Resolving Structural Influences on Water-Retention Properties of Alluvial Deposits

Kari A. Winfield, John R. Nimmo,* John A. Izbicki, and Peter M. Martin

ABSTRACT

With the goal of improving property-transfer model (PTM) predictions of unsaturated hydraulic properties, we investigated the influence of sedimentary structure, defined as particle arrangement during deposition, on laboratory-measured water retention (water content vs. potential [\(\theta(\psi)\)]) of 10 undisturbed core samples from alluvial deposits in the western Mojave Desert, California. The samples were classified as having fluvial or debris-flow structure based on observed stratification and measured spread of particle-size distribution. The \(\theta(\psi)\) data were fit with the Rossi–Nimmo junction model, representing water retention with three parameters: the maximum water content \(\theta_{\text{max}}\), the \(\psi\)-scaling parameter \(\theta_o\), and the shape parameter \(\lambda\). We examined trends between these hydraulic parameters and bulk physical properties, both textural—geometric mean, \(M_r\), and geometric standard deviation, \(\sigma_g\)—and structural—bulk density, \(\rho_b\), the fraction of unfilled pore space at natural saturation, \(A_e\), and porosity-based randomness index, \(\Phi_c\), defined as the excess of total porosity over 0.3. Structural parameters \(\Phi_c\) and \(A_e\) were greater for fluvial samples, indicating greater structural pore space and a possibly broader pore-size distribution associated with a more systematic arrangement of particles. Multiple linear regression analysis and Mallow’s \(C_p\) statistic identified combinations of textural and structural parameters for the most useful predictive models for \(\theta_{\text{max}}\) including \(A_e, \Phi_c\), and \(\sigma_g\) and for both \(\theta_o\) and \(\lambda\), including only textural parameters, although use of \(A_e\) can somewhat improve \(\theta_o\) predictions. Textural properties can explain most of the sample-to-sample variation in \(\theta(\psi)\) independent of deposit type, but inclusion of the simple structural indicators \(A_e\) and \(\Phi_c\) can improve PTM predictions, especially for the wettest part of the \(\theta(\psi)\) curve.

A more complete accounting for structural effects is critical for the development of property-transfer models that estimate unsaturated hydraulic properties, including water retention, the relation of water content \(\theta\) to water potential \(\psi\), and unsaturated hydraulic conductivity \(K(\theta)\), from easy-to-measure bulk physical properties. Such models typically use particle-size distribution (PSD) and bulk density \(\rho_b\) as their primary inputs (e.g., Gupta and Larson, 1979; Arya and Paris, 1981; Haverkamp and Parlange, 1986). Most PTMs rely on textural effects represented by the PSD. However, in many if not most soils, structural effects are at least equally important. Structure is defined as the arrangement of soil components resulting from aggregate formation, natural depositional sorting, animal burrows, shrink–swell phenomena, root channels, and similar processes.

Bouma (1989) introduced the term pedotransfer function to refer to the transfer of soil textural data into hydraulic data using a regression equation. We use a more general term, property-transfer model (PTM), which applies to soils and deeper sediments and to both classes of such models, empirical and quasiphysical. Empirical models rely on statistical methods to determine patterns among the bulk physical and hydraulic properties. These PTMs typically employ multiple linear regression or neural-network procedures to estimate either \(\theta(\psi)\) or \(K(\theta)\) from textural variables (particle-size statistics or textural-class percentages) and \(\rho_b\). Quasiphysical models are based on theoretical physical relationships between pore sizes and particle or aggregate sizes (Arya and Paris, 1981; Haverkamp and Parlange, 1986; Nimmo, 1997; Haverkamp and Reggiani, 2002). Empirical PTMs can be further subdivided based on the specific approach chosen. One approach involves fitting a parametric \(\theta(\psi)\) function (or set of functions) to the \(\theta(\psi)\) measurements, and developing separate regression equations for each of the \(\theta(\psi)\) parameters (Campbell, 1985; Saxton et al., 1986; Wösten and van Genuchten, 1988; Vereecken et al., 1989; Campbell and Shiozawa, 1992; Schaap et al., 1998). Another involves developing unique equations for \(\theta\) at the values of \(\psi\) determined during measurement of \(\theta(\psi)\) (Gupta and Larson, 1979; Rawls and Brakensiek, 1982; Puckett et al., 1985; Mecke et al., 2002). A third approach uses at least one measured value of \(\theta(\psi)\), in addition to bulk physical properties, as input (Gregson et al., 1987; Schaap et al., 1998).

Measures of structure, besides \(\rho_b\), are seldom included as input to PTMs. Arya and Paris (1981) and Haverkamp and Parlange (1986) used PSD and porosity \(\Phi\) or \(p_b\), as inputs to their models, but did not include additional measures of structure. A modification to the Arya and Paris (1981) model to include aggregate-size distribution as an index of soil structure (Nimmo, 1997) improved agreement between modeled and measured \(\theta(\psi)\) values by \(\Delta R^2 = 12.4\%\), on average, for 17 samples tested. Nimmo (1997) also partitioned \(\Phi\) into textural and structural parts approximating the fraction of \(\Phi\) related to random and nonrandom aspects of structure, respectively. Qualitative structural descriptors collected as part of a soil survey—such as plasticity, stickiness, consistency, pedality, and root density—have been used in some studies for PTM development. Lin et al. (1999a) derived a system that allowed inclusion of soil structure in PTMs by assigning points to four structural categories (initial moisture state, pedality, macroporosity, and root density), in addition to texture. The final “morphometric index” varied between 0 and 1, allowing interrelations among the morphologic features to be examined. Tomasella et al. (2003), Rawls and Pachepsky (2002), and Lin et al. (1999b) found that including some measure of soil struc-
tured, even if qualitative, as input to PTMs led to better predictions of \( \theta(\psi) \) than if textural data were used alone.

Trapped air content at \( \psi = 0 \) may also serve as a structural indicator. It may be taken as \( A_e \), the fraction of the total pore volume that remains air-filled after \( \psi \) has been raised from a negative value to 0 by typical soil-wetting processes. Maximum water contents (\( \theta_{\text{max}} \)) are sometimes estimated from \( \Phi \) using a rule of thumb that \( A_e = 10\% \) for a typical soil (Mualem, 1974). Several researchers have measured the amount of air trapped during ponded infiltration or sprinkler irrigation tests (Fayer and Hillel, 1986; Conant et al., 1988; Faybishenko, 1995). Fayer and Hillel (1986), in controlled water-table fluctuation tests to measure the amount and persistence of air trapping near the water table, and have observed volumetric trapped air contents (\( \Phi A_e \)) ranging from 1.1 to 6.3% of the bulk soil volume. (Some authors report \( A_e \) or \( \Phi A_e \) without giving \( \Phi \) for converting one to the other, so it is necessary to use both quantities in reviewing past work.) The soil profile studied by Fayer and Hillel (1986) graded from a fine sandy loam at the land surface to loamy sand at 1.95 m; the maximum \( A_e \) was 13% at 0.6 m where the median particle size was approximately 0.05 mm and the uniformity coefficient was near 3.5. Conant et al. (1988) found that \( A_e \) ranged from 4 to 19% during lab and field ponded infiltration tests. Packed columns (140 cm long) of well-sorted, commercial-grade medium sand had the largest amount of trapped air (\( A_e = 19\% \), \( \Phi A_e = 5\% \)) in the upper 50 cm of the transmission zone. Faybishenko (1995) found that the amount of trapped air, in laboratory saturation experiments on loam-textured cores, depended on both the direction of wetting and the saturation method. Values of \( \Phi A_e \) were as great as 10% by downward infiltration and <5% for upward wetting. After vacuum saturation, \( \Phi A_e \) decreased to <0.2% for upward wetting. Although the results of these studies agree approximately with the \( A_e = 10\% \) guideline, the materials studied typically were fine sands and loams without significant gravel content. Other researchers (Orlob and Radhakrishna, 1958; Bond and Collins-George, 1981) suggested that the amount of trapped air is related to the range of pore sizes and mean particle size, with more air trapped in materials with broad pore-size distributions and coarse texture. These observations suggest that \( A_e \), being directly related to the particle packing, might be useful as a measure of structure.

