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Prediction of annual and seasonal soil temperature variation using artificial neural network

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The back propagation algorithm, an artificial neural network (ANN) training algorithm, is a widely applied mathematical implementation for spatial monitoring and is used in the present study for the analysis and prediction of soil temperature. The soil temperature data at 10 and 20 cm soil depths were collected from the Agricultural College and Research Institute, Killikulam, Tuticorin District of Tamil Nadu. The observed values during the year 2004 at 10 and 20 cm soil depths were plotted to understand the annual and seasonal behaviour of the temperature wave. The wave characteristics such as range of soil temperature and rate of change of temperature/week were estimated and tabulated. Data for 1993 – 1997 (5 years) and 1993 – 2002 (10 years) were separately used as inputs for the prediction of soil temperature in 2004 using ANN. The predicted values were compared with the observed values and statistically validated. The characteristics of predicted annual and seasonal wave were also compared with observed values. It was found that the predicted values of annual wave fitted well with observed ones with little variation for the seasonal waves. The range of soil temperature for predicted values coincided almost with the observed ones with regard to the annual and the seasonal waves for both 10 and 20 cm soil depths. The rate of change of temperature/week of the predicted values coincided well with the observed ones for 10 cm soil depth. For 20 cm soil depth, the predicted values deviated from the observed ones for the winter season while the annual and pre-monsoon seasonal waves coincided well with the observed values. The surface temperature was also predicted independently from 10 and 20 cm soil temperature and error validation was done. From these, it may be convincingly stated that the ANN can be used as a good mathematical model for the prediction of soil temperature.

Keywords: Artificial neural network (ANN), Back propagation algorithm, Multi-layer perceptron, Soil temperature prediction.

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1 Introduction

Weather prediction and meteorology is a very complex and imprecise science. The main reason for this complexity is that the atmosphere of the earth is essentially a chaotic system. Changes in soil temperature with time are very regular compared to the atmosphere. The near surface temperature variation is periodic over the course of a day and a year.

The need for accurate weather prediction is apparent when considering the benefits it has. Soil temperature plays an important role in various ecosystems from deserts[1] to forests[2]. Soil temperature affects infiltration of water through the soil surface[3]. Soil temperature also influences the biological process of plants, insects and other organisms[4,5]. Moreover, the rate of decomposition and movement of nutrients and chemicals in the soil profile are significantly affected by the fluctuations of soil temperature[6,7].

Degradation of pesticides and rate of bio-degradation processes in soils are greatly affected by soil temperature. However, it is usually quite cumbersome to measure temperature (*in situ*) especially at depth. Consequently, it has become necessary to develop models to predict, accurately and quickly, the fluctuations of soil temperature in natural and agricultural ecosystems.

A generalized equation which represents the relationship between soil temperature with time and depth is:

$$C_v(\theta)\frac{\partial T}{\partial t} = \frac{\partial}{\partial z}[K_T(\theta, T)\frac{\partial T}{\partial z}] \qquad \dots (1)$$

where, T, is soil temperature (^{0}C); C_v, thermal capacity [Jm^{-3} ^{0}C^{-1}]; θ, water content (m^{3}m^{-3}); t, time (s); z, soil depth (m); and K_T, thermal conductivity [Wm^{-1} ^{0}C^{-1}]. However, assumption and boundary conditions of thermal capacity and thermal conductivity of soil are needed to solve this equation[2,4].

Many conceptual models based on Eq. (1) have been developed to simulate the fluctuations of soil temperature at different depths[1,8,9]. Even complex equations can be solved quickly with computers, it is necessary to develop models requiring widely available input data[4,5,10]. Ideally a model should yield results quickly.

The World Meteorological Organization standardizes the instrumentation observing practices and timing of these observations worldwide. Artificial neural network (ANN) is parallel computational model, comprising closely interconnected adaptive processing units. ANNs are designed to emulate the highly non–linear functions of human natural neural networks. The important characteristics of neural networks are their adaptive nature, where learning by example replaces programming. This feature makes the ANN techniques very appealing in application domains for solving highly non–linear phenomena.

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. During the last four decades, various complex problems like weather predictions[11,12], heat transfer prediction[13], short term load forecasting[14-17], numerical simulation of non–linear equations[18-20], etc. have been proved to be areas with ample scope of application of this highly useful mathematical tool. A multi-layer neural network can approximate any smooth, measurable function between input and output vectors by selecting a suitable set of connecting weights and transfer functions.

The aim of this study is to show how ANN based models can be developed to predict annual and seasonal soil temperatures during 2004 at two soil depths 10 and 20 cm by using meteorological data. Moreover, this paper presents a comparison of the accuracy of the model in prediction of soil temperature using different variations on the standard back propagation algorithm provided by MATLAB Neural Network Tool Box[21,22].

