THE TENTH LUMB LECTURE

THE STORY OF STATISTICS IN GEOTECHNICAL ENGINEERING

KOK KWANG PHOON

方国光

NATIONAL UNIVERSITY OF SINGAPORE

Rank	$S(x_{db})$	LL (%)	PI (%)	LI	σ'_v/P_a	σ'_p/P_a	s_u/σ'_v	S_t	B_q	q_{t1}	q_{tu}	OCR	Location
1	367.1	61.8	28.1	1.10	0.44	0.46	0.38	12.0				1.04	Okishin (Japan)
2	142.8	65.6	37.9	1.01	0.55	0.88		3.0	0.43	6.13	4.45	1.60	Drammen (Norway)
3	132.6				0.31	1.40		12.0	0.41	8.86	6.19	4.47	232nd St. (Canada)
4	104.9	73.6	36.5		0.46	0.66	0.49		0.40	7.76	5.24	1.43	Bothkennar (UK)
5	63.7	58.3	21.7	1.37	0.18								Canada
6	61.7	75.8	60.5	0.77	0.74	1.13	0.21	3.0	0.50	5.37	3.67	1.54	Drammen (Norway)
7	58.8	78.2	42.5	0.69	0.74	0.79	0.24	4.0				1.06	Shellhaven (UK)
8	49.6	[illegible]	[illegible]	[illegible]	[illegible]	1.54	[illegible]					2.10	[illegible] (USA)
9	48.8	76.3	42.5	0.72	0.69	0.95	0.44		0.53	6.54	4.10	1.37	Grangemouth (UK)
10	[illegible]	[illegible]	[illegible]	[illegible]			[illegible]						[illegible]
11	47.5	72.7	46.8	0.82	0.70	0.70	0.22	6.3				1.00	Shellhaven (UK)
12	40.7	72.4	47.2	1.00	0.59		0.21	3.0	0.46	5.94	4.18		Drammen (Norway)
13	40.4	69.0	31.0	1.05				[illegible]					Bromma (Sweden)
14	39.1	64.4	40.0	1.00	0.68	0.78	[illegible]					1.15	Canada
15	37.0	62.0	31.0				[illegible]	[illegible]					USA
16	35.9	75.4	41.5	0.82	1.35		0.20						Belfast (UK)
17	34.8	77.1	49.7	0.68	0.91	1.44		3.1	0.54	5.69		1.58	Singapore
18	34.3	60.0	30.0	0.93	0.17	0.38	0.54					2.28	USA
19	32.6	70.0	30.0	1.07	0.87	1.04						1.20	San Francisco (USA)
20	31.4	75.9	35.9	0.71	0.52			6.2					Canada

ACKNOWLEDGMENTS

- DEPARTMENT OF CIVIL ENGINEERING, THE UNIVERSITY OF HONG KONG
- GEOTECHNICAL DIVISION, THE HONG KONG INSTITUTION OF ENGINEERS
- PROF ZHONGQI QUENTIN YUE, THE UNIVERSITY OF HONG KONG
- HONORARY PROF C F LEE, THE UNIVERSITY OF HONG KONG
- IR DR VICTOR LI, DIRECTOR, VICTOR LI & ASSOCIATES LTD
- PROF JIANYE CHING, NATIONAL TAIWAN UNIVERSITY

ice
Institution of Civil Engineers

State Of The Nation 2017:
Digital Transformation

ICE (2017)

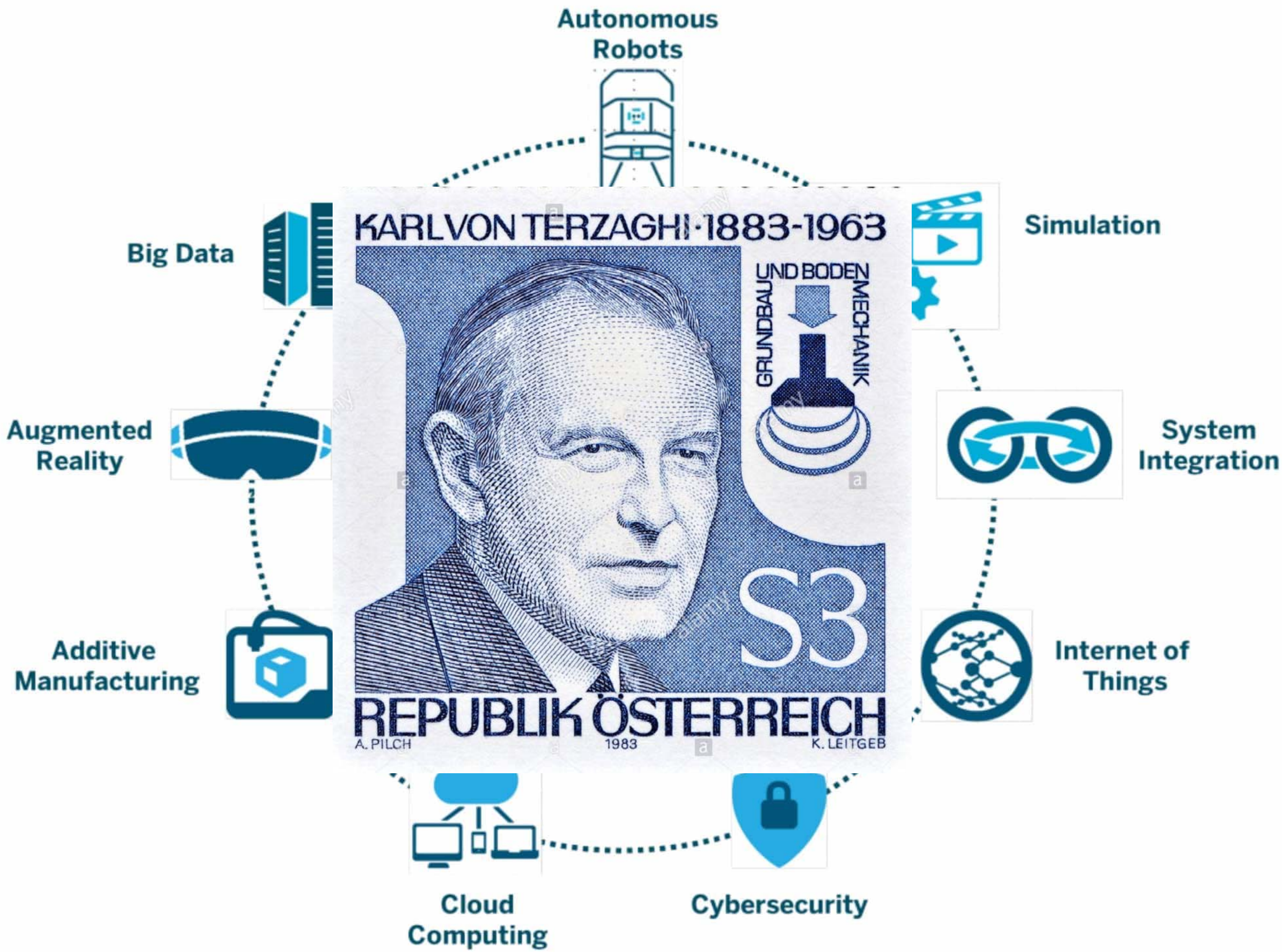
- INFRASTRUCTURE PROVIDES THE BASIC MEANS FOR MOVING AND CONNECTING GOODS, RESOURCES AND PEOPLE, IN TURN ENABLING ECONOMIC GROWN AND THRIVING COMMUNITIES
- WE MUST THINK ABOUT NOT ONLY THE PHYSICAL ASSET, BUT ALSO ITS DIGITAL TWIN – ALL THE ASSOCIATED DATA AND THE INFORMATION THAT THIS CAN REVEAL
- IF WE TRULY CONSIDER INFRASTRUCTURE AS A SERVICE, THEN MAKING THIS MENTAL SHIFT IS ESSENTIAL
- DELIVERING INFRASTRUCTURE BASED ON OUTCOMES FOR USERS DRIVES US TOWARD WHOLE LIFE DECISIONS AND RECOGNIZING THE VALUE OF THE ENTIRE DATA ESTATE

Institution of Civil Engineers (2017). State of the Nation: Digital Transformation. London.

ICE (2017)

- DIGITAL TRANSFORMATION, WHICH INCLUDES DIGITAL DELIVERY AND SMART INFRASTRUCTURE (OR CYBER-PHYSICAL INFRASTRUCTURE SOLUTIONS), IS A MORE COST-EFFECTIVE WAY OF ADDING VALUE TO INFRASTRUCTURE THAN TRADITIONAL APPROACHES
- THE INFRASTRUCTURE SECTOR HAS BEEN SLOW TO ENGAGE WITH THE UPTAKE OF NEW DIGITAL TECHNOLOGIES COMPARED WITH OTHER INDUSTRIES
- 64% OF FIRMS OPERATING IN EUROPE & THE MIDDLE EAST ARE RATED AS EITHER ‘INDUSTRY FOLLOWING’ OR ‘BEHIND THE CURVE’ IN TERMS OF TECHNOLOGY ADOPTION

Institution of Civil Engineers (2017). State of the Nation: Digital Transformation. London.



Autonomous Robots
Simulation
System Integration
Internet of Things
Cybersecurity
Cloud Computing
Additive Manufacturing
Augmented Reality
Big Data
KARL VON TERZAGHI·1883-1963
GRUNDBAU UND BODEN MECHANIK
S3
REPUBLIK ÖSTERREICH
A. PILCH
1983
K. LEITGEB

TRANSITION TO INDUSTRY 4.0

- **SMART ASSET MANAGEMENT**
- **CULTURE & BEHAVIOURS**
- **VALUE OF DATA**
- **SECURITY**
- **BUSINESS MODEL TRANSFORMATION**

https://www.ice.org.uk/knowledge-and-resources/digital-engineering-and-the-built-environment.

WHAT HAS *CHANGED*?

USD 18.8 TRILLION

- 1 BYTE = 1 CHARACTER
- 1 KB = 10^{3} BYTES = 1 PAGE
- 1 MB = 10^{6} BYTES = 1 PHOTO
- 1 GB = 10^{9} BYTES = 1 MOVIE
- 1 TB = 10^{12} BYTES = 1 NYSE TRADING SESSION
- 1 PB = 10^{15} BYTES = ALL PRINTED INFO IN 1995
- 1 EB = 10^{18} BYTES = ALL SPOKEN WORDS
- 1 ZB = 10^{21} BYTES BY 2020
- 1 YB = 10^{24} BYTES

Sources: McKinsey Global Institute, Twitter, Cisco, Gartner, EMC, SAS, IBM, MEPTEC, QAS

IBM.

Source: iFLYTEK 科大讯飞

Four waves of Artificial Intelligence Applications

2015 Wave 4: Autonomous AI

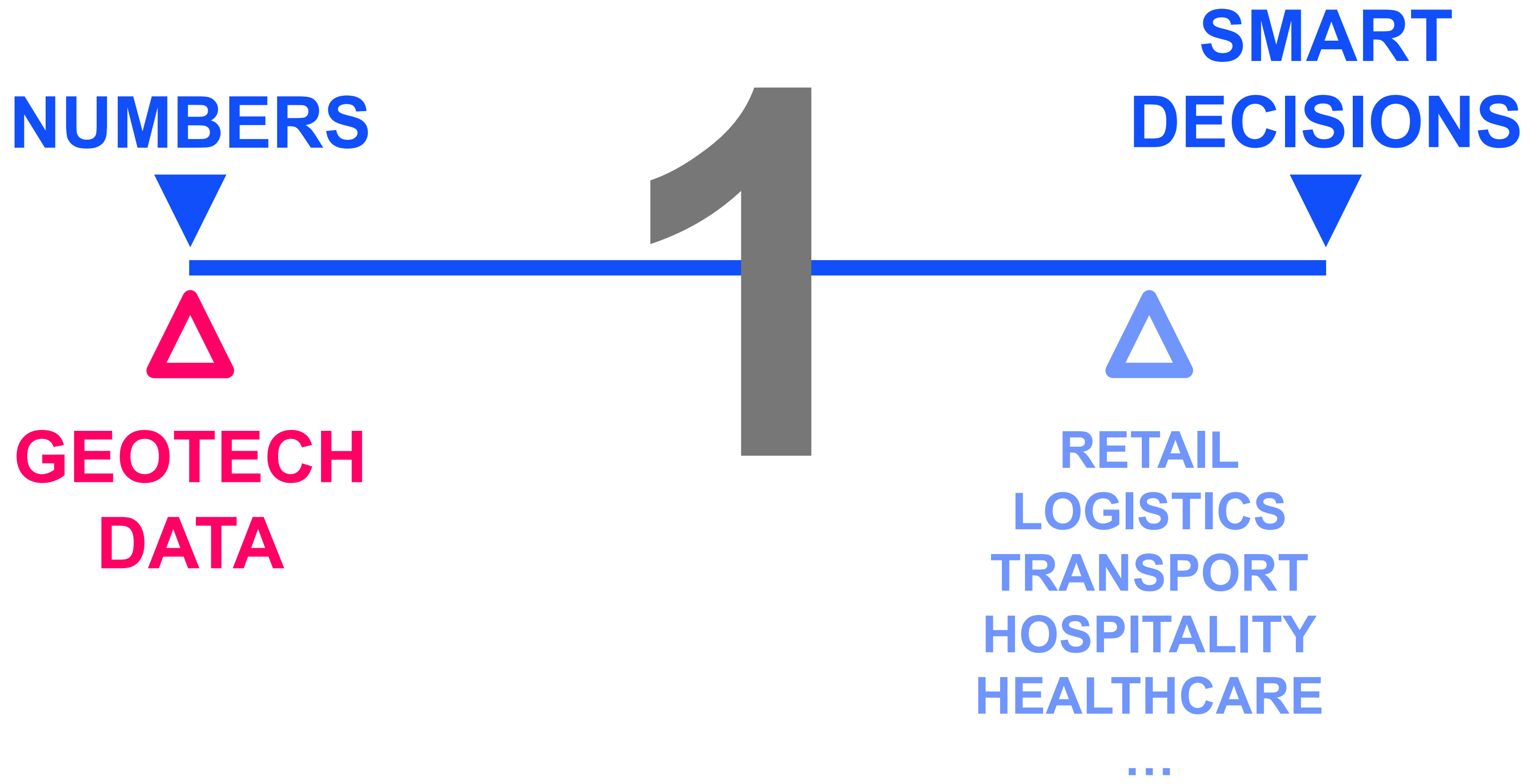
2011 Wave 3: Perception AI (digitized physical world)

2004 Wave 2: Business AI

1998 Wave 1: Internet AI

Kai Fu Lee, The Era of AI, **www.aisuperowers.com**

VALUE OF DATA?



ROLE OF DATA IN DESIGN

– NO DATA (ALMOST)

INFORMAL RISK MANAGEMENT

EXPERIENCE → DECISION

VERY CONSERVATIVE VALUES

"SAFE" DECISION

PRESUMPTIVE BEARING VALUES

Table 54.1
Soil Pressures Allowed by Various Building Codes

Citing Kidder-Parker Architects' and Builders' Handbook (1931)

Character of Foundation Bed, Loads in tons/ft²	Akron, 1920	Atlanta, 1911	Boston, 1926	Cleve-land, 1927	Denver, 1927	Louis-ville, 1923	Minne-apolis, 1911	New York, 1922	St. Paul, 1910	Jackson-ville, 1922
1 Quicksand or alluvial soil	½	–	–	½	–	–	–	–	–	–
2 Soft or wet clay, at least 15′ thick	1	1	–	2	–	–	1	1	–	1
3 Soft clay and wet sand	1½	–	–	1½	–	–	–	–	1	–
4 Sand and clay mixed or in layers	–	2	–	–	–	–	2	2	2	2
5 Firm clay	–	–	–	–	–	–	–	2	–	–
6 Wet sand	–	–	–	–	–	–	–	2	–	–
7 Fine wet sand	2	–	–	2	–	–	–	–	–	–
8 Soft clay held against displacement	–	–	2	–	–	–	–	–	–	–
9 Clay in thick beds, mod. dry	–	–	–	–	2–4	–	–	–	–	–
10 Dry solid clay	–	–	–	–	–	–	–	–	–	3
11 Loam, clay or fine sand, firm and dry	–	–	–	–	–	2½	3	–	–	–
12 Firm dry loam	2½	2–3	–	–	1–2	–	–	–	–	–
13 Firm dry sand	3	2–3	–	–	2–4	–	–	3	–	3
14 Quicksand when drained	–	–	–	3	–	–	–	–	–	–
15 Hard clay	–	3–4	–	3	–	4	4	–	4	–
16 Fine-grained wet sand	–	–	3	–	–	–	–	–	–	–
17 Very firm coarse sand	–	3–4	–	–	4–6	4	4	–	4	4
18 Gravel	–	3–4	–	–	–	4	4	6	–	4
19 Dry hard clay	–	–	–	–	–	–	–	4	–	–
20 Clay in thick beds always dry	4	–	–	–	4–6	–	–	–	–	–
21 Fine dry clay	–	2–3	–	–	–	–	–	–	–	–
22 Fine-grained dry sand	–	–	4	4	–	–	–	–	–	–
23 Compact coarse sand and gravel	–	–	–	–	–	–	–	–	–	4

1 ton/ft^2 = 95.7 kPa

Terzaghi, K. & Peck, R. B. (1967). Soil Mechanics in Engineering Practice. John Wiley.

BS 8004 (1986)

SOIL TYPE	BEARING VALUE (kPa)	REMARKS
DENSE GRAVEL OR DENSE SAND & GRAVEL	> 600	WIDTH OF FOUNDATION NOT LESS THAN 1 M. WATER TABLE AT LEAST AT THE DEPTH EQUAL TO THE WIDTH OF FOUNDATION, BELOW BASE OF FOUNDATION
DENSE GRAVEL OR MEDIUM DENSE SAND & GRAVEL	200-600	-
LOOSE GRAVEL OR LOOSE SAND & GRAVEL	< 200	-
COMPACT SAND	> 300	-
MEDIUM DENSE SAND	100 - 300	-
VERY STIFF BOULDER CLAYS & HARD CLAYS	300 - 600	SUSCEPTIBLE TO LONG TERM CONSOLIDATION SETTLEMENT
STIFF CLAYS	150 - 300	-
FIRM CLAYS	75 -150	-
SOFT CLAYS & SILTS	< 75	-
VERY SOFT CLAYS & SILTS	-	-

BS 8004 (1986). Code of practice for foundations. Table 1 — Presumed allowable bearing values under static loading

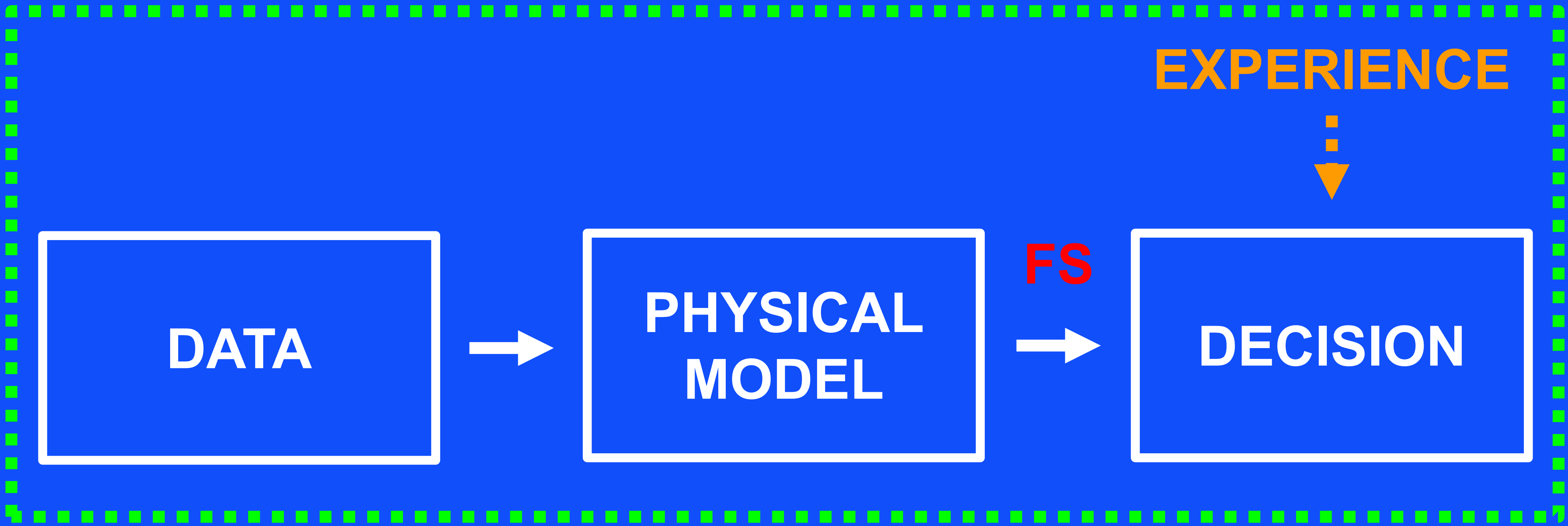
DATA → DECISION

- NO DATA (OTHER THAN SURFACE SOIL TYPE)
- BASED ON EXPERIENCE
- PRESCRIBED BY CODES
- SIMPLE
- NOT GENERAL
- VERY CONSERVATIVE
- PRELIMINARY DESIGN (?)

ROLE OF DATA IN DESIGN

– DATA + PHYSICAL MODEL

INFORMAL RISK MANAGEMENT

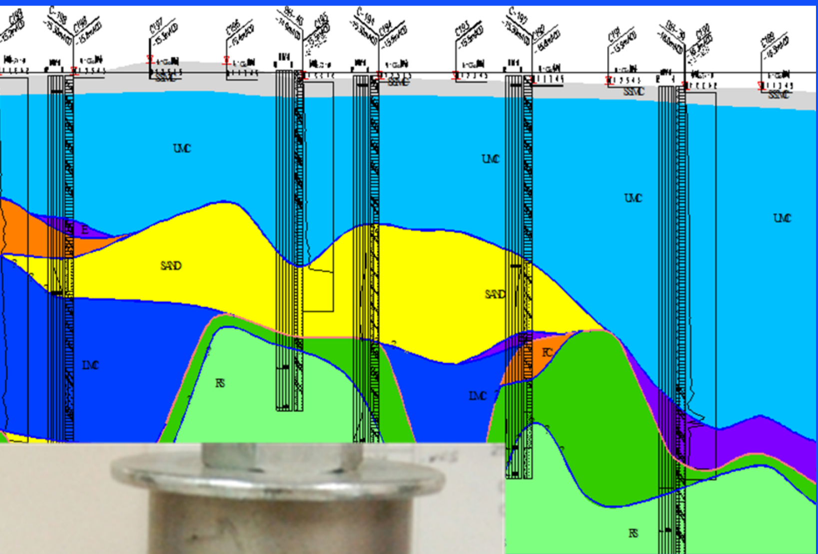


CONSERVATIVE VALUES

CONSERVATIVE MODEL

“SAFE” DECISION

BURLAND TRIANGLE



Genesis/geology

Ground Profile

Site invest
ground de

Empiricism, precedent, experience, risk management

Soil Behaviour

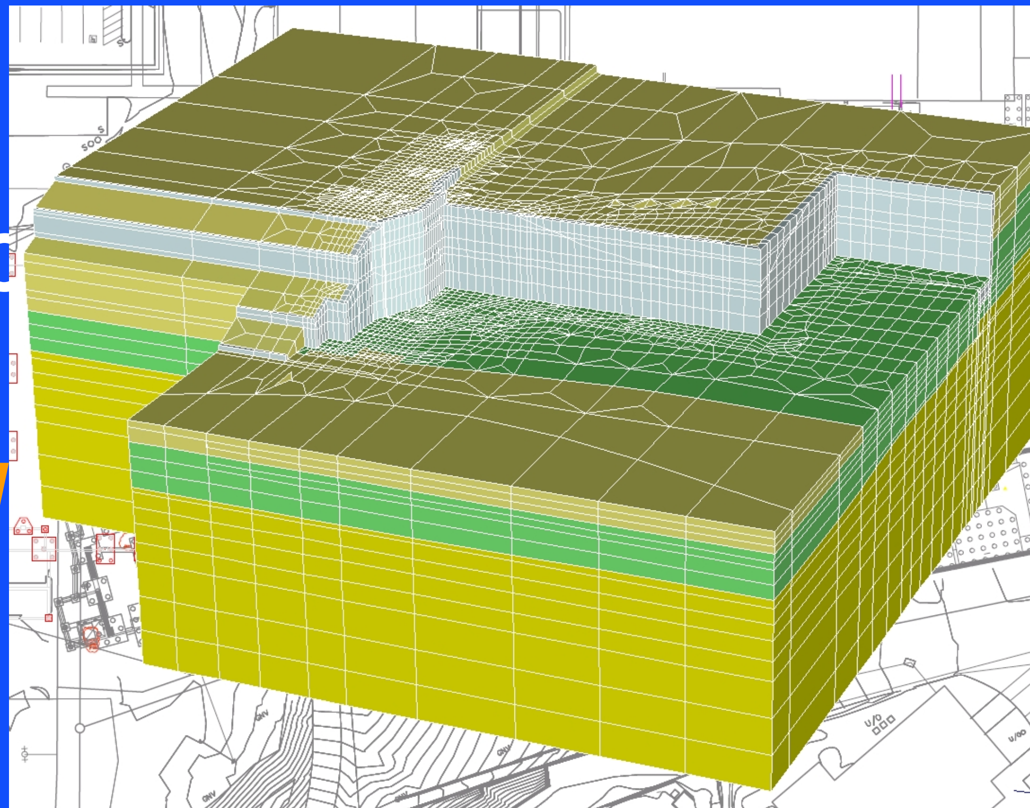
Modeling

Idealization followed by evaluation. Conceptual or physical modeling, analytical modeling

Burland, J. B. (1987). Nash Lecture: The teaching of soil mechanics – a personal view. Proceedings, 9th ECSMFE, Dublin, Vol. 3: 1427-1447.

