

Original Research

Flood Routing Calculation with ANN, SVM, GPR, and RTE Methods

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Abstract

Flood routing analysis is of great importance in predicting floods and taking all necessary precautions in the area where the flood occurred. By applying different machine learning algorithms to historical flood data, the success of the established models in flood routing calculations has been measured. In this study, flood hydrograph data on 05.05.2014 was passed through the training and testing stages using the Support Vector Machine (SVM), Gaussian Process Regression (GPR), Regression Tree Ensembles (RTE), and Artificial Neural Networks (ANN) methods, then routing calculations were made by applying the flood data on 03.06.2015 to these models. The results were compared with either ANN, SVM, GPR, RTE, or measured values. Root Mean Square Errors (RMSE) and Correlation Coefficient (R) values were calculated at the end of the comparative analysis. In conclusion, it has been determined that verifying the flood routing results performed by the SVM is the best result.

Keywords: flood routing, Artificial Neural Network, Support Vector Machine, Gaussian Process Regression, Regression Tree Ensemble

Introduction

Whatever the reason is, it is considered flooding when the water level in any stream is higher than normal, crosses natural shores, and covers surrounding lands. Floods, one of the most important natural events, cause a lot of damage to the world every year [1-2]. Precipitation, soil permeability, and land slope play an essential role as rainfall causes flooding in a certain period [3]. Storm floods also occur frequently and have complex features in arid mountainous areas; this has created a weak link in flood predictions for a long time [4]. Direct impacts include casualties, loss

of agricultural production damage to infrastructure after floods occur [5], degradation of trade and education, indirect social effects on communities, [6], and human health [7-8]. Especially in arid mountainous areas where precipitation intensity is high, very dry and crusty soil structures can rapidly convert precipitation into a flow, which can cause higher flood risks [9-10]. The early adoption of flood warnings, flood control, and other flood relief measures by accurate flood forecast can be effectively supported to reduce flood losses [11-12]. Management of flood risk remains a major problem in many urban environments, moreover, rapid urbanization poses special challenges, including the diminution of flood risks and the protection against flash flood hazards [13-14]. Flood Routing is the calculation of the time variation of values such as flow rate, velocity, etc., at any specified location along

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a stream or reservoir of a flood wave. This situation is important in predicting floods and taking all necessary precautions in the area where the flood occurred. One essential engineering technique that controls floods is the flood routing method [15-16].

Today, artificial intelligence computing methods are preferred mainly by researchers because of their high ability to analyze complex problems. In many areas, it has been proven that computational intelligence techniques such as Artificial Neural Networks (ANN), which simulate complex and nonlinear systems, can create a logical correlation between observed, input, and output data [17]. ANN models for estimating daily flows at multiple metering stations in the Eucha Watershed show useful tools for predicting hydrological outcomes [18]. Artificial neural network models were discussed to predict daily flows from the Khosrow Shirin basin [19]. ANN model was also used to estimate daily unsteady flows [20]. Using the artificial neural network method, multiple inputs were taken into account, and the downstream flood was determined [21]. ANN model was used to estimate the flow, sediment and water level [22-23]. Different new input models are proposed to forecast the inflow to the Zayandehroud dam reservoir using ANN and Support Vector Machine (SVM) models [24]. A flood hazard assessment methodology was introduced using multi-criteria analysis and ANN techniques in a Geographical Information System environment, thereby determining Greece's overall flood hazard map [25]. ANN does not require detailed knowledge of the physically complex processes of a system to recognize the relationship between input and output data [26]. The best model for analyzing storm surge flood susceptibility in Sundarban Biosphere was found to be the SVM model [27]. A new architecture has been proposed for the flood routing model. Its efficiency is validated on three different flood routing problems by employing the SVM approach, a powerful alternative in the flood routing model [28]. Two new algorithms were used for the first time in flood susceptibility analysis. These models are multivariate discriminant analysis (MDA), classification and regression trees (CART) incorporated with a widely used algorithm, the support vector machine (SVM), which creates a flood susceptibility map using an ensemble modeling approach [29]. A new ensemble method was proposed by integrating frequency ratio (FR) and SVM to produce spatial modeling in flood susceptibility assessment [30]. Statistical models and eight individual machine learning are implemented and compared. In the end, Boosted Regression Trees (BRT) was the best accurate unique model [31]. Boosted Regression Trees (BRT) and Extreme Gradient Boosting (XGBoost), Classification and Regression Tree (CART) methodology, and its ensemble models of random forest (RF) were implemented to create a flash-flood susceptibility map of the Basca Chiojdului River Basin [32]. A hybrid model was presented that the flooded waste classification

model using a 3D-wavelet transform (3D DWT) and a SVM was developed to address these challenges [33].

