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Applied smart hydrology: integration of the GR2M model and machine learning methods in the Oued El Athmania basin (Northeastern Algeria)

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Hydrological modeling in semi-arid areas remains difficult due to a lack of data and high spatial and temporal variability. This study proposes a hybrid approach combining the GR2M conceptual model with machine learning algorithms (Random Forest, XGBoost, and Isolation Forest) in Python. Its application to the Oued El Athmania watershed (Algeria) highlights the limitations, but also the relevance, of GR2M alone, with an NSE of 0.836 in calibration and 0.891 in validation. The integration of machine learning significantly improves hydrological forecasts with increased performance (NSE=0.930–0.941; R^2=0.933–0.943) and a significant reduction in errors (RMSE, MAE). The Isolation Forest algorithm also demonstrates notable effectiveness in the automatic detection of atypical flows. This combination optimizes both flow forecasting and the anticipation of extreme events. The complementarity between conceptual modeling and data-based approaches thus proves to be a robust solution. It paves the way for smart hydrology that is better adapted to climate uncertainties. Finally, this approach is a strategic tool for sustainable and proactive water resource management in semi-arid contexts.

KEY WORDS: GR2M model; Random Forest; XGBoost; Hybrid modeling; Isolation Forest

Introduction

Integrated watershed management in semi-arid areas remains a major challenge due to the complexity of hydrological regimes and the lack of continuous data. In this context, parsimonious conceptual models such as GR1A and GR2M, developed by CEMAGREF, stand out for their simplicity and low data requirements (Inan et al., 2024).

GR2M, based on a reservoir structure, has proven effective, but its performance depends on the calibration period, climatic conditions, and the morphometric characteristics of the basin (Bhadani et al., 2023; Mouelhi et al., 2013; Mvoundou et al., 2022).

However, assessment using indicators such as NSE remains limited, as it does not always guarantee the physical validity of the parameters (Jaffar et al., 2024). In semi-arid contexts such as the Biskra wadi, empirical approaches have shown their limitations (Boumessenegh and Hadda, 2022), which justifies the growing interest in hybrid approaches combining GR2M and artificial intelligence.

This study, conducted on the El Athmania wadi, aims to optimize the simulation of monthly flows by testing the sensitivity of the model to calibration (Mouelhi et al., 2013; Herizi and Sofiane, 2024) and integrating machine learning algorithms such as Random Forest, XGBoost, and Isolation Forest, implemented in Python, to refine forecasts and detect anomalies (Fathi et al., 2023).

The proposed hybrid approach, combining physical rigor and analytical power (Roy et al., 2023; Berbić and Ocvirk, 2017), is part of an intelligent computational hydrology adapted to the current requirements of sustainable water resource management (Hublart et al., 2015; Mosavi et al., 2018).

Study area

The study area is located in northeastern Algeria and corresponds to the upper sub-basin of the Kébir (code 10-3), also known as the upper Rhumel basin, one of the seven sub-basins of the greater Kébir-Rhumel basin (No. 10) (Ramzi et al., 2024) as defined by the NWRA.

Located south of the wilaya of Mila, in the upper Rhumel valley between 36°08' and 36°15' N and 6°10' and 6°18' E, the basin has a subcircular morphology and extends along the Djebel Grouz. It is mainly drained by the Rhumel wadi, whose flow is regulated by the Grouz dam, near the town of Oued El Athmania, a key infrastructure for water management (Zineb and Meriem, 2024). The relationship between surface water and groundwater is considered significant and predictable based on the hydrogeological characteristics described in previous reports (DRE, 2016; NIDA, 2013). (Fig. 1).

