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FIELD EVALUATION OF THE NEW PHILIP-DUNNE PERMEAMETER FOR MEASURING SATURATED HYDRAULIC CONDUCTIVITY

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One of the most sensitive parameters in hydrological models, the saturated hydraulic conductivity (K_s), is also one of the most problematic measurements at field scale in regard to variability and uncertainty. The performance of a new type of simple and inexpensive field permeameter, the Philip-Dunne permeameter (PD), is compared with two established alternatives, the laboratory constant head permeameter (LP) and the field Guelph permeameter (GP). A PD prototype, a protocol of usage, and a numerical routine to find K_s were developed and tested on a 70-point array laid out on an 850-m^2 volcanic soil plot. A power transformation was applied to the raw data using the three methods, and the transformed data were shown to be normally distributed. The LP and GP data were better described by a log-normal distribution, whereas the PD data could also be approximated with a power-normal distribution. A factor of 3 was found to relate PD, LP, and GP hydraulic conductivity estimates, E[Ks], such that $E[K_s\text{-PD}] \cong 3\ E[K_s\text{-LP}]$; $E[K_s\text{-LP}] \cong 3\ E[K_s\text{-GP}]$. Such differences may be explained by the different water infiltration geometries and sample wetted volume for the three methods. The PD has advantages over the other two methods in terms of personnel involved, preparation time, and ease of operation. Additionally, the PD methodology required a smaller number of samples (41% less than GP and 69% less than LP) to estimate the population mean K_s. Both PD and GP also give the suction at the wetting front, an important parameter that characterizes the unsaturated flow properties of the soil. (Soil Science 2002;167:9–24)

Key words: Saturated hydraulic conductivity, Philip-Dunne permeameter, representative elementary volume, power-normal distribution, field method.

FIELD and laboratory methodologies for measuring saturated hydraulic conductivity (K_s) have been the focus of much attention because K_s is recognized to be one of the most sensitive parameters in predictive hydrological models. Direct measurements are preferred for its determination because indirect methods, usually based on soil textural characteristics combined with aggregate analyses, do not always lead to reliable results (Kutilek and Nielsen, 1994). In addition, K_s values exhibit large variability in soils (Warrick and Nielsen, 1980; Jury et al., 1991). This means that a large number of samples is usually required to estimate the mean value of the population (Warrick and Nielsen, 1980). Field variability and measuring technique are, therefore, two important issues when determining the effective value of K_s.

A number of laboratory (Klute and Dirksen, 1986) and field methods (Amoozegar and Warrick, 1986; Elrick and Reynolds, 1992; Ankeny, 1992) have been proposed to measure this soil property, varying in simplicity and applicability with the scenario studied (Dorsey et al., 1990; Gallichant et al., 1990; Gupta et al., 1993). Laboratory methods, usually based on a simple application of Darcy's law in one dimension, have the ad-

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vantage of being conducted in a controlled environment. These methods, however, are subject to the limitation that some disturbance is introduced in manipulating the sample, even when "undisturbed" soil cores are used, and the soil measurement is inhibited in addition by other dominant hydraulic effects present in the field (capillary effects, other dimensional components, etc). A well-established and representative method of this category, selected for this work, is the laboratory constant head permeameter (LP) technique (Klute and Dirksen, 1986). Field methods have the advantage of dealing with soil in natural conditions. However, flow in the field is rarely one-dimensional, and small scale heterogeneity in soil conditions (structure, texture, flora, fauna, soil composition, etc.) may introduce large variations in measured values. The Guelph permeameter (GP) technique (Reynolds et al., 1983) belongs to this group, and as a widely used methodology was also selected for this work.

Previous studies have compared existing field and laboratory permeameters using criteria of accuracy, speed, ease of use, cost, etc. Gómez et al. (2001) compared the PD with the ring and rainfall infiltrometers and found no significant differences in K_s values other than in the suction at the wetting front. Lee et al. (1985) compared GP and laboratory soil core methods, and Dorsey et al. (1990) compared four field methods, including the GP. This research showed both a high variability in K_s values and also that the GP technology gives lower K_s estimates than the other methods compared. A multiplying factor of 2 to 3 between K_s values determined from soil cores and those obtained with the GP method has been proposed to account for air entrapment in the field soil (Reynolds et al., 1985; Gupta et al., 1993). However, Paige and Hillel (1993) discuss the difficulty of explaining the discrepancy of 1 to 3 orders of magnitude between K_s values from those two methods, even when the effects of air entrapment are considered. Such discrepancies may actually arise from the different theoretical assumptions made by each method regarding the way water flows out of a borehole-one-dimensional flow through a small confined soil column, the shape of the saturated bulb around a well approximated to a sphere of increasing diameter, etc.

When comparing different methods for K_s determination, measurements are not usually carried out on the same sample volume. Thus, a point-to-point comparison of K_s is not feasible. To get around this problem, data are fitted to a probability distribution function (PDF). Statistics, such as variance and mean, obtained from equivalent PDFs of two different K_s populations, can then be rigorously compared (Lee et al., 1985). The K_s PDF has been found to be skewed with respect to the normal (Gaussian) distribution, and it has traditionally been described by a log-normal PDF (Law, 1944; Nielsen et al., 1973; Freeze, 1975; Anderson and Cassel, 1986). However, other authors have found that although their conductivity data were skewed toward the lower end, the best distribution was not log-normal (Tabrizi and Skaggs, 1983; Cooke et al., 1995). Benson (1993) showed that the spatial variability of hydraulic conductivity was not described successfully by a classic two-parameter, log-normal distribution but by a generalized extreme event value or three-parameter, log-normal PDF.

The main goal of this study is to assess the applicability of the Philip-Dunne permeameter (PD) as a new, simple, and inexpensive field technique for measuring saturated hydraulic conductivity. As a first step, a PD prototype was developed and tested (the apparatus, a field usage protocol and a numerical routine for K_s calculation). The second step was the comparison of the PD performance against two well-established alternatives: the laboratory constant head permeameter and the Guelph permeameter. To achieve this last objective, it was necessary to analyze the probability distribution functions for the measured values before estimating the expected K_s values and uncertainty of each method. Finally, the relationship among the K_s values obtained with these three methods is discussed.

