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Disaggregated monthly SWAT+ model versus daily SWAT+ model for estimating environmental flows in Peninsular Spain

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ABSTRACT

The Water Framework Directive requires all water bodies in EU countries to ensure the ecological integrity of freshwater ecosystems in all water bodies. A “good” status in water bodies leads to their biological elements to reproduce reference conditions, so quantity and timing should be considered in describing environmental flows. However, the availability of daily natural flow data is one of the major drawbacks, especially in highly water-regulated countries, such as Spain, and hydrological models, such as the Soil and Water Assessment Tool (SWAT+) model, can be used to generate them. This work evaluated three different approaches for obtaining daily flows used to characterise the natural regime and to estimate environmental flows in the Piloña River (northern Spain) and Tagus River (centre Spain) basins: Scenario 1) daily flows simulated by the SWAT+ model calibrated on a monthly scale; Scenario 2) daily flows estimated by applying monthly-to-daily disaggregation techniques from the monthly series obtained from the SWAT+ model calibrated on a monthly scale using Water Rights Analysis Package (WRAP) software; and Scenario 3) daily flows simulated by the SWAT+ model calibrated on a daily scale. The Kling–Gupta efficiency (KGE), percent bias (PBIAS), Nash–Sutcliffe efficiency (NSE), root mean square error (RMSE) and standard deviation ratio (RSR) were used to evaluate the model’s performance. Furthermore, the indicators of hydrologic alteration in rivers (IAHRIS) and the basic flow methods were assessed and compared with those obtained directly using the real data observed at the gauging station. Our results indicated that Scenario 2 outperformed the rest of the approaches for all the statistics used. KGE and NSE varied between 0.78 and 0.92 for both basins in Scenario 2 while these values decreased to 0.50–0.60 for KGE and 0.20–0.40 for NSE in Scenarios 1 and 3. Moreover, PBIAS ranged between 3.24 and 4.47% in validation periods in Scenario 2, while it decreased to –14.64% in Scenario 3. Likewise, Scenario 2 was also observed to show better performance related to both the patterns of the natural regime and the basic flow values, which were generally underestimated by the other scenarios. The methodology proposed provides a valuable tool for evaluating and managing the hydrological and environmental status of river basins.

1. Introduction

During the last decades, the constant increase in human activity has caused considerable negative impacts in different fields of study, such as hydrology. In rivers with intense anthropisation, including Spanish rivers, discharge represents one of the most important factors (Norris and Thomas, 1999) for defining the fundamental ecological characteristics of a riverine ecosystem. Therefore, the implementation of environmental flows indicates the amount of water necessary to maintain a

river ecosystem in its desired state (Aceman and Dunbar, 2004) and defines the appropriate flow regime for sustaining the ecological health of the receiving waters (Arthington et al., 2006; Poff and Zimmerman, 2010). The Water Framework Directive (WFD) requires EU countries to ensure the ecological integrity of freshwater ecosystems in all water bodies and to support human well-being by 2027. The WFD defines the ecological status of surface water bodies as “good” when their biological elements deviate only slightly from reference conditions (natural regime). However, surface water bodies with significant flow alterations

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are unlikely to achieve good ecological status due to the importance of flow regimes for riverine biological communities. Although the WFD does not explicitly use the term “environmental flows”, their implementation is considered a crucial measure for achieving the environmental objectives of the directive (Mezger et al., 2019). In fact, Spanish legislation has required the definition and implementation of environmental flows in the River Basin Management Plans (RBMP) since 2001 but this concept has not been implemented so far in any national hydrological classification (Belmar et al., 2011). The availability of hydrological data that reflects these reference conditions is one of the major limitations to the calculation of environmental flows (Harwood et al., 2017). This issue is particularly significant in countries such as Spain, whose rivers are among the most regulated in the world. According to the global georeferenced database of dams (GOODD), only 25% of the surface area of Peninsular Spain does not drain into one of the 823 large dams included in this database (Mulligan et al., 2020). Most of these dams were built in the mid-20th century and have made a significant contribution to the socio-economic development of the country (Mezger et al., 2021). Such a high degree of anthropisation of the natural regime of rivers highlights the need to establish a methodological framework that enables, through the use of hydrological models, a reconstruction of the series of natural daily flows for the evaluation of environmental flows, both in Spain and other countries whose rivers are highly anthropised.

The estimation of environmental flows is usually challenging due to the complex connections between river flows and river ecosystems (Smakhtin and Eriyagama, 2008). Many experts argue that the definition of environmental flows should focus not only on minimum values but also include flow variability to assess the river and floodplains influence on biodiversity and ecosystem integrity (Bunn and Arthington, 2002). Thus, the *Brisbane Declaration* (2007) envisages that the quantity, timing, and quality of freshwater flows should be considered in describing environmental flows. Furthermore, the Spanish Hydrological Planning Instruction for the elaboration of the RBMP (Orden ARM/2656/2008) requires that environmental flows be defined according to minimum and maximum flows, rates of change and channel maintenance discharges (Mezger et al., 2021). Since the 1970s more than 200 environmental flow methodologies have been identified (Tharme, 2003). Among them, hydrological methods vary from the simplest, which take only minimum flows into account (Gippel and Stewardson, 1998; Tennant, 1976) to the more complex, such as the range of variability approach (Richter et al., 1997) which considers 32 hydrological parameters (indicators of hydrologic alteration). In this study, we have used the indicators of hydrologic alteration in rivers (IAHRIS) software (Martínez Santa-María et al., 2008), especially recommended in Spanish and Mediterranean watersheds (Pérez-Sánchez et al., 2020; López-Ballesteros et al., 2020). The results will be also compared with the basic flow method (Palau and Alcázar, 2012), which consists of a minimum value of discharge in the river based on daily flow variability and has a rather negative impact on Spanish hydrological planning. The main problem when estimating environmental flows using hydrological methods is the scarcity of daily average flow data at the watershed level. The existing reference gauging stations must be in a natural regime, which reduces the availability of data (Alcázar et al., 2008). This data limitation is significant in Spain because the gauging stations, typically located in the main channels, can be affected by the different management and exploitation mechanisms of reservoirs (Belmar et al., 2011).

Hydrologic modelling is essential to the management of water resources and a key factor in simulating the hydrological cycle and forecasting watershed responses (McMillan, 2021; Wagena et al., 2020). In general, hydrological models can be categorised into two main groups (Solomatine and Ostfeld, 2008): physical and empirical. The former relies on equations that attempt to reproduce the physical laws describing the processes involved (i.e., SWAT, HEC-HMS, HBV, MIKE-SHE WASH123D, IAHCRES, MODHMS, etc.). In contrast, empirical or

data-driven models (DM) are based on input–output time series relationships, without any attempt to depict the behaviour of individual processes (Liu et al., 2019). In the last decade, the reported use of DM has greatly increased due mainly to the development of artificial intelligence, in particular as regards machine learning techniques (Husic et al., 2022; Hussain et al., 2021). The main differences between the models lie in the fact that physically based models (PM) require high-quality data and in-depth knowledge of the hydrological parameters, while DM performance is based mainly on basic information related to forecasting streamflow regardless of the watershed characteristics (Mosavi et al., 2018). However, there is no clear consensus on the widespread use of either of the two modelling approaches (Todini, 2007). While some studies support the idea that DM is more accurate than PM (Husic et al., 2022; Abbot and Marohasy, 2014; Abrahart and See, 2007) and numerous combinations of DMs have been recently developed, such as the long short-term memory neural network and ant lion optimiser model (Yuan et al., 2018), the adaptive neuro-fuzzy inference system and gradient-based optimiser (Nguyen, 2022), the convolution neural network and long-short-term memory network (Ghimire et al., 2021) and the support vector regression and simulated annealing and mayfly optimisation algorithms (Adnan et al., 2022), other research has questioned their overall performance. For example, Hussain et al. (2021) found that support vector machines hardly model flow peaks; the Soil and Water Assessment Tool (SWAT) proved to be more successful than artificial neural networks in simulating lower flows (Jimeno-Sáez et al., 2018) and the uncertainties provided by PM were more robust than those of DM (Shrestha and Nestmann, 2009). In this study, we have used a PM because of its capability to simulate streamflow variations not only in the gauge stations but also within the watershed, a key factor in environmental flow assessment and ecological monitoring, as well as because of its robustness in dealing with uncertainties.

SWAT (Arnold et al., 1998) has been accepted and tested worldwide in significant studies over the last decades as a PM at the basin level (López-Ballesteros et al., 2020; Senent-Aparicio et al., 2021c). The number of articles related to the SWAT model in the last decade has reached the figure of almost 4000 papers (Janjić and Tadić, 2023). Given the importance of this model, numerous papers have assessed and compared its performance and accuracy with many others. A thorough analysis of 21 hydrological models implemented in a wide range of watersheds demonstrated that the models MIKE-SHE (Abbott et al., 1986), HEC-HMS (<https://www.hec.usace.army.mil/software/hec-hms>), MODHMS (<https://www.usgs.gov/mission-areas/water-resources/science/modflow-and-related-programs>), SWAT and WARMF (Chen et al., 1998) outperformed the rest in terms of functionality, availability and applicability (Keller et al., 2023). Likewise, a comparison of 11 watershed hydrology models carried out by Borah and Bera (Borah and Bera, 2003) demonstrated that MIKE SHE and SWAT showed better performances. However, MIKE-SHE has large data requirements, whereas SWAT obtains good results with little direct calibration, making the latter the most appropriate for a wide variety of watersheds and hydrologic predictions. Similarly, SWAT has been proven to be a satisfactory model for assessing environmental flow (Kumar et al., 2022; Joseph et al., 2021; Zeiger and Hubbard, 2018) or hydrological ecosystem services (Ha and Bastiaanssen, 2023; Behboudian et al., 2023; Aznarez et al., 2021). SWAT operates on a daily time scale and is designed to predict the impact of agricultural practises on water, sediment and agricultural yields in large, complex watersheds over a long time period (Dile et al., 2016). The SWAT model is a suitable option for simulating different scenarios of historical environmental flow regimes (Kennen et al., 2009). The present study used an updated, restructured version of this software (SWAT+) (Bieger et al., 2017) to simulate various historical scenarios. Similarly, the SWAT+ post-processing tool (Senent-Aparicio et al., 2021b) included in the visualisation section has facilitated the estimation of environmental flows from the daily data obtained from the model. The daily time scale is usually the primary

choice for specific modelling situations, such as exploring dominant hydrological processes (Khatami et al., 2019) or attempting to simulate historical river operations related to water allocation activities (Perera et al., 2005). However, the difficulty with daily time scale models is that they can become deficient in specific contexts (e.g. drier climates) and require higher computational performance; thus, they can create uncertainty when studying some scenarios (John et al., 2021).

Considering the difficulties of modelling and calibration on a daily scale, other alternatives have been sought to obtain daily scale flows based on a monthly scale model with disaggregation techniques. Several studies support the hypothesis of present work (Kim, 2018; Verma, 2021; Wurbs, 2021a) and indicate that modelling and calibration on a monthly scale based on a daily flow pattern can provide valid results for environmental objectives related to water volumes, timing and sequences. Therefore, model calibration on a monthly scale has been found to be effective in simulating flow volumes. In contrast, observed daily flow patterns provide additional hydrological information for proper model performance (John et al., 2021). The Water Rights Analysis Package (WRAP) model, in addition to being a modelling system focused on the analysis of the development, management, control and allocation of water resources in different river systems (Wurbs, 2021b), is known for including different tools for managing hydrological data over different time series and scales related to the previously mentioned uses. In the present study, the disaggregation techniques included in the WRAP daily module (Wurbs, 2021c) were used to obtain a better distribution of the flows coming from the monthly calibration and to preserve monthly volumes by following and replicating a daily flow pattern. Some previous studies have combined SWAT and WRAP models to provide valuable information on daily scale flows (Kim, 2015; Ryu, 2015; Verma, 2017); however, these studies used an approach different to that of this work, as they addressed the goal of estimating the daily flow pattern using the daily flow series generated by SWAT to disaggregate monthly naturalised flows to daily flows using WRAP. However,

Verma (2017) discourages the use of SWAT for estimating the daily flow pattern. For this reason, a different approach using daily flows observed at nearby stations to calculate the daily flow pattern, is proposed in this study. Thus, the objective of this work is to analyse which of the following methodological approaches is more suitable for estimating environmental flows: 1) use of simulated daily streamflow from a SWAT+ model calibrated at a monthly scale; 2) use of simulated daily streamflow from a SWAT+ model calibrated at a daily scale; or 3) use of simulated daily streamflow from simulated monthly streamflow from a SWAT+ model calibrated at a monthly scale and subsequently disaggregated to a daily scale using the disaggregation techniques included in the WRAP model (using daily streamflow observed at nearby stations for the estimation of the daily flow pattern). The development of this methodology could be significant for government institutions facing contemporary environmental issues. This would allow for alternatives for studying and maintaining natural ecosystems threatened by constant environmental degradation, as long as the method is applied correctly and the right decisions are made for the ecosystems' management.

