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THE FLOW-RATE PREDICTION IN ERGENE WATERSHED

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Abstract: This paper presents an experimental study about prediction of the highest monthly average flow-rate of the Ergene River. Hydro-meteorological data from Luleburgaz Meteorology Station (MS) and Luleburgaz Flow Observation Station (FOS) have been used for prediction. Ergene watershed has point and non-point sources pollution and has seasonal floods. The study area is located in the middle of the watershed. First of all, hydro-meteorological data of all months between 1995 and 2017 were obtained from Luleburgaz FOS. After that, the relationship between the data were modeled by Artificial Neural Network (ANN), Multiple Linear Regression (MLR) and Support Vector Machine (SVM). Also, the monthly flow-rate of Ergene River Luleburgaz Station is predicted annually for the years 2017 and 2018. The results demonstrate that the ANN, MLR and SVM models can predict the flow-rate with high accuracy, but the ANN is the most appropriate model to the Ergene watershed data set.

Keywords: artificial neural networks, Ergene watershed, flow-rate prediction, multiple linear regression, support vector machine

1. INTRODUCTION

Flood prediction has limitations and uncertainty because of not caused only by meteorological conditions and needs data about precipitation, temperature, topography, vegetation cover, and impermeable land area etc. In EU (European Union), with respect to legal documents, the flood is described as "the temporary covering by water of land not normally covered by water" and flood risk is described as "the combination of the probability of a flood event and the potential adverse consequences for human health, the environment, cultural heritage and economic activity associated with a flood event" (Directive 2007/60/EC, 2007). Floods lead to loss of life and property, damage to environmental resources, serious degradation of cities and agricultural lands, thereby, resulting in human migration. All these negative effects impede the development with the cessation of economic activities. Furthermore, big budgets and long periods are required to eliminate the damages caused by floods. The factors posing a flood risk include climate, land use, social and economic conditions, current technology and policies. The level of the flood risk necessitates not only assessing potential material and non-material losses, but also analyzing the negative impacts of the disaster on the environment. Some examples of these impacts are contamination and unfavourable geo-morphological processes, which permanently change the land relief and river valley. In order to reduce flood risk, the areas of a river basin which are prone to floods and the areas which require immediate action should be determined in a river basin (Directive 2007/60/EC, 2007, Glosinska, 2014).

Within the framework of flood risk management plans, certain steps should be determined for preventing floods that may occur in river basins, protection from damages and preparation processes. Flood risk management plans, should include maps of diverse scenarios, taking into account the land use and sources of environmental pollution, and should be updated considering the natural and anthropogenic changes taking place within the basin and the effects of the climate change (Directive 2007/60/EC, 2007).

Defining various flood risk levels is the initial point to determine the zones within an area that require diverse planning limitations. Such an analysis should also be utilized to review the current development plans and to introduce requisite changes to minimize the negative economic, social and ecological impact of flooding. Moreover, the analysis on the management of the flood-prone areas and the risks of flooding in urban areas may lead to a debate about the future form of the urban fabric between the city authorities and the local communities (Glosinska, 2014).

ANN is a parallel system which processes data via numerous highly interconnected neurons responding to inputs through modifiable weights, thresholds and mathematical transfer functions (Haykin, 2009). Through its parallelism property, the ANN method has been extensively employed in various fields such as water quality (Liu et. al., 2015, Nikoo et. Al. 2011, Sanders et. al., 2013), sedimentation (Olyaie et al., 2015), precipitation and river flow property prediction (Dastorani et al., 2010, Maier et al., 2010, Samli et al., 2014, Sivri et al., 2007, 2009), rainfall-runoff process (Cannas et al., 2004, Dawson & Wilby, 1998, Meng et al., 2016) in the literature. A large number of studies have demonstrated that the application of this method has led to success especially in predicting flow-rates based on hydro-meteorological data (Campolo et al., 1999, Dawson et al., 2002, Gumus et al., 2011, Lekkas et al., 2004, Minns & Hall, 1996, Seckin et al., 2010). In literature, flow-rate estimation studies are conducted by using ANN (Demirel et al., 2009, Shamseldin, 2010, Teschl & Randeu, 2006), MLR (Asati & Rathore, 2012, Rezaeianzadeh et al., 2014, Rosenberg et al., 2011, Veiga et al., 2015), fuzzy logic (Liong et al., 2000, Nayak et al., 2005), adaptive neuro-fuzzy inference system (Fırat & Gungor, 2007, Hamaamin et al., 2016, Rezaeianzadeh et al., 2014, Saez et al., 2017) and time-series model (Rosenberg et al., 2011). Some studies have made comparisons between these methods for flow-rate prediction (Asati & Rathore, 2012, Hamaamin et al., 2016, Rezaeianzadeh et al., 2014). In this study, ANN, MLR and SVM methods have been implemented, and the results of these methods have been evaluated comparatively.

