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Evaluating the Spatial and Temporal Transferability of Model Parameters of a Distributed Soil Conservation Service–Soil Moisture Antecedent–Simple Lag and Route Model for South Mediterranean Catchments

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Abstract: Accurately predicting the impacts of climate change on hydrological fluxes in ungauged basins continues to be a complex task. In this study, we investigated the transferability of the model parameters SCS-SMA-LR, available in the ATHYS platform, to simulate hydrological behavior within catchments of a large South Mediterranean transboundary basin, i.e., the Medjerda bordering Tunisia and Algeria, characterized by contrasting climatic and physiographic conditions. A robustness analysis was set up for donor and receptor catchments situated in the Medjerda catchment in Tunisia. The model was initially calibrated for two donor catchments, for the 127 km^2 catchment of the Lakhmess watershed situated on the right bank and for the 362 km^2 catchment of the Raghay watershed situated on the left bank of the Medjerda basin in Tunisia, using input data from 1990 to 1994. The model performance was evaluated through multiple accuracy criteria based on the Best Linear Unbiased Estimator (BLUE) for the automatic calibration to quantify the model simulation, proving its good performance. The temporal transferability was assessed by evaluating model performance, transferring the calibrated parameters for the two catchments as validation on data for 3-year periods outside the calibration domain to test the robustness of the model through a diachronic analysis from different decades, i.e., for the periods 1994–1997, 2001–2004, and 2014–2017, respectively. The spatial transferability was assessed by transferring the parameters calibrated on the donor catchments to be applied to the receptor catchments based on similarity and data availability. The model was upgraded to a greater catchment for data from 1994 to 2016 for the right bank, the Siliana Upstream catchment, and to the nearest catchment with a similar

Academic Editors: Alexander Shiklomanov and Avi Ostfeld

Received: 28 December 2024
Revised: 27 January 2025
Accepted: 11 February 2025
Published: 16 February 2025

Citation: Gara, A.; Gader, K.; Khlifi, S.; Bouvier, C.; Ouessar, M.; Vanclooster, M.; Al-Ansari, N.; El-Hendawy, S.; Mattar, M.A. Evaluating the Spatial and Temporal Transferability of Model Parameters of a Distributed Soil Conservation Service–Soil Moisture Antecedent–Simple Lag and Route Model for South Mediterranean Catchments. *Water* **2025**, *17*, 569. https://doi.org/10.3390/w17040569

area for the data from 2008 to 2017 for the left bank of the Medjerda basin, the Bouheurtma catchment. The capacity of the soil reservoir and the flow velocity parameters proved to have an important impact on the modeling implementations at, respectively, 123.03 mm and 1 m/s for Raghay, and 95.05 mm and 2.5 m/s for Lakhmes. The results show that the space–time transfer process of model parameters produces an acceptable simulation of flow volumes and timing. The proposed methodology proved to be a successful way to monitor ungauged catchments and strengthens the robustness of the SCS-SMA-LR model for hydrological modeling and impact studies in ungauged basins of the Southern Mediterranean region.

Keywords: spatiotemporal transferability; conceptual distributed hydrological model; ATHYS; Medjerda basin

1. Introduction

Hydrological modeling constitutes an essential foundation for efficient water resource planning, management, and impact studies, particularly in vulnerable regions such as the South Mediterranean [1]. These regions are considered climate change hotspots, where sustainable water resource management is fundamental to attenuate the potential effects of climate alterations and the important decrease in water availability [2]. Accurate parameterization serves as a cornerstone for robust hydrological models, which also need calibration with high-quality hydrometeorological input data. Unfortunately, access to appropriate hydrometeorological data is often a key issue in African countries, including those in the South Mediterranean [3,4].

Data scarcity, when coupled with the predominance of ungauged catchments, largely contributes to the aggravation of the difficulty in predicting hydrological discharges [5]. This challenge highlights the importance of predicting and employing accurate parameterization methods that can attenuate these gaps [6]. Predicting hydrological processes in ungauged basins remains one of the fundamental hydrological challenges, particularly for countries with limited data availability [7,8]. Different approaches have been proposed to resolve the problem of ungauged basins using different types of hydrological models and different regionalization methods [9]. Regionalization, which involves model parameters transferring from gauged (donor) catchments to ungauged (receptor) catchments, has been extensively investigated using several methods.

For instance, Merz and Blöschl [10] demonstrated the deep dependence between hydrological resemblances and parameter transferability, while Oudin et al. [11] assessed regionalization methods based on several characteristics of catchments such as climatic and physical aspects. Pagliero et al. [12] further enhanced these techniques by adding advanced statistical analyses to find the best combination within the donor–receptor relationship. Recently, Acharki et al. [13] brought to light novel methods dealing with the amelioration of regionalization performance within regions that have insufficient data.

Models such as the physically based Soil and Water Assessment Tool model (SWAT) [14,15] and the lumped conceptual GR4J model [16] give completely different aspects of hydrological modeling. The SWAT model's parameters generally have physical significance and can be directly measured, while GR4J simplifies the modeling process by using four lumped parameters, making it suitable for discharge prediction in catchments with limited observed data [17].

The simplest and most often used method is to calibrate a hydrological model for a gauged 'donor' catchment and then to transfer the calibrated parameters to similar ungauged 'receptor' catchments. The selection of appropriate donor catchments for regionalization purposes often depends on the similarity of the catchments' metrics, which may combine various components such as land use, soil type, topography, climate, etc. [18,19].

Moreover, the quality of the parameter transfer and following predictions depend on the degree of similarity between the donor and receptor catchments [20]. Several studies underlined the significance of quantifying and evaluating these similarities to improve model accuracy in ungauged basins. For instance, Choubin et al. [21] established the added value of geo-environmental signatures for discharge regionalization in Iran's Karkheh River Basin, achieving important improvements in predictive accuracy.

In addition to space-parameter transferability, time transferability has also gathered considered importance, especially for basins with scarce or intermittent hydrometeorological ground data. Temporal transferability or diachronic transferability concerns using the calibrated model's parameters for a given period (donor period) to another period (receptor period) with different conditions such as climatic or hydrological characteristics. The robustness of this methodology depends on the hydrometeorological similarity between the donor and receptor durations [22].

Understanding temporal transferability is critical for long-term hydrological simulations, particularly in regions experiencing significant climatic shifting. For example, Sellami et al. [23] focused on the uncertainty analyses of regionalized parameters in different southern and northern Mediterranean catchments using in-depth statistical analysis, highlighting the important impact of climatic variability on the modeling robustness.

Despite the up-to-date progress made in regionalization methods and parameter transfer techniques, difficulties are mainly encountered in arriving at solid predictions for ungauged catchments, especially in the Mediterranean context. Recently updated methodologies, such as machine learning techniques, brought to light additional improvements in parameter regionalization. Thus, Senent-Aparicio et al. [24] developed novel machine learning clustering methods to regionalize the SWAT model's parameters, permitting the enhancement of the predictions of discharge in data-limited catchments.

In addition, Li et al. [25] suggested an effective method for estimating continuous runoff in ungauged catchments, which combined the transfer parameters with the drainage area ratio method. This innovative method demonstrated significant ameliorations in the accuracy of estimations by coupling physical and regionalization approaches employing the minimum amount of data. These studies underline the urge to use creative techniques to improve the spatiotemporal transferability of hydrological model parameters. Since the regionalization methods and the performance of different models are various across catchments, it is methodically fundamental to test their applicability and robustness. In this context, Roth et al. [26] assessed the transferability of the distributed physically based model's parameters in watersheds with tropical climates and detected the important factors impacting sediment and discharge estimations. Their results pointed out the importance of such parameter transfer methods for similar conditions from a hydrological point of view.

Hence, the previous studies focused basically and extensively on spatial transferability with different hydrological models [18]. However, the space–time coupling issue when facing climatic variability remains underexplored. In this study, we aimed to contribute to this challenge when addressing the scientific gaps in spatial and temporal parameter transferability for hydrological modeling in Southern Mediterranean catchments. This study focuses on two crucial questions:

(1) Can a simple conceptual hydrological model effectively simulate hydrological behavior under varying spatiotemporal and climatic conditions?
(2) How robust is the model when addressing the challenges posed by poor data quality and limited data availability?

We chose to address this issue by using a spatially distributed version of the SCS-SMA-LR model, originally conceptualized and made available on the ATHYS platform by Bouvier [27]. Recently, several research studies employed the ATHYS platform using available models. For instance, Louis et al. [28], Bouadila et al. [29], and Miller et al. [30] utilized this model with the simplest combination when running the SCS simple Lag and Route Model to reproduce events, while Aqnouy et al. [31] assessed the same hydrological model using continuous daily data as input. This simple modeling exercise proved to be a successful tool in different countries by taking into consideration the topography and the infiltration–evaporation process.

The recently added SCS-SMA-LR hydrological model has been successfully integrated within the ATHYS platform to adapt to the regional conditions in the South Mediterranean catchments and was validated in previous studies of the Medjerda catchment, demonstrating its added value for a small South Mediterranean catchment [32]. The novelty of this research study is presented through the conjoint interest in spatial and temporal transferability, as well as the integration of the minimum amount of data in regionalization techniques to assess the robustness of the adapted hydrological model in data-scarce catchments when enhancing its performance for a large transboundary catchment.

In this paper, we further assessed the use of the SCS-SMA-LR model by testing its parameter transferability for variable spatial and temporal conditions, thereby highlighting its robustness and accuracy for various ungauged catchments and different durations. The Medjerda catchment, a transboundary South Mediterranean catchment, is characterized by a semi-arid climate and significant hydrological variability, bringing additional challenges in testing parameter transferability and the robustness of the selected hydrological model.

