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RESEARCH

Methodological Framework for the Evaluation of Climate Change Impacts on Rural Basins Using the GR2M Model

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Abstract

The goal of the present work is to introduce a framework to assess climate change impacts on water resources in rural basins. The proposed framework was applied and tested in the Platanovrisi river basin, located in Northern Greece. A hydrological model for the basin was developed and implemented using the GR2M, and calibrated-validated using observed rainfall, temperature and streamflow data. Climate change projections from three climate models and two Shared Socioeconomic Pathways (SSP) scenarios were used as drivers to the calibrated-validated hydrological model to assess the impact of climate change on the hydrological regime of the basin. Climate change impacts were assessed in terms of precipitation, temperature, evapotranspiration, and meteorological drought. Results indicated that, for the period 2015–2050, the annual precipitation and discharge will decrease by 13–23% and 32–47%, respectively, while temperature will increase on an average of about 13% (about 1 °C) compared to the reference period (historical period spanning from 1974 to 2014). The results revealed significant changes in the annual and seasonal water flow, with a net reduction in the river flow during winter and spring and a slight increase during autumn and summer. Therefore, difficulties may arise for ensuring hydropower production and storage, agricultural needs and ecological flows. The results revealed significant sensitivity and variability of rainfall, evapotranspiration and river flows based on the climate model and the climate scenario examined. Overall, the proposed framework constitutes a robust approach for the assessment of climate change impacts on water resources in different hydrological regimes, and can be easily modified and applied to diverse watersheds worldwide. In addition, the proposed methodology can help and guide practitioners and decision makers towards adaptation and mitigation efforts for sustainable water management under climate change conditions.

Highlights

- A methodology is presented to evaluate climate change impact on hydrology.
- Projections indicate that precipitation and river flow will decrease on annual basis.
- The river flows will decrease substantially in winter and spring.

Extended author information available on the last page of the article

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Keywords GR2M · Hydrological modeling · SSP1-2.6 and SSP5-8.5 · Climate change impact assessment · CMIP6 · Temperature · Rainfall · Meteorological drought

1 Introduction and Background

Climate change is expected to pose significant challenges to water resources (Bayazit 2015), particularly in regions such as the Mediterranean which is recognized as hotspot of climate change with multiple interlinked risks (Calvin et al. 2023; Cramer et al. 2023). In particular, climate change is projected to alter and accelerate the hydrological cycle, and as a result, extreme weather events, such as floods and droughts, are projected to become more frequent and more devastating in the future (Seneviratne et al. 2021), and have negative impacts on energy production, irrigation and food production, water supply, and ecological flows. Therefore, estimating the regional impacts of climate change on water resources is of paramount importance from the social, economic and environmental perspectives.

During the recent years, observed hydrometeorological data and/or climate projections based on different climate models and various climate scenarios have been used to study the regional impacts of climate change on: (i) freshwater resources (e.g., Alehu and Bitana 2023); (ii) flooding on urban and peri-urban catchments (e.g., Kourtis et al. 2021); (iii) design and/or assessment of water projects and water resources (e.g., Mendez et al. 2022; Stamou et al. 2024); (iv) generation of projected flow records for flood frequency analysis (e.g., Ditthakit et al. 2021); (v) update of Intensity-Duration-Frequency curves (e.g., Kourtis et al. 2023a); and (vi) water availability (e.g., Dau et al. 2021; Papadopoulou et al. 2016, 2020), among others. Researchers have assessed different statistical downscaling methods, exploring their applicability in generating future climate change scenarios and discussed the main challenges and uncertainties associated with these statistical downscaling techniques (e.g., Gutiérrez et al. 2018; Maraun et al. 2015). The associated uncertainties can have significant effects on the results of hydrological simulations (Kourtis et al. 2021). Pushpalatha et al. (2012) assessed the performance, in terms of low flow simulation of two hydrological models, namely GR4J and the six-parameter version of the MORDOR model, in 940 basins in France. Uncertainty in climate projections and hydrologic-hydraulic simulations stems from various sources, i.e., climate models, climate scenarios, spatial downscaling techniques, temporal disaggregation techniques, model-structure uncertainty, parametric uncertainty, and can have significant impacts on hydrological modeling (Kourtis and Tsihrintzis 2021, 2022).

Monthly meteorological data (i.e., precipitation and temperature) are the most common input variables on monthly rainfall-runoff models (e.g., Ouali et al. 2023). Monthly hydrological models are often preferred and widely used due to their simplicity for general balance of water resources, and the small number of parameters needed especially for ungauged basins where data are scarce (Rani and Sreekesh 2021). Various researchers around the globe have employed different models and methods for: (i) streamflow prediction in ungauged basins (e.g., Vicente-Guillén et al. 2012; Turan and Yurdusev 2016); (ii) climate change impact assessment on different sectors (e.g., Khajeh et al. 2017; Alehu and Bitana 2023; De Filippi and Sappa 2024; Kashem et al. 2024); (iii) assessment of the ecological risk based on climate projections (e.g., Ramos et al. 2016); (iv) studying the relationship of meteorological and hydrological droughts (e.g., David and Davidová 2017); and

(v) assessment of hydropower generation (e.g., Obahoundje et al. 2021). Gao et al. (2024) reviewed the impacts of climate change on the Water-Energy-Food Nexus. They concluded that most climate impact assessment studies are focusing on the regional scale, while future challenges are associated among others with temporal and spatial scales of climate projections and the inherited uncertainty.

Monthly hydrological models are widely used tools for water resources management, especially in regions with limited data availability. GR2M constitutes a robust tool for the simulation of monthly streamflows and assessment of water resources dynamics in diverse hydrological regimes. GR2M hydrological model has been used in various studies around the globe for water resources design and assessment (e.g., Mendez et al. 2022), streamflow forecasting (e.g., Ditthakit et al. 2021) and assessment of climate change impacts (e.g., Okkan and Fistikoglu 2014). For instance, Mahdaoui et al. (2024) employed the GR2M model and bias corrected climate data from the previous generation of the Coupled Model Intercomparison Project (CMIP5) in order to assess climate change impacts in a basin in Morocco. Okkan and Fistikoglu (2014) used the GR2M hydrological model in assessing the impacts of climate change on runoff in the Izmir-Tahtali freshwater basin, Turkey. Future precipitation and temperature projections were statistically downscaled and used as an input in the calibrated-validated GR2M hydrological model. Their findings suggested that climate change is likely to affect runoff patterns in the study areas with decrease in runoff projections depending on the scenario and the future horizon examined. Fathi et al. (2023) proposed an enhanced version of the GR2M model by incorporating seasonal variations in order to increase its applicability for snow climates. Their results revealed a significant improvement in the water balance accuracy of the proposed model. Sadio et al. (2023) assessed the impacts of climate change on the hydrological regime by employing the GR2M hydrological model on the Casamance and Kayanga-Géva tropical river basins in Senegal and Guinea-Bissau, respectively. Their results suggested significant variability in the hydrological responses of the river basins according to the projected climate scenario, but the general trends were reduced runoff and altered seasonal flow patterns with the uncertainty mainly stemming from the emission scenarios. Sadio et al. (2023) argued about potential significant impacts of climate change on water resources in tropical river basins, and their study revealed the urgent need for adaptive water management strategies to mitigate and adapt to the impacts of climate change. Ouali et al. (2023) assessed the impacts of climate change on the Upper Ziz basin, Morrocco, an arid climate region, employing different daily (such as GR4J), and monthly hydrological models (such as GR2M), and their results suggested a significant decrease in future streamflow, differing according to the climate scenario (i.e., RCP4.5 or RCP8.5) and the season examined. Hrour et al. (2023) proposed a framework for water resources management, including uncertainty estimation stemming from future climate projections in the Bas-Loukkos basin, Morocco, under climate change conditions. They used nine climate models (five regional climate models forced by four global climate models) under two representative concentration pathways (i.e., RCP4.5 and RCP8.5). Future climate data, with and without bias correction, were used as an input to the GR2M hydrological model. Their results revealed significant variability in projected rainfall, evapotranspiration and discharge (both decreasing and increasing trends) based on the climate model and the climate scenario examined. El Boute et al. (2024) compared the performance of two monthly hydrological models, namely GR2M and a model based on artificial neural networks, in terms of runoff forecasting. The comparison took place in the Upper Inaouene basin in Morocco. Their results showed that the artificial neural network model outperformed the GR2M model. Lerat et al. (2024) proposed a data-driven approach called Data Assimilation Informed model Structure Improvement (DAISI) aiming to improve hydrological models. The proposed approach was tested in 201 basins in Australia using the monthly GR2M model. They concluded that the proposed approach resulted in a significant improvement of the model, especially for low flows.

