

Article

Permeability of Saturated Sands and Gravels: Pore Constriction Size Perspective

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Abstract. This study re-analyzes saturated permeability data for sands and gravels to identify the key predictors. The dataset (76 tests) is evaluated against void ratio, specific surface area, mean pore size, and mean constriction size. The strongest correlation is found with mean constriction size. Based on this finding, the validated and refined predictive permeability model is proposed using mean constriction size as a representative parameter. The uncertainty and statistical analysis of the model indicates promising accuracy and reliability in predicting permeability for the dataset. The model is applicable for soils with coefficient of uniformity (C_u) up to 76 and effective particle size (D_{10}) up to 6 mm.

Keywords: Sand, gravel, particle-size distribution, constriction size, permeability.

1. Introduction

Soil permeability, often referred to as hydraulic conductivity, is described as the rate at which water flows through a soil mass. In non-plastic materials such as sands and gravels, permeability plays a pivotal role in various geotechnical engineering applications. It significantly influences water movement within slopes, thereby impacting slope stability (Likitlersuang et al. [1]; Latief et al. [2]; Mase et al. [3]; Ngo et al. [4], [5]), liquefaction of sand (Mase et al. [6], [7]) and controls seepage through geo-structures such as earth dams and embankments (Li and Desai [8]; Athani et al. [9]).

The saturated permeability (k) of non-plastic soils can be estimated using various theoretical and empirical methods, which typically relate permeability to soil properties such as particle size, void ratio, specific surface area, and pore geometry (e.g., Hazen [10]; Kozeny [11]; Carman [12]; Carrier [13]; Chapuis and Aubertin [14]; Chapuis [15]; Chapuis [16]; Indraratna et al. [17]). The following section summarizes several commonly used equations that link permeability to key material parameters, including particle size, specific surface area, and void ratio.

Hazen's equation [10] highlights the significant influence of the finer fraction. This equation is applicable to a loose state of sands with a coefficient of uniformity ($C_U = D_{60}/D_{10}$, where D_{60} and D_{10} are diameters of particle-size equivalent to 60% and 10% finer, respectively) less than or equal to 5 and D_{10} values in between 0.1 mm and 3 mm. Its accuracy hinges on meeting conditions: the soil is sand, which is in a loose state (void ratio, e , is nearly maximum void ratio, e_{max}), $C_U \leq 5$, and $0.1 \text{ mm} \leq D_{10} \leq 3 \text{ mm}$. A common reference in textbooks is Hazen [18], widely cited in textbooks, proposed the predictive equation:

$$k = C_H D_{10}^2 \quad (1)$$

where k is the permeability (in cm/s), C_H is an empirical coefficient that varies with water temperature (T in °C, where $C_H = 1.50$ when $T = 20^\circ \text{C}$) and D_{10} is the effective particle size (in mm).

The Kozeny-Carman equation, derived from Kozeny [11] and Carman [12], models porous media as a collection of tubes and relies on the assumption of laminar fluid flow within these conduits, as described by Poiseuille's law. Therefore, the equation relates permeability to void ratio and specific surface area (S_s) and of the porous media. Chapuis [16] presented a revised form of the Kozeny-Carman equation:

$$k = C_{KC} \frac{g}{\mu_w \rho_w} \frac{e^3}{S_s^2 G_s^2 (1+e)} \quad (2)$$

where C_{KC} is a dimensionless parameter that accounts for the geometry of the porous space ($C_{KC} \approx 0.2$, suggested by Carrier [13], Chapuis and Aubertin [14], and Taylor et al. [19]), g is gravitational constant ($\approx 9.81 \text{ m/s}^2$), μ_w is water

viscosity (in kg/m.s), ρ_w is the water density (in kg/m³), G_s is soil specific gravity of ($G_s = \rho_s/\rho_w$), ρ_s is soil density (in kg/m³). The experiment is conducted in a controlled environment with an average water temperature of 20 °C, yielding $\rho_w = 998.2 \text{ kg/m}^3$, and $\mu_w = 1.002 \times 10^{-3} \text{ kg/m.s}$.

The Kozeny-Carman equation is notable for its attempt to relate permeability to fundamental soil properties such as specific surface area and void ratio, which is fundamentally linked to particle size and its distribution. However, its applicability is mainly limited to coarse-grained soils like sands. Studies have shown that the equation performs less reliably for fine-grained soils such as clays due to factors not adequately captured by the model (Carrier [13]; Chapuis and Aubertin [14]).

Chapuis [15] proposed a predictive equation for the permeability (in cm/s) of homogenized, fully saturated specimens tested under laboratory conditions. This equation, correlating $(D_{10})^2 e^3/(1+e)$ with estimated permeability, is also applicable to granular materials. The method provided reasonable predictions for soils having D_{10} in between 0.003 mm and 3 mm and e greater than 0.3. The predictive equation is:

$$k = 2.4622 \left(\frac{D_{10}^2 e^3}{1+e} \right)^{0.7825} \quad (3)$$

The permeability of granular materials is fundamentally controlled by the interconnected network of pore spaces that allows water to flow through, rather than being determined by individual particle sizes, specific surface area, and void ratio (Kovacs [20]; Kenney et al. [21]; Trani and Indraratna [22]; Indraratna et al. [17]). This highlights the importance of considering overall pore geometry and tortuosity when developing accurate models for seepage in granular materials. Permeability is thus a direct consequence of these interconnected pore characteristics, which can be effectively explained by the dimensions of the pore constrictions within granular materials. The statistical distribution of these constrictions is characterized by the constriction-size distribution (CSD) (e.g., Indraratna and Raut [23]; Indraratna et al. [24]; Raut and Indraratna [25]). Therefore, CSD provides a fundamental link between soil microstructure and its macroscopic hydraulic behavior.

Indraratna et al. [17] proposed an empirical relationship to estimate permeability (in mm/s) from the mean constriction size (D_{mc} , in mm), representing the characteristic dimension of the narrowest flow paths:

$$k = 36.91 (D_{mc})^{1.644} \quad (4)$$

It is noted that the model proposed by Indraratna et al. [17] provided good predictions for soils with D_{10} values ranging from 0.10 to 9.60 mm and C_U values between 1.07 and 7.10.

Although the permeability of sands and gravels is widely recognized to be governed by their interconnected

pore network, predictive models that explicitly incorporate this feature remain limited in literature. To address this gap, the present study undertakes a comprehensive re-evaluation of 76 published laboratory permeability tests on sands and gravels, covering a broad range of particle-size distributions and densities. The compiled dataset is used to develop a relationship between saturated permeability and microscopic pore geometry, represented by pore constriction size. Furthermore, the study assesses the predictive performance of existing permeability models for granular soils.

2. Data Compilation

Table 1 summarizes the test conditions and key parameters of the permeability database used for this reanalysis. This database includes 76 laboratory permeability test results on saturated sands and gravels, obtained from rigid-wall and flexible-wall permeameters and compiled from existing published sources (USDA, [26]; Sherard et al., [27]; Tsai, [28]; Indraratna et al., [17]; Feia et al., [29]; Prasomsri et al., [30]). The database covers remolded deposits ranging from silts to coarse gravels (including mixtures) with varying densities (loose and dense). Notably, the source publications provided all essential data for permeability estimation, such as void ratio, particle-size distribution curve (PSD) and relative density (R_d).

2.1. Sand Tested by USDA [26] and Sherard et al. [27]

USDA [26] and Sherard et al. [27] presented permeability data from tests on 14 different sands and gravels, classified under ASTM D2487-11 [31] as SP, SW, GP, and GW. These materials, ranging from fine sands to fine gravels, are commonly used in dam filters and drains. These materials, characterized by D_{10} values between 0.15 and 9.60 mm and C_U from 1.40 to 37, were tested in a constant head rigid wall permeameter.

