AN INTERACTIVE APPLICATION USING C-SHARP LANGUAGE FOR PREDICTING CUMULATIVE INFILTRATION RATE OF WATER IN SOIL

AL-SULAIMAN,M. A.[1] and A. M. ABOUKARIMA[2]

1. *Community College, Huraimla, Shaqra University, Saudi Arabia*
2. *Agricultural Engineering Research Institute, ARC, Egypt*

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Abstract

The objective of this study was to develop an interactive application using C-Sharplanguage to predict cumulative infiltration rate of water in a soil.Cumulative infiltration rate seems to be very simple issue, but field determination of it is very tedious and time consuming task due to many factors affectingit. Thus, researchers should be encouraged to develop a simple and accurate model to predict the cumulative infiltration. The actual measurements of infiltrationin this study were obtained using double ring infiltrometer.The measurements were conducted in the field on different soil textures namely sand, sandy loam, loam and loamy sand. Moreover, different water qualities were utilized. The inputs to the interactive application were soil electric conductivity, soil sodium adsorption ratio, percentage of organic matter in the soil,initial soil water contents, initial soil bulk density, sodium adsorption ratio of water, electric conductivity of water and an index to represent soil texture.The mean error between actual and predicted cumulative infiltration rate by the help of the developed interactive application after three hours was-39.25 mm. Consequently, the developed C-Sharp application is recommended for estimating cumulative infiltration rate in soilsto provide data for irrigation water management.

Key words: Modeling, double ring, artificial neural network.

INTRODUCTION

Water infiltration of rainfall or irrigation is an important topic of soil and water conservation in semi-arid regions. Furthermore, it controls leaching, runoff and crop water availability (Franzluebbers, 2002). Soil texture, soil structure, organic matter in the soil, management and type of soil layers are some factors which affect infiltration rate (Skandarinia*et al.*, 2005).Additionally, infiltration rate depends on amount of the initial soil moisture content, the soil slope, the soil roughness, the type of vegetative cover, the water depth, the soil and water temperature, the applied water quality, the amount of dissolved salts particularly exchangeable sodium in water and soil and the dispersion of the soil surface particles (Mazloom and Foladmand, 2013). Moreover, infiltration rate of water into a soil can be greatly influenced by the quality of the irrigation water, degree of compaction andthe organic matter content in the soil (Ayers and Westcot, 1994).

Cumulative infiltration rate is the total quantity of water that enters the soil in a given time. Thus, it commonly used in evaluating the infiltration characteristics of a soil. On the other hand, empirical equations are used to describe infiltration process of a soil through determining their empirical constants. Theempirical equations that used to describe infiltration process of a soilare ranged from simple to complex and the famous one is Kostiakov's infiltration model. The empirical constants of Kostiakov's infiltration model were obtained statistically by several researches (Uloma*et al.*, 2014; Al-Sulaiman *et al.*, 2015). Recently, artificial neural networks technique has been applied in prediction of soil infiltration with great success (Matte *et al.*, 2015).

Prediction of infiltration in a soil is of prime importance in irrigation studies as it influences the application rate of irrigation water(Jejurkar and Rajurkar, 2015). However, infiltration seems to be very simple topic, but field determination of it is very tedious and time consuming task. So, researchers are encouraged to developa simple and accurate model to predict the cumulative infiltration rate due to many factors affecting it. Thus, in this research the empirical constants of Kostiakov equation (Kostiakov, 1932) for cumulative infiltration rate were predicted by the help ofan artificial neural network (ANN) model. The obtained ANN weights after training process were formulated into C-Sharp application for estimating cumulative infiltration rate easily based on soil and water characteristics. This proposed simple-to-use computer application can be utilized as a good tool for soil scientists and agricultural engineers to have a rapid data about infiltration at wide range of soil and irrigation water characteristics without the necessity to conduct field experiments.

MATERIALS AND METHODS

Characteristics of the used soil and water

The experimental sites were located in different regions in Saudi Arabia. The soil particle sizes were determined by using the laboratory standard methods. Prior to infiltration run, five soil samples were collected randomly from the top of 21cm using soil auger from each site. These soil samples were bulked for the determination of the initial soil moisture content and soil bulk density using standard laboratory procedures. Chemical analysis for each soil and for each water type was conducted. Nine soil texture and twenty water types with different characteristics were considered in this study. Sodium adsorption ratio (SAR) for the soil and the water were calculated from the chemical analysis using the following formula (Suarez *et al.*, 2006):

$$SAR = \frac{Na^{+}}{\sqrt{\frac{1}{2}\left(Ca^{++} + Mg^{++}\right)}} \quad (1)$$

Where Na^{+}, Ca^{++} and Mg^{++} represent concentrations of sodium, calcium and magnesium in a soil or in waterexpressed in milliequivalents per liter (meq/L).Also, electric conductivity (EC) for soil and water was measured in dS/m.

