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EFFECT OF SEASONAL-TREND DECOMPOSITION ON MACHINE LEARNING-BASED SUSPENDED SEDIMENT LOAD PREDICTION PERFORMANCE

MEVSİMSEL-TREND AYRIŞTIRMASININ MAKİNE ÖĞRENMESİ TABANLI ASKIDA SEDİMENT YÜKÜ TAHMİN PERFORMANSI ÜZERİNDEKİ ETKİSİ

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ABSTRACT

Forecasting of sediment is vital for water resources management. In this study, the machine learning-based prediction performance of suspended sediment load (SSL) at Bulakbaşı station of Kızılırmak River was investigated. Also, the effect of seasonal decomposition on the prediction performance was searched. Accordingly, Support Vector Machine (SVM), Adaptive Boosting (AdaBoost), and Generalized Regression Neural Network (GRNN) methods were used for SSL prediction. Grid Search (GS) algorithm was preferred for hyperparameter optimization. The seasonal component was obtained by Seasonal-Trend decomposition using the LOESS (STL) method. Six input combinations were generated using flow (Q_t), flow lag (Q_{t-1}), and the seasonal component of SSL (S-SSL_t). According to the findings, AdaBoost (M6-NSE_{Train}=0.914, M4-NSE_{Test}=0.765), SVM (M6-NSE_{Train}=0.912, M6-NSE_{Test}=0.863), and GRNN (M6-NSE_{Train}=0.912, M4-NSE_{Test}=0.834) models produced quite consistent results. In the test phase, SVM-M6 (R^2=0.893, NSE=0.863) is the most successful model according to various evaluation metrics. It was also observed that the last three input combinations, where the seasonal component of SSL was added, generally improved the performance. For SVM in the test phase, which is the most successful model, R^2=0.873, NSE=0.820 values were obtained in the combination without the seasonal component (M3), and R^2=0.893, NSE=0.863 values were obtained in the combination with the seasonal component (M6).

Keywords: Adaptive boosting, Kızılırmak, seasonal decomposition, support vector machine, suspended sediment load

ÖZET

Sedimentin tahmin edilmesi, su kaynakları yönetimi için hayati önem taşımaktadır. Bu çalışmada, Kızılırmak Nehri'nin Bulakbaşı istasyonundaki askıda sediment yükünün (SSL) makine öğrenmesi tabanlı tahmin performansı araştırılmıştır. Ayrıca mevsimsel ayrıştırmanın tahmin performansı üzerindeki etkisi incelenmiştir. Bu doğrultuda, Destek Vektör Makinesi (SVM), Adaptif Boosting (AdaBoost) ve Genelleştirilmiş Regresyon Sinir Ağı (GRNN) algoritmaları SSL tahmini için kullanılmıştır. Hiperparametre optimizasyonu için Grid Search (GS) algoritması tercih edilmiştir. Mevsimsel bileşen, Mevsimsel-Trend ayrıştırması LOESS (STL) yöntemi kullanılarak elde edilmiştir. Akış (Q_t), akış gecikmesi (Q_{t-1}) ve SSL'nin mevsimsel bileşeni (S-SSL_t) kullanılarak altı girdi kombinasyonu oluşturulmuştur. Bulgulara göre AdaBoost (M6-$NSE_{Eğitim}$=0,914, M4-NSE_{Test}=0,765), SVM (M6-$NSE_{Eğitim}$=0,912, M6-NSE_{Test}=0,863) ve GRNN (M6-$NSE_{Eğitim}$=0,912, M4-NSE_{Test}=0,834) modelleri oldukça tutarlı sonuçlar üretmiştir. Test aşamasında, SVM-M6 (R^2=0,893, NSE=0,863) çeşitli değerlendirme ölçütlerine göre en başarılı modeldir. SSL'nin mevsimsel bileşeninin eklendiği son üç girdi kombinasyonunun genel olarak performansı artırdığı da gözlemlenmiştir. En başarılı model olan test aşamasındaki SVM için mevsimsel bileşenin olmadığı

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kombinasyonda (M3) R^2=0,873, NSE=0,820 ve mevsimsel bileşenin olduğu kombinasyonda (M6) R^2=0,893, NSE=0,863 değerleri elde edilmiştir.

Anahtar Kelimeler: Adaptif boosting, Kızılırmak, mevsimsel ayrıştırma, destek vektör makinesi, askıda sediment yükü

INTRODUCTION

Measurement of suspended sediment load (SSL) and a better understanding of the physical processes affecting SSL are vital for water resources. Sediment transport has a negative impact on the management of the usability of water structures built along the river (Adnan et al., 2019). It can also lead to inefficiency as a result of its accumulation in hydraulic structures. Rivers whose cross-sections narrow due to sediment accumulation can cause danger during floods. Another negative effect of sediment on the environment is the pollutants and heavy metals it contains (Xie et al., 2022). Measurement at specific sections along the river provides the opportunity to take precautions against possible dysfunctions in the early stages. In addition, simulation studies on sediment transport are also useful for predicting sediment movement in the future (Onüçyıldız et al., 2014; Mohammadi et al., 2021; Saplıoğlu and Acar, 2020).

Although measurements made at sediment observation stations provide the most accurate results in determining the amount of sediment, they are quite costly and time-consuming (Koycegiz et al., 2021). For this reason, various methods are adopted by researchers for sediment estimation. These can be generally categorized as sediment rating curves (SRC), empirical equations, physics-based models (PBM), and machine learning (ML) models. There are various studies in the literature using these methods in sediment estimation (Piraei et al., 2023; Koycegiz et al., 2021; Nourani et al., 2019). SSL, which is very difficult to measure, is affected by various processes, especially climatological, geological, and morphological (Koycegiz et al., 2021). It is not also an easy task to estimate the amount of sediment with empirical equations. Because the use of these methods also requires basin characteristics that are difficult to determine. On the other hand, the use of PBMs in sediment estimation, as in other hydrological processes, requires simulation of all hydrological processes in the basin and calibration of many parameters. PBMs require many accurate hydrological input data about the basin. Furthermore, the implementation of PBMs requires high computational time and expert knowledge (Koycegiz et al., 2021; Noori and Kalin, 2016). The use of PBMs in sediment estimation is not very common due to its impracticality. For these reasons, the use of ML methods in SSL estimation, as in other hydrological processes, is quite popular (Acar and Saplıoğlu, 2022; Gupta et al., 2021).

ML methods such as artificial neural networks (ANN), support vector machines (SVM), and Adaptive Network Based Fuzzy Inference Systems (ANFIS) are among the ML methods that are frequently used in both sediment estimation and the estimation of many other hydrometeorological data. Kisi and Yaseen (2019) compared the performance of evolutionary fuzzy (EF) and ANFIS models for SSC estimation in the Eel River located in northwestern California. Subtractive clustering (SC), grid partition (GP), and fuzzy c-means (FCM) approaches were used in the generation of rules in ANFIS models. The results showed that the EF model was more successful than the ANFIS models. Buyukyildiz and Kumcu (2017), who performed ML-based SSL estimation on the Çoruh River in Türkiye, found that SVM was the most successful model. They stated that SSL estimation for this river, which has a high energy production potential, is very important for the water structures planned to be built. Kisi et al. (2009) investigated the performance of neuro-fuzzy computing methods in SSL prediction in the Kızılırmak Basin, a cross-section of which was selected as the study area. Accordingly, it was found that ML models made more successful predictions compared to empirical models. In the study by Asadi et al. (2021), where traditional ML algorithms are used in SSL prediction, it is stated that all models produce satisfactory results when geomorphological parameters are included.