Considering the Ergene River with its high flood frequency (TUBITAK-MAM., 2013), it is aimed to obtain the most-predictive and the least error-prone model so as to reveal how the following peak value of flow-rate can vary according to hydro-meteorological conditions. In line with this aim, the long-term hydrological data have been utilized in order to estimate the flow rates belonging to previous years. The next highest flow rate has been estimated by means of the ANN, MLR and SVM methods, based on hydro-meteorological data between 1995-2017. Although there are numerous studies on the pollution and the basin of the Ergene River (Bayrak Yılmaz, 2011, Bayrak Yilmaz & Sivri, 2014, Dokmeci, 2017, Emadian et al., 2021, Nigdeli et al., 2020, Orak et al., 2020, Sungur et al., 2014, Tokatli, 2020), the number of studies on flow-rates and flood prediction in the study area is quite low (Ayvaz et al., 2018, Bayrak Yilmaz et al., 2014, Kisi, 2009, Kisi & Cigizoglu, 2007, Kisi et al., 2012). There are many studies on flow-rate modeling in rivers. A summary of these studies is given in Table 1.

2. Material and Methods

2.1. The Study Area

Ergene basin, located in Meriç basin, is an inland basin and covers an area of 10733 km^2. It is surrounded by the Black Sea, Marmara Sea and North Aegean Sea (Fig. 1). The Ergene River, which is the main river of the basin, has a length of 264 km and 28.73 m^3/s average annual flow rate (TU, 2007).

The General Directorate of State Hydraulic Works operates the Ergene river FOS. Before the year 1991, FOS records show that the flow-rate of the river increases in rainy seasons, but approaches to zero at the end of the water year. The flow peaks are usually observed in early spring. Since 1991, flows have existed in the river even in dry seasons. This fact indicates that the natural flow mechanism of the river is destroyed by industrial and domestic wastewater discharges (TRMEF, 2008a, TRMEF, 2008b).

In Ergene basin; monthly average precipitation is 602.18 mm with the lowest precipitation in August, the highest precipitation registered in November and located in the northeast of the basin. Winter precipitation is generally higher than spring precipitation. It is seen that there was a long dry period between 1982-1995 and a short rainy period between 1995-2000 (TRMEF, 2008a, TRMEF, 2008b).

This study aims to predict the highest monthly average flow-rate of the Ergene River. For this purpose, hydrological data from Luleburgaz FOS and meteorological data from Luleburgaz MS have been utilized for prediction. Ergene basin has point and diffuse sources pollution with seasonal floods. The study area is in the middle of the basin. The monthly average flow-rate between 1995-2017 in Luleburgaz FOS is shown in Figure 2.

