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Performance enhancement of models through discrete wavelet transform for streamflow forecasting in Çarşamba River, Türkiye

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ABSTRACT

Streamflow forecasts play an active role in hydrological planning and taking precautions against natural disasters. Streamflow prediction models are frequently used by scientists, especially in dam management, sustainable agriculture, flood control, and flood mitigation. Hence, streamflow prediction modeling was performed in this study, and six models were employed through four different machine learning (ML) algorithms, namely, the artificial neural network (ANN), random forest (RF), support vector machine (SVM), and decision tree (DT) that are well known in the literature, in order to predict the monthly streamflow of Çarşamba River, Türkiye. To further enhance model performance, wavelet transform (WT) was applied to ML algorithms. In this study, monthly average streamflow and precipitation data between 1974 and 2015 was used, and the minimum redundancy maximum relevance method (MRMR) and the cross-correlation method were performed to determine model input data. Results of this study revealed that RF had superiority over the other models before WT, followed by the SVM model. The SVM after WT (W-SVM), M04 (*r*: 0.9846, NSE: 0.9695, and RMSE: 0.3536) gave the most effective performance results, while the W-ANN model (*r*: 0.9797, NSE: 0.9588, and RMSE: 0.4108) showed the second best performance.

Key words: dam management, risk assessment, SDI, streamflow forecasting, wavelet transform

HIGHLIGHTS

- We frequently preferred SVM, ANN, RF, and DT.
- As an innovative method, we used wavelet transform, which improves model performance results.
- We both compared these algorithms with each other and examined the effect of model input data on the model result.
- We hope this study will be useful for future water planning and water resources management.

INTRODUCTION

Forecasting streamflow accurately presents a formidable challenge owing to the intricate non-linearities and stochastic nature inherent in hydrological processes. These processes encompass variables like precipitation, temperature, evapotranspiration, and watershed characteristics, contributing to the complexity of prediction (Adnan *et al.* 2019; Pinarlik *et al.* 2021; Pinarlik & Selek 2024). Nevertheless, owing to their crucial role in the efficient management of water resources, like dam management, there has been a notable focus on estimating monthly streamflow over the past few decades. After all this, streamflow prediction studies are included in the literature from past to present. Advancements in technology pave the way for achieving precise streamflow forecasting, offering benefits across various domains, including flood risk mitigation, risk assessment, water channel and drainage planning and design, water resource management, safeguarding dams, and dam management.

In recent years, literature has revealed that hydrological studies have managed to go beyond physical modeling, and data-based models are increasingly preferred. Data-based models use inputs to produce outputs without requiring a deep understanding of hydrology or the specific physical features of the case study. They are applicable even in scenarios where the gauge distribution is sparse and there are few available data points (Mirzaei *et al.* 2021). Besides, the streamflow forecasting commonly makes use of data-driven approaches, as evidenced by studies such as Hadi & Tombul (2018a, b) and Liu *et al.*

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(2016). Machine learning (ML) models are among the earliest data-driven techniques for streamflow forecasting (Parisouj *et al.* 2020; Oruc *et al.* 2024a, b; Tuğrul & Hinis 2024).

Recently, a set of models has been developed by researchers to forecast the streamflow by means of ML. These models can be created in different structures depending on input data: (1) input data including only the streamflow; (2) a set of data, combining precipitation, streamflow, and drought index. Some of them (Aghelpour & Varshavian 2020) preferred the streamflow drought index (SDI), which was developed to monitor, detect, and track, including a set of lagged months. They used the streamflow in input data, the daily data from 2001 to 2015, including 5-lagged months, to compare ML algorithms such as the group method of data handling (GMDH), multilayer perceptron (MLP), and stochastic processes. They stated that GMDH and MLP performed the best in terms of prediction validation. The support vector machine (SVM), proposed by Cortes & Vapnik (1995), based on dimension theory and the structural risk minimization principle, has long been used to forecast the streamflow. In some studies, SVM is compared with the artificial neural network (ANN) and its modifications, and SVM is superior to these methods (Liu & Lu 2014; Parisouj *et al.* 2020). Parisouj *et al.* (2020), who did not make any comparisons in the model input data, also used input data including temperature and precipitation between 1950 and 2019 in their study. Comparing different ML, convolutional neural network (CNN), random forest (RF), and gradient tree boosting (GTB) with each other using only the streamflow in input data, Naganna *et al.* (2023) revealed that the CNN model performed better at forecasting over the ML method in the Cauvery River basin. Indeed, some studies employ varying parameters as inputs in the model, whereas others utilize a single type of data in the model's input structure to enhance forecast accuracy and minimize ambiguity.

For instance, Ayana *et al.* (2023) employed only the streamflow data in their study and various ML algorithms, such as ML, support vector regression (SVR), RF, linear regression (LR), and long short-term memory (LTSM), in the Çatalan Dam. Their results exhibited that the LSTM network has the better performance score compared with the other methods. Besides, they said that the appropriate lagged numbers are determined by the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

Because the streamflow has a complex non-linear structure and various stochastic properties, it has been stated by many researchers that more successful results are obtained from hybrid models, such as the wavelet transform (WT) or optimization techniques, in ML. Some examples of prominent studies are given here: mentioning different results between ML models, Yadav *et al.* (2016) compared four different algorithms, including ANN, SVM, genetic programming (GP), and online sequential extreme learning machine (OS-ELM), using as input data only the streamflow in different lagged values. They stated in their studies that OS-ELM gives better results than other algorithms and that is particularly good in RMSE values. Borji *et al.* (2016) used ANN and SVR from ML algorithms in Iran to study how to predict hydrological droughts using only SDI values as input data. They found that the SVR algorithm was better at predicting long-term droughts than the ANN. Using hybrid Extreme Learning Machine (ELM) in Algeria, Achite *et al.* (2023b) investigated the performance of models, ELM, and ELM with WT (W-ELM) by benefiting from different values which lagged the standardized runoff index (SRI) in input data in drought forecasting. Their findings showed that for accurate forecasts of the region's drought, the W-ELM model can be utilized. Attar *et al.* (2024) underscored the significance of hybrid models by conducting a prediction streamflow modeling study in Iran, utilizing daily streamflow input data. They employed a combination of ML, complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN), the M5 tree model, and the reduced error pruning tree (REF) model. They first applied trend analysis to the data they obtained, namely the streamflow data between 1969 and 2020. Then, they analyzed the models and created with each algorithm. In their findings, they mentioned that hybrid models gave better results than other models, and the prominent algorithm was CEEMDAN-RF for the fortnight scale. The type of data in the model input structure is as important as the ML algorithms for obtaining successful model results. Typically, the streamflow data is used in model input structures. Another study related to prediction of streamflow is that of Rozos *et al.* (2022). LSTM and the recurrent neural networks (RNNs) were used to predict streamflow in three different stations, Karveliotis, Alagonia, and Bakas, which are located in Greece. Besides the ML-based approach, LRHM and HYMOD2, known as hydrological models, were used in this study to get more comparable results. This study's results unveiled that hydrological models and ML models could give different results for different regions and available data and hydrological models could be used as a filter to improve the efficiency of the results.

Some researchers, however, including Rasouli *et al.* (2012), Yin *et al.* (2018), and Tongal & Booij (2018), attempted to use meteorological and hydrological data, such as temperature and precipitation, to forecast streamflow in their model input data. It has been stated that data diversity in model input structures and the algorithms used may give different performance results

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depending on the region studied. Latifoğlu & Kaya (2024) conducted a modeling study with daily and monthly streamflow data using a series of ML algorithms, including SVR, ANN, GPR, ensemble learning, and a set of data in the inputs, in Schuylkill River, Pennsylvania. According to the results, for peak streamflow prediction, different modifications of the ANN model, circulant spectrum analysis (ciSSA), are superior to the other models. They also used the minimum redundancy maximum relevance (MRMR) method to determine the model input data. Mentioning that streamflow modeling is of paramount important in the management of hydrological and dam management for decision-makers, Beddal *et al.* (2020) conducted a study on streamflow prediction using multilinear regression (MLR) and back propagation neural network (BPNN) models to predict the streamflow in northwestern Algeria. They preferred the precipitation and streamflow lagged values in their model inputs, and their outcomes demonstrated that BPNN is the best performing model among the others. Sharma *et al.* (2023) predicted the drought by means of a set of ML, LTSM, SVM, RF, and multivariate adaptive regression splines (MARS) in the region, rivers of Southern India. They also used temperature, precipitation, and streamflow data in the model input structure during the periods 1989 and 2009. In their study, they stated that SVM gave more effective performance than others. Investigating the feasibility of modeling monthly streamflow using a relevance vector machine (RVM) adjusted with the dwarf mongoose optimization method, Adnan *et al.* (2024) presented a study to forecast streamflow by incorporating new hybrid methods: the RVM tuned with the dwarf mongoose optimization algorithm (DMOA) (RVM-DMOA), RVM tuned with particle swarm optimization (PSO) (RVM-PSO), RVM tuned with the whale optimization algorithm (WOA) (RVM-WOA), and RVM tuned with the marine predators algorithm (MPA) (RVM-MPA). In their study, they compared each method with the other by using performance criteria parameters and using temperature, precipitation, and streamflow data as inputs. The findings indicated that precipitation had the least impact on input data, while streamflow and lagged streamflow data were the most beneficial variables. The RVM-DMOA enhanced the accuracy of the single RVM in monthly streamflow data. In another study that chose to use different ML algorithms, some of which were used in this study, RF, ANN, the extreme gradient boosting (XGBoost), and SVM, is that of Akbarian *et al.* (2023). This study was conducted in Iran and used streamflow, precipitation, and temperature data between 1981 and 2015. In this study, different models were created with the help of cross-correlation. It was mentioned in the results of the study that ANN and XGBoost provide more effective results than other algorithms. Dimitriadis *et al.* (2021) are also researchers who benefit from meteorological data diversity, which are relative humidity, wind speed, dew point, near-surface temperature, sea level pressure, and precipitation, in model inputs. They used the robust stochastic metrics, such as the K-moments and a second-order climacogram, to investigate the stochastic similarities of the key hydrological cycle processes. They discovered that, in terms of both the marginal and dependent structures, they permit a unified stochastic view of the hydrological cycle processes under the Hurst–Kolmogorov (HK) dynamics.

