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

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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. Other smaller databases (which may represent a specific data subset) can also be benchmarked against larger ones. Use of databases is especially valuable for assessing permeability (or hydraulic conductivity) – an important parameter that exhibits a very large range of variation across soil types and within individual laboratory testing campaigns. The issue of parameter uncertainty is often difficult to discount when permeability is a key parameter in a geotechnical model due to said variation. This chapter provides a comprehensive review of the variability and uncertainty in soil permeability with a focus on fine-grained materials, followed by a comparative study on the compilation of fine-grained soil permeability database and the construction of transformation model using the newly established laboratory permeability database, FG/KSAT-1358. Recommendations have been made for future development and analysis of permeability databases.

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PERMEABILITY OF SOILS

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 soil is of crucial importance in any geotechnical engineering design work since it is closely associated with many geotechnical phenomenon (e.g., Taylor, 1948; Lambe & Whitman, 1969). The percolation of water through soil is often characterised by the hydraulic conductivity k (often termed hydraulic conductivity) ($L.T^{-1}$), described in the Darcy's empirical law (e.g., Darcy 1856, Taylor 1948, Craig 2004):

$$\frac{Q}{A} = v = ki \quad (1)$$

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:

$$k = K\frac{\gamma}{\mu} \quad (2)$$

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 ($M.L^{-2}. T^{-2}$), μ is the dynamic viscosity ($M.L^{-1}.T^{-1}$).

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 geotechnical mechanics textbooks are generally ranging from 1×10^{-11} m/s to 1×10^{0} m/s i.e. over 11 orders of magnitude (e.g., Terzaghi & Peck 1948, Lambe &

Whitman 1969, Craig 2004), and ranges up to 14 orders of magnitude in some compiled hydraulic conductivity datasets (databases) (e.g., Ren & Santamarina 2018, Feng 2022, Feng *et al.* 2023).

Table 1 summarised the parameter variation range of four global multivariate databases focusing on fine-grained/ clay soils in 304dB (the TC304 database of databases which 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}, overconsolidation 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 to 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 range of all types of soil properties reported are mostly within 3 orders of magnitude across all four global fine-grained soil/ clay databases available from TC304.

Table 1. Soil properties variation range in some global multivariate fine-grained soil database (see: http://140.112.12.21/issmge/tc304.htm[3] 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 & Vardanega (2019a, b)	Fine-grained soil	1358	33	$\boldsymbol{k}$	**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 %

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

					w	5.8 to 559.5 %
					C_c	0.01 to 14.50
					C_{ur}	0.002 to 2.16
CLAY/10/7490	Ching & 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 & 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

Definition: 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} = $(q_t-s_v)/s'_v$ = normalized 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} = remolded s_u; σ_v' = vertical total stress; σ_p' = preconsolidation stress

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 of the value measured at 20°C, and k at 40°C is 0.58 times of value measured at 20°C. The hydraulic conductivity measured at a specific test temperature can be converted to a corresponding permeability at different temperatures based on Equation 2, using a correction factor (e.g., British Standard Institution (BSI) 2019). A test temperature of 20°C is commonly deemed as the standard or reference temperature condition for laboratory measurement (e.g., ASTM 2022, BSI 1990).

The permeant percolation mechanism in most geo-materials 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 mostly 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 ($r_k = kh / k_v$) typically falls below 4, the maximum r_k observed in most engineering soil is around 2.5 (Liu, 2015). The anisotropic behaviour in soil permeability is often less pronounced at a higher void ratio level, e.g., for static compacted sand r_k = 1.8 for e = 0.4, r_k = 1 for e = 0.8 (Chapuis *et al.* 1989).