In the literature, improving the prediction success of hydrological parameters such as precipitation, runoff, evaporation, and sediment has also been the focus of researchers. For this purpose, both various data preprocessing/decomposition techniques and ML models hybridized with metaheuristic methods come to the fore. Metaheuristic algorithms such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Artificial Bee Colony Optimization (ABCO), Particle Swarm Optimization (PSO), and Gray Wolf Optimization (GWO) are used alone or as a hybrid with other artificial intelligence methods, and their effects on model performance are evaluated (Aghelpour et al., 2023; Katipoğlu et al., 2024; Sales et al., 2021; Mohammadi et al., 2021; Kilinc and Yurtsever, 2022). Wavelet transform (WT), variational mode decomposition (VMD), empirical mode decomposition (EMD), Singular Spectrum Analysis (SSA), and Fourier transform (FT) are examples of the most widely used data decomposition/data preprocessing techniques (Zhou et al., 2017). A new method proposed to improve the prediction success of models is the Band Similarity (BS) method developed by Yilmaz (2022). There are a limited number of studies in the literature using this method. These studies include water consumption (Yılmaz, 2022; Yilmaz and Alpars, 2023), pan evaporation (Yılmaz, 2023), and streamflow (Yilmaz et al., 2024a, 2024b). In all these studies, findings were obtained that the BS method improved the prediction performance.

Samantaray et al. (2024) performed SSL prediction by hybridizing the traditional SVM with various metaheuristic optimization algorithms. Among the metaheuristic algorithms they applied, they found that the new sparrow search algorithm produced the most successful hybrid model with SVM. Besides hybrid models, ensemble ML algorithms are also known to produce consistent results. Piraei et al. (2023) tested various traditional and ensemble model algorithms on the SSL prediction. They state that eXtreme Gradient Boosting (XGBoost), an ensemble model, has the best prediction performance. Zhang et al. (2021) investigated the performance of the Least Absolute Shrinkage and Selection Operator (LASSO) model in predicting suspended sediment concentration (SSC) in the subaqueous Yellow River Delta in China. In addition, the prediction success of LASSO was compared with classification and regression tree (CART), support vector regression (SVR), multilayer perceptron (MLP), and stepwise regression (SR) models. As a result of the analysis, it was determined that the LASSO method performed better than other models in SSC prediction. In another study, AlDahoul et al. (2021) used Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGB), MLP, and ElasticNet Linear Regression (LR) methods in the estimation of suspended sediment load (SSL) in the Johor River basin in Peninsular Malaysia. In the study where SSL estimation was examined in 4 different scenarios (daily, weekly, 10-day, and monthly), the analyses were carried out for the period 1988-1998. The LSTM method showed higher estimation performance than the other 3 models in all scenarios.

There are studies investigating the effect of decomposition and transformation methods on the success of ML algorithms in SSL prediction. Özger and Kabataş (2015) investigated the effect of wavelet transform (WT) on the success of fuzzy logic models in SSL estimation. It was found that WT significantly increased the success compared to the stand-alone model at 4 SSL measurement points located in the Black Sea region of Türkiye. Ghasempour et al. (2021) investigated the effect of WT and Ensemble Empirical Mode Decomposition (EEMD) on the success of ML models. According to the findings, it was found that the forecasting performance of hybrid models increased significantly. Seasonal and trend decomposition using LOESS (locally weighted regression and scatterplot smoothing) (STL) (Cleveland et al., 1990) method is also an alternative data decomposition method. In addition to being used in the temporal analysis of hydrometeorological parameters, the STL method is also used as a data preprocessing/data decomposition method in forecasting studies (Yuan et al., 2023; Yilmaz et al., 2024a; Yin et al., 2024; Shaqiri, 2024).

In line with the information obtained from the literature, studies on improving the performance of ML models in SSL forecasting have an important place. However, there is no study investigating the effect of Seasonal-Trend decomposition using LOESS (STL), one of the decomposition techniques, on the performance of ML models in SSL prediction. All processes affecting the physical mechanism of SSL are under the influence of various periodicities. With this motivation, the aim of this study;

- to estimate the SSL parameter using three different machine learning methods, namely SVM, Adaptive Boosting (AdaBoost), and Generalized Regression Neural Network (GRNN) algorithms,
- to examine the effect of using the seasonality component obtained using the STL technique as input on model estimation performance.

In this respect, Bulakbaşı station on the Kızılırmak River was chosen as the study area. The novelty of this study is that, to the best of our knowledge, there is no study in the literature where STL is used in sediment estimation. In this context, it is thought that the success to be achieved by using the STL technique in estimating sediment, which has a chaotic and nonlinear structure, will make a significant contribution to the solution of sediment-focused problems and therefore to both water resources management and sustainability clean environment applications.

MATERIALS AND METHODS

To make the methodology applied in this study easy and clear to follow, the workflow diagram given in Figure 1 was created. In addition, ArcGIS Pro (version 3.1.1) was used to create the location map shown in Figure 2, and Matlab (version 2022b) was used for statistical calculations. Python (version 3.10.9) and Spyder (version 5.4.1) scientific python development environments were preferred for the creation and decomposition of machine learning models. The NumPy (NumPy, 2008), pandas (Pandas, 2024), and sklearn (Pedregosa et al., 2011) libraries in Python were used.

