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Original scientific paper

Flowrate Forecasting and Ecohydrodynamic Insights from the Eşen Stream (Southwestern Türkiye): Time Series Perspectives

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Abstract: Accurate flowrate forecasting is vital for sustainable water management, supporting flood control, drought mitigation, hydropower optimization, and agricultural planning. This study analyzes daily discharge data from the Eşen Stream in southwestern Türkiye for 2017 to 2022, provided by the General Directorate of State Hydraulic Works. Three statistical approaches were applied: Autoregressive Integrated Moving Average, Trigonometric Box-Cox ARMA Trend Seasonal, and Multiple Linear Regression with lagged predictors. A Box-Cox transformation was used to stabilize variance, and model performance was evaluated with Akaike Information Criterion, Bayesian Information Criterion, Root Mean Square Error, and the coefficient of determination. Results showed that Autoregressive Integrated Moving Average captured short term dependencies, Trigonometric Box-Cox ARMA Trend Seasonal achieved the highest predictive accuracy with strong seasonal patterns, and Multiple Linear Regression offered a simple framework for operational forecasts. All models indicated a declining discharge trend toward 2030. The findings demonstrate the value of complementary approaches for practical water management and contribute to understanding ecohydrodynamic processes at the freshwater-marine interface.

Keywords: ecohydrodynamics; fluid flow; surface hydrology; time series analysis; water resources

1 INTRODUCTION

Water resources are fundamental for sustaining life, supporting agriculture, industry, and energy production, and maintaining the balance of aquatic ecosystems [1, 2]. However, rapid population growth and the escalating impacts of climate change have made the sustainable management of these resources more critical than ever [3-5]. Within this context, accurate Flowrate forecasting has become increasingly important, as it provides essential support for both short- and long-term water management strategies.

Reliable discharge prediction has a wide range of applications. For instance, flood forecasting enables timely preventive measures to reduce risks to human life and property [6, 7], while low-flow estimation helps mitigate drought impacts and guides water allocation policies [8, 9]. Accurate flow predictions also play a key role in hydropower generation by optimizing water use and improving energy efficiency [10]. In agriculture, Flowrate forecasting supports precise irrigation scheduling, thereby enhancing water-use efficiency and increasing productivity [11, 12]. Furthermore, flow predictions are essential for maintaining ecological balance, monitoring water quality, and supporting the sustainable management of aquatic environments [13].

The Mediterranean Basin is increasingly recognized as a climate change hotspot, where shifting precipitation patterns significantly impact river discharge dynamics. Particularly the southwestern coast of Türkiye, located in the Mediterranean Basin, is under serious hydrological pressure due to irregular rainfall patterns and rising temperatures caused by climate change. While several studies have focused on major river systems in the region, smaller but ecologically critical basins like the Eşen Stream [14-16], located in southwestern Türkiye, serve as a natural linkage between freshwater and marine ecosystems, thereby providing a valuable case for advancing the fundamental understanding of discharge dynamics at the river-sea interface. Variations in the flow rate of the Eşen River directly determine the dynamics of the freshwater-marine interface in the marine environment where the river flows into. Predicted periods of low flow can cause the salinity wedge to advance inland in the coastal zone, threatening brackish water ecosystems and local fisheries productivity. This eco-hydrodynamic link proves that flow rate predictions are a critical input not only from an engineering perspective but also from the point of view of marine biodiversity conservation [10-13]. Systematic monitoring of its flowrate is not only crucial for evaluating ecosystem sustainability and regional aquaculture productivity but also for elucidating ecohydrodynamic processes that govern material transport, biogeochemical cycling, and habitat connectivity across coupled hydrosphere-biosphere systems [14-16]. In this context, predicting the future behavior of the strategically important Eşen River is essential not only for local water management but also for the development of basin-based adaptation strategies.