Permeability was determined by approximately 0% and 70% of relative densities. While minimum and maximum dry densities [$\gamma_{d(min)}$ and $\gamma_{d(max)}$] were obtained from the USDA [26], the specific gravity was not given in the publications. Therefore, a value of 2.65 is assumed for all soils in this analysis to estimate void ratio. It was noted that seepage tests on specimens 11-14 showed turbulent flow and a decrease in permeability as the hydraulic gradient increased. The permeability values in Table 1 were obtained at a small hydraulic gradient of 0.1. Their publication mentioned the saturation procedure; however, the specific degree of saturation achieved for each specimen remained unreported.

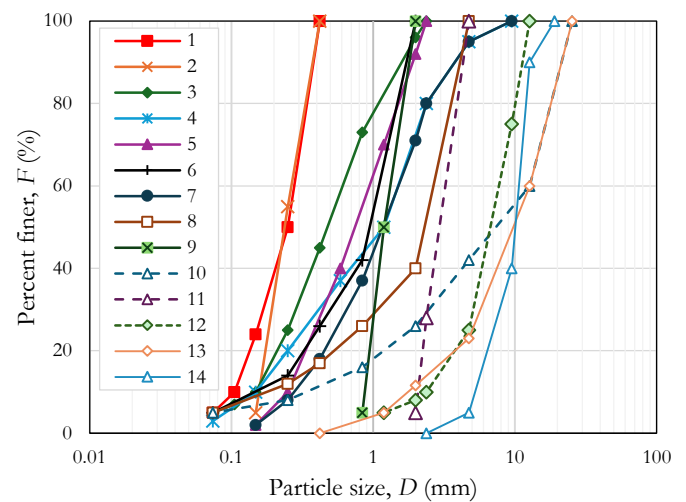


Fig. 1. PSD curves of materials used in permeability testing reported by USDA [26] and Sherard et al. [27].

2.2. Sands and Gravels Tested by Tsai [28]

Tsai [28] publication detailed permeability measurements from constant head tests performed on 22 sand and gravel specimens, whose PSDs are illustrated in Fig. 2. These materials, ranging from fine to coarse, exhibited D_{10} values between 0.16 mm and 0.45 mm, and C_U values from 1.28 to 2.21.

Permeability was evaluated at approximately 84% and 100% relative densities. Furthermore, the study included data on dry unit weight ($\gamma_d = 1.59 - 1.83 \text{ g/cm}^3$) and specific gravity ($G_s = 2.65 - 2.67$), which allows for the determination of void ratios. Notably, although the saturation procedure was mentioned, the specific degree of saturation achieved for each specimen was not reported.

2.3. Sand Tested by Indraratna et al., [17]

Indraratna et al. [17] used a rigid-wall permeameter and the constant head method to test sand specimens. The investigation included six distinct soil particle-size distributions (G1, G2, G3, G4, G5, and G6), illustrated in Fig. 3, which exhibited C_U between 1.51 and 4.03. These sands shared a D_{10} values of 0.3 mm and had particle sizes of 0.075 - 4.75 mm. Their G_s ranged from 2.605 to 2.612, while $\gamma_{d(min)}$ and $\gamma_{d(max)}$ differed from 1.431 to 1.506 g/cm^3 and 1.617 to 1.779 g/cm^3 , respectively. The corresponding dry densities and void ratios were directly obtained from the publication.

Table 1. Selected permeability test data and their key parameters.

Test ID	PSD	C_U	D_{10} (mm)	G_s	R_d	e	S_s (m ² /kg)	D_{cm} (mm)	k (mm/s)
USDA [26] and Sherard et al. [27]									
1	1	2.70	0.11	2.65	0.02	0.68	13.96	0.073	0.180
2	1	2.70	0.11	2.65	0.70	0.52	13.96	0.044	0.060
3	2	1.70	0.16	2.65	0.00	0.70	10.54	0.083	0.250
4	2	1.70	0.16	2.65	0.69	0.55	10.54	0.051	0.180
5	3 (Rounded)	3.90	0.15	2.65	0.00	0.53	9.56	0.129	0.194
6	3 (Rounded)	3.90	0.15	2.65	0.70	0.40	9.56	0.076	0.106
7	3 (Angular)	3.90	0.15	2.65	0.24	0.74	9.56	0.111	0.318
8	3 (Angular)	3.90	0.15	2.65	0.71	0.49	9.56	0.075	0.035
9	4	10.00	0.15	2.65	0.00	0.43	8.03	0.190	1.200
10	4	10.00	0.15	2.65	0.67	0.32	8.03	0.111	0.088
11	5	3.60	0.25	2.65	0.00	0.56	6.12	0.182	0.490
12	5	3.60	0.25	2.65	0.70	0.43	6.12	0.109	0.220
13	6	7.40	0.15	2.65	0.00	0.52	8.92	0.189	0.300
14	6	7.40	0.15	2.65	0.70	0.37	8.92	0.112	0.260
15	7 (Rounded)	5.50	0.28	2.65	0.00	0.48	4.55	0.261	0.512
16	7 (Rounded)	5.50	0.28	2.65	0.70	0.35	4.55	0.151	0.388
17	7 (Angular)	5.50	0.28	2.65	0.00	0.65	4.55	0.261	1.517
18	7 (Angular)	5.50	0.28	2.65	0.70	0.41	4.55	0.151	0.265
19	8	14.40	0.18	2.65	0.00	0.46	4.92	0.196	2.40
20	8	14.40	0.18	2.65	0.70	0.34	4.92	0.110	0.95
21	9	1.40	0.87	2.65	0.00	0.71	2.22	0.427	5.60
22	9	1.40	0.87	2.65	0.69	0.59	2.22	0.263	2.50
23	10	37.00	0.34	2.65	0.00	0.38	4.90	0.407	7.80
24	10	37.00	0.34	2.65	0.46	0.31	4.90	0.227	1.40
25	11	1.40	2.08	2.65	0.00	0.70	0.93	1.058	38.1
26	11	1.40	2.08	2.65	0.69	0.60	0.93	0.650	26.0
27	12 (Rounded)	3.10	2.38	2.65	0.00	0.71	0.62	1.693	53.9
28	12 (Rounded)	3.10	2.38	2.65	0.70	0.50	0.62	1.017	46.2
29	12 (Angular)	3.10	2.38	2.65	0.00	0.80	0.62	1.693	84.5
30	12 (Angular)	3.10	2.38	2.65	0.54	0.56	0.62	0.176	18.8
31	13	7.10	1.76	2.65	0.02	0.54	0.77	1.378	56.1
32	13	7.10	1.76	2.65	0.71	0.41	0.77	0.795	18.1
33	14 (Rounded)	2.00	5.26	2.65	0.00	0.73	0.35	3.128	121.5
34	14 (Rounded)	2.00	5.26	2.65	0.69	0.55	0.35	1.914	87.2
35	14 (Angular)	2.00	5.26	2.65	0.00	0.91	0.35	3.128	127.6
36	14 (Angular)	2.00	5.26	2.65	0.59	0.66	0.35	2.105	97.9
Tsai [28]									
37	1a	2.21	0.16	2.65	0.99	0.47	9.10	0.049	0.250
38	1b	2.21	0.16	2.65	0.88	0.52	9.08	0.058	0.220
39	1c	2.21	0.16	2.65	0.96	0.50	9.07	0.056	0.270
40	1d	2.21	0.16	2.65	0.97	0.50	9.03	0.063	0.240
41	1e	2.21	0.16	2.65	0.99	0.49	8.99	0.098	0.290
42	2a	1.33	0.45	2.65	0.98	0.67	3.95	0.098	1.680
43	2b	1.33	0.22	2.65	0.97	0.59	7.23	0.063	0.311
44	2c	1.29	0.22	2.65	0.95	0.57	8.69	0.085	0.254
45	2d	1.31	0.21	2.65	0.95	0.55	8.90	0.084	0.257
46	2e	1.33	0.16	2.65	0.98	0.50	11.12	0.093	0.129
47	3a	1.35	0.16	2.65	0.98	0.47	10.96	0.055	0.124
48	3b	1.35	0.16	2.65	1.00	0.48	11.13	0.051	0.133
49	3c	1.34	0.16	2.65	0.97	0.45	11.27	0.054	0.135
50	3d	1.34	0.16	2.65	0.96	0.54	11.40	0.054	0.126
51	4a	1.40	0.21	2.65	0.84	0.53	9.02	0.068	0.218
52	4b	1.38	0.21	2.65	0.90	0.53	9.10	0.069	0.171
53	4c	1.36	0.21	2.65	0.98	0.52	9.16	0.062	0.233
54	4d	1.34	0.21	2.65	0.92	0.54	9.21	0.066	0.240
55	4e	1.32	0.21	2.65	0.90	0.55	8.93	0.093	0.257
56	4f	1.30	0.21	2.65	0.95	0.54	9.06	0.103	0.247
57	4g	1.29	0.21	2.65	0.96	0.52	9.12	0.095	0.241
58	4h	1.28	0.21	2.65	0.98	0.57	9.23	0.092	0.279

Table 1. continued.

