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LSTM AND ANFIS MACHINE LEARNING ALGORITHMS IN ESTIMATING THE SEA WATER TEMPERATURE IN TÜRKİYE AT VARIOUS SEA LOCATIONS

TÜRKİYE'DE FARKLI DENİZ MEVKİLERİNDEKİ DENİZ SUYU SICAKLIĞININ LSTM VE ANFIS MAKİNE ÖĞRENMESİ ALGORİTMALARI KULLANILARAK TAHMİN EDİLMESİ

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ABSTRACT

The World's temperature is experiencing a rapid increase, leading to negative consequences for aquatic ecosystems such as oceans, seas, lakes, and rivers. There are also other negative influences consisting of changing precipitation patterns, disruptions in marine current circulation, and formation of negative impacts on marine life. Ultimately, there is a compelling need for careful monitoring of sea temperatures to understand and address these interconnected environmental changes. The daily temperature of seawater (SWT) is a crucial abiotic variable that changes both the chemical composition of water and aquatic life in seas and oceans. The present study explored the capabilities of artificial intelligence techniques in one-day-ahead SWT predictions. These techniques are fuzzy c-means adaptive neuro-fuzzy inference system (ANFIS-FCM), subtractive clustering ANFIS (ANFIS-SC), grid segmentation ANFIS (ANFIS-GP), and long short-term memory (LSTM) and artificial neural network (ANN). Accordingly, daily SWT data that was collected from Alanya, Bodrum, and Akcakoca measurement stations located in Türkiye's Mediterranean, Aegean, and Black Sea locations were used in SWT predictions. Estimated results obtained by these five estimation methods were compared to the real observed values by interpreting four statistical metrics. Consequently, the most accurate estimates were obtained utilizing the fuzzy c-means (FCM) of ANFIS. Besides, it was reported that the LSTM approach closely followed the accuracy of this prediction of FCM. Both proposed models have generated superior statistical accuracy results corresponding to 0.34% MAPE, 0.0765 ºC MAE, 0.1585 ºC RMSE, and 0.9990 R. Those results have indicated the closest match of the predictions on the real measured data that have been acquired by ANFIS-FCM and LSTM models.

Keywords: Machine learning, artificial neural network, prediction of seawater temperature

ÖZET

Dünyanın sıcaklığında hızlı bir artış yaşanmaktadır ve bu durum, yağış düzenlerinde değişimlere, deniz akıntısı dolaşımında bozulmalara ve deniz yaşamında olumsuz etkilere neden olur. Ayrıca, bu durumun, okyanuslar, denizler, göller ve nehirler gibi su ekosistemleri üzerinde diğer olumsuz etkileri de bulunmaktadır. Sonuçta, birbiriyle bağlantılı olan bu çevresel değişiklikleri anlamak ve ele almak için deniz sıcaklıklarının dikkatli bir şekilde

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izlenmesine ve yorumlanmasına zorunlu bir ihtiyaç vardır. Diğer taraftan, deniz suyunun günlük sıcaklıkları (SWT), denizlerdeki ve okyanuslardaki hem suyun hem de su yaşamının kimyasal bileşimini değiştiren çok önemli bir abiyotik değişkendir. Bu çerçevede, bu çalışma, bir gün sonrası SWT tahminlerinde yapay zekâ tekniklerinin kabiliyetlerini araştırmıştır. Bu teknikler, bulanık c-ortalamalar uyarlamalı nöro-bulanık çıkarım sistemi (ANFIS-FCM), çıkarımlı kümeleme ANFIS (ANFIS-SC), ızgara bölümleme ANFIS (ANFIS-GP) ve uzun kısa süreli bellek (LSTM) sinir ağı ve yapay sinir ağıdır (ANN). Bu doğrultuda, Türkiye'nin Akdeniz'de yer alan Alanya, Ege'de bulunan Bodrum ve Karadeniz'de kurulmuş olan Akçakoca ölçüm istasyonlarından elde edilen günlük SWT verileri kullanılmıştır. Beş farklı tahmin yöntemi kullanılarak üretilen tahmin sonuçları, gerçek gözlemlenen değerlere göre dört farklı istatistiksel ölçüm yaklaşımı kullanılarak karşılaştırıldı ve yorumlandı. Neticede, en doğru tahminlerin, ANFIS'in bulanık c-ortalamalar (FCM) yöntemi kullanıldığında elde edildiği sonucuna varılmıştır. Bu modeli en yakından takip eden ikinci en iyi modelin ise; LSTM yaklaşımı olduğu sonucuna varılmış ve bulunan sonuçlar rapor edilmiştir. Önerilen bu iki model de %0,34'lük MAPE, 0,0765 ºC'lik MAE, 0,1585 ºC'lik RMSE ve 0,9990'lık *R*'ye karşılık gelen üstün istatistiksel doğruluk sonuçlarını üretmiştir. Bu sonuçlar, gerçek ölçülen verilere en yakın eşleşmelerin ANFIS-FCM ve LSTM modelleri ile elde edildiğini göstermiştir.

