Databases for Data-Centric Geotechnics

Site Characterization

Edited by
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First edition published 2025

ISBN: 978-1-032-57895-8 (hbk)
ISBN: 978-1-032-57988-7 (pbk)
ISBN: 978-1-003-44194-6 (ebk)

Chapter 6

New laboratory database of hydraulic conductivity measurements on fine-grained soils

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DOI: 10.1201/9781003441946-6

The funder of the Open Access version of this chapter is University of Bristol.

CRC Press
Taylor & Francis Group
Boca Raton London New York

CRC Press is an imprint of the
Taylor & Francis Group, an **informa** business

Chapter 6

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Shuyin Feng and Paul J. Vardanega

Geotechnical databases are vital for engineers wishing to make well-informed, empirical estimations of key soil mechanics parameters. Transformation models linking more difficult-to-measure parameters from readily attainable ones allow engineers to make low-cost a-priori estimations of the more difficult-to-measure parameters. Databases and associated transformation models allow for new test data to be benchmarked against prior knowledge. Other smaller databases (which may represent a specific data subset) can also be benchmarked against larger ones. The use of databases is especially valuable for assessing permeability (or hydraulic conductivity) – an important parameter that exhibits a very large range of variation across different soil types and within datasets obtained from individual laboratory testing campaigns. The issue of parameter uncertainty is often difficult to discount when hydraulic conductivity is a key parameter in a geotechnical model due to said variation. This chapter provides a comprehensive review of the variability and uncertainty of soil hydraulic conductivity with a focus on fine-grained materials, followed by a comparative study on the compilation of fine-grained soil hydraulic conductivity databases and transformation models for hydraulic conductivity making use of the recently established soil hydraulic conductivity database, FG/KSAT-1358. This chapter concludes with recommendations for future development and analysis of soil hydraulic conductivity databases.

6.1 PERMEABILITY OF SOILS

6.1.1 Definitions

Water, as one of the three phases of soil, governs both the physical and mechanical properties of the material. Understanding the distribution and percolation of water (or other permeants) in the soil is of crucial importance in geotechnical engineering design work since it is associated with many geotechnical phenomena (e.g., Taylor 1948, Lambe & Whitman 1969). The percolation of water through soil is often characterised by the hydraulic conductivity k (Length, L. Time, T^{-1}), described in Darcy's empirical law (e.g., Darcy 1856, Taylor 1948, Craig 2004):

$$\frac{Q}{A} = v = ki \tag{6.1}$$

where Q is the flow rate ($L^3.T^{-1}$), A is the area of cross section of the soil (L^2), v is the superficial velocity ($L.T^{-1}$), and i is the hydraulic gradient in the flow direction. The hydraulic conductivity k is governed by both the soil and the permeating fluid (i.e., water), and can be expressed as:

DOI: 10.1201/9781003441946-6

$$k = K\frac{\gamma}{\mu} \tag{6.2}$$

where K is the intrinsic permeability (L^2) which is independent of the permeating pore fluid, γ is the unit weight of the pore fluid (Mass, $M.L^{-2}.T^{-2}$), and μ is the dynamic viscosity ($M.L^{-1}.T^{-1}$). The reader is also directed to the doctoral thesis of Feng (2022) for preliminary work on some of the topics presented in this chapter.

6.1.2 Variation of hydraulic conductivity

Compared to the other commonly used geotechnical parameters, one of the most notable characteristics of k is its extensive range of variation (e.g., Carrier & Beckman 1984, Mbonimpa *et al*. 2002). The k value reported in soil mechanics textbooks generally ranges from 1×10^{-11} m/s to 1×10^{0} m/s, i.e., over 11 orders of magnitude (cf., Terzaghi & Peck 1948, Lambe & Whitman 1969, Craig 2004), and ranges up to 14 orders of magnitude in some compiled hydraulic conductivity datasets (databases) (cf., Ren & Santamarina 2018, Feng 2022, Feng *et al*. 2023).

Table 6.1 summarises the parameter variation range of four global multivariate databases focusing on fine-grained/clay soils in 304dB (the TC304 database of databases that can be found at: http://140.112.12.21/issmge/tc304.htm). The collected soil parameters in the databases encompass basic physical properties (e.g., void ratio (e), specific gravity (G_S), water content (w)), soil classification properties (e.g., liquid limit w_L, plasticity index I_P, liquidity index I_L), mechanical properties (e.g., compression index C_c, unload–reload index C_{ur}, over-consolidation ratio OCR, sensitivity S_t, undrained shear strength s_u), and hydraulic conductivity k. The variation range of k for fine-grained soil (FG/KSAT-1358) spans over 7 orders of magnitude, while the corresponding physical and intrinsic soil parameters within the same database show variations within 2 orders of magnitude. The variation of the soil properties listed in Table 6.1 is mostly within 3 orders of magnitude across four global fine-grained soil/clay databases available from the TC304 website mentioned above (with the exception of k).

6.1.3 Factors influencing hydraulic conductivity

As both γ and μ are temperature-dependent parameters, a specific soil with a specific permeating fluid may exhibit different k levels under different **testing temperatures**, i.e., k measured at 0°C is 1.8 times the value measured at 20°C, and k at 40°C is 0.58 times the value measured at 20°C (data from BSI 1990). The hydraulic conductivity measured at a specific test temperature can be converted to a corresponding permeability at different temperatures based on Equation (6.2), using a correction factor (e.g., BSI 2019). A test temperature of 20°C is often deemed as the standard or reference temperature condition for laboratory measurement (e.g., ASTM 2022, BSI 1990).

The permeant percolation mechanism in most geomaterials exhibits an anisotropic nature. The **flow direction** during testing is another factor that influences the measured level of k. The horizontally measured hydraulic conductivity k_h is generally greater than the vertically measured hydraulic conductivity k_v as reported in various studies (e.g., Al-Tabbaa & Wood 1987, Dewhurst *et al.* 1996, Clennell *et al.* 1999). The reported anisotropy ratio ($r_k = k_h/k_v$) typically falls below 4, and the maximum r_k observed in most engineering soil is around 2.5 (Liu, 2015). The anisotropic behaviour in soil k is often less

Table 6.1 Soil properties variation in some global multivariate fine-grained soil database (see: http://140.112.12.21/issmge/tc304.htm[a] for the downloadable database files, available at the time of writing)

Database	*Reference*	*Soil type*	*Data points*	*No. studies/sites*	*Range of parameters*	
FG/KSAT-1358	Feng and Vardanega (2019a, b)	Fine-grained soil	1358	33	k	1.44×10^{-13} to 7.5×10^{-6} m/s
					e	0.19 to 8.57
					w_L	22 to 675%
					I_P	5 to 625.9%
					G_S	2.09 to 2.9
CLAY-C_C/6/6203	Ching *et al.* (2022)	Clay	6203	429	e	0.13 to 14.66
					w_L	19 to 612.69%
					I_P	5 to 493%
					w	5.8 to 559.5%
					C_c	0.01 to 14.50
					C_{ur}	0.002 to 2.16
CLAY/10/7490	Ching and Phoon (2014)	Clay	7490	251	w_L	18.1 to 515 %
					I_P	1.9 to 363%
					I_L	−0.75 to 6.45
					q_{t1}	0.48 to 95.98
					q_{tu}	0.61 to 108.20
					B_q	0.01 to 1.17
					S_t	1 to 1467
					OCR	1.0 to 60.23
CLAY/5/345	Ching and Phoon (2012)	Clay	345	37	I_L	0.14 to 4.85
					s_u^{re}	0.06 to 33.69 kPa
					$s_{u(test)}$	1.97 to 162.95 kPa
					$s_{u(mob)}$	1.19 to 162.52 kPa
					σ_v'	3.70 to 364.09 kPa
					σ_p'	7.94 to 712.71 kPa

Definitions: e = void ratio; w_L = liquid limit; I_P = plasticity index; G_S = Specific gravity; w = water content; C_c = compression index; C_{ur} = unload–reload index; I_L = liquidity index; $q_{t1} = (q_t - s_v)/s'_v$ = normalised cone tip resistance; $q_{tu} = (q_t - u_2)/s'_v$ = effective cone tip resistance; B_q = pore pressure ratio = $(u_2 - u_0)/(q_t - s_v)$; S_t = sensitivity; OCR = overconsolidation ratio; s_u = undrained shear strength; s_u^{re} = remoulded s_u; σ_v' = vertical total stress; and σ_p' = preconsolidation stress.

