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Development of an adaptive neuro-fuzzy inference system (ANFIS) model to predict sea surface temperature (SST)

by

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Abstract

An accurate estimation of the sea surface temperature (SST) is of great importance. Therefore, the objective of this work was to develop an adaptive neuro-fuzzy inference system (ANFIS) model to predict SST in the Çanakkale Strait. The observed monthly air temperature, evaporation and precipitation data from the Çanakkale meteorological observation station were used as input data. The Takagi–Sugeno fuzzy inference system was applied. The grid partition method (ANFIS-GP) and the subtractive clustering partitioning method (ANFIS-SC) were used with Gaussian membership functions to generate the fuzzy inference system. Six performance evaluation criteria were used to evaluate the developed SST prediction models, including mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), Nash-Sutcliffe efficiency (NSE) and correlation of determination (R^2). The dataset was randomly divided into training and testing datasets for the machine learning process. Training data accounted for 75% of the dataset, while 25% of the dataset was allocated for testing in ANFIS. The hybrid algorithm was selected as a training algorithm for the ANFIS. Simulation results revealed that the ANFIS-SC4 model provided a higher correlation coefficient of 0.96 between the observed and predicted SST values. The results of this study suggest that the developed ANFIS model can be applied for predicting sea surface temperature around the world.

Key words: artificial intelligence, ANFIS, fuzzy, forecast, modelling, water temperature, SST, climate

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Introduction

Sea surface temperature (SST) is one of the most important parameters in Earth observation aimed at monitoring the global climate (Mahongo & Deo 2013). SST plays an important role in the process of interactions between the atmosphere and the Earth's surface (Zhang et al. 2017). It is a critical parameter for understanding and forecasting rainfall and hurricanes (Nobre & Shukla 1996).

Assessment and reconstruction of the ocean dynamics are key challenges (Ouala et al. 2018). Estimation and reconstruction of geophysical properties of the sea surface rely on model-based techniques that make significant use of a dynamic model to perform simulations based on specific ocean conditions (Gordon et al. 2000). On the other hand, the selection and parameterization of a dynamic model are still a complex issue for understanding the relationships between spatial and temporal changes in the ocean surface. Data-driven approaches have emerged as an attractive strategy to describe certain dynamic models with an increased amount of observational and simulation data. Neural networks are a state-of-the-art approach to many different issues related to machine learning (Ouala et al. 2018). They are an efficient and remarkable data-driven approach to estimating and reconstructing sea surface dynamics. An artificial neural network (ANN) has an important advantage in the system modelling, which does not require a well-defined physical relationship to systematically transform input data into output data (Farokhnia et al. 2011).

Predicting water temperature of seas, lakes, and streams is important in planning and management of water resources (Heddam et al. 2020). Several machine learning approaches have been extensively used to model water temperature. Their performance varies depending on the input variables and models used. Piccolroaz et al. (2013) proposed a simple lumped model (air2water) to forecast lake water surface temperature by using air temperature as an input predictor. The proposed model has been broadly used by several researchers for forecasting lake water surface temperature due to its higher accuracy and simplicity (Toffolon et al. 2014; Piccolroaz 2016; Piccolroaz et al. 2016; Zhu et al. 2020). As documented by Graf et al. (2019) and Zhu et al. (2020), the use of hybrid models offers some advantages in forecasting water temperature. Heddam et al. (2020) proposed machine learning approaches, including extremely randomized trees (ERT), multivariate adaptive regression splines (MARS), the M5 Model Tree (M5Tree), the random forest (RF), and the multilayer perceptron neural network (MLPNN) to model daily lake surface water temperature by using air temperature. The authors compared the results of the proposed approaches with the air2stream model and reported that none of the proposed approaches provided better results in predicting water temperature than the air2stream model. Graf et al. (2019) forecasted water temperature in the Warta River in Poland using the wavelet-neural network hybrid modelling approach. The authors proposed a hybrid model that combines discrete wavelet transforms and the ANN for forecasting water temperature. They used daily air temperatures from seven meteorological stations to predict daily water temperature. Zhu et al. (2020) developed and applied the multi-layer perceptron neural network (MLPNN) model and an integrated model of the wavelet transform and the MLPNN (WT-MLPNN) to forecast daily lake surface water temperature of eight lowland lakes in Poland. The authors used long-term daily lake surface water temperature and daily air temperatures as input variables. It was found that the hybrid WT-MLPNN model performed slightly better than the traditional MLPNN model in forecasting the lake surface water temperature. Zhu et al. (2019a) applied four different machine learning models, including multilayer perceptron neural network models (MLPNN), ANFIS with the subtractive clustering method (ANFIS-SC), ANFIS with the grid partition method (ANFIS-GP) and ANFIS with the fuzzy c-mean clustering algorithm (ANFIS-FC), to predict daily river water temperature. The authors used air temperature, river flow discharge, and the components of the Gregorian calendar as input variables. Piotrowski et al. (2020) employed shallow neural networks to model stream water temperature in six catchments. The authors used air temperature, river discharge, and the declination of the Sun as input parameters.

Zadeh (1965) first introduced the theory of fuzzy sets and fuzzy logic to describe basic properties and implications of a concept that plays an important role in human thinking. The principal idea underlying the fuzzy logic control was proposed and described in detail by Zadeh (1968) and Zadeh (1973). Jang (1993) developed a neuro-fuzzy approach that is a combined method to improve the efficacy of a model compared to the ANN and fuzzy logic. The neuro-fuzzy system combines neural networks and fuzzy logic and implements learning techniques developed in the ANN into the fuzzy inference system (FIS; Brown and Harris 1994). The adaptive neuro-fuzzy inference system (ANFIS) is a specific approach in neuro-fuzzy systems and Jang et al. (1997) indicated that the ANFIS produced noteworthy results in modelling of nonlinear functions. The ANFIS uses an adaptive network for learning and is a popular approach for predicting parameters related to water resources (Nayak et al. 2004; Aqil et al. 2007; Sönmez et al. 2018).

In recent years, artificial intelligence (AI) techniques have become increasingly important in water and climate applications due to their capability of learning concealed patterns from historical data and estimating non-linear systems (Awan and Bae 2016). Several researchers applied some artificial intelligence (AI) techniques to forecast water temperature in rivers and streams (Piccolroaz et al. 2013, 2016; Graf et al. 2019; Zhu & Heddam 2019; Zhu et al. 2019a,b,c; 2020; Heddam et al. 2020; Piotrowski et al. 2020) and sea surface temperature (Garcia-Gorriz and Garcia-Sanchez 2007; Mahongo & Deo 2013; Piotrowski et al. 2015; Patil et al. 2016; Samadianfard et al. 2016; Zhang et al. 2017; Ouala et al. 2018). However, there is no study on the SST prediction for the Çanakkale Strait. Therefore, the main objective of the present study was to develop an adaptive neuro-fuzzy inference system (ANFIS) model to predict SST by using climate data for the Çanakkale Strait.

Materials and methods

Data and study area

The Çanakkale Strait is located in the northwestern part of Turkey and is part of the Turkish Straits System that includes the Bosporus Strait, the Marmara Sea and the Çanakkale Strait. It connects the Aegean Sea and the Marmara Sea. The Çanakkale Strait has a special two-layer flow regime and is a route for low salinity waters moving from the Black Sea to the Aegean Sea. In addition, the strait is also a route for high salinity waters originating in the Aegean Sea flowing into the Marmara Sea and then into the Black Sea (Jarosz et al. 2012). The Çanakkale Strait is approximately 61 km long and the average depth is 55 m. The Çanakkale Strait is under anthropogenic pressure such as urbanization, marine traffic, harbor activities, commercial fishing and pollutants coming from the Black Sea Basin.

The region has a typical transitional climate characterized by rainy and cold winters, and dry and hot summers. Cengiz and Akbulak (2009) reported that July is the warmest month and January is the coldest month. Kale (2017a) documented that the air temperature in the region had an upward trend, similar to Kale's (2017b) report that indicates that trends in evaporation were increasing.