Recent hydrological assessments in similar Mediterranean catchments emphasize that standard forecasting models often struggle with the complex seasonal fluctuations unique to this region [13-17]. This study addresses this gap by integrating advanced time series methodologies to provide a more localized and accurate forecasting framework for the Eşen Stream.

Over the past decades, numerous statistical and computational approaches have been developed to improve Flowrate forecasting. The Autoregressive Integrated Moving Average (ARIMA) model has been widely adopted due to its ability to capture temporal dependencies in hydrological data [18, 19]. More advanced approaches, such as the Trigonometric Box-Cox ARMA Trend Seasonal (TBATS) model, have been proposed to address complex seasonal patterns [20]. Methods like TBATS, which combine the Box-Cox transform and Fourier series, moreover, offer advantages in overcoming the limitations of traditional time series models [20], Regression-based techniques, including MLR [21], offer interpretable and computationally efficient alternatives, particularly for short-term forecasting with lagged variables [22].

Given the importance of reliable forecasting, the present study focuses on predicting the daily discharge of the Eşen Stream using ARIMA, TBATS, and MLRmodels. Model performance was evaluated through statistical indicators including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Root Mean

Square Error (RMSE), and the coefficient of determination (R^2). The findings are intended to provide practical insights into the effectiveness of these models for short- and long-term Flowrate management.

2 MATERIALS AND METHODS

In hydrological modeling, ARIMA models have long been used as a fundamental tool due to their ability to analyze non-stationary series. However, the limitations of traditional methods in data dominated by complex and multiple seasonal cycles (daily, weekly, annual) have led to the development of more advanced exponential smoothing methods such as Box-Cox transform and TBATS, which combine Fourier series [20-22]. In this study, both classical autoregressive approaches (ARIMA) and advanced seasonal decomposition techniques (TBATS) were chosen because they can simultaneously evaluate both short-term dependencies and long-term periodic fluctuations in flow rate data.

2.1 Study Area and Data Collection

Daily discharge (FR, dm³/s) data of the Eşen Stream were collected from Republic of Türkiye Ministry of Agriculture and Forestry, General Directorate of State Hydraulic Works (DSİ) for the period 2017-2022. Since data after 2022 were not available in the DSİ database, the analysis was limited to six years of observations.

2.2 Data Pre-Processing

The raw dataset was imported from the file DATASET.csv, cleaned, and structured for time series analysis. The FR variable was selected as the target, and the date column was converted into a "year-month-day" format. The time series was defined in R using the *ts*() function with a daily frequency of 365. To stabilize variance and approximate normality, a Box-Cox transformation was applied, defined as [23]:

$$\begin{aligned} &\lambda \neq 0 \quad \mathrm{y}(\lambda) = \frac{y^{\lambda} - 1}{\lambda} \\ &\lambda = 0 \quad \mathrm{y}(\lambda) = \log(y) \end{aligned} \tag{1}$$

where y represents the original flowrate and λ is the transformation parameter. The optimal λ was calculated as –0.4909.

2.3 Time Series Models

To forecast the daily discharge of the Eşen Stream, three approaches were applied: ARIMA, TBATS, and MLR. The ARIMA model was used as a benchmark for capturing short-term dependencies and autocorrelation structures, given its interpretability and wide application in hydrology [18, 19]. The TBATS model was selected for its ability to address complex seasonal and nonlinear patterns through Box-Cox transformations, trigonometric components, and ARMA errors [20]. Finally, the MLRmodel employed lagged discharge values (Lag_1, Lag_2, Lag_3) to provide a simple and computationally efficient framework for short-term forecasting [22].

Together, these models offer complementary strengths: ARIMA as a baseline, TBATS for advanced seasonal modeling, and MLR as a practical short-term tool, providing a comprehensive perspective on the Flowrate dynamics of the Eşen Stream.

