Toride, N., F.J. Leij, and M.Th. van Genuchten. 1995. The CXTFIT code for estimating transport parameters from laboratory or field tracer experiments. Version 2.0. Research Rep. 137. U.S. Salinity Lab, Riverside, CA.
Torstensson, N.T.L. 1987. Microbial decomposition of herbicides in soil. p. 249–270. *In* D.H. Hutson and T.R. Roberts (ed.) Herbicides. John Wiley & Sons, Chichester, UK.
Veeh, R.H., W.P. Inskeep, and A.K. Camper. 1996. Soil depth and temperature effects on microbial degradation of 2,4-D. J. Environ. Qual. 25:5–12.
Walker, A., Y.-H. Moon, and S.J. Welch. 1992. Influence of temperature, soil moisture and soil characteristics on the persistence of alachlor. Pestic. Sci. 35:109–116.
Weber, J.B. 1991. Fate and behaviour of herbicides in soils. Appl. Plant Sci. 5:28–41.
Weber, J.B., and C.T. Miller. 1989. Organic chemical movement over and through soil. p. 305–334. *In* Reactions and movements of organic chemicals in soil. SSSA Spec. Publ. 22. SSSA and ASA, Madison, WI.

Use of Brooks-Corey Parameters to Improve Estimates of Saturated Conductivity from Effective Porosity

D. J. Timlin,* L. R. Ahuja, Ya. Pachepsky, R. D. Williams, D. Gimenez, and W. Rawls

ABSTRACT

Effective porosity, defined here as the difference between satiated total porosity and water-filled porosity at a matric potential of 33 kPa, has been shown to be a good predictor for saturated hydraulic conductivity (K_s) using a modified Kozeny-Carman equation. This equation is of the form of a coefficient (B) multiplied by effective porosity raised to a power (n). The purpose of this study was to improve the predictive capability of the modified Kozeny-Carman equation by including information from moisture release curves (soil water content vs. matric potential relation). We fitted the Brooks-Corey (B-C) equation parameters (pore size distribution index and air entry potential) to moisture release data from a large database (>500 samples). Values of K_s were also available from the same source. Inclusion of the pore size distribution index into the Kozeny-Carman equation improved the K_s estimation over using only effective porosity, but only slightly. The improvement came through a better estimation of large values of K_s. We also fit a relationship for the coefficient (B) of the Kozeny-Carman equation as a function of the two B-C parameters with a constant value of $n = 2.5$ for the exponent. Overall the use of Brooks-Corey parameters from moisture retention data improved estimates of K_s over using effective porosity (ϕ_e) alone. There is still considerable error in predicting individual K_s values, however. The best forms of the equation was when λ was included in the term for the coefficient for the modified Kozeny-Carman equation. The next best form was when λ was included in the exponent for ϕ_e The two best models appeared to better preserve the mean, standard deviation and range of the original data.

Saturated soil hydraulic conductivity (K_s) is an important soil parameter in models that simulate infiltration and runoff processes. This soil parameter is difficult to measure and can be highly variable, necessitating a large number of samples. For this reason indirect methods have held promise as an alternative to making direct measurements. A further advantage of indirect methods is that they allow researchers to obtain an estimate of the variability of saturated conductivities based on the variability of an easily measured predictor variable (Ahuja et al., 1989).

A number of relationships have been developed that can be used to calculate K_s with easily measured soil properties. Some are purely empirical and are often related to soil texture (Rawls et al., 1992; Puckett et al., 1985). Other relationships use physically based equations. Ahuja et al. (1984, 1989) showed that a modified Kozeny-Carman equation

$$K_s = B_1\phi_e^n \tag{1}$$

was applicable to a wide range of soils from the Southern Region of the USA, Hawaii, and Arizona. Here ϕ_e is the effective porosity calculated as saturated water content (θ_s) minus the water content at 33 kPa matric potential, and B_1 and n are coefficients.

Even though the coefficients of Eq. [1] fitted to the data varied with soil type within a certain range, Eq. [1] fitted to K_s data for all nine different soils had an r^2 as good as for individual soils (Ahuja et al., 1989). In other words, Eq. [1] exhibited a degree of universality. In fact, the coefficients, B_1 and n obtained from the above fit of Eq. [1] to data for nine soils estimated K_s for several soils from Korea (Ahuja et al., 1989) and a variety of soils from Indiana (Franzmeier, 1991) with acceptable accuracy. Messing (1989) presented data for some Norwegian soils where Eq. [1] fitted the data for individual soils well, but the coefficients varied with soil type. Some of these soils had high clay contents and probably exhibited swelling–shrinking behavior, which could possibly affect the value of fitted coefficients. In any case, further research is needed to test and improve the universality of Eq. [1] for a variety of nonswelling soils and possibly for swelling soils.