Anahtar Kelimeler: Makine öğrenmesi, yapay sinir ağı, deniz suyu sıcaklığının tahmini

INTRODUCTION

Over the last few decades, the impacts of global warming that is eventuated by increased greenhouse gas emissions have become a significant issue, this is not only a case in terrestrial areas but has also become a problem within aquatic ecosystems including oceans, seas, lakes, and rivers (Kayhan et al., 2015). Global temperature is increasing rapidly and this situation has adversely affected various marine events such as precipitation regimes, sea current circulation, and the lives of marine creatures. Moreover, they have also brought many problems, such as the efforts of fish living in cold seas to adapt to warm seas with changes in their migration routes, changing the variety and quality of products obtained from the sea, and decreasing the number of the products (Bilgili, 2023). On the other hand, a detailed analysis of trends and changes in SWT data is necessary to assess the negative influences of weather alteration on various fields such as hydrology, meteorology, agriculture, animal farming, and tourism. This analysis will also make important contributions to the prediction and determination of various atmospheric events such as future precipitation, evapotranspiration, wind speed, humidity, and temperature (Şişman, 2019). In this sense, the SWT greatly affects the efficiency of these applications. Because of these compelling factors, precise estimates of SWT play a pivotal role in the analysis and planning of marine events, as well as in the effective planning, operation, and management of energy generation plants.

Recently, several approaches were constructed to estimate and determine the magnitude of SWT. These approaches have been used to examine various processes: Cooling water discharges from thermal power plants, the interaction of increasing flood hydraulics with the environment, spatial and seasonal heat fluxes, volatility, and most importantly, environmental changes increase substantially (Gooseff et al., 2005; Webb and Zhang, 1997; Sinokrat and Stefan, 1993; Bowles et al., 1977; Morse, 1970). However, it is possible to develop some models for these cases as well, although the exact estimation of SWT is rather uncertain and complex since the heat flux, solar radiation, and wind speed differences are quite large; and usually, there are not direct available analytical equations to solve such cases to configure the magnitude of SWT. Consequently, a range of methods are employed, encompassing basic statistical and stochastic methods, as well as advanced artificial intelligence and machine learning techniques are considered for this purpose (Patil and Deo, 2017). Among modern data-based techniques, recently, ANNs have recently become one of the most prevalent types of prediction methods due to the flexibility of fitting stochastic data, they have comparatively simple developing characteristics, and generally, ANNs could be easily developed with a limited background of programming knowledge. On the other hand, SWT has been predicted using ANNs in several works of past researchers, available in the literature. For instance, seasonal SWT predictions have been performed by Tangang et al. (1997), and in the study, a specific area located in the tropical Pacific was taken into account. Besides, ANN was utilized considering wind stress as well as temperature anomalies of sea surface water as inputs to empirical orthogonal functions. Similarly, in the tropical Pacific region, the SWT was predicted by Wu et al. (2006), by utilizing ANN. Here, the artificial neural network (ANN) architecture involved extracting the key factors affecting the sea surface temperature (SST) throughout 3 to 15 months. These factors included the SWT itself and the sea level pressure. On the other hand, in the context of estimating the increase in SWT during the desalination process, several ANN-based correlations have been established with the work of Tanvir and Mujtaba (2006) (Patil and Deo, 2017). The forecasting skills of distinct models regarding regressions, transfer functions, and ANN at the Antarctic and Pacific Oceans were compared by the prediction capabilities of the models implemented by Gupta and Malmgren

(2009). This study determined that the ANN method performed superior estimation outcomes compared to the other approaches. The SWT estimate was exerted by Mahongo and Deo (2013), and it was applied to the east African coastline to approximately predict the SWT for subsequent months and seasons. Furthermore, the predictions of SWT also included the applications of various ANN models and the autoregressive integrated moving average (ARIMA) techniques. This analysis shows that data-driven methodologies used in previous research often revolve around time-series predictions. In these studies, it was observed that SWT predictions were performed by shifting such a pattern upwards along the time axis. The conducted overview of the available literature studies stated above demonstrates that the ANN is an interesting method in SWT forecasts. Also, ANN can be made more beneficial by taking into account the fast developments in this area, and this may be the main opportunity in this direction. The SWT is a significant indicator that influences the overall health of seas, and accordingly, precise anticipation of the SWT is one of the most important issues for a lot of agencies in the World. The tasks of those agencies may be diverse such that the monitoring of climate variability, obtaining seasonal predictions, performing operational weather and ocean predictions, executing operations regarding the military and the defense, verifying or enforcing models for the ocean and the atmosphere, the assessment of the ecosystems, and achieving researches on the tourism as well as the fishery jobs.

A review of the available literature in this study addresses the challenge of estimating SWT through short-term time-series analysis. There are a limited number of researchers working with the methods studied here in this area. The methods considered in this study are ANFIS models using subtraction clustering (ANFIS-SC) and grid partitioning (ANFIS-GP), as well as a deep learning (DL) model using fuzzy c-means (ANFIS-FCM). Additionally, the LSTM neural network and ANN models were taken into account.