DATA → DECISION

- SOIL DATA AS INPUTS
- BASED ON PHYSICS
- CAN BE VERY SOPHISTIC
- CAN BE VERY GENERAL
- NEED FS TO HANDLE ***UN***
- NEED EXPERIENCE FOR



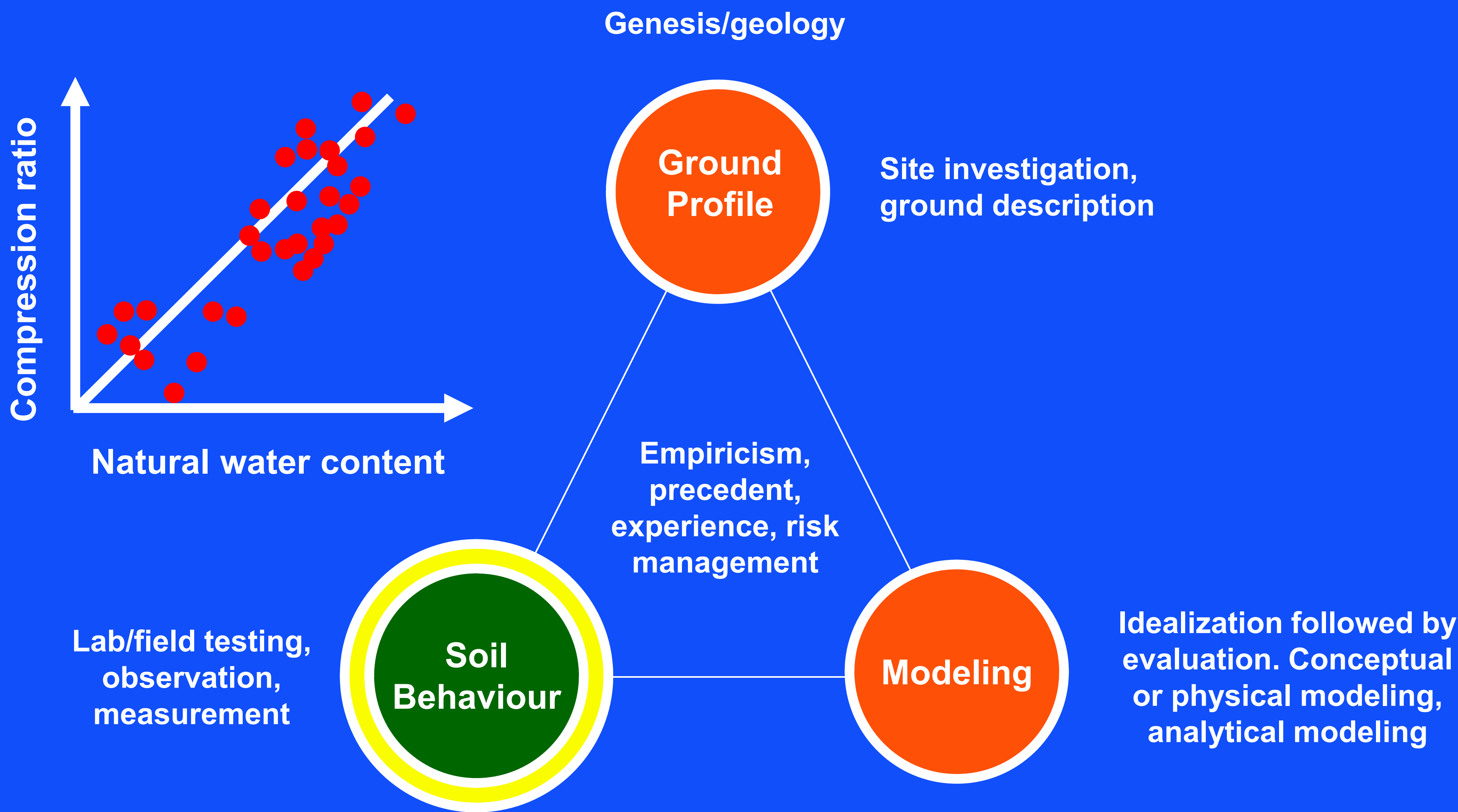
SKUA® Software Suite

FS FROM EXPERIENCE

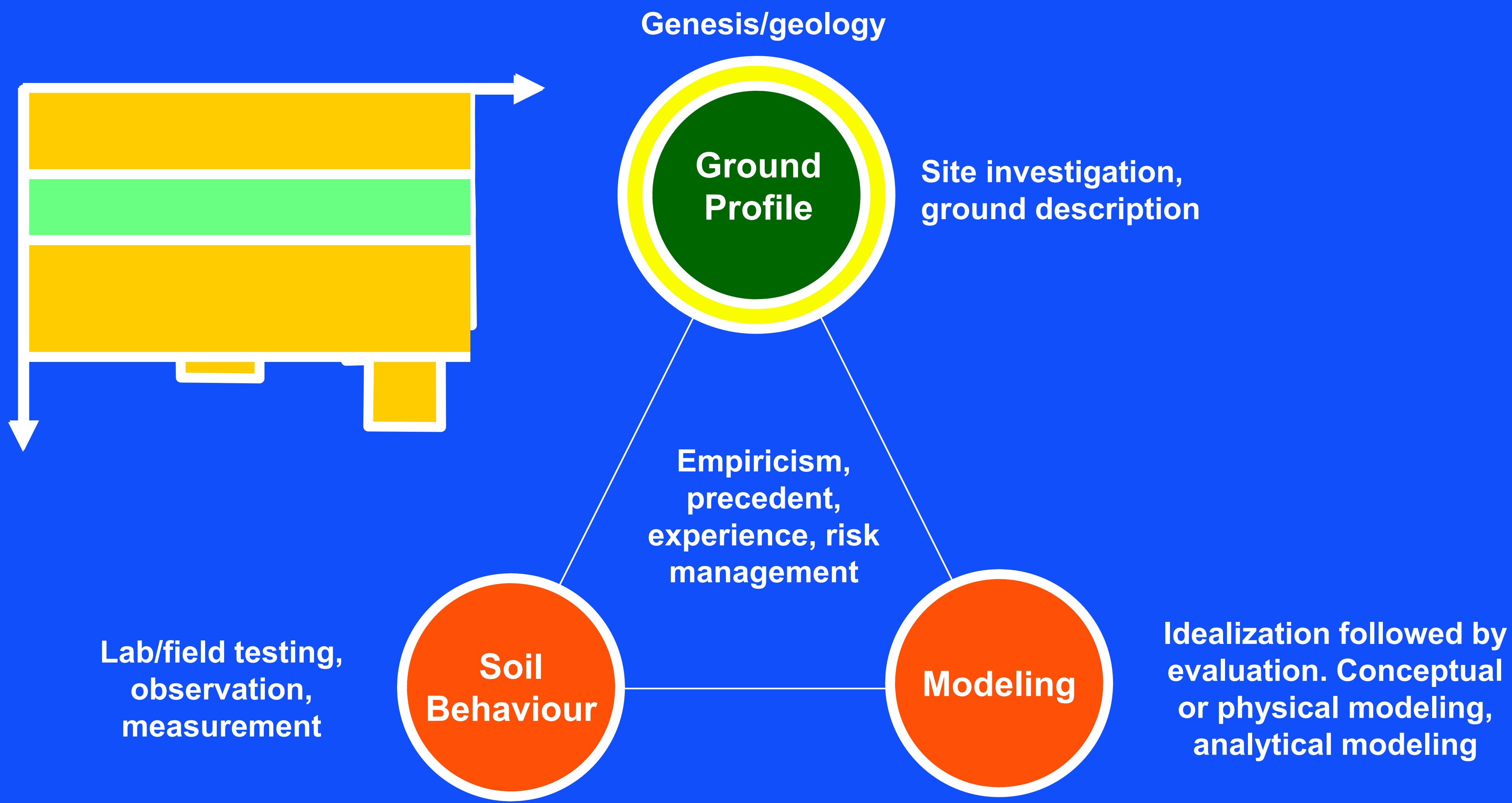
TYPE OF STRUCTURES	FACTOR OF SAFETY (FS)	REMARKS
RETAINING STRUCTURE	1.5	AGAINST SLIDING
	1.5	BASE HEAVE
	2.0	STRUT BUCKLING
SLOPE STABILITY	1.3-1.5	
EMBANKMENTS	1.5	
	1.1-1.2	WITH MONITORING
FOOTINGS & RAFTS	2.0-3.0	
SINGLE PILES	2.5-3.0	WITH LOAD TESTING
	6.0	WITH ENGINEERING NEWS FORMULA
FLOATING PILE GROUPS	2.0-3.0	W.R.T. BASE FAILURE

Terzaghi, K. & Peck, R. B. (1948). Soil Mechanics in Engineering Practice. John Wiley.

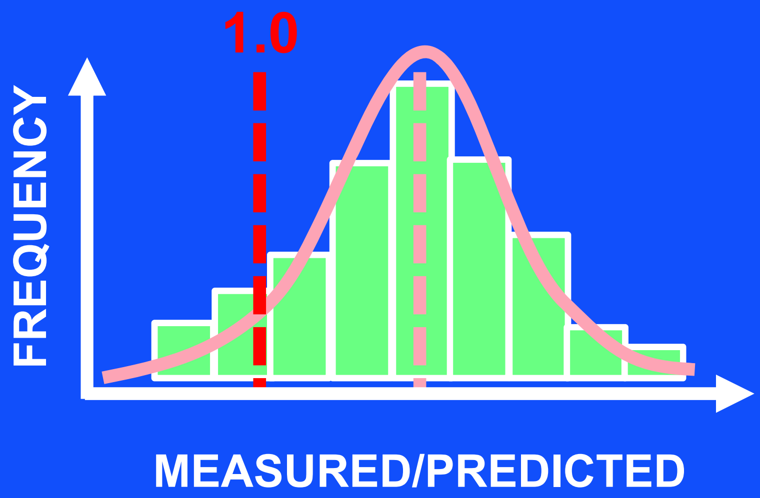
BURLAND TRIANGLE W. UNCERTAINTY

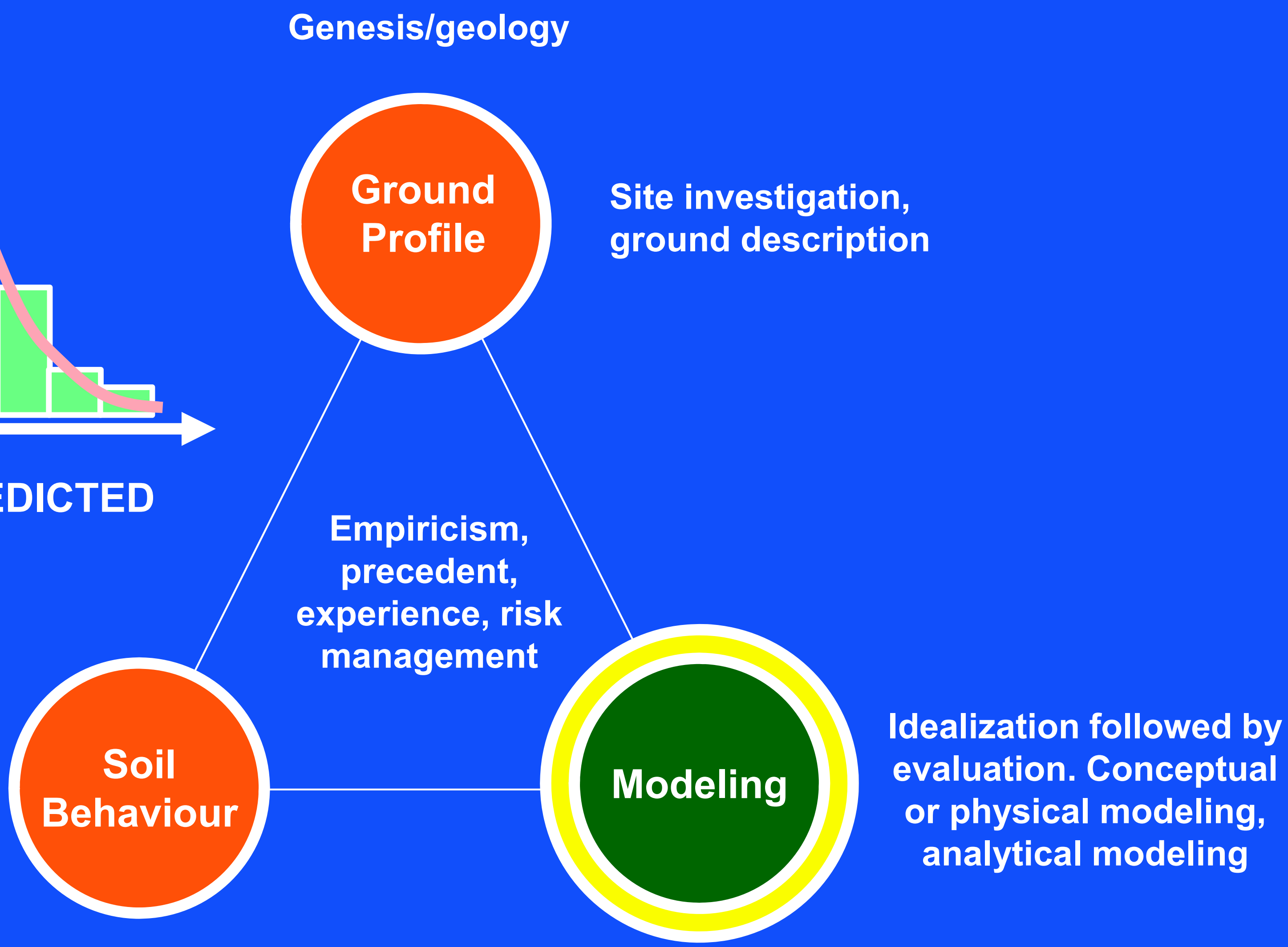


BURLAND TRIANGLE W. UNCERTAINTY



BURLAND TRIANGLE W. UNCERTAINTY





ROLE OF DATA IN DESIGN

– DATA + STATISTICAL MODEL

ALL MODELS ARE WRONG

- WHEN BUILDING STATISTICAL MODELS, WE MUST NOT FORGET THAT THE AIM IS TO UNDERSTAND SOMETHING ABOUT THE REAL WORLD. OR PREDICT, CHOOSE AN ACTION, MAKE A DECISION, SUMMARIZE EVIDENCE, AND SO ON, BUT ALWAYS ABOUT THE REAL WORLD, NOT AN ABSTRACT MATHEMATICAL WORLD: OUR MODELS ARE NOT THE REALITY - A POINT WELL MADE BY GEORGE BOX IN HIS OFT-CITED REMARK THAT "ALL MODELS ARE WRONG, BUT SOME ARE USEFUL"

Hand, D. J. (2014). "Wonderful examples, but let's not close our eyes". Statistical Science, 29-98.
Box, G. E. P.; Draper, N. R. (1987), Empirical Model-Building and Response Surfaces, John Wiley & Sons.

DATA-DRIVEN MODELS

– UNIVARIATE STATISTICS

Lumb, P. (1966). “Variability of Natural Soils”, Canadian Geotechnical Journal, 3(2), 74 – 97.

THE VARIABILITY OF NATURAL SOILS

PETER LUMB*

ABSTRACT

The variations in properties of four typical natural soils are shown to be random variations about a mean or linear trend, related to the "normal" or "Gaussian" statistical distribution. Examples are given of soil properties following the normal, log-normal, and bi-normal distributions. Properties studied include Atterberg limits, grading, and, for undisturbed samples, strength and compressibility characteristics.

A rational basis for the choice of a design parameter, such as strength or compressibility, is the probability that the parameter could be less than the design value. For any particular probability the design parameter can be determined using the normal distribution.

In the case of bearing capacity estimates, an analysis of the conventional factor of safety suggests that a suitable value of probability or "risk" of failure for design is of the order of 10^{-2} to 10^{-3} per cent.

In the case of settlement estimates, upper and lower bounds to the magnitude and rate of settlement can be associated with a particular probability or risk.

SOMMAIRE

Il est démontré que les variations dans les propriétés de quatre sols naturels typiques présentent une dispersion autour d'une ligne moyenne à tendance linéaire et qui est en relation avec la distribution statistique normale ou de Gauss. Des exemples sont donnés de propriétés de sols qui suivent des distributions normales, normales logarithmiques ou bi-normales. Les propriétés étudiées incluent les limites d'Atterberg, la granulométrie et, pour les échantillons non-remaniés, les caractéristiques de la force de cisaillement et de la compressibilité.

Une base rationnelle pour le choix de paramètres à employer dans le calcul, tels que les paramètres de la force de cisaillement et de la compressibilité, est la probabilité que la valeur du paramètre puisse être inférieure à celle adoptée pour le calcul. Pour n'importe quelle probabilité, le paramètre employé dans le calcul peut être déterminé en employant la distribution normale.

Dans le cas des estimations de la capacité portante, une analyse du facteur de sécurité conventionnel montre que pour le calcul, une valeur convenable de probabilité ou « risque » de rupture est de l'ordre de 10^{-2} à 10^{-3} pour cent.

Dans le cas des estimations de tassement, les limites supérieures et inférieures de la grandeur et du taux de tassement peuvent être reliées à une probabilité ou « risque » particulier.

All natural soils show variations in properties from point to point in the ground because of inherent variations in composition and consistency during formation. The object of this paper is to show that most soil properties can be regarded as random variables conforming to the "normal" or "Gaussian" theoretical distribution. Consequently established statistical methods based on the normal distribution may safely be applied in estimating design parameters and in other problems.

Four natural soils of differing type will be discussed; a soft marine clay deposited in shallow coastal waters, an alluvial sandy clay, a residual silty sand, and a residual clayey silt.

After showing that the composition and properties of undisturbed samples

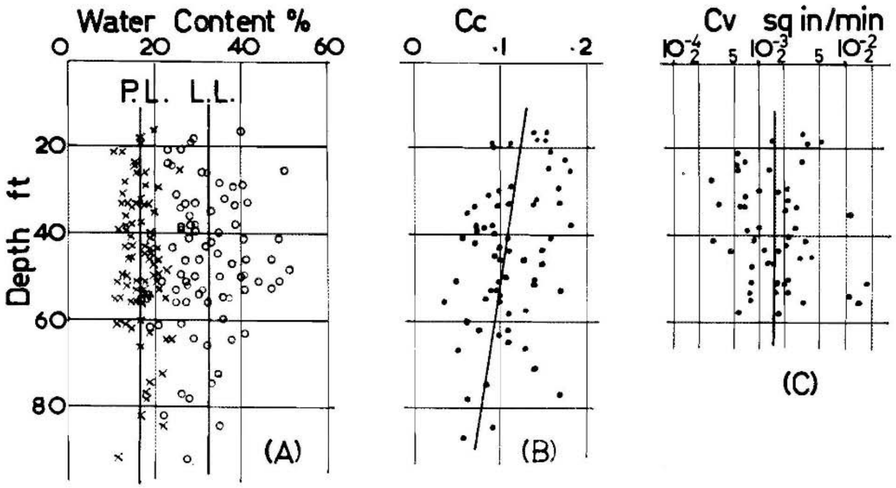


FIGURE 2. (a) Atterberg limits against depth for sandy clay. (b) Compression index against depth for sandy clay. (c) Coefficient of consolidation against depth for sandy clay

expected since the soil is normally consolidated. The actual results are plotted against the standardized normal variate ζ_P in Figure 4, and this and Table I show good agreement with the normal distribution. The Atterberg limit tests on the sandy clay were performed on the finer fraction of the soil passing the

TABLE I

χ^2 for Marine Clay

Property	N	χ^2	ν	$P_\nu(\chi^2)\%$
Liquid limit	120	17.5	17	42.1
Plastic limit	120	7.0	7	42.9
Plasticity index	120	15.7	17	54.6
Liquidity index	120	24.4	17	10.9
Plasticity index v. liquid limit	120	19.0	14	16.5
Cohesion	114	19.0	16	26.9

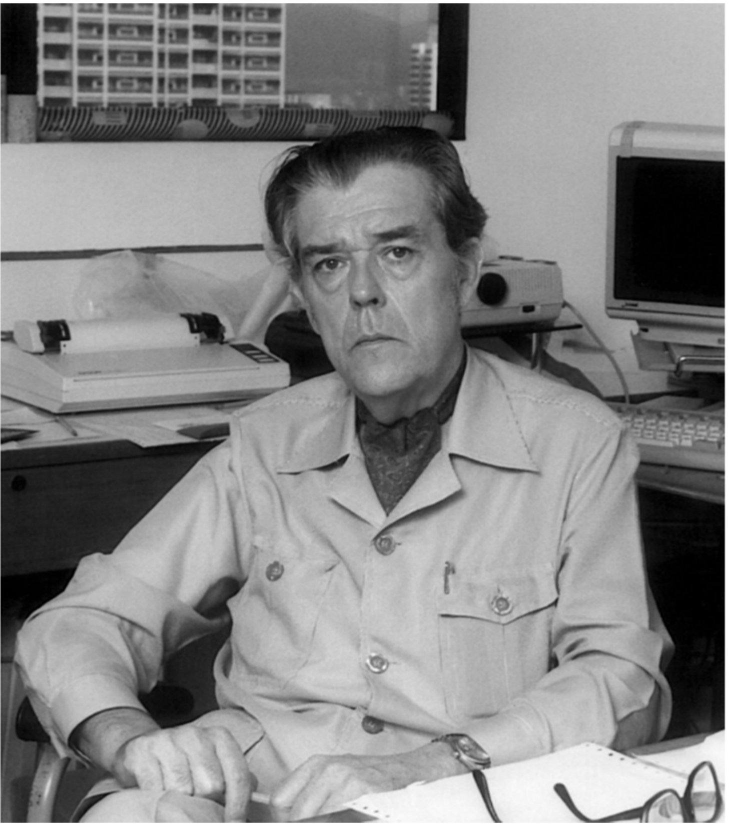
TABLE II

χ^2 for Alluvial Sandy Clay

Property	N	χ^2	ν	$P_\nu(\chi^2)\%$
Liquid limit	83	6.3	7	51.0

Excerpts from Interview with Professor Peter Lumb

K. Lam and W. K. Li



Courtesy Victor Li

On Feelings towards the Importance of Statistics as a Tool in Engineering Applications

Traditionally engineering and civil engineering are very deterministic in their teaching and in the attitude of their practitioners. When something goes wrong, it takes them by surprise. And yet all the things they are handling, the raw materials, the input and output, are random processes. If that can be taken seriously the method of design can be improved considerably. Instead of the old fashioned safety factor, the probability of failure type of approach is more satisfactory and practically far more useful.