Soil in its naturally occurring state is commonly found to be unsaturated. 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., Lambe & Whitman 1969, Bear 1972), i.e., for an undisturbed sandy soil, the k measured at 70% saturation level is approximately 10% of its saturated k value, while k measured at 96% saturation level is approximately 75% of its saturated k value. The unsaturated k may be estimated from the saturated k value in conjunction with the soil water retention curve (correlation between degree of saturation and suction in soil) 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. The presence of certain chemical constituents in the permeant may cause the soil particles to either flocculate or disperse, and lead to changes in hydraulic conductivity (Lambe & Whitman 1969, Mesri & Olson 1971). The ratio of hydraulic conductivity measured using permeants with different chemical constituents for the same soil under a given 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).

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, 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.* 2018). While each permeability testing approach has its merits (and limitations), they are all established based on specific assumptions, e.g. Darcian flow, homogenous soil, saturation soil conditions. The results obtained from the test are dependent on the underlying assumptions implicit in the selected testing methodology, with the acknowledgment that these assumptions cannot always be guaranteed, even under laboratory conditions (Chapuis 2012). The inherent "inaccuracy" of permeability measurement approaches leads to a degree of variation close to one order of magnitude from the same test method (Pane *et al.* 1983, Nagy *et al.* 2013), and up to orders of magnitude high when comparing results from different test methods (Moulton & Seals 1979, Chapuis 2012, Nagy *et al.* 2012). 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 determination of soil permeability challenging – this challenge can be partially mitigated by the availability of extensive geotechnical databases.

TRANSFORMATION MODELS

Predictors of hydraulic conductivity

Transformation models are used to estimate soil parameters using more easily accessible ones. Similar to all the other geotechnical parameters, the permeability of soil can also be assessed with more basic soil parameters using empirical correlations established from past database studies. The main soil characteristics which 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, 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 & Santamarina 2018, Feng *et al.* 2019a, Feng *et al.* 2019b), coefficient of uniformity C_U (Shahabi *et al.* 1984), mean constriction size D_c^m (Jaafar & Likos 2014), normalised grading entropy co-ordinates A, B (, Feng *et al.* 2019, Feng 2022);

(c) **Plasticity related parameters:** 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), 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), soil shape (Cabalar & Akbulut 2016, Taiba *et al.* 2019, Katagiri *et al.* 2020, Nguyen & Indraratna 2020).

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

Model Structure

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

Feng *et al.* (2023) reviewed the 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 over 50 studies. The model adequacy analysis of the prediction models revealed that all linear-correlating models all exhibited a 'funnel' pattern in the residuals versus predicted plots indicating anomalies (see Figure 1, full results are given in the recent paper of Feng *et al.* 2023) when calibrated using generic permeability database. This observation indicates the need of data transformation in the predicted value *k* (Montgomery *et al.* 2007, p.303). The need of such data transformation may be attributed to the difference in the range of variation between *k* and corresponding predictors, as illustrated in Table 1.