Test ID	PSD	C_U	D_{10} (mm)	G_s	R_d	e	S_s (m ² /kg)	D_{cm} (mm)	k (mm/s)
Indraratna et al. [17]									
59	G1	1.51	0.30	2.61	0.53	0.71	6.00	0.102	0.609
60	G2	2.00	0.30	2.61	0.55	0.66	5.11	0.122	0.759
61	G3	2.64	0.30	2.61	0.47	0.66	4.59	0.146	0.942
62	G4	3.16	0.30	2.60	0.47	0.62	4.26	0.154	1.029
63	G5	3.60	0.30	2.61	0.44	0.62	4.12	0.184	1.131
64	G6	4.03	0.30	2.61	0.47	0.61	3.88	0.175	1.364
Feia et al. [29]									
65	NE34	1.50	1.37	2.65	0.94	0.58	13.25	0.035	0.064
66	HN31	1.30	0.25	2.65	0.91	0.70	7.74	0.059	0.094
67	HN34	1.60	0.15	2.65	0.87	0.76	12.45	0.039	0.068
68	HN34	2.30	0.16	2.65	0.90	0.65	8.85	0.052	0.092
Prasomsri et al. [30]									
69	K10	45.77	0.05	2.65	0.07	0.67	18.88	0.063	0.086
70	K10	45.77	0.05	2.65	0.27	0.59	18.88	0.055	0.077
71	K10	45.77	0.05	2.65	0.53	0.50	18.88	0.044	0.060
72	K10	45.77	0.05	2.65	0.53	0.50	18.88	0.044	0.059
73	K20	75.69	0.05	2.65	0.34	0.60	14.29	0.090	0.200
74	K20	75.69	0.05	2.65	0.34	0.60	14.29	0.090	0.220
75	K20	75.69	0.05	2.65	0.59	0.51	14.29	0.071	0.150
76	K20	75.69	0.05	2.65	0.78	0.45	14.29	0.057	0.130

Note: C_U is coefficient of uniformity; PSD is particle-size distribution; S_s is specific surface area calculated using method proposed by Chapuis and Aubertin [14].

2.4. Sand Tested by Feia et al. [29]

Feia et al. [29] investigated the permeability of two distinct sands, using four different PSDs, namely Fontainebleau (NE34), Hostun I (HN31), Hostun II (HN34), and Hostun III (HN34), as shown in Fig. 3. Fontainebleau sand was categorized as sub-rounded, whereas Hostun sand was sub-angular.

They utilized a flexible wall permeameter under various constant confining pressures and applied the constant head method to fully saturated specimens. The tested sands exhibited D_{10} values of about 0.15 mm to 1.37 mm and C_U values between 1.3 and 2.3. With G_s of 2.65, the minimum and maximum void ratios (e_{min} and e_{max}) for these sands varied from 0.557 to 0.696 and 0.884 to 1.145, respectively. The publication provided the relationship between post-consolidation void ratio and permeability, allowing for the back-calculation of R_d based on the given e_{min} and e_{max} .

2.5. Sand Tested by Prasomsri et al. [30]

Prasomsri et al. [30] examined the permeability of two non-plastic, well-graded sands, designated K10 and K20. The sands were produced by combining twelve sieve fractions, spanning a range of 0.025 mm to 5 mm, obtained from eight distinct non-plastic silica sands (Silica Nos. 1 through 8). The constituent sand particles were noted to be sub-angular to angular in shape. Their PSDs are illustrated in Fig. 3.

Key properties of the sand included D_{50} value of 1.54 mm and C_U value of 45.80 for K10, a D_{50} value of 3.02 mm and a C_U value of 75.70 for K20. G_s was found to be 2.645. $\gamma_{d(max)}$ reported for K10 and K20 were 1.947 g/cm³ and 1.906 g/cm³, respectively. The specimens were saturated under a high back pressure of 400 kPa, ensuring a B-value greater than 0.95 to indicate full saturation.

Given the availability of the compaction curve in the publication, the relative density for each test was estimated using the correlation between relative compaction (R_c) and R_d proposed by Lee and Singh [32] as in Eq. (5).

$$R_c = 80 + 0.2R_d \quad (5)$$

$$R_c = \frac{\gamma_d}{\gamma_{d(max)}} \quad (6)$$

$$R_d = \frac{e_{max} - e}{e_{max} - e_{min}} = \frac{\gamma_{d(max)} - \gamma_d}{\gamma_{d(max)} - \gamma_{d(min)}} \quad (7)$$

where R_c and R_d are in percent.

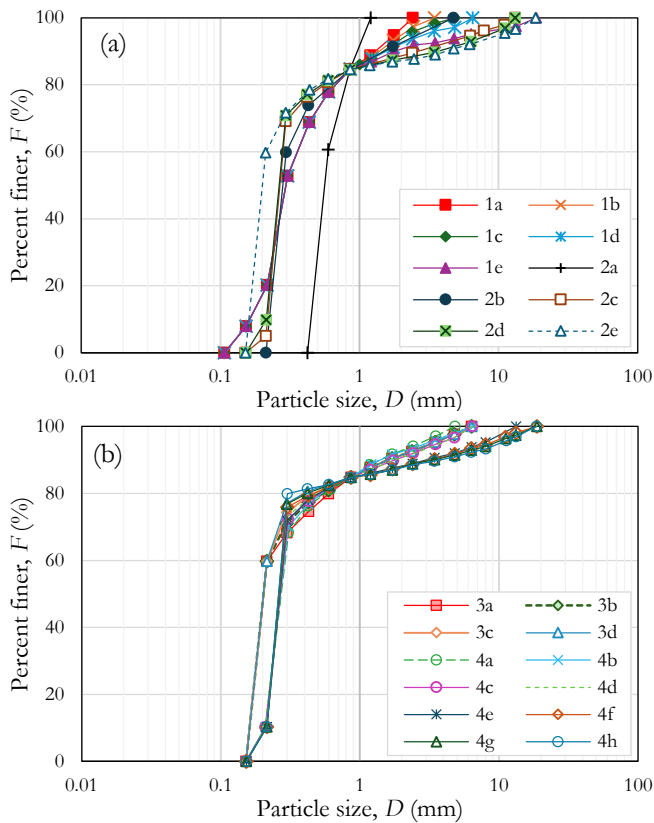


Fig. 2. PSD curves of materials used in permeability testing reported by Tsai [28]: (a) groups 1a-1e and 2a-2e; (b) groups 3a-3d and 4a-4h.

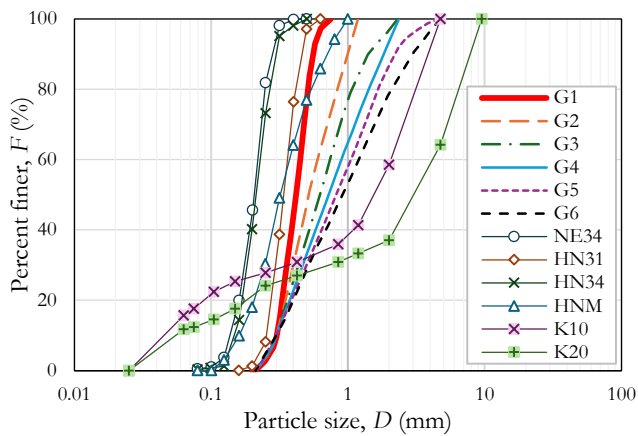


Fig. 3. PSD curves of materials employed in permeability tests, as reported by Indraratna et al. [17] (G1-G5), Feia et al. [29] (NE34, HN31, HN34, HNM), and Prasomsri et al. [30] (K10, K20).