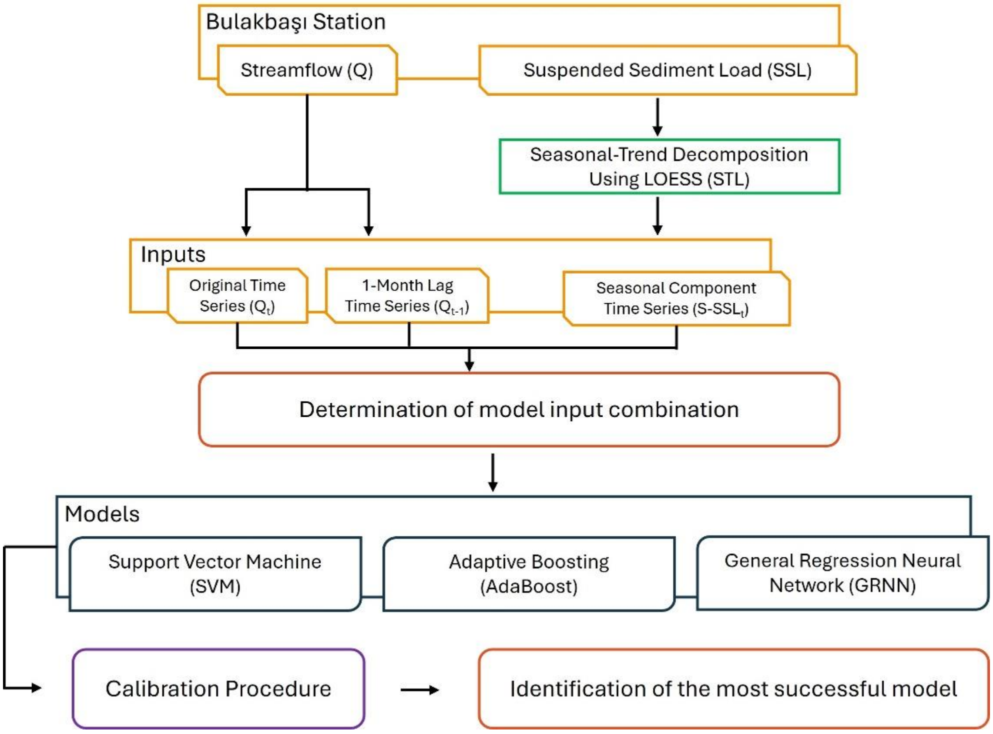

Figure 1. Workflow Diagram for This Study

Study Area and Data

Located in the central-northern part of Türkiye, the Kızılırmak Basin has a surface area of approximately 78000 km^2. The elevation of the basin reaches up to 3000 m. Continental climate prevails throughout the basin. However, it is observed that the average precipitation increases from south to north. While the average annual total precipitation is around 250 mm in the south of the basin, it increases to 900 mm towards the north. There are agricultural areas and perennial forests in the basin. In addition, the geological characteristics and morphology of the basin contain a tendency to cause erosion (Acar, 2019). Existing water resources and fertile lands cause intensive agricultural activities in the basin. The Kızılırmak River is important not only for agriculture but also for the socioeconomic, energy, and drinking water supply of the region. The headwaters of the Kızılırmak Basin and the drainage area of Bulakbaşı gauge (No: 1539) are located in the east of the basin. The location map of the Kızılırmak Basin and Bulakbaşı gauge is given in Figure 2. The altitude of the station is 1298 m. The drainage area is 1642 km^2. It has coordinates 39.87°N, 37.56°E. Bulakbaşı station is located in Canova village, Zara district of Sivas province. Although there are several surface water bodies near the measurement station, Lake Tödürge is the largest surface water body in the vicinity.

The main statistical characteristics of the streamflow and SSL data obtained from Bulakbaşı gauge are given in Table 1. In the study, measurements of SSL and the corresponding runoff, which were not made in equal temporal steps in the period 1973-2015, were used. The data used in the study were obtained from the General Directorate of State Hydraulic Works.

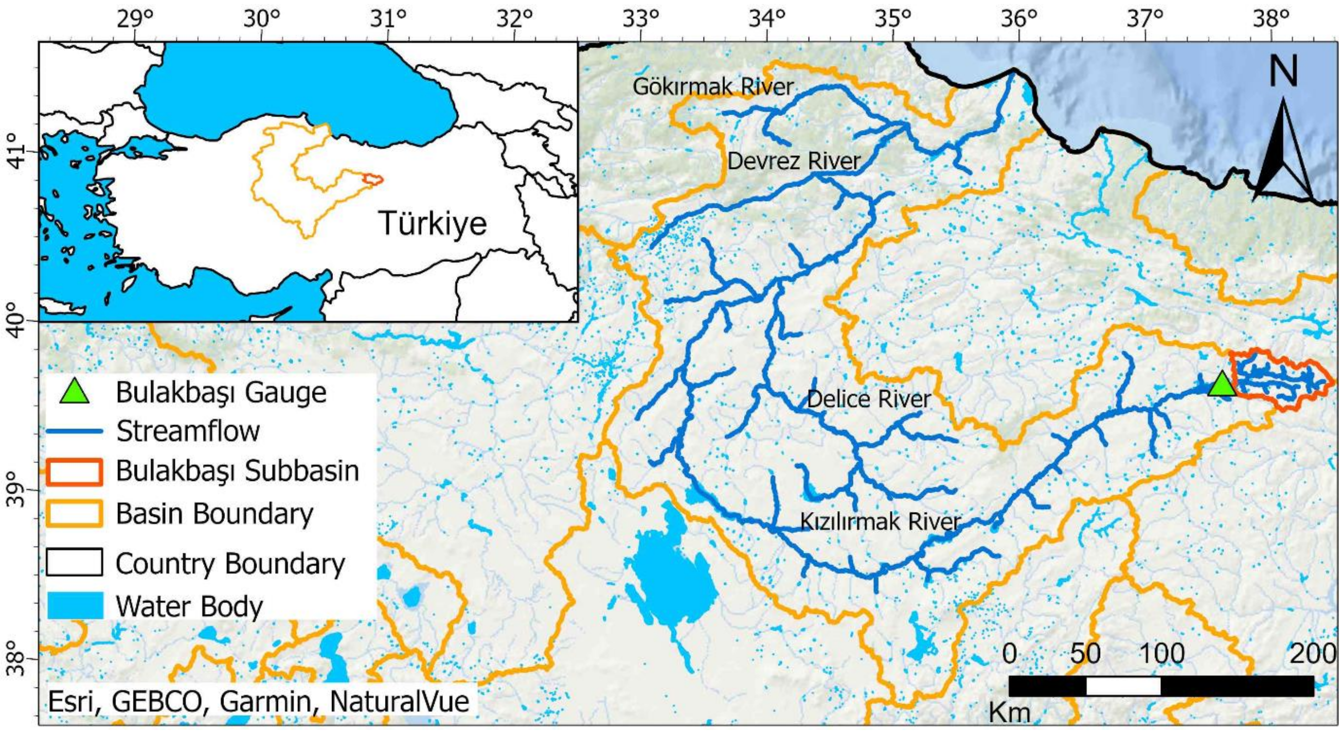

Figure 2. Location Map of Bulakbaşı Gauge and The Kızılırmak Basin

Table 1. Descriptive Statistics of The Data Used in The Study

	Min	**Mean**	**Max**	**Standard Deviation (SD)**	**Skewness (C_s)**	**Kurtosis (C_k)**
Q (m^3/s)	0.36	15.93	119.60	24.61	2.72	10.78
SSL (ton/day)	0.51	1536.01	30138.23	4173.68	4.02	18.32

Support Vector Machine (SVM)

SVM, which is widely used in classification and regression problems, was introduced by Vapnik (1995). The application of SVM to classification and regression problems has some differences. Figure 3 shows an illustration of how SVM is applied to classification and regression problems.

