Feng, S., Vardanega, P., & Ibraim, E. (2019). Comparison of Prediction Models for the Permeability of Granular Materials Using a Database. In S. Hemeda, & M. Bouassida (Eds.), *Contemporary Issues in Soil Mechanics: Proceedings of the 2nd GeoMEast International Congress and Exhibition on Sustainable Civil Infrastructures, Egypt 2018 – The Official International Congress of the Soil-Structure Interaction Group in Egypt (SSIGE)* (pp. 1-13). (Sustainable Civil Infrastructures). Springer, Cham. https://doi.org/10.1007/978-3-030-01941-9_1

Peer reviewed version

Comparison of prediction models for the permeability of granular materials using a database

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ABSTRACT: The hydraulic conductivity characteristics of the materials which comprise pavement structures are linked to in service performance. This paper briefly reviews a series of well-known models to predict hydraulic conductivity. An approach which makes use of the grading entropy coordinates is also studied. The database includes information on the gradation, hydraulic conductivity and porosity characteristics for over 150 gravel mixtures. Comparison of the studied models reveals that the 'Kozeny-Carman' model gives the best predictions when considering the entire database. The results of the regression analysis reveal that for granular mixtures comprising greater than 50% sand, the 'Shepherd' or 'Hazen' approaches may be preferred. However, for mixtures comprising less than with 50% sand, the 'Kozeny-Carman' and 'grading entropy' approaches are preferred.

INTRODUCTION

Water ingress into road pavements is potentially detrimental to the mechanical properties of the structure (e.g., Kandhal & Rickards, 2001; Mallick & El-Korchi, 2008; Thom, 2014; Ghabchi et al., 2015). Engineers need to make rapid assessments of the hydraulic conductivity of pavement materials. This paper follows a detailed laboratory study which compared the 'Hazen', 'Shepherd', 'Kozeny-Carman' and 'Chapuis' models along with a regression model that uses the grading entropy coordinates (Feng, 2017; Feng et al. 2018a). Feng (2017) and Feng et al. (2018a) presented results on only one material but testing was conducted over a wide range gradations. This paper aims to investigate the relative merits for the aforementioned models using a larger database of experimental observations.

Traditional Models for Hydraulic Conductivity

The hydraulic conductivity k (in Length.Time^{-1}) is given by (e.g., Craig, 2004, p.31):

$$k = \frac{\gamma}{\mu} K \tag{1}$$

Where μ (in Mass.Time^{-1}.Length^{-1}) are the unit weight and the dynamic viscosity of the permeant respectively, and K (in Length^{2}) is the intrinsic permeability.

The 'Hazen' formula (e.g., Hazen, 1893, p.553) is one of the most commonly-used models which can be expressed as follows:

$$k = (0.7 + 0.03t)C_H {D_{10}}^2 \tag{2}$$

where t is the temperature in degrees Celsius, D_{10} represents the sieve aperture through which ten percent of the material passes, and C_H is an empirical coefficient.

Shepherd (1989) presented a modification to the 'Hazen' approach using an equation of the following form:

$$k = C_{HS} {d_{eff}}^a \tag{3}$$

where a (for most materials) generally varies from 1.65 to 1.85 (according to Shepheard 1989), C_{HS} is a regression constant, d_{eff} is the representative particle size (which for consistency is taken in this paper to be D_{10}).

The 'Kozeny-Carman' formulation (Carman, 1937, 1939; Kozeny, 1927) is another well-known semi-empirical model to describe hydraulic conductivity. Carrier (2003) gives a variant of this formulation, shown as Eq. (4):

$$k = \left(\frac{\gamma}{\mu}\right)\left(\frac{1}{C_{K-C}}\right)\left(\frac{1}{{S_A}^2}\right)\left(\frac{e^3}{1+e}\right) \tag{4}$$

where C_{K-C} is an empirical coefficient (which can be taken as approximately 5), S_A is the specific surface area per unit volume of particles, and e is the void ratio.

Chapuis (2004, 2012) developed an amalgamated permeability model for non-plastic sand by combining aspects of the 'Kozeny-Carman' and 'Hazen' approaches. Using a database, Chapuis (2004) found Eq. (5) statistically:

$$k(cm/s) = 2.4622[{D_{10}}^2 e^3/(1 + e)]^{0.7825} \tag{5}$$

where the D_{10} is in mm. Chapuis (2004) suggested that Eq. (5) only provides good predictions for natural soils with 0.003mm< D_{10}< 3mm and 0.3< e< 1 (137 out of 166 of the collected database in this study fit both criteria).