In trying to answer these issues, this paper is organized as follows: In the first part, the study catchments, the Rainfall–Runoff model and its inputs, the similarity, and the transferability approaches are described. The second section highlights the calibration on donor catchments and describes the temporal and spatial transferability outcomes. And lastly, the main findings of the summary and the conclusions are reported.

2. Materials and Methods

2.1. Study Area

The Medjerda basin remains the only perennial river and the main surface water resource in Tunisia, providing nearly half of the country's supply of freshwater [33]. This catchment exhibits significant climatic variability, especially when comparing its right bank, the southern side characterized by frequent drought and arid conditions, with the left bank, the northern side which is more humid and experiences larger rainfalls [34].

Based on the available data and geographic proximity, we identified and selected four sub-catchments within the Medjerda basin to evaluate the transferability of model parameters, both spatially and temporally. Two of these sub-catchments are situated on the left bank, while the remaining two are located on the right bank of the basin, allowing for a comparative analysis through various geographical and hydrological aspects (Figure 1).

The topography of the study catchments is demonstrated within the Digital Elevation Model (DEM) provided by the Advanced Spaceborne Thermal Emission and Reflection Parameter (ASTER) DEM, with a 30 m resolution, from the mission of 19 June 2014. This model, with a fine grid mesh resolution, allows us to outline to the latitude of any point at Raghay. These DEMs were clipped using version 10.2 of the ArcGIS software to present the gradient of altitude and to probe the drainage network and the direction of slopes of the terrain within the studied catchments.

The selected catchments from the northern side (the left bank of the Medjerda basin) include the Raghay catchment, stretching an area of 362 km², and the Bouheurtma catchment, covering an area of 390 km². Both catchments are situated in the Jendouba governorate (36°29′0″ N, 8°47′0″ E) and exhibit stretched shapes, with significant altitudinal gradients. However, they have a main difference: the Raghay catchment is considered a rural catchment with no important anthropic activities bordering Tunisia and Algeria [35], while the Bouheurtma catchment is considered a catchment with remarkable anthropic activities. The last catchment also encompasses two dams: the Bni Mtir dam and the Bouheurtma dam [36]. The Bni Mtir dam is situated in the upstream part of the catchment and controls almost one-fourth of its surface. This dam is one of the oldest large-scale hydraulic dams constructed in Tunisia. The dam was designed in 1954 and has a storage capacity of 57 million m³. Its main usage is to supply drinking water and energy for the capital Tunis. The Bouheurtma dam, which was constructed in 1976, has a capacity of 117 million m³ and is located at the outlet of the studied catchment. The main purpose of the dam is the provision of irrigation water and drinking water, which play a crucial role in water management within the region.

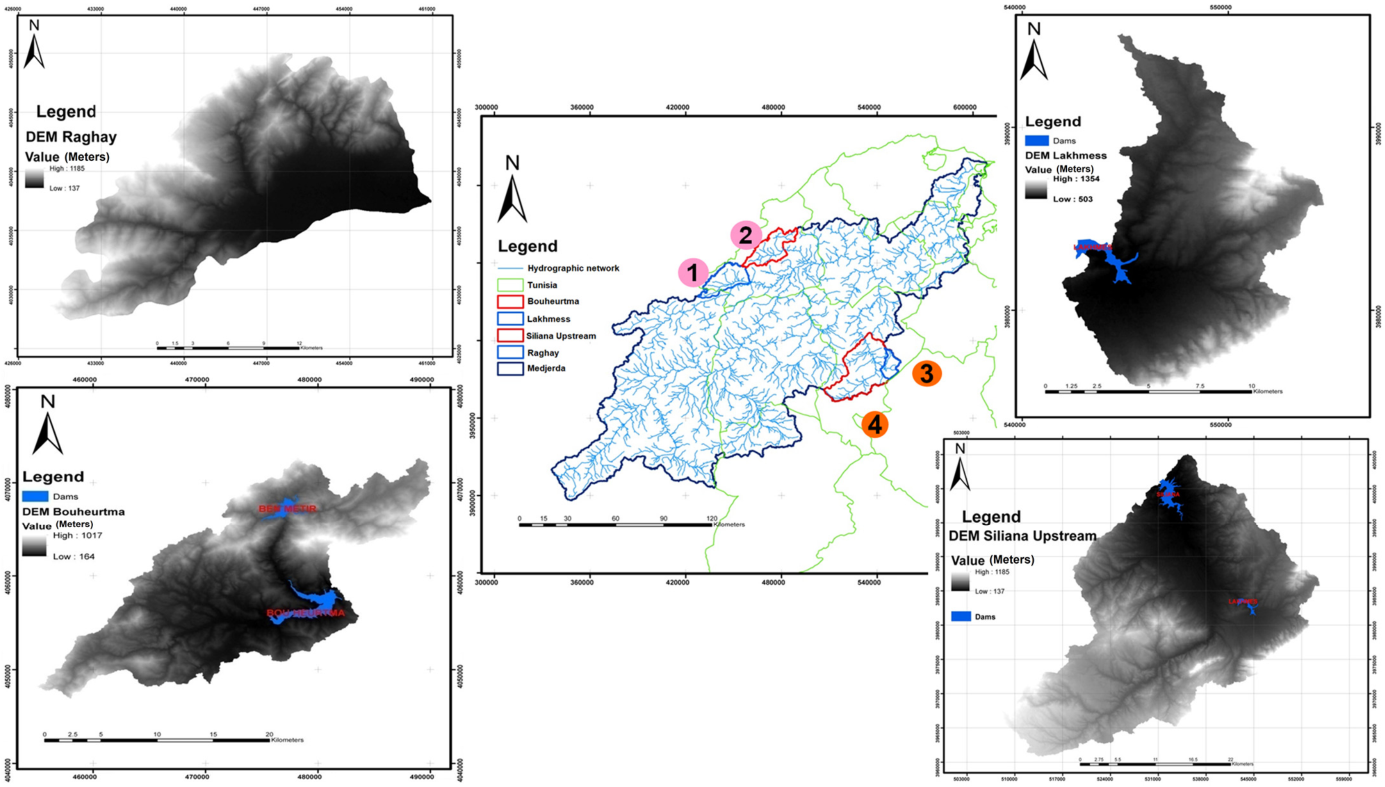

Figure 1. Map showing the location of the Raghay watershed (1) (situated at the left bank of the Medjerda River), associated with the transferred Bouheurtma catchment (2), and the Lakhmess catchment (3) (situated at the right bank of the Medjerda River) with the associated greater catchment: Siliana Upstream (4).

The two selected catchments from the southern side (the right bank of the Medjerda basin) are the Lakhmess and Siliana Upstream catchments. Both catchments are situated in the Siliana governorate (36°10′0″ N, 9°22′0″ E).

The Lakhmess catchment spans an area of 127 km² and is drained by the Touirillil and Lakhmess tributaries; their flow is regulated by the Lakhmess dam located at the catchment outlet. This catchment is a sub-basin of the Siliana Upstream catchment and features a substantial altimetric gradient with uneven terrain, in which approximately

30% of its surface exceeds 900 m of elevation. This steep topography intensifies flood propagation and results in pronouncing peak flows in the catchment.

The catchment shows a remarkable climatic variability, characterized by an upper semi-arid bioclimatic stage with a cold winter and a hot dry summer. The annual rainfall shifts between 300 and 536 mm, marked by a strong irregularity and seasonality. The catchment's outlet is approximately 15 km away from the city of Siliana.

The Siliana Upstream catchment is considered one of the main tributaries of the Medjerda basin, covering a surface area of 1040 km^2 and showcasing a significant geological heterogeneity between its upstream and downstream parts. Near the dam, the geological formations predominately consist of limestone and clay, allowing the infiltration and subsequently the attenuation of flows that reach the Siliana Dam. This eastern part of the catchment is primarily occupied by forests and rain-fed crops associated with irrigated areas. In contrast, the western part is marked by the presence of uncultivated land and bare soil at high altitudes, as well as field crops. These conditions promote water and sediment transport during intense rainfall events, leading to the rapid silting of the Siliana Dam. The Siliana Dam receives an average annual rainfall of 550 mm, enabling it to intercept an estimated 57 million m^3 of water per year, mostly intended for irrigation purposes [37,38].

2.2. The Spatially Distributed Conceptual Rainfall-Runoff Model

In this study, we applied the modified version of the SCS-SMA-LR model version 6.0, available in the open platform for hydrological modeling, ATHYS (www.athys-soft.org), developed by the Research Institute for Development (IRD) in Montpellier in France. This platform creates a separate environment permitting the visualization and treatment of hydrometeorological data and cartographic data to prepare the input data for modeling procedures [39]. The ATHYS platform contains numerous available production and transfer functions in which every combination leads to a new hydrological model. Moreover, this open platform permits adding new models that can be tested and validated for continuous or event scales and with different time steps and data resolution as input [32].

2.2.1. The Production Function SCS-SMA Runoff Model

The model employed for the production function combines the Soil Conservation Service (SCS) model, developed by the U.S. Soil Conservation Service, with the Soil Moisture Antecedent (SMA) [39]. The used version of this model promotes a spatially distributed hydrological implementation with an integrated GIS-based interface, permitting the generation of its maps, and then the subdivision of the study area into a regular squared mesh [40]. This formulation considers every mesh as a soil reservoir, controlling the runoff and generating a delayed runoff. In its spatially distributed implementation, the runoff model takes into consideration the geographically interpolated rainfall and Potential Evapotranspiration (PET) for the studied climatic gauges of the study area. The model is implemented with a daily time step. The integration of the SMA has an important influence on the modeling response since the daily runoff is largely influenced by the water balance process [41].

