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2019 AUSTRALIAN GEOMECHANICS SOCIETY VICTORIAN SYMPOSIUM

Geotechnical characterisation – managing design and construction risk

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Rydges Hotel, 186 Exhibition Street, Melbourne

AUSTRALIAN GEOMECHANICS SOCIETY
VICTORIA CHAPTER

reducing geotechnical uncertainty

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PREFACE

The Victorian chapter of the Australian Geomechanics Society invited academics and practitioners in the field of geotechnical and ground engineering to attend the 2019 Australian Geomechanics Society Victorian Symposium held on 30 October 2019.

In recent years Victoria has seen significant growth in the construction industry. Investment in both public infrastructure and commercial real estate is growing, and as our cities and infrastructure grow, so too does the need to develop parcels of land with challenging ground conditions. Economical and safe geotechnical design requires efficient and well thought through ground investigation and characterisation to identify and manage ground risks and opportunities.

The 2019 Australian Geomechanics Society Victorian Symposium presents an overview of current state of-the-art practices, innovation, new research results and case studies relating to geotechnical characterisation with an emphasis on its implications for addressing and managing design and construction risk. The 2019 Symposium brought together professional engineers, researchers, specialist contractors, regulators, educators and students to share and discuss their experiences on the topic of ground characterisation.

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AUSTRALIAN GEOMECHANICS SOCIETY

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Keynote Address

Application of statistical techniques for geotechnical site investigation and design

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ABSTRACT

Uncertainty is a universal and important aspect of geotechnical engineering and it is comprised of several different aspects. The most significant is likely that derived from spatial variability, where the properties vary from one location to another as a result of the processes that form the ground. Secondly, statistical uncertainty is a critical element of geotechnical engineering. Other important sources of uncertainty are those associated with the testing process itself, the transformation of the test results to design values, and uncertainties derived from human error. The paper discusses each of these uncertainties in some detail and provides examples and guidance on how to quantify and account for these in the geotechnical design process. The paper also presents two examples that demonstrate the power of statistical simulation in geotechnical engineering practice.

Keywords: site investigation, uncertainty, spatial variability, statistical methods, errors

1 INTRODUCTION

At the heart of geotechnical engineering is uncertainty and it is manifested in several ways. Probably the most significant aspect of uncertainty is that derived from natural variability, or spatial variability, where, because the ground is formed by natural processes, the properties of soil and rock vary from one location to another. Secondly, statistical uncertainty is a critical element of geotechnical engineering, because one is only ever able to test, and hence characterise, a small fraction of the ground that is involved in any particular infrastructure project. Other important aspects of uncertainty are those associated with the testing process itself, the transformation of the test results to design values, and uncertainties derived from human error.

During the 1980s and 1990s, the late Fred Kulhawy and his co-workers at Cornell University, USA, undertook extensive work in the area of reliability-based design of transmission towers for the US Electric Power Research Institute. This research endeavour provided, among several other important aspects of risk and reliability, an extremely valuable contribution to the understanding and modelling of the uncertainty associated with the estimation of geotechnical engineering properties derived from site investigations. This is summarised diagrammatically in Figure 1.

As can be seen, the various uncertainties described above combine to affect the reliability of the estimated soil property. The individual uncertainties shown in Figure 1, along with human error, are examined in this paper, and examples and guidance are provided on how to quantify and account for these in the geotechnical design process. It should be noted, in the treatment that follows, the terms 'uncertainty' and 'errors' are used interchangeably. Finally, two examples are presented which highlight the potential of spatial simulation in geotechnical engineering practice.