[a]This website was last accessed on 10 July 2023.

pronounced at a higher void ratios, e.g., for static compacted sand, $r_k = 1.8$ for $e = 0.4$ and $r_k = 1$ for $e = 0.8$ (Chapuis *et al.* 1989).

The permeability of soil, when tested under different **saturation levels,** is closely dependent on the air–water interface (Baver 1948). The k value measured under partially saturated conditions is generally lower than under saturated conditions (e.g., Corey 1957, Lambe & Whitman 1969, Bear 1972). The unsaturated k may be estimated from the saturated k value in conjunction with the soil water retention curve (correlation between soil suction and its degree of saturation) and hydraulic conductivity function (relationship between k and soil suction) (e.g., Mualem 1976, Van Genuchten 1980, Zhai *et al.* 2021).

In addition to the aforementioned factors, the **chemical constituent**(s) of the permeant can also have a substantial influence on the k measured in soil with high clay content (see also the discussion in Feng 2022). The presence of certain chemical constituents in the permeant may cause the soil particles to either flocculate or disperse, thus leading to changes in hydraulic conductivity (e.g., Lambe & Whitman 1969, Mesri & Olson 1971). The ratio of hydraulic conductivity for the same soil, measured using permeants with different chemical constituents at a constant void ratio, can vary significantly by several orders of magnitude, e.g., measured k of smectite at e = 2 is around 10^{-11} cm/s in water with NaCl, 10^{-9} cm/s in water with $CaCl_2$, 10^{-7}cm/s in ethyl alcohol, and 10^{-5} cm/s (Mesri & Olson 1971).

6.1.4 Uncertainty in permeability test results

Soil permeability can be measured with various laboratory and field tests (e.g., falling head tests, constant head tests, oedometer test, and well pumping tests; see the detailed discussion in Feng 2022). The application of different permeability testing methods has been discussed in various publications (e.g., Tavenas *et al.* 1983, Chapuis 2012, Nagy *et al.* 2013, Daniel *et al.* 1985). While each permeability testing approach has its merits (and limitations), they are all established based on specific assumptions, e.g., Darcian flow, homogeneous soil, and soil saturation. The results obtained from the tests are dependent on the selected testing methodology (Chapuis 2012). The inherent "inaccuracy" of permeability measurement approaches leads to a degree of variation close to an order of magnitude from the same test method (e.g., Pane *et al.* 1983, Nagy *et al.* 2013), and up to three orders of magnitude higher when comparing results from different test methods (cf. Moulton & Seals 1979, Chapuis 2012, Nagy *et al.* 2013). The range of variation of measured permeability data coupled with laborious and time-consuming testing procedures (see Feng 2022 for further discussion of soil testing methodologies) make the determination of soil permeability challenging – this challenge can be partially mitigated by the availability of extensive geotechnical databases.

6.2 TRANSFORMATION MODELS

6.2.1 Predictors of hydraulic conductivity

Transformation models can be used to estimate soil parameters using more easily accessible ones. Similar to all the other geotechnical parameters, the k of soil can also be assessed with more basic soil parameters using empirical correlations established from past database studies. The main soil characteristics that influence the hydraulic conductivity k are summarised as follows:

(a) **Void ratio/structure-related parameters:** Void ratio e, porosity n, water content w, void ratio function $e^3(1+e)$ (e.g., Kozeny 1927, Carman 1937, Carman 1939, Taylor 1948, Terzaghi & Peck 1948, Baver 1948, Lambe & Whitman 1969, Carrier 2003, Chapuis 2004, Liu 2015, Ren & Santamarina 2018, Nagaraj *et al.* 1993, Nagaraj *et al.* 1994, Mbonimpa *et al.* 2002);

(b) **Particle size distribution-related parameters:** Effective particle size D_{10} D_{50} (e.g., Hazen 1895, Taylor 1948, Shahabi *et al.* 1984, Shepherd 1989, Alyamani & Sen 1993, Chapuis 2004), specific surface by volume S_A (Feng 2022, Feng *et al.* 2023), specific surface by mass S_S (Ren *et al.* 2016, Ren & Santamarina 2018, Feng and

Vardanega 2019a), coefficient of uniformity C_U (Shahabi *et al.* 1984), mean constriction size D_c^m (Jaafar & Likos 2014), and normalised grading entropy coordinates A, B (Feng *et al.* 2019, Feng 2022);

(c) **Atterberg Limits:** Liquid limit (w_L) (Feng & Vardanega 2019a, Feng & Vardanega 2019b, Nagaraj *et al.* 1993, Nagaraj *et al.* 1994, Chapuis 2012, Ren & Santamarina 2018), plastic limit (w_p) (Carrier & Beckman 1984, Mbonimpa *et al.* 2002), and shrinkage limit (w_s) (Sridharan & Nagaraj 2005);

(d) **Soil fabric, shape, and composition:** Soil composition (Jones 1955, Shahabi *et al.* 1984, Indrawan *et al.* 2006, Shafiee 2008, Gao *et al.* 2019), soil fabric (Lambe & Whitman 1969, Qiu & Wang 2015), and soil shape (Cabalar & Akbulut 2016, Taiba *et al.* 2019, Katagiri *et al.* 2020, Nguyen & Indraratna 2020).

Burnham and Anderson (2004) suggested that the selection of predictors should always follow the principle of "simplicity and parsimony." The complexity of the prediction model is controlled based on whether the selection of parameters can be assessed from a relatively small number of standard tests (Whittle 1993). There is always a trade-off between model accuracy and the number of constituent parameters – the more the parameters in a model, the more difficult the calibration is.

6.2.2 Model structure

A prediction model can be established using one or multiple predictors, with a generalised form of prediction model allowing further determination of the empirical factors in the model. The generalised form may be structured directly between the predictors and k using simple linear correlation, famous examples include Hazen's formula (Hazen 1985) and the Kozeny–Carman equation (Kozeny 1927, Carman 1937, Carman 1939). More recently developed prediction models often involve the data transformation of k, such as the works of Carrier and Beckman (1984), Nagaraj *et al.* (1994), Mbonimpa *et al.* (2002), and Chapuis (2012).

Feng *et al.* (2023) reviewed some commonly used prediction models for assessing the permeability of coarse-grained soil, with a compiled permeability database (CG/KSAT/7/1278) consisting of 1278 test data sourced from over 50 studies. The model adequacy analysis of the prediction models revealed that all linear-correlating models exhibited a "funnel" pattern in the residuals versus predicted plots, indicating anomalies in prediction (see Figure 6.1, full results are given in the recent paper of Feng *et al.* 2023) when calibrated using CG/KSAT/7/1278. This observation indicates the need for data transformation in the predicted value k (Montgomery *et al.* 2007, p. 303). The need for such data transformation may be attributed to the difference in the range of variation between k and corresponding predictors, as detailed in Table 6.1.