Especially in catchments with conflicting water uses, future climate projections based on various climate scenarios and climate models must be included in the design procedure to accurately design, assess and test robust water resources management adaptation strategies to cope with the effects of climate variability. The goal of the present work is to assess climate change impacts on Platanovrisi basin, located in Northern Greece, which is used as pilot study area for rural basins. More specifically, the present work aims to evaluate the impacts of climate change on the hydrological behavior of the Platanovrisi basin by analyzing projected changes in temperature, precipitation, potential evapotranspitration (PET) and runoff. The hydrological model of the basin was developed using the GR2M hydrological model which was calibrated and validated based on the observed streamflow data of the basin. Calibration and validation of the GR2M model was specifically tailored to the mountainous Platanovrisi river basin, which presents unique hydrological challenges such as conflicting water uses and limited observed data availability. The impact of climate change on the basin was assessed based on historical and future climate projections from three climate models (i.e., GFDL-ESM4, IPSL-CM6A-LR and MPI-ESM1-2-HR) under two future climate scenarios (i.e., SSP1-2.6 and SSP5-8.5). The main aims of this paper are to: (i) introduce a framework for climate change impact assessment at the monthly scale for rural basins; (ii) develop a calibrated-validated model for the river basin; (iii) assess the main impacts of climate change on the basin; and (iv) demonstrate the applicability of the proposed procedure. The proposed framework can be easily used for the assessment of climate change impacts in rural basins with limited data availability.

The paper is organized as follows: Sect. 2 describes the proposed framework, the study area and the observed and future hydrometeorological data. Then, Sects. 3 and 4 present, analyze and discuss the results, followed by summary and concluding remarks.

2 Materials and Methods

2.1 Proposed Framework

The proposed methodological framework for climate change impact assessment in a rural basin is presented in Fig. 1. Part I of the proposed framework is related to the collection of observed data for the study area (i.e., rainfall, temperature, and runoff), the estimation of PET (the Hargreaves (1975) method is used due to its simplicity, but any method can be used if the necessary meteorological data is available), and calibration-validation of the hydrological model (GR2M is used in the present work but other appropriate models can also be used) based on the runoff measurements at the monthly scale. Part II is associated with future climate projections. In the present work, future climate data from three climate models were used, namely GFDL-ESM4, IPSL-CM6A-LR and MPI-ESM1-2-HR (hereinafter named GFDL, IPSL, and MPI, respectively) and two future climate scenarios, namely

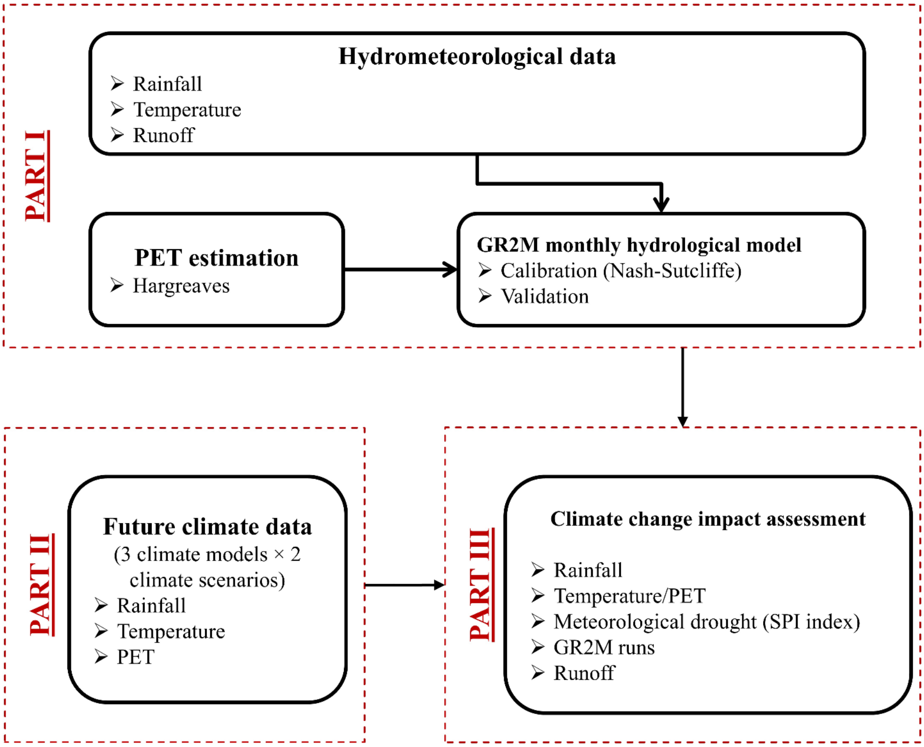


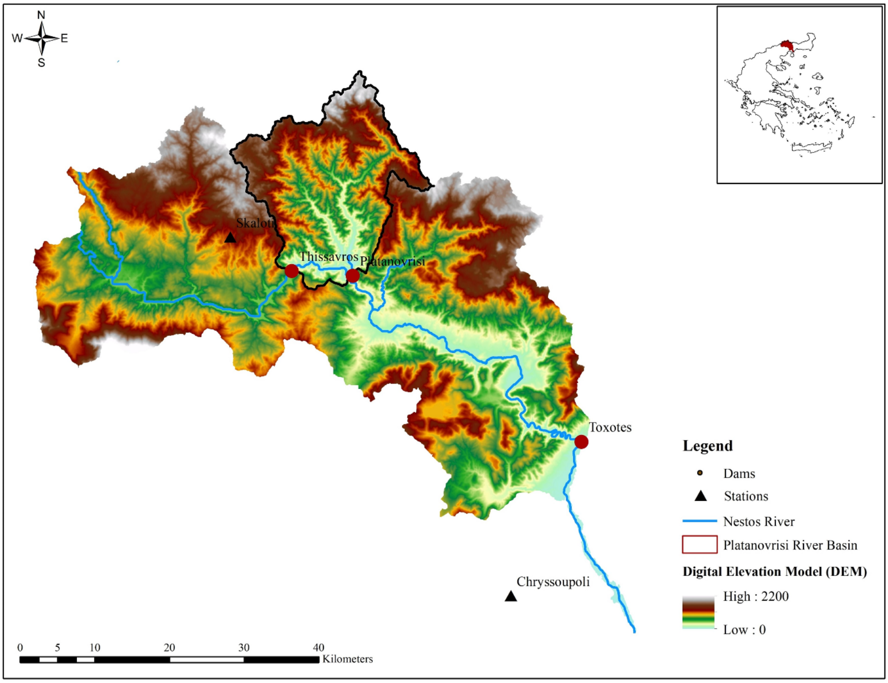
Fig. 1 Flowchart of the proposed framework

SSP1-2.6 and SSP5-8.5. The final part of the proposed framework (Part III) is related to the assessment of climate change impacts, in terms of rainfall, temperature/PET and runoff, at the rural basin scale. The climate change impact assessment was conducted by comparing climate signals from the historical period (i.e., 1974–2014) with those from the future period (i.e., 2015–2050).

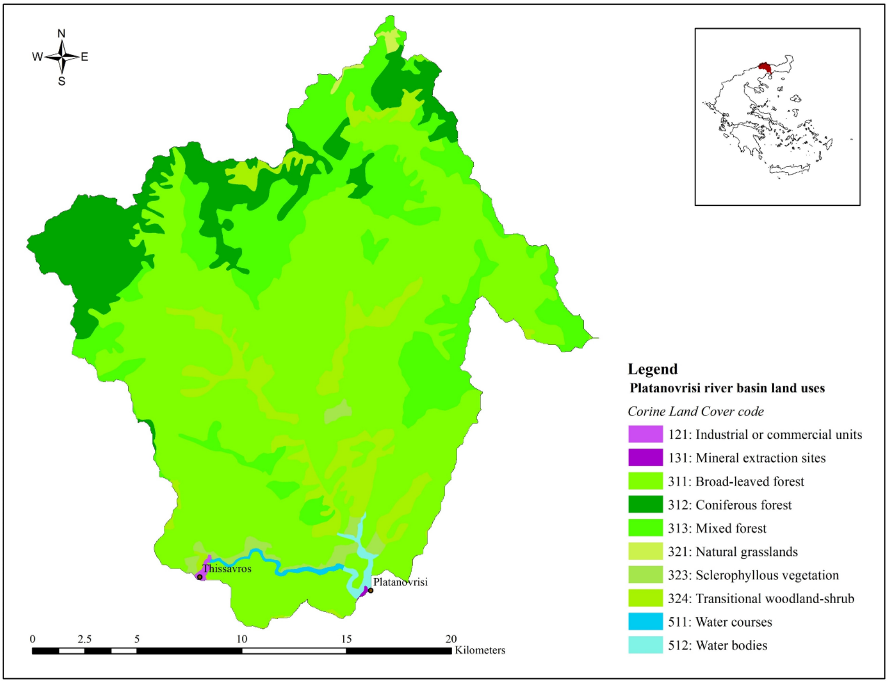
The proposed framework incorporates a robust bias correction and statistical downscaling methodology based on the latest, ISIMIP3, protocol. It also offers the advantage not only to evaluate changes in hydrological parameters (e.g., precipitation, temperature and streamflow) but also in drought phenomena. By incorporating the proposed approach in the design procedure, decision makers would be able to explore the climate change implications on critical water management aspects such as: irrigation supply, hydropower generation, water supply, and ecological flow.