The second thing is that once you think of all these things as being random processes, it does clear up the engineer's mind as well as improving his design. It makes him realize that he cannot predict what is going to happen precisely. This is what most engineers try to do. That is what they taught in schools and in universities in general: Engineering is precise, it is a science. Yet, in reality, it is vague. It is not a science. It is more an art.

On the Role of Statistics in Professor Lumb's Career

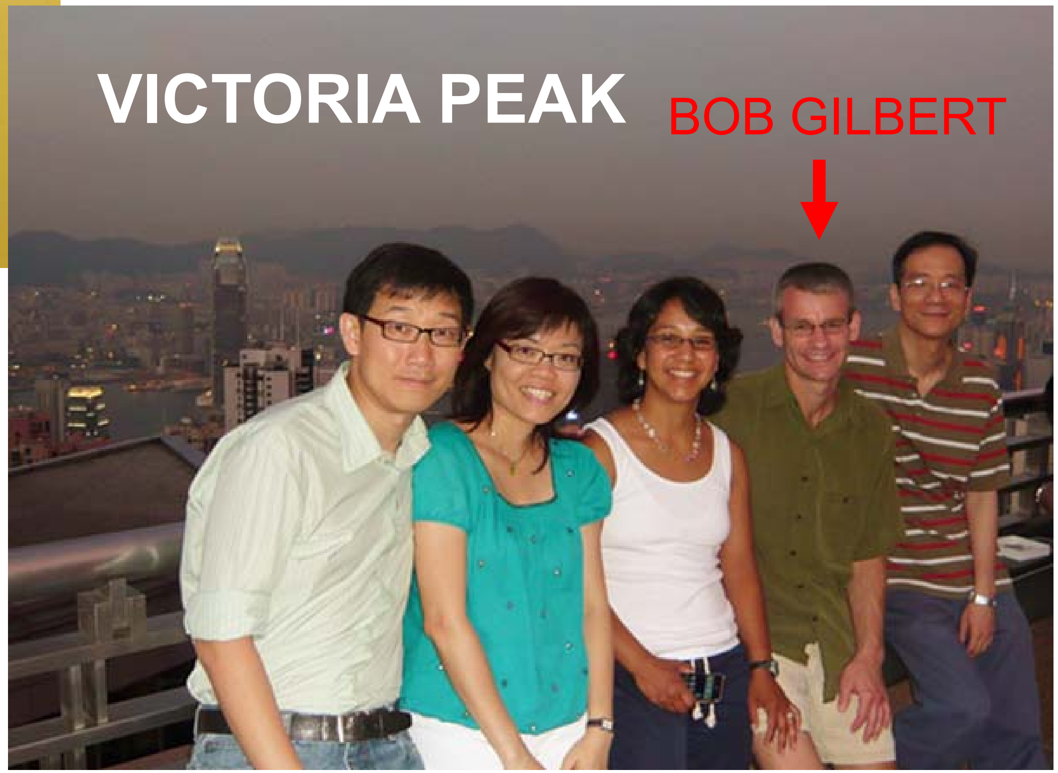
It started in the early sixties when I was doing a lot of testing with Hong Kong soils. Honestly, the only way I could make sense out of the results was to use statistical methods. From then on, I got interested in the whole topic. Then I found out that, for civil engineering, not mush sensible work has been published. Mechanical and electrical engineering, yes. Civil engineering until the 1960's, no. As far as engineering is concerned, it was quality control that statistics has been applied to, not really to design. Of course, gradually reliability theory and all the rest of these things become more fashionable. And from the 1970's onward it has been a respectable part of civil engineering. There is a journal "Structural Safety", for

Hong Kong Statistical Society Newsletter, Vol. 9, Issue 1, 1986, pp. 2-5

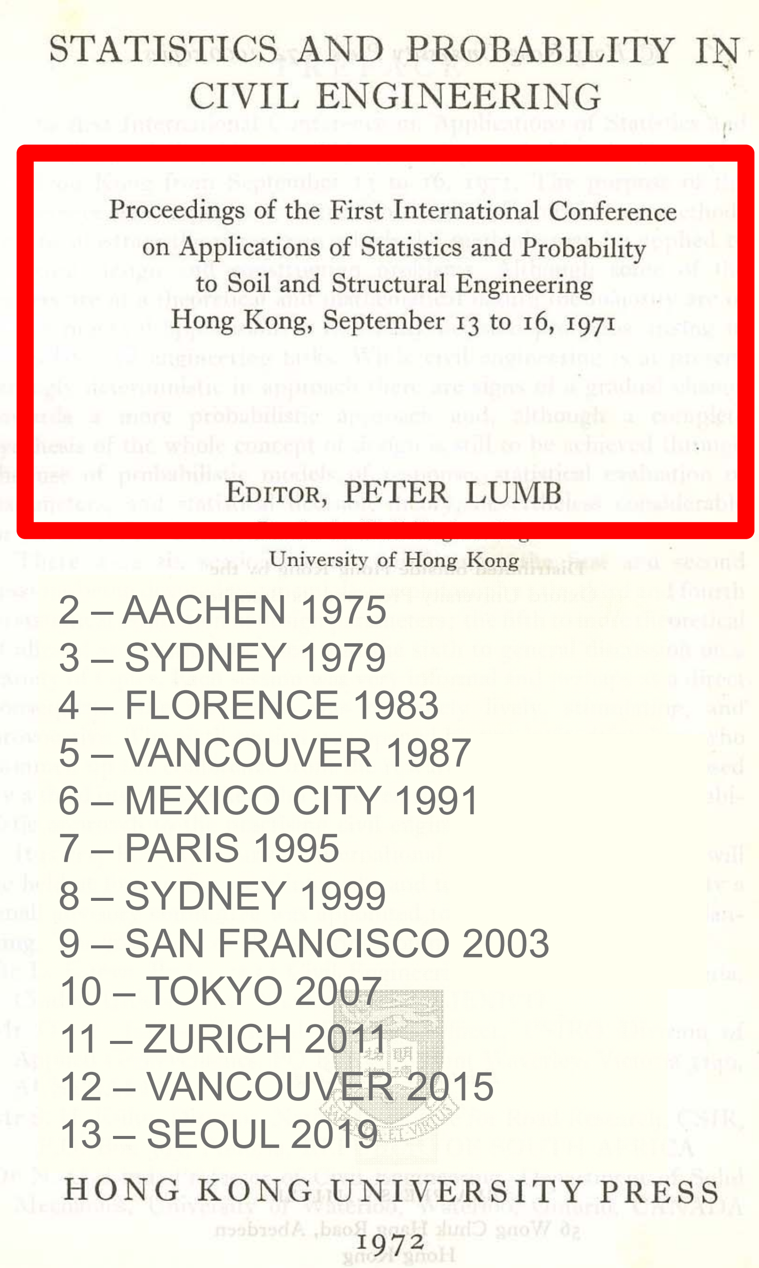
6 DEGREES OF SEPARATION

International Symposium on Limit State Design in Geotechnical Engineering
Copenhagen, Denmark, **May 26-28, 1993**

VICTOR LI



Fourth Asian Pacific Symposium on Structural Safety and Reliability, Hong Kong, **19-20 June 2008**


STATISTICS AND PROBABILITY IN
CIVIL ENGINEERING

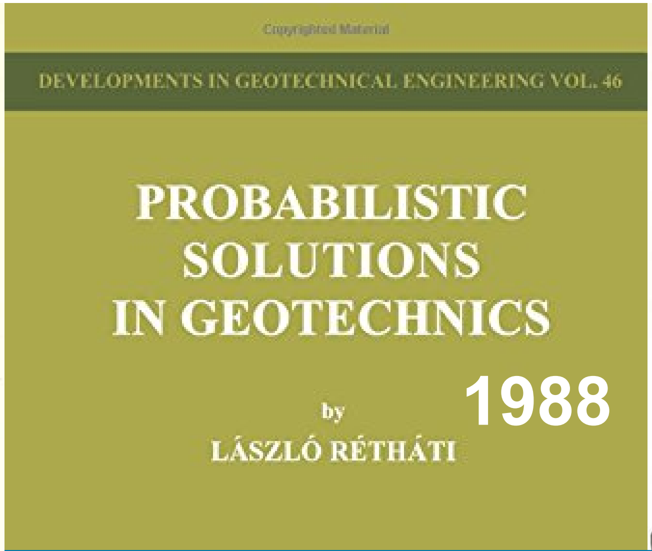
Proceedings of the First International Conference
on Applications of Statistics and Probability
to Soil and Structural Engineering
Hong Kong, September 13 to 16, 1971

EDITOR, PETER LUMB

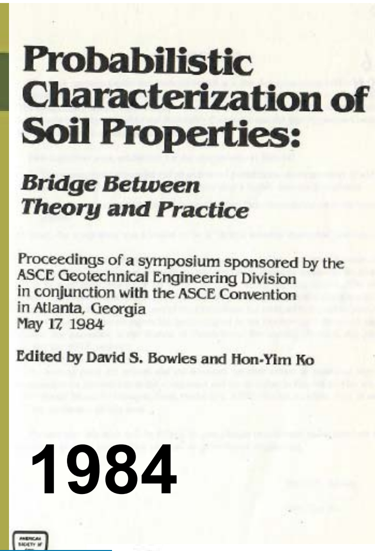
University of Hong Kong

HONG KONG UNIVERSITY PRESS
1972

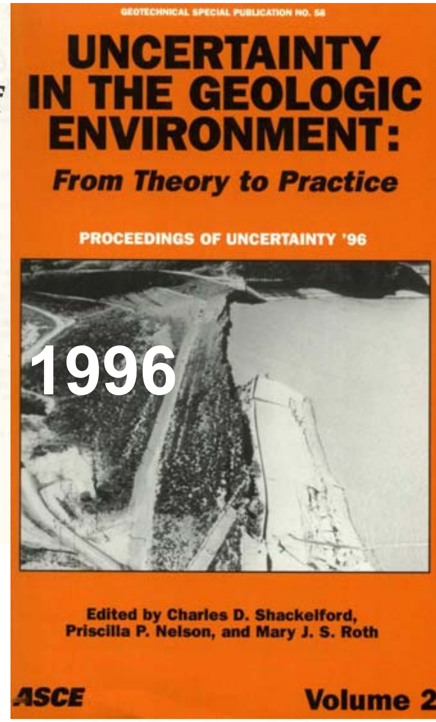
2 – AACHEN 1975
3 – SYDNEY 1979
4 – FLORENCE 1983
5 – VANCOUVER 1987
6 – MEXICO CITY 1991
7 – PARIS 1995
8 – SYDNEY 1999
9 – SAN FRANCISCO 2003
10 – TOKYO 2007
11 – ZURICH 2011
12 – VANCOUVER 2015
13 – SEOUL 2019



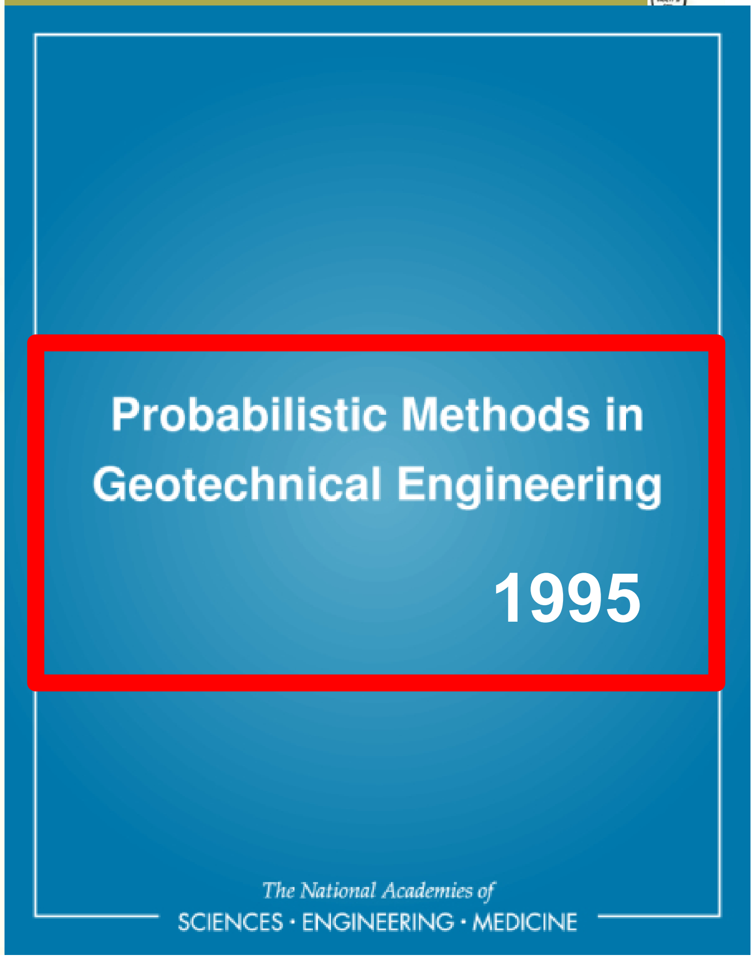
1988



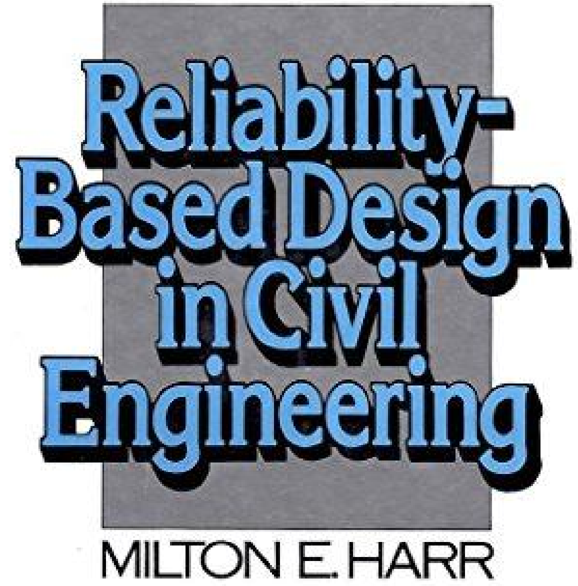
1984



1996



1995



1987

PROBABILISTIC METHODS IN GEOTECH ENGRG (1995)

- VARIABLE NATURE OF SOIL & ROCK,
- CHANGEABLE ENVIRONMENTAL CONDITIONS, &
- UNCERTAINTIES IN PREDICTING FIELD PERFORMANCE FROM AVAILABLE GEOTECHNICAL MODELS,
- *COPING WITH UNCERTAINTY IS A HALLMARK* OF GEOTECHNICAL ENGINEERING

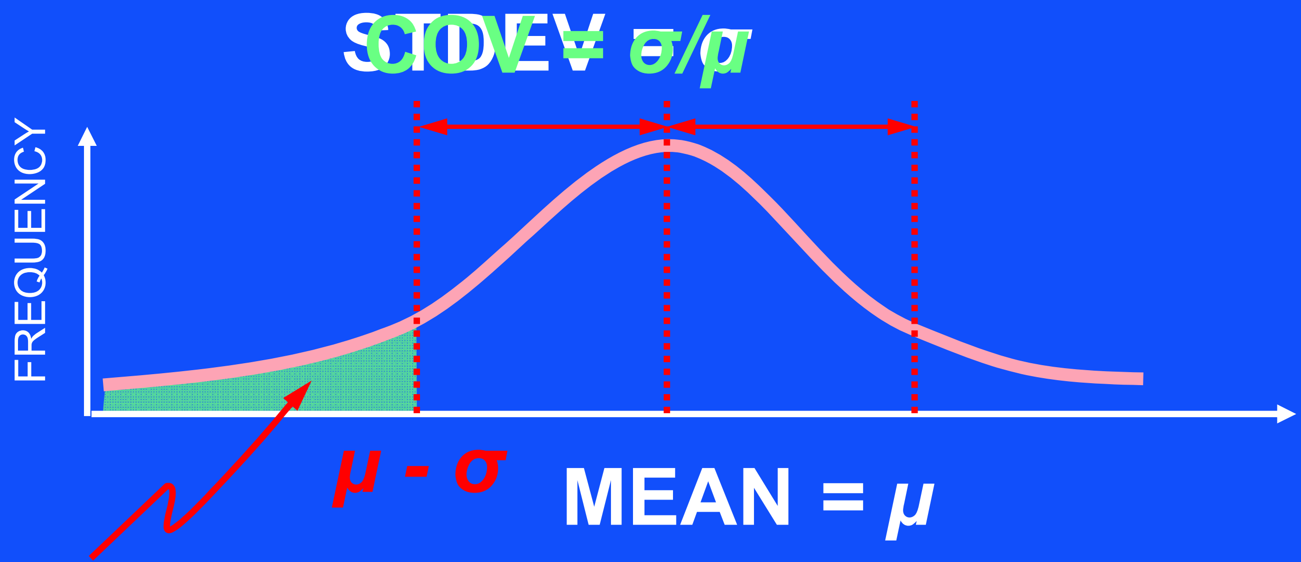
“COPE” OR “CAPITALIZE”?

- VARIATIONS = “NUISANCE”
  - AVERAGE AWAY
  - “COPE” WITH STATISTICS
- VARIATIONS = SECOND-ORDER EFFECTS WE DO NOT KNOW HOW TO USE
- DEEP LEARNING IS ABOUT SQUEEZING INSIGHTS FROM SECOND-ORDER EFFECTS!
- *VARIATIONS = “VALUE”?*

Site (region)	LI	s_u	s_u^{re}	σ'_v	σ'_p	Reference
Ariake Bay (Japan) UC tests S_t = 9.9 ~ 42.4	1.28	2.58	0.22	9.56	7.94	Ohtsubo et al. (1995)
	1.27	4.74	0.16	12.82	29.41	
	1.45	5.42	0.39	16.44	17.14	
	1.20	5.82	0.59	20.06	27.63	
	1.26	6.97	0.65	24.04	23.37	
	1.36	6.83	0.44	27.30	26.53	
	1.29	11.08	0.44	31.65	34.10	
	1.24	10.36	0.52	34.54	29.30	
	1.24	13.10	0.39	38.53	40.84	
	1.31	15.88	0.63	41.79	42.82	
	1.22	15.77	0.68	45.05	46.16	
	1.44	16.66	1.01	50.48	52.61	
	1.55	19.19	1.47	54.82	77.45	
	1.22	25.00	0.59	59.53	75.70	
	1.22	29.38	1.17	63.87	82.35	
	1.05	40.89	1.43	69.31	127.24	
	0.89	49.35	2.94	73.65	181.98	
Gosport (U.K) UC tests S_t = 2.4 ~ 3.1	0.59	8.93	3.67	39.01	29.61	Skempton (1948)
	0.38	34.55	13.67	130.66	128.31	
	0.55	9.87	3.22	35.72	31.49	
	0.42	20.68	6.75	110.45	88.36	
	0.46	12.22	4.13	33.37	46.06	
Åsrum (Canada) UC tests	2.02	10.56	0.14	7.70	29.98	Parry and Wroth (1981)

Ching, J. Y. & Phoon, K. K. (2012). "Modeling Parameters of Structured Clays as a Multivariate Normal Distribution", Canadian Geotechnical Journal, 49(5), 522-545

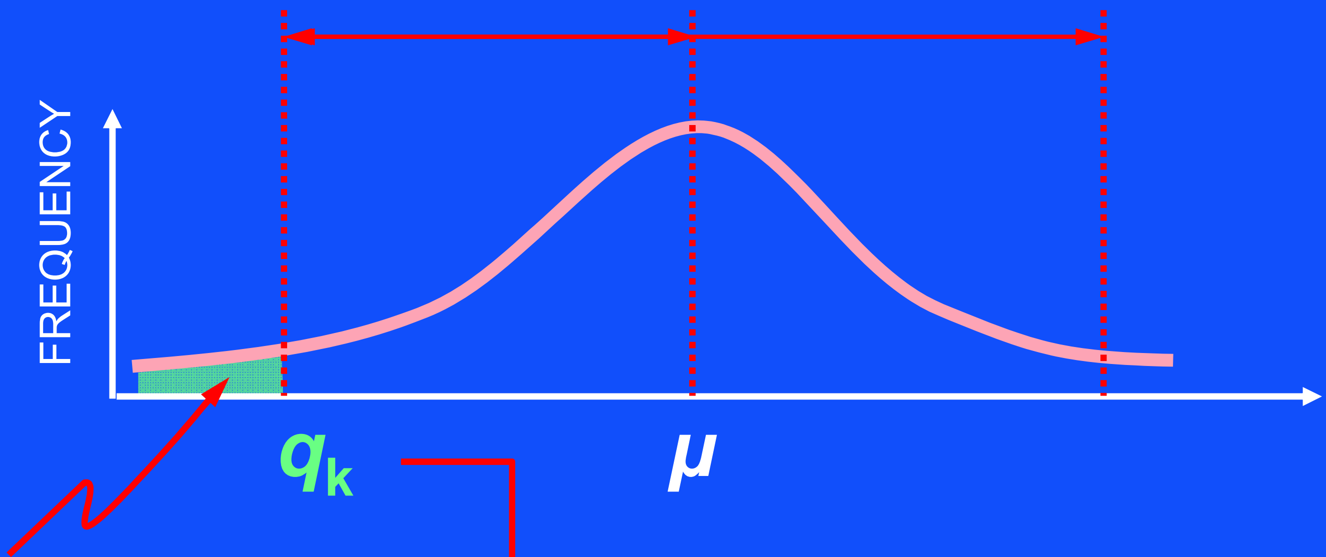
MEAN, STDEV, COV



% “DEFECTIVES”
= 16%

95% CONFIDENCE INTERVAL

$1.96 \times \sigma$



% "DEFECTIVES"
= 2.5%

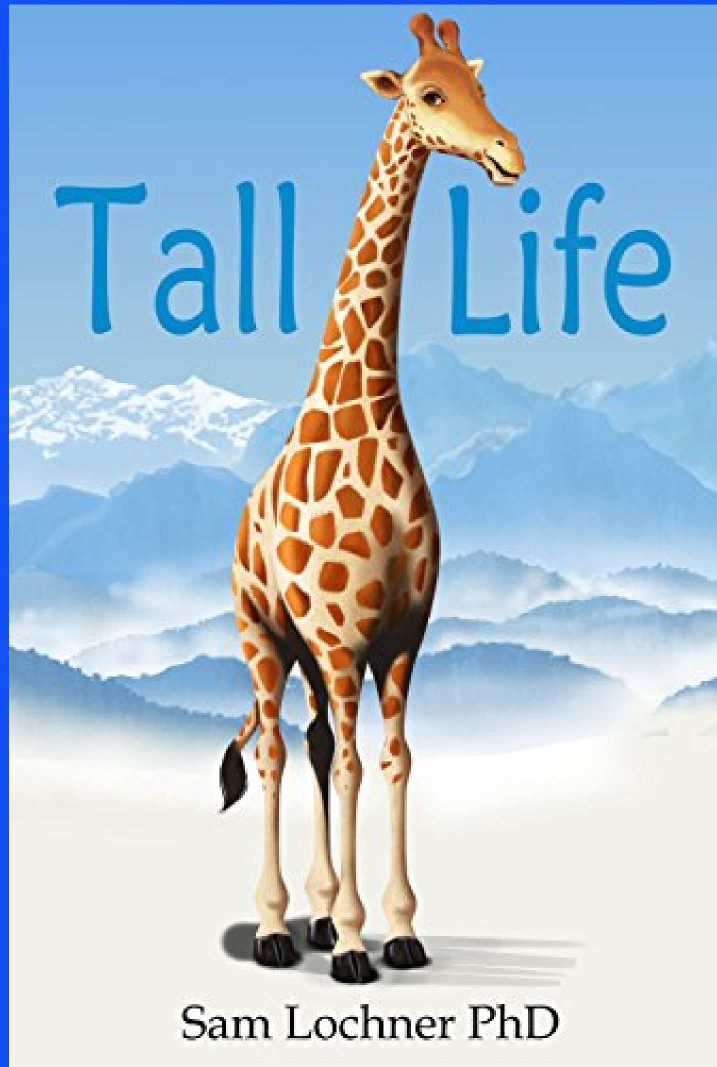
$$\mu - \alpha\sigma = \mu - \underline{1.96} \times \sigma$$

COEFFICIENT OF VARIATION

- ADULT MALE (FEMALE) HONG KONG
- MEAN = 171.7 (158.7) CM
- STDEV = 7.42 (7.11) CM
- **COV = 7.42/171.7 = 4.3%**

- 95% IS BETWEEN MEAN ± 1.96 STDEV = **[157.5, 186.5]** **[144.8, 172.6]**

https://tall.life/height-percentile-calculator-age-country/



Phoon, K. K. and Kulhawy, F. H. (1999). Characterization of geotechnical variability. Canadian Geotechnical Journal, 36(4), 612-624.