2. Description of the study area

To compare the accuracy of the proposed methodology, two different basins in Spain were selected (Fig. 2): the Piloña River Basin (PRB) and the Tagus River Basin (TRB). Peninsular Spain presents significant climatic variability due to its complex orography and unique geographical position between the subtropical zone and the European mild zone (Senent-Aparicio et al., 2018). This variability includes diverse climatic conditions, ranging from some of the driest regions in Europe, found in the southeast, to the most precipitation-rich areas, found in the north (Pérez-Sánchez et al., 2019). In this study, the selection of basins was guided by the prominent climatic zones present in Spain, using the Köppen-Geiger climate classification system (Kottek et al., 2006).

As shown in Fig. 2, the PRB is located in northern Spain, covering the

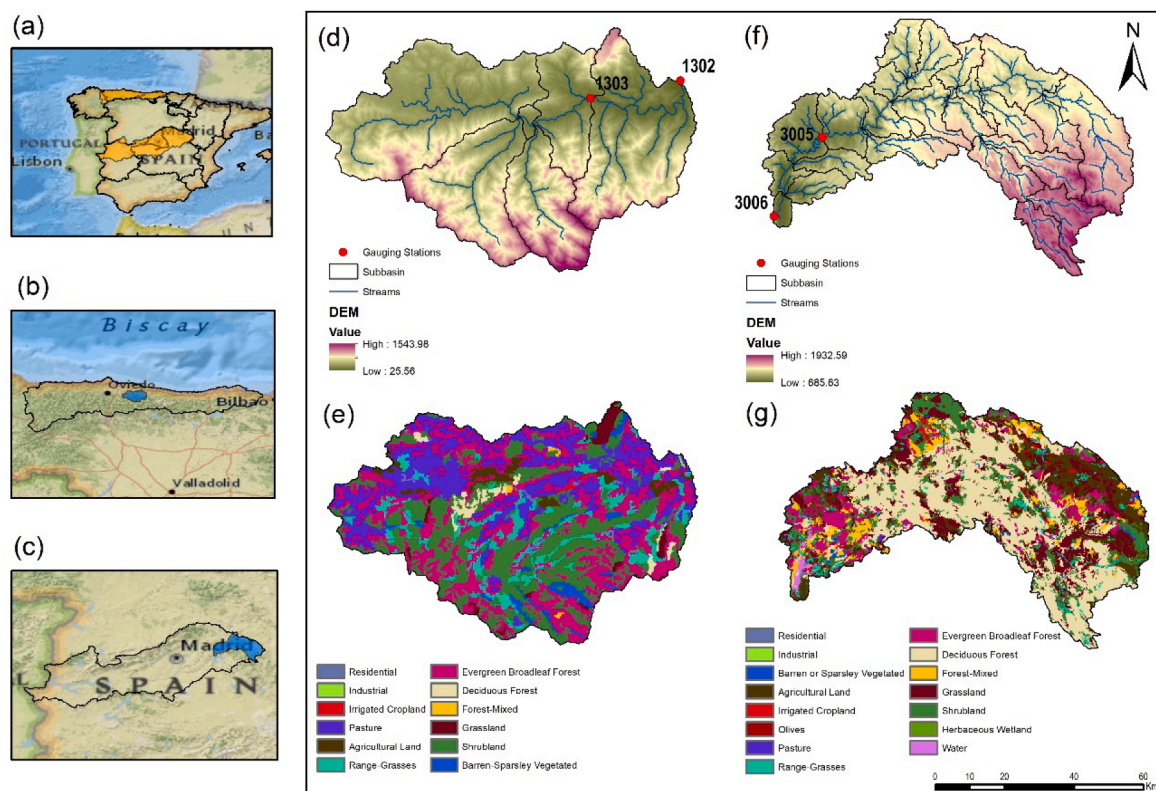


Fig. 2. (a) Location of the Eastern Cantabrian and Tagus River Basins in Peninsular Spain; (b) Location of the PRB in the Eastern Cantabrian River Basin; (c) Location of the TRB in the Tagus River Basin; DEM, stream gauges and sub-basin boundaries of the (d) PRB and (f) TRB; Land use of the (e) PRB and (g) TRB.

central-eastern part of Asturias, and the weather in this area is generally humid with warm temperatures and hot summers (Cfb). The PRB is an area of high natural value, especially at its confluence with the Sella River, proposed as a Site of Community Importance (SCI) in 1999 and designated as a Special Conservation Area (SAC) in 2014 by the European Union. The TRB is located in Guadalajara municipality, on the outskirts of Madrid, and has a climate characterised by cold and wet winters and warm and dry summers (Csa/Csb), a climate that is dominant in a large part of the Iberian Peninsula (AEMET, 2011). The TRB is part of a large extension of the Tagus headwaters, declared a UNESCO Global Geopark due to its unique and varied geology (Molina-Navarro et al., 2014). The study areas are covered by different types of soils, with leptosols and cambisols being predominant in both cases. Based on the UNESCO aridity index (Nastos et al., 2013), the PRB and TRB can be classified as humid and sub-humid climates. The PRB has different types of forests, shrubland and pasture, combined with a smaller portion designated for crops and other agricultural uses and an insignificant surface area for residential and industrial use (Fig. 2e). In the TRB, the most common land uses (Fig. 2g) are associated with forest and grassland, with a significant part dedicated to agriculture and very little dedicated to residential activity. Table 1 summarises the characteristics of both watersheds.

2.1. SWAT+ model description

SWAT (Arnold et al., 2012a) was developed to assess the impact of different land management practises on water resources, sediment and the application of chemicals of agricultural origin, such as nitrogen or phosphorus, in watersheds with different soils, land uses and management conditions over long periods of time. This tool has been implemented in many important studies worldwide (Shen et al., 2015). SWAT+ (Bieger et al., 2017) is an updated version of SWAT. It is based on the same equations but has greater flexibility in the configuration of the model processes. However, it is not as well-tested as SWAT because it is relatively new (Chawanda et al., 2020; Jiménez-Navarro et al., 2021). SWAT+ is based on the concept of hydrologic response units (HRU), through which areas in each sub-basin with unique properties of slope class, land use and soil are related. SWAT+ also works with a new feature of landscape units (LSUs): smaller-scale subdivisions of the sub-basins to separate the upland processes and floodplain (Bieger et al., 2017). Then, sub-basins are delimited according to stream thresholds during the model configuration, and LSUs are delimited according to channel thresholds. The water balance equation used in the SWAT+ model is as follows:

$$SW_t = SW_0 + \sum (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw})$$

Where SW_t and SW_0 are the final and initial water content, respectively, at a given time (t) (days). Q_{surf} is the surface runoff produced by the precipitation on a given day (R_{day}). E_a is the evapotranspiration, W_{seep} is

Table 1

Characteristic of study basins. Obtained for the period 1972–2014 for PRB and 1971–1986 for TRB.

Characteristic	PRB	TRB
Area (km ²)	511	3781
Mean elevation (m)	688	1217
Mean annual precipitation (P) (mm)	1446	662
Mean annual potential evapotranspiration (PET) (mm)	829	1060
Köppen climate	Cfb	Csa/Csb
Aridity index (P/PET)	1.74	0.62
Dominant land uses (%)	Forest (34%) Shrublands (28%)	Forest (37%) Range- Grasses (17%)
Dominant soils (%)	Leptosols (72%) Cambisols (15%)	Cambisols (46%) Leptosols (20%)

the percolation and Q_{gw} is associated with the amount of baseflow on a day (all the components are in mm).

2.1.1. Dataset and model set-up

The general structure of SWAT+ model input files is similar to that of SWAT. The new open-source Quantum Geographical Information System (QGIS) interface for SWAT+ (QSWAT+ 2.2.5) generated the model setup. As shown in Table 2, the digital elevation model (DEM), necessary for calculating flow accumulation, stream links and the delineation of the PRB and TRB was obtained from the Spanish National Center for Geographic Information (IGN) with a 25-meter grid cell resolution. Applying the criteria established by the Food and Agriculture Organisation of the United Nations (FAO, 1980), the slope ranges of the SWAT+ model were divided into three well-defined groups (<8%, 8–30% and >30%). Land use data were extracted from the European Project Corine Land Cover 2000 (1:100.000). Finally, the soil map with soil profile description, standardised soil texture and geology classes was extracted from the Harmonized World Soil Database (HWSD) (FAO, 1990).

The climatic variables required for SWAT+ include daily total precipitation and maximum and minimum temperatures, which have the most influence on variations in the flow rate (Zaman et al., 2018). They were collected from the Spanish National Meteorological Agency (AEMET) grid, which provided minimum and maximum temperatures and daily precipitation from 1951 to 2019 with a 5-km spatial resolution (Senent-Aparicio et al., 2021a). Streamflow data observed at gauging stations included in the Spanish National River Flow Network (ROEA) were provided by the Hydrographical Studies Center. These stations correspond to codes 1303 and 1302 (Fig. 2d) in the PRB and to codes 3005 and 3006 in the TRB. The first code was used to calibrate the SWAT+ model in Step 1, and the second was used as a “donor station” intended as a flow pattern for applying disaggregation techniques in Step 2. In the present study, the Soil Conservation Service (SCS) curve number method was used for modelling surface runoff, and the Hargreaves method was used to determine potential evapotranspiration values (Hargreaves, 1994).

2.1.2. Model calibration and validation

Model calibration is necessary to reduce the uncertainty of the parameters integrated into the SWAT+ to the greatest extent possible (Arnold et al., 2012b). The present study used a SWAT parameter estimator (SPE) algorithm to calibrate the SWAT+ model. The SPE is the updated version of the Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm in the new version of SWAT+ Calibration and Uncertainty Program (SWATplus-CUP). This algorithm has been widely used for the automatic calibration and a sensitivity analysis of the SWAT model parameters (Abbaspour, 2012), and it has been compared in numerous

Table 2

SWAT+ model inputs.

Data	Description	Source
DEM	25 m × 25 m resolution map	Spanish National Geographic Institute (IGN)
Gauging stations	N° 1303: Piloña River in Villamayor N° 3005: Tagus River in Trillo	Spanish National River Flow Network (ROEA)
Flow pattern for disaggregation	N° 1302: Piloña River in Ozanes N° 3006: Tagus River in Entrepeñas	
Land use map	Vector database	2000 Corine Land Cover program (CLC2000)
Soil map	1 km × 1 km resolution map	Harmonized World Soil Map (HWSD)
Climate data	Daily precipitation, maximum and minimum air temperature	Spanish National Meteorological Agency (AEMET)

studies with other uncertainty analysis methods, such as the generalised likelihood uncertainty estimation (GLUE) and the parameter solution (ParaSol) (Wu and Chen, 2014; Zhang et al., 2019). These works demonstrate the advantages of employing the SUFI-2 (SPE in the new version) method, taking into account both modelling performance accuracy and computational efficiency. SWATplus-CUP automatic calibration was performed between 1972 and 2014 (43 years) for the PRB and 1971–1986 (16 years) for the TRB using available monthly and daily observed streamflow data. The calibration periods were from 1972 to 1993 and from 1971 to 1978 for the PRB and TRB, respectively. The rest of the periods were used for the model validation. Following recommendations in the available literature, such as the importance of the regionalisation process through a graphical comparison of simulated and observed flows (Abbaspour et al., 2015, 2018) and those of previous studies in nearby areas (Jimeno-Sáez et al., 2018; Senent-Aparicio et al., 2021d), ten commonly used parameters and their ranges were selected for the first monthly calibration (SCS runoff curve number, *cn2*; lateral flow travel time, *lat_time*; maximum canopy storage, *canmx*; baseflow recession constant, *alpha*; minimum aquifer storage to allow return flow, *flo_min*; plant uptake compensation factor, *epco*; available water capacity of the soil layer, *awc*; percolation coefficient, *revap_co*; soil evaporation compensation factor, *esco*; and threshold depth of water in the shallow aquifer for percolation to the deep aquifer, *revap_min*), which incorporated aspects of runoff, subsurface flow, and soil data. Likewise, another five parameters were selected for a second daily calibration (average slope steepness, *slope*; surface runoff lag coefficient, *surlag*; Manning's "n" value for overland flow, *ov_n*; average slope length, *slope_len*; and Manning's "n" value for the main channel, *chn*) considering indicators directly related to the basin morphology (Yacoub and Foguet, 2013). Two iterations of 500 simulations each were run to adjust the parameter ranges. In the same way, the 10 best simulations were analysed to observe parameter dispersion with respect to the objective function and to clarify the equifinality phenomenon during the calibration process (Brochet et al., 2023). In the present study, the Kling–Gupta efficiency (KGE) (Gupta et al., 2009), the percent bias (PBIAS), the Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), the root mean square Error (RMSE) and the standard deviation ratio (RSR) were used as indicators for evaluating the model's performance in terms of amount and timing, according to the statistical criteria proposed by Moriasi et al. (2015). The KGE was adopted for the objective function in the calibration. Krause et al. (2005) did not recommend the NSE for low flow conditions because it overestimates the largest values, meaning the peaks, and disregards the lower flows because it uses the square of the difference between observed and simulated flows. To more efficiently evaluate the behaviour of low flows and overcome the uncertainty of the NSE in evaluating the extreme values, the Nash–Sutcliffe logarithm (LnNSE) was also employed as an indicator for the SWAT+ model. Previous studies have successfully employed the transformation of this parameter (Senent-Aparicio et al., 2021b; Parra et al., 2019; Chen et al., 2018; Osuch et al., 2018).

