Australian Journal of Basic and Applied Sciences, 4(8): 3869-3879, 2010
ISSN 1991-8178

Modeling Water Infiltration Rate under Conventional Tillage Systems on a Clay Soil Using Artificial Neural Networks

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Abstract: This study presents the application of artificial neural networks for modeling the parameters of Lewis–Kostiakov infiltration under conventional tillage systems on a clay soil. The conventional tillage systems are moldboard, chisel and rotary plows. Water infiltration rate is defined experimentally by double ring infiltrometer. Artificial neural network estimation indicated strong correlations (R^2 = 0.999) between the parameters of Lewis–Kostiakov infiltration (k and n of Eq. $I = kt^n$) and affected variables (soil total porosity, soil moisture content, working index, and aspect ratio). The simulated data from the developed artificial neural network formulated the parameters of Lewis–Kostiakov infiltration (k and n) as a function of tillage implement weight and width, speed and depth of plowing, tractor nominal power, soil total porosity, and soil moisture content with R^2 around 0.60. The developed model can help managers of irrigation systems to modify field practices during growing season to conserve irrigation water. The working index has more contribution on constant (k). Meanwhile, soil total porosity has more contribution on constant (n). Using the developed model, infiltration rate could be optimized during seedbed preparation process.

Key words: artificial neural networks, tillage process, infiltration rate, Kostiakov equation

INTRODUCTION

Infiltration is considered as an important process in the management of water resources for crop production in both irrigated agriculture and dry-farming conditions. In irrigated agriculture, it is a fundamental prerequisite for designing, evaluating and managing irrigation systems. Likewise, under dry-farming conditions, knowledge of infiltration is needed to model, evaluate and design management technologies to conserve soil and water resources (Talaat, 2009). The accurate evaluation and consequently, modeling and application of infiltration data may be influenced significantly by different variables. Also, precise design for surface irrigation is required for higher irrigation efficiency and accurate prediction of the infiltration rate is of prime importance (Zerhun *et al*., 1996; Rasoulzadeh and Sepaskhah, 2003).

As our agricultural land and water resources are becoming more strained, conservation is becoming an increasingly important topic. There are different ways to conserve water and one of them by improving soil properties using alternative cropping systems and/or different practice farming systems. However, tillage process is considered as one of the main practice farming system in the agricultural production routine. So, researchers are interested to determine whether tillage systems have a negative, positive or no effect on soil physical properties. Therefore, studying and presenting the effects of field practices on infiltration during tillage process is important job in irrigation studies. Field practice styles differ from area to area during seedbed preparation, depending on many factors. So, it is better to develop an accurate model to determine infiltration characteristics because local measurements of infiltration rates using various techniques are time-consuming procedure. On the other hand, quicker estimate of infiltration may be useful in management of surface irrigation (Holzapfel, *et al*., 2004).

Due to the importance of infiltration in irrigation methods, several empirical and theoretical equations have been developed (Sadeghzadh *et al*., 2003). The development of a modified simple empirical model based on the Kostiakov equation has been achieved. Indeed, the modified model could predict soil infiltration rate as

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a function of soil characteristics and sequence of irrigation events (Al-Ghobari, 2003). A model based on Takagi-Sugeno fuzzy system to get Kostiakov equation parameters has also been developed. The main input variables for the former system are; soil mean weight diameter, number of wheel passes and plowing depth. Comparison of the simulated and observed cumulative infiltration indicated that the model could simulate infiltration process quite well (Aboukarima *et al*., 2007). A simple empirical model based on the Kostiakov equation has also been accomplished. The model could predict infiltration rate under soil mean weight diameter, number of wheel passes and plowing depth. Firstly, the values of empirical constants (k and n) of the Kostiakov equation could be determined then infiltration rate was computed. This could be useful to predict infiltration at any time interval in the studied rang of affecting variables. The results showed that the coefficient of determination (R^2) was 0.90 between measured and predicted basic infiltration rate (El Marazky *et al*., 2007). An empirical relationship between field-wide furrow infiltration and independent variables such as the opportunity time, initial soil water content, flow depth, flow section area, wetted perimeter and wet bulk density was developed. The results showed that 63.52% of the variation in cumulative infiltration could be explained by the opportunity time when the other variables were held constant. To describe the field-wide cumulative infiltration as a function of independent variables, a model was developed by using least squares regression (Nasser *et al*., 2004).