The Grading Entropy Method

The 'grading entropy' approach allows a grading curve to be represented vectorially on the normalised grading entropy diagram (Figure 1). The coordinates are calculated using:

$$A = \frac{\sum_{i=1}^{N} x_i(i-1)}{N-1} \tag{6}$$

$$B = -\frac{\sum_{i=1}^{N} x_i \log_2 x_i}{log\, N} \tag{7}$$

where 'A' is the relative base entropy, 'B' is the normalised entropy increment, N is the fraction number, and x_i is the relative frequency of fraction i. Lőrincz et al. (2005)

and Singh (2014) provide more extensive commentary on the origins and details of the 'grading entropy' approach. Using a similar database to that presented in Vardanega et al (2017), Feng et al (2018b) performed multiple linear regression analysis to a large database of hydraulic conductivity measurements on asphalt concrete using the grading entropy co-ordinates as predictors. Feng et al. (2018a) performed similar analysis for a set of laboratory data on a single gravel and found Equation (8):

$$k_{20°C}\,(\mathrm{mm/s}) = 145.47A^{8.90}B^{-2.30} \quad r = 0.95, R^2 = 0.90, n = 30, p < 0.0001 \quad (8)$$

Like the 'Hazen' and 'Shepherd' approaches no measurement of void ratio is included in this approach.

DATABASE

Table 1 shows the list of ten publications used to source the information for inclusion in the database studied in this paper. 164 hydraulic conductivity tests are included in the database. The test methods (where stated in the original publication), material types, void ratios and gradation parameters of each data source are given in Table 1. The collected database comprises mostly sands and gravels with D_{10} generally ranging from 0.001mm to 10mm and void ratio (e) ranging from 0.23 to 1.13. The collected hydraulic conductivity data were converted to intrinsic permeability K (in mm^2) based on the water temperatures reported in the original publications (ranging from 10 to 20°C).

ANALYSIS

Complete Database

Data from different sources are shown with different markers on Figure 2 to 6. The numbering of the data entries follows that given in Table 1.

Hazen (Hazen, 1893)

Figure 2 shows the regression function linking between K and D_{10}^2 for the database:

$$K(\mathrm{mm}^2) = 0.00054{D_{10}}^2 \quad r = 0.82, R^2 = 0.68, n = 164, p < 0.0001 \quad (9)$$

The K-predicted is plotted against K-measured in Figure 2. The plot shows that 110 out of 164 data points lie between the ±75% bounds (red dashed lines), about 40.8% of the total data points fall above the line of equality (45 degree line) while around 59.2% of the points fall beneath. Figure 2 indicates Eq. (9) generally under-predicts K.

Shepherd (Shepherd, 1989)

'Shepherd' model gives essentially the same result as Eq. (9) (for the data analysed in this paper), the regression result between lnK and lnD_{10} can be rearranged to:

$$K(\mathrm{mm}^2) = 0.00059{D_{10}}^{1.99} \quad r = 0.87, R^2 = 0.75, n = 164, p < 0.0001 \quad (10)$$

The K-predicted versus K-measured (Figure 3) shows that 108 out of 164 of the total points fall within the ±75% margin, 42.7% of the total points lie above the line of equality, while the remainder (57.3%) of the points lie below. Similar to Eq. (9), the Eq. (10) also slightly under-predicts the value in this database.

Kozeny-Carman (Carman, 1937)
Regression of K with $\frac{\gamma}{\mu}.\frac{1}{{S_A}^2}.\frac{e^3}{1+e}$ (denoted as K-C function in Figure 3) gave Eq. (11):

$$K(\mathrm{mm}^2) = 0.015\,\frac{\gamma}{\mu} \times \frac{1}{{S_A}^2} \times \frac{e^3}{1+e} \quad r = 0.97, R^2 = 0.93, n = 164, p < 0.0001 \qquad (11)$$

where the specific surface (S_A) is calculated based on the method introduced by Chapuis and Légaré (1992). The corresponding predicted versus measured plot (Figure 4) shows that 97 out of 164 of the total points locate within the ±75% margins, 61.0% of the data points lie above the line of equality while the rest of the data points fall beneath. Eq. (11) generally over-predicts the measurements contained in this database.