In fact, when looking at the literature, researchers have used various data in the model input structure. But generally, most researchers chose model inputs from only one process, specifically, the streamflow one. The innovative aspect of this study is to determine the most appropriate ML algorithm for the study area by determining the most appropriate data in the model input structure.

In this study, we aim to make future predictions with different ML algorithms, SVM, ANN, RF, and decision tree (DT) and to strengthen the results we obtained with WT. While doing this, we want to determine the most appropriate model structure by means of cross-correlation and the MRMR. In the literature, it is frequently stated that the use of hydrological and meteorological data in the model input structure improves the model results. So, we also used the drought index, SDI, and precipitation in the model input structure to assist model development in improving performance. The aim of this study is to determine the effectiveness of the mentioned method for the region. Figure 1 gives a visual summary or graphical abstract of this study.

MATERIALS AND METHODS

Study area and data

The study area is the Çarşamba River, located in the Konya Closed Basin in the Central Anatolia region of Türkiye. An elevation map of the Çarşamba River is given in Figure 2. The elevation of this study area varies around 1,000–1,100 m. The Çarşamba River, which flows toward the northeast, provides water to fertile land in the region through the Apa Dam fed by the river. The Çarşamba River rises near Karacahisar village within the borders of Bozkır district and merges with the channel coming from Beyşehir Lake in the Blue Channel. Despite the region's abundance of big and small rivers, it is one of the most significant water resources for irrigation of agriculture. The average monthly precipitation in the region is

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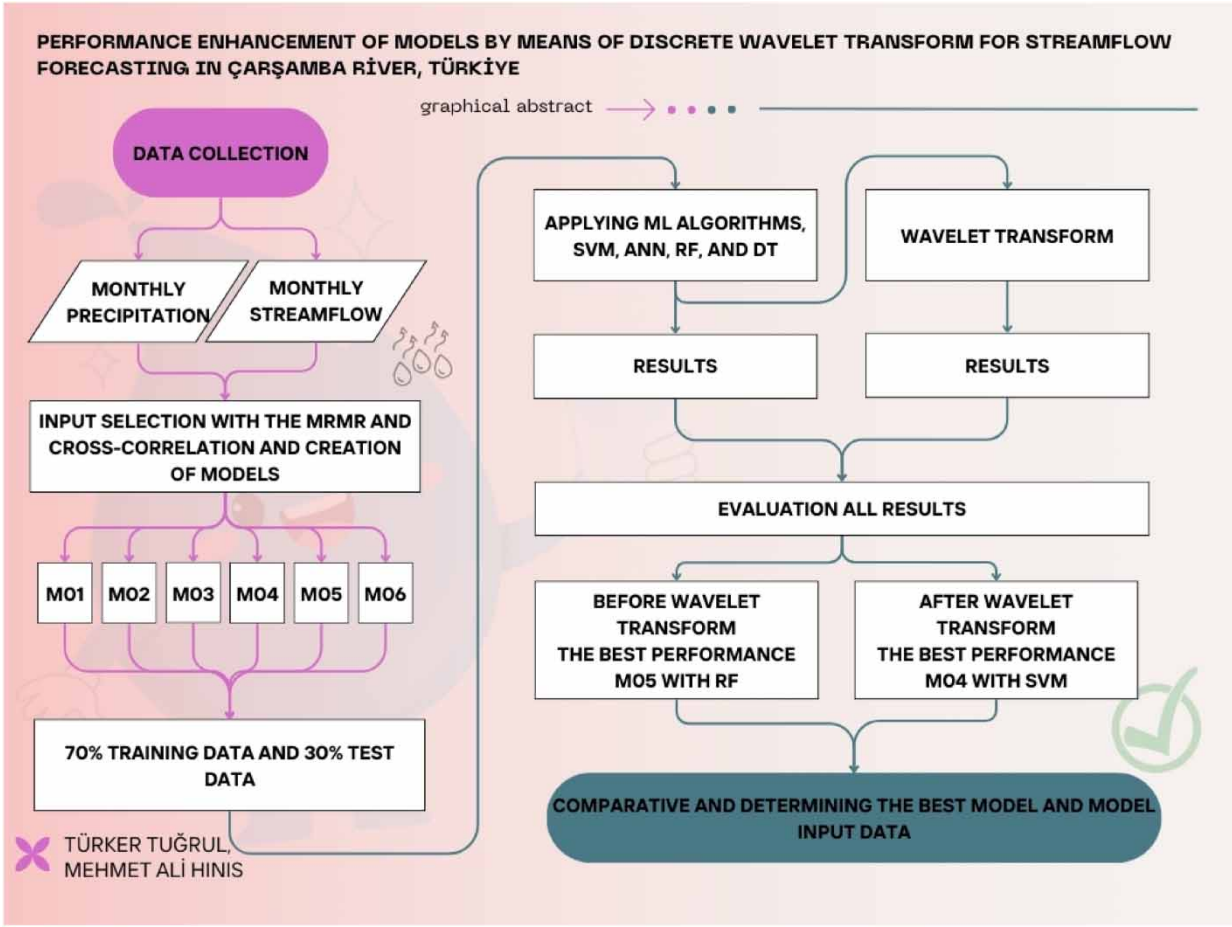


Figure 1 | Graphical abstract for this study.

27 mm, which is below the country average. There is a station on the river belonging to the General Directorate of State Hydraulic Works (DSİ). While the streamflow data used in this study was obtained from this station, D16A115, precipitation data is obtained from the General Directorate of Meteorological Affairs (MGM). Summary information about the data used, monthly precipitation, and streamflow is shown in Table 1, and times series for these data are given in Figure 3.

Figure 3 reveals that the streamflow data reached a peak value of 4/2002, 5/1973, and 4/1975 and precipitation for 4/1977, 5/2000, and 12/1996. The average precipitation value is 26.96 mm, and the average streamflow value is 2.18 m^3/s.

In the data set used in this study, it was determined that measurements could not be made in some months, 3 in total, due to station resource reasons. These were corrected by using the averages of that month throughout the year. When the entire data set was examined, zero (i.e., 0 mm) precipitation was measured only during 4 months, and it is shown in Table 1 that there was no month with a zero (0 m^3/s) value in the streamflow data.

Artificial neural network

Haykin (1998) proposed the ANN, which is based on the working principle of biological neural networks that constantly interact with each other, just like humankind. In ANN learning, information obtained from past experiences is stored in neurons and used by the neuron of interest when needed, which replicates the brain's biological nervous system (Demuth & Beale 1998). The data stored in the input layers is processed by neurons and other layers until the desired result is achieved. This process may have intermediate, hidden layers, and information that will affect the prediction may be transferred to the neurons in advance. ANN comes in a variety of forms, including MLP and feed forward propagation (FFP), which are based on these learning variations. The ANN model used in this study includes a feed-forward MLP architecture that was trained by means of the Levenberg–Marquardt (LM) backpropagation technique because of its superior hydrological forecasting performance (Piri *et al.* 2009). An input layer, one or more hidden layers, and an output layer make up an MLP.

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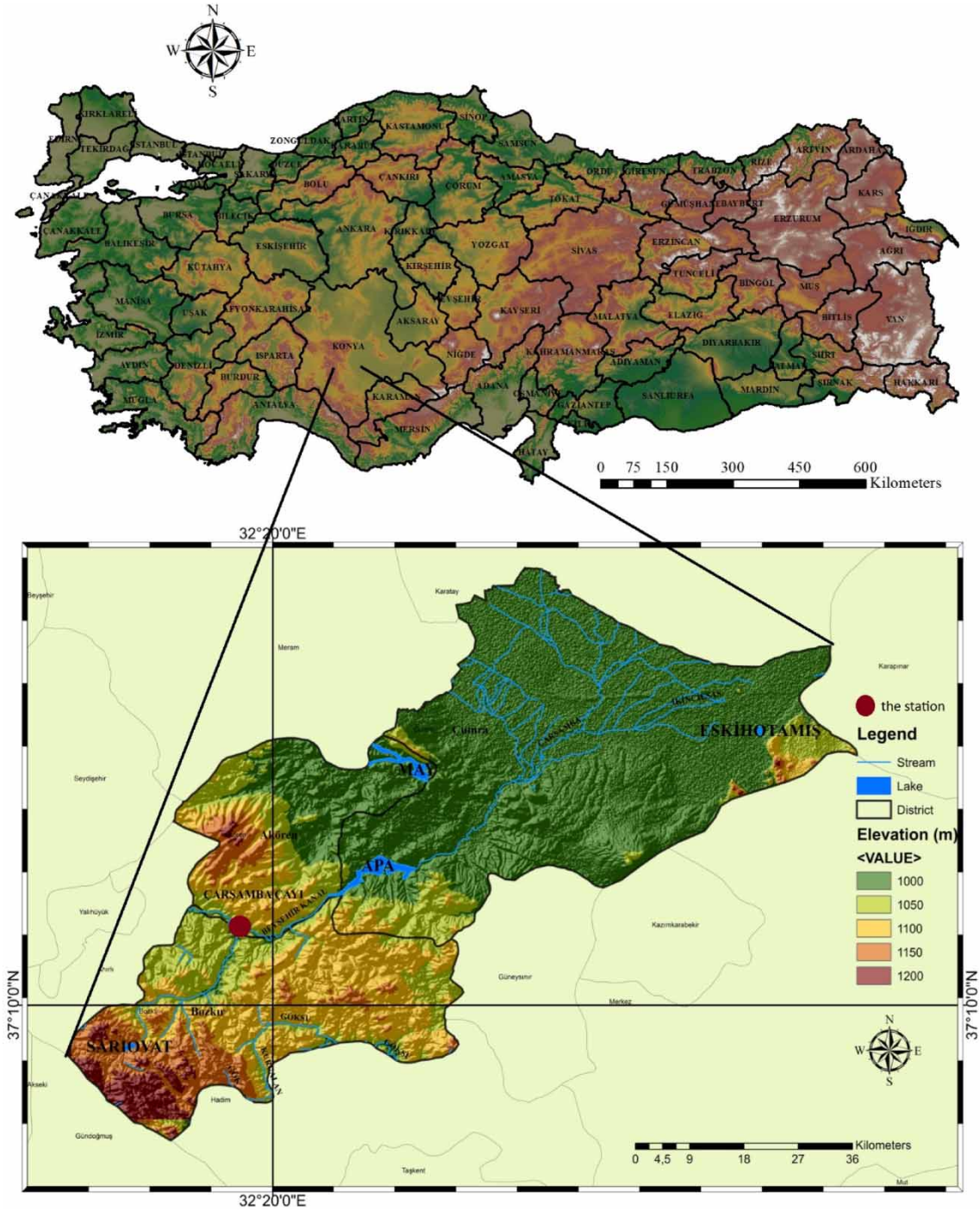


Figure 2 | Elevation map of the study area.