A few laboratory studies (Croney and Coleman, 1954; Elrick and Tanner, 1955; Nimmo and Akstin, 1988; Jayawardane and Prathapar, 1992; Perkins, 2003) showed structural effects on hydraulic properties by comparing samples packed to different \( \rho_b \) values or comparing “undisturbed” samples with repacked ones. Croney and Coleman (1954) reported increases in the saturated water content of minimally expansive soils by repacking less densely. The decreased \( \rho_b \) only slightly affected the scaling parameter for water potential, \( \psi_{\text{eq}} \), defined such that scaling \( \psi \) by \( \psi_{\text{eq}} \) equilibrates the \( \psi \) dependence of a set of \( \theta(\psi) \) curves, and strongly steepened the rapid-drainage portion of the \( \theta(\psi) \) curve. Perkins (2003) measured \( \theta(\psi) \) on two deep, aggregated sediment samples in their undisturbed state and after repacking to the same \( \rho_b \). The \( \theta(\psi) \) curves for the repacked samples had smaller (more negative) \( \psi_{\text{eq}} \) values and an increased steepness in the middle range of \( \psi \), reflecting the destruction of macropores associated with aggregation. Other studies of repacked soil columns showed similar effects (Elrick and Tanner, 1955; Nimmo and Akstin, 1988; Jayawardane and Prathapar, 1992), in that packing reduced the heterogeneity of pore sizes, decreased the apparent \( \psi_{\text{eq}} \) value, and steepened the drainage portion of the \( \theta(\psi) \) curve.

Most PTMs available in the literature have been developed for surficial soils, often with characteristics particular to a given site and soil type, such as Lower Coastal Plain Ultisols (Puckett et al., 1985) or glacially derived Podzols (Mecke et al., 2002). Soil structural descriptors found in soil surveys (e.g., root density, plasticity, aggregate-size distribution, pedality, and stickiness) are not usually available for sediments deeper than the zone of soil development. Reliable PTMs for deeper sediments are needed, however, especially with the increasing application of unsaturated hydraulic properties to aquifer recharge and contaminant transport problems. In this study, we considered sediments that are subject primarily to a single structure-forming process, namely depositional sorting of particle sizes. This process results in relatively uncomplicated structural differences whose influence on hydraulic properties may be more systematic than other processes (e.g., biological), and may be more likely to influence both large and small pores.

The natural deposition of particles of various sizes can produce a relatively random sedimentary structure, as in a debris-flow deposit, or a more ordered structure, as in a normally graded fluvial deposit. Such a structural difference is especially relevant in applying PTMs, such as that of Arya and Paris (1981), which are applicable to sandy media and which do not account for particle arrangement. Hypothetical \( \theta(\psi) \) curves are shown in Fig. 1 for an identical particle-size distribution in the two deposit types. In a normally graded fluvial deposit consisting of multiple, well-sorted (i.e., having little variation in particle size) layers with different mean particle sizes, large pores are created adjacent to the largest particles. Therefore graded fluvial samples are expected to have a wide range of pore sizes, reflected in the \( \theta(\psi) \) curve by a gentler slope in the middle range of \( \psi \). In a debris-flow deposit like that in Fig. 1, whether stratified or not, the spaces next to large particles are occupied by smaller particles and large pores are absent. At the other end of the pore-size range, no mechanism exists to make the smallest pores smaller in the debris-flow material. This deposit would thus have a narrower pore-size distribution than a fluvial deposit of identical texture. The larger pores present in normally graded fluvial deposits should cause \( \psi_{\text{eq}} \) to have smaller magnitude than in debris flow deposits. The filling of large voids with small particles in debris flow deposits should also cause \( \Phi \), and likely \( \theta_{\text{max}} \), to be smaller than in fluvial deposits.

Our primary objective was to determine whether structural differences arising from depositional processes could be discerned in the measured \( \theta(\psi) \) curves of...
These structural differences are subtle compared with those of typical agricultural soils of mostly finer texture and significant aggregation, so that such differences are best investigated with methods of high precision and many samples. It is difficult to incorporate both of these features into a single study. In this study we emphasized the accuracy and reliability of measurements, and used several statistical techniques, subject to limitations imposed by a relatively small data set, to explore the bounds within which these types of structural differences may be significant. To investigate the relations between $\theta(\psi)$ properties and bulk physical properties of sediments with different depositional histories, we collected core samples from two washes in the Mojave Desert where both fluvial and debris-flow deposits were known to be present. Field observations near the land surface showed that one wash was dominated by fluvial deposits, the other by debris-flow deposits. Because of uncertainty about the deposit type at depth, and to treat near-surface and deep core samples on an equal basis for comparison, additional means were necessary to distinguish the characteristic depositional history of each sample, and independent indices of the degree of structural difference had to be developed.

A secondary goal, to directly quantify the degree of structural difference in the types of particle arrangement, could not be straightforwardly achieved because textural variations prevented a strict isolation of structure as an independently apparent characteristic of the available samples. Therefore additional statistical analyses were applied to texture-related and structure-related variables to achieve a similar purpose.

**MATERIALS AND METHODS**

**Site Description and Sampling**

Oro Grande (OG) Wash and Sheep Creek (SC) Wash, both part of the upper Mojave River basin of the western Mojave Desert, are ephemeral streams that drain northward from the eastern San Gabriel Mountains of the greater Transverse Range province (Fig. 2). The unsaturated zone in this area ranges in thickness from 400 m near the mountain front to 70 m toward the basin. The San Andreas Fault passes through the headwater regions of these streams along the northern margin of the San Gabriel Mountains.

The recent channel fill of OG Wash consists mainly of reworked alluvial fan deposits. The older sediments adjacent to and underlying the fill are part of the Victorville Fan Complex,
a system of coalesced fans that were shed northward off the San Gabriel Mountains beginning about 1.5 million years ago (Weldon, 1985; Meisling and Weldon, 1989). With movement along the San Andreas Fault, headward erosion of the south-flowing Cajon Creek has beheaded the active fan complex. The source rocks for the Victorville fan deposits consist of schist, granodiorite, and sandstone, which reflect the changing source area as the southern block of the San Andreas moved northwestward (Meisling and Weldon, 1989). Because the source area has been removed by stream capture, parts of the wash have incised into the fan surface to reach the new base-level of the Mojave River, which lies about 1.5 km to the northeast of the lower part of the wash. Sediments along the channel walls near borehole L-1 (Fig. 2) appear to be dominantly fluvial in character, with abundant cross-bed sets and gravel lenses, perhaps from a braided stream environment.

SC Wash is the current trunk stream of the Holocene (Miller and Bedford, 2000) SC fan (Fig. 2), whose source area is located in the San Gabriel Mountains near the town of Wrightwood. Source rocks include a muscovite-quartz-garnet schist known as the Pelona Schist and, to a lesser degree, granite. The Pelona Schist is highly foliated and landslide-prone, and is associated with debris flows and mudflows that have affected Wrightwood (Sharp and Nobles, 1953; Morton and Sadler, 1989) and have reached as far down fan as El Mirage Lake. Along incised portions of the wash (e.g., near Borehole L, Fig. 2), deposits appear to be debris-flow dominated. The incision may have resulted from uplift of the San Gabriel Mountains during the deposition of the fan sediments.