Chapuis (Chapuis, 2004)
The fitted correlation linking lnK and $ln[D_{10}^2e^3/(1+e)]$ can be rearranged to give:

$$K(\mathrm{mm}^2) = 0.0023(\frac{{D_{10}}^2e^3}{1+e})^{0.85} \quad r = 0.79, R^2 = 0.63, n = 164, p < 0.0001 \qquad (12)$$

Eq. (12) can be converted using the units adopted in Chapuis (2004, 2012):

$$k(\mathrm{cm/s}) = 2.254[{D_{10}}^2e^3/(1+e)]^{0.85} \qquad (13)$$

The coefficient of 2.254 and the exponent of 0.85 in Eq. (13) generally conform with the finding of Chapuis (2004, 2012) who gives 2.4622 and 0.7825 for the coefficient and exponent (Eq. 5), note only 1 data source is common between two databases analysed. The predicted versus measured plot (Figure 5) shows that 78 out of 164 of the total data points fall between the ±75% margins and 43.9% of the data points lie above the line of quality while the remainder of the data points (56.1%) fall beneath, which indicates that the Eq. (12) gives a slightly skewed (under-predicted) prediction of K.

Grading Entropy Model
The normalized grading entropy coordinates A and B of the whole database were calculated using Eqs. (6), and (7). The calculated A and B are then regressed against K, the result gives:

$$K(\mathrm{mm}^2) = 0.0048A^{6.04}B^{-0.34} \quad r = 0.83, R^2 = 0.69, n = 164, p < 0.0001 \qquad (14)$$

which can also be expressed as:

$$k_{20^\circ\mathrm{C}}(\mathrm{mm/s}) = 47.04A^{6.04}B^{-0.34} \qquad (15)$$

The coefficient and exponents obtained based on this database (in Eq. 15) differ with

Feng et al. (2018a) (in Eq. 8), which might be due to the diversity of gradation ranges and material types involved in this study. Figure 6 shows that 84 out of 164 of the total data points lie within the ±75% bounds, and 41.5% of the points fall above the line of equality which presents over-predicted results, while 58.5% of the data points, fall beneath which give under-predictions of *K*.

Summary
All five models over-predict the results for data entry 5 (Wang et al., 2017) which is possibly due to the specific type of materials used in this study (calcareous soils). Also, noticeable deviation in permeability predictions can be noticed in data source 6 (Table 6) (Xiao et al., 2013), which may be due to the fact that the gas permeameter was used. Based on the regressed results, all five of the studied models have sufficiently low *p*-values (<0.0001) and are statistically significant. The analysis results using all five models are summarised in Table 2.

Influence of Particle Size
To investigate the potential effect of particle size, the whole database is divided into two subsets, which are samples with sand component> 50% and samples with sand component< 50%. The classification of sand and gravel follows Craig (2004, p. 5). The results of the analysis of these two subsets are given in Table 3 and Table 4.

Table 3 shows that for the data subset sand> 50%, 'Shepherd' model is favoured based on the R^2 (= 0.64) as well as the data points (68 out of 96) fall within ±75% prediction range, while the 'Hazen' formula gives the second highest R^2 (= 0.59) and least biased predictions (45 over-predicted, 51 under-predicted).

For the data subset with sand< 50% (Table 4), 'Kozeny-Carman' model does yield the highest R^2 (= 0.93) among these fives models, however, the 'grading entropy' provides the second highest R^2 (= 0.74) with most data points (45 out of 68) within ±75% prediction range and the most symmetrical prediction (38 over-predicted, 30 under-predicted) but without the need of void ratio (*e*) measurement.

CONCLUDING REMARKS

Some of the scatters shown in Figure 2 to 6 is inevitably due to the variety of test methods for *K* and *e* in the database. Despite this the following conclusions may be drawn:
(1) for the database with a wide range of particle sizes (the whole database), the 'Kozeny-Carman' model is favoured for the highest R^2 value, while 'Shepherd' model provides the second highest R^2 value and one of the most symmetrical predictions;
(2) for the data subset with > 50% sand component in the tested mixtures, the 'Shepherd' (highest R^2, most points within ±75% margins) and 'Hazen' models (most symmetrical prediction) are preferred;
(3) for the data subset with <50% sand component, the 'Kozeny-Carman' model yields the highest R^2. However, the 'grading entropy' gives the most symmetrical prediction (38 over-predictions and 30 under-predictions) with most points fall within

±75% margins.
Further data may reveal different trends to those found in this paper and additional data to study the effect of varying testing procedures may be helpful for future research.