2 Data and Method

2.1 Data collection

Weekly soil temperature data during 1993 – 2007 at two soil depths 10 and 20 cm were collected from the Meteorological Department of Agricultural College and Research Institute at Killikulam, Tuticorin District of Tamil Nadu. From the given data, soil temperature for the year 2004 has been predicted using the data for the period 1993 – 2002 as inputs. The chosen weather data were split into four seasons, namely winter, pre-monsoon, south-west monsoon (SWM) and north-east monsoon (NEM) and analysis were carried out. The 10 years data during 1993 – 2002 are divided into two cases such as:

Case (i) : 1993, 1994, 1995, 1996, 1997
Case (ii) : 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001, 2002

Using the above sets of data, it was proposed to predict the soil temperature for the year 2004 at both 10 and 20 cm soil depths. The observed and predicted annual and seasonal variation of soil temperature during the contrast seasons: winter (cold weather period) and pre–monsoon (hot weather period) during 2004 were drawn into graphs for this study. The range of soil temperature (R) was computed from the maximum (T_1) and minimum (T_2) soil temperature at both 10 and 20 cm soil depths using the relation:

$$R = T_1 \sim T_2 \qquad \dots (2)$$

where, R, is the range of soil temperature (^{0}C); T_1, maximum temperature (^{0}C); and T_2, minimum temperature (^{0}C). The rate of change of temperature/week was found using the relation:

$$G = \frac{T_2 - T_1}{t_2 - t_1} \qquad \dots (3)$$

where, G, is the rate of change of temperature/week (^{0}C/week); and T_1 and T_2, soil temperatures at the respective periods t_1 and t_2 (^{0}C).

2.2 Details of the experimental site

The location is geographically situated in Tuticorin District of Tamil Nadu state, at $8^0$46'N latitude and $77^0$4'E longitude with an altitude of 40 m above the mean sea level (MSL). It lies within the campus of Agricultural Research Institute and has a total extent of 480 hectares. The soil of the land is red in colour and is classified as laterite. The location map of the site is given in Fig. 1. The area has semi–arid tropical climate. Winter and summer seasons are from January to May. The average annual precipitation is 786.6 mm. The mean annual, summer and winter temperatures are 29.6, 31.3 and 26.6^{0}C, respectively.

2.3 Soil characteristics

The soil of this region is sandy, clay and loam and it has lower terrace geographical landscape. The ground water is found at a depth of 10 m. The soil temperature regime is qualifying for iso-megathermic soil temperature as per the guideline given by Wambekke[23]. The natural covers of the land are wild grasses and bushes. The pH value of soil upto the depths of 18 cm is 7.6 and thereafter, it is 7.8. The surface texture varies between sandy clay loam and sandy clay; and it is sandy clay to gravelly sandy clay in subsurface. The colour of the surface is yellowish brown and subsurface is yellowish red. The stickiness of the soil is low upto 18 cm and sticky thereafter. Similarly, the plasticity is also low upto 18 cm and is plastic thereafter.

2.4 Neural network models

An ANN is a non–algorithmic technique based on systems of equations that are usually non–linear and linked, in which the output value (result) of an equation is the input for other several equations of the network. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. Also, it is a distributed parallel processor, consisting of simple units of processing with which knowledge can be stored and used for consecutive assessments[24]. Its behaviour resembles the human brain in the following two ways:

1. A neural network acquires knowledge through learning.
2. A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

A neural network is formed by processing units called artificial neuron. Each neuron has the following behaviour – input data is multiplied by synaptic weights (w_{kj}), which are added and subjected to an activation function that provides the output. The true power and advantage of neural network lies in its ability to represent both linear and non-linear relationships. It has also the ability to learn these relationships directly from the data already modeled.

2.5 Multi-layer perceptron (MLP) network

The most common neural network model is multi-layer perceptron (MLP). This model was chosen because its implementation is easy and relatively simple. This type of neural network is known as a supervised network because it requires a desired output in order to learn. The goal of this type of network is to create a model that correctly maps the input to the output using historical data so that the model can then be used to produce the output when the desired output is unknown. A graphical representation of MLP is shown in Fig. 2.

The MLP networks show a great completing power to the insertion of intermediate layers. The solution for separable non-linear problems can be worked out by the use of networks with one or more intermediate layers. The network is then formed by at least three layers: the input, the intermediate or hidden one and the output.