2.3.1 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model combines autoregressive (AR), differencing (I), and moving average (MA) components. Its general form is [24]:

$$\phi(B)(1-B)^d (1-B_s)^D Y_t = \theta(B)\theta(B_s)\varepsilon_t \tag{2}$$

where $\phi(B)$ and $\theta(B)$ represent AR and MA polynomials, dd is the differencing order, B is the backshift operator, Y_t is the observed value, and ε_t is the error term. For this study, the best-fitting model was ARIMA (2, 1, 4) (0, 1, 0) [26], expressed as:

$$\begin{aligned} &\left(1-\phi_1 B-\phi_2 B^2\right)(1-B)\left(1-B^{365}\right)Y^t = \\ &\left(1-\theta_1 B-\theta_2 B^2-\theta_3 B^3-\theta_4 B^4\right)\varepsilon_t \end{aligned} \tag{3}$$

2.3.2 Trigonometric Box-Cox ARMA Trend Seasonal (TBATS)

The TBATS model incorporates Box-Cox transformation, ARMA errors, trend, and seasonal components. The general formulation is [25]:

$$y_t = l_t + b_t + \sum_{j=1}^{J} s_t^{(j)} + \varepsilon_t \tag{4}$$

where l_t is the level, b_t is the trend, $s_t^{(j)}$ is the seasonal component, and ε_t is the error term.

Seasonality is captured using Fourier series [26]:

$$S_t = \sum_{j=1}^{K} \gamma_{(j,1)} \, cos\left(\frac{2\pi jt}{m}\right) + \sum_{j=1}^{K} \gamma_{(j,2)} \cos\left(\frac{2\pi jt}{m}\right) \tag{5}$$

where $\gamma_{(j,1)}$ and $\gamma_{(j,2)}$ are the seasonal coefficients, m is the seasonal period, and K represents the number of terms used in the Fourier series.

Error terms follow an ARMA structure [27]:

$$\varepsilon_t = \phi_1 \varepsilon_{t-1} + \ldots \phi_p \varepsilon_{t-p} + \theta_1 \mathrm{v}_{t-1} + \ldots \theta_1 \mathrm{v}_{t-q} + \mathrm{v}_t \tag{6}$$

where ϕ_1, ϕ_2, …, ϕ_p are the autoregressive coefficients, θ_1, θ_2, …, θ_q are the moving average coefficients, p is the autoregressive order, and q is the moving average order.

2.3.3 Durbin-Watson Test

Residual independence was tested using the Durbin-Watson (*DW*) statistic, defined as [28]:

$$DW = \frac{\sum_{t=2}^{n}\left(e_t - e_{t-1}\right)^2}{\sum_{t=1}^{n} e_t^2} \tag{7}$$

where e_t represents the residual at time t, and e_{t-1} represents the residual at the previous time step.

2.3.4 Multi Linear Regression (MLR)

A regression-based approach was also applied using lagged FR values (Lag_1, Lag_2, Lag_3) as predictors. The general model is:

$$\begin{gathered} Predicted\ FR = \\ 0.0467 + 0.9882 * Lag_1 - 0.2275 * Lag_2 + 0.2161 * Lag_3 \end{gathered} \tag{8}$$

An illustrative calculation using sample lag values is:

$$\begin{gathered} Predicted\ FR = \\ 0.0467 + 0.9882 * 2.5 - 0.2275 * 3.0 + 0.2161 * 1.8 = 2.23 \end{gathered} \tag{9}$$

This model provides interpretable short-term predictions based on recent discharge values.

3 RESULTS AND DISCUSSION

3.1 Dataset Characteristics

The dataset consists of 2,190 rows and four attributes. The dataset includes four attributes: Year, Month, Day, and Flowrate, all of which are numeric variables. A time series of daily flowrates between 2017 and 2022 is presented in Fig. 1. The seasonal average discharge values were 20,391.32 dm³/s in fall, 32,880.25 dm³/s in spring, 17,235.94 dm³/s in summer, and 41,012.94 dm³/s in winter, indicating that winter had the highest flows while summer had the lowest.