Observational data on monthly air temperature, evaporation and precipitation from the Çanakkale

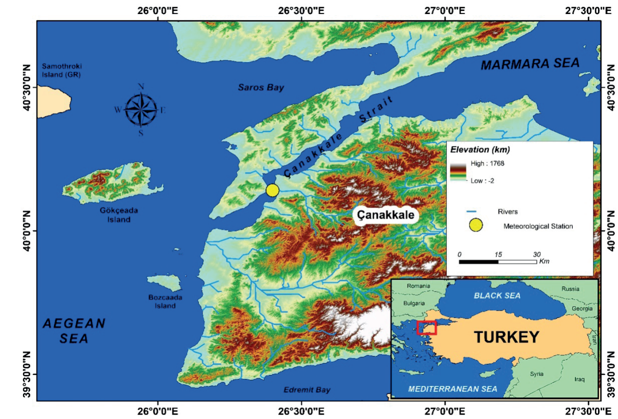

Figure 1

Location of the study area

meteorological observation station of Turkish State Meteorological Services (Fig. 1) were used in this study. The data cover a period of 42 years from 1971 to 2012. The SST data were recorded from the same station.

ANFIS Architecture

Mamdani (1974) documented that the fuzzy inference system (FIS) consists of four major components. These components were identified as (i) a fuzzification interface converting crisp values into fuzzy values depending on the corresponding degrees with linguistic variables, (ii) an interface engine executing inference operations on the rules, (iii) a rule base encompassing fuzzy if-then rules, and (iv) a defuzzification interface converting fuzzy consequences back into a crisp output. The Takagi–Sugeno (T-S) fuzzy inference system, which is proposed by Takagi and Sugeno (1985), is one of the most widely used precise fuzzy models. A weighted linear mixture of crisp inputs establishes a fuzzy rule rather than a fuzzy set in the T-S fuzzy inference system (Talei et al. 2013). A fuzzy set is a set without a crisp and defined boundary. Jang (1993) proposed an adaptive network-based fuzzy inference system, which is a machine learning model combining the ANN and the fuzzy logic. The architecture of the ANFIS contains fuzzification by the fuzzy inference system and several layers like the ANN (Jang et al. 1997). The system contains two inputs (x_1 and x_2) in the ANFIS structure. Takagi–Sugeno's type of if-then rules and one output (y) are usually considered as follows:

$$\text{Rule 1: } \textit{if } (x_1 \textit{ is } A_1) \textit{ and } (x_2 \textit{ is } B_1) \textit{ then } f_1 = p_1x_1+q_1x_2+r_1$$

$$\text{Rule 2: } \textit{if } (x_1 \textit{ is } A_2) \textit{ and } (x_2 \textit{ is } B_2) \textit{ then } f_2 = p_2x_1+q_2x_2+r_2$$

In these equations, *A* and *B* indicate fuzzy sets, while *p*, *q*, and *r* indicate the resulting parameters of the obtained model in the training step. The fuzzy inference system converts the input variables by using membership functions. Hence, the outcomes of the membership functions create the rule bases (Jang et al. 1997). Jang (1993) divided the ANFIS structure into five layers and described the node functions in the same layer of the same function family as given below:

Layer 1: the fuzzification layer

Layer 1 is the input variables, fuzzy sets. Each node in layer 1 fits a function parameter. A frequently used activation function is the Gaussian function.

$$O_i^1 = \mu A_i(x);\ \ \mu A_i(x) = \frac{1}{1+\left[\left(\frac{x-c_i}{a_i}\right)^2\right]^{b_i}}$$

In this equation, O_i^1 is the membership function of A_i and specifies the degree to which a given *x* satisfies the quantifier. In addition, *x* is the input to the node *i*, and A_i is the linguistic label related to this node function. Furthermore, (a_i, b_i, c_i) is the parameter set. The bell-shaped functions change accordingly, while the values of these parameters change indicating different membership functions on linguistic label A_i. Continuous and fragmented functions, such as triangular or trapezoidal membership functions, are in fact also capable candidates for node functions in this layer. The parameters in this layer are called preliminary parameters.

Layer 2: the base rule layer

Layer 2 computes any two memberships acquired by the fuzzy sets to characterize the fuzzy rules. Each node output characterizes the firing strength of a rule.

$$\mathrm{w}_i = \mu A_i(x) \times \mu A_i(\mathrm{x}),\ i = 1,2$$

Layer 3: normalized firing strengths

Each node in layer 3 is fixed or non-adaptive. Outputs of this layer are called normalized firing strengths.

$$\overline{w_I} = \frac{w_i}{w_1 + w_2},\ i=1,2$$

Layer 4: the defuzzification layer

Each node fits an output in layer 4. The parameters in layer 4 are returned as the following parameters.

$$O_i^4 = \overline{w_I} f_i = \overline{w_I}\left(p_i x + q_i y + r_i\right)$$

$\overline{w_I}$ is the output of layer 3 and (p_i, q_i, r_i) is the parameter set. Parameters in this layer are referred to as consequent parameters.

Layer 5: the output of the ANFIS model

Layer 5 is the last layer and contains only one node. In this layer, the single node is a non-adaptive or fixed node. As a summary of all received signals from the prior node, this most recent node calculates the total output.

$$O_1^5 = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

As summarized by Zhu et al. (2019a), the parameters of the ANFIS model kept in the fuzzification layer that encompasses the nonlinear parameters for the membership functions are updated through the training process using the back-propagation algorithm (forward step). The parameters kept in the defuzzification layer are updated through the training process using the least squares method (backward step). The membership functions have a significant role in the ANFIS models. An excellent selection of membership functions within various available types with the best optimization of parameters helps to develop a highly accurate model.

The Matlab software and the anfisedit toolbox (Matlab R2015a) were used to analyze the data and generate the ANFIS. The classical ANFIS was recognized as a basic model due to its ability to model hydrological phenomena. The Takagi–Sugeno fuzzy inference system (Takagi & Sugeno 1985) was applied. In the adaptive neuro-fuzzy inference system, the model-developing process starts with the separation of datasets between training and testing datasets. In the present study, the entire dataset was randomly divided into the training and testing datasets. The training data accounted for 75% of the dataset, while 25% of the dataset was allocated for testing in ANFIS. The hybrid algorithm was nominated as a training algorithm for the ANFIS. The training stage included an iterative procedure that aimed to compute optimum values by minimizing the sum of squared differences between training data values and model predictions. The hybrid learning algorithm was designated to train the fuzzy inference system. The modification process of the adaptive parameters in the adaptive neuro-fuzzy inference system depends on a backward and forward hybrid learning algorithm. In the backward stage, the subsequent parameters (in layer 4) are fixed, while the antecedent parameters are tuned using the gradient descent method. In the forward stage, on the other hand, the antecedent parameters comprising membership functions and fuzzy rules are fixed, whereas the subsequent parameters are restructured by the least square error algorithm (Jang 1993). The construction of the fuzzy rule base is the most important stage in the development of the ANFIS model (Zhu et al. 2019a). The number of fuzzy rules for the ANFIS models is directly related to the method used for partitioning the input dataset.

The ANFIS could be developed by using diverse methods to achieve machine learning of the input dataset. These methods are subtractive clustering (SC), fuzzy c-means clustering, and grid partitioning (GP). The grid partition method calculates the number of fuzzy rules by multiplying the number of input variables by the number of fuzzy subsets for each input (Wei et al. 2007). Jang (1993) documented that the grid partition method is not appropriate when the input number is greater than six. On the other hand, the number of fuzzy rules is equal to the number of clusters in the subtractive clustering method (Cakmakci 2007). The subtractive clustering method clusters a dataset in the feature space by defining the number of clusters and their associated centers (Alizamir et al. 2020). In the present study, the grid partition method and the subtractive clustering method were used with the Gaussian membership functions to generate a fuzzy inference system to fuzzify the input data. Both methods were used to develop the ANFIS model to predict SST in the Çanakkale Strait, and then their performance in modelling SST was compared. The structure of the adaptive neuro-fuzzy inference system is presented in Figure 2. The ANFIS architecture used in the present study comprises five layers containing the fuzzy layer, the product layer, the normalized layer, the de-fuzzy layer and the output layer. The method of the weighted average of all rule outputs (wtaver) was used as the defuzzification method to compute crisp output values from the aggregated output fuzzy set. The training process was continued until the number of epochs reached 1000.