2.2. Disaggregation techniques

The availability of hydrological information on a daily time scale is significant for different water resource management objectives (John et al., 2021). A monthly time scale can indicate the satisfactory performance of the model, facilitating its application in the development of objectives. However, a daily time step can improve the precision and performance of the model and the forecasted flows, expanding the possible applications of the data obtained from the model. Therefore, applying disaggregation techniques from monthly SWAT+ model streamflow data to a daily scale is integral to obtaining alternatives in studying environmental flows. WRAP modelling system has been applied in multiple studies (Kim, 2018; Wurbs, 2021a) to simulate various types of water management and was used in the present study to disaggregate naturalised monthly flows into daily ones. The WRAP

modelling system has been incorporated into the Water Availability Modelling (WAM) system (Wurbs, 2021b) and is maintained by the Texas Commission on Environmental Quality (TCEQ), which simulates the management of a river basin's water resources (Kim, 2018) and is composed of a set of programmes with specific water management applications. WRAP software is freely available on the Texas A&M University (TAMU) WRAP website (<https://wrap.engr.tamu.edu/>). The present study applied the WRAP daily module (SIMD program) to obtain daily streamflow data from naturalised monthly flows.

The daily simulation model SIMD (Wurbs, 2021c) integrates all the modelling capabilities of the monthly time step model (SIM program) and significant extra features made possible by disaggregation from a monthly to a daily time scale. The monthly values of input variables are disaggregated within the SIMD programme into daily amounts following four techniques included in the WRAP model system: (1) uniform distribution, (2) linear interpolation, (3) variability adjustment and (4) the replication of daily flow patterns. Finally, WRAP post-simulation allows one to create, read and organise collection data in digital speech standard (DSS) files. The DSS interface HEC-DSSVue (Hydrologic Engineering Center U.S. Army Corps of Engineers, 2009) manages these files with time-series data, including inputs and results, and is an integral component of WRAP. It is available on the United States army corps of engineers (USACE) HEC website (<https://www.hec.usace.army.mil/software/hecdssvue/>).

The uniform distribution option (1) is the simplest disaggregation method. Daily flow data were obtained through it by dividing the monthly flow volumes by the number of days in each month (28, 30 or 31 days, or 29 days in leap years). In contrast, the linear interpolation option (2) defines daily flows at the beginning, middle and end of each month based on the last, current and next month. The connection of these points forms linear splines, which represent the instantaneous flow rates at various points in time. The areas under the splines represent the flow volumes in a given time period. When monthly volumes are disaggregated into daily flows using the linear interpolation method, the resulting daily flow sequences are smoother and more closely related than the actual observed daily flow rates. The third disaggregation technique directly relates to the previously described option with an important nuance: the need for input data. The adjustment variability option (3) methodology uses daily flow variation patterns to adjust the daily flows obtained using the linear interpolation method. In this option, the aggregated monthly sums of the daily flows were used to calculate the interpolated flow for each day using linear interpolation. The sequence of daily variability ratios reflects the pattern of variability in daily flows as a ratio of the actual daily flow volume to the daily flow volume, which was calculated using a linear interpolation routine. The fourth and last option, replicating a daily flow pattern (4), is the most recommended default method for disaggregating monthly naturalised flows to a daily time scale in the SIMD programme. The monthly naturalised flow volume was disaggregated into daily flows using a daily flow series previously included as input data. Each monthly flow volume was proportioned to daily volumes according to the ratio of the daily flow pattern divided by its monthly total.

2.3. Characterisation of the natural flow regime and basic flow

Ecosystems provide significant benefits to human welfare, but their preservation presents a major challenge due to the many current changes occurring worldwide (Volk, 2015; Seifert-Dähnn et al., 2015). Global river flow has been impacted by the growth and development of water resources (Tharme, 2003). Every river has its own natural flow regime responsible for physical habitat, biological diversity and ecological processes. In this study, we have employed the indicators of hydrologic alteration in rivers (IAHRIS) to assess the hydrological parameters that determine the good status of the rivers. This method has been developed by the Centre for Public Works Studies and Experimentation (CEDEX) of Spain, and as stated previously, it is particularly

recommended for Spain because it is based on Spanish Hydrological Planning Instruction criteria. Table 3 shows the 19 parameters integrating this method, which relies on the usual and extreme values (floods and droughts) of annual, monthly, and daily streamflow. The characterisation of a natural regime is carried out based on five main items: magnitude, frequency, variability, duration, seasonality and change rates, that is, availability, diversity, resilience, synchrony and

Table 3
Parameters of IAHRIS.

Group		Aspect	Description	Parameter
Usual values	Annual and monthly volumes	Magnitude	Mean of annual volumes	P1
		Variability	Difference between maximum and minimum volume in the year	P2
		Seasonality	Months of maximum and minimum volume in the year	P3
	Daily flows	Variability	Differences between average flows of 10% and 90% percentiles	P4
Extreme values	Maximum daily flow (floods)	Magnitude and frequency	Average of yearly maximum daily flow	Qc (P5)
			Effective discharge	QGL (P6)
			Connectivity flow	QCONEC (P7)
			Usual flow in flooding (5% exceedance percentile)	Q5% (P8)
		Variability	Coefficient of variation of yearly maximum daily flow	Cv (Qc) (P9)
			Coefficient of variation of usual flow in flooding	Cv (Q5%) (P10)
		Duration	Consecutive days in a year with exceedance percentile below 5%	Duration of flooding (P11)
			Average number of days per month with exceedance percentile above 5%	Range of 12 values (P12)
	Minimum daily flow (droughts)	Magnitude and frequency	Average of yearly minimum	Qs (P13)
			Usual flow in droughts (95% exceedance percentile)	Q95% (P14)
		Variability	Coefficient of variation of yearly minimum daily flow	Cv (Qs) (P15)
			Coefficient of variation of usual flow in droughts	Cv (Q95%) (P16)
		Duration	Consecutive days in a year with exceedance percentile below 95%	Duration of droughts (P17)
			Average number of days per month with null flow	Range of 12 values (P18)
		Seasonality	Average number of days per month with exceedance percentile below 95%	Range of 12 values (P19)

response capacity, respectively. The usual values determine the general availability of water in the ecosystem, while the extreme values (maximum-floods, minimum-droughts) represent the most critical environmental conditions (Martínez Santa-María et al., 2008).

In addition to the IAHRIS method, we have used a SWAT+ post-processing tool to estimate the so-called basic flow in the Piloña and Tagus Rivers. A more detailed description of the tool's performance can be found in Senent-Aparicio et al. (2021b). The basic flow method, proposed and developed in Spain by Palau and Alcázar (2012), has achieved a certain degree of recognition in Spain for hydrological planning and determines the absolute minimum discharge that should flow in a channel. This technique has been tested in various studies (Senent-Aparicio et al., 2021b; Herrera and Burneo, 2017; Peñas et al., 2014; Efstratiadis et al., 2014) and includes a set of indicators to consider variability and irregularities in a daily mean flow series. Only one, called basic flow (Qb), was integrated into the post-processing tool, representing this flow as a minimum that should be maintained in the river. It is based principally on the moving averages applied at intervals of consecutive daily average flow data in the order of 1 to 100 values. It is associated with discontinuities throughout the series. The justification for this limit is that 100 days would include the lowest flow period of the year in the study area (water levels in the summer months) by covering just over three months of daily flow values. Through this process, the minimums of the moving average model applied to each interval were identified in an increasing way. Next, the value of Qb for each year was defined based on the ending of the longest flow in the study period, which was identified by the highest relative increment between two consecutive increasing intervals between minimum average flows. Finally, the final Qb value was calculated as the average of the individual Qb values for each of the years of the study period, following the recommendations to have a study period of at least 10-years (in this case, 30 and 16 years for the PRB and TRB, respectively).

3. Methodology

The methodology used in this study is shown in Fig. 1. It is based on three main steps:

- (1) A hydrological model of the studied basins using the SWAT+ model and its calibration was divided into three scenarios with different approaches. The first scenario was calibration on a monthly scale, with the objective of better adjusting the water volumes and the base flows according to daily simulations. The second scenario used the same calibration as the previous one, but simulations were performed monthly. The third scenario involved daily calibration, with the objective of improving the temporality and accuracy of the model flows.
- (2) As a result of the monthly simulation in the second scenario, four different disaggregation techniques were applied using the WRAP modelling system to obtain daily flows, following a daily flow pattern from a nearby donor gauging station.
- (3) The environmental flows of each daily flow series obtained in the previous steps were determined based on the estimation of the basic flow (Qb) (Palau and Alcázar, 2012) using the SWAT+ post-processing tool, and a group of indicators associated with the magnitude, frequency, variability, seasonality and duration of the flows included in the IAHRIS software. Based on these parameters, we compared the accuracy of these flows in each of the previously explained calibration scenarios.

4. Results and discussion

4.1. SWAT+ model performance in monthly calibration and daily simulation (Scenario 1)

As previously mentioned, the SWAT+ model was calibrated using

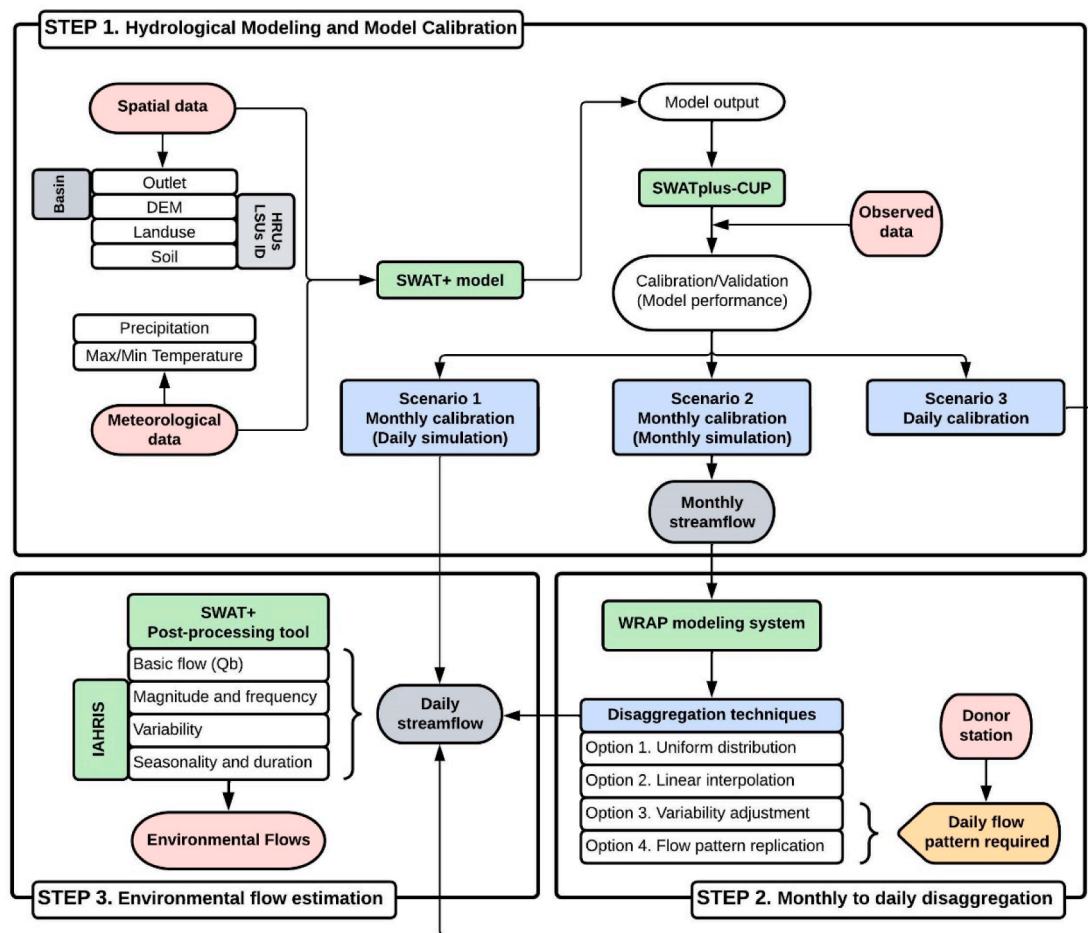


Fig. 1. Methodology flowchart.