Table 1. Literature Studies about Flow-rate Modelling

Study	Method(s)	Major research focus	Findings
Adnan et al. (2017)	ANN, SVM	Streamflow Forecasting Using ANN and SVM	SVM models can be employed for prediction of monthly streamflows successfully.
Asadi et al. (2019)	ANN, NDVI, IC	Rainfall-Runoff Modelling Using Hydrological Connectivity Index and ANN	Time series inputs proved to be significantly effective in estimating monthly runoff by using ANN data-driven models, which are valuable for water resources planning and management.
Azad et al. (2018)	ANFIS EA as GA, ACOR, PSO	Prediction of river flow using hybrid neuro-fuzzy models	Whereas classic ANFIS managed to predict river flow only one day ago, EA was able to do so five days ago.
Chhantyal et al. (2016)	DANN	Flow Rate Estimation using DANNs with Ultrasonic Level Measurements	Ultrasonic level measurement of the drilling fluid in an already existing open channel is a possible alternative to expensive devices to measure flow drilling fluid.
Daliakopoulos and Tsanis (2016)	ANN, CM	Comparison of an ANN and a conceptual rainfall-runoff model in the simulation of ephemeral streamflow	ANN is superior to conventional CMs.
El-shafie et al. (2013)	ANN, regression	Rainfall-Runoff Prediction with ANN and regression techniques	ANN is capable of explaining the behaviour of rainfall-runoff connection more precisely than the classical regression model.
Ghorbani et al. (2016a)	SVM, ANN, RC, MLR	Modeling river discharge time series using SVM and ANN	Diverse performance measures demonstrate that SVM and ANN are above the results of the traditional RC and MLR models.
Ghorbani et al. (2016b)	MLP, RBF, SVM	Comparison of ANN and SVM models in predicting river flow	As regards the prediction of monthly river flow, the uncertainty in MLP and RBF models is more than that in SVM.
Granata et al. (2016)	SVR	Rainfall-Runoff Modeling in Urban Drainage	Despite having a significant potential for utilization in the area of urban hydrology, SVR has considerable limitations as to the model calibration.
Hosseini and Mahjouri (2016)	SVR, GANN	Integrating SVR and GANN for daily rainfall-runoff modeling	The prediction reliability of SVR-GANN model is generally superior to that of ANN-based models.
Kisi (2008)	FFNN, GRNN, RBF	River flow forecasting and estimation using different ANN techniques	Forecasting and estimation of the monthly streamflow could be achieved through ANN.
Kratzert et al. (2018)	LSTM	Rainfall-runoff modeling using LSTM networks	Runoff can be predict using LSTM from meteorological data with accuracies comparable to a hydrological model.
Mekanik et al. (2013)	MR, ANN	Long-term rainfall forecasting using large scale climate modes	ANN models showed better generalisation ability for different correlation coefficients.
Meshram et al. (2019)	FNN, PSOGSA	River flow prediction using hybrid PSOGSA algorithm based on feed-forward NN	FNN-PSOGSA model improves accuracy and is a feasible method in predicting the river flow.
Ni et al. (2020)	LSTM, WLSTM, CLSTM	Streamflow and rainfall forecasting by two LSTM based models	LSTM was applicable for time series prediction, but WLSTM and CLSTM were superior alternatives.
Patel and Joshi (2017)	ANN	Modeling of Rainfall-Runoff Correlations in Dharoi Watershed of a Sabarmati River Basin, India	The models can help the water resource managers operate the reservoir properly in extreme events such as flooding and drought.
Shiri and Kisi (2010)	ANFIS	Investigating hybrid wavelet-neuro-fuzzy model for daily, monthly, and yearly streamflows	WNF model increases the accuracy of the single NF models, especially in forecasting yearly streamflows.
Snieder et al. (2020)	ANN	A comprehensive comparison of four input variable selection methods for ANN flow forecasting models	This type of validation is essential for ensuring that the methods are sufficiently robust to be useable for different hydrological regions.
Sundara et al. (2016)	ANN	Rainfall-Runoff Modelling for Sarada River Basin	ANN was able to predict runoff from rainfall data reasonably well for a small semi-arid catchment area.
Unes et al. (2019)	ANN, MLR	Prediction of Rainfall-Runoff Relation with ANN and MLR	Both methods give similar values.
Wang et al. (2015)	ANN, EEMD	Prediction of medium and long-term hydrological runoff time series.	EMD can effectively enhance the forecasting accuracy of ANN.
Wu and Chau (2011)	ANN, MANN	Rainfall-runoff modeling with singular spectrum analysis	MANN does not exhibit significant advantages over ANN.

where EEMD is Ensemble Empirical Mode Decomposition, ANFIS is Adaptive Neuro-Fuzzy System, NF is Neuro-Fuzzy, WNF is Wavelet-Neuro-Fuzzy, MANN is Modular Artificial Neural Network, SVR is Support Vector Regression, GANN is Geomorphologic-Based ANN, FFNN is Feed Forward Neural Networks, GRNN is Generalized Regression Neural Networks, RBF is Radial Basis ANN, EA is Evolutionary Algorithms, GA is Genetic Algorithm, ACOR is Ant Colony Optimization for Continuous Domain, PSO is Particle Swarm Optimization, CM is Conceptual Model, DANN is Dynamic Artificial Neural Network, MLP is Multilayer Perceptron, RC is Rating Curve, LSTM is Long Short-Term Memory, FNN is Feed-Forward Neural Network, PSOGSA is Hybrid Algorithm of the Particle Swarm Optimization and Gravitational Search Algorithms, WLSTM is Wavelet-LSTM, CLSTM is Convolutional LSTM, NDVI is Normalized Difference Vegetation Index, IC is Index of Connectivity, MR is Multiple Regression, SAC-SMA is Sacramento Soil Moisture Accounting Model.