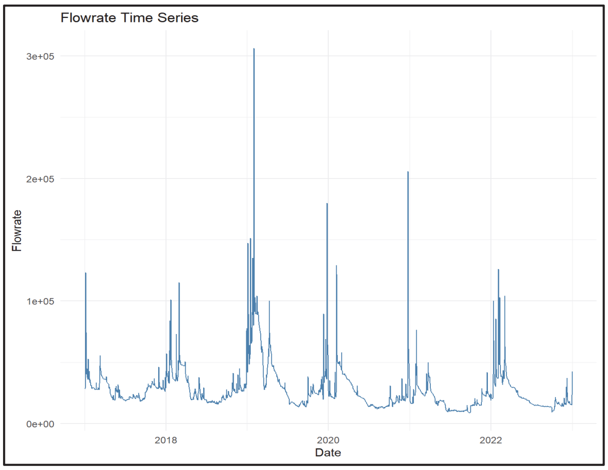

Figure 1 Daily flowrate time series of the Eşen Stream between 2017 and 2022

Interannual variability is displayed in Fig. 2, with 2019 showing the highest median discharge and 2021 the lowest. Seasonal boxplots (Fig. 3) confirm that 2019 maintained high flows across all seasons, while 2021 and 2022 had reduced values. Outliers reflect sudden and extreme variations in flow, often associated with rainfall or flood events. Such interannual variability is consistent with previous hydrological studies highlighting the sensitivity of Flowrate to precipitation extremes [29-31].

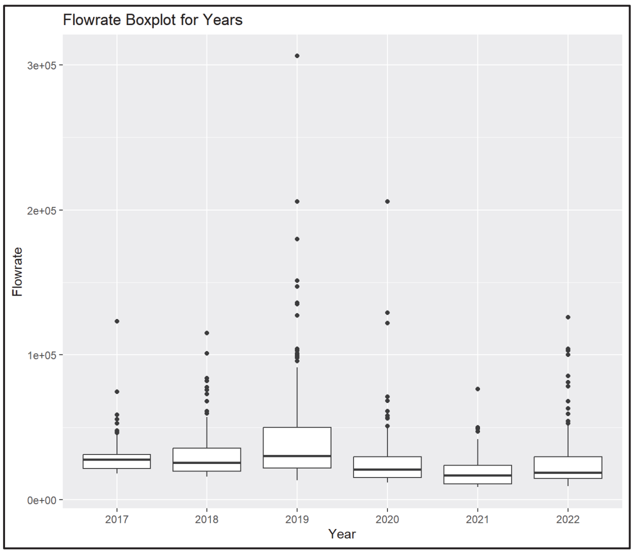

Figure 2 Annual variability of daily discharge in the Eşen Stream (2017-2022) illustrated by boxplots

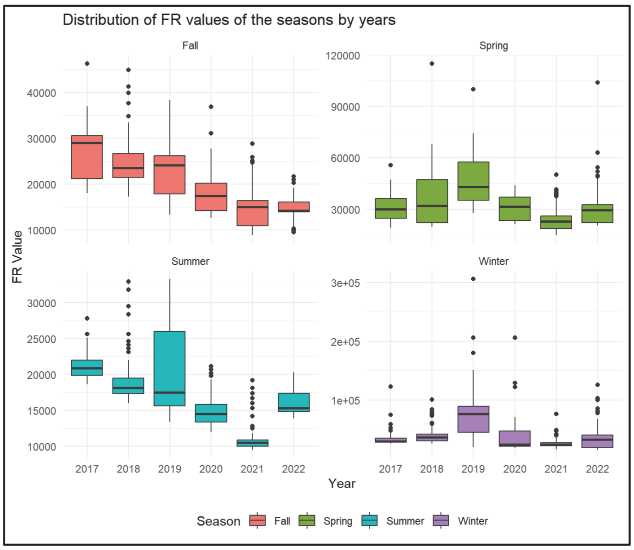

Figure 3 Seasonal distribution of daily discharge in the Eşen Stream between 2017 and 2022

3.2 Box-Cox Transformation

The histogram of raw FR values revealed right-skewness, while the transformed series approximated normality (Fig. 4). This variance stabilization improved model performance, confirming the effectiveness of Box-Cox transformations in hydrological forecasting [32, 33].