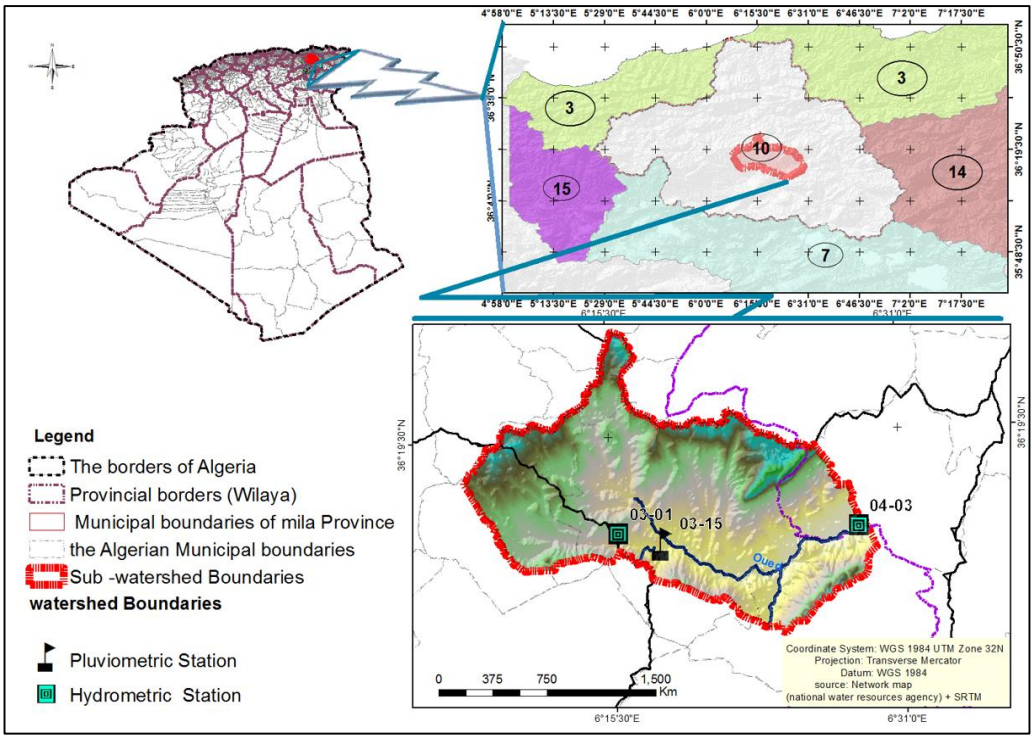


Fig. 1. Location of the study area and distribution of rainfall and hydrometric stations (developed under ArcGIS 10.5 using data from the National Water Resources Agency).

Material and methods

The GR2M monthly model

The implementation and validation of the GR2M hydrological model require reliable hydrometeorological data in order to assess the robustness and predictive power of the model over equally distributed calibration and validation periods (Mvoundou et al., 2022; Nash and Sutcliffe, 1970).

The study was conducted on the Oued El Athmania watershed (386.4 km²), on an annual and monthly scale, using precipitation and potential evapotranspiration (PET) estimated according to the Thornthwaite method (Thornthwaite, 1948), with runoff as the output variable. The model was implemented using Excel's "Solver" tool, splitting the time series into two sub-periods dedicated to calibration and validation. Parameters X1 and X2 were optimized by maximizing the Nash-Sutcliffe criterion (Nash and Sutcliffe, 1970; Sadio et al., 2023). The hydrological period adopted follows a cycle from September to August, with the first year used as a ramp-up phase for the reservoir, in accordance with the recommendations of (Mvoundou et al., 2022).

Hydrological and climatic data

(ETP) and observed flows at the outlet of the El Athmania wadi over a period of twenty-two years (1990–2011). These series were used to calibrate and validate the GR2M hydrological model and to train machine learning algorithms for flow forecasting. Statistical tests confirmed the consistency and temporal reliability of the data for hydrological *analyses.*

Precipitation (P)

Precipitation, expressed in millimeters, corresponds to monthly totals measured at the Boumalek station, the only station with usable data for the period studied. These data were provided by the National Water Resources Agency (NWRA, 2020).

Potential evapotranspiration (PET)

PET was estimated using the Thornthwaite method (1948), based solely on average monthly temperatures. It is calculated using the following equations:

$$ETP = 16.(\frac{10t}{I})^{\alpha} \quad (1)$$

where

ETP – monthly potential evapotranspiration [mm];

I – thermal index cancels; it is the sum of twelve-monthly indices:

$$I = \left(\frac{t}{5}\right)^{1.514} \quad (2)$$

t – monthly average temperature [°C].

α – Complex function of the index I defined by the relation:

$$\alpha = 0.016\, I + 0.5 \quad (3)$$

where

t – is the average monthly temperature [°C]. This

method has been validated for semi-arid climatic conditions (Al-Sudani, 2019).

Thornthwaite's (1948) method was chosen for estimating potential evapotranspiration (ETP), as it is a simple, robust approach, adapted to the limited data conditions characteristic of semi-arid zones. It is based solely on temperature, a parameter that is reliably and continuously measured in the Oued El Athmania basin. More physical methods, such as Penman-Monteith, require often incomplete data (radiation, wind, humidity), the absence of which could increase uncertainties. On the other hand, in the context of hybrid modelling combining conceptual modelling and machine learning, the empirical biases of ETP can be offset by the ability of the learning model to capture non-linear relationships between variables. Thornthwaite's choice thus appears methodologically justified, guaranteeing the temporal consistency and reproducibility of hydrological simulations.(Hlaváčiková et al., 2024; Holko et al., 2024; Tegos et al., 2013;).