DATA AVAILABILITY STATEMENT

This study has not generated new experimental data.

ACKNOWLEDGEMENTS

This first author is grateful for the financial support given by the scholarship from China Scholarship Council (CSC) under the Grant CSC No. 201708060067.

NOTATION LIST

The following notations are used in this paper (dimension given in brackets):
A= Relative base entropy;
B= Normalized entropy increment.
C_H= Hazen empirical coefficient (Length^{-1}.Time^{-1});
C_{HS}= Shepherd empirical coefficient;
$C_{K\text{-}C}$= Kozeny- Carman coefficient;
C_U= Coefficient of Uniformity, $C_U = \frac{D_{60}}{D_{10}}$;
d_{eff}= Representative particle size
D_{10}= Effective particle size, for which 10% of the soil is finer (Length);
e= Void ratio;
k= Coefficient of permeability (Length.Time^{-1});
K= Intrinsic permeability (Length^2);
n= Number of data points;
N=Number of fractions/successively doubled sieves;
p= p-value;
R^2= Coefficient of determination;
S_A= Specific surface area per unit volume of particles (Length^{-1});
S_o= Base entropy;
t= Temperature (in ℃)
x_i= Relative frequency of fraction i;
γ= Unit weight (Force.Length^{-3});
μ= Dynamic viscosity (Mass.Time^{-1}.Length^{-1});
ρ= Density (Mass. Length^{-3})

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TABLES

Table 1. Summary of database

No.	Sources	Air voids testing method	Hydraulic conductivity testing method	Materials type as described in the original publication	D_{10} (mm)	C_U (mm)	e	n
1	Cabalar and Akbulut (2016)	-	constant head test	narli sand	0.10-2.29	1.20-4.22	0.52-0.87	16
				crushed stone sand	0.10-2.29	1.20-4.22	0.67-1.02	16
2	Indraratna et al. (2012)	-	constant head test (ASTM D2434-68)	river sand	0.3	1.51-4.03	0.61-0.71	6
3	Mavis and Wilsey (1936)	geometric	constant head test	Iowa river sand	0.22-1.81	1.73-5.54	0.50-0.73	12
4	Morris and Johnson (1967)	geometric	constant/ variable head test	water laid gravel	1.37-5.45	1.70-2.36	0.61-0.79	3
				water laid sand	0.001-0.69	1.56-54.39	0.39-0.81	4
5	Wang et al. (2017)	-	constant head penetration test	calcareous soil	0.03-0.14	3.30-10.00	0.73-1.13	20
6	Xiao et al. (2013)	-	gas permeameter test	crushed aggregate	0.06-1.81	5.67-142.33	0.29-0.35	5
7	Yin et al. (1998)	-	constant head test	single-sized crushed stones	2.35-11.00	1.42-1.92	0.40-0.44	3
				sand	0.15-0.17	2.00-4.76	0.45-0.57	2
				mechanical stabilized crushed stones	0.14-0.23	15.86-36.51	0.23-0.26	4
8	Dolzyk et al. (2014)	-	constant head test	soil	0.07-0.34	1.95-60.80	0.3-0.923	24
9	Goetz (1971)	-	constant head test (ASTM D2434-68)	20-30 ottawa sand	0.61	1.20	0.56-0.72	8
				2 ns concrete sand	0.22	4.62	0.37-0.51	4
				dune sand	0.13	1.88	0.61-0.77	3
				22a gravel	0.15	31.17	0.25-0.41	4
10	Feng (2017) and Feng et al. (2018a)	WA732.2-2011/ BS1377:2-1990	constant head test (BS 1377-5:1990)	road construction material (mostly crushed aggregate)	0.72-7.02	1.51-7.29	0.53-0.85	30
	Total							164

