means a reduction of the water resource availability for the near future that requires management options to be defined and adopted urgently (i.e., precision agriculture). The reduction of the summer streamflow could cause the death of some fish species due to the increase in water temperature and the reduction of dissolved oxygen (Pradhanang et al., 2013). This circumstance is particularly relevant in the Mediterranean environment where non-perennial rivers show natural low flows and zero flows, especially in the summer months. As demonstrated by Owusu et al. (2022), low flows and natural annual floods support native species life cycles and riverine habitats.

No water quality data were available in the basin under consideration, but it is plausible that water discharges from WWTPs in a context that is naturally dry and probably aggravated by CC will make water quality standards lower than those currently existing because less water will be able to dilute certain substances present in wastewater. The reduction of the 1- and 7-day maximum annual flows foreseen by both models could affect the river channel morphology and physical habitat conditions (Arthington, 2012). The implementation of the E-Flow regime is considered one of the main actions in countering the degradation of river habitats (Tickner et al., 2020) and restoring, or maintaining, the good ecological status of rivers according to the provisions of the WFD. This work is an example of a cascade methodology, i.e., a starting point for evaluating the possible alterations that can be induced on the hydrological regime in conditions not impacted by CC to then be able to set the E-Flow regime of the Locone River. The definition of the E-Flow regime for temporary rivers is still a topic for research: most of the existing methods have been validated for perennial rivers, and neglecting the temporary character of non-perennial rivers could damage their ecology (Leone et al., 2023a; Acuña et al., 2020). Setting an E-Flow regime should always be considered an iterative process; the evolution of the ecology should be evaluated over time, as well as the quantitative variations due to CC and water needs. The results of the RVA can be used as guidelines for setting an E-Flow regime to achieve the WFD objectives. However, monitoring of the ecological status is needed to verify that the E-Flow regime adopted can protect the river ecosystem. In addition, setting an E-Flow regime is linked to the problem of balancing human and ecosystem water needs (Derepasko et al., 2021a); hence, different options for E-Flow management should be developed and compared, and optimization models should be developed to improve the process of option selection (Derepasko et al., 2021b).

5. Conclusions

This work assesses the hydrological regime alterations due to CC and the implications on the E-Flow regimes for the Locone basin, an area with limited data availability and with a river network showing a temporary character. The new SWAT+ executable (revision 60.5.5) was used to simulate natural streamflow for baseline and future decades. The difficulties in simulating the low flow, highlighted in previous work, were also addressed in this paper. Specifically, the SWATplusR package in the R environment was tested to improve the simulation of the low flow. The final simulation results showed that SWAT+ is capable of simulating discharge in extended low-flow periods, which are frequent in the Mediterranean regions. The results clearly showed that the revised calibration strategy adopted in this work improved the low-flow simulation compared to the previous model setup, which employed the SWAT+ executable revision 60.5.3 and was calibrated using the SWAT+ Toolbox (v0.7.6).

This work analysed the climate for the near future predicted by two models (i.e., CMCC and MPI). It demonstrated the importance of carrying out bias correction operations by identifying those parameters capable of providing as much adherence as possible between historically measured and modeled climatic data. In the near future (2020–2049), the two models predicted, with some slight discrepancies, an increase in temperatures and a reduction in rainfall that led to a reduction in freshwater availability and to flow regime alterations. A number of IHAs (19) were used to evaluate the alterations induced in the hydrological regime by CC. Both models predicted greater biases in the magnitude of monthly discharges and in the magnitude of yearly extreme conditions. Therefore, the E-flows defined on the flow regime of the past decades, without considering the changes taking place, would not sustain human needs and river ecosystems.

The lesson learned from this study was that several difficulties may be faced when setting the E-Flow regime for temporary rivers, mainly related to the limited data availability. However, a first attempt for designing the E-Flows can be done by using the hydrological method based on the RVA and modeled streamflow data. Indeed, the RVA method makes it possible to consider the temporariness of the streamflow, which is an important peculiarity of temporary rivers. On the other hand, this study clearly showed that the CC will have a huge influence on water resource availability in the near future. Specifically, alterations of all the components of the flow regime are expected; therefore, the effects of CC must be included in the E-Flows.

This study has several limitations. On the one hand, the limited data availability of streamflow for calibrating the model could have introduced a parameterization that is not indicative of all the peculiarities of the flow regime (i.e., extremely wet years are missed). On the other hand, the limited number of model projections (i.e., CMCC, MPI) used in this study could have increased the uncertainty that generally affects the results of climate predictions. Last, the E-Flow defined with a hydrological method is only a first step because, although the relationship between hydrological components and ecology is reported in the literature, it would be advisable to make site-specific ecological assessments. Temporary rivers are characterized by naturally specific aquatic habitats with different biogeochemical processes and biological communities compared to perennial rivers that require specific studies.