Samples containing a broad range of particle sizes were selected for detecting structural differences of the type shown in Fig. 1. Four boreholes were drilled and core-sampled in 1994, 1995, and 1997 at the lower reaches of the washes (Fig. 2) to depths of approximately 30 m below land surface (Izbicki et al., 1995, 1998, 2000; Izbicki, 1999). Boreholes L and L-1 were drilled directly in the channels and Boreholes L-2 and F were drilled on the adjacent fan surfaces. Two borehole samples from each wash (OGL-1 11.5, OGL-2 82, SCF 57, and SCL 58) were chosen based on textural descriptions in the lithology logs (Izbicki et al., 2000) and their minimally disturbed state. (Note sample nomenclature is as follows: for borehole samples, wash abbreviation followed by borehole number and sample depth in feet; for surficial samples, wash abbreviation followed by sample number, numbered sequentially in order of collection by wash). In 1998, nine shallow core samples were collected along the incised part of each wash. Sampling criteria included apparent texture and deposit type. The collection method involved (i) creating a horizontal bench in the channel wall, (ii) placing a core liner identical to that used for borehole sampling (10-cm diameter, 15-cm length) on the resultant flat surface, and (iii) pushing the liner vertically downward as sediment was carved away from the sample base (Winfield, 2000). For most shallow samples, water was added to the core liners to aid in collection. A subset of three shallow core samples from each wash (OG-1, OG-2, OG-4, SC-1, SC-2, and SC-4) was selected based on apparent textural similarity, determined by measuring PSDs of bulk samples collected adjacent to the core sampling locations. The samples did not display significant aggregation or ped development, and there was no observable caliche, so these samples were suitable for analysis in terms of the simple structural characteristics described above and systematically illustrated in Fig. 3.

Laboratory Methods

Before measuring θ(ψ) curves, samples were wetted from the bottom upward to “natural saturation” by either (i) submerging samples in a dish filled to approximately half-height with the wetting solution or (ii) (for Samples SC-1 and OG-4) adding water incrementally using the controlled-liquid volume apparatus (Fig. 4; Winfield and Nimmo, 2002). For the submerged samples, saturation to θ_{max} was completed when sample weight no longer changed with repeated weighing. With the controlled-liquid volume apparatus, water was added in small amounts (typically 5–15 mL) until the ψ value, indicated by closing off the water supply and switching to a transducer,
was equivalent to about one-half the sample height. Then by either method \( \psi \) would equal zero near the midpoint of the sample. For saturating the samples and measuring \( \theta(\psi) \), the wetting solution consisted of deionized water with calcium chloride (\( \text{CaCl}_2 \cdot 2\text{H}_2\text{O} \)) added to establish a near-natural electrolyte concentration, and sodium hypochlorite (NaOCl) added to inhibit microbial growth in the sample and ceramic pores.

Immediately after saturation, \( \theta(\psi) \) curves were measured by removing water in fixed steps, and allowing the samples to reach equilibrium (\( \psi \) constant with time). For rapid and high-resolution measurement of \( \theta(\psi) \) for \( \psi > -50 \text{kPa} \), water was extracted using the controlled-liquid volume method (Winfield and Nimmo, 2002). Values of \( \psi \) were controlled by extracting with external suction a prescribed amount of water, monitored volumetrically in a burette. After water was extracted, equilibration was initiated by closing off the burette and monitoring \( \psi \) with a transducer. For \( \psi < -50 \text{kPa} \), forced evaporation of water was used to control \( \theta \), with \( \theta \) determined by sample weighing and expressed volumetrically using the measured dry \( \rho_o \) of the sample. At equilibrium, for \(-10\,000 \text{kPa} < \psi < -50 \text{kPa} \), \( \psi \) was measured by the filter paper method (Greacen et al., 1987), using Whatman (Brentford, UK) no. 42 ashless filters. For \( \psi < -10\,000 \text{kPa} \), additional \( \theta(\psi) \) points were measured by evaporating water from small (1 to 3 g) representative splits of the samples in a desiccating chamber and immediately measuring \( \psi \) with a Decagon model CX-2 chilled-mirror hygrometer (Greacen et al., 1992).

For the controlled-liquid volume and filter paper methods, core samples were kept in their original liners to minimize sample disturbance and to retain the influence of structural features. For the hygrometer method, disturbed samples were acceptable because in the dry range of \( \theta(\psi) \) water coats particles as thin films, making structural influences on \( \psi \) negligible.

Bulk physical properties, including PSD, \( \rho_o \) and particle density (\( \rho_p \)), were determined after the \( \theta(\psi) \) measurements were completed. Bulk sample volume was calculated from the dimensions of the core liner after adjusting the core length to account for recesses and protrusions at the sample ends. Samples were then carefully pushed from their liners, cut in half longitudinally, and examined for stratification or other features that would allow classification of the dominant depositional mode (Fig. 3). Samples were oven dried at 105°C, and \( \rho_o \) was calculated from the oven-dry weight and bulk sample volume. Values of \( \rho_p \) were determined by the pycnometer method (Blake and Hartge, 1986), using approximately 5 g of material from the size range < 0.85 mm. Values of \( \Phi \) were calculated as \( 1 - (\rho_p/\rho_o) \). The relative abundance of particles with effective diameters (\( d \)) between 0.85 and 90 mm (for 14 particle-size intervals, or “bins”) was determined by dry sieving, and between \( 4 \times 10^{-5} \) and 0.85 mm (for 107 bins) by optical light scattering (Gee and Or, 2002) with a Coulter LS 230 Series (Beckman Coulter, Fullerton, CA) particle-size analyzer. The bin spacing, \( \Delta d \), is defined as \( \log_{10}(d_{\text{upper}}) - \log_{10}(d_{\text{lower}}) \), where \( d_{\text{upper}} \) represents the upper and \( d_{\text{lower}} \) the lower bin limit. The average \( \Delta d \) changed at 0.85 mm, from 0.0404 for the optical method to 0.1446 for the dry sieve method.

Two other parameters were computed from measured data and used to evaluate structure: \( A_s \), and a porosity-based randomness index (\( \Phi \)). The trapped-air fraction (\( A_s \)) was computed from the difference between the measured \( \Phi \) and \( \theta_{\text{max}} \).

A medium that has more pronounced structure in terms of greater deviation from a random arrangement of particles will in general have greater \( \Phi \). For quantitative emphasis of this effect as a departure from randomness, instead of using \( \Phi \) directly, we use \( \Phi^n \), defined as \( \Phi - 0.30 \). The value 0.30 was chosen as a value exceeded by \( \Phi \) of most granular media, and which approximates \( \Phi \) for particles arranged with perfect randomness (Nimmo, 1997). Negative values of \( \Phi^n \) are possible because it is a difference from an artificially fixed datum.

### Representation of Water-Retention Curves

Measured \( \theta(\psi) \) points were fit with the Rossi and Nimmo (1994) junction model, represented by different functions in each of three segments of the complete \( \theta(\psi) \) curve:

\[
\theta = \theta_{\text{max}} \left[ 1 - e^{\left( \frac{\psi}{\psi_0} \right)^2} \right] \quad 0 \geq \psi \geq \psi_i \tag{1a}
\]

\[
\theta = \theta_{\text{max}} \left( \frac{\psi_i}{\psi} \right)^{\lambda} \quad \psi_i \geq \psi \geq \psi_j \tag{1b}
\]

\[
\theta = \theta_{\text{max}} \ln \left( \frac{\psi_d}{\psi} \right) \quad \psi \geq \psi \geq \psi_d \tag{1c}
\]

where \( \psi_0 \) is the matric potential at which \( \theta = 0 \) (oven-dryness), and \( \lambda, \alpha, \phi_0, \psi_0, \psi_i, \psi_j, \psi_d \) are empirical parameters. This model realistically represents \( \theta(\psi) \) in the driest as well as the wetter ranges. The parabolic function near saturation allows the pore-size distribution [the first derivative of the \( \theta(\psi) \) curve] to be computed without a discontinuity near \( \psi_0 \).