Infiltration rates of soil decrease over time until a steady state is reached. In addition, the infiltration is dependent on several factors, including soil texture, structure, initial soil water content, pore size, soil metric potential and vegetation (Lowery *et al*., 1996). Management practices that affect soil crusting and compaction, vegetative cover and soil porosity will increase or decrease the rate of water infiltration. For example, slow infiltration could be caused by increased soil compaction (Abu-Hamdeh, 2004). Increasing plowing depth significantly enhanced the final infiltration rate (Hemmat *et al*., 2007).

Different methods were used to quantify infiltration rate of soil and each was yielding different results. However, ring infiltrometers were frequently used to determine the infiltration rate in clay soils (Mohammed, 1982; Elkhidir, 1985; Abdel Nour, 1988). However, estimation of infiltration rate is a difficult task especially in clay soils due to: (a) temporal and spatial variations caused by soil heterogeneity, difference in soil moisture content, compaction, surface crust and cracking depth, (b) difficulty in choosing most suitable technique to best duplicate field conditions while making accurate measurement, and (c) use of empirical infiltration models rather than physical based mathematical ones and the difficulty in the characterization of coefficients of the empirical relations (Elramlawi *et al*.,2007). The most widely used empirical equation is the Kostiakov equation (Von Bernuth and Gilley, 1985), which is a simple powerful one. It takes the form:

$$I=kT^n \qquad (1)$$

Where:
I = infiltration rate (mm/hr).
T = time of infiltration (min).
k,n = empirical constants; k (mm/hr) and n (dimensionless).

This equation is very popular in irrigation engineering and it is relatively easy to determine the values of the two constants k and n. These empirical constants k and n are dependent of soil properties and initial water content of the soil (Fok, 1985).

The quality of prediction depends on the methodology and the selection of appropriate inputs in the computation model. Often non-availability of enough data sets, influenced by technological and cost constraints of data collection equipment, restricts the number of inputs to be used, affecting the accuracy of prediction. The popular prediction methods are statistical models, neural network or fuzzy logic techniques (Panickar *et al*., 2000).

Artificial neural networks are one promising method which can be used to represent more generalized relationships. An artificial neural network is a set of highly interconnected mathematical processing elements which are capable of representing non-linear multivariate mapping functions between input and output data sets.

The forms of the mapping functions are determined through 'training' the artificial neural network using sets of input and output data. Artificial neural network could model water infiltration into the soil. Artificial neural network model was developed for calibrating infiltration equation. It was consisted of rainfall and runoff as the inputs and the infiltration parameters as the outputs. The obtained results indicated that the artificial neural networks technique could be successfully employed for the purpose of calibration of infiltration equations (Jain and Kumar, 2006). Also, artificial neural network model was employed to model infiltration using data derived from plot-scale rainfall simulator experiments. Comparing the results with the traditional

Philip and Green-Ampt models, the artificial neural networks provided the highest accuracy in term of cumulative infiltration. However, the inputs in the artificial neural networks model were intensity of water from rain simulator, soil moisture content, the percentage of sand and clay contents in the soil, soil slope, soil bulk density and soil hydraulic conductivity (Nestorl, 2006).

Infiltration varied with different variables and is a complex process for modeling infiltration over the field. So, the design and simulation of irrigation methods are most likely to consider empirical relationships between water infiltration and the independent variables (Nasser, 2004). Therefore, the objectives of this research project were:

(1) to determine the parameters of Kostiakov infiltration equation using artificial neural networks based on data obtained by double ring under different combination of tillage implement weight and width, speed and depth of plowing, and tractor power on clay soil. These combinations create different soil total porosity and soil moisture content.
(2) to formulate the parameters of Kostiakov infiltration with tillage implement weight and width, speed and depth of plowing, tractor power, soil total porosity and soil moisture content using the simulated data from artificial neural networks.