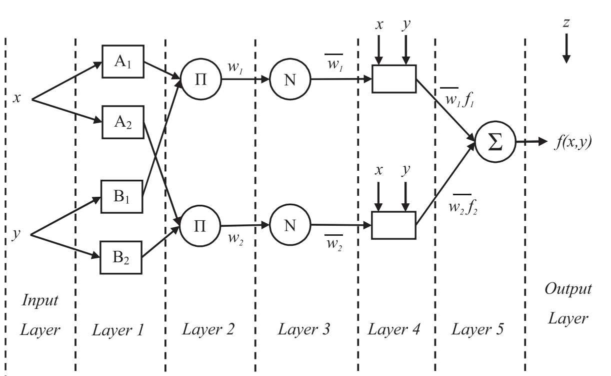

Figure 2

ANFIS structure

Performance evaluation of the ANFIS Model

In this study, six evaluation criteria were used to evaluate the performance of the model: mean absolute error (MAE), mean square error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), Nash–Sutcliffe efficiency (NSE) and the coefficient of determination (R^2).

Mean square error (MSE)

The mean square error is possibly the most frequently used error metric. It penalizes larger errors, because squaring larger numbers has a greater impact than squaring smaller numbers. The MSE is the sum of the squared errors divided by the number of observations. The MSE can be explained as follows:

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}$$

In this formula, n is the total number of observations, A_t is the actual value, while F_t is the forecasted value at observation t.

Root mean square error (RMSE)

The root mean square error is the square root of the mean square error. Dawson et al. (2006) noted that the RMSE attaches extra significance on the outliers in the dataset. Therefore, the RMSE is frequently used in numerous iterative estimation and optimization schemes (Azad et al. 2018). The RMSE can be calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}}$$

In this formula, n is the total number of observations, A_t is the actual value, while F_t is the forecasted value at observation t.

Mean Absolute Error (MAE)

The mean absolute error calculates all deviations from the original data without considering a sign. The MAE can be computed as follows:

$$MAE = \frac{1}{n}\left(\sum_{t=1}^{n}\left|A_t - F_t\right|\right)$$

In this formula, n is the total number of observations, A_t is the actual value, while F_t is the forecasted value at observation t.

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error is the average of absolute errors divided by the actual observation values. The MAPE can be calculated as follows:

$$MAPE = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} \times 100$$

In this formula, n is the total number of observations, A_t is the actual value, while F_t is the forecasted value at observation t.

Nash–Sutcliffe Efficiency (NSE)

The Nash–Sutcliffe efficiency is a normalized statistic that defines the comparative degree of the residual variance related to the observed data variance (Nash and Sutcliffe 1970). The NSE shows how well the plot of actual versus forecasted data fits the 1:1 line. The NSE ranges from -∞ to 1. Basically, the more accurate the model is, the closer the value is to 1. A positive NSE matches the perfect model to the actual data, whereas a negative NSE indicates that the actual mean is a better predictor than the model. If the NSE is 0, the model forecasts are as precise as the mean of the actual data. The NSE calculation is described as follows:

$$NSE = 1 - \frac{\sum_{t=1}^{n}\left(A_t - F_t\right)^2}{\sum_{t=1}^{n}\left(A_t - \overline{A}_t\right)^2}$$

In this formula, n is the total number of observations, A_t is the actual value, F_t is the forecasted value, and $A_t$bar is the average of the actual value at observation t.

Coefficient of determination (R^2)

The coefficient of determination defines the relationship between the actual and forecasted values. The coefficient of determination ranges between 0 and 1. Higher R-squared values indicate a higher co-linearity. The coefficient of determination can be calculated as follows:

$$R^2 = \left[\frac{\sum_{t=1}^{n}\left(A_t - \overline{A}_t\right)\left(F_t - \overline{F}_t\right)}{\sum_{t=1}^{n}\left(A_t - \overline{A}_t\right)^2 \sum_{t=1}^{n}\left(F_t - \overline{F}_t\right)^2}\right]^2$$

In this formula, n is the total number of observations, A_t is the actual value, F_t is the forecasted value, $A_t$bar is the average of the actual value, and $F_t$bar is the average of the forecasted value at observation t.

Results

Four categories of input data (air temperature, evaporation, precipitation, and month) were considered when developing the prediction models for SST. Descriptive statistics of observed parameters are given in Table 1. The table shows that the air temperature was the most correlated parameter with SST.

Both the grid partition method and the subtractive clustering method have four different versions in terms of the number of inputs. In both methods, version 1 (GP1 and SC1) includes only air temperature, version 2 (GP2 and SC2) includes air temperature and evaporation, version 3 (GP3 and SC3) includes air temperature, evaporation and precipitation, while version 4 (GP4 and SC4) includes all parameters (month, air temperature, evaporation, and precipitation) as input parameters.

The accuracy of the prediction relative to the observation was checked during the training and testing stages. Six performance evaluation parameters were used to evaluate the developed models for the prediction of SST: mean square error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), mean absolute error (MAE), Nash-Sutcliffe efficiency (NSE) and coefficient of determination (R^2). The application of multiple error criteria allowed for a better understanding of the differences between the

Table 1

Basic statistics of the measured factors in the Çanakkale meteorological observation station

Variable	Mean	Unit	SE	SD	Maximum	Minimum	Correlation with SST
Air Temperature	18.90	°C	0.30	5.37	28.50	5.30	0.91
Evaporation	169.05	mm	4.23	75.32	366.60	29.50	0.75
Precipitation	33.73	mm	2.16	38.50	222.20	0.00	−0.48
SST	18.96	°C	0.26	4.71	26.70	7.50	1.00

Note: SE: standard error; SD: standard deviation; SST: sea surface temperature

observed and predicted SST values. The comparison between the four versions of the ANFIS-SC and ANFIS-GP models revealed that ANFIS-SC4 (the model with four inputs as predictors: month, air temperature, evaporation and precipitation) yielded the best accuracy among all the developed models. The ANFIS-SC4 model performs better than all the other versions of SC and GP with regard to lower MAE and RMSE and higher NSE and R-squared values. Moreover, since R-squared and NSE values closer to 1 indicate a better model, the ANFIS-SC4 was considered the best model. The performance measures of the hybrid ANFIS models are presented in Table 2. A clear increase in model performance from version 1 to version 4 can be observed for both ANFIS-SC and ANFIS-GP models. Predicted SST values usually correlate with observed SST values for most models during the training stage. The R-squared values gradually increased during the training stage for all models. On the other hand, the R-squared values have decreased from version 1 to version 2 for both ANFIS-SC and ANFIS-GP models during the validation stage. Versions 3 of both models have similar values with versions 2. Then, versions 4 showed increased R-squared values in both models. Although ANFIS-GP4 had the highest R-squared value for the training stage in all models, this case was reversed in the validation stage and ANFIS-GP2, ANFIS-GP3 and ANFIS-GP4 had lower performance during the validation stage compared to ANFIS-GP1. The fact remains that the overall performance of

Table 2

Performance of different ANFIS models in modelling SST (°C) for the Çanakkale Strait