Characterization of geotechnical variability

Kok-Kwang Phoon and Fred H. Kulhawy

Abstract: Geotechnical variability is a complex attribute that results from many disparate sources of uncertainties. The three primary sources of geotechnical uncertainties are inherent variability, measurement error, and transformation uncertainty. Inherent soil variability is modeled as a random field, which can be described concisely by the coefficient of variation (COV) and scale of fluctuation. Measurement error is extracted from field measurements using a simple additive probabilistic model or is determined directly from comparative laboratory testing programs. Based on an extensive literature review, the COV of inherent variability, scale of fluctuation, and COV of measurement error are evaluated in detail, along with the general soil type and the approximate range of mean value for which the COVs are applicable. Transformation uncertainty and overall property uncertainty are quantified in a companion paper.

Key words: inherent soil variability, measurement error, coefficient of variation, scale of fluctuation, geotechnical variability.

Résumé : La variabilité géotechnique est un caractère complexe qui résulte de nombreuses sources d'incertitudes. Les trois causes principales d'incertitude géotechnique sont la variabilité intrinsèque, l'erreur de mesure et l'incertitude de transformation. La variabilité intrinsèque peut-être modélisée par un champ aléatoire pouvant être décrit succinctement par le coefficient de variation (COV) et par l'échelle de fluctuation. L'erreur de mesure est extraite des relevés en place, en utilisant un modèle probabiliste simple additif. Elle peut aussi être déterminée directement par des programmes d'essais comparatifs de laboratoire. A partir d'un examen fouillé de la littérature, le COV de variabilité intrinsèque, l'échelle de fluctuation et le COV de l'erreur de mesure ont été évalués en détail, de même que le type général de sol et la plage approximative des valeurs moyennes sur laquelle on peut appliquer les COV. L'incertitude de transformation et l'incertitude générale sur la propriété étudiée sont quantifiées dans un papier conjoint.

Mots clés : variabilité intrinsèque su sol, erreur de mesure, coefficient de variation, échelle de fluctuation, variabilité géotechnique.

[Traduit par la Rédaction]

Introduction

Since the early 1980s, an extensive research study to develop a sound reliability-based design (RBD) approach for foundations has been in progress at Cornell University under the sponsorship of the Electric Power Research Institute. As a part of this RBD methodology, it was necessary to establish realistic statistical estimates of the variability of design soil properties. A series of five studies on geotechnical variabilities (Spry et al. 1988; Orchant et al. 1988; Filippas et al. 1988; Kulhawy et al. 1992; Phoon et al. 1995) was conducted to quantify realistic "best case" and "worst case" scenarios and provide property guidelines for the calibration of the RBD equations. These results are useful for all types of RBD studies. For foundations, extensive calibration studies by Phoon et al. (1995) indicated that the foundation resistance factors in the RBD equations are functions of the

site. In the absence of site-specific data, or where the soil data are too limited for meaningful statistical analyses to be performed, guidelines on the probable range of soil property COV are useful as first-order approximations. Even when there is sufficient information for statistical analyses, a more robust estimate of geotechnical variability can be obtained by combining the site-specific data with prior information from these generalized guidelines using Bayesian updating techniques. Details on the application of Bayesian techniques to site characterization are described elsewhere (e.g., Spry et al. 1988; Filippas et al. 1988) and are not repeated herein. Finally, the establishment of typical soil property COV values would help design engineers develop an appreciation for the probable range of variability inherent in the overall estimation of common design soil properties and therefore identify atypical geotechnical variabilities.

Unfortunately, a number of the soil property statistics re-

Fig. 1. Uncertainty in soil property estimates (source: Kulhawy 1992, p. 101).

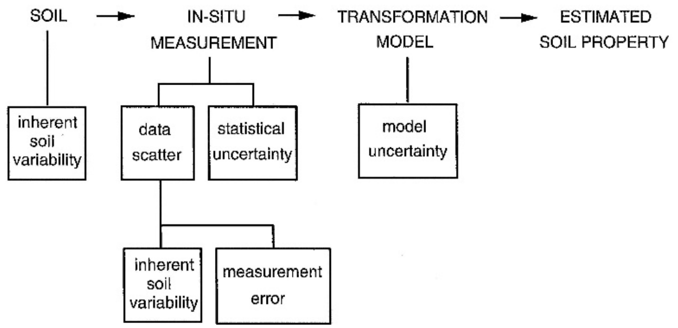
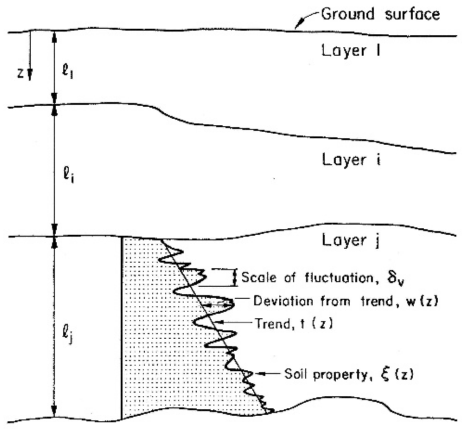


Fig. 2. Inherent soil variability.



source of uncertainty. However, geotechnical variability is more complex and results from many disparate sources of uncertainties, as illustrated in Fig. 1. As shown, the three primary sources of geotechnical uncertainty are inherent variability, measurement error, and transformation uncertainty. The first results primarily from the natural geologic processes that produced and continually modify the soil mass in situ. The second is caused by equipment, procedural operator, and random testing effects. Collectively, these two sources can be described as data scatter. In situ measurements also are influenced by statistical uncertainty or sampling error that result from limited amounts of information. This uncertainty can be minimized by taking more samples, but it is commonly included within the measure-

of equipment and procedural control, and precision of the correlation model. Therefore, soil property statistics that are determined from total variability analyses only can be applied to the specific set of circumstances (site conditions, measurement techniques, correlation models) for which the design soil properties were derived.

In this paper, the inherent soil variability is modeled as a random field, which can be described concisely by the COV and the scale of fluctuation. Measurement error is extracted from field measurements using a simple additive probabilistic model or is determined directly from comparative laboratory test results. Based on an extensive literature review, the COV of inherent variability, the scale of fluctuation, and the COV of measurement error are evaluated in detail, along with the general soil type and the approximate range of mean value for which the COVs are applicable. A companion paper (Phoon and Kulhawy 1999) discusses the transformation uncertainty and illustrates how these component uncertainties can be combined consistently, for a variety of common soil parameters, to quantify the variability of design soil properties for general geotechnical use.

Modeling inherent soil variability

Soil is a complex engineering material that has been formed by a combination of various geologic, environmental, and physical–chemical processes. Many of these processes are continuing and can be modifying the soil in situ. Because of these natural processes, all soil properties in situ will vary vertically and horizontally. As shown in Fig. 2, this spatial variation can be decomposed conveniently into a smoothly varying trend function [$t(z)$] and a fluctuating component [$w(z)$] as follows:

$$[1] \qquad \xi(z) = t(z) + w(z)$$

in which ξ is the in situ soil property, and z is the depth. The fluctuating component defined in eq. [1] represents the in-

Phoon, K. K. and Kulhawy, F. H. (1999). Characterization of geotechnical variability. Canadian Geotechnical Journal, 36(4), 612-624.

Table 3. Summary of inherent variability of field measurements (source: Phoon et al. 1995, p. 4-10).

Test type[a]	Property[b]	Soil type	No. of data groups	No. of tests per group: Range	No. of tests per group: Mean	Property value: Range	Property value: Mean	Property COV (%): Range	Property COV (%): Mean
CPT	q_c (MN/m^2)	Sand	57	10–2039	115	0.4–29.2	4.10	10–81	38
CPT	q_c (MN/m^2)	Silty clay	12	30–53	43	0.5–2.1	1.59	5–40	27
CPT	q_T (MN/m^2)	Clay	9	—	—	0.4–2.6	1.32	2–17	8
VST	s_u(VST) (kN/m^2)	Clay	31	4–31	16	6–375	105	4–44	24
SPT	N	Sand	22	2–300	123	7–74	35	19–62	54
SPT	N	Clay, loam	2	2–61	32	7–63	32	37–57	44
DMT	A (kN/m^2)	Sand to clayey sand	15	12–25	17	64–1335	512	20–53	33
DMT	A (kN/m^2)	Clay	13	10–20	17	119–455	358	12–32	20
DMT	B (kN/m^2)	Sand to clayey sand	15	12–25	17	346–2435	1337	13–59	37
DMT	B (kN/m^2)	Clay	13	10–20	17	502–876	690	12–38	20
DMT	E_D (MN/m^2)	Sand to clayey sand	15	10–25	15	9.4–46.1	25.4	9–92	50
DMT	E_D (MN/m^2)	Sand, silt	16	—	—	10.4–53.4	21.6	7–67	36
DMT	I_D	Sand to clayey sand	15	10–25	15	0.8–8.4	2.85	16–130	53
DMT	I_D	Sand, silt	16	—	—	2.1–5.4	3.89	8–48	30
DMT	K_D	Sand to clayey sand	15	10–25	15	1.9–28.3	15.1	20–99	44
DMT	K_D	Sand, silt	16	—	—	1.3–9.3	4.1	17–67	38
PMT	p_L (kN/m^2)	Sand	4	—	17	1617–3566	2284	23–50	40
PMT	p_L (kN/m^2)	Cohesive	5	10–25	—	428–2779	1084	10–32	15
PMT	E_{PMT} (MN/m^2)	Sand	4	—	—	5.2–15.6	8.97	28–68	42

[a]CPT, cone penetration test; VST, vane shear test; SPT, standard penetration test; DMT, dilatometer test; PMT, pressuremeter test.
[b]q_c, CPT tip resistance; q_T, corrected CPT tip resistance; s_u(VST), undrained shear strength from VST; N, SPT blow count (number of blows per foot or per 305 mm); A and B, DMT A and B readings; E_D, DMT modulus; I_D, DMT material index; K_D, DMT horizontal stress index; p_L, PMT limit stress; E_{PMT}, PMT modulus.

ments has been discussed by Phoon and Kulhawy (1996) and will not be repeated herein. However, since these specialty conference proceedings have rather limited circulation internationally, it is wise to repeat key data where pertinent. Therefore, the basic data plots of COV of inherent variability versus the mean in situ tests parameters are given in the Appendix. These data support the interpretations given in Table 3.

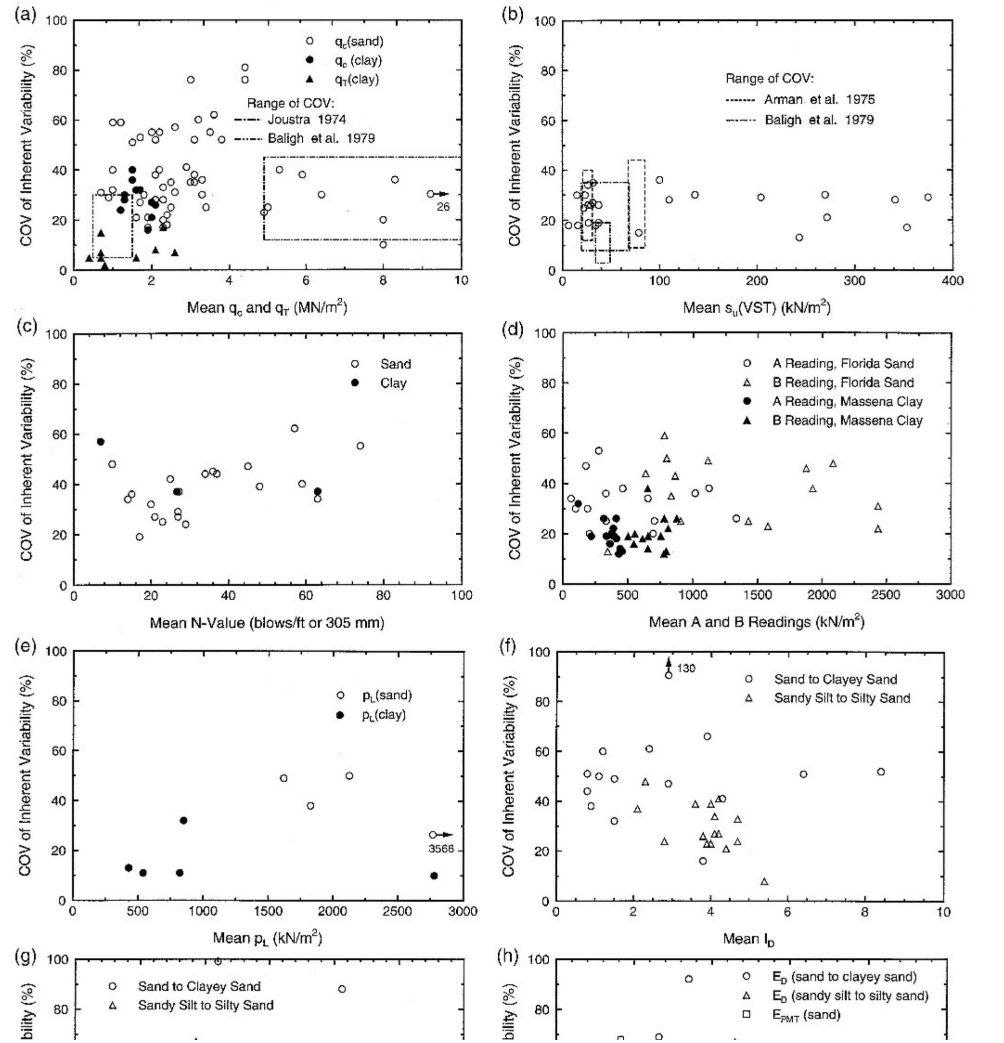
Scale of fluctuation

An extensive literature review was conducted to estimate the typical scales of fluctuations for a variety of common geotechnical parameters. The results of this review are summarized in Table 4. Full details are given elsewhere (Phoon et al. 1995). The scales of fluctuation are generally calculated using the method of moments. Information on the soil type and the direction of fluctuation also are included in the table. It is apparent that the amount of information on the scale of fluctuation is relatively limited in comparison to the

Table 4. Summary of scale of fluctuation of some geotechnical properties (source: Phoon et al. 1995, p. 4-20).

Property[a]	Soil type	No. of studies	Scale of fluctuation (m): Range	Scale of fluctuation (m): Mean
Vertical fluctuation				
s_u	Clay	5	0.8–6.1	2.5
q_c	Sand, clay	7	0.1–2.2	0.9
q_T	Clay	10	0.2–0.5	0.3
s_u(VST)	Clay	6	2.0–6.2	3.8
N	Sand	1	—	2.4
w_n	Clay, loam	3	1.6–12.7	5.7
w_L	Clay, loam	2	1.6–8.7	5.2
$\bar{\gamma}$	Clay	1	—	1.6
γ	Clay, loam	2	2.4–7.9	5.2
Horizontal fluctuation				
q_c	Sand, clay	11	3.0–80.0	47.9
q_T	Clay	2	23.0–66.0	44.5
s_u(VST)	Clay	3	46.0–60.0	50.7
w_n	Clay	1	—	170.0

Fig. A1. COV of inherent variability versus mean in situ test parameters: (a) CPT q_c and q_T; (b) s_u(VST); (c) SPT N; (d) DMT A and B readings; (e) PMT p_L; (f) DMT I_D; (g) DMT K_D; (h) DMT E_D and PMT E_{PMT}.



CATEGORIES OF DATA QUALITY

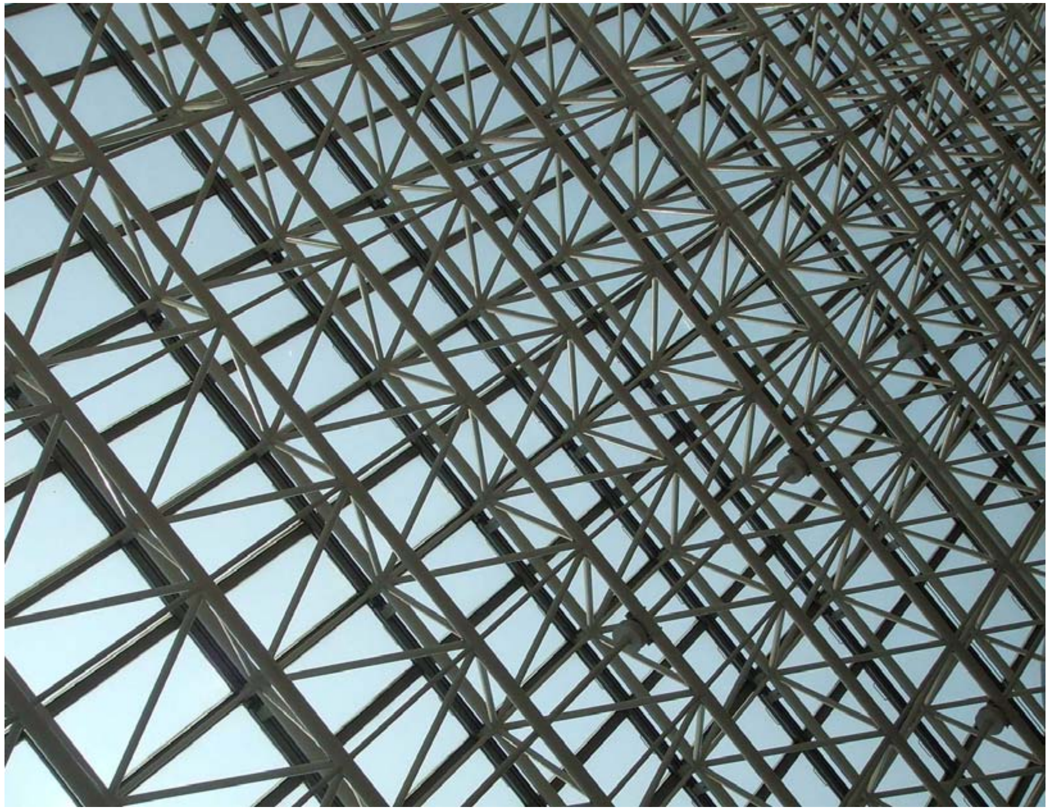
- CONCRETE (f_{cu}) (ACI 1965)
  - COV < 10% EXCELLENT
  - COV = 10 – 15% GOOD
  - COV = 15 – 20% SATISFACTORY
  - COV > 20% BAD

10 - 20%

- SOIL (s_u) (EPRI TR105000)
  - COV = 10 – 30% LOW
  - COV = 30 – 50% MEDIUM
  - COV = 50 – 70% HIGH

10 - 70%

Phoon, K. K., Kulhawy, F. H., & Grigoriu, M. D. (1995). Reliability-Based Design of Foundations for Transmission Line Structures, Report TR-105000, Electric Power Research Institute, Palo Alto.



STRUCTURE

GEOLOGY

CLASSIFICATION OF SOIL VARIABILITY

GEOTECH PARAMETER	VARIABILITY	COV (%)
UNDRAINED SHEAR STRENGTH	LOW[A]	10 – 30
	MEDIUM[B]	30 – 50
	HIGH[C]	50 – 70
EFFECTIVE STRESS FRICTION ANGLE	LOW[A]	5 – 10
	MEDIUM[B]	10 – 15
	HIGH[C]	15 – 20
HORIZONTAL STRESS COEFFICIENT (ALSO SOIL MODULUS)	LOW[A]	30 – 50
	MEDIUM[B]	50 – 70
	HIGH[C]	70 – 90

A – GOOD QUALITY DIRECT LAB/FIELD MEASUREMENTS

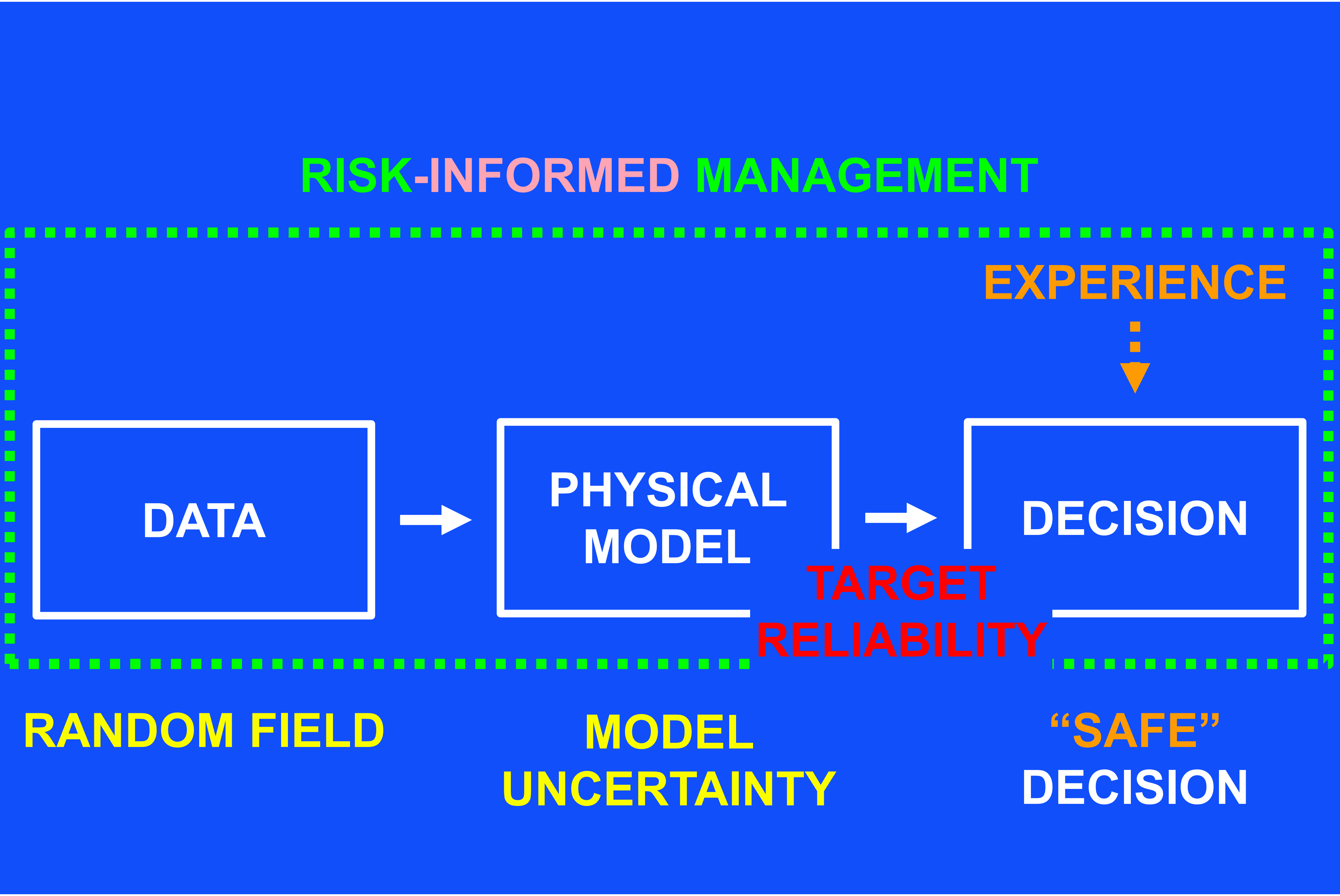
B – INDIRECT CORRELATIONS W. GOOD FIELD DATA, EXCEPT SPT

C – INDIRECT CORRELATIONS W. SPT & W. STRICTLY EMPIRICAL CORRELATIONS

Phoon, K. K. & Kulhawy, F. H. (2008). “Serviceability Limit State Reliability-based Design”, Chapter 9, Reliability-Based Design in Geotechnical Engineering: Computations and Applications, Taylor & Francis, April 2008, 344-383.