2.6. Permeability and Void Ratio

Figure 4 illustrates the database from Table 1 plotted with all linear-log scale combinations, revealing linear relationships between $\log(k)$ and $\log(e)$ for individual datasets. Generally, the data suggests that permeability tends to increase with void ratio within a specific soil type. However, certain permeability tests present a contrasting observation. For instance, the data from Indraratna et al. [17] demonstrate that soils with larger void ratios (characterized by larger pore sizes) consistently exhibit lower permeability compared to soils with smaller void

ratios (smaller pore sizes). In addition, data from Feia et al. [29] and Prasomsri et al. [30] exhibits the low permeability with high void ratio. This can be attributed to the presence of finer particles (which reduce the pore constriction sizes) even when the void ratio is high. The finer particles in soil mass may obstruct pore throats and cause flow retention, thereby reducing permeability. This highlights that void ratio alone is insufficient to characterize flow behavior, and that pore constriction size, governed by particle gradation and fines content, is a critical factor.

Moreover, the scattered relationship of permeability and void ratio relation indicates a poor linear correlation, as supported by the low coefficients of determination (R^2) with value of 0.28. Based on these observations, it appears that void ratio or porosity alone is not a reliable predictor for fluid transport within the granular material.

Indeed, the Kozeny-Carman model, Eq. (2), emphasizes the significance of pore size over void ratio or porosity in predicting fluid flow. This relationship is rooted in the single capillary tube concept described by the Hagen–Poiseuille equation (Sutera and Skalak, [33]).

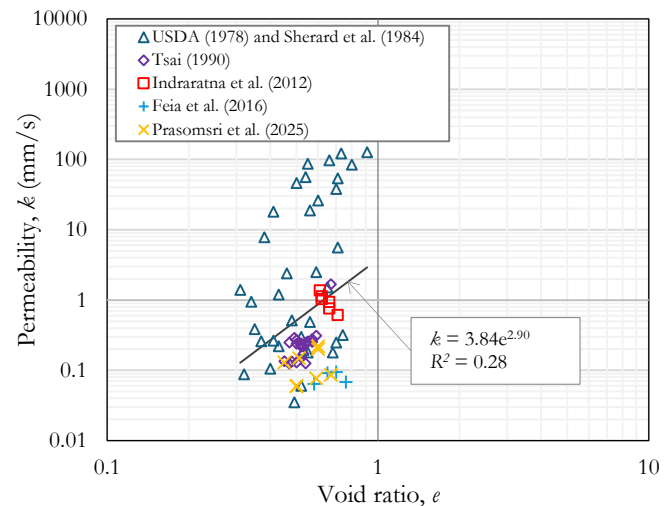


Fig. 4. Permeability versus void ratio.

2.7. Permeability and Pore Size

As noted above, pore size—rather than void ratio or porosity alone—appears to be the primary control on fluid flow through granular materials. This observation necessitates a quantifiable parameter that effectively represents pore size within the soil matrix. Consequently, Phadnis and Santamarina [34] and Ren and Santamarina [35] proposed that the mean pore size (d_p) (in mm) can be estimated from the specific surface area (S_s , in m^2/kg), void ratio (e), and the mass density of the soil solids (ρ_s , in kg/m^3), as follows:

$$d_p = 2 \frac{e}{S_s \rho_s} \quad (8)$$

While specific surface area is a key parameter in Eq. (8), it is rarely evaluated in soil mechanics. However, several predictive equations offer practical alternatives by

estimating the specific surface area from the available PSD data. For instance, Chapuis and Légaré [36] introduced a method based on simple geometric considerations for non-plastic soils. For a spherical particle with diameter D (in mm), or a cubic particle with side length D , the specific surface area, S_s (in m^2/kg) is given by:

$$S_s(D) = \frac{6}{D\rho_s} \quad (9)$$

where ρ_s is soil density (in kg/m^3). For fine-grained non-plastic soils, Chapuis and Légaré [36] recommended using Eq. (9) as follows:

$$S_s = \frac{6}{\rho_s} \sum \left(\frac{P_{\text{No } D} - P_{\text{No } d}}{D} \right) \quad (10)$$

where $(P_{\text{No } D} - P_{\text{No } d})$ is the percentage of mass of particles passing size D but retained on size d . Chapuis and Aubertin [14] suggested that the equivalent size (D_{eq}) defined as the smallest particles with respect to specific surface area:

$$D_{eq}^2 = \frac{D_{min}^2}{3} \quad (11)$$

where D_{min} is measurable smallest particle size (in mm).

Most studies presented in Table 1 do not report the specific surface area in this re-analysis. Therefore, we have undertaken an estimation using supplementary data from other published soil descriptions using the well-established method proposed by Chapuis and Légaré [36] and Chapuis and Aubertin [14]. To illustrate this estimation procedure, Table 2 presents the estimation of the specific surface area of soil no. 3, derived from its PSD according to USDA [26] and Sherard et al. [27].

Table 2. Specific surface (S_s) estimation for a sand specimen ($\rho_s = 2650 \text{ kg}/\text{m}^3$) based on particle-size distribution curve “3” from USDA [26] and Sherard et al. [27].

Size (mm)	Passing (%)	Difference X ($P_{\text{No } D} - P_{\text{No } d}$)	S_s (m^2/kg)	XS_s (m^2/kg)
2.38	100			
2.00	96	0.04	1.13	0.05
0.84	73	0.23	2.70	0.62
0.42	45	0.28	5.39	1.51
0.25	25	0.2	9.06	1.81
0.149	10	0.15	15.20	2.28
0.105	7	0.03	21.56	0.65
0.074	5	0.02	30.60	0.61
0.0427		0.05	52.99	2.65

Note: Specific surface area (S_s) is calculated as $\Sigma(XS_s) = 10.17 \text{ m}^2/\text{kg}$. Eq. (11) gives $D_{eq} = 0.0427 \text{ mm}$.

As shown in Fig. 5, there is a strong linear correlation between the logarithm of permeability and specific surface area, with a coefficient of determination $R^2 = 0.90$.

Furthermore, Fig. 6 reveals a similar strong linear relationship ($R^2 = 0.89$) between the logarithms of permeability and mean pore size. These findings align with the strong relationships observed by Ren and Santamarina [35] across various soils. The stronger correlation between permeability and specific surface area and mean pore size (Figs. 5 and 6) compared to permeability and void ratio (Fig. 4) highlights the greater influence of pore size characteristics over bulk porosity in controlling fluid flow through granular materials.

3. Pore Constriction Size

In sands and gravels, pore constriction sizes refer to the narrowest passages within the interconnected pore network. As water flows through this network, it encounters these randomly distributed constrictions, which are considered the primary control on permeability. This subsection outlines a potential approach for estimating the dimensions of these pore constrictions based on the soil's particle-size distribution.

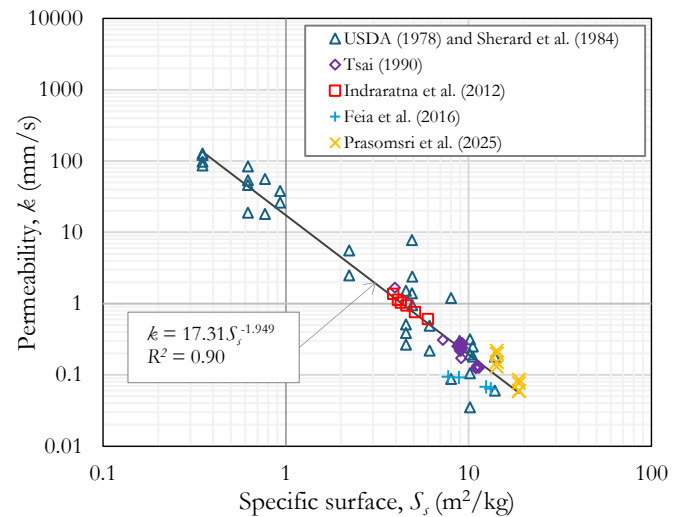


Fig. 5. Permeability versus specific surface.