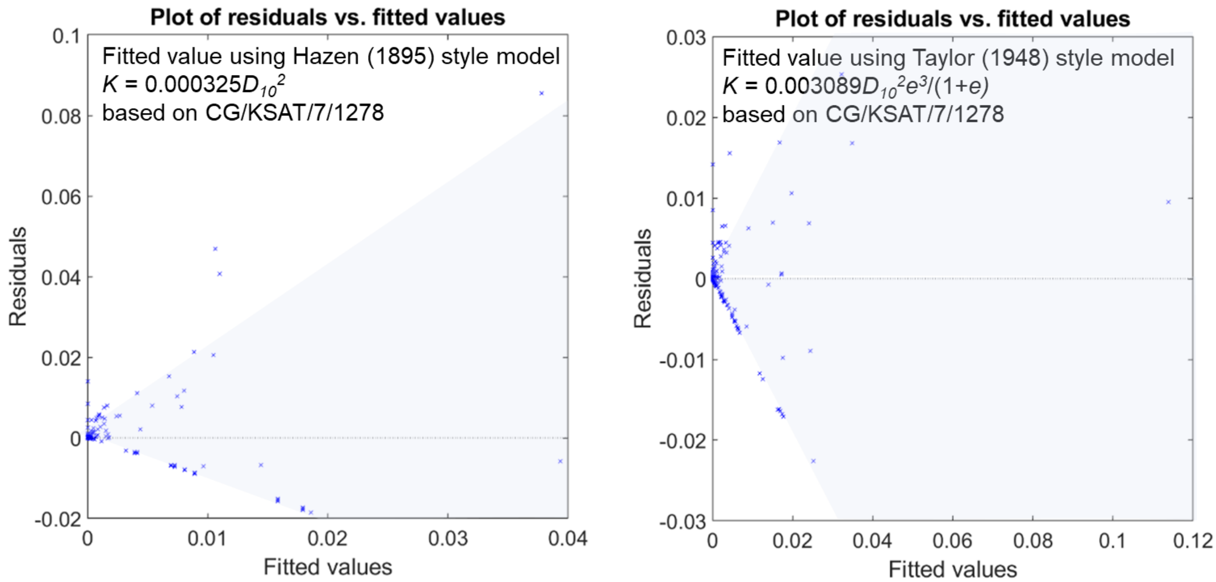

Figure 1 Examples of "funnel" pattern residuals versus predicted plot: a) Residual versus predicted plot using Hazen (1895) style model using CG/KSAT/7/1278; b) Residual versus predicted plot using Taylor (1948) style model using CG/KSAT/7/1278 (adapted from Feng et al. 2023)

Evaluation of Regression Strength

Kulhaway & Mayne (1990) suggested that any correlation for estimating soil properties should be accompanied bymeasure(s) of validity. 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 assess the strength of fitted models. Phoon & Kulhawy (1999a, 1999b) emphasized the significance of reporting the standard error (SE) to provide a measure of "transformation uncertainty" in correlations. The *p-value* of the 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.

Database Subdivision Analyses

Further subdivision analysis is often required in model development, especially when dealing with data varies over an extensive range (e.g., soil permeability *k*) to evaluate how generally applicable a developed transformation model. Correlation may exhibit distinct pattern among data over different value ranges or under various test conditions, as illustrated in Figure 2. The subdivision analysis helps to examine the potential influencing factors (e.g., permeability testing methods) and uncover underlying trends or correlations that may exist within specific subgroup which may be rather different from the transformation model calibrated with the whole dataset (detailed discussion in Feng 2022).

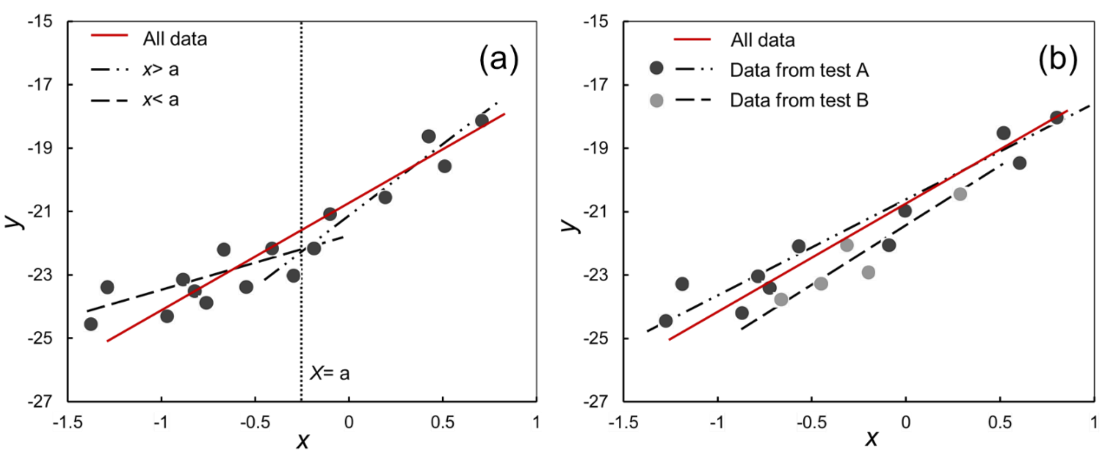

Figure 2 Divergency in subdivision analysis (a - subdivision over different value range; b - subdivision over different test conditions) (adapted from Feng 2022)

PERMEABILITY DATABASES FOR FINE GRAINED SOIL

Database Summary

As discussed previous, 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 the proposed model (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 sourcing from geotechnical literatures (e.g., RFG/TXCU-278 from Beesley & Vardanega 2020). Some databases compiled using a combination of literature and industry sources (e.g., DINGO database on piled foundation, Vardanega *et al.* 2021).