2.2.2. The Transfer Function Simple Lag and Route Model

The routing model is the simple Lag and Route Model (LR), which was already present in the previous versions of the ATHYS platform. This LR model permits the routing of the runoff collected from every mesh to the outlet of the catchment. The runoff obtained for the catchment results from summing all the elementary hydrographs produced at the outlet of each mesh [42].

The LR model was coupled with the runoff model, forming a unique combination of the model, i.e., the SCS-SMA-LR model, and was previously tested in the South Mediterranean context [32].

Figure 2 illustrates the overall modeling methodology used in this research study.

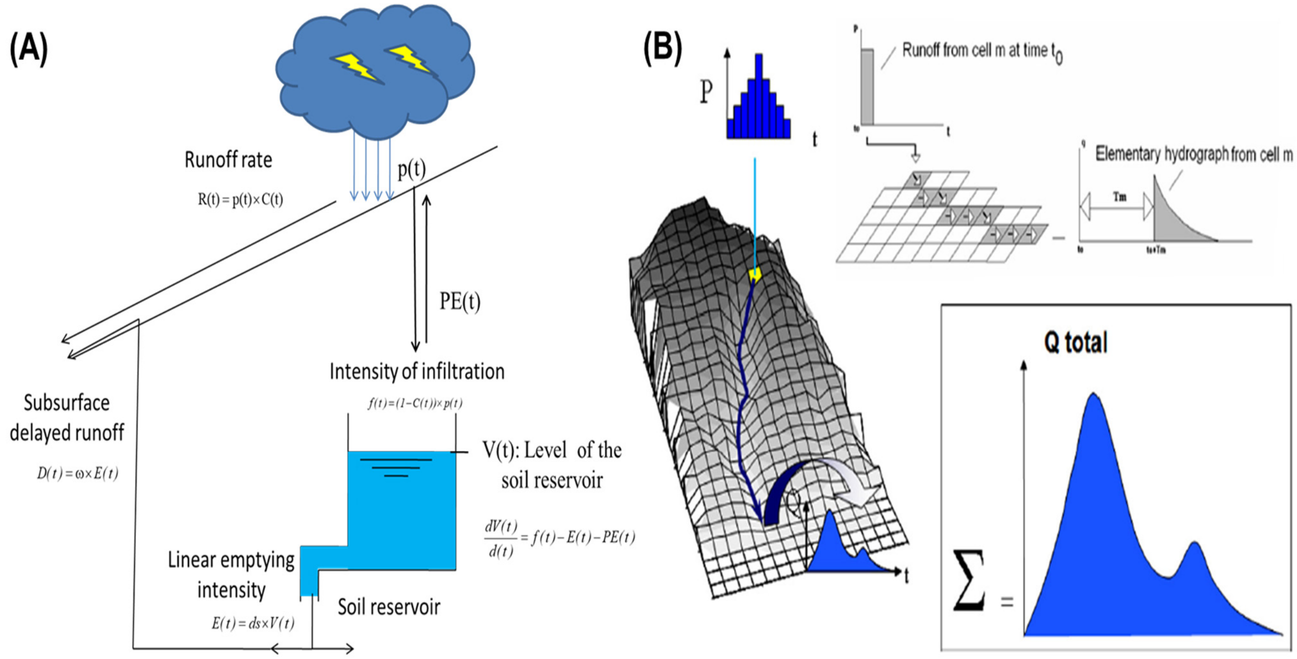

Figure 2. The processes of the SCS-SMA runoff model (**A**) [32] and the simple LR Model (**B**). (www.athys-soft.org, accessed on 2 February 2024).

2.3. Input Data

The data needed to run the hydrological model are hydro-climatic data and geographical data.

Sufficiently long hydro-climatic time series are needed for the calibration and validation of the selected model. The collected data for running the model are given in Table 1.

Table 1. Input data for the model implementation in the selected catchments.

Data Type	Source	Description
Discharge flow	DGBGTH (Ministry of Agriculture Tunisia) and DGRE (Ministry of Agriculture Tunisia)	Daily water balance of Lakhmess dam station (1990–2017) Daily discharge flow of the Raghay Plaine station (1990–2017) with missing data from 1 September 2014 to 10 October /2014 Daily water balance of Siliana Dam station (1990–2017) Daily water balance of the Bou Heurtma dam station (2008–2017)
Rainfall	DGRE (Ministry of Agriculture Tunisia)	For the Lakhmess catchment: daily rainfall data from 2 rainfall stations (1992–2016) For the Raghay catchment: daily rainfall data from 6 rainfall stations: Chemtou Raoudet, Chemtou Ferme, Feija SM, Raghay, Oued Mliz, and Sraya (1990–2017) For the Siliana Upstream catchment: daily rainfall data from 6 rainfall stations: Makthar PF, Sened Hadded, Sidi Hmada, Lakhmess dam, Siliana Dam, and Siliana INM (1990–2017). For the Bou Heurtma catchment: daily rainfall data from 5 rainfall stations: Ain Beya, Ain Debba, Bni Mtir, Bou Heurtma, and Jantoura (1990–2017).
DEM	https://gdex.cr.usgs.gov/gdex/ (accessed on19 June 2014)	30 m resolution Aster GDEM image, mission of 19 June 2014
Potential Evapotranspiration	National Institute of Meteorology	Siliana climatic station and Jendouba climatic station (1990–2017)

The daily rainfall (mm/day), daily discharge flow (m^3/day), and daily water balance data (mm/day) were obtained from the General Directorate of Water Resources in Tunisia (DGRE). Moreover, the minimum and the maximum daily temperature (°C) were obtained from the National Institute of Meteorology in Tunisia (INM) and used to calculate the daily PET [43], while the Aster GDEM maps were downloaded from the USGS site (LP DAAC—ASTGTM (usgs.gov)).

The mean annual rainfall showed a drastic decrease in the Lakhmess catchment of approximately 33% from the period of observation 2001–2004 compared with the period 2014–2017. However, the mean annual rainfall remains comparable for the observed duration of 1990–1994 and 1994–1997, respectively. This variability proved important climate shifts within the studied catchments and the need for temporal transferability. Moreover, recent studies showed an important alteration in Land Use/Land Cover (LULC) within the studied catchments. However, El Ghoul et al. [38] showed that the variability in LULC can be contained within the model prediction uncertainty.

2.4. The Transferability Evaluation Methodology

This research study focuses on evaluating the spatial and temporal transferability of the calibrated SCS-SMA-LR model parameters within the Medjerda catchment. To achieve this, a parameter regionalization approach associated with a diachronic analysis is implemented.

Hence, the SCS-SMA-LR model in this employed version encompasses six calibrated parameters: the maximal capacity of the soil reservoir (S [$L \cdot T^{-1}$]), the linear emptying of the soil reservoir's coefficient caused by the deep aquifer percolation (ds2 [T^{-1}]), the part of the soil discharge to simulate the delayed runoff (ω (dimensionless)), the fraction limiting the lateral emptying of the reservoirs (Sa/S (dimensionless)), the flow velocity (Vo[[$V \cdot T^{-1}$]]), and the coefficient of diffusion (Ko (lag, dimensionless)).

The study is conducted in two phases: First, the temporal transferability is evaluated by applying model parameters calibrated for a specific donor time duration to a different receptor duration, from a decade to another characterized by potentially varying climatic and hydrological conditions. Secondly, the spatial transferability is evaluated by examining whether the parameters of the model can be efficiently applied to ungauged receptor catchments after being extracted from a donor catchment. This process deals with similar detection between catchments in terms of hydrological and geo-environmental aspects [44,45] (Figure 3).

The evaluation of modeling performance within these different phases is assessed based on several accuracy criteria and graphical interpretations.

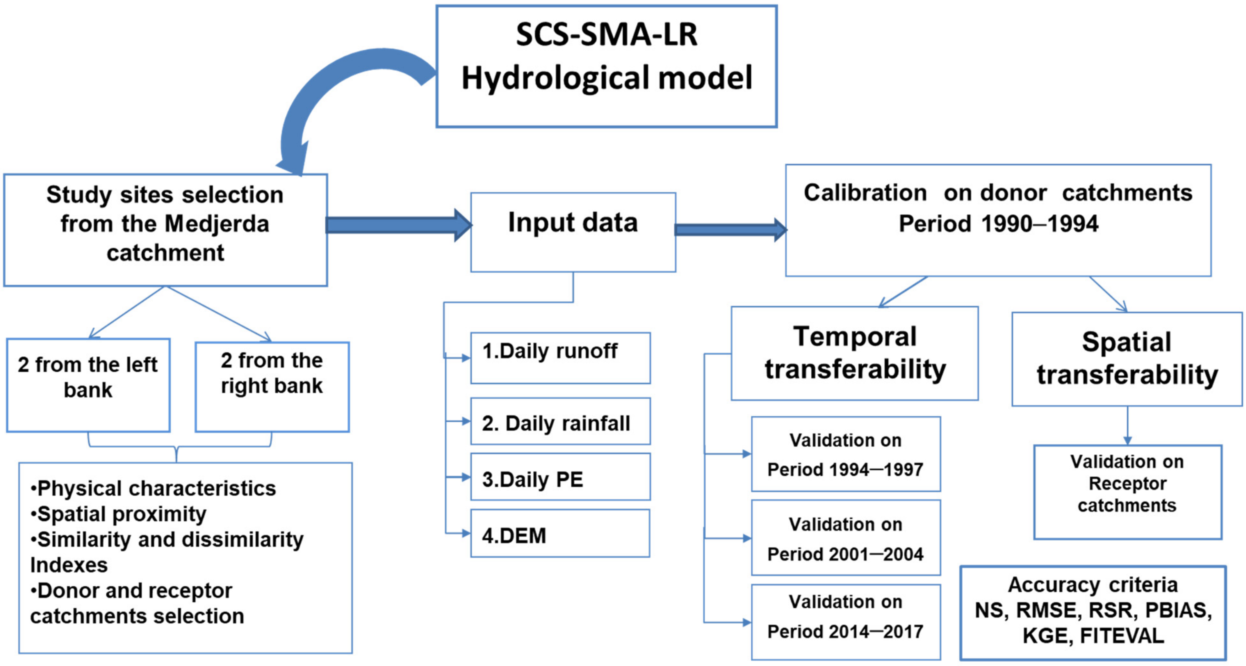

Figure 3. The overall transferability evaluation methodology.