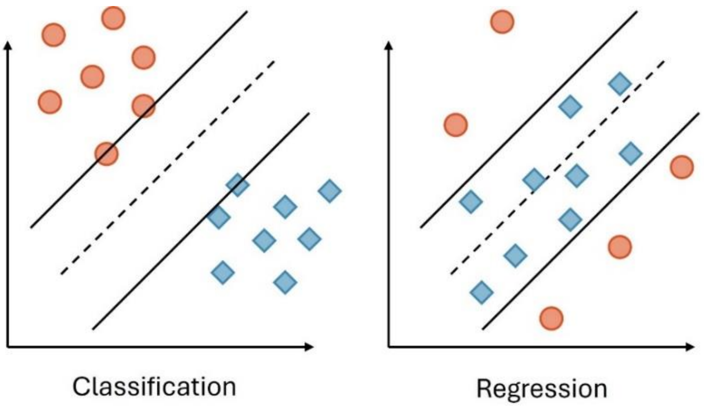

Figure 3. Conceptual Illustration of SVM for Classification and Regression Problems

In this study, the regression adaptation of SVM is used. It can produce successful results in solving linear and nonlinear problems. Its working principles are based on structural risk minimization and statistical learning theory

(Koycegiz and Buyukyildiz, 2019). There are two versions of SVM used in regression problems, Nu (υ-SVR) and Epsilon (Ɛ-SVR). Ɛ-SVR was used in this study. Ɛ-SVR has three parameters that have a significant impact on model success. These are the kernel function parameters (γ) which vary depending on the kernel function selected, the insensitive error term (Ɛ), and the regularization factor (C). The Radial Basis Function (RBF) was chosen as the kernel function. The following objective function is used to apply SVM to nonlinear problems.

$$f(x) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(x, z) + b_i \quad (1)$$

where $K(x, z)$ is the kernel function, $(\alpha_i - \alpha_i^*)$ is the Lagrange multipliers and b_i is the bias. The RBF kernel function chosen in this study is given below.

$$K(x, z) = exp\left(\gamma \left\| x_i - x_j \right\|^2\right) \quad (2)$$

where γ is the kernel function parameter for RBF. For more detailed information on the theoretical background, please see references (Hamida et al., 2020; Miao et al., 2024; Misra et al., 2009).

Adaptive Boosting (AdaBoost)

The AdaBoost machine learning model is characterized as an ensemble model in which weak learners collaborate to produce a stronger learning framework. The AdaBoost algorithm proposed by Freund and Schapire (1995, 1996, 1997) is designed to be successfully applied to a variety of problems, in some cases weaker but from a fairly general perspective. AdaBoost achieves excellent outcomes in hydrological problem solving by effectively utilizing decision trees. It may be less susceptible to overfitting in certain of the problems it addresses. It's also a popular model among boosting algorithms (Zounemat-Kermani et al., 2021). Three parameters of the AdaBoost model significantly affect the model's success. Therefore, optimizing these parameters is vital for building a consistent model. These parameters are the number of estimators (n_estimators) learning rate (lr) and loss function type (Freund and Schapire, 1997). In this study, we tested 3 different loss function types: linear (ln), square (sq), and exponential (ex).

AdaBoost basically aims to create a strong prediction architecture with the help of error functions by weighting the predictions of weak learners. Accordingly, the following equation summarizes the general working principle of the AdaBoost algorithm.

$$f(x) = \sum_{i=1}^{N} \alpha_i \, . \, h_i(x) \qquad i = 1, 2, 3, \ldots, N \quad (3)$$

$$\alpha_i = \frac{1}{2} \log\left(\frac{1 - e_i}{e_i}\right) \quad (4)$$

$$Linear\ Loss\ Function\ L(y_o, y_M) = |y_o - y_M| \quad (5)$$

$$Square\ Loss\ Function\ L(y_o, y_M) = (y_o - y_M)^2 \quad (6)$$

$$Exponential\ Loss\ Function\ L(y_o, y_M) = e^{-y_o \cdot y_M} \quad (7)$$

where α_i, the weight of the weak learner, e_i, error rate of the weak learner and $h_i(x)$ represents the prediction of the weak learner. AdaBoost aims to minimize the objective function. In this equation, weights are determined according to loss functions. The objective function is updated so that the weight of the learner with more loss is less and the weight of the learner with less loss is more. Thus, a progressively stronger prediction model is obtained from weaker learners (Hastie et al., 2009).

Generalized Regression Neural Network (GRNN)

GRNN can be defined as a network architecture based on the artificial neural network model, which was introduced to produce more successful solutions to regression problems. In addition to regression, it is also used in prediction and classification problems. Due to its fast convergence, it can be used to analyze online dynamic systems. It is a variation of the Radial Basis Neural Network (RBNN) (Naghizadeh et al., 2024). It was first proposed by Specht

(1991). It requires little data to train. It can cope with noise in the inputs. It is optimized with few parameters, making it very useful. In GRNN, the spread parameter (n) is defined as a variable upon optimization. The outputs of the GRNN model are calculated with the help of the following equations. GRNN includes two additional layers: pattern and summation layers. The pattern layer realizes the nonlinear behavior of the model. Improvement is done by adding spread parameter (n) to this layer. The summation layer of GRNN contains two types of neurons. These are summation neurons (S) and single-division neurons (D). Thus, GRNN is a highly effective model that can converge quickly by establishing a strong relationship between input and output.

$$E_i^2 = (X - X_i)^T (X - X_i) \tag{8}$$

$$S = \sum_{i=1}^{k} y_i \ exp\left(-\frac{E_i^2}{2n^2}\right) \tag{9}$$

$$D = \sum_{i=1}^{k} exp\left(-\frac{E_i^2}{2n^2}\right) \tag{10}$$

$$Y(x) = \frac{S}{D} \tag{11}$$

where E is the Euclidean distance from X, k is the number of neurons, T is the matrix transpose operation, X is the input and Y is the output. For detailed information on the theoretical background of GRNN, see references (Cai et al., 2021; Cigizoglu, 2005; Naghizadeh et al., 2024).

Seasonal-Trend Decomposition Using LOESS (STL)

The method is a decomposition method commonly used in various sectors, particularly economics, meteorology, health, and marketing, to identify seasonal, trend, and residual components in time series. The foundations of the method were laid by Cleveland (1979). Afterward, it was gradually developed and reached the current version applied in this study (Cleveland et al., 1990; Cleveland and Devlin, 1988). STL's decomposition technique relies on local regression. The trend component is derived from the slopes of a region. It is particularly successful at detecting trends and seasonal regularity in nonlinear issues (Lafare, et al., 2016). In this study, only the seasonal component (S_t), which reflects the periodicity of the time series, was used to investigate its effect on the success of machine learning methods.

There are two different implementations of the STL method, additive and multiplicative. In this study, the additive method is used. The additive method is recommended as a highly effective method if no significant variations of the standard deviation are observed during the period under study (Yang and Li, 2023). The equation for the additive method is given below.

$$Y_t = S_t + T_t + R_t \tag{12}$$

where Y_t is the original time series of SSL, S_t is the seasonal component of SSL time series, T_t is the trend component of the original time series, and R_t is the residual component of the original time series.

Evaluation Metrics

Nash-Sutcliffe Efficiency (NSE) coefficient was used as the objective function to determine the optimum parameter set of the models. However, various performance metrics were applied to observe the model performance from different perspectives. The equations and references for these performance metrics can be found in Table 2. Here we denote the simulated SSL y_M, the observed SSL y_o, and the total number of data N. $\overline{y_m}$ and $\overline{y_o}$ represent the means of the simulated and observed SSL time series. Statistical metrics (minimum, mean, maximum, standard deviation, skewness, and kurtosis) were also used to evaluate model performance.