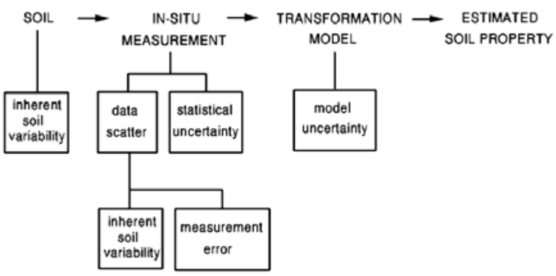

Figure 1. Uncertainty in soil property estimation (Source: Kulhawy 1992)

2 SPATIAL VARIABILITY

By the very nature of the manner by which soils are formed and evolve, their properties vary from one location to another, sometimes markedly, and this is generally known as *spatial variability*. Processes that affect soil formation, and hence spatial variability, include sedimentation; parent material; weathering and erosion; climate; topography; organisms; structural defects, such as faults, folds, joints, fractures, slickensides and fissures; stratigraphy; stress history; suction; and time. Figure 2 shows a typical example, from the South Expressway in Adelaide, of spatial variability due to stratigraphy; that is the lateral variation in the interface between subsequent soil layers. It is not uncommon in geotechnical engineering for such interfaces to be complex, as shown in Figure 2 by the irregular and somewhat haphazard shape of the interface between the upper dark layer and the lower light horizon.

Figure 2. Example of stratigraphic variability

2.1 Characterising Spatial Variability

Given the complex and seemingly random nature of this variability, the spatial characterisation of soil properties has, as a consequence, naturally gravitated towards stochastic methods. At present, two different, yet complementary, mathematical techniques – namely random field theory and geostatistics – are adopted to characterise the spatial variability of geotechnical properties. These are described below. Alternative methods have also been used, such as regression analysis and fractals, but these are not as popular as the two methods mentioned above, for very different reasons. Firstly, regression analysis, which is an aspect of classical statistics, is too simplistic as it treats properties at different spatial locations as being independent. It is well understood in geotechnical engineering that, for example, two soil samples obtained relatively close to one another (say within 0.5 m or so) will exhibit very similar properties, whereas those separated by greater distances (say 100 m or so) are likely to be less similar. As the separation distance increases, so too does the extent of dissimilarity. As a consequence, regression analysis is not particularly helpful in the context of characterising spatial variability. Secondly, fractal theory, which recognises the self-similar nature of spatial variability at different scales of observation, provides little additional, if any, benefit over the methods of random field theory and geostatistics mentioned above. Interested readers will find the following references useful, in respect to: (1) limitations of regression analysis: Mann (1987); and (2) the application of fractal theory to geotechnical engineering: Fenton (1999); Jaksa and Fenton (2002).

2.1.1 Random field theory

Random field theory (RFT), as it is known in geotechnical engineering, is the *n*-dimensional extension of classical time series analysis. A time series is a chronological sequence of observations of a particular variable usually, but not necessarily, at constant time intervals, and which may be thought of as a one-dimensional random field. When applied to the spatial variability of geotechnical materials, time is replaced by the distance domain and the data set is referred to as a random field. A geotechnical example of a 1D random field is the measurement of cone tip resistance, q_c, with depth as obtained from the cone penetration test (CPT). Unlike classical statistics, RFT incorporates the observed behaviour that values at adjacent locations are more related, that is *autocorrelated*, than those at greater distances.

The application of both RFT, as well as geostatistics, is greatly simplified if the data are stationary. This concept is discussed in the next section.

2.1.1.1 Stationarity and de-trending

Data are stationary if the probabilistic laws which govern the series are independent of the location of the samples. Data are said to be stationary, in a strict sense, if (Brockwell and Davis, 1987):

- the mean is constant with distance, i.e. no trend exists in the data;
- the variance is constant with distance;
- there are no seasonal variations; and
- there are no irregular fluctuations.