available observed streamflow data from 1972 to 1993 (22 years) and validated from 1994 to 2014 (21 years) for the PRB, and it was calibrated from 1971 to 1978 (8 years) and validated from 1979 to 1986 (8 years) for the TRB. This first calibration scenario focused on adjusting monthly volumes to provide more controlled peak flows and better low-flow performance. The parameters selected in this scenario also focused on their potential effect on the volumes and base flow, with the objective of subsequently influencing the estimation of environmental flows. Table 4 represents the description of these parameters and their evaluation using the *p*-value, which determined the importance of the sensitivity of each parameter in the model calibration. In the same way, the fitted values of these parameters reflect the contrasting climatic characteristics of the two basins. In the TRB, parameters associated with groundwater (such as *flo_min* and *revap_co*) were more significant, as expected in continental Mediterranean basins where aquifers are more relevant. Senent-Aparicio et al. (2021d) employed similar values to those obtained in our calibration for those parameters (*GW_REVAP* and *GWQMN*, respectively, in the previous version of SWAT). In the PRB case, one of the most sensitive parameters, according to *p*-value, was *lat_time*, and its calibrated value was low, indicating that the water pathways travelling through the soil profile were short; the opposite is true in the TRB. In relation to the three parameters mentioned above, Fig. 3 shows the dispersion of their values to the best 10 simulations with respect to the objective function (KGE) and the different behaviour in each of the basins. The close alignment of the Y-axis bounds with the parameter range indicates a minimal dispersion in values, indicating heightened parameter sensitivity and a diminished presence of equifinality. In both the PRB and TRB, the curve number (*cn2*) was sensitive, decreasing its value by 6.72% and 11.25% respectively, from the default

value, indicating an increase in stream infiltration and a reduction in runoff. Another significant difference between the two basins are the calibration values obtained for the soil evaporation compensation factor. The highly calibrated value for *esco* in the PRB was expected, as this area has an Atlantic climate in which evapotranspiration is not of significant relevance (Jimeno-Sáez et al., 2018). However, in the TRB, *esco* was the most sensitive parameter because, in semi-humid climates, evapotranspiration is more relevant (Senent-Aparicio et al., 2017). Molina-Navarro et al. (2014) employed *esco* values in other studies in the upper Tagus similar to those obtained in our monthly calibration. As the *esco* value decreases with respect to its default value, the model's ability to extract evaporative demand from deeper soil layers increases (Neitsch et al., 2009). The *alpha* factor is crucial for adjusting low flow rates, and our calibration values were 0.72 in the PRB and 0.89 in the TRB. Arnold et al. (2012b) stated that *alpha* values vary between 0.1 and 0.3 for land with a slow response and between 0.9 and 0.1 for land with a rapid response. The *sol_awc* increased in all soils in both basins, reducing water movement within the soil profiles (Qiu et al., 2012). The values obtained in the PRB for the remaining parameters were similar to those used in other study areas in northern Spain (Jimeno-Sáez et al., 2022).

Figs. 4 and 5 show the daily values in the monthly calibration and validation periods obtained in simulations before and after automatic calibration. Daily model performance in this scenario was sufficient in both watersheds, with KGE values close to 0.5 for PRB and values greater than 0.6 for TRB, according to the criteria established by Kouchi et al. (2017). The LnNSE indicator was the most important indicator for determining the low-flow model's efficiency. This value notably improved with respect to the initial values, reaching values of 0.35 and 0.40 in the calibration and validation periods, respectively, for the PRB

Table 4

Calibrated SWAT+ model monthly parameters. (r_) is a relative change, which means that the parameter is modified by a specific percentage, and (v_) means that the parameter is replaced by a specific value determined in the calibration.

Parameter	Description	PRB		TRB	
		p-Value	Fitted value	p-Value	Fitted value
r_cn2.hru	SCS runoff curve number (dimensionless)	0.0000	−6.72%	0.0237	−11.25%
v_lat_ttime.hru	Lateral flow travel time (days)	0.0000	16.0875	0.3147	147.465
v_canmx.hru	Maximum canopy storage (mmH ₂ O)	0.0061	74.5625	0.1156	0.6349
v_alpha.aqu	Baseflow recession constant (days ^{−1})	0.2686	0.7206	0.7067	0.8937
v_flo_min.aqu	Minimum aquifer storage to allow return flow (mm)	0.2743	865.625	0.0006	203.184
v_epco.hru	Plant uptake compensation factor (dimensionless)	0.3012	0.7618	0.3279	0.0285
r_awc().sol	Available water capacity of the soil layer (mm H ₂ O/mm Soil)	0.5438	8.28%	0.9714	3.37%
v_revap_co.aqu	Percolation coefficient (dimensionless)	0.5628	0.7768	0.4881	0.1651
v_esco.hru	Soil evaporation compensation factor (dimensionless)	0.6825	0.7493	0.0000	0.6596
v_revap_min.aqu	Threshold depth of water in the shallow aquifer for percolation to the deep aquifer (mm H ₂ O)	0.7298	513.125	0.2663	128.199

and 0.41 and a lower value of 0.21 in calibration and validation, respectively, for TRB. The NSE indicator highlights the accuracy with respect to the extreme values of the models, which is also of great importance for the environmental objectives of the study. In this case, the TRB showed a better performance with respect to this indicator. According to Moriasi et al. (2007) guidelines, the remaining statistical values were within the range of acceptable performance and showed a significant improvement during the model validation period. The attached figures indicate that, for monthly calibration, the water volumes improved slightly with respect to the first scenario, although the base flow was still underestimated.

4.2. SWAT+ model performance in monthly calibration and monthly simulation (Scenario 2)

The second scenario could be considered complementary to the calibration performed in the previous scenario, maintaining the same SWAT+ calibration parameters and simply changing the simulation time scale for further disaggregation from the WRAP programme. Table 5 compares the daily flows obtained from each disaggregation technique with the observed flows. The KGE objective function, LnNSE, NSE, RMSE and RSR were the main indicators for evaluating the model's behaviour. Option 4 (Flow pattern replication) was selected as best fitting the observed flows due to the distribution based on the pattern of daily flow from the donor station (gauging stations 1302 for PRB and 3006 for TRB). It was also considered the most appropriate option because it was the default method in the WRAP program's daily module (Wurbs, 2021c), being the most optimal way to replicate the hydrological behaviour of nearby stations.

This change in the simulation time scale was indicated by a simple graphical analysis of the improvement in model performance (Figs. 6 and 7), with adjusted flow volumes over the entire simulation period. Likewise, this first visual graphical inspection was performed to compare simulated and observed streamflows because using only metric values to evaluate model performance can be misleading, generating statistically satisfactory scenarios but not entirely realistic ones (Dagupati et al., 2015). According to the performance criteria followed in the previous scenario, the model's statistical indicators were good in both cases, consistently achieving objective function values of 0.83 and 0.92 for the PRB and values close to 0.8 for the TRB. The LnNSE significantly improved in this calibration scenario for the PRB, reaching average values of 0.85 and 0.89, representing a good correlation between the simulated and observed low flow values throughout the study period. However, in the case of the TRB, only satisfactory values of about 0.5 were obtained. In the same way, NSE values improved significantly in both basins, reaching mean values above 0.84. Furthermore, the lowest values of RMSE were achieved in Scenario 2, as well as RSR results were also below 0.50 for both models (PRB, TRB) and both stages (calibration and validation) which indicated a very good model according Moriasi et al. (2007). The calibration of the model on a monthly scale is more accurate for achieving this study's objectives, as it allows for a better adjustment of water volumes than a daily calibration. Therefore, because the model performs better, it is sufficient for obtaining daily-scale flows by applying different disaggregation techniques based on a daily flow pattern from a donor gauging station.

4.3. SWAT+ model performance in daily calibration (Scenario 3)

In this third and last scenario, the parameters for daily calibration were selected with the main objective of improving the timing of the model on a daily scale to catch low flows. As in the previous calibration scenario, the sensitivity of the parameters (p-value) as well as the value obtained in the automatic calibration are shown in Table 6. Similar parameters and calibration ranges were chosen based on studies conducted in nearby basins with comparable morphological characteristics (Senent-Aparicio et al., 2019). *Slope* and *slope.len* (SLSUBBSN in the previous version of SWAT) are parameters directly related to topographic characteristics, and the first one showed a significant sensitivity for both basins. It was observed that despite having a low p-value in both basins, the dispersion of the parameter was much lower in the case of the PRB (Fig. 8), being more important in mountainous areas. According to Yacoub and Foguet (2013), the value of their ranges usually varies according to soil type and land use. The high value obtained for *ovn* is associated with abundant vegetation, such as in the PRB in northern Spain (Raposo et al., 2013); the opposite is true in the TRB, where vegetation is affected by climatic variations that are more characteristic of Mediterranean areas, with aridity having a major effect, thus, a much lower *ovn* value is obtained. In the PRB, the calibrated *chn* value for the main channel was similar to that used by Jimeno-Sáez et al. (2018). The *surlag* parameter associated with controlling the total amount of available water that can enter the main channel daily allows for increased the accuracy of runoff predictions for large river basins by adding a temporal storage factor to the basins. The sensitive values were similar in both basins, although with a lesser dispersion in the case of the PRB, as shown in Fig. 8. Different calibration values were obtained, which were expected due to the significant difference in surface between the two study areas (White et al., 2009). Previous studies have shown that the *surlag* parameter may or may not be sensitive depending on the size of the studied watershed (van Griensven et al., 2006; Feyereisen et al., 2007). As *surlag* increases with respect to the default value (as is the case in both basins), the temporary storage available decreases (Neitsch et al., 2002).

Figs. 9 and 10 show the daily values obtained in the simulations before and after daily automatic calibration for the PRB and TRB. According to Kouchi et al. (2017), the daily model performance was

