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Modeling Soil Temperature Using Artificial Neural Network

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Abstract. In this study, implementation of artificial neural network model has been done to estimate soil temperatures at various depths and different measuring times, in terms of soil surface temperature, by using the back propagation algorithm model. The data of soil temperature is taken from research department of soil and water / Nineveh province for the period from 1980 to 1983 and it include daily measurements of soil at depths of 5,10, 20, 30,50 and 100 cm and for three periods at 9, 12 and 15 clock for cultivated and non-cultivated soil. The data of two years was used to train the network and the data of one year was used for evaluation and compare its output with the measured data, three performance functions, namely root mean square errors (RMSE) , determination coefficient (R^2) and mean square errors (MSE), were used to evaluate the neural models and to find the adequacy between estimated data and the outputs of neural network for one year, the values of R2 ranging between 0.95 - 0.99 and the values of MSE and RMSE decreased significantly for all cases of estimation. The results shows the possibility of using neural networks in the composition of the model that can be used in the estimation of deep soil temperatures by using of surface soil temperature for three times of measurement, the successful use of neural networks in the composition of the model that can be used to estimate the deep soil temperatures through the use of soil-surface temperatures, which are measured at different time periods. Successful construction of General ANN model that predict soil temperature at any depth and time by using soil surface temperature of any time have been constructed.

Keywords: ANN, modeling, soil temperature back propagation, RMSE, MATLAB.

1. Introduction

Artificial neural networks are well known effective tools for building mathematical models which deal with many issues with unknown variables. Neural networks provide synthetic method which is suitable for solving many data problems.

Artificial neural network is applicable to a wide variety of developments and applications. On the other hand the Practical applications of the artificial neural network concepts of soil and water resources fields is rapidly increased since the nineties of the last century. Modeling and implementation of groundwater projects using ANN yield excellent results [1]. The researcher [2] used ANN to predict the evapo-transpiration using monthly climate data as the input such as air temperature , relative humidity , wind speed and solar brightness from January 1977 to December 1996, the network output were the evapo-transpiration which have been calculated from the equation of Penman [3] used ANN to estimate the soil surface temperature in terms of air temperature.

The aim of the present study is to apply the model of ANN to predict soil temperature at various depths and different times of measurement with two types of soils (cultivated and bare) in terms of the soil surface temperature rather than field measurement which consumes costly time and materials.

2. Materials and Methods

Data of soil temperature has been collected from the office of soil and water / Nineveh province for the period from 1980 to 1983, it includes daily soil temperature degrees of cultivated and bare soils at depths of 5, 10, 20, 30, 50 100 cm for three periods of times (9, 12, 15).

The ANN models are designed using the MATLAB Toolbox (Fitting Neural Networks, FTNN) .The ANN models are trained using 2 input variables: Day, soil surface temperature. While the output is the soil temperature at the required depth. Different ANN topologies were trained using back propagation training algorithm and tested in order to find the optimum network structure that gives the best modeling accuracy. The ANN topologies were selected as: Multi Layer Perceptron (MLP) and Back Propagation (BP). A maximum two hidden layers is selected [4]-[6]. The MLP activation functions are sigmoid for the input hidden layers and linear for the output layer. The data selected are 60% for training, 20% for validation, and 20% for testing. Three types of accuracy measurements the coefficient of determination (R^2), root mean square (RMSE) and mean square error (MSE) are selected. Validation and testing based on the training and testing error are applied) [7], [8].

Soil temperatures for depths of 10.20, 30, 50 100 cm have been considered as the target of learning the neural network for each measurement time, the temperature of the surface at 5 cm is used as input data for ANN as shown in Table 1.

Table 1: ANN cases.

Input data (Soil temperature depth 5 cm)	Output data (Soil temperature depths 10, 20, 30, 50, 100 cm at 9 clock)	ANN case
9 clock	9 clock	9-9
9 clock	12 clock	9-12
9 clock	15 clock	9-15
12 clock	9 clock	12-9
12 clock	15 clock	12-15
15 clock	9 clock	15-9
15 clock	12 clock	15-12
9,12,15 and day No.	Any time of 9,12 and 15	General

The data of 1982-83 is used for training the ANN using back propagation algorithm and the data of 1984 is used for validating the ANN results.

It is worth to mention that the learning of ANN is based on spreading the missing values in all the links in order to estimate the values of the weights of the ANN layers starting from output towards the input layers.

3. Results and Discussion

The differences between the outputs of the ANN and the target values will be feed back to the input of the ANN in order to minimize the errors between them as shown in Fig. 1, this method is considered to be one of the most common method in the training of networks [9].