Table 2 presents a summary of eight fine-grained soil permeability database/sets used for constructing permeability prediction models, including the recent 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 of 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 corresponding sources.

Database Evaluation

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

It was noticed that more recent compiled databases tend to encompass data from earlier databases, reflecting collective efforts in database compilation. 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 & Nagaraj (2005) and Sivapullaiah et al. (2000). The data sources collected to develop FG/KSAT-1258 detailed in Feng & Vardanega (2019a, 2019b) also overlap with the compiled databases in Mbonimpa *et al.* (2002) and Ren & Santamarina (2018). There has been an obvious increase in the size of databases for soil permeability due to the aforementioned research efforts. Among the compiled databases, FG/KSAT-1358 by Feng & Vardanega (2019a, 2019b) contains the largest number of permeability test data on fine-grained soil (over 1300), along with comprehensive details on the key factors influencing permeability.

Table 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 & 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	n/a; more than two types of tests involved (constant head, falling head)	n/a	n/a	saturated	n/a
Multi-source (global) compiled database									
Carrier & Beckman (1984)	66	22 phosphatic; 13 dredged materials; 26	k (10^{-10} to 10^{-5} m/s)	8	constant head; consolidation	n/a	one dimensional	n/a	permeating fluid with same

		remoulded natural clays			test (stress-controlled & constant rate of deformation)				chemical composition as the porewater
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' test conducted under constant head or falling head condition.	20°C	n/a	saturated	n/a
Ren & Santamarina (2018)	1440 (include sandy soil)	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 & Vardanega (2019a)	1358	natural or laboratory fine grained soil with less than 50% coarse particles (d >75 mm) and a measured plasticity limit.	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

Model Calibration

Table 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 & 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 & Santamarina 2018, and Feng & 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 compile database (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 database with relatively larger sample size, such as Carrier & Beckman (1984) with n = 66, Mbonimpa et al. (2002) with n = 342, and Ren & Santamarina (2018) with n = 1440 (size of the sample also include sandy soils).

Transformation models calibrated with larger sample size, 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 implemented in Ren & Santamarina (2018) and Feng &

Vardanega (2019a) to further analyse and verify the accuracy and applicability of the established transformation models.

Table 3 Summary of calibrated prediction models (data sources as shown in Table 2)

Sources	Database/set	Calibrated transformation models	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 sample 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 sample (no. of data digitised from plot, includes mixture with over 50% sand)	$\log_{10} k = \frac{e-0.0535w_L-5.286}{0.0063w_L+0.2516}$; k in m/s for $w_L > 50\%$	r = 0.94, SE = 1.486	n/a	n/a
Sridharan & Nagaraj (2005)	laboratory testing dataset on 10 soil types, 70 sample (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 & Beckman (1984)	compiled database from 8 studies on 66 clay samples; cover data from 2 test types	$k(m/s) = \mu \frac{(e-\delta)^\nu}{1+e}$; $\mu = \left[\frac{0.389}{PI}\right]^{4.29}$ $\delta = 0.027\left[w_p - 0.242I_p\right]$ $\nu = 4.29$	n/a	within an order of magnitude	n/a