6.2.3 Evaluation of regression strength

Kulhaway and Mayne (1990) suggested that for any correlation for estimating soil properties it is essential to supplement the coefficient of determination (R^2) with other statistical measures, particularly the number of data points used in the regression (n), to properly assess the strength of fitted models (see also e.g. Paradine and Rivett 1953). Phoon and Kulhawy (1999a, 1999b) emphasised the significance of reporting the standard error (SE) to provide a measure of "transformation uncertainty" in correlations. The *p-value* of the

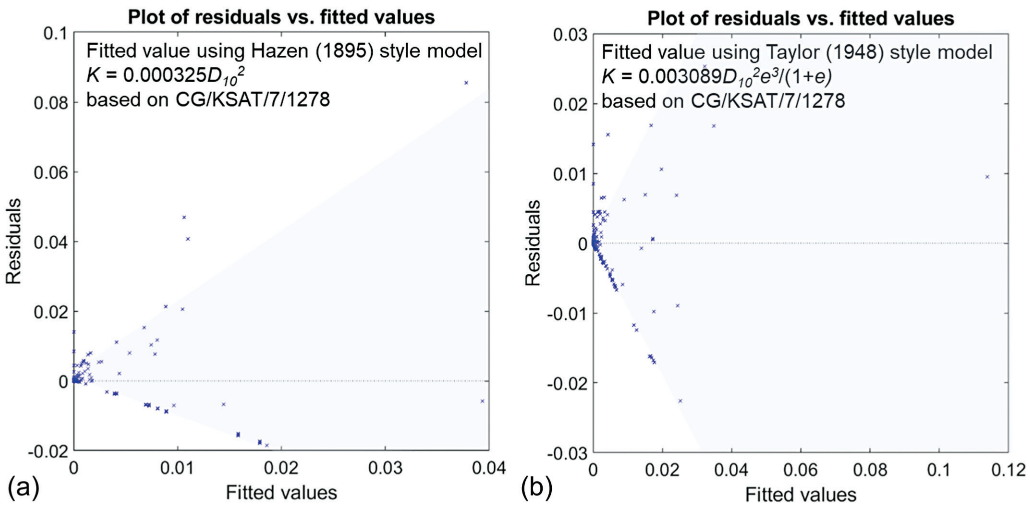

Figure 6.1 Examples of "funnel" pattern residuals versus predicted plot: (a) residual versus predicted plot using Hazen (1895) style model using CG/KSAT/7/1278; (b) residual versus predicted plot using Taylor (1948) style model using CG/KSAT/7/1278 (Source: adapted from Feng *et al.* 2023, used under the terms of the cc-by 4.0 licence).

correlation, which explains the probability of the absence of correlation (i.e., rejecting the null hypothesis, see Montgomery *et al.* 2007), should also be considered. For details on the statistical measures employed in this work, see Feng (2022).

6.2.4 Database subdivision analyses

Further subdivision analysis is often required in model development, especially when dealing with data that varies over an extensive range (e.g., k) to evaluate how generally applicable a developed transformation model is. Correlation may exhibit distinct patterns among data over different value ranges or under various test conditions, as illustrated in Figure 6.2. The subdivision analysis helps to examine the potential influencing

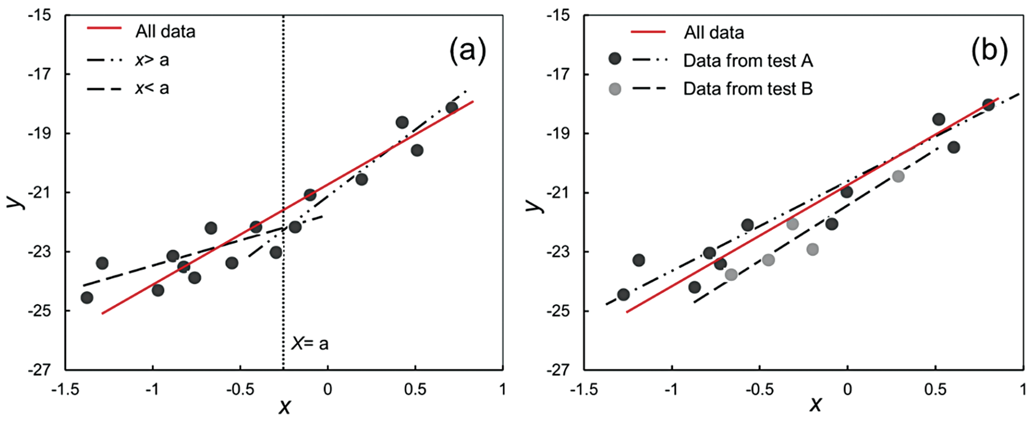

Figure 6.2 Divergency in subdivision analysis: (a) subdivision over different value ranges and (b) subdivision over different test conditions (Source: adapted from Feng 2022).

factors (e.g., permeability testing methods) and uncover underlying trends or correlations that may exist within specific subgroups which may be rather different from the transformation model calibrated with the whole dataset (see the detailed discussion in Feng 2022).

6.3 PERMEABILITY DATABASES FOR FINE-GRAINED SOIL

6.3.1 Database summary

As discussed previously, databases play a crucial role in geotechnical engineering (e.g., Phoon *et al*. 2020). Geodatabases with sufficient and reliable data are often used to improve understanding of geotechnical phenomena and further calibrate proposed models (Phoon & Tang 2019). Geotechnical databases (or datasets) can be populated through direct laboratory/on-site testing (e.g., FI-CLAY/7/216 from D'Ignazio *et al*. 2016) or sourced from geotechnical literature (e.g., RFG/TXCU-278 from Beesley & Vardanega 2020). Some databases are compiled using a combination of literature and industry sources (e.g., the DINGO database on piled foundations, Vardanega *et al*. 2024).

Table 6.2 presents a summary of eight fine-grained soil permeability database/sets used for constructing permeability prediction models, including the recently compiled database FG/KSAT-1358 (Feng & Vardanega 2019a, 2019b). These databases include datasets from individual laboratory campaigns, regional compiled databases, and global compiled databases. Each database has been supplemented with information on the size of database, soil type, property range, number of studies, and details regarding the permeability influencing factors, including the test type, test temperature, flow direction, saturation level, and chemical constituent. The property ranges are given for the soil properties that have been reported or can be digitised from the listed sources.

6.3.2 Database evaluation

All database/set sources reviewed in this chapter have offered detailed information on the soil type, reported/digitisable size, k range, and the number of studies. As discussed earlier in this chapter, different test types can introduce significant uncertainty and lead to variations up to orders of magnitude in the measured k value. However, there is a noticeable information gap concerning the permeability test type, particularly in the compiled databases, i.e., the test type is either missing or partially reported in 3 out of 5 compiled database sources. Similarly, there appear to be gaps in the reported data pertaining to other factors influencing k, including test temperatures, saturation levels, and permeant chemical constituents. Half of the reviewed databases (4 out of 8) provide information on one factor influencing k, and only two databases (Sridharan & Nagaraj 2005, Feng & Vardanega 2019a, 2019b) report relevant information on all four influencing factors.

It was noticed that more recently compiled databases tend to encompass data from earlier databases. For example, Mbonimpa *et al*. (2002) incorporated data from Nagaraj *et al*. (1994), Sivapullaiah *et al*. (2000), while Ren & Santamarina (2018) included data from Sridharan and Nagaraj (2005) and Sivapullaiah *et al*. (2000). The data sources collected to develop FG/KSAT-1258 detailed in Feng and Vardanega (2019a, 2019b) also overlap with the compiled databases in Mbonimpa *et al*. (2002) and Ren and Santamarina (2018).