The combination of the net weighted input and biases, denoted as net_j for the jth neuron in the hidden layer, can be expressed using Equation (1), following Bishop (1995).

$$\text{net}_j = \sum_{i=1}^{p} (w_{ji} x_i + b_j) \tag{1}$$

where x_i and b_j separately are the input value to the ith neuron of the input layer and the bias of the jth hidden neuron.

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Table 1 | Statistics of data used in this study

Data	Range	Number of data	Total mean	Minimum	The number of missing data	The number of zero (0)
Monthly precipitation (p) (mm)	3.1974–9.2015	499	26.9	0	3	4
Monthly streamflow (Q) (m^3/s)	3.1974–9.2015	499	2.2	0	2	–
Data (Cont.)	**Range**	**Standard deviation (std)**	**Maximum**	**Skewness**	**Kurtosis**	–
Monthly precipitation (p) (mm)	3.1974–9.2015	23.12	144.3	1.22	1.88	–
Monthly streamflow (Q) (m^3/s)	3.1974–9.2015	2.3	18.2	2.54	8.01	–
Seasonal data	**Range**		**Autumn**	**Winter**	**Spring**	**Summer**
Monthly precipitation (p) (mm)	3.1974–9.2015	**Total mean**	37.3	22.9	42.2	5.2
Monthly streamflow (Q) (m^3/s)	3.1974–9.2015	**Total mean**	2.7	1.3	4.11	0.7
Monthly precipitation (p) (mm)	3.1974–9.2015	**Std**	28.8	13.1	48.5	2.1
Monthly streamflow (Q) (m^3/s)	3.1974–9.2015	**Std**	3.1	1.5	3.8	0.8
Related data/lagged time for Q	–	$p/(-1)$	**SDI3/(−5)**	**SDI12/(−1)**	$Q/(-1)$	–
The cross-correlation values	–	0.32	0.35	0.59	0.63	–
Related data/lagged time for Q	–	$Q/(-1)$	$Q/(-4)$	$p/(-4)$	**SDI3/(−5)**	$p/(-2)$
The MRMR values	–	0.47	0.38	0.35	0.24	0.23

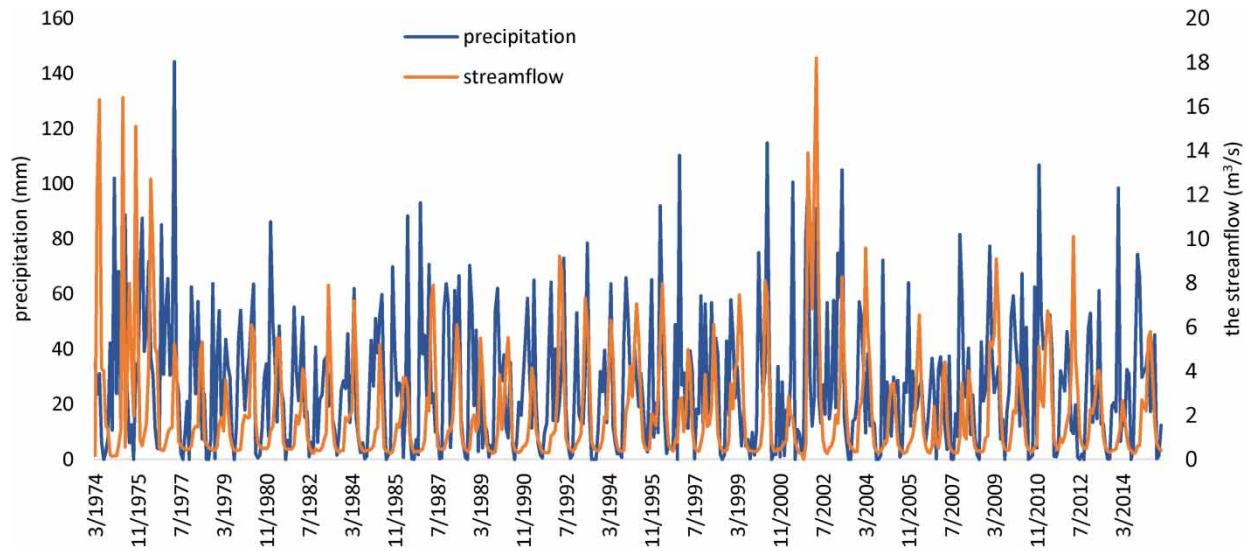


Figure 3 | Includes times series of precipitation and streamflow.

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net_j, a transfer function, is given in Equation (2):

$$\text{net}_j = f_h\left(\sum_{i=1}^{p} w_{ji}x_i + b_j\right) \tag{2}$$

where y_j is the output from the jth hidden neuron. See Bishop (1995) for further information in greater detail.

ANNs have many advantages. (1) Flexibility: ANNs can work with different types of data. They can process various types of data, such as images, texts, and signals. (2) Learning ability: ANNs have the ability to learn as they are exposed to a specific data set and receive feedback. This learning process has the potential to improve the network's performance and enable it to perform a specific task better. (3) Parallel processing: Large ANNs can quickly process large data sets by leveraging parallel processing power. Because of their many advantages, the ANNs have been widely preferred in many hydrological studies to forecast streamflow, precipitation, and droughts (Saab *et al.* 2022).

Support vector machine

SVMs are an ML method used in both classification and regression processes. SVM is a robust ML algorithm. Some advantages of SVM are: (1) Effective classification: SVM can effectively classify linear or non-linear separable data sets. It is quite successful in identifying discrete classes and drawing decision boundaries. (2) Working in multiple dimensions, such as 3D: SVM can also work well on high-dimensional data sets. It is especially effective in reducing overfitting problems in high-dimensional data sets. (3) Flexible kernel selection: SVM's kernel functions can be used to make non-linearly separable data sets linearly separable. This provides flexibility in modeling complex relationships between data. (4) Suitable for small data sets: SVM performs well on small data sets and can learn from such data sets effectively. Although they can be called both SVM and SVR in the literature, there is no difference in the calculation methods. They are referred to by different names depending on the operations performed as classification or regression. SVM, proposed by Cortes & Vapnik (1995), is a learning method that does not require a single distribution function to function, regardless of the data's underlying distribution. This method, which was initially used in linear regressions, later began to be used in solving non-linear problems. In some studies, it is even used in 3D classifications. The aim of this method is to best separate or estimate the data in the optimum range, which was called a marjin, with the help of auxiliary vectors. Meanwhile minimizing empirical risks is the primary goal of ANN, ensuring that statistical learning minimization is the primary goal of SVR (Belayneh *et al.* 2014). SVM is calculated using Equation (3), which is stated below.

$$f(x) = (w, \phi(x)) + b \tag{3}$$

where $f(x)$ is a high-dimensional feature space, b is the bias term, and w is a weight of the output variable.

By applying different kernel functions, such as sigmoid, poly, Gaussian, linear, and radial basis functions (RBF), model outcomes may vary depending on the performance results. As the kernel function, we set the Gaussian function, which has a positive effect when considering the model performances. Furthermore, with the use of the Gauss function, we automatically determined three different parameters: (γ) as the active function scale parameter, positive constant (C), and epsilon (ε) (Belayneh *et al.* 2016a, b).

Decision tree

A non-parametric supervised learning technique, used for prediction in hydrological models the Decision Tree (DT) is employed in not only classification but also for regression tasks during model development. The DT offers numerous advantages, including the following: (1) Easy to understand: Because of its simple structure, DT can be easily understood and interpreted by people. This is useful for understanding how the model makes decisions and what features are important. (2) Fast predictions: DT is fast at making predictions. This is advantageous in real-time applications or when working with large data sets. (3) Feature selection: During the feature selection process, DT can automatically identify important features. This can help simplify the model and improve its performance by eliminating unnecessary attributes. DT creates a conditional, if-then-else, model structure to predict the target in a similar way to the tree structure. Several tree-based algorithms are used to repeat this process until the end goal is reached. These include unbiased, Chi-squared automatic interactive detectors (CHAID), C5.0, quick, efficient statistical trees (Quest), algorithms, and classification and regression trees

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(CART). These algorithms were chosen for this study because they improve the model results. For further details, refer to the works of Jia *et al.* (2024) and Quinlan (1992).

Random forest

Breiman (2001) introduced RF as an ML approach for regression and classification in miscellaneous branches of science such as health, energy, genetics, electric, and marketing. RF has many of the advantages. Some of them: High accuracy: (1) RF generally provides high accuracy because it is created by combining many DTs. This can reduce noise in the data set and prevent overfitting. (2) Generalization ability: RF generally works well with a variety of data types and attributes. Thanks to this feature, it can be applied to different types of data sets and produce generalizable results. (3) Tree independence: Because RF is created by training each DT independently and then combining the predictions, there is little correlation between trees. This allows each tree to focus on different patterns and characteristics, resulting in a more diverse pattern. (4) Fast training: Even when working with particularly large data sets, RF can generally be trained quickly. This provides an advantage in large-scale data analysis or real-time applications. The RF consists of multiple DTs, each constructed by randomly selecting samples and features from the entire set of predictors (Oliveira *et al.* 2012; Naghibi *et al.* 2017). Besides this randomness, two important aspects of RF are ensemble learning (Breiman 2001; Biau & Scornet 2016). In a training data set containing N samples with M features, the randomness in RFs can be characterized by the process of randomly selecting features for the creation of each tree. A sample set of size N could be created at random using the bootstrap resampling technique. This method, known as 'out-of-bag data', uses one-third of the data. RF is considered a function of DTs, and the difference in their range is that RF starts with the branch that gives the best results. You can find more information about the formula in Breiman (2001) and Oshiro *et al.* (2012).