	(constant head, consolidation test)				
Mbonimpa *et al.* (2002)	compiled database from 6 studies on 342 plastic/cohesive soils sample	$k_{sat}\ (cm/s) = C_P \frac{\gamma_w}{\mu_w} \frac{e^{3+x}}{1+e} \frac{1}{\rho_s{}^2 w_L{}^{2\chi}}$; $C_P = 5.6\ g^2/m^4$ $x = 7.7 w_L{}^{-0.15} - 3$ $\chi = 1.5$ $\gamma_w \approx 9.8\ kN/m^3$ $\mu_w \approx 10^{-3}\ Pa.s$	n/a	usually within half an order of magnitude	n/a
Ren & Santamarina (2018)	compiled database from 23 studies on 1440 natural and remoulded sediment sample, from coarse sand to fine-grained soil	$k(cm/s)\ =\ 10^{-5}(\frac{S_s}{m^2/g})e^{\beta}$; $S_S = 1.8 w_L - 34$ β may be derived from the power relation between k and e for the specific soil type: $\beta = 3 \pm 1$ 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 & 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 & Vardanega (2019a) with identified outliers removed	$k_{sat}(m/s) = 1.86 \times 10^{-9} \left({}^{w}/{}_{w_L}\right)^{4.226}$	$R^2 = 0.65$, $n = 1272$, $SE = 1.202$, $p < 0.0001$	mostly within an order of magnitude	

Benchmarking databases

In order to validate and compare the predictive performance of permeability transformation models calibrated using database of varying source type, size, and data range, a benchmarking analysis is conducted using the largest fine-grained soil database - FG/KSAT-1358. Figure 3 summarizes 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 can be 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. Models developed based on regional compiled database and individual laboratory test campaign tend to exhibit an overall biased prediction trend for the global compiled database FG/KSAT-1358. This is to be expected as smaller data-sets 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 use of empirical models based only on small data-sets 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 data-set.

Among the reviewed fine-grained soil database studies, the database compiled by Ren & Santamarina (2018) stands out due to its extensive variation in k value and a database size comparable to FG/KSAT-1358. Figure 4 presents the benchmarking analysis results using the model presented in Ren & Santamarina (2018) with β = 4, 5, and 6 (selection of β based on the range reported by Ren & Santamarina 2018: $\beta = 5 \pm 1$ for fine-grained soils), in comparison with the model developed by Feng & Vardanega using FG/KSAT-1358. The prediction models by Ren & 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 & Vardanega (2019a) yields slightly overpredicted results, with 89% of the prediction within the same prediction range. It should also be noted that while Ren & Santamarina (2018) report a β range of 5 ± 1 for fine-grained soil, individual soil type in FG/KSAT-1358 gives 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.