Table 6.2 Summary of permeability database/set for fine-grained soil

Sources	*Size*	*Soil type*	*Property range*	*No. of studies*	*Test type*	*Test temp.*	*Flow direction*	*Saturation level*	*Chemical constituent*
Dataset from individual laboratory test campaign									
Nagaraj *et al.* (1994)	54	Four local residual soils: red soil, brown soil, black cotton soil, marine soil	k (9.19×10^{-12} to 1.82×10^{-9} m/s); w_L (50% to 106%); G_s (2.68 to 2.9)	1	Falling head test	n/a	Vertical, one dimensional	n/a	n/a
Sivapullaiah *et al.* (2000)	291 (no. digitised, include sand and sand mixture)	Bentonite–sand mixture (includes mixture with over 50% sand)	k (1.21×10^{-12} to 3.76×10^{-8} m/s); w_L (35% to 344%); G_s (2.60 to 2.75)	1	Consolidation test	n/a	One dimensional	n/a	n/a
Sridharan and Nagaraj (2005)	63 (no. digitised)	Red earth, silty soil, kaolinite, Cochin clay, brown soil, illitic soil, B C soil	k (1.20×10^{-11} to 6.89×10^{-8} m/s); e (0.53 to 1.84); w_L (37.0% to 73.5%); w_P (18.0% to 51.9%); w_S (11.9% to 46.4%); G_s (2.58 to 2.70)	1	Falling head test	20°C	One dimensional	Saturated	Distilled water
Regional compiled database									
Chapuis (2012)	76 (no. digitised)	Quebec Champlain Sea clay	k (2×10^{-11} to 5×10^{-9} m/s)	4	More than two types of tests involved (constant head, falling head)	n/a	n/a	Saturated	n/a
Multi-source (global) compiled database									
Carrier and Beckman (1984)	66	22 phosphatic; 13 dredged materials; 26 remoulded natural clays	k (10^{-10} to 10^{-5} m/s)	8	Constant head; consolidation test (stress-controlled and constant rate of deformation)	n/a	One dimensional	n/a	Permeating fluid with same chemical composition as the porewater

(*Continued*)

Table 6.2 (Continued) Summary of permeability database/set for fine-grained soil

Sources	*Size*	*Soil type*	*Property range*	*No. of studies*	*Test type*	*Test temp.*	*Flow direction*	*Saturation level*	*Chemical constituent*
Mbonimpa *et al.* (2002)	342	Bentonite silts mixture, Kaolin, marine soil, black cotton soil, clay, Louiseville soil, St-Esprit soil, Bächebol soil, Matagami soil, New Liskeard soil, Don Valley soil, and Leda soil	*k* (1.3×10^{-12} to 6.79×10^{-9} m/s); w_L (33.4% to 436.3%); e (0.51 to 5.96); G_s (2.61 to 2.78)	8	n/a; author's test conducted under constant head or falling head condition.	20°C	n/a	Saturated	n/a
Ren and Santamarina (2018)	1440 (includes sandy soil data)	Natural and remoulded sediments, from coarse sands to fine-grained clays	*k* (2.55×10^{-14} to 9.33×10^{-4} m/s, range for silty and clayey soil, data digitised from plot); e (0.24 to 9.1, data digitised from plot)	23	n/a	n/a	Most likely to be vertical	n/a	n/a
Feng and Vardanega (2019a)	1358	Natural or laboratory fine-grained soil with less than 50% coarse particles ($d >$ 75 mm) and a measured w_L	*k* (1.44×10^{-13} to 7.5×10^{-6} m/s); e (0.19 to 8.57); w_L (22% to 675%); I_P (5% to 625.9%); G_S (2.09 to 2.9)	33	Constant head test, falling head test, consolidation test, flow pump test	20 ± 1°C to 26 ± 0.1°C	Vertical	Saturated	Water

There has been an obvious increase in the size of databases for soil k due to the aforementioned research efforts. Among the compiled databases, FG/KSAT-1358 by Feng and Vardanega (2019a, 2019b) contains the largest number of k test data on fine-grained soil (over 1300), along with comprehensive details on the key factors influencing k.

6.3.3 Model calibration

Table 6.3 provides a summary of the calibrated transformation models to assess the permeability of fine-grained soil. The majority of the established models are based on fundamental soil parameters such as e, w, w_L, void ratio at liquid limit e_L, w_L, I_P, and G_S. Sridharan and Nagaraj (2005) used the shrinkage limit (w_s) as a predictor, which is widely used especially in pavement engineering in dry regions. Most of the calibrated prediction models, such as the transformation model developed by Nagaraj *et al.* (1994), Sivapullaiah *et al.* (2000), Chapuis (2012), Ren and Santamarina 2018, and Feng and Vardanega 2019a, 2019b, involve some form of data transformation for k.

Statistical measures have been reported in prediction models calibrated using individual laboratory test datasets and regional compiled databases (Nagaraj *et al.* 1994, Sivapullaiah *et al.* 2000, Sridharan & Nagaraj 2005, Chapuis 2012). However, the sample size (n) used in model calibration is missing in some cases (e.g., Sivapullaiah *et al.* 2000, Sridharan & Nagaraj 2005, Chapuis 2012). Statistical measures are largely missing (i.e., unreported) from the model calibration when using compiled databases with relatively larger sample sizes, such as Carrier and Beckman (1984) with n = 66, Mbonimpa *et al.* (2002) with n = 342, and Ren and Santamarina (2018) with n = 1440 (including data on sandy soils).

Transformation models calibrated with larger sample sizes, encompassing a range of soil types and sourced from multiple studies, tend to exhibit a wider range of prediction accuracy up to an order of magnitude, which is to be expected as the model has to account for a wider range of materials and testing conditions. Therefore, this transformation uncertainty may be attributed to the inherent variability among soil types and sources within the database (Phoon & Kulhawy 1999a, 1999b). Subdivision analysis has been conducted in Ren and Santamarina (2018) and Feng and Vardanega (2019a) to further analyse and verify the accuracy and applicability of the established transformation models.

6.3.4 Benchmarking databases

In order to validate and compare the predictive performance of transformation models for k calibrated using databases of varying source type, size, and data range, a benchmarking analysis is conducted using the largest fine-grained soil database – FG/KSAT-1358. Figure 6.3 summarises the analysis results for the hydraulic conductivity prediction models of fine-grained soil calibrated using database/sets with a smaller variation range of k compared to FG/KSAT-1358. The measured k values from FG/KSAT-1358 are plotted against the predicted k values based on the examined model with the corresponding calibration dataset range following the method described in Piñeiro *et al.* (2008). It was observed that models established using the global compiled database generally demonstrate better predictive performance for FG/KSAT-1358, with a higher percentage of the data points falling within the one-order-of-magnitude prediction range. Transformation models developed based on regional compiled databases and individual laboratory test campaigns tend to exhibit an overall biased prediction trend for the global compiled database FG/KSAT-1358.

Table 6.3 Summary of calibrated prediction models (data sources as shown in Table 6.2)

Sources	*Database/set*	*Calibrated transformation models*	*Reported statistical measures*	*Prediction accuracy*	*Subdivision analysis*
Dataset from individual laboratory test campaign					
Nagaraj *et al.* (1994)	Regional soil database from laboratory testing dataset on 54 samples of four local residual soils	$\frac{e}{e_L} = 2.162 + 0.195 \log k$	r = 0.98, n = 54	n/a	n/a
Sivapullaiah *et al.* (2000)	Laboratory testing dataset on bentonite–sand mixtures, 291 samples (no. of data digitised from plot, includes mixture with over 50% sand)	$\log_{10} k = \frac{e - 0.0535 w_L - 5.286}{0.0063 w_L + 0.2516}$; k in m/s for $w_L > 50\%$	r = 0.94, SE = 1.486	n/a	n/a
Sridharan and Nagaraj (2005)	Laboratory testing dataset on 10 soil types, 70 samples (no. of data digitised from plot)	$k_p = Ce^x / (1+e)$; $C = 2.5 \times 10^{-4} (I_S)^{-3.69}$ $x = 4$	$SEE = 24.34 \times 10^{-10} m/s$	Usually within 0.4 to 2.5 times range	n/a
Regional compiled database					
Chapuis (2012)	Regional clay database from 4 studies on 76 Quebec Champlain Sea clays (no. of data digitised from plot); test type not available	$k_{sat}(m/s) = 6.68 \times 10^{-6} \left[\frac{e^3}{(1+e)(w_L^{-1} + z)^2} \right]^{1.339}$; z = 0.00836	$R^2 = 0.81$; n = 76 (number digitised)	Within 1/3 to 3 times range	n/a
Global compiled database					
Carrier and Beckman (1984)	Compiled database from 8 studies on 66 clay samples; cover data from 2 test types (constant head, consolidation test)	$k(m/s) = \mu \frac{(e-\delta)^{\nu}}{1+e}$; $\mu(\mathrm{m/s}) = \left[\frac{0.389}{PI} \right]^{4.29}$ $\delta = 0.027 [w_p - 0.242 I_p]$ $\nu = 4.29$	n/a	Within an order of magnitude	n/a