ANFIS Model	Stage	MAE	MSE	RMSE	MAPE	NSE	R-squared
SC1	Training	1.004	2.190	1.480	6.366	0.885	0.922
	Validation	0.459	1.219	1.104	2.596	0.608	0.831
	Total	1.463	3.409	1.846	8.963	0.846	0.846
SC2	Training	0.800	1.412	1.188	4.725	0.926	0.932
	Validation	0.327	0.751	0.867	1.919	0.758	0.770
	Total	1.127	2.163	1.471	6.644	0.902	0.902
SC3	Training	0.792	1.368	1.169	4.669	0.928	0.934
	Validation	0.328	0.746	0.864	1.924	0.760	0.770
	Total	1.120	2.114	1.454	6.594	0.904	0.905
SC4	Training	0.571	0.725	0.851	3.323	0.962	0.962
	Validation	0.205	0.254	0.504	1.196	0.918	0.900
	Total	0.776	0.978	0.989	4.519	0.956	0.956
GP1	Training	1.057	2.440	1.562	6.664	0.872	0.907
	Validation	0.453	1.164	1.079	2.569	0.625	0.842
	Total	1.510	3.604	1.898	9.233	0.837	0.838
GP2	Training	0.812	1.480	1.217	4.894	0.922	0.929
	Validation	0.339	0.865	0.930	1.975	0.722	0.734
	Total	1.152	2.346	1.532	6.869	0.894	0.894
GP3	Training	0.793	1.443	1.201	4.763	0.924	0.931
	Validation	0.341	0.862	0.928	1.972	0.723	0.736
	Total	1.134	2.305	1.518	6.735	0.896	0.896
GP4	Training	0.486	0.533	0.730	2.709	0.972	0.972
	Validation	0.262	0.677	0.823	1.556	0.782	0.753
	Total	0.748	1.210	1.100	4.265	0.945	0.946

ANFIS-GP4 was better than other versions of ANFIS-GP models in terms of higher NSE and R-squared values, lower MAE, MSE, RMSE, and MAPE values.

The results of ANFIS-SC2 and ANFIS-SC3 indicate that the inclusion of the precipitation in the models provides almost similar outcomes. In this case, it can be concluded that the use of precipitation is not compulsory for predicting SST in the Çanakkale Strait. Similar conclusions were also reached for ANFIS-GP2 and ANFIS-GP3 models. In the models with two inputs, on the other hand, the use of evaporation provided more improvement than the consideration of precipitation for both ANFIS-SC and ANFIS-GP. These results confirm that the role of air temperature and evaporation in SST modelling is much more important than precipitation.

First, the ANFIS creates suitable membership functions for each input variable at the training stage. Then, the membership functions are modified according to the error correction training method by using the back-propagation algorithm. In addition, the constant parameter of the linear output functions is adapted for the period of the learning stage based on the least mean square algorithm. The ANFIS model operates 1000 training data items during training periods. The training data constituted 75% of the dataset, while 25% of the dataset was allocated for testing in the ANFIS. The hybrid algorithm was selected as a training algorithm for the ANFIS. Figure 3 presents the diagram of the observed values for the monthly SST and the predicted values obtained using the ANFIS models. It illustrates the comparison between the observed and predicted SST values.

The highest correlation coefficient (0.96) was found between the observed and predicted SST values in the ANFIS-SC4 model for the overall prediction of SST time series. Moreover, the ANFIS-GP4 model outperformed during the training stage in terms of the R-squared value (0.97). Figure 4 presents the scatter plots of the observed and predicted SST values for all models. The respective correlation coefficient indicates an acceptable estimation of the model.

The output surface maps for the developed ANFIS-SC4 and ANFIS-GP4 models were presented in Figure 5 and Figure 6. In addition, the input-output surfaces produced by the ANFIS-SC3 and ANFIS-GP3 models are presented in Figure 7. These figures show the relationships between the predicted SST values and the other two inputs, respectively. The 3D surface visualization of the relationships between the inputs and the output for the ANFIS-SC2 and ANFIS-GP2 models was plotted in Figure 8.

Discussion

This study presents the ANFIS models developed to predict SST in the Çanakkale Strait in Turkey. Six performance evaluation criteria were used to evaluate the ANFIS models developed for SST prediction. The Takagi–Sugeno fuzzy inference system was implemented and the training data accounted for 75% of the dataset, while 25% of the dataset was allocated for testing in the ANFIS. The hybrid algorithm was selected as a training algorithm for the ANFIS. The average testing error was 0.91. The rules of the models were determined according to the relationships between the inputs and the output by the adaptive neuro-fuzzy inference system. The observed and predicted SST values were compared and Figure 4 presents the scatter plots of the observed and predicted SST values in the Çanakkale Strait. The respective correlation coefficient of 0.96 was found between the observed and predicted SST values in the ANFIS-SC4 model. The output surface maps for the developed ANFIS models were plotted and presented in Figures 5–8.

The SST is an important parameter in oceanographic research and planning of miscellaneous offshore activities (scientific, traditional, commercial and recreational events such as research, fishing, and marine transportation). It is one of the most important parameters in Earth observation aimed at monitoring the global climate (Mahongo & Deo 2013). Therefore, an accurate estimation of SST is very important. Data-driven approaches and physical observations are used to predict SST. Data-driven approaches range between traditional stochastic techniques, such as regression analysis (Kug et al. 2004), empirical canonical correlation analysis (Collins et al. 2004), trend analysis (Kale et al. 2016a,b, 2018; Ejder et al. 2016a,b; Kale & Sönmez 2018a,b; 2019a,b,c; Sönmez & Kale 2020, Arslan et al. 2020), Markov model (Xue & Leetmaa 2000), genetic algorithms (Neetu et al. 2011), and modern artificial intelligence approaches, such as neural networks (Patil et al. 2016), adaptive neuro-fuzzy inference systems (Sönmez et al. 2018).

Many researchers applied artificial intelligence techniques in research on water resources and climate with respect to environmental monitoring, assessment and forecasting (Altunkaynak et al. 2005; Kisi 2005; Ocampo-Duque et al. 2006; Sengorur et al. 2006; Terzi et al. 2006; Icaga 2007; Elhatip & Kömür 2008; Ay & Kisi 2011; Areerachakul 2012; Hisar et al. 2012; Qasaimeh et al. 2012; Ranković et al. 2012; Sönmez et al. 2012; Sönmez et al. 2013a,b; Ay & Kisi 2014; Emamgholizadeh et al. 2014; Heddam 2014; Alte & Sadgir 2015; Piotrowski et al. 2015; Khadr & Elshemy 2016; Bayatzadeh