To make any mathematicalmodel more universal, a variable describing the soil type was added to the model (Altendorf *et al.*, 1999). By browsing through literatures, different formulas were found to represent soil components (sand, silt, and clay) in one numeric value to be used in the mathematical models. In this study, soil texture index (STI) which developed by Oskoui and Harvey (1992) was selected to represent soil texture components and it was calculated as follows:

$$STI = \frac{log\ (S_i^{CC_a})}{100} \quad (2)$$

Where S_i and CC_a are % of silt and clay fractions in the soil, respectively. Meanwhile, the sand fraction is represented implicitly since the sum of sand, silt and clay fractions is always constant. Oskoui and Harvey (1992) showed that the STI reflects the effects of all three of the soil fractions. The STI produces unique numbers for every combination of sand, silt and clay contents. The raw data were illustrated in Al-Sulaiman *et al.* (2015) for soil and water characteristics. Meanwhile, Table (1) shows minimum, maximum and stranded deviation of the soil and water characteristics.

Table 1. Minimum, maximum and stranded deviation of soil and water characteristics.

Statistical parameters	STI	MC	BD	ECw	SARw	ECs	SARs	OM
	(--)	(%,db)	(g/cm^3)	(dS/m)	(---)	(dS/m)	(---)	(%)
Minimum	0.0060	3.28	1.25	0.22	1.64	1.06	2.00	0.26
Maximum	0.3722	16.92	1.76	5.28	8.80	91.10	57.60	2.62
Standard deviation	±0.1197	±3.03	±0.13	±1.38	±1.96	±27.50	±16.51	±0.78

ECs=Electric conductivity of soil, SARs=Soil sodium adsorption ratio, OM=Organic matter in the soil,MC=Initial soil water contents, BD=Initial soil bulk density, SARw=Sodium adsorption ratio of water, ECw=Electric conductivity of water and STI=Soil texture index calculated by Eq.2.

Experimental procedures

The double-ring infiltrometer was used to get infiltration readings in the field. Different water qualities were transported to each site in two barrels with capacity of 100 liters. The double-ring infiltrometer 30 cm high was used and it had inner and outer galvanized iron rings of diameters 30 cm and 60 cm, respectively. The rings were driven at about 10 cm deep in the soil by using falling weight type hammer striking on a wooden plank placed on top of ring uniformly without or undue disturbance to soil surface. Water was poured slowly into the inner ring. The outer ring, which acts as a buffer, was also filled with water to the same height in order to minimize the lateral seepage from the inner ring. A graduated metal rulerwas placed in the inner ring. The ruler was adjusted to the desired level to which water was to be added. A digital stopwatch was used to note the time the water begins to infiltrate. The soil intake rate was measured directly by observing the rate at which the water level declined with respect to time. The experiments were carried out for a period of 180 minutes as indicated by Uloma *et al.* (2014). This was based on the fact that infiltration usually takes 120-360 minutes for the process to reach steady state as reported byLili *et al.* (2008).The observations for infiltration rate were carried out on the inner ring. A field experiment was conducted to test the effect of water quality on the infiltration rate of soils having different properties. Three infiltration measurements were conducted using each water quality and average was taken later.

Kostiakov's infiltration model

Despite the availability of a large number of infiltration models, some of the available empirical models have been quite popular and frequently used in infiltration experiments because of their simplicity and yielding reasonably satisfactory results (Uloma *et al.*, 2014). Kostiakov's infiltration model (Kostiakov, 1932)is derived using the data observed either in the field or the laboratory. Kostiakov's infiltration model suggested a formula which assumed that at time T = 0, the infiltration rate is infinite and at time T = ∞, the rate approaches zero. The Kostiakov's infiltration model is given bythe following formula:

$$Z = \kappa T^{\alpha} \quad \text{.........} \quad (3)$$

Where T is the time elapsed for the experiment (hr), Zis the cumulative infiltration rate (mm), α and κ are empirical constants that are site specific and depend on different parameters (Uloma *et al.*, 2014). The parameter α was accepted by most authors to be less than one (Moroke *et al.*, 2009). Unit of the empirical constant κ is mm/hr^{α} and the empirical constant α is without unit. As a Kostiakov infiltration model is an empirical one, no physical meanings are attached to its associated constants (Khaliq *et al.*, 1994). To determine the constants α and κ, the log of Eq. (3) was taken, then the Kostiakov's constants α and κ were determined graphically. However, the slop linear relation of Z and T presented the value of α, while log κ

presented the intercept of Z axis. The value of κ was obtained from the anti-log κ. i.e.

$$\kappa = 10^{\log \kappa} \qquad (4)$$

In this study, 180 values for the Kostiakov's infiltration model constants α and κ were calculated. The raw data for these values were shown in Al-Sulaiman *et al.* (2015). Table (2) shows minimum, maximum and stranded deviation of the calculated Kostiakov's infiltration model constants α and κ.