Discrete wavelet transform

A WT is a method used to find dominant frequencies and dominant periods in a series. This transformation uses the main wavelet to create sub-wavelets connected to it (Torrence & Compo 1998). Depending on the time series, there are two variants of this transformation: discrete wavelet transform (DWT) and continuous wavelet transform (CWT). According to Sang *et al.* (2016), in hydrological time series, DWT is more applicable than CWT because the data ranges are clear and measurable (Adamowski & Sun 2010). While CWT may suffer from missing data in the time series, DWT overcomes such a problem. In wavelet analysis, there is more than one type of wavelet, such as Daubechies (db), Coiflets (coif), Haar, and Symlets (sym). The most effective type should be chosen according to the result obtained.

DWT, also known as a high-pass filter and a low-pass filter, employs wavelet and scaling functions. Hadi & Tombul (2018a, b) define the DWT mathematically, as shown in Equations (4) and (5):

$$Wf(j,k) = \int_{-\infty}^{+\infty} f(t)\psi_{j,k}(t)d_t \tag{4}$$

$$\psi_{j,k}(t) = a_0^{-j/2}\psi(a_0^{-j}t - b_0k) \tag{5}$$

where k is the time convertor factor, the constants are a_0 and b_0, and j is the decomposition level.

DWT consists of two main wavelets, approximated by a low-pass filter, and details. The level of detail can vary depending on the data in order to clearly identify the target. We determined five levels of detail in the study and Db45 because effective results were obtained.

Streamflow drought index

To detect and investigate hydrological droughts, the basis of the SDI proposed by Nalbantis & Tsakiris (2009) is the first one that depends on SPI to detect and investigate hydrological droughts. Easy computability is one of SPI's biggest advantages. Additionally, its ability to calculate in various time steps attracts users, much like SPI does. This index's calculation is derived from the monthly discharge data based on a hydrological year, from October to September. The calculation is carried out as given in Equation (6):

$$V_{i,k} = \sum_{j=1}^{3k} Q_{i,j}, \quad i = 1, 2, \ldots, N,\ j = 1, 2, 3, \ldots, 12,\ k = 1, 2, 3, 4, 5, 6 \tag{6}$$

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N represents the calculated number of years, and k represents specific periods ($k = 1$ is the period of October–December, $k = 2$ is the period of October–March, $k = 3$ is the period of October–June, $k = 4$ is the period of October–September). k values of 1, 2, 3, 4, 5, and 6 show 3-, 6-, 9-, 12-, 24-, and 48-month periods, respectively. In cumulative totals, it represents October–September. Then, the SDI is derived from Equation (7) for each hydrological year based on each k-reference period. SDI is calculated with Equation (7). Where $V_{i,k}$ for the hydrological year of i, which corresponds to the base period of k.

$$\mathrm{SDI}_{i,k} = \frac{V_{i,k} - \overline{V_k}}{\overline{S_k}} \tag{7}$$

where $\overline{V_k}$ is the average of the total streamflow volume, and S_k is the standard deviation of the amount of streamflow volume. The streamflow data generally follows a normal distribution. If the flow data does not fit this distribution, it can be switched to a normal distribution (Al-Faraj *et al.* 2014). Our data in this study follows a normal distribution. Therefore, no conversions, including gamma, log-gamma, exponential, log-normal, and Pearson type II, were performed. Detailed calculations can be found in Nalbantis & Tsakiris (2009). It is discovered that the 3- and 12-month SDI and SPI time periods, respectively, more accurately depict agricultural and hydrological droughts (Mohammed *et al.* 2022). Therefore, the 3- and 12-month periods of SDI were used in the present study.

MRMR method

Finding the optimal features in the input data to obtain the output data by analyzing the relationship between the input and output data is one of the key goals of the MRMR. The method ensures that features are used as efficiently as feasible for ML algorithms in regression or classification (Ding & Peng 2005). The MRMR technique can improve model accuracy and mitigate overfitting by identifying crucial and uncorrelated features within the data set. When working with several characteristics or high-dimensional data sets, its efficacy is especially noteworthy. By identifying crucial and uncorrelated features within the data set, the MRMR method has the potential to improve model performance while mitigating the risk of overfitting. It demonstrates notable efficacy, particularly in data sets with high dimensionality or instances with a large number of features. In this study, the model input structure was created by using the MRMR method. In the literature, this method is preferred by some researchers to create model inputs, and it has been said that significant results are achieved (Latifoğlu & Kaya 2024). However, in contrast to these researchers, the models created using the MRMR method did not yield positive results in this study. For further details, refer to the work of Ding & Peng (2005).

Model performance criteria

Three distinct statistical techniques were used on the developed models to determine and interpret their prediction accuracy: correlation coefficient (r) (Equation (8)), root mean square error (RMSE) (Equation (9)), and Nash–Sutcliffe efficiency coefficient (NSE) (Equation (10)). In Equations (8)–(10), N is the number of data, $P_{\mathrm{p}i}$ is the predicted value, $\overline{N_{\mathrm{o}}}$ is the average observed value, and O_{oi} is the observed value.

Correlation coefficient (r) is calculated in Equation (8):

$$r = \frac{\sum_{i=1}^{N} (P_{\mathrm{p}i} - \overline{P_{\mathrm{p}}})(O_{oi} - (\overline{O_{\mathrm{o}}}))}{N \sigma_{P_{\mathrm{p}i}} \sigma_{O_{oi}}} \tag{8}$$

RMSE is calculated in Equation (9):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=0}^{N} (O_{oi} - P_{\mathrm{p}i})^2} \tag{9}$$

NSE is susceptible to proportionate and additive discrepancies between data and forecasts (Nash & Sutcliffe 1970).

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NSE is calculated in Equation (10):

$$\mathrm{NSE} = 1 - \left[\frac{\sum_{i=1}^{N}(O_{oi} - P_{pi})^2}{\sum_{i=1}^{N}(O_{oi} - \overline{N_o})^2}\right] \tag{10}$$

Model structures

Examining similar studies on streamflow estimation in the literature reveals that model input structures typically rely solely on the streamflow data, without the use of meteorological data. In some studies, methods such as partial correlation, cross-correlation, and MRMR have been used to determine the model input structure (Katipoğlu *et al.* 2023; Naganna *et al.* 2023). In this paper, the cross-correlation and the MRMR methods were used to determine the model input structure. The results for the cross-correlation and the MRMR are shown in Figures 4 and 5, respectively.

The analysis conducted using the model inputs determined by means of the MRMR approach and cross-correlation did not yield satisfactory results, because the correlation values obtained here were low. It has been emphasized in many studies that the same type of data at time $t-1$ has the most impact on the model output data of time t. The most important detail here is finding the optimum lagged value. Based on this, we created a model with the streamflow data lagged by up to 6 months, although some studies say that 3-month delayed data gives important results (Sun *et al.* 2019). Besides, some researchers

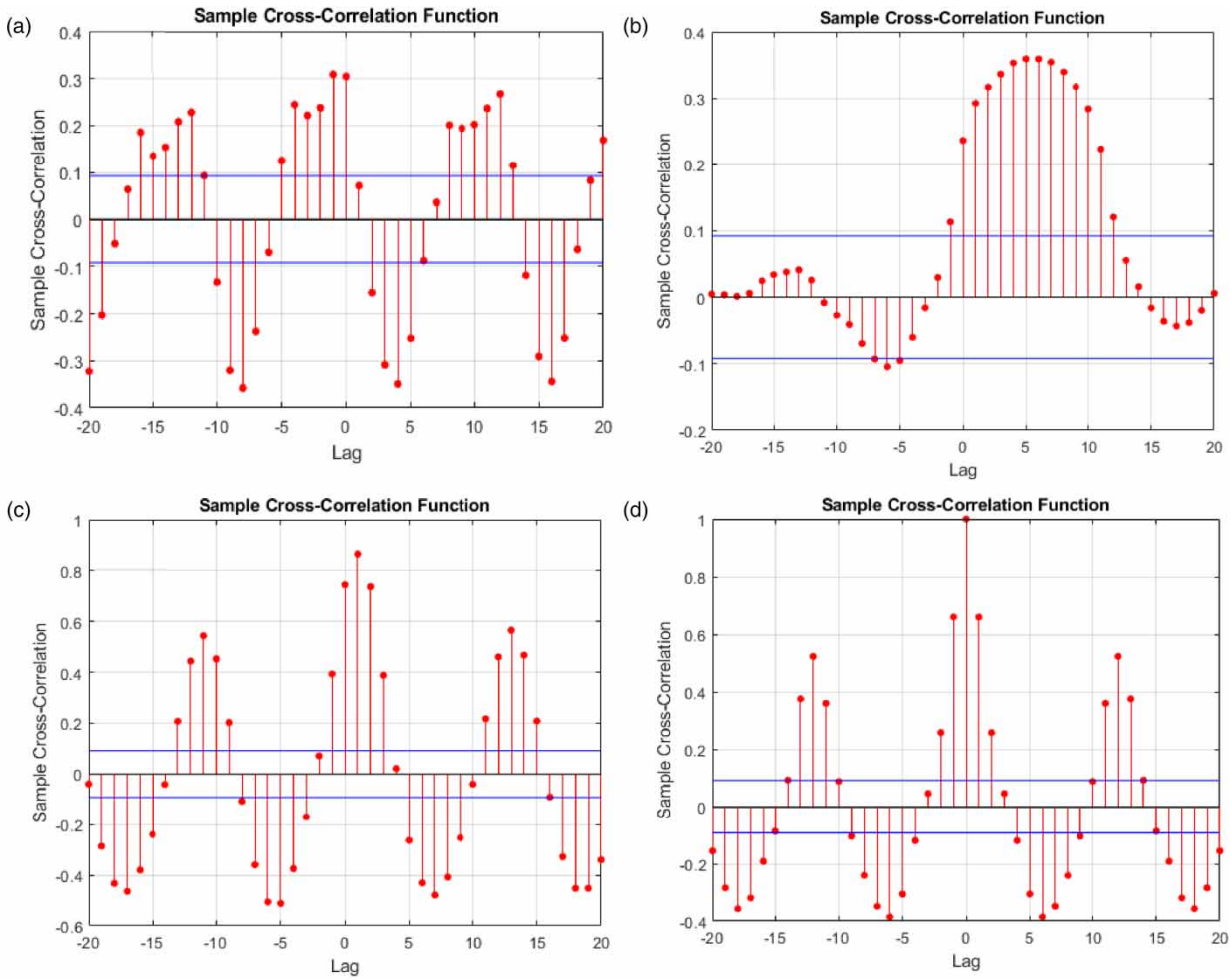


Figure 4 | The result of cross-correlation of the lagged data of (a) precipitation, (b) SDI3, (c) SDI12, and (d) streamflow.