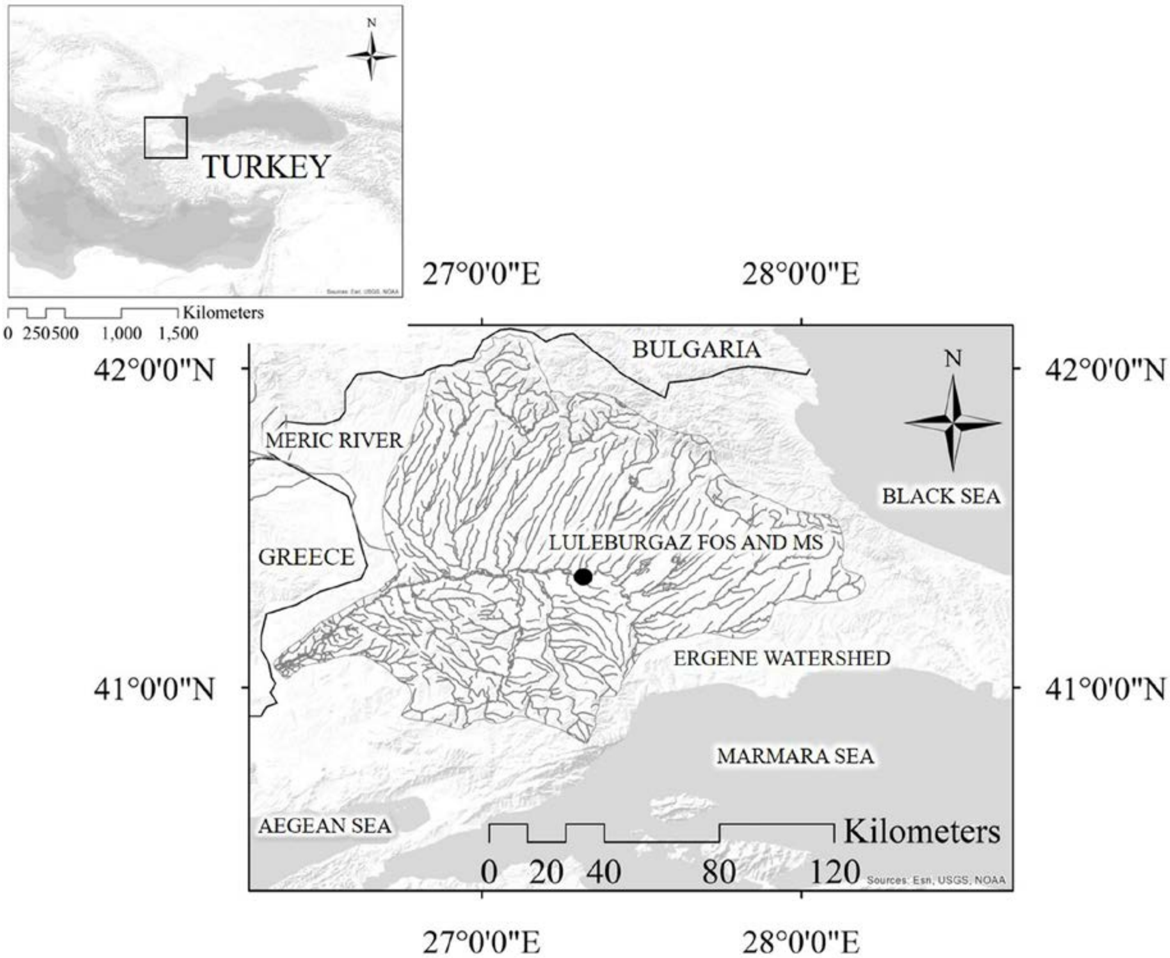

Figure 1. Ergene Watershed Geographical Location (26º35’- 42º06’)