MATERIALS AND METHODS

Field Experimental Work

An 850-m^2 (33.3 $\times$ 25.5 m) drip-irrigated banana plot was selected for sampling and testing (Fig. 1). The plot is terraced with an average soil effective depth of 85 cm over basaltic fractured rock. The soil is homogenous, with loamy-sand texture, and exhibits andic properties. These soils, developed on volcanic rock materials, are composed of very stable microaggregates that confer unusual values of soil bulk density (0.87 $\pm$ 0.08 g/cm^3), porosity (66.42 $\pm$ 2.42%), and particle density (2.70 $\pm$ 0.01 g/cm^3). A uniform grid (2.5 $\times$ 5 m) was laid out on the plot surface yielding 70 grid intersection points. Three methods to estimate the K_s (PD, LP, and GP) were applied at each of the 70 points at about the same time in order to avoid or reduce artifact effects caused by changes in soil structure. Measurements (GP and

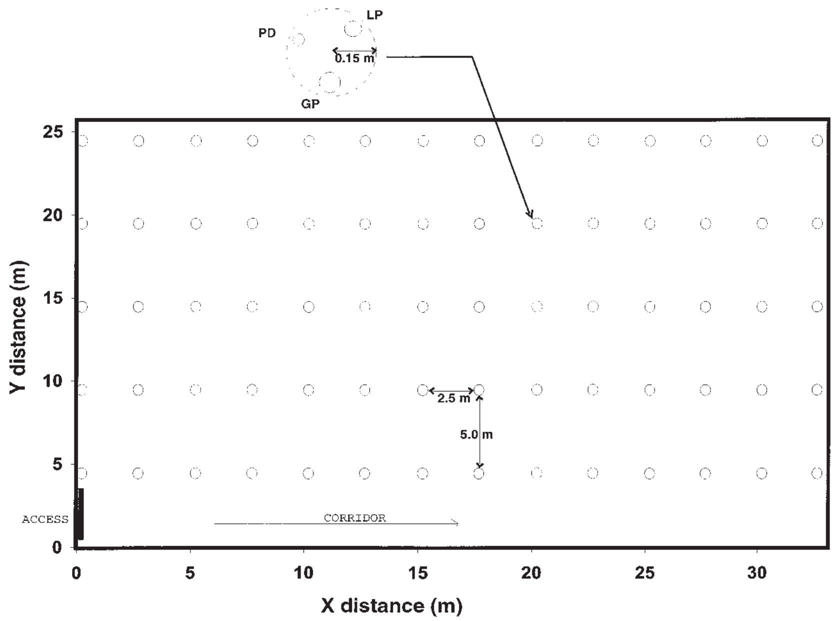

Fig. 1. Field experimental work layout.

PD) and sampling (LP) were applied side-by-side at each grid point within a circle of about 15 cm radius and always at a soil depth of 15 cm (Fig. 1).

Philip-Dunne Permeameter

This new type of permeameter is based on the T. Dunne apparatus and data from the Amazon River basin, as presented by Philip (1993). The device consists of a clear plastic tube of internal radius r_i, vertically inserted to a certain depth into an unsaturated soil borehole with zero gap, and then filled with water up to a height h_o at time $t = 0$. During infiltration, the times when the pipe is half full (t_{med} at $h = h_o/2$) and is empty (t_{max} at $h = 0$) are recorded, along with soil moisture at the beginning (θ_o) and at the end of the test (θ_l). The prototype designed for this work ($r_i = 1.8$ cm; $h_o = 30$ cm) is shown in Fig. 2. A 2-mm-mesh plastic screen was glued to the lower edge of the pipe to avoid soil erosion when filling the permeameter quickly at $t = 0$ with the aid of a funnel. An electrical sensor (bridge) was added to detect the moment when the pipe empties (LED off). For installation a 3.8-cm-diameter, 15-cm-depth hole was bored with an auger. The last 5 cm of soil were used for soil moisture determination either by sampling or by inserting a 5-cm TDR probe in the hole before finishing. A 3.8-cm diameter flat bottom sizing auger was

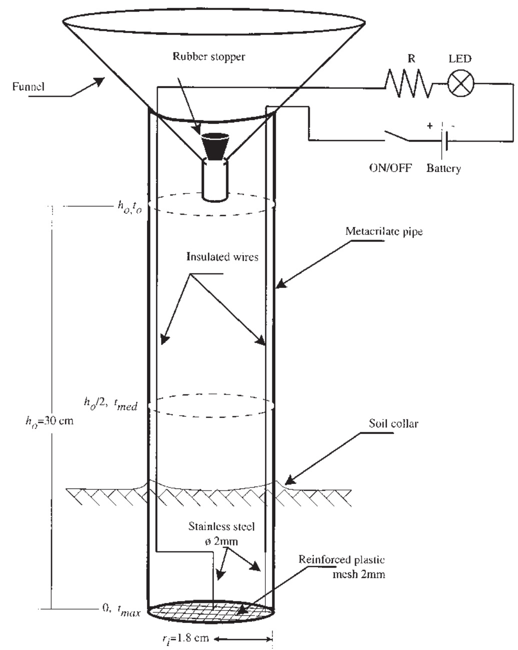

Fig. 2. Schematic of the Philip-Dunne permeameter developed for the study.

then used to produce a hole of uniform geometry, 2 mm smaller than the plastic pipe, to ensure a tight insertion of the 4-cm external diameter plastic pipe (3.6-cm internal diameter). Soil was pressed around the pipe at the surface to ensure a close fit. A field protocol for this permeameter was developed and used as depicted in Fig. 3. Observance of this protocol during field sampling provided uniform conditions for measurement, thus reducing experimental error. Care should be taken to ensure that the pipe is inserted snugly in order to prevent upflow of water. By contrast, the sensitivity of the method to soil moisture variations is small (De Haro et al., 1998), and, therefore, errors in water content determination (e.g., due to microvariability of water content, uncalibrated TDR measures, etc.) are minimized.

To obtain the K_s values with this device, Philip (1993) applied a spherically symmetric Green-Ampt analysis based on the "effective hemisphere

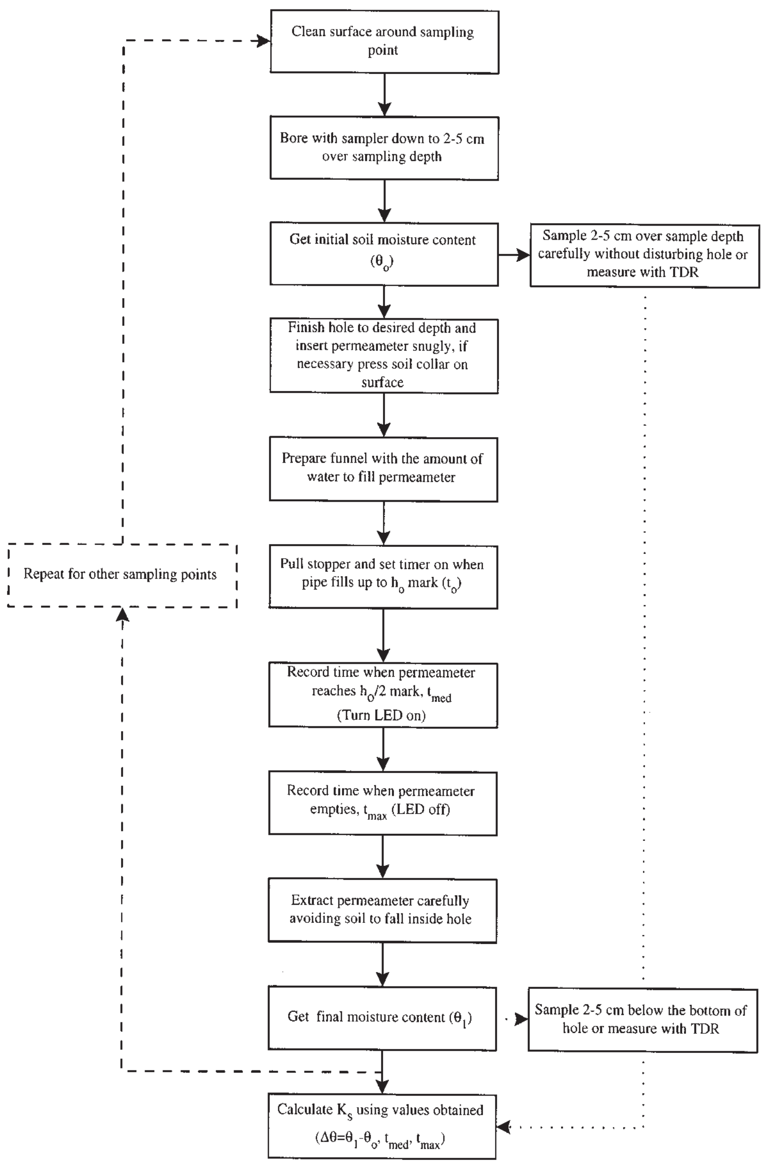

Fig. 3. Field use of the Philip-Dunne permeameter.