RELIABILITY-BASED DESIGN

PROBABILITY(CAPACITY < LOAD) < P_T


RISK-INFORMED MANAGEMENT
EXPERIENCE
DATA
PHYSICAL MODEL
DECISION
TARGET RELIABILITY
RANDOM FIELD
MODEL UNCERTAINTY
“SAFE” DECISION

INFORMATION SENSITIVE LRFD

UNDRAINED SHEAR STRENGTH		Ψ_u	
MEAN (kN/m^2)	COV (%)	RESISTANCE FACTOR (ULS)	DEFORMATION FACTOR (SLS)
25 – 50	10 - 30	0.44	0.65
MEDIUM CLAY	30 - 50	0.43	0.63
	50 - 70	0.42	0.62
50 – 100	10 - 30	0.43	0.64
STIFF CLAY	30 - 50	0.41	0.61
	50 - 70	0.39	0.58
100 - 200	10 - 30	0.40	0.61
VERY STIFF	30 - 50	0.37	0.57
CLAY	50 - 70	0.34	0.52

1. DRILLED SHAFTS UNDER UNDRAINED UPLIFT
2. TARGET RELIABILITY INDEX FOR ULS = 3.2; SLS = 2.6

Phoon, K. K., Kulhawy, F. H., & Grigoriu, M. D. (1995). Reliability-Based Design of Foundations for Transmission Line Structures, Report TR-105000, Electric Power Research Institute, Palo Alto.

2014 CANADIAN HIGHWAY BRIDGE DESIGN CODE

Application	Limit State	Test Method/Model	DEGREE OF UNDERSTANDING		
			LOW	TYPICAL	HIGH
Shallow foundations	Bearing	Analysis	0.45	0.50	0.60
		Scale model test	0.50	0.55	0.65
	Sliding, Frictional	Analysis	0.70	0.80	0.90
		Scale model test	0.75	0.85	0.95
	Sliding, Cohesive	Analysis	0.55	0.60	0.65
		Scale model test	0.60	0.65	0.70
	Passive resistance,	Analysis	0.40	0.50	0.55
	Settlement or	Analysis	0.70	0.80	0.90

Fenton, G.A., Naghibi, F., Dundas, D., Bathurst, R. J. & Griffiths, D. V. (2016). Reliability-based geotechnical design in the 2014 Canadian Highway Bridge Design Code. Canadian Geotechnical Journal, 53(2), 236-251

HKIE THE HONG KONG INSTITUTION OF ENGINEERS 香港工程師學會

Geotechnical Division 岩土分部

Reliability Based Design, Risk Analysis, Limit State Design (Half-day Seminar)

Presented by
Prof Kok-Kwang Phoon of
the National University of Singapore

Prof Jianye Ching of
National Taiwan University

Mr. Xavier Monin of
Dragages /Bouygues TP

Mr. Mahad Naseer of
AECOM

Coordinator
Ir Clifford Phung
Dr Andy Y F Leung

Date: 7 Dec 2018
Application deadline: 29 Nov 2018

Organiser
HKIE Geotechnical Division

Objective:
This seminar aims to provide participants with design knowledge related to Reliability Based Design, Risk Analysis and Limit State Design, supplemented with recent project examples in Tunnel Excavation and ELS.

Who Should Attend:
This half-day seminar is designed for young engineers in geotechnical disciplines and also civil and structural engineers who are interested in geotechnical design.

CPD Hours:
The half-day seminar is designed for 4 hours CPD.

Medium of Instruction:
English

Fee:
HK$400

Venue:
Wang Gungwu Lecture Hall, Graduate House, The University of Hong Kong

Applications:
Online application should be made on or before **29 November 2018**, at the following website: http://www.hkieged.org/geodiv/activity.aspx. Seats are limited to **200 persons**. If more than 200 applications are received, participants will be selected on a random basis. The Organiser reserves the right to select the participants. Successful

Programme:

8:45– 9:00	Registration
9:00 – 9:10	Opening Address
Session I	
9:10 – 9:50	***Characterization of Geotechnical Model Factors*** Prof Kok-Kwang Phoon
9:50 – 10:30	***Statistical Estimation of Soil Design Parameters*** Prof Jianye Ching
10:30 – 10:45	Discussion
10:45 – 11:05	Coffee Break
Session II	
11:05 – 11:45	***Liantang Tunnel - Traditional Tunnel Excavation by Observational Approach*** Mr. Xavier Monin
11:45 – 12:25	***Comparison of ELS design using Global Factor of Safety, C580 and C760*** Mr. Mahad Naseer
12:25 – 12:40	Discussion

Enquires:
For enquiries, please contact Ir Clifford Phung (clifford_hkiegdc@meinhardt.com.hk) or Dr Andy Y F Leung (yfleung@polyu.edu.hk).

DATA-DRIVEN MODELS

– MULTIVARIATE STATISTICS

GENERIC DATABASES (1)

- *CLAYS* (REGIONAL - COMPLETE)
  - M_r, q_c, f_s, w_n, γ_d (J-Clay/5/124)

Liu, S., Zou, H. Cai, G., Bheemasetti, B. V., Puppala, A. J. & Lin J. 2016. Multivariate correlation among resilient modulus and cone penetration test parameters of cohesive subgrade soils, Engineering Geology, 209: 128–142

  - s_u, σ'_p, σ'_v, LL, PL, w_n, S_t (F-CLAY/7/216)

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

GENERIC DATABASES (2)

- *CLAYS* (GLOBAL - COMPLETE)
  - LI, s_u, s_u^{re}, σ'_p, σ'_v (CLAY/5/345)

    Ching, J. Y. & Phoon, K. K. (2012). "Modeling Parameters of Structured Clays as a Multivariate Normal Distribution", Canadian Geotechnical Journal, 49(5), 522-545
  - s_u/σ'_{vo}, OCR, $(q_t – \sigma_{vo})/\sigma'_{vo}$, $(q_t – u_2)/\sigma'_{vo}$, $(u_2 – u_0)/\sigma'_{vo}$, B_q (CLAY/6/535)

    Ching, J. Y. & Phoon, K. K. (2014). "Modeling CPTU Parameters of Clays as a Multivariate Normal Distribution", Canadian Geotechnical Journal, 2013, 51(1), 77-91

GENERIC DATABASES (3)

- *CLAYS* (GLOBAL – INCOMPLETE)
  - CIUC, CK_0UC, CK_0UE, DSS, FV, UU, UC (CLAY/7/6310)

Ching, J. Y. & Phoon, K. K. (2013). “Multivariate Distribution For Undrained Shear Strengths Under Various Test Procedures”, Canadian Geotechnical Journal, 50(9), 907-923

  - LL, PI, LI, σ'_v/P_a, σ'_p/P_a, s_u/σ'_p, S_t, $(q_t-\sigma_{vo})/\sigma'_{vo}$, $(q_t-u_2)/\sigma'_{vo}$, B_q (CLAY/10/7490)

Ching, J. and Phoon, K.K. (2014). “Transformations and Correlations Among Some Clay Parameters – The Global Database”, Canadian Geotechnical Journal, 51(6), 663-685

Ching, J. and Phoon, K.K. (2014). “Correlations Among Some Clay Parameters – the Multivariate Distribution”, Canadian Geotechnical Journal, 51(6), 686-704

GENERIC DATABASES (4)

- ***SANDS*** **(GLOBAL – INCOMPLETE)**
  - D_{50}, C_u, D_r, σ'_v/P_a, ϕ', q_{t1}, $(N_1)_{60}$ **(SAND/7/2794)**

Ching, J. Y., Lin, G. H., Chen, J. R. & Phoon, K. K. (2017). "Transformation Models for Effective Friction Angle and Relative Density Calibrated based on Generic Database of Coarse-grained Soils", Canadian Geotechnical Journal, 54(4), 481-501

Ching, J. Y., Lin, G. H., Phoon, K. K. & Chen, J. R. (2017). "Correlations Among Some Parameters of Coarse-Grained Soils – the Multivariate Probability Distribution Model", Canadian Geotechnical Journal, 54(9), 1203-1220

- ***ROCKS*** **(GLOBAL – INCOMPLETE)**
  - n, γ, R_L, S_h, σ_{bt}, I_{s50}, V_p, σ_c, E **(ROCK/9/4069)**

Ching, J. Y., Li, K .H., Weng, M. C. & Phoon, K. K. (2018). "Generic Transformation Models for Some Intact Rock Properties", Canadian Geotechnical Journal, in press

Ching, J. Y., Phoon, K. K., Lin, K. H. & Weng, M. C. (2018). "Multivariate Probability Distribution for Some Intact Rock Properties", Canadian Geotechnical Journal, in press

TC304 Engineering Practice of Risk Assessment & Management

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Last revision Feb 02 2018

304dB – TC304 databases

One of the key findings of the recently concluded ISSMGE 2017 SOA/SOP Survey is that publically-available databases that include information available for properties, and risk databases be available to the profession. Thus, compiling geotechnical databases represents one of the key missions of the current TC3 and we encourage the use of them to advance the state of the art and practice of the geotechnical profession; we also invite you to contact the task force le effort.

Acknowledgments
For those interested in using any of 304dB, please download the data and feel free to use it subject to the constraints described in the Disclaimer and Restri any derivative work (defined here as a thesis, dissertation, conference paper, journal paper, engineering report, etc.) requires the Acknowledgement of this indicated in the last column of each table. Please include the following text in the derivative work where appropriate (e.g., in the "Front Matter" of a disserta typically presented after the Conclusions and before the References): **"The authors would like to thank the members of the TC304 Committee on En the International Society of Soil Mechanics and Geotechnical Engineering for developing the database 304dB used in this study and making <insert name of Database Owner> for contributing this database to the TC304 compendium of databases."**

CPT databases
Leader: Armin Stuedlein
These databases are mostly CPT clusters, i.e., multiple CPTs are conducted in a local site.
The names of the databases are in the format of A/B/C:
A: Type of in-situ test (CPT or CPTU)
B: number of soundings
C: rough size of sounding area
Please contact Armin armin.stuedlein@oregonstate.edu if you want to contribute databases.

Database	Sounding details	File format			Database owner	
		Text	Excel	Matlab		
A-CPT/232/2500m^2 Adelaide, Australia Stiff, OC alluvial clay (CH)	Total depths = 3.5 ~ 5.6 m Horizontal spacing = 0.2 m ~ 71 m Site Map	Link	Link	Link	M Jaksa mark.jaksa@adelaide.edu.au	1. Jaksa, M. (1995). T Properties of a Stif Adelaide, Australia 2. Jaksa, M., Kaggwa scale of fluctuation on Application of S Researchgate link
A-CPT/1/horizontal						1. Jaksa, M. (1995). T

CLAY/5/345

- STRUCTURED CLAY DATABASE CONTAINING *345* PTS (Y_1, Y_2, Y_3, Y_4, Y_5)
- *37* SITES (CANADA, USA, SWEDEN, JAPAN, THAILAND, UK, BRAZIL, INDIA):
  - Y_1 = LI = LIQUIDITY INDEX
  - $Y_2 = S_u$ = UNDRAINED SHEAR STRENGTH
  - $Y_3 = S_u^{re}$ = REMOULDED S_u
  - $Y_4 = \sigma'_p$ = PRECONSOLIDATION STRESS
  - $Y_5 = \sigma'_v$ = EFFECTIVE VERTICAL STRESS

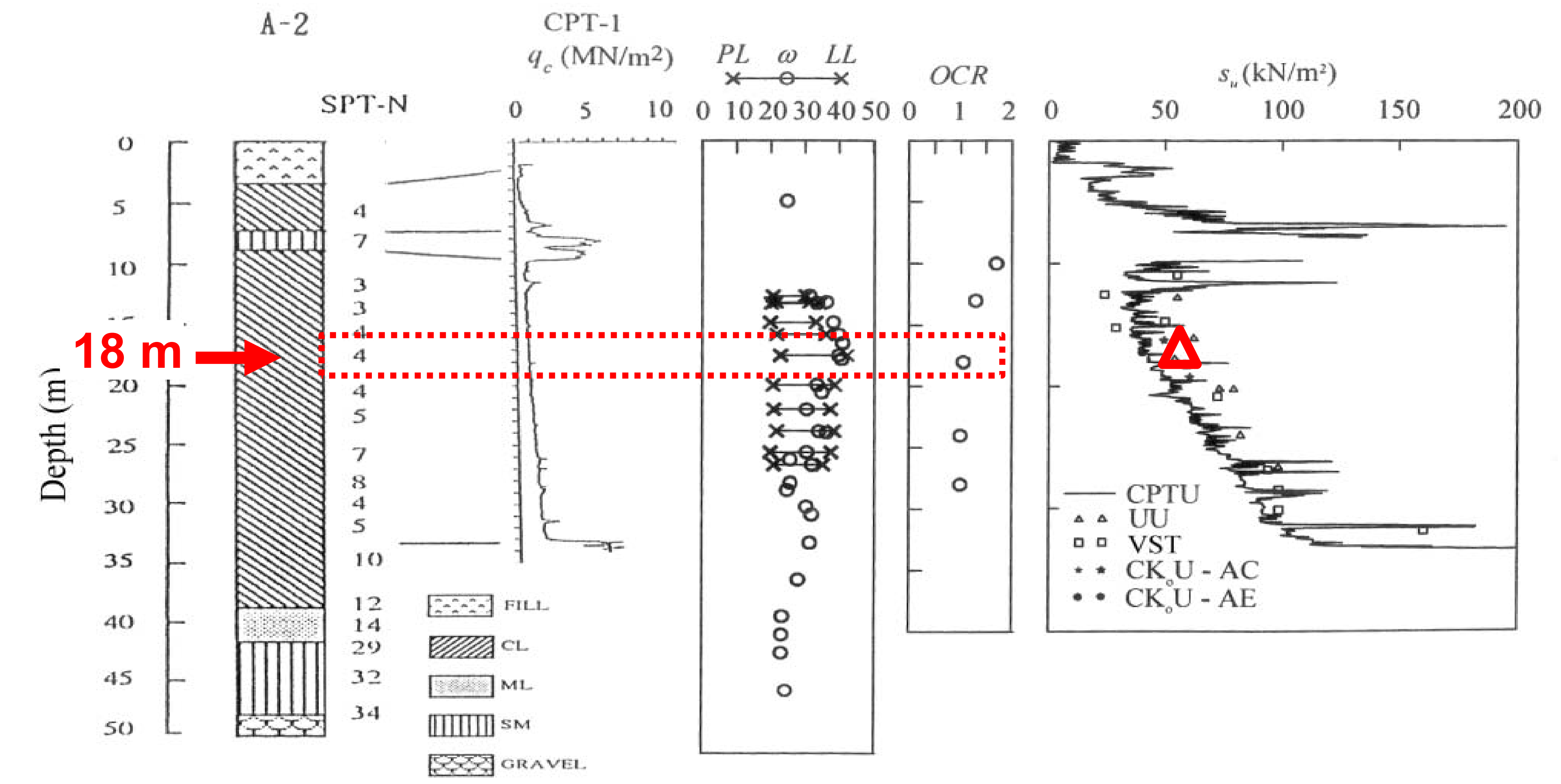
Ching, J. Y. & Phoon, K. K. (2012). "Modeling Parameters of Structured Clays as a Multivariate Normal Distribution", Canadian Geotechnical Journal, 49(5), 522-545

Site (region)	LI	s_u	s_u^{re}	σ'_v	σ'_p	Reference
Ariake Bay (Japan) UC tests S_t = 9.9 ~ 42.4	1.28	2.58	0.22	9.56	7.94	Ohtsubo et al. (1995)
	1.27	4.74	0.16	12.82		
	1.45	5.42	0.39	16.44	17.14	
	1.20		0.59	20.06	27.63	
		6.97		24.04		
	1.36	6.83	0.44	27.30	26.53	
	1.29	11.08	0.44	31.65	34.10	
		10.36	0.52	34.54	29.30	
	1.24	13.10	0.39	38.53	40.84	
	1.31	15.88	0.63	41.79	42.82	
	1.22	15.77	0.68	45.05	46.16	
	1.44	16.66		50.48		
		19.19	1.47	54.82		
	1.22	25.00	0.59	59.53	75.70	
	1.22		1.17	63.87	82.35	
	1.05		1.43	69.31	127.24	
	0.89	49.35	2.94	73.65	181.98	
Gosport (U.K) UC tests S_t = 2.4 ~ 3.1	0.59	8.93		39.01	29.61	Skempton (1948)
	0.38	34.55	13.67	130.66		
	0.55	9.87	3.22	35.72	31.49	
		20.68	6.75	110.45		
	0.46	12.22	4.13	33.37	46.06	
Åsrum (Canada) UC tests S_t = 35.8 ~189.8	2.02	10.56	0.14	7.70	29.98	Parry and Wroth (1981)

M-U-S-I-C

- MULTIVARIATE
- UNCERTAIN & UNIQUE (SITE-SPECIFIC)
- SPARSE
- INCOMPLETE

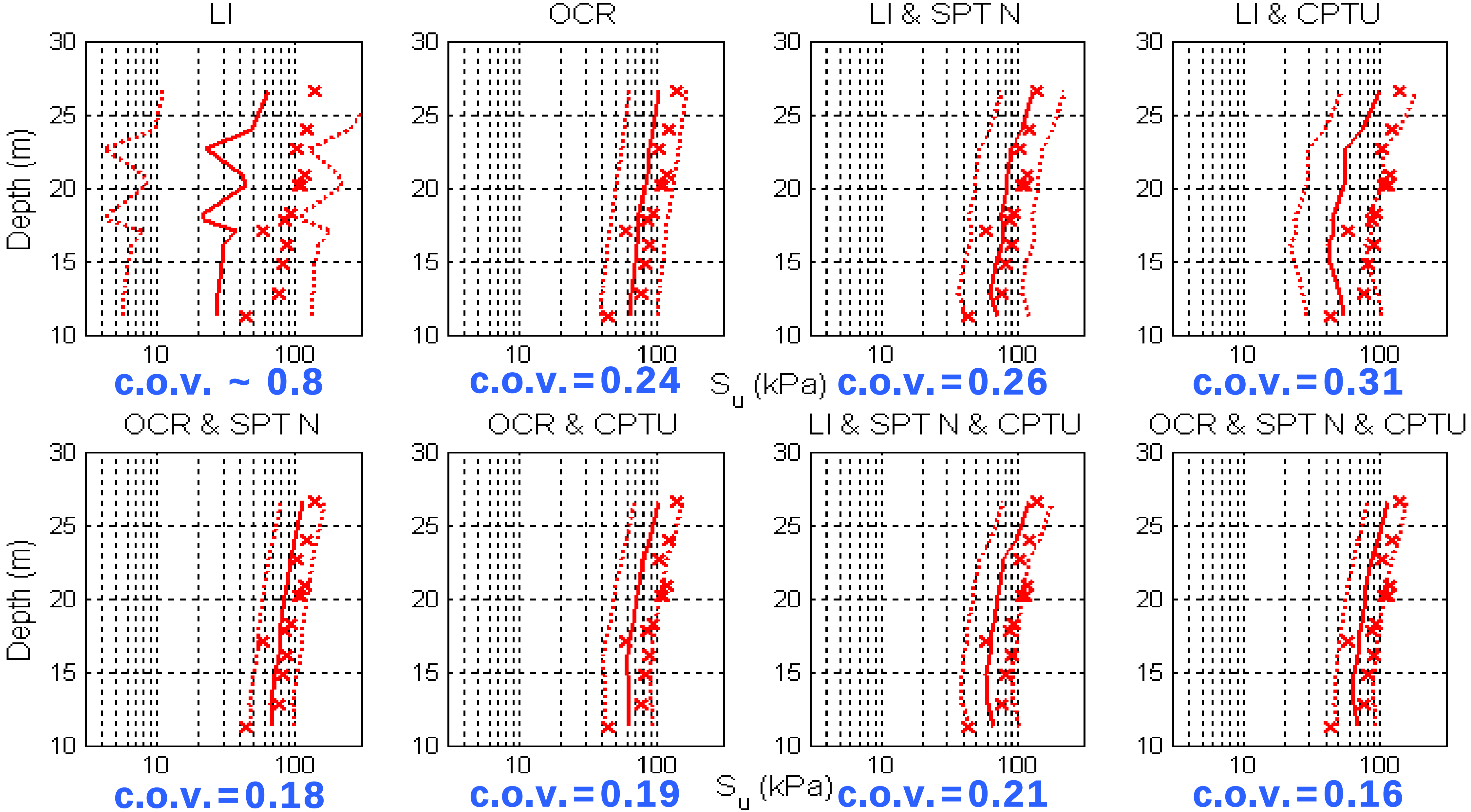
SITE DATA - FIELD & LAB



CASE STUDY

Depth (m)	Test type	S_u value (kN/m²)	Test indices						
			OCR	LI	N_{60}	σ_{v0} (kN/m²)	σ'_{v0} (kN/m²)	q_c (kN/m²)	q_T'' (kN/m²)
11.3	CK_0U		1.55	1.34	3.96	206.36	115.52	835.26	787.60
12.8	UU		1.35	1.34	3.00	233.41	127.95	810.50	731.09
14.8	VST		1.22	1.31	3.34	270.22	144.86	730.12	598.62
16.1	UU		1.16	1.28	4.00	293.61	155.61	713.62	555.60
17.1	CK_0U		1.11	1.18	4.00	311.96	164.04	766.82	600.56
17.8	UU		1.07	0.94	4.00	324.68	169.88	803.69	631.71
18.3	VST		1.05	0.94	4.00	334.65	174.47	830.02	653.07
20.2	UU		1.04	0.72	4.00	368.39	189.97	911.86	716.72
20.2	UU		1.04	0.72	4.00	369.16	190.32	913.72	718.17
20.9	VST		1.03	0.73	4.00	381.05	195.79	942.55	740.58
22.7	VST		1.01	0.59	4.80	413.86	210.86	1050.60	836.35
24.0	UU		1.00	0.68	5.58	437.42	221.69	1210.20	1002.72
26.6	UU		1.00	0.38	7.20	485.35	243.72	1532.60	1338.44

ESTIMATION OF S_U



MORE VALUE FROM DATA?

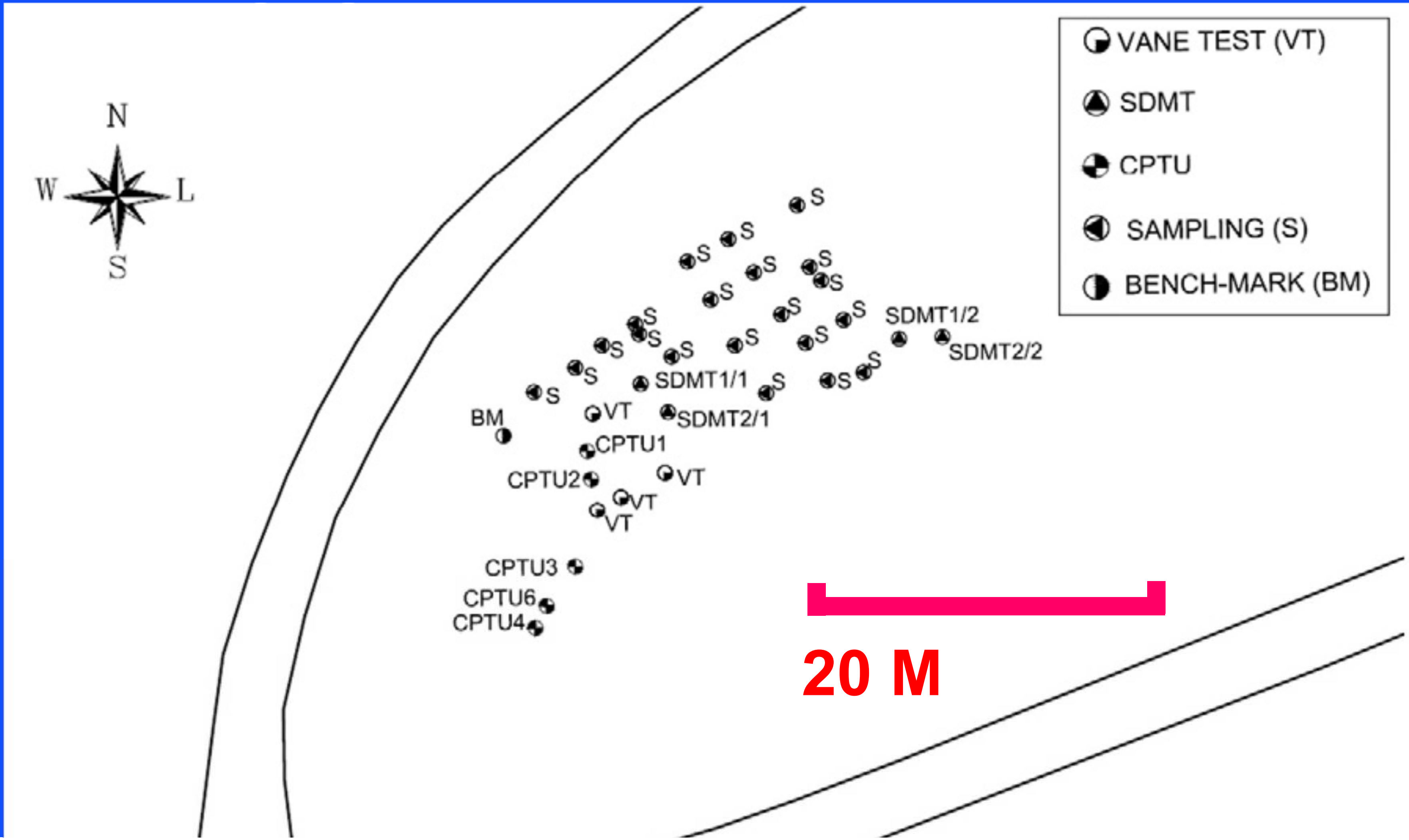

... AND WE CAN SAVE 700 LIRA BY NOT TAKING SOIL TESTS.

data is the new oil

we need to find it, extract it, refine it, distribute it and monetize it.