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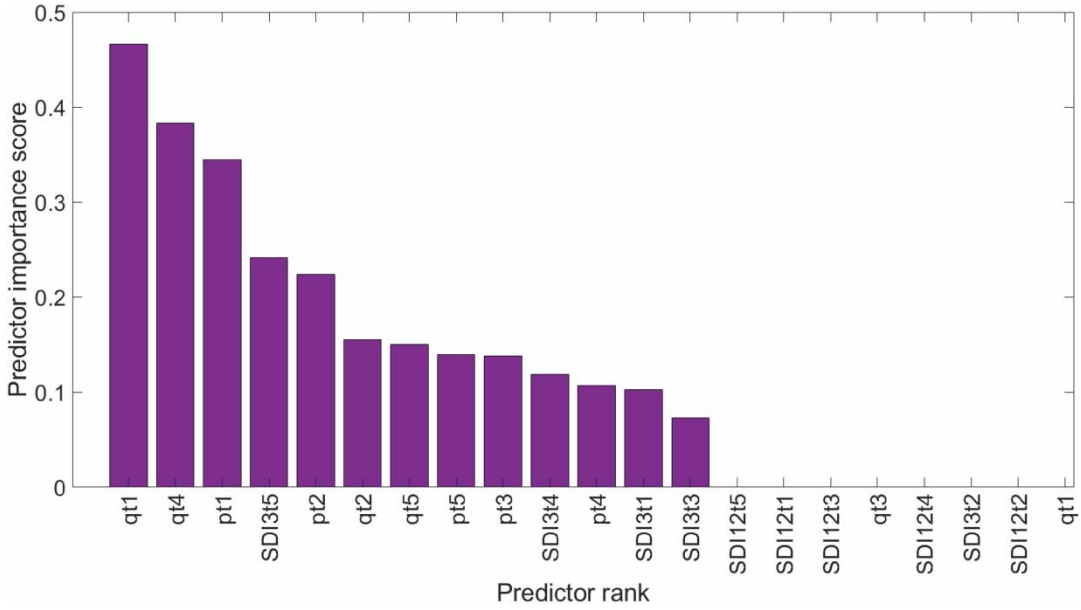


Figure 5 | The results of the MRMR where *qt*1 monthly streamflow value 1-lagged, *pt*4 monthly precipitation value 4-lagged, *SDI3t*5 monthly SDI3 value 5-lagged, *SDI12t*5 monthly SDI12 value 5-lagged, etc.

have stated that the MRMR method gives significant results when creating model input parameters (Latifoğlu & Kaya 2024). Based on that, we used this method. In this content, only one model structure, called M06, was created regarding information given in Figure 5. The input structure of the M06 model was created according to the inputs obtained from these graphics. Other model inputs were created according to the model inputs frequently preferred in the literature. Information on model structures constructed for the study is given in Table 2.

Figure 6 serves the time series of results obtained with SDI3 and SDI12. Cross-correlations of the precipitation, streamflow, SDI3 and SDI12 data, and the MRMR method were used to construct the model input structures. Whereas the M06 model was created directly with the MRMR, the cross-correlation was used to create the input structure for the other models. According to the cross-correlation, it was determined that using SDI12 and SDI3 data in model inputs would have a positive effect. However, the use of SDI12 and SDI3 data in the model input negatively affected the model results. This result is also consistent with the results of Figure 5. For this reason, while SDI12 was not included in the input structure of the models, SDI3 data was also used only in M06. As a result, while the cross-correlation was partially used when creating model data, only a model was created according to the MRMR.

RESULTS

Four different ML methods, SVM, ANN, RF, and DT, were used to test the six models that had been created. In the literature, many researchers create their scenarios in their article through the learning and testing phase (Klemeš 1986; Darabi

Table 2 | Input structure of the models used in the analysis

Model	Inputs						Output
M01	Q_{t-1}	Q_{t-2}					Q_t
M02	Q_{t-1}	Q_{t-2}	Q_{t-3}				Q_t
M03	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}			Q_t
M04	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}		Q_t
M05	Q_{t-1}	Q_{t-2}	Q_{t-3}	Q_{t-4}	Q_{t-5}	Q_{t-6}	Q_t
M06	$SDI3_{t-5}$	p_{t-1}	Q_{t-4}	Q_{t-1}			Q_t

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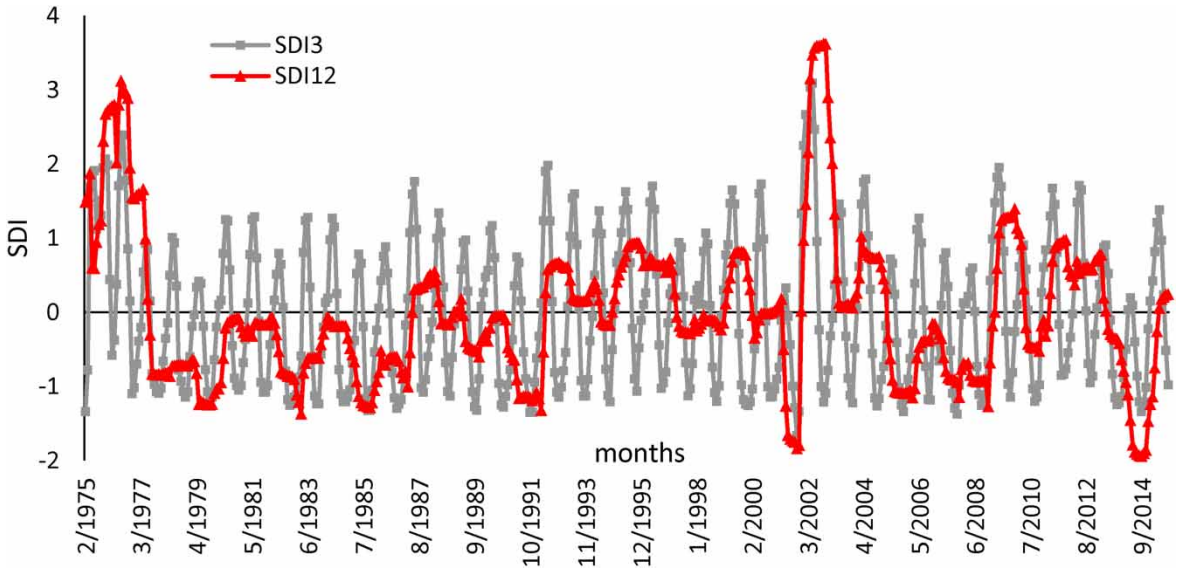


Figure 6 | The time series of results obtained with SDI3 and SDI12.

Cheghabaleki *et al.* 2024; Thota *et al.* 2024; Tuğrul & Hinis 2024). Upon the above mention, during the application of these methods, 70% of the total data was used as training data and 30% as test data. These rates may also vary depending on the data set. However, we saw that there is almost no difference between our statistical values in the training and test data. That's why we chose 70 and 30% rates, training and testing, respectively.

Then, to improve the model predictions, the WT was applied to the data, and the model results created after the WT were compared with the model results created before the WT. Three different statistical criteria consisting of *r*, NSE, and RMSE were used for comparison. The obtained results are given in Table 3.

Table 3 shows that, in the analysis performed without WT, the most successful result in all models was obtained in M05 except for DT. The input structure of M05 was created from the streamflow data 6-lagged months. Although the input structure of M06 was created with the MRMR method, it fell behind M05 in terms of performance. The results obtained in DT are low compared with other algorithms. The M06 model was the most successful in DT, with performance values of *r*: 0.5604, NSE: 0.3049, and RMSE: 1.6874. Another remarkable result here is that SVM achieved the most success among all methods after RF. While the most successful result in RF was obtained in M05 with performance values of *r*: 0.7539, NSE: 0.5678, and RMSE: 1.3305, the worst result was obtained in M02 with performance values of *r*: 0.7253, NSE: 0.5253, and RMSE: 1.3945. All models' performance values are quite low compared with those obtained after WT.

SVM is one of the models that is successful in analyzing without WT. Whereas the most successful results in this class were obtained in M05 with performance values of *r*: 0.7230, NSE: 0.4805, and RMSE: 1.4586, the worst results were obtained in M01 with performance values of *r*: 0.7012, NSE: 0.4431, and RMSE: 1.5103. In ANN analysis, M05 yielded the most successful results, while M01, the poorest model in this category, saw a decrease in NSE values to negative levels.