The model includes constraints of continuity and smoothness at the junction points \( \psi_i \), and \( \psi_j \), which link the empirical parameters such that only two of the six, usually taken as \( \lambda \) and \( \psi_i \), are independent. Sometimes \( \psi_0 \) is called the “air-entry” potential, but air actually begins displacing water in the largest pores between \( \psi_i \) and 0 (Fig. 1). The \( \lambda \) parameter indicates the relative steepness of the middle portion of the \( \theta(\psi) \) curve.
RESULTS AND DISCUSSION

Hydraulic and Bulk Physical Properties

The cumulative PSDs for the 10 core samples, divided into groups by wash, are shown in Fig. 5. Bulk physical properties, including \( \rho_g \), \( \rho_s \), texture, textural class percentages, and geometric particle-size statistics (\( M_u \) and \( \sigma_g \)), are summarized in Table 1. On average, SC Wash samples had larger \( \rho_s \) than OG Wash samples because of the greater presence of heavier minerals such as garnet and muscovite (derived from the schistose source rocks). The samples contained significant gravel and ranged in texture from sandy loams to very gravelly sands according to the USDA soil classification system (Soil Survey Staff, 1975).

The \( \theta(\psi) \) curves, including measured points and Ross-Nimmo (1994) junction model fits, are shown in Fig. 6. Measured values of \( \theta_{\text{max}} \), optimized values of \( \lambda \) and \( \psi_{\text{or}} \), and calculated values of \( \psi, \Phi_x \), maximum percentage saturation (\( S_o \)), and \( A_e \) are listed in Table 2. The trapped air fraction \( A_e \) ranged from 2.8 to 35.9\%. Initial \( \theta \) values (\( \theta_{\text{init}} \)) determined immediately before laboratory saturation, are also given in Table 2. The six surficial samples were partially saturated in the field during their collection, so their \( \theta_{\text{init}} \) values were larger. Samples with large

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Descriptive Univariate Statistics

Because sediment PSDs typically follow lognormal distributions (Krumbein, 1938; Pettijohn, 1975), core sample PSDs were characterized using geometric particle-size statistics (geometric mean \( M_u \) and \( \sigma_g \)). We chose the geometric mean rather than the median particle diameter to characterize the PSD because the mean incorporates the influence of all particle sizes, including multiple modes and skewness, on the normal distribution. Values of \( M_u \) were computed using the method of moments (Beyer, 1991):

\[
\log_{10}(M_u) = \frac{\sum_{i=1}^{n} f(d_c) \log_{10}(d_c)}{\sum_{i=1}^{n} f(d_c)} \tag{3}
\]

where \( n \) is the number of bins, \( d_c \) is the geometric center of the ith bin (or \( 10^{\log_{10}(d_{\text{center}}) + \log_{10}(d_{\text{lower}}))} \)), and \( f(d_c) \) corresponds to the frequency of particles occurring within the ith bin assigned to \( d_c \). Values of \( \sigma_g \) were calculated by:

\[
[\log_{10}(\sigma_g)]^2 = \frac{\sum_{i=1}^{n} f(d_c)[\log_{10}(d_c) - \log_{10}(M_u)]^2}{\sum_{i=1}^{n} f(d_c)} \tag{4}
\]

Because \( \Delta d \) of the measured PSD changed at 0.85 mm, a slight discrepancy exists between the statistical values calculated using the unequal, measured bin sizes and the values calculated from a distribution with an equal \( \Delta d \) for the entire range of particle sizes. Values of \( M_u \) and \( \sigma_g \) calculated from the PSDs with the original, irregular bin spacing (average \( \Delta d = 0.052d \)) were compared with those calculated from PSDs where the number of bins was reduced from 121 to 40, so that \( \Delta d \) was equal to 0.16 on average (approximating the \( \Delta d \) of the sieved particle-size fraction). The average difference between these two ways of calculating \( M_u \) was 0.005 mm, with smaller \( M_u \) resulting from the larger \( \Delta d \) (0.16) for all samples. The average difference in \( \sigma_g \) was 0.009, with smaller \( \sigma_g \) for about one-half of the samples. These results indicate that the change in \( \Delta d \) at 0.85 mm does not significantly affect the final values of \( M_u \) and \( \sigma_g \). Scheinost et al. (1997) treated this problem in a similar way and also concluded that the effect of bin size was small.

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Fig. 5. Cumulative particle-size distributions for core samples collected from (a) Oro Grande Wash and (b) Sheep Creek Wash.
Table 1. Summary of core samples collected from Oro Grande (OG) Wash and Sheep Creek (SC) Wash, including depths, measured bulk ($\rho_b$) and particle ($\rho_p$) densities, USDA textural class percentages, and geometric particle-size statistics.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Depth interval</th>
<th>$\rho_b$ (g cm$^{-3}$)</th>
<th>$\rho_p$ (g cm$^{-3}$)</th>
<th>Texture</th>
<th>Particle-size fraction (mm)</th>
<th>Geometric particle-size statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Gravel (2–0.05)</td>
<td>Sand (0.05–0.002)</td>
</tr>
<tr>
<td>OG-1</td>
<td>1.5–1.65†</td>
<td>1.73</td>
<td>2.79</td>
<td>gravelly sand</td>
<td>18.11</td>
<td>79.19</td>
</tr>
<tr>
<td>OG-2</td>
<td>2.4–2.55†</td>
<td>1.70</td>
<td>2.66</td>
<td>gravelly sand</td>
<td>21.38</td>
<td>75.29</td>
</tr>
<tr>
<td>OG-4</td>
<td>4.0–4.15†</td>
<td>1.79</td>
<td>2.65</td>
<td>loamy sand</td>
<td>12.65</td>
<td>71.76</td>
</tr>
<tr>
<td>OG-1 11.5</td>
<td>3.5–3.7†</td>
<td>1.92</td>
<td>2.69</td>
<td>very gravelly sand</td>
<td>20.31</td>
<td>44.93</td>
</tr>
<tr>
<td>OG-2 82</td>
<td>25–25.2</td>
<td>1.83</td>
<td>2.79</td>
<td>loamy sand</td>
<td>8.35</td>
<td>46.73</td>
</tr>
<tr>
<td>SC-1</td>
<td>0.9–1.06†</td>
<td>1.88</td>
<td>2.77</td>
<td>loamy sand</td>
<td>19.98</td>
<td>69.27</td>
</tr>
<tr>
<td>SC-2</td>
<td>0.6–0.75†</td>
<td>1.67</td>
<td>2.77</td>
<td>sand</td>
<td>9.01</td>
<td>84.89</td>
</tr>
<tr>
<td>SC-4</td>
<td>0.6–0.75†</td>
<td>1.80</td>
<td>2.76</td>
<td>gravelly sand</td>
<td>24.80</td>
<td>65.84</td>
</tr>
<tr>
<td>SCF 57</td>
<td>17.38–17.53</td>
<td>1.60</td>
<td>2.74</td>
<td>sandy loam</td>
<td>2.32</td>
<td>56.70</td>
</tr>
<tr>
<td>SCL 58</td>
<td>17.68–17.84</td>
<td>1.93</td>
<td>2.71</td>
<td>sandy loam</td>
<td>8.68</td>
<td>57.03</td>
</tr>
</tbody>
</table>

† Approximate depth below adjacent fan surface. Samples collected along incised portions of SC Wash and OG Wash.

$\theta_{sat}$ values had $A_c$ values ranging from 7.4 to 35.9%; the initial “wet” state of these samples did not correlate with greater $A_c$ ($r = 0.071$).