Table 2. Minimum, maximum and stranded deviation of the calculated infiltration model parameters α and κ.

Statistical parameters	Kostiakov's infiltration model (Eq. 3)	
	α (--)	κ (mm/hr^{α})
Minimum	0.2375	3.663
Maximum	0.8722	202.91
Standard deviation	±0.0780	±43.66

Artificial neural network (ANN) for modeling the empirical constants (κ) and (α)

Briefly, an ANN model operates by propagating various linear combinations of the input values through a series of one or more layers consisting of processing elements or neurons. The nonlinear aspect of the modeling is incorporated in the transfer function, which is applied to the linear combination at each layer. The network learns through back propagating the error. The training data set contains the desired output vector associated with each input vector. On completion of the forward propagation, the desired network output is compared with the actual output. A gradient descent process is used to adjust the weights such that the error will be decreased. The objective at each step is to adjust weights to reduce the error, not to find the weights, which will minimize error. Typically, the network must run in the training mode through great much iteration, and a reactively large set of training data may be required (Altendorf *et al.*, 1999). The mathematics of the back propagation algorithm was described in Haykin (1999).

In this study, commercially available software called QNET 2000 was employed (Vesta Services, 2000). This software is a Windows-based package, which supports standard back-propagation algorithm for training purposes. QNET 2000 operates via a graphical user interface that enables the user to load the training and test sets, design the network architecture and feed values for the training parameters. It must be noted that because the variables (input or output) presented were of different orders of magnitude, all of the original input or output parameters were normalized between 0.15 and 0.85 before entering into the network structure using the following equation:

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

Where t is the original values of input and output parameters, X is the normalized value; $x_{\min}$ and $x_{\max}$ are the minimum and the maximum values of the input and the output parameters in training data set, respectively. The training data set was used to compute the network parameters. The testing data set was used to ensure robustness of the network parameters. In the study, trial and error approach was used to determine the optimum neurons in the hidden layers of the network. Transfer function was also varied; however, they were sigmoid and hyperbolic tangent (tanh) in the hidden layers. The training data set consisted of 180 patterns for empirical constants (α and κ) of cumulative infiltration rate corresponding to different 8inputs, which were electric conductivity of soil, soil sodium adsorption ratio, initial soil water content, soil texture index, soil bulk density, organic matter in the soil, electric conductivity of water and sodium adsorption ratio of water. The output (target) variable in this study was empirical constant (κ) and empirical constant (α) of Kostiakov cumulative infiltration rate equation (Eq.3).

Preliminary trails indicated that one hidden layer network performed better results to learn and predict the correlation between input and output parameters. To determine the optimal number of neurons in the hidden layer, training was used for 8-n1-1 architectures. The number of neurons in the hidden layer (n1) was studied from 1 to30. Results showed that among the various structures, the best training performance to predict empirical constant(κ) belonged to the 8-20-1 ANN structure. Meanwhile, the best training performance to predict empirical constant (α) belonged to the 8-25-1 ANN structure. However, the best ANN model was elected based on the highest correlation coefficient and the lowest training error. Training error for empirical constant (κ) was 0.031834 and it was 0.026145 for empirical constant (α).Table (3) illustrates statistics criteria of the best ANN models from QNET 2000software after training process to predict empirical constants (α and κ).

Table 3. Statistics criteria of the best ANN models from QNET 2000 software after training process to predict empirical constants (α and κ).

Empirical constants	Statistics criteria			
	Standard deviation	Bias	Maximum error	Correlation coefficient (r)
κ (mm/hr^{α})	±50.2913	-0.25652	9.061	0.97813
α (---)	±0.02371	-1.52E-05	0.15275	0.95318

Evaluation of ANN models predictability

The performance of an ANN model can be attributed to its structural and functional characteristics (Singh *et al.*, 2013), thus the ANN output error between the actual and the predicted values should be evaluated. Popular error criteria for performance measure are mean absolute error (MAE) and mean relative error (MRE) which were used and they are calculated as follows:

$$MAE = \frac{1}{N} \times \sum_{i=1}^{i=N} \left| K_{viobs} - K_{vipre} \right| \quad \text{.........} (6)$$

$$MRE = \frac{100}{N} \times \sum_{i=1}^{i=N} \left(\frac{K_{vipre} - K_{viobs}}{K_{iobs}} \right) \quad \text{.........} (7)$$

Where K_{viobs} and K_{vipre} were calculated (observed) and predicted empirical constants(α and κ), respectively and N is number of observations. The correlation coefficient (r) was selected to be a criterion for measuring the linear correlation between the calculated and the predicted values.