Recently, data predictions have gained significant importance. In this way, the future unrealized magnitude of the considered physical parameter can be easily forecasted. And more importantly, precautions can be taken against some negative situations, when the future value of the considered parameter is known before. For example, predictions related to the SWT are so important in taking prevention for the benefit of nature, the sea itself, life on the sea, and the sea animals. Furthermore, excess rise of the sea temperature due to greenhouse gas emissions and global warming can be known earlier and some measures against those can be brought to life. Of course, there may be many other advantages of data estimates that are not covered here. On the other hand, there are lots of application areas of machine learning and artificial intelligence taken into account in physical and engineering sciences. For instance, they are mainly considered in estimations of air pressure and temperature, wind speed as well as direction, humidity anticipations, and precipitation forecasts. Besides, machine learning can also be utilized to obtain predictions on water flow speeds of the rivers, or information on sea wave height can be obtained by usage of proper artificial intelligence algorithms. More recently, guesses on wind power and solar energy have been achieved by different types of algorithms created by machine learning and artificial intelligence.

In this study, in the following sections, initially, the working principles and the methodologies of five algorithms including ANFIS-FCM, ANFIS-SC, ANFIS-GP, LSTM, and ANN have been given. Later, the study region and SWT data for the three stations are introduced. The plot of the fluctuating distributions of SWT data for all stations given for five years has been demonstrated. The tuning parameters of the algorithms that are used to have the best quality predictions are given in the model structure. Finally, the performance of the estimation algorithms is determined for three stations with the utilization of the tabulated results and by the usage of a graphical representation of the functional distributions of the real measured SWT data versus the forecast functions. Finally, the obtained prediction outcomes are interpreted.

MATERIALS AND METHODS

Adaptive Neuro-Fuzzy Inference System

The techniques developed using artificial intelligence (AI) methods to perform predictions in engineering applications with minimal error require a combination of two different techniques. Those techniques are ANN and FIS (fuzzy inference system). Namely, the ANFIS model combines the strengths of these two approaches, effectively capturing the intricacies of complex processes. This combination ultimately results in an advanced and superior technique. There are a lot of investigations about the ANFIS machine learning technique in the prediction of different environmental aspects and matters (Reddy and Krishna, 2023; Alver et al., 2020; Mashaly and Alazba, 2018; Saghafi and Arabloo, 2017). The ANFIS model works by training the system initially, similar to artificial neural networks (ANNs). In this way, a proper algorithm and link between each instantaneous data of all data clouds can be formed.

Next, the trained system functions as a FIS. This dual combination of FIS and ANN within ANFIS creates an integrated framework that maximizes the benefits of each component (Jang, 1993).

In the typical process of developing an ANFIS model, there are distinct stages involving construction and training, which are private to those found in other similar models. Throughout the model's creation, crucial decisions revolve around selecting the appropriate membership functions (MFs) and the associated parameters. This entails segmenting the data of input and output into the rule patches. The ANFIS approach thus streamlines the training phase by integrating commonly used clustering methods, facilitating a comprehensible organization and finally categorization of the input data. To accomplish this objective, three distinct clustering techniques were employed: Fuzzy c-means (FCM), inferential clustering (SC), else grid partitioning (GP). These techniques serve the purpose of enhancing the understanding and arrangement of the input data, ultimately contributing to the overall efficacy of the training process of the ANFIS model.

Long Short-Term Memory (LSTM)

A pioneering role by Hochreiter (1997) was played in the introduction of LSTM. While initially classified as a kind of RNN (recurrent neural network), this approach tackles the challenges faced by traditional RNNs by incorporating memory cells or cell states, which effectively manage the issue of vanishing errors. Figure 1 illustrates the LSTM layer. In the figure, how a time series indicated by X, having C properties (channels), as well as the length of S, progresses through the LSTM layer is demonstrated. Besides, the hidden element that is labeled with h_t, serves as both the output and a representation of the cell status at a time step of t. In the initial time step and for the first state of the network, the first LSTM component reckons the initial output as well as updates the cell state. As the sequence unfolds, the subsequent time step and the current network status (c_{t-1}, h_{t-1}) are used by this component to reckon both the output as well as the updated cell status (c_t) at a time step of t (Mathworks, 2020).