2.5. Similarity Assessment Between Donor and Receptor Catchments

The spatial transferability was supported by analyzing the similarity between donor and receptor catchments using hydro-geomorphic catchment descriptors [46]. The use of hydro-geomorphic attributes in similarity analysis is based on the hypothesis that physiographic similarity drives similarity in hydrological functioning [47]. Yet there is no general agreement on the most appropriate descriptor for assessing catchment similarity [48,49].

Combining physical similarity and spatial proximity is expected to give better performance than using only physical similarity or spatial closeness when selecting catchments [50]. In this study, we used the following physical geographic indicators: drainage density, mean elevation, compactness index, average slope, dominant soil, forest, crops, olives, and mean interannual rainfall. Moreover, we used a physical proximity indicator since Raghay and the Bouheurtma are adjacent catchments on the left bank of the Medjerda and Lakhmess is a sub-catchment of the Siliana Upstream catchment.

We assessed similarity by first calculating the Jaccard Similarity Index (JSI) [51]. The JSI is a simplified statistical method to evaluate the similarity between two groups of data. Mathematically, it is expressed as follows:

$$\mathrm{JSI(X, Y)} = \frac{\sum_{i=1}^{N} \min(X_i, Y_i)}{\sum_{i=1}^{N} \max(X_i, Y_i)} \tag{1}$$

where JSI(X, Y) is the Jaccard coefficient between the descriptors of the donor catchment X and the receptor catchment Y, i is the descriptor used in this study, and N is the length of the series of descriptors. This method computes the number of common descriptors between the donor and the receptor datasets and symbolizes the percentage of the total amount of data in both sets, where a higher percentage represents a better similarity between the donor and the receptor descriptor. The selection of this similarity index was based on previous studies [52], which compared 20 known similarity indices and where the JSI appeared to be the most suitable one.

We also calculated the Duncan Dissimilarity Index (DSI) [53]. This index is expressed as follows:

$$\mathrm{DSI}(X,Y) = \frac{1}{2}\sum_{i=1}^{N}|X_i - Y_i| \quad (2)$$

where DSI (X, Y) is the Duncan Dissimilarity Index between the descriptors of the donor catchment X and the receptor catchment Y, i is the descriptor used in this study, and N is the length of the series of the descriptors.

Similarly to the JSI, the DSI also provides a percentage but in the reverse way, where a lower percentage means a better similarity between the donor and the receptor catchments.

2.6. Model Calibration

The SCS-SMA-LR model was calibrated for the donor catchments and periods using the Best Linear Unbiased Estimator (BLUE) method [54]. This method minimizes a cost function by taking a synchronous form when detecting the differences between the simulated and observed model values (e.g., volumes, discharge, soil moisture, discharge velocities) and the alterations between the initial optimized model parameters. The model contains 6 parameters to be calibrated. The accuracy of the model was assessed based on several evaluation criteria such as the Nash–Sutcliffe efficiency (NS) [55], the Root Mean Square Error (RMSE), the ratio of RMSE to the standard deviation of the observations (RSR) [56], the Percent BIAS (PBIAS), the Pearson correlation coefficient R^2 [57], the Kling–Gupta Efficiency (KGE) [58], and the FITEVAL classification [59].

The evaluation criteria of the model's aptitude to predict are, respectively, shown in the following formulas:

$$\mathrm{NS} = 100\left(1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(S_i - \bar{S})^2}\right) \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \quad (4)$$

$$\mathrm{RSR} = \frac{\sqrt{\sum_{i=1}^{n}(O_i - S_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2}} \quad (5)$$

$$\mathrm{PBIAS} = 100\left(\frac{\sum_i(O_i - S_i)}{\sum_i O_i}\right) \quad (6)$$

$$R^2 = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})}\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})}} \quad (7)$$

$$\mathrm{KGE} = 1 - \sqrt{(A-1)^2 + (B-1)^2 + (C-1)^2} \quad (8)$$

where $A = \frac{\sqrt{\sum_i(S_i - \bar{S})^2}}{\sqrt{\sum_i(O_i - \bar{O})^2}}$, $B = \frac{\sum_i S_i}{\sum_i O_i}$, and $C = \frac{\sum_i(S_i - \bar{S})(O_i - \bar{O})}{\sqrt{\sum_i(S_i - \overline{S_i})^2 \times \sum_i(O_i - \bar{O})^2}}$.

O_i: the observed runoff; S_i: the simulated runoff; $\overline{O}$: the mean observed runoff; $\bar{S}$: the mean simulated runoff; n: the number of pairs of the measured and simulated variables.

The NS is extensively employed to judge the quality of hydrologic models. Models are considered acceptable when NS is higher than 50% [60]. The RMSE describes the difference between the observed and simulated discharge, where smaller values of RMSE lead to a better runoff prediction. The RSR, derived from the RMSE, is considered satisfactory when its values are under 70% [56]. On the other hand, a zero value of PBIAS means a perfect fit between the observed and the simulated values, and positive (or negative) bias results show that the model tends to underestimate (overestimate) the predicted data. Generally, PBIAS is deemed acceptable when it is under 25% [57]. R^2 estimates the correlation between the simulated and observed discharge [61]. Similar to NS, KGE is considered satisfactory when its values are over 50% and considered better when moving close to 100%. This accuracy criterion has been widely used recently to assess modeling performance and is usually compared to NS. The Fitting Evaluation (FITEVAL) includes a statistical test to assess the performance [62], allowing the identification of the significance (p-value) of the model performance (NS $\geq$ 0.5).

2.7. Assessing the Spatial and Temporal Transferability

The spatial transferability of the model was assessed by using the parameters calibrated on the donor catchments to be applied to the receptor catchments based on spatial proximity, data availability, and physical similarity.

For the catchment situated on the right bank of the Medjerda, the calibrated model of the Lakhmess catchment was scaled up to the 10-times-bigger Siliana Upstream catchment. The two catchments are controlled at their outlets with dams and are highly anthropized.

For the catchment situated on the left bank of the Medjerda River, the calibrated parameters for the Raghay donor catchment were transferred to the nearby Bouheurtma catchment. Both catchments are similar in terms of previously defined physiographic indices. Yet the Bouheurtma catchment contains two dams and develops different functional behavior.

For assessing the temporal transferability, a diachronic analysis was performed. Diachronic analysis is the study of a phenomenon over staggered periods, usually every ten years. This method is widely used for studies of climate change and land use change [63].

The parameters calibrated for the 1990–1994 period were directly applied to the donor catchments for three 3-year periods from three different decades: 1994–1997, 2001–2004, and 2014–2017. These periods were selected based on available data.

3. Results

3.1. Model Calibration on the Donor Catchments

Calibration was carried out using the BLUE method for the two donor catchments and for the period from September 1990 to August 1994. The obtained parameters were included within the acceptable range (Table 2).

Table 2. Calibrated parameters' median values for the donor catchments.

Parameters	Raghay	Lakhmes	Optimization's Value Range
S (mm)	123.03	95.05	0–600
Sa/S (dimensionless)	0.3	0.55	0–1
ω (dimensionless)	0.8	1	0–1
ds2 (1/day)	0	0	0–1
V0 (m/s)	1	2.50	0.01–50
K0 (dimensionless)	0.67	4.53	0–100

The simulated flow for the Raghay donor catchments slightly underestimates the peak flow by about 30 m^3/s and overestimates the flow volume for the whole observation by about 12% (Figure 4). The scattered plot (A1) shows that the model can generally predict the magnitude of medium to weak flows. However, several important floods could not be fairly reproduced. One of the possible explanations relies on the ungauged flows coming from the Algerian part.

Accordingly, the calibrated model gives an NS criterion of 71%, considered a good accuracy value to predict discharge. Moreover, we obtained suitable values for RMSE (5.1 m^3/s) and RSR (53%), also confirming good model quality. As for the PBIAS, the obtained coefficient of accuracy is about 11%, which is considered a good model ranking. The KGE yields 80%, confirming good modeling quality.