Table 2. Equations and References of The Performance Metrics Used in The Study

Performance Metric	Equation	Reference
Coefficient of Determination (R^2)	$\frac{\left[\sum_{i=1}^{N}(y_O-\overline{y_O})(y_M-\overline{y_M})\right]^2}{\sum_{i=1}^{N}(y_O-\overline{y_O})^2\sum_{i=1}^{N}(y_M-\overline{y_M})^2}$	(Wright, 1921)
Nash–Sutcliffe Efficiency (NSE)	$1-\frac{\sum_{i=1}^{N}(y_O-y_M)^2}{\sum_{i=1}^{N}(y_O-\overline{y_O})^2}$	(Nash and Sutcliffe, 1970)
Root Mean Square Error (RMSE)	$\sqrt{\frac{\sum_{i=1}^{N}(y_O-y_M)^2}{N}}$	(Hodson, 2022)
Mean Absolute Error (MAE)	$\frac{\sum_{i=1}^{N}\lvert y_O-y_M\rvert}{N}$	(Hodson, 2022)

RESULTS

Model Structure and Calibration

In this study, different combinations of inputs are constructed using runoff (Q_t), runoff lag (Q_{t-1}), and the seasonal component of SSL (S-SSL_t). As a result, 6 models are obtained. The input-output combinations of the 6 models used in the study are presented in Table 3. The first three models include only the runoff time series, while the last three models include the seasonal component of the SSL. 70% of the time series were used for training and 30% for testing. Based on the general assumption that SSL data are log-normally distributed (Holtschlag, 2001), a logarithmic transformation was applied to the data.

Table 3. Input-output Structure of Models

Models	Input Parameters	Output
M1	Q_t	
M2	Q_{t-1}	
M3	Q_t, Q_{t-1}	SSL_t
M4	Q_t, S-SSL_t	
M5	Q_{t-1}, S-SSL_t	
M6	Q_t, Q_{t-1}, S-SSL_t	

The search space and the optimum parameter sets of the machine learning model parameters that significantly affect the model performance are given in Table 4. In this study, the Grid Search (GS) algorithm was used to determine the optimum parameter set in the search space of machine learning models. GS, which is widely used in model optimization, is effective in machine learning and produces solutions with low computational costs depending on the data set (James et al., 2021).

Performance of Models in Simulating Suspended Sediment Load

Training and testing performance metric statistics for 6 input combinations of AdaBoost, SVM, and GRNN models are given in Table 5. RMSE and MAE values given in Table 5 are for normalized data. High values in R^2 and NSE and low values in RMSE and MAE mean better prediction accuracy. Accordingly, the metric values of the most successful scenarios for each method are indicated in bold in Table 5.

Table 4. Optimal Parameters of Machine Learning Models

Models	Parameters	Search Space	Increment	M1	M2	M3	M4	M5	M6
AdaBoost	n_estimators	10-50	1	39	10	13	28	14	24
	Loss function	ln, sq, ex	-	ex	ex	ln	ex	ex	ln
	lr	0.01-0.5	0.01	0.08	0.29	0.39	0.24	0.02	0.37
SVM	C	1-100	1	99	1	40	93	1	69
	ε	0.01-5	0.01	0.04	0.01	0.02	0.03	0.04	0.03
	γ	0.1-8	0.1	0.20	0.10	7.70	0.50	8.0	0.70
GRNN	n	0.01-1	0.01	0.18	0.17	0.1	0.16	0.1	0.13

Table 5. Performance Metrics for 6 Input Combinations of AdaBoost, SVM, and GRNN Models

Method	Scenario	Train				Test				Performance Rating
		R^2	NSE	RMSE	MAE	R^2	NSE	RMSE	MAE	
AdaBoost	**M1**	0.895	0.895	0.865	0.675	0.854	0.747	1.153	0.953	Good
	M2	0.369	0.367	2.126	1.666	0.227	0.173	2.084	1.692	Unsatisfactory
	M3	0.901	0.900	0.846	0.658	0.842	0.746	1.154	0.946	Good
	M4	0.910	0.909	0.805	0.630	**0.852**	**0.765**	**1.110**	**0.935**	Very good
	M5	0.639	0.634	1.617	1.169	0.498	0.498	1.623	1.140	Unsatisfactory
	M6	**0.915**	**0.914**	**0.783**	**0.625**	0.846	**0.765**	1.112	0.936	Very good
SVM	**M1**	0.881	0.881	0.922	0.709	0.864	0.790	1.050	0.859	Very good
	M2	0.293	0.259	2.300	1.688	0.285	0.283	1.940	1.435	Unsatisfactory
	M3	0.900	0.900	0.845	0.629	0.873	0.820	0.973	0.766	Very good
	M4	0.897	0.896	0.859	0.634	0.875	0.831	0.942	0.762	Very good
	M5	0.618	0.612	1.665	1.050	0.569	0.558	1.523	0.996	Satisfactory
	M6	**0.912**	**0.912**	**0.793**	**0.588**	**0.893**	**0.863**	**0.848**	**0.687**	Very good
GRNN	**M1**	0.867	0.835	1.087	0.846	0.843	0.798	1.031	0.828	Very good
	M2	0.288	0.279	2.269	1.790	0.287	0.269	1.959	1.572	Unsatisfactory
	M3	0.883	0.880	0.927	0.711	0.836	0.793	1.043	0.837	Very good
	M4	0.886	0.873	0.954	0.729	**0.850**	**0.834**	**0.934**	0.741	Very good
	M5	0.673	0.667	1.542	1.066	0.556	0.552	1.534	1.079	Satisfactory
	M6	**0.917**	**0.912**	**0.791**	**0.599**	0.843	0.830	0.945	**0.737**	Very good

Accordingly, while the M6 combination produces the best results among the three models in the training period, this situation varies in the test period. In the training period, the R^2 and NSE metrics for the most successful combinations generally have values between 0.912 and 0.917. In SSL estimation, the error metrics (RMSE and MAE) in the most successful scenarios obtained in all three methods ranged between 0.588-0.793 for the training period. In general, it was decided which method is more successful in SSL prediction according to the NSE value with the highest value in the test period. In the test period, the best successful combinations are M4 for AdaBoost, M6 for SVM, and M4 for GRNN. However, it is seen from Table 5 that metric values very close to the M4 scenario are also obtained in the M6 scenario in AdaBoost and GRNN. While the R^2 and NSE values in the scenarios with the most successful estimation success for all three methods in the test period varied between 0.765 and 0.893, the error metrics varied between 0.687 and 1.11. According to these findings, we can say that results with high prediction accuracy were obtained for all three models. However, when compared to the other models, the SVM-M6 model has the best simulation performance with R^2=0.893, NSE=0.863, RMSE=0.848, and MAE=0.687 values according to the test period. On the other hand, when the performance metrics are analyzed, it is observed that the first three models (M1, M2, and M3) without the seasonal component generally have lower performance compared to the last three models (M4, M5, and M6).