model" for trickle source unsteady infiltration of Ben-Asher et al. (1986). He proposed that for a pipe of internal radius r_i, the disk-shaped water supply can be replaced by a spherical water supply of equal area, i.e., of radius $r_o = 0.5\ r_i$. If $R = R(t)$ is the soil-wetted bulb radius from the water supply at time t, then the following differential equation holds,

$$\frac{\pi^2}{8}\ \frac{R(R - r_o)}{r_o K_s}\ \frac{dR}{dt} = \frac{\psi_f + h_o + \pi^2\ r_o/8}{\Delta\theta} - \frac{R^3 - r_o^3}{3r_0^2} \quad (1)$$

where ψ_f (>0) is the suction at the wetting front (from the Green-Ampt equation), and $\Delta\theta = \theta_1 - \theta_o$ is the increment in volumetric moisture content after the pipe, initially filled up to a height h_o, empties (i.e., $h = 0$). Equation (1) is subject to the initial condition,

$$R = r_o \text{ for } t = 0 \quad (2)$$

The rate of water descent in the pipe is given by continuity as,

$$h(t) = h_o - \frac{\Delta\theta}{3}\left(\frac{R(t)^3}{r_o^2} - r_o\right) \quad (3)$$

Equation (3) can be used to calculate the average soil-wetted volume after infiltration (mean volume of 2087 cm^3 for this study). The above equations consider flow during infiltration as a gravity perturbed pressure-capillarity flow. Philip (1993) showed that the solution proposed, in fact a simplification derived from an approximate analysis, is acceptable for the relative magnitude of the components of the total flow present (pressure-capillarity » gravity) during a PD infiltration event.

Philip (1993) found that a solution to (1)–(3) can be obtained given $\Delta\theta$ and two measured times, t_{med} and t_{max} at known water levels. A simplified procedure to solve the resulting equations presented by De Haro et al. (1998) will be used herein (details are given in Appendix A).

Guelph Permeameter

The Guelph permeameter is a constant head well permeameter (Reynolds et al., 1983; Reynolds et al., 1985) consisting of a mariotte bottle that maintains a constant water level inside a hole augered into unsaturated soil. Flow from this permeameter is assumed to reach steady state after a transient state during which the soil saturated bulb and the wetting zone increase in size by migrating quasi-spherically from the infiltration surface. At steady state, the saturated bulb remains essentially constant in size (depending on the water level in the well and soil characteristics) while the wetting front continues to increase. The Richard's-based solution to the steady flow equation for this permeameter (Philip, 1985; Elrick and Reynolds, 1992) requires measurements to be made at two different water levels in the same well (double-head method),

$$2\pi H_i^2 K_{fs} + C_i \pi a^2 K_{fs} + 2\pi H_i \phi_m = C_i Q_i \quad (4)$$

where K_{fs} (ms^{-1}) is the field saturated hydraulic conductivity, ϕ_m (m^2s^{-1}) is the matrix flux potential, Q_i (m^3s^{-1}) is the steady-state flow rate out of the well, when the steady depth of water in the well is H_i (m), a (m) is the well radius, and C_i is a dimensionless proportionality constant dependent on H_i/a. The augered wells used in this study were 0.06 m in diameter, with 0.05 and 0.1 m constant water levels (H_i), and $C_1 = 0.8$, $C_2 = 1.2$, following the manufacturer recommendations (SoilMoisture Eq. Corp., 1986). The average soil-wetted volume in our conditions, using this device, can be estimated at ~4000 cm^3 (Gallichant et al., 1990).

The double-head method may yield negative values of K_s as a result of soil profile discontinuity (Elrick and Reynolds, 1992) and ill-conditioning of the simultaneous equations in K_s and $\alpha^* = K_s/\phi_m$ (see Appendix B in Philip, 1985). Additional criteria for checking the validity of the GP results have been published (Elrick et al., 1989; Elrick and Reynolds, 1992). These criteria are based on the sign obtained for the matric flux potential, ϕ_m, (i.e. $\phi_m > 0$) and on the magnitude of α^* ($1\ m^{-1} \leq \alpha^* \leq 100\ m^{-1}$ for field soils), which is a measure of the capillarity properties of the soil. To get around the problem of negative K_s values, a one-head procedure has been proposed, whereby a site estimated α^*, obtained from textural properties, is introduced to avoid the need of a second ponded head (Elrick et al., 1989). In this study we shall use the 10-cm ponded head for the one-head approach. Alternatively, Vieira et al. (1988) have proposed recomputing the anomalous K_s values arising from the two-head method, making use of the conductivity values obtained from the Laplace solution, K_L (which neglects the capillarity forces in the soil) and the correct K_s values, K_s^*, (i.e., $\phi_m > 0$, $1\ m^{-1} \leq \alpha^* \leq 100\ m^{-1}$) via the empirical relation $K_s = \beta\ K_L^{\gamma}$. Following, we shall concentrate on the GP K_s values obtained with Vieira's analysis unless otherwise stated.

Laboratory Constant Head Permeameter

Vertical undisturbed soil cores were collected in stainless steel rings using a centered, hammer-driven sampler, at a 15-cm soil depth (top of the core). The core dimensions were 5.6 cm internal diameter and 4 cm height (soil sample volume 98.5 cm^3). The cores were extracted carefully and cleaned so as to avoid surface sealing. Soil samples were slowly saturated in the laboratory from bottom to top, to prevent air entrapment, using a deaerated 0.005 *M* $CaSO_4$ solution with thymol. Measurements were made on a recirculating constant head permeameter following the procedure described by Klute and Dirksen (1986). This method can yield unusually high K_s values in some cores because of soil cracking and shrinkage.