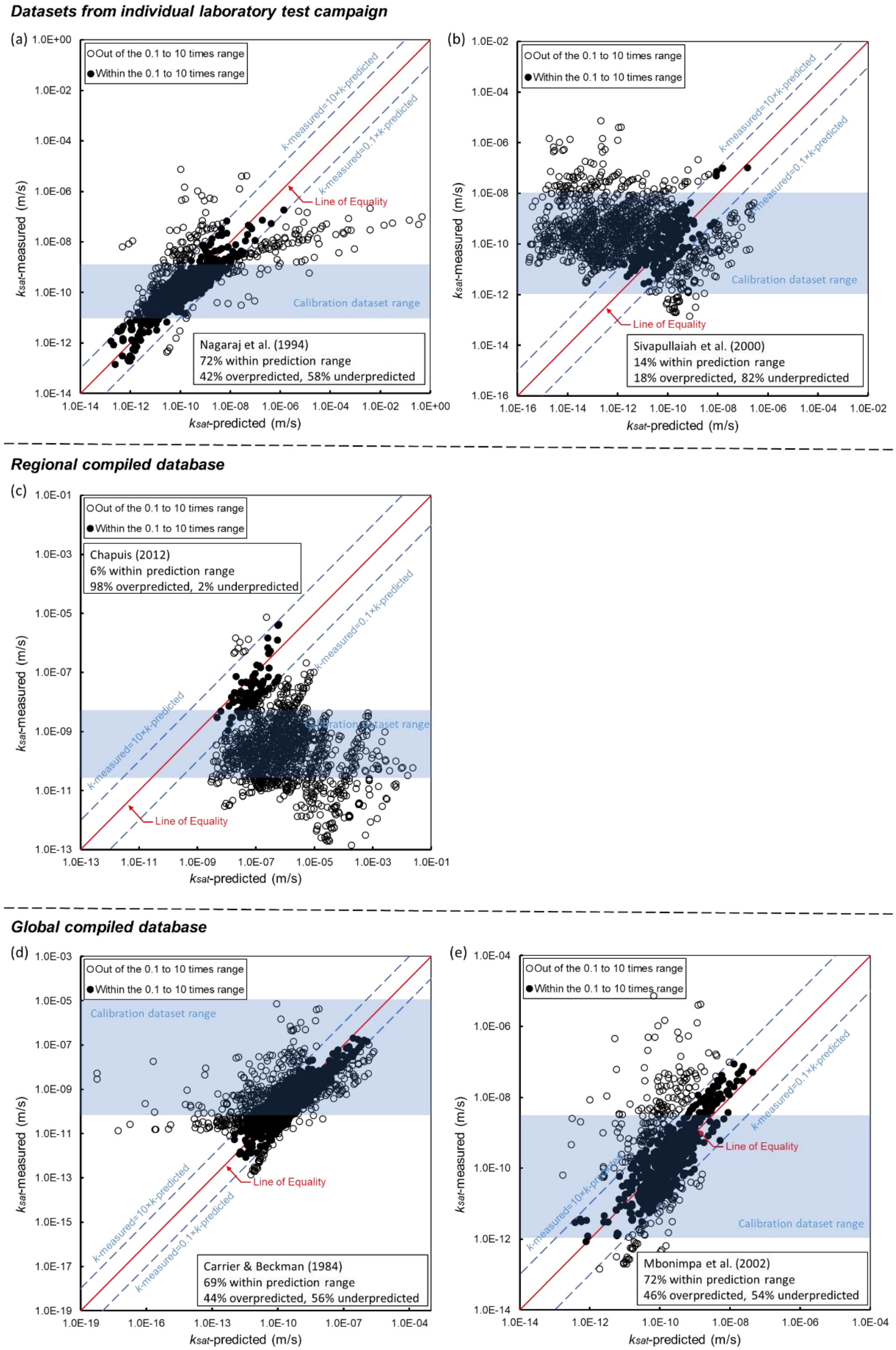

Figure 3 Benchmarking analysis result for models with smaller calibration dataset range using FG/KSAT-1358 : a) Predicted values using transformation model from Nagaraj et al. (1994); b)

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 & Beckman (1984); e) Predicted values using transformation model from Mbonimpa et al. (2002)