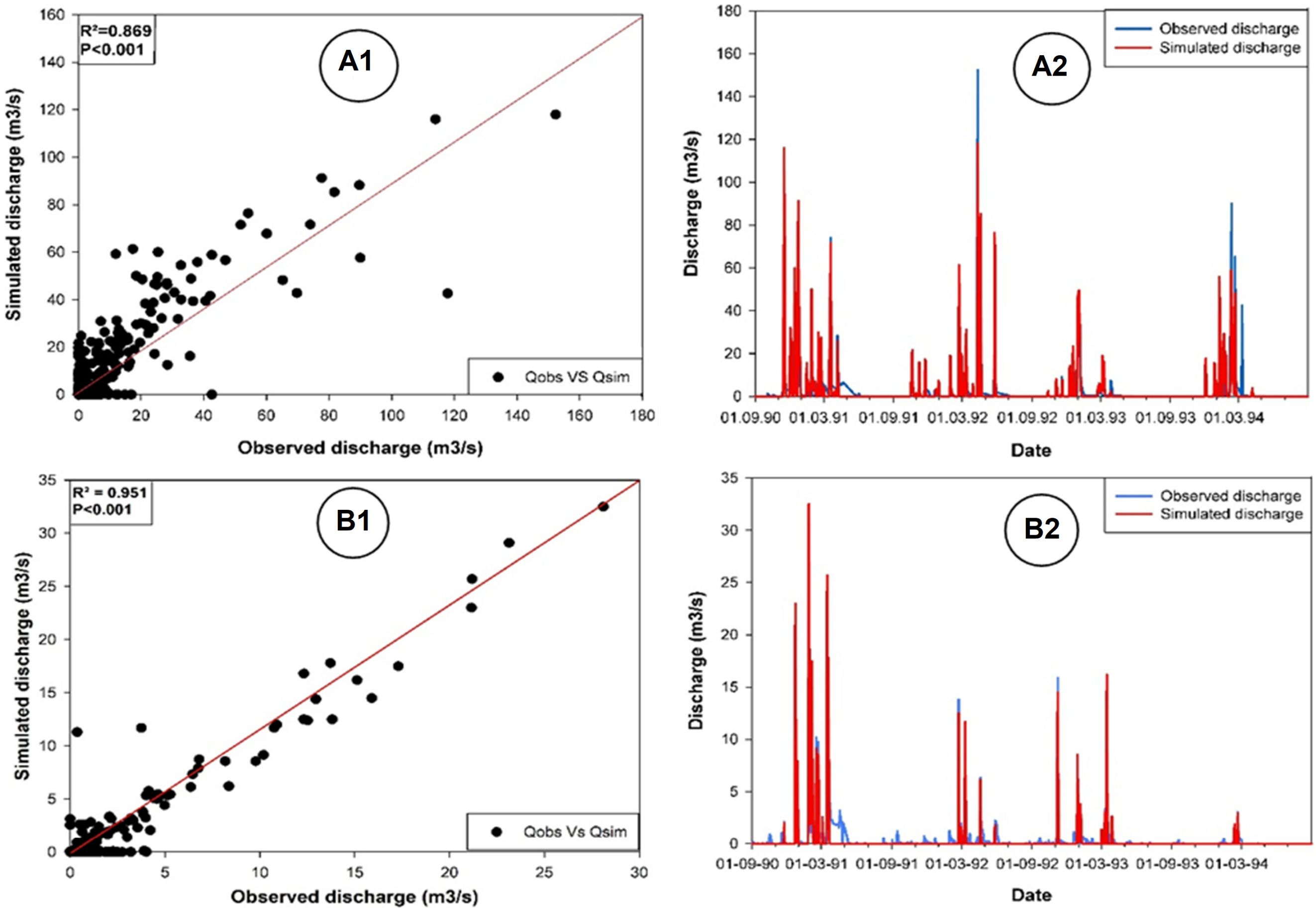

Figure 4. Scatter plot and timeline presentation of the calibration on the period 1990–1994 for the donor catchments using daily discharge: (**A1**) the scatter plot of the observed versus simulated daily discharge in the Raghay catchment; (**A2**) the comparison between the simulated and observed continuous timeline discharge in the Raghay catchment; (**B1**) the scatter plot of the observed versus simulated daily discharge in the Lakhmess catchment; (**B2**) the comparison between the simulated and observed continuous timeline discharge in the Lakhmess catchment.

For the Lakhmess donor catchment, the simulated model overestimates the peak flow by about 4 m^3/s and underestimates the volume by about 23%. The scatter plot (B1) indicates a better fit than for the first donor catchment (Figure 4). Despite this good fit, the timeline series (B2) showed an overestimation of an event on the date of 18 March 1991. An insight assessment of the employed data during this event highlighted the possible error in observed data, since the discharge in the Lakhmess dam is obtained from the daily measurements of the water balance of the dam, which are manual operations. This interpretation was reinforced based on the daily discharge flows from two days before this date and two days after this date, reaching 21.19 m/s, with cumulative rainfall spanning 137 mm in the Sidi Hmada rainfall station since the beginning of the event. This good fit is also verified through the evaluation performance criteria. Hence, we obtain a very good NS criterion (NS = 87%). The RMSE, the RSR, the PBIAS, and the KGE are also very good, with values of 6.72 m^3/s, 35%, −24%, and 72%, respectively.

3.2. Temporal Transferability Analysis

For temporal transferability, we assessed model performance for three distinguished time intervals for the two donor catchments (Figure 5).

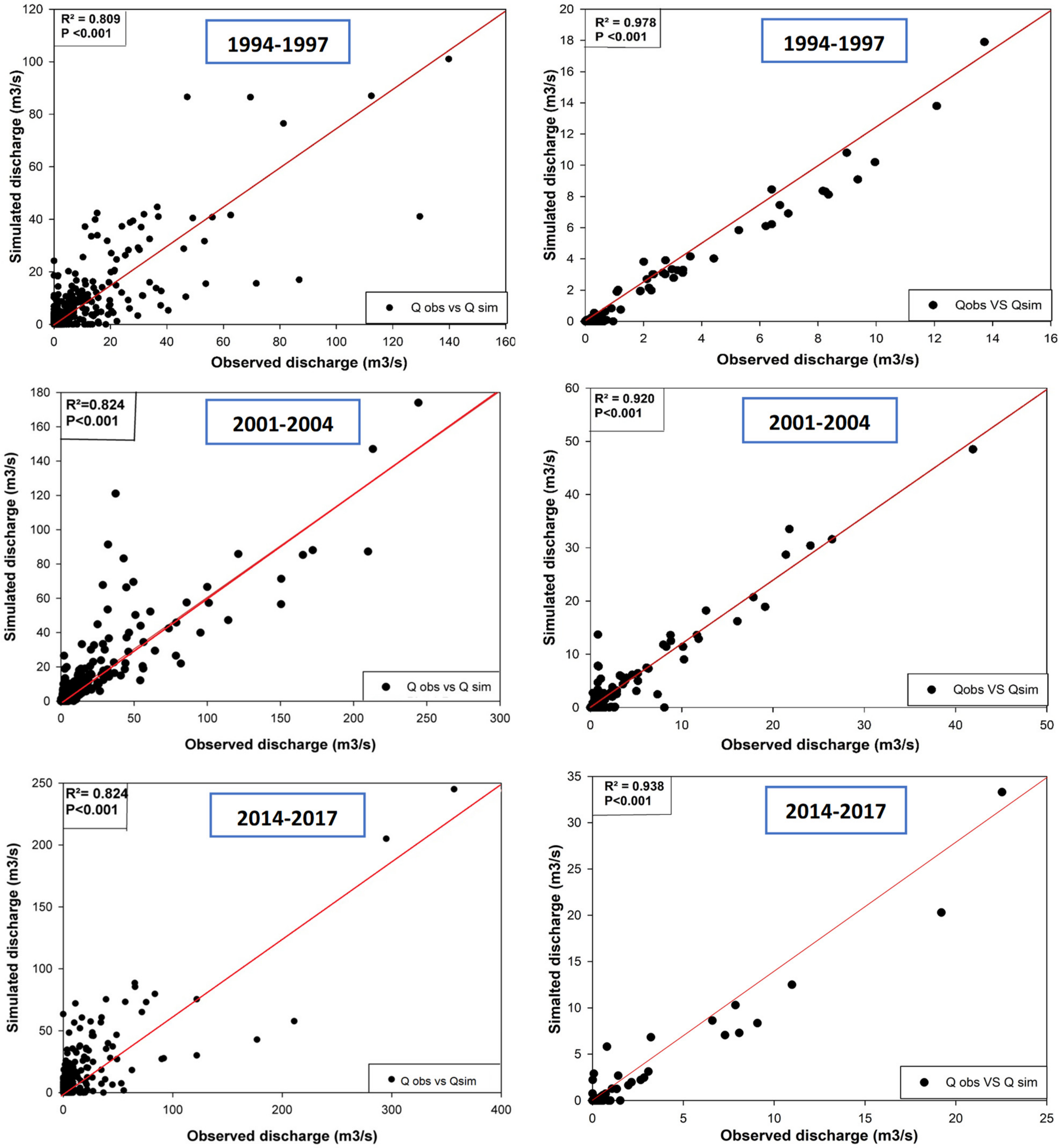

Figure 5. The scatter plot of the observed versus simulated daily discharge in the two donor catchments for the temporal transferability assessment. The left part of the figure concerns the Raghay catchment, and the right part concerns the Lakhmess catchment. Diachronic analysis is shown for three time intervals: 1994–1997, 2001–2004, and 2014–2017.

3.2.1. Validation of the Period 1994–1997

The validation of the model parameters for Raghay for the receptor period of 1994–1997 yields an NS of 63%. The underestimation of the maximum flow is about 30 m^3/s. The regression slope of the scatter plot of 0.809 affirms the model's suitability for this period. For the Lakhmess catchment, the NS of 96% is higher than that of Raghay while simulating a good regression slope of 0.978. Moreover, the difference between the predicted and the observed volume does not exceed 8% for all three years of the period 1994–1997 (Figure 5).