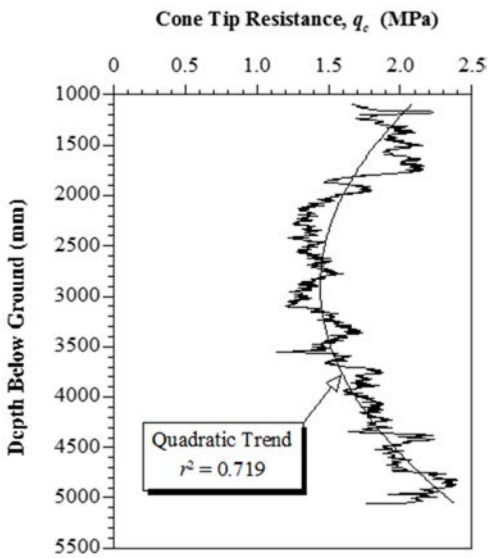

Figure 3. Example of non-stationary data (Source: Jaksa 2006)

Figure 3 presents an example of a non-stationary data set, which involves CPT measurements of q_c with depth below the ground surface. As can be seen by the significant quadratic trend, both the mean and variance are functions of depth.

Prior to performing RFT and geostatistical analyses, it is preferable first to transform the data so that they are stationary. This is usually achieved by performing ordinary least squares regression, obtaining the curve of best fit (usually linear or quadratic), and subtracting this from the original data. Figure 4 shows what is referred to as the *residual* data, i.e. those obtained by subtracting the quadratic curve from the CPT data, both of which were shown in Fig. 3. Stationarity is assessed using a variety of tests and these are discussed in detail by Jaksa (2006).

2.1.1.1 Scale of fluctuation

In his seminal paper, Vanmarcke (1977) stated that, in order to characterise the spatial variability of geotechnical materials, at least 3 parameters are

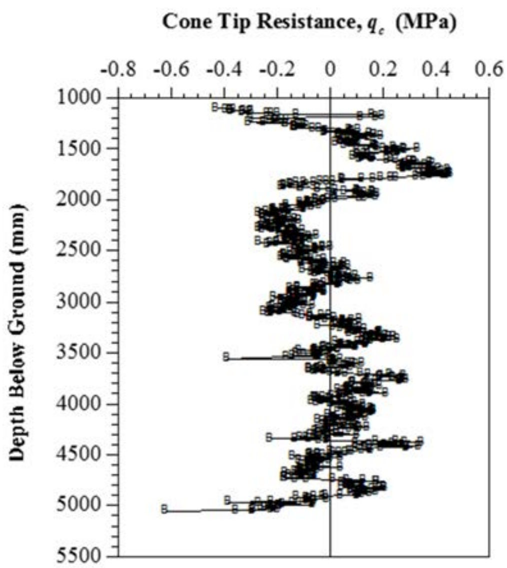

Figure 4. Example of detrended, stationary data (Source: Jaksa 2006)

required: (1) the mean; (2) the variance (or standard deviation or coefficient of variation, $\mathrm{COV} = \sigma/\mu$); and (3) the scale of fluctuation, θ. The scale of fluctuation expresses the correlation of properties with distance. A large value of θ, for a particular soil property, implies the property fluctuates with distance slowly about the mean, suggesting a somewhat continuous deposit, whereas a small θ implies the property fluctuates rapidly about the mean, suggesting a more randomly varying material. For example, a fractal process has an infinite scale of fluctuation (Fenton and Griffiths, 2008). The scale of fluctuation is usually evaluated by means of the *autocorrelation function*, which is described below.

2.1.1.2 Autocorrelation function

The autocorrelation function (ACF) is determined from the following relationship (Jaksa, 2006):

$$r_k = \frac{\sum_{i=1}^{n-k}(X_i - \bar{X})(X_{i+k} - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{1}$$

where: r_k is the autocorrelation coefficient at lag (or spacing increment) k;
X_i is the value of the property at location i;
$\bar{X}$ is the average of the properties $X_1 \dots X_n$;
n is the total number of data points.

The ACF is the plot of r_k against k, usually for values of $k = 1$ to $n/4$. The ACF for the data given in Fig. 4 is shown in Figure 5.