Table 2. Analysis result of the complete database

n= 164	R^2	*p*-value	Within ±75%	Over-prediction	Under-prediction
Hazen	0.68	< 0.0001	110	67	97
Shepherd	0.75	< 0.0001	108	70	94
Kozeny-Carman	0.93	< 0.0001	97	100	64
Chapuis	0.63	< 0.0001	78	72	92
Grading entropy	0.69	< 0.0001	84	68	96

Table 3. Analysis result of data subset: sand component> 50%

n= 96	R^2	*p*-value	Within ±75%	Over-prediction	Under-prediction
Hazen	0.59	< 0.0001	68	45	51
Shepherd	0.64	< 0.0001	73	39	57
Kozeny-Carman	0.50	< 0.0001	62	24	72
Chapuis	0.51	< 0.0001	58	43	53
Grading entropy	0.48	< 0.0001	49	57	39

Table 4. Analysis result of data subset: sand component< 50%

n= 68	R^2	*p*-value	Within ±75%	Over-prediction	Under-prediction
Hazen	0.67	< 0.0001	45	21	47
Shepherd	0.67	< 0.0001	43	29	39
Kozeny-Carman	0.93	< 0.0001	43	28	40
Chapuis	0.67	< 0.0001	40	30	38
Grading entropy	0.74	< 0.0001	45	38	30

FIGURES

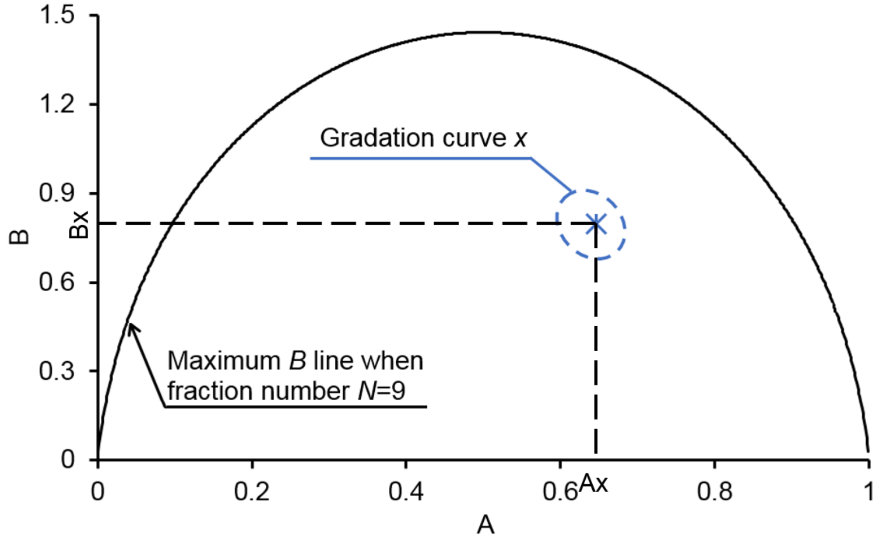

Figure 1 Sketch example of gradation curve interpretation on normalised grading entropy diagram