Statistical Methods

Outliers (extremely high/low values), detected by means of a stem and leaf plot (Stedinger et al., 1992), were removed from the raw data for further statistical analysis since these are not representative of the data set probability distribution. Basic statistics such as mean, median, and variance were computed. The means were compared on a pairwise basis using the Tukey test at the 1% level. This test uses the Studentized statistic to make all pairwise comparisons between groups (Steel and Torrie, 1980). Skewness and kurtosis were also evaluated as indicators of deviation from normality. When data are unevenly spread, a nonlinear transformation of the original K_s values may improve normality. With this purpose in mind, a power transformation, P(q), was applied to the raw data such that

$$\mathbf{P}(q) = \begin{cases} K_s^{\,q} \text{ if } q > 0 \\ \log(K_s) \text{ if } q = 0 \\ -K_s^{\,q} \text{ if } q < 0 \end{cases} \quad (5)$$

Note that when $q = 0$, the transformation reverts to a logarithmic transformation. Probability plots represent a useful tool for discerning between different statistical distributions that may fit the data set. The original data, X, is thus ordered such that $X_i > X_{i-1}$, and plotted against the expected value, Z_{pi}, of the hypothesized cumulative distribution function (CDF) to be fitted. If the distribution is to be normally distributed, as in our case, then Z_{pi} is approximated by the inverse of the standard normal CDF (Φ^{-1}) as (Stedinger et al., 1992),

$$Z_{pi} = \Phi^{-1}(p_i) \approx \frac{(1-p_i)^{0.135} - p_i^{0.135}}{0.1975} \quad (6)$$

where the plotting position p_i is given by

$$p_i = \frac{i-b}{n+1-2b} \quad (7)$$

with n being the number of samples and b a plotting position parameter. A traditional choice is Hazen's $b = 0.5$; another alternative is Blom's plotting position, $b = 3/8$, which ensures the quantiles lack of bias (Stedinger et al., 1992). Visual inspection of the plot of X_i versus Z_{pi} will thus show that data that follow the hypothesized distribution should yield a straight line through the origin.

Visual inspection of probability plots is, however, rather subjective, and, hence, the need for a more objective goodness-of-fit test, such as Filliben's test (Vogel, 1986), to decide about the distribution of K_s. Filliben's test uses the correlation r between the ordered X_i and the corresponding fitted quantiles at each plotting position, with $r = 1$ indicating that the population follows the prescribed distribution. Confidence levels are given in the test for $r < 1$ (Hirsch et al., 1992). Consequently, Filliben's test represents an objective decision test for rejecting or accepting a candidate distribution in terms of different significance levels, such that the smaller the significance level the greater the probability that the true distribution in not the selected one. When required, a robust estimator was used for downweighting the influence of extreme residuals on the r estimate (Engelman and Wilkinson, 1997).

RESULTS AND DISCUSSION

Check of Validity in PD Field Measurements: Drawdown Curves

Because of the approximations built into the theoretical PD analysis, Philip (1993) and De Haro et al. (1998) advise checking the validity of the method for a given site by recording at a few sampling points a full set of times versus water elevation in the tube, not just t_{med} and t_{max}. The drawdown data can then be plotted on top of the drawdown curve fitted using just $\Delta\theta$, t_{med}, and t_{max}. If the data points lay on the curve, the consistency of the method is ensured. Figure 4 shows such a test for several sample points where a good fit is obtained in all cases except Case 26. This corresponds to a badly behaved solution to (A2) (see Appendix A), and it is thus rejected.

Probability Distribution Functions for Field Data Sets

The uniformly sampled population described above was analyzed to investigate possible statisti-

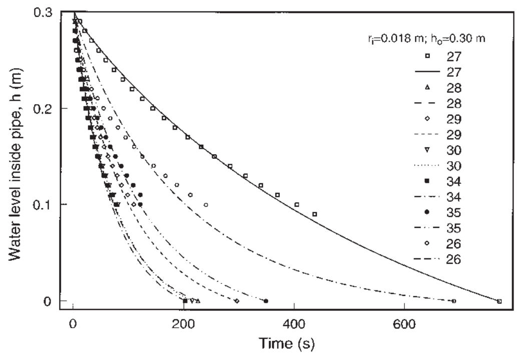

Fig. 4. Field check of water level drawdown predictions against observed data.

cal trends. K_s outliers were first removed from the original data set such that 60 K_s-LP points out of 70 were finally analyzed. Extremely high values obtained with the LP may be attributed to shrinkage/swelling, which arises quickly in such volcanic soils, and to the presence of other preferential flow paths (root channels, microfauna, etc). For the PD method, 7 of the 70 K_s measures did not meet the fitting criterion described above, two were detected as outliers, leaving 61 K_s-PD values to be considered in the analysis. For the GP two-head method, only 17 of the 70 K_s values satisfied the required criteria ($K_s > 0$, $\phi_m > 0$, $1\ m^{-1} \leq \alpha^* \leq 100\ m^{-1}$). This is in agreement with the high failure rate (47–83%) obtained by previous authors (Vieira et al., 1988; Wilson et al., 1989; Dafonte-Dafonte et al., 1999). Two-head method solutions were recomputed using the analysis of Vieira et al. (1988), discussed in the Methods section, in order to avoid negative hydraulic conductivity values. The fitted value of $\gamma = 0.7$, obtained from the regression line $K_s^* = \beta\ K_L^{\gamma}$ ($r^2 = 0.73$), indicates that α^* is not constant (Reynolds et al., 1992). The mean value of α^* derived from the Vieira analysis was $\alpha^* = 0.22 \pm 0.14\ cm^{-1}$. This value is consistent with the expected α^* for the soil in this study deducible from textural soil characteristics and proposed by Elrick et al. (1989), i.e., $\alpha^* = 0.22\ cm^{-1}$ is placed between a value of $0.12\ cm^{-1}$, proposed for structured clay-loamy soils and unstructured sands, and $0.36\ cm^{-1}$ for highly structured soils and coarse sands. For comparison purposes GP K_s values were also computed using the single-head approach of Elrick et al. (1989) and with $\alpha^* = 0.22\ cm^{-1}$ obtained from the previous Vieira analysis. For the one-head, GP method, a stem-leaf plot detects the two upper and the two lower one-head GP-K_s values as possible outliers.

The α^* parameter is related to the unsaturated flow properties of the soil via K_s/ϕ_m and also as an estimate of the Green-Ampt's suction at the wetting front ($\alpha^* = \psi_f^{-1}$). Both the PD and GP give estimates of this important parameter. The α^* parameter for the PD gives a mean value of $\alpha^* = 1.3\ cm^{-1}$—in disagreement with the value $\alpha^* = 0.22$ obtained with the GP (see above). Gómez et al. (2001) also found discrepancies in their ψ_f values when comparing the PD with the ring and rainfall infiltrometers. They also did not find an explanation for the large ψ_f values obtained with the PD method.

The basic statistics of the hydraulic conductivity data set are summarized in Table 1. Mean, median, and the summation of K_s values show that the saturated hydraulic conductivity values measured using the PD permeameter are 1 order of magnitude greater than those obtained by the

TABLE 1

Statistics of the K_s(cm/s) data sets obtained for each of the permeameters

Statistics	GP		PD	LP
	Single-head	Vieira		
n	66	70	61	60
Minimum	0.000088	0.000144	0.000174	0.000058
Maximum	0.002801	0.001735	0.024410	0.016119
Sum	0.054	0.047	0.533	0.167
Median	0.00070	0.00064	0.00835	0.00188
Mean	0.00078	0.00067	0.00873	0.00279
Mode	0.00065	0.00062	0.00677	0.00173
Standard Deviation	0.00044	0.00026	0.00495	0.00282
CV (%)	56.6	38.9	56.7	101.2
Skewness	2.24	1.47	0.68	2.33
Kurtosis	7.94	4.53	0.95	7.69

GP method (both solutions). Lab K_s is placed in between the two (compare also minimum and maximum values). Comparison of the means of the log-transformed data on a pairwise basis with the Tukey test and at the 1% level (Stedinger et al., 1992) confirms that the mean GP (both solutions), PD, and LP log-K_s are significantly different, whereas the Vieira-GP and single-head log-K_s are not significantly different (Table 2).