2.2 Study Area

The Platanovrisi river basin in Greece, located upstream of the Platanovrisi dam, is part of the Nestos/Mesta transboundary river basin. The basin has an area of approximately 375 km^2. It occupies approximately 7% of the total area of the Nestos/Mesta River basin. The basin is semi-mountainous with an average elevation of about 976 m. The minimum and maximum elevations were estimated at about 220 m and 1951 m, respectively. Figure 2a



(a)



(b)

Fig. 2 The Platanovrisi river basin (black line): (**a**) Elevations (digital elevation model); and (**b**) land uses (Corine) presents the elevations (digital elevation model) of the basin. The main land uses are forests, natural grassland and sclerophyllous vegetation (Fig. 2b). The Platanovrisi river basin is characterized by complex hydrology and conflicting water uses (e.g., irrigation, hydroelectric power). In addition, the basin is extremely vulnerable to shifts in climate patterns and anthropogenic changes (e.g., Skoulikaris et al. 2021).

3 Hydrometeorological Data

Local observed historical rainfall data was available from the Skaloti meteorological station (Latitude = 41.41°, Longitude = 24.28°; Fig. 2a) for the period 2008–2019, where the average accumulated monthly rainfall ranges from approximately 45 mm (August; Fig. 3a) to 125 mm (January; Fig. 3a), while the average accumulated annual rainfall is estimated at about 1050 mm. Local observed historical temperature data (mean temperature, and maximum and minimum temperature) were available from the Chryssoupoli meteorological station (latitude = 40.92°, longitude = 24.62°; Fig. 2a) for the period 1984–2022. According to the observed temperature data, for the period 2008–2019, the mean monthly temperature ranges from approximately 6 °C (January; Fig. 3a) to 26 °C (August; Fig. 3a), the maximum monthly temperature ranges from approximately 8 °C (January; Fig. 3a) to 29 °C (August; Fig. 3a) and the monthly minimum temperature ranges from approximately -5 °C (January; Fig. 3a) to 17 °C (July; Fig. 3a).

Different approaches and methods for PET estimation have been reported in the literature and various researchers have assessed their applicability in different regions around the

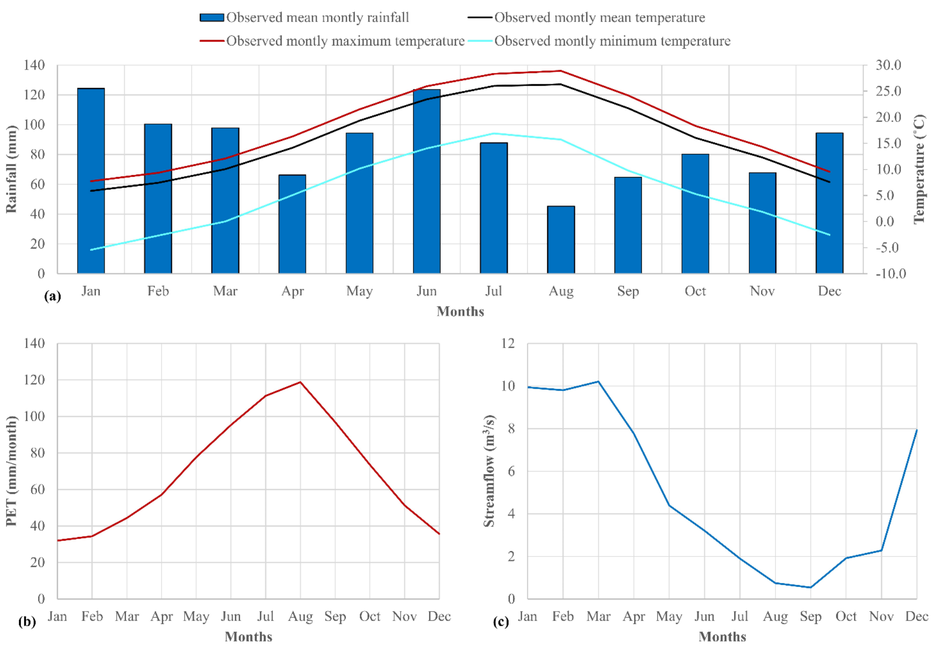


Fig. 3 (**a**) Average monthly rainfall and mean, maximum and minimum monthly temperature (September 2008 to November 2019); (**b**) average monthly PET (September 2008 to November 2019); and (**c**) average daily streamflow (September 2008 to December 2021)

Table 1 Sample statistics of daily inflow in the Platanovrisi river basin (m^3) for the period 2008 to 2021

Statistic	Value (m^3)
Sample size	4,870
Maximum	20,866,400
Minimum	0
Mean	430,964
Median	184,600
Standard deviation	954,646
Coefficient of skewness	8.86
Coefficient of kurtosis	123
Coefficient of variation (CoV)	2.22
Q1	35,200
Q3	457,800
IQR	422,600
Quartile Skew	0.29

Table 2 Set of global climate model used in this study

Global climate model	Original resolution	Reference
GFDL-ESM4	288 × 180	Dunne et al. 2020
MPI-ESM1-2-HR	384 × 192	Muller et al. 2018
IPSL-CM6A-LR	144 × 143	Boucher et al. 2020

globe (e.g., Proutsos et al. 2024). Vangelis et al. (2013) compared different temperature-based PET methods for various meteorological stations in Greece, using the Penman-Monteith as the reference method for PET estimation, and concluded that the Hargreaves model performs adequately. Charchousi et al. (2015) have shown the critical role of PET process in the hydrological water balance of a region due to the fact that PET fluxes are difficult to be predicted and quantified. In the present study, the mean monthly PET calculated by the Hargreaves (1975) method varied from 32 mm (January; Fig. 3b) to 119 mm (August; Fig. 3b), while the mean annual PET was estimated equal to 828 mm, which is in agreement with the results reported by Tsakiris et al. (2007) for the Nestos river basin.

Monthly streamflow (Fig. 3c) data were provided for the Platanovrisi dam by the Public Power Corporation SA (PPC) of Greece. The aforementioned data have been estimated after measuring the daily variation of the Platanovrisi reservoir volume. It can be observed (Fig. 3c) that average daily inflows in the Platanovrisi reservoir from the hydrological catchment ranges from about 10.0 m^3/s (March; Fig. 3c) to 0.50 m^3/s (September; Fig. 3c). Table 1 presents the sample statistics of daily inflow in the Platanovrisi river basin (in m^3) for the period 2008 to 2021.

3.1 Climate Change Data

Climate change scenarios consist of an ensemble of three global climate model (GCM; Table 2) simulations included in the Sixth Assessment Report of the IPCC (IPCC 2021) and produced in the context of the CMIP6 initiative (Eyring et al. 2016). Each ensemble member is driven by two Shared Socioeconomic Pathways (SSP1-2.6 and SSP5-8.5; O'Neill et al. 2014) providing trajectories to the climate simulations in terms of the temporal evolution of the atmospheric radiative forcing. To represent the largest forcing-related uncertainty, SSPs choice spans from the most optimistic (SSP1-2.6) namely foreseeing a considerable greenhouse gasses emissions reduction aligned with the Paris Agreement goals, to the most pessimistic (SSP5-8.5) with a future linear increase of emissions combined with no, or not relevant, mitigation measures.

Albeit representing climate modeling state-of-the-art, CMIP6 GCMs still present systematic biases and a too coarse resolution for regional scale applications. This prevents GCM outputs from being directly usable as inputs for climate change impacts modeling, and especially over heterogenous and rugged environments. To mitigate biases and bridge the spatial resolution gap between GCMs and the hydrological model, a well-established bias-correction and statistical downscaling method was applied following the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3; Lange 2019, 2021). This consists of a two-step statistical postprocessing, where in the first step a bias correction is applied to adjust climate simulations considering observations with the same resolution. In the second step, a statistical downscaling to the destination resolution (50 km) of the W5E5 reference product (Lange 2019) was applied. The bias correction consists of a parametric quantile mapping (QM) which defines a correction function adjusting each quantile of the simulated statistical distribution. This correction function is built on the mismatch between simulated and observed statistical distribution during a reference period (1979–2014). In future climate projection applications, QM can modify the original simulated climate change signal, i.e., future trends (Maraun 2016; Sangelantoni et al. 2019a), and subsequently the result of hydrological simulations (Sangelantoni et al. 2019b). For avoiding the introduction of unphysical artifacts, a trend-preserving QM configuration is adopted. The statistical downscaling step still consists of a QM but according to multivariate formulation (Gennaretti et al. 2015). In fact, downscaling can be regarded as a bias adjustment procedure where the statistical properties of the simulations are adjusted considering the multivariate distribution built on all the time series falling within one grid cell of the climate model. A third step is finally applied, and it is represented by a statistical downscaling applied to the already bias-adjusted and downscaled simulations. This latter points to downscale climate simulations to the final destination resolution of ~10 km and performed considering ERA5-Land as reference product (Muñoz-Sabater et al. 2021).