C-Sharp application

C-Sharp programming language available under NET programming environment has been used for developing an interactive computer application to predict empirical constants(α and κ). This application has been developed keeping in view its user friendliness and easily operable. C-Sharp language was chosen because it is a generic portable language and could be run on other operating systems (Post, 2007). The current C-Sharp application was developed based on the weights obtained from the developed ANN models for empirical constants (α and κ) during training stage. These weights were formulated into equations with the help of programming by C-Sharp to be easily used. The developed C-Sharp application was validated with experimental data to ascertain its suitability for (α and κ) predictions and then cumulative infiltration rate . Fig. (1) shows screenshot of the inputs screen, besides, Fig. (2) indicates screenshot of the output screen.

RESULTS AND DISCUSSION

Performance of the developed ANN models

A comparison of the empirical constants (α and κ) of cumulative infiltration rate equation (Eq. 3) values predicted using the developed ANN models with those calculated graphically is presented point by point in Figs. (1 and 2) for training data set for the empirical constants (κ) and the empirical constant (α), respectively. Better agreement of points presented in Figs. (3 and 4) with a straight line (1:1) which means better agreement between the calculated and the predicted points.

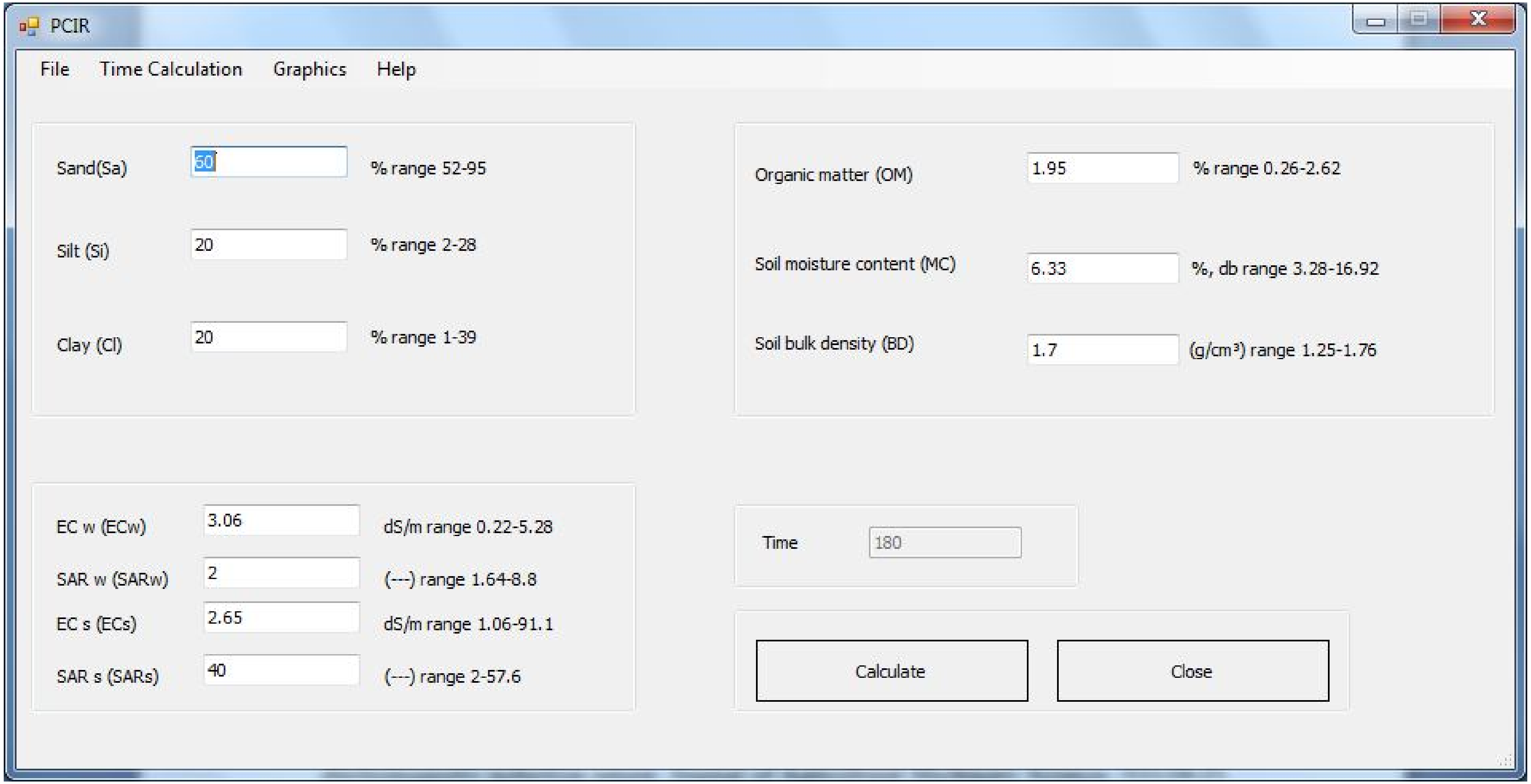

Fig. 1. Screenshot of the inputs screen in the developed C-Sharp application.

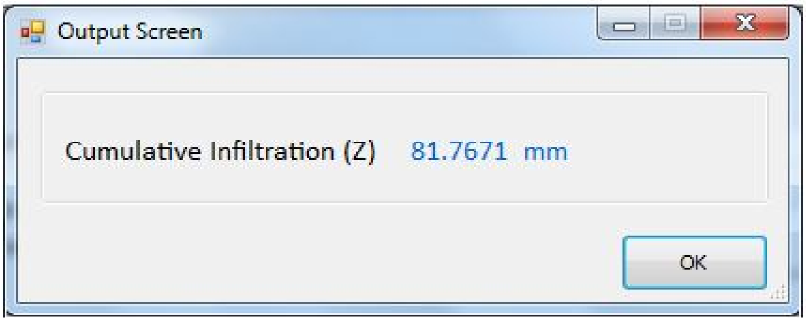

Fig. 2. Screenshot of the output screen in the developed C-Sharp application.

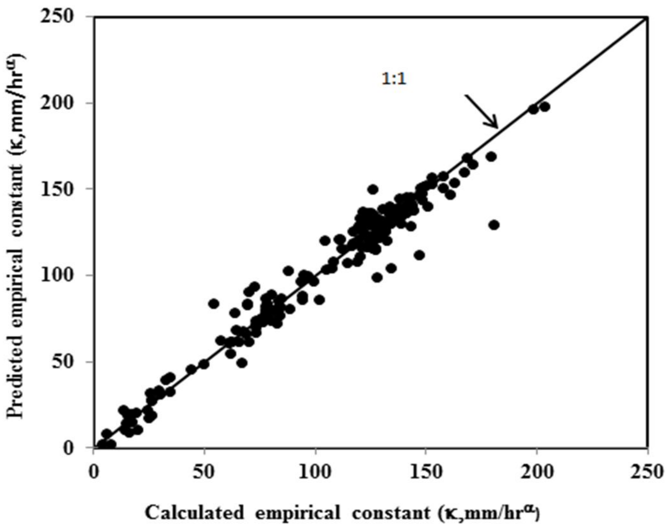

Fig. 3. Relationship between the predicted empirical constant (κ) from the developed ANN model and the empirical constant (κ) calculated graphically for training patterns.

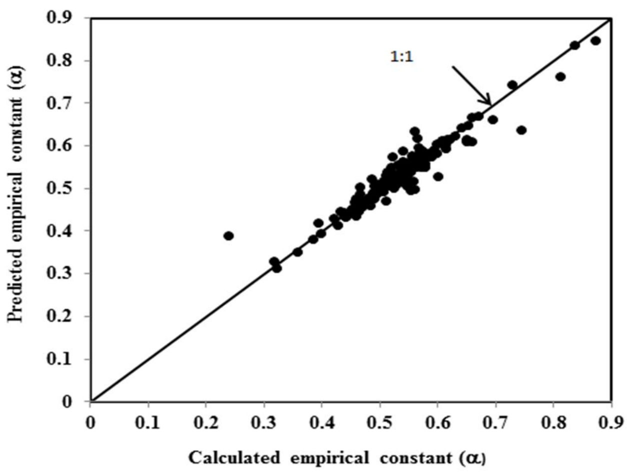

Fig. 4. Relationship between the predicted empirical constant (α) from the developed ANN model and the empirical constant (α) calculated graphically for training patterns.