Jaksa et al. (1999) proposed a relatively straightforward method for determining the scale of fluctuation, θ, from the ACF. The method involves evaluating Bartlett's limits, using the following relationship:

$$|r_k| = \pm\frac{1.96}{\sqrt{n}} \tag{2}$$

Figure 6 shows the Bartlett's limits for the data given in Fig. 4. The scale of fluctuation is determined by the first intersection of Bartlett's limits with the ACF and determining the associated *x*-coordinate, in this case 240 mm.

2.1.2 Geostatistics

As mentioned above, geostatistics is a spatial modelling approach, similar in nature to that of RFT, although developed independently as a result of the work of Krige (1951) and Matheron (1965), to facilitate the estimation of changes in ore grade in a mining context. Since then, geostatistics has been successfully applied to the spatial modelling of many natural phenomena (Journel and Huijbregts, 1978). Geostatistics provides a sophisticated framework for the estimation of properties at unsampled locations, as well as simulation.

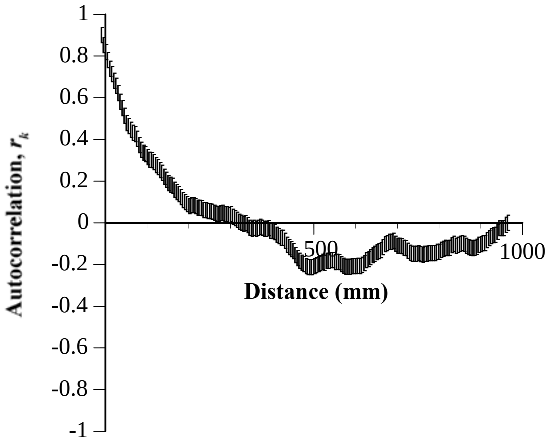

Figure 5. ACF of data in Fig. 4 (Source: Jaksa 2006)

As the ACF is the fundamental statistical measure of RFT, the *semivariogram* (sometimes simply referred to as the variogram) is the equivalent function in geostatistics.

2.1.2.1 Semivariogram

The semivariogram is a measure of the degree of spatial dependence between samples along a specific orientation and represents the degree of continuity of the property in question. The *experimental semivariogram*, γ_h^*, i.e. the semivariogram derived from the spatial data, is defined as:

$$\gamma_h^* = \frac{1}{2N}\sum_{i=1}^{N}(X_{i+h} - X_i)^2 \tag{3}$$

where: N is the number of data pairs separated by displacement, h.

As it is based on the spatial data, the experimental semivariogram is known only at discrete points. In order to undertake estimation, known as *kriging*, and simulation, a continuous form of the semivariogram is

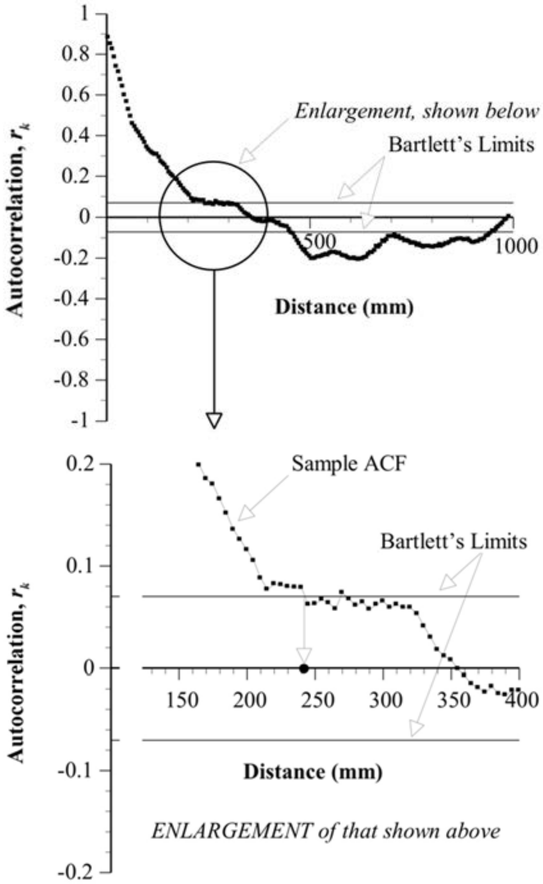

Figure 6. Determination of scale of fluctuation using Bartlett's limits. (Source: Jaksa 2006)

required. Hence, it is necessary to fit a theoretical model to the experimental semivariogram. Whilst several models are available (see Journel and Huijbregts, 1978), the spherical model is the most ubiquitous. It is expressed by the following function and is shown graphically in Figure 7.