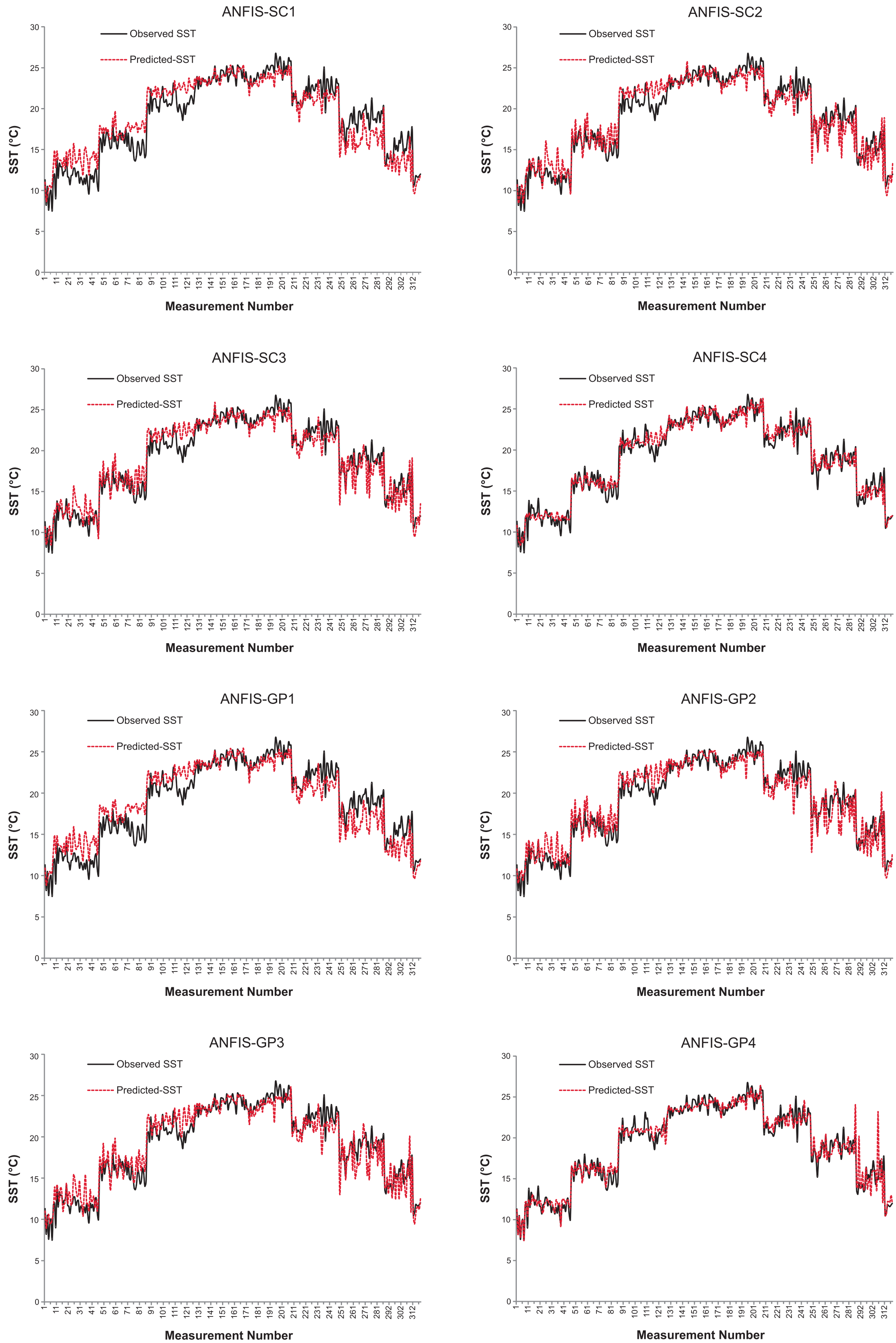

Figure 3

Comparison of ANFIS-SC and ANFIS-GP models for the observed and predicted SST values in the Çanakkale Strait

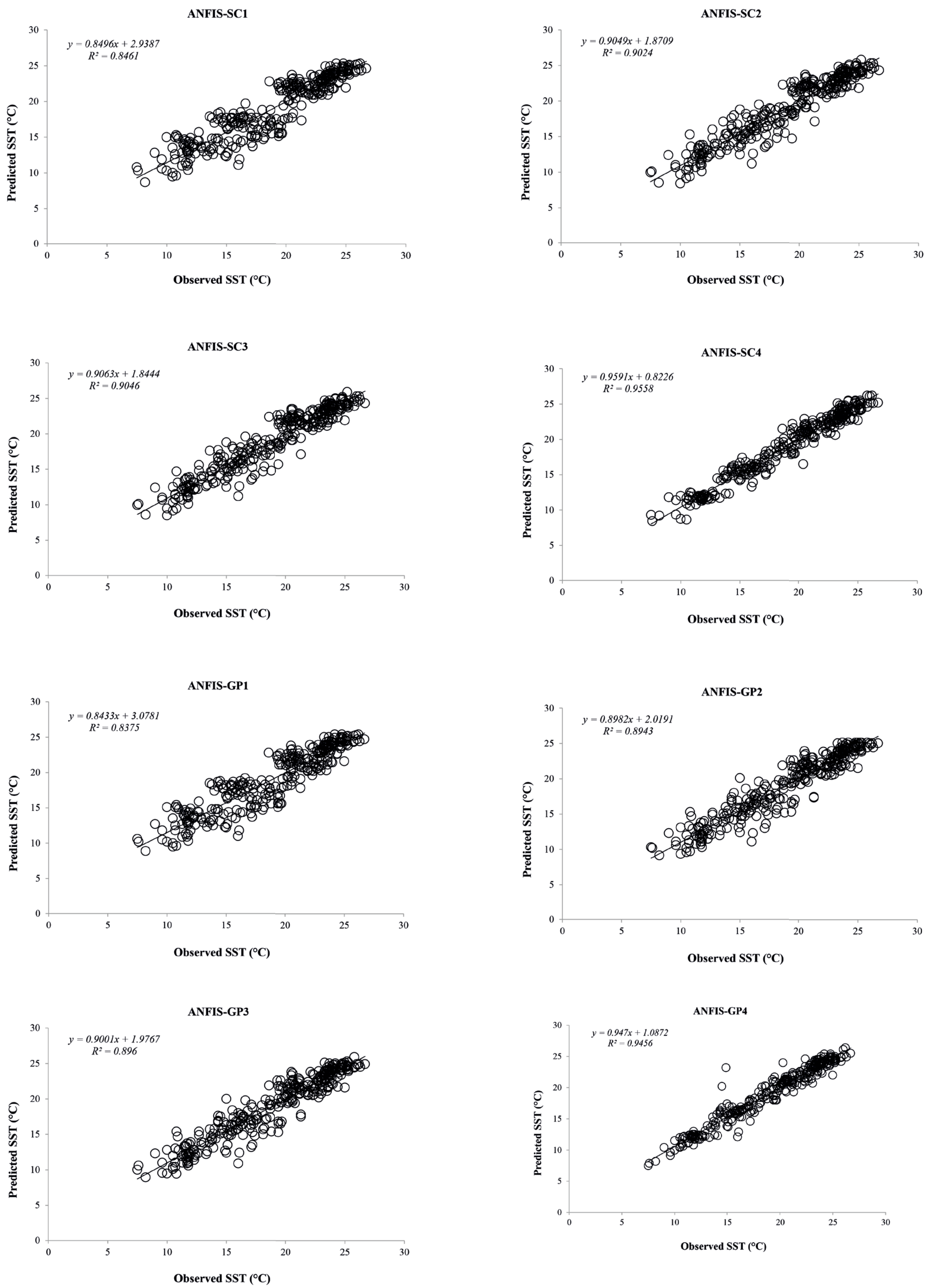

Figure 4

Scatter plots of ANFIS-SC and ANFIS-GP models for the observed and predicted SST values in the Çanakkale Strait