The maximum errors between the calculated graphically empirical constants (κ) and (α)and the predicted values using the developed ANN models was 9.061 mm/hr^{α} and 0.15275 as shown in Table (3) during training phase, respectively. However, the predictability of the developed ANN models for prediction of (α) and (κ) was tested during testing process by calculating ofmeanabsolute error (MAE), mean relative error (MRE) and correlation coefficient. However, Table (4) shows values of meanabsolute error (MAE), mean relative error (MRE) and correlation coefficient (r) during testing process of the developed ANN models for prediction of empirical constants (α and κ)of cumulative infiltration rate equation (Eq. 3). From Table (4), it is clear that MRE and MAE values showed a small error between the calculated graphically and the predicted values of (α) and (κ), suggesting that the employed ANN models were very accurate in predicting the values of the two empirical constants at any values of the independent variables, falling within the range of values in the study. MAE and MRE for (κ) were 4.835 mm/hr^{α} and -0.371%, respectively. Meanwhile, MAE and MRE for (α) were 0.0145 and-1.148 %, respectively.

Table 4. Meanabsolute error (MAE),mean relative error (MRE) and correlation coefficient (r) during testing process of the developed ANNmodels for prediction of empirical constants (α and κ) of cumulative infiltration rate equation (Eq. 3).

Error criteria	The empirical constant (κ)	The empirical constant(α)
(MAE)	4.835(mm/hr^{α})	0.0145 (---)
(MRE)	-0.371 (%)	-1.148 (%)
(r)	0.909	0.720

Contribution of inputs on predicted the empirical constants (α) and (κ) with the developed artificial neural network models

Infiltration problems could not be attributed to any specific soil chemical or physical property. Under the given conditions, infiltration seemed to be determined by a combination of soil properties, i.e. EC, SAR, type of clay mineral and bulk density as reported by Haghnazari *et al.* (2015). So, thecontribution analysis for how the change in each input in the developed ANN infiltration models, changes the output prediction is significant task to display the importance of each variable. In this study, the QNET 2000software provided a contribution calculation for how the change in each input, changes the output prediction. Consequently, the contribution percentage of the eight input variables to the outputs was calculated using the developed ANNmodels and the results are illustrated in Table (5). It can be deduced from Table (5) that the major contribution to the the empirical constant (κ) was attributed to the parameter of soil electric conductivity with a contribution percentage of 16.82% and this means areas of saline soils need to be managed differently than areas of no saline soils (Haghnazari *et al.*, 2015). Myburgh and Howell (2012) also indicated that infiltration is affected by soil salinity and it decreased as the soil salinity increased.

Table 5. Contribution percentage of eight independent variables for prediction of the empirical constants (α) and (κ) by the help of the developed ANN models.

Input variables	Contribution (%)	
	Empirical constant (κ)	Empirical constant (α)
Soil texture index (STI, dimensionless)	16.28	14.94
Initial soil water content (MC, %,db)	11.32	12.17
Soil bulk density (BD, g/cm^3)	10.21	10.09
Water electric conductivity (ECw, dS/m)	9.95	10.57
Water sodium adsorption ratio (SARw,---)	12.99	12.81
Soil electric conductivity (ECs,dS/m)	16.82	13.02
Soil sodium adsorption ratio (SARs, ---)	11.79	12.20
Organic matter in the soil (OM,%)	10.64	14.20

The major contribution to the empirical constant(α) was attributed to the variable of soil texture indexwith a contribution percentage of 14.94% as shown in Table (5), however, soil texture (percentage of sand, silt, and clay) was the major inherent factor affecting infiltration. Moreover, the infiltration is strongly influenced by the soil texture, i.e the relative proportions of sand, silt and clay (Haghnazari *et al.*, 2015) since water moves more quickly through large pores of sandy soil than it does through small pores of clayey soil, especially if clay is compacted.The rest of input variables were nearly equal in the contribution percentage to the empirical constant (α) and the empirical constant (κ).

Performance of the developed C-Sharpapplication

To validate the developed C-Sharp application to predict cumulative infiltration rate, an interface window for the required inputs data was developed.In Table (6), thepredicted final cumulative infiltration rate after three hours(Z3) by the application wasobtained for soil having sand, silt and clay percentage of 80%, 13% and 7%, respectively and having soil electric conductivity, soil sodium adsorption ratio and organic matter of 10.86 dS/m, 8.2 and 1.34%, respectively using different water characteristics and different initial soil moisture contents and soil bulk densities. It is clear from Table (6) that the mean error between actual and predicted cumulative infiltration rate after three hours was -39.25 mm. Moreover,when the inputs variables of sand, silt, clay, water electric conductivity, water sodium adsorption ratio, soil electric conductivity, soil sodium adsorption ratio, organic matter in the soil, initial soil water content, soil bulk density and the required time were 60%,20%,20%, 3.06 dS/m, 2, 2.65 dS/m, 40, 1.95%, 6.33 %db, 1.70 g/cm^3 and 180 min, respectively, initially,the application started up to estimate soil texture index to be 0.260206using Eq. (2), then it directed to estimate both the constant κ to be 71.73 mm/hr^{α} and the constant α to be 0.11855. By substitution of the two constants in the Eq.(3) and at time of 180 min inside the application, the estimated final cumulative infiltration rate was 81.7671 mm.