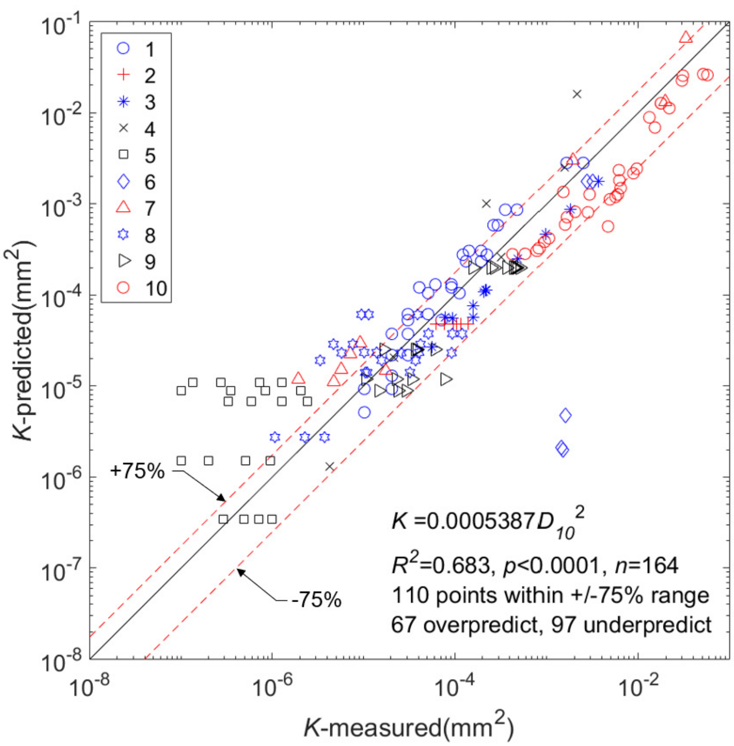

Figure 2 *K*-predicted versus *K*-measured using Hazen`s formula

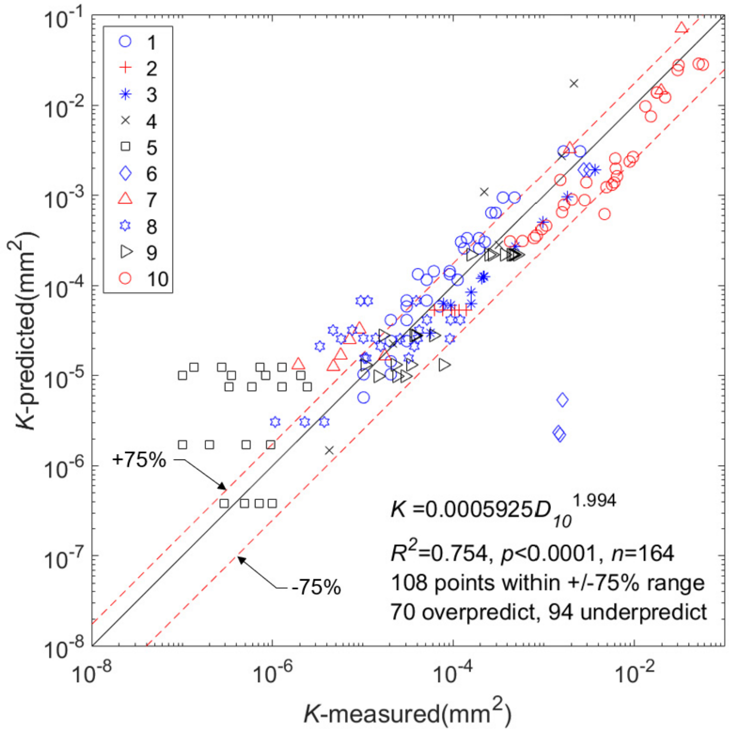

Figure 3 *K*-predicted versus *K*-measured using Shepherd`s model

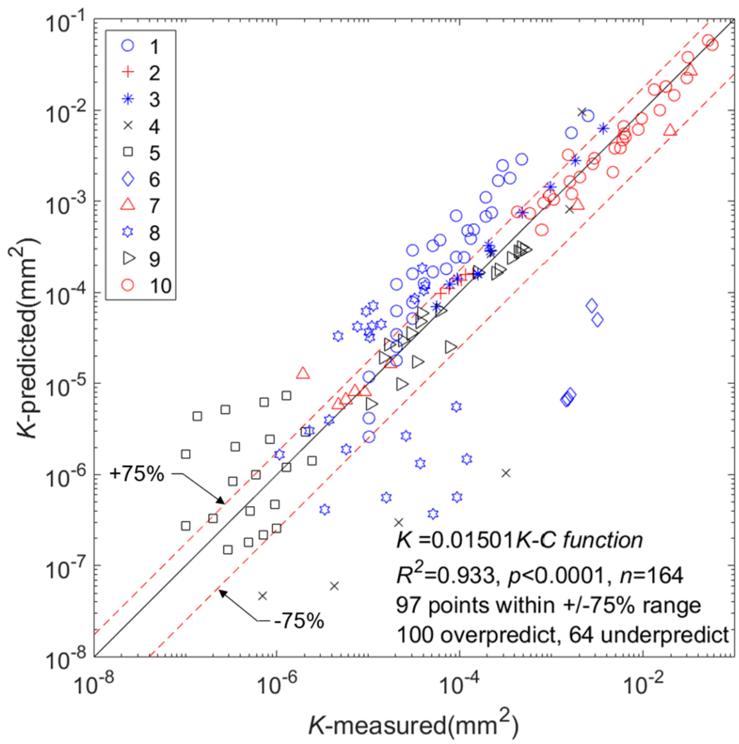