MATERIALS AND METHODS

2.1Treatments and data collection:

To develop an artificial neural network model, tillage experiments in clay soil were carried out to collect infiltration data. Tillage was achieved by moldboard, chisel and rotary plows. These plows had different weights and widths and hitched by different tractors. The description of the experimental procedures, tillage implements specifications were reported previously (El Biely, 1995). The double ring infiltrometer was used to determine infiltration rate in the field. The water used for the measurement of infiltration rate of soil was the same as the irrigation water. Readings were taken at specified time intervals for 3 hours (180 min) to get infiltration rate (mm/hr). The infiltration data corresponding to different treatment were collected from another study (El Biely, 1995). The ratio of soil fractions; sand, silt and clay at depth from 0-20 cm were 17.15%, 30.58% and 52.27%, respectively.

Three tillage implements, two plowing depths and three plowing speeds were used in order to determine the infiltration rate. Initial soil bulk density and initial total porosity at depth from 0-20 cm were 1.31 g/cm^3 and 50.56%, respectively. Furthermore, soil bulk density, total porosity and soil moisture content were measured after tillage experiments. Subsequently, soil total porosity was calculated using the following equation:

$$TP= \frac{\rho_r-\rho}{\rho_r} \qquad (2)$$

Where:
TP= soil total porosity,%.
ρ_r = real density in clay soil and equals of 2.65 g/cm^3.
ρ= final soil bulk density, g/cm^3.

The infiltration data was analyzed at different treatments to get parameters of Kostiakov infiltration (k,n). Eighteen observations were obtained for parameters of Kostiakov infiltration. Four variables in this study were selected as inputs in the developed artificial neural network model namely: soil total porosity (TP, %), soil moisture content (M, % db), working index (dimensionless) and aspect ratio (dimensionless). Working index (WI) and aspect ratio (AR) were calculated as follows:

$$WI= \frac{W \ x \ S}{P} \qquad (3)$$

$$AR= \frac{b}{d} \qquad (4)$$

Where:
W = tillage implement weight (N).
d = plowing depth (cm).
b = tillage implement width (cm).
S = plowing speed (m/sec).
P = power for the tractor which hitched the tillage implement (kW).

2.2 Artificial Neural Network Infiltration Model:

One of the earliest infiltration equations was Kostiakov empirical model (Kostiakov, 1932). Kostiakov empirical constants (k,n) can be determined by curve fitting to experimental data for infiltration rate. As the infiltration rate was plotted versus time on log-log paper to find the intercept and the slope of the straight line as shown in Fig.1. Many researchers used Kostiakov equation for infiltration and proposed methods for determination of its parameters (Scaloppi *et al*.,1995).

There are many types of artificial neural network structures and training algorithms. Different neural network structures (i.e. systems of connections between neurons) are used for different purposes, for example approximating relationships between variables. The artificial neural network approach most commonly used for agricultural engineering applications is a multi-layer feedforward network structure with a (supervised learning) back-propagation training algorithm. The input layer of the artificial neural network model consists of the nodes corresponding to the following variables: soil total porosity, soil moisture content, working index and aspect ratio. The output layer (representing the variable that is being estimated) also consists of the two nodes related to the parameters of Kostiakov infiltration k and n. The effects of tillage implement width, tillage implement weight, tractor power, plowing speed, plowing depth, soil moisture content and soil total porosity upon Kostiakov empirical constants and the basic infiltration rate at 180 min were investigated. Table 1 lists minimum, maximum and average of the selected inputs in the artificial neural network model.

Table 1: Minimum, maximum and average of the inputs and outputs in the developed artificial neural network model.

	Soil total porosity*	Soil moisture content*	Working index	Aspect ratio	Kostiakov empirical constants	
	(%)	(%,db)	(----)	(----)	k (mm/hr)	n(---)
Minimum	57.62	21.07	7.03	5.31	191.75	-0.7122
Maximum	63.28	24.37	26.99	18.04	241.98	-0.6422
Average	59.76	22.74	13.66	12.06	213.13	-0.6784

*after tillage

The whole data set (18 data points) was randomized and used for training the artificial neural network. The logistic function of neuron activation in the hidden layer was chosen. The input and output values were normalized between 0.15 and 0.85 prior to use with the model, according to the following equation:

$$X = X(t) = \frac{(t - t_{\min})}{(t_{\max} - t_{\min})} \times (0.85 - 0.15) + 0.15 \tag{5}$$

Where:

t= the original values of input and output variables.