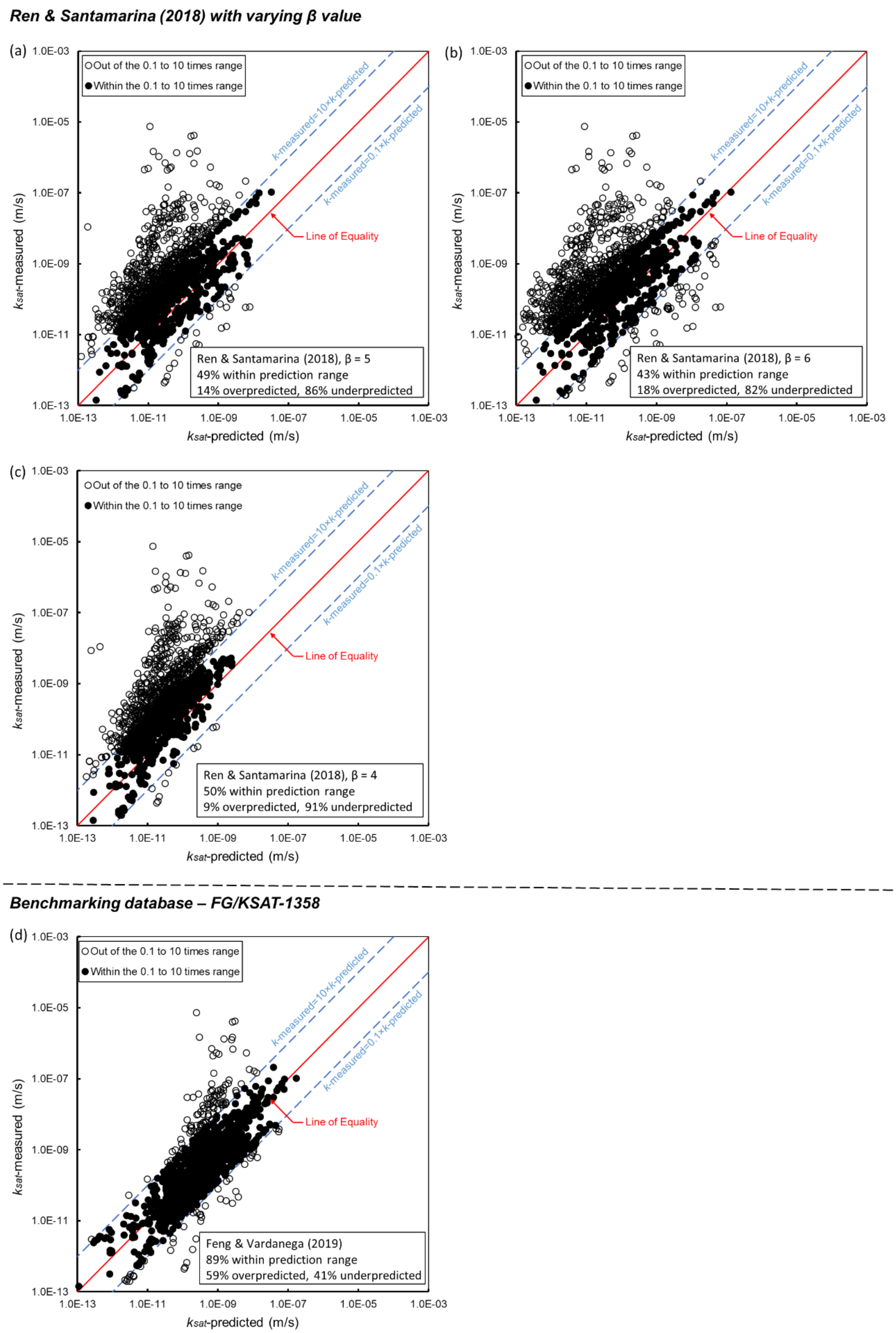

Figure 4 Benchmarking analysis result for Ren & Santamarina (2018) model with varying β: a)

Predicted values using transformation model from Ren & Santamarina (2018) with $\beta = 5$; b) Predicted values using transformation model from Ren & Santamarina (2018) with $\beta = 6$; c) Predicted values using transformation model from Ren & Santamarina (2018) with $\beta = 4$; d) a) Predicted values using transformation model from Feng & Vardanega (2019a)

CONCLUSION AND SUGGESTIONS

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

Permeability Database Compilation

It is important to stress the variability and uncertainty in permeability measurements during the database compilation process. The measured k value of the soil is high dependent on factors such as the test type, test condition, and sample state. Therefore, information on the relevant influencing factors, such as permeability testing type, test temperature, sample states, and permeating fluid, should always be supplemented with the assembled permeability 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 harmonization efforts.

Permeability 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 permeability transformation models. Considering the inherent uncertainty and variability of soil permeability assessment, adequate model evaluations that include 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 digitization of geotechnical resources, significant efforts have been made to compile and publish studies on permeability databases. However, even with the availability of such studies, the prediction obtained using existing transformation models still exhibit a considerable range of variation, often spanning up to an order of magnitude, particularly when considering global compiled databases. High quality soil sampling and testing program 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 permeability assessments.

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