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Modeling of Soil Infiltration Rate Based on Soil Physical Properties Using Linear Regression Models

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Abstract: Soil infiltration rate is often determined using laborious and time consuming field tests, but it may be more suitable and economical to develop a method which predicts soil infiltration rate based on easily available physical properties of soil. Therefore, a relation between soil infiltration rate and some physical properties of soil is needed. In this study, for modeling soil infiltration rate (IN) based on some physical properties of soil such as sand (SA), silt (SI), clay (CL), bulk density (BD), organic matter (OM) and moisture content (MC), sixty-three multiple-variable linear regression models were suggested. Models were divided into six main classes and the soil infiltration rate was modeled as a function of one, two, three, four, five and six independent variables. The statistical results of study indicated that in order to model soil infiltration rate based on some physical properties of soil the one-variable linear regression model IN = 0.391 SA - 2.917 with R^2 = 0.8905 (as the simplest model), the two-variable linear regression model IN = 37.87 - 0.315 SI - 0.527 CL with R^2 = 0.9042, the three-variable linear regression model IN = 28.38 - 0.274 SI - 0.505 CL + 4.431 BD with R^2 = 0.9071, the four-variable linear regression model IN = 29.29 - 0.227 SI - 0.521 CL + 4.074 BD - 1.271 OM with R^2 = 0.9090 and the five-variable linear regression model IN = 28.13 - 0.220 SI - 0.518 CL + 4.592 BD - 1.440 OM + 0.022 MC with R^2 = 0.9092 (as the most complex model) may be suggested. However, experimental verification of the selected models is necessary before these models can be recommended for wider use.

Key words: Soil · Infiltration rate · Modeling · Soil texture · Physical properties

INTRODUCTION

Surface irrigation methods are widely used throughout the world [1, 2]. Recent advances in the theoretical description and model simulation of surface irrigation methods permit the evaluation of existing procedures and the development of new technologies of irrigation systems and their management. Free water at the soil-atmosphere interface is a source of great importance to man. Efficient management of this water will require greater control of infiltration. Increased infiltration control would help to solve such wide ranging problems as upland flooding, pollution of surface and ground-waters, declining water tables and inefficient irrigation of agricultural lands [3]. For these reasons, soil infiltration rate is perhaps the most crucial process affecting surface irrigation uniformity and efficiency as it is the mechanism that transfers and distributes water from the surface to the soil profile. It is essential to predict the cumulative infiltration in order to estimate the amount of water entering the soil and its distribution. Infiltration also affects both the advance and recession processes and thus is important in estimating the optimal discharge that should be directed to the field [4]. The infiltration process depends on the physical, chemical and biological properties of the soil surface, the initial distribution of water in the soil prior to irrigation, the movement of water over the surface and the depth of water on the soil surface. These properties and conditions vary over a field and collectively cause infiltration itself to exhibit large variation at the field scale. Therefore, infiltration is difficult to characterize on a field scale because of the large number of measurements generally necessary [5].

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In the engineering evaluation and design of surface irrigation systems, it has been useful to predict the soil infiltration rate [4]. In general, prediction of the soil infiltration rate involves the adoption of a functional form to be used and the determination of the value of the numerical constants in the adopted equation. Prediction of soil infiltration rate is a major problem in irrigation studies due to proper selection of the technique used to determine the parameters of the empirical infiltration models, the use of empirical infiltration models and its dependence on soil moisture, soil characteristics and surface roughness. Thus, the technique used to determine the soil infiltration rate characteristics must be appropriate for the purpose of the study [6-8].

Despite the considerable amount of research done, which shows the relationship between soil infiltration rate and soil properties, very limited work has been conducted to model soil infiltration rate based on physical properties of soil. Therefore, the main objectives of this research were to determine optimum soil infiltration rate model(s) based on soil physical properties.

MATERIALS AND METHODS

Experimental Site: Field experiments were carried out at the agricultural fields of Karaj, Alborz Province, Iran. This site is located at latitude of 35° 59' N, longitude of 51° 6' E and altitude of 1300 m above mean sea level in semi-arid climate (345 mm rainfall annually) in the center of Iran.