Observed flows (Q)

The monthly flows observed at the Oued El Athmania hydrometric station, initially expressed in [$m^3 s^{-1}$], were used as a reference for calibrating and validating the GR2M model. To ensure consistency and integration into the model, all hydrological variables (precipitation, ETP, and flows) were converted to millimeters, in accordance with the recommendations of (Fathi et al., 2023). This normalization ensures dimensional consistency and the reliability of runoff simulations.

Results and discussion

Modeling using the GR2M model

The performance of the GR2M model applied to the Oued El Athmania watershed was evaluated using a 50% calibration/50% validation split, in accordance with hydrological modeling standards (Mvoundou et al., 2022; Perrin et al., 2003). The results show excellent calibration performance (presented in Table 1 and illustrated in Figs. 2 and 3): (NSE=0.836; R^2=0.82; Pearson correlation=0.87) with low errors (RMSE=5.89; MAE=2.76), reflecting an accurate reproduction of monthly flows. In validation, the model confirms its robustness with an even higher NSE (0.891), but errors increase (RMSE=23.05; MAE=11.86), revealing limitations in the representation of extreme events. The optimized parameters (X1=5.23 mm, reservoir capacity; X2=1.005 months, exponential discharge time) remained stable between the calibration and validation phases, in accordance with the GR2M conceptual framework. Overall, the model proves reliable for monthly hydrological modeling of the basin, while highlighting the value of a hybrid approach incorporating machine learning to better predict complex situations (Kraft et al., 2022; Hlaváčiková et al., 2024).

Table 1. Summary of the performance of the GR2M model for the El Athmania river basin

Period	NSE (Nash-Sutcliffe)	R^2	Pearson (R)	RMSE	MAE	X1	X2
Calibration	0.836	0.82	0.87	5.89	2.76	5.23	1.005
Validation	0.891	0.77	0.78	23.05	11.86	—	—

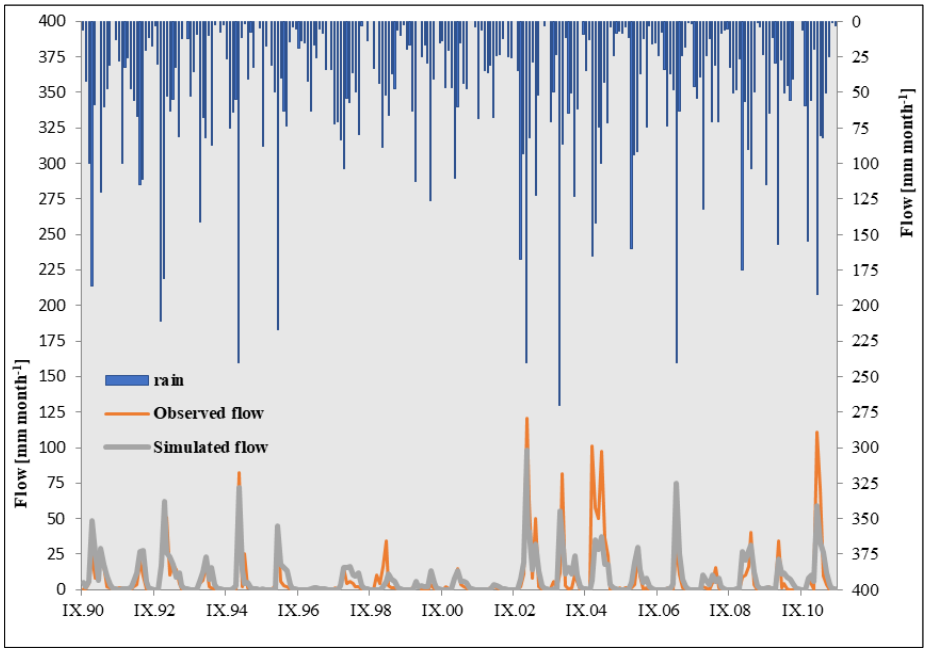


Fig. 2. Modeling using the GR2M model.