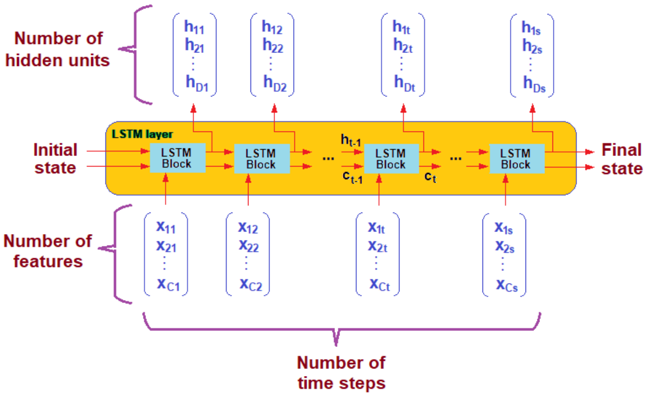

Figure 1. A Structure of an LSTM Layer (Mathworks, 2020)

Three learnable weights of the LSTM layer include input weights exposed by the denotation of W, recurrent weights signified by the abbreviation of R, and bias pointed by a symbol of b. Accordingly, three matrices are formed to include the combinations of input weights, recurrent weights, else the bias, respectively, comprising each gate component. Namely, Eq. (1) below shows the combination of these matrices including each gate component;

$$W = \begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix}, R = \begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix}, b = \begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix} \quad (1)$$

In Eq. (1), while the input gate is designated by the abbreviation i, the forget gate and the cell candidate are demonstrated by the abbreviations f and g, respectively. Moreover, the designation of o refers to the output gate, given at each learnable weight matrices.

Artificial Neural Networks (ANNs)

An ANN in the form of a three-layered structure including i, j, as well as k layers having the weights of W_{ij} else W_{jk} are presented in Figure 2. In this figure, i, j, and k layers correspond respectively to the layer of input, a layer of hidden as well as the layer of output. On the other hand, weights W_{ij} and W_{jk} are defined between input and hidden layers as well as hidden and output layers. The structure is composed of the layer of input, the layer of hidden, and the layer of output from the multilayer perceptron (MLP), as presented in this figure. Besides, the input and output layers include input and output variables, respectively (Kisi et al., 2016). In ANN structures, every neuron owns an adjustable weight factor (w) as well as a bias (b), defined between successive layers. In this context, the input variables at the network's input layer are multiplied with regard to the connection weights, and then biases are added to these multiplications. In the network's hidden layer, the formation of many artificial links associated with the previous layer, results in the collection of variables. Then, the output for the neuron is obtained by adjusted parameters which are passed through a function of transfer. Namely, the activation process is performed by this transfer function. Finally, the first hidden layer's outputs eventuate as the inputs of the network output layer (Kisi et al., 2015).

The widely utilized activation function, i.e., the definition of the logistic function is provided in Eq. (2) (Mansouri et al., 2016). This is defined with the reciprocal of the addition of the negative power of the exponential function added to the unity.

$$f(y) = \frac{1}{1+e^{-y}} \tag{2}$$

To decrease the errors during the training operation, the most appropriate learning algorithm should be searched and implemented. After the training process, the assimilation of the network can be observed as the output. A back propagation (BP) technique is generally taken into account in the learning algorithms for a multi-layer perceptron approach. The main intent of BP method is to acquire a significant reduction in the total amounts of network errors.

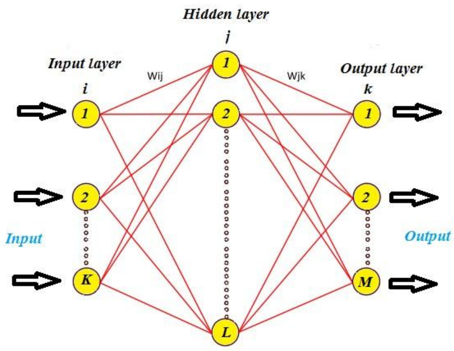

Figure 2. ANN Structure of a Multilayer Perceptron Presented in Three-layered Form (Sharma et al., 2023)

The accuracy of the machine learning and artificial intelligence estimations have been evaluated according to four statistical accuracy parameters, given with Eqs. (3), (4), (5), and (6). Namely, in those equations, mathematical statements of mean absolute percentage error, mean absolute error, root mean square error, and the correlation coefficient, corresponding to abbreviations of MAPE, MAE, RMSE, and R have been respectively indicated. In this way, comparison as well as the assessment of the implemented models are acquired by these 4 statistical accuracy parameters. In short, those parameters indicate which method is better than the other.

$$MAPE = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\left(\frac{r(i)-f(i)}{r(i)}\right)\right|\right)x100 \tag{3}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|f(i)-r(i)| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[f(i)-r(i)]^2} \tag{5}$$

$$R = \left(\sum_{i=1}^{N}[f(i)-\bar{f}][r(i)-\bar{r}]\right)/\left(\sqrt{\sum_{i=1}^{N}[f(i)-\bar{f}]^2}\ \sqrt{\sum_{i=1}^{N}[r(i)-\bar{r}]^2}\right) \tag{6}$$

The *f(i)* function shown in all four above equations demonstrates the instantaneous forecasted SWT data at the instantaneous observation of *i*, obtained by five models. Besides, the function of *r(i)* used in the same four equations exhibits the instantaneous actual measured SWT data at the instantaneous observation of *i*. Eventually, the mean values of the forecasts and the real observations in the computations of the *R* given in Eq. (5), are respectively exposed by symbols $\bar{f}$ and $\bar{r}$.