Figure 4 *K*-predicted versus *K*-measured using Kozeny-Carman`s function

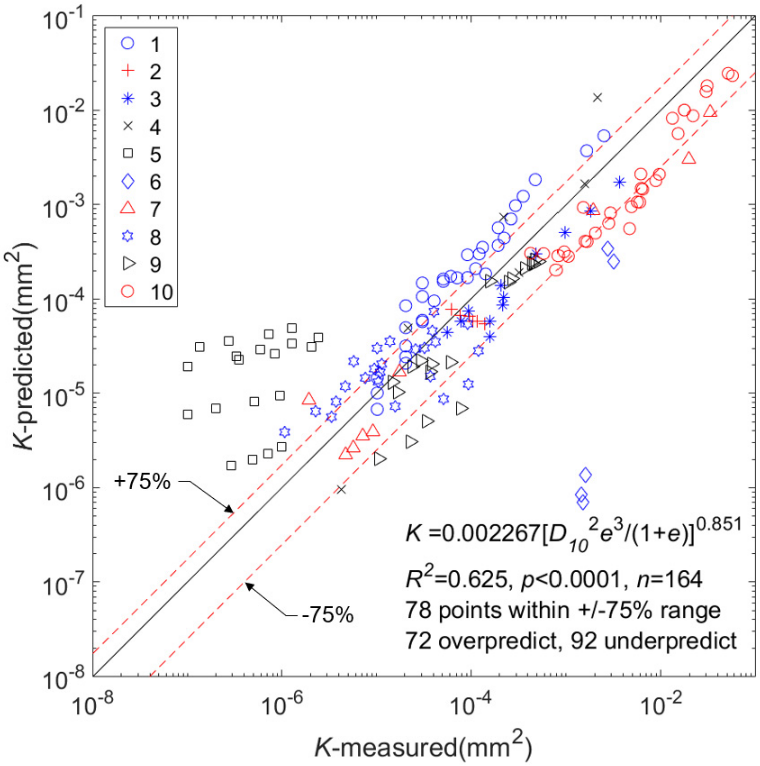

Figure 5 *K*-predicted versus *K*-measured using Chapuis`s model

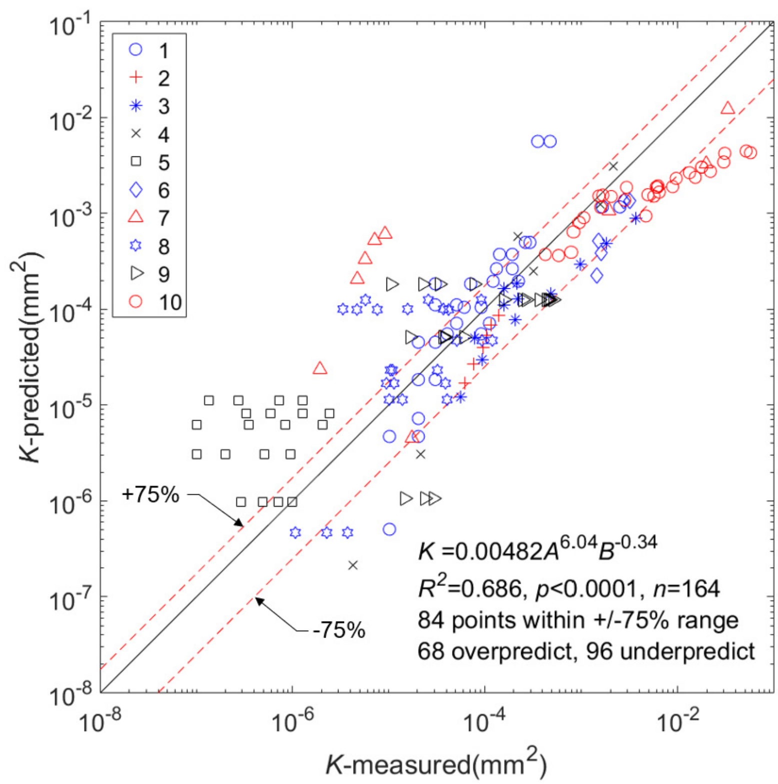

Figure 6 *K*-predicted versus *K*-measured using grading entropy model