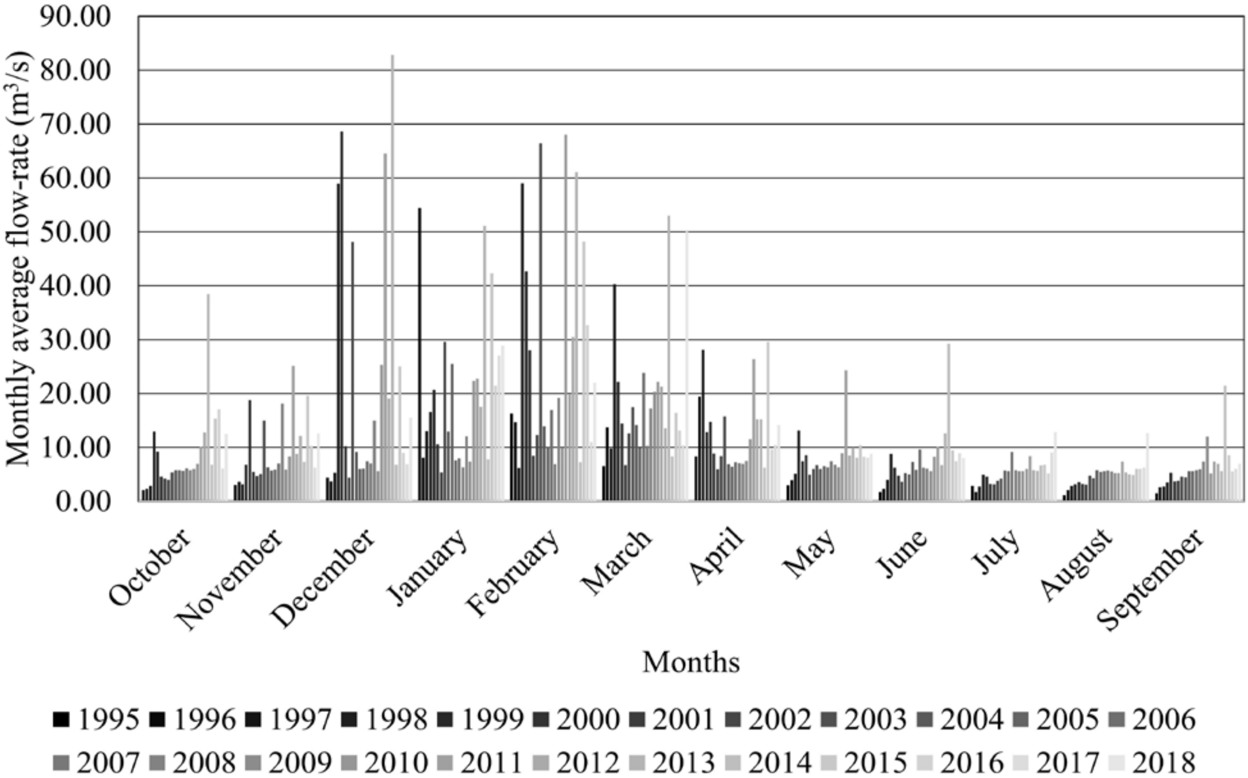

Figure 2. The monthly average flow-rate (m^3/s) between 1995-2018 in Luleburgaz FOS

2.2. Artificial Neural Networks

Inspired by the operation of biological neural networks, ANN is a computational model to process information mathematically. Researches on this topic started by modeling neurons, which are biological units of a brain, and applying it to computer systems. Later, in line with the advancements in computer systems, this approach became applicable to several fields. (Haykin, 2009). ANN has been used in various fields, especially for classification, modeling, and prediction processes (Demir et al., 2016, Wang et al., 2015). In this study, a feed-forward ANN with three layers (input layer, hidden layer, and output layer) has been used. Interconnection weights of the network are updated to minimize the error between the predicted values of the network and desired values while training a feed-forward ANN. The mathematical expression of the neurons in the hidden and output layers of such a network is defined as follows (Eq.1) (Haykin, 2009):

$$y_j = f\left(\sum_{i=1}^{m} w_{ji}\, x_i + b_j\right) \quad (1)$$

i=1,2,3,…,m; j=1,2,3,…,n

where m denotes the number of inputs, n represents the number of outputs, y_j is the output, f is the activation function, w_{ji} is the interconnection weight from ith neuron to j_{th} neuron, x_i is i_{th} input, and b_j is a bias in the j_{th} neuron.

The model used in this study is shown in Fig. 3. There are four neurons in the input layer as total flow, average flow, total precipitation and average temperature measured monthly; four neurons in the hidden layer, and one neuron in the output layer as a monthly average flow-rate value (Ha et al., 2016).

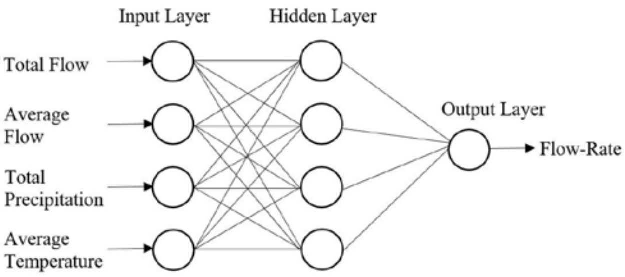

Figure 3. ANN architecture

Determining appropriate hidden neuron number for an ANN structure is a very important point. There is no a specific rule to define this value in literature. Hence, different approaches have been proposed for it. One is for the hidden layer's size to be somewhere between the input layer size and the output layer size (Blum, 1992). Swingler (1996) proposed a formula to calculate the size of the hidden layer: (Number of inputs +outputs) * (2/3). The other basic rule is that it should not be more than twice as large as the input layer (Berry & Linoff, 1997). In this study, according to preprocesses, the hidden layer's neuron number is determined as four.

MATLAB software offers an environment to implement simulation studies. 70% of the data are used for training, 15% for validation, and 15% for testing. Various training algorithms and activation functions are employed during simulations. In this study, many combinations of learning algorithm and activation functions were tried and the best result is obtained by combining the Levenberg-Marquardt learning algorithm and logsig activation function, whose formula is given below (Eq. 2).

$$\mathrm{logsig(net)} = \frac{1}{(1+e^{-net})} \quad (2)$$

To update the interconnection weight coefficients, the mean square error (MSE) function is utilized;

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{Y}_i - Y_i)^2 \quad (3)$$

where $\widehat{Y}_i$ denotes the vector of predicted values, Y_i represents the vector of real values (Wackerly and Scheaffer, 2008).