In AdaBoost models, in the M1 scenario where Qt is used as input, the R^2 (NSE) values were obtained as 0.895 (0.895) and 0.854 (0.747) for the training and testing periods, respectively. On the other hand, in the M4 scenario where Q_t and the seasonal component of SSL (S-SSL_t) are used as input, these metrics were obtained as 0.910 (0.909) for the training period and 0.852 (0.765) for the testing period. Similarly, when comparing the M2 (O_{t-1}) and M5 (Q_{t-1} and S-SSL_t) scenarios, it is observed that the inclusion of the seasonality component obtained with the SLT decomposition technique increases the forecast success according to the R^2 and NSE metrics for both the training and testing periods. According to Table 3, unlike M3, in the M6 scenario, Q_t is used as an input in S-SSL_t together with Q_{t-1} inputs, and increases in R^2 and NSE metrics are obtained in the M6 scenario compared to M3, where seasonality is not included. The fact that SSL prediction accuracy increases in the scenarios where S-SSL_t is included as input, i.e. in M4 compared to M1, in M5 compared to M2 and in M6 compared to M3, is also supported by the lower values obtained in RMSE and MAE metrics for AdaBoost models (Table 5). If a similar evaluation made for AdaBoost is made in the other two models, when the scenarios (M1-M4, M2-M5, and M3-M6) in which the seasonality effect is included and not included as input are compared with each other in both SVM and GRNN models, it is seen that the inclusion of S-SSL_t increases R^2 and NSE, while decreasing RMSE and MAE. This shows that the SLT data decomposition technique improves SSL prediction accuracy in all models used.

According to Moriasi et al. (2007), the performance ratings in the prediction models are" unsatisfactory" for NSE≤05, "satisfactory" for 05<NSE≤0.65, "good" for 0.65<NSE≤0.75, and "very good" for 0.75<NSE≤1, respectively. According to these criteria, the performance rates obtained in each scenario and each model for the test period are given in Table 5. The performance ratios given in Table 5 show that the degree of success increases in scenarios where the seasonal effect is used for some methods. In addition, the performance rates given for the test period show that all three methods used, namely AdaBoost, SVM, and GRNN, generally produced SSL predictions with high accuracy. The scenario where the lowest estimate was obtained in all three methods is the M2 scenario where Q_{t-1} with the "unsatisfactory" performance rating is used as input. The fact that M2 has the lowest performance among scenarios where S-SSL_t is not used as input and M5 has the lowest performance among scenarios where S-SSL_t is used as input shows that the input parameter Qt-1 used in both scenarios is the input with the lowest effect. It is observed that the observation and model statistics for the train and test periods given in Table 6 confirm the results obtained from the evaluation metrics in Table 5. In addition, according to the statistical features given in Table 6, it is seen that the model that gives the closest results to the observation data in the training and test periods is SVM-M6.

Table 6. Statistical Performance of The Most Successful Input Combination of Each Model

	Train				Test			
	Observation	**AdaBoost-M4**	**SVM-M6**	**GRNN-M4**	**Observation**	**AdaBoost-M4**	**SVM-M6**	**GRNN-M4**
Min	1.00	1.86	1.03	3.78	2.33	3.76	3.51	7.46
Mean	1520.30	1002.36	1323.93	696.58	1570.77	1080.97	1131.57	647.02
Max	30138.23	7630.59	35981.64	8653.96	23700.36	7510.14	14928.22	5009.62
SD	3914.69	1872.96	3590.83	1352.15	4695.79	2036.60	2662.98	1174.45
C_s	4.35	2.06	5.54	2.90	3.58	2.08	3.19	2.05
C_k	23.52	3.33	42.07	10.37	11.99	3.09	10.40	3.19

Comparison of the Most Successful Simulations

After examining the performance metrics, AdaBoost-M4, SVM-M6, and GRNN-M4 were found to be the most successful models. The time series and scatter diagrams of these models for the training and test phases are given in Figure 4 and Figure 5, respectively. Accordingly, it can be said that all models produce results consistent with the observations. However, there are minor differences. Compared to the observation data, GRNN-M4 is less successful in capturing the peaks. Peak and dip timing of all models are quite consistent. SVM and AdaBoost were more successful in catching the peaks. For low SSL values, it was determined that SVM performed the most successful simulation, while GRNN showed overestimated performance. The models showed similar behavior in the training and testing phases. The models successfully simulated high SSL during periods of high flow and low SSL during periods of low flow.

To compare the observation and simulation time series, a Scatter diagram in Figure 5 shows the distributional comparison of the three most successful models. Accordingly, AdaBoost and SVM show similar behavior in the training phase. GRNN has a deviation in low data and a scatter in high data. However, in general, it can be said that consistent results are produced in all three models. In the test phase, no significant outliers were observed in all three models. This can be considered as another sign that all three models produce satisfactory results.

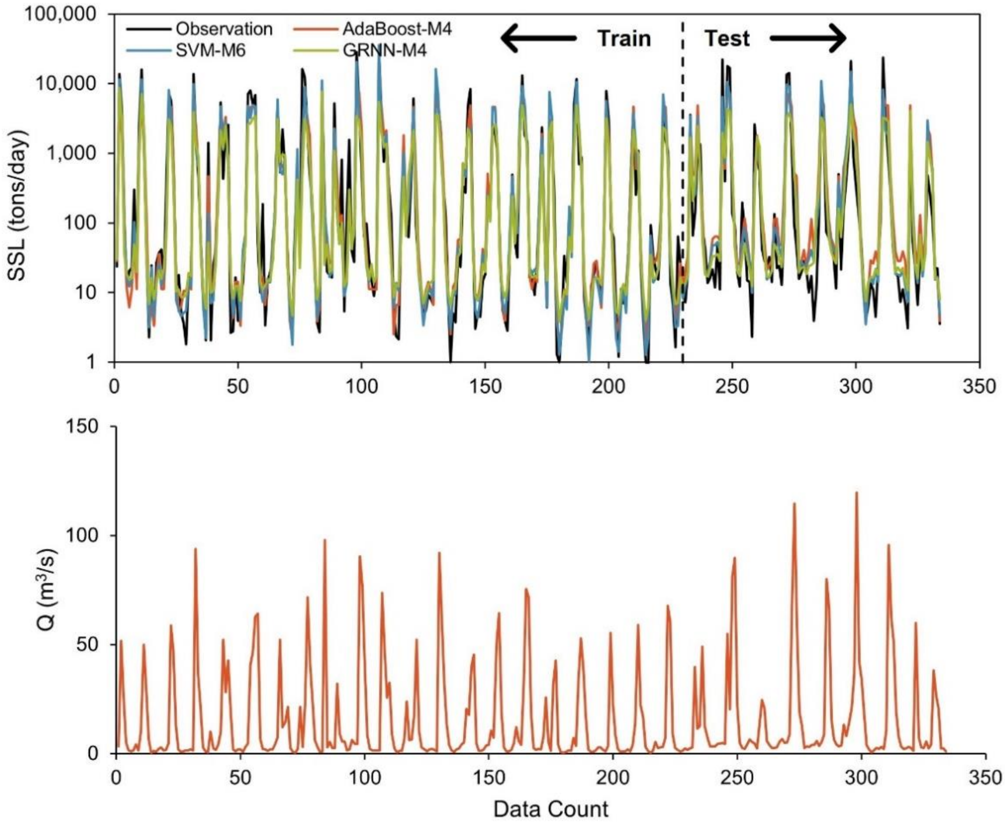

Figure 4. Time Series of The Most Successful Input Combination of The Three Models, SSL and Runoff (Q) Time Series