In this study, four verification criteria including MAPE, MAE, RMSE, and *R* have been utilized. Those are the most commonly used statistical accuracy parameters in the evaluation of the accuracy of the implemented models. They enable comparison of the predictions with respect to the actual observed data clouds. With the utilization of those error parameters, how much an estimation function approximates the counterpart's actual data function can be evaluated and answered. On the other hand, it also provides answers to the quality of the predictions and thus compares all anticipation obtained by different methodologies. The studies of Bilgili (2010) and Ilhan (2023) have considered those parameters in the evaluation of the comparison of the estimations according to the real observed data clouds.

In this study, the prediction models defined above were tested on a total of 1,826 data for each station that corresponded to five years of daily average SWT magnitudes of three different measurement stations found in Türkiye. For each station, four years of a total of five years were chosen as the training data cluster, whereas, the rest of one year of cumulative of five years was selected as testing data cluster. The forecast capacities of the implemented LSTM, ANFIS-FCM, ANFIS-SC, ANFIS-GP, and ANN models were tested according to the testing phases of the simulations, namely last year's predictions were revealed on the actual data SWT function for three measurement stations in the following figures of the text.

RESULTS AND DISCUSSIONS

The Study Region and SWT Data

Special attention was given to collecting SWT data from various regions and seas found in Türkiye. The SWT data that was obtained from Turkish meteorological stations (MS) found in Alanya, Bodrum, and Akcakoca provinces, were utilized for this purpose. These stations are strategically located, representing the geographical regions of the Mediterranean, Aegean, and Black seas.

On the other hand, Figure 3 presents all of the SWT instantaneous data found in the data cloud that was used in predictions, considering these three MSs. In this figure, those cited stations are shown with the color patterns corresponding to blue, red, and green, showing Akcakoca, Bodrum, and Alanya MSs, respectively. On the other hand, the daily instantaneous SWT values at these measurement stations were measured in the date range between 01 January 2015 and 31 December 2019. The measured temperature values ranged from 7.5 ^{o}C to 27 ^{o}C at Akcakoca MS, from 15 ^{o}C to 28 ^{o}C at Bodrum MS, and from 16 ^{o}C to 31 ^{o}C at Alanya MS. As seen from this figure that the minimum daily SWT was generally realized in January months, whereas, the maximum daily SWT was actualized in August months for all of the measurement stations. And, this is also a feature of the northern hemisphere of the globe. When the alteration of daily data for five years is examined, it is clear that the data of three MSs has an annual periodic fluctuation and therefore is quite appropriate for the time-series forecasting models created by machine learning.

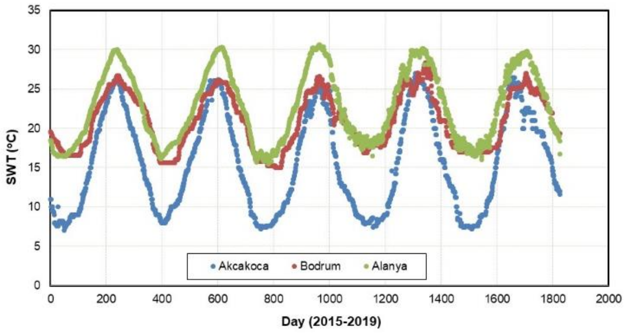

Figure 3. Time-series of Observed Daily SWT Data for Akcakoca, Bodrum, and Alanya MSs

The Model Structure

The SWT predictions were conducted by considering the daily average values of SWT data measured at three different locations of measurement stations (MS), found in Türkiye. For the predictions, the instantaneous input data in the models were derived from the average values of 1,826 daily SWTs obtained from measurement stations located in Akcakoca, Bodrum, and Alanya provinces of the country. However, a split on these data was implemented to form a discretization including two data clouds, in which one is formed to consist of 80% of the cumulative and named as training data cluster; whereas, the rest is formed of 20% of the cumulative and named as testing data cluster. Then, following the planned workflow of the forecasting methods, the selected forecasting models were trained to utilize the data cloud that was allocated for training. After, the validation was implemented using the data cloud that was allocated for testing. The time-series methodology includes the univariate modeling approach that was implemented to the time-series data of the targeted variable. This approach captures patterns within the dataset by recognizing the natural periodicities of the time-series data function. For instance, in SWT data distributions, an annual periodic trend is occurring on the data of all stations. Thus, for a considered station, the next periodic cycle imitates the former one, however being slightly different than the former one. For the current study, initially, the SWT estimates were made using a time-series analysis depending on the LSTM approach. Then, SWT estimations were actualized using the ANFIS-FCM method as a second technique. As a third method, SWT estimates were modeled using the ANFIS-SC configuration. Then, the ANFIS-GP tool was used as the fourth approach, and then the method of ANN was utilized and discussed as the last step.