Despite the above mentioned limitations, this study may be very useful to the River Basin Authorities for setting the E-Flow in data-scarce areas. For a better analysis of the E-Flow, we recommend that River Basin Authorities improve the monitoring of the hydrological and ecological status and data accessibility and finally take into account the CC impacts on the flow regime. Last, we also recommend that stakeholders (e.g., farmers' associations, irrigation consortia) implement all the necessary measures to reduce water use right now since, due to CC, water resources availability is expected to decrease.

Further studies are needed to develop different options for E-Flow management considering a number of factors (e.g., operations schemes, supply competition, changing environmental conditions) and for implementing optimization models to improve the process of option selection.

CRediT authorship contribution statement

Marianna Leone: Writing- Original draft preparation, Writing- Reviewing and Editing, Data curation, Formal analysis, Methodology, Software, Visualization. **Anna Maria De Girolamo:** Conceptualization, Validation, Supervision, Writing- Original draft preparation; Writing - Reviewing and Editing, Funding acquisition. **Martin Volk:** Writing-Reviewing and Editing; validation. **Francesco Gentile:** Writing - Reviewing and Editing. **Christoph Schürz:** Writing - Reviewing and Editing, Software, Methodology, Formal analysis. **Michael Strauch:** Writing - Reviewing and Editing, Software, Methodology, Validation. **Antonio Lo Porto:** Funding acquisition. **Giovanni Francesco Ricci:** Writing-Original draft preparation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Conflicts of interest statement

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2024.101698.

References

Acuña, V., Jorda-Capdevila, D., Vezza, P., De Girolamo, A.M., McClain, M.E., Stubbington, R., Datry, T., 2020. Accounting for flow intermittency in environmental flows design. J. Appl. Ecol. 57, 742–753. https://doi.org/10.1111/1365-2664.13590.

Aloui, S., Mazzoni, A., Elomri, A., Aouissi, J., Boufekane, A., Zghibi, A., 2023. A review of soil and water assessment tool (SWAT) studies of Mediterranean catchments: applications, feasibility, and future directions. J. Environ. Manag. 326, 116799 https://doi.org/10.1016/j.jenvman.2022.116799.

Althoff, D., Rodrigues, L.N., 2021. Goodness-of-fit criteria for hydrological models: model calibration and performance assessment. J. Hydrol. 600, 126674 https://doi.org/10.1016/j.jhydrol.2021.126674.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., 1998. Large area hydrologic modelling and assessment part I: model development. J. Am. Water Resour. Assoc. 34 (1), 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05961.x.

Arthington, A., 2012. Environmental flows. Saving Rivers in the Third Millennium. University of California Press, Berkeley, CA.

Barresi Armoa, O.L., Sauvage, S., Houska, T., Bieger, K., Schürz, C., Sánchez Pérez, J.M., 2023. Representation of hydrological components under a changing climate—a case study of the Uruguay River Basin using the new version of the soil and water assessment tool model (SWAT+). Water 15 (14), 2604. https://doi.org/10.3390/w15142604.

Bieger, K., Arnold, J.G., Rathjens, H., White, M.J., Bosch, D.D., Allen, P.M., 2019. Representing the connectivity of Uplandareas to floodplains and streams in SWAT+. J. Am. Water Resour. Assoc. 55 (3), 578–590. https://doi.org/10.1111/1752-1688.12728.

Bieger, K., Arnold, J.G., Rathjens, H., White, M.J., Bosch, D.D., Allen, P.M., Volk, M., Srinivasan, R., 2017. Introduction to SWAT+, a completely restructured version of the soil and water assessment tool. J. Am. Water Resour. Assoc. 53 (1), 115–130. https://doi.org/10.1111/1752-1688.12482.

Bonada, N., Resh, V.H., 2013. Mediterranean-climate streams and rivers: geographically separated but ecologically comparable freshwater systems. Hydrobiologia 719, 1–29. https://doi.org/10.1007/s10750-013-1634-2.

Borg Galea, A., Sadler, J.P., Hannah, D.M., Datry, T., Dugdale, S.J., 2019. Mediterranean intermittent rivers and ephemeral streams: challenges in monitoring complexity. Ecohydrology 12 (8), e2149. https://doi.org/10.1002/eco.2149.

Bradford, R.B., 2000. Drought Events in Europe. Springer, Netherlands, p. 319. https://doi.org/10.1007/978-94-015-9472-1_2.