DISCUSSION

In this study, the prediction performance of machine learning-based algorithms for SSL obtained from the Bulakbaşı gauge in the Kızılırmak Basin is analyzed. In addition to algorithms such as SVM and GRNN, which produce consistent results in many different problems, AdaBoost, an ensemble model, was also used in the study. In addition, the STL method, in which the seasonal component is obtained in addition to the runoff lags, was also applied to determine the input combination. According to the findings, AdaBoost-M4, SVM-M6, and GRNN-M4 models produced quite consistent results. To the test statistics, the SVM-M6 model produced more successful results among these three models. However, the prediction performance of all three models is quite satisfactory. The use of the seasonality component (S-SSL_t) obtained with the STL technique increased the NSE performance between 2.4% and 5.2% in the M4 and M6 scenarios compared to the M1 and M3 scenarios where S-SSL_t was not used, in general for the test period in all three models. According to Table 5, the prediction accuracy is at the level of “good” and “very good” according to the performance ratings given by Moriasi et al (2007) in the M1 and M3 scenarios with AdaBoost, SVM and GRNN models. Therefore, the STL technique provided lower improvement performance in scenarios where success was already high, such as in the M1 and M3 scenarios. However, in the M5 scenarios obtained by adding the S-SSL_t component to the M2 scenario where performance was low, model performances increased by 188% (2.9 times) for AdaBoost, 97% (2 times) for SVM and 105% (2 times) for GRNN compared to NSE in the test period. And overall, it increased the success from "unsatisfactory" to "satisfactory" level in all three models. These results show that the STL technique is especially effective in improving the performance of low-performing ML models.

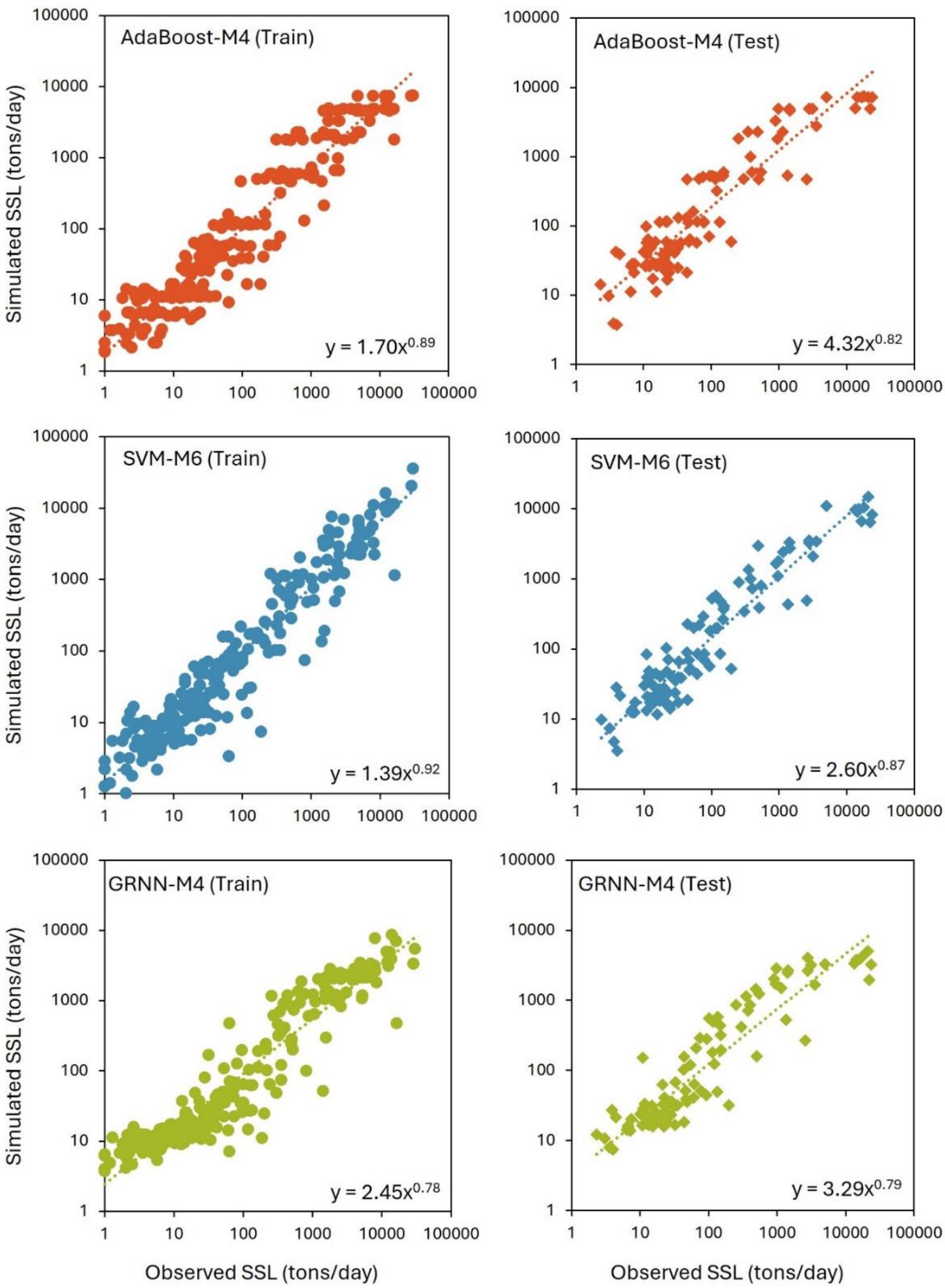

Figure 5. Scatter Plots of The Most Successful Input Combination of The Three Models

In the literature, studies are using various techniques on the prediction performance of SSL. Piraei et al. (2023) examined the prediction performance of sediment measurements of 93 rivers obtained from the United States Geological Survey (USGS) with various machine learning algorithms. According to the results obtained, the XGBoost model, which is an ensemble model among many algorithms including eXtreme Gradient Boosting

(XGBoost), Artificial Neural Networks (ANN), Gradient Boost Regressor (GBR) algorithms, showed the most successful prediction performance. Sharafati et al. (2020) simulated sediment transport in the Mississippi River with machine learning models. As a result, AdaBoost, GBR and random forest regression (RFR) models performed above 0.9 in R^2 and NSE statistics. There are also examples where different stand-alone and hybrid versions of SVM are used in sediment modeling studies (Samantaray and Sahoo, 2022; Samantaray et al., 2020). The test statistics obtained within the scope of the study also show consistency in terms of model performance.