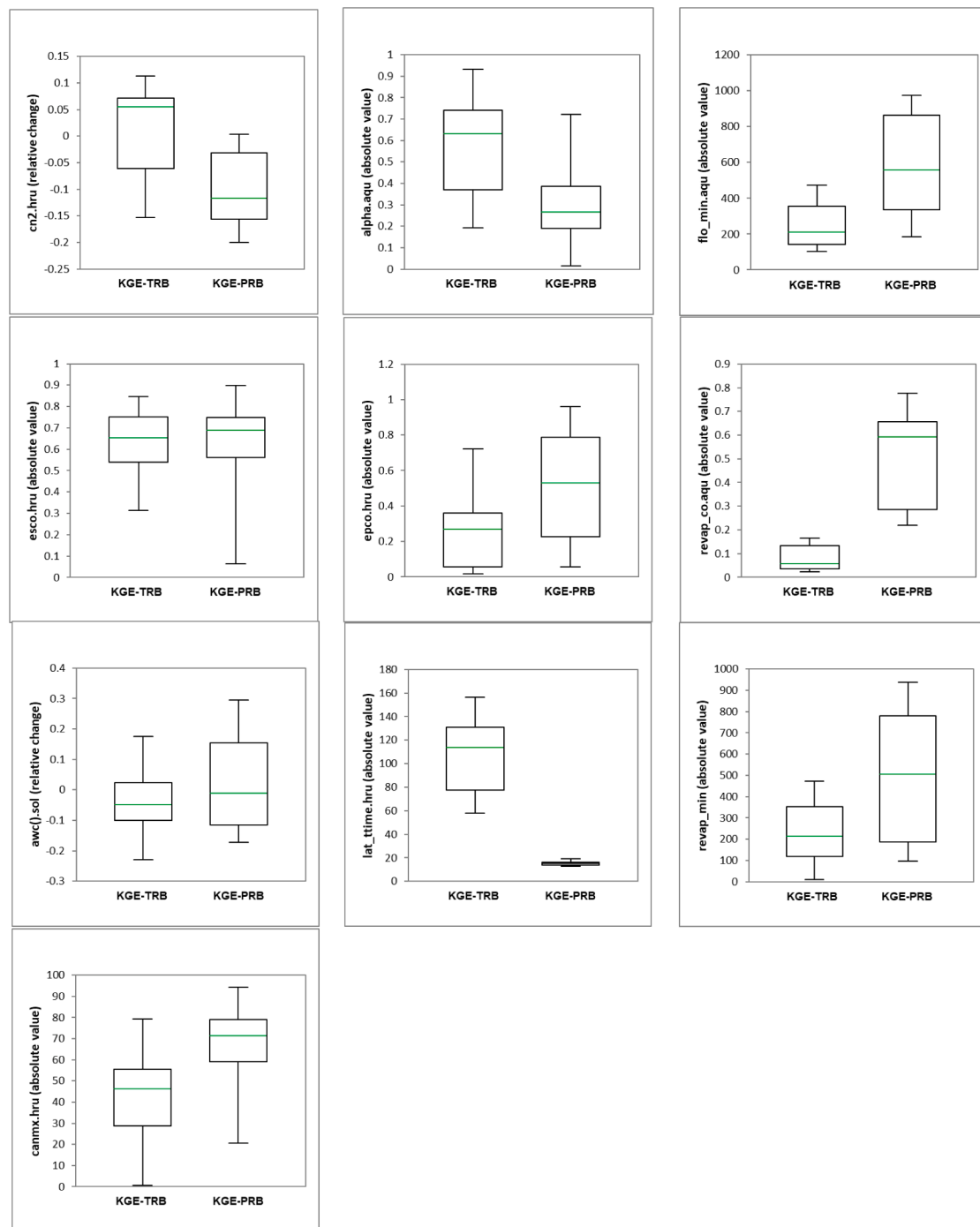


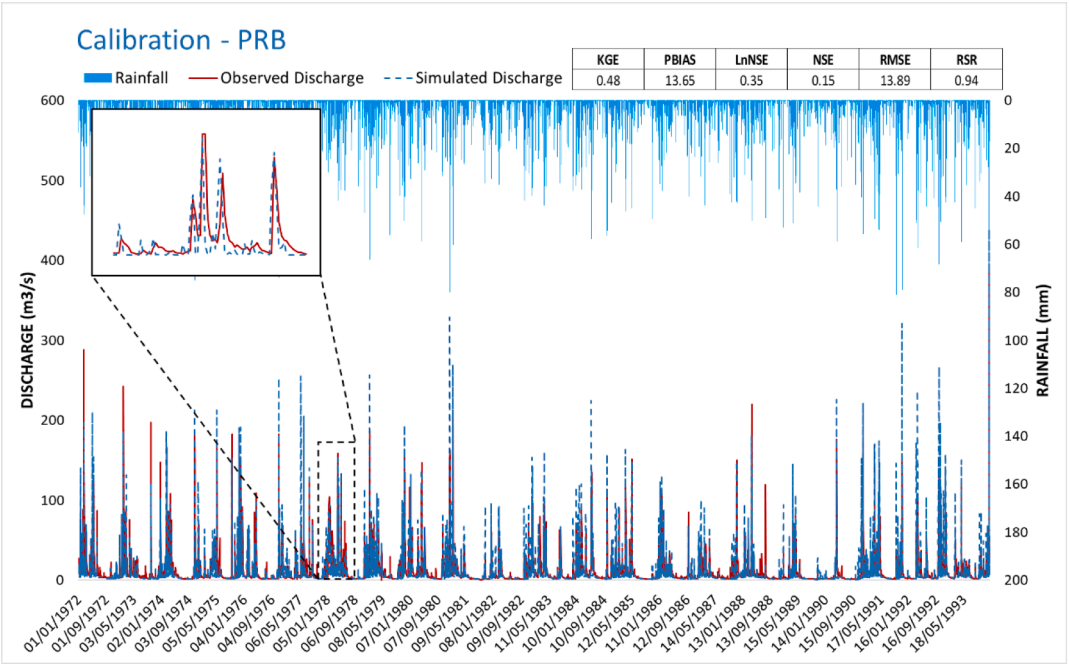
Fig. 3. Box plot analysis of the monthly parameter values of the 10 best simulations according to the objective function KGE in the PRB and TRB.

satisfactory in both cases from an objective function approach, consistently obtaining KGE values above 0.5. For this study, the LnNSE indicator in this last scenario represents a slight improvement over the model base flows, although average values below 0.5 were still obtained in both periods, indicating an underestimation of environmental flows, as observed in the subsequent results. Verma (2017) discourages the use of SWAT for estimating the daily flow pattern, and the results obtained in this calibration scenario support this. The NSE indicators with respect to peak flows did not improve significantly either, being considered unsatisfactory for both study basins according to the criteria of the literature consulted.

4.4. Characterisation of the natural flow regime and basic flow

From the daily scale flows obtained in the three proposed study scenarios of (1) monthly calibration and daily simulation, (2) monthly calibration and monthly simulation and disaggregation from a flow pattern and (3) daily calibration and daily simulation, the characterization of the natural flow regime in the Piloña and Tagus rivers was assessed following the IAHRIS methodology for the periods 1980–2009 and 1971–1986, as shown in Tables 7 and 8, respectively. In general, the comparison between statistics of gauge station and the three models makes clear that Scenario 2 outperformed the other two in the PRB both for usual and extreme values. However, in the case of the TRB, the similarities with recorded values depended mostly on the parameter

a)



b)

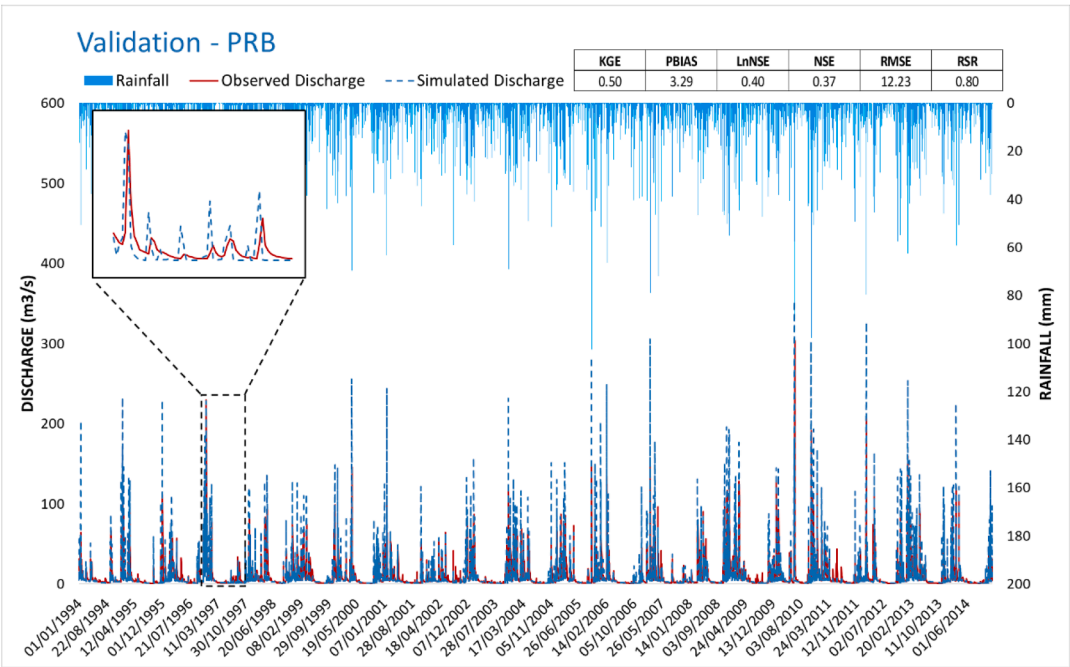


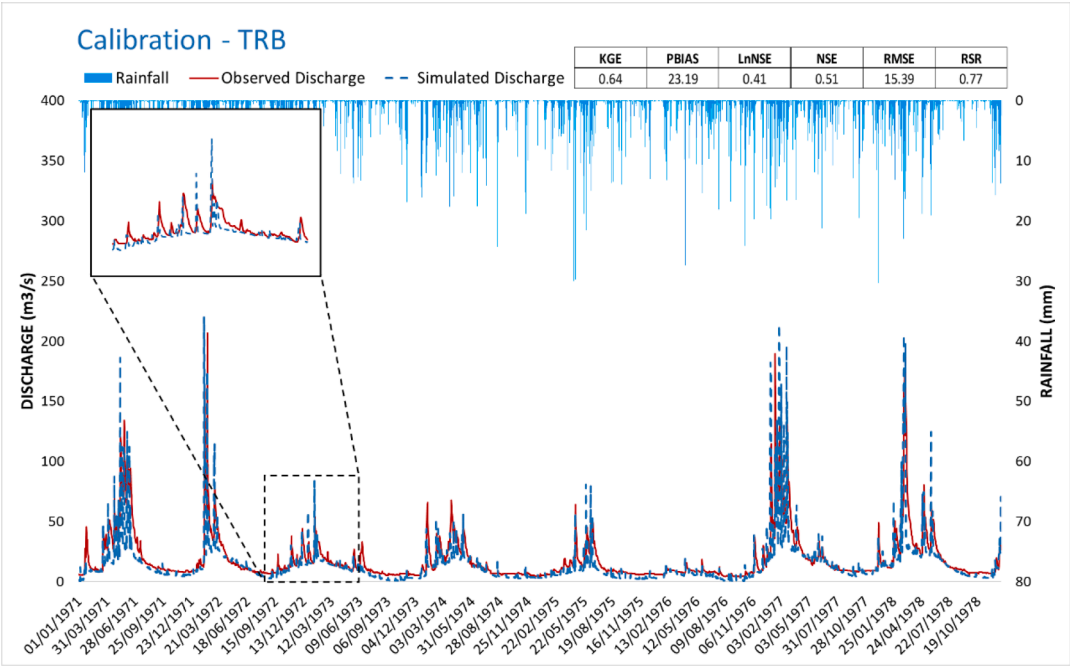
Fig. 4. Daily model performance for a) calibration and b) validation periods for monthly calibration in the PRB.

considered, whereas in droughts, where Scenario 2 outperformed the other models.

The usual values were carried out on three temporal scales: year, month, and day. Although yearly and monthly volumes are not related to any geomorphological or ecological role, they are essential to obtaining accurate knowledge of ecosystem water availability (Richter

et al., 1997). With regard to the PRB, the value of the average of annual volumes (P1) in recorded data is around 298 Hm³ and the models predicted values within a range of 210–341 Hm³, with a minimum error of –5.68% for Scenario 2. The variability of usual values (P2) is the main driver of ecological and geomorphological dynamics (Brizga et al., 2001). As before, Scenario 2 in the PRB obtained a reading 1.5% away

a)



b)

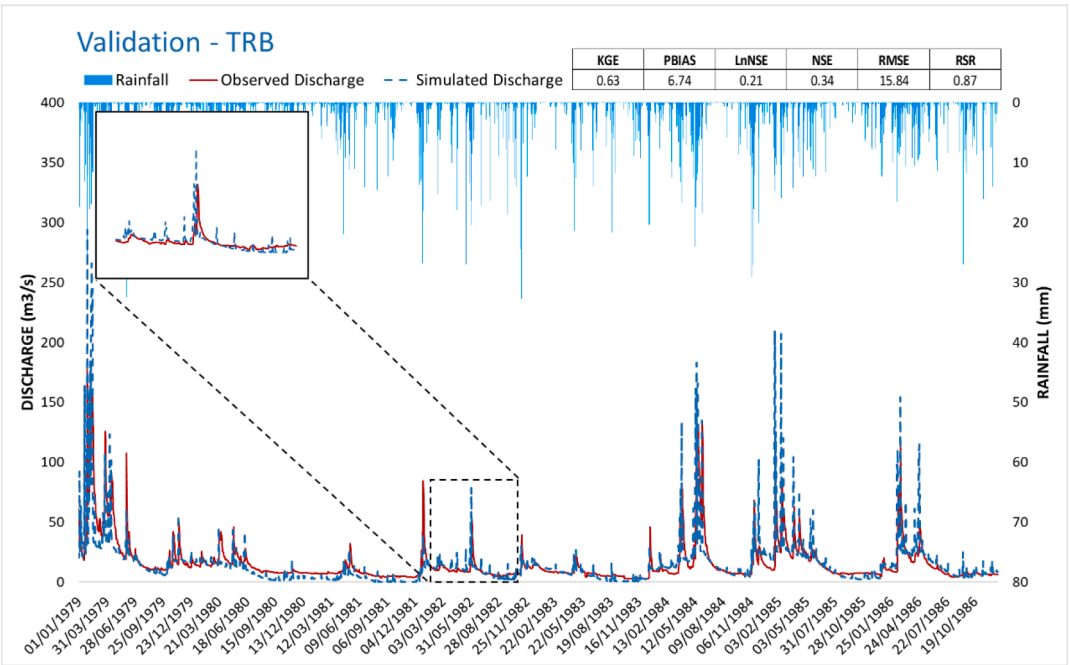


Fig. 5. Daily model performance for a) calibration and b) validation periods for monthly calibration in the TRB.

from that of the gauging station. This value increased or decreased from around -17% to $+22\%$ with daily and monthly calibration, respectively. The variability in flow regime has a direct impact on hyporheic habitat heterogeneity and quality, as well as the riverbed composition, stability, clogging and hydraulic characteristics (Sedimentation Committee, 1992). Concerning seasonality, all the models showed a one-

month lag in both directions (wet and dry). Although seasonality is ecologically more meaningful in extreme values than in usual values (Martínez Santa-María et al., 2008), the seasonality of usual values is critical for the temporary biodiversity of habitats, as well as a stimulus for germination and dispersion (Brizga et al., 2001). Daily variability for usual values (P4) showed identical behaviour to previous parameters.