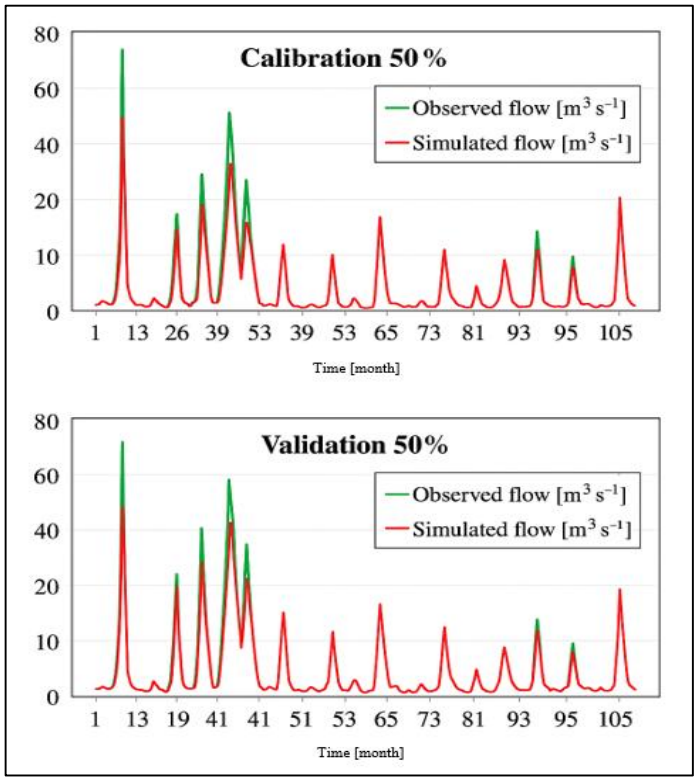


Fig. 3. Visualization of calibration and validation quality (120-month period) using the GR2M model for the Oued El Athmania watershed.

In order to improve the accuracy of hydrological simulations and explore complementary approaches to the GR2M model, a hybrid methodology integrating machine learning algorithms has been implemented. This approach aims, on the one hand, to predict monthly flows in a more flexible manner and, on the other hand, to automatically identify outliers in the time series of simulated flows.

Three models were used:

Two supervised models: Random Forest and XGBoost, applied to estimate monthly flows based on precipitation and potential evapotranspiration (PET).

1. Random Forest (RF):

Based on the creation of multiple decision trees, this model is known for its robustness and ability to handle complex interactions.(Breiman, 2001; Jibril et al., 2022; Kumar et al., 2023) Formalization: Let: $D = \{(x_i, y_i)\}_{i=1}^{n}$ a training set, the construction of M decision trees $\{T_m\}_{m=1}^{M}$, The final prediction is obtained by averaging or majority vote :

$$\hat{y} = \frac{1}{M}\sum_{m=1}^{M} T_m\,(x) \tag{4}$$

2. XGBoost (Extreme Gradient Boosting):

Uses a boosting method to improve predictive performance, particularly on large datasets (Chen and Guestrin, 2016; Ciner et al., 2024; Korkmaz, 2024) With a decision tree *f_m* with iteration *m*, we have the predictive model given by:

$$\hat{y}_i = \sum_{m=1}^{M} f_m\,(x_i) \tag{5}$$

And the regular loss function is given by:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i + f_t(x_i)\right) + \Omega(f_t) \tag{6}$$

where

$\Omega(f_t)$ – is a regularization term to control the complexity of the model; by optimizing using gradient descent:

$$L^{(t)} \approx \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2} h_i f_t(x_i)^2\right] + \Omega(f_t) \tag{7}$$

where

$$g_i = \frac{\partial l(y_i, \hat{y}_i)}{\partial \hat{y}_i} \tag{8}$$

and

$$h_i = \frac{\partial^2 l(y_i, \hat{y}_i)}{\partial \hat{y}^2{}_i} \tag{9}$$

However, the machine learning models, namely Random Forest and XGBoost, were trained on 70% of the data and validated on the remaining 30% in order to optimize the learning phase while maintaining a robust evaluation on an independent test set.(Breiman, 2001; Wang et al., 2021) (Breiman, 2001; Wang et al., 2021).

3. An unsupervised model:

The Isolation Forest method is used for automatic anomaly detection in time series, including simulated flow rates. It works by isolating atypical points using randomly constructed decision trees, without requiring labels for learning. (Qin and Lou, 2019; Xu et al., 2023). The technique consists of generating a forest of t random isolation trees in order to calculate the average path

length *h(x)* required to isolate a point x (Liu et al., 2009; Shao et al., 2020) have shown that a subsample of size ψ (here 264) is sufficient to preserve performance while reducing computation time. The value *h(x)* is obtained by averaging the isolation lengths across the trees. Finally, an anomaly score is defined as follow:

$$s(x) = 2^{-\frac{E[h(x)]}{c(\phi)}} \quad (10)$$

where

s(x) – this is the anomaly score assigned to point *x;*

h(x) – This is the number of separations (cuts) required in an isolation tree to isolate *x*;

E[h(x)] – average path length across all isolation trees in the forest;

c(ϕ) – the expected value of the path length in a random binary tree, given a subsample of size ϕ (here ψ=264\psi = 264ψ=264).