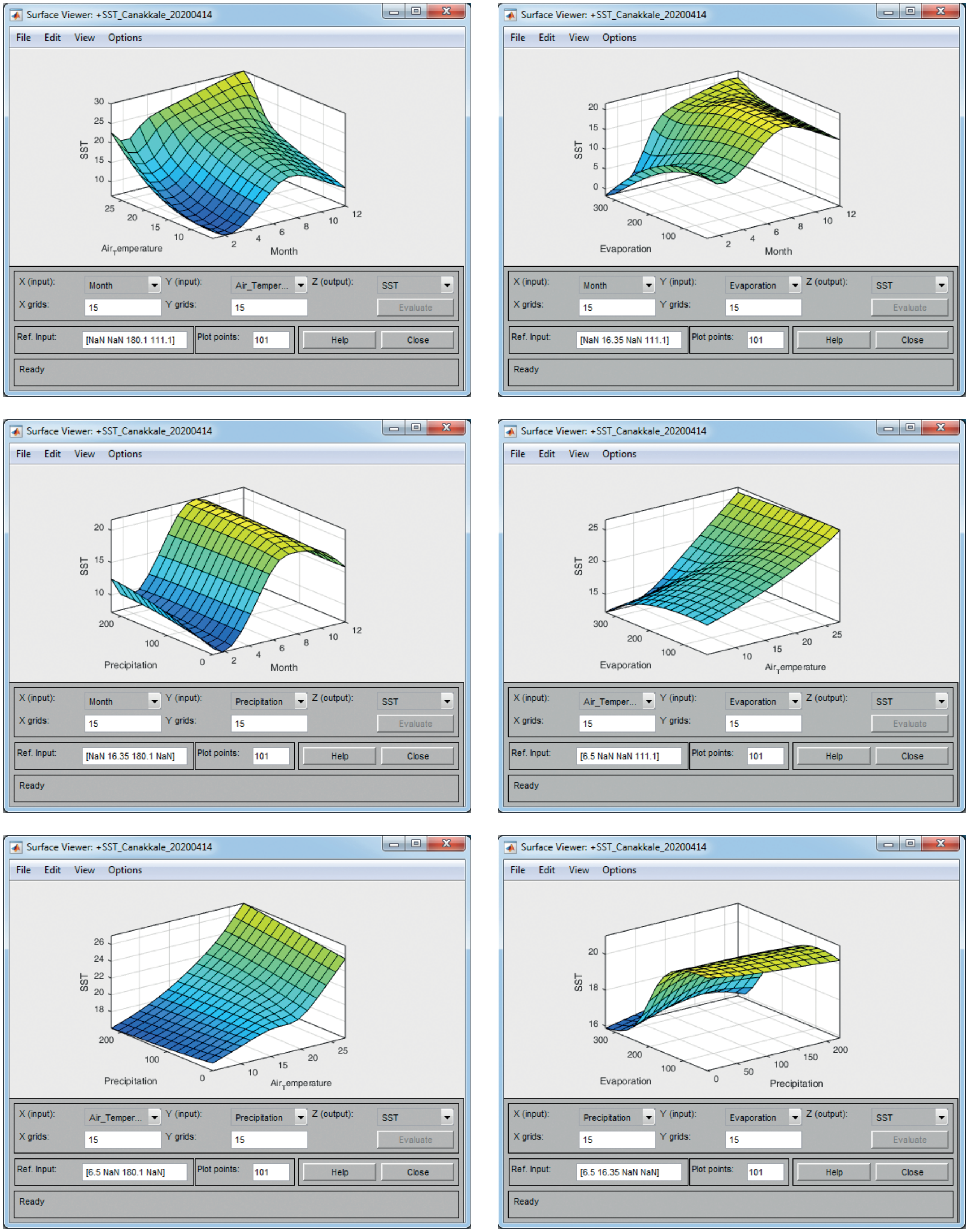

Figure 5

3D surface visualization of the relationship between the input and output for the ANFIS-SC4 model

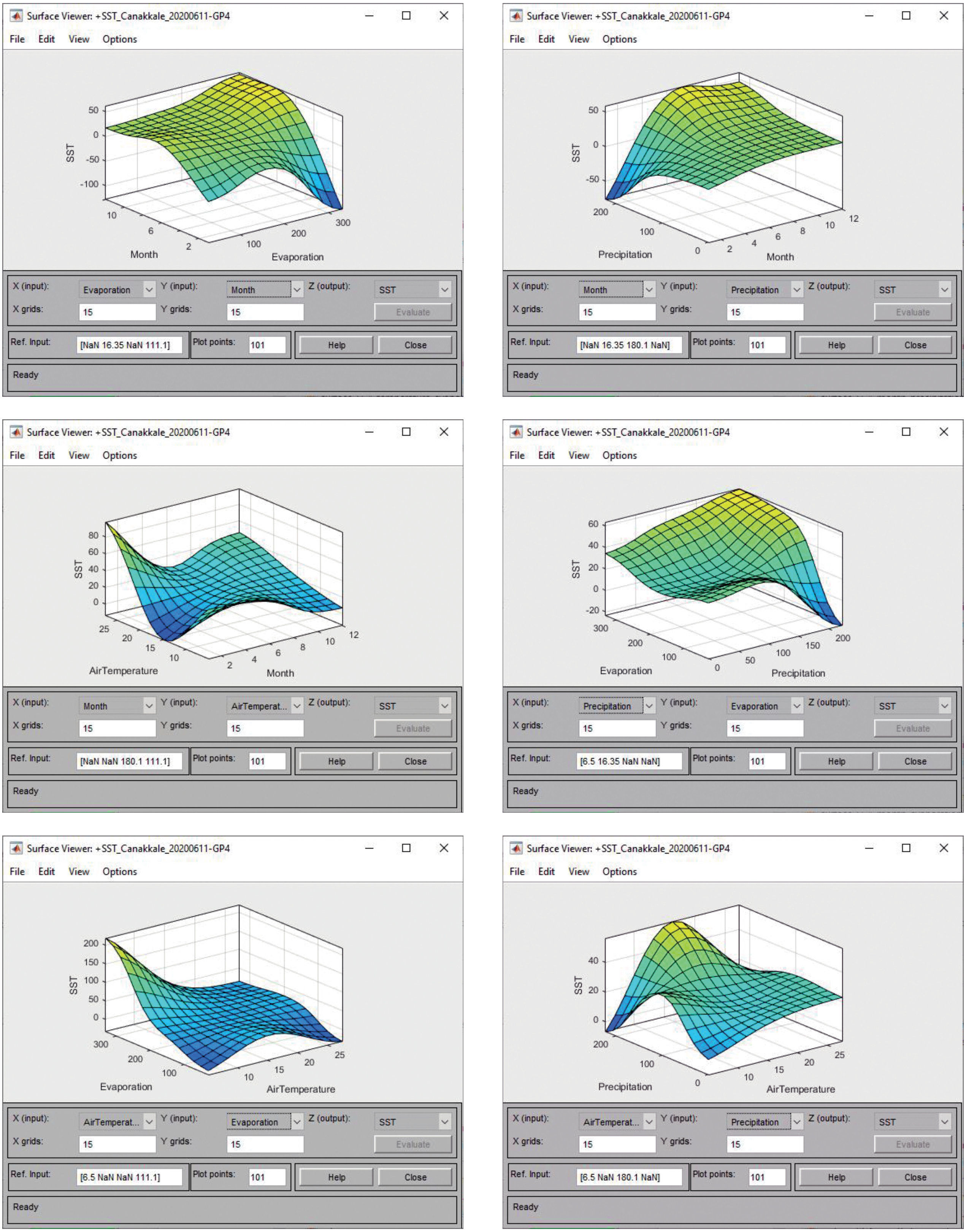

Figure 6

3D surface visualization of the relationship between the input and output for the ANFIS-GP4 model