3.2.2. Validation of the Period 2001–2004

For the validation interval 2001–2004, a slightly better simulation performance is obtained for the Raghay catchment compared to the 1994–1997 receptor interval. The NS in this case yields 67%. The model still underestimates the peak flow by about 30%. The slight variation in the accuracy criteria may be due to climatic variability; during the 2001–2004 period, the Medjerda catchment experienced several high flood events, giving a cumulative rainfall that largely exceeded the annual average of the majority of the study region [64]. This is noticed when observing the maximum flows. In the Raghay catchment, a flow of 357 m^3/s was observed, while the peak simulated flow of the model was 247 m^3/s.

This is in contrast to the peak flow in the Lakhmess catchment, where the simulated peak reaches 48.51 m^3/s, compared to the observed peak of 41.90 m^3/s. The evaluation criteria remain very good, with 84% for both NS and regression. The difference between the simulated and observed volumes does not exceed 7%. This may be explained by the saturation of the soil reservoir due to the heavy rainfall coupled with a high velocity, which can exceed the calibrated one, of about 2.5 m/s.

3.2.3. Validation of the Period 2014–2017

The transferability assessment during the 2014–2017 receptor period for the Raghay catchment indicated a rather good but slightly underestimated maximum observed flow of about 244 m^3/s, with an underestimation of about 20%. Nevertheless, this difference did not influence the quality of the hydrological modeling for the considered period. The NS for this period yields 72%. The good transferability is related to the fact that the Raghay catchment is transboundary and not strongly affected by human development. The catchment is only subject to climatic variability, which the model can reproduce accurately based on the evaluation criteria.

For the Raghay catchment and based on the diachronic analysis, the conceptual spatially distributed model proves to be robust. It has to be noted that due to hydrometric equipment dysfunction, daily discharge data were not available from 1 September 2014 to 10 October 2014.

The validation applied to the second donor catchment for this third period also led to good evaluation criteria, with an NS criterion equal to 84% and an R^2 higher than 93%. The very good performance of the model, according to the accuracy criteria, indicates its validation for the Lakhmess catchment during this period. However, the model reproduces an overestimation of the maximum observed flow, equal to 30%, in addition to the underestimation of the produced volume. The overall quality of the validation on the period 2014–2017 of Lakhmess can be considered very good, leading to the validity of the temporal transferability process.

3.3. Spatial Transferability of the Rainfall–Runoff Model

The calculated descriptor, JSI, and DSI for similarity and dissimilarity indexes are summarized in Table 3.

Table 3. Physical characteristics of the studied catchments including similarity and dissimilarity indices.

Data Type	Raghay	Bouheurtma	Lakhmess	Siliana Upstream
Drainage density (km/km^2)	3.44	3.25	4.22	3.98
Mean elevation (m)	661	590	924	949.5
Compactness index (km/km)	1.57	1.61	1.207	1.273
Average slope (m/m)	13	11	17	13
Dominant soil (%)	27	22	18	21
Forest (%)	35	28	40	32
Crops (%)	25	29	17	21
Olives (%)	31	35	7	13
Mean interannual rainfall (mm)	720	660	420	470
Jaccard Similarity Index (%)	89.95		93.44	
Duncan Dissimilarity Index (%)	2.67%		4.71%	
Drainage area (km)	362	390	127	1040

According to the obtained JSI, we can affirm that the similarity index between the donor and the receptor catchments is good with values of approximately 90%, confirming the good similarity between the selected catchments. Moreover, the DSI indicates a very low dissimilarity percentage, which confirms the JSI and gives additional proof of the good similarity between the studied catchments.

For spatial transferability, we validated the calibrated model parameters on the two receptor catchments: the Bouheurtma and Siliana Upstream catchments. For Bouheurtma, and due to limited accessibility of continuous data, we used a daily data set of five rain gauges, one climatic gauge, and the daily water balance in the Bouheurtma reservoir with a period of observation going from September 2008 to August 2017. For the Siliana Upstream catchment, we used six rain gauges, one climatic gauge, and the daily water balance of the Siliana reservoir for a duration of 22 years (from September 1994 to August 2016).

3.3.1. Validation on the Bouheurtma Catchment (Left Bank)

The validation of the Bouheurtma led to an NS of 78% and an RMSE of 4.5 m^3/s, considered as good accuracy. Unlike the calculated accuracy criteria, the graphical comparison of the observed versus simulated discharge at the level of the Bouheurtma reservoir shows an overestimation of the peak flow by about 13% and of the produced volume by about 20% (Figure 6). This may be explained by the fact that one-fourth of the Bouheurtma catchment's area is controlled by the Bni Mtir dam. The latter dam is directly interconnected with the other dams of the Medjerda basin, permitting it to evacuate the surplus of the arriving discharge during floods. This can affect the modeling results since there is an important high modification in the catchment's response.

According to FITEVAL, the model is considered acceptable for an NS higher than 50%, in the case of this study. The cumulative probability showed that 100% of the computed discharge values are considered acceptable. It also shows that the values of NS in the whole series of the data set vary between 61% and 85%. The RSME also varies between 3.4 m^3/s and 6.7 m^3/s, considered acceptable, since it is under 10 m^3/s (Figure 6). Based on this classification, more than 90% of the NS values are considered good to very good [56].

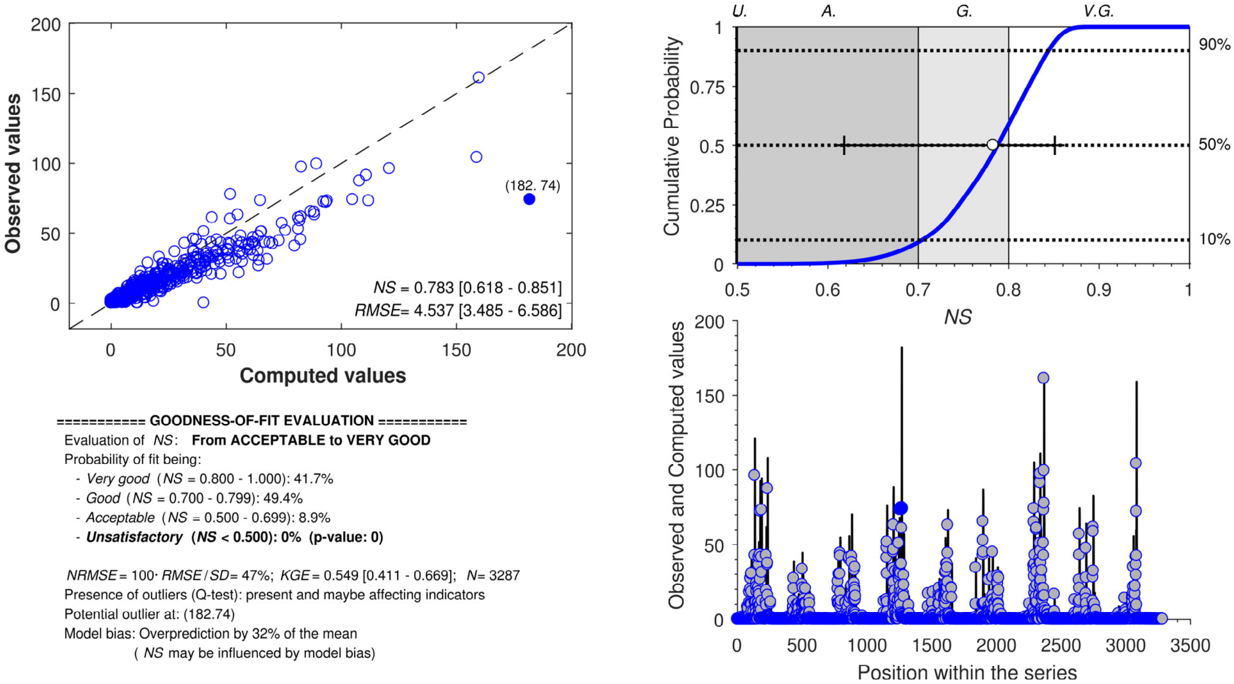

Figure 6. The FITEVAL results for the Bouheurtma catchment (2008–2017).

3.3.2. Validation on the Siliana Upstream Catchment (Right Bank)

The validation of the Siliana Upstream led to an NS of 61% and an RMSE of 4.4 m^3/s, considered as good [56]. The graphical comparison of the observed discharge against the simulated discharge at the Siliana Upstream outlet showed an important underestimation of about 62%, an exceptional peak flow of 260 m^3/s, and an underestimation of the produced volume of 20% (Figure 7). As for Bouheurtma, one-tenth of the surface area of the Siliana Upstream catchment is restrained by the Lakhmess dam, which is the donor catchment for this study.