Software tools and computing environment

All of these models were developed in Python (version 3.10), using the scikit-learn and XGBoost libraries. The data used are identical to those used for the GR2M (1990–2011), allowing for direct comparability of results (Kratzert et al., 2019; Mosavi et al., 2018; Wang et al., 2021) illustrated in Fig. 4.

Comparison of simulated/predicted flows from the GR2M, Random Forest, and XGBoost models with observed flows from the Oued El Athmania (1990–2011): The two machine learning models (Random Forest and XGBoost) show a significantly higher capacity than the GR2M model to reproduce the temporal variability of flows, particularly during floods. The absolute error graph confirms this superiority, with smaller and more stable deviations for the machine learning approaches.

A comparative table (Table 2 and Fig. 5) summarizing the performance results of the three approaches.

Comparative analysis

A comparative analysis of the performance of the GR2M, Random Forest, and XGBoost models applied to modeling monthly flows in the Oued El Athmania reveals a clear superiority of machine learning-based approaches:

Although the GR2M conceptual model offers acceptable performance with a Nash-Sutcliffe efficiency (NSE) coefficient of 0.828 and an R^2 of 0.841, it has limitations inherent to its rigid deterministic structure, which restricts its ability to capture the complex variability of hydrological processes. On the other hand, Random Forest models, and XGBoost in particular, stand out for their ability to accurately reproduce the dynamics of observed flows. The XGBoost model achieves the best results across all indicators considered, with a high NSE, of 0.941, a reduced RMSE of 16.80 mm, an MAE

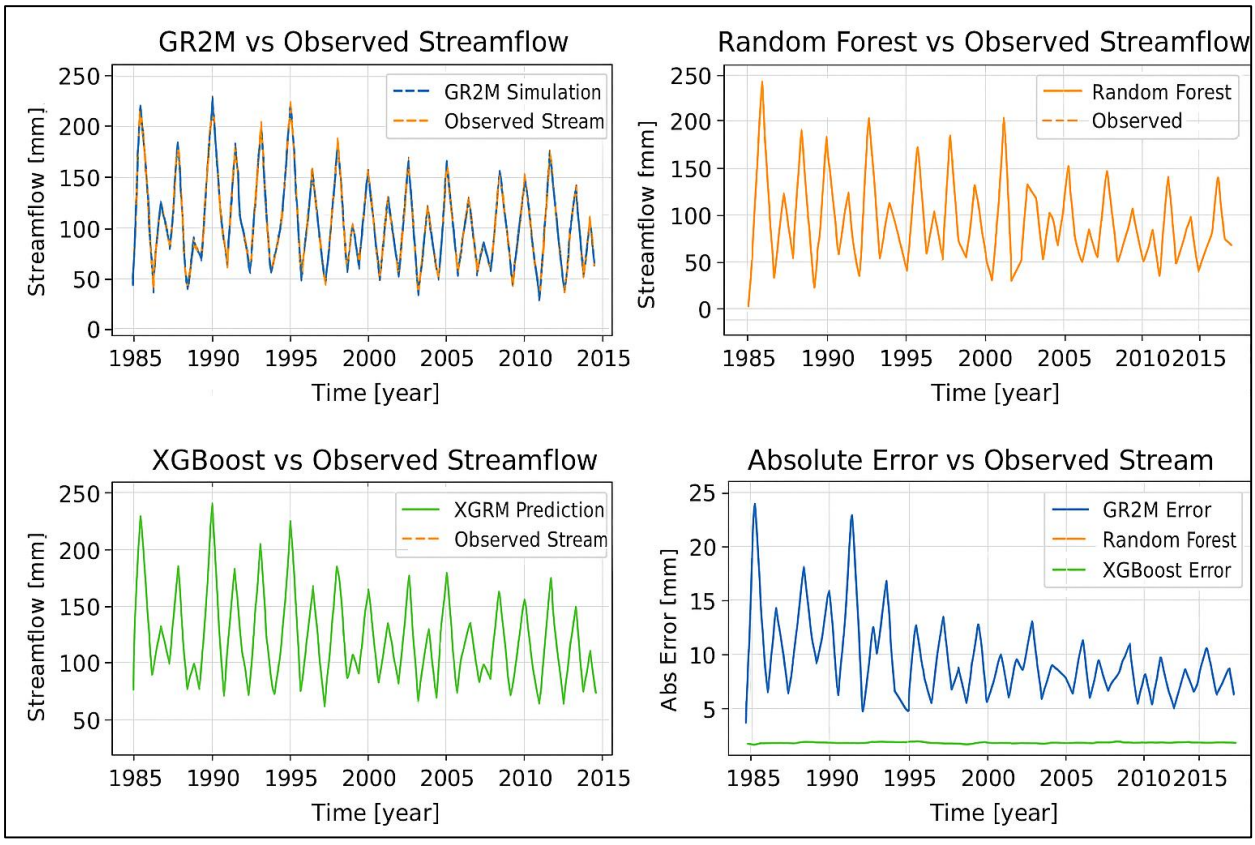


Fig. 4. Comparison of simulated and predicted flows with observed flows and associated errors (1990–2011) for the El Athmania river basin using the three models.