Table 5

Statistical comparison of monthly-to-daily disaggregated flows and observe data.

Disaggregation method	PRB				TRB				
	KGE	LnNSE	NSE	RMSE	RSR	KGE	LnNSE	NSE	RMSE
Uniform distribution	0.66	0.24	−0.58	15.48	1.26	0.57	0.16	0.50	14.98
Linear interpolation	0.65	0.33	−0.40	15.60	1.18	0.58	0.21	0.51	13.87
Adjustment variability	0.82	0.73	0.80	9.98	0.45	0.71	0.48	0.65	9.44
Flow pattern replication	0.88	0.86	0.86	8.61	0.38	0.77	0.52	0.66	8.36

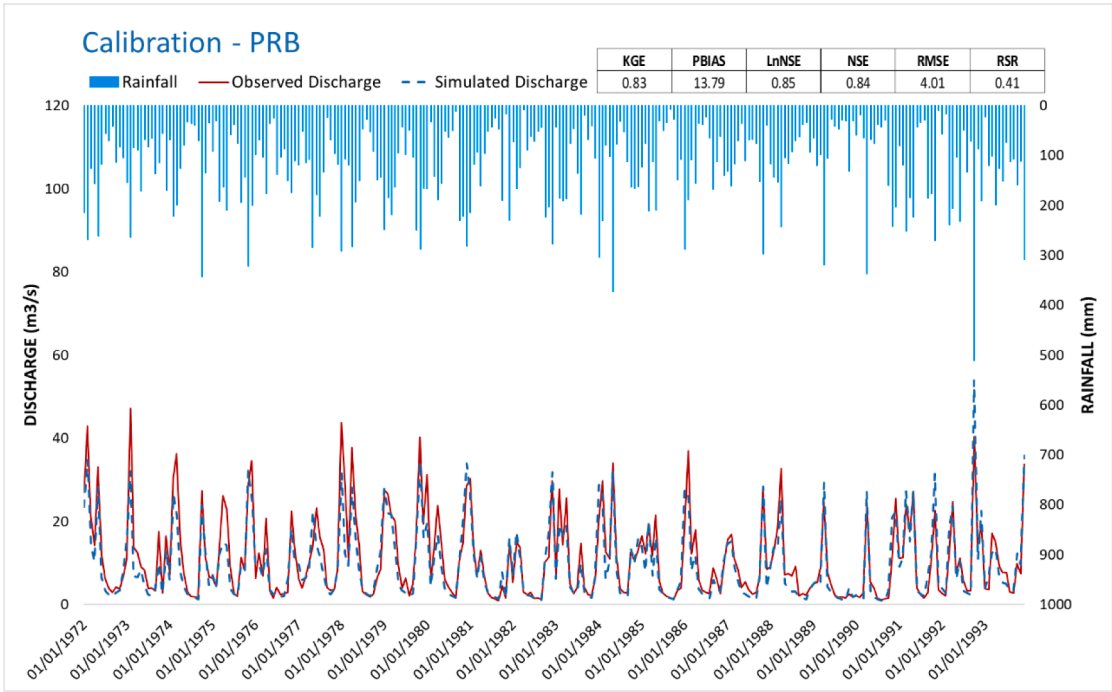
Besides the above statements concerning variability, a decline in the difference between percentiles 10% and 90% could enable the intrusion and expansion of exotic species (Poff et al., 1997). The analysis of maximum extreme values in IAHRIS is based mainly on the annual daily average flow (P5) and the flow percentile Q5% (P8) or the so-called usual flood. Although the performance of Scenario 2 is quite good for most of the parameters, maximum extreme values did not highlight any model among the rest, as usual values did. Notwithstanding the foregoing, the best prediction for parameters P5 and P8 was also reached with Scenario 2. The scale and frequency of floods, which are defined in IAHRIS by the parameters P5, P6, P7 and P8, play an essential role in river ecosystem dynamics because of the geomorphological dynamic (Bunn and Arthington, 2002; Poff et al., 1997), vertical and transverse continuity (Bunn and Arthington, 2002; Naiman et al., 2002) and species movements and the balanced control of populations (Naiman et al., 2002; Strange et al., 1999). While P6 influences mainly riverbed geomorphology, P7 is representative of streamflow, ensuring linkages between riverbeds and floodplains. Both parameters showed the best performance with Scenario 3 model in the PRB. P8 corresponds to the 5% exceedance percentile flow and assesses the cleaning up of fine aggregates from the substratum (Schmidt and Potyondy, 2004). All the considered models provided results similar to those of the gauging station. The variability of floods was considered with P9 and P10. All the models underestimated the maximum annual daily variability (P9) with differences higher than 15%. In contrast, they all slightly overestimated the usual floods variability (P10), responsible for the sedimentation and erosion processes and the circulation of nutrients (Thoms and Sheldon, 2002). The number of consecutive days of floods (P11) is linked to the consequences of magnitude and frequency (P5–P8), as well as changes in geomorphology, vegetation and fauna. For example, the mortality rate of the most sensitive species will increase if the flood period is longer or if the no-flood period is prolonged (Gregory, 1985). Once again, P11 for Scenario 3 came closer to the recorded statistics. The seasonality of maximum flows (P12) might distort the functioning of the river ecosystem, losing its life cycle synchrony (Martínez Santa-María et al., 2008). No significant differences in gauging stations were detected with any model. Furthermore, the extreme minimum values (droughts) highlighted Scenario 2, as its results were very similar to those of the gauging station. The magnitude and frequency of droughts (P13 and P14) have many important environmental implications for river corridor continuity (Richter et al., 1997; Strange et al., 1999), aquatic and riparian biota (Bunn and Arthington, 2002; Gonçalves Moreira de Jesús, 2002; Strange et al., 1999) and water quality (Brizga et al., 2001). All the models underestimated the usual drought (P14), though the error of Scenario 2 was slightly above 10% while Scenario 3 reached higher than 70%, which would threaten the riparian bands in drought season (Richter et al., 1997). Variability losses in droughts, as with floods, constrain the adaptation of species life cycles (Jalon, 1998). IAHRIS considers the parameters P15 and P16 to assess the variability in droughts, and while the variation in annual minimum daily flows (P15) in Scenario 2 is very similar to recorded values (0.27/0.30), the variation of usual droughts was underestimated with Scenario 1 and overestimated with Scenario 3. Concerning maximum drought duration in the PRB (P17), all the models reduced the number of consecutive days of flow below the percentile of 95%, which improved the natural regime series regarding the nitrogen cycle (Pinay et al., 2002). Alteration of

drought seasonality could produce strong distortions in river ecosystems, such as physiological stress (Poff et al., 1997), biodiversity loss (Bunn and Arthington, 2002) or the rates of growth and reproduction of individual species (Poff et al., 1997). The parameters showing the seasonality in IAHRIS (P18 and P19) of all models followed the same patterns as the gauging station statistics.

Table 8 shows the IAHRIS parameters for the Tagus watershed according to the three models. As discussed previously, the results did not highlight any particular model in terms of usual and flood values. In contrast, Scenario 3 proved to be the model that fitted the best for droughts. In general, Scenario 1 overestimated flows both for usual and flood values, significantly increasing volumes in magnitude and variability. Although for usual values Scenario 3 reached similar figures to the recorded ones, they were below most cases, which implied lower moisture and water availability, endangering the status of the plants and animals, respectively (Bejarano et al., 2018). Scenario 1 ensures adequate variability in streamflow, while daily calibration was around −30% and Scenario 2 doubled the estimated volume. The highest values obtained in TRB with Scenario 1 might be due to the remoteness of the donor station, concerning the studied watershed and the downstream influence of the parameters of the rest of the watershed (Heuvelmans et al., 2004). Likewise, the magnitude of the flood was automatically overestimated for all the models by 50–100%. The climatic zone seemed to have a great influence on flow peaks and closely linked to responses and resilience of the organisms in the riverine (McCluney et al., 2014). Climatic conditions and variations in the TRB throughout the year may well be behind the differences in flow and the usual magnitude and frequency estimated by the models. Indeed, the coefficients of variations in the yearly maximum daily flood (P9) and usual flood (P10) were 22% and 103% higher than in the PRB, respectively, which clearly affected the maximum flow estimations of the models in the TRB. This also caused an underestimation of the number of flooding days (P11), which dropped by half of what was recorded at the gauging station. However, extreme droughts were, as with the PRB, extreme droughts were adequately estimated by Scenario 2 in most parameters. Though the average yearly minimum daily flow (P13) was underestimated for all the models, usual drought flow (P14) in the disaggregation model was similar. Many (Sugiyama et al., 2003; Grown, 2000) have preferred to characterise minimum flow with percentiles of exceedance than with averages or medians, as established in numerous RBMPs in Spain (Mezger et al., 2019). Variability in droughts (P15, P16) is considered to be higher than in observed values, which would benefit the development of the benthos (Barmuta, 2001). Regarding the duration of droughts (P17–P19), Scenario 2 also outperformed compared to the other scenarios, as in the PRB.

Concerning the basic flow (Qb), Table 9 shows the results obtained for both basins after applying the SWAT+ post-processing tool. This method attempts to simplify the environmental flow to a unique value of discharge to meet the needs for river regulation.. As expected, given the statistical results obtained in the previous sections, Scenario 3 showed a significant underestimation of the environmental flow with respect to the observed data from the gauging stations in both basins. In fact, the differences between the observed and predicted Qb were −43.19% and −48.96% in the PRB and TRB, respectively, making it unsuitable as an appropriate index in environmental flow assessment. This underestimation was due to the difficulty of calibration and the adjustment of low

a)



b)

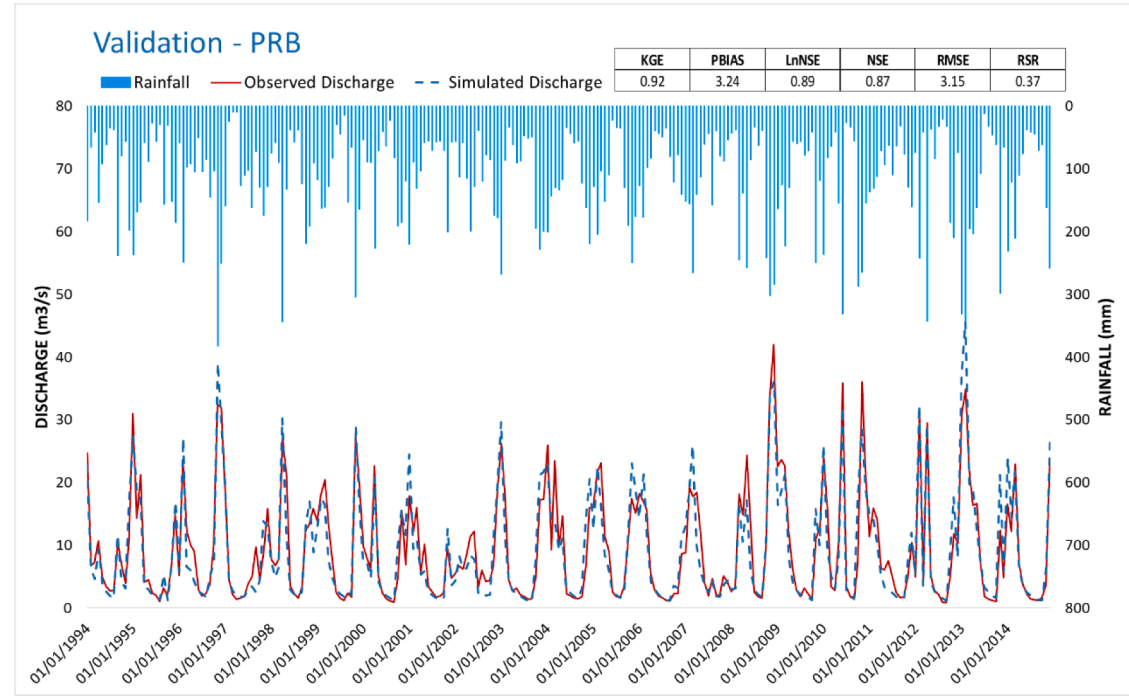
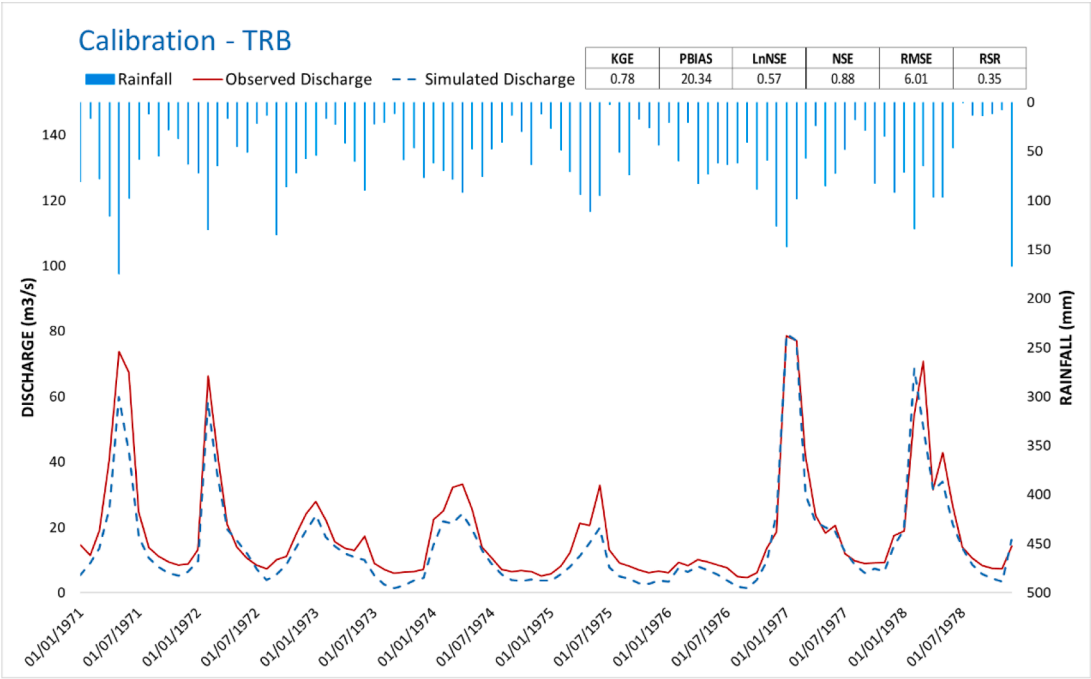