The K_s coefficient of variability (CV) is highest for the LP (101%), followed by the PD (56%) and GP (56% and 38% for the single-head and Vieira-K_s, respectively). All of these remain within bounds reported previously by other authors (Warrick and Nielsen, 1980; Jury et al., 1991). The low CV obtained for the Vieira analysis is rather misleading. Note that, although this makes use of the two ponded head infiltration rates to compute the fitting parameters β and τ, the Vieira solution is essentially a single-head method, with the 10-cm height being used in this study to compute the Laplace solution. Consequently, a large number of computations render identical K_s values, and, hence, this yields a low standard deviation and a small coefficient of variability (Table 1).

TABLE 2

Matrix of pairwise comparison probabilities (P) for the Tukey test at 1%†

Permeameter	LP	PD	GP one-head	GP Vieira
LP	1.000			
PD	0.000	1.000		
GP one-head	0.000	0.000	1.000	
GP Vieira	0.000	0.000	0.988	1.000

†Pairs are significantly different when $P<0.01$.

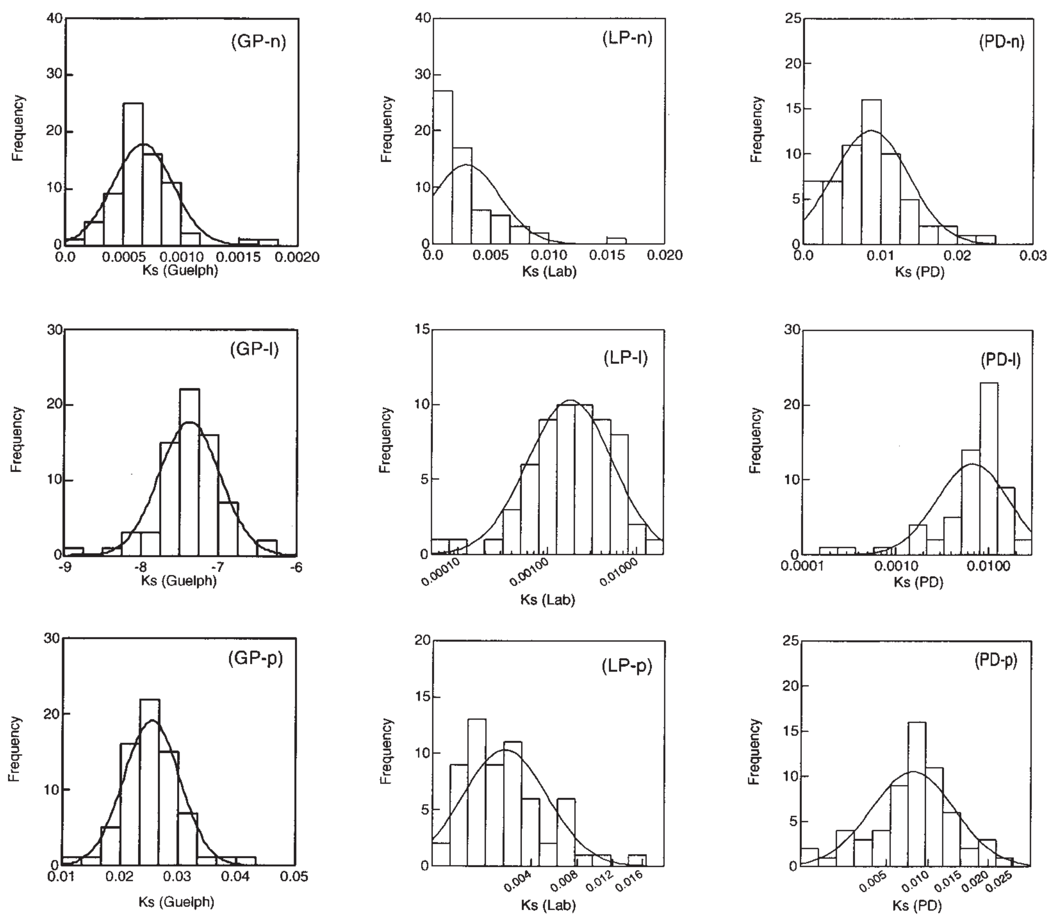

Fig. 5. Histograms of the data sets (n = nontransformed, l = log-transformed, p = power-transformed) for each of the permeameters (GP, LP, PD).

The values for the kurtosis and skewness shown in Table 1 suggest that, inasmuch as the data are unevenly spread, a nonlinear transformation of the original K_s measures would improve normality. Histogram plots of the nontransformed data and of K_s values after a logarithmic and power transformation ($q = 0.5$) are shown in Fig. 5. It shows that, compared with the overlaying normal curves (generated using mean and variance of the sample data set), symmetry is clearly improved after transformation.

Probability plots of both the nontransformed and transformed data are shown in Fig. 6. No significant differences were found using Hazen's or Blom's plotting position, and, thus, only the latter is shown. The exponent $q = 0.5$ was selected as the best fitting power for the power transformation. Inspection of Fig. 6 reveals that none of the values are normally distributed (as suggested above) and that GP and LP follow a log-normal (i.e., the natural logarithm of the K_s measures are normally distributed) or a power-normal distribution (i.e., $K_s^{0.5}$ is gaussian). For the PD data set, the log-normal distribution is poorly fitted: nonlinearity is observed at the long lower tail (Fig. 6 PD-l). Although this is also the case for the power-normal distribution, this nonlinearity trend for the lower values is reduced (Fig. 6 PD-p). Nor can the normal distribution be discarded as a possible candidate for the PD data. Notice, however, that assuming a normal distribution would imply that about 4% of the K_s data have negative values, which is physically unrealistic.

Filliben's r values for the normal, log-normal, and power-normal distributions are summarized in Table 3. With a 0.1 significance level, the log-