Table 2. Comparison of GR2M vs. Random Forest vs. XGBoost performance for the Oued El Athmania watershed (1990–2011)

Model	NSE	Pearson R	RMSE [mm]	R^2	MAE [mm]
GR2M	0.828	0.92	27.45	0.841	17.265
Random Forest	0.930	0.965	17.92	0.933	11.693
XGBoost	0.941	0.970	16.79	0.943	10.971

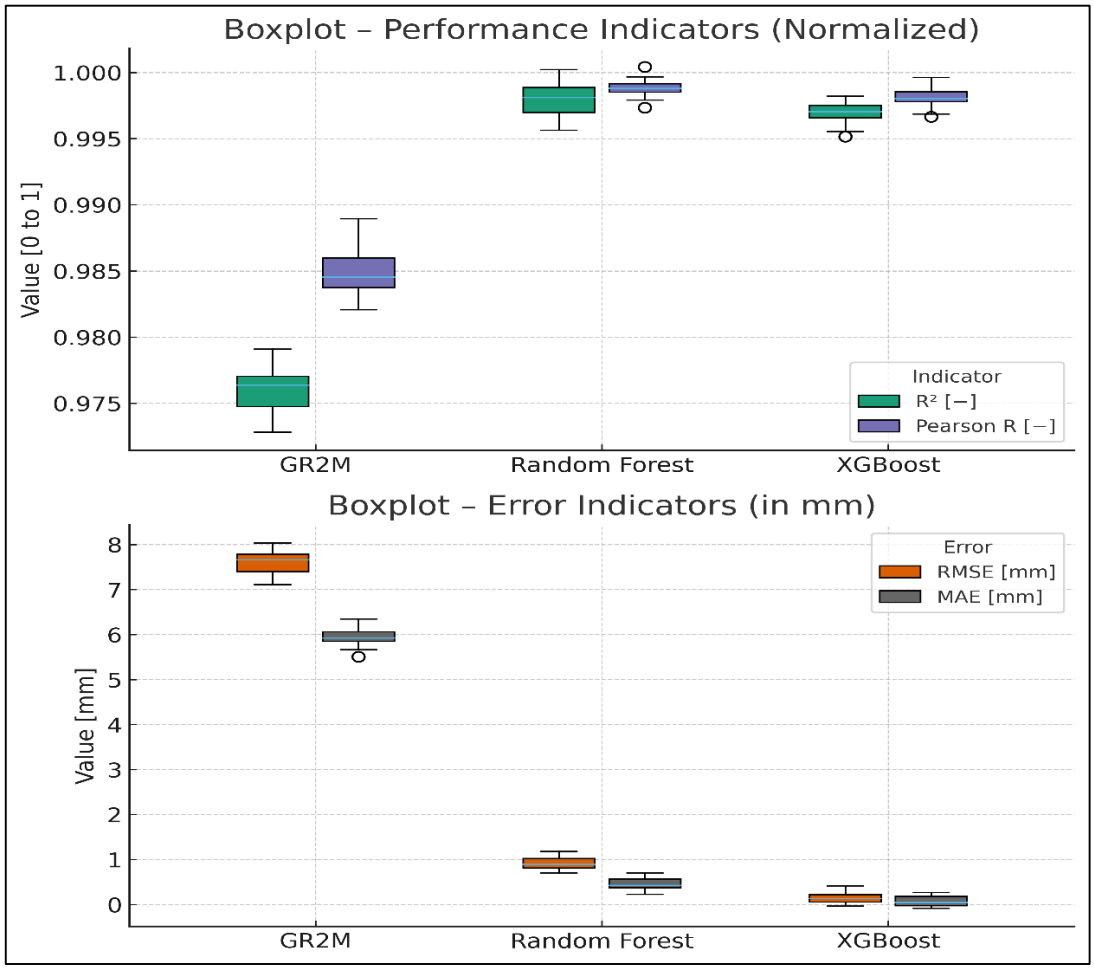


Fig. 5. Comparison of the performance of the GR2M model and machine learning methods for hydrological modelling of the Wadi El Athmania watershed.

of 10.97 mm, and a Pearson correlation coefficient of 0.970, reflecting remarkable accuracy. Random Forest although slightly behind, remains effective with an NSE of 0.930 and an R^2 of 0.933. These results are summarized in Fig. 5, which highlights the ability of machine learning models to consistently outperform the GR2M model, both in calibration (1990–2000) and validation (2001–2010), with lower errors and higher correlations.