Table 6. Final cumulative infiltration rate after three hours (measured,calculated graphically and predicted using C-Sharp application), the calculated empirical constants of Kostiakov equation, the predicted empirical constants of Kostiakov equation using the developed C-Sharp application for soil having sand, silt and clay percentage of 80 %, 13% and 7%, respectively and having soil electric conductivity, soil sodium adsorption ratio and organic matter of 10.86 dS/m, 8.2 and 1.34%, respectively using different water characteristics and different initial soil moisture contents and soil bulk densities.

Sample No.	MC	BD	ECw	SARw	Z1	Calculated graphically: The empirical constants κ	Calculated graphically: The empirical constants α	Calculated graphically: Z2	Predicted using C-Sharp application: The empirical constants κ	Predicted using C-Sharp application: The empirical constants α	Predicted using C-Sharp application: Z3	Mean error*
	(% db)	(g/cm^3)	(dS/m)	(---)	(mm)	(mm/hr^{α})	(---)	(mm)	(mm/hr^{α})	(---)	(mm)	(mm)
1	10.32	1.49	3.25	7.6	225	161.76	0.5399	293	169.31	0.4788	287	-62
2	12.86	1.69	2.30	4.14	103	32.522	0.8722	85	37.48	0.8518	96	7
3	6.48	1.57	1.78	3.52	160	120.4	0.3570	178	117.59	0.3502	173	-13
4	9.83	1.33	2.26	4.81	201	179.11	0.4651	299	169.63	0.4564	280	-79
5	9.17	1.66	2.38	3.34	211	142.73	0.5202	258	132.59	0.5791	250	-39
6	8.70	1.34	0.38	2.77	235	202.91	0.4707	340	195.66	0.4702	328	-93
7	13.66	1.45	0.22	4.00	280	140.81	0.6144	277	145.67	0.6364	293	-13
8	5.51	1.56	3.32	7.34	205	116.78	0.5316	209	126.96	0.5290	227	-22
Mean error												-39.25

Z1= final cumulative infiltration rate after three hours (measured), Z2= final cumulative infiltration rate after three hours (calculated graphically), Z3= final cumulative infiltration rate after three hours (predicted using C-Sharp application),

$$* \text{Mean error} = \frac{\sum_{i=1}^{i=8}\left(Z1_i - Z3_i\right)}{8}$$

When the inputs variables of sand, silt, clay, water electric conductivity, water sodium adsorption ratio, soil electric conductivity, soil sodium adsorption ratio, organic matter in the soil, initial soil water content and soil bulk density, respectively were changed to be 80%, 13%, 7%, 3.25 dS/m, 7.6, 10.86 dS/m, 8.2, 1.34%, 10.32 %db and 1.49 g/cm^3 at changing time from 0 to 3 hours, the application was utilized to estimate cumulative infiltration rate at different times. However, Fig. (5) illustratescomparison between the measured and the estimated cumulative infiltration rate for such inputs. It is clear from Fig. (5)that the predicted constant κ was 169.31 mm/hr^{α} while the calculated one was 161.76 mm/hr^{α} and the predicted constant α was 0.4788 while the calculated onewas 0.5399 as illustrated on Fig. (5).