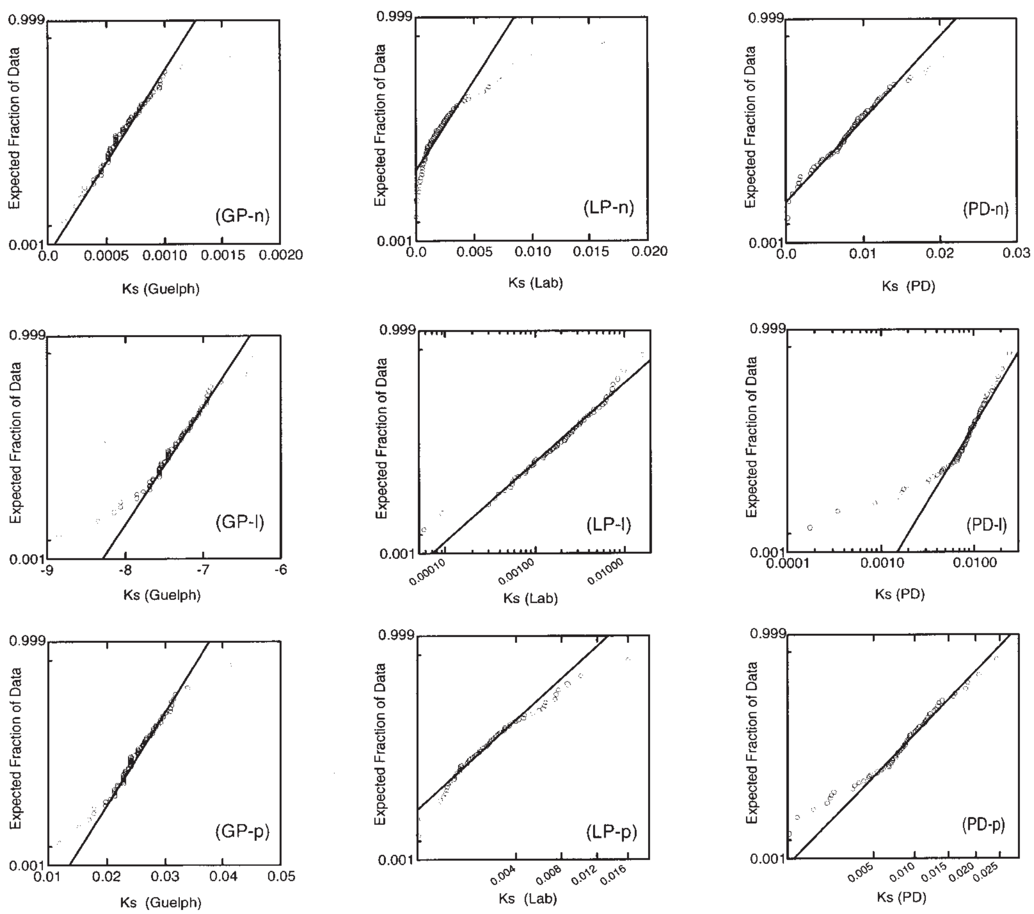

Fig. 6. Probability plots of the data sets (n = nontransformed, l = log-transformed, p = power-transformed) for each of the permeameters (GP, LP, PD).

TABLE 3

Filliben's test for the different data sets and distributions†

Permeameter	Normal	Log-normal	Power-normal	Log-normal robust	Power-normal robust
GP	0.9443 (<0.01)	0.9782 (0.01)	0.9647 (<0.01)		
PD	0.9824 (0.05)	0.9436 (<0.01)	0.9921 (0.1)	0.9797 (0.01)	0.9927 (0.1)
LP	0.8762 (<0.01)	0.9850 (0.1)	0.9680 (<0.01)		

†Significance levels in parenthesis.

normal distribution is accepted for the LP data set, and with a 0.01 level it is accepted for the GP, whereas the normal and power-normal are rejected. By contrast, Filliben's test seems to indicate that the log-normal distribution must be rejected, even for a 0.01 significance level ($r < 0.971$), in favor of the power-normal ($r > 0.9835$) or normal ($r > 0.9799$) for the PD data (Table 3).

Logarithmic transformations may be misleading since small values of K_s are given greatly increased weight. Thus, a robust estimator (Engelman and Wilkinson, 1997) was used for the PD data set in order to downweight the influence of outside values on the *r* estimate. The value of *r* is then improved, such that the log-normal distribution may be accepted with a significance level of almost 0.05 ($0.9799 < r < 0.9710$). Obviously, the *r* value for the power transformation also increases, and, hence, the power-normal distribution cannot be rejected as a plausible candidate.

Because only probability distributions that are equivalent can be compared, and knowing that the log-normal distributions are acceptable for the three data sets, they will be used herein. For fitting the K_s data to a log-normal distribution, the CDF

$$P[K_s] = \frac{1}{2} + \aleph\left(\frac{\log (K_s) - \mu}{\sigma}\right) \quad (8)$$

was used where μ and σ are fitting parameters and $\aleph(z)$ is the normal curve of error. The CDF (Eq. (8)) was employed instead of the corresponding log-normal probability distribution function (PDF) because arbitrary selection of class intervals in the latter would affect the regression outcome. A least square estimation, combined with a modified Gauss-Newton to compute the derivatives, was used to estimate the parameters μ and σ in Eq. (8). The outcome of this nonlinear regression procedure is shown in Fig. 7, and the estimates of μ and σ are summarized in Table 4. The correlation coefficient for the 1:1 line ($r^2_{1:1}$), measured data versus fitted $\ln(K_s)$ values obtained with the calculated μ and σ, is close to 1 for the GP and LP data. For the PD data, $r^2_{1:1} = 0.982$, indicating a poorer fit, most probably caused by the contribution of the lower tail residuals to the correlation coefficient. This may be confirmed if residuals are plotted against predicted PD $\ln(K_s)$ frequencies. If outliers are removed, the PD correlation coefficient improves up to $r^2_{1:1} = 0.992$ (results not shown).

Relationship among K_s Values Estimated with the Three Methods

A plot of the frequency versus the K_s measured with the three permeameters is depicted in Fig. 8. Laboratory K_s exhibits a larger variability (CV = 138.4%), compared with the field methods, with a coefficient of variability about 34 to 60% (Table 4). In terms of the coefficient of vari-

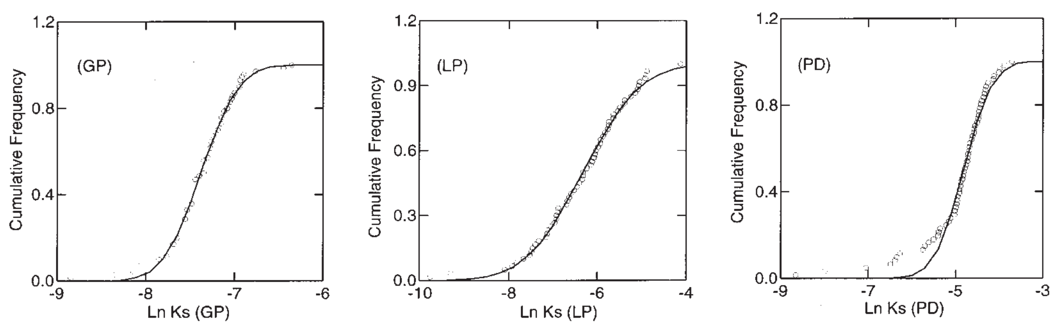

Fig. 7. Fitted log-normal distribution for each of the permeameter data sets (GP, LP, PD).

TABLE 4

Regression results for the log-normal distributions with the different permeameter data sets

Permeameter	μ	σ	r^2 1:1	E[K_s]	Var [K_s]	CV(%)	Skewness
GP	−7.380	0.333	0.996	0.0007	3.70×10^{-7}	34.2	1.00
PD	−4.820	0.525	0.982	0.0092	2.72×10^{-5}	56.3	1.87
LP	−6.321	1.035	0.996	0.0031	1.81×10^{-5}	138.4	6.80

ability, the skewness coefficient ($\hat{\gamma}$) for the log-normal distribution reads

$$\hat{\gamma} = 3\text{CV} + \text{CV}^3 \quad (9)$$

Thus, because the skewness describes the asymmetry of a distribution, the GP and LP curves appear more symmetric than the LP distribution in Fig. 8. That the LP coefficient of variability is higher may mean that it is capturing an intrinsic variability of the soil hydraulic properties that the other field methods cannot detect, but it is more likely to be the result of soil manipulation. In this sense, field determinations can be considered less destructive, and from that point of view more accurate and with a smaller variability. In addition, the differences in the CV may be at least in part explained in terms of the volume explored by the three methods. The field methods sample a larger volume of soil than the laboratory permeameter (2087 cm^3 and 4000 cm^3 vs 98.5 cm^3). Hence, the larger volume averages include more heterogeneities, and this results in a lower standard deviation and, thus, a smaller CV.