Seven of the ten $A_c$ values exceeded the 10% guideline. In general, samples with greatest $M_g$ had the greatest $A_c$ values, and samples with greatest $\sigma_g$ had the smallest. Samples OG-1 and OGL-1 11.5, two of the most coarsely textured samples, had the largest $A_c$. Sample OGL-1 11.5 contained a large gravel clast (effective diameter 53 mm, representing about 7% of the bulk sample volume) that increased $M_g$ and $\sigma_g$. Large $A_c$ values may also result from the difficulty in maintaining full saturation as water drains out of the samples before weighing. Unfortunately little experimental work has been done on the effect of wetting rate, which was not completely controlled in our experiments, on the amount of air trapped. Davidson et al. (1966) measured differences in satiated water content ($\theta_{sat}$ after wetting) due to the related issue of wetting pressure-step size. They showed more air was trapped with larger step sizes (analogous to faster wetting), but the differences in $\Phi A_c$ were about 0.03, much smaller than the sample-to-sample differences in our measurements. Our results suggest the typical $A_c$ guideline of 10% may be much too small for coarse-textured alluvial deposits. Expectations for generally lower $A_c$ values may derive from the large body of published data for samples that had been sieved and repacked with gravel removed.

**Sample Classification According to Depositional Environment**

A significant research difficulty arose from the fact that samples from OG Wash displayed debris-flow as well as the expected fluvial structural features and that the converse was true for SC Wash, preventing separation of samples into structural categories independently of observable features of the samples. Both fluvial and debris-flow facies can exist at an individual wash because of possible shifting of positions and local reworking of fan deposits. Therefore, additional means of categorizing the samples were necessary, using combinations of degree of particle-size sorting and stratification, as shown in Fig. 3.

For most samples, the degree of stratification was described by examining the core samples after $\theta(\psi)$ measurement. For Samples OG-4 and SC-1, the degree of stratification was discerned from photographs taken along the channel walls during sample collection. In general, samples with three or more visible layers in...
their 15-cm length were considered well stratified; fewer than this would mean that the sample did not capture a single complete layer.

The degree of particle-size variation within each sample was computed in terms of sorting using sedimentological units $\phi = -\log_2(d)$, where $d$ is effective diameter in millimeters. The cutoff between moderately sorted to well sorted and poorly sorted materials occurs at $1 \phi$, with $\phi < 1$ indicating better sorting (Folk, 1980). Because equivalent sorting definitions do not exist for the geometric standard deviation ($\sigma_g$), we defined the sorting criterion at $\sigma_g = 5$, which approximates a graphical particle-size standard deviation of $2\phi$. Samples with $\sigma_g < 5$ are considered here as well sorted.

Depositional environment was inferred for each type based primarily on degree of sorting. Types 1, 2, and 4A are inferred to represent fluvial materials because each type is characterized by a narrow range of particle sizes either for the entire sample or for individual layers. Types 3 and 4B are inferred to represent debris flow deposits because the range of particle sizes for each layer or for the entire sample is broad. Type 4A, with well-sorted layers, and Type 4B, with poorly sorted layers, are of most interest for determining structural effects on $\psi$, especially for samples of comparable PSDs.

Sample classification results are presented in Table 3. Three samples were identified as fluvial (OG-1, OG-2, and SC-2) and three as debris flow (OGL-1 11.5, OGL-2 82, and SC-1). The remaining four samples could not be classified because of lack of information about sorting within individual layers (Type 4 samples) or about the degree of stratification. Thus there is not enough information to completely correlate observed structural influences as hypothesized in Fig. 1 with features of measured $\psi$ curves. However, the degree of textural and structural influence may be inferred by comparing $\psi$ parameters ($\theta_{\text{max}}$, $\psi_o$, and $\lambda$) with the textural indicators $M_g$ and $\sigma_g$, and the structural indicators $A_c$ and $\Phi_g$.

### Parameter Correlation Analysis

Correlations among the unsaturated hydraulic parameters $\theta_{\text{max}}$, $\psi_o$, and $\lambda$ and the indicators $M_g$, $\sigma_g$, $\psi_o$, and $A_c$ are examined in Fig. 7 and 8, and quantified as correlation coefficients ($r$) in Table 4 for $n = 10$ samples. In this discussion, we make a number of comparisons, a few of which are supported by all or nearly all samples, whereas some are clearly less well supported as general conclusions because data were available for only three each of fluvial and debris-flow samples.

### Table 2. Summary of core-sample hydraulic properties, including initial water content, calculated total porosity, maximum saturated water content, porosity-based randomness index, trapped air fraction of porosity, and optimized water-retention parameters for the Rossi–Nimmo (1994) junction model.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Initial water content†</th>
<th>Total porosity $\Phi$</th>
<th>Porosity-based randomness index‡</th>
<th>Max. water content $\theta_{\text{max}}$</th>
<th>Max. saturation§</th>
<th>Trapped air fraction of porosity§</th>
<th>Scaling parameter for water potential $\psi_o$</th>
<th>Curve-shape parameter $\lambda$</th>
</tr>
</thead>
<tbody>
<tr>
<td>OG-1</td>
<td>0.198</td>
<td>0.379</td>
<td>0.079</td>
<td>0.244</td>
<td>64.4</td>
<td>35.6</td>
<td>−0.746</td>
<td>0.472</td>
</tr>
<tr>
<td>OG-2</td>
<td>0.181</td>
<td>0.359</td>
<td>0.089</td>
<td>0.278</td>
<td>77.4</td>
<td>22.6</td>
<td>−0.997</td>
<td>0.770</td>
</tr>
<tr>
<td>OG-4</td>
<td>0.273</td>
<td>0.323</td>
<td>0.023</td>
<td>0.299</td>
<td>92.6</td>
<td>7.4</td>
<td>−2.789</td>
<td>0.435</td>
</tr>
<tr>
<td>OGL-1 11.5</td>
<td>0.061</td>
<td>0.287</td>
<td>−0.013</td>
<td>0.184</td>
<td>64.1</td>
<td>35.9</td>
<td>−0.464</td>
<td>0.274</td>
</tr>
<tr>
<td>OGL-2 82</td>
<td>0.049</td>
<td>0.343</td>
<td>0.043</td>
<td>0.282</td>
<td>82.2</td>
<td>17.8</td>
<td>−7.839</td>
<td>0.393</td>
</tr>
<tr>
<td>SC-1</td>
<td>0.276</td>
<td>0.321</td>
<td>0.021</td>
<td>0.281</td>
<td>87.5</td>
<td>12.5</td>
<td>−5.101</td>
<td>0.436</td>
</tr>
<tr>
<td>SC-2</td>
<td>0.215</td>
<td>0.397</td>
<td>0.097</td>
<td>0.299</td>
<td>75.3</td>
<td>24.7</td>
<td>−0.848</td>
<td>0.585</td>
</tr>
<tr>
<td>SC-4</td>
<td>0.074</td>
<td>0.350</td>
<td>0.050</td>
<td>0.280</td>
<td>80.0</td>
<td>20.0</td>
<td>−1.478</td>
<td>0.449</td>
</tr>
<tr>
<td>SCF 57</td>
<td>0.042</td>
<td>0.417</td>
<td>0.117</td>
<td>0.396</td>
<td>95.0</td>
<td>5.0</td>
<td>−5.335</td>
<td>0.325</td>
</tr>
<tr>
<td>SCI 58</td>
<td>0.045</td>
<td>0.288</td>
<td>−0.012</td>
<td>0.280</td>
<td>97.2</td>
<td>2.8</td>
<td>−6.504</td>
<td>0.241</td>
</tr>
</tbody>
</table>

† $\theta_{\text{init}}$ is the initial water content before saturation and does not represent the field water content.

‡ $\Phi_g = \Phi - 0.3$.