This article covers the application of ANN, SVM, Gaussian Process Regression (GPR), and Regression Tree Ensembles (RTE) to runoff problems in a complex river network. The aim is to construct an ANN, SVM, GPR, and RTE channel network model for flow estimation along a river and express these methods' efficiency and effectiveness.

While analyzing classical flood routing methods, many data such as stream cross-section, stream slope, and roughness coefficient are needed. Muskingum flood routing is a prevalent used method for hydrological flood routing. Although it is an easy method to apply, the data of the downstream region is also needed to make the flood routing calculations. The most crucial aim of this article is to establish a model with ANN, SVM, GPR, and RTE methods with hourly hydrograph data and to investigate the possibility of making next flood routing forecasts with the help of the established models without the need for any other data. It is hoped that the resulting modeling can be easily applied to other regions. The first stage of the research is to set up a model after training and testing in ANN, SVM, GPR, and RTE methods using a flood hydrograph of the previous year in a stream. In the next step, flood routing is estimated the downstream region by applying the upstream flood data of the next year to this established model. In this way, it is thought that this model, which is established by ANN, SVM, GPR, and RTE methods without the need for any other data, will allow the prediction of a future flood by adding only input data. In addition, there is no need to calculate parameters such as friction coefficient and slope when calculating the routing processes, and it will have an important place in terms of time-saving, creating models quickly and in a short time. As a result, it is thought that it will easily allow the prediction of a flood that may occur in the downstream region by entering the only flood data of the current year into the models established in the ANN, SVM, GPR, and RTE without the need for any other data.

Material and Methods

Study Area and Data

The characteristics and parameters of the Discharge Observation Stations (DOS) from which the study data were obtained are shown in Table 1 and Table 2, and hydrographs are plotted in Fig. 1.

The data used in the study (hourly flood data, cross-sectional area, and velocity values) were obtained from the General Directorate of State Hydraulic Works (DSI), Rasatlar Branch Office, and DSI Regional Directorates.

Discharge Observation Stations located on Mera Stream, where flood routing will be made, are located

Table 1. Discharge Observation Stations.

Province/ District Name	Station Number	Station Code	Station Name	Basin Name	River Name	Station Opening Date	Area (km ²)
Ankara / Kızılcahamam	1	D12A242	Uğurlu	Sakarya	Mera	2003	120,9
	2	D12A126	Pazar Yol Ayırımı	Sakarya	Mera	1974	197,2

Table 2. Flood Dates and Parameters Used.

Station Number	Flood Dates	Distance (m)	Slope (S_0)	Friction Coefficient (n)
1	05.05.2014	2061	0.024	0.073
2	03.06.2015			

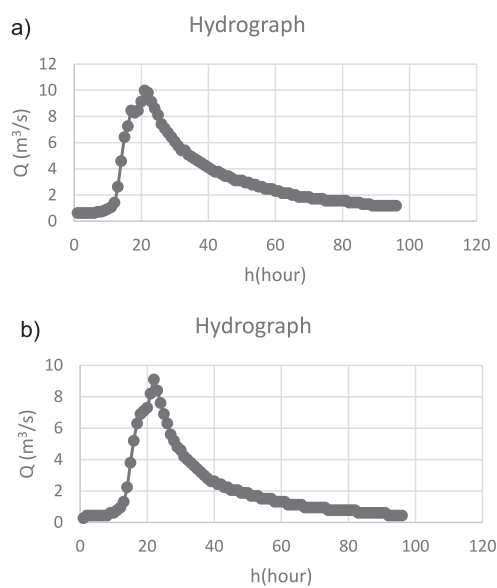


Fig. 1. Hourly hydrograph of D12A242 and D12A126 DOS.

in Sakarya Basin, Kızılcahamam District of Ankara Province. Locations of DOS are shown in Figs 2, 3.