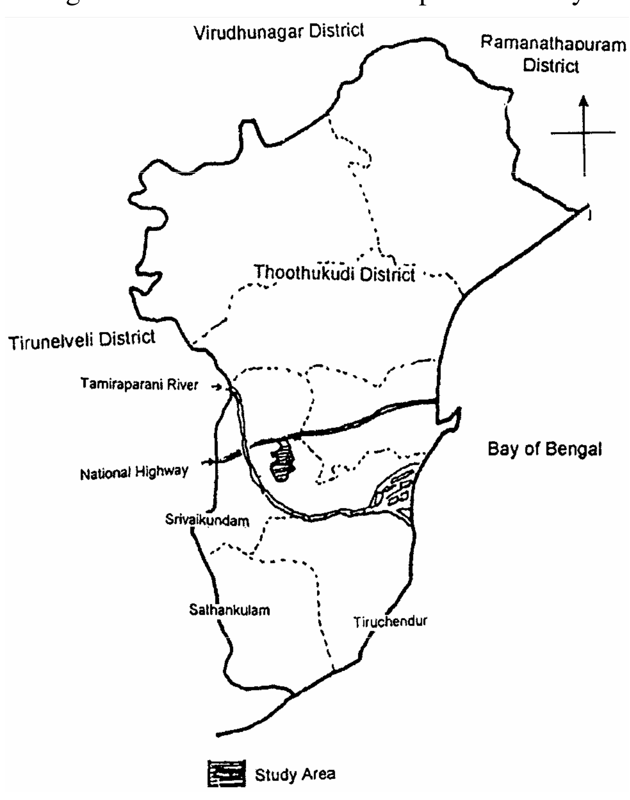

Fig. 1 — Location map of the site

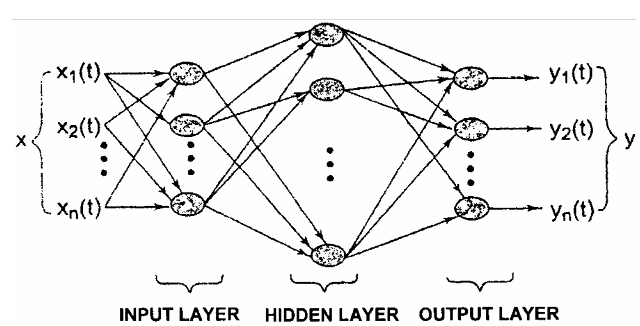

Fig. 2 — Multi-layer perceptron

Its units perform a biased weighted sum of their inputs and pass this activation level through a transfer function to produce their input and the units are arranged in a layered feed forward topology. The network, thus, has a simple interpretation as a form of input–output model, with the weights and thresholds (biases) as the free parameters of the model. Such networks can model functions of almost arbitrary complexity, with the number of layers and number of units in each layer, determining the function complexity. Important issues in MLP design include specification of the number of hidden layers and the number of units in these layers[25-27]. Once the number of layers and number of units in each layer has been selected, the network's weights and thresholds must be set so as to minimize the prediction error made by the network. This is the role of the training algorithms. The best known example of a neural network training algorithm is back propagation algorithm[25,28]. Modern second order algorithm such as conjugate gradient descent and Levenbag Marquardt[26] are substantially faster for many problems, but the chosen back propagation still has advantages in some circumstances and is the easiest algorithm to understand.

The back propagation algorithm is responsible for the calculation of the error functions. The difference between the predicted output and the observed one is the error. The aim of the training phase is to constantly reduce its value. For this, the weights must be updated for new iteration. It is important to mention that ANN's input and output data go through a process of normalization where they are usually grouped with intervals between [0 and 1] or [-1 and 1].

Three statistical parameters were used to evaluate the simulated results, namely root mean square error (RMS), standard deviation (SD) and coefficient of determination (r^2) for linear regression. The RMS represents the general difference between the observed values and the predicted results, the SD displays the range of distribution of these differences and r^2 measures the agreement between the observed values and the predicted values[29]. Moreover, root mean square percentage error (RMSPE) and mean absolute percentage error (MAPE) were used to validate the predicted values[30].

$$\mathrm{RMS} = \sqrt{\frac{\sum(Y-X)^2}{\mathrm{N}}} \qquad \dots (5)$$

$$\mathrm{SD} = \sqrt{\frac{\sum(Y-X)^2 - \frac{[\sum(Y-X)]^2}{\mathrm{N}}}{\mathrm{N}-1}} \qquad \dots (6)$$

$$r^2 = 1 - \frac{\mathrm{E}}{\mathrm{T}} \qquad \dots (7)$$

$$E = \Sigma Y^2 - b_o \times \Sigma Y - b_1 \times \Sigma XY \qquad \dots (8)$$

$$\mathrm{T} = \Sigma Y^2 - \frac{(\sum Y)^2}{\mathrm{N}} \qquad \dots (9)$$

$$b_1 = \frac{\mathrm{N} \times \Sigma(XY) - \sum X \times \sum Y}{\mathrm{N} \times \sum X^2 - (\sum X)^2} \qquad \dots (10)$$

$$b_0 = \frac{\sum Y - b_1 \times \sum X}{\mathrm{N}} \qquad \dots (11)$$

$$\mathrm{RMSPE} = \sqrt{\frac{\sum[(Y-X)/X]^2}{\mathrm{N}}} \qquad \dots (12)$$

$$\mathrm{MAPE} = \frac{\Sigma[(X-Y)/X]}{\mathrm{N}} \qquad \dots (13)$$

where, X, is the measured data; Y, the ANN simulations; and N, the number of training pairs.