Brouziyne, Y., De Girolamo, A.M., Aboubdillah, A., Benaabidate, L., Bouchaou, L., Chehbouni, A., 2021. Modelling alterations in flow regimes under changing climate in a Mediterranean watershed: an analysis of ecologically-relevant hydrological indicators. Ecol. Inform. 61, 101219 https://doi.org/10.1016/j.ecoinf.2021.101219.

Brunetti, M., Maugeri, M., Nanni, T., Auer, I., Böhm, R., Schöner, W., 2006. Precipitation variability and changes in the greater Alpine region over the 1800–2003 period. J. Geophys. Res. Atmospheres 111 (D11). https://doi.org/10.1029/2005JD006674.

Bucchignani, E., Montesarchio, M., Zollo, A.L., Mercogliano, P., 2016. High resolution climate simulations with COSMO-CLM over Italy: performance evaluation and climate projections for the 21st century. Int. J. Climatol. https://doi.org/10.1002/joc.4379.

Carnell R., 2022. lhs: Latin Hypercube Samples_. R package version 1.1.6, <⟨https://CRAN.R-project.org/package=lhs⟩>.

Ćosić-Flajsig, G., Karleuša, B., Glavan, M., 2021. Integrated water quality management model for the rural transboundary river basin—a case study of the Sutla/Sotla River. Water 13 (18), 2569. https://doi.org/10.3390/w13182569.

D'Agostino, D.R., Scardigno, A., Lamaddalena, N., El Chami, D., 2014. Sensitivity analysis of coupled hydro-economic models: quantifying climate change uncertainty for decision-making. Water Resour. Manag. 28, 4303–4318. https://doi.org/10.1007/s11269-014-0748-2.

Daccache, A., D'Agostino, D., Lamaddalena, N., El Chami, D., 2016. A decision tool for sustainable agricultural policies: the case of water saving scenarios for Apulia Region (Southern Italy). Water Policy 18 (1), 126–142. https://doi.org/10.2166/wp.2015.050.

D'Ambrosio, E., Ricci, G.F., Gentile, F., De Girolamo, A.M., 2020. Using water footprint concepts for water security assessment of a basin under anthropogenic pressures. Sci. Total Environ. 748, 141356 https://doi.org/10.1016/j.scitotenv.2020.141356.

Datry, T., Larned, S.T., Tockner, K., 2014. Intermittent rivers: a challenge for freshwater ecology. BioScience 64 (3), 229–235. https://doi.org/10.1093/biosci/bit027.

De Girolamo, A.M., Barca, E., Pappagallo, G., Lo Porto, A., 2017b. Simulating ecologically relevant hydrological indicators in a temporary river system. Agric. Water Manag. 180, 194–204. https://doi.org/10.1016/j.agwat.2016.05.034.

De Girolamo, A.M., Barca, E., Leone, M., Lo Porto, A., 2022a. Impact of long-term climate change on flow regime in a Mediterranean basin. J. Hydrol. Reg. Stud. 41, 101061 https://doi.org/10.1016/j.ejrh.2022.101061.

De Girolamo, A.M., Lo Porto, A., Pappagallo, G., Tzoraki, O., Gallart, F., 2015. The hydrological status concept: application at a temporary River (Candelaro, Italy). River Res. Appl. 31, 892–903. https://doi.org/10.1002/rra.2786.