(*Continued*)

Table 6.3 (Continued) Summary of calibrated prediction models (data sources as shown in Table 6.2)

Sources	*Database/set*	*Calibrated transformation models*	*Reported statistical measures*	*Prediction accuracy*	*Subdivision analysis*
Mbonimpa *et al.* (2002)	Compiled database from 6 studies on 342 plastic/cohesive soils sample	$k_{sat}(cm/s) = C_P \frac{\gamma_w}{\mu_w} \frac{e^{3+x}}{1+e} \frac{1}{\rho_s{}^2 w_L{}^{2\chi}}$; $C_P = 5.6g^2/m^4$ $x = 7.7w_L{}^{-0.15} - 3$ $\chi = 1.5$ $\gamma_w \approx 9.8kN/m^3$ $\mu_w \approx 10^{-3}\,Pa.s$	n/a	Usually within half of one order of magnitude	n/a
Ren and Santamarina (2018)	Compiled database from 23 studies on 1440 natural and remoulded sediment sample, from coarse sand to fine-grained soil	$k(cm/s) = 10^{-5}\left(\frac{S_s}{m^2/g}\right)e^{\beta}$; $S_S = 1.8w_L - 34$ β may be derived from the power relation between k and e for the specific soil types: $\beta = 3 \pm 1$ for coarse-grained soils $\beta = 5 \pm 1$ for fine-grained soils	n/a	Mostly within 0.2 to 5 times, significant scatter below $k < 10^{-5}$ cm/s (silty/clayey soil region).	Prediction model with varying β for each soil type
Feng and Vardanega (2019a)	Compiled database from 33 studies on 1358 fine-grained soil sample	$k_{sat}(m/s) = 1.91 \times 10^{-9}\left(w/w_L\right)^{4.083}$	$R^2 = 0.62$, $n = 1352$, SE = 1.58, $p < 0.0001$	Mostly within an order of magnitude	Sub database analysis on Atterberg limits, test types, sample states
Feng *et al.* (2022)	Compiled database from Feng and Vardanega (2019a) with identified outliers removed	$k_{sat}(m/s) = 1.86 \times 10^{-9}\left(w/w_L\right)^{4.226}$	$R^2 = 0.65$, $n = 1272$, SE = 1.303, $p < 0.0001$	Mostly within an order of magnitude	

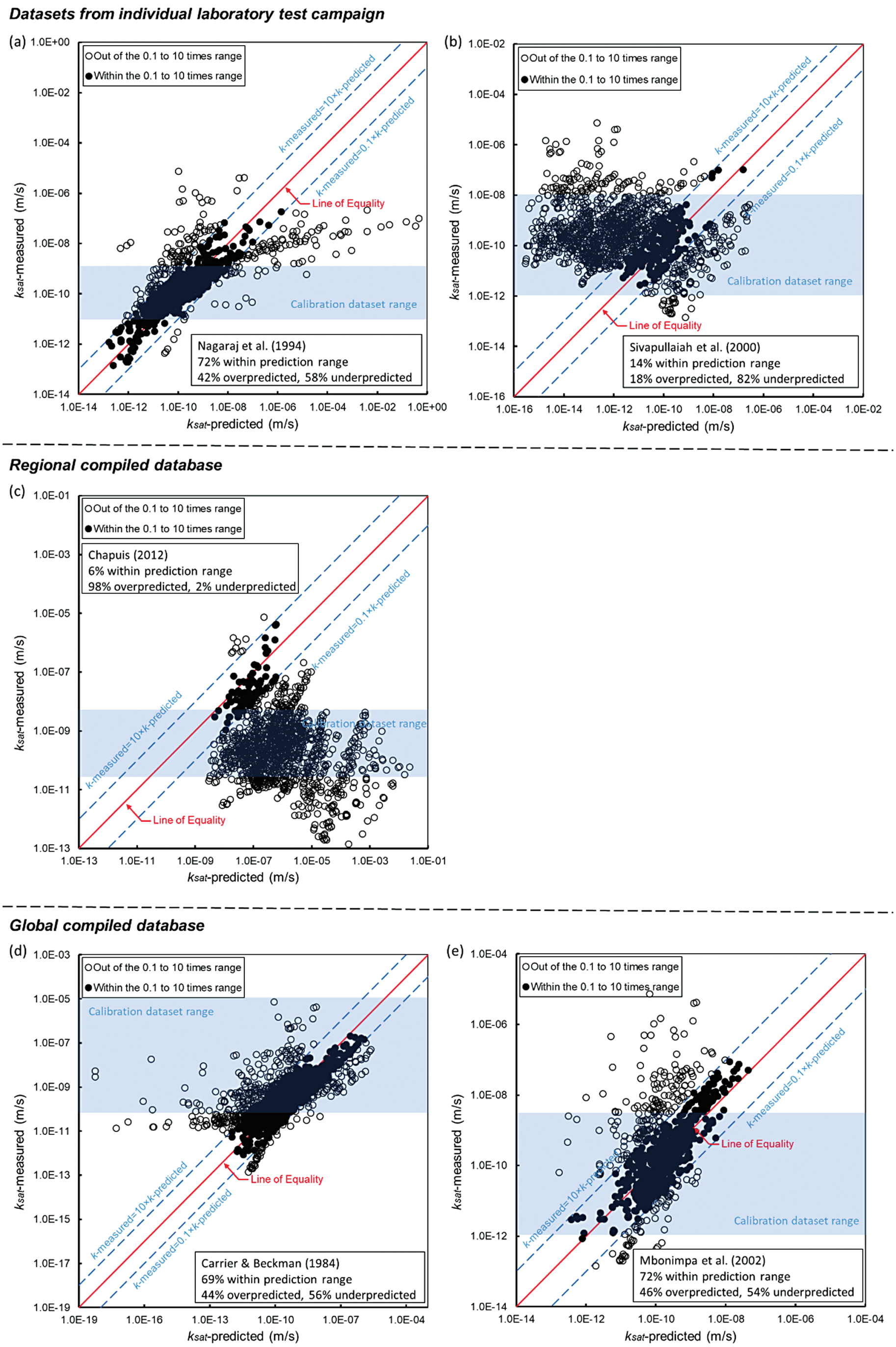

Figure 6.3 Benchmarking analysis result for models with smaller calibration dataset range using FG/KSAT-1358 as the measured values on the plots: (a) predicted values using transformation model from Nagaraj *et al.* (1994); (b) predicted values using transformation model from Sivapullaiah *et al.* (2000); (c) predicted values using transformation model from Chapuis (2012); (d) predicted values using transformation model from Carrier and Beckman (1984); (e) predicted values using transformation model from Mbonimpa *et al.* (2002).

This is to be expected as smaller datasets are unlikely to yield models representing the behaviour of a wide range of soil types/testing approaches, and this observation serves as a reminder that the use of empirical models based only on small datasets should be used with caution (even if they have a high coefficient of determination, for instance) unless calibration of the model form is undertaken with a larger and more extensive dataset.