Muskingum Method

In this method, which is based on applying the continuity equation to a stream segment, the difference between the flood hydrographs in the inlet and outlet cross-section of a stream segment is equal to the amount of change in volume at that moment. It is based on the assumption that the accumulated volume of the stream segment depends on the incoming and outgoing flows and that there is a linear relationship between them [34]. While solving this method, firstly, the entrance and exit hydrographs between the two determined sections are considered. Then Muskingum parameters are determined. In this way, the relationship between storage and input, and the output is determined. Finally, the calculation is completed by translating the flood values.

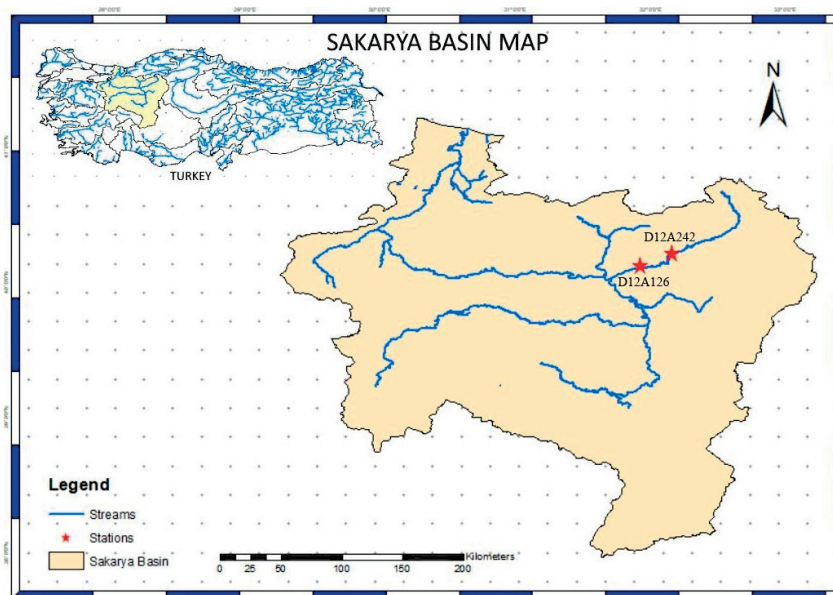


Fig. 2. Location of DOS (D12A242 and D12A126).

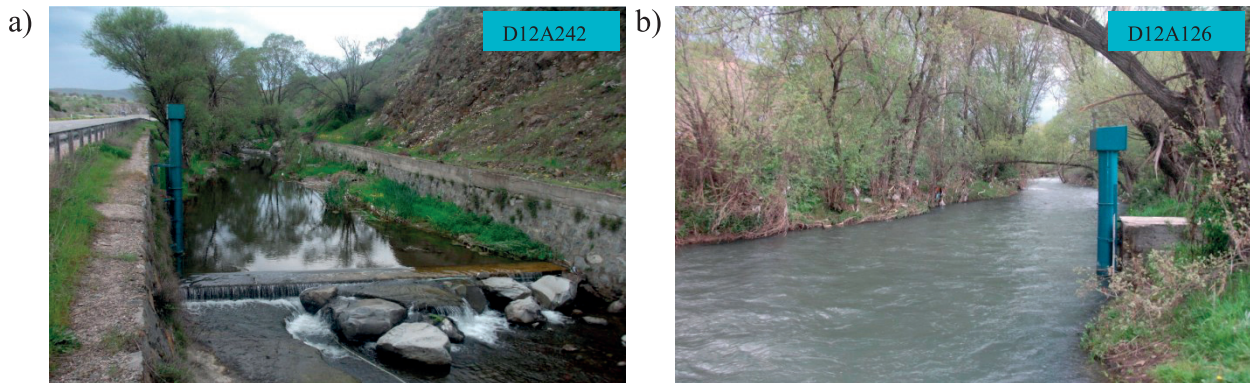


Fig. 3. DOS a) D12A242 and b) D12A126 in Ankara Kızılcahamam.