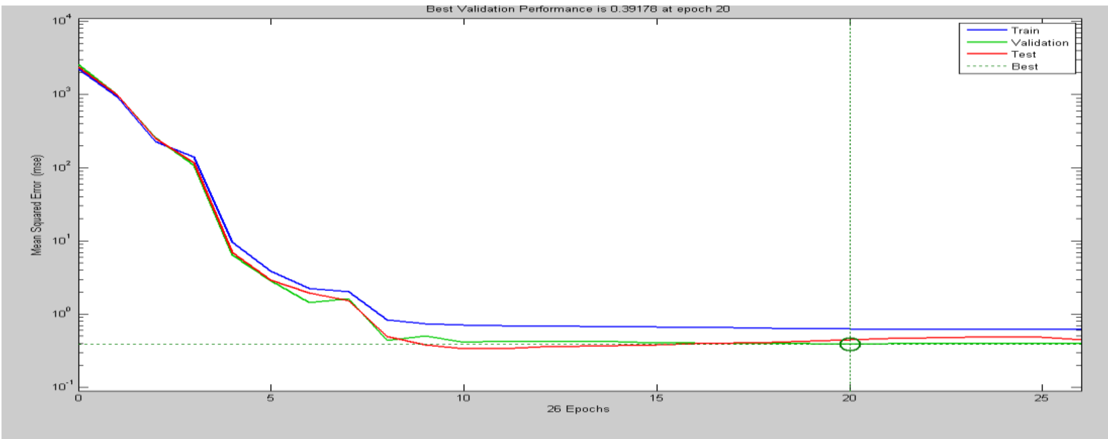

Fig. 1: Represents the training algorithm.

The results obtained by the application of ANN model using data of one year which have not been used by ANN training, show the possibility to predict the temperature of soil at various depths using the temperature of the soil surface by using appropriate neural network. (Table 2) shows the comparison parameter (R^2, RMSE, MSE) between the different ANN models outputs and observed data for different cases. The ANN cases 9-9, 12-12, 15-15 show high degree of applicability as the value of R^2 reach 0.99 with low values of both RMSE and MSE. Case 9-9 show more accuracy than the two other cases 12-12 and 15-15 according to the confidence parameter. As it is also evident from (Fig. 2), a high degree of applicability had been noticed.

Table 2: Parameters for accuracy test between observed and output data from the proposed ANN models.

		Depth Cm				
Soil status	**Mesa red Test**	**10**	**20**	**30**	**50**	**100**
		ANN case 9-9				
Cultivated	R^2	0.9951	0.9944	0.9941	0.9642	0.9788
	RMSE	0.7373	0.7780	0.7515	0.8420	0.9016
	MSE	0.5436	0.6054	0.5648	0.4024	0.8128
Bare	R2	0.9909	0.9896	0.9860	0.9777	0.9525
	RMSE	1.0185	1.0817	1.1913	1.3214	1.4444
	MSE	1.0373	1.1702	1.4193	1.7461	2.0862
		ANN case 12-12				
Cultivated	R^2	0.9949	0.9850	0.9799	0.9827	0.9874
	RMSE	0.7695	1.2629	1.3946	1.1105	0.6884
	MSE	0.5922	1.5949	1.9450	1.2332	0.4739
Bare	R2	0.9841	0.9857	0.9810	0.9855	0.9740
	RMSE	1.3520	1.2638	1.3828	1.0602	1.0714
	MSE	1.8280	1.5971	1.9121	1.1241	1.1478
		ANN case 15-15				
Cultivated	R^2	0.9677	0.9792	0.9706	0.9654	0.9718
	RMSE	2.0563	1.5131	1.6736	1.5759	1.0230
	MSE	4.2283	2.2894	2.8008	2.4836	1.0464
Bare	R2	0.9796	0.9750	0.9788	0.9733	0.9650
	RMSE	1.5985	1.6838	1.4616	1.4364	1.2287
	MSE	2.5552	2.8352	2.1363	2.0633	1.5097
		ANN case 9-12				
Cultivated	R^2	0.9913	0.9917	0.9825	0.9881	0.9828
	RMSE	1.0042	0.9381	1.3018	0.9227	0.8025
	MSE	1.0085	0.8800	1.6946	0.8514	0.6439
Bare	R2	0.9787	0.9746	0.9766	0.9768	0.9630
	RMSE	1.5660	1.6826	1.5366	1.3408	1.2783
	MSE	2.4523	2.8313	2.3613	1.7979	1.6341
		ANN case 9-15				
Cultivated	R^2	0.9622	0.9864	0.9911	0.9870	0.9875
	RMSE	2.2248	1.2249	0.9226	0.9638	0.6818
	MSE	4.9499	1.5005	0.8512	0.9289	0.4648
Bare	R2	0.9849	0.9856	0.9894	0.9868	0.9818
	RMSE	1.3761	1.2770	1.0346	1.0102	0.8861
	MSE	1.8937	1.6308	1.0705	1.0204	0.7851
		ANN case 12-9				
Cultivated	R^2	0.9935	0.9917	0.9811	0.9864	0.9845
	RMSE	0.8716	0.9419	1.3501	0.9849	0.7614
	MSE	0.7597	0.8872	1.8227	0.9701	0.5797
Bare	R2	0.9896	0.9887	0.9848	0.9823	0.9675
	RMSE	1.0964	1.1234	1.2396	1.1716	1.1984
	MSE	1.2020	1.2621	1.5366	1.3727	1.4362
		ANN case 12-15				
Cultivated	R^2	0.9931	0.9789	0.9819	0.9774	0.9687
	RMSE	0.8940	1.4962	1.3220	1.2676	1.0828
	MSE	0.7992	2.2387	1.7477	1.6067	1.1725
Bare	R2	0.9805	0.9781	0.9818	0.9848	0.9700
	RMSE	1.4968	1.5622	1.3544	1.0872	1.1507
	MSE	2.2403	2.4403	1.8345	1.1821	1.3241
		ANN case General				
Cultivated	R^2	0.9942	0.984	0.983	0.9731	0.9724
	RMSE	1.288	1.48	1.34	1.252	1.16
	MSE	1.6578	2.1876	1.7894	1.5678	1.3456
Bare	R2	0.9941	0.9821	0.9823	0.9776	0.9751
	RMSE	1.49	1.46	1.341	1.084	1.126
	MSE	2.213	2.4321	1.7984	1.1765	1.2678