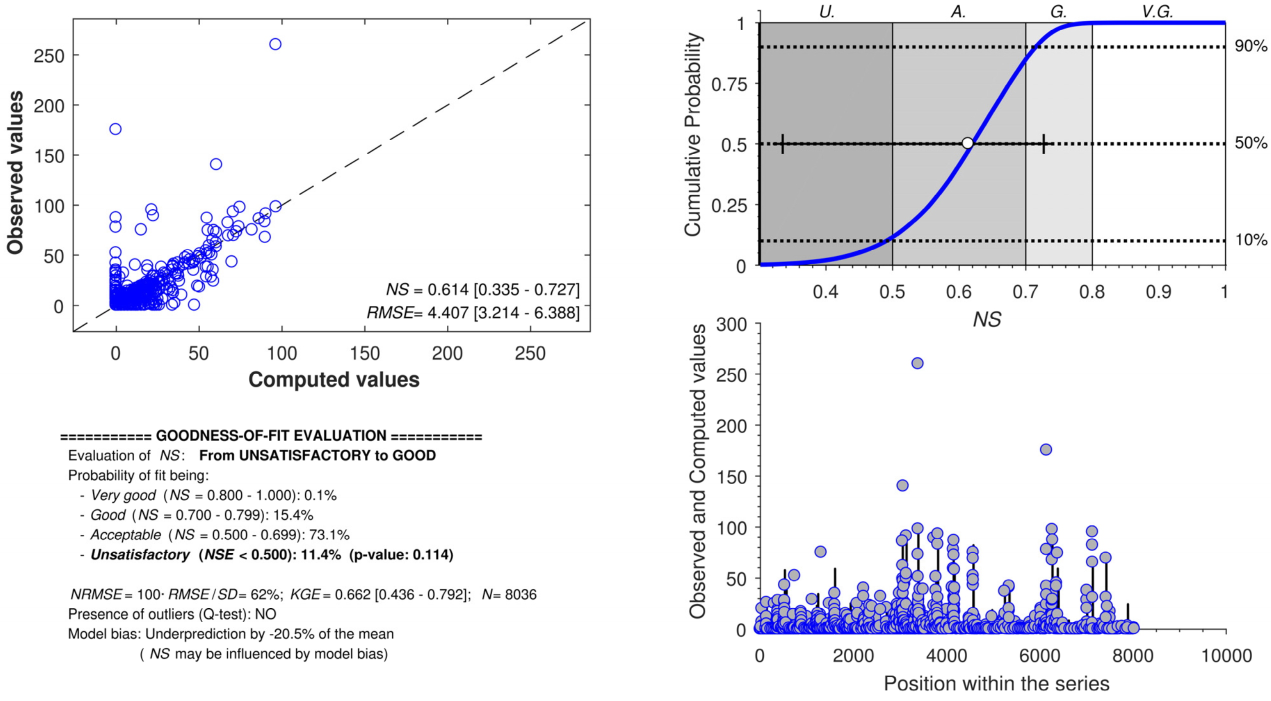

Figure 7. The FITEVAL results for the Siliana Upstream catchment (1994-2016).

The FITEVAL classification shows unacceptable reproduction of the hydrological behavior of the Siliana Upstream catchment for about 11.4% of the produced discharge values. NS values rank between 33% and 72% and RMSE ranks between 3.2 and 6.5 m^3/s, which is considered partially unacceptable for the NS and acceptable for the RSME (Figure 7).

The less well-performing transferability, in this case, can be explained by the fact that the model was calibrated for a donor period of 4 years, while it was applied to the receptor catchment for a receptor period of 22 years. The difference in surface area between the donor and receptor can also explain this poorer performance. Another possible explanation is that the donor catchment is a sub-catchment of the receptor catchment and is partially controlled by the Lakhmess dam operated by the Ministry of Agriculture, Water Resources, and Fishery. The poorer performance could also partially be explained by the quality of the hydrometric data recorded at the entrance of the Siliana Dam. Indeed, the capacity of the dam varies significantly from one year to another because of the important high sedimentation rates that rest in its watershed's bed after each important high flood. Variable storage will have an impact on the estimated observed inflow which is deduced from the reservoir mass balance calculation.

Although the values of the ranking evaluation criteria vary between acceptable and unacceptable criteria, the majority of the values of these criteria are still considered acceptable. Indeed, 73% of the simulations have an acceptable NS, while 15% have a good NS. We therefore can affirm that the model can be spatially transferred within the right bank of the Medjerda but we have to give additional importance to the similarity of the length of the data series and surface area to be introduced in the similarity index calculation. Studies affirm that using the weighted area is crucial to define the similarity indexes within catchments [65], especially for those with small surface areas. The clustered accuracy criteria map summarizes the model performance (Figure 8).

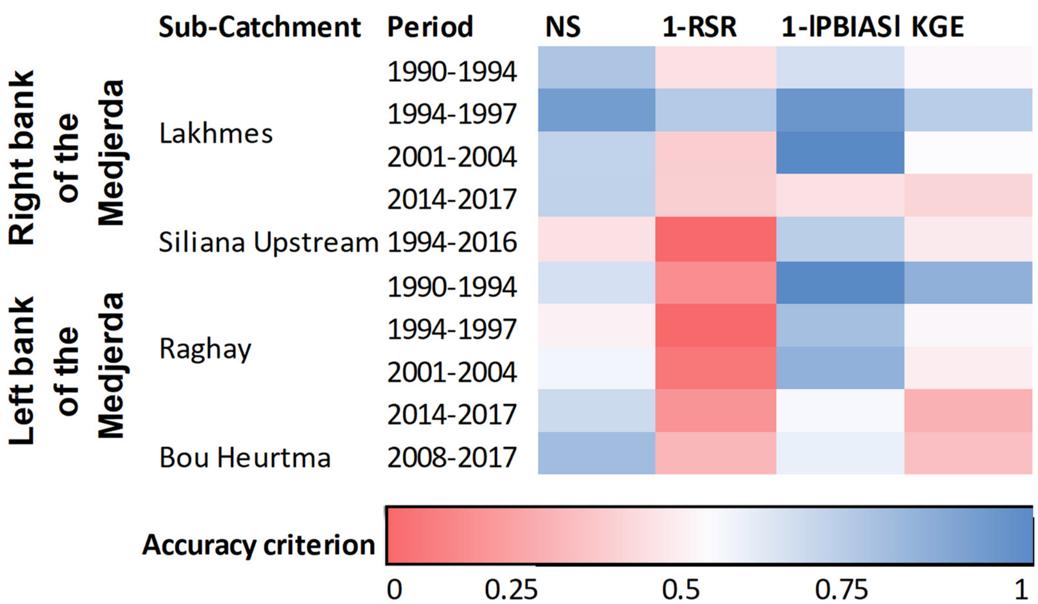

Figure 8. Clustered heat map of the accuracy criteria for the spatial and temporal transferability process within the Medjerda catchment.

4. Discussion

The calibrated parameters present a large difference between the two catchments. For instance, the value of the soil reservoir capacity (S) is greater in the catchment situated in the left bank than the one situated in the right bank. This difference can be explained by the fact that the Raghay catchment is less entropized than the Lakhmess catchment since it is a catchment bordering two countries: Tunisia and Algeria. Another explanation is based on the difference in rainfall between the two regions, since Raghay has rainfall varying from 394 mm per year to 921 mm per year for the Feija rainfall station but a mean rainfall of 565 mm per year for the calibration period. However, the rainfall for Lakhmess is less prominent, with precipitation of about 455 mm per year for the same period. The flow velocity (V0) presented a significant difference between the studied catchments since Lakhmess has an area of about one-third that of Raghay and presents a crucial altimetric gradient with a compact shape, while Raghay has a stretched shape, permitting attenuation of the flow velocity. The obtained results are comparable to the results obtained by Aqnouy et al. [31]. The most sensitive parameters highlighted through the modeling exercise proved to be S and V0, having had the most impact on the runoff results, which is aligned with the results obtained by Bouadila et al. [29]. The parameter Sa/S, which is the modified presentation of the Curve Number, is normally set to be fixed with a value of 0.2 for most cases. However, the modified version of the model permits its calibration within a limited range. The calibrated value of this parameter for Raghay proved to align with the results obtained for the SCS models, while the value for Lakhmess is more important, and partially can be explained by the active alterations in this catchment by human activity. For instance, the differences in the geographical locations of these catchments have a significant impact on entropized activities since Raghay is far from the center of the governorate.

The clustered heat map confirmed the good performance of the selected model in reproducing flow at different catchments and for different periods, where NS is higher than 50%, KGE is higher than 50%, RSR is lower than 70% and the absolute value of PBIAS is lower than 25%, for the overall calibration and validation process. For the temporal transferability applied to the donor catchments, the process showed a difference in statistical accuracy criteria for the two parts of the Medjerda catchment. This is probably related to the different climatic conditions between the left and right banks of the basin [66] and the differences in similarities between donor and receptor catchments. For instance, Raghay and Lakhmess both share an important altimetric gradient. Therefore, further importance should be given to plain catchments in relatively low altitudes, such as the lower valley of the Medjerda catchment [67].

Figure 9 shows the cumulative discharge, illustrating the quality of the temporal transferability process. The calibrated model can adequately reproduce the overall shape of the hydrological response for the two catchments and different decades. However, the model tends to overestimate the base flow and underestimate a few exceptional floods. This result is in concordance with previous studies [68] when testing several hydrological models. It also demonstrates that calibrated spatially distributed conceptual models like SCS-SMA-LR can be valid for simulation beyond the calibration horizon.