3 Results and Discussion

3.1 Analysis of the observed soil temperature

The variation of the observed annual and seasonal soil temperature during 2004 at both 10 and 20 cm soil depths are shown in Figs (3-5).

3.1.1 Annual variations

From Fig. 3, it is seen that the pattern of the progressive nature of soil temperature throughout the year is almost the same at both 10 and 20 cm soil depths. The maximum and minimum temperature occurs at the same period in both the depths. It is obvious that there is one minimum in the 46th week falling in NEM season and two maxima in

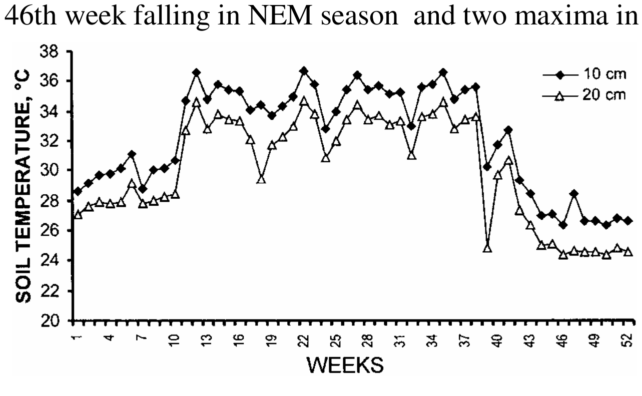

Fig. 3 — Annual variation of soil temperature at 10 and 20 cm soil depths

pre–monsoon during 12th and 22nd week and one maxima in SWM season in 35th week. Moreover, it is seen that for a long duration of 28 weeks ranging 10th - 38th week of the annual wave, the soil temperature remains hot which reveals the warming nature of the soil.

3.1.2 Seasonal soil temperature

Winter season

Eight weeks starting from January reveals winter season. In Fig. 4, minimum and maximum temperature could be seen during the 1st and 6th week, respectively. The summer season begins from the 7th week. The rate of change of temperature/week at 10 and 20 cm soil depths is estimated to be 0.11^{0}C/week and 0.18^{0}C/week, respectively indicating that the thermal wave of soil temperature at 20 cm is faster than the other.

Pre–monsoon season

The seasonal soil temperature during pre-monsoon is given in Fig. 5. The minimum and maximum value of the soil temperature is found in 10th and 12th week, respectively. The season remains hot for 6 weeks starting from the 11th week. The maximum temperature and the range of temperature at 10 and 20 cm depths are seen as 34.6°C (6.4°C) and 36.6°C (6.5°C), respectively. The rate of change of temperature/week at 10 and 20 cm depths are found to be 0.37°C/week and 0.38°C/week, respectively indicating that the thermal wave is faster at 20 cm soil depth.

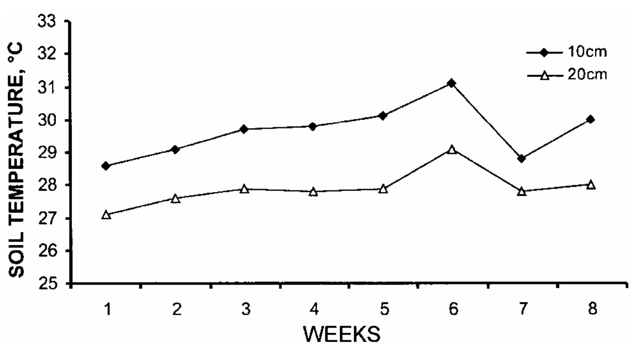

Fig. 4 — Variation of soil temperature in winter season at 10 and 20 cm soil depths

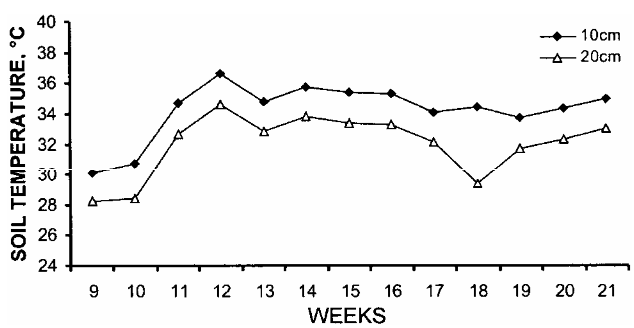

Fig. 5 — Variation of soil temperature in pre-monsoon season at 10 and 20 cm soil depths

3.1.3 Range of temperature

The range of soil temperature in the year 2004 during the year and contrast seasons at 10 and 20 cm soil depths for the observed values are deduced using Eq. (2) and tabulated in Table 1. The range of soil temperature reduces to a low value of 2.0ºC during winter for 10 cm soil depth and 2.5º C during winter for 20 cm soil depth.