An expansion to multivariate QM can be generalized through the following steps:

1) the mathematical expression for the marginal QM bias correction procedure is as follows

$$X_i^{adj} = F_i^{-1}\left(G\left(X\right)\right) \tag{1}$$

where: $G\left(X\right)$ is the Cumulative Distribution Function (CDF) of the coarse-resolution simulation, F_i^{-1} is the inverse CDF (quantile function) of the observed values at finer grid point i, and X_i^{adj} is the marginally bias-corrected values at finer grid point i.

2) The dependency structure between finer-resolution grid points within the coarse-resolution grid cell is modeled using a copula approach allowing for the correction of the joint dependencies to match those observed at the finer-resolution grid:

$$U = \Phi^{-1}\left(F(X_i^{adj}\right) \tag{2}$$

3) After correcting the joint structure, the data are mapped back to the physical space to generate downscaled values:

$$X_i^{final} = F_i^{-1}\left(\Phi\left(U_i^{adj}\right)\right) \tag{3}$$

A more detailed description of all the methodological steps for the bias correction and statistical downscaling configurations of the QM can be found in Lange (2019).

3.2 Hydrological Model

The GR2M (Génie Rural à 2 Modèles Mensuels) constitutes a lumped, conceptual hydrological model designed for monthly time step simulations of streamflow (Mouelhi et al. 2006). It is one of the simplest models in the GR family, originally developed by the French National Institute for Agricultural Research (INRAE). The GR2M model uses as input monthly timeseries of precipitation and PET. The model consists of two parameters that govern its behavior. The first parameter *X1* is a production store capacity parameter, and the second parameter *X2* is a groundwater exchange parameter. The model assumes a production reservoir to account for soil moisture and evapotranspiration losses, and a routing reservoir in order to simulate runoff and streamflow. Its lumped structure assumes that the catchment characteristics are uniform, and its monthly time step simplifies long-term water resources management. The GR2M model provides a simple and computationally effective and efficient approach for hydrological modeling, especially in data scarce regions. It is relatively easy to calibrate, and robust across diverse climatic conditions. For more information about the GR2M hydrologic model, the reader is referred to Mouelhi et al. (2006).

4 Results and Discussion

4.1 Calibration-Validation of the GR2M Model

Figure 4 presents the calibration (Fig. 4a) and the validation (Fig. 4b) results for the GR2M hydrological model for the Platanovrisi river basin. A 12-month warm-up period was used prior the calibration period of the GR2M model, in order to initialize the model parameters. The Nash-Sutcliffe coefficient (NSE) was used as the objective function. For the calibration period (September 2008 to December 2015) results revealed a very good agreement (NSE = 0.88; Fig. 4a) between the observed and the simulated runoff. In addition, it can be observed (Fig. 4a) that the model is able to simulate quite well the peak flows, the low flows and the runoff volume in the basin under study. For the validation period (January 2016 to November 2019) results revealed a good agreement (NSE = 0.67; Fig. 4b) between the observed and the simulated runoff.

Several other metrics were also used to assess the model performance (Table 3). These included the Correlation coefficient, the Root Mean Square Error (RMSE), the Coefficient of determination (R^2), and the percent BIAS (PBIAS). According to Moriasi et al. (2007), the NSE values reveal a very good performance of the model for both calibration and validation periods, while the PBIAS values reveal a very good performance of the monthly hydrological model for the calibration period and a satisfactory performance for the vali-

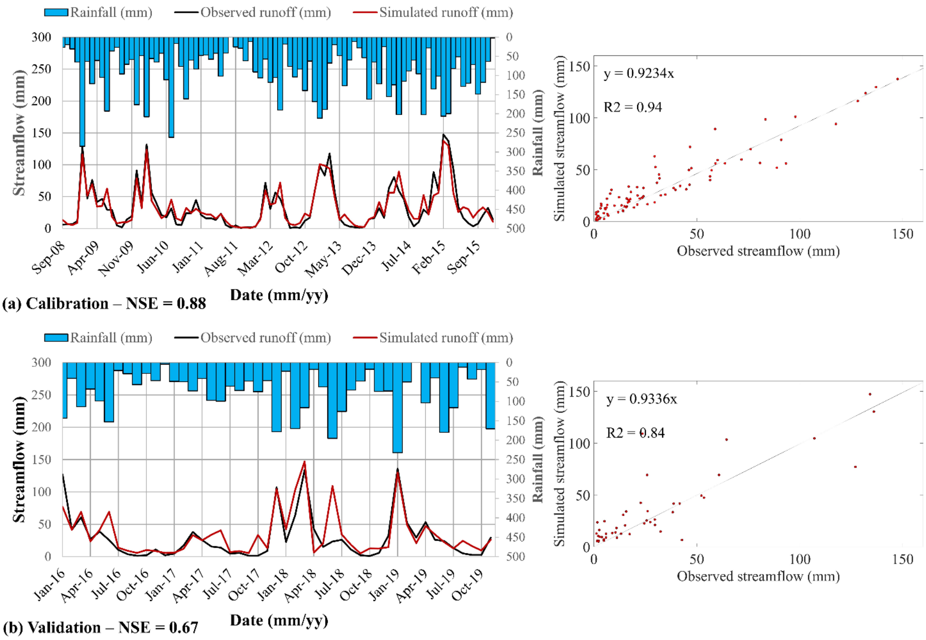


Fig. 4 Monthly streamflow prediction results and comparison with measured values: (**a**) Calibration (September 2008 to December 2015; NSE=0.88); and (**b**) Validation (January 2016 to November 2019; NSE=0.67)

Table 3 Calibration and validation metrics for streamflow

Metric	Units	Calibration period	Validation period
NSE	-	0.88	0.67
Correlation coefficient	-	0.94	0.85
RMSE	mm	18.1	95.0
R^2	-	0.94	0.84
PBIAS	%	-2.26	-18.29

dation period. The reported metrics indicated good overall performance of the hydrological model during both the calibration and the validation. However, these metrics primarily reflect aggregate performance and may not fully capture spatial and temporal variability within Platanovrisi basin. The GR2M model operates in a lumped scale, which simplifies spatial heterogeneity; thus, the calibration procedure was carefully conducted using the only available monthly rainfall and streamflow data that are representative of the basin's general hydrological behavior.

Boskidis et al. (2011) reported measured discharge values downstream of the Platanovrisi dam and near the Paschalia village ranging from 4 m^3/s to 233 m^3/s. In the present work, the modeled discharge upstream of the Platanovrisi dam ranges from 1 m^3/s to approximately 240 m^3/s which is in very good agreement with the aforementioned study.