After WT, all models' results improved. The results obtained from these models are also shown in Table 3. One of the first striking findings in the analysis results was the improvement in all the model results. But while some models, W-RF and W-DT, have low improvement rates, some, such as W-SVM and W-ANN, higher improvements. The highest model performance values in this category were obtained in M04, for W-SVM and W-ANN, and M05, for W-RF and W-DT. Although the performance values of M04 are close to the performance values of M05 and M03, with M04 of performance of *r*: 0.9846, NSE: 0.9695, and RMSE: 0.3536, W-SVM has the best performance values in this class. In W-SVM, the model with the lowest performance values was M06, whose model input structure was created with MRMR, as in ANN.

While the model performance values in W-RF and W-DT increase compared with their pre-WT values, they lag significantly behind those of W-SVM and W-ANN. The most successful results in these two methods were obtained in M05, which consisted of the streamflow data 6-lagged months for input data. Meanwhile M06, with *r*: 0.8409, NSE: 0.6968, and RMSE: 1.1145, whose input data consisted MRMR, stands out as the poor model in W-RF. In W-DT, the weakest model was found to be M01, with *r*: 0.6515, NSE: 0.3894, and RMSE: 1.5814.

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Table 3 | Analysis results for all models based on SVM, ANN, RF, and DT

Before wavelet transform

	SVM			ANN			RF			DT		
Models	***r***	**NSE**	**RMSE**	***r***	**NSE**	**RMSE**	***r***	**NSE**	**RMSE**	***r***	**NSE**	**RMSE**
M01	0.7012	0.4431	1.5103	0.5405	−0.2933	2.3016	0.7366	0.5411	1.3710	0.5451	0.1062	1.9133
M02	0.7019	0.4437	1.5095	0.6735	0.3668	1.6104	0.7253	0.5253	1.3945	0.6089	0.1411	1.8756
M03	0.7101	0.4579	1.4900	0.6370	0.3047	1.6876	0.7339	0.5384	1.3750	0.5865	0.2042	1.8054
M04	0.7174	0.4649	1.4804	0.6671	0.3255	1.6621	0.7532	0.5655	1.3340	0.5477	0.1189	1.8997
M05	**0.7230**	**0.4805**	**1.4586**	**0.6930**	**0.4072**	**1.5583**	**0.7539**	**0.5678**	**1.3305**	0.5123	0.1782	1.8346
M06	0.7266	0.4717	1.4710	0.5832	0.0375	1.9855	0.7448	0.5527	1.3536	**0.5604**	**0.3049**	**1.6874**

After wavelet transform

	W-SVM			W-ANN			W-RF			W-DT		
Models	***r***	**NSE**	**RMSE**	***r***	**NSE**	**RMSE**	***r***	**NSE**	**RMSE**	***r***	**NSE**	**RMSE**
M01	0.9610	0.9230	0.5614	0.9089	0.7173	1.0761	0.8792	0.7519	1.0081	0.6515	0.3894	1.5814
M02	0.9649	0.9305	0.5337	0.9243	0.8410	0.8070	0.8849	0.7608	0.9897	0.6550	0.3919	1.5782
M03	0.9822	0.9646	0.3807	0.9708	0.9380	0.5039	0.8775	0.7593	0.9929	0.6579	0.3798	1.5939
M04	**0.9846**	**0.9695**	**0.3536**	**0.9797**	**0.9588**	**0.4108**	0.8824	0.7737	0.9629	0.6844	0.4286	1.5299
M05	0.9845	0.9689	0.3568	0.9610	0.9200	0.5723	**0.8874**	**0.7811**	**0.9468**	**0.8540**	**0.7271**	**1.0572**
M06	0.8695	0.7559	0.9999	0.7447	0.3091	1.6823	0.8409	0.6968	1.1145	0.8048	0.6274	1.2354

The most successful models are shown in bold.

A Taylor diagram was used to analyze the model results by taking into account the variance in the observation values and to see which model gives results that are closer (appropriate) to the observation value, and the results of the models before applying WT are given as a Taylor diagram in Figure 7. When compared with other models in the Taylor diagram, the result closest to the observation value was obtained in RF-M04 and RF-M05, which is the same as the findings obtained from the analysis results as in the Taylor diagram. In order to better analyze the predictive power and performance of the models, the violin chart was used in addition to the Taylor diagram, and the violin chart results of the models before applying WT are given in Figure 8. The models most similar to the observation pattern in the violin diagram are SVM-M04 and SVM-M05. According to both diagrams, the models showing the best results are in RF, while the poor models are in DT. According to Figure 8, one of the most striking findings in this section is that SVM produces better results than RF, in contrast to the analysis results and Taylor diagram.

Figure 9 shows a comparison of the two most successful models, namely SVM-M05 and RF-M05, from different algorithms with observation values in the time series. Figure 9 shows that the observation values do not typically capture the peaks.

In order to better compare how well the models work with each other, the results of WT are shown in Figure 10 as a Taylor diagram and in Figure 11 as a Violin diagram. Figure 10 shows the Taylor diagram of the model's results after WT. Figure 10 reveals that because the results closest to the observation value were obtained in W-SVM-M04 and W-SVM-M05, their performance is better than other models. In terms of performance, W-ANN-M04 and W-ANN-M05 models follow W-SVM-M04 and W-SVM-M05 in terms of performance, respectively.

Another conclusion is that the performance of the W-DT and W-RF models is inferior to that of the other models. In this section, the violin diagram displays the results obtained using WT, similar to the previous section. In Figure 11, the analysis results of all models with different algorithms are shown in the Violin diagram. According to this diagram, W-SVM-M04 and W-SVM-M05 gave the closest and most similar results to the observation values, just as similar results were obtained in the Taylor diagram and the analysis results. In this diagram, it is understood that the analyses performed with W-RF are weaker than other models. From here, it can be deduced that the WT does not give very important results in RF and DT.

Figure 12 compares the results of the two most successful models, W-SVM-M05 and W-ANN-M05, from different algorithms with their observation values in the time series. It can be seen in Figure 12 that generally the peaks in the observation values are captured.

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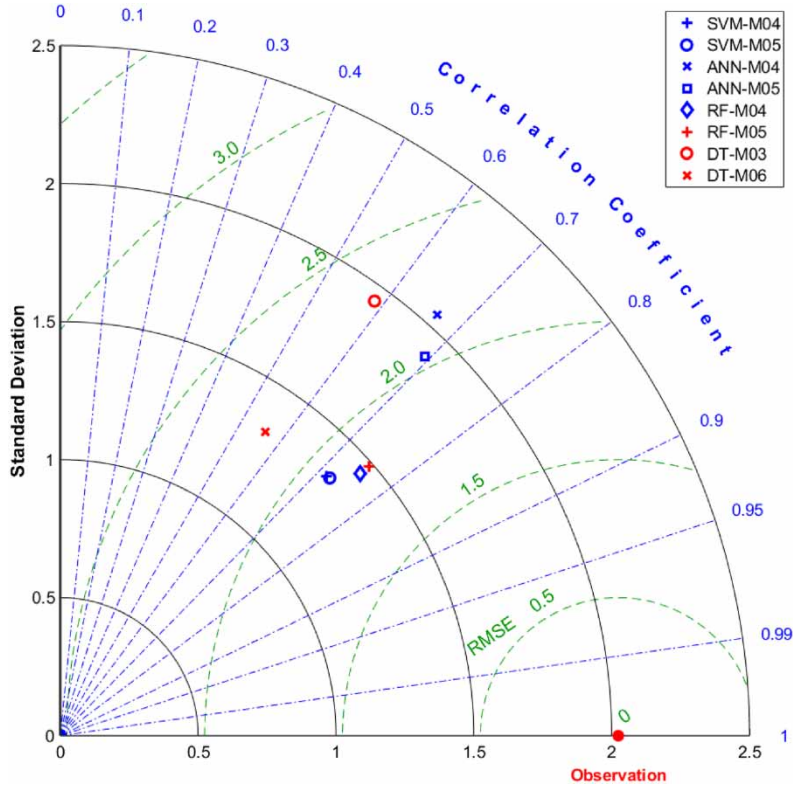


Figure 7 | Taylor diagram for all model results without WT where *SVM-M04* using SVM-M04's results, *SVM-M05* using SVM-M05's results, *ANN-04* using ANN-M04's results, *ANN-05* using ANN-M05's results, etc.

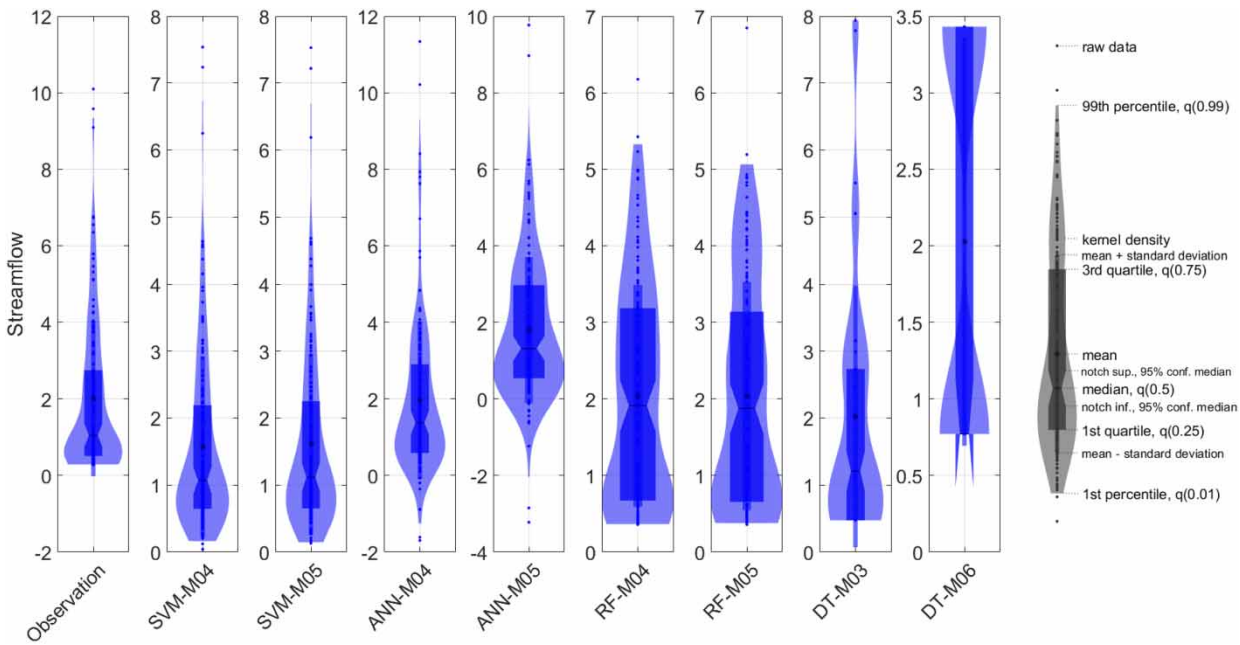


Figure 8 | Violin diagram for all model results without WT where *SVM-M04* using SVM-M04's results, *SVM-M05* using SVM-M05's results, *ANN-04* using ANN-M04's results, *ANN-05* using ANN-M05's results, etc.