3.1.4 Rate of change of temperature/week

The rate of change of temperature/week (^{0}C/week) for the year 2004 during annual wave and contrast seasons at soil depths 10 and 20 cm are calculated using Eq. (3) and tabulated in Table 2. From Table 2, it is clear that the thermal wave is faster at 20 cm than 10 cm for the annual and contrast seasons.

Rate of change of temperature/week from 2003 to 2007

The rate of change of temperature/week (^{0}C/week) from the year 2003 to 2007 during annual wave and contrast seasons at soil depths 10 and 20 cm are calculated using Eq. (3) and tabulated in Table 3. From Table 3, it is clear that the thermal wave is faster at 20 cm than 10 cm for the annual and contrast seasons.

3.2 Prediction of soil temperature using ANN

The soil temperature of the year 2004 is predicted using ANN by considering 1993 – 2003 data as inputs. The selection of the inputs has been mentioned in case (i) and case (ii). The predicted values are

Table 1 — Range of soil temperature (R) at two soil depths 10 and 20 cm

Wave pattern	R_{10}, ^{0}C	R_{20}, ^{0}C
Annual wave	10.3	10.3
Winter season	2.0	2.5
Pre-monsoon season	6.4	6.5

Table 2 — Rate of change of temperature/week (G) at two soil depths 10 and 20 cm

Wave pattern	G_{10}, ºC/week	G_{20}, ºC/week
Annual wave	-0.05	-0.04
Winter season	0.11	0.18
Pre–monsoon season	0.37	0.38

compared with the observed values and it is validated by means of statistical method.

Table 4 presents the statistical performance for the year 2004 on the basis of ANN for 10 and 20 cm soil depths under different input strategies (wave patterns). In case (i), the statistical performance at 10 cm soil depth shows that the values of RMS varies from 2.19 to 2.57^{0}C; SD varies from 2.33 to 2.54^{0}C; r^2 varies from 0.004 to 0.478; RMSPE varies from 7.81 to 9.33%; and MAPE varies from 0.35 to 2.37%. For case (ii), values of RMS varies from 1.78 to 2.60^{0}C; SD varies from 1.89 to 2.41^{0}C; r^2 varies from 0.001 to 0.607; RMSPE varies from 6.33 to 7.93%; and MAPE varies from 0.66 to 3.40%. The statistical performance at 20 cm soil depth in case (i) shows that the values of RMS varies from 0.91 to 2.02^{0}C; SD varies from 0.81 to 1.08^{0}C; r^2 varies from 0.015 to 0.495; RMSPE varies from 3.04 to 6.11%; and MAPE varies from 0.37 to 5.47%. For case (ii), the values of RMS varies from 0.79 to 1.33^{0}C; SD varies from 0.49 to 0.84^{0}C; r^2 varies from 0.522 to 0.926; RMSPE varies from 2.67 to 3.84%; and MAPE varies from 2.19 to 3.36%.

In general, RMS varies from 0.79 to 2.6^{0}C, SD from 0.49 to 2.54^{0}C; r^2 varies from 0.001 to 0.926; RMSPE varies from 2.67 to 9.33%; and MAPE varies from 0.35 to 5.47%. From this validation, it is found that the predictions by ANN were significant to actual soil temperature. Since the predicted values have negligible error, it is used for the analysis of soil temperature.

3.3 Analysis of the predicted soil temperature

The variations of the observed and predicted soil temperature in 2004 at 10 and 20 cm soil depths are shown in Figs (6 and 7).

3.3.1 Annual variations

Figure 6(a) depicts the annual prediction of soil temperature for 2004 at 10 cm soil depth for the observed and predicted values. From the graph, it is evident that the maximum temperature for observed value occurs during the 33rd week and the minimum temperature occurs during the 46th week both for the observed and predicted values. The annual prediction of soil temperature in 2004 at 20 cm soil depth is shown in Fig. 7(a). From the figure, it is seen that the maximum temperature occurs during the 22nd week for the observed and predicted values for case (i); but for case (ii) it lies in the 23rd and 34th week. For the observed and predicted values, the minimum temperature occurs during the 46th and 50th week. From the Fig. 6(a), it is observed that maximum temperature lies in the SWM season and the minimum temperature lies in the NEM season at both 10 and 20 cm soil depths.