Artificial Neural Network (ANN)

ANN is a processor made up of neurons that learn information during the training process that has wide application in hydrology, flood hydrograph prediction, and overcoming nonlinearity [35].

Support Vector Machine (SVM)

SVM is an algorithm based on optimization which is a classification algorithm that minimizes error [36]. SVM is considered a non-parametric technique because it depends on kernel functions. SVM is created by taking the maximum value into the structure; thanks to this feature, it has become more efficient than other regression models. However, SVM, which is widely preferred due to its ease of application and compatibility with linear and nonlinear data, also has disadvantages such as difficulties interpreting model parameters and long model training.

Gauss Process Regression (GPR)

Gauss Process Regression (GPR) is a non-parametric model based on the conversion of prior functions to posterior functions in the Gaussian distribution for solving nonlinear regression problems [37].

Regression Tree Ensemble (RTE)

The decision tree structure was first published by Quinlan in 1986 [38]. This method consists of leaf nodes and decision nodes. In the first stage, a standard deviation of the target set is calculated. In the second stage, binary standard deviation values are calculated between the target and other clusters. The result of each is subtracted from the target cluster's standard deviation value. The cluster with the largest standard deviation value is determined as the root. The tree structure is created by continuing these steps for each node.

Testing Routing Success

Root Mean Square Error (RMSE) is the standard deviation of the difference between the calculated value and the actual value. The second method is used to measure the success of the model. The correlation coefficient (R) indicates the direction and magnitude of the relationship between the independent variables.

Taylor Diagram

Taylor diagram is the diagram created to provide a graphical summary of the model results. The diagram shows the correlations, standard deviations and RMSE values of the data obtained as a result of the models. It is created in order to compare model performances more easily in complex studies involving many models. When the Taylor diagram is examined, it shows the standard deviation values in the x and y axes, the correlation coefficient on the quarter circle arc and the RMSE values in the diagram [39].

In this study, Uğurlu DOS numbered D12A242 located at an altitude of 1015 m at 40:21:02 North, 32:40:54 East, and D12A126 numbered at 40:20:02 North, 32:42:02 East at an altitude of 965 m. Pazar Yol Ayırımı DOS stations data were used. The flood data that occurred in Mera Stream on 05.05.2014 was modeled with ANN, SVM, GPR, and RTE methods and passed through training and testing stages. Routing results were obtained by applying the flood data on 03.06.2015 to this model. The results were compared with the measured values, then RMSE and R values analysis was made. ANN, SVM, GPR, and RTE methods were carried out using ANN and Regression Learner plug-in in MATLAB program, and its graphics

Table 3. Muskingum Method 2015 Flood Result Error Analysis

Model	Verification	
	RMSE	R
Muskingum Method	3.765	0.97

Table 4. Model types and functions used.

Support Vector Machine (SVM)						
Model Type	Linear	Quadratic	Cubic	Fine Gaussian	Medium Gaussian	Coarse Gaussian
Kernel Function	Linear	Quadratic	Cubic	Gaussian	Gaussian	Gaussian
Gaussian Process Regression (GPR)						
Model Type	Rational Quadratic	Squared Exponential	Matern 5/2	Exponential		
Kernel Function	Rational Quadratic	Squared Exponential	Matern 5/2	Exponential		
Regression Tree Ensembles						
Model Type	Boosted Trees	Bagged Trees				
Minimum Leaf Size	8	8				
Artificial Neural Network(ANN)						
Model Type	Tangent Sigmoid	Logarithmic Sigmoid				
Learning Function	Levenberg-Marquardt	Levenberg-Marquardt				
Neuron Number	3-8	3-8				