Among the reviewed fine-grained soil database studies, the database compiled by Ren and Santamarina (2018) stands out due to its extensive variation in k value and a database size comparable to FG/KSAT-1358. Figure 6.4 presents the benchmarking analysis results using the model presented in Ren and Santamarina (2018) with β = 4, 5, and 6 (selection of β based on the range reported by Ren and Santamarina 2018: $\beta = 5 \pm 1$ for fine-grained soils), in comparison with the model developed by Feng and Vardanega using FG/KSAT-1358 (Feng and Vardanega 2019a). The prediction models by Ren and Santamarina (2018) generally underpredict k for FG/KSAT-1358, with approximately 50% of the data points within the one order of magnitude prediction range, while the model by Feng and Vardanega (2019a) yields slightly overpredicted results, with 89% of the prediction within the same prediction range. It should also be noted that while Ren and Santamarina (2018) report a β range of 5 ± 1 for fine-grained soil, individual soil types in FG/KSAT-1358 give a variation of β mostly ranging from 2 to 7 (full results in online supplement, Feng & Vardanega 2019a). This discrepancy in the β value range used in the analysis may partially account for the reduced prediction accuracy of k.

6.4 SUMMARY AND CONCLUSIONS

This chapter has explored the variability and uncertainty associated with fine-grained soil k. This was followed by a comparative analysis of the compilation of fine-grained soil k databases and the development of transformation models, using the recently established fine-grained laboratory k database, FG/KSAT-1358. Information gaps regarding the factors influencing k and transformation model prediction strength have been identified for the reviewed databases and datasets.

6.4.1 Database compilation

It is important to stress the variability and uncertainty in k measurements during the database compilation process. The measured k value of the soil is highly dependent on factors such as the test type, test condition, and sample state. Therefore, information on the relevant influencing factors, such as k testing type, test temperature, sample states, and permeating fluid, should be included in the assembled test database, together with the other corresponding soil properties where possible – this assists the development of new transformation models and also future database expansion and harmonisation efforts.

6.4.2 Transformation models

There remain information gaps in the published literature regarding the prediction strength (i.e., sample size, means of statistical measures) and accuracy (i.e., prediction bandwidth) of transformation models used to predict k. Considering the inherent uncertainty and variability of soil k assessment, adequate model evaluations that include

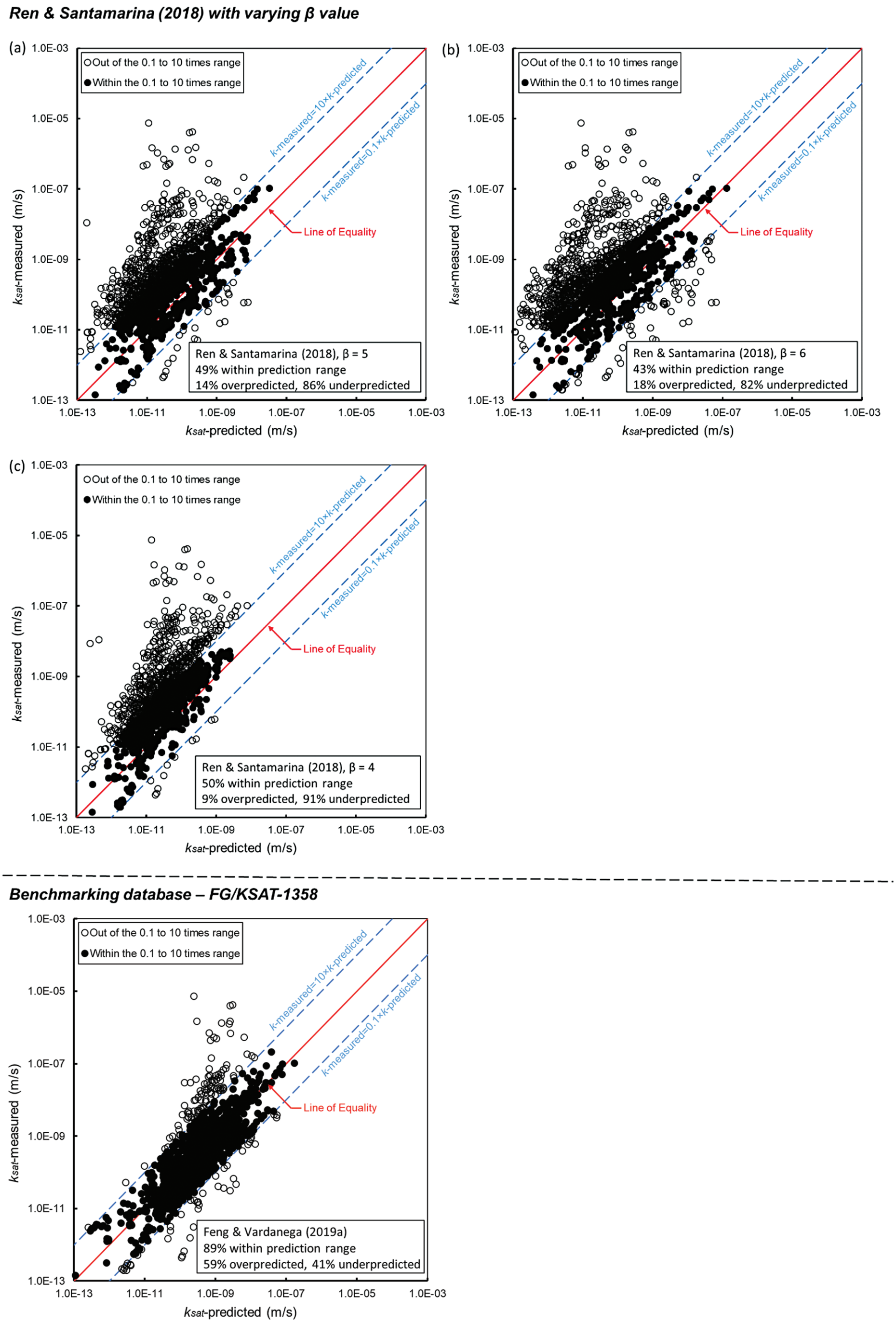

Figure 6.4 Benchmarking analysis results (using data from FG/KSAT-1358 as the measured data on the plots) for Ren and Santamarina (2018) model with varying β: (a) predicted values using transformation model from Ren and Santamarina (2018) with β = 5; (b) predicted values using transformation model from Ren and Santamarina (2018) with β = 6; (c) predicted values using transformation model from Ren and Santamarina (2018) with β = 4; (d) Predicted values using transformation model from Feng and Vardanega (2019a), data from FG/KSAT-1358, plot based on Feng *et al.* (2022).

statistical measures, prediction accuracy, and model adequacy should be provided to measure the validity and reliability of the calibrated model. For compiled databases, further subdivision analysis should also be performed to examine the variations in model prediction performance across different soil types, testing conditions, and sample states to further evaluate the uncertainty in the calibrated transformation model.

With the digitisation of geotechnical resources, significant efforts have been made to compile and publish studies on databases of *k* measurements. However, even with the availability of such studies, the predictions obtained using existing transformation models still exhibit a considerable range of variation, often spanning up to an order of magnitude, particularly when considering globally compiled databases. High-quality soil sampling and testing programs are still essential to reduce the uncertainty and variation associated with permeability prediction. Complete database compilation and classification are also required to enhance the accuracy of future assessments of soil hydraulic conductivity.

REFRENCES

Al-Tabbaa, A. & Wood, D.M. (1987). Some measurements of the permeability of kaolin. *Géotechnique*, **37**(4): 499–514. https://doi.org/10.1680/geot.1987.37.4.499

Alyamani, M.S. & Sen, Z. (1993). Determination of Hydraulic Conductivity from Complete Grain-Size Distribution Curves. *Groundwater*, **31**(4): 551–555. https://doi.org/10.1111/j.1745-6584.1993.tb00587.x

ASTM International (2022). *Standard test methods for measurement of hydraulic conductivity of coarse-grained soils*. D2434-22, West Conshohocken, PA.

Baver, L. (1948). *Soil Physics*. John Wiley Sons, New York, NY.

Bear, J. (1972). *Dynamics of Fluids in Porous Media*. American Elsevier, New York, NY.

Beesley, M.E.W. & Vardanega, P.J. (2020). Parameter variability of undrained shear strength and strain using a database of reconstituted soil tests. *Canadian Geotechnical Journal*, **57**(8): 1247–1255. https://doi.org/10.1139/cgj-2019-0424

British Standards Institution (BSI) (1990). *Methods of test for soils for civil engineering purposes – Part 5: Compressibility, permeability and durability tests*. BS 1377-5:1990, London, UK.