Fig. 6. Monthly model performance for a) calibration and b) validation periods for monthly calibration in the PRB.

flows for daily-scale events. Similarly, in Scenario 1, the flows obtained on a daily scale were still below average, resulting in undervalued environmental flows with respect to the reference flows that maintain the same criteria as in the previous scenario but on a smaller scale. When this calibration was performed on a monthly scale, the water volumes of the model were better adjusted. However, the difficulty of efficiently

distributing these volumes of water on a daily scale remained. Therefore, other monthly-to-daily disaggregation techniques from the WRAP programme were applied, indicating that Option 4 (replicating daily flow patterns) provided the distribution most aligned with the referenced daily flow pattern distribution. After the previously mentioned disaggregation, the environmental flow results of Scenario 2 were best

a)



b)

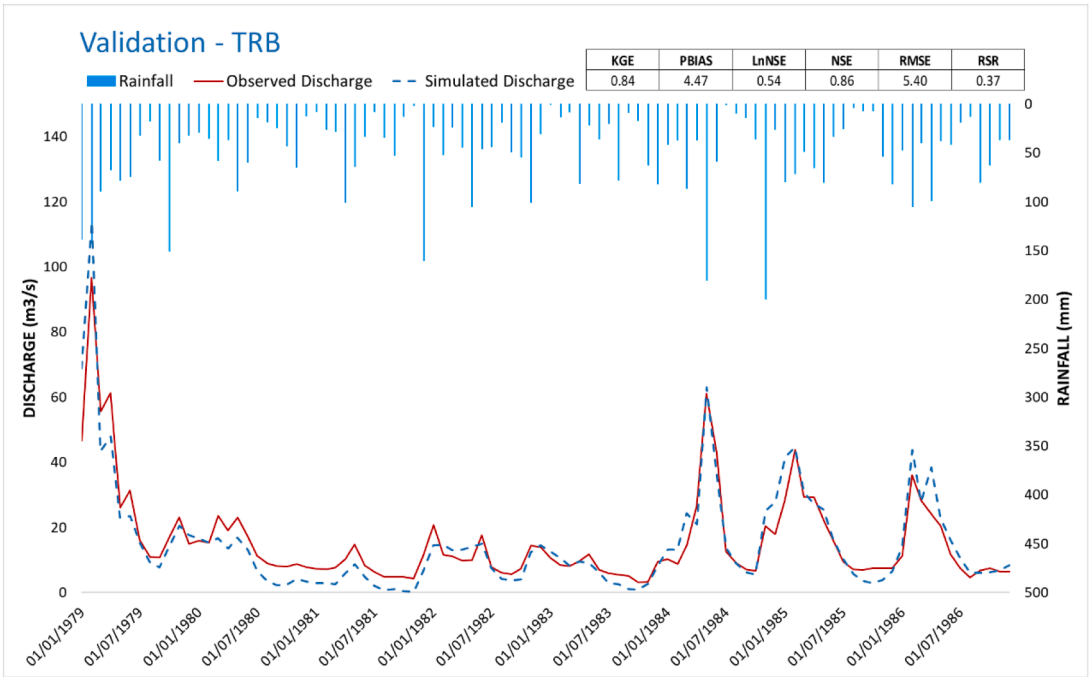


Fig. 7. Monthly model performance for a) calibration and b) validation periods for monthly calibration in the TRB.

adjusted according to reference flows, forming a valid alternative to obtaining flows on a daily scale to meet this study's objectives. Nonetheless, similarities with the values observed at the gauge station varied highly depending on the basin. While Qb in the PRB for Scenario 2 was 93.49% of the gauging station, this value decreased by up to 66.40% in the TRB. Climate type and irregular precipitation throughout the year

may be the reason of this significant difference. The mean annual precipitation in the PRB is more than double that in the TRB and dry summers in the latter region set the differences between rainfall patterns in both basins. Furthermore, the length of the data series may also affect the detection of the inter- and intra-annual variability of streamflow because the available period for the TRB (16 years) was almost the half

Table 6

Calibrated SWAT+ model daily parameters. (r_) is a relative change, which means that the parameter is modified by a specific percentage, and (v_) means that the parameter is replaced by a specific value determined in the calibration.

Parameter	Description	PRB		TRB	
		p-Value	Fitted value	p-Value	Fitted value
r_slope.hru	Average slope steepness (m/m)	0.0000	19.93%	0.0078	20.93%
v_surlag.bsn	Surface runoff lag coefficient (days)	0.0174	12.0699	0.0841	20.2578
v_ovn.hru	Manning's "n" value for overland flow (dimensionless)	0.3437	0.8718	0.4957	0.1331
r_slope_len.hru	Average slope length (m)	0.4105	9.18%	0.5164	19.06%
v_chn.rte	Manning's "n" value for the main channel (dimensionless)	0.4547	0.1192	0.5982	0.0190

that of the PRB (30 years).

The basic flow method provides minimum discharge values to ensure biological functioning of a river (Palau and Alcázar, 2012) taking into account the daily variability of streamflow, as well as its effects on riverbed and floodplain habitats. However, the IAHRIS not only highlighted the magnitude of minimum flow in droughts, but also other relevant information related to the frequency, variability, duration and seasonality of extreme values both in floods and droughts. The set of parameters of IAHRIS, in addition to providing valuable information about the availability of water in more critical conditions as the Qb also does, considers other significant issues such as diversity, resilience and synchronicity. These issues are essential not only in volume discharges but also in the assessment of modifications in ecological and geomorphological dynamics. Moreover, the analysis of usual values with the IAHRIS method allows for environmental knowledge in non-extreme conditions, preventing interannual variability from going unnoticed because of extreme values.

5. Conclusion

Although the SWAT+ model is a relatively new tool that is not as widely used as its predecessor (SWAT), the results obtained in the present study demonstrated its validity and effectiveness for the objectives of the hypotheses proposed. After the calibration and validation of the SWAT+ model in the Piloña and Tagus River basins at different time scales, excellent performance on a monthly scale and satisfactory performance on a daily scale was obtained, considering that the calibration approaches were different. Therefore, we concluded that the SWAT+ model could be effectively applied for analysing and adjusting low flow volumes to determine environmental indicators.

Following a detailed study of the results obtained by combining the SWAT+ model and the WRAP model to obtain daily flows, we concluded that the application of disaggregation techniques is not only a viable alternative for daily modelling but, in specific cases, such as the present work, can even surpass the daily model for acquiring hydrological information for a wide range of purposes. Thus, the evaluation of the model's low flow volumes to obtain environmental flows is favoured by the accuracy of adjusting the calibration on a monthly scale. In addition, water resource management benefits from an ecological perspective by better handling the sensitive transitions that flow variability may present at a given time scale. Notably, the model's performance is satisfactory in all statistical metrics studied on a monthly scale, even providing ecological improvement when considering scenarios with dry conditions during model calibration and subsequent disaggregation.

The disaggregation approach applied in this work demonstrates the potential to reformulate daily modelling, with all the advantages it provides, based on a simpler conceptualisation of fluvial systems. Therefore, it is possible to obtain hydrological information on a daily scale and to facilitate the handling of computational data by the model, which would enable many of the uncertainties generated in this type of complex model to be addressed. Similarly, this work shows how the estimation of environmental indicators is affected by the simulation scenario, thus reflecting a significant underestimation in daily calibration and simulation scenarios. However, conducting monthly calibration by applying disaggregation methods from a daily flow pattern results in a more accurate estimation of environmental flows.

A possible limitation of our study is associated with the necessity of

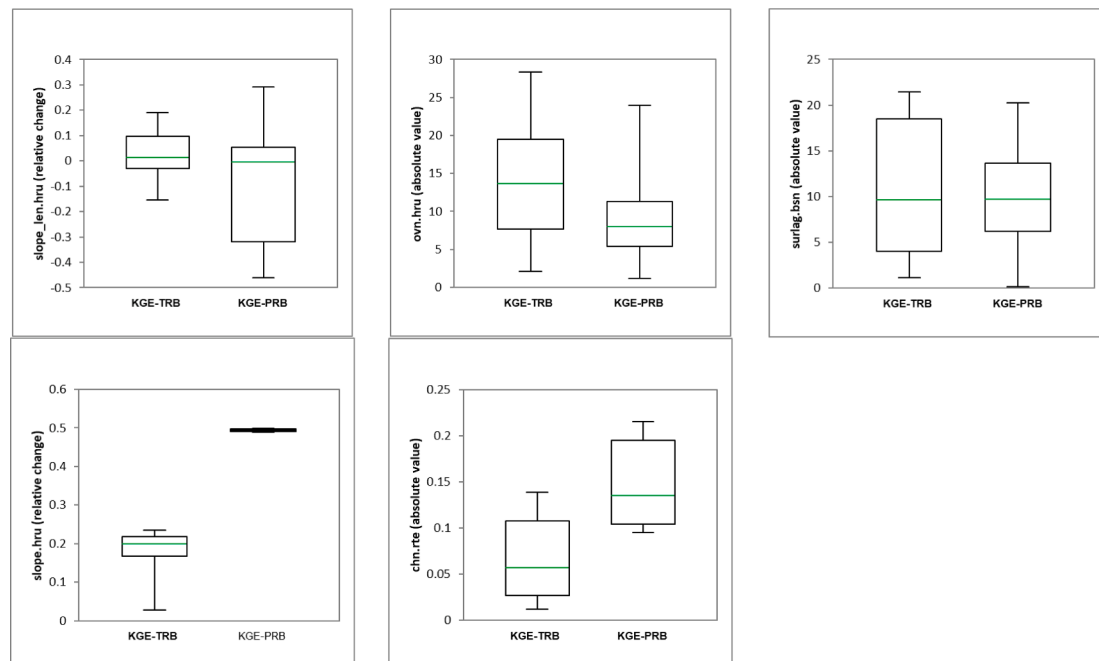
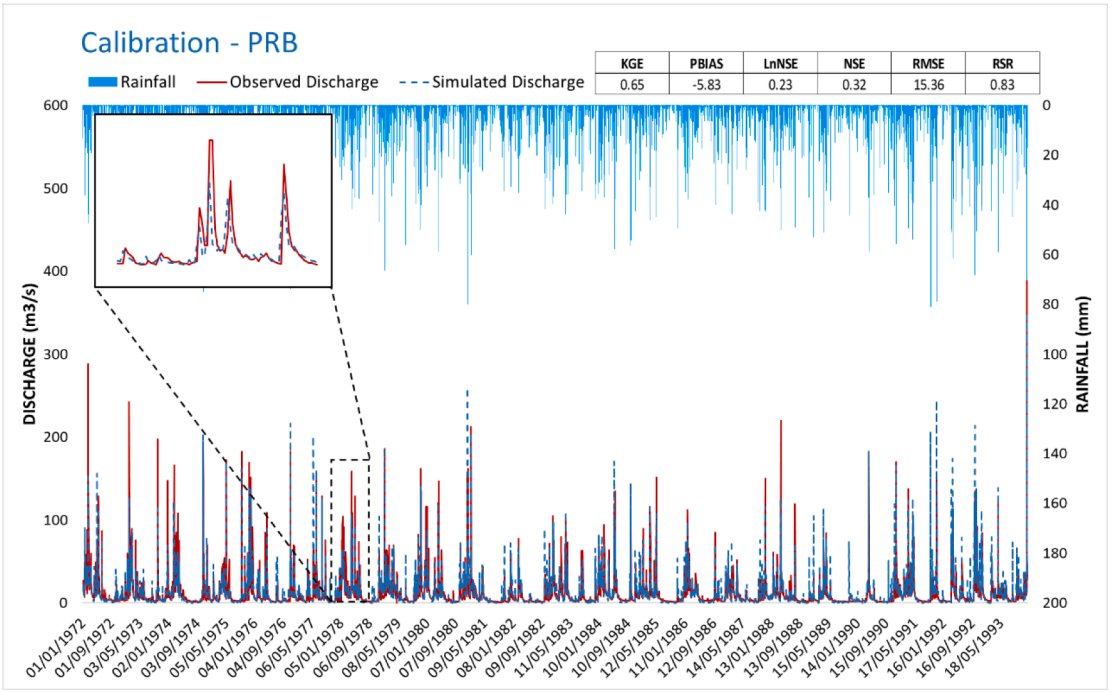