§ $M_g$ was calculated from the relation $100(\theta_{\text{max}}/\Phi)$. $A_c$ was then calculated as $100 - M_g$.

### Table 3. Sample classification based on the geometric particle-size standard deviation and degree of stratification observed from the core samples after water retention measurement.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Geometric particle-size standard deviation $\sigma_g$</th>
<th>Number of layers†</th>
<th>Sorting description‡</th>
<th>Stratification description§‡</th>
<th>Type§</th>
<th>Inferred depositional environment¶</th>
</tr>
</thead>
<tbody>
<tr>
<td>OG-1</td>
<td>3.34</td>
<td>8</td>
<td>well</td>
<td>well</td>
<td>2</td>
<td>F</td>
</tr>
<tr>
<td>OG-2</td>
<td>4.29</td>
<td>1</td>
<td>well</td>
<td>poor</td>
<td>1</td>
<td>F</td>
</tr>
<tr>
<td>OG-4</td>
<td>6.92</td>
<td>(ND)</td>
<td>poor</td>
<td>(ND)</td>
<td>3 or 4</td>
<td>ND</td>
</tr>
<tr>
<td>OGL-1 11.5</td>
<td>9.49</td>
<td>1</td>
<td>poor</td>
<td>poor</td>
<td>3</td>
<td>D</td>
</tr>
<tr>
<td>OGL-2 82</td>
<td>6.55</td>
<td>2</td>
<td>poor</td>
<td>poor</td>
<td>3</td>
<td>D</td>
</tr>
<tr>
<td>SC-1</td>
<td>7.17</td>
<td>(1)</td>
<td>poor</td>
<td>Poor</td>
<td>3</td>
<td>D</td>
</tr>
<tr>
<td>SC-2</td>
<td>3.88</td>
<td>1</td>
<td>well</td>
<td>poor</td>
<td>1</td>
<td>F</td>
</tr>
<tr>
<td>SC-4</td>
<td>6.72</td>
<td>3</td>
<td>poor</td>
<td>well</td>
<td>4</td>
<td>ND</td>
</tr>
<tr>
<td>SCF 57</td>
<td>6.38</td>
<td>8</td>
<td>poor</td>
<td>well</td>
<td>4</td>
<td>ND</td>
</tr>
<tr>
<td>SCI 58</td>
<td>8.88</td>
<td>4</td>
<td>poor</td>
<td>well</td>
<td>4</td>
<td>ND</td>
</tr>
</tbody>
</table>

† ND = not determined; † indicates observation made from field photographs.

‡ Well-sorted samples have $\sigma_g < 5$. Well-stratified samples have three or more layers.

§ Type refers to the unique combination of sorting and stratification description as shown in Fig. 3.

¶ F, fluvial; D, debris flow.
The $\theta_{\text{max}}$ value increases with decreasing $M_g$ (Fig. 7a), but shows no clear trend with $s_g$ (Fig. 7b), even though one might expect $\theta_{\text{max}}$ to decrease with greater $s_g$, as small particles infill voids near large particles. Samples classified as fluvial do not have consistently greater $\theta_{\text{max}}$ values than debris flow samples, as suggested by Fig. 1.
The increase in \( u_{\text{max}} \) with decreasing \( M_g \) is likely due to structural differences arising from “house of cards” stacking of platy minerals rather than from depositional sorting. Small particles in the SC Wash samples should be platy due to the muscovite-rich source rock.

The \( c_0 \) parameter increases toward zero as \( M_g \) increases (Fig. 7c), consistent with known textural effects on \( u \). Samples classified as fluvial tend to have larger \( c_0 \) values than debris flow samples, possibly due to a greater abundance of structure-related large pores. The fluvial samples, all with large \( M_g \), also follow the general \( c_0 \) vs. \( M_g \) (textural) trend of the entire data set. Smaller \( s_g \) values for fluvial samples may create, on average, larger pores that effectively increase the \( c_0 \) values. Figure 7d illustrates this effect: as \( s_g \) increases, \( c_0 \) usually decreases, suggesting a reduction of pore sizes from small particles occupying voids between large particles.

Greater \( \lambda \) values correspond to increased steepness of the middle range of the \( u \) curve. The correlation between \( \lambda \) and \( M_g \) is weak \((r = -0.032, \text{Table 4})\) overall, consistent with Miller and Miller (1956) similitude theory that a linear scaling of all particle and pore sizes of the medium would not affect \( \lambda \). In one of the more strongly established trends, Fig. 7f shows that \( \lambda \) decreases as \( s_g \) increases, indicating the spread in pore size correlates with the spread in particle size. This trend is consistent with a predominantly textural influence on \( u \), although scatter in the data may result in part from structural influences as well as measurement uncertainty.

The scatter plots (Fig. 7) and correlation coefficients (Table 4) show that the \( \theta(\psi) \) parameters (\( \theta_{\text{max}}, \psi_0, \) and \( \lambda \)) are, as expected, influenced by texture, represented by \( M_g \) or \( s_g \). Of these parameters, \( M_g \) strongly affects \( \theta_{\text{max}} \) and \( \psi_0 \), while \( s_g \) strongly affects \( \lambda \). Structural influences are suggested, however, in that the fluvial samples have consistently larger (closer to zero) \( \psi_0 \) values and larger \( \lambda \) values than nearly all other samples. Both of these structural trends are consistent with the hypotheses in

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Fig. 8. Structural variables compared with maximum water content (\( u_{\text{max}} \)) and Rossi–Nimmo (1994) fit parameters (\( \psi_0 \) and \( \lambda \)). Scatter plots show comparisons with (a, d, g) bulk density (\( \rho_b \)); (b, e, h) trapped air fraction of porosity (\( A_e \)); and (c, f, i) porosity-based randomness index (\( F_s \)), for \( n = 10 \) samples. Symbols indicate sample categories of Fig. 3, with results for individual samples listed in Table 3. Solid symbols represent fluvial samples and open symbols represent debris flow samples.
Scaling parameter for water potential, $r$, and $l$ (among hydraulic parameters. The “all possible subsets” approach was best able to explain the variation in the hydraulic parameters. The candidates for “best” model typically have the highest $R^2$ per $p$ variable subset. Mallow’s $C_p$ suggests the best subset of explanatory variables for each response variable, by comparing computed $C_p$ values to the criterion of $C_p = p + 1$. Values of $C_p < p + 1$ (i.e., $\Delta C_p = C_p - p - 1$ is negative) indicate that the model is overspecified, or that more explanatory variables are included in the regression variate than are necessary to fit the data.

Multiple linear-regression analyses were conducted using custom programs written with Matlab (The MathWorks, Inc., Version 6, Release 12) and the Statistics Toolbox utility. In Table 5, the set of explanatory variables with the highest $R^2$ is shown for each $p$ variable subset. The best set for each of the parameters $\theta_{\text{max}}$, $\psi_o$, and $\lambda$ (underlined in Table 5) had a calculated $C_p$ value closest to the criterion $p + 1$ while preserving the smallest number of explanatory variables. For $\theta_{\text{max}}$, the best model occurred for $p = 3$, and included $A_e$, $\Phi_s$, and $\sigma_g$. For $\psi_o$, the best model was for $p = 2$, and included $M_g$ and $\sigma_g$. This model was slightly overspecified (calculated $C_p = 1.56 < p + 1 = 3$). Although $C_p$ for the four-variable model was closest to the $C_p$ criterion ($\Delta C_p = 0.88$), this model was not chosen because the slight improvement in fit it may have offered was insufficient to justify the use of two more explanatory variables. For $\lambda$, the best subset involved $\sigma_g$ only.