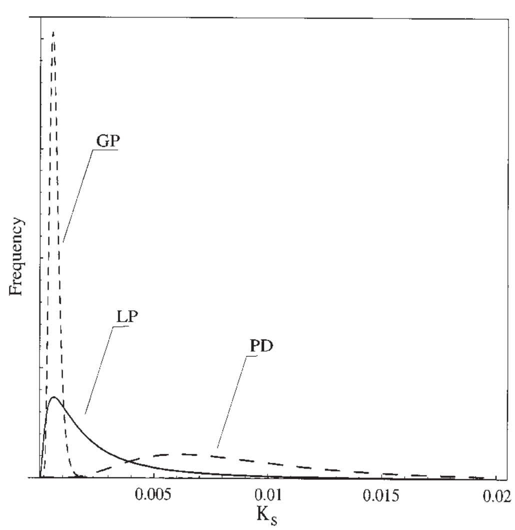

Fig. 8. Probability distribution functions of the data sets for each of the permeameters.

Another relevant feature of Fig. 8 is that although there is some overlapping between the three K_s sets, the sets lie within three distinctive regions, with the LP population placed between the two field methods. Since the three types of measurements have been carried out under similar conditions, such differences may be regarded as inherent to the method used. The three methods have very different infiltration surface areas, sample volumes, and flow geometries, which in an inherently heterogeneous and anisotropic porous medium such as soil generally results in K_s distributions that have very different mean values and/or shapes. It has also often been shown in the literature that K_s can be a function of sample size when this is too small to capture the representative elementary volume (REV) of the soil (Bear, 1969). Structureless soils have a REV of about 100 cm^3, whereas the REV of highly structured soils may be 1 or 2 orders of magnitude higher (Kutilek and Nielsen, 1994). Furthermore, vertical-horizontal anisotropy in K_s is common in soil, and this may introduce differences between permeameters that prefer to explore the vertical flow component (PD, LP) and those whose flow is primarily horizontal (GP). Taking all the above factors into consideration, we still cannot explain fully the large K_s values obtained with the Philip-Dunne permeameter. In addition, the expected K_s values for the three methods, based on our analysis, show the following relationships: $E[K_s$-PD$] \cong 3\ E[K_s$-LP$]$; $E[K_s$-LP$] \cong 3\ E[K_s$-GP$]$. These values agree with the factor of 2–3 between the Guelph field saturated hydraulic conductivity K_{fs} and the corresponding K_s-LP given previously by authors to account for air entrapment in the field.

Usability Criteria of the Permeameters

Other features of the permeameters were also evaluated in the study (Table 5). The PD met satisfactorily the criteria selected: quick serial measurements involving just 1 to 2 researchers using a rather inexpensive and easy-to-use method. Water

TABLE 5
Summary of usability criteria for the permeameters

Criteria	Evaluation†			
	GP-1 head	GP-Vieira	PD	LP
Cost	+	+	++	+
Preparation time	++	++	+++	+
Test duration (min)	25	40	7	20
Personnel/measurements	1/2	1/2	1/3	2/10
Ease of operation	++	++	+++	+
Failure rate (f)	6%	76%	13%	14%
Shallow soil	++	+	+++	+++
Number of samples to estimate mean	+++	++	+++	+

†Symbols for criteria evaluation: +++ good; ++ fair; + poor.

content evaluation was shown to be the most time consuming part of the method since it required core sampling, oven-drying, and weighting. However, this disadvantage was overcome by measuring soil moisture using Time Domain Reflectrometry (TDR), to the detriment of method cost. However, using a programmable calculator or handheld computer, drawdown times and TDR measurements can be input into the PD software developed for the study, such that K_s values may be obtained directly in the field. This allows immediate detection of abnormal PD solutions, which may be repeated at once.

In this respect, a criterion to be considered is the failure rate (f), i.e., the number of failures (statistical outliers, PD criterion not met, negative GP K_s values, etc.) divided by the number of K_s measurements times 100. A high failure rate was seen in this study with the two-head GP (76% K_s values do not satisfy $\phi_m > 0$, $1\ m^{-1} \leq \alpha^* \leq 100\ m^{-1}$) compared with the 13–14% rate of the PD and LP (Table 5). This may be the result of violations of some of the assumptions on which the analysis is based, i.e., soil heterogeneity, nonuniform moisture at start time, etc. From that point of view, the PD method may be regarded as a less restrictive model (only 10% were ill-behaved). In addition, the infiltration volume is greater in the GP than in the PD, and, therefore, a greater probability of exploring variable soil layers in the former, and, thus, the Guelph method may appear at a disadvantage to the PD when dealing with shallow or stratified soils. For example, Wilson et al. (1989) found more than 47% negative GP-K_s values working on forested hillslopes; Dafonte-Dafonte et al. (1999) around 67%.

Another important criterion when deciding between different measuring methods is the number of samples necessary to estimate the population mean ($\underline{K_s}$). This question may be solved in terms of the accepted range d about the mean (i.e. $\underline{K_s} - d$, $\underline{K_s} + d$) for different confidence levels (CL). The number of samples (n) necessary to estimate the mean of a population with a standard deviation of σ^2 is given by (Warrick and Nielsen, 1980)

$$n = Z^2_{0.5\alpha} \frac{\sigma^2}{d^2} \tag{10}$$

where $Z_{0.5\alpha}$ is the normalized difference from the mean. This number can be corrected to account for the extra number of measurements needed to counteract the failures in each method by using

$$n^* = n(1 - 0.01f)^{-1} \tag{11}$$

These results are summarized in Table 6. It can be seen that the number of measurements necessary to obtain an estimate of K_s is smaller for the PD and one-head GP than for the other methods (about 41% less for the PD than for the GP-Vieira and 69% less than LP). For the datasets in this study and with a 10% tolerance and 80% CL, the minimum number of samples necessary to estimate the K_s is met only by the PD and one-head GP; at 20% tolerance and 95% CL by the PD and the GP; and by the three methods at 20% tolerance and 80% CL. Reducing the tolerance and increasing the confidence level makes the sampling number impractical (about 460 samples would be necessary with the LP). The above results are, in fact, not surprising if we consider the coefficient of variability for the three methods (Table 1) since n is proportional to CV^2 (Gupta et al., 1993).

TABLE 6

Corrected number of measurements (n^*) required to obtain an estimate of the population mean

Permeameter	Failure, f	CV(%)	d=10% $\overline{K}_s$		d=20% $\overline{K}_s$		d=25% $\overline{K}_s$	
			95% CL†	80% CL	95% CL	80% CL	95% CL	80% CL
GP-1 head	6%	56.6	131	56	33	14	21	9
GP-Vieira	76%	38.9	241	103	60	26	39	17
PD	13%	56.7	142	61	36	16	23	10
LP	14%	101.2	457	196	114	49	73	31

†CL: Confidence levels.