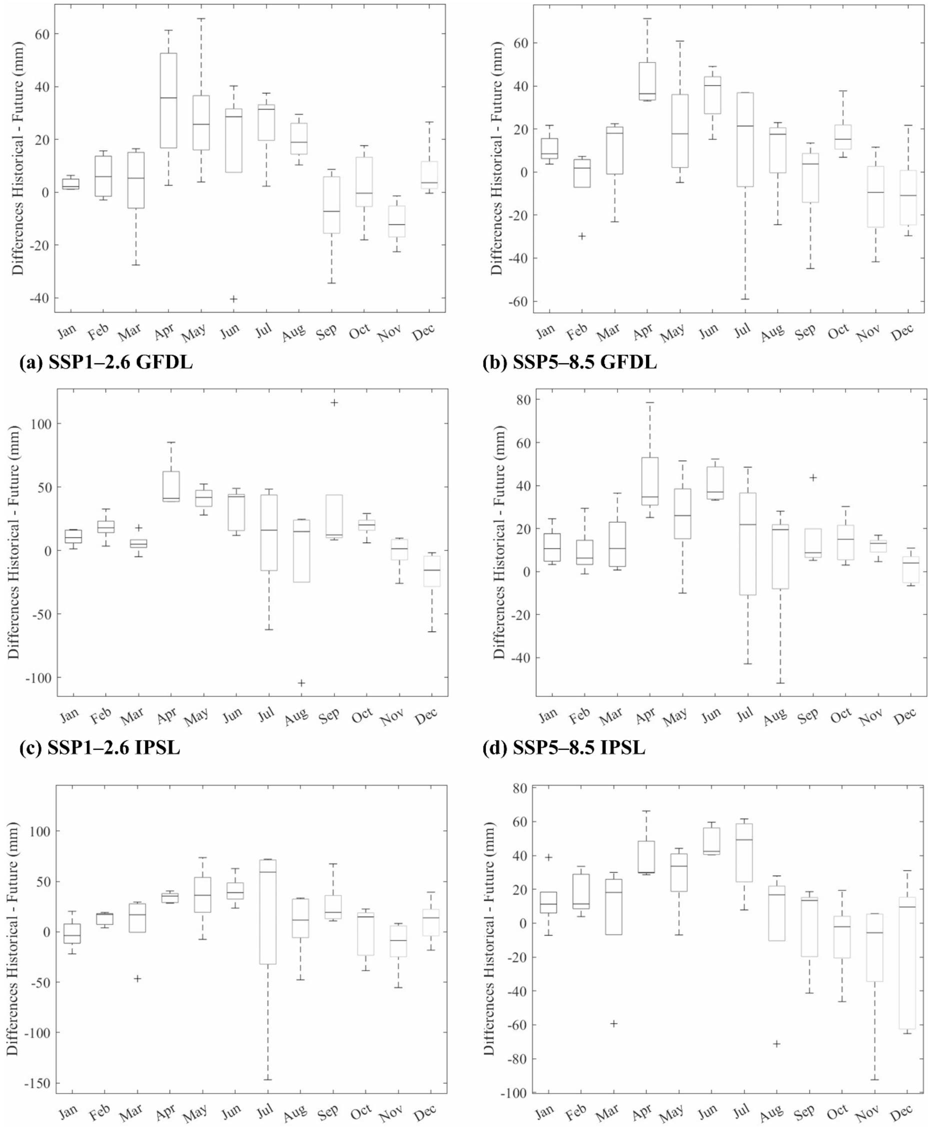
For the basin under study, the calibrated and validated hydrological model can remain relevant study under future climate scenarios; however, this mainly depends on the extent of changes in the catchment characteristics as the calibrated model assumes that the behavior of the basin (geomorphology and anthropogenic alterations) will not change significantly. Non-stationarity in climate (e.g., changing precipitation patterns) can challenge this assumption, leading to increased uncertainty (Guo et al. 2018); to this end, it is proposed the use of different climate models and scenarios. In practice, using multi-model ensembles can enhance model reliability under future climate change conditions by capturing a range of possible future scenarios. Her et al. (2019) demonstrated that using multi-model climate ensembles can make calibrated hydrological models more resilient to non-stationarity, enhance the robustness of projections and support decision-making even under considerable climate uncertainties.

4.2 Statistical Downscaling of Climate Data and Processing

Future climate data for the pixel closest to the Skaloti and Chryssoupoli meteorological stations were extracted using an in-house MATLAB developed code (Kourtis et al. 2023b). Figure 5 presents the monthly rainfall boxplots for the differences between the historical rainfall (1974–2014) simulated by the climate models and the future rainfall (2015–2050) for: GFDL SSP1-2.6 (Fig. 5a), GFDL SSP5-8.5 (Fig. 5b), IPSL SSP1-2.6 (Fig. 5c), IPSL SSP5-8.5 (Fig. 5d), MPI SPP1-2.6 (Fig. 5e), and MPI SSP5-8.5 (Fig. 5f). Figure 6 presents the monthly temperature boxplots for the differences between the historical temperature (1974–2014) simulated by the climate models and the future temperature (2015–2050) for: GFDL SSP1-2.6 (Fig. 6a), GFDL SSP5-8.5 (Fig. 6b), IPSL SSP1-2.6 (Fig. 6c), IPSL SSP5-8.5 (Fig. 6d), MPI SPP1-2.6 (Fig. 6e), and MPI SSP5-8.5 (Fig. 6f). The boxes are limited to the 25th and 75th percentiles of the sample (2025–2050), and the black line shows the median value. According to the climate scenarios, the annual rainfall for the pixel of Skaloti station ranges from 833 mm to 938 mm based on the climate model and the climate scenario examined.

In the present work, we utilized projections from three climate models (i.e., GFDL-ESM4, IPSL-CM6A-LR, and MPI-ESM1-2-HR) under two Shared Socioeconomic Pathways (SSP1-2.6 and SSP5-8.5). Without performing a detailed uncertainty analysis, the proposed approach can account for a range of uncertainties arising from differences in the climate models and the climate scenarios, offering a comprehensive perspective on the potential variability in climate projections. In addition, the proposed methodology adopted a well-established bias correction approach and a statistical downscaling technique (ISIMIP3 protocol). This approach can account for the systematic biases and reduce the uncertainty in hydrological outputs. Furthermore, the GR2M hydrological model was calibrated-validated using observed data, with the performance metrics demonstrating high reliability during both the calibration and the validation periods. While scenario-wise confidence intervals for projections are not explicitly presented, the multi-model approach effectively captures a range of potential hydrological responses of the basin under study. Finally, we introduced a simplified approach for climate change impact assessment in data scarce rural basins. In case the proposed framework is to be adopted, included in the design procedure and implemented by practitioners and decision makers, it must remain relatively easy. In addition, it should also be able to provide valuable insights into the potential range of outcomes, supporting robust decision-making.

Downscaling, statistical and dynamic, and bias-correction approaches are essential for hydrological modeling, especially in mountainous basins where complex topography and



(a) SSP1–2.6 GFDL

(b) SSP5–8.5 GFDL

(c) SSP1–2.6 IPSL

(d) SSP5–8.5 IPSL

(e) SSP1–2.6 MPI

(f) SSP5–8.5 MPI

Fig. 5 Monthly rainfall boxplots for the differences between historical and (**a**) GFDL SSP1-2.6; (**b**) GFDL SSP5-8.5; (**c**) IPSL SSP1-2.6; (**d**) IPSL SSP5-8.5; (**e**) MPI SPP1-2.6; and (**f**) MPI SSP5-8.5

orographic effects influence weather patterns. However, these methods may further introduce uncertainties. Downscaling methods are often not able to capture localized extreme events, such as intense rainfall or temperature anomalies, especially in fine timescales, due to the inherent simplifications and assumptions used. On the other hand, statistical methods rely on historical relationships between large-scale atmospheric variables and local climate, which may not account for changes in climate dynamics or extreme weather events. Fur-

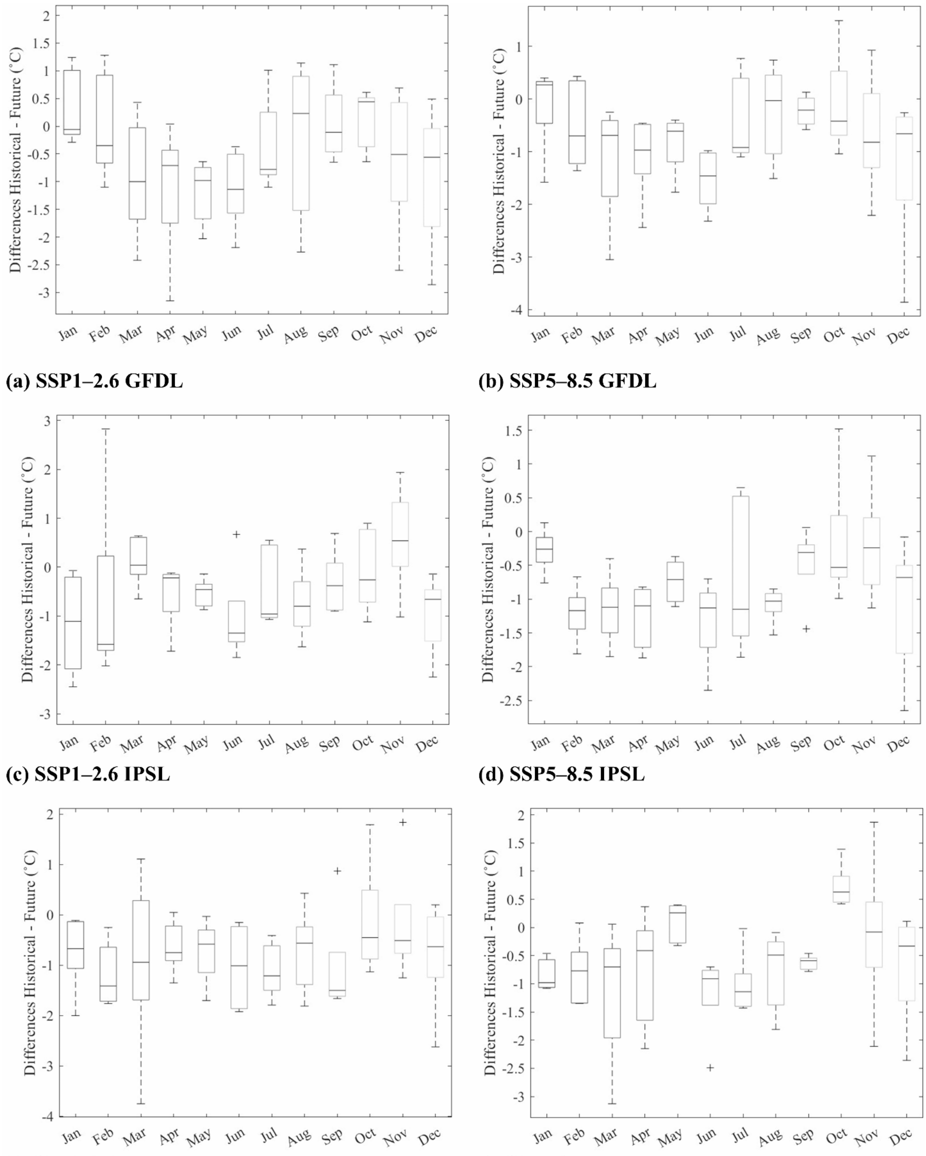


Fig. 6 Monthly temperature boxplots for the differences between historical and (**a**) GFDL SSP1-2.6; (**b**) GFDL SSP5-8.5; (**c**) IPSL SSP1-2.6; (**d**) IPSL SSP5-8.5; (**e**) MPI SPP1-2.6; and (**f**) MPI SSP5-8.5