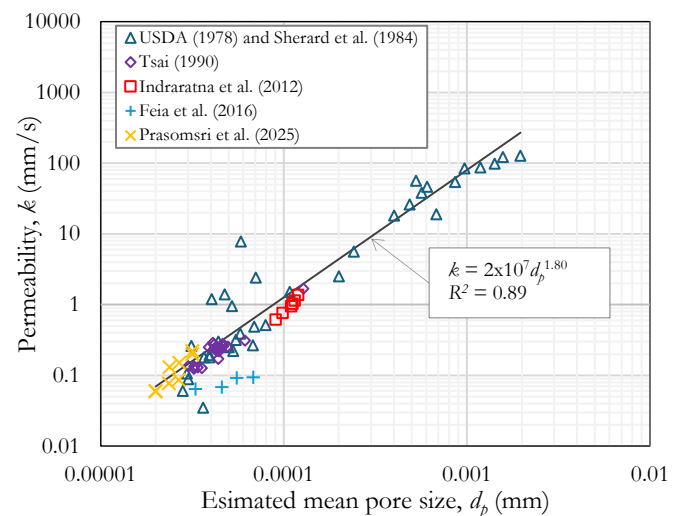


Fig. 6. Permeability versus mean pore size.

3.1. Pore Constriction Size Distribution: Probabilistic Approach

Analytical probabilistic methods for calculating the constriction-size distribution (CSD) in sands and gravels typically focus on identifying the largest “inscribed circle” that fits within the spaces formed by three or four idealized circular soil particles, as depicted in Fig. 7. The inscribed circle method, established by Silveira et al. [37], computes the densest and loosest possible CSDs by considering combinations of three and four touching circular particles. The likelihood of particles with an assumed diameter producing a constriction depends on PSD by number. For the densest possible packing, illustrated in Fig. 7(a), Silveira et al. [37] determined the constriction size, denoted as D_{cd} .

$$\left(\frac{2}{D_1}\right)^2 + \left(\frac{2}{D_2}\right)^2 + \left(\frac{2}{D_3}\right)^2 + \left(\frac{2}{D_{cd}}\right)^2 = 0.5 \left[\left(\frac{2}{D_1}\right) + \left(\frac{2}{D_2}\right) + \left(\frac{2}{D_3}\right) + \left(\frac{2}{D_{cd}}\right) \right]^2 \quad (12)$$

where D_1 , D_2 , and D_3 represent diameters of circular particles in the densest packing.

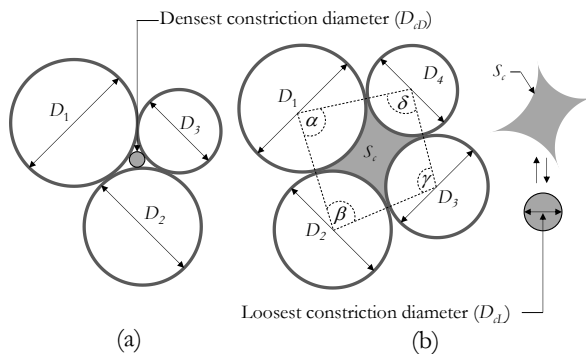


Fig. 7. Particle combinations used to calculate constriction sizes (a) “densest” packing of three circular particles; (b) “loosest” packing of four circular particles, where D_1 , D_2 , D_3 and D_4 represent soil particle diameters; S_c is the inter-particle contact area; and α , β , γ , and δ are angles formed by lines connecting the centers of four particles in their loosest packing arrangement.

The probability ($\bar{p}$) of a constriction having size D_{cd} is:

$$\bar{p} = \frac{3!}{r_1!r_2!r_3!} (p_1)^{r_1} (p_2)^{r_2} (p_3)^{r_3} \quad (13)$$

where p_1 is probability of a particle with diameter D_1 , and similarly for p_2 (diameter D_2) and p_3 (diameter D_3). This probability can be derived from PSD by number, surface area or volume, depending on the specific implementation. The values of r_1 , r_2 and r_3 represent the number of times D_1 , D_2 , and D_3 , respectively, appear in each arrangement, with the constraint that $r_1 + r_2 + r_3 = 3$.

The equivalent diameter (D_{cl}) representing the loosest possible packing constriction is determined by the maximum surface area (S_c) formed between four touching soil particles, as illustrated in Fig. 7(b). This S_c is calculated using the following equation:

$$S_c = \frac{1}{8} [(D_1 + D_2)(D_1 + D_4)\sin\alpha + (D_2 + D_3)(D_2 + D_4)\sin\gamma - (\alpha D_1^2 + \beta D_2^2 + \gamma D_3^2 + \delta D_4^2)] \quad (14)$$

where the diameters D_1 , D_2 , D_3 , and D_4 characterize the particles in the loosest packing, and their associated angles α , β , γ , and δ are geometrically constrained within the plane.

The equivalent diameter (D_{cl}), which characterizes the loosest packing, is calculated using the following equation:

$$D_{cl} = \sqrt{\frac{4S_c}{\pi}} \quad (15)$$

Because the centers of the four particles (D_1 , D_2 , D_3 , and D_4) are highly unlikely to be coplanar, a correction factor of 0.82, which is the mean chord length (Silveira et al., [33]), is generally applied to the constriction size calculated previously. Consequently, the probability $\bar{p}$ of constrictions being of size D_{cl} is:

$$\bar{p} = \frac{4!}{r_1!r_2!r_3!r_4!} (p_1)^{r_1} (p_2)^{r_2} (p_3)^{r_3} (p_4)^{r_4} \quad (16)$$

As depicted in Fig. 8, for a granular material characterized by a PSD curve with n discrete (D_1 , D_2 , D_3 , ..., D_n) and their likelihoods of occurrence (p_1 , p_2 , p_3 , ..., p_n), the characteristic particle sizes representing the densest (D_{cd}) and loosest (D_{cl}) states, along with their associated probabilities, are obtained by considering all possible unique combinations of these particles.

Locke et al. [38] highlighted that using PSD by mass or number can lead to inaccuracies in characterizing CSD in certain scenarios. Consequently, using surface area-based soil PSD is likely the most suitable approach for constriction size analysis. Furthermore, granular soil typically exists in a state between their maximum and minimum densities.

According to Locke et al. [38], the actual constriction size (D_c) for granular soils, within the full range of relative densities (R_d) from loosest to densest, can be determined by:

$$D_c = D_{cd} + P_c(1 - R_d)(D_{cl} - D_{cd}) \quad (17)$$

where the real constriction size (D_c) for a given percentage finer (P_c) is determined relative to the constriction sizes of the densest (D_{cd}) and loosest (D_{cl}) models at that same P_c .

Indraratna et al. [17] introduced the mean constriction size (D_m) as a parameter to characterize CSD curve of the soil, calculated with the following equation:

$$D_{mc} = \frac{\sum_{i=1}^n P_{ci} D_{ci}}{\sum_{i=1}^n P_{ci}} \quad (18)$$

where D_{ci} is constriction sizes ($D_{c1}, D_{c2}, D_{c3}, \dots, D_{cn}$) and P_{ci} are their corresponding probabilities of occurrence ($P_{c1}, P_{c2}, P_{c3}, \dots, P_{cn}$), as shown in Fig. 9.