Some ambiguity in the use of $C_p$ for selecting the best subset is often encountered in the approach using all possible regressions. However, an alternative approach, backward elimination of variables, produced the same best subsets of explanatory variables for $\theta_{\text{max}}$, $\psi_o$, and $\lambda$. Backward elimination starts from the complete set of explanatory variables, with subsequent removal of variables (one at a time) until an optimum variate is achieved. Removing a variable requires testing whether any of the partial $t$ values of the coefficients for the

### Table 4. Correlation coefficients between water retention parameters and indicators of texture or structure.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>$M_g$</th>
<th>$\sigma_g$</th>
<th>$\rho_b$</th>
<th>$A_e$</th>
<th>$\Phi_s$</th>
<th>$\sigma_g$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Max. saturated water content, $\theta_{\text{max}}$</td>
<td>$-0.777^{**}$</td>
<td>$-0.232$</td>
<td>$-0.662^*$</td>
<td>$-0.716^*$</td>
<td>$0.645^*$</td>
<td></td>
</tr>
<tr>
<td>Scaling parameter for water potential, $\psi_o$</td>
<td>0.663*</td>
<td>$-0.384$</td>
<td>$-0.247$</td>
<td>0.713*</td>
<td>0.156</td>
<td></td>
</tr>
<tr>
<td>Shape parameter, $\lambda$</td>
<td>$-0.032$</td>
<td>$-0.776^{**}$</td>
<td>$-0.519$</td>
<td>0.289</td>
<td>0.458</td>
<td></td>
</tr>
<tr>
<td>$M_g$</td>
<td>1</td>
<td>$0.221$</td>
<td>0.281</td>
<td>$0.778^{**}$</td>
<td>$0.338$</td>
<td></td>
</tr>
<tr>
<td>$\rho_b$</td>
<td>$0.754^*$</td>
<td>1</td>
<td>$-0.334$</td>
<td>$-0.778^{**}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_e$</td>
<td>1</td>
<td>$-0.006$</td>
<td>$-0.955^{***}$</td>
<td>0.060</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>$\Phi_s$</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significant at the 0.05 level of probability.
** Significant at the 0.01 level of probability.
*** Significant at the 0.001 level of probability.

Fig. 1. Textural influences on the fluvial samples are also evident; these samples, in general, have larger $M_g$ values and are better sorted (with smaller $\sigma_g$ values) than the debris-flow samples. Structural influence on the fluvial samples is suggested by data in Table 2; on average, $A_e$ values were 28% for fluvial samples and 22% for debris-flow samples. This difference goes in the expected direction if greater variation in pore size correlates with greater air trapping, but a larger data set is needed to establish the significance of this trend.

This study’s second objective, quantifying structural differences, would ideally be accomplished by comparing samples with identical PSDs. The PSDs of samples vary too much for this objective to be accomplished through direct comparison, but structure in this study vary too much for this objective to be accomplished through direct comparison, but structure may be evaluated in terms of $A_e$ or $\Phi_s$ values.

The relations among the $\theta(\psi)$ parameters ($\theta_{\text{max}}$, $\psi_o$, and $\lambda$) and the structural parameters ($\rho_b$, $A_e$, and $\Phi_s$) are shown in Fig. 8. As expected, and to a large extent required for self-consistency, $\theta_{\text{max}}$ tends to decrease with increasing $\rho_b$ and $A_e$ and tends to increase with $\Phi_s$. Among these, $A_e$ most strongly correlates with $\theta_{\text{max}}$ ($r = -0.716$; Table 4). The strong correlation of $\Phi_s$ with $\rho_b$ ($r = -0.955$) is necessary by definition, and thus not of interest. Although trends for $\psi_o$ are less clear, $\psi_o$ most strongly correlates with $A_e$ ($r = 0.713$), increasing toward zero as $A_e$ increases (Fig. 8e). Values of $\lambda$ decrease with smaller $\rho_b$ ($r = -0.519$), but have no clear trends for $A_e$ or $\Phi_s$.

The fluvial samples SC-2, OG-1, and OG-2 have greater $A_e$ values than all other samples except the coarsest sample, OGL-1 11.5, suggesting structural influences that are not obvious from Fig. 7 and 8, and that accord with the hypothetical relationships in Fig. 1. The fluvial samples had larger $\Phi_s$ values than all other samples except SCF 57, also consistent with the expected structural trends.

### Regression Analysis

Multiple linear-regression analyses were conducted to determine which of the textural and structural parameters were best able to explain the variation in the hydraulic parameters. The “all possible subsets” approach (Draper and Smith, 1981; Rawlings et al., 1998) was used to determine the best set of explanatory variables (among $M_g$, $\sigma_g$, $\rho_b$, $A_e$, and $\Phi_s$) for estimating each of the three hydraulic parameters ($\theta_{\text{max}}$, $\psi_o$, and $\lambda$). All possible multiple linear-regression equations involving the potential explanatory variables are computed (for $2^m - 1$ equations, where $m$ is the maximum number of potential explanatory variables, i.e., $m = 5$ in our application), and statistics such as the coefficient of determination ($R^2$), adjusted $R^2$ ($R^2_{\text{adj}}$), residual mean square, and Mallow’s $C_p$ are evaluated. Results are grouped according to the number of variables in the equation ($p$) and ordered from highest to lowest $R^2$. The best model occurred for $p = 3$, and included $A_e$, $\Phi_s$, and $\sigma_g$. This model was slightly overspecified (calculated $C_p = 1.56 < p + 1 = 3$). Although $C_p$ for the four-variable model was closest to the $C_p$ criterion ($\Delta C_p = 0.88$), this model was not chosen because the slight improvement in fit it may have offered was insufficient to justify the use of two more explanatory variables. For $\lambda$, the best subset involved $\sigma_g$ only.

Some ambiguity in the use of $C_p$ for selecting the best subset is often encountered in the approach using all possible regressions. However, an alternative approach, backward elimination of variables, produced the same best subsets of explanatory variables for $\theta_{\text{max}}$, $\psi_o$, and $\lambda$. Backward elimination starts from the complete set of explanatory variables, with subsequent removal of variables (one at a time) until an optimum variate is achieved. Removing a variable requires testing whether any of the partial $t$ values of the coefficients for the
Table 5. Stepwise regression results.

<table>
<thead>
<tr>
<th>Response variable</th>
<th>$p^t$</th>
<th>$R^2$</th>
<th>$C_p^+$</th>
<th>$F$</th>
<th>Explanatory variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_{\max}$</td>
<td>1</td>
<td>0.604</td>
<td>707.02</td>
<td>12.22</td>
<td>$M_e$</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.987</td>
<td>18.80</td>
<td>273.11</td>
<td>$A_e$, $\Phi_e$</td>
</tr>
<tr>
<td></td>
<td>3§</td>
<td>0.996</td>
<td>4.71</td>
<td>535.67</td>
<td>$A_e$, $\Phi_e$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.998</td>
<td>4.00</td>
<td>561.84</td>
<td>$\rho_b$, $A_e$, $\Phi_e$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.998</td>
<td>6.00</td>
<td>359.60</td>
<td>$\rho_b$, $A_e$, $\Phi_e$, $M_e$, $\sigma_g$</td>
</tr>
<tr>
<td>$\psi_o$</td>
<td>1</td>
<td>0.508</td>
<td>4.33</td>
<td>8.27</td>
<td>$A_e$</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.735</td>
<td>1.56</td>
<td>9.72</td>
<td>$M_e$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>3§</td>
<td>0.793</td>
<td>2.34</td>
<td>7.68</td>
<td>$A_e$, $\Phi_e$, $G_s$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0.804</td>
<td>4.12</td>
<td>5.11</td>
<td>$\rho_b$, $A_e$, $M_e$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>0.810</td>
<td>6.00</td>
<td>3.40</td>
<td>$\rho_b$, $A_e$, $\Phi_e$, $G_s$, $\sigma_g$</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>1</td>
<td>0.602</td>
<td>1.64</td>
<td>12.09</td>
<td>$\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0.671</td>
<td>2.31</td>
<td>7.14</td>
<td>$\Phi_e$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0.761</td>
<td>2.59</td>
<td>6.36</td>
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<td></td>
<td>4</td>
<td>0.791</td>
<td>4.00</td>
<td>4.74</td>
<td>$\rho_b$, $A_e$, $\Phi_e$, $G_s$, $\sigma_g$</td>
</tr>
<tr>
<td></td>
<td>5§</td>
<td>0.791</td>
<td>6.00</td>
<td>3.04</td>
<td>$\rho_b$, $A_e$, $\Phi_e$, $G_s$, $\sigma_g$</td>
</tr>
</tbody>
</table>