De Girolamo, A.M., Bouraoui, F., Buffagni, A., Pappagallo, G., Lo Porto, A., 2017a. Hydrology under climate change in a temporary river system: potential impact on water balance and flow regime, 2017 River Res Applic. 33, 1219–1232. https://doi.org/10.1002/rra.3165.
De Girolamo, A.M., Cerdan, O., Grangeon, T., Ricci, G.F., Vandromme, R., Lo Porto, A., 2022b. Modelling effects of forest fire and post-fire management in a catchment prone to erosion: impacts on sediment yield. Catena 212, 106080. https://doi.org/10.1016/j.catena.2022.106080.
De Girolamo, A.M., Drouiche, A., Ricci, G.F., Parete, G., Gentile, F., Debieche, T.H., 2022c. Characterising flow regimes in a semi-arid region with limited data availability: the Nil Wadi case study (Algeria. J. Hydrol. Reg. Stud. 41, 101062 https://doi.org/10.1016/j.ejrh.2022.101062.
Derepasko, D., Guillaume, J.H., Horne, A.C., Volk, M., 2021a. Considering scale within optimization procedures for water management decisions: balancing environmental flows and human needs. Environ. Model. Softw. 139, 104991 https://doi.org/10.1016/j.envsoft.2021.104991.
Derepasko, D., Peñas, F.J., Barquín, J., Volk, M., 2021b. Applying optimization to support adaptive water management of rivers. Water Management of Rivers. Water 2021 (13), 1281. https://doi.org/10.3390/w13091281.
Dile Y., Srinivasan R., George, C., 2023. QGIS Interface for SWAT+: QSWAT+ version 2.4.
Döll, P., Schmied, H.M., 2012. How is the impact of climate change on river flow regimes related to the impact on mean annual runoff? A global-scale analysis. Environ. Res. Lett. 7 (1), 014037 https://doi.org/10.1088/1748-9326/7/1/014037.
Dumitrescu, A., Amihaesei, V.A., Cheval, S., 2023. RoCliB–bias-corrected CORDEX RCM dataset over Romania. Geosci. Data J. 10 (2), 262–275. https://doi.org/10.5281/zenodo.6336837.
Dyson, M., Berkamp, G., Scanlon, J. (Eds.), 2003. Flow: the essentials of environmental flows. IUCN, Gland, Switzerland and Cambridge, UK.
EC, 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for community action in the field of water policy (Water Framework Directive)" (European Commission). Off. J. Eur. Communities L327, 1–72.
EC: European Commission, 2015. Ecological flows in the implementation of the water framework directive. Guidance document n°31, Office for Official Publications of the European Communities, Luxembourg.
EEA: CORINE Land Cover 2006 raster data, Version 20u1 (24/02/2020), available at: ⟨http://www.eea.europa.eu/data-and-maps/data/corine-land-cover-2006-raster-3⟩, last access: December 2021.
García-Ruiz, J.M., López-Moreno, J.I., Vicente-Serrano, S.M., Lasanta–Martínez, T., Beguería, S., 2011. Mediterranean water resources in a global change scenario. Earth-Sci. Rev. 105 (3-4), 121–139. https://doi.org/10.1016/j.earscirev.2011.01.006.
Gentilucci, M., Bufalini, M., Materazzi, M., Barbieri, M., Aringoli, D., Farabollini, P., Pambianchi, G., 2021. Calculation of potential evapotranspiration and calibration of the Hargreaves equation using geostatistical methods over the last 10 years in central Italy. Geosciences 11 (8), 348. https://doi.org/10.3390/geosciences11080348.
Glavan, M., Ceglar, A., Pintar, M., 2015. Assessing the impacts of climate change on water quantity and quality modelling in small Slovenian Mediterranean catchment–lesson for policy and decision makers. Hydrol. Process. 29 (14), 3124–3144. https://doi.org/10.1002/hyp.10429.
Godinho, F., Costa, S., Pinheiro, P., Reis, F., Pinheiro, A., 2014. Integrated procedure for environmental flow assessment in rivers- environ (2014). Process 1, 137–147. https://doi.org/10.1007/s40710-014-0012-z.
Gordo, O., Sanz, J.J., 2010. Impact of climate change on plant phenology in Mediterranean ecosystems. Glob. Change Biol. 16 (3), 1082–1106. https://doi.org/10.1111/j.1365-2486.2009.02084.x.
Gudmundsson, L., Bremnes, J.B., Haugen, J.E., Engen-Skaugen, T., 2012. Technical note: downscaling RCM precipitation to the station scale using statistical transformations - a comparison of methods. Hydrol. Earth Syst. Sci. 16 (9), 3383–3390. https://doi.org/10.5194/hess-16-3383-2012.
Gudmundsson L., 2016. qmap: Statistical transformations for post-processing climate model output. R package version 1.0–4.
Gupta, H.V., Kling, H., Yilmaz, K.K., Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. J. Hydrol. 377 (1-2), 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003.