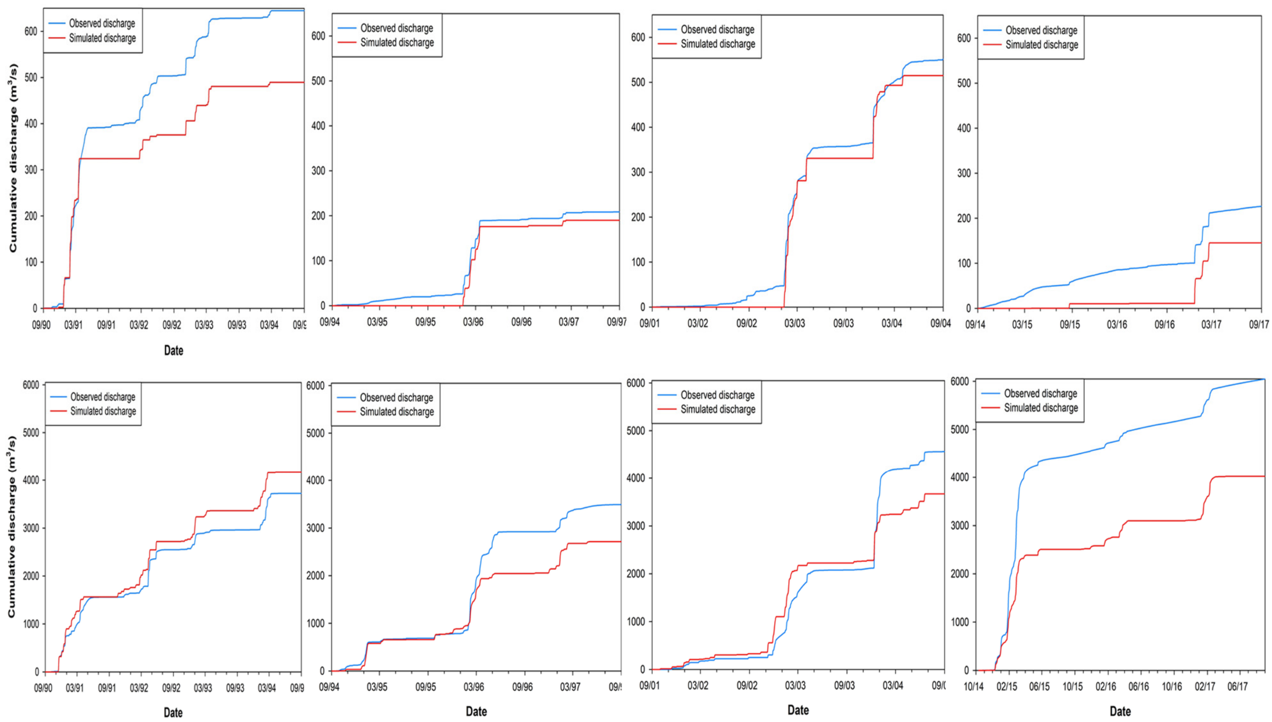

Figure 9. The cumulative observed and simulated discharge illustrating the temporal transferability process for the Medjerda catchment (the Lakhmess catchment (upper part of the figure) and the Raghay catchment (lower part of the figure)).

It should be noted, however, that further attention should be given to data input quality, calibration process, and accuracy criteria selection to test the robustness of the model [69].

Accessibility to high-quality and abundant data emerged as the most difficult task facing this research study. For the Raghay catchment, approximately 40 km^2 of its forested area lies within the Algerian border making accessibility to this area and its data challenging. Similarly, the Lakhmess catchment faces significant hydrological challenges due to the abundant and intense flash floods. These floods lead to the transportation of important amounts of water and soil to the Lakhmess reservoir, causing an increase in its sediment volume and a decrease in its storage capacity.

This phenomenon may cause errors in the estimation of the discharge fluxes which are inferred from the reservoir mass balance. The results are consistent with similar previous studies [19], which tested the temporal transferability of several hydrological models. They however suggested that the temporal transferability is more robust with more complex models when facing a changeable climate.

Concerning the spatial transferability process, the results obtained for the Bouheurtma catchment, on the left bank of the Medjerda, surpass the ones obtained for the Siliana Upstream catchment on the right bank of the Medjerda. These results can partially be explained by the important difference in drainage area from the donor and receptor catchments [70], which was not included when calculating the similarity and dissimilarity indexes. An earlier investigation confirms that the spatial transferability of the model is largely affected by the difference between the drainage areas of the catchments [71]. Hence, for our study, only four catchments are considered; therefore, the conclusions may not be representative of all sub-catchments of the Medjerda. Further studies should contain more selected catchments with different characteristics and aspects. Another suggestion is to use an alternative data-driven approach to be used for future prediction in the Mediterranean context which facilitates modeling for ungauged catchments [72]. As only one hydrological conceptual model, the SCS-SMA-LR model, is considered in this study, it should also be evaluated whether these conclusions remain for other more complex spatially distributed hydrological models. Therefore, using an ensemble of hydrological models will be helpful to enrich the study of spatial and temporal transferability for hydrological modeling [73].

5. Conclusions

Robust hydrological models are crucial for discharge prediction within ungauged catchments, especially with regions facing important climate shifts. Successfully adapting these models to regional scales remains one of the most fundamental yet challenging tasks for researchers. This study purposed to advance our knowledge of hydrological modeling in ungauged catchments by addressing important gaps in spatial and temporal parameter transferability using a spatially distributed conceptual hydrological model within the Medjerda catchment. The analyses focused on two catchments from the left bank (Raghay and Bouheurtma) and two catchments from the right bank (Lakhmess and Siliana Upstream) of the Medjerda. The donor and receptor catchments were selected based on spatial proximity, data availability, and the similarity index.

The optimized calibration of the SCS-SMA-LR for the Raghay and Lakhmess catchments highlight the most sensitive parameters and their values to be transferred to different temporal durations for temporal validation purposes. The diachronic analysis proved to be a successful way to monitor discharges when facing climate variability based on different accuracy criteria. However, a graphical comparison between observed and simulated discharges showed the underestimation of several episodes mainly caused by the data input quality.

Spatial transferability was implemented for the Bouheurtma catchment and for the Siliana Upstream catchment, employing the calibrated parameters obtained from the donor catchments. The modeling results seemed to be performant for the Bouheurtma catchment since the areas of the donor and receptor catchments are comparable with the least entropized action within these catchments, providing a robust framework for improving hydrological predictions in the South Mediterranean region. However, Siliana Upstream presented a certain variability and inaccuracy. This inconsistency could be attributed to the semi-arid watershed having high climatic variability, an important altimetric variability and surface area difference, and inconsistencies in the quality of the hydro-climatic data. Additionally, probable cause is related to the model calibration uncertainty which contributed to this variability in volumes and flows, especially for catchments with dam interconnection. The findings of this research have the potential to inform future studies and guide water resource management and mitigations in similar data-scarce regions internationally. Therefore, future research should focus on expanding these findings when applying this methodology to the Algerian border Medjerda catchment with future assessment of climate change impacts using recent projections.

Author Contributions: Conceptualization and writing—original draft preparation, A.G., K.G. and M.V.; data curation and formal analysis, A.G, K.G., S.K. and N.A.-A.; methodology and validation, A.G., K.G, C.B., S.K., M.V., S.E.-H., and M.A.M.; writing—review and editing, A.G., K.G., S.K., C.B., M.O., M.V., S.E.-H., N.A.-A. and M.A.M.; funding acquisition, S.K., C.B., M.V., S.E.-H., and M.A.M. All authors have read and agreed to the published version of the manuscript.

Funding: Researchers Supporting Project number (RSPD2025R730), King Saud University, Riyadh, Saudi Arabia. The authors received funding from the project "SMART Medjerda: Capacity building in monitoring for intelligent management of the Medjerda water resources" through the project of Wallonia Brussels International and Tunisia, under grant No. 1.1.2 . This work was alsosupported by the OurMED PRIMA Program project funded by the European Union's Horizon 2020 research and innovation under grant agreement No. 2222 (www.ourmed.eu). Moreover, part of this research study was accomplished in the laboratory of HydroSciences in Montpellier with the funding of the mobility program provided by the Ministry of Higher Education and Scientific Research in Tunisia.

Data Availability Statement: The hydrological input data used for the SCS-SMA-LR hydrological model presented in this research study are available upon request from the author Ahlem Gara. The original time series of daily water balance were given by the DGBGTH for the dams, whereas daily rainfall data and discharge flow data were given by DGRE in Tunisia. For the climate data, daily temperature observations were obtained from INM. All data series are not publicly available due to the restrictions of DGRE and INM, and data should be provided upon specific request.

Acknowledgments: The authors would like to thank the Researchers Supporting Project number (RSPD2025R730), King Saud University, Riyadh, Saudi Arabia. The data sets utilized in this study in part originated from the thesis dissertation of the author Ahlem Gara, which was supported by the National Agronomic Institute of Tunisia, University of Carthage, and the Research Unit GDRES, the Higher School of Engineers of Medjez El Bab, University of Jendouba in Tunisia, under the supervision of Slaheddine Khlifi and Christophe Bouvier. The authors would like to thank the Tunisian General Directorate of Water Resources (DGRE), the General Directory of Dams and Studies of Hydraulic Structures (DGBGTH), and the National Institute of Meteorology (INM) for the data provided.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SCS-SMA-LR	Soil Conservation Service (SCS)–Soil Moisture Antecedent (SMA)–simple Lag and Route (LR)
ATHYS	Atelier HYdrologique Spatialisé
SWAT	Soil and Water Assessment Tools
GR4j	Génie Rural 4 Journalier
PET	Potential EvapoTranspiration
N	North
E	East
DGRE	Direction Générale des Ressources en Eau
INM	Institut National Météorologique
USGS	United States Geological Survey
°C	Degree Celsius
DGBGTH	Direction Générale des Barrages et des Grands Travaux Hydrauliques
BLUE	Best Linear Unbiased Estimator
AsterGDEM	Aster Global Digital Elevation Model
JSI	Jaccard Similarity Index
DSI	Duncan Dissimilarity Index
NS	Nash–Sutcliffe efficiency
RMSE	Root Mean Square Error
KGE	Kling–Gupta efficiency
R^2	Pearson correlation coefficient
RSR	Ratio of the Root Mean Square Error
PBIAS	Percentage Bias

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