However, the value of GR2M lies in its physically interpretable dimension, justifying its potential integration into a hybrid approach. Thus, the complementarity between conceptual modeling and artificial intelligence paves the way for more robust forecasting systems, combining physical interpretability and predictive performance. (Kraft et al., 2020)

These results confirm that, provided the input variables are carefully selected and prepared, machine learning models offer a highly effective alternative to traditional hydrological approaches.

Anomaly detection

Automatic anomaly detection was performed using the Isolation Forest algorithm, which identified 26 atypical values (~10.3% of the data), concentrated around extreme floods or low flows that may reflect either measurement errors or rare hydrological events (Talagala et al., 2019). Fig. 6 shows the effects of data cleaning, which has improved the robustness of hydrological

simulations and forecasts.

Although interpolated versions were generated for comparison (Almeida et al., 2019; Chau, 2006), anomalies detected in the observed flows were replaced by linear interpolation to ensure a continuous and consistent series. (Table 3 and Fig. 7).

In short, this study highlights the complementarity between conceptual models and learning algorithms: while GR2M provides a useful explanatory structure, ML models enhance predictive accuracy. The combination of these approaches thus appears to be a promising avenue for robust hydrological modeling, adapted to Mediterranean realities and the challenges of water management in a semi-arid climate.

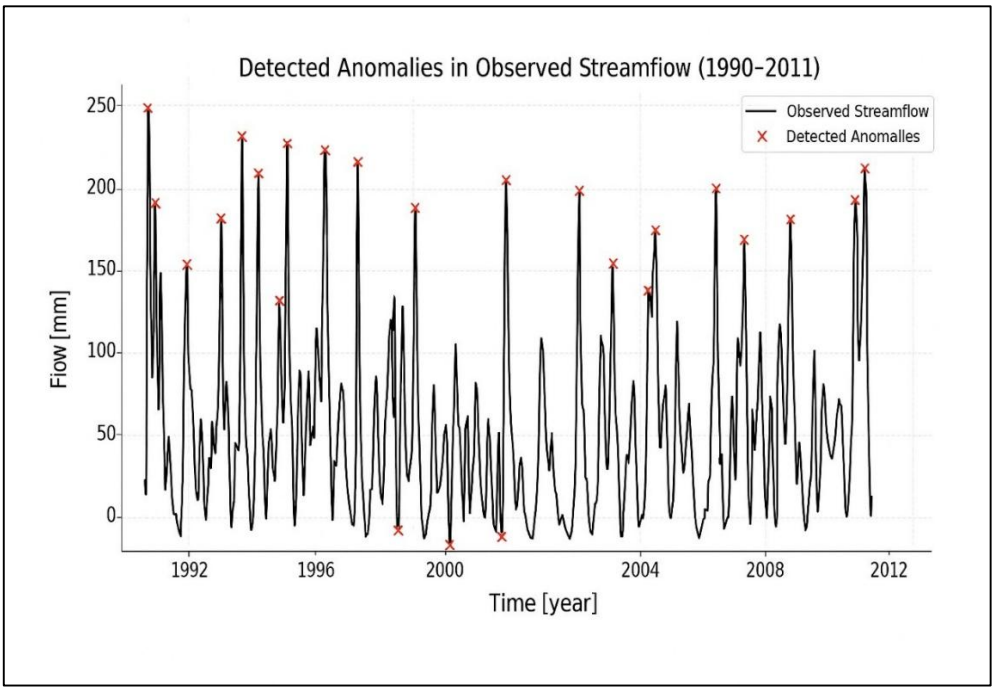


Fig. 6. Detection of anomalies in observed monthly flows using the Isolation Forest algorithm (1990–2011).