2.3. Multiple Linear Regression

MLR presents a relationship between the independent variables some of which affect the dependent variables. Regression models are classified as linear and nonlinear models (Montgomery et al., 2012). In this study, the sum of the sine model with six terms has been used. This model is defined by the equation (Eq. 4) as follows:

$$y = \sum_{i=1}^{n} a_i \sin(b_i x + c_i) \quad (4)$$

a is the amplitude, b is the frequency, c is the phase constant for each sine wave term, n is the number of terms in the series ($1 \leq n \leq 8$) (Cheng, 2015).

2.4. Support Vector Machine

SVM is a nonparametric supervised learning algorithm used for general classification and modeling. It is a popular model in classification studies because of its strength in non-linear classification. It is a helpful model for classifying various types of data such as numerical data, text, image and so on.

3. RESULTS AND DISCUSSION

Prediction of the flow-rates has been implemented by ANN, MLR and SVM methods with the data of Luleburgaz region of Ergene basin between the years 1995 and 2017. In this study, initially, ANN, MLR and SVM have been trained by the data between 1995-2016 and validated by data of 2017. In Figures 4a, 4b and 4c, the comparisons of the 2017 results between experimental data and estimated data are given for ANN, MLR and SVM modelling, respectively.

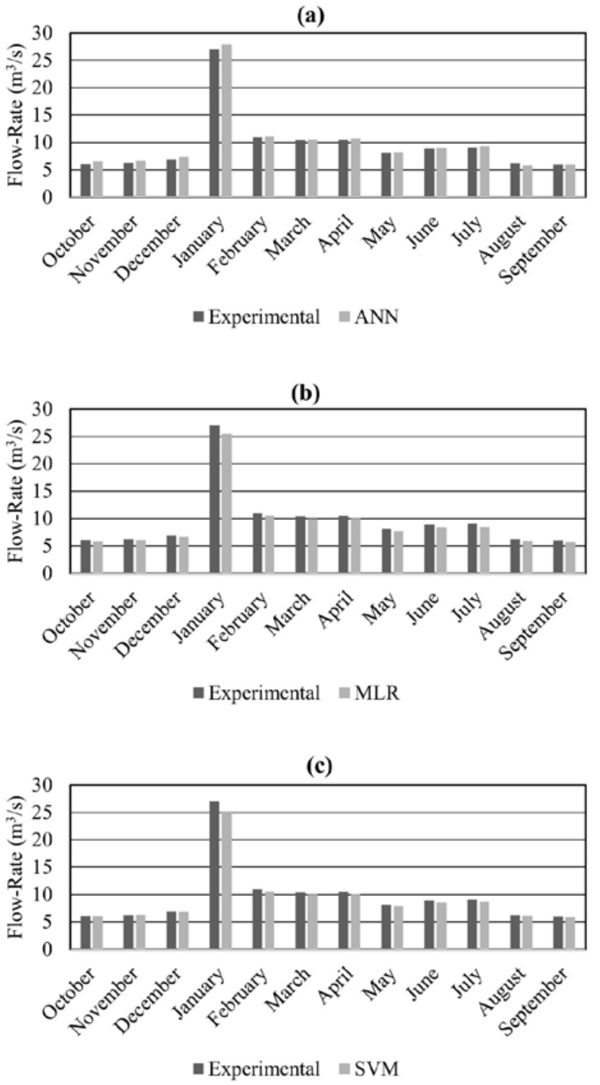

Figure 4. The comparison between experimental and predicted results of 2017

Two performance criteria have been employed in this study to assess the goodness of fit of the models: determination coefficient (R^2) and "mean absolute percentage error" (MAPE). The R^2 value, varying between 0 and 1, is a statistical measure that indicates how well the regression line approximates the observed data are to the regression line. A coefficient of 1 denotes that the fit of the regression line to the experimental data is 'perfect.' The MAPE value of < 10 indicates a high forecast accuracy, 10 - 20 indicates a good forecast accuracy, 20 - 50 indicates a reasonable forecast, > 50, on the other hand, indicates inaccuracy in forecasting (Lewis, 1982). Mean absolute percentage error (MAPE) is calculated by the difference of experimental values and obtained values (Eq. 5) (de Myttenaere et al., 2016).

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_t - \widehat{y}_t}{y_t}\right| \times 100 \qquad (5)$$

y_t, denotes experimental values whereas $\widehat{y}_t$ denotes predicted values, and n is the number of predictions.