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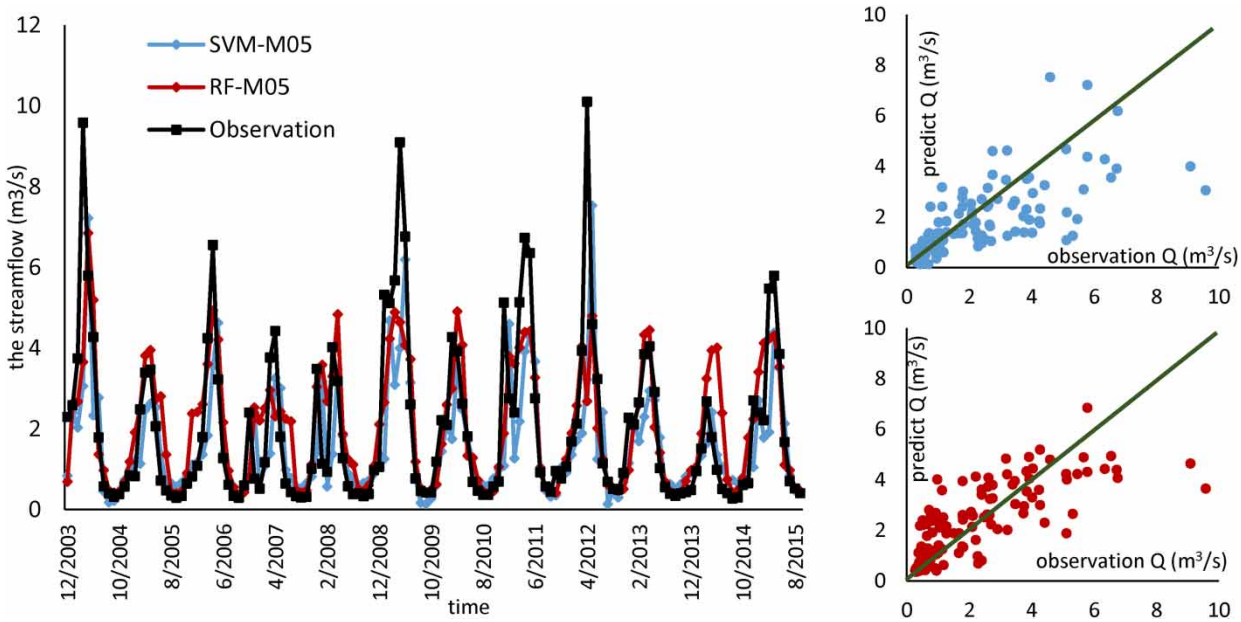


Figure 9 | Time series and scatter diagram of the two most successful models in analyses without WT where *SVM-M05* using SVM-M05's results and *RF-M05* using RF-M05's results.

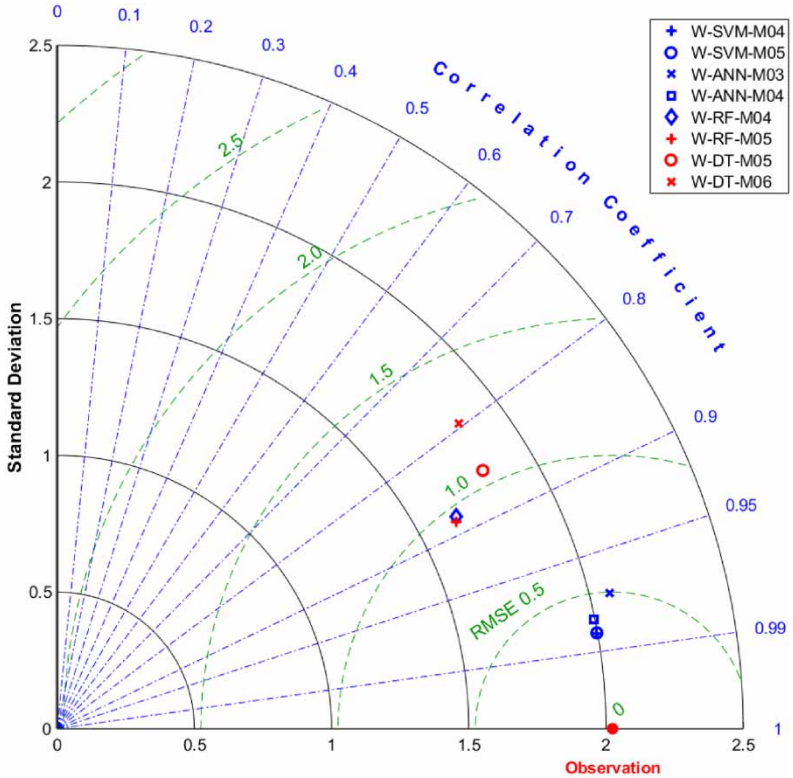


Figure 10 | Taylor diagram for all model results with WT where *W-SVM-M04* using SVM-M04's results with WT, *W-SVM-M05* using SVM-M05's results with WT, *W-ANN-M04* using ANN-M04's results with WT, *W-ANN-M04* using ANN-M04's results with WT, etc.

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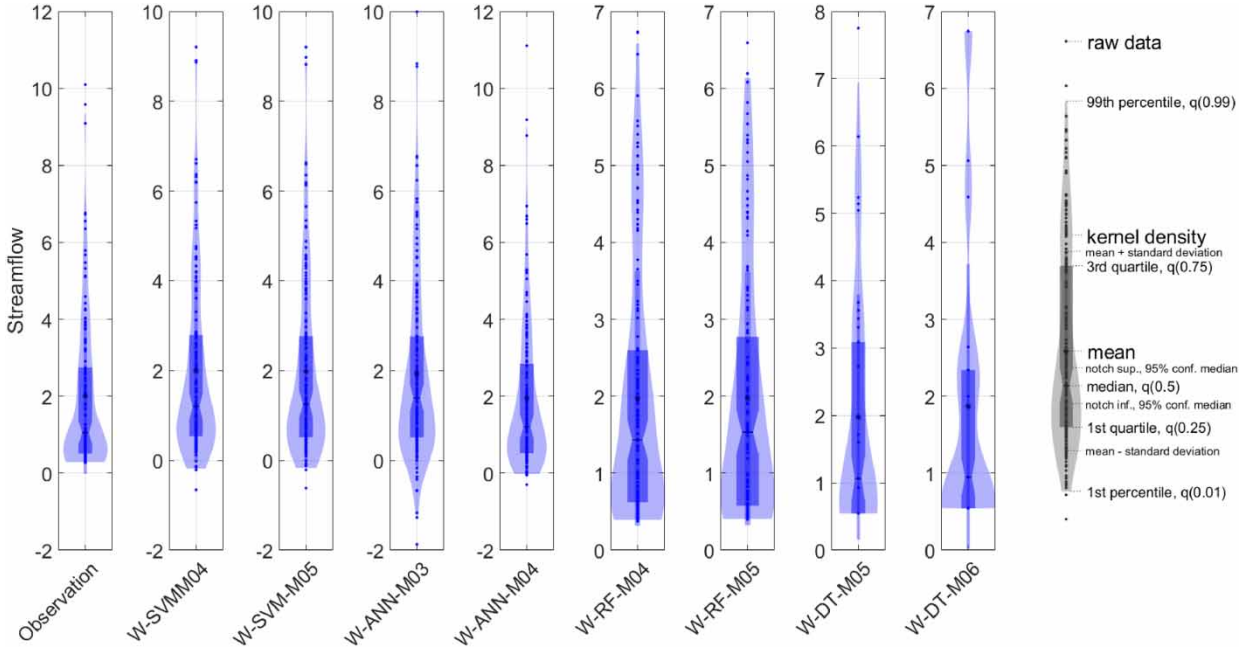


Figure 11 | Violin diagram for all model results with WT where *W-SVM-M04* using SVM-M04's results with WT, *W-SVM-M05* using SVM-M05's results with WT, *W-ANN-M04* using ANN-M04's results with WT, *W-ANN-M04* using ANN-M04's results with WT, etc.