Hargreaves, G.H., Samani, Z.A., 1985. Reference crop evapotranspiration from temperature. Appl. Eng. Agric. 1, 96–99.
Iglesias, A., Garrote, L., Flores, F., Moneo, M., 2007. Challenges to manage the risk of water scarcity and climate change in the Mediterranean. Water Resour. Manag. 21, 775–788. https://doi.org/10.1007/s11269-006-9111-6.
ISTAT, 2010. Sesto Censimento Generale dell'Agricoltura. Istituto Nazionale di Statistica.
Keith E. Saxton, Patrick H. Willey, and Walter J. Rawls (2019). SPAW (Soil-Plant-Air-Water), Model Item, OpenGMS, https://geomodeling.njnu.edu.cn/modelItem/28b4afd0-723b-40bc-8bcd-74609a271d2c.
Kirkby, M.J., Gallart, F., Kjeldsen, T.R., Irvine, B.J., Froebrich, J., Lo Porto, A., De Girolamo, A.M., 2011. The MIRAGE team: classifying low flow hydrological regimes at a regional scale. Hydrol. Earth Syst. Sci. 15, 3741–3750. https://doi.org/10.5194/hess-15-3741-2011.
Knoben, W.J., Freer, J.E., Woods, R.A., 2019. Inherent benchmark or not? comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. Hydrol. Earth Syst. Sci. 23 (10), 4323–4331. https://doi.org/10.5194/hess-23-4323-2019.
Legislative Decree 152/2006 (Official Gazette No. 88 of 14 April 2006). Environmental standards. ⟨https://www.isprambiente.gov.it/it/garante_aia_ilva/normativa/normativa-ambientale/Dlgs_152_06_TestoUnicoAmbiental.pdf⟩.
Leone, M., Gentile, F., Porto, A.L., Ricci, G.F., De Girolamo, A.M., 2023a. Ecological flow in southern Europe: status and trends in non-perennial rivers. J. Environ. Manag. 342, 118097 https://doi.org/10.1016/j.jenvman.2023.118097.
Leone, M., Gentile, F., Lo Porto, A., Ricci, G.F., De Girolamo, A.M., 2023b. Setting an ecological flow regime in a Mediterranean basin with limited data availability: the Locone River case study (S-E Italy). Ecohydrol. Hydrobiol. https://doi.org/10.1016/j.ecohyd.2023.03.005.
Lionello, P., Congedi, L., Reale, M., Scarascia, L., Tanzarella, A., 2014. Sensitivity of typical Mediterranean crops to past and future evolution of seasonal temperature and precipitation in Apulia. Reg. Environ. Change 14 (5), 2025–2038. https://doi.org/10.1007/s10113-013-0482-y.
Maraun, D., 2013. Bias correction, quantile mapping, and downscaling: revisiting the inflation issue. J. Clim. 26, 2137–2143. https://doi.org/10.1175/JCLI-D-12-00821.1.
Maraun, D., Shepherd, T.G., Widmann, M., Zappa, G., Walton, D., Gutiérrez, J.M., Mearns, L.O., 2017. Towards process-informed bias correction of climate change simulations. Nat. Clim. Change 7 (11), 764–773. ⟨https://doi.org/10.1038/nclimate3418⟩.
Marini, G., Fontana, N., Mishra, A.K., 2019. Investigating drought in Apulia region, Italy using SPI and RDI. Theor. Appl. Climatol. 137, 383–397. https://doi.org/10.1007/s00704-018-2604-4.
MATTM: Ministero dell'Ambiente e della Tutela del Territorio e del Mare. Decreto Legislativo (D. Lgs.) 131/2008. Criteri tecnici per la caratterizzazione dei corpi idrici. ⟨https://www.gazzettaufficiale.it/eli/id/2008/08/11/008G0147/sg⟩.
Mauricio Zambrano-Bigiarini. 2020. hydroGOF: Goodness-of-fit functions for comparison of simulated and observed hydrological time seriesR package version 0.4–0. ⟨https://github.com/hzambran/hydroGOF⟩. 10.5281/zenodo.839854.
McKay, M., Beckman, R., Conover, W., 1979. Comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21, 239–245. https://doi.org/10.1080/00401706.1979.10489755.
McLeod A., 2022. _Kendall: Kendall Rank Correlation and Mann-Kendall Trend Test_. R package version 2.2.1,
Mereu, V., Gallo, A., Trabucco, A., Carboni, G., Spano, D., 2021. Modelling high-resolution climate change impacts on wheat and maize in Italy. Clim. Risk Manag. 33, 100339 https://doi.org/10.1016/j.crm.2021.100339.
Molina-Navarro, E., Trolle, D., Martínez-Pérez, S., Sastre-Merlín, A., Jeppesen, E., 2014. Hydrological and water quality impact assessment of a Mediterranean limno-reservoir under climate change and land use management scenarios. J. Hydrol. 509, 354–366. https://doi.org/10.1016/j.jhydrol.2013.11.053.
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE 50, 885–900. https://doi.org/10.13031/2013.23153.
Neitsch, S.L., Arnold, J.G., Kiniry, J.R., Williams, J.R., 2005. Soil and water assessment tool theoretical manual. Tex. Grassl. Soil Water Res. Lab. ⟨https://swat.tamu.edu/docs/⟩.