Experimental Procedure: Eighty-five soil samples were taken at random from different fields of the experimental site. In order to obtain required parameters for determining soil infiltration rate models, some physical properties of soil such as sand (SA), silt (SI), clay (CL), bulk density (BD), organic matter (OM) and moisture content (MC) of the soil samples were measured using laboratory tests as described by the Soil Survey Laboratory Staff [9]. Also, infiltration rate (IN) of the soil in all treatments was measured using a double ring infiltrometer. The infiltrometer was installed in the position of each treatment, filled with water and the initial reading was noted. The depth of water in the infiltrometer was noted after frequent intervals until the rate of infiltration became constant. Table 1 shows infiltration rate and physical properties of the eighty-five soil samples used to determine soil infiltration rate models.

Regression Model: A typical multiple-variable linear regression model is shown in equation 1:

Table 1: Infiltration rate and physical properties of the eighty-five soil samples used to determine soil infiltration rate models

Sample No.	Infiltration rate (mm/h)	Sand (%)	Silt (%)	Clay (%)	Bulk density (g/cm^3)	Organic matter (%)	Moisture content (%)
1	8.82	28	34	38	1.826	1.002	7.376
2	3.63	20	38	42	1.610	1.030	7.897
3	9.14	22	40	38	1.667	0.960	8.181
4	4.61	20	40	40	1.685	1.310	7.446
5	7.45	28	34	38	1.528	1.010	10.47
6	3.15	18	40	42	1.527	1.320	7.442
7	4.12	20	38	42	1.538	1.070	11.88
8	3.28	24	36	40	1.619	1.190	9.048
9	2.03	22	36	42	1.595	1.320	10.45
10	6.79	24	40	36	1.546	0.940	7.076
11	3.60	22	36	42	1.626	1.100	12.22
12	2.50	16	38	46	1.535	1.040	10.53
13	2.20	26	34	40	1.526	1.190	11.25
14	1.70	24	36	40	1.606	1.160	2.620
15	7.46	22	40	38	1.557	1.010	4.272
16	3.30	18	38	44	1.688	1.050	6.683
17	2.90	20	36	44	1.437	1.003	8.904
18	3.10	26	32	42	1.685	1.040	9.040
19	9.32	28	34	38	1.561	1.006	7.874
20	7.06	28	34	38	1.677	1.003	9.738
21	4.30	20	38	42	1.495	1.020	6.193
22	14.8	36	36	28	1.670	0.600	8.770
23	2.50	20	40	40	1.677	1.350	8.082
24	1.70	20	38	42	1.546	1.040	6.971

Table 1: Continued

25	6.90	30	36	34	1.628	1.060	5.175
26	6.50	28	38	34	1.481	1.130	11.88
27	11.9	38	36	26	1.698	0.560	5.453
28	9.60	22	40	38	1.596	1.020	5.537
29	6.10	26	38	36	1.594	1.060	3.433
30	7.11	28	34	38	1.574	1.140	7.540
31	2.30	22	36	42	1.690	1.240	6.477
32	3.20	26	36	38	1.693	1.110	5.022
33	9.60	24	40	36	1.743	1.050	6.518
34	8.90	28	36	36	1.555	1.004	4.602
35	2.27	26	36	38	1.583	1.210	4.731
36	23.5	71	7	22	1.843	0.390	3.243
37	26.0	78	5	17	1.845	0.320	4.607
38	22.1	69	10	21	1.923	0.360	6.392
39	25.5	68	12	20	2.032	0.350	5.923
40	25.2	65	15	20	1.832	0.290	4.044
41	22.5	65	15	20	1.839	0.310	3.524
42	24.5	65	15	20	1.935	0.300	2.349
43	22.8	70	11	19	1.919	0.390	7.240
44	26.3	67	9	24	1.980	0.320	1.913
45	23.6	79	9	12	2.070	0.360	3.538
46	24.3	65	10	25	2.181	0.340	3.899
47	27.2	72	9	19	2.181	0.320	3.925
48	28.5	70	10	20	2.038	0.340	1.858
49	26.2	76	13	11	2.016	0.390	4.008
50	27.5	68	14	18	1.904	0.300	3.315
51	22.1	79	5	16	1.872	0.310	1.438
52	23.5	54	16	30	1.718	0.320	6.320
53	6.90	22	46	32	1.722	1.800	12.67
54	7.30	24	44	32	1.572	1.780	13.82
55	7.10	34	38	28	1.698	1.340	14.33
56	9.10	20	48	32	1.463	1.680	13.58
57	9.30	22	48	30	1.500	1.830	15.43
58	6.00	26	42	32	1.678	1.850	7.225
59	7.10	24	44	32	1.524	1.800	8.895
60	7.90	16	52	32	1.639	1.630	12.53
61	5.40	20	48	32	1.473	1.800	15.71
62	6.00	24	50	26	1.424	1.670	16.49
63	8.70	24	46	30	1.423	1.280	13.90
64	8.90	24	44	32	1.336	1.780	13.74
65	9.00	32	38	30	1.700	1.880	14.51
66	6.60	28	42	30	1.452	1.780	16.70
67	8.22	20	48	32	1.472	1.880	14.41
68	6.80	20	48	32	1.684	1.280	11.40
69	7.10	20	48	32	1.575	1.360	3.634
70	7.70	28	42	30	1.671	0.750	5.037
71	7.90	28	40	32	1.593	0.860	7.399
72	6.84	32	38	30	1.612	0.830	6.266
73	7.90	30	44	26	1.727	0.740	8.629
74	6.50	28	42	30	1.628	1.840	5.894
75	9.00	28	40	32	1.652	1.860	5.963
76	8.80	32	40	28	1.594	1.740	4.595
77	8.30	20	48	32	1.567	1.910	7.307
78	7.10	24	46	30	1.621	1.880	5.970
79	8.00	30	44	26	1.599	1.820	3.159
80	9.70	22	46	32	1.619	1.780	4.628
81	7.60	34	38	28	1.476	1.580	3.317
82	7.30	22	46	32	1.486	1.800	5.325
83	8.40	24	44	32	1.650	1.880	3.724
84	7.60	20	48	32	1.608	1.880	3.664
85	6.90	24	44	32	1.551	1.800	3.960

Table 2: Sixty-three multiple-variable linear regression models categorized in six classes based on the number of independent variables

Model class	Model No.	Model
First	1	$IN = k_0 + k_1$ SA
	2	$IN = k_0 + k_1$ SI
	3	$IN = k_0 + k_1$ CL
	4	$IN = k_0 + k_1$ BD
	5	$IN = k_0 + k_1$ OM
	6	$IN = k_0 + k_1$ MC
Second	7	$IN = k_0 + k_1$ SA + k_2 SI
	8	$IN = k_0 + k_1$ SA + k_2 CL
	9	$IN = k_0 + k_1$ SA + k_2 BD
	10	$IN = k_0 + k_1$ SA + k_2 OM
	11	$IN = k_0 + k_1$ SA + k_2 MC
	12	$IN = k_0 + k_1$ SI + k_2 CL
	13	$IN = k_0 + k_1$ SI + k_2 BD
	14	$IN = k_0 + k_1$ SI + k_2 OM
	15	$IN = k_0 + k_1$ SI + k_2 MC
	16	$IN = k_0 + k_1$ CL + k_2 BD
	17	$IN = k_0 + k_1$ CL + k_2 OM
	18	$IN = k_0 + k_1$ CL + k_2 MC
	19	$IN = k_0 + k_1$ BD + k_2 OM
	20	$IN = k_0 + k_1$ BD + k_2 MC
	21	$IN = k_0 + k_1$ OM + k_2 MC
Third	22	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL
	23	$IN = k_0 + k_1$ SA + k_2 SI + k_3 BD
	24	$IN = k_0 + k_1$ SA + k_2 SI + k_3 OM
	25	$IN = k_0 + k_1$ SA + k_2 SI + k_3 MC
	26	$IN = k_0 + k_1$ SA + k_2 CL + k_3 BD
	27	$IN = k_0 + k_1$ SA + k_2 CL + k_3 OM
	28	$IN = k_0 + k_1$ SA + k_2 CL + k_3 MC
	29	$IN = k_0 + k_1$ SA + k_2 BD + k_3 OM
	30	$IN = k_0 + k_1$ SA + k_2 BD + k_3 MC
	31	$IN = k_0 + k_1$ SA + k_2 OM + k_3 MC
	32	$IN = k_0 + k_1$ SI + k_2 CL + k_3 BD
	33	$IN = k_0 + k_1$ SI + k_2 CL + k_3 OM
	34	$IN = k_0 + k_1$ SI + k_2 CL + k_3 MC
	35	$IN = k_0 + k_1$ SI + k_2 BD + k_3 OM
	36	$IN = k_0 + k_1$ SI + k_2 BD + k_3 MC
	37	$IN = k_0 + k_1$ SI + k_2 OM + k_3 MC
	38	$IN = k_0 + k_1$ CL + k_2 BD + k_3 OM
	39	$IN = k_0 + k_1$ CL + k_2 BD + k_3 MC
	40	$IN = k_0 + k_1$ CL + k_2 OM + k_3 MC
	41	$IN = k_0 + k_1$ BD + k_2 OM + k_3 MC
Forth	42	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 BD
	43	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 OM
	44	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 MC
	45	$IN = k_0 + k_1$ SA + k_2 SI + k_3 BD + k_4 OM
	46	$IN = k_0 + k_1$ SA + k_2 SI + k_3 BD + k_4 MC
	47	$IN = k_0 + k_1$ SA + k_2 SI + k_3 OM + k_4 MC
	48	$IN = k_0 + k_1$ SA + k_2 CL + k_3 BD + k_4 OM
	49	$IN = k_0 + k_1$ SA + k_2 CL + k_3 BD + k_4 MC
	50	$IN = k_0 + k_1$ SA + k_2 CL + k_3 OM + k_4 MC
	51	$IN = k_0 + k_1$ SA + k_2 BD + k_3 OM + k_4 MC
	52	$IN = k_0 + k_1$ SI + k_2 CL + k_3 BD + k_4 OM
	53	$IN = k_0 + k_1$ SI + k_2 CL + k_3 BD + k_4 MC
	54	$IN = k_0 + k_1$ SI + k_2 CL + k_3 OM + k_4 MC
	55	$IN = k_0 + k_1$ SI + k_2 BD + k_3 OM + k_4 MC
	56	$IN = k_0 + k_1$ CL + k_2 BD + k_3 OM + k_4 MC

Table 2: Continud

Fifth	57	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 BD + k_5 OM
	58	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 BD + k_5 MC
	59	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 OM + k_5 MC
	60	$IN = k_0 + k_1$ SA + k_2 SI + k_3 BD + k_4 OM + k_5 MC
	61	$IN = k_0 + k_1$ SA + k_2 CL + k_3 BD + k_4 OM + k_5 MC
	62	$IN = k_0 + k_1$ SI + k_2 CL + k_3 BD + k_4 OM + k_5 MC
Sixth	63	$IN = k_0 + k_1$ SA + k_2 SI + k_3 CL + k_4 BD + k_5 OM + k_6 MC

$$Y = k_0 + k_1X_1 + k_2X_2 + \ldots + k_nX_n \qquad (1)$$

where:

Y = Dependent variable, for example soil infiltration rate (mm/h)

$X_1, X_2, \ldots, X_n$ = Independent variables, for example sand (%), silt (%), clay (%), bulk density (g/cm^3), organic matter (%) and moisture content of soil (%)

$k_0, k_1, k_2, \ldots, k_n$ = Regression coefficients

In order to model soil infiltration rate from some physical properties of soil, i.e. sand, silt, clay, bulk density, organic matter and moisture content, sixty-three multiple-variable linear regression models were suggested and all the data were subjected to regression analysis using the Microsoft Excel 2007. All the multiple-variable linear regression models are shown in Table 2.

RESULTS AND DISCUSSION

A total of sixty-three multiple-variable linear regression models have been categorized in six classes based on the number of independent variables (Table 2). The p-value of independent variables and coefficient of determination (R^2) for the sixty-three multiple-variable linear regression models are shown in Table 3.

First Class Models: In the first class models, soil infiltration rate can be predicted as a function of one independent variable. As indicated in Table 3, among the first class models (models No. 1-6), model No. 1 where sand was considered as independent variable had the highest R^2 value (0.8905) and the lowest p-value (1.29E-41). Thus, based on the statistical results model No. 1 was selected as the best model of first class models, which is given by equation 2.

$$IN = 0.391\ SA - 2.917 \qquad (2)$$

Second Class Models: In the second class models, soil infiltration rate can be predicted as a function of two independent variables. As indicated in Table 3, among the second class models (models No. 7-21), model No. 12 where silt and clay were considered as two independent variables had the highest R^2 value (0.9042) and the lowest mean p-value (3.82E-20). Therefore, based on the statistical results model No. 12 was selected as the best model of second class models, which is given by equation 3.

$$IN = 37.87 - 0.315\ SI - 0.527\ CL \qquad (3)$$

Third Class Models: In the third class models, soil infiltration rate can be predicted as a function of three independent variables. As indicated in Table 3, among the third class models (models No. 22-41), model No. 32 where silt, clay and bulk density were considered as three independent variables had the highest R^2 value (0.9071) and the lowest mean p-value (2.39E-10). As a result, based on the statistical results model No. 32 was selected as the best model of third class models, which is given by equation 4.

$$IN = 28.38 - 0.274\ SI - 0.505\ CL + 4.431\ BD \qquad (4)$$

Forth Class Models: In the forth class models, soil infiltration rate can be predicted as a function of four independent variables. As indicated in Table 3, among the forth class models (models No. 42-56), model No. 52 where silt, clay, bulk density and organic matter were considered as four independent variables had the highest R^2 value (0.9090) and the lowest mean p-value (1.06E-06). Thus, based on the statistical results model No. 52 was selected as the best model of forth class models, which is given by equation 5.

$$IN = 29.29 - 0.227\ SI - 0.521\ CL + 4.074\ BD - 1.271\ OM \qquad (5)$$

Fifth and Sixth Class Models: In these classes, soil infiltration rate can be predicted as a function of five and six independent variables, respectively. As indicated in Table 3, among the fifth and sixth class models (models No. 57-63), model No. 62 where silt, clay, bulk

Table 3: The p-value of independent variables and coefficient of determination (R^2) for the sixty-three multiple-variable linear regression models

	P-value						
Model No.	SA	SI	CL	BD	OM	MC	R^2
1	1.29E-41	---	---	---	---	---	0.8905
2	---	7.62E-25	---	---	---	---	0.7229
3	---	---	9.21E-26	---	---	---	0.7366
4	---	---	---	2.36E-20	---	---	0.6449
5	---	---	---	---	1.74E-13	---	0.4819
6	---	---	---	---	---	2.79E-05	0.1916
7	1.79E-20	0.000980	---	---	---	---	0.9034
8	1.09E-19	---	0.000967	---	---	---	0.9042
9	8.54E-23	---	---	0.410591	---	---	0.8914
10	1.38E-29	---	---	---	0.353796	---	0.8916
11	2.23E-37	---	---	---	---	0.675083	0.8907
12	---	1.09E-19	1.34E-20	---	---	---	0.9042
13	---	2.90E-08	---	0.001152	---	---	0.7566
14	---	5.88E-13	---	---	0.347104	---	0.7258
15	---	9.27E-21	---	---	---	0.896183	0.7229
16	---	---	7.58E-16	7.46E-11	---	---	0.8424
17	---	---	2.07E-26	---	2.75E-14	---	0.8705
18	---	---	5.56E-24	---	---	0.001158	0.7686
19	---	---	---	4.71E-10	0.004667	---	0.6781
20	---	---	---	2.54E-16	---	0.716416	0.6455
21	---	---	---	---	4.55E-10	0.107647	0.4981
22	1.34E-20	0.000967	#NUM!	---	---	---	0.9042
23	1.29E-18	0.000393	---	0.115361	---	---	0.9071
24	1.25E-20	0.000539	---	---	0.150402	---	0.9066
25	2.26E-20	0.001114	---	---	---	0.832590	0.9042
26	9.19E-11	---	0.000393	0.115361	---	---	0.9071
27	2.94E-07	---	0.000539	---	0.150402	---	0.9066
28	3.49E-17	---	0.001114	---	---	0.832590	0.9042
29	4.55E-21	---	---	0.305573	0.267372	---	0.8930
30	1.35E-22	---	---	0.340227	---	0.519770	0.8919
31	1.07E-28	---	---	---	0.389882	0.800859	0.8917
32	---	9.19E-11	1.29E-18	0.115361	---	---	0.9071
33	---	2.94E-07	1.25E-20	---	0.150402	---	0.9066
34	---	3.49E-17	2.26E-20	---	---	0.832590	0.9042
35	---	1.19E-06	---	0.001093	0.294047	---	0.7599
36	---	3.17E-08	---	0.001043	---	0.565557	0.7575
37	---	2.93E-12	---	---	0.342849	0.834986	0.7260
38	---	---	4.84E-20	0.001076	3.46E-07	---	0.8866
39	---	---	3.26E-16	1.33E-08	---	0.368596	0.8450
40	---	---	9.42E-26	---	4.95E-12	0.331568	0.8720
41	---	---	---	2.22E-09	0.005258	0.910308	0.6782
42	1.29E-18	0.000393	#NUM!	0.115361	---	---	0.9071
43	1.25E-20	0.000539	#NUM!	---	0.150402	---	0.9066
44	2.26E-20	0.001114	#NUM!	---	---	0.832590	0.9042
45	1.55E-18	0.000331	---	0.147446	0.193264	---	0.9090
46	2.45E-18	0.000526	---	0.119554	---	0.890689	0.9071
47	2.20E-20	0.000601	---	---	0.156618	0.927714	0.9066
48	2.87E-05	---	0.000331	0.147446	0.193264	---	0.9090
49	1.79E-10	---	0.000526	0.119554	---	0.890689	0.9071
50	5.62E-07	---	0.000601	---	0.156618	0.927714	0.9066
51	7.08E-21	---	---	0.270391	0.306289	0.623545	0.8933
52	---	2.87E-05	1.55E-18	0.147446	0.193264	---	0.9090
53	---	1.79E-10	2.45E-18	0.119554	---	0.890689	0.9071
54	---	5.62E-07	2.20E-20	---	0.156618	0.927714	0.9066
55	---	1.23E-06	---	0.001054	0.316601	0.622990	0.7606
56	---	---	8.19E-20	0.001900	6.14E-07	0.902567	0.8866
57	1.55E-18	0.000331	#NUM!	0.147446	0.193264	---	0.9090
58	2.45E-18	0.000526	#NUM!	0.119554	---	0.890689	0.9071
59	2.20E-20	0.000601	#NUM!	---	0.156618	0.927714	0.9066
60	2.78E-18	0.000399	---	0.145962	0.191947	0.823075	0.9091
61	3.17E-05	---	0.000399	0.145962	0.191947	0.823075	0.9091
62	---	9.42E-05	2.36E-18	0.111719	0.157132	0.786337	0.9092
63	2.78E-18	0.000399	#NUM!	0.145962	0.191947	0.823075	0.9091

density, organic matter and moisture content were considered as five independent variables had the highest R^2 value (0.9092) and the lowest mean p-value (1.98E-05). Therefore, based on the statistical results model No. 62 was selected as the best model of fifth and sixth class models, which is given by equation 6.

$$IN = 28.13 - 0.220\ SI - 0.518\ CL + 4.592\ BD - 1.440\ OM + 0.022\ MC \quad (6)$$

These results are in line with those of Mustafa *et al.* [3], Walker *et al.* [4] and Holzapfel *et al.* [6], who reported that soil texture was the most important factor which affected the soil infiltration rate. These results are also in agreement with those reported by Smerdon *et al.* [1], Rashidi & Seyfi [2], Walker [5] and Walker & Busman [7], who also reported that physical properties of soil had significant effect on the soil infiltration rate.

CONCLUSIONS

For modeling soil infiltration rate (IN) based on some physical properties of soil such as sand (SA), silt (SI), clay (CL), bulk density (BD), organic matter (OM) and moisture content (MC), sixty-three multiple-variable linear regression models were suggested. The statistical results of study indicated that in order to model soil infiltration rate based on soil physical properties the one-variable linear regression model IN = 0.391 SA - 2.917 with R^2 = 0.8905, the two-variable linear regression model IN = 37.87 - 0.315 SI - 0.527 CL with R^2 = 0.9042, the three-variable linear regression model IN = 28.38 - 0.274 SI - 0.505 CL + 4.431 BD with R^2 = 0.9071, the four-variable linear regression model IN = 29.29 - 0.227 SI - 0.521 CL + 4.074 BD - 1.271 OM with R^2 = 0.9090 and the five-variable linear regression model IN = 28.13 - 0.220 SI - 0.518 CL + 4.592 BD - 1.440 OM + 0.022 MC with R^2 = 0.9092 may be suggested. However, experimental verification of the selected models is necessary before these models can be recommended for wider use.

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