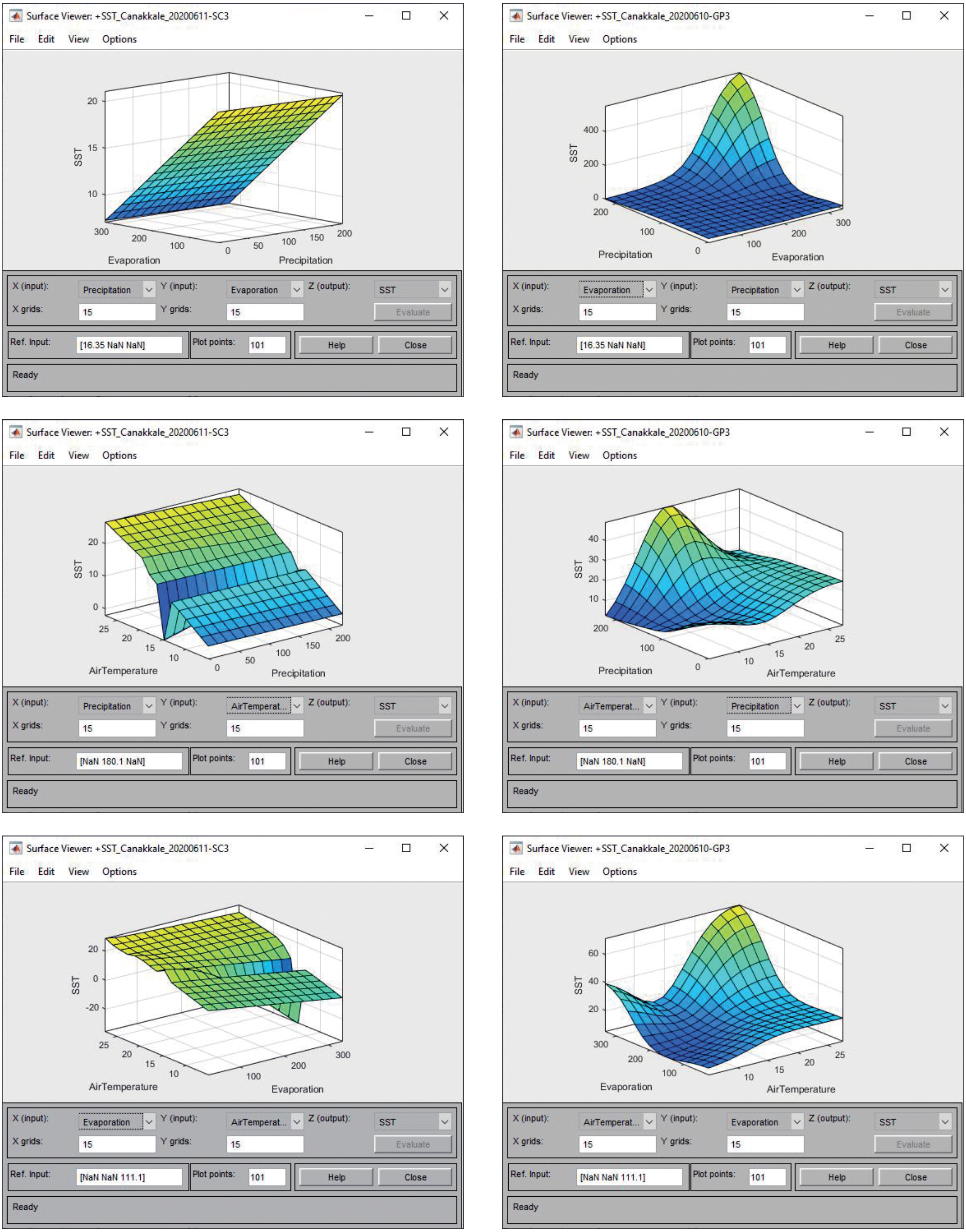

Figure 7

3D surface visualization of the relationship between the input and output for ANFIS-SC3 and ANFIS-GP3 models

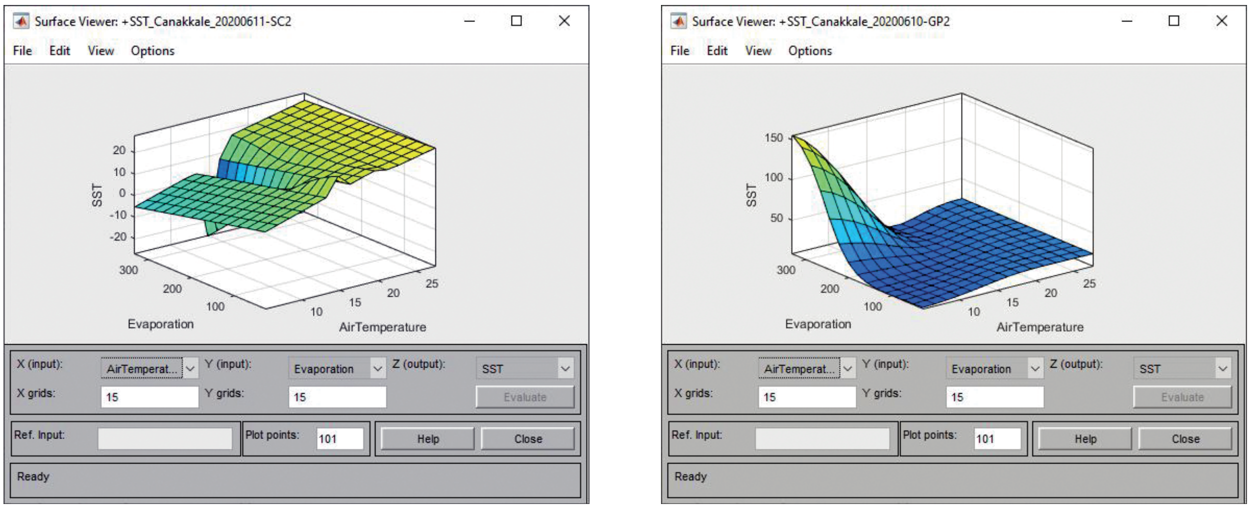

Figure 8

3D surface visualization of the relationship between the input and output for ANFIS-SC2 and ANFIS-GP2 models

Fard et al. 2017; Csábrági et al. 2017; Sönmez et al. 2018). On the other hand, several attempts have been made to predict SST globally (Garcia-Gorriz & Garcia-Sanchez 2007; Mahongo & Deo 2013; Patil et al. 2016; Samadianfard et al. 2016; Zhang et al. 2017; Ouala et al. 2018). Unfortunately, there is no research on the assessment of the adaptive neuro-fuzzy inference system for predicting SST. However, some researchers developed adaptive neuro-fuzzy models to estimate SST and compare the accuracy of the performance with other techniques. Garcia-Gorriz and Garcia-Sanchez (2007) used the ANN to predict sea surface temperatures in the western Mediterranean Sea. The authors trained the ANN with meteorological variables and documented that the ANN successfully predicted the mean monthly SST consistent with in situ observations. Similarly, Patil et al. (2016) combined numerical and neural networks to predict SST of the Indian Ocean at daily, weekly and monthly time scales. The authors reported that by combining the two techniques it was possible to make precise forecasts for selected locations. Zhang et al. (2017) developed a neural network and implemented a long short-term memory to predict SST in the coastal seas of China. The authors confirmed the efficacy of the suggested method. Ouala et al. (2018) proposed neural networks for the forecasting of SST off the coast of South Africa. Researchers indicated that the suggested patch-level neural network-based representations surpassed other data-driven models in terms of forecasting and missing data interpolation performance. Xu et al. (2020) predicted a spatio-temporal distribution of SST time series in the offshore waters of China. To achieve this objective, the authors developed a regional convolution long short-term memory (RC-LSTM) model. The prediction accuracy of the model was enhanced by merging spatial and temporal information. The authors reported that the developed model was more accurate than traditional estimation models. Therefore, they suggested that the developed model should be applied in future research. Wei et al. (2019) predicted SST in the South China Sea by the ANN and the authors recommended discrete time series of SST data in two datasets to construct two neural network models. The researchers stated that the suggested training method provides adequate forecasting accuracy. In the present study, a commonly used method that separates the dataset into training and testing stages was used to train and test the time series of SST. The method proposed by Wei et al. (2019) reduced the standard deviation of the prediction outputs and thus improved the accuracy of the prediction. Therefore, it may be considered for further research.

Artificial neural networks and adaptive neuro-fuzzy inference system models have also been developed and proposed by several scientists to predict surface water temperature of lakes, rivers, and streams. Zhu et al. (2019a) applied four different machine learning models, including multilayer perceptron neural network models (MLPNN), ANFIS with the subtractive clustering method (ANFIS-SC), ANFIS with the grid partition method (ANFIS-GP), and ANFIS with the fuzzy c-mean clustering algorithm (ANFIS-FC) to predict daily river water temperature. The authors used air temperature, river flow discharge and the components of the Gregorian calendar as input variables. They reported that the MLPNN model generally provided the highest performance, even though ANFIS-FC and ANFIS-GP were slightly more accurate at some river stations. In the present study, although the developed ANFIS models include similar methods (ANFIS-SC and ANFIS-GP), ANFIS-SC4 was found to be more accurate to predict SST in the Çanakkale Strait. On the other hand, Zhu et al. (2019a) documented that the highest correlation value between the observed and predicted water temperature was 0.9764, while in the present study it was 0.956. The values were relatively close to each other. Therefore, the prediction capacity of the developed models is relatively applicable to predict SST for other locations. Zhu et al. (2020) developed and applied the multi-layer perceptron neural network (MLPNN) model and integrated the model of the wavelet transform and MLPNN (WT-MLPNN) to forecast daily lake surface water temperature of eight lowland Polish lakes. The authors used long-term daily lake surface water temperature and daily air temperatures as input variables. It was found that the hybrid WT-MLPNN model performed slightly better than the traditional MLPNN model for forecasting lake surface water temperature. The use of hybrid models has some advantages in forecasting water temperature, as documented by both Zhu et al. (2020) and Graf et al. (2019). Graf et al. (2019) forecasted river water temperature of the Warta River in Poland using the wavelet-neural network hybrid modelling approach. The authors proposed a hybrid model that combines discrete wavelet transforms and artificial neural networks (ANN) for forecasting water temperature. They used daily air temperatures from seven meteorological stations to predict daily water temperature. The authors reported that the WT-ANN models performed well in modelling and forecasting water temperature of the river. In addition, it was also documented that the superior performance of the WT-ANN models is principally observed for extreme weather conditions, such as heat waves and drought. Similarly, the ANFIS models developed in this study outperformed during such conditions, with the highest temperature and evaporation recorded.