Nerantzaki, S.D., Giannakis, G.V., Efstathiou, D., Nikolaidis, N.P., Sibetheros, I., Karatzas, G.P., Zacharias, I., 2015. Modeling suspended sediment transport and assessing the impacts of climate change in a karstic Mediterranean watershed. Sci. Total Environ. 538, 288–297. https://doi.org/10.1016/j.scitotenv.2015.07.092.

Ngai, S.T., Tangang, F., Juneng, L., 2017. Bias correction of global and regional simulated daily precipitation and surface mean temperature over Southeast Asia using quantile mapping method. Glob. Planet. Change 149, 79–90. https://doi.org/10.1016/j.gloplacha.2016.12.009.

Noto, L.V., Cipolla, G., Francipane, A., Pumo, D., 2022. Climate change in the mediterranean basin (part I): induced alterations on climate forcings and hydrological processes. Water Resour. Manag. https://doi.org/10.1007/s11269-022-03400-0.

Noto, L.V., Cipolla, G., Pumo, D., Francipane, A., 2023. Climate change in the Mediterranean Basin (Part II): a review of challenges and uncertainties in climate change modelling and impact analyses. Water Resour. Manag. 1–17. https://doi.org/10.1007/s11269-023-03444-w.

Nyeko, M., 2015. Hydrologic modelling of data scarce basin with SWAT model: capabilities and limitations. Water Resour. Manag. 29, 81–94. https://doi.org/10.1007/s11269-014-0828-3.

Owusu, A., Mul, M., Strauch, M., van der Zaag, P., Volk, M., Slinger, J., 2022. The clam and the dam: a Bayesian belief network approach to environmental flow assessment in a data scarce region. Sci. Total Environ. 810, 151315 https://doi.org/10.1016/j.scitotenv.2021.151315.

Papadaki C., Konstantinos S., Ntoanidis L., Zogaris S., Dercas N., Dimitriou E., 2017. Comparative Assessment of Environmental Flow Estimation Methods in a Mediterranean Mountain River- Environmental Management. 10.1007/s00267–017-0878–4.

Pastor, A.V., Ludwig, F., Biemans, H., Hoff, H., Kabat, P., 2014. Accounting for environmental flow requirements in global water assessments. Hydrol. Earth Syst. Sci. 18, 5041–5059. https://doi.org/10.5194/hess-18-5041-2014.

Peres, D.J., Senatore, A., Nanni, P., Cancelliere, A., Mendicino, G., Bonaccorso, B., 2020. Evaluation of EURO-CORDEX (Coordinated Regional Climate Downscaling Experiment for the Euro-Mediterranean area) historical simulations by high-quality observational datasets in southern Italy: insights on drought assessment. Nat. Hazards Earth Syst. Sci. 20 (11), 3057–3082. https://doi.org/10.5194/nhess-20-3057-2020.

Pfannerstill, M., Guse, B., Fohrer, N., 2014. Smart low flow signature metrics for an improved overall performance evaluation of hydrological models. J. Hydrol. 510, 447–458. https://doi.org/10.1016/j.jhydrol.2013.12.044.

Poff, N.L., Allan, J.D., Bain, M.B., Karr, J.R., Prestegaard, K.L., Richter, B.D., Sparks, R.E., Stromberg, J.C., 1997. The natural flow regime: a paradigm for river conservation and restoration. BioScience 47 (11), 769–784. https://doi.org/10.2307/1313099.

Polemio, M., Lonigro, T., 2015. Trends in climate, short-duration rainfall, and damaging hydrogeological events (Apulia, Southern Italy). Nat. Hazards 75 (1), 515–540. https://doi.org/10.1007/s11069-014-1333-y.

Pradhanang, S.M., Mukundan, R., Schneiderman, E.M., Zion, M.S., Anandhi, A., Pierson, D.C., Steenhuis, T.S., 2013. Streamflow responses to climate change: analysis of hydrologic indicators in a New York City water supply watershed. *JAWRA*. J. Am. Water Resour. Assoc. 49 (6), 1308–1326. https://doi.org/10.1111/jawr.12086.

Prat, N., Gallart, F., Von Schiller, D., Polesello, S., García-Roger, E.M., Latron, J., Froebrich, J., 2014. The mirage toolbox: an integrated assessment tool for temporary streams. River Res. Appl. 30 (10), 1318–1334. https://doi.org/10.1002/rra.2757.

Ricci, G.F., De Girolamo, A.M., Abdelwahab, O.M., Gentile, F., 2018. Identifying sediment source areas in a Mediterranean watershed using the SWAT model, 2018 Land Degrad. Dev. 29, 1233–1248. https://doi.org/10.1002/ldr.2889.

Ricci, G.F., Zahi, F., D'Ambrosio, E., De Girolamo, A.M., Parete, G., Debieche, T.H., Gentile, F., 2022. Evaluating flow regime alterations due to point sources in intermittent rivers: a modelling approach. J. Agric. Eng. 53 (2) https://doi.org/10.4081/jae.2022.1333.