thermore, dynamic downscaling is computationally expensive and may still inadequately resolve fine-scale topographic features or convective processes driving extreme events. The aforementioned limitations may affect the reliability of calibrated-validated hydrological models. For instance, underestimation of extreme precipitation can lead to poor simulation of flood risks, while overestimating it may exaggerate water resources availability.

Addressing these challenges requires the use of multi-model ensembles in order to quantify uncertainty.

4.3 Climate Change Impact Assessment

Figure 7 presents the comparison of monthly mean temperature between the historical temperature and the projected temperature from the climate models used. The results indicate increased variability in changes in annual temperature ranging from 5 to 7.5% (Fig. 7) with an average increase of about 6%. The annual rainfall was projected to decrease by approximately 18% compared to the historical rainfall (Fig. 8a; Table 4) with the percent change ranging from about -13% to about -23% based on the climate model and the climate scenario examined (Table 4). According to the results (Fig. 8a; Table 4), the seasonal mean projected precipitation shows a significant decrease in spring and summer ranging from 20 to 37% based on the climate model and the climate scenario examined, with an average decrease of about 27%. Autumn and winter projected rainfalls present greater variability with the percentage changes ranging from about 10% increase to 20% decrease. The variability of the results can be attributed to the climate model and the different climate scenarios examined. The results presented herein are in accordance with the results reported by Skoulikaris and Ganoulis (2015). The results indicate an increase in annual PET ranging from 10 to 14% (Fig. 8b). The increase for spring months ranges from 6 to 13% while for the summer months the percentage increase ranges from 15 to 17%. The results for temperature are in accordance with the results for PET, which is to be expected as the Hargreaves method uses as an input only temperature.

Overall, it can be observed that the impact of climate change on rainfall, PET and temperature differs based on the climate model and the climate scenario examined. However, a clear tendency for decrease in rainfall, and an increase in temperature and PET can be observed. This may result in significant impacts on energy production, availability of water for irrigation purposes, ecological flow, and summer droughts. In addition, it may have significant impact on sustainable energy production as Platanovrisi hydropower plant is used for pump-storage, filling with water its upstream Thissavros reservoir, during low energy

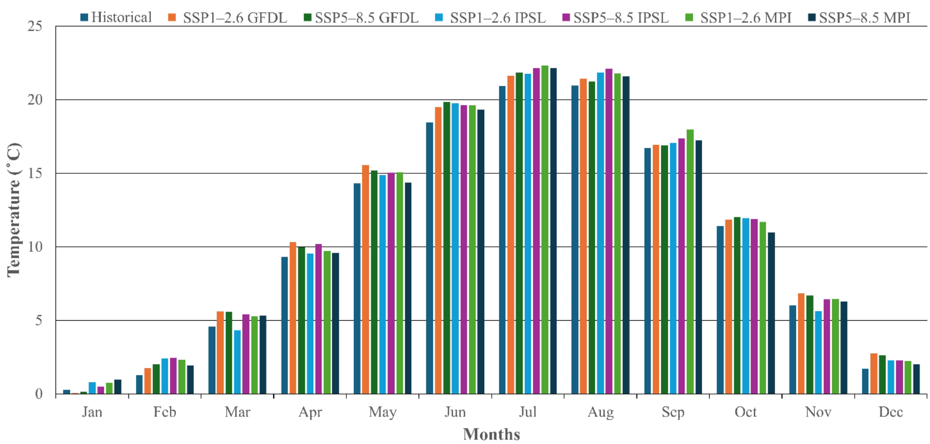


Fig. 7 Variation of monthly mean temperature simulated by climate models

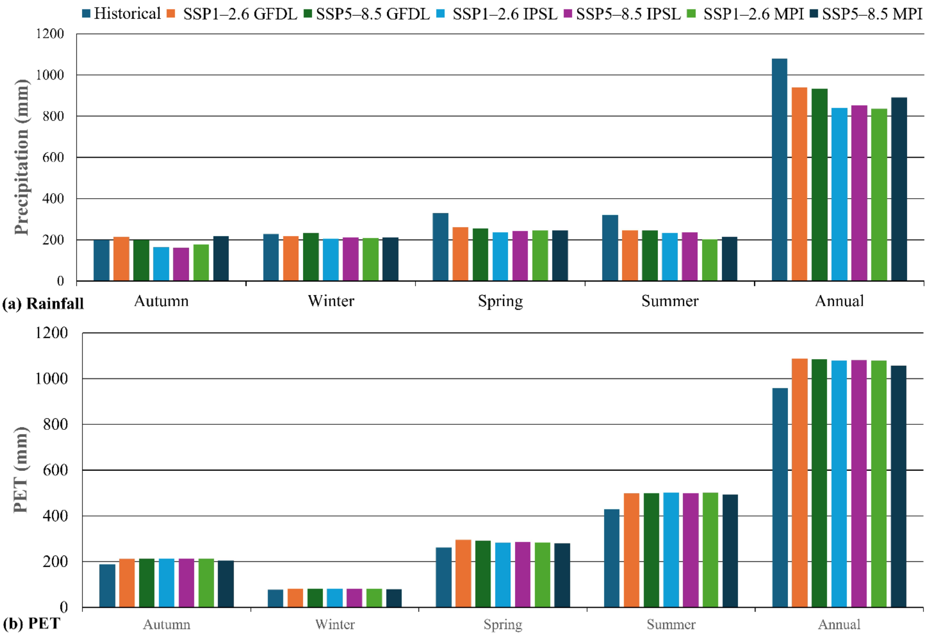


Fig. 8 Climate change impact on: (**a**) seasonal and annual rainfall; and (**b**) seasonal and annual PET for the projected climate scenarios

Table 4 Percent change of seasonal and annual rainfall

Season	GFDL		IPSL		MPI	
	SSP1-2.6	SSP5-8.5	SSP1-2.6	SSP5-8.5	SSP1-2.6	SSP5-8.5
Autumn	7.0	0.1	-17.9	-19.3	-11.1	9.5
Winter	-4.8	1.7	-9.9	-7.1	-8.6	-7.7
Spring	-20.5	-22.2	-28.1	-26.0	-25.3	-25.3
Summer	-23.4	-23.8	-27.5	-26.5	-36.8	-33.0
Annual	-12.9	-13.5	-22.2	-20.9	-22.6	-17.4

demand periods. As a result, decreased water availability, especially during spring and summer months where irrigation water is needed, may have significant negative impacts on reservoir storage, energy production, and irrigation water availability.