* Significant at the 0.05 level of probability.
** Significant at the 0.01 level of probability.
† Number of explanatory variables in model, excluding intercept term.
‡ Mallow’s $C_p$ statistic is computed from $2(p + 1) - n + \frac{n \cdot S\Sigma M_{res}}{S\Sigma x^2}$, where $n$ is the number of observations, $S\Sigma M_{res}$ is the residual sum of squares for the $p$ variable model being tested, and $S\Sigma x^2$ is an estimate of the population variance (calculated from the $p$ variable model containing all possible variables). The $C_p$ value of a particular subset that most closely approaches the criterion $C_p = p + 1$ may indicate the “best” subset of $x$ variables. Values of $C_p < p + 1$ indicate model overspecification.
§ Underlined values indicate the “best” subset selected for $\theta_{\max}$, $\psi_o$, and $\lambda$.

Variables in the regression variate are significantly different from zero. The partial $t$ value is calculated by dividing the coefficient determined for each explanatory variable during the regression process by its standard error. The variable whose partial $t$ value is the lowest is removed from the regression equation, and a new regression equation is developed from the smaller subset of explanatory variables. For $\theta_{\max}$, $M_e$ was the first variable removed using backward elimination, followed by $\rho_b$. For $\psi_o$, the first variable eliminated was $\Phi_e$, followed by $\rho_b$ and $A_e$. For $\lambda$, the variables were eliminated in the following order until $\sigma_g$ was left as the only significant variable: $\Phi_e$, $\rho_b$, $A_e$, $M_e$. The coefficients for the explanatory variables included in the best regression equations for $\theta_{\max}$, $\psi_o$, and $\lambda$ were all significantly different from zero at a significance level of 0.05.

For $\theta_{\max}$ examination of the goodness of fit of the models in the regression analysis allows further interpretation of the trends noted above, that correlation is strongest with $M_e$, $\rho_b$, $A_e$, and $\Phi_e$. The trend with $M_e$ is noteworthy because of its fundamental independence of $\theta_{\max}$. Regression analysis shows that although $M_e$ ($R^2 = 0.604$) is the best choice for a one-variable model of $\theta_{\max}$, fit improved as much as 39% for the two- and three-variable models that included $A_e$, $\Phi_e$, and $\sigma_g$. The correlations with $A_e$ and $\Phi_e$ must be discounted because $\theta_{\max}$ is arithmetically determined by these parameters, although other structural indicators not used in this study may have predictive value.

For $\psi_o$, which correlated most strongly with $A_e$ followed by $M_e$ (Table 4), the one-variable model included $A_e$, although the variation was best explained by the combination of textural parameters $M_e$ and $\sigma_g$, with $R^2 = 0.735$. The addition of $A_e$ in the equation for $p = 3$ improved the model fit by 6%. The strong collinearity between $M_e$ and $A_e$ ($r = 0.778$), however, makes this model less desirable than the one involving only $M_e$ and $\sigma_g$. Overall, these results suggest that structural information implicit in $A_e$ has value in a PTM.

For $\lambda$, which correlated most strongly with $\sigma_g$, a one-variable model involving $\sigma_g$ best explained the variation in $\lambda$ ($R^2 = 0.602$). Adding more variables provided only slight improvements in model fit and overspecified the model by the $C_p$ criterion, even though the $R^2$ was only 0.602 for $p = 1$.

Although the data set is small, regression results suggest that in addition to textural information, structural indicators may be useful as explanatory variables to predict $\theta(\psi)$. Most noteworthy is the potential value of $A_e$ for explaining the variation in $\psi_o$. Independent determination of $A_e$ (e.g., from field studies) may prove useful for estimating $\theta_{\max}$.

SUMMARY AND CONCLUSIONS

Property-transfer models are generally based more strongly on textural than on structural indicators, and are often considered to work best in media composed primarily of randomly arranged particles, as frequently is true of sands. We explored the validity of these generalizations and the possible benefits of incorporating structural indicators into PTMs for the case of structural influences deriving from the mode of sediment deposition. Because of systematic differences in particle arrangement arising from distinct depositional processes, investigation of structural effects due to deposition is simpler and in some ways more instructive than those due to aggregation or biotic processes. For this evaluation we measured water retention [$\theta(\psi)$] curves on 10 undisturbed core samples from washes in the western Mojave Desert. Samples were categorized as originating from fluvial or debris flow environments by analyzing the stratigraphy of the cores and by comparing $\sigma_f$ for the bulk sample. Textural ($M_e$ and $\sigma_g$) and structural ($\rho_b$, $A_e$, and $\Phi_e$) parameters were used as candidate explanatory variables in parameter-correlation and multiple linear-regression analyses to evaluate possible improvements in predictions of $\theta(\psi)$ parameters ($\theta_{\max}$, $\psi_o$, and $\lambda$) over texture-based PTMs.

Texture had greater influence than structure on the $\theta(\psi)$ properties of our samples. Values of $\theta_{\max}$ and $\psi_o$ correlated strongly with $M_e$ ($r = -0.777$ and $r = 0.663$, respectively), whereas $\lambda$ correlated best with $\sigma_g$ ($r = -0.776$). Values of $\psi_o$, correlated strongly with the structural indicator $A_e$ ($r = 0.713$), and $\lambda$ correlated weakly with all of the structural indicators ($r < -0.519$). Most $A_e$ values exceeded the general guideline of 10% and correlated significantly with texture, being greater for coarser material.

Other evidence of structural influence is apparent in that debris flow samples generally had smaller $\Phi_e$ and $A_e$; the three fluvial samples ranked in the four highest values of both $\Phi_e$ and $A_e$. Smaller $\Phi_e$ indicates a more random structure (Nimmo, 1997), which is expected
from the more rapid, disorderly deposition of debris flows. Smaller \( A_p \) may correlate with a narrower pore-size distribution (Orlob and Radhakrishna, 1958; Bond and Collins-George, 1981), likewise a probable characteristic of debris flows. For predictions, the best one-variable model for \( \phi_s \) was based on \( A_p \left( R^2 = 0.508 \right) \), although the best \( \psi_s \) model overall involved \( M_g \) and \( \phi_s \left( R^2 = 0.735 \right) \). While the evidence in this study indicates only a slight influence of structure on \( \psi \), it should be noted that structure-affecting mechanisms associated with differences in depositional environment (Fig. 1) are subtle compared with those associated with aggregation and macropores.

The development of more general and improved PTMs that can be applied to multiple sites, and that are based on theoretical relationships between the bulk physical and hydraulic properties, will benefit from improved knowledge of structural effects, perhaps quantified by \( A_p \), \( \Phi_s \), or related parameters. Further work might explore the influence of structural mechanisms such as that of smaller particles infilling large pores next to large particles (for randomly structured media like debris-flow deposits). While not precluding the role of texture as the primary basis for PTMs for sandy media, we have shown that supplemental use of the simple structural indicators \( A_p \) and \( \Phi_s \) can improve PTM predictions.

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