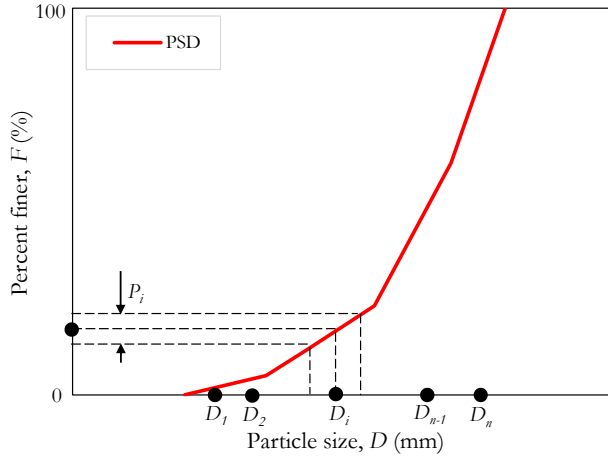


Fig. 8. Discretized PSD curve shows the probability of occurrence (P_i) for various particle sizes (D_i) in a granular material.

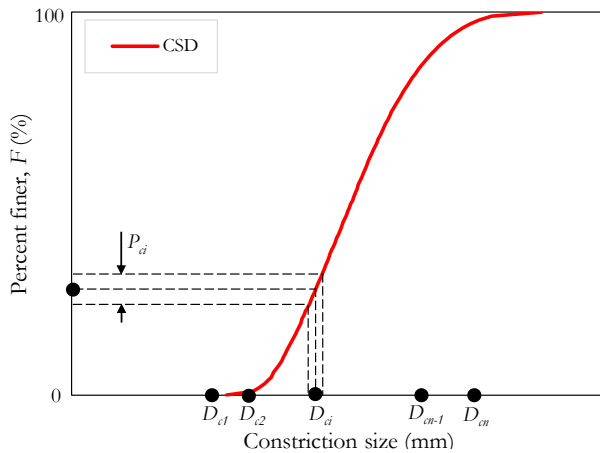


Fig. 9. Discretized CSD curve of a granular material.

3.2. Validation of Constriction Size Distribution Implementation

This study implements the inscribed circle method for CSD measurement using a custom MATLAB subroutine. The MATLAB subroutine discretizes the PSD curve and calculates the constriction sizes for the densest (three-particle) and loosest (four-particle) packings using Eqs. (12)-(16). The actual constriction size for a given

relative density is then computed by linear interpolation (Eq. (17)). The CSD is then used to compute the mean constriction size (Eq. (18)). Figure 10 illustrates CSD curves generated for a given soil PSD at relative densities of 40%, 70%, and 100%. As anticipated, increased density resulted in smaller constriction sizes and, consequently, lower permeability.

To validate the developed MATLAB subroutine, its output is compared with experimental CSD data obtained through micro-CT scanning by Taylor et al. [19]. Their investigation provided PSD and experimental CSD data for glass beads and sands with uniformity coefficients $C_U = 1.5$ (Beans-Cu1.5 and Sand-Cu1.5) and $C_U = 3.0$ (Beans-Cu3 and Sand-Cu3), prepared using dry deposition at relative densities of approximately 50–70%. For a relative density of 70%, the calculated CSDs show good agreement with the experimental data (Fig. 11), confirming the validity of the probabilistic approach—especially when based on surface area PSD. It is acknowledged that the validation is based on four examples and suggests that more validation with experimental CSD (e.g., from micro-CT) is needed in future.

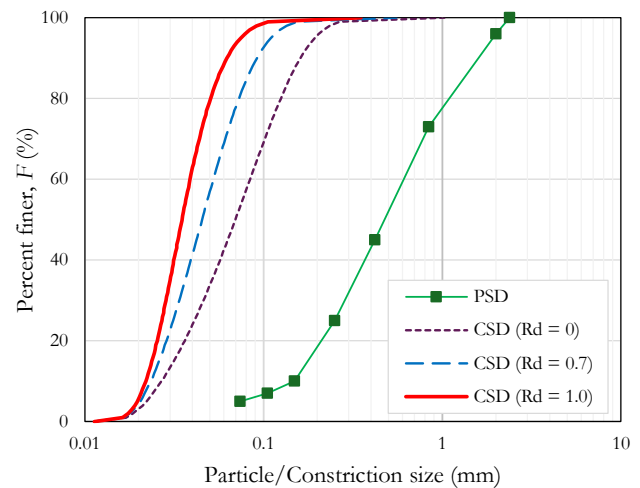


Fig. 10. CSDs calculated from PSD of soil no “3” (USDA [26]; Sherard et al. [27]) for various relative densities.

4. Permeability and Pore Constriction Size

We propose that the distribution of pore constriction sizes—intrinsically related to particle size distribution (PSD) and material density—offers a more fundamental and reliable basis for predicting permeability than conventional approaches that rely solely on single particle size metrics or void ratio. This section explores the quantitative correlation between pore constriction size distribution and the permeability of granular materials.

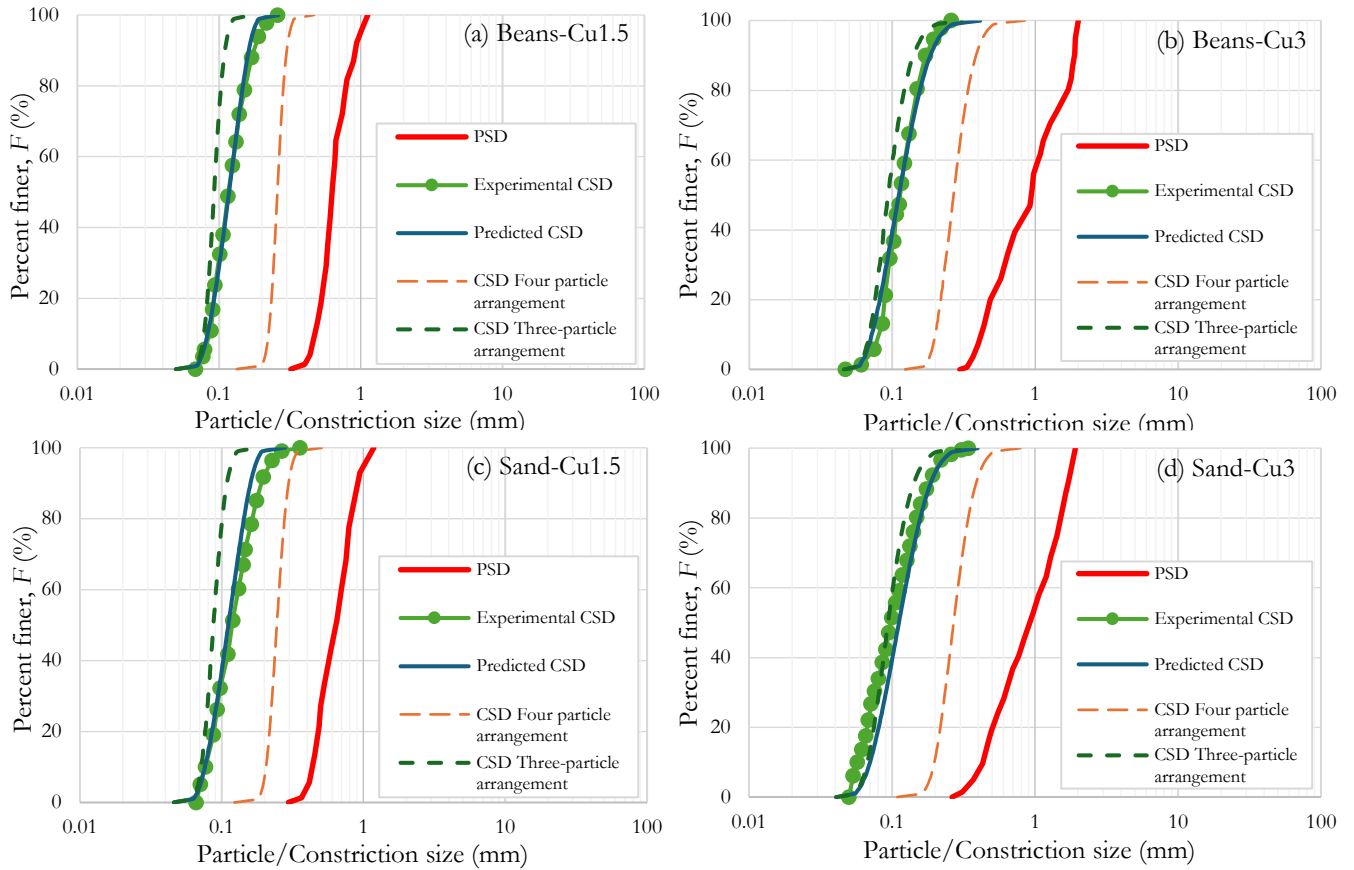


Fig. 11. Comparison of the CSD at 70% relative density with the experimental CSD from Taylor et al. [19]: (a) Beans-Cu1.5, (b) Beans-Cu3, (c) Sand-Cu1.5, (d) Sand-Cu3.