Richter B.D., Baumgartner J.V., Powell J., Braun D.P., 1996. A method for assessing hydrologic alteration within ecosystems, Conservation Biology, 1163–1174, 10 (4), https://doi.org/10.1046/j.1523–1739.1996.10041163.x.

Richter, B.D., Baumgartner, J.V., Wigington, R., Braun, D.P., 1997. How much water does a river need. Freshw. Biol. 37 (1), 231–249. https://doi.org/10.1046/j.1365-2427.1997.00153.x.

Richter, B.D., Baumgartner, J.V., Braun, D.P., Powell, J., 1998. A spatial assessment of hydrological alteration within a river network, Regul. River.: Res. Mgmt. 14, 329–340. https://doi.org/10.1002/(SICI)1099-1646(199807/08)14:4<329::AID-RRR505>3.0.CO;2-E.

Richter, B.D., Mathews, R., Harrison, D.L., Wigington, R., 2003. Ecologically sustainable water management: managing river flows for ecological integrity. Ecol. Appl. 13 (1), 206–224. https://doi.org/10.1890/1051-0761(2003)013[0206:ESWMMR]2.0.CO;2.

Rivas-Tabares, D., Tarquis, A.M., Willaarts, B., De Miguel, Á., 2019. An accurate evaluation of water availability in sub-arid Mediterranean watersheds through SWAT: Cega-Eresma-Adaja. Agric. Water Manag. 212, 211–225. https://doi.org/10.1016/j.agwat.2018.09.012.

Rolls, R.J., Arthington, A.H., 2014. How do low magnitudes of hydrologic alteration impact riverine fish populations and assemblage characteristics? Ecol. Indic. 39, 179–188. https://doi.org/10.1016/j.ecolind.2013.12.017.

Ronco, P., Zennaro, F., Torresan, S., Critto, A., Santini, M., Trabucco, A., Marcomini, A., 2017. A risk assessment framework for irrigated agriculture under climate change. Adv. Water Resour. 110, 562–578. https://doi.org/10.1016/j.advwatres.2017.08.003.

Schneider, C., Laizé, C.L.R., Acreman, M.C., Flörke, M., 2013. How will climate change modify river flow regimes in Europe? Hydrol. Earth Syst. Sci. 17, 325–339. https://doi.org/10.5194/hess-17-325-2013.

Schürz C., 2022. _SWATplusR: Running SWAT2012 and SWAT+ Projects in R_. doi:10.5281/zenodo.3373859 , R package version 0.6.7,

Scoccimarro, E., Gualdi, S., Bellucci, A., Sanna, A., Fogli, P., Manzini, E., Vichi, M., Oddo, P., Navarra, A., 2011. Effects of tropical cyclones on oceanheat transport in a high resolution coupled general circulation model. J. Clim. 24, 4368–4384. https://doi.org/10.1175/2011JCLI4104.1.

SEETCP: South East Europe Transnational Cooperation Programme SEE /C/0001/2.2./X Project: "A structured network for integration of climate knowledge into policy and territorial planning" / OrientGate (2012–2014).

Senatore, A., Fuoco, D., Maiolo, M., Mendicino, G., Smiatek, G., Kunstmann, H., 2022. Evaluating the uncertainty of climate model structure and bias correction on the hydrological impact of projected climate change in a Mediterranean catchment. J. Hydrol. Reg. Stud. 42, 101120 https://doi.org/10.1016/j.ejrh.2022.101120.

Senent-Aparicio, J., George, C., Srinivasan, R., 2021b. Introducing a new post-processing tool for the SWAT+ model to evaluate environmental flows. Environ. Model. Softw. 136, 104944 https://doi.org/10.1016/j.envsoft.2020.104944.

Senent-Aparicio, J., López-Ballesteros, A., Cabezas, F., Pérez-Sánchez, J., Molina-Navarro, E., 2021a. A modelling approach to forecast the effect of climate change on the Tagus-Segura interbasin water transfer. Water Resour. Manag. 35, 3791–3808. https://doi.org/10.1007/s11269-021-02919-y.

Shanafield, M., Bourke, S.A., Zimmer, M.A., Costigan, K.H., 2021. An overview of the hydrology of non-perennial rivers and streams. Wiley Interdiscip. Rev. Water 8 (2), e1504. https://doi.org/10.1002/wat2.1504.

Skoulikidis, N.T., Vardakas, L., Karaouzas, I., Economou, A.N., Dimitriou, E., Zogaris, S., 2011. Assessing water stress in Mediterranean lotic systems: insights from an artificially intermittent river in Greece. Aquat. Sci. 73, 581–597. https://doi.org/10.1007/s00027-011-0228-1.