Fig. 8. Box plot analysis of the daily parameter values of the 10 best simulations according to the objective function KGE in the PRB and TRB.

a)



b)

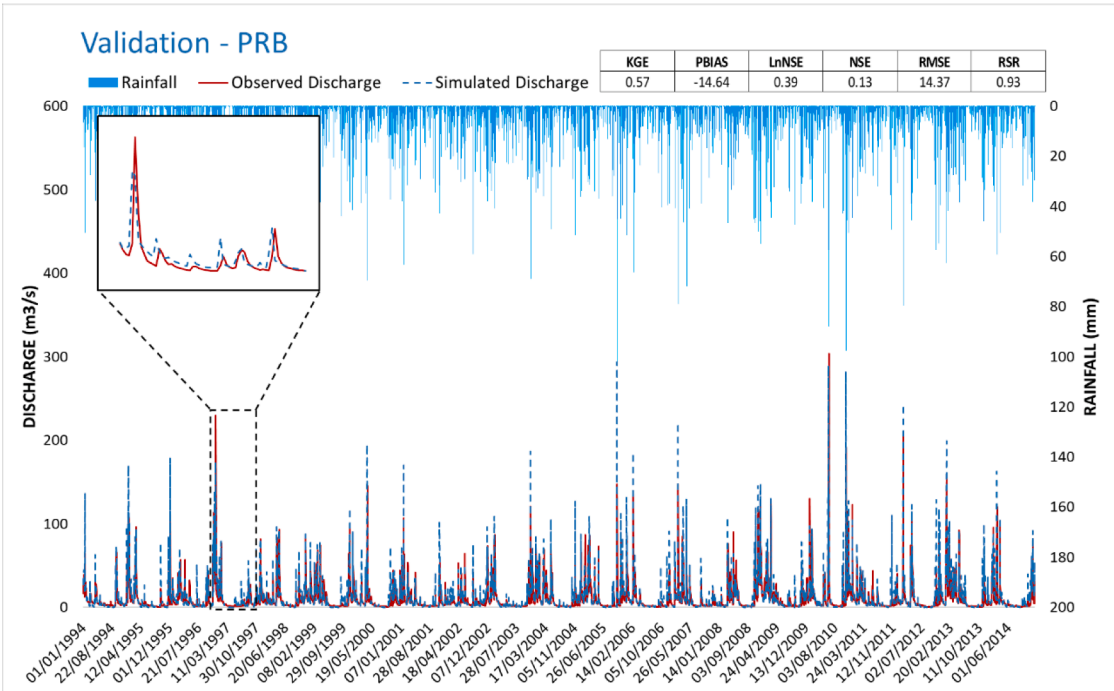
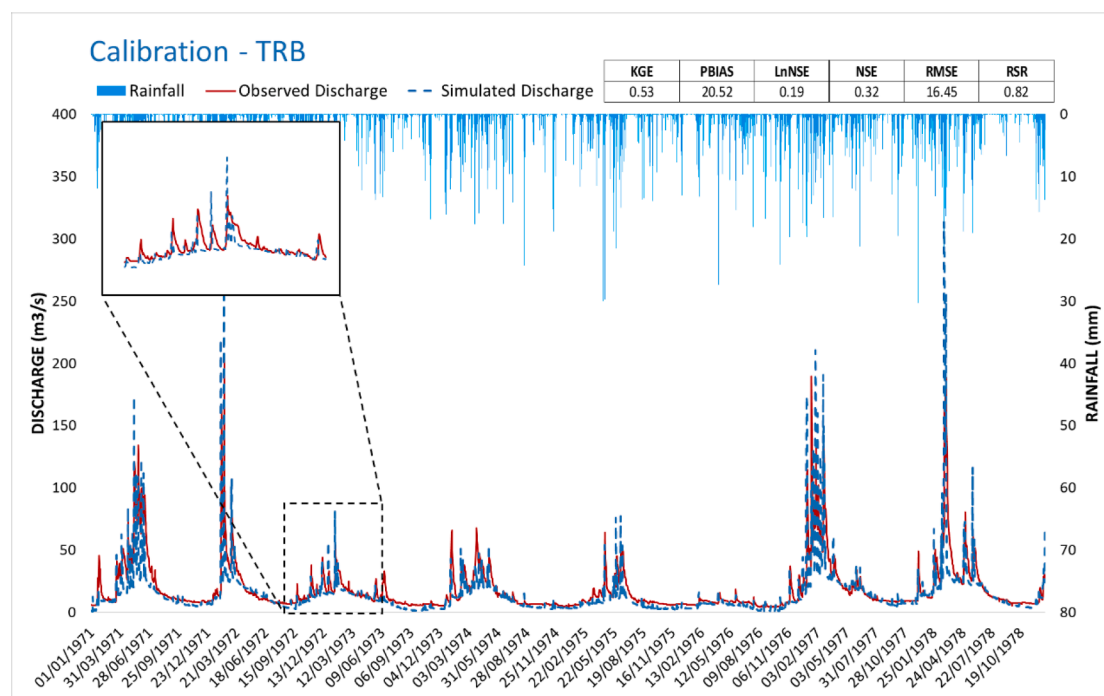


Fig. 9. Daily model performance for the a) calibration and b) validation periods for daily calibration in the PRB.

daily scale flow data availability, both from the study area and from a nearby gauging station, to apply the disaggregation techniques associated with a daily flow pattern. In the same way, it is necessary that these data series have a minimum length to enable the hydrological regime of the basin to be better studied through the application of IAHRIS and Qb

techniques. The simplicity and ease of interpretation of the Qb method make it a useful tool in providing an overall outlook of river vulnerability and environmental status, boosting its performance with the increasing humidity of an area. Nevertheless, the use of a more complex set of indicators, such as IAHRIS, is essential in hydrological planning

a)



b)

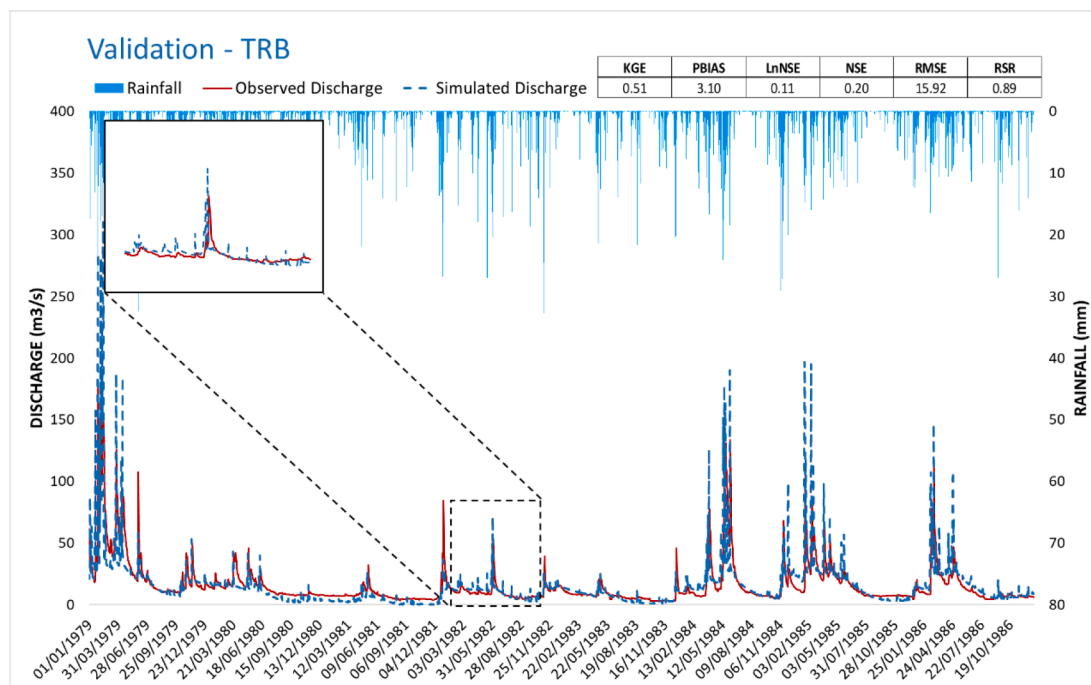


Fig. 10. Daily model performance for the a) calibration and b) validation periods for daily calibration in the TRB.

and water resources management due to the environmental significance of every aspect of the natural regime flow. This is why the application of new methodologies, such as the one proposed in this work, helps to provide viable alternatives for obtaining the indicators necessary for the hydrological and environmental evaluation of river basins.

CRediT authorship contribution statement

Gerardo Castellanos-Orsorio: Conceptualization, Methodology, Writing – original draft. **Adrián López-Ballesteros:** Formal analysis, Data curation, Validation. **Julio Pérez-Sánchez:** Methodology, Validation, Writing – original draft. **Javier Senent-Aparicio:**

Table 7

Characterisation of natural regime according IAHRS in the PRB.

	Parameter	Gauging Station	Scenario 1	Scenario 2	Scenario 3
Usual Values	P1	297.91	210.50	280.67	341.56
	P2	67.91	52.43	69.90	79.64
	P3	Jan-Aug	Jan-Sep	Jan-Sep	Dec-Aug
	P4	19.89	12.37	19.42	25.26
Extreme Values (Floods)	P5	140.50	162.53	129.64	165.90
	P6	136.3	147.2	117.0	154.8
	P7	178.6	186.6	148.2	199.2
	P8	35.39	32.20	33.82	38.89
	P9	0.45	0.34	0.34	0.39
	P10	0.28	0.43	0.32	0.29
	P11	5.69	3.9	6.45	4.9
	P12	0.0–2.8	0.0–3.2	0.0–3.2	0.0–3.0
Extreme Values (Droughts)	P13	1.34	0.97	1.13	0.17
	P14	1.55	1.07	1.36	0.41
	P15	0.30	0.23	0.27	0.66
	P16	0.32	0.23	0.22	0.53
	P17	21.41	19.69	14.79	13.10
	P18	0.0–0.0	0.0–0.0	0.0–0.0	0.0–0.0
	P19	0.0–10.9	0.0–11.1	0.0–9.1	0.0–5.6

Table 8

Characterization of natural regime according IAHRS in TRB.

	Parameter	Gauging Station	Scenario 1	Scenario 2	Scenario 3
Usual Values	P1	382.84	438.75	687.52	327.29
	P2	69.68	91.81	144.96	66.33
	P3	Mar-Sep	Apr-Oct	Apr-Oct	May-Sep
	P4	20.41	20.92	44.07	14.77
Extreme Values (Floods)	P5	75.83	145.99	127.23	103.92
	P6	78.3	158.1	146.1	114.6
	P7	105.5	217.6	206.0	158.9
	P8	33.85	39.73	66.14	28.93
	P9	0.55	0.64	0.75	0.67
	P10	0.57	0.71	0.68	0.75
	P11	14.53	4.60	5.73	4.47
	P12	0.0–6.4	0.0–4.3	0.0–6.8	0.0–4.2
Extreme Values (Droughts)	P13	3.92	2.17	1.90	1.88
	P14	4.44	2.86	4.00	2.42
	P15	0.34	0.75	0.60	0.70
	P16	0.29	0.67	0.70	0.62
	P17	31.07	18.47	22.13	20.80
	P18	0.0–0.0	0.0–1.3	0.0–0.0	0.0–0.0
	P19	0.0–9.8	0.0–12.9	0.0–11.7	0.0–12.9

Table 9

Basic flow (Qb) estimation by SWAT+ post-processing tool in the PRB and TRB.

Scenario	Qb-PRB	Qb-TRB
(1) Monthly Calibration – Daily Simulation	1.16	2.28
(2) Monthly Calibration – Monthly-To-Daily Disaggregation	1.58	2.55
(3) Daily Calibration – Daily Simulation	0.96	1.96
Gauging Station	1.69	3.84

Conceptualization, Funding acquisition, Supervision, Writing – review & editing.

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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