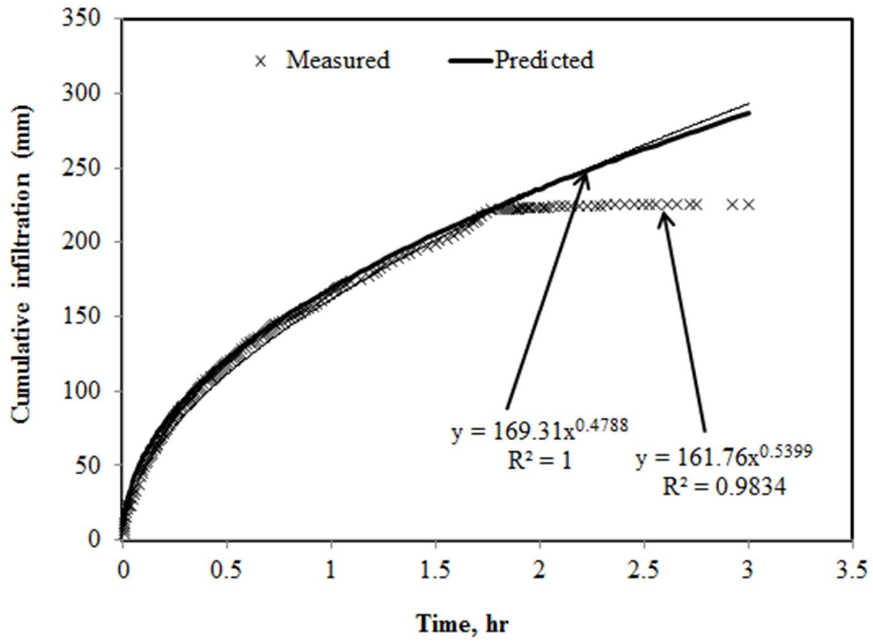

Fig. 5. Comparison between the measured and the predicted cumulative infiltration rate using the developed C-Sharp application (the inputs were 80%, 13%, 7%, 3.25 dS/m, 7.6, 10.86 dS/m, 8.2, 1.34%, 10.32 %db and 1.49 g/cm^3 forsand, silt, clay, water electric conductivity, water sodium adsorption ratio, soil electric conductivity, soil sodium adsorption ratio, organic matter in the soil, initial soil water content and soil bulk density) at changing time from 0 to 3 hours.

CONCLUSION

In this work,the empirical constantsofcumulative infiltration rate equation (α and κ) were predicted by developing two ANN models. Thefirst ANNmodel and the second ANN modelhad 20 and 25 neurons in the first hidden layer, respectively.However, the first and the second ANN models were used for prediction of the empirical constants κ and α, respectively. The inputsto ANN models wereelectric conductivity of soil, soil sodium adsorption ratio, initial soil water contents, soil texture index, soil bulk density, percentage of organic matter in the soil, electric conductivity of water and sodium adsorption ratio of water. For training of the ANNmodels, the graphically calculated data of the empirical constants (α and κ) of cumulative infiltration rate equation corresponding to different soil and water characteristics were used. The comparison of calculated and predicted empirical constants (α and κ)by ANN modelsshowed goodagreement in both training and testing stages. The weights of the trained ANN models were formulated and an interactiveC-Sharp application was built to predict the cumulative infiltration rate and it was tested displaying that it could be a useful tool in irrigation and soil studies.

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تطبيق حاسوبي تفاعلي باستخدام لغة السي شارب للتنبؤ بتسرب المياه التجميعي في التربة

محمد عبد العزيز السليمان[١] ، عبد الواحد محمد أبوكريمة[٢]

١. *كلية المجتمع بحريملاء، جامعة شقراء، المملكة العربية السعودية*
٢. *معهد بحوث الهندسة الزراعية، مركز البحوث الزراعية، ج.م.ع*

هدفت الدراسة إلى تطوير تطبيق حاسوبي تفاعلي باستخدام لغة الحاسوب التفاعلية المسماة سي شارب، للتنبؤ مباشرة بمعدل تسرب المياه التجميعي في التربة، حيث يتأثر هذا المعدل بعدة متغيرات منها جودة المياه ونوع التربة. ومن ناحية أخرى، يحتاج قياس معدل تسرب المياه ترتيبات وأجهزة خاصة سواء كان القياس معمليًا أو حقليًا، ويفضل القياسات الحقلية لتكون معبرة عن القياسات الفعلية، ولكن إجرائها في الحقل يتطلب أجهزة وتكاليف مادية، لذا من الأفضل تطوير وسيلة للتنبؤ بتسرب المياه التجميعي في التربة بطريقة فعالة ودقيقة. وفي هذه الدراسة استخدمت الحلقة المزدوجة في قياس تسرب المياه في الحقل حتى ثلاث ساعات في ترب مختلفة مابين رملية ورملية طمييه وطمييه رملية وباستخدام مياه ذي جودة مختلفة. كانت المدخلات للتطبيق الحاسوبي عبارة عن ثمانية متغيراتشملت قوام التربة والذي تمثل برقم وحيد سمى دليل قوام التربة، والكثافة الظاهرية للتربة والمحتوى الرطوبي الابتدائي للتربة ونسبة المادة العضوية بالتربة والموصلية الكهربية لمياه الري والتربة ونسبة امتزاز الصوديوم لمياه الري والتربة، بينما مخرجات التطبيق عبارة عن معدل التسرب التجميعي للمياه في التربة عند الزمن المحدد وحتى ثلاث ساعات. ومن خلال مقارنة القراءات المتنبأ بها لمعدل التسرب التجميعي النهائي بعد ثلاث ساعات باستخدام التطبيق الحاسوبي بالقراءات الفعلية، وجد أن متوسط الخطأ يساوي 39.25- مم، لذا يوصى باستخدام التطبيق الحاسوبي المطور في إدارة المياه من خلال التنبؤ بمعدل تسرب المياه التجميعي في التربة.