Soil Survey Staff. 2022. Keys to Soil Taxonomy, 13th ed. USDA-Natural Resources Conservation Service.

Staudinger, M., Stahl, K., Seibert, J., Clark, M.P., Tallaksen, L.M., 2011. Comparison of hydrological model structures based on recession and low flow simulations. Hydrol. Earth Syst. Sci. 15 (11), 3447–3459. https://doi.org/10.5194/hess-15-3447-2011.

Stewardson, M.J., Gippel, C.J., 2003. Incorporating flow variability into environmental flow regimes using the flow events method. River Res. Appl. 19 (5-6), 459–472. https://doi.org/10.1002/rra.732.

Teutschbein, C., Seibert, J., 2012. Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. J. Hydrol. 456, 12–29. https://doi.org/10.1016/j.jhydrol.2012.05.052.

Teutschbein, C., Seibert, J., 2013. Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions? Hydrol. Earth Syst. Sci. 17, 5061–5077. https://doi.org/10.5194/hess-17-5061-2013.

Tharme, R.E., 2003. A global perspective on environmental flow assessment: emerging trends in the development and application of environmental flow methodologies for rivers. River Res. Appl. 19, 397–441. https://doi.org/10.1002/Rra.736.

The Nature Conservancy, 2009. Indicators of Hydrologic Alteration Version 7.1 User's Manual.

Theodoropoulos, C., Skoulikidis, N., Rutschmann, P., Stamou, A., 2018. Ecosystem-based environmental flow assessment in a Greek regulated river with the use of 2D hydrodynamic habitat modelling, 2018 River Res Applic. 34, 538–547. https://doi.org/10.1002/rra.3284.

Tickner, D., Opperman, J.J., Abell, R., Acreman, M., Arthington, A.H., Bunn, S.E., … & Young, L., 2020. Bending the Curve of Global Freshwater Biodiversity Loss: An Emergency Recovery Plan XX, 1–13. https://doi.org/10.1093/biosci/biaa002.

Tramblay, Y., Rutkowska, A., Sauquet, E., Sefton, C., Laaha, G., Osuch, M., Datry, T., 2021. Trends in flow intermittence for European rivers. Hydrol. Sci. J. 66 (1), 37–49. ⟨https://doi.org/10.1080/02626667.2020.1849708⟩.

USDA-SCS, 1972. National Engineering Handbook, Section 4, Hydrology. Washington, DC USDA Soil Conserv. Serv.

van Meerveld, H.J.I., Sauquet, E., Gallart, F., Sefton, C., Seibert, J., Bishop, K., 2020. Aqua temporaria incognita. Hydrol. Process. 34, 5704–5711. https://doi.org/10.1002/hyp.13979.

Wagner, P.D., Bieger, K., Arnold, J.G., Fohrer, N., 2022. Representation of hydrological processes in a rural lowland catchment in Northern Germany using SWAT and SWAT+. Hydrol. Process. 36 (5), e14589 https://doi.org/10.1002/hyp.14589.

Wetterhall, F., Pappenberger, F., He, Y., Freer, J., Cloke, H.L., 2012. Conditioning model output statistics of regional climate model precipitation on circulation patterns. Nonlin. Process. Geophys. 19, 623–633. https://doi.org/10.5194/npg-19-623-2012.

Wieners, K.H., Giorgetta, M., Jungclaus, J., Reick, C., Esch, M., Bittner, M., Roeckner, E., 2019. MPI-M MPI-ESM1.2-LR model output prepared for CMIP6 CMIP historical. Version YYYYMMDD. Earth Syst. Grid Fed. https://doi.org/10.22033/ESGF/CMIP6.6595.

Williams, J.R., 1995. Chapter 25. The EPIC Model. p. 909-1000. Computer Models of Watershed Hydrology. Water Resources Publications, Highlands Ranch, CO.

Zimmer, M.A., Kaiser, K.E., Blaszczak, J.R., Zipper, S.C., Hammond, J.C., Fritz, K.M., Allen, D.C., 2020. Zero or not? Causes and consequences of zero-flow stream gage readings. Wiley Interdiscip. Rev. Water 7 (3), e1436. https://doi.org/10.1002/wat2.1436.

Zollo, A.L., Rillo, V., Bucchignani, E., Montesarchio, M., Mercogliano, P., 2016. Extreme temperature and precipitation events over Italy: assessment of high-resolution simulations with COSMO-CLM and future scenarios. Int. J. Climatol. https://doi.org/10.1002/joc.4401.