X= normalized value

t_{max} and t_{min} = maximum and minimum values of input and output variables as shown in Table 1.

The final step in neural network activity is the denormalization of output. Using commercially available software, Qnet2000 (Vesta Services,2000), the artificial neural network used in the present study was characterized by the parameters shown in Table (2). The choice of the artificial neural network type was done based on the results of preliminary investigations (data not included). Fig. 2 illustrates the developed artificial neural network model.

Table 2: Characteristics of the developed artificial neural network model.

Item	Value
Input Layer Nodes	4
Transfer Function	Linear
Hidden Layer 1 Nodes	6
Transfer Function	Sigmoid
Hidden Layer 2 Nodes	3
Transfer Function	Sigmoid
Hidden Layer 3 Nodes	2
Transfer Function	Sigmoid
Output Layer Nodes	2
Transfer Function	Sigmoid
Iterations	200000
Training Error	0.002959
Learn Rate	0.038375
Momentum Factor	0.8

2.3 Performance Evaluation:

The performance of the model developed in this research was assessed using various standards statistical criteria and the coefficient of determination (R^2) is selected to measure the linear correlation between the observed and the estimated constants. However, the used standard statistical criteria were as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=N} (Measured - Estimated)^2}{N}} \tag{6}$$

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| Measured - Estimated \right| \tag{7}$$

Where:
RMSE = root mean square error.
MAE = mean absolute error.
N = number of observations.

RESULTS AND DISCUSSION

3.1 Relationship Between Dependent and Independent Variables:

The correlation matrix, in training set, with the parameters of Kostiakov infiltration k and n, as the dependent variables (Table 3), indicates that there is a positive fair relationship between soil total porosity and constant k (r = 0.542), and working index and constant k (r = 0.489). There is also a positive fair relationship between soil total porosity (r = 0.642) and constant n, and soil moisture content and constant n (r = 0.431). Also, there is a negative fair relationship between aspect ratio and constant n (r = -0.631).From this analysis, it is obvious that these variables influence the soil water movement, which in turn affects the infiltration. However, working index shows weak correlation with constant n. Soil moisture content and aspect ratio also show weak correlation with constant k.

Table 3: Correlation matrix for inputs and outputs training data.

	Inputs				Outputs	
	Soil total porosity	Soil moisture content	Working index	Aspect ratio	k	n
Soil total porosity	1					
Soil moisture content	0.061	1				
Working index	0.056	0.028	1			
Aspect ratio	-0.398	-0.829	0.314	1		
k	0.524	0.199	0.489	-0.171	1	
n	0.642	0.431	-0.060	-0.631	-0.045	1

3.2 Accuracy of the Developed Artificial Neural Network Model:

The criteria of accuracy for the developed artificial neural network model to estimate constants ‘k’ and ‘n’ during training process are shown in (Table 4). Higher coefficients of determination (R^2) indicate that the model has good prediction capability.

Table 4: The criteria of accuracy of the developed artificial neural network model to estimate constants k and n during training processes.

Criteria of accuracy	Units	Value	
		Constant ‘k’	Constant ‘n’
Root mean square error (*RMSE*)	(mm/hr)	0.17471	------
	(----)	------	0.00034
Mean absolute error (MAE)	(mm/hr)	0.12131	------
	(----)	------	0.00023
R^2	(----)	0.99988	0.99965

3.3 Relationship Between Kostiakov Empirical Constants and Affected Parameters:

The relationship between Kostiakov empirical constants (k, n) and affected parameters was investigated by taking data rang of the affected parameters. For tillage implement width, the data range was 120-175 cm, for tillage implement weight, the data range was 260-900 kg, and for tractor power, the data range was 25-80 kW. For plowing speed, the data range between 2.3 and 4.6 km/hr, for plowing depth, between 9.8 and 20 cm, for soil moisture content, between 21.0 and 24.3% db and for soil total porosity, between 57.6 and 63.2%.