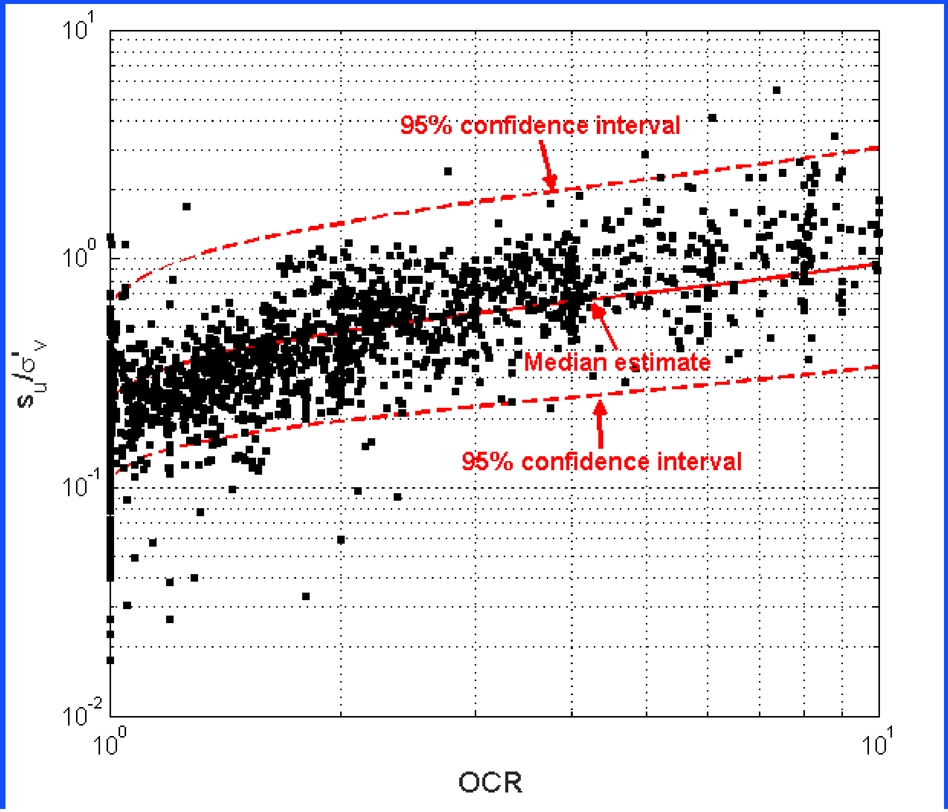
- David Buckingham

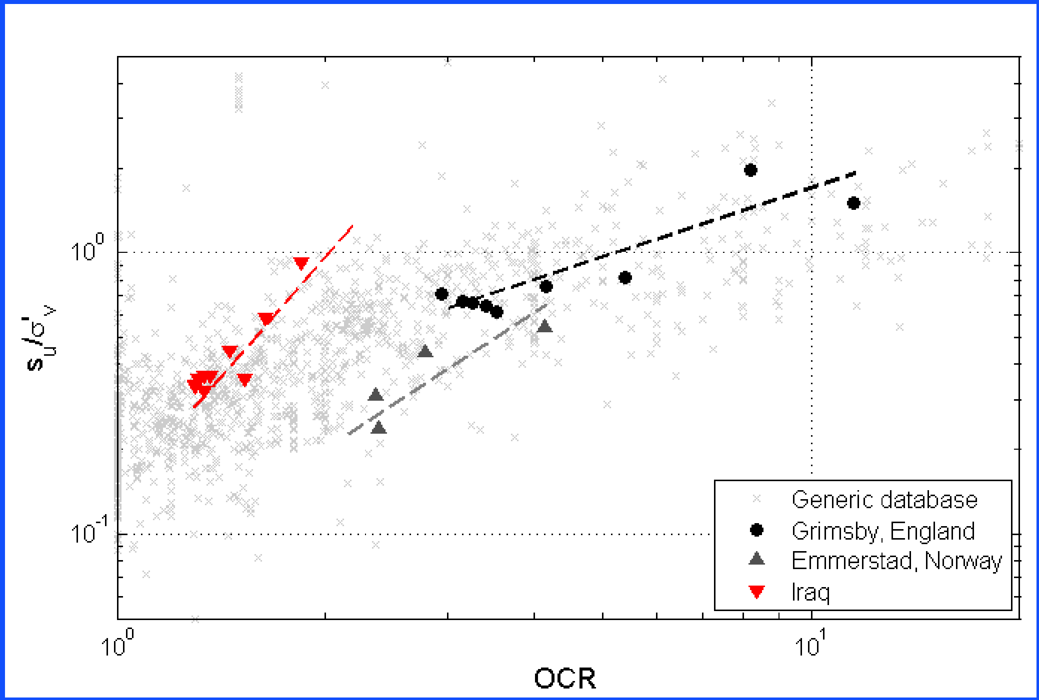
SITE-SPECIFIC DATA



U = UNIQUE (SITE-SPECIFIC)

- GENERIC TRANSFORMATION UNCERTAINTY IS TOO LARGE FOR ONE SITE





“SITE” CHALLENGE

- SINGLE SITE – SPARSE & INCOMPLETE DATA
- MULTIPLE SITES – EXCESSIVE UNCERTAINTY

- *SITE CHALLENGE* – “BEST” SITE-SPECIFIC ESTIMATOR OF A DESIGN PARAMETER FROM
  – SITE INFO (ACTUAL DATA)
  – “EXPERIENCE” (DATA FROM COMPARABLE SITES)

BAYESIAN LEARNING

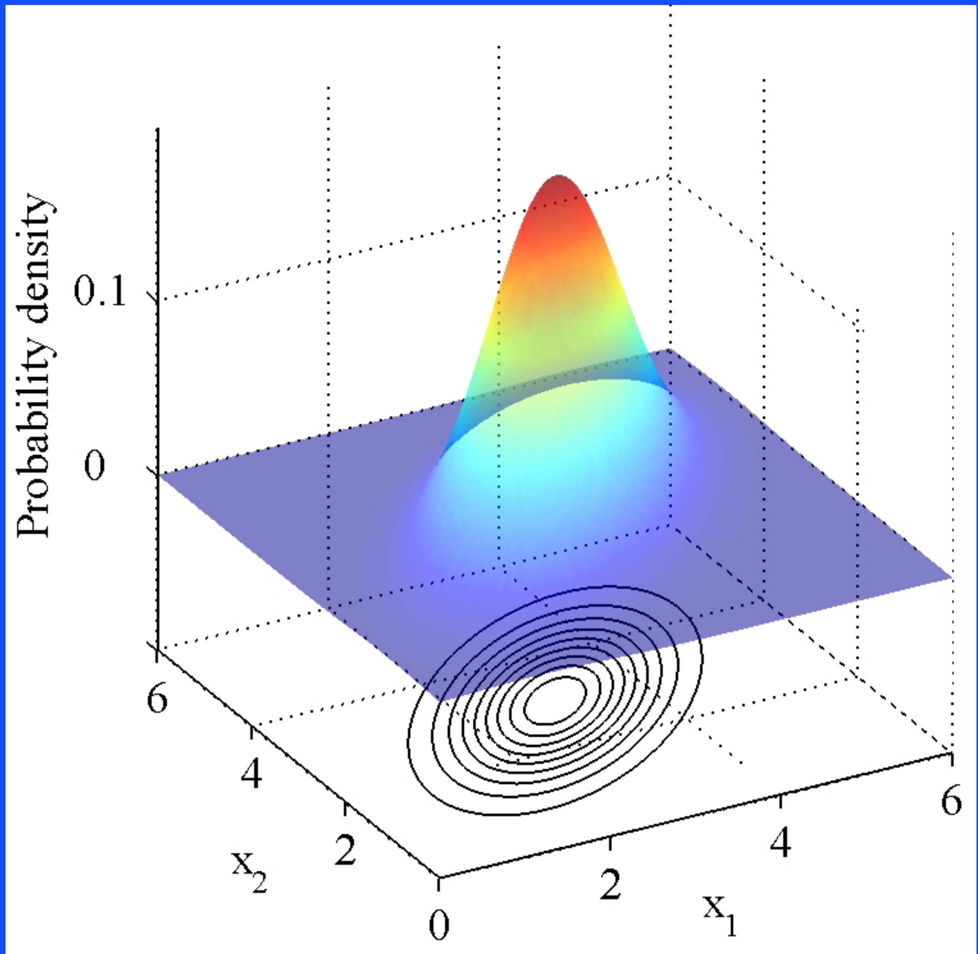
HOW TO OBTAIN LOCAL MODEL FROM “MUSIC” DATA?

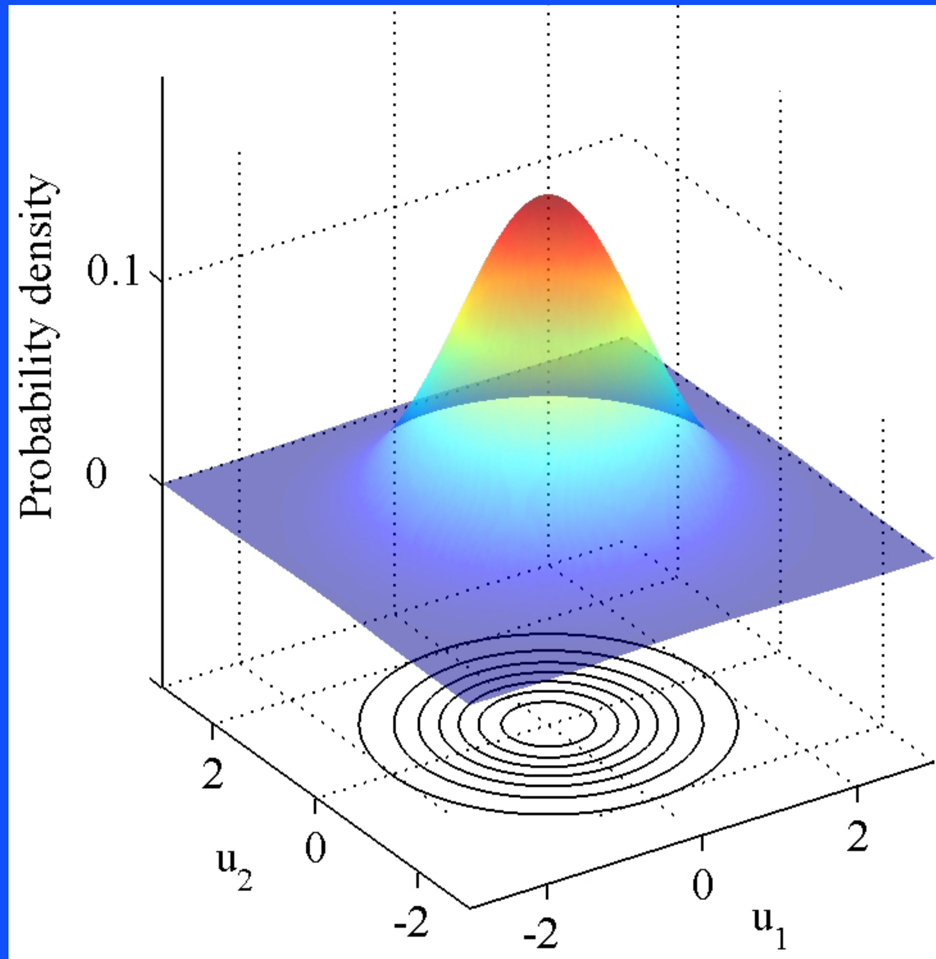
Ching, J. Y. & Phoon, K. K. (2019). “Constructing Site-specific Probabilistic Transformation Model by Bayesian Machine Learning”, Journal of Engineering Mechanics, ASCE, 145(1), 04018126

SITE-SPECIFIC PDF

- GIBBS SAMPLER = SPECIAL CASE OF MCMC
- WORK IN STD NORMAL (X) SPACE:
  - μ – MEAN VECTOR
  - C – COVARIANCE MATRIX
  - X^u – MISSING DATA
- (μ,C,X^u) UNKNOWN

MULTIVARIATE GAUSSIAN





$$f(\mathbf{X}) = (2\pi)^{-\frac{n}{2}}|\mathbf{C}|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(\mathbf{X}-\mu)^T \mathbf{C}^{-1}(\mathbf{X}-\mu)\right]$$

SITE-SPECIFC PDF

- GIBBS SAMPLER + CONJUGATE PRIOR
  - $f(\underline{\mu}|C,X^u,DATA)$ MULTIVARIATE NORMAL IF $f(\underline{\mu})$ MULTIVARIATE NORMAL
  - $f(C|\underline{\mu},X^u, DATA)$ INVERSE WISHART IF $f(C)$ INVERSE WISHART
  - $f(X^u|\underline{\mu},C, DATA)$ MULTIVARIATE NORMAL

- SAMPLE FROM $f(\underline{\mu}|C,X^u,DATA)$, $f(C|\underline{\mu},X^u,DATA)$, AND $f(X^u|\underline{\mu},C,DATA)$ ITERATIVELY

BAYESIAN LEARNING

- GIBB'S SAMPLER + CONJUGATE PRIORS
  - ASSIGN CONJUGATE PRIORS $f(\underline{\mu})$ & $f(C)$
  - INITIALIZE ($\underline{\mu}, C, X^U$) SAMPLES (X IS NOW COMPLETE)

$\underline{\mu}$

0
0
0

C

1	0	0
0	1	0
0	0	1

X

X_1	-1.2	1.4
X_2	0	0.9
X_3	-2.2	0

BAYESIAN LEARNING

- GIBB'S SAMPLER + CONJUGATE PRIORS
  - ASSIGN CONJUGATE PRIORS $f(\underline{\mu})$ & $f(C)$
  - INITIALIZE $(\underline{\mu}, C, X^U)$ SAMPLES (X IS NOW COMPLETE)
  - SAMPLE $\underline{\mu} \sim f(\underline{\mu} | C, X, \text{DATA})$ (MULTIVARIATE NORMAL)

$\underline{\mu}$

0.7
-1.2
1.8

C

1	0	0
0	1	0
0	0	1

X

X_1	-1.2	1.4
X_2	0	0.9
X_3	-2.2	0

BAYESIAN LEARNING

- GIBB'S SAMPLER + CONJUGATE PRIORS
  - ASSIGN CONJUGATE PRIORS f($\underline{\mu}$) & f(C)
  - INITIALIZE ($\underline{\mu}$,C,X^U) SAMPLES (X IS NOW COMPLETE)
  - SAMPLE $\underline{\mu}$ ~ f($\underline{\mu}$|C,X,DATA) (MULTIVARIATE NORMAL)
  - SAMPLE C ~ f(C|$\underline{\mu}$,X,DATA) (INVERSE WISHART)

$\underline{\mu}$

0.7
-1.2
1.8

C

0.9	-0.5	0.6
-0.5	1.5	0.03
0.6	0.03	0.7

X

X_1	-1.2	1.4
X_2	0	0.9
X_3	-2.2	0

BAYESIAN LEARNING

- GIBB'S SAMPLER + CONJUGATE PRIORS
  - ASSIGN CONJUGATE PRIORS $f(\underline{\mu})$ & $f(C)$
  - INITIALIZE $(\underline{\mu}, C, X^U)$ SAMPLES (X IS NOW COMPLETE)
  - SAMPLE $\underline{\mu} \sim f(\underline{\mu}|C,X,\text{DATA})$ (MULTIVARIATE NORMAL)
  - SAMPLE $C \sim f(C|\underline{\mu},X,\text{DATA})$ (INVERSE WISHART)
  - SAMPLE $X^U \sim f(X^U|\underline{\mu},C,X^O,\text{DATA})$ (MULTIVARIATE NORMAL)

$\underline{\mu}$

0.7
-1.2
1.8

C

0.9	-0.5	0.6
-0.5	1.5	0.03
0.6	0.03	0.7

X

X_1	-1.2	1.4
X_2	-0.9	0.9
X_3	-2.2	0.6

BAYESIAN LEARNING

- GIBB'S SAMPLER + CONJUGATE PRIORS
  - ASSIGN CONJUGATE PRIORS $f(\underline{\mu})$ & $f(C)$
  - INITIALIZE ($\underline{\mu}, C, X^U$) SAMPLES (X IS NOW COMPLETE)
  - SAMPLE $\underline{\mu} \sim f(\underline{\mu}|C,X,\text{DATA})$ (MULTIVARIATE NORMAL)
  - SAMPLE $C \sim f(C|\underline{\mu},X,\text{DATA})$ (INVERSE WISHART)
  - SAMPLE $X^U \sim f(X^U|\underline{\mu},C,X^O,\text{DATA})$ (MULTIVARIATE NORMAL)
  - (PREDICTION) $X_{SIM} \sim f(X_{SIM}|\underline{\mu},C)$ (MULTIVARIATE NORMAL)

$y_{sim} = F^{-1}[\Phi(x_{sim})]$

$\underline{\mu}$

0.7
-1.2
1.8

C

0.9	-0.5	0.6
-0.5	1.5	0.03
0.6	0.03	0.7

X

X_1	-1.2	1.4
X_2	-0.9	0.9
X_3	-2.2	0.6

x_{sim}

0.4
-0.9
1.7

CASE STUDY #1 (COMPLETE DATA)

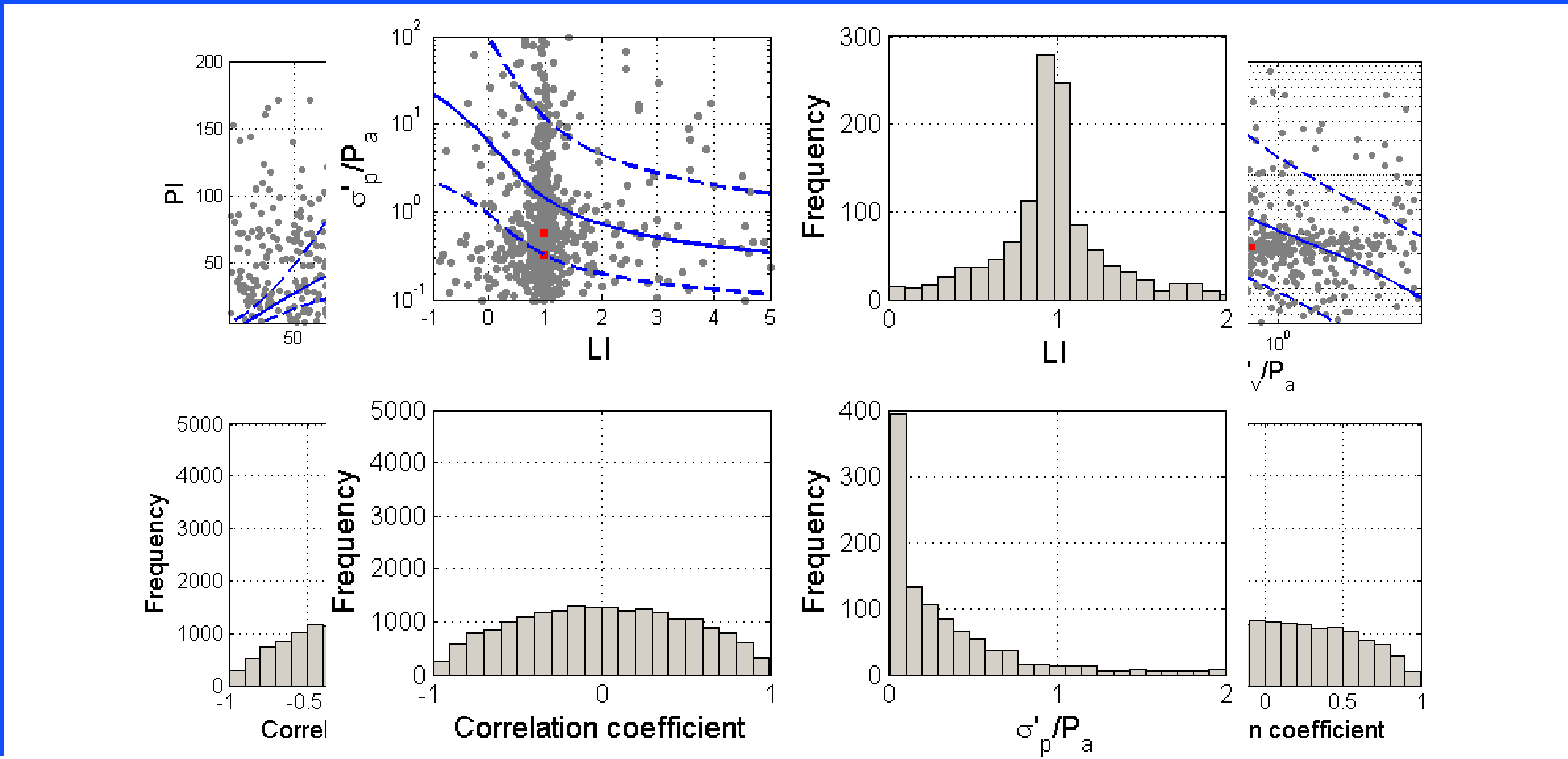
- **Lilla Mellösa (Sweden)**

Depth (m)	s_u (kN/m^2)	LL	PI	LI	σ'_v/P_a	σ'_p/P_a
2.1	8.7	129.7	82.2	1.01	0.15	0.21
3.6	8.6	124.2	80.5	0.88	0.22	0.25
4.2	9.4	119.3	78.3	0.90	0.24	0.28
5.0	10.3	110.0	71.8	0.98	0.28	0.32
5.7	10.8	105.1	69.0	0.94	0.32	0.35
6.4	11.2	100.7	69.0	0.95	0.35	0.40
7.9	13.2	84.8	57.5	0.97	0.43	0.49
8.5	14.2	82.1	55.9	1.01	0.46	0.54
9.0	17.0	76.0	51.0	0.88	0.49	0.64
9.1	15.3	78.8	53.7	0.99	0.50	0.58
9.9	17.4	73.8	51.5	0.97	0.55	0.64
10.7	18.4	71.1	47.7	1.00	0.60	0.71
12.4	18.6	73.3	50.4	1.20	0.74	0.86