Furthermore, future meteorological drought was assessed using the well-established and widely used (e.g., David and Davidová 2017; Kourtis et al. 2023b) SPI drought meteorological index (McKee et al. 1993) using the gamma theoretical distribution. The SPI index was estimated using the Drinc software (Tigkas et al. 2015) for the 12-month timescale for both observed and projected climate change scenarios. Trend analysis for the SPI index took place using the Sen's slope (Sen 1968; Theil 1992) estimator and the non-parametric Mann–Kendall (Mann 1945; Kendall 1975) statistical test. Results for the observational period (Fig. 9a) revealed non-significant decreasing trend at the 5% significance level. According to the SPI drought index, two years can be classified as dry, one year as wet and eight years as normal (Fig. 9a). Regarding the future period (i.e., 2015–2050; Fig. 9b and c), it can be observed that the number of dry years (SPI<-1) range from three to seven, while extreme

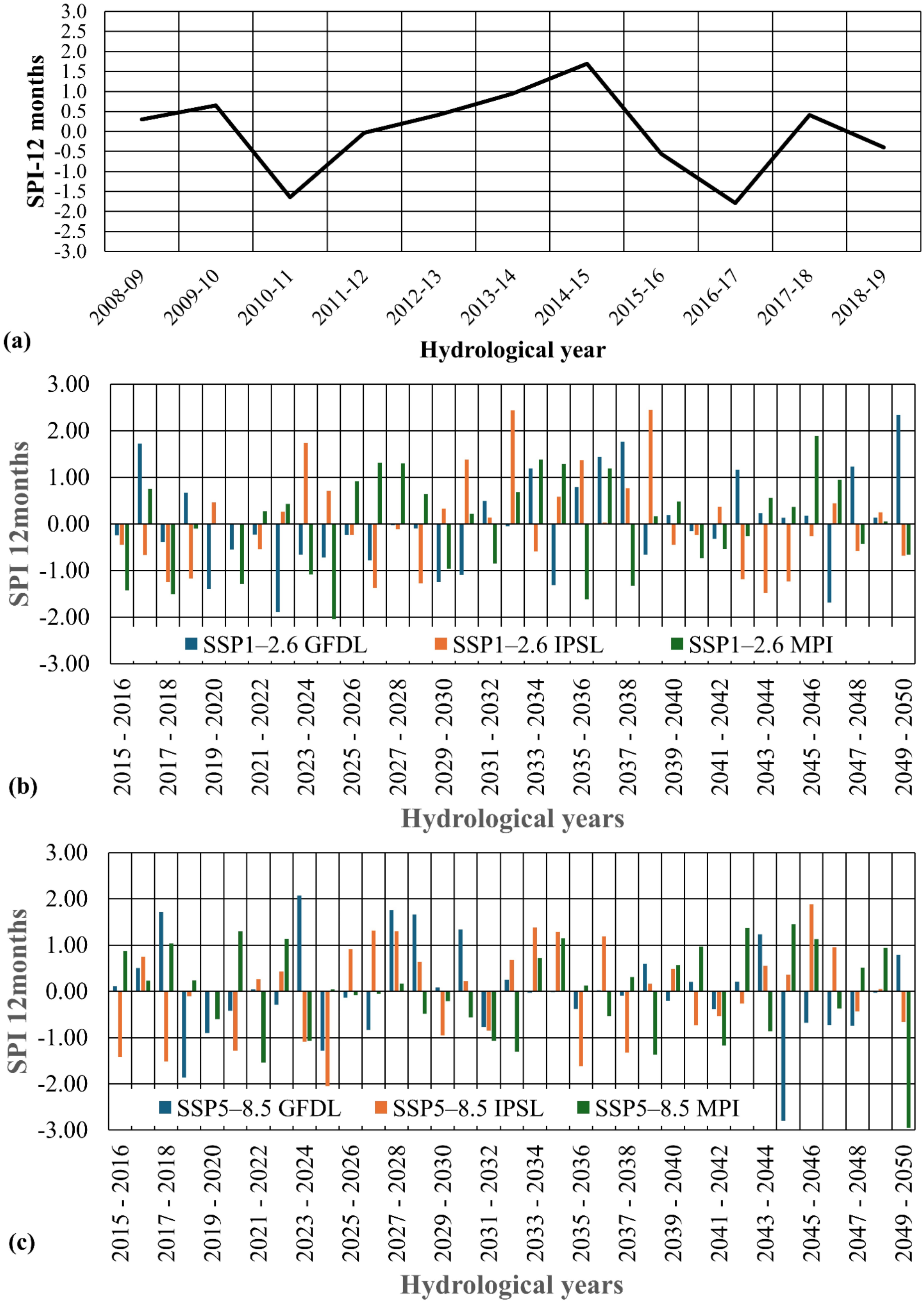


Fig. 9 SPI-12 month for (**a**) observed data; (**b**) SSP1-2.6 scenario and all climate models; and (**c**) SSP5-8.5 scenario and all climate models

drought events (SPI<-2) may arise. In addition, the wet years range from five to seven and the normal years range from twenty-one to twenty-six. Trend analysis revealed a statistically significant increasing trend, at the 5% significance level, for the GFDL SSP1-2.6 and the IPSL SSP1-2.6. On the other hand, a non-significant at the 5% significance level decreasing trend was observed for GFDL SSP5-8.5, IPSL SSP5-8.5 and MPI SSP5-8.5, while a non-significant at the 5% significance level increasing trend was observed for MPI SSP1-2.6. Overall, the results indicated that the projected trends on drought phenomena depend on the climate model and the climate scenario examined.

Changes in future streamflow were assessed, comparing the historical period with the future period of the climate models, employing the calibrated-validated GR2M model developed for the basin (Sect. 3.1). Table 5 presents the simulated mean monthly streamflow for the historical period (1974–2014) and for the future period (2015–2050) for all climate models and all climate scenarios. Future projected streamflow was estimated for six scenarios (i.e., three climate models × two climate scenarios) using as input the projected precipitation and evapotranspiration previously presented and discussed. Figure 10 presents the monthly runoff boxplots for the differences between the historical period (1974–2014) simulated with the GR2M model and the future period (2015–2050) for: GFDL SSP1-2.6 (Fig. 10a), GFDL SSP5-8.5 (Fig. 10b), IPSL SSP1-2.6 (Fig. 10c), IPSL SSP5-8.5 (Fig. 10d), MPI SPP1-2.6 (Fig. 10e), and MPI SSP5-8.5 (Fig. 10f). Finally, Fig. 11 presents the impact of climate change on seasonal and annual streamflow (Fig. 11). The annual streamflow is expected to be significantly decreased with percent changes ranging from -32% to -47% according to the climate scenario and the climate model used. Furthermore, the results revealed a significant decrease in winter and spring streamflow (Fig. 11) ranging from -14% to -47%. The results presented herein are in accordance with the results presented by previous researchers (e.g., Skoulikaris et al. 2009).

The significant changes in seasonal water flows of the Platanovrisi basin may result in: (i) decrease of river flows; (ii) decrease of available water, especially during the spring and summer periods; (iii) decrease of available water for energy production and storage; (iv) increase of extreme weather events in the summer and autumn months, resulting in flood and/or drought phenomena. Overall, climate change is projected to substantially impact the

Table 5 Mean monthly simulated streamflow (mm)

Month	Historical	GFDL		IPSL		MPI	
		SSP1-2.6	SSP5-8.5	SSP1-2.6	SSP5-8.5	SSP1-2.6	SSP5-8.5
January	23.8	20.3	20.4	17.4	15.4	19.5	21.9
February	27.8	22.0	25.0	15.8	17.9	17.5	20.1
March	32.7	26.0	24.4	22.4	21.3	21.1	23.8
April	35.8	21.1	19.7	17.1	17.6	19.9	20.1
May	43.0	27.5	26.9	19.9	22.6	23.4	23.7
June	36.2	22.2	18.7	15.6	17.2	17.7	17.1
July	27.2	14.0	13.6	13.0	13.5	12.1	10.9
August	17.1	8.1	8.7	8.6	8.1	7.6	7.6
September	11.9	7.8	8.2	4.9	5.4	4.2	8.4
October	10.2	6.7	5.6	3.6	4.2	4.1	8.4
November	11.3	9.1	8.7	5.4	5.4	6.5	10.2
December	22.2	18.3	19.4	16.2	13.4	14.0	26.8