Processing the data was based on fixing one parameter a time at its average value when changing the other parameters. The proposed ranges were used to calculate working index and aspect ratio. The new data set (126 observations) was used to estimate the Kostiakov empirical constants using the developed artificial neural network model. Multiple linear regression was run on the created data set which resulted in the following equations:

$$k = 37.391 + 0.071 \times b - 0.076 \times W + 0.467 \times P - 18.166 \times S - 0.307 \times d - 5.493 \times M + 5.974 \times TP \quad R^2 = 0.60 \tag{8}$$

$$n = -1.603 - 0.00008 \times b + 0.00007 \times W - 0.00051 \times P + 0.01859 \times S + 0.00041 \times d + 0.01641 \times M + 0.00832 \times TP \quad R^2 = 0.64 \tag{9}$$

3.4 Effect of Working Conditions on Basic Infiltration Rate (I_0, mm/hr) at 180 min:

Figs. (3 through 9) depict the effect of tillage implement working width, tillage implement weight, tractor power, plowing speed, plowing depth, soil moisture content and soil total porosity on basic infiltration rate at 180 min, respectively.

It could be optimize the basic infiltration as shown in Figs. (3 through 9). The increasing implement width results decreasing basic infiltration until 145 cm, and then increasing as shown in Fig. 3. Also, this tend was observed when increasing tillage implement weight, the basic infiltration rate decrease until 420 kg then increasing as shown in Fig.4. Meanwhile, increasing tractor power results in increasing in basic infiltration rate until 45 kW then the basic infiltration decrease as shown in Fig. 5. As listed in Fig. 6, increasing plowing speed results in deceasing in basic infiltration until 2.6 km/hr then it increased. Also, this trend was observed, increasing plowing depth results in deceasing in basic infiltration until 14 cm then it increased (Fig. 7).

Meanwhile, Figs. 8 and 9 show the positive relationship between soil moisture content and soil total porosity on the one hand and the basic infiltration.

3.5 Comparison Between Actual Infiltration Rate and Artificial Neural Network Simulation:

To assess the performance of the identified artificial neural network model, the estimated constants 'k' and 'n' values were obtained then substituted these values in Eqn (1) to get the infiltration rate. Fig. (10) illustrates the example of the results. It is obvious that the simulated infiltration rate behaves as the observed infiltration rate at any infiltration time with good correlation.

3.6 Contributions of Input Variables and Relationship Between Input Parameters and Basic Infiltration Rate at 180 min:

Contributions of input variables on Kostiakov empirical constants are shown in (Fig. 11). It is obvious that working index has more contribution on constant k. Meanwhile, soil total porosity has more contribution on constant n. For the two constants, the aspect ratio has low contribution. The creation data set (126 observations) was used to estimate the basic infiltration rate (I_0, mm/hr) based on the estimated Kostiakov empirical constants using infiltration time of 180 min and multiple linear regression was achieved the following equation:

$$I_0 = -19.788 + 0.302 \times TP + 0.356 \times M - 0.004 \times WI - 0.003 \times AR \quad R^2 = 0.867 \tag{10}$$

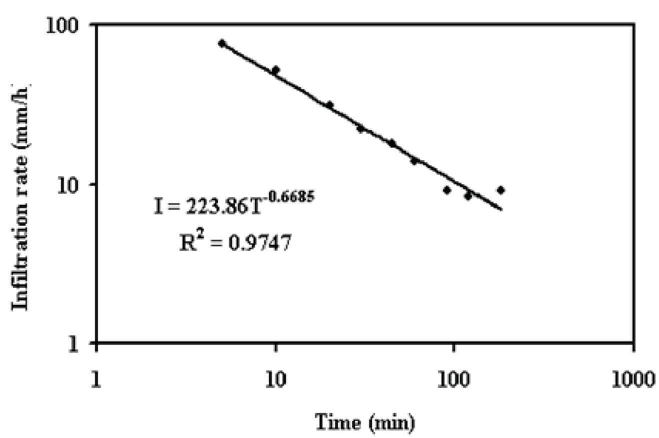

Fig. 1: Infiltration rate versus time on log-log paper to find the Kostiakov empirical constants k and n.