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

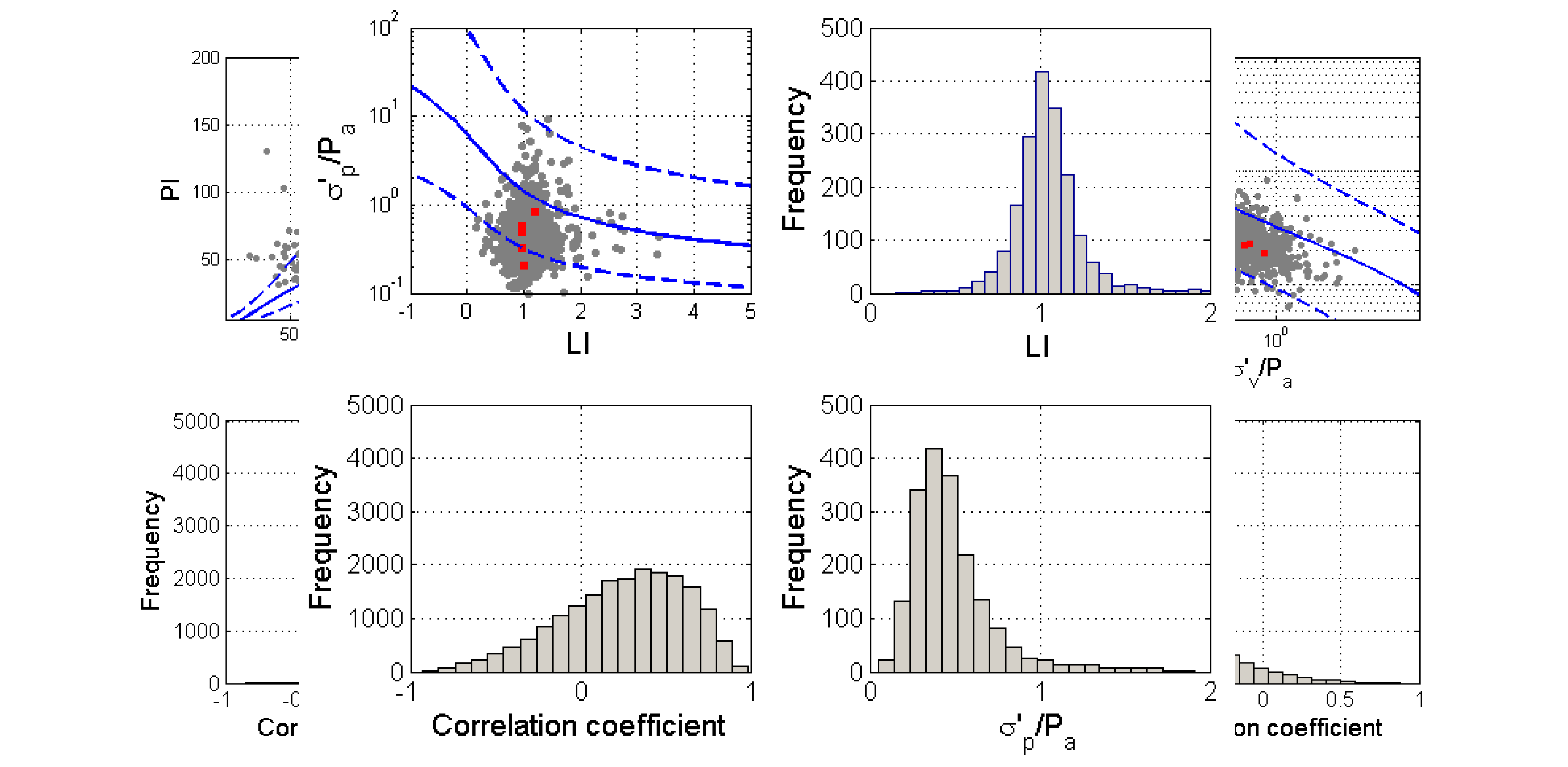
CASE STUDY #1 – 2 PTS

- Lilla Mellösa (Sweden)



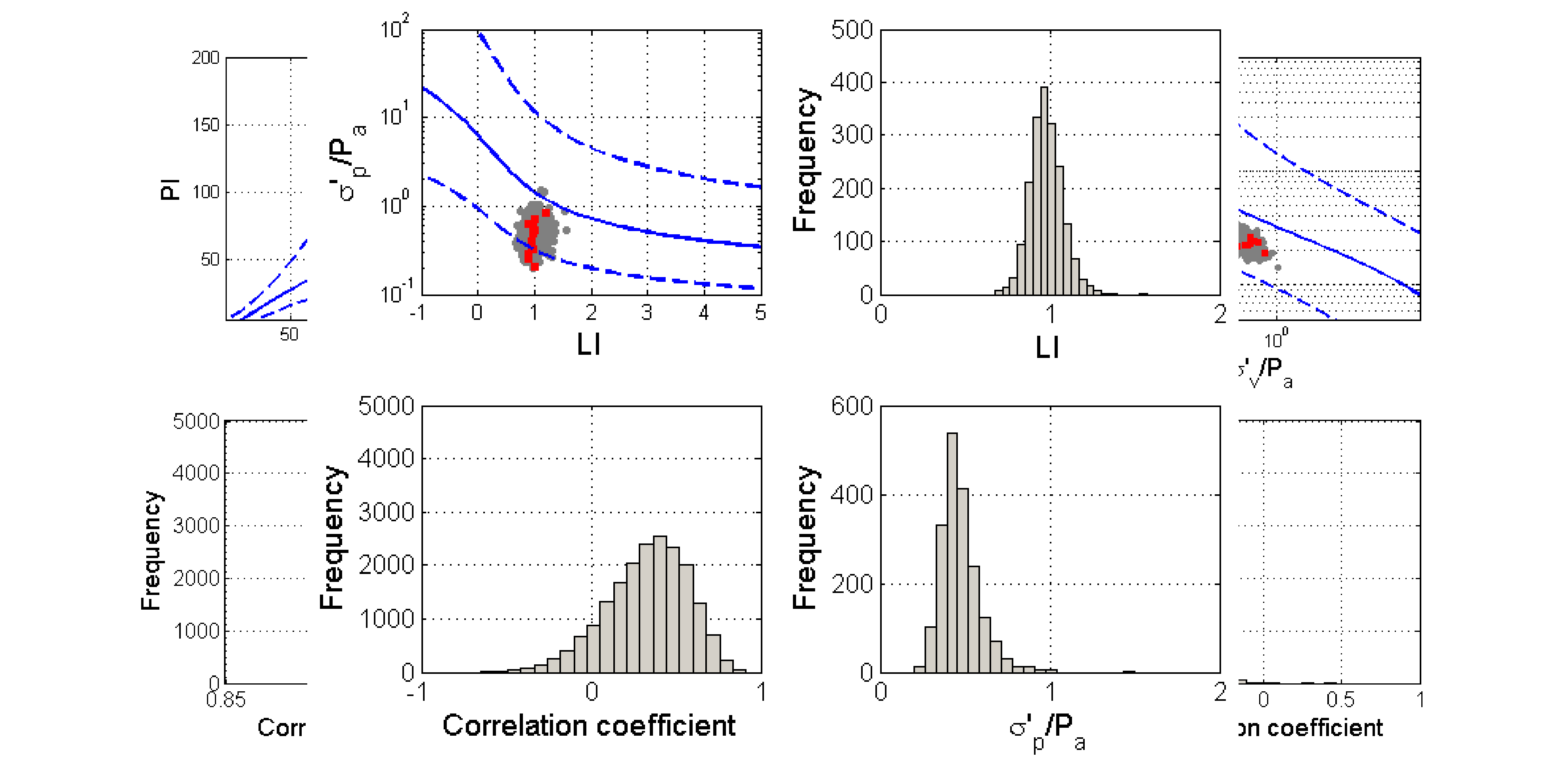
CASE STUDY #1 – 5 PTS

- Lilla Mellösa (Sweden)



CASE STUDY #1 – 13 PTS

- Lilla Mellösa (Sweden)



SIMILARITY INDEX

IDENTIFYING "SIMILAR" SITES FROM GENERIC DATABASE

Ching, J. Y. & Phoon, K. K. (2019) "Measuring Similarity Between Site-specific Data and Records in a Geotechnical Database", ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering (under review)

WHAT IS “SIMILAR”?

- MINING DATABASE RECORDS *SIMILAR* TO SITE DATA

SPARSE INCOMPLETE *SITE* DATA

Depth (m)	LL	PL	w	σ'_v (kPa)	σ'_p (kPa)	s_u (kPa)	S_t	Q_{tn}	B_q
1.0	56.2	36.2	67.0	6.08	86.11	11.85	6	28.66	0.15
1.9	50.2	32.1	65.0	12.16	60.78	10.82	14	16.42	[illegible]
3.5	59.9	29.4	57.8	22.29	48.62	10.70	15	9.6	0.28
5.2	56.8	33.9	58.4	32.42	45.59	11.67	7	7.45	0.37
7.6	66.3	34.8	62.2	47.61	54.70	11.90	14	5.7	0.46
9.5	65.1	35.5	64.2	58.75		13.51	12	6.01	0.42
10.8	74.4	38.3	67.5	65.85	85.09	15.14		5.72	0.47
13.4	71.4	35.6	66.7	82.05	106.37	19.69		6.1	0.51
16.3	72.7	38	64.4	100.29	100.29	24.07		5.82	0.55

SIMILAR?

MANY INCOMPLETE *GENERIC* DATA

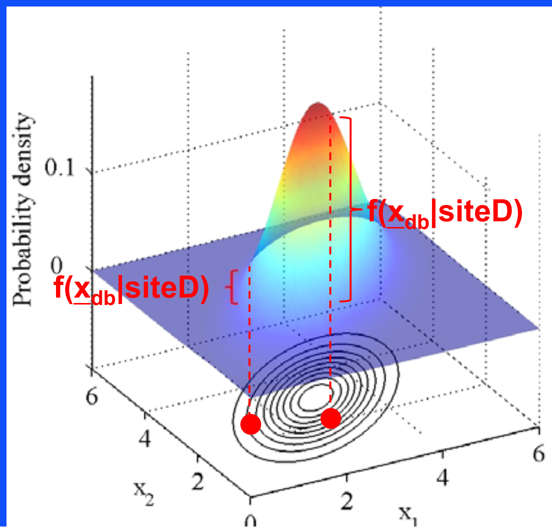
Location	PI (%)	LI	σ'_v/P_a	σ'_p/P_a	s_u/σ'_v	S_t	q_{t1}
Okishin (Japan)	28.1	1.10	0.44	0.46	0.38	12.0	
lorway)	37.9	1.01	0.55	0.88		3.0	6.13
anada)			0.31	1.40		12.0	8.86
Bothkennar (UK)	36.5		0.46	0.66	0.49		7.76
Canada	21.7	1.37	0.18				
Drammen (Norway)	60.5	0.77	0.74	1.13	0.21	3.0	5.37
Shellhaven (UK)	42.5	0.69	0.74	0.79	0.24	4.0	
Anacostia (USA)	35.0	0.80	0.73	1.54	0.26		
Grangemouth (UK)	42.5	0.72	0.69	0.95	0.44		6.54
	35.0	0.80			0.19		
Shellhaven (UK)	46.8	0.82	0.70	0.70	0.22	6.3	
Drammen (Norway)	47.2	1.00	0.59		0.21	3.0	5.94

MINING DATABASE RECORDS

- **STEP 1: CONSTRUCT SITE MODEL f(x|siteD) USING SITE DATA**
- **STEP 2: COMPUTE SIMILARITY INDEX FOR EACH $\underline{x}_{db}$ W.R.T. f($\underline{x}$|siteD)**

CLAY/10/7490

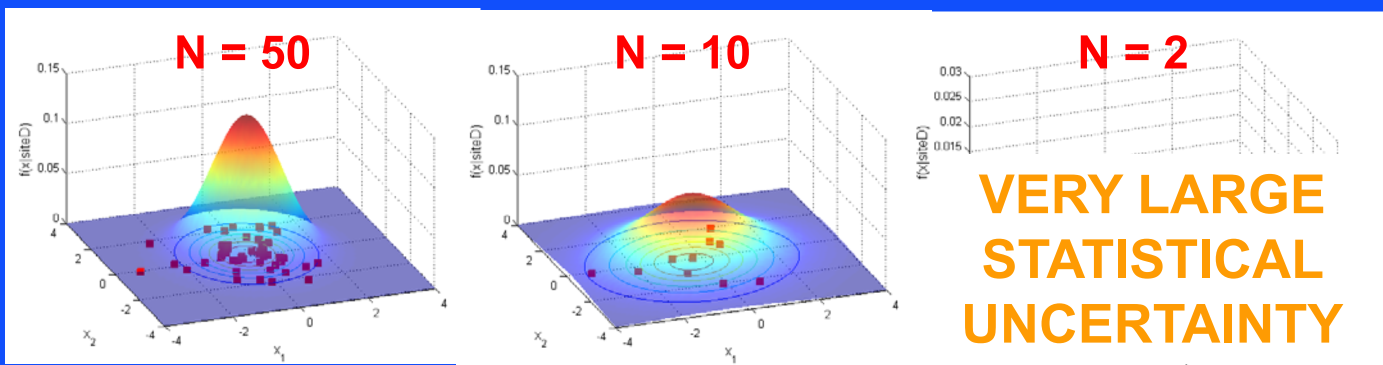
$S(x_{db})$	LL (%)	PI (%)	LI	σ'_v/P_a	σ'_p/P_a	s_u/σ'_v	OCR	Location
367.1	61.8	28.1	1.10	0.44	0.46	0.38	1.04	Okishin (Japan)
142.8	65.6	37.9	1.01	0.55	0.88		1.60	Drammen (Norway)
132.6				0.31	1.40		4.47	232nd St. (Canada)
104.9	73.6	36.5		0.46	0.66	0.49	1.43	Bothkennar (UK)
63.7	58.3	21.7	1.37	0.18				Canada
61.7	75.8	60.5	0.77	0.74	1.13	0.21	1.54	Drammen (Norway)
58.8	78.2	42.5	0.69	0.74	0.79	0.24	1.06	Shellhaven (UK)
49.6	67.0	35.0	0.80	0.73	1.54	0.26	2.10	Anacostia (USA)
48.8	76.3	42.5	0.72	0.69	0.95	0.44	1.37	Grangemouth (UK)



STEP 1: CONSTRUCT SITE MODEL f(x|siteD)

- **DEAL WITH *SPARSE* SITE DATA USING GIBBS SAMPLER**

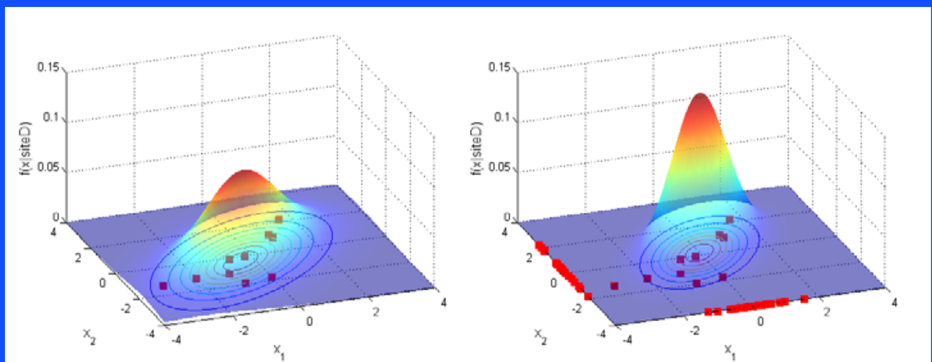
$$f(\mathbf{X}|\mathrm{siteD}) \approx \frac{1}{T}\sum_{t=1}^{T}(2\pi)^{-\frac{n}{2}}\left|\mathbf{C}^{(t)}\right|^{-\frac{1}{2}}\exp\left[-\frac{1}{2}\left(\mathbf{X}-\mu^{(t)}\right)^{T}{\mathbf{C}^{(t)}}^{-1}\left(\mathbf{X}-\mu^{(t)}\right)\right]$$



STEP 1: CONSTRUCT SITE MODEL f(x̲|siteD)

- CAN DEAL WITH *INCOMPLETE* SITE DATA

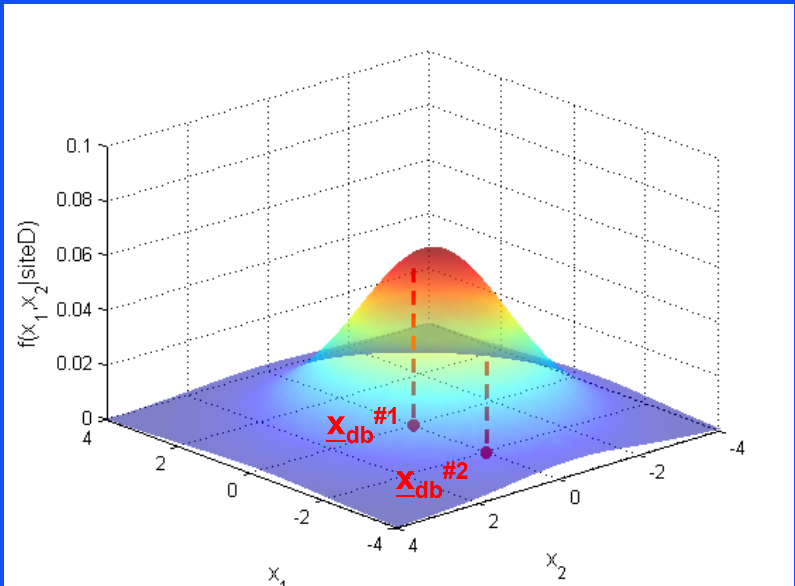
10 COMPLETE PTS | **10 COMPLETE + 40 INCOMPLETE PTS**



	x_1	x_2
#1	-0.20	-0.03
#2	-2.01	**?**
#3	-0.82	-1.86
#4	**?**	0.98
#5	**?**	2.15
…		
#48	-3.03	**?**
#49	0.96	**?**
#50	-0.67	-0.11
#10	1.01	0.76

STEP 2: SIMILARITY INDEX

- *COMPLETE* $\underline{x}_{db}^{\#1}$ and $\underline{x}_{db}^{\#2}$
- $f(\underline{x}_{db}^{\#1}|siteD)$ & $f(\underline{x}_{db}^{\#2}|siteD)$ can be compared

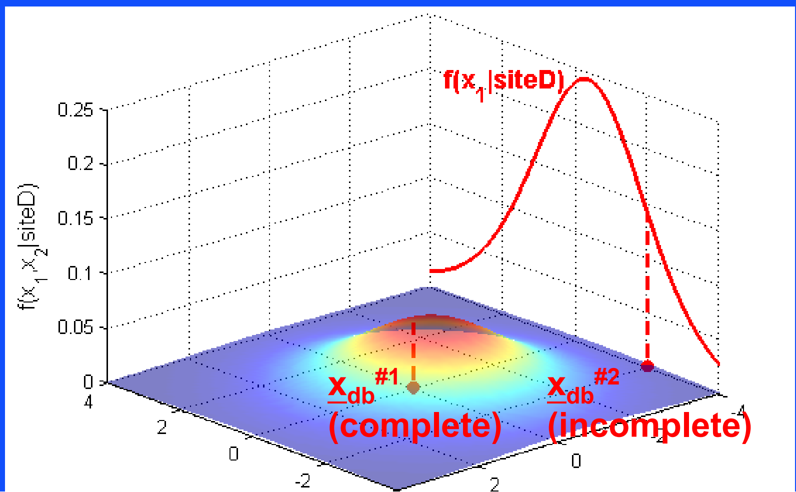


	x_1	x_2
#1	-0.20	-0.03
#2	-2.01	-0.06

SIMILARITY INDEX

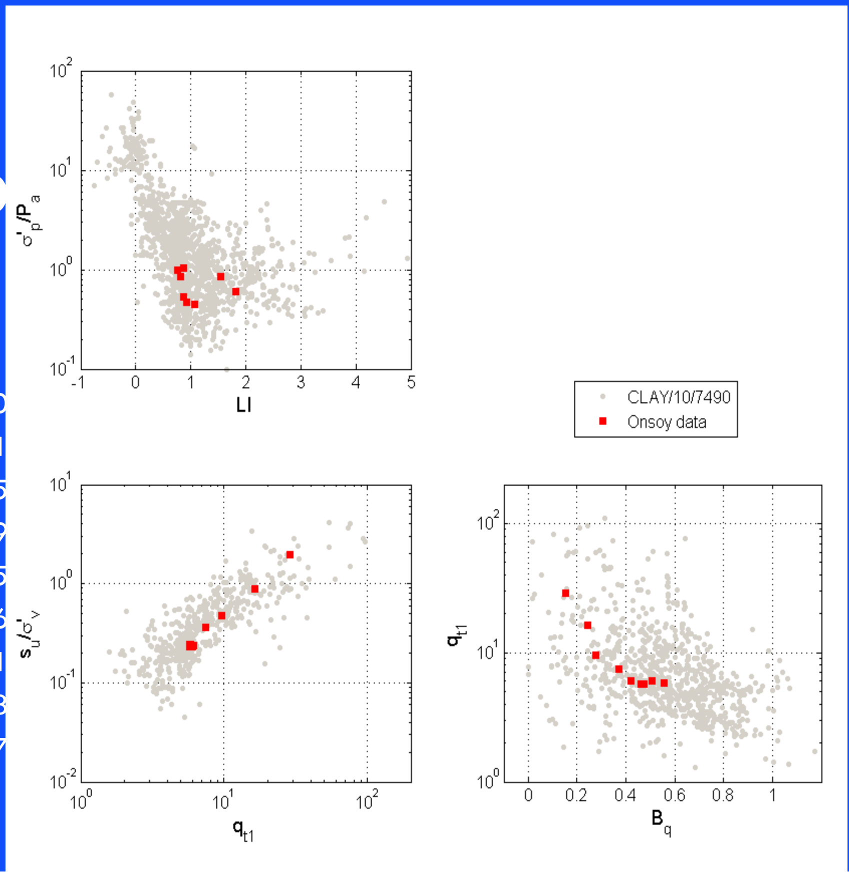
- *INCOMPLETE* $\underline{x}_{db}^{\#1}$ and $\underline{x}_{db}^{\#2}$
- $f(\underline{x}_{db}^{\#1}|siteD) = f(x_1^{\#1}, x_2^{\#1}|siteD)$
- $f(\underline{x}_{db}^{\#2}|siteD) = f(x_1^{\#2}|siteD)$

CANNOT COMPARE



	x_1	x_2
#1	-0.20	-0.03
#2	-2.01	?