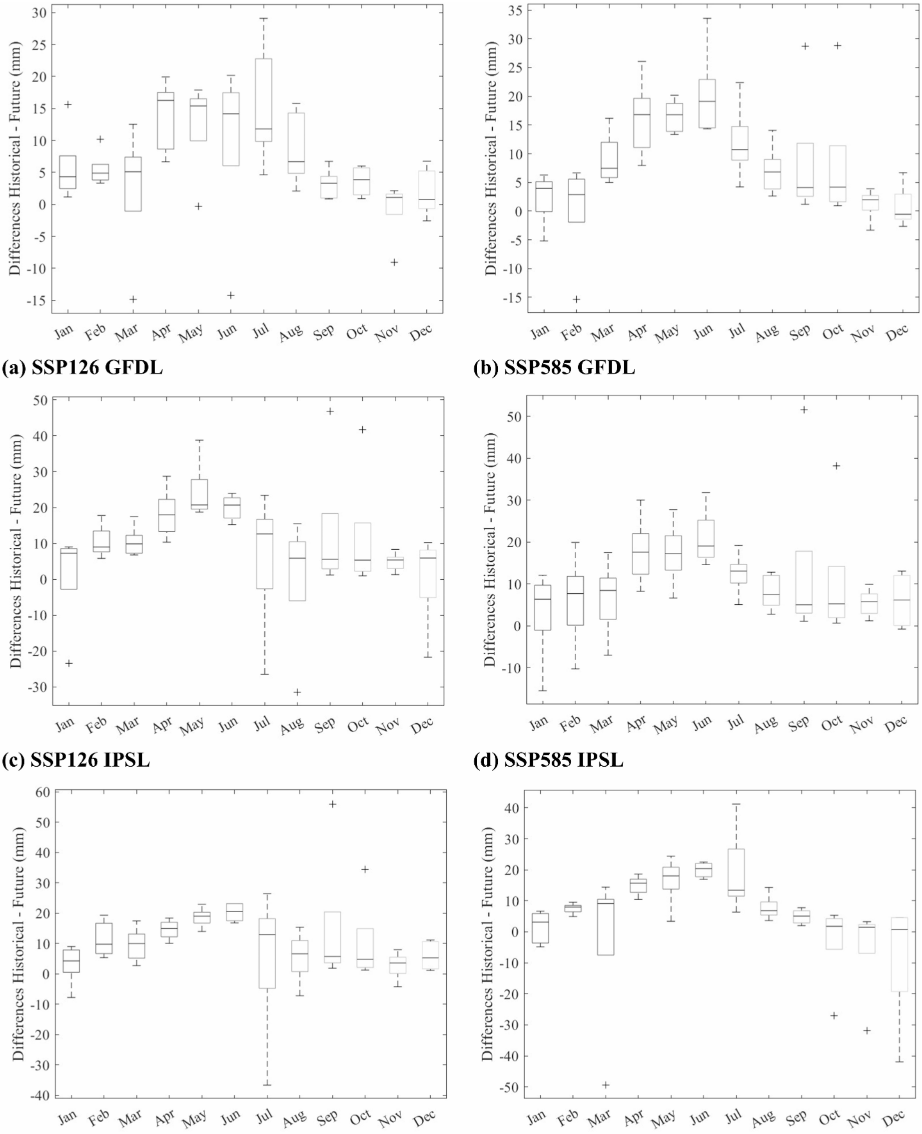


Fig. 10 Monthly streamflow boxplots for the differences between historical and (**a**) GFDL SSP1-2.6; (**b**) GFDL SSP5-8.5; (**c**) IPSL SSP1-2.6; (**d**) IPSL SSP5-8.5; (**e**) MPI SPP1-2.6; and (**f**) MPI SSP5-8.5

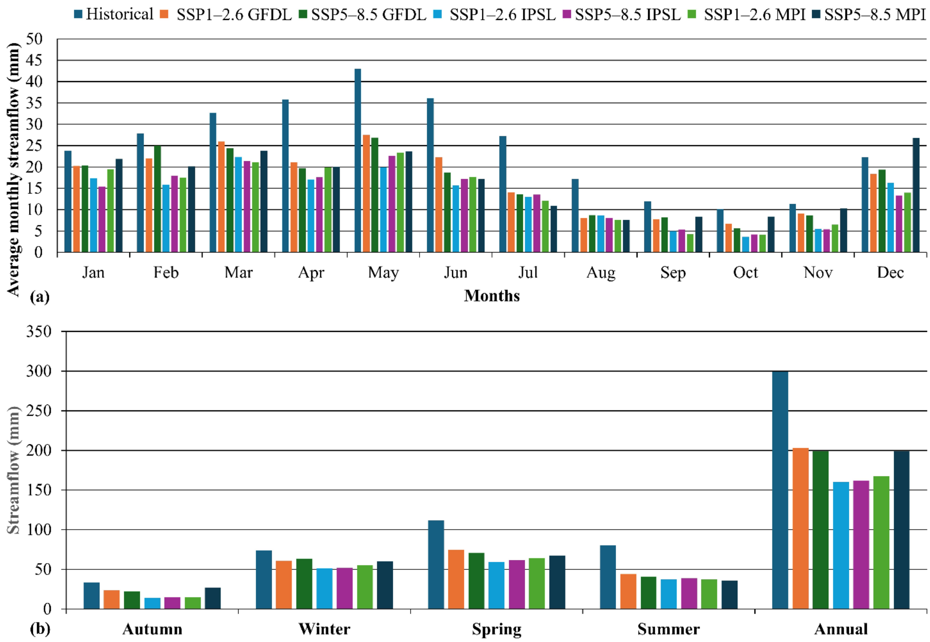


Fig. 11 Climate change impact on: (**a**) monthly streamflow; and (**b**) seasonal and annual streamflow. Note that the historical columns display the multimodel mean for the 1974–2014 period, while separate columns are used for each of the six model-scenario combinations

hydrological regime of the Platanovrisi river basin, influencing available water resources and increasing the occurrence and magnitude of both floods and droughts.

5 Conclusions

The main aim of the current work was to present a methodology to assess climate change impacts on precipitation, temperature, evapotranspiration, drought and streamflow in rural basins. The methodology was demonstrated in Platanovrisi basin located upstream of the Platanovrisi hydroelectric dam. Hydrological modeling was carried out employing the GR2M hydrological model which was calibrated and validated based on observed hydrometeorological data. Climate change impact assessment was based on the results of three climate models under two future climate scenarios. The results revealed significant decreases in streamflow during winter and spring and a slight increase in summer and autumn flows, which is consistent with the impacts of climate change. The magnitude of rainfall, temperature, evapotranspiration and river flow changes vary based on the climate model and climate scenario examined. As a result, analysis of future impacts of climate change at the rural basin scale is subject to increased uncertainty. Therefore, it is proposed to use an ensemble of different climate models and different climate scenarios.

Integrated water resources management of the Platanovrisi river basin requires a holistic approach and should incorporate and take into account the basin's mountainous topography, the conflicting water uses (e.g., energy, ecological flow, irrigation), and also the projected climate change impacts. Key strategies may include, among others, the enhancement of supply reliability (e.g., construction of a new dam), the optimization of water allocation (e.g., energy production, irrigation), and the promotion of integrated land-use planning. In order to address the projected reduction in streamflow, especially during winter and spring months, adaptive irrigation scheduling in the downstream plain, and the adoption of water-efficient irrigation technologies (e.g., micro and drip irrigation) can mitigate water scarcity during peak agricultural demand in spring and summer. Nature-based solutions, such as afforestation and riparian zone restoration, could play a supporting role in stabilizing the hydrological regime of the upstream part of the basin by reducing soil erosion and enhancing groundwater recharge. Hydropower operation can adapt to projected streamflow variability by optimizing dynamic storage management and pumped storage with the upstream Thissavros dam, in order to maintain energy production efficiency. At the policy level, integrating climate projections into water resources management strategies may ensure equitable distribution among the competing water uses, such as energy generation, irrigation, and ecological flow, even under reduced water resources availability. Furthermore, development and application of a real-time hydrometeorological monitoring system and flood and drought early-warning systems will support decision-making and emergency preparedness for extreme weather events. Finally, scenario-based planning using multi-model ensembles, as presented in the present work, could inform long-term climate change adaptation strategies, ensuring that integrated water resources management of the Platanovrisi river basin can remain robust under future uncertainty.

The present study highlighted the impacts of climate change on the hydrological regime and demonstrated the urgent need for integrated water resources management. Overall, the proposed framework can be used as a benchmark to assess the sustainability and the adaptation ability of new water related projects and management strategies under climate variability for holistic water management strategies. By incorporating in the design procedure future climate projections from different climate models and scenarios, through the proposed framework, decision makers and practitioners may be able to proceed to more informed decisions. In addition, the proposed framework can help identifying vulnerabilities and resilience thresholds for the water related infrastructure and management strategies. The framework can also be used to simulate and assess the performance of water projects (e.g., reservoirs, irrigation systems, flood control measures) under varying climate conditions, facilitating the development of adaptation strategies that ensure long-term sustainability. It also allows for scenario-based planning, enabling stakeholders to compare project outcomes across different future climate scenarios, hereafter, supporting climate-resilient designs and policies aimed at mitigating climate hazards and optimizing water use efficiency. Finally, to achieve the sustainable management of water resources in the era of climate change, it is proposed to revise the current design procedure of water resources projects and new infrastructure, and include climate change projections and/or land use-land cover changes.

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Author Contributions I.M. Kourtis: Conceptualization, Methodology, Software, Formal analysis, Data Curation, Visualization; Writing - original draft; C-A. Papadopoulou: Conceptualization, Methodology, Writing - review & editing; A. Trabucco: Formal analysis, Data curation. Writing - review & editing; D. Peano: Formal analysis, Data curation, Writing - review & editing; L. Sangelantoni: Formal analysis, Data curation, Writing - review & editing; N. Mellios: Conceptualization, Data curation, Writing - review & editing; C. Laspidou: Conceptualization, Methodology, Supervision, Writing - review & editing. M.P. Papadopoulou: Conceptualization, Methodology, Resources, Funding, Supervision, Writing - review & editing. V.A. Tsihrintzis: Conceptualization, Methodology, Resources, Supervision, Writing - review & editing.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent To Publish All authors agreed with the content and gave explicit consent to publish the manuscript.

Competing Interests The authors declare no competing interests.

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