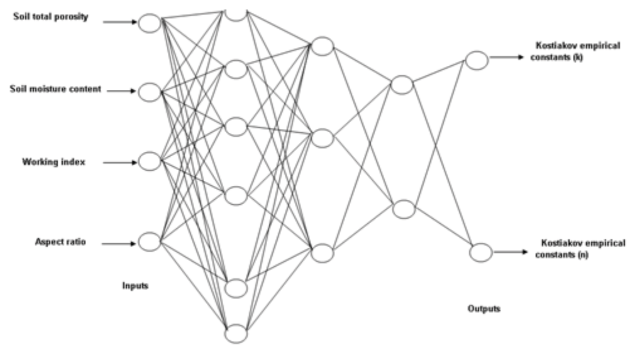

Fig. 2: The developed artificial neural network model (4-6-3-2-2) for estimating Kostiakov empirical constants (k,n).

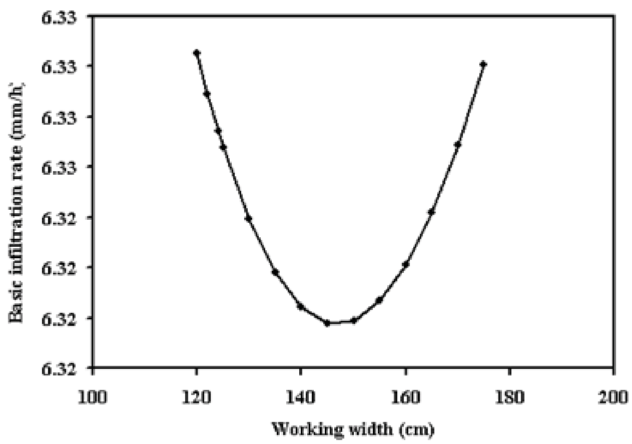

Fig. 3: Effect of tillage implement working width on basic infiltration rate at 180 min (plowing speed =3.5 km/hr, plowing depth = 13.8 cm, soil total porosity = 59.76%, soil moisture content = 22.74%, db, tractor power = 63 kW and tillage implement weight = 550 kg).

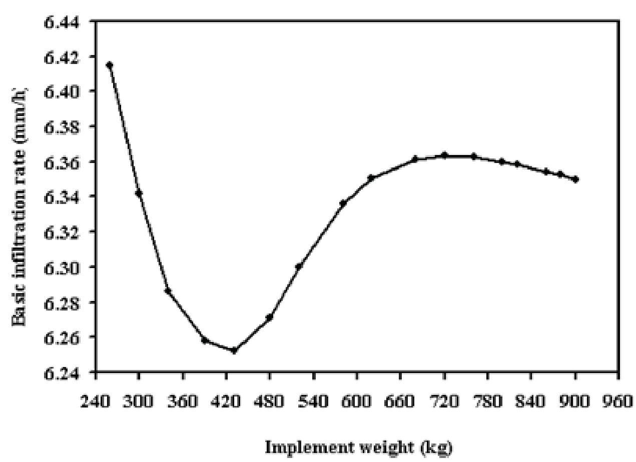

Fig. 4: Effect of tillage implement weight on basic infiltration rate at 180 min (plowing speed =3.5 km/hr, plowing depth = 13.8 cm, soil total porosity = 59.76%, soil moisture content = 22.74%, db, tractor power = 63 kW and tillage working width = 150 cm).