Table 3 — Rate of change of temperature/week (G) at two soil depths 10 and 20 cm from 2003 to 2007

Wave pattern	G_{10}, ^{0}C/week					G_{20}, ^{0}C/week				
	2003	2004	2005	2006	2007	2003	2004	2005	2006	2007
Annual wave	0.01	-0.05	0.08	0.12	0.02	0.02	-0.04	0.09	0.21	0.03
Winter season	0.05	0.11	0.5	0.33	0.39	0.89	0.18	0.59	0.52	0.14
Pre-monsoon season	0.57	0.37	0.26	0.25	0.32	0.59	0.38	0.28	0.26	0.49

Table 4 — Root Mean Square Error (RMS), Standard Deviation (SD), Co-efficient of determination (r^2), Root Mean Square Percentage Error (RMSPE) and Mean Absolute Percentage Error (MAPE) for soil temperature simulations by ANN models in 2004 under different input strategies

Soil depth, cm	Wave pattern	Case (i)					Case(ii)				
		RMS, ^{0}C	SD, ^{0}C	r^2	RMSPE, %	MAPE, %	RMS, ^{0}C	SD, ^{0}C	r^2	RMSPE, %	MAPE, %
10	Annual wave	2.57	2.54	0.478	9.33	2.37	2.21	2.22	0.607	7.75	1.21
	Winter season	2.19	2.33	0.004	7.81	0.35	1.78	1.89	0.001	6.33	0.66
	Pre-monsoon season	2.53	2.51	0.049	7.83	2.04	2.60	2.41	0.063	7.93	3.40
20	Annual wave	1.94	1.08	0.015	6.11	5.01	1.24	0.84	0.926	3.63	2.74
	Winter season	0.91	0.88	0.032	3.04	0.37	0.79	0.49	0.727	2.67	2.19
	Pre-monsoon season	0.02	0.81	0.495	5.93	5.47	1.33	0.69	0.522	3.84	3.36

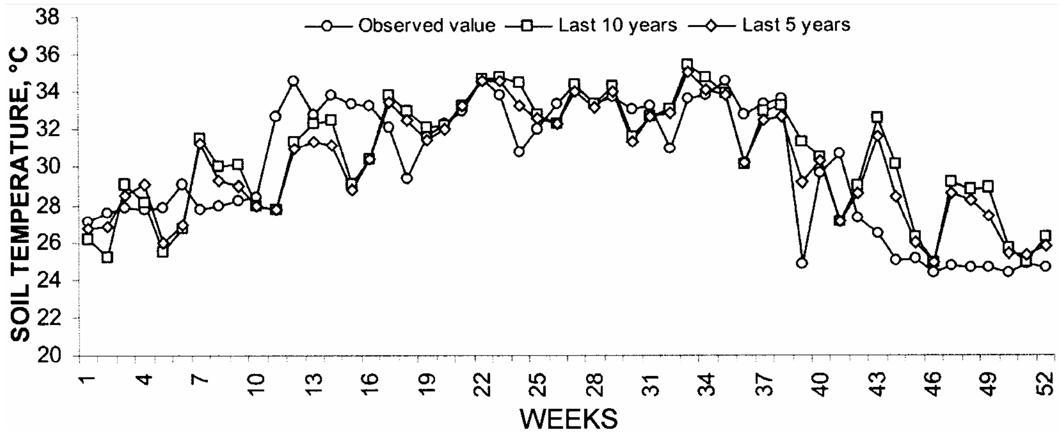

Fig. 6(a) — Annual variation of soil temperature for observed and predicted values at 10 cm soil depth

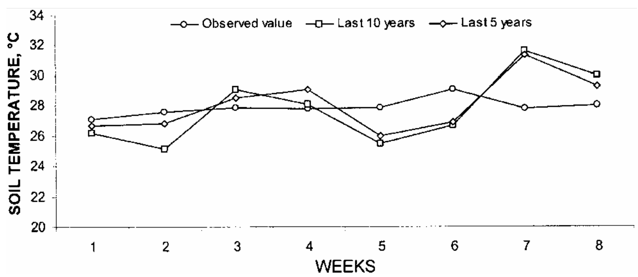

Fig. 6(b) — Variation of soil temperature in winter season for observed and predicted values at 10 cm soil depth

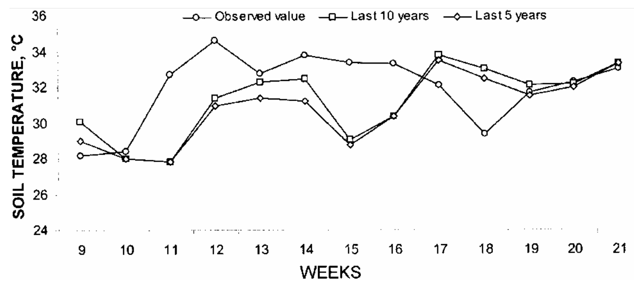

Fig. 6(c) — Variation of soil temperature in pre-monsoon season for observed and predicted values at 10 cm soil depth