The comparison of experimental results and all three method results for 2017 is given in Figure 5.

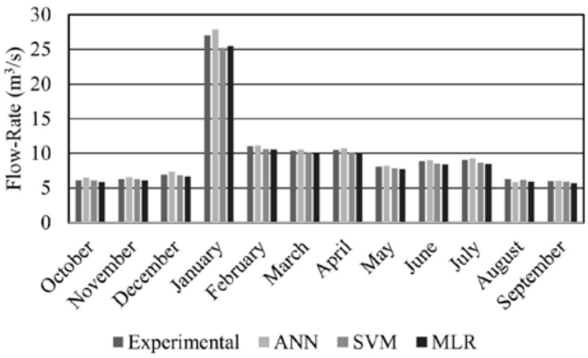

Figure 5. The comparison between experimental and ANN, SVM, MLR predicted results of 2017

The determination coefficients of the simulations are 0.9320 for ANN and 0.9334 for MLR.

Secondly, all these three methods were used to model 2018 data. In Figures. 6a, 6b and 6c, the comparisons of the 2018 results between experimental data and estimated data are given for ANN, MLR and SVM modeling, respectively.

The comparison of experimental results and all three method results for 2018 is given in Figure 7.

The determination coefficients of the simulations are 0.9348 for ANN, 0.9340 for MLR.

Mean absolute percentage errors (MAPE) for ANN, MLR and SVM of the years 2017 and 2018 are given in Table 2.

Table 2. Mean absolute percentage error (MAPE) for ANN, MLR and SVM

Years	ANN	MLR	SVM
2017	0.3753	0.5585	0.5674
2018	0.6365	1.1917	1.4302

For both 2017 and 2018, the best prediction results have been obtained by ANN. In this study, also

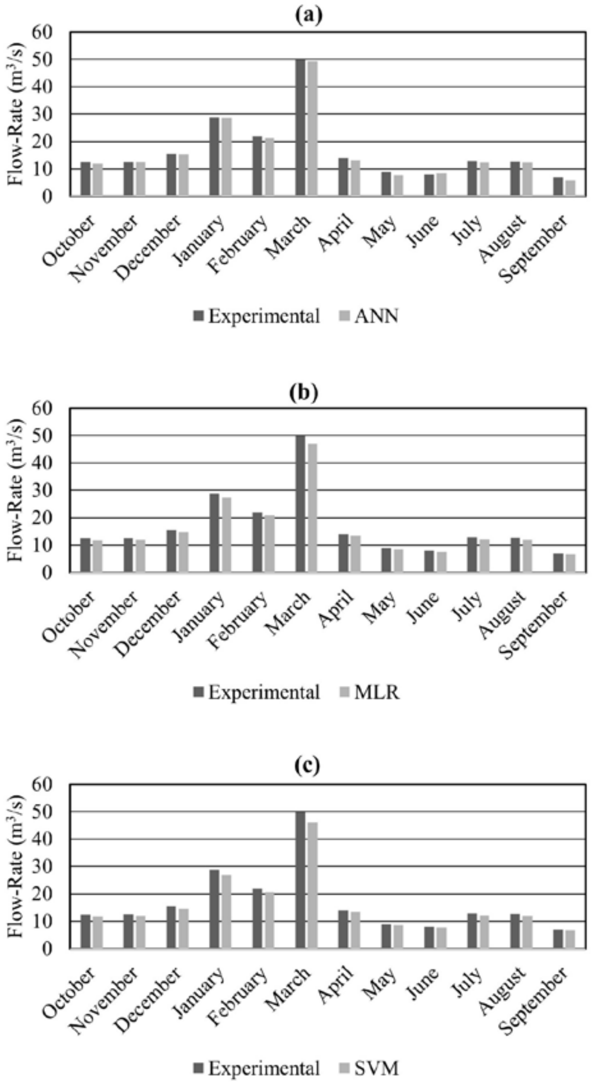

Figure 6. The comparison between experimental and predicted results of 2018

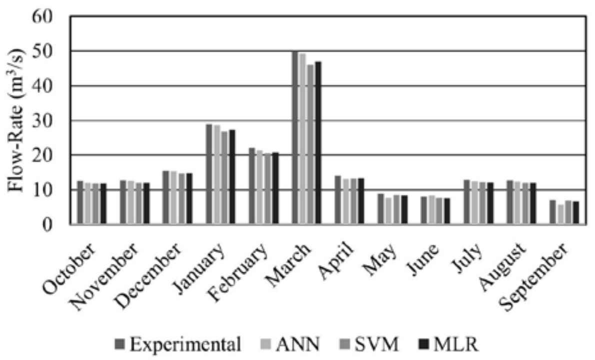

Figure **7.** The comparison between experimental and ANN, SVM, MLR predicted results of 2018

various ANN structures with different numbers of hidden neurons (3 – 10) have been used to make the simulations and to see the effect of the ANN structure on the results. It is known that there is a relationship between the number of hidden neurons and the complexity of the system. Too many hidden layer neurons provide successful training and memorizing, but unsuccessful testing and generalizing. The results for the year 2018, MAPE and determination coefficients are given in Table 3. As seen from the table, the most accurate values have been obtained with 10 neuron-ANN.