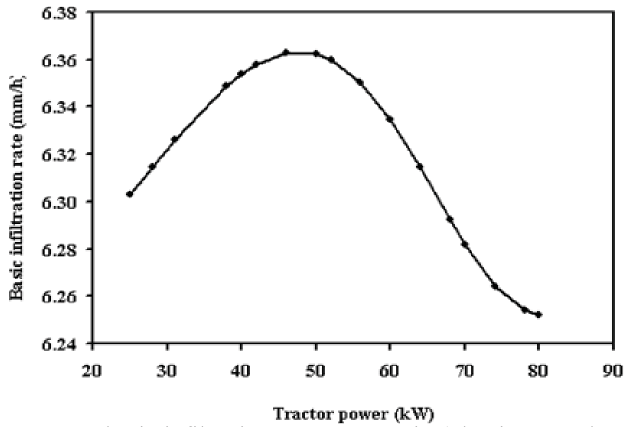

Fig. 5: Effect of tractor power on basic infiltration rate at 180 min (plowing speed =3.5 km/hr, plowing depth = 13.8 cm, soil total porosity = 59.76%, soil moisture content = 22.74%, db, tillage working width = 150 cm and tillage implement weight = 550 kg).

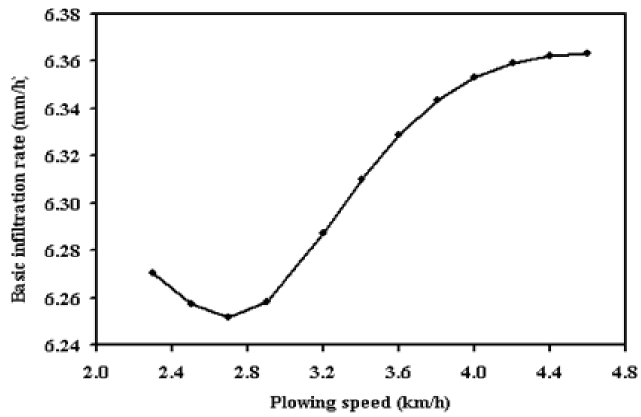

Fig. 6: Effect of plowing speed on basic infiltration rate at 180 min (plowing depth = 13.8 cm, soil total porosity = 59.76%, soil moisture content = 22.74%, db, tillage working width = 150 cm, tractor power = 63 kW and tillage implement weight = 550 kg).

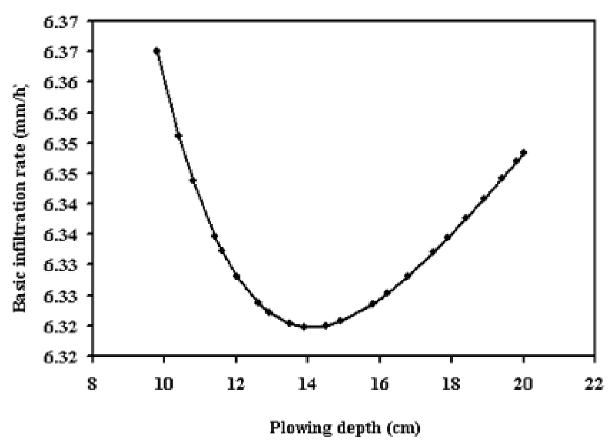

Fig. 7: Effect of plowing depth on basic infiltration rate at 180 min (plowing speed = 3.5 km/hr, soil total porosity = 59.76%, soil moisture content = 22.74%, db, tillage working width = 150 cm, tractor power = 63 kW and tillage implement weight = 550 kg).

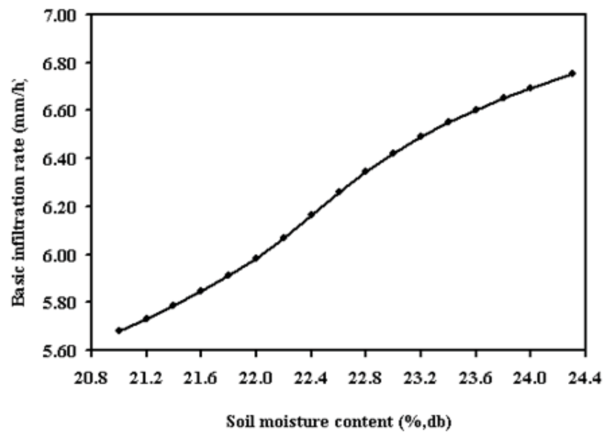

Fig. 8: Effect of soil moisture content on basic infiltration rate at 180 min (plowing speed = 3.5 km/hr, plowing depth=13.8 cm, soil total porosity = 59.76%, tillage working width = 150 cm, tractor power = 63 kW and tillage implement weight = 550 kg).