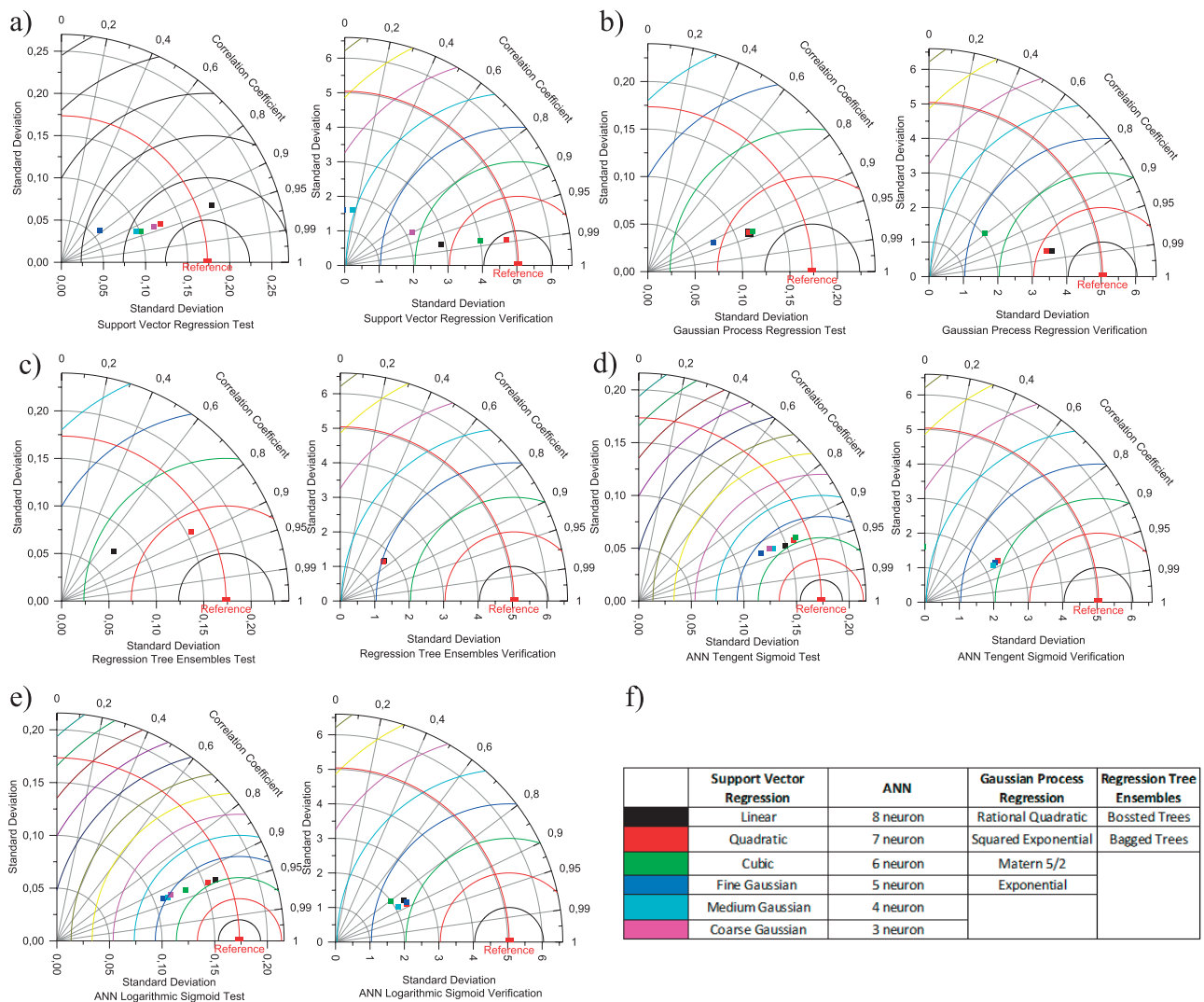


Fig. 4. Taylor Diagrams of SVM a), GPR b), RTE c) and ANN d) Models and Colour scale f).

Table 5. RMSE and R analysis of models.

Model	Model Type	Verification	
		RMSE	R
Support Vector Machine (SVM)	Quadratic	0.90	0.99
Gaussian Process Regression (GPR)	Rational Quadratic	1.40	0.98
Regression Tree Ensemble (RTE)	Bagged Trees	3.90	0.74
Artificial Neural Network Tanjant Sigmoid (ANN)	3 neuron	3.30	0.88

were drawn. In addition, the 03.06.2015 flood data was applied to the Muskingum Method, and the routing calculations were made. The results data were compared with the measured data, and an evaluation analysis was made. While setting up the models, the Excel program was used in all of them, calculations and graphics were also created in the Excel program. At the last stage of the study, the results of ANN, SVM, GPR, and RTE methods and Muskingum deferral calculations were compared, and evaluation analyzes were made.