4. CONCLUSIONS

In this study, it is aimed at estimating the highest monthly average flow rate and the probability of flooding in the Ergene River Luleburgaz region. For this purpose, data from Luleburgaz FOS and MS have been used for modeling. ANN, MLR and SVM methods have been employed to evaluate data between 1995 and 2017, and to predict 2018. The accuracy of the models is demonstrated by statistical comparison of observed values and predicted values. Models have been compared in terms of prediction of monthly flow. According to the results;

1. In 2018, the highest average flow rate (50 m^3/s) is expected to be seen in March. The prediction result coincides with the observed value.
2. High R^2 (0.9348 and 0.9340, respectively) values have been determined in ANN and MLR.
3. The MAPE results for three models can be evaluated as "highly accurate".
4. According to the MAPE results, ANN has performed better than SVM and MLR, MLR than SVM.
5. The most accurate MAPE values have been obtained with 10 hidden neuron-ANN.
6. The results show that ANN, MLR and SVM are suitable prediction models for hydrological studies.
7. It appears that the predicted monthly flow-rates fit the observed flow- rates well.

As remarked in similar studies, ANN is a suitable method to predict monthly average flow rates. Since the number of studies on Ergene basin flood risk is quite few, this study will play an important role for the region and for literature. In the other studies about Ergene watershed, the input values between 1980 – 1994 were used in general. Because the river's flow rate changed after 1991 as explained in "The Study Area" section, to study with 1997 – 2018 values have an importance. The recent input data set can present the new characteristics of the river much better than former input data set. When the studies on Ergene watershed and other studies as to the subject in literature are reviewed, it is seen that daily flow data is mostly used as input, and ANN and other methods are compared. The studies using daily dataset instead of monthly also show accurate results.

Table 3. MAPE and determination coefficients for the year 2018

Flow Rate	3 neurons	4 neurons	5 neurons	6 neurons	7 neurons	8 neurons	9 neurons	10 neurons
12.5	12.1575	11.7003	12.3821	11.9341	11.8678	12.4165	12.2594	12.0109
12.6	12.2925	11.8435	12.4047	11.9426	12.0773	12.4501	12.2295	12.5433
15.5	15.2559	14.8425	14.8056	14.7928	14.4664	14.7877	14.8257	15.3680
28.9	26.8819	26.4825	27.2332	27.1631	27.2082	27.5967	27.2392	28.7398
22.0	20.8600	20.9679	20.4597	20.5764	20.8162	20.0261	20.7853	21.4322
50.0	47.3820	48.1506	47.9341	48.4953	48.3214	50.1717	47.3601	49.3050
14.1	13.7178	13.2838	13.9402	13.7147	13.2435	14.0317	13.1804	13.1419
8.81	8.5683	8.0145	8.8129	8.3439	8.2182	8.3745	8.5225	7.7781
8.03	7.7492	7.2266	7.8345	7.0136	7.2493	7.4732	7.5905	8.3539
12.9	12.8524	12.0840	12.4599	12.5966	12.6531	12.4672	12.3296	12.4330
12.7	12.6705	11.8286	12.6865	12.9177	13.0515	12.2490	12.5641	12.3581
6.98	6.6502	6.3463	6.7862	6.4052	6.4317	6.3924	6.6103	5.8185
MAPE	**1.0365**	**1.1454**	**0.9241**	**0.9322**	**0.9574**	**0.7853**	**1.0588**	**0.6365**
R^2	**0.9335**	**0.9331**	**0.9347**	**0.9666**	**0.9343**	**0.9344**	**0.9351**	**0.9348**

This study differs from literature in that it uses four different types of values as input. This study reveals that when the daily data set cannot be obtained, the predictions made using the monthly data set give accurate results.

In conclusion, floods play an important role in basin management and urban planning. River flows should be predicted in advance to prevent or reduce the damages in rural and urban areas in planning studies. Many models are used for future flow and flood predictions. Better predictions are thought to increase input data and diversify it with land use data and soil data. In future studies, various methods such as different ANN types, genetic algorithm and neuro-fuzzy etc. can be used to predict the flow rate in the Ergene basin.

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