BSI (2019). *Geotechnical investigation and testing. Laboratory testing of soil. Permeability tests*. BS EN ISO 17892-11:2019, London, UK.

Burnham, K.P. & Anderson, D.R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods and Research* **33**(2): 261–304. https://doi.org/10.1177/0049124104268644

Cabalar, A.F. & Akbulut, N. (2016). Evaluation of actual and estimated hydraulic conductivity of sands with different gradation and shape. *SpringerPlus*, **5**(1): 820. https://doi.org/10.1186/s40064-016-2472-2

Carman, P.C. (1937). Fluid flow through granular beds. *Transaction Institution of Chemical Engineers*, **15**: 150–166.

Carman, P.C. (1939). Permeability of saturated sands, soils and clays. *The Journal of Agricultural Science*, **29**(2): 262–273.

Carrier, W.D. & Beckman, J.F. (1984). Correlations between index tests and the properties of remoulded clays. *Géotechnique*, **34**(2): 211–228. https://doi.org/10.1680/geot.1984.34.2.211

Carrier, W.D. (2003). Goodbye, Hazen; Hello, Kozeny-Carman. *Journal of Geotechnical and Geoenvironmental Engineering*, **129**(11): 1054–1056. https://doi.org/10.1061/(ASCE)1090-0241(2003)129:11(1054)

Chapuis, R. P., Gill, D. E. & Baass, K. (1989). Laboratory permeability tests on sand: Influence of the compaction method on anisotropy. *Canadian Geotechnical Journal*, **28**(1): 172–173. https://doi.org/10.1139/t89-074

Chapuis, R.P. (2004). Predicting the saturated hydraulic conductivity of sand and gravel using effective diameter and void ratio. *Canadian Geotechnical Journal*, **41**(5): 787–795. https://doi.org/10.1139/t04-022

Chapuis, R.P. (2012). Predicting the saturated hydraulic conductivity of soils: A review. *Bulletin of Engineering Geology and the Environment*, **71**(3): 401–434. https://doi.org/10.1007/s10064-012-0418-7

Ching, J. & Phoon, K-K. (2012). Modeling parameters of structured clays as a multivariate normal distribution. *Canadian Geotechnical Journal*, **49**(5): 522–545. https://doi.org/10.1139/t2012-015

Ching, J. & Phoon, K-K. (2014). Transformations and correlations among some clay parameters – the global database. *Canadian Geotechnical Journal*, **51**(6): 663–685. https://doi.org/10.1139/cgj-2013-0262

Ching, J., Phoon, K-K. & Wu, C.T. (2022). Data-centric quasi-site-specific prediction for compressibility of clays. *Canadian Geotechnical Journal*, **59**(12): 2033–2049. https://doi.org/10.1139/cgj-2021-0658

Clennell, M.B., Dewhurst, D.N., Brown, K.M. & Westbrook, G.K. (1999). Permeability anisotropy of consolidated clays. In: *Muds and mudstones: Physical and fluid flow properties*, vol. 158, Aplin, A.C., Fleet, A.J. & MacQuaker, J.H.S. (eds.). Geological Society of London, London, UK, pp. 79–96. http://doi.org/10.1144/GSL.SP.1999.158.01.07

Corey, A.T. (1957). Measurement of water and air permeability in unsaturated soil. *Soil Science Society of America Journal*, **21**(1): 7–10. https://doi.org/10.2136/sssaj1957.03615995002100010003x

Craig, R.F. (2004). *Craig's soil mechanics*. 7th Edition. Taylor & Francis, Abingdon, UK.

D'Ignazio, M., Phoon, K-K., Tan, S.A. & Länsivaara, T.T. (2016). Correlations for undrained shear strength of finnish soft clays. *Canadian Geotechnical Journal*, **53**(10): 1628–1645. https://doi.org/10.1139/cgj-2016-0037

Daniel, D., Anderson, D., & Boynton, S. (1985). Fixed-wall versus flexible-wall permeameters. In *Hydraulic barriers in soil and rock*. Johnson, A. I., Frobel, R. K., Cavalli, N. J., & Pettersson, C. B., (eds.), American Society for Testing and Materials, Philadelphia, PA, pp. 107–126.

Darcy, H. (1856). *Les fontaines publiques de la ville de Dijon. Victor Dalmont.*

Feng, S. & Vardanega, P.J. (2019a). Correlation of the hydraulic conductivity of fine-grained soils with water content ratio using a database. *Environmental Geotechnics*, **6**(5): 253–268. https://doi.org/10.1680/jenge.18.00166

Feng, S. & Vardanega, P.J. (2019b). A database of saturated hydraulic conductivity of fine-grained soils: probability density functions. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, **13**(4): 255–261. https://doi.org/10.1080/17499518.2019.1652919

Feng, S., Vardanega, P.J., Ibraim, E., Widyatmoko, I., & Ojum, C. (2019). Permeability assessment of some granular mixtures. *Géotechnique*, **69**(7): 646–654. https://doi.org/10.1680/jgeot.17.T.039

Feng, S. (2022). *Hydraulic conductivity of road construction materials: With a focus on freeze-thaw effects*. Ph.D. thesis, University of Bristol, Bristol, UK.

Feng, S., Ibraim, E. & Vardanega, P.J. (2022). Databases to assess the hydraulic conductivity of road construction materials. In: *Proceedings of twentieth international conference on soil mechanics and geotechnical engineering (ICSMGE 2022), A Geotechnical Discovery Down Under, Sydney, New South Wales, Australia, 1–5 May 2022*, vol. 2, Rahman, M.M. & Jaksa, M. (eds.), Australian Geomechanics Society, Sydney, Australia, pp. 4547–4552. <https://www.issmge.org/uploads/publications/1/120/ICSMGE_2022-777.pdf> [19/10/2024].

Feng, S., Barreto, D., Imre, E., Ibraim, E. & Vardanega, P.J. (2023). Use of hydraulic radius to estimate the permeability of coarse-grained materials using a new geodatabase. *Transportation Geotechnics*, **41**: [101026]. https://doi.org/10.1016/j.trgeo.2023.101026

Gao, Q.F., Dong, H., Huang, R. & Li, Z.F. (2019). Structural characteristics and hydraulic conductivity of an eluvial-colluvial gravelly soil. *Bulletin of Engineering Geology and the Environment*, **78**(7): 5011–5028. https://doi.org/10.1007/s10064-018-01455-1

Hazen, A. (1895). *The filtration of public water supplies*. John Wiley & Sons, New York, NY.

Indrawan, I.G.B., Rahardjo, H. & Leong, E.C. (2006). Effects of coarse-grained materials on properties of residual soil. *Engineering Geology*, **82**(3): 154–164. https://doi.org/10.1016/j.enggeo.2005.10.003

Jaafar, R. & Likos, W.J. (2014). Pore-scale model for estimating saturated and unsaturated hydraulic conductivity from grain size distribution. *Journal of Geotechnical and Geoenvironmental Engineering*, **140**(2): 04013012. https://doi.org/10.1061/(ASCE)GT.1943-5606.0001031

Jones, C.W. (1955). The Permeability and Settlement of Laboratory Specimens of Sand and Sand-Gravel Mixtures. *Symposium on Permeability of Soils*, ASTM, Philadelphia, PA, pp. 68–79.

Kozeny, J. (1927). *Über kapillare leitung des wassers im boden:(aufstieg, versickerung und anwendung auf die bewässerung). Hölder-Pichler-Tempsky* (in German).

Kulhawy, F.H. & Mayne, P.W. (1990). *Manual on estimating soil properties for foundation design*, Electric Power Research Institute, Report No. EL-6800, Palo Alto, CA.

Lambe, T.W. & Whitman, R.V. (1969). *Soil mechanics*. John Wiley Sons, New York, NY.