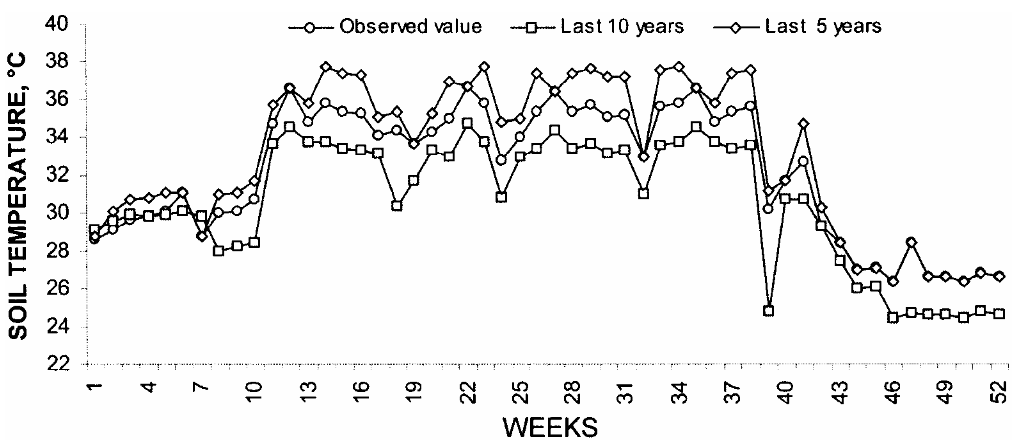

Fig.7 (a) — Annual variation of soil temperature for observed and predicted values at 20 cm soil depth

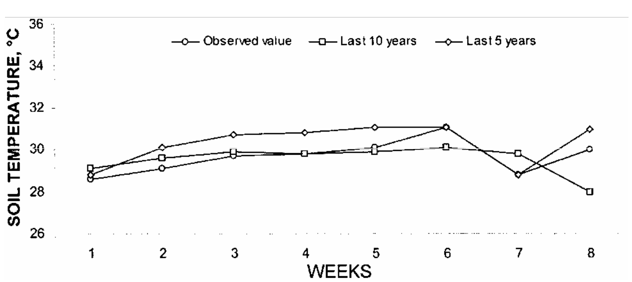

Fig.7 (b) — Variation of soil temperature in winter season for observed and predicted values at 20 cm soil depth

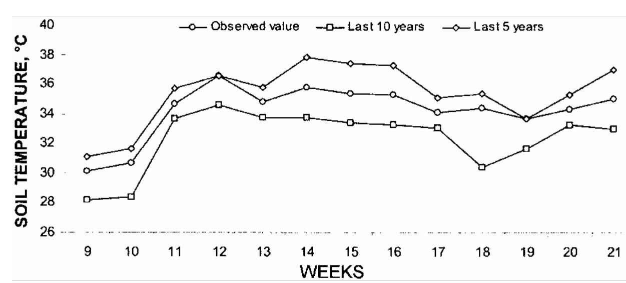

Fig.7 (c) — Variation of soil temperature in pre-monsoon season for observed and predicted values at 20 cm soil depth

3.3.2 Seasonal soil temperature

Winter season

The observed and the predicted soil temperature data for 2004 at 10 cm for winter season under the two cases are given in Fig. 6(b). The figure shows the dips and peaks of the predicted values which follow the observed values. But there is a slight variation in the 7th week. The observed and predicted soil temperature data at 20 cm soil depth for the two cases are shown in Fig. 7(b). Out of the two cases of predictions, prediction under case (i) fits to the observed data. From the graph, it is clear that the observed and predicted values match well except certain deviations during the 7th week.

Pre-monsoon season

The predicted and observed soil temperature data for the year 2004 at 10 and 20 cm soil depths under two cases are given in Figs [6(c) and 7(c)]. Figure 6(c) shows that the predicted values follow the observed values upto 14th week. In the 15th week, there is a sudden decrease in the predicted values instead of gradual decrease in the observed values and in 17th and 18th weeks, the variations of observed and predicted values are out of phase. From Fig. 7(c), it is found that the observed and predicted values go in phase upto 17th week and a dip occurs in 18th week for case (i) and in 19th week for case (ii).

In general, the nature of the annual soil temperature variations of the observed values fit well with the predicted values for case (i) and case (ii) with minimum error. However, the predicted graphs of the seasonal soil variations show deviations during certain periods.

Table 5 — Range of soil temperature at 10 cm soil depth for the observed and predicted values

Wave pattern	Observed value, ºC	Predicted value, ºC	
		Case (i)	Case (ii)
Annual wave	10.3	10.3	11.4
Winter season	2.5	2.1	2.3
Pre-monsoon season	6.5	6.4	6.7

Table 6 — Range of soil temperature at 20 cm soil depth for the observed and predicted values

Wave pattern	Observed value, ºC	Predicted value, ºC	
		Case (i)	Case (ii)
Annual wave	10.3	10.5	10.2
Winter season	2.0	6.4	5.3
Pre- monsoon season	6.4	6.0	5.7

3.3.3 Range of temperature

The computed range of soil temperature for both the observed and predicted values at 10 and 20 cm soil depths are given in Tables 5 and 6. From Table 5, it is clear that for 10 cm soil depth, the range of soil temperature gets reduced to a low value of 2.5ºC for the observed value and for the predicted it gets reduced to a value of 2.1^{0}C and 2.3^{0}C during winter season. From Table 6, it is evident that for the observed value and for case (ii), the range of soil temperature reduces to a low value of 2.0 and 5.3^{0}C during winter. For case (i), it reduces to a low value of 6.0ºC during pre-monsoon season for 20 cm soil depth.