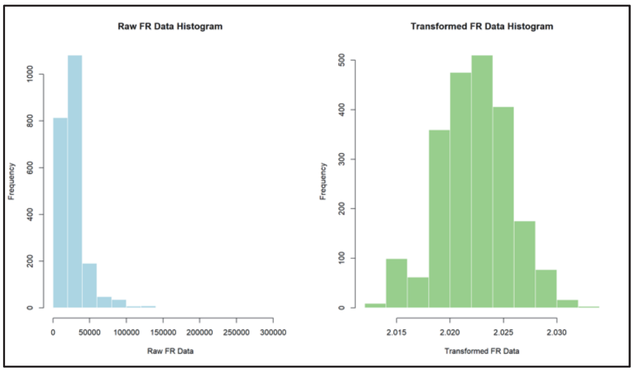

Figure 4 Histograms of daily discharge values before and after Box-Cox transformation

3.3 ARIMA Model

All estimated coefficients for the ARIMA (2, 1, 4) (0, 1, 0) [365] model were found to be statistically significant ($p < 0.05$). The 95% confidence intervals for the autoregressive and moving average parameters confirmed the stability and reliability of the model. The model estimated two autoregressive coefficients ($\phi_1 = 0.6751$, $\phi_2 = 0.2301$) and four moving average coefficients ($\theta_1 = –0.7256$, $\theta_2 = –0.5088$, $\theta_3 = 0.1192$, $\theta_4 = 0.1297$). These values indicate that the model was able to effectively capture the autocorrelation and error-correcting structures in the data.

Model evaluation metrics further confirmed the robustness of the ARIMA model, with an AIC of –18,805.6 and a BIC of –18,767.03. Performance indicators demonstrated strong predictive capability, with a mean error (ME) of $–1.5119 \times 10^{–5}$, a RMSE of $127.10 \times 10^{–5}$, and a mean absolute error (MAE) of $52.0464 \times 10^{–5}$. In terms of percentage-based measures, the mean percentage error (MPE) was $–75.6328 \times 10^{–5}$ and the mean absolute percentage error (MAPE) was $2572.24 \times 10^{–5}$. Additional diagnostics included a mean absolute scaled error (MASE) of $23{,}319.34 \times 10^{–5}$ and an AFC1 value of $1{,}786.98 \times 10^{–5}$.

Taken together, these results indicate that the ARIMA (2, 1, 4) (0, 1, 0) [365] model adequately captured short-term dependencies in the Flowrate data and produced forecasts with acceptable error levels. However, its inability to fully capture multiple seasonalities remains a limitation. This finding is consistent with previous research, which has shown that while ARIMA performs well for short-term hydrological prediction, it struggles with complex seasonal patterns [34-36].

3.4 TBATS Model

The TBATS model successfully captured both seasonal and error dynamics of the discharge series. The seasonal component estimates were $\gamma_{1,1} = 4.54 \times 10^{–5}$ and $\gamma_{1,2} = –9.54 \times 10^{–5}$, with a seasonal period of 365 days and $K = 1$, confirming the presence of strong annual seasonality. The ARMA error structure included one autoregressive coefficient ($\varphi_1 = 0.8995$) and two moving average coefficients ($\theta_1 = 0.0326$, $\theta_2 = –0.2179$), with $p = 1$ and $q = 1$. The ARMA error structure in the TBATS model demonstrated strong statistical significance, with p-values for φ_1, θ_1, and θ_2 falling well below the 0.05 threshold. The 95% confidence intervals for these seasonal and error components indicate a high degree of precision in capturing the long-term discharge patterns.