Among the configuration adjustments for the LSTM algorithm: The hidden layer (HL) number was set to 5 for all MSs. On the other hand, the max epoch number was kept at a constant value of 300, throughout all trials. In the field of LSTM applications, although experiments involved the alteration of the *HL* in the range of 5 and 150, in the end, it was concluded to keep the hidden layer at a constant value of 5, since it revealed the highest accuracy for all constructed models.

On the other hand, the ANFIS approach was adopted to obtain the desired output values from the input variables. In ANFIS-FCM type of models, the number of members per step is gradually increased by setting the number of MFs to be in a range of 2 to 10. Conversely, the ANFIS-SC model was examined with radius spacing to evaluate the effect of radius. In SC type of models, an increment of 0.1 was implemented at the influence radius range between 0.2 to 0.9. Finally, while the number of entries and the maximum number of periods were adjusted alike in GP of ANFIS, resembling FCM and SC algorithms of ANFIS; the number of MFs was adjusted either to 2 or 3 in this particular type of modeling.

Case Study 1: Results of Akçakoca MS

The displayed prediction results in Table 1, which were exhibited in terms of the statistical error parameters, demonstrate the acceptability of LSTM, ANFIS, and ANN models which showed satisfactory performance in daily SWT predictions. However, the best outcome was achieved by the ANFIS-FCM model, yielding a result of MAE of 0.1939 ºC, a MAPE of 1.20%, an RMSE of 0.3597 ºC, and an R statistic of 0.9983. When all of the model results were analyzed, it can be observed that these statistical accuracy results are the lowest with regards to MAE, MAPE as well as RMSE, whereas, the highest with regards to R. In this regard, a model that already has these features is referred to be the model that produces the best quality and the best prediction. In a similar approach, the second superior model evaluated in terms of the statistical error parameters, was also reported. Namely, the second superior model for Akçakoca MS was determined and reported to be ANFIS-SC, generating statistical results of 0.1948 ºC MAE, 1.21% MAPE, 0.3624 ºC RMSE, and an R-value of 0.9983. Accordingly, Figure 4 provides the function of the measured actual SWT data obtained from this station, given with respect to the five different prediction approaches. In this figure, the predicted values of one day ahead of SWT using five distinct models were compared against the actual measured SWT values obtained from Akçakoca MS; revealing the high degree of alignment between the measured and predicted results.

Table 1. Statistical Results of SWT Forecasts for Akçakoca MS

Model	MAPE (%)	MAE (ºC)	RMSE (ºC)	R
LSTM	1.34	0.2118	0.3707	0.9982
ANFIS-FCM	1.20	0.1939	0.3597	0.9983
ANFIS-SC	1.21	0.1948	0.3624	0.9983
ANFIS-GP	1.49	0.2523	0.5809	0.9958
ANN	1.23	0.1982	0.3648	0.9983

This figure clearly demonstrates the exceptional congruence between the time-series functions of the applied models performing prediction calculations and the real measured time-series function. This alignment is also evident from the statistical error parameters presented in Table 1.

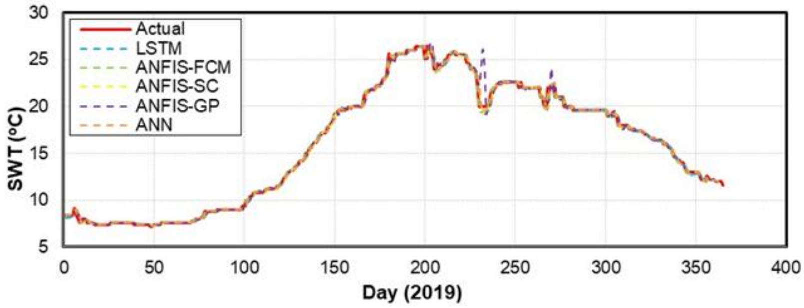

Figure 4. The Forecasts on the Actual SWT Data of Akcakoca MS

Case Study 2: Results of Bodrum MS

The procedure applied to Bodrum MS follows the same process as the previous Akçakoca station. In this context, a summary of the error estimation obtained through statistical evaluation results from the testing process of this station is presented in Table 2. The models used perform commendable outcomes in estimating daily SWTs. In particular, optimal and fairly accomplished results were achieved through LSTM and ANFIS-FCM methodologies in this case study. Specifically, the ANFIS-FCM method gave superior results when MAPE and MAE error outcomes were taken into account, while the LSTM method was superior when RMSE and *R* statistical evaluation parameters were considered. Namely, it was concluded that the error results of MAPE and MAE of FCM method are the lowest among the five models, whereas, the error outcomes of RMSE of LSTM are the lowest among the others and *R* of LSTM is highest among the others. Accordingly, as observed from Table 2, ANFIS-FCM model generated 0.34% MAPE and 0.0765 ºC MAE, whereas, the LSTM model gave the results of 0.1585 ºC RMSE and 0.9990 *R*; indicating to be the best two models among the others.