Liu, Y. (2015). *Permeability and pore structure of granular materials*. Ph.D. thesis. McMaster University, Hamilton. Available from: <https://macsphere.mcmaster.ca/bitstream/11375/18104/2/Dissertation%20final.pdf> [10/07/2023]

Mbonimpa, M., Aubertin, M., Chapuis, R. & Busssière, B. (2002). Practical pedotransfer functions for estimating the saturated hydraulic conductivity. *Geotechnical and Geological Engineering*, **20**(3): 235–259. https://doi.org/10.1023/A:1016046214724

Mesri, G. & Olson, R. E. (1971). Mechanisms controlling the permeability of clays. *Clays and Clay Minerals*, **19**(3): 151–158. https://doi.org/10.1346/CCMN.1971.0190303

Montgomery, D. C., Runger, G. C., & Hubele, N. F. (2007). *Engineering statistics* (4th ed.). John Wiley & Sons Inc, New York, NY.

Moulton, L. & Seals, D. (1979). *Determination of the in situ permeability of base and subbase courses*. Federal Highway Administration, Washington, D.C.

Mualem, Y. (1976). A new model for predicting the hydraulic conductivity of unsaturated porous media. *Water Resources Research*, **12**(3): 513–522. https://doi.org/10.1029/WR012i003p00513

Nagaraj, T.S., Pandian, N.S. & Narashimha Raju, P.S.R. (1993). Stress state–permeability relationships for fine-grained soils. *Géotechnique*, **43**(2): 333–336. https://doi.org/10.1680/geot.1993.43.2.333

Nagaraj, T.S., Pandian, N.S. & Narashimha Raju, P.S.R. (1994). Stress state–permeability relations for overconsolidated clays. *Géotechnique*, **44**(2): 349–352. https://doi.org/10.1680/geot.1994.44.2.349

Nagy, L., Tabácks, A., Huszák, T., Mahler, A. & Varga, G. (2013). Comparison of permeability testing methods. In *18th International Conference on Soil Mechanics and Geotechnical Engineering, Paris, France*, Presses des Ponts, Paris, France, pp. 399–402. Available from: <https://www.issmge.org/uploads/publications/1/2/399-402.pdf> [10/07/2023].

Nguyen, T.T. & Indraratna, B. (2020). The role of particle shape on the hydraulic conductivity of granular soils captured through Kozeny-Carman approach. *Géotechnique Letters*, **10**(3): 398–403. https://doi.org/10.1680/jgele.20.00032

Pane, V., Croce, P., Znidarcic, D., Ko, H.-Y., Olsen, H.W. & Schiffman, R.L. (1983). Effects of consolidation on permeability measurements for soft clay. *Géotechnique*, **33**(1): 67–72. https://doi.org/10.1680/geot.1983.33.1.67

Paradine, C.G. & Rivett, B.H. (1953). Statistics for technologists. English Universities Press, London, UK.

Phoon, K-K. & Kulhawy, F.H. (1999a). Characterization of geotechnical variability. *Canadian Geotechnical Journal*, **36**(4): 612–624. https://doi.org/10.1139/t99-038

Phoon, K-K. & Kulhawy, F.H. (1999b). Evaluation of geotechnical property variability. *Canadian Geotechnical Journal*, **36**(4): 625–639. https://doi.org/10.1139/t99-039

Phoon, K-K. & Tang, C. (2019). Characterisation of geotechnical model uncertainty. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, **13**(2): 101–130. https://doi.org/10.1080/17499518.2019.1585545

Phoon, K-K., Ching, J. & Wang, Y. (2020). Managing risk in geotechnical engineering – From data to digitalization. In: *Proceedings of the 7th international symposium on geotechnical safety and risk (ISGSR)*, Research Publishing, Taipei, Taiwan, pp. 13–34. Available from: <http://rpsonline.com.sg/proceedings/isgsr2019/index.html> [10/07/2023]

Piñeiro, G., Perelman, S., Guerschman, J. P., & Paruelo, J. M. (2008). How to evaluate models: Observed vs. predicted or predicted vs. observed? *Ecological Modelling*, **216**(3–4), 316–322. https://doi.org/10.1016/j.ecolmodel.2008.05.006

Qiu, Z.F. & Wang, J.J. (2015). Experimental study on the anisotropic hydraulic conductivity of a sandstone-mudstone particle mixture. *Journal of Hydrologic Engineering*, **20**(11): 04015029. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001220

Ren, X., Zhao, Y., Deng, Q., Kang, J., Li, D. & Wang, D. (2016). A relation of hydraulic conductivity — void ratio for soils based on Kozeny-Carman equation. *Engineering Geology*, **213**: 89–97. https://doi.org/10.1016/j.enggeo.2016.08.017

Ren, X.W. & Santamarina, J.C. (2018). The hydraulic conductivity of sediments: A pore size perspective. *Engineering Geology*, **233**: 48–54. https://doi.org/10.1016/j.enggeo.2017.11.022

Shahabi, A., Das, B., and Tarquin, A. (1984). An Emperical Relation for Coefficient of Permeability of Sand. In *Fourth Australia-New Zealand Conference on Geomechanics*, , vol. 1, The Institution of Engineers, Australia, Barton, ACT, pp. 54–57. Available from: <https://www.issmge.org/uploads/publications/89/91/4ANZ_008.pdf> [19/10/2024]

Shepherd, R.G. (1989). Correlations of permeability and grain size. *Groundwater*, **27**(5): 633–638. https://doi.org/10.1111/j.1745-6584.1989.tb00476.x

Sivapullaiah, P.V, Sridharan, A. & Stalin, V.K. (2000). Hydraulic conductivity of bentonite-sand mixtures. *Canadian Geotechnical Journal*, **37**(2): 406–413. https://doi.org/10.1139/t99-120

Sridharan, A. & Nagaraj, H.B. (2005). Hydraulic conductivity of remolded fine-grained soils versus index properties. *Geotechnical and Geological Engineering*, **23**(1): 43–60. https://doi.org/10.1007/s10706-003-5396-x

Taiba, C.A., Mahmoudi, Y., Hazout, L., Belkhatir, M. & Baille, W. (2019). Evaluation of hydraulic conductivity through particle shape and packing density characteristics of sand–silt mixtures. *Marine Georesources and Geotechnology*, **37**(10): 1175–1187. https://doi.org/10.1080/1064119X.2018.1539891

Tavenas, F., Leblond, P., Jean, P. & Leroueil, S. (1983). The permeability of natural soft clays. Part I: Methods of laboratory measurement. *Canadian Geotechnical Journal*, **20**(4): 629–644. https://doi.org/10.1139/t83-072

Taylor, D.W. (1948). *Fundamentals of soil mechanics*. John Wiley & Son Inc. New York, NY.

Terzaghi, K. & Peck, R.B. (1948). *Soil mechanics in engineering practice*. John Wiley & Sons, New York, NY.

Van Genuchten, M.T. (1980). A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. *Soil Science Society of America Journal*, **44**(5): 892–898. https://doi.org/10.2136/sssaj1980.03615995004400050002x

Vardanega, P.J., Othman, M., Voyagaki, E., Crispin, J.J., Gilder, C.E.L. & Ntassiou, K. (2024). *The DINGO database: Summary report: March 2024, v1.2*. University of Bristol, Bristol, UK. https://doi.org/10.5523/bris.1jraem68g7ara21p2oi6hv4z22

Whittle, A. (1993). Evaluation of a constitutive model for overconsolidated clays. *Géotechnique*, **43**(2): 289–313. https://doi.org/10.1680/geot.1993.43.2.289

Zhai, Q., Rahardjo, H., Satyanaga, A., Zhu, Y., Dai, G. & Zhao, X. (2021). Estimation of wetting hydraulic conductivity function for unsaturated sandy soil. *Engineering Geology*, **285**: 106034. https://doi.org/10.1016/j.enggeo.2021.106034