From Tables 5 and 6, it may be concluded that the predicted values in the two cases for 10 and 20 cm soil depths coincide almost with the observed range of soil temperature for the annual wave and for the contrast seasonal waves.

3.3.4 Rate of change of temperature/week

The estimated rate of change of temperature/week for the observed and predicted soil temperature at 10 and 20 cm soil depths are tabulated in Tables 7 and 8. From Table 7, it may be found that for 10 cm soil depth, the annual and seasonal predicted values coincide well with the observed values. From Table 8, it may be concluded that for 20 cm soil depth, the observed values and the predicted values coincide well for the annual and pre-monsoon seasonal wave. For the winter season, the predicted values deviate from the observed values. From Tables 7 and 8, it is clear that the heat is depleted during the annual period and it is accumulated during the contrast seasons.

Table 7 — Rate of change of temperature/week at 10 cm soil depth for observed and predicted values

Wave pattern	Observed value, ºC/week	Predicted value, ºC/week	
		Case (i)	Case (ii)
Annual wave	-0.04	-0.05	-0.04
Winter season	0.18	0.11	0.28
Pre- monsoon season	0.38	0.37	0.45

Table 8 — Rate of change of temperature/week at 20 cm soil depth for observed and predicted values

Wave pattern	Observed value, ºC/week	Predicted value, ºC/week	
		Case (i)	Case (ii)
Annual wave	-0.05	0.00	-0.02
Winter season	0.11	0.48	0.33
Pre- monsoon season	0.37	0.25	0.33

Table 9 — Statistical performance of surface temperature for the year 2004 at 10 and 20 cm soil depths

Wave pattern	10 cm					20 cm				
	RMS, ^{0}C	SD, ^{0}C	r^2	RMSPE, %	MAPE, %	RMS, ^{0}C	SD, ^{0}C	r^2	RMSPE, %	MAPE, %
Annual wave	2.25	1.60	0.86	6.54	4.55	2.36	1.77	0.83	7.38	4.67
Winter season	1.86	0.86	0.15	6.19	5.61	2.01	0.66	0.20	7.18	6.84
Pre-monsoon season	2.84	1.35	0.49	8.07	7.25	2.93	1.56	0.46	8.80	7.63

3.4 Prediction of surface temperature

The surface temperature for the year 2004 is predicted using ANN independently using soil temperature at 10 and 20 cm depths as inputs. The predicted values are compared with the input values and it is validated by means of statistical method.

Table 9 represents the statistical performance of the surface temperature for the year 2004 at soil depths of 10 and 20 cm. From Table 9, it is evident that at soil depth of 10 cm, the value of RMS varies from 1.86 to 2.84^{0}C; SD varies from 0.86 to 1.60^{0}C; r^2 varies from 0.15 to 0.86; RMSPE varies from 6.19 to 8.07%; and MAPE varies from 4.55 to 7.25%. While at 20 cm soil depth, the value of RMS varies from 2.01 to 2.93^{0}C; SD varies from 0.66 to 1.77^{0}C; r^2 varies from 0.20 to 0.83; RMSPE varies from 7.18 to 8.80%; and MAPE varies from 4.67 to 7.63%.

In general, the error analysis of soil temperature gives low value of error at 10 and 20 cm soil depth. Hence, it can be concluded that the prediction of surface temperature at 10 cm soil temperature is the best prediction.

4 Conclusions

The analysis of the annual soil temperature indicates that the soil remains hot for a period of 27 weeks which is greater than 50% of annual duration that reveals the warming nature of the soil.

The graphical analysis of annual soil temperature variations fit well with the predicted values, but for the seasonal soil variations, the predicted seasonal soil temperature deviates from the observed soil temperature for a few weeks.

The range of soil temperature for 10 cm soil depth supports the accurate prediction whereas the same for 20 cm winter season deviates from the observed values. Similarly, rate of change of temperature/week for 10 cm supports the accurate prediction which is the same for 20 cm and the winter seasons deviate from the observed values. Also, it is concluded that the heat will be depleted during the annual period and accumulated during the contrast seasons.

The error analysis of soil temperature regarding the prediction of surface temperature shows low value of error at 10 cm depth when compared to 20 cm depth.

The statistical validation shows that the predicted values have insignificant error when compared with the observed values.

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