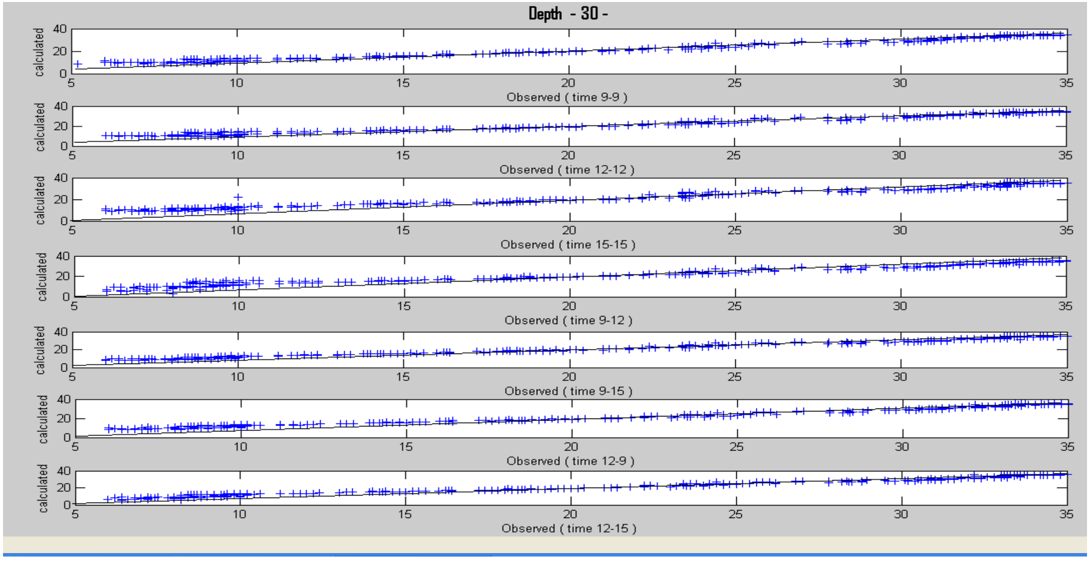

Fig. 2: The (1:1) relation between observed and output data of the proposed ANN models at the effective depth of soil 30 cm.

The proposed ANN models have a very good ability even with different times of prediction. It has been found that the ANN cases 9-12 and 9-15 have R^2 range from .96 to .99 and RMSE, MSE values are within acceptable range. These results can be approved from fig 2, since the data values are very close to 1:1 line. The same have been observed with ANN cases 15-9 and 15-12, so it can be said that the fitting between all ANN models and the field observations data is the best, this means that one can estimate soil temperature at any soil depth from soil surface temperature successfully with high confidence level, this results are the same as in [10], [11] and [12].

It is better for any system to have general model to predict any soil temperature value form a given input values. It is possible to conclude that the proposed ANN general model can be constructed to predict soil temperature at any depth and time (9, 12 or 15 clock) by providing the required day No. and soil surface temperature of that day, this model have a high R^2 value (0.96), which means 4% of error, and also have a low MSE and RMSE values of errors.

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