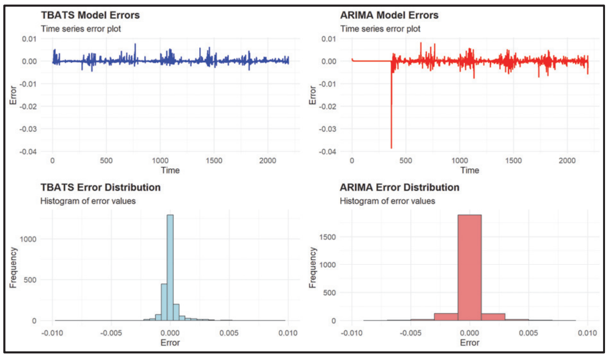

Figure 5 Residual and error histograms of ARIMA and TBATS models

Model evaluation criteria indicated an AIC of -14,798.98 and a BIC of 29,661.35, suggesting a better overall fit compared to ARIMA despite increased complexity. Residual and error histograms in Fig. 5 confirmed that TBATS residuals were more narrowly distributed than those of ARIMA. The model achieved an R^2 value of 0.95, substantially higher than ARIMA (0.85). The superior accuracy of TBATS can be attributed to its ability to capture long-term seasonal fluctuations, a result consistent with previous hydrological studies where TBATS outperformed ARIMA in datasets characterized by strong seasonality [37-39].

3.5 Comparative Analysis of ARIMA and TBATS

The comparative evaluation revealed that both ARIMA and TBATS models successfully forecasted Flowrate up to 2030, with forecast trajectories displayed in Fig. 6, indicating a decreasing long-term trend. However, their performance metrics highlighted important differences.

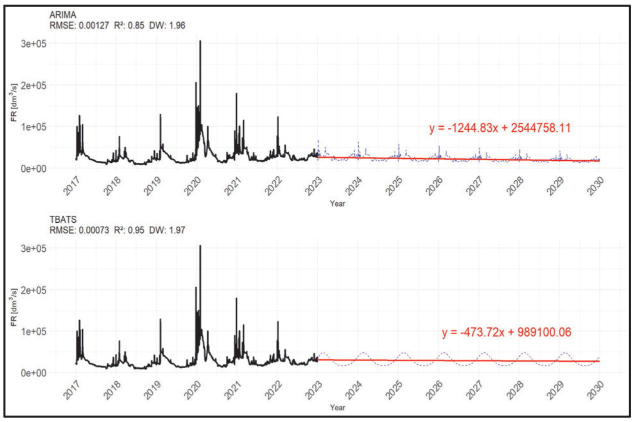

Figure 6 Forecast trajectories of ARIMA and TBATS models for Flowrate up to 2030

The ARIMA (2, 1, 4) (0, 1, 0) [365] model achieved lower information criteria values (AIC = –18,805.6; BIC = –18,767.03), reflecting a better penalized likelihood balance and simpler structure. By contrast, TBATS had higher complexity, with AIC = –14,798.98 and BIC = 29,661.35. Despite this, TBATS achieved a higher log-likelihood (9409.8), demonstrating stronger probabilistic fit.

In terms of residual independence, both models performed similarly, with Durbin-Watson statistics of 1.96 (ARIMA) and 1.97 (TBATS), values close to 2.0 that indicate the absence of significant autocorrelation. When error measures were considered, TBATS clearly outperformed ARIMA: RMSE was 0.00073 compared to 0.00127, and R^2 reached 0.95 compared to 0.85 for ARIMA. These results show that TBATS provided more accurate forecasts and explained a greater proportion of variance in Flowrate.

Overall, while ARIMA offers advantages in terms of model parsimony and penalized fit, TBATS demonstrated stronger generalization capacity and predictive accuracy, making it more suitable for capturing seasonal complexity in hydrological datasets.