Table 3. Anomalies detected in the observed flows of Oued El Athmania and values corrected by linear interpolation (1990–2011)

N°	Date of anomaly	Observed flow rate [mm]	Corrected flow rate [mm]	N°	Date of anomaly	Observed flow rate [mm]	Corrected flow rate [mm]
1	1990-11-01	245.71	95.06	**14**	1999-12-01	191.73	61.94
2	1991-04-01	201.17	67.62	**15**	2000-07-01	0.24	12.31
3	1991-08-01	0.65	80.94	**16**	2000-08-01	2.04	15.20
4	1993-07-01	2.56	23.60	**17**	2001-07-01	0.93	5.25
5	1993-08-01	1.63	41.19	**18**	2003-01-01	206.51	103.62
6	1994-01-01	230.85	92.17	**19**	2003-07-01	0.53	14.24
7	1994-06-01	214.12	30.74	**20**	2003-08-01	0.41	25.54
8	1995-01-01	230.85	60.66	**21**	2004-07-01	0.84	8.76
9	1995-06-01	214.12	30.74	**22**	2007-03-01	199.99	86.14
10	1996-02-01	225.80	74.96	**23**	2007-07-01	2.15	15.01
11	1997-08-01	2.25	35.57	**24**	2009-06-01	1.73	21.40
12	1997-09-01	217.87	65.41	**25**	2011-02-01	198.80	64.68
13	1998-07-01	0.16	25.67	**26**	2011-04-01	216.59	92.65

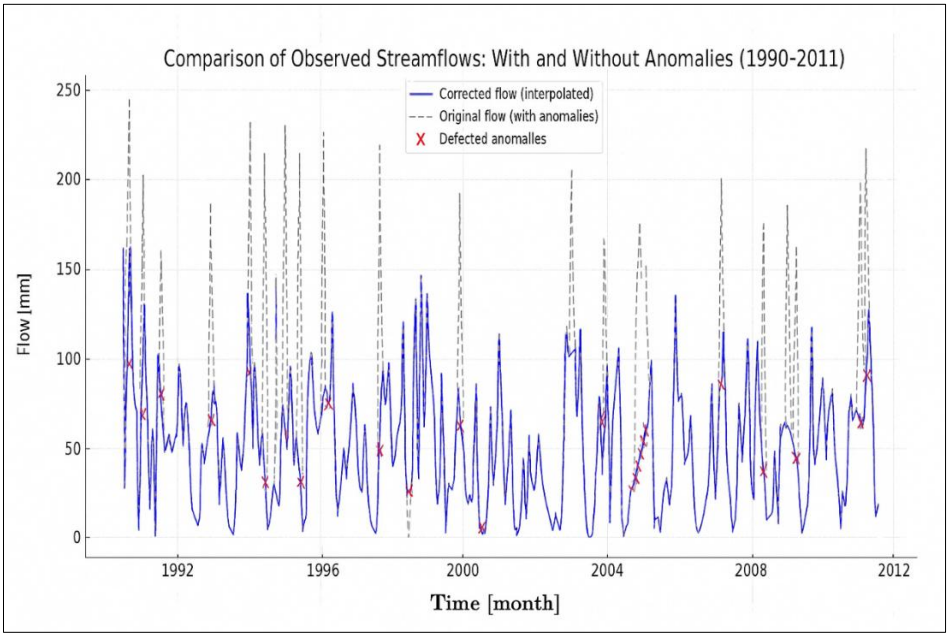


Fig. 7. Comparative visualisation of anomaly detection before and after correction.

Conclusion

This study evaluated and compared the performance of a conceptual hydrological model (GR2M) and two machine learning models (Random Forest and XGBoost) for modeling monthly flows in the Oued El Athmania watershed in a semi-arid context.

- The results obtained reveal the superiority of machine learning models, notably XGBoost, in terms of predictive accuracy, ability to model complex hydrological variability and to identify extreme or non-linear behavior. However, the GR2M model demonstrated appreciable robustness in a data-limited context, thanks to its parsimonious structure and physical interpretability.
- Over and above performance comparisons, this study highlights the strategic value of the hybrid approach: by combining the physical foundations of a conceptual model with the exploratory power of machine learning algorithms, it is possible to benefit simultaneously from the transparency of hydrological processes and the predictive efficiency of data-driven models. This complementarity not only improves the quality of simulations, but also refines anomaly detection, anticipates extreme events and informs decision-making in water resource management.
- In a context marked by growing climatic uncertainties and pressure on water resources, this integration of methods offers a promising path towards intelligent hydrology, capable of local adaptation, operational resilience and greater responsiveness to future environmental challenges...
- Future prospects include enriching input data (drought indices, satellite data, land use), automating learning processes, and extending the approach to other Mediterranean basins to test the transferability and genericity of hybrid models.

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Abbreviation

DRE	Water Resources Directorate
GR2M	2-parameter Rural Engineering Monthly
ML	Machine Learning
MAE	Mean Absolute Error
NIDA	National Investment Development Agency
NSE	Nash–Sutcliffe Efficiency
NWRA	National Water Resources Agency
R	Pearson correlation coefficient
R^2	coefficient of determination
RMSE	Root Mean Squared Error
XGBoost	Extreme Gradient Boosting

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