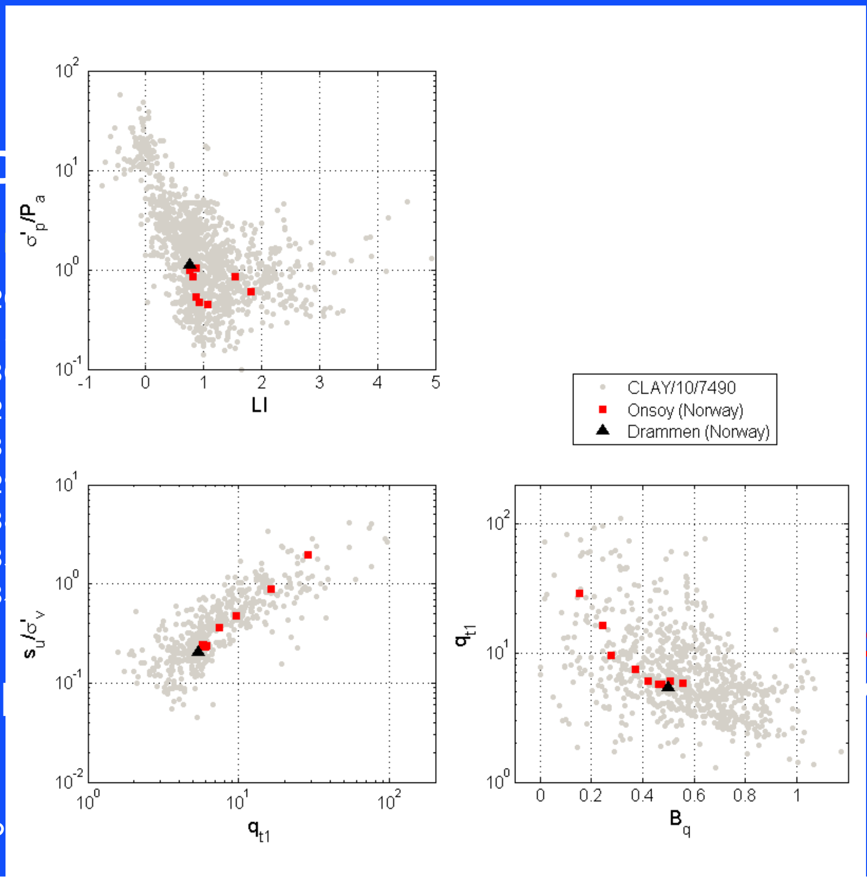
• **SITE D**



Depth (m)	LL	PI	q_{t1}	q_{tu}	OCR
1.0	56.2	20.0	28.66	25.60	13.54
1.9	50.2	18.1	16.42	13.61	5.02
3.5	59.9	30.5	9.60	8.08	2.15
5.2	56.8	22.9	7.45	5.76	1.39
7.6	66.3	31.5	5.70	4.10	1.14
9.5	65.1	29.6	6.01	4.52	
10.8	74.4	36.1	5.72	4.05	1.29
13.4	71.4	35.8	6.10	4.05	1.29
16.3	72.7	34.7	5.82	3.61	1.00

• **SITE D**

Depth (m)	LL	q_{t1}	q_{tu}	OCR
1.0	56.2	28.66	25.60	13.54
1.9	50.2	16.42	13.61	5.02
3.5	59.9	9.60	8.08	2.15
5.2	56.8	7.45	5.76	1.39
7.6	66.3	5.70	4.10	1.14
9.5	65.1	6.01	4.52	
10.8	74.4	5.72	4.05	1.29
13.4	71.4	6.10	4.05	1.29
16.3	72.7	5.82	3.61	1.00



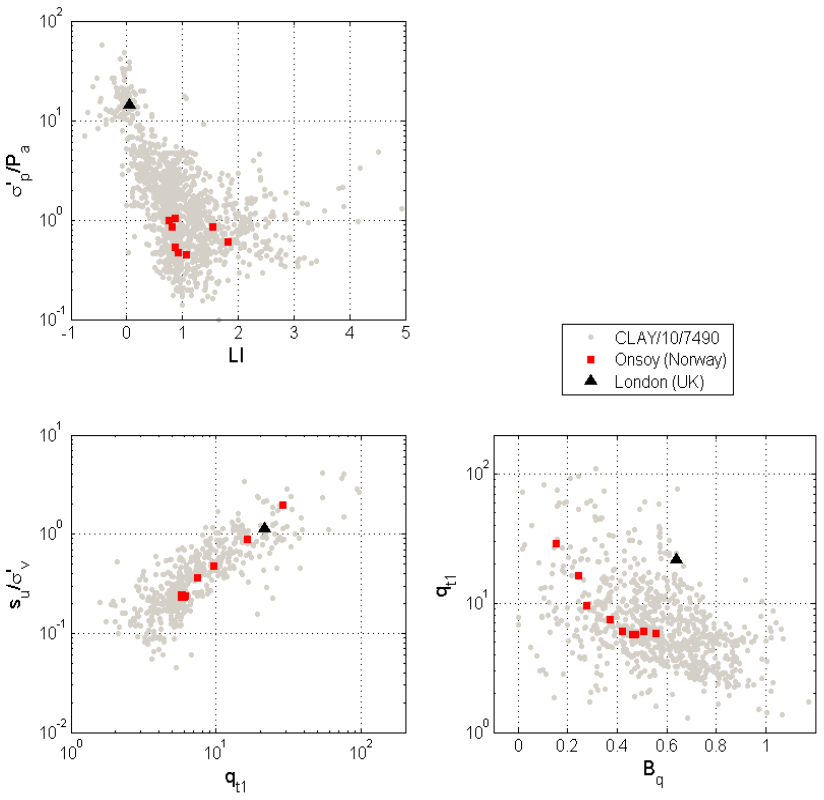
S

• **DATA**)

Depth (m)	LL	q_{t1}	q_{tu}	OCR
8.5	75.8	5.37	3.67	1.54

- **SITE DA**

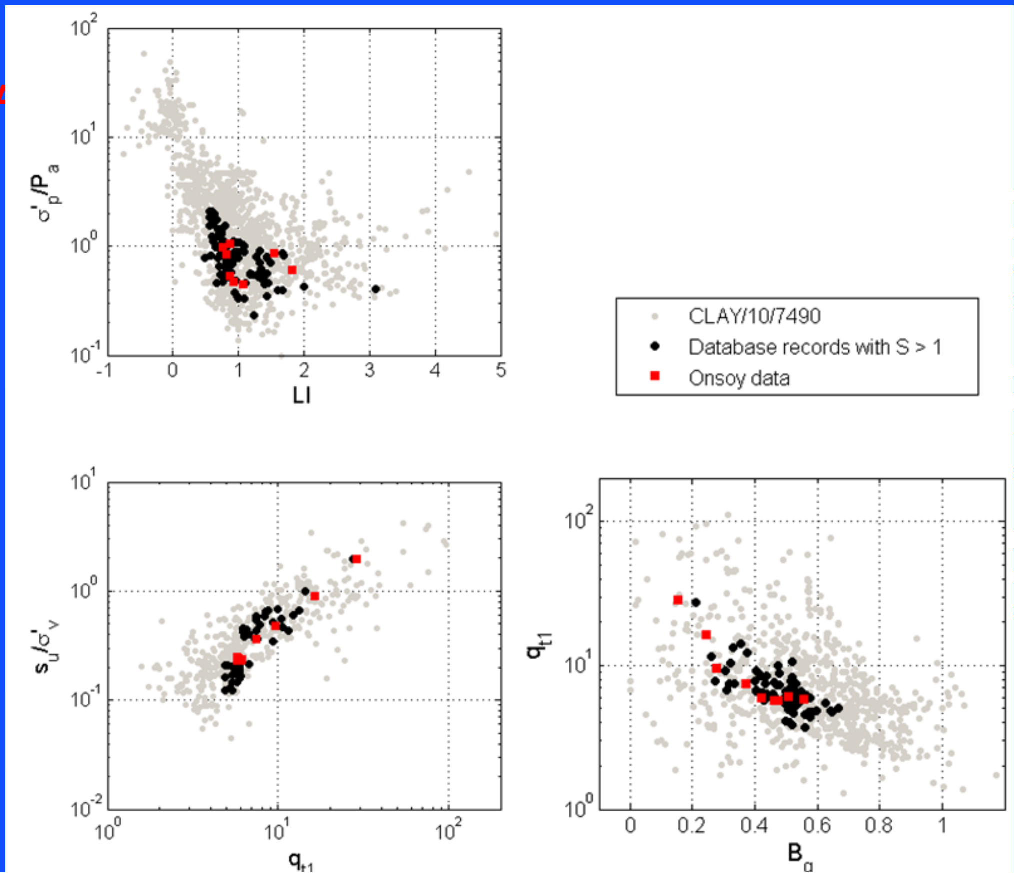
Depth (m)	LL	PI	q_{t1}	q_{tu}	OCR
1.0	56.2	20.0	28.66	25.60	13.54
1.9	50.2	18.1	6.42	13.61	5.02
3.5	59.9	30.5	9.60	8.08	2.15
5.2	56.8	22.9	7.45	5.76	1.39
7.6	66.3	31.5	5.70	4.10	1.14
9.5	65.1	29.6	6.01	4.52	
10.8	74.4	36.1	5.72	4.05	1.29
13.4	71.4	35.8	6.10	4.05	1.29
16.3	72.7	34.7	5.82	3.61	1.00



- **DATABA**

Depth (m)	LL	PI	q_{t1}	q_{tu}	OCR
9.4	70.8	45.9	1.61	8.51	11

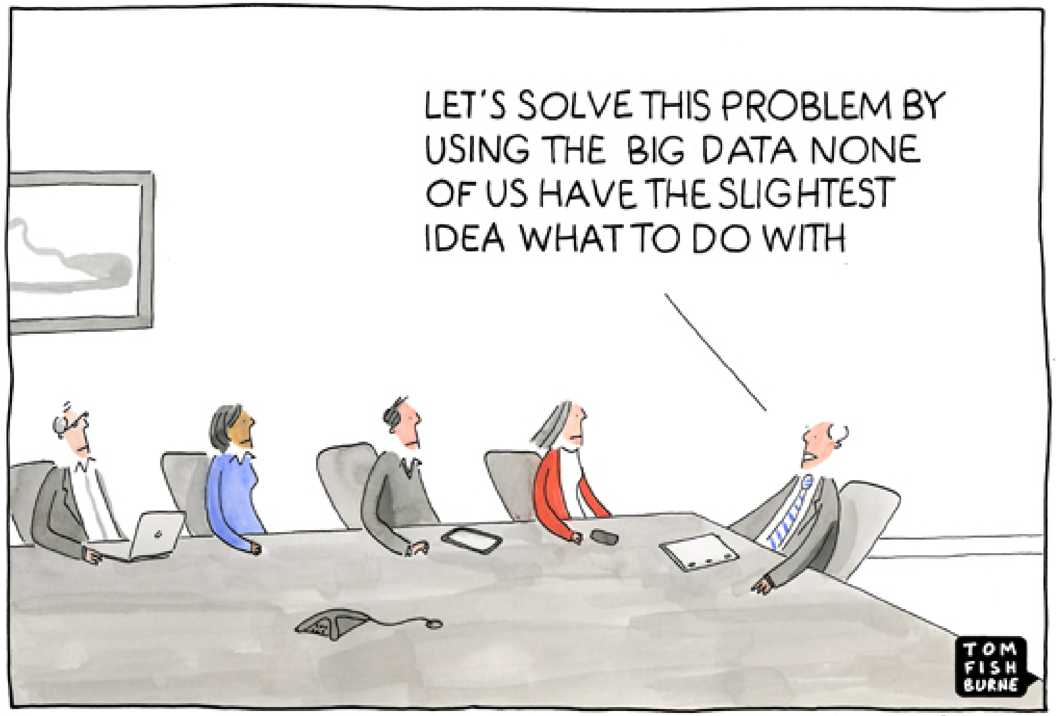
S > 1 → SIMILA



Rank	$S(x_{db})$	Location
1	367.1	kishin (Japan)
2	142.8	mmen (Norway)
3	132.6	nd St. (Canada)
4	104.9	thkennar (UK)
5	63.7	Canada
6	61.7	mmen (Norway)
7	58.8	hellhaven (UK)
8	49.6	acostia (USA)
9	48.8	angemouth (UK)
10	48.7	
11	47.5	hellhaven (UK)
12	40.7	mmen (Norway)
13	40.4	mma (Sweden)
14	39.1	Canada
15	37.0	USA
16	35.9	Belfast (UK)
17	34.8	Singapore
18	34.3	USA
19	32.6	Francisco (USA)
20	31.4	Canada

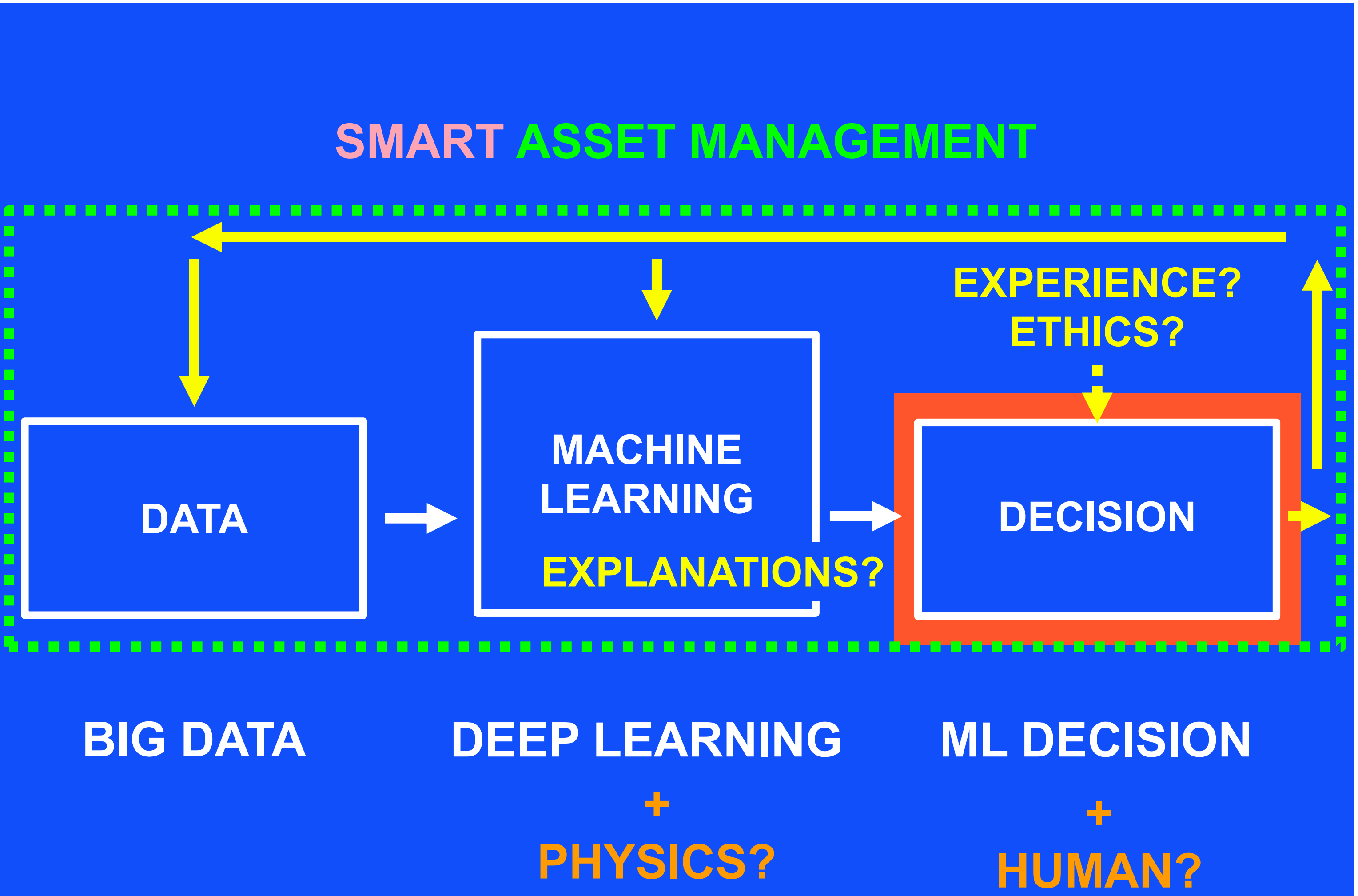
CHOTTO MATTE

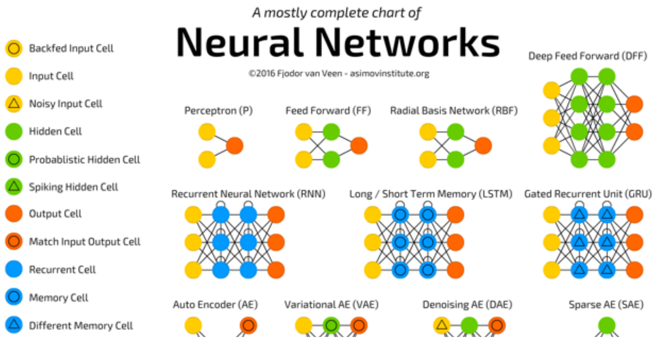
Kudasai


LET'S SOLVE THIS PROBLEM BY USING THE BIG DATA NONE OF US HAVE THE SLIGHTEST IDEA WHAT TO DO WITH
TOM FISH BURNE

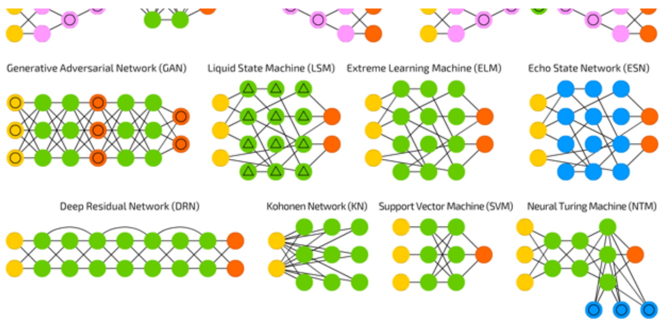
DATA-DRIVEN MODELS

– MACHINE LEARNING


SMART ASSET MANAGEMENT
EXPERIENCE?
ETHICS?
MACHINE LEARNING
DATA
DECISION
EXPLANATIONS?
BIG DATA
DEEP LEARNING
+
PHYSICS?
ML DECISION
+
HUMAN?



1990: SHALLOW NEURAL NETS
2006: DEEP LEARNING

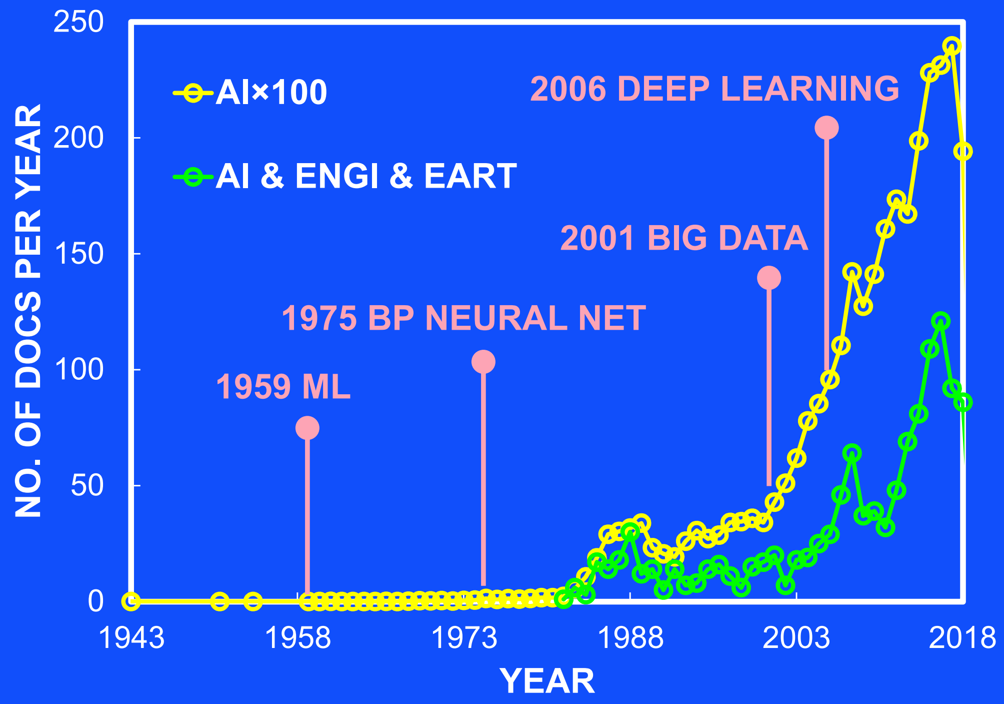


FOOD FOR THOUGHT

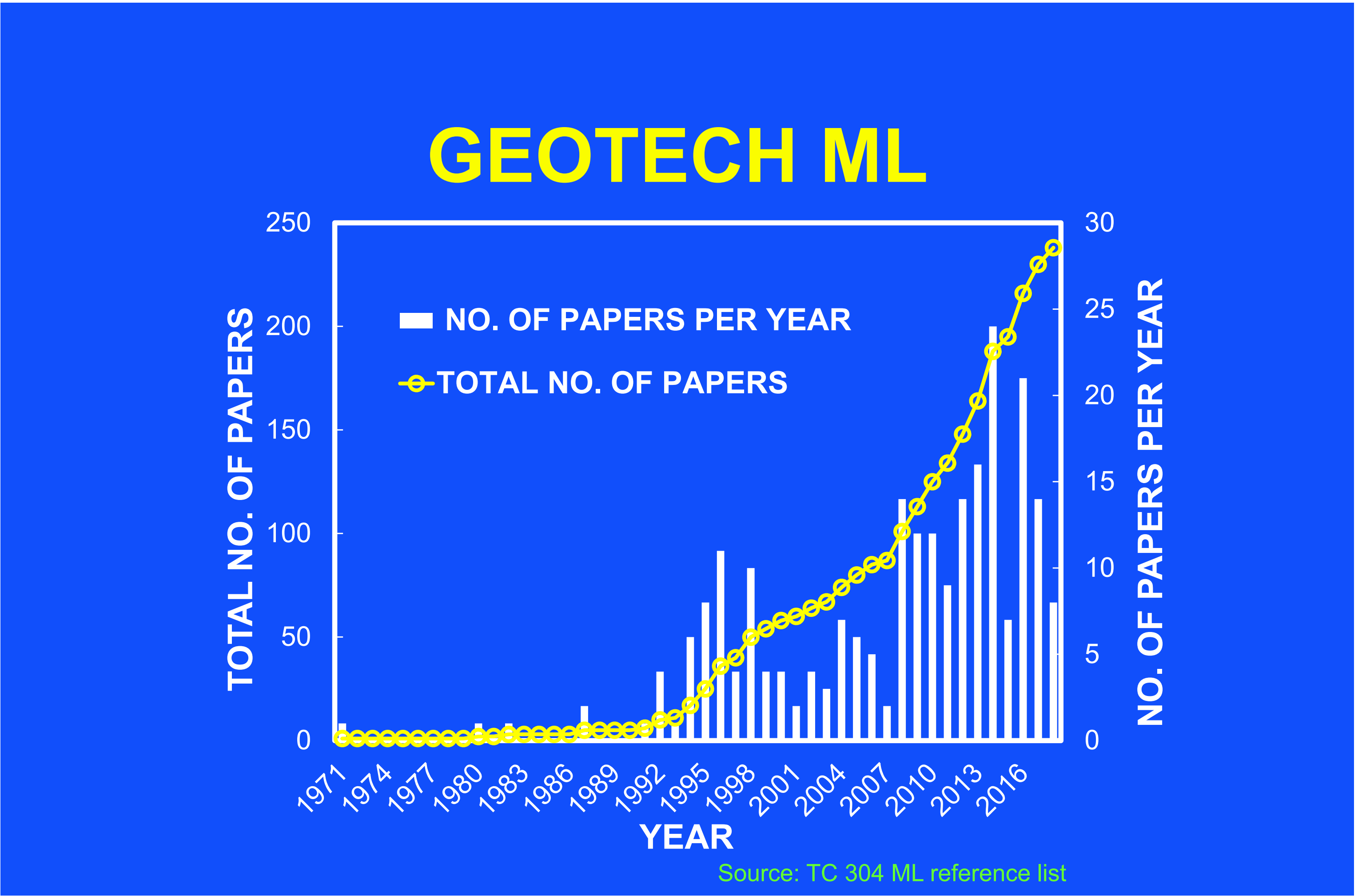
1. ROBUSTNESS UNDER A WIDE RANGE OF CONDITIONS – OVERFITTING PROBLEM
2. EXTRAPOLATION BEYOND CALIBRATION & VALIDATION
3. “BLACK BOX” – DOES NOT EXPLAIN PHYSICS (EXPLAINABLE AI OR XAI)
4. UNCERTAINTIES IN PREDICTIONS

Jaksa, M.B., Maier, H.R. & Shahin, M.A. (2008). “Future challenges for artificial neural network modelling in geotechnical engineering”, 12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG), 1-6 October 2008, Goa, India, 1710-1719.

AI RESEARCH



Source: Scopus, 15 Nov 2018


GEOTECH ML
NO. OF PAPERS PER YEAR
TOTAL NO. OF PAPERS
TOTAL NO. OF PAPERS
NO. OF PAPERS PER YEAR
YEAR
0
50
100
150
200
250
0
5
10
15
20
25
30
1971
1974
1977
1980
1983
1986
1989
1992
1995
1998
2001
2004
2007
2010
2013
2016
Source: TC 304 ML reference list

	SUPERVISED LEARNING		UNSUPERVISED LEARNING			BAYESIAN LARNING
	ANN	SVM	CL	DR	OD	
SITE CHARACTERIZATION	○	○	○		○	○
GEOMATERIAL BEHAVIOR MODELLING	○	○				
FOUNDATION	○	○				
RETAINING STRUCTURE	○	○		○		
SLOPE	○	○	○	○		○
TUNNELS AND UNDERGROUND OPENINGS	○	○		○		○
LIQUEFACTION	○	○	○			○
OTHERS	○		○	○	○	

ANN = ARTIFICIAL NEURAL NETWORK SVM = SUPPORT VECTOR MACHINE

CL = CLUSTERING DR = DIMENSIONALITY REDUCTION OD = OUTLIER DETECTION

TC304 ML REFERENCE LIST

- **SUPERVISED LEARNING METHODS WERE USED MOST IN GEOTECH ENG**
- **BAYESIAN LEARNING WAS USED FREQUENTLY (ROUGHLY 1/3)**
- **SEMI-SUPERVISED AND REINFORCEMENT LEARNING WERE RARELY USED**
- **MOST OF ANN APPLICATIONS USED “SHALLOW” NN WITH ONE HIDDEN LAYER**
- ***DEEP LEARNING WAS NOT USED***

WE DO NOT KNOW HOW WE MAKE A DECISION

H. Q. GOLDER (1966)