On the other hand, Figure 5 demonstrates testing time-series of real observed data, presented for Bodrum MS. The data cloud function of actual data is given in this figure according to the predicted SWT data clusters, under the usage of the same five prediction tools, including LSTM, ANFIS-FCM, ANFIS-SC, ANFIS-GP, and ANN. A comparison of the predictions against the actual observed data of this Bodrum station is visualized in this figure, similarly, to show the degree of the quality of the computations. Namely, SWT machine learning anticipation models coincided very well with the counterpart actual values and even better than the former analyzed Akcakoca MS. In general, the error parameters including MAPE, MAE, and RMSE were computed to be significantly lower than the corresponding error values of Akçakoca MS, whereas, the correlation coefficient (*R*) was determined to be substantially higher than the counterpart correlation coefficient (*R*) value of the Akçakoca MS. In this regard, the statistical error calculations that are shown in Table 2, belonging to these models also prove the related overlapping incidents and the high qualities of the implemented models.

Table 2. Statistical Results of SWT Forecasts for Bodrum MS

Model	MAPE (%)	MAE (ºC)	RMSE (ºC)	R
LSTM	0.35	0.0786	0.1585	0.9990
ANFIS-FCM	0.34	0.0765	0.1600	0.9989
ANFIS-SC	0.35	0.0785	0.1602	0.9989
ANFIS-GP	0.41	0.0934	0.1831	0.9986
ANN	0.36	0.0807	0.1609	0.9989

A variety of studies on different areas using different algorithms are available in the literature. In this context, Chen et al. (2018) have considered a model formed of EnsemLSTM using wind speed data of ten-minute intervals. In their study performed in China, they computed a correlation result of *R*=0.9619. On the other hand, Yucel et al. (2016) constructed a forecasting model for daily precipitation predictions in Türkiye. They have concluded a correlation outcome of *R*=0.2939. Khosravi et al. (2018) have performed monthly solar irradiance estimations in Iran. They have obtained a correlation result reaching to *R*=0.9999. Liang et al. (2018) have actualized LSTM anticipations of wind speed using data measured at five-minute intervals. The study that was executed in the USA turned a correlation inference of *R*=0.9996. Benmouiza and Cheknane (2019) who carried out ANFIS-FCM hourly solar radiation predictions in Algeria have obtained a correlation result of *R*=0.9742. Ultimately, Bilgili and Sahin (2010) made a monthly wind speed forecast in Türkiye. They have concluded a correlation outcome of *R*=0.9311. Accordingly, the SWT prediction performance of the current study obtained from Bodrum station that resulted in a value of *R*=0.9990 has been concluded and signified to be generally higher than the literature studies.

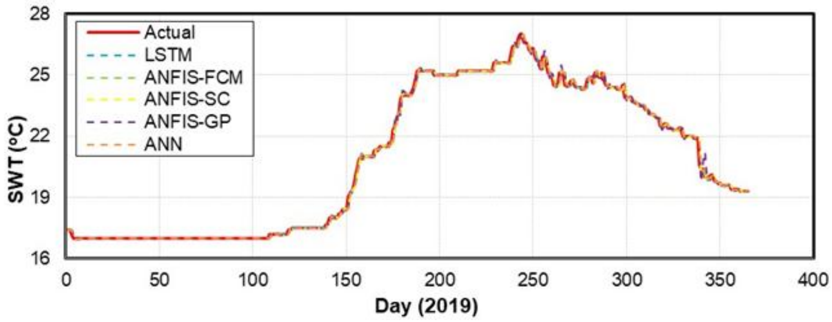

Figure 5. The Forecasts on the Actual SWT Data of Bodrum MS

Case Study 3: Results of Alanya MS

The processes tracked for prior Akcakoca and Bodrum MSs are implemented similarly for Alanya MS. Accordingly, for this MS, the statistical evaluation outcomes obtained from the testing processes of the computations are given in Table 3. The outcomes indicated that these utilized models for daily SWT forecasting had a good performance; however, it is also reported to be unfortunately slightly poorer than case studies 1 and 2 in terms of performance. In addition, interesting findings emerged from the statistical comparison parameters. For instance, while LSTM and ANFIS-FCM methods gave superior outcomes depending on the MAPE and MAE statistics; LSTM and ANFIS-SC methods, withal, generated the best outcomes considering the RMSE and *R* error statistics. Accordingly, the LSTM method gave 1.48% MAPE and 0.3135 ºC MAE, in predictions of SWT. Close to these results, the ANFIS-FCM method produced 1.48% MAPE and 0.3123 ºC MAE, in SWT forecasts. On the other hand, the LSTM approach generated prediction values on the real data corresponding to 0.4510 ºC in terms of the RMSE and 0.9950 in terms of the *R*. Lastly, ANFIS-SC method had prediction results close to the LSTM outcomes, procured values of 0.4513 ºC for the RMSE and 0.9950 for *R*.