$$\begin{aligned} \gamma_h &= C\left(\frac{3h}{2a} - \frac{h^3}{2a^3}\right) + C_0 \quad \text{when } h \le a \\ \gamma_h &= C + C_0 \qquad\qquad\qquad\quad \text{when } h \ge a \end{aligned} \tag{4}$$

where: C_0 is the *nugget*;
$C + C_0$ is the *sill*; and
a is the *range of influence.*

The nugget, C_0, arises from the spatial variable in question being so erratic over a short distance that the semivariogram goes from zero to the level of the nugget in a distance less than the sampling interval. The nugget is the result of three separate phenomena: microstructures within the geological material, sampling or statistical errors, and measurement errors (Journel and Huijbregts, 1978).

The sill is half the maximum, on average, of the squared difference between the data pairs. The range of influence, a, is the distance at which samples become independent of one another. Data pairs separated by distances up to a are correlated, but not beyond. Hence, a is essentially a correlation distance, which is similar in definition to the scale of fluctuation, θ, discussed above.

The semivariogram of the data shown previously in Figure 4, is calculated using Equation (3) and is presented in Figure 8, along with the best fit spherical model.

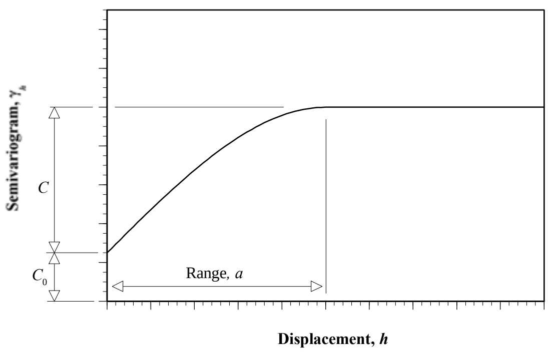

Figure 7. Spherical model. (Source: Jaksa 2006)

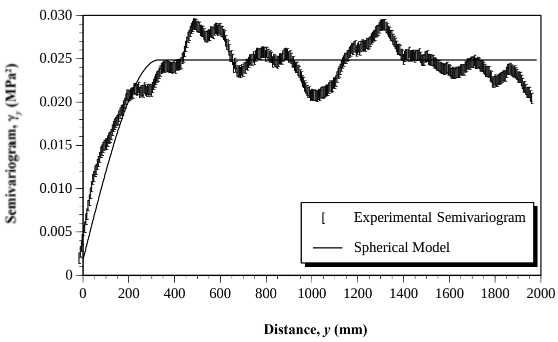

Figure 8. Semivariogram of data in Fig. 4 with superimposed spherical model (Source: Jaksa 2006)

The three parameters that define the spherical model in Fig. 8 are: a = 330 mm; C = 0.0231 MPa^2; and C_0 = 0.0018 MPa^2. The value of a is similar to that of θ, as one would expect, however, they are not identical. By examining many pairs of a and θ, Jaksa (1995), expressed the relationship between these two parameters empirically as:

$$\theta = 2.023a^{0.765} \tag{5}$$

Examples of evaluating a and θ from in situ test measurements are given by Jaksa (2006) for the CPT, and Jaksa et al. (2004) for the dilatometer test (DMT). Due to the processes that form the ground, it is common for the scale of fluctuation to be anisotropic and for it to be greater in the horizontal direction, sometimes by an order of magnitude, than that in the vertical direction. Phoon et al. (1995) provides guidance on the scale of fluctuation associated with several different soils.

Spatