

Soil temperature modeling at different depths using neuro-fuzzy, neural network, and genetic programming techniques

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Abstract The applicability of artificial neural networks (ANN), adaptive neuro-fuzzy inference system (ANFIS), and genetic programming (GP) techniques in estimating soil temperatures (ST) at different depths is investigated in this study. Weather data from two stations, Mersin and Adana, Turkey, were used as inputs to the applied models in order to model monthly STs. The first part of the study focused on comparison of ANN, ANFIS, and GP models in modeling ST of two stations at the depths of 10, 50, and 100 cm. GP was found to perform better than the ANN and ANFIS-SC in estimating monthly ST. The effect of periodicity (month of the year) on models' accuracy was also investigated. Including periodicity component in models' inputs considerably increased their accuracies. The root mean square error (RMSE) of ANN models was respectively decreased by 34 and 27 % for the depths of 10 and 100 cm adding the periodicity input. In the second part of the study, the accuracies of the ANN, ANFIS, and GP models were compared in estimating ST of Mersin Station using the climatic data of Adana Station. The ANN models generally performed better than the ANFIS-SC and GP in modeling ST of Mersin Station without local climatic inputs.

1 Introduction

Soil temperature is the most important factor influencing the growth, development, and yield of a crop to a particular climatic condition. It depends on climatic and environmental factors such as solar radiation, air temperature, rainfall, albedo, topographical variables, and other surface characteristics. Plant growth progresses are deeply bound up with soil temperature through various phenological stages such as germination stage towards maturity level (Rosenzweig and Liverman 1992a, b). Plants can grow only within certain limit of temperatures. Seed germination is highly dependent on soil temperature (ST) and other climatic variables. However, the range of ST in which seeds perform better growth depends largely on crop types (Hasanuzzaman et al. 2013). Accordingly, the ST defines which species can live in a particular region. In literature, there are many studies about the importance of soil temperature for the plant life. Soil temperatures affect the rates of photosynthesis, respiration, and transpiration of plants. In most temperate zone species, the rate of photosynthesis is reported to increase from near freezing until it attains a maximum between 15 and 25 °C. For tropical species, the minimum temperature for photosynthesis is several degrees above freezing and the maximum well above 25 °C (Creamer and Fox 1980). Respiration often continues to increase above a critical high temperature at which photosynthesis begins to decrease. Anderson and McNaughton (1973), investigating 17 populations of 12 vascular plant species, reported that decreasing soil temperature from 20 to 3 °C had no adverse effect on transpiration or photosynthesis. However, it was observed that plant growth was significantly reduced. Growth reduction at low soil temperature was therefore concluded to result from impaired turgor, decreased root growth and metabolism, or impaired cytokinin synthesis and translocation and not from direct limitation of carbon assimilation. Temperatures where active plant cells die is reported

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to vary from 120 to 140 °F (49 to 60 °C) and depend on species, age of tissues, and length of exposure to high temperature (Swank and Vose, 1988). Temperatures in excess of 140 °F (60 °C) have been found to produce injury due to breakdown of proteins. Labanauskas et al. (1975) found that Yecora wheat grown at soil temperature of 25 °C yielded less grain than those plants grown in 15 and 5 °C temperatures. Changes in soil temperature cause some alterations on the soil properties. Creamer and Fox (1980) reported that lowering soil temperature appeared to inhibit nitrification and helped maintain high pH. Moragham (1980) concluded that nutrient stresses in flax (*Linum usitatissimum*) due to P and Zn deficiencies were likely to develop at soil temperature of 25 °C. Munevar and Wollum (1981) reported that increasing root temperature from 28 to 40 °C had detrimental effect on the number of nodules, the specific nitrogenase activity, the N content, and dry weight of tops and roots of inoculated plants. Mackay and Barber (1984), investigating com yield, reported that phosphorus uptake was two- to fourfold greater at soil surface temperature of 25 °C than at 18 °C.

For agricultural engineering problems, it is necessary to know the variation of the soil temperature values for increasing the performance of the germination, growth, and yield of the crops, which are commonly estimated local climatic conditions and soil properties (Mihalakakou 2002). Furthermore, several studies compared the artificial neural networks (ANNs) with simple empirical equations in estimating meteorological and hydrological parameters such as air temperature, evapotranspiration, solar radiation, relative humidity, soil temperature, water quality, and water discharge, (e.g., Trajkovic et al. 2000; Sudheer et al. 2003; Rahimikhoob 2010; Trajkovic 2010; Tabari et al. 2011; Cobaner 2011, 2013; Rezaeian-Zadeh et al. 2012; Kisi and Tombul 2013; Kisi et al. 2013; Cobaner et al. 2014; Citakoğlu et al. 2014; Kisi et al. 2015). George (2001) reported that the estimation of climatic variables such as soil temperature, air temperature, relative humidity, and wind speed are essential for agricultural purpose and all these are strongly correlated as a result of surface solar radiation.

The accurate prediction of soil temperature values plays a significant role on plant growth processes. Therefore, soft computing models such as especially ANNs and adaptive neuro-fuzzy inference system (ANFIS) models have been used for modeling ST values. Mihalakakou (2002) investigated the estimation capability of ANN and deterministic models in annual and daily soil surface temperature values for bare and short-grass-covered soil. It was reported that the soft computing method was able to accurately predict the surface STs. Bilgili (2010) compared the estimation performance of the linear and nonlinear regression models versus three-layer ANN models for monthly ST values at different depths. In his study, best input combination between the meteorological variables and soil temperature was determined with the stepwise linear regression technique. These selected

metrological variables such as air temperature, relative humidity, atmospheric pressure, solar radiation, rainfall, and wind speed were used as input variables to the regression and ANN models. It was concluded that the prediction performance of the ANN model was significantly better than the regression techniques. Tabari et al. (2011) also compared the ANN and regression techniques for modeling ST values at different depths in Iran. They have reported similar results with Bilgili (2010). Tabari et al. (2011) compared multilayer ANN and linear regression in estimating daily ST at different depths in Iran, and they reported that the ANN estimates provided better accuracy than the regression. Kim and Singh (2014) examined the applicability of multilayer perceptron (MLP) and neuro-fuzzy models in modeling STs at 10 and 20 cm depths. Bilgili (2010) estimated monthly ST of Adana City, Turkey, using linear/nonlinear regressions and MLP and they showed that MLP provided better accuracy than the regression models. Kisi et al. (2015) used different neural computing methods for modeling monthly ST. Wu et al. (2013) employed the ANN for modeling monthly mean ST at 10 cm depth over a large region with complex terrain. They have used grid-based input variables obtained from digital elevation model and remote sensing images such as including latitude, longitude, elevation, topographic wetness index, and normalized difference vegetation index for soil temperature estimation. In this study and as well as all other studies, the authors reported that the ANN models are effective tool for modeling ST.

From the related literature, it is clear that the ANN was previously used for modeling ST. In addition, limited ANFIS studies were carried out with this area, but to the authors' knowledge, the application of genetic programming (GP) model has not been studied and/or reported for estimating soil temperature in the literature. In the current study, an attempt is made to investigate the accuracy of GP model versus two data-driven models such as three-layer ANN and ANFIS models for modeling monthly soil temperature values in Iran.

2 Used data

The monthly weather data of Mersin (36° 48' N, 34° 38' E) and Adana (latitude 37° 00' N, longitude 35° 19' E) stations operated by the Turkish State Meteorological Service were used in the study. The location of the Mersin and Adana stations are shown in Fig. 1. The elevations for these stations are 3 and 27 m, respectively. The Mediterranean region has a Mediterranean climate that has warm to hot, dry summers and mild to cool, wet winters. The winter temperature reaches its max. as 24 °C and it may be as high as 40 °C in summer. The winter precipitation can be very heavy and hence inundating is a problem in many areas. There is snow in the high mountain areas while it never snows on the coastal area. The data cover 25-year (1986–2010) monthly values of air



Fig. 1 The map of the region and locations of the stations

temperature, solar radiation, relative humidity, wind speed, and soil temperature at different depths (10, 50, and 100 cm). Data division rule used in the study is 60:20:20, that is, the first 60 % of the whole data was used for training, the second 20 % of the whole data was used for validation, and the last part of the data was used for testing.

3 Methods

3.1 Genetic programming

Genetic programming is an effective symbolic regression technique that solves a given problem using natural selection and evolution (Koza, 1992). The essential difference between GP and genetic algorithm (GA) is related to the representation of the solution. GA creates a string of numbers that represent the solution. In the traditional GP, chromosomes and expression trees are the main components of model and the result of GP model is represented by tree-based structures built from terminals and functions. Tree-based structure of the GP model with a simple example equation (example function: $X_1^2 - X_2/3$) is expressed in Fig. 2. Solution of a given problem has a fixed length and constant structure consisting of one or several genes. Genes are composed of “nodes” representing functions (like +, −, *, /, √, sin) or terminals containing independent variables and numerical constants. A number of genes can be linked by functions to form a chromosome. Genetic operations such as mutation, transposition, insertion sequence, root insertion sequence, and recombination take place on genes and chromosomes. GP solutions of the problems are selected based on their fitness function. The fitness function is specific to the problem but

generally root mean square or mean square error between the actual and the predicted output is used as a fitness function. The minimum the fitness value, the better the program (individual) is. Selection for reproduction, mutation, and crossover for better models is based on fitness criteria and continues until a termination condition is met. Termination condition can be the maximum number of generations or user-defined threshold error of the model (Goldberg 1989).

3.2 Adaptive neuro-fuzzy inference system

Jang (1993) combined the advantages of two techniques, namely, fuzzy inference systems and neural network, and proposed a new method called the adaptive neuro-fuzzy inference system. This method uses linguistic expressions of the fuzzy

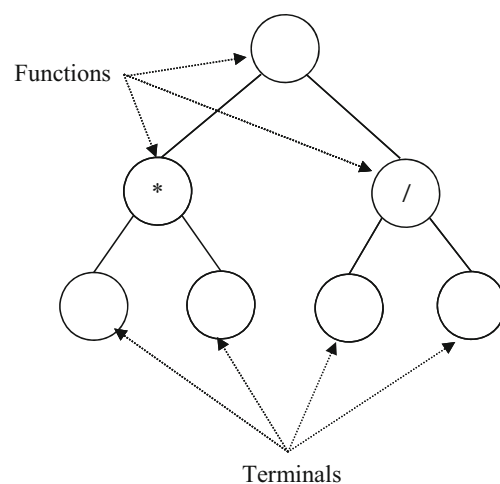


Fig. 2 The GP structure

logic method and has the adaptive learning ability of neural networks in order to improve the system performance.

Learning or training stage of network is a process to adjust the membership functions parameters to determine the relationship between the input and output data. The well-known basic learning rule is backpropagation method which attempts to minimize the error statistics of the model result, generally sum-of-squared differences between target and expected network's outputs (Drake, 2002). The two most commonly used fuzzy inference types are Mamdani's system (Mamdani and Assilian, 1975) and Sugeno's system (Takagi and Sugeno 1985). The difference between these two fuzzy inference systems is the specification of the consequent part. The consequent part is presented as a fuzzy set in the Mamdani's method (Mamdani and Assilian, 1975), and real numbers, which can be either linear or constant in the Sugeno's method (Sugeno, 1985). Sugeno's system is more compact and numerically effective; the output of the model is crisp without defuzzification operation, and it uses the adaptive techniques for training data based fuzzy modeling (Takagi and Sugeno, 1985). The main characteristic attribute of fuzzy modeling is using linguistic variables instead of or in addition to numerical variables. The developed system involves some if/then fuzzy rules to determine the connections between fuzzy variables. The fuzzy rule of the first-order Sugeno's style has the following form (Sayed et al. 2003; Cobaner 2011):

$$\text{Rule 1 : If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1 \quad (1)$$

$$\text{Rule 2 : If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2 \quad (2)$$

where A and B are the linguistic terms with fuzzy meaning, and x and y are input and output variables, respectively. The if-part of the rule "x is A" is known as the antecedent or prior, while the then-part of the rule "y is B" is called the final or consequent. The p , q , and r are the consequent parameters. A detailed description of ANFIS can be found in Jang (1993).

3.2.1 Subtractive clustering

There are different ways to find a valid combination of input dataset to design a collection of fuzzy rules and membership functions such as fuzzy C-means, equalizer partitioning, and subtractive clustering. One of the easiest ways to determine the degree of membership functions also to automatically generate fuzzy rules of the input from a given dataset is subtractive clustering (Chiu, 1994). A major point of the subtractive algorithm is to find regions with a high density of data points in the feature space. The subtractive clustering method of Chiu (1994) is a modified form of the mountain clustering method proposed by Yager and Filev (1994). The mountain clustering method is an easy and efficient method for estimation of the number of clusters and the cluster centers of the given data points (Yager and Filev, 1994). After that, Chiu (1995)

recommended modified mountain clustering method to reduce the computational difficulty of the previous method. The method grids the data space and calculate a potential value for each grid point depending on distance between the real and potential data points. Then the highest potential grid point is treated as a potential first cluster center based on its possible value. After that, the potential of data points close to the first cluster center is invalid and the following cluster center is defined by revising the potential of data points in order to cancel the prior cluster center's effect. Each data point is a candidate for cluster centers, and a density measure for each potential data point is defined as (Chiu, 1994)

$$P_i = \sum_{j=1}^n e^{-\alpha \|x_i - x_j\|^2} \quad (3)$$

where $\alpha = 4/r_a^2$, x_i is the i th data point, r_a is a vector which is a positive constants representing the hyper-sphere cluster radius in data space. The constant r_a is effectively the radius defining a neighborhood. Data points outside this radius have insignificant impact on the potential. A data point surrounding with many neighboring data points will have a great potential value. Thus, the mountain and subtractive clustering methods are less sensitive to noise than other algorithms, such as the C-means and the fuzzy C-means (Du and Swamy 2006; Cobaner 2011).

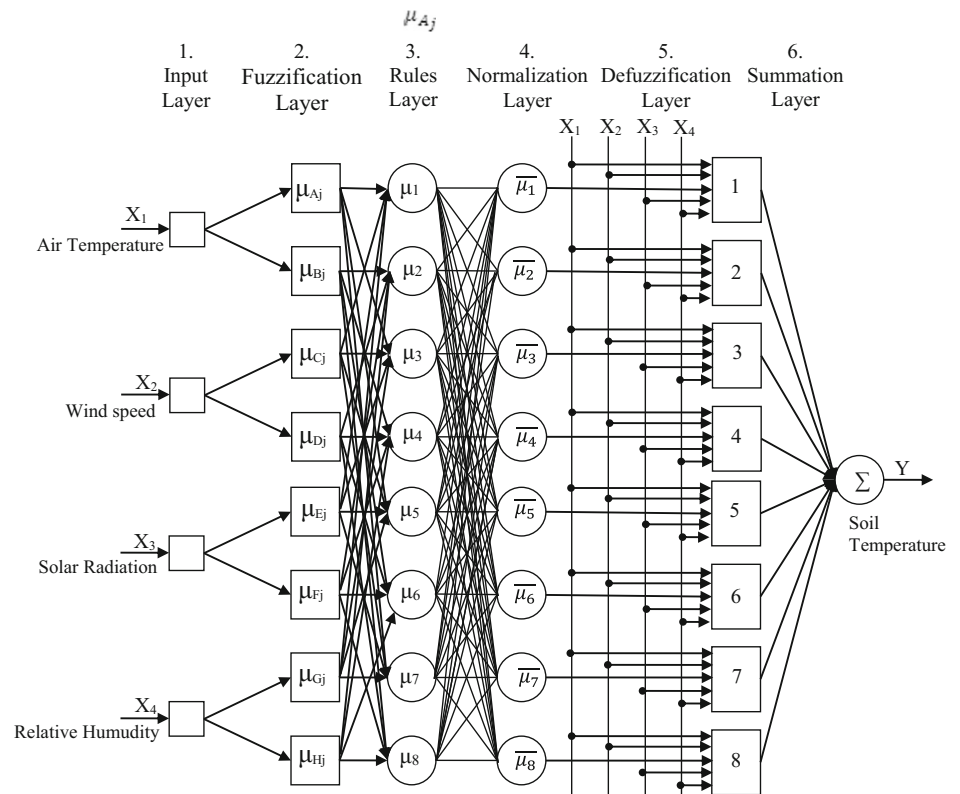
After the data point with the highest potential, x_1 , is selected as the first cluster center, x_1^* , and P_1^* is its maximum potential value. To generate the cluster centers, the potential value for each data point is revised by the following formula:

$$P_i = P_i - P_i^* e^{-\beta \|x_i - x_1^*\|^2} \quad (4)$$

where $\beta = 4/r_b^2$ is a vector which is a positive constant which defines a neighborhood that has measurable reductions in density measure being close to each other; r_b must be greater than 1.5 times r_a (Chiu, 1994).

The influential radius is significant parameter for specifying the number of clusters. Determining smaller radius outcomes with too many smaller clusters in the data space means more rules and vice versa. Therefore, determination of the proper influential radius is very important for clustering the data space. After determination of the number of fuzzy rules and membership function, the consequent parameters in the output MF are adjusted based on the linear squares approximation for a valid fuzzy inference system. The structure of the ANFIS model used to estimate the monthly soil temperature data based on four input parameters is shown in Fig. 3. The coupled ANFIS with subtractive clustering method has been widely applied in water resources engineering such as reservoir inflow estimation (Bae et al. 2007), long-term precipitation estimation (Kisi and Sanikhani 2015), and spatial estimation of monthly air temperature (Kisi and Shiri 2014).

Fig. 3 The structure of the ANFIS model used to estimate the monthly soil temperature data



3.3 Artificial neural networks

Neural networks are data processing techniques that mimic the structure and functioning of the human brain. They do so by simulating the brain’s basic components which include cell body, dendrites, synaptic connections, and axons; they apply the knowledge gained from past experience to find solutions to new problems or situations. The reason behind the extraordinary success of neural networks can be attributed to their capability to model highly nonlinear complex problems. ANNs are very arguably sophisticated nonlinear computational

tools. They can learn from examples and predict the form of the function that governs the relationship between independent input variables and targeted output values. In the real world, there are many problems in which the relationship between input and output is complex and cannot be easily identified using traditional statistical methods. Alternatively, neural networks are employed to deal with such problems.

The ANNs consist of a number of interconnected neurons such as input, hidden, and output layers (Fig. 4). These layers consist of parallel processing elements, namely neurons, with each layer being fully linked to the proceeding layer by interconnection

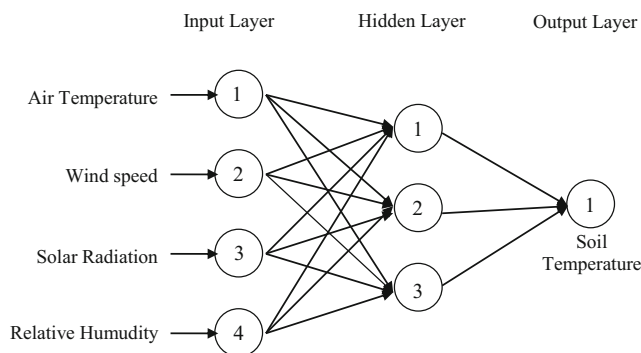


Fig. 4 A three-layer ANN architecture used for monthly soil temperature estimation

Table 1 Test results of the ANN models

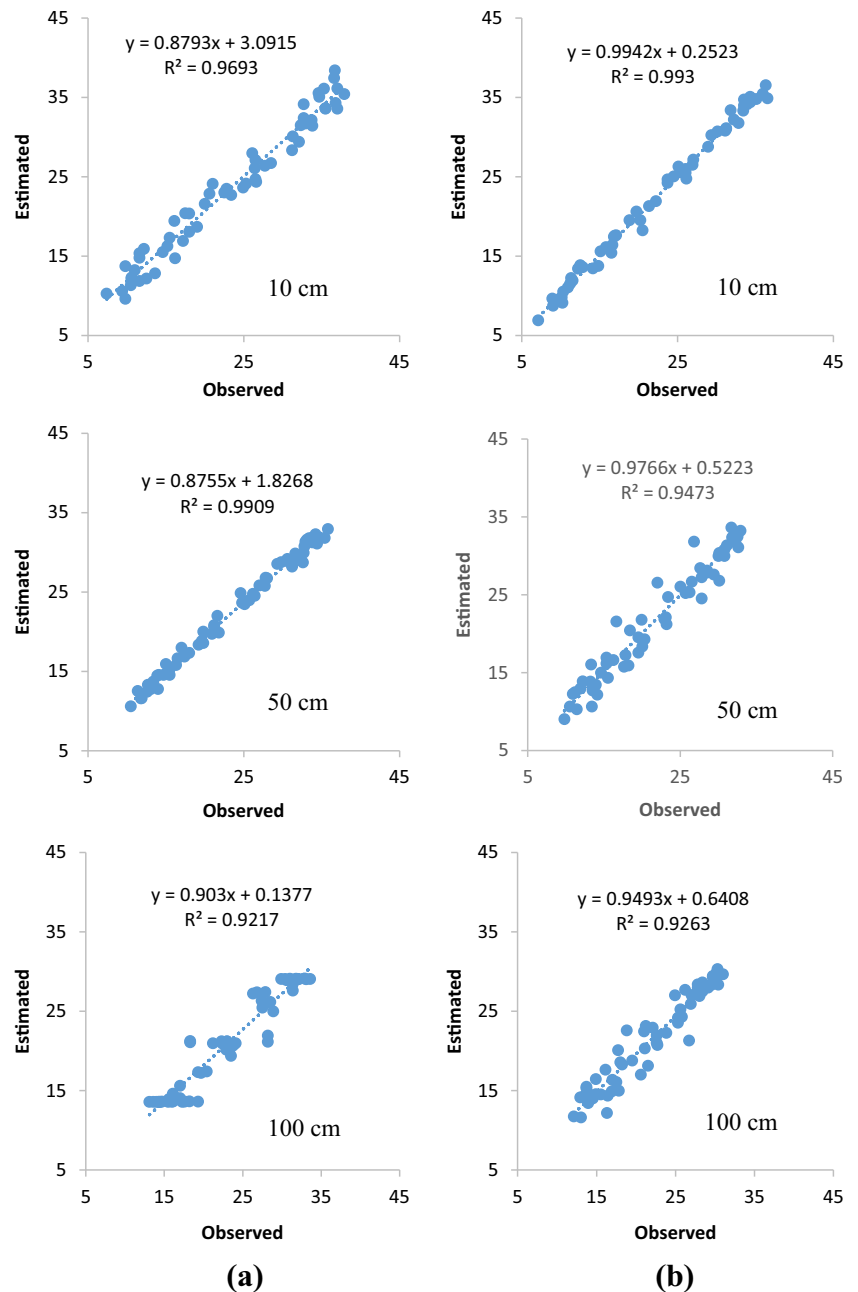
Depth	Structure	Iteration	R ²	RMSE (°C)	MARE (%)	NS
Mersin						
10	4 6 1	1000	0.969	1.90	8.91	0.950
50	4 1 1	1000	0.991	1.63	5.06	0.947
100	4 7 1	1000	0.922	2.79	10.4	0.815
Adana						
10	4 1 1	1000	0.993	0.76	3.24	0.993
50	4 3 1	1000	0.947	1.71	6.75	0.947
100	4 6 1	1000	0.926	1.69	6.56	0.918

Table 2 Test results of the ANFIS-SC models

Depth (cm)	Radii	R^2	RMSE ($^{\circ}\text{C}$)	MARE (%)	NS
Mersin					
10	0.47	0.983	1.64	6.17	0.962
50	0.80	0.955	1.98	6.89	0.930
100	0.55	0.630	4.61	15.9	0.468
Adana					
10	0.85	0.991	0.88	3.36	0.991
50	0.64	0.946	1.75	6.72	0.945
100	0.75	0.938	1.55	6.48	0.935

strengths or weights. These weights correspond to synaptic efficiency in biological neurons. Commonly, initial the weights are set of random values or based on some previous experience. After that, weights are methodically adjusted by the learning algorithm based on the set of training examples. The backpropagation algorithm proposed by Rumelhart et al. (1986) was used to train the ANN in this study. All neuron in the network pass from a transfer function to change the activation level of a neuron into an output signal. The behavior of the ANN depends on both all

Fig. 5 The scatterplots of the optimal ANN models in estimating soil temperatures in **a** Mersin and **b** Adana stations



interconnection weights and the activation function that is stated for the each layer of the network. Commonly used activation functions are the step function, sign function, sigmoid function, and linear function (Andries, 2002). Determination of a suitable ANN architecture for a required problem has basically three steps (Carling, 1995): (1) determination of the structure of network, (2) training the network, and (3) testing the network. All these procedure are described in detail in literature (ASCE Task Committee, 2000a, b) and Maier and Dandy (1998).

4 Application and Results

Root mean square errors (RMSE), mean absolute relative errors (MARE), determination coefficient (R^2), and Nash–Sutcliffe (NS) efficiency were used for evaluating the accuracy of ANN, ANFIS-SC, and GP models. The RMSE, MARE, R^2 , and NS can be expressed as

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (STp_i - STo_i)^2} \tag{5}$$

Fig. 6 The scatterplots of the optimal ANFIS-SC models in estimating soil temperatures in **a** Mersin and **b** Adana stations

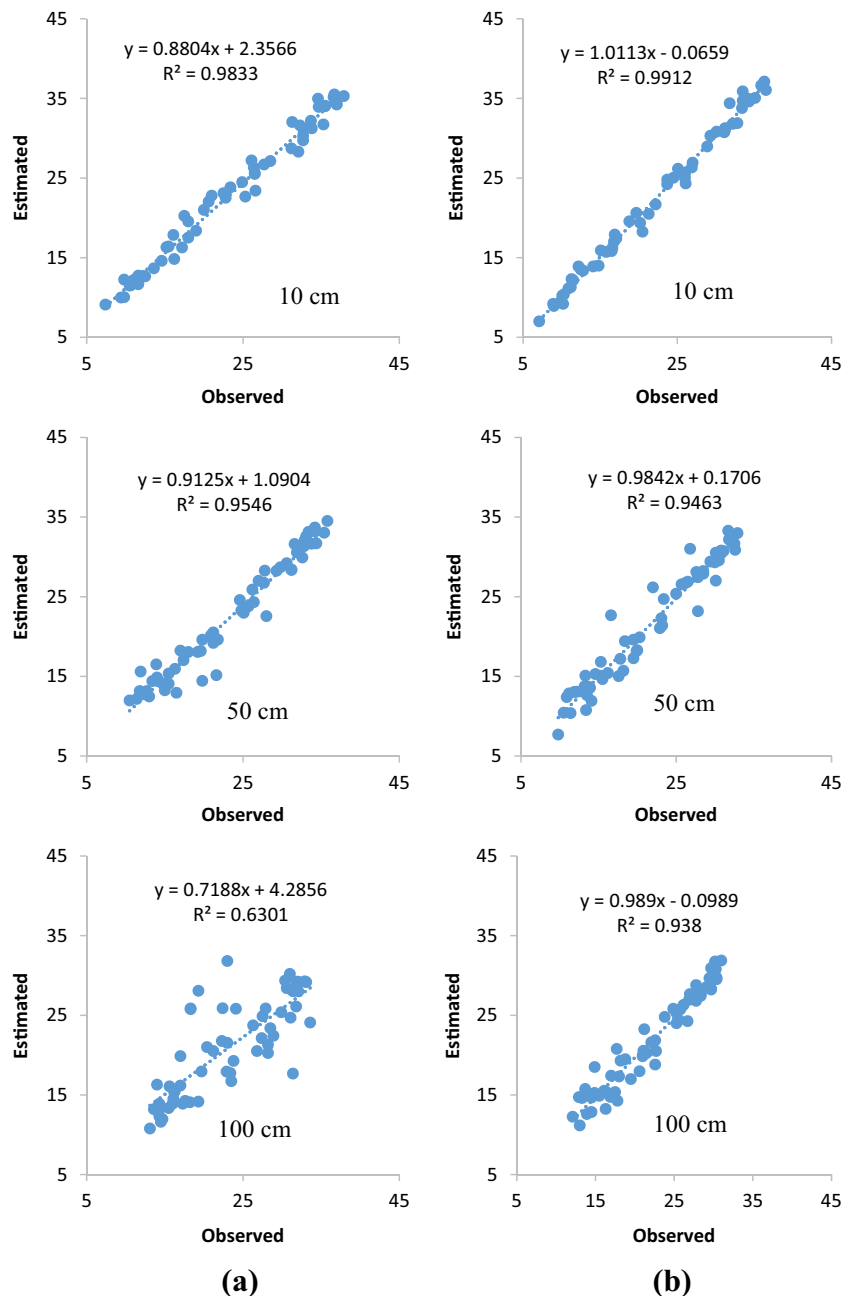


Table 3 Test results of the GP models

Depth (cm)	R ²	RMSE (°C)	MARE (%)	NS
Mersin				
10	0.992	1.71	5.69	0.961
50	0.990	1.39	4.31	0.963
100	0.899	4.97	22.0	0.682
Adana				
10	0.991	0.87	3.28	0.991
50	0.953	1.64	5.19	0.949
100	0.936	1.58	6.78	0.926

$$MARE = \frac{1}{N} \sum_{i=1}^n \frac{|STp_i - STo_i| \cdot 100}{STo_i} \tag{6}$$

$$R^2 = \frac{\left(\sum_{i=1}^n (STp_i - \overline{STp})(STo_i - \overline{STo}) \right)^2}{\sum_{i=1}^n (STp_i - \overline{STp})^2 \sum_{i=1}^n (STo_i - \overline{STo})^2} \tag{7}$$

$$NS = 1 - \frac{\sum_{i=1}^n (STo_i - STp_i)^2}{\sum_{i=1}^n (STo_i - \overline{STo})^2} \tag{8}$$

Fig. 7 The scatterplots of the optimal GP models in estimating soil temperatures in **a** Mersin and **b** Adana stations

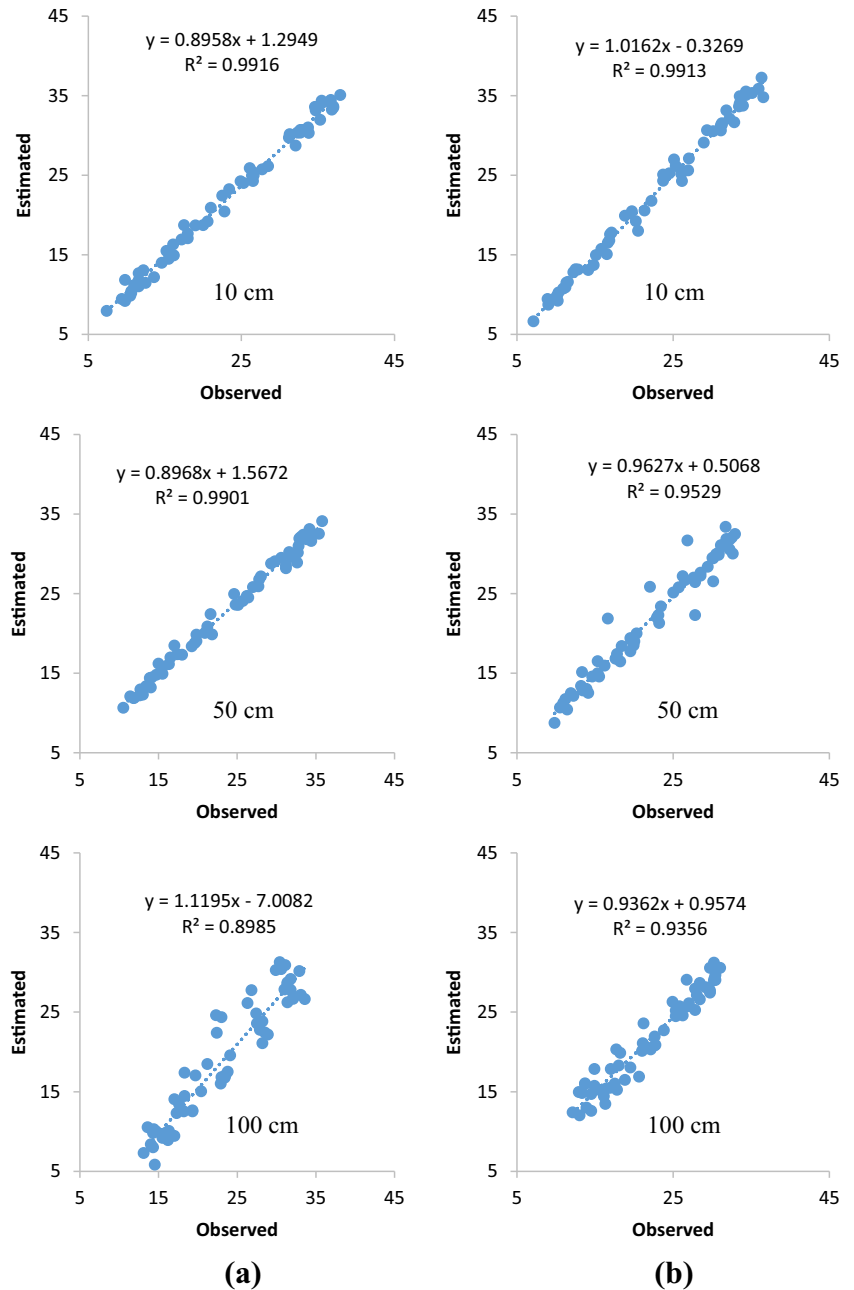


Table 4 Test results of the periodic PANN models

Depth (cm)	Structure	Iteration	R^2	RMSE (°C)	MARE (%)	NS
Mersin						
10	5 6 1	1000	0.988	1.26	5.30	0.979
50	5 1 1	1000	0.989	1.33	4.33	0.967
100	5 5 1	1000	0.976	2.04	7.32	0.886
Adana						
10	5 1 1	1000	0.993	0.75	3.14	0.993
50	5 2 1	1000	0.962	1.47	4.78	0.960
100	5 3 1	1000	0.989	1.16	4.66	0.961

Fig. 8 The scatterplots of the optimal PANN models in estimating soil temperatures in **a** Mersin and **b** Adana stations

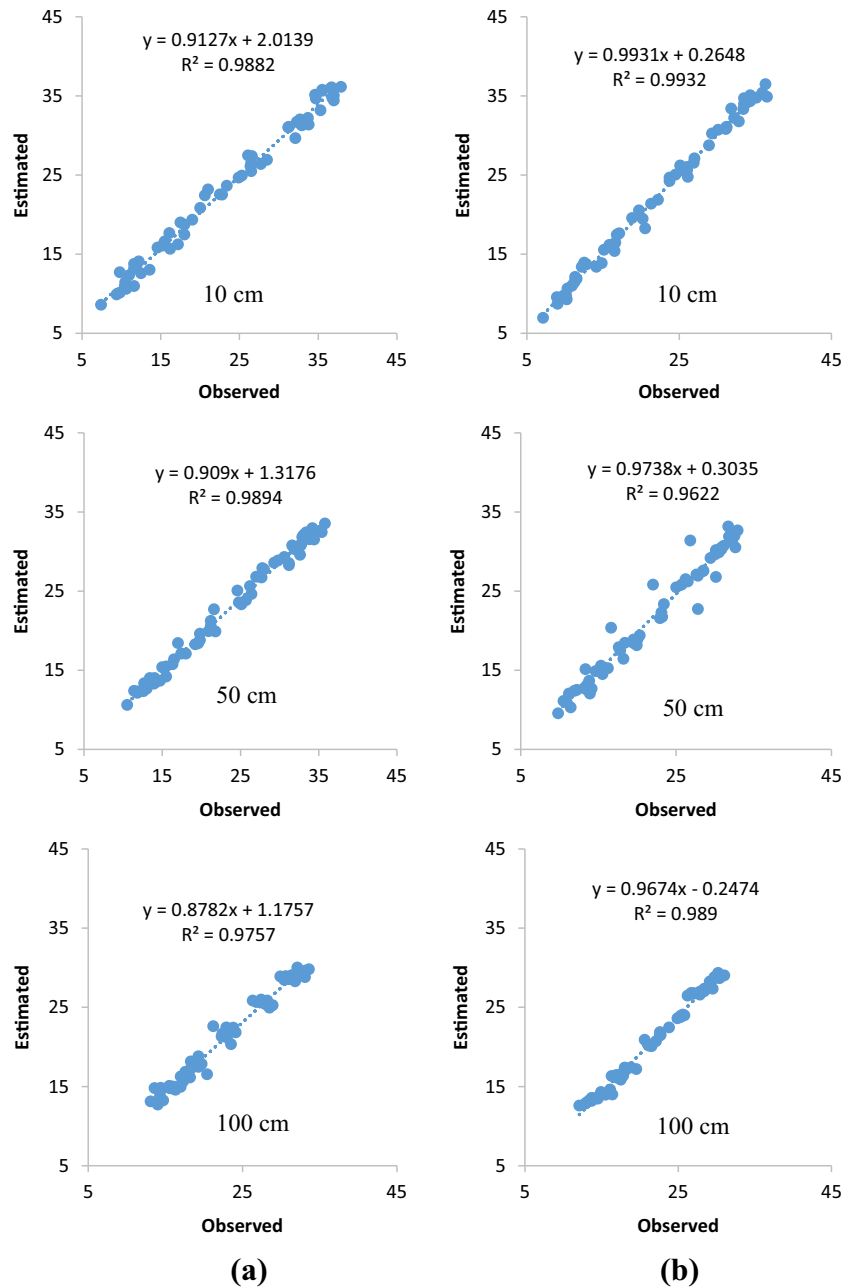


Table 5 Test results of the periodic PANFIS-SC models

Depth (cm)	Radii	R^2	RMSE ($^{\circ}\text{C}$)	MARE (%)	NS
Mersin					
10	0.82	0.985	1.29	4.73	0.982
50	0.86	0.984	1.65	5.35	0.945
100	0.50	0.873	2.96	11.9	0.819
Adana					
10	0.82	0.993	0.77	2.80	0.993
50	0.73	0.961	1.52	5.06	0.957
100	0.81	0.985	1.21	4.64	0.956

where N and $\bar{\cdot}$ respectively show the data number and mean of the variable, ST_p and ST_o indicate the predicted and observed monthly STs.

In the current study, three different applications were employed: (1) accuracy comparison of ANN, ANFIS-SC, and GP models in estimating STs at different depths; (2) the periodicity effect on accuracy of the applied models, and (3) accuracy comparison of ANN, ANFIS-SC, and GP methods in modeling STs of one station using input data of nearby station.

Fig. 9 The scatterplots of the optimal PANFIS-SC models in estimating soil temperatures in **a** Mersin and **b** Adana stations

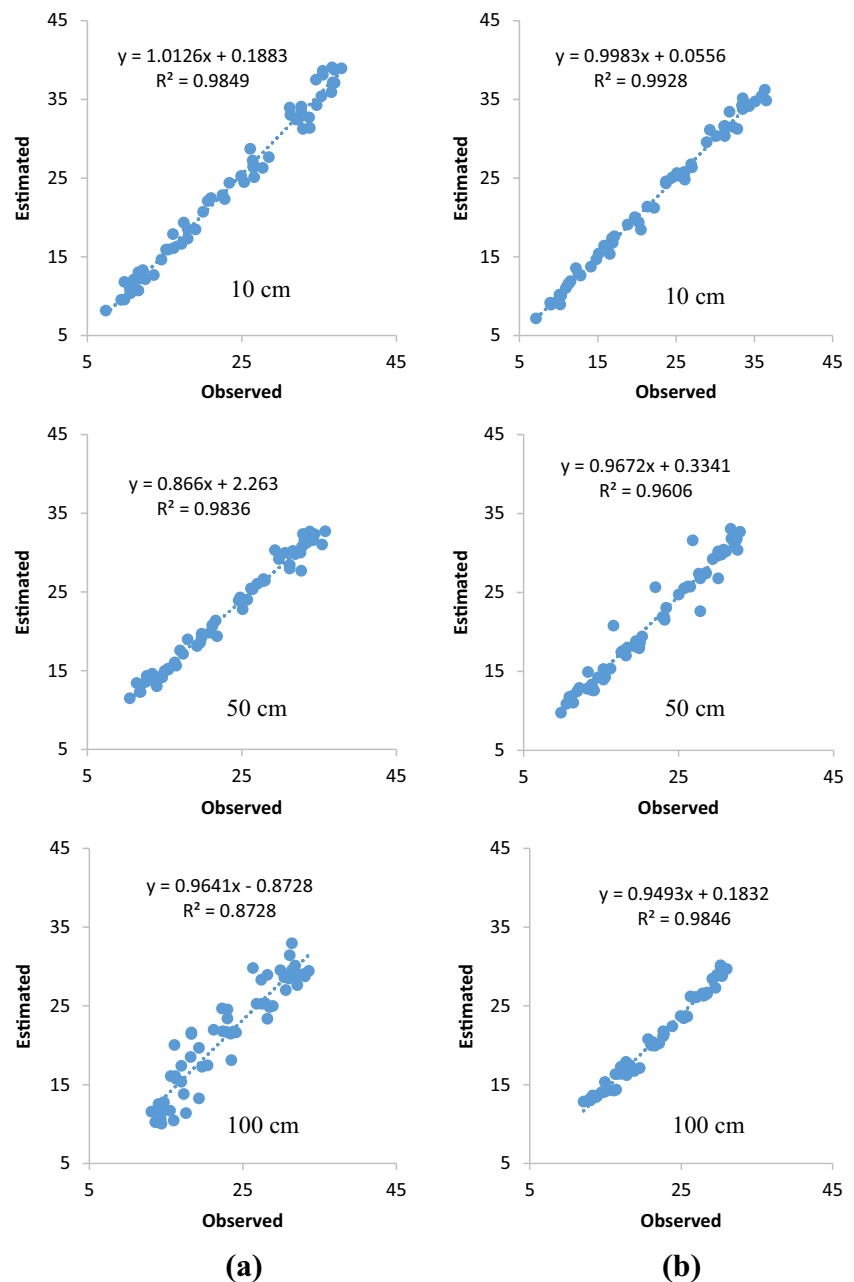


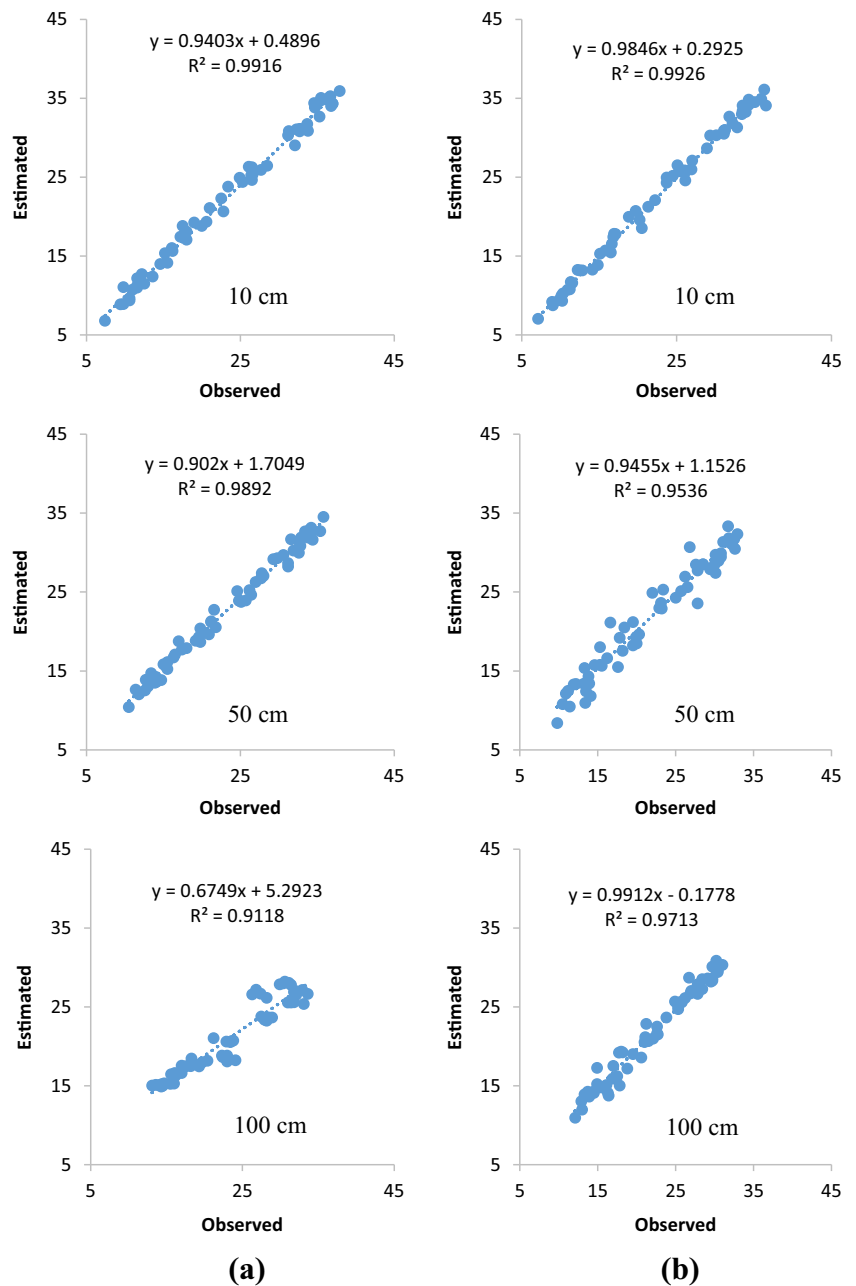
Table 6 Test results of the periodic PGP models

Depth (cm)	R ²	RMSE (°C)	MARE (%)	NS
Mersin				
10	0.992	1.35	4.91	0.978
50	0.989	1.24	4.09	0.971
100	0.911	3.37	10.0	0.568
Adana				
10	0.993	0.77	2.92	0.992
50	0.954	1.59	6.50	0.950
100	0.971	1.08	4.32	0.967

4.1 The comparison of ANN, ANFIS-SC, and GP models in modeling soil temperatures at different depths

Test results of the best ANN models for modeling ST at three different depths are given in Table 1 for the Mersin and Adana stations. The optimal structures are also provided in this table. Here, 4 3 1 indicates an ANN model comprising 4 inputs corresponding to air temperature, wind speed, solar radiation, and relative humidity; 3 hidden node; and 1 output nodes (Fig. 4). The hidden node number was determined by trial and error method for each ANN model. The optimum number of hidden nodes was found to vary between 1 and 7 in modeling ST. The estimates of the ANN models in the test period are

Fig. 10 The scatterplots of the optimal PGP models in estimating soil temperatures in **a** Mersin and **b** Adana stations



illustrated in Fig. 3 in the form of scatterplot. It is clear from Table 1 and scatterplots that the ANN model has the highest accuracy for the 50 cm depth while the 100 cm depth provided the worst accuracy in Mersin Station. In Adana Station, the ANN model gave the best estimates for the 10 cm depth while the 50 cm depth has the lowest accuracy. Test results of the ANFIS-SC models are compared in Table 2 for the Mersin and Adana stations. The optimal radii values of the ANFIS-SC models are also given in this table for each depth. Figure 6 demonstrates the ST estimates of the ANFIS-SC models in the test period. From Table 2 and scatterplot given in Fig. 6, it is clear that the ANFIS-SC model has the highest accuracy for the 10 cm depth while the 100 cm depth gave the worst accuracy in Mersin Station. In Adana Station, the ANFIS-SC model provided the best estimates for the 10 cm depth while the 50 cm depth has the lowest accuracy. A comparison of Tables 1 and 2 and Figs. 5 and 6 reveals that the ANN model performs better than the ANFIS-SC in estimating ST at 50 and 100 cm depths in Mersin while the ANFIS-SC model has a better accuracy than the ANN in estimating ST at 100 cm depth in Adana. The ANN generally performs better than the ANFIS-SC in estimating ST. Test results of the GP models are provided in Table 3 for the both stations. The ST estimates of the GP models in the test period are shown in Fig. 7. It is apparent from Table 3 and Fig. 5 that the GP model has the highest accuracy for the 50 cm depth while the 100 cm depth provided the worst accuracy in Mersin Station. In Adana Station, the GP model gave the best estimates for the 10 cm depth while the 50 cm depth has the lowest accuracy similar to the ANN models. A comparison of Tables 1–3 and Figs. 5–7 indicates that the GP generally performs better than the ANN and ANFIS-SC in estimating ST.

4.2 The periodicity effect on accuracy of the ANN, ANFIS-SC, and GP models

One more input (*p*) indicating the month of the year was added into the applied models in order to see the periodicity effect in monthly ST estimation following the studies of Kisi (2008) and Sanikhani and Kisi (2012). They investigated the effect of periodicity on river flow forecasting and found that adding periodicity as input to the ANN and ANFIS models significantly increases their accuracy. The accuracies of the periodic ANN (PANN) models are compared in Table 4. The estimates of the PANN models in the test period are illustrated in Fig. 8. From Table 4 and scatterplots, it is obvious that the PANN model has the lowest accuracy for the 100 cm depth while the 10 cm depth performed the best in Mersin Station. In Adana Station, the ANN model gave the worst estimates for the 50 cm depth while the 10 cm depth has the best accuracy. Test results of the periodic ANFIS-SC (PANFIS-SC) models are compared in Table 5. Figure 9 demonstrates the ST estimates of the PANFIS-SC models in the test period. It is clear from the table and scatterplots that the PANFIS-SC model has

Table 7 The RMSE accuracy increment of each model by adding periodicity component

Model	Accuracy increment by adding periodicity component (%)			
	10 cm	550 cm	100 cm	Total
Mersin				
ANN	34	18	27	79
ANFIS-SC	1.3	14	31	46
GP	21	11	32	64
Adana				
ANN	21	17	36	74
ANFIS-SC	13	13	22	48
GP	12	3.0	32	47

the best accuracy for the 10 cm depth while the 100 cm depth gave the worst accuracy in Mersin Station. In Adana Station, the PANFIS-SC model provided the best estimates for the 10 cm depth while the 50 cm depth has the lowest accuracy. A comparison of Tables 4–5 and Figs. 8 and 9 clearly indicates that the PANN models have better accuracy than the PANFIS-SC models in estimating ST at all depths in Mersin and Adana. Test results of the periodic GP (PGP) models are provided in Table 6 for the both stations. ST estimates of the PGP models are illustrated in Fig. 10 for three different depths. It is apparent from Table 6 and scatterplots given in Fig. 10 that the PGP model has the highest accuracy for the 50 cm depth while the 100 cm depth provided the worst accuracy in Mersin Station. In Adana Station, the PGP model gave the best estimates for the 10 cm depth while the 50 cm depth has the lowest accuracy. A comparison of Tables 4–6 and Figs. 8–10 indicates that the PGP generally performs better than the ANN and ANFIS-SC in estimating ST in Adana while the PANN has a better accuracy than the PGP and ANFIS-SC in Mersin. A comparison of the Tables 1–6 and Figs. 5–10 obviously indicates that adding periodicity component (month of the year) into the inputs considerably increase models’ accuracies. The increment in RMSE and MARE accuracy of the applied models by adding periodicity is given in Tables 7 and 8. It is clear from the tables that the ANN is more sensitive to the periodicity than the other models. The relative RMSE

Table 8 The MARE accuracy increment of each model by adding periodicity component

Model	Accuracy increment by adding periodicity component (%)			
	10 cm	550 cm	100 cm	Total
Mersin				
ANN	41	14	30	85
ANFIS-SC	23	22	25	70
GP	14	5	55	74
Adana				
ANN	3	29	29	61
ANFIS-SC	17	25	28	70
GP	11	–25	28	14

Table 9 Test results of the ANN and PANN models—soil temperature estimation of Mersin by using input data of Adana Station

Depth (cm)	Structure	Iteration	R^2	RMSE (°C)	MARE (%)	NS
ANN						
10	4 1 1	1000	0.988	1.45	4.84	0.972
50	4 4 1	1000	0.970	2.02	6.92	0.924
100	4 3 1	1000	0.870	3.47	11.8	0.685
PANN						
10	5 2 1	1000	0.992	1.44	4.65	0.973
50	5 3 1	1000	0.988	1.88	5.98	0.932
100	5 3 1	1000	0.985	2.06	7.14	0.880

Fig. 11 The scatterplots of the optimal **a** ANN and **b** PANN models in estimating soil temperatures of Mersin by using input data of Adana Station

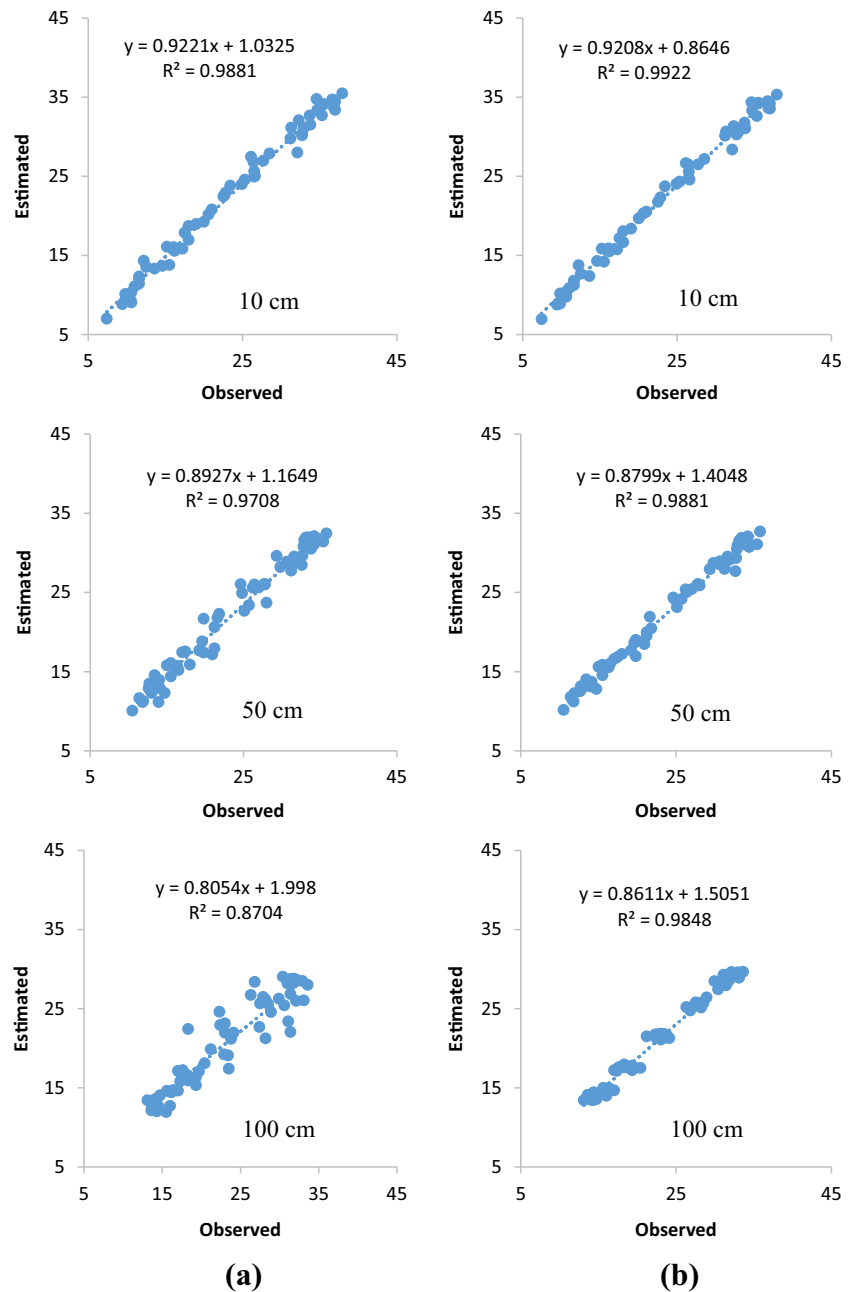
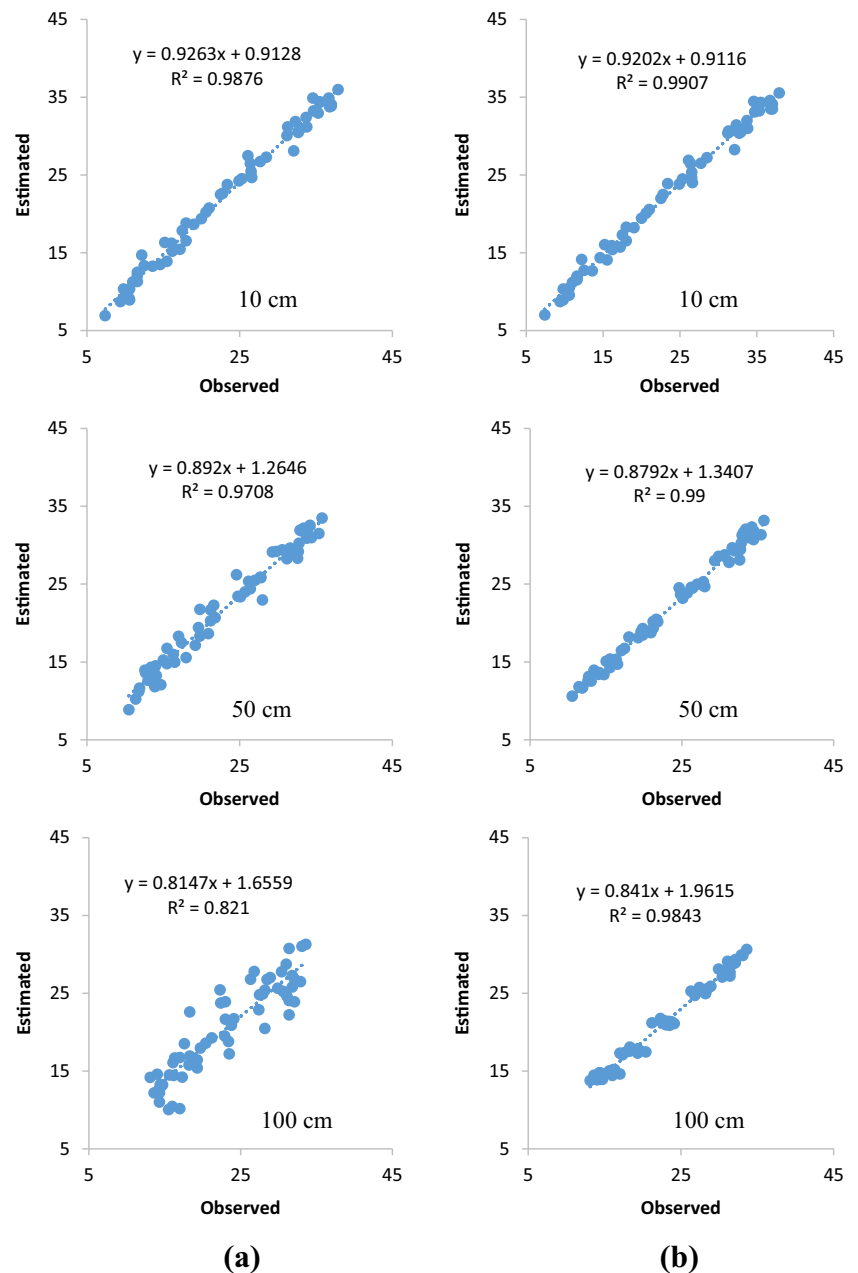


Table 10 Test results of the ANFIS-SC and PANFIS-SC models—soil temperature estimation of Mersin by using input data of Adana Station

Depth (cm)	Radii	R^2	RMSE (°C)	MARE (%)	NS
ANFIS-SC					
10	0.89	0.988	1.46	5.26	0.972
50	0.60	0.971	1.97	7.07	0.927
100	0.99	0.821	3.82	13.3	0.649
PANFIS-SC					
10	0.99	0.991	1.44	4.89	0.973
50	0.78	0.990	1.91	5.98	0.929
100	0.85	0.984	2.12	7.27	0.866

Table 11 Test results of the GP and PGP models—soil temperature estimation of Mersin by using input data of Adana Station

Depth (cm)	R^2	RMSE (°C)	MARE (%)	NS
GP				
10	0.989	1.48	4.94	0.972
50	0.976	2.01	7.02	0.919
100	0.815	3.87	12.0	0.521
PGP				
10	0.987	1.34	4.97	0.978
50	0.986	1.87	5.77	0.931
100	0.936	2.97	8.96	0.673

Fig. 12 The scatterplots of the optimal **a** ANFIS-SC and **b** PANFIS-SC models in estimating soil temperatures of Mersin by using input data of Adana Station

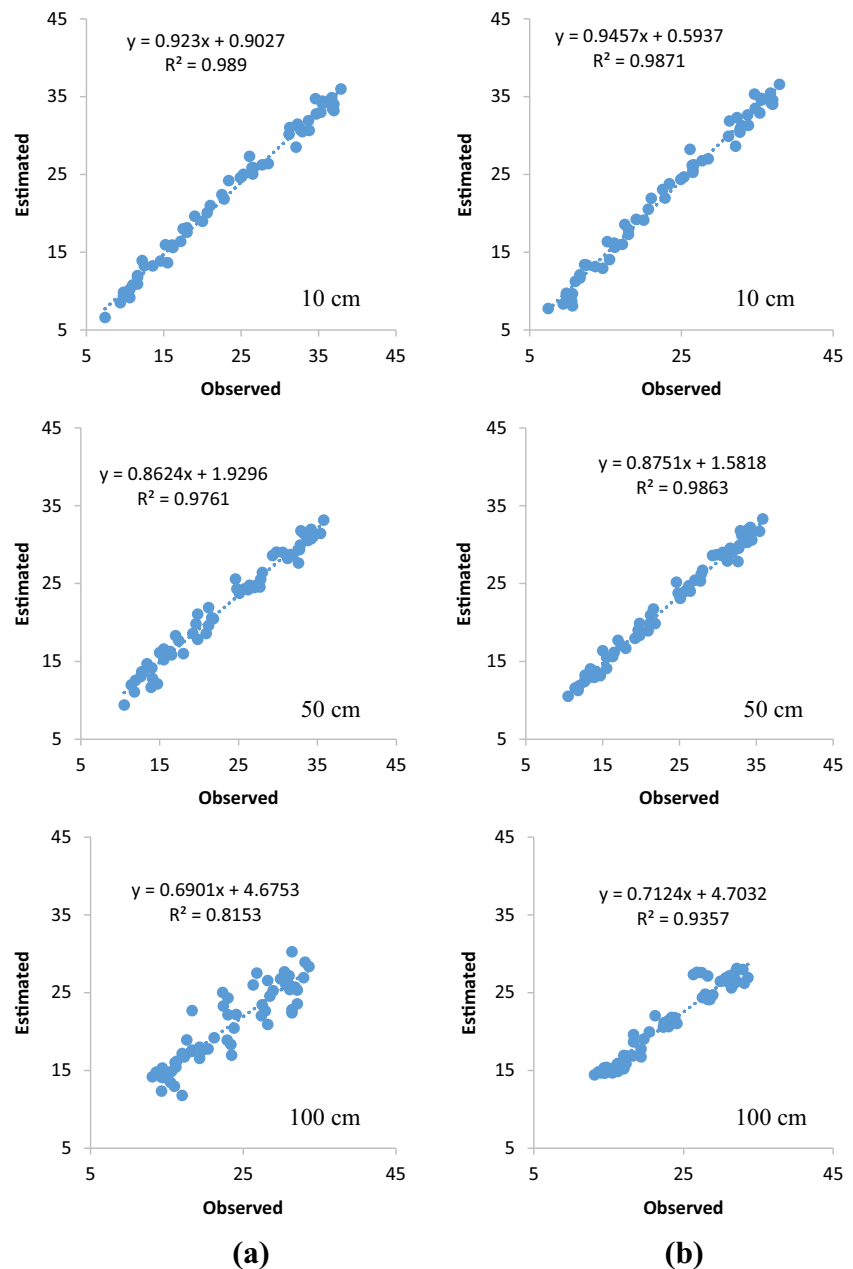
(MARE) differences of the ANN and PANN are as high as 34 % (41 %) and 27 % (30 %) for the 10 and 100 cm depths in Mersin, respectively. Periodicity component seems to be more effective for the 100 cm depth than the others.

4.3 The comparison of ANN, ANFIS-SC, and GP models in modeling soil temperatures of Mersin Station using input data of Adana

In this section, the ability of ANN, ANFIS-SC, and GP models and their periodic versions were investigated in estimating ST of Mersin Station using input data of Adana. Test results of the ANN and PANN models are provided in Table 9. The ST

estimates of the ANN and PANN models in the test period are shown in Fig. 11. From Table 9 and scatterplots, it is clear that the ANN and PANN models have the lowest accuracy for the 10 cm depth while the 100 cm depth performed the best. Adding periodicity component significantly increased the ANN model accuracy in estimating ST at 50 and 100 cm depths. Table 10 gives the test results of the ANFIS-SC and PANFIS-SC models. Figure 12 shows the ST estimates of the Mersin Station without local climatic data. It is clear from the Table 10 and Fig. 12 that the ANFIS-SC and PANFIS-SC models provided the worst accuracy for the 100 cm depth while the 10 cm depth performed the best similar to the ANN models. The accuracy of the ANFIS-SC model in estimating ST at 100 cm depth was

Fig. 13 The scatterplots of the optimal **a** GP and **b** PGP models in estimating soil temperatures of Mersin by using input data of Adana Station



significantly increased by considering periodicity input. Test results of the GP and PGP models are given in Table 11 and Fig. 13. From the Table 9 and scatterplots given in Fig. 13, it is apparent that the GP and PGP models have the lowest accuracy for the 10 cm depth while the 100 cm depth performed the best similar to the ANN and ANFIS-SC models. Periodicity component considerably increased the GP model accuracy in estimating ST at 100 cm depth. A comparison of Tables 9–11 and Figs. 11–13 clearly indicates that the ANN models generally performs better than the ANFIS-SC and GP models in estimating ST of Mersin Station without local climatic inputs.

5 Conclusion

The ability of ANN, ANFIS, and GP methods in modeling monthly soil temperatures at three different depths was investigated in the study. In the first part of the study, monthly ST data of Mersin and Adana stations at depths of 10, 50, and 100 cm were predicted by ANN, ANFIS, and GP models using climatic data of air temperature, wind speed, solar radiation, and relative humidity. The results revealed that the GP generally performed better than the ANN and ANFIS in estimating monthly ST. The effect of periodicity on accuracy of the applied models was also investigated. Adding periodicity component into the inputs significantly increased the models' accuracies. The ANN models were found to be more sensitive to the periodicity than the ANFIS and GP models. Adding periodicity increased the RMSE accuracy of ANN models by 34 and 27 % for the depths of 10 and 100 cm, respectively. Periodicity component was found to be more effective on 100 cm depth than the others. The second part of the study focused on comparison of ANN, ANFIS, and GP models in estimating soil temperatures of Mersin Station using input data of nearby Adana Station. Comparison results indicated that the ANN models generally performed better than the ANFIS and GP models in estimating ST of Mersin Station without local climatic inputs.

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