Results and Discussion

Muskingum Method Flood Routing Findings

As a result of the Muskingum flood routing calculation made for this region, the RMSE Error and R values between the observed and calculated values are presented in Table 3.

ANN, SVM, GPR, RTE Flood Routing Findings

In all methods, 70% of the flood hydrograph data was carried out as training and the remaining 30% as a test. The input values of the model were selected as D12A242 Ugurlu DOS data, and the output values were chosen as D12A126 Pazar Yol Ayırımı DOS data which belonged to the flood in 2014. The features such as model types and learning functions used in the models constructed with ANN, SVM, GPR, RTE methods are shown in Table 4.

Using the upstream and downstream flood hydrograph data of 05.05.2014, ANN, SVM, GPR, and RTE methods were trained and tested, and models were established. Upstream flood data for 03.06.2015 were entered into these models, obtaining downstream flood data. Related to this, Taylor diagrams with test and validation graphs and color scale of the models used in Taylor diagrams are shown in Fig. 4.

When Taylor diagrams are examined, the model type that gives the best results for each SVM, GPR, RTE, and ANN models have been determined. Quadratic SVR model gives the best results among all models. RMSE and R values of all models are shown in Table 5.

Conclusion

While analyzing classical flood routing methods, many data such as stream cross-section, stream slope, and roughness coefficient are needed. In this study, a forward-looking flood routing calculation was made using the flood hydrograph data on 05.05.2014. In recent years, the applicability of ANN, SVM, GPR and RTE models, widely used in many scientific fields, to flood data from hydrological events has been investigated. Due to the strong internal dependence on hydrograph data, excellent test verification values were found for SVM, ANN, GPR models ranging between $R = 0.90-0.95$, for the RTE model ranging from $R = 0.70-0.85$.

For the flood that occurred on 03.06.2015, the flood routing was made by entering only the upstream flood hydrograph data into the models formed, without using any other parameters of that year. As a result of the routing made for the downstream region, it was calculated between $R = 0.90-0.99$ for the SVM model, $R = 0.96-0.98$ for the GPR model, $R=0.85-0.89$ for the ANN model, and $R = 0.75-0.78$ for the RTE model. As a result, SVM and GPR models showed good verification success. As a result of the analysis made for the flood on 03.06.2015 with the Muskingum method, which is one of the classical flood routing methods, it was calculated as $RMSE = 3.765$ and $R = 0.97$.

When all models were compared, it was determined that the Quadratic SVR model has the best validation model. Quadratic SVR and Rational GPR models give the best result for all models. The analysis results of these two methods are close to each other, and it is predicted that they can be easily used in flood routing calculations.

In stochastic models, many operations need to be checked before creating the model, such as normal distribution, stationarity, constant variance, and some flood translation methods, such as determining the boundary conditions. These processes cause researchers to lose a lot of effort and time. No boundary conditions were used in SVM, ANN, GPR and RTE models. It can be simply applied to modeling many physical phenomena without taking any action. For those who research flood, it is predicted that by using such methods and adding different algorithms, using very little

data, future forecasting possibilities can be developed and used frequently.

It is thought that it will easily predict a flood that may occur in the downstream region by entering only the flood entry data into the models established in SVM and GPR models with the previous flow data without the need for any other data. In addition, it is hoped that the models to be established with SVM and GPR models for different stations will provide an incredible convenience in flood routing calculations in other downstream regions. Accordingly, preventive measures will be vital.

In this study, the future predictions of the models to be created with artificial intelligence techniques gave very good results. The investigated area is limited to only two DOS. It is thought that models can be made for other regions and a model can be created for each region. In fact, it is hoped that the effects of a flood can be predicted, thanks to the fact that all regions are connected to each other in such a way that a network can be formed and controlled from a center. Thus, it is thought that taking precautions by informing the relevant units in advance will save many lives accordingly.

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Conflict of Interest

The authors declare no conflict of interest.

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