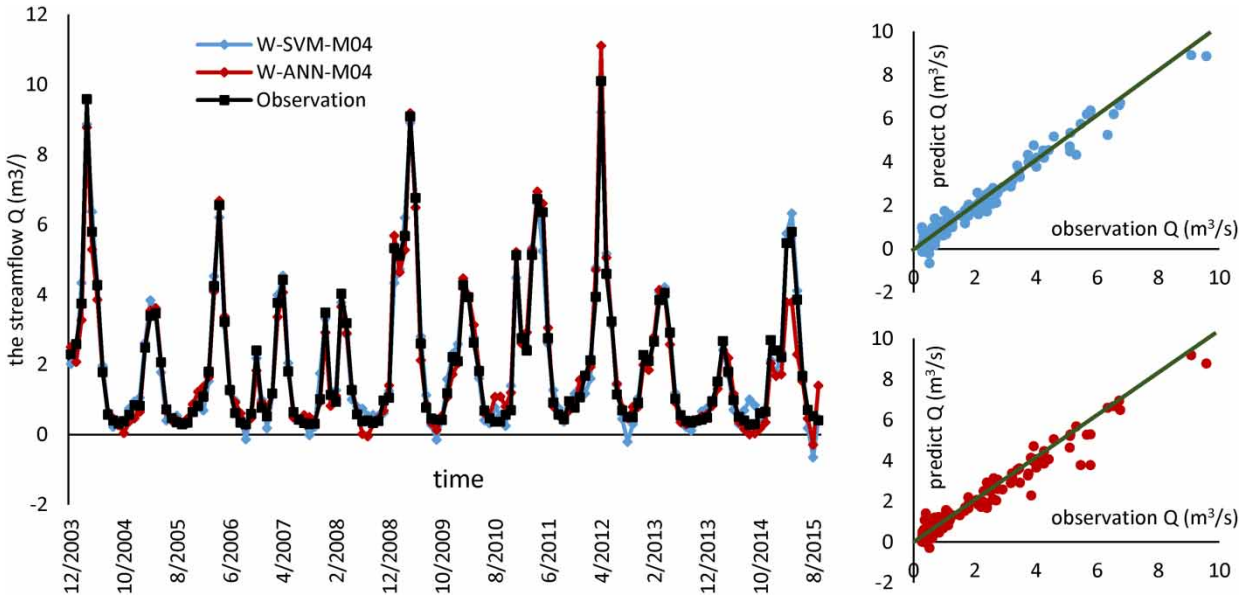


Figure 12 | Time series and scatter diagram of the two most successful models in analyses with WT where *W-SVM-M04* using SVM-M05's results with WT, *W-ANN-M04* using RF-M05's results with WT, etc.

One of the most striking results of this study, and one of its innovative methods, is the strengthening of model performances after WT. Table 4, which was created from r values, serves the improvements as percentages. Since NSE and RMSE values may cause confusion, these performance metrics are not mentioned.

Examining Table 4, it was found that M01 ANN achieved the highest percentage improvement. The performance values of this model are *r*: 0.5405, NSE: −0.2933, and RMSE: 2.3016 before WT, while they are *r*: 0.9089, NSE: 0.7173, and RMSE: 1.0761 after WT. This model demonstrates that the NSE value notably transitions from negative to positive. Consequently,

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Table 4 | Improvement percentages based on the *r* metric in models after WT

Models	SVM (%) *r*	ANN (%) *r*	RF (%) *r*	DT (%) *r*
M01	37.05	**68.16**	19.36	19.52
M02	37.47	37.24	**22.00**	7.571
M03	**38.32**	52.40	19.57	12.17
M04	37.25	46.86	17.15	24.96
M05	36.17	38.67	17.71	**66.70**
M06	19.67	27.69	12.90	43.61

The most successful models are shown in bold.

the maximum rate of improvement was established here. Despite the percentage improvement indicated in this table, it fails to elucidate the most effective model. The results section indicated that the least effective learning algorithm was DT. As seen in Table 4, M02 for DT was found to be the model with the lowest success rate. This shows that the model input structure significantly affects the model performance.

DISCUSSION

Although many recent studies in the literature have used the same methodology as this study, the findings determined here may show different results. Some are summarized as follows: It was stated by Latifoğlu & Kaya (2024) that the MRMR method is useful according to the order of data importance when creating model input. This may be true regionally, but it was not helpful in this study. Although it has been explained in some studies that autocorrelation may be useful in the model input structure (Katipoğlu 2023), it was not completely effective in determining the model input in this study. Although Basak *et al.* (2022) stated that for both short- and long-term projections for the study area, the MRMR approach achieved forecast accuracy that was satisfactory. However, in this study, significant results were not obtained with the model, M06, created according to the MRMR.

Some of the previous streamflow prediction studies using ML have also obtained similar results to the present study. Some of these are summarized as follows: Katipoğlu (2023) conducted a study using a set of ML algorithms including GPR and SVM in order to predict wind speed by means of WT and empirical mode decomposition (EMD) in Burdur, Türkiye. He stated that the standalone ML model's WT prediction performance was improved by both WT and EMD signal processing. Comparing RF and other methods, such as SVM, Peng *et al.* (2020) reveal that the results in the Jinsha River Basin demonstrate that the RF model performs better in terms of prediction accuracy and requires less computation than the others when handling complex non-linear hydrologic time series. It was determined by Achite *et al.* (2023a) that wavelet-based models using the Daubechies mother wavelet ML models, SVM and GPR, showed superior results than standalone ML models. Preferring to work with SVM and ANN, WT, and the bootstrap, Belayneh *et al.* (2016a) estimated drought using precipitation in the Awash River basin, located in Ethiopia. They stated that WT was more effective than the other methods without WT. Kambalimath & Deka (2021) conduct a study forecasting 1-, 3-, and 5-day ahead streamflow using daily streamflow. They used the SVM to predict the streamflow and DWT to improve the model performances. Their results showed that DWT improved the model performance in future forecasting. Choosing RF-based ML models to predict daily streamflow, Dogan (2023) studied two types of models, a single model having a single station (SS) and a multiple model with a lot of stations, in the Kızılırmak River. He stated that when estimating missing historical streamflow, the SS model is beneficial and reveals the effective results of RF. Ayana *et al.* (2023) forecasted streamflow benefiting from LSTM, SVR, RF, and LR and mentioned that the appropriate number of lags is determined by the correlation of partial and auto. Their results showed that LSTM is superior to the other methods. Precipitation had the least impact on model performance, according to Adnan *et al.* (2024), while input data generated from merely lagged streamflow data was determined to be the most beneficial variable. Tuğrul & Hinis (2024), in their drought prediction modeling at the Apa Dam with a series of ML algorithms, demonstrated that analyses made with WT are more effective on models created with the only type of data. It has been determined that their results overlap with some of the results obtained in this study.

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In this study, both the importance of the selection of input data and the performance of ML algorithms are mentioned. Many methods such as cross-correlation, autocorrelation, and MRMR are used in the selection of model input data. However, the performance of these methods may vary depending on the estimated parameter. While the cross-correlation can give good results in predicting meteorological droughts, this method may not give satisfactory performance in predicting hydrological droughts. As a matter of fact, similar situations exist in autocorrelation and MRMR methods. In data-based modeling, diversification of input data can directly affect the model result. Here, even though researchers intend to choose the parameters in the hydrological cycle (Beven 1989; Montanari *et al.* 2013), the model results may not be satisfactory due to unknown parameters in data-based modeling. In particular, parameters that are thought to have a significant impact on the output parameter, such as precipitation, drought index, and temperature, may not affect the model result and may even negatively affect model performance. This result may vary for different regions. Therefore, the most suitable model and the most appropriate parameter for each region should be determined separately. Although the selection of the appropriate parameter is achieved by certain methods, their model performances may vary according to ML algorithms and analysis methods to be used. In the MRMR method, although it was determined that the SDI3 and precipitation parameters in the model input parameters would positively affect the model result, it was found that the model results made with WT were not good. As in this study, more effective results were obtained by using uniform data in WT.

CONCLUSIONS

The streamflow in the Çarşamba River in this study was investigated to forecast potential future streamflow using different ML algorithms, including SVM, ANN, RF, and DT. In addition, with the help of WT, the model results were improved. Overall, the most effective model structure, which is the best presented, was determined, and the most useful ML algorithm was indicated in the region. The most remarkable results of the research are as follows:

- It has been stated by some researchers that better results are obtained with uniform data, the only type of data, which is the streamflow in this study, in WT. In this study, using too many types of data, such as temperature, drought index, and precipitation, in the input structure negatively affects the wavelet result. However, it should not be forgotten that in analyses performed without WT, the use of more than one type of data, which may be precipitation, evaporation, temperature, and humidity, in some algorithms affects the model result positively just like M06 for DT in this study. When creating the input structure in streamflow prediction modeling studies, either 4- or 5-lagged months' delay data should be used according to the WT. Since higher success rates are achieved in models containing only the streamflow data, different meteorological or hydrological data should not be used in the model input structure.
- SVM demonstrated superior performance in WT, while RF performed better without WT. In addition, we determined that DT was the least successful model, both with and without WT.
- In order to obtain successful model results in streamflow predictions, drought index data must not be used in the model input structure.
- While it is partially useful cross-correlation, the MRMR method used to determine the model input structure was not useful for this region.
- ANN is the most successful model without WT after RF, SVM, respectively, after WT, ANN is the most successful after SVM.
- After WT, in SVM and ANN, a higher success rate was determined compared with other algorithms, RF and DT.
- The WT substantially enhances model performance. The results section indicates that performance measures, particularly r and NSE, are enhanced by a factor of 2–3. In fact, one of the most striking results is that the NSE value, which was determined to be negative, turned positive and showed a successful performance. In summary, it is among the remarkable results that the performance of algorithms with low performance metrics has reached satisfactory levels with WT.
- The significance of data diversity in the model input structure, together with the lag duration in models where the only type of data is generated, also influences the model outcome. For instance, although the M02 model exhibited one of the lowest performances in DT, the M05 model demonstrated significantly superior performance inside the same algorithm after WT.

The study's findings provide improved streamflow estimates and valuable insights for water-related institutions and organizations responsible for managing water resources, risk assessment, and addressing meteorological-based natural disasters like floods and droughts. Due to excessive water use and its geographical location, the Konya Closed Basin suffers greatly from precipitation deficiencies and consequent streamflow. The region's scarcity of green spaces also contributes to this

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problem. Recommendations for future studies can be listed as follows: (1) A more detailed streamflow prediction study can be made by using data including evaporation and temperature obtained from several stations that can represent the region. (2) Future studies can evaluate the models' performance across various models and regions.

CONSENT TO PARTICIPATE

All authors agree with the content and all authors give explicit consent to submit and that they obtained consent from the responsible authorities at the institute/organization where the work has been carried out before the work is submitted to the journal.

ETHICAL RESPONSIBILITIES OF AUTHORS

All authors have read, understood, and have complied as applicable with the statement on 'Ethical responsibilities of Authors' as found in the Instructions for Authors.

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DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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