Conversely, distributions of the real and prediction time series at testing stages for Alanya MS are all demonstrated together in Figure 6. In this figure, SWT data clusters for this province were predicted with the same methodology that was also used in the previous two case studies. Besides, the actual measured data of Alanya MS were also provided in this figure to compare the predictional models for Alanya MS and the real data of the station. According to the figure, it is reported that the functions belonging to the SWT forecasting models generally coincided well with the function of the actual counterpart, but the accuracy of the predictions was reported to be slightly lower concerning the previous two MSs. Especially, when the purple colored curve indicating the predictions acquired by GP tool of the ANFIS is carefully analyzed, it is initially observed from the tabulated results that GP tool had generated higher results depending on MAPE, MAE as well as RMSE. Secondly, depending on the statistical accuracy error of the correlation coefficient (*R*), GP approach gave lower results. Finally, huge deviations from the general trend of real observed SWT data and other predictions occurred for SWT predictions obtained by the GP algorithm. This is especially the situation in the data range of sample day number of 75 to 100, as well as through the end of the considered data samples, such as in the vicinity of 360, as observed from Figure 6. On the other hand, the statistical evaluation parameters presented in Table 3 generally confirm the high success of the overlapping incidents of the predictions on the observed data function, which are shown in Figure 6.

Table 3. Statistical Results of SWT Forecasts for Alanya MS

Model	MAPE (%)	MAE (ºC)	RMSE (ºC)	R
LSTM	1.48	0.3135	0.4510	0.9950
ANFIS-FCM	1.48	0.3123	0.4540	0.9949
ANFIS-SC	1.49	0.3148	0.4513	0.9950
ANFIS-GP	1.80	0.3752	0.5779	0.9918
ANN	1.51	0.3184	0.4655	0.9947

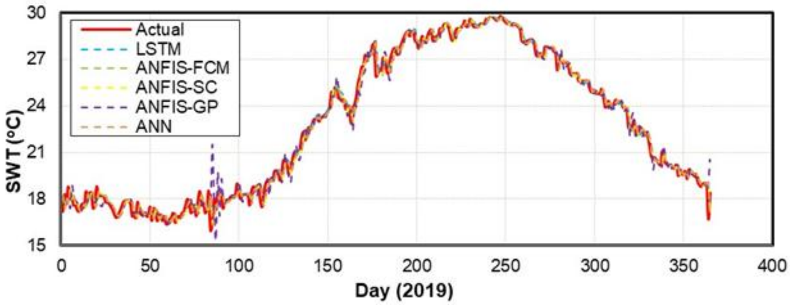

Figure 6. The Forecasts on the Actual SWT Data of Alanya MS

CONCLUSIONS

In this study, SWT predictions were performed utilizing a variety of algorithms of machine learning and artificial intelligence. Those mainly included LSTM, FCM, SC, GP, and ANN tools. To this end, three MSs in Türkiye were considered, that are named Akcakoca MS, Bodrum MS, and Alanya MS. Later, the generated forecast results that were obtained by these approaches were compared with the actual observed SST values. Accordingly, these comparative analyses were performed by evaluating key statistical parameters including MAPE, MAE, RMSE, as well as *R*. The detailed analysis revealed that the most accurate forecast results were obtained at Bodrum MS. Specifically, higher correlation coefficient (*R*) values were obtained simultaneously for this station, especially while recording lower MAPE, MAE and RMSE values, which is generally the case for all implemented models. In comparisons of data clouds, lower values of statistical error outcomes for MAPE, MAE, and RMSE mean higher quality and correspond to less prediction error within the models, while a higher correlation coefficient (*R*) means a better fit between actual measured and estimated data distributions. In conclusion, it can be concluded that the best estimates were made in data clusters of Bodrum MS. Among the tested methods, ANFIS-FCM approach gave the most suitable and qualified results for Bodrum MS in terms of MAPE (%) and MAE (°C). Simultaneously, for the same station, the LSTM method outperformed the others in terms of RMSE (°C) and coefficient of determination (*R*). Based on these best outcomes, those two algorithms generated MAPE, MAE, RMSE, and *R* results of 0.34 %, 0.0765 °C, 0.1585 °C, and 0.9990, respectively for Bodrum MS. The quality and the success of the estimations were slightly lower in other two stations apart from Bodrum including Akçakoca and Alanya. In Akçakoca MS, the best prediction results were obtained by ANFIS-FCM and ANFIS-SC algorithms. Those two gave satisfactory estimation performance that quite approached the actual measured SWT data function. On the other hand, in Alanya MS, interesting results were acquired. Namely, LSTM, ANFIS-FCM, and ANFIS-SC algorithms gave more or less similar results of statistical error parameters. Besides, the prediction capacities of the three approximated the actual data function by almost the same amount. Moreover, when estimated data of three MSs and whole prediction methods are taken into consideration, the best predictions were reported to be obtained by the ANFIS-FCM method, and secondly by the LSTM method. However, in general, it was concluded that methods including LSTM, ANFIS methods, and ANN, all performed very good estimations, and these methods were shown to be quite suitable for use in SWT estimates.

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