Nourani et al. (2019) compared the performance of ANN, Wavelet-ANN (W-ANN), M5 Model Tree (M5), and Wavelet-M5 (W-M5) models in estimating daily and monthly SSL of Lighvanchai River in northwestern Iran and Upper Rio Grande river in western USA. The results showed that the performance of hybrid models (W-ANN and W-M5) was higher than the single models (ANN and M5) for both training and validation periods in predicting the SSL phenomenon. Applying the wavelet transform improved the performance of the ANN model for the Lighvanchai River by 13% and 62% on daily and monthly time scales, respectively, while it improved the performance of the M5 model by 10% and 30% (according to the NSE metric in validation period). For the SSL of the Upper Rio Grand River, WT-ANN models increased the prediction success by 58% and 2.56 times on daily and monthly scales, respectively, while WT-M5 models increased it by 19% on a daily scale and 23% on a monthly scale. For all models, the prediction successes were higher in Lighvanchai River than in the Upper Rio Grand River. In addition, the prediction successes obtained on a daily scale were also better than the monthly scale successes. In terms of overall performance, both single and hybrid M5 models showed higher success in SSL prediction in both rivers. Himanshu et al. (2017) used data obtained from measurement stations and satellite images for the estimation of daily SSL for the period 1998-2013 in two basins (Marol and Muneru) in South India. They applied single SVM and hybridized SVM with wavelet analysis (WASVM) methods in SSL estimation. The findings showed that the accuracy of WASVM in SSL prediction was higher than single SVM.

Sediment studies in the Kızılırmak River have focused on the measurement and monitoring of pollutants and heavy metals. However, some studies simulate sediment transport. Kisi et al. (2009) used adaptive neuro-fuzzy computational techniques for modeling at gauging stations on the Kızılırmak River. Neuro-fuzzy, artificial neural networks, and sediment rating curve models produced successful results, respectively. The consistent performance statistics obtained by Kisi et al. (2009) are in parallel with this study. Acar (2019) examined the prediction performances of ANN and wavelet transformed-ANN (WT-ANN) models at various stations in the Kızılırmak River. It was found that model prediction performance increased with wavelet transformation. The fact that the seasonal decomposition method increased the prediction performance in this study shows that various decomposition methods improve SSL model prediction performance. In addition, findings similar to the performance statistics obtained by Acar (2019) at Bulakbaşı station were obtained within the scope of this study. Acar (2019), who investigated the effect of WT on the prediction performance of the ML model for SSL prediction in various sections of the Kızılırmak Basin, found that the success increased significantly. Accordingly, a performance increase of 10-30% was observed at the examined stations.

Researchers have focused on some factors, basic difficulties, and limitations affecting the performance of models used in SSL estimation. Nourani et al. (2019) reported that both temporal scale and basin behavior are effective in the estimation performance of the models. It has been suggested that SSL, which is a complex hydrological phenomenon by nature, is affected not only by flow but also by several hydraulic, hydrographic, meteorological and basin structure-related complex factors such as evaporation, temperature, precipitation, precipitation intensity, basin topography, land use, soil properties (Himanshu et al., 2017; Pandey et al., 2016; Merritt et al., 2003). In addition to these factors affecting SSL, the processes of the models to be used (such as input variables, data availability, model efficiency, model capability, required hardware, and expert knowledge) also affect prediction success (Pandey et al., 2016). Due to the complex nonlinear structure of SSL, the necessity of a complete data screening procedure for reliable estimation has limitations attributed to the simplification of boundary conditions and important parameters in the model processes to be used in rivers or basins with dominant hydrological behavior (Shiri et al., 2022; Nourani et al., 2019).

Another limitation is that in the studies in the literature, researchers generally conducted their studies with a limited number of stations/rivers/basins in the ML applications they used in SSL estimation. This means that a generalization cannot be made regarding the use of ML successes obtained in the studies conducted in every basin, river, or station (Fang et al., 2022). The behavior of SSL depends on many natural factors mentioned above which vary spatially, as well as anthropogenic effects. Therefore, an ML method suitable for one region may not be suitable for another region. In addition, the inadequacy of meteorological and hydrological data affecting SSL also limits the use of data-based ML methods, especially in ungauged basins.

One of the main limitations of our study is that SSL measurements are not available at equal time intervals and for long periods. In this case, machine learning-based algorithms have difficulty in discovering seasonal patterns. In addition, due to the long computation time, the search space was run in parameter spaces commonly used in the literature. Parameter optimization in a wider search space on computers with high computational power may affect the model prediction performance. In addition, conducting prediction studies at all stations along the Kızılırmak River may provide important information on SSL dynamics. In this case, the importance of data acquisition comes to the forefront again. Within the scope of this study, care has been taken to use the most reliable data period that is available.

CONCLUSION

In this study, many machine learning models were used to assess suspended sediment load. The data for this instance came from the Bulakbaşı station on the Kızılırmak River. The seasonal component of sediment, as well as runoff lags, were taken into account while determining input combinations. Sediment forecasting performance is evaluated using six different input combinations and three machine learning models, as well as several performance measures. Significant findings are included below.

• Among the various model and input combinations, SVM achieved the best prediction performance with input combinations including runoff series, 1-time step lag of runoff, and a seasonal component of sediment, while AdaBoost and GRNN achieved the best prediction performance with input combinations including runoff series and a seasonal component of sediment.
• All three models performed quite consistently in prediction. SVM was the most successful model among them.
• The seasonal component of sediment significantly improved the forecast performance in all models.
• Suspended sediment load is directly connected to flow. The suspended sediment load is considerable in measurements with high flow, whereas it is modest elsewhere.
• It was found that flow lag had a much lower impact on model performances than the flow and seasonal sediment components.

The main limitation of the study is that the sediment phenomenon is influenced by a wide variety of factors and model successes may change their behavior under different conditions. The station used in the study (Bulakbaşı) is quite important in terms of the basin in which it is located. However, spatial distribution should be investigated to deeply understand the sediment transport process of the basin. This is one of the limitations of the study. The limited frequency of measurements taken within the time period considered in the study limits the investigation of temporal variability. Increasing the frequency of measurements may allow the analysis of sediment transport before and after flood catastrophes.

It is hoped that this study, which is thought to be the first application of the STL data decomposition technique in sediment estimation, will contribute to the relevant literature, guide private and legal practitioners, and help the use of accurate and appropriate techniques for SSL estimation, which is a challenging hydrological phenomenon. Additionally, we hope that such studies will be useful in river basins where there is little or no adequate information about the hydrological processes occurring.

In future studies, it is planned to test the performance of the STL data decomposition technique by hybridizing it with different learning models (metaheuristic, ensemble, etc.) and comparing it with hybridized models with different data decomposition tools, to examine it in basins with different characteristics and at different time scales, to investigate its effectiveness in study areas where human impacts and climate change effects are intense, and to test its usability in estimating various hydro-meteorological parameters in addition to sediment, and it is recommended to researchers.

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