Notice that although the coefficient of variability is about the same for both the PD and the one-head GP, the latter requires a smaller number of samples to estimate the mean K_s because the failure rate is smaller for the one-head method (6%). Care must be taken, however, with this result since the uncertainty in the textural estimation of α^* in the one-head method would affect the accepted range about the mean (d) and, therefore, n^*. For example, choosing a value of $\alpha^* = 0.12$ cm^{-1} (that according to Reynolds et al. (1992) would correspond to the first choice for most soils) renders a mean one-head GP $K_s = 0.00059$ cm/s. In percentage terms, this represents about 25% of the true mean ($K_s = 0.00078$ cm/s) (see also Reynolds et al., 1992).

SUMMARY AND CONCLUSIONS

When measuring soil hydraulic properties, a reliable, inexpensive and quick method to carry out field experiments is desirable. With this purpose in mind, a Philip-Dunne permeameter prototype, a field-use protocol, and the software necessary to calculate the hydraulic conductivity data were developed. We compared this new method with two other well-established permeameters in terms of K_s values, cost, ease of operation, preparation time and test duration, personnel involved, and number of samples necessary to capture field variability. The PD permeameter has advantages in terms of cost, preparation time, and ease of operation. The implemented numerical routine requires only the soil water content before and after the experiment and the recording of two times during the infiltration. No extra parameters need to be known in advance (such as the form factors C_i or α^* for the GP).

A factor of 3 was found to relate PD, GP, and LP hydraulic conductivity estimates. Such differences may be explained by the different water infiltration geometries and sample wetted volume for the three methods. In all cases, the skewness and kurtosis values of the sample distribution indicated that a nonlinear transformation would improve normality. The investigation of the frequency distribution of K_s revealed that a log-normal distribution is acceptable in all three cases, although the PD data also suggest that the hydraulic conductivity may be better described by a power-law relation. The results are not contradictory since the logarithmic transformation belongs to the so called family of power transformations, K_s^q, with $\ln(K_s)$ corresponding to the case $q = 0$.

APPENDIX A

Calculation of K_s from the Philip-Dunne Permeameter Data

Philip (1993) proposed the following nondimensional variables for time (τ), wetted bulb radius (ρ), and water depth inside the pipe (δ),

$$\tau = \frac{8K_s t}{\pi^2 r_o}; \rho = \frac{R}{r_o}; \delta = \frac{3h}{r_o \Delta\theta} \quad \text{(A1)}$$

Equation (1) can then be presented in nondimensional form as,

$$\frac{d\tau}{d\rho} = \frac{3\rho(\rho-1)}{a^3-\rho^3} \quad \text{(A2)}$$

where a is a parameter that gathers the soil and permeameter characteristics

$$a^3 = \frac{3(h_o+\psi_f+\pi^2 r_o/8)}{r_o\Delta\theta} + 1 \quad \text{(A3)}$$

Making use of the initial condition, $\rho = 1$ for

TABLE 7
Performance of De Haro et al. (1998) solution against two alternative procedures

Point No.	K_s-A	K_s-B	K_s-B/K_s-A	K_s-C	K_s-C/K_s-A
27	1.522×10^{-5}	1.522×10^{-5}	1.00	1.516×10^{-5}	1.00
28	1.190×10^{-4}	1.190×10^{-4}	1.00	1.160×10^{-4}	0.97
29	8.602×10^{-5}	8.626×10^{-5}	1.00	8.408×10^{-5}	0.98
30	1.180×10^{-4}	1.200×10^{-4}	1.01	1.170×10^{-4}	0.99
34	1.270×10^{-4}	1.310×10^{-4}	1.03	1.260×10^{-4}	0.99
35	7.426×10^{-5}	7.244×10^{-5}	0.98	7.233×10^{-5}	0.97

$\tau = 0$, (A2) can be integrated to yield the variation of wetted radius with time,

$$\tau = \left(1+\frac{1}{2a}\right)\log\left(\frac{a^3-1}{a^3-\rho^3}\right) - \frac{3}{2a}\ln\left(\frac{a-1}{a-\rho}\right) + \frac{\sqrt{3}}{a} \arctan\left(\frac{a(\rho-1)\sqrt{3}}{2a^2+(\rho+1)a+2\rho}\right) \quad (A4)$$

and of water depth with time (drawdown),

$$\delta = \delta_o - (\rho^3 - 1) \quad (A5)$$

To solve for these equations, Philip proposed the use of two measured times: the time required for the water level to reach the midpoint of the pipe (t_{med}), and the time the tube takes to empty (t_{max}). Using equation (A1) De Haro et al. (1998) showed that the ratio between those two measured times leads to

$$\frac{\tau_{max}}{\tau_{med}} = \frac{t_{max}}{t_{med}} \Rightarrow f(a) = \frac{\tau_{max}}{\tau_{med}} - \frac{t_{max}}{t_{med}} = 0 \quad (A6)$$

where τ_{max}, τ_{med} are calculated from (A4) setting ρ to ρ_{max} or ρ_{med}, respectively, as given by (A5). We can now obtain a solution to the problem by finding the root *a* that satisfies the nonlinear equation $f(a) = 0$. The K_s and ψ_f values are then calculated from (A1) and (A3) as

$$K_s = \frac{\pi^2 r_o \tau_{max}(a)}{8 t_{max}}; \psi_f = \frac{(a^3-1) r_o \Delta\theta}{3} - h_o - \frac{\pi^2 r_o}{8} \quad (A7)$$

A program to calculate K_s can be obtained from the authors. This program finds a root of (A6) using Brent's method (Press et al., 1992). This robust root-finding algorithm requires an initial range of *a* to conduct the search. The upper limit ($a = 20$) was chosen as a value higher than the ones calculated from characteristic properties for a range of soil textures (De Haro et al., 1998). Since $\psi_f > 0$, from (A3) the lower limit for *a* is,

$$a > \left(1+\delta_o+\frac{3\pi^2}{8\Delta\theta}\right)^{1/3} = \left(\rho^3_{max}+\frac{3\pi^2}{8\Delta\theta}\right)^{1/3} > \rho_{max} \quad (A8)$$

If a root was found to lie outside the given boundaries, it was considered ill-behaved, and the data point was rejected.

The performance of the proposed algorithm was tested against two alternative solutions using the data set from the curves included in Fig. 4. A first solution (K_s-A) was obtained from the De Haro et al. (1998) procedure using t_{med} and t_{max} as described above. A second solution (K_s-B) was calculated from a system of two equations, (A4) with t_{max} and t_{med}, and two unknowns, K_s and ψ_f. Finally, the third solution (K_s-C) was calculated by Levenverg-Marquardt nonlinear fitting of (A4) (substituting ρ with (A5) and δ with (A1) against the full drawdown data (*h* vs *t*). The De Haro et al. (1998) procedure gives results almost identical to the other two as shown in Table 7, the differences depending on the tolerance of the root finding and nonlinear fitting algorithms. The advantage of the proposed solution is that it resolves into a root-finding routine that is typically faster and computationally less demanding than a nonlinear fitting procedure, and, thus, it can be implemented easily in an inexpensive pocket computer or programmable calculator.

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