Following the CSD determination procedure outlined in Section 3 and employing Eq. (18), we calculate the D_{mc} for each test based on the PSD curve and relative density. Table 1 summarizes the calculated D_{mc} values together with their corresponding saturated permeability values, which were obtained from laboratory experiments. The values of D_{mc} are plotted against permeability k and fitted using a power function as shown on Fig. 12. The results reveal a strong linear relationship on a logarithmic scale. This suggests that a generalized power function effectively describes the relationship between mean constriction size and permeability, finding consistent with Indraratna et al. [17]. Best-fit parameters from statistical analysis of the 76 datasets in Table 1 are as follows:

$$k = 24.37(D_{mc})^{1.848} \quad (19)$$

5. Performance of Permeability Prediction Models

This section evaluates the accuracy and reliability of the proposed permeability model (Eq. (19)) in comparison with several widely cited prediction models from the literature (Eqs. (1)–(4)). Table 3 lists the statistical analysis results, which evaluate across four key indicators; Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2).

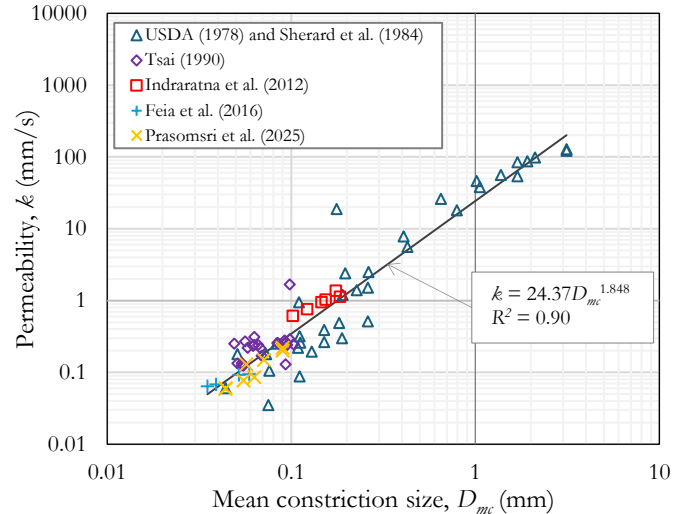


Fig. 12. Permeability versus mean constriction sizes.

Mean Absolute Error (MAE) quantifies the average magnitude of the errors between predicted values (P_i) and the measured values (M_i), which is expressed as:

$$MAE = \frac{1}{n} \sum_{i=1}^n |M_i - P_i| \quad (20)$$

Mean Squared Error (MSE) is used for evaluating the performance of regression models. It quantifies the average of the squared differences between predicted values (P_i) and the measured values (M_i). It is expressed as:

$$MSE = \frac{1}{n} \sum_{i=1}^n (M_i - P_i)^2 \quad (21)$$

Root Mean Square Error (RMSE) is the standard deviation of the residuals (forecast errors). It represents the distance of data points from the regression line. The equation is:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (M_i - P_i)^2} \quad (22)$$

The Coefficient of Determination (R^2) is a regression analysis indicator that quantifies the proportion of variance in the dependent variable explained by the independent variables. R^2 ranges from 0 to 1. The equation is:

$$R^2 = 1 - \frac{\sum_{i=1}^n (M_i - P_i)^2}{\sum_{i=1}^n (M_i - M_m)^2} \quad (23)$$

Table 3 and Figs. 13–17 illustrate model performance, including 95% confidence intervals for the mean response and 95% prediction bands. The confidence interval shows the 95% probable range of the true mean dependent variable for given predicted values, reflecting uncertainty in the average response. The prediction band incorporates both the regression line's uncertainty and the variability of individual data points.

In general, the Chapuis model (Eq. (3)) stands out with the highest R^2 value of 0.84, indicating it best explains the variance in the dependent variable. However, its error metrics (MAE = 4.17, RMSE = 11.07) are higher than some other models, suggesting that while it captures the general trend effectively, individual predictions might have larger errors. Conversely, the Kozeny-Carman model (Eq. (2)), despite a lower R^2 of 0.58, boasts the lowest MAE (2.32) and RMSE (9.06), implying its predictions are, on average, closer to the actual values. This could mean it provides good average predictions but may not fully capture the range or non-linearities in the data.

The Hazen model (Eq. (1)), though evaluated on a smaller dataset ($n = 52$), shows a balanced performance with a respectable R^2 of 0.76 and relatively low error metrics (MAE = 2.70, RMSE = 7.69). In contrast, the

Indraratna model (Eq. (4)) performs poorly with the lowest R^2 (0.48) and the highest RMSE (19.82), indicating weak predictive capability and significant errors, despite a surprisingly low MSE of 0.063. This unusual combination might suggest a few very large errors disproportionately inflate the RMSE.

The model developed in this study (Eq. (19)), evaluated on the full dataset ($n = 76$), presents a strong and competitive performance. Its R^2 of 0.77 is comparable to Hazen and second only to Chapuis. While its MAE (3.76) and RMSE (13.28) are higher than Kozeny-Carman and Hazen, they are more favorable than Indraratna's and competitive with Chapuis's. A crucial advantage of this study model is its significantly broader applicable range ($C_U \leq 76$, $D_{10} \leq 6$ mm). This extended range makes it potentially more versatile and practical for a wider array of scenarios compared to the other models, which often have more restricted applicability.

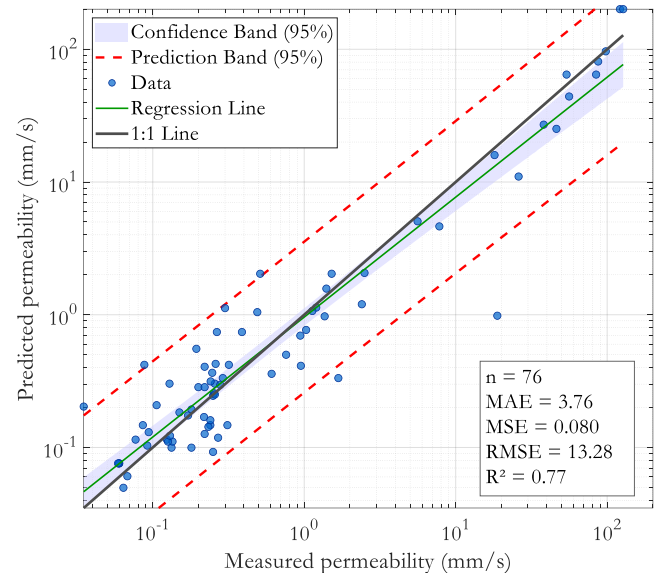


Fig. 13. Permeability predicted using Eq. (19) versus the measured permeability.

6. Limitations and Practical Considerations

The compiled dataset in Fig. 12 reveals a significant trend, but experimental limitations and potential biases detailed in Chapuis [16] must be taken into account. Nevertheless, the observed trends are compelling because the dataset includes a wide range of sand and gravel tested with various test devices among different laboratories.

Table 3. Performance measurements of the permeability prediction models.