Samadianfard et al. (2016) predicted hourly water temperatures at a buoy station in Yuan-Yang Lake, Taiwan, at different depths. They used different soft computing techniques, including the ANN, ANFIS, and gene expression programming (GEP). The authors noted that the GEP provided rationally realistic trends for predicting an hourly water temperature at different depths. However, the correlation coefficient of GEP (0.73) was relatively lower for all depths to accurately predict the water temperature. The developed ANFIS model has a much higher correlation according to the findings of Samandianfard et al. (2016). In addition, the researchers noted that the ANFIS model considerably underestimated high values (> 13°C). Conversely, the ANFIS model developed in the present study predicted sea surface temperature with high accuracy. The difference in the estimation performance of ANFIS models between the two studies could be related to input variables and water characteristics. The sea surface is more saline than lake waters. Lower salinity can lead to higher fluctuations in the surface temperature. Therefore, the comparison of all techniques should be conducted by using a more comprehensive dataset.

A relatively higher correlation (0.96) was found between the observed and predicted SST values. The forecasting capability of the ANFIS model is closely equal to the findings reported by Soyupak et al. (2003) and Zhao et al. (2007). Soyupak et al. (2003) documented that the coefficient of determination was 0.95, whereas Zhao et al. (2007) noted that it was 0.94 between the observed and predicted dissolved oxygen (DO) values. Moreover, the correlation in this study was relatively higher compared to Sönmez et al. (2018), Singh et al. (2009) and Akpomie et al. (2016). Sönmez et al. (2018) developed an ANFIS model to predict Cd ion concentration in the Filyos River. The authors investigated the hybrid learning algorithm and used the Gaussian membership function to design a Takagi–Sugeno type fuzzy inference system. They documented that the correlation was 0.91 between the observed and predicted Cd ion concentrations. Singh et al. (2009) indicated that the coefficient of correlation was 0.85 for the observed and predicted DO values, while Akpomie et al. (2016) reported a similar finding, i.e. 0.86 for Cd ion concentration. On the other hand, Daneshmand et al. (2015) used the ANFIS to model the minimum temperature based on spectral analysis of climate indices. The authors used a hybrid training algorithm to train the system, and they found a high correlation coefficient of 0.987 between the predicted and observed values. Mahongo and Deo (2013) used the ANN to estimate seasonal and monthly SST anomalies in the western Indian Ocean and informed that the neural network model had provided the best overall performance. The authors noted that RMSE between predictions and observations was about 0.06°C and 0.13°C for seasonal and monthly SST anomalies, whereas the mean coefficient of correlation was about 0.98 and 0.88, respectively. The difference between those studies and this study may be related to dissimilarities in the data period. In the present study, mean annual SST data (obtained from the monthly average) were analyzed, while Mahongo and Deo (2013) analyzed both monthly and seasonal SST data and Daneshmand et al. (2015) experimented with the daily minimum temperature to estimate the monthly minimum temperature. In addition, correlations show similarities for both studies in terms of the monthly SST time series. Sönmez et al. (2013a) implemented a fuzzy logic assessment method to evaluate the quality of water in the Karasu Stream and the authors endorsed the fuzzy logic assessment method as a tool for water quality assessment. Sönmez et al. (2018) reported that the ANFIS presented high reliability and robustness. Similarly, the present study revealed that the ANFIS achieved high accuracy in predicting the SST values in the Çanakkale Strait by using a limited set of climatic data.

The analyses provided evidence that SST responds to changes (both increase and decrease) in air temperature. They support the argument that SST will be susceptible and strongly affected by climate change. Similarly, Kale (2017a) reported that the increase in temperature trends causes climatic changes. The author stated that the city of Çanakkale would be affected by global warming and climate change, and also would have a warmer climate in the future. Similarly, Kale (2017b) also reported that the annual evaporation would increase in the future, similarly to temperature. Therefore, accurate estimation of SST is important for aquatic ecosystems.

Piotrowski et al. (2015) compared different ANN types (multi-layer perceptron ANN, product-unit ANN, adaptive-network-based fuzzy inference systems, and wavelet ANN) for the prediction of water temperature in rivers. The authors reported that the multi-layer perceptron ANN performed better than the product-unit ANN. The performance of adaptive-network-based fuzzy inference systems and the wavelet ANN was found to be poor. Similarly, Ay and Kisi (2014) indicated the advantage of the multi-layer perceptron ANN over the ANFIS in modelling the chemical oxygen demand in rivers. On the other hand, Kisi et al. (2012) noted that the ANFIS outperformed the multi-layer perceptron ANN in modelling the suspended sediment, whereas Wang et al. (2009) documented that the ANFIS performed better than the multi-layer perceptron ANN in estimating monthly rive discharges. In addition, He et al. (2014) reported that the performance of the ANFIS and the multi-layer perceptron ANN was similar and the superiority of one model over another could depend on the number of input variables. The present paper revealed that the developed ANFIS model is highly efficient in predicting SST.

One of the limitations of the present study could be the limited input dataset. Shaltout (2019) indicated that SST of the Red Sea was correlated with the mean sea level pressure, air temperature at 2 m above sea level, cross-coast wind stress and sensible heat flux. Similarly, the air temperature at 2 m above sea level was used as an input variable to train the neuro-fuzzy model in the present study. In addition, evaporation and rainfall are key parameters in the hydrological cycle. Therefore, this limitation could be overcome by using these parameters in the training phase of the ANFIS model. On the other hand, there is no information about the most effective parameters on the SST in the Çanakkale Strait. Consequently, more research should be carried out to understand the most effective parameters on the SST in the Çanakkale Strait in the forthcoming periods. Nevertheless, as documented by Nayak et al. (2004), one of the advantages of the ANFIS is that it does not require an a priori model structure, unlike most of the time series modelling methods. Thus, the developed ANFIS model stands out among other SST prediction techniques.

One of the problems sometimes encountered when training a fuzzy system is the over-fitting of data where the model cannot be generalized and instead begins to learn certain patterns. This may be due to the use of a large number of hidden nodes or training examples. In this study, several experiments have been conducted on the ANFIS architecture and the rate of training and test data to ensure that this is not the case. The epoch number was set as 1000 to resolve this issue. The ANFIS implements a multiple iterative learning procedure and rapidly converges due to the hybrid learning algorithm used. The high level of accuracy that occurs during the testing stage can show that there is no excessive fit.

Finally, the size of training data is one of the most critical factors increasing the accuracy of the developed model to predict SST. The ANFIS uses the excellent learning algorithms of the ANN and the excellent estimate functions of the FIS. It can provide computations without mathematical modelling and offer an agreeable solution to the non-linear prediction problem. The ANFIS has an adaptable background and uses training data to produce a fuzzy inference system. Therefore, the ANFIS was preferred in this study. The results of the study showed that the developed ANFIS model is capable of predicting SST values.

Conclusions

In the present study, an adaptive neuro-fuzzy inference system has been developed and suggested for predicting sea surface temperature in the

Çanakkale Strait. A relatively higher correlation (0.96) was achieved between the observed and predicted SST values. The analyses provided evidence that SST responds to changes in air temperature. Thus, the SST will be susceptible and extremely affected by climatic changes. Therefore, an accurate estimation of SST is crucial for aquatic ecosystems. It can be concluded that the developed ANFIS model is able to predict SST values in the Çanakkale Strait by using a limited set of climatic data. The proposed model can be effectively used to predict sea surface temperature.

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Data availability statement

The data that support the findings of this study are available from the author upon reasonable request.

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