3.6 Multi Linear Regression (MLR)

For the MLR model, the lagged Box-Cox transformed discharge values were 2.5 for Lag_1, 3.0 for Lag_2, and 1.8 for Lag_3. These Lag variables served as predictors in the regression equation. The regression analysis indicated that the model structure reflects the persistence effect commonly observed in river discharge dynamics: the coefficient of Lag_1 (0.9882) showed that Flowrate is highly dependent on the most recent discharge value, implying that "what happened yesterday is very likely to happen today". The negative coefficient of Lag_2 (–0.2275) suggested that higher flow two days earlier reduces today's flow, while the positive coefficient of Lag_3 (0.2161) indicated that high flow three days earlier continues to influence the present, albeit with weaker intensity. The constant term (0.0467) represents the baseline flowrate of the Eşen Stream, even if all lagged discharge values are zero.

Although less accurate than TBATS or ARIMA, the MLR model remains valuable for short-term operational forecasts due to its simplicity and interpretability. Such regression-based approaches have been successfully applied in other hydrological studies, particularly where rapid and practical decision-making is required [40,41]. Our findings align with contemporary hydrological research in the Mediterranean, which highlights a general declining trend in river discharge toward the end of the decade. However, the superior performance of the TBATS model in our study demonstrates its unique capability to capture the long-term seasonal fluctuations of the Eşen Stream more effectively than traditional ARIMA models used in similar basins. Compared to studies in larger Turkish basins such as the Susurluk or Seyhan, the Eşen Stream exhibits a more pronounced ecohydrodynamic sensitivity at the freshwater-marine interface, making precise forecasting essential for maintaining the salinity balance of the downstream estuary [42-47]. This localized accuracy highlights the originality of our approach, as it bridges the gap between general hydrological theory and practical, site-specific water management.

The coefficients of the lagged variables used in the Multiple Linear Regression (MLR) model are directly related to the physical characteristics of the basin. For example, a high positive effect of the Lag_1 variable (0.9882) indicates that the basin has a strong hydrological memory and that the surface runoff attenuation period is longer than one day. The effects of the Lag_2 and Lag_3 variables represent lagged runoff processes such as basin width, soil saturation, and groundwater contribution.

4 CONCLUSION

This study demonstrated that daily Flowrate forecasting of the Eşen Stream can be effectively achieved through statistical approaches including ARIMA, TBATS, and MLR. Among these, TBATS provided the highest predictive accuracy, reflecting its superior ability to capture complex seasonal dynamics, whereas ARIMA offered a simpler yet less comprehensive representation of flow variability. The MLR model, although less accurate, retained practical value for short-term operational forecasting due to its simplicity and interpretability.

Beyond their methodological comparison, the results emphasize the potential of integrating different forecasting frameworks to advance the understanding of hydrological processes at freshwater-marine interfaces. Accurate discharge forecasts are not only relevant for applied purposes such as flood risk reduction, drought mitigation, hydropower optimization, irrigation scheduling, aquaculture production planning, and ecosystem protection, but also serve as critical inputs for elucidating ecohydrodynamic mechanisms, biogeochemical exchanges, and connectivity patterns across coupled water systems. In this regard, the Eşen Stream provides a representative natural laboratory where insights derived from forecasting contribute to both sustainable resource management and broader hydrological theory.

Nevertheless, the study faced certain limitations. Its reliance on discharge-only data and a relatively short observation period constrained the explanatory power of the models. Incorporating additional climatic variables (e.g., precipitation, evapotranspiration, and temperature) and extending the temporal dataset would enhance predictive reliability. Future research should also consider advanced data-driven approaches, including hybrid machine learning methods, which hold promise for improving long-term forecasts and for capturing the nonlinearities and feedback inherent in complex hydrological systems. Importantly, the findings also provide actionable knowledge that can support policy makers and water managers in developing adaptive strategies for sustainable governance of water resources at both regional and national scales.

Code availability

The R Shiny code developed and used in this study is publicly available via Zenodo and can be accessed at https://doi.org/10.5281/zenodo.17114915 [48].

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