Model	Eq.	n	MAE	MSE	RMSE	R^2	Applicable Range
Hazen	(1)	52	2.70	0.148	7.69	0.76	$C_U \leq 5$, $0.1 \text{ mm} \leq D_{10} \leq 3 \text{ mm}$
Kozeny-Carman	(2)	76	2.32	0.112	9.06	0.58	-
Chapuis	(3)	76	4.17	0.192	11.07	0.84	$0.003 \text{ mm} \leq C_U \leq 3 \text{ mm}$, $e > 0.3$
Indraratna	(4)	76	5.35	0.063	19.82	0.48	$C_U \leq 4$, $0.10 \text{ mm} \leq D_{10} \leq 9.6 \text{ mm}$
This study	(19)	76	3.76	0.080	13.28	0.77	$C_U \leq 76$, $D_{10} \leq 6 \text{ mm}$

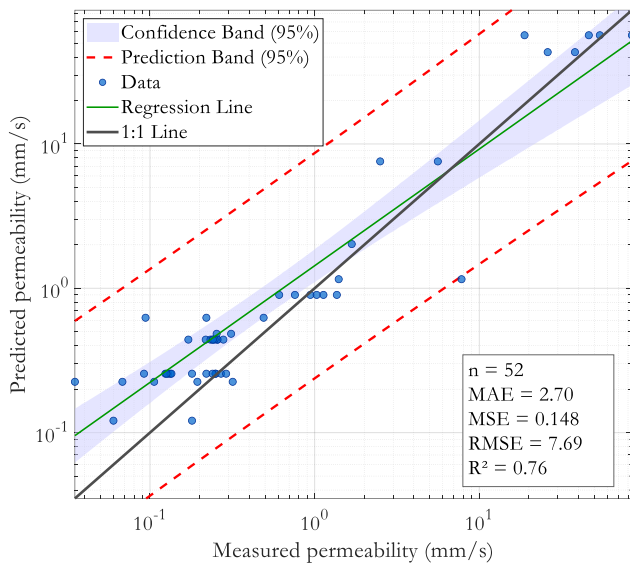


Fig. 14. Permeability predicted using Hazen model, Eq. (1), versus the measured permeability.

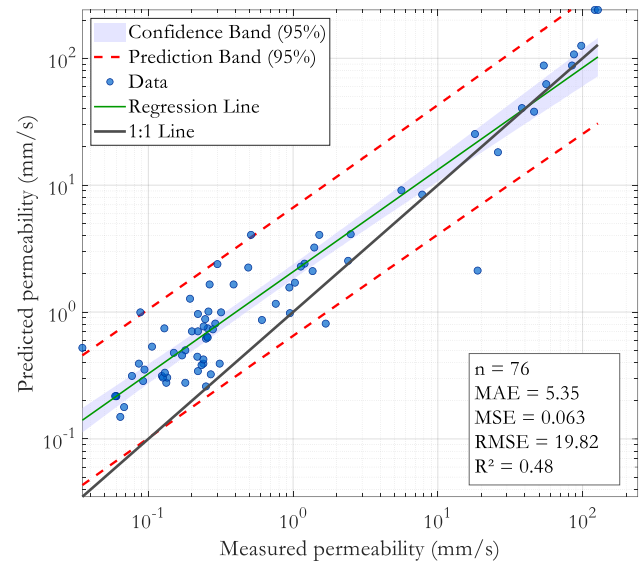


Fig. 17. Permeability predicted using Indraratna model, Eq. (4), versus the measured permeability.

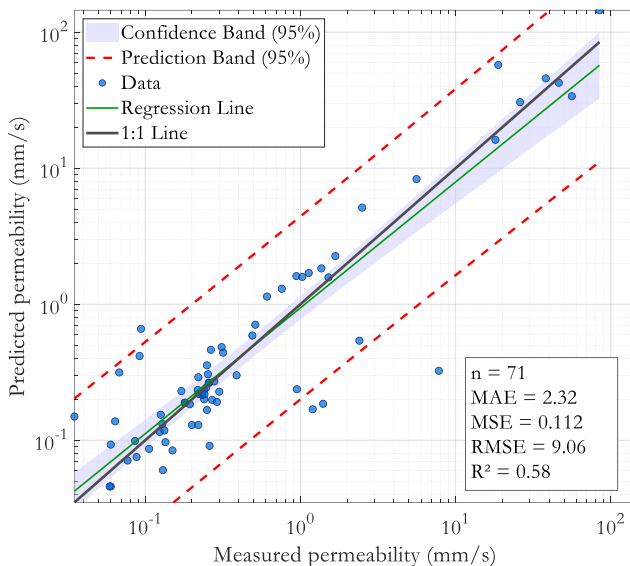


Fig. 15. Permeability predicted using Kozeny–Carman model, Eq. (2), versus the measured permeability.

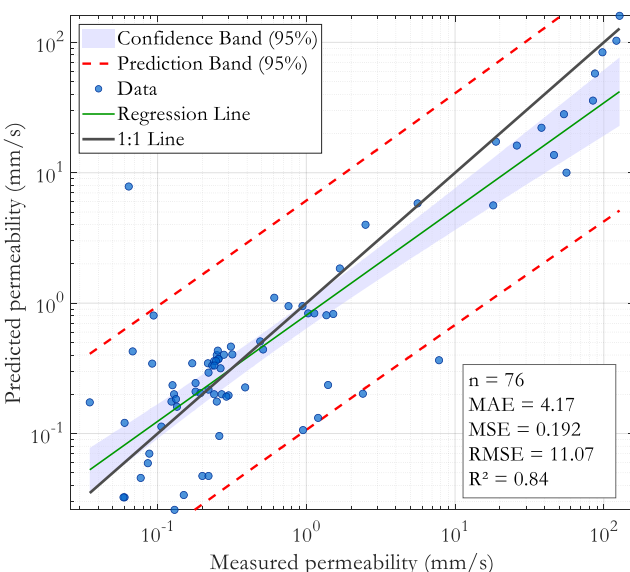


Fig. 16. Permeability predicted using Chapuis model, Eq. (3), versus the measured permeability.

The updated predictive permeability model, Eq. (19), is derived from the permeability test results of granular materials with $C_U \leq 76$ and $D_{10} \leq 6$ mm. Extrapolation beyond these bounds may introduce significant errors, particularly for gap-graded or coarser materials. Gap-graded or well-graded soils ($C_U > 76$) may exhibit complex pore geometries not captured by current constriction models, while coarser soils ($D_{10} > 6$ mm) may exhibit non-Darcian flow during seepage testing.

This study adopts the inscribed circle method for calculating the CSD of granular materials of the granular materials. While the models offer valuable insights, it does not fully capture the complex behavior of real soils, particularly due to the non-spherical nature of soil particles. Even though the inscribed circle models may not perfectly represent pore networks in actual granular materials, their use in calculations remains widespread (Indraratna et al. [17]; Indraratna and Raut [23]; Indraratna et al. [24]; Raut and Indraratna [25]; Silveira et al. [37]).

7. Conclusions

A comprehensive dataset of published permeability values has been compiled, encompassing a diverse range of sands and gravels characterized by different particle-size distribution curves and packing densities. This dataset covers five orders of magnitude in permeability. The principal findings of the subsequent analysis are:

- The convergence of permeability trends with specific surface area (Fig. 5), mean pore size (Fig. 6), and mean constriction size (Fig. 12) strongly indicates that pore size dimensions are critical in governing fluid flow through granular materials, rather than bulk properties like void ratio or single particle size metrics.
- The validated and refined predictive permeability model (Eq. (19)), which is based on mean constriction size, shows strong predictive

capability ($R^2 = 0.77$) and is statistically robust (MAE = 3.76, RMSE = 13.28). It performs comparably or better than the established models across the compiled dataset.

- This analysis of 76 distinct datasets underscores the enhanced predictive capability of the proposed model (Eq. (19)), which incorporates pore constriction size, relative to the conventional Hazen and Kozeny–Carmen models that rely on simplified assumptions such as uniform particle size or void ratio. Nevertheless, as the derivation of Eq. (19) is validated and refined the constriction-based approach strictly applicable for granular materials with $C_U \leq 76$ and $D_{10} \leq 6$ mm, its applicability to more well-graded soils, gap-graded soils, and coarser soils should be approached with caution.

Data Availability Statement

Data and code supporting this study are available from the corresponding author upon reasonable request.

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