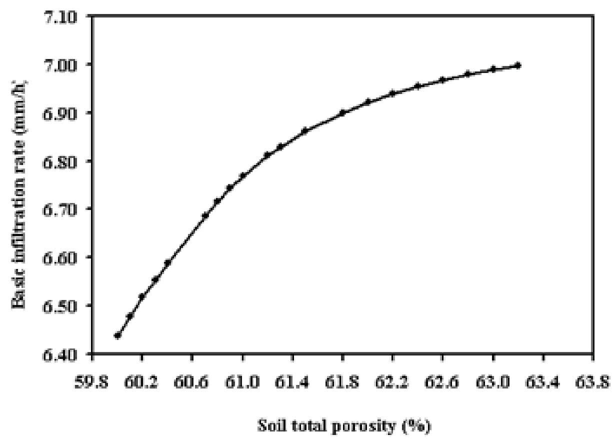

Fig. 9: Effect of soil total porosity on basic infiltration rate at 180 min (plowing speed = 3.5 km/hr, plowing depth=13.8 cm, soil moisture content = 22.74%, db, tillage working width = 150 cm, tractor power = 63 kW and tillage implement weight = 550 kg).

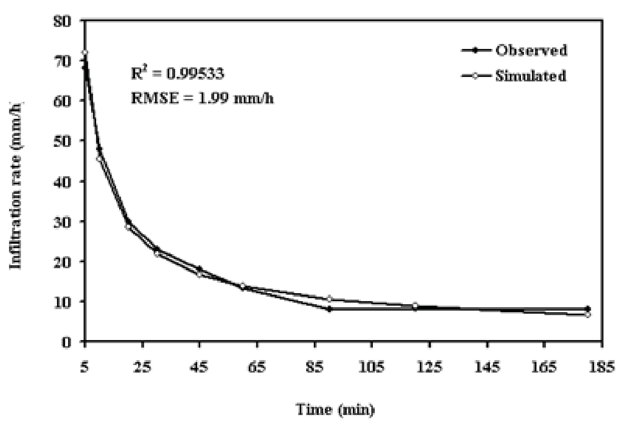

Fig. 10: Observed and simulated infiltration rate versus infiltration time (plowing speed = 2.34 km/hr, plowing depth=10.3 cm, soil moisture content = 21.67%, db, tillage working width = 175 cm, tractor power = 80 kW and tillage implement weight = 470 kg).

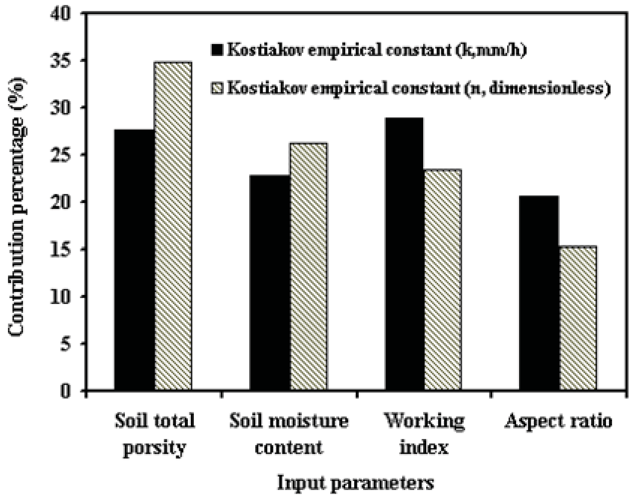

Fig. 11: Contribution percentage of input variables on Kostiakov empirical constants.

Conclusion:

This research presents the application of artificial neural networks for modeling the parameters of Kostiakov infiltration (k,n) under conventional tillage systems on clay soil. The artificial neural network approach was accurate in simulating infiltration rate and R^2 was around 0.9953. The simulated infiltration rate behaves as the observed infiltration rate at any infiltration time with good correlation. The effect of working width and weight of tillage implements, tractor power, plowing speed and depth, soil moisture content and soil total porosity on basic infiltration rate at 180 min could be studied with the help of the developed model.

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