Rawls et al. (1998) used Eq. [1] and proposed the

D.J. Timlin, USDA-ARS Systems Research Lab, Bldg. 007, Rm 116, 10300 Baltimore Ave, Beltsville, MD 20705; L.R. Ahuja, USDA-ARS Great Plains Systems Research Unit, P.O. Box E, Ft. Collins, CO. 80522; Ya. A. Pachepsky, Dept of Botany, Duke University, Durham, NC 27708; R.D. Williams, USDA-ARS Grazing Lands Research Laboratory, P.O. Box 1199, El Reno, OK 73036-1199; D. Gimenez, Dept. of Environmental Sciences, Rutgers, The State University of NJ, 14 College Farm Rd., New Brunswick, NJ 08901; and W. Rawls, USDA-ARS Hydrology Laboratory, Bldg 007, Rm 112, 10300 Baltimore Ave., Beltsville, MD 20705. Received 24 Nov. 1997. *Corresponding author (dtimlin@asrr.arsusda.gov).

Published in Soil Sci. Soc. Am. J. 63:1086–1092 (1999).

Abbreviations: B-C, Brooks-Corey; RA, Rawls data; RMSE, root mean square error; SR, Southern region data.

use of the fractal dimension as an exponent (n) in an equation of the form:

$$K_s = B_2\phi_e^{3-\lambda} \quad [2]$$

Here ϕ_e is effective porosity and λ is the pore-size distribution index from the Brooks-Corey equation. Rawls et al. (1998) showed that the exponent $(3 - \lambda)$ can be considered to be a measure of the pore fractal dimension. When fit to mean values of ϕ_e and λ from soil textural classes, this equation was shown to give a good estimate of K_s with an r^2 of 0.92 and the intercept B_2 equal to 0.00053 m s^{-1} (190 cm h^{-1}).

Earlier, Rawls et al. (1993) modified the Marshall equation to obtain an equation for matrix saturated hydraulic conductivity. These workers used a Sierpinski carpet generator to represent a two-dimensional soil matrix porosity and used water retention parameters from the Brooks-Corey equation. The modified Marshall's equation used by Rawls et al. (1993) is of the form:

$$K_s = 4.41 \times 10^7 \left(\frac{\phi^x}{l^2}\right) R^2 \quad [3]$$

Here l is a parameter related to the fractal dimension, ϕ is total porosity, x is an exponent, and R (cm) is the largest continuous pore radius for the Seirpinsky carpet. R is calculated from the capillary rise equation

$$R = \frac{0.148}{h_b} \quad [4]$$

In this equation h_b is the absolute value of the air-entry potential (cm). The value l is estimated from the fractal dimension D

$$l = 1.86D^{5.34} \quad [5]$$

Here D is the fractal dimension of soil porosity and is estimated as $D = 2 - \lambda$, and λ is the Brooks-Corey pore-size distribution index. Rawls et al. (1993) used a value of 4/3 for the exponent, x.

The modified Kozeny-Carman equation (Ahuja et al., 1984; Rawls et al., 1998) and the modified Marshall equation (Rawls et al., 1993) represent related approaches to indirect calculation of K_s. There is still a potential to improve the universality of the $K - \phi_e$ relationship. The objective of our study was to develop a combined method that uses information from the moisture release curve to improve Ahuja's modified Kozeny-Carman equation (Eq. [1]).

MATERIALS AND METHODS

The data set used by Ahuja et al. (1984, 1989) is denoted here for convenience as the Southern Region (SR) data. These data were fully described in Ahuja et al. (1989). The names and taxonomic classifications of these soils are given in Table 1. The data consist of moisture retention values (water content, θ, and pressure head, h), bulk density, soil texture, and saturated hydraulic conductivity measured on replicated (4–10), undisturbed soil cores taken from different soil horizons at several sites for each soil. These data are published in Southern Cooperative Series Bulletins or elsewhere (Bruce et al., 1983; Dane et al., 1983; Quisenberry et al., 1987; Nofziger et al., 1983; Green et al., 1982.). For all K_s data used in the present study, the soil cores were 60 to 85 mm in diameter and 60 to 75 mm in length. Constant-head methods were used to measure K_s and hanging water column and pressure plate procedures to measure water retention curves. The differences in water retention at saturation and at −33 kPa matric potential were used to obtain the effective porosity, ϕ_e. For some soils, where water retention at saturation was not initially measured, θ_s was calculated using measured soil bulk density and particle density data. The value of θ_s was calculated as 0.90 times total porosity. There were 571 sets of moisture retention data with associated values of K_s. The pressures for the moisture release curves ranged from 0.2 to 1500 kPa. Only curves with at least five retention values were used. The data set was also averaged by texture class as was the data of Rawls et al. (1993). The texture classes and the number of samples in each class are given in Table 2.

Table 1. Taxonomic classifications for soils from the Southern Region (SR) database.

Soil name	Taxonomic group
Bethany	Fine mixed, thermic Pachic Argiustall
Captina	Fine-silty, siliceous, mesic Typic Fragiudults
Cecil	Clayey kaolinitic, thermic Typic Hapludults
Dothan	Fine-loamy, kaolinitic, thermic Plinthic Kandiudults
Goldsboro	Fine-loamy, siliceous, semiactive, thermic Aquic Paleudults
Grenada	Fine-silty, mixed, thermic Glossic Fragiudalfs
Kirkland	Fine, mixed, thermic Udertic Paleustolls
Konowa	Fine loamy mixed, thermic Ultic Haplustalfs
Lahaina	Clayey, kaolinitic, isohyperthermic Tropeptic Haplustox
Lakeland	Sandy, thermic, coated Typic Quartzipsamments
Molokai	Clayey, kaolinitic, isohyperthermic Typic Torrox
Norfolk	Fine-loamy, siliceous thermic Typic Paleudults
Pima	Fine-silty, mixed (calcareous), thermic Typic Torrifulvents
Renfrow	Fine, mixed, thermic Udertic Paleustolls
Tipton	Fine-loamy, mixed, thermic Pachic Argiustolls
Teller	Fine-loamy, mixed, thermic Udic Argiustolls
Troup	Loamy, kaolinitic, thermic Grossarenic Kandiudults
Wagram	Loamy, siliceous, thermic Arenic Paleudults
Wahaiwa	Clayey, kaolinitic, isohyperthermic Tropeptic Eutrustox

The second data set is fully described in Rawls et al. (1982) and is denoted for convenience as the Rawls data (RA). These data came from 1323 soils with about 5350 horizons and were compiled from data of nearly 400 soil scientists. We believe that the RA data set is independent of the SR data set, although there may be a small amount of overlap. These data are reported as textural class means in Rawls et al. (1982) and Rawls et al. (1993).

Moisture Release Curve Parameters

Parameters for the Brooks-Corey equation were used to define the pore-size distribution index (λ) and the air entry potential (h_b). These parameters were empirically derived from moisture release data. The Brooks-Corey equation is

Table 2. Soil textural classes in the Southern Region (SR) data base.

Texture	n
Sand	111
Loamy sand	42
Sandy loam	96
Loam	64
Silt loam	12
Sandy clay loam	60
Clay loam	75
Silty clay loam	22
Sandy clay	8
Silty clay	8
Clay	73

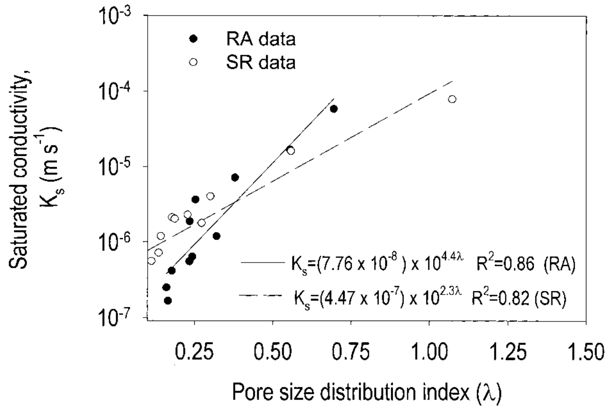

Fig. 1. Pore-size distribution index vs. K_s for the Southern Region (SR) and Rawls (RA) data sets. Values are means for textural classes.

$$\frac{\theta - \theta_r}{\theta_s - \theta_r} = \left(\frac{h_b}{h}\right)^{\lambda} \quad [6]$$

where λ is pore-size distribution index, h_b is air entry potential (kPa), θ_r (cm^3 cm^{-3}) is residual water content, and θ_s is saturated water content. λ, θ_r, and h_b were estimated using a combination of linear regression and a nonlinear optimization method (van Genuchten et al., 1981). A linearized form was obtained by taking a logarithmic transform of both sides of Eq. [6]:

$$\log\left(\frac{\theta - \theta_r}{\theta_s - \theta_r}\right) = \lambda\log(h_b) - \lambda\log(h) \quad [7]$$

and using the left-hand side of Eq. [7] as the dependent variable. A robust median fit linear regression algorithm (Press et al., 1986) was used to obtain values of λ and h_b, given an initial estimate of θ_r. A median fit regression method was used because the model is linear when θ_r is known. The nonlinear optimization program then iterated across a range of values of θ_r. New values of λ and h_b were fit for each new value of θ_r. This process continued until the value of θ_r that gave the smallest sum of squared differences (measured − observed) with corresponding values of λ and h_b was found. Only h-θ pairs where the absolute value of h was greater than 0.02 kPa were used. The root mean square error (RMSE) from the nonlinear optimization was <0.005 cm^3 cm^{-3} for 90% of the samples.

THEORY

An examination of Eq. [1], [2], and [3] show that they all have the form of a coefficient (or coefficients), which we will refer to as "B", multiplied by a measure of porosity (ϕ_e or ϕ) that is raised to a power (n, $3 - \lambda$, or x). The Kozeny-Carman equation (Eq. [1]) can be parameterized by fitting the coefficient, B, and the exponent, n to measured $K_s - \phi_e$ data. Equations [2] and [3] are more complex since the coefficient and exponent are expressed as functions of additional variables, namely h_b and λ. The terms for h_b and λ in Eq. [3], when taken together, can be considered to be a coefficient, "B". We can consider Eq. [1] in the form

$$K_s = B_3(\lambda, h_b)\ \phi_e^n \quad [8]$$

In this study, we consider two approaches to determining $B(\lambda, h_b)$. If we consider B as a function of λ only, a possible candidate function for K_s is

$$K_s = A\ f(\lambda)\ \phi_e^n \quad [9]$$

Here A is an empirical coefficient and $f(\lambda)$ is a function to be derived later. Another possible candidate function for K_s where $B = B(\lambda, h_b)$ can be obtained by inspection of the modified Marshall equation (Eq. [3]):

$$B(\lambda, h_b) = A\left(\frac{R}{l}\right)^m \quad [10]$$

Here R and l are defined as in Eq. [4] and [5] and A and m are empirical coefficients.

In order to investigate relationships among λ, h_b, and B, the coefficient, B can be expressed as

$$B = \frac{K_s}{\phi_e^n} \quad [11]$$

By expressing B in this manner we can investigate the possible functional relationships among λ, h_b, and B for constant n.

Statistical Calculations

Regressions were carried out using SAS software (SAS Institute, 1995). Except where noted and for model comparisons, regressions were carried out on log (base 10)–transformed input data. Comparisons of the models were accomplished by comparing residuals from a regression of the predicted K_s on measured K_s values from the SA data set.

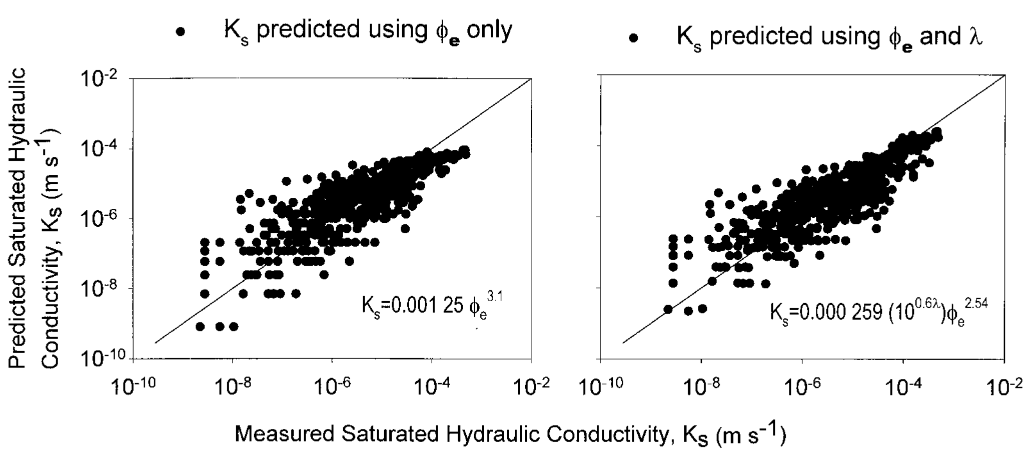

Fig. 2. Predicted and measured K_s for the Southern Region data set determined using (a) effective porosity (ϕ_e) only as a predictor and (b) effective porosity (ϕ_e) and the pore size distribution index (λ).

Table 3. Root mean square error (RMSE) as a function of soil texture for the four K_s models using the Southern Region (SR) data.

Texture	$K(\phi_e)$ Eq [1]	$K(\phi_{ei}, \lambda)$ Eq. [13]	Calculated 'B' Eq. [15]	Rawls et al., (1998) Eq. [2]
	log (m s^{-1})			
Sand	0.43	0.29	0.34	0.34
Loamy sand	0.44	0.42	0.37	0.51
Sandy loam	0.55	0.58	0.54	0.63
Loam	0.52	0.49	0.48	0.59
Silt loam	0.54	0.48	0.27	0.68
Sandy clay loam	0.72	0.68	0.79	0.70
Clay loam	0.65	0.63	0.67	0.65
Silty clay loam	0.45	0.43	0.56	0.49
Sandy clay	0.74	0.70	0.81	0.75
Silty clay	0.53	0.46	0.56	0.55
Clay	0.66	0.85	0.84	0.86

Transformed and untransformed values of K_s were used in these regressions. Comparisons of regression slopes were carried out by using a method given by Snedecor and Cochran (1980, p. 387).

RESULTS AND DISCUSSION

The Coefficient B as a Function of λ Alone

Figure 1 shows mean K_s as a function of λ for the RA and SR mean texture class data, where K_s is shown in logarithmic (base 10) scale. The relationships are similar for the two data sets except for small values of K_s and λ. Using all the data in the SR data set we fitted the function

$$K_s = C_1\, 10^{C_2\lambda} \quad [12]$$

Here $C_1 = 6.94 \times 10^{-7}$ m s^{-1}, $C_2 = 1.89$, and the $r^2 = 0.47$.

Equation [12] suggests that the form of $f(\lambda)$ given in Eq. [9] is $f(\lambda)=10^{C_2\lambda}$. Using all the data in the SR data set we fitted the following expression using regression on log-transformed values of ϕ_e and K_s

$$K_s = C_3\, 10^{C_4\lambda}\, \phi_e^n \quad [13]$$

Here $C_3 = 2.59 \times 10^{-4}$ m s^{-1}, $C_4 = 0.60$, and $n = 2.54$, RMSE of the $\log(K_s) = 0.57$, and $r^2 = 0.73$. All the coefficients were significant ($P < 0.001$). Figure 2 shows the predicted and measured values for the original and modified relationships. Eq. [13] is similar to Eq. [1] where the coefficient B in Eq. [1] is replaced by $C_3 10^{C_4\lambda}$. The RMSEs are given in Table 3 as a function of textural class. The largest change in RMSE is in the sand texture class, where the RMSE for estimates by the new Eq. [13] are less than the RMSEs for estimates by the original Eq. [1]. An inspection of the predicted and measured values in Fig. 2 shows that the predicted K_s values are closer to the 1:1 line for Eq. [13] (with λ) for the largest values of K_s.

The Coefficient B as a Function of λ and h_b

Earlier work (Ahuja et al., 1984, 1989) established that the slope n in Eq. [1] could be assigned a constant value for different soils but suggested that the intercept, B, could vary. We have proposed functional dependencies for B on λ and h_b in Eq. [10]. The dependency of

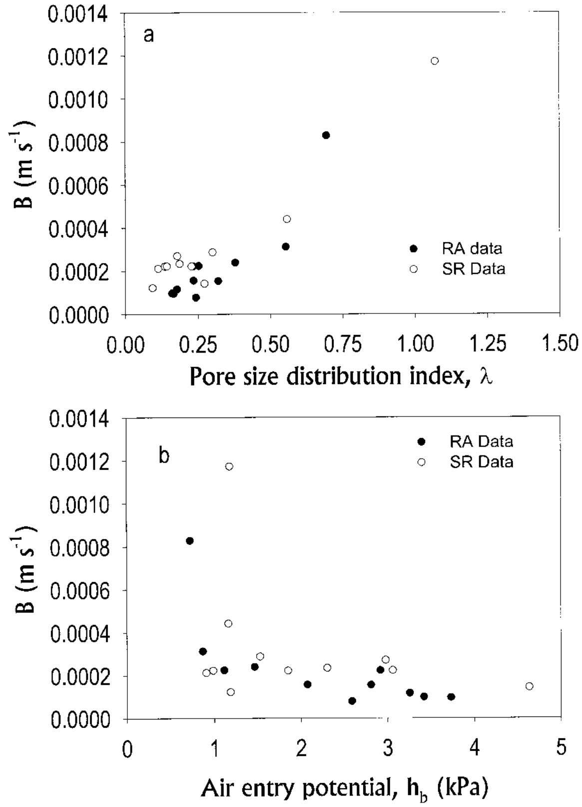

Fig. 3. The intercept of the Kozeny-Carman equation (B) as a function of (a) λ, and (b) h_b. The value of B is calculated as K_s ($\phi_e^{2.5}$). The data are means for textural classes.

B (Eq. [11]) on λ and h_b is shown in Fig. 3a and 3b for the RA and the SR data sets. We chose a value of 2.5 for the exponent n of ϕ_e on the basis of previous work by Ahuja et al. (1989). The exact value for an exponent is not critical, we only need a reasonable, fixed value. The relationships for B vs. λ and B vs. h_b are similar for both data sets, although there is more scatter in the SR data. In both cases, the relationship is approximately linear for λ and highly nonlinear for h_b.

Figures 3a and 3b suggest that the air entry potential

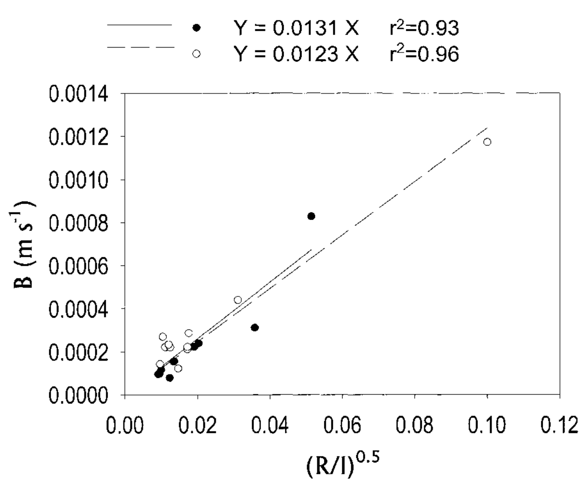

Fig. 4. Relationship between the intercept B and R/I for Southern Region (SR) and Rawls (RA) data sets. The value of B is calculated as K_s ($\phi_e^{2.5}$). The data are means for textural classes.

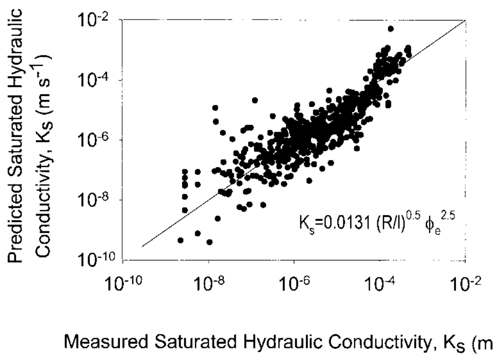

Fig. 5. Calculated and measured values of K_s, where the intercept (B) for Eq. [1] has been calculated using values of λ and h_b, and the relationship between B and R/l for the Rawls data set given in Fig. 4.

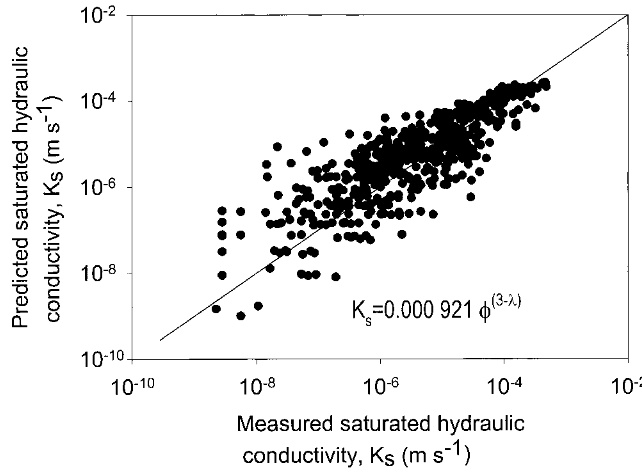

Fig. 6. Relationship between measured K_s and values predicted using Eq. [2] when fit to the Southern Region (SR) data set.

is a better predictor of low values of B (Eq. [11]) and λ is a better predictor of high values. This is consistent with the results shown in the previous section of this paper. The air entry potential provides a measure of the largest continuous pore that becomes increasingly important as texture becomes less coarse. The pore size distribution index (λ) is a measure of the slope of the moisture release curve and as such is an indirect measure of the tortuosity of soil. Larger values of λ are associated with coarse-textured soils that have lower tortuosity and higher permeability and drainability.

With reference to the Rawls et al. (1993) modified Marshall equation (Eq. [3]) we used a combination of λ and h_b as predictors for B in the form of $f(R/l)$ (Eq. [10]) where R and l are given by Eq. [4] and [5] respectively. We found that $(R/l)^{0.5}$ gave the best results with textural class mean data. Figure 4 shows the relationship between $(R/l)^{0.5}$ and the coefficient B from Eq. [11] for the RA and mean SR data sets. We fit a linear function for $B(h_b,\lambda)$ that had an intercept of zero (Fig. 4). The slopes for the two relationships were not significantly different ($F = 0.34$). The relationship for the RA data set is:

$$B(h_b,\lambda) = 0.0131\left(\frac{R}{l}\right)^{0.5} \qquad [14]$$

Substituting Eq. [14] into Eq. [1] and using $n = 2.5$ we have:

$$K_s = 0.0131\left(\frac{R}{l}\right)^{0.5} \phi_e^{2.5} \qquad [15]$$

Predicted K_s (m s^{-1}) values from Eq. [15] using Brooks-Corey parameters and ϕ_e values from the SR data set are plotted against measured K_s values in Fig. 5. The relationship fits the data well with an $r^2 = 0.75$ for the log-transformed data that is similar to the r^2 for the original and modified Ahuja's relationships (Tables 3 and 4), although the RMSE is slightly higher than for the original method. The parameters for this relationship were fit from the RA data and are completely independent of the SR data. The results could be improved using parameters fit to the SR data set. However, the differences will not be large since the slopes of the relationships for the two data sets shown in Fig. 4 are similar. The applicability of Eq. [15] to the SR data set where the coefficients were derived from the RA data set does demonstrate the generality of this relationship. It is also encouraging to note that the error is not that much larger than the error in estimates from the other models fit to the SR data set.

Rawls et al. (1998) have developed another form of the modified Kozeny-Carman equation that uses a function of the pore-size distribution index for the exponent, n (Eq. [2]). This equation fitted the SR data well an r^2 of 0.73 and an RMSE of 3.40×10^{-5} m s^{-1} for the untransformed values (Table 4, Fig. 6). Only the intercept in Eq. [2] has been fit to the SR data.

Tables 3 and 4 show statistics for a comparison of the four models. The four models were fit with different methods (regression with log-transformed values, regression with untransformed values, and directly calculated,). Therefore, we show statistics of regression of

Table 4. Comparison of measured K_s vs. values predicted by the four models for the Southern Region (SR) data.

		No transform				Log transform			
Model	Eq.	RMSE	r^2	Intercept‡	Slope	RMSE†	r^2	Intercept§	Slope
		10^5 m s^{-1}		10^5 m s^{-1}		Log (m s^{-1})		Log (m s^{-1})	
$K(\phi_e)$	1	5.34	0.66	6.80	0.25	0.60	0.70	−1.62	0.70
$K(\phi_{ei}\ \lambda)$	13	3.61	0.77	4.26	0.56	0.57	0.73	−1.48	0.73
Calculated 'B'	15	8.75	0.72	−9.05	1.74	0.59	0.75	−0.83	0.87
Rawls et al. (1998)	2	3.40	0.73	9.84	0.72	0.61	0.72	−1.05	0.77

† In log 10-transformed units.
‡ Intercept and slope for K_s (predicted) = $a + b\ K_s$ (measured).
§ Intercept and slope for log K_s (predicted) = $a + b$ log K_s (measured).

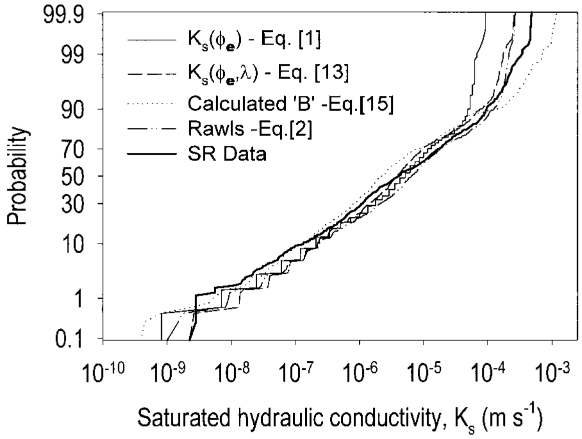

Fig. 7. Probability plot of measured K_s and values estimated by the four models. K_s values are from the full Southern Region (SR) data set.

log(10)-measured vs. log(10)-predicted values as well as a similar regression for untransformed values in Table 4. Looking at the comparisons with untransformed values, the two models that give the lowest error and highest r^2 are Eq. [13] and [2], the two that use λ as well as ϕ_e as predictors. The slope of the measured vs. predicted is closest to one for K_s values calculated from Eq. [2]. Where log (base 10)–transformed K_s values were used, Eq. [13] and [15] gave the lowest RMSE. The intercepts and slopes for the measured vs. predicted regressions are also given in Table 4. The closer the intercept is to zero, the less bias there is, and the closer the slope is to one, the better the predictions throughout the range of data. In untransformed units, Eq. [2] gave the lowest bias and the best correspondence between measured and predicted values, Eq. [13] and [15] gave similar results.

The results given in Tables 3 and 4 suggest that a particular equation may be more applicable to a specific range of data. Regression with log-transformed variables acts like a weighted regression, where small values of K_s are given higher weights than would be given if the fitting method evaluated deviations of untransformed values. As a result, Eq. [1] and [13] may be more appropriate for estimating small values of K_s in finer-textured soils for example, and Eq. [2] for larger values of K_s in coarser-textured soils.

The probability plots in Fig. 7 indicate how well each model describes the original distribution of data. The distribution of the predicted values of the four models are not greatly different in the mid ranges of the data. Equations [2] and [13] both come closest to the distribution at high values of K_s. The distribution of K_s predicted using a calculated value of B (Eq. [15]) is quite close to the SR data distribution for lower values of K_s. This is encouraging considering this equation was parameterized with an independent data set. Of the four models, the distribution of K_s predicted by Eq. [13] appears closest to the distribution of measured K_s values. However, these differences are not large but are important to consider when an estimation is used to generate a distribution of K_s values across a field as a function of spatial variability.

In spite of these improvements, there is still considerable prediction error in K_s. Soil retention data do not contain enough information on the continuity of pores and soil structure, two important determinants of saturated conductivity. Further research into the use of methods that can characterize these factors may improve our predictive capabilities.

There is also the question of the use of these methods to estimate saturated conductivities for use at the field scale. Ahuja et al. (1993) have shown that a harmonic mean K_s of layered soil can be estimated from a 2-d drainage of surface soil. This may extend the usefulness of the methods developed in our study. Ahuja has observed (Ahuja, 1993, unpublished data) that final infiltration rates taken in 25-cm-diameter infiltration rings are related to average effective porosity, ϕ_e, of the 1-m profile, as well as soil water content of the profile measured 2 to 3 d after the soil was fully wetted. These relationships are similar to Ahuja et al.'s (1989) $K_s(\phi_e)$ relationships. Soil water content measured 2 to 3 d after rainfall is probably a better estimator of drainable porosity than 33 kPa water content. It is likely that this property can be easily scaled up to larger areas. Research into this area would be a promising extension to this work.

SUMMARY AND CONCLUSIONS

The modified Kozeny-Carman equation was used to calculate saturated conductivity (K_s) from effective porosity (ϕ_e). We were able to obtain better predictions of K_s when the pore size distribution index (λ) from the Brooks-Corey equation was used along with ϕ_e. The coefficient of determination (r^2) for log(K_s) increased from 0.70 to 0.73 and the RMSE of log(K_s) decreased from 0.60 to 0.57. The use of λ improved the fit for larger values of K_s ($>2.5 \times 10^{-5}$ m s^{-1}).

We determined a functional relationship for the intercept B ($K_s\phi^{-2.5}$) in the modified Kozeny-Carman equation (with an exponent of 2.5) as a function of h_b and λ from the Brooks-Corey equation. The equation for B vs. $f(\lambda, h_b)$ was linear with an intercept of 0 when fit to a data set of textural mean values that was available in the literature. Independent predictions of K_s using parameters from a data set different from the one for which the B vs. $f(\lambda, h_b)$ relationship was fit had an r^2 of 0.75 and RMSE = 0.59 for log(K_s).

Overall, the use of Brooks-Corey parameters from moisture retention data improved estimates of K_s, compared with using effective porosity (ϕ_e) alone. However, in spite of the improvement, there is still substantial prediction error. There was not a large difference in prediction error among the four models. The best form of the equation was when the Brooks-Corey pore-distribution factor, λ, was included in the term for the coefficient of the modified Kozeny-Carman equation. The next best form was when λ was included in the exponent for ϕ_e. The use of the air entry potential (h_b) did not measurably improve the estimates of K_s. The RMSEs for the two best models were not greatly different. The two best models appeared to retain the distribution of the original data better. The use of λ improved the estimate of K_s in coarse-textured soils, and so models that incorporate λ would be more appropriate for estimation of K_s in this texture class.

REFERENCES

Ahuja, L.R., D.K. Cassel, R.R. Bruce, and B.B. Barnes. 1989. Evaluation of spatial distribution of hydraulic conductivity using effective porosity data. Soil Sci. 148:404–411.

Ahuja, L.R., J.W. Naney, R.E. Green, and D.R. Nielsen. 1984. Macroporosity to characterize spatial variability of hydraulic conductivity and effects of land management. Soil Sci. Soc. Am. J. 48:699–702.

Ahuja, L.R., O. Wendroth, and D.R. Nielsen. 1993. Relationship between drainage of surface soil and average profile saturated conductivity. Soil Sci. Soc. Am. J. 57:19–25.

Bruce, R.R., J.H. Dane, V.L. Quisenberry, N.L. Powell, and A.W. Thomas. 1983. Physical characteristics of soils in the Southern Region: Cecil Southern Coop. Ser. Bull. 267. Georgia Agric Exp. Stn., Univ. of Georgia, Athens.

Dane, J.H., D.K. Cassel, J.M. Davidson, W.L Pollans, and V.L. Quisenberry. 1983. Physical characteristics of soil in the Southern Region Troup and Lakeland series. Southern Coop. Ser. Bull. 262. Alabama Agric. Exp. Stn., Auburn.

Franzmeier, D.P. 1991. Estimation of hydraulic conductivity from effective porosity data for some Indiana soils. Soil Sci. Soc. Am. J. 55:1801–1803.

Green, R.E., L.R. Ahuja, S.K. Chong, and L.S. Lau. 1982. Water conduction in Hawai'i oxic soils. Water Resources Research Center. Technical Report 143. Univ. of Hawaii at Manoa, Honolulu.

Messing, I. 1989. Estimation of saturated hydraulic conductivity in clay soils from soil moisture retention data. Soil Sci. Soc. Am. J. 53:665–668.

Nofziger, D.L., J.R. Williams, A.G. Hornsby, and A.L. Wood. 1983. Physical characteristics of soils of the Southern Region. Southern Cooperative Series Bull. 265. Central Mailing Services, Oklahoma State Univ., Stillwater.

Press, W.H., B.P. Flannery, S.A. Teukolsky, and W.T. Vetterling. 1986. Numerical Recipes. Cambridge Univ. Press, New York.

Puckett, W.E., J.H. Dane, and B.F. Hajek. 1985. Physical and mineralogical data to determine soil hydraulic properties. Soil Sci. Soc. Am. J. 49:831–836.

Quisenberry, V.L., D.K. Cassel, J.H. Dane, and J.C. Parker. 1987. Physical characteristics of soils in the Southern Region: Norfolk, Dothan, Goldsboro, Wagram. Southern Coop. Ser. Bull. 263. South Carolina Agric. Exp. Stn., Clemson Univ., Clemson, SC.

Rawls, W.J., L.R. Ahuja, and D.L. Brakensiek. 1992. Estimating soil hydraulic properties from soils data. p. 329–340. *In* M. Th. van Genuchten et al. (ed.) Proc. Int. Workshop on Indirect Methods for Estimating the Hydraulic Properties of Unsaturated Soils. Riverside, CA. 11–13 Oct. 1989. USDA and Univ. of California, Riverside.

Rawls, W.J., D.L. Brakensiek, and S.D. Logsdon. 1993. Predicting saturated hydraulic conductivity utilizing fractal principles. Soil Sci. Soc. Am. J. 57:1193–1197.

Rawls, W.J., D.L. Brakensiek, and K.E. Saxton. 1982. Estimation of soil water properties. Trans. ASAE 25:1316–1320.

Rawls, W.J., D. Gimenez, R. Grossman. 1998. Use of soil texture, bulk density, and slope of the water retention curve to predict saturated hydraulic conductivity. Trans ASAE 41:983–988.

SAS Institute. 1995. SAS/STAT guide for personal computers. Version 6.07 ed. SAS Inst., Cary, NC.

Snedecor, G.W., and W. Cochran. 1980. Statistical methods. 7th ed. Iowa State Univ. Press, Ames.

van Genuchten, M. Th. 1981. Non-equilibrium transport parameters from miscible displacement experiments. Research Rep. 119. U.S. Salinity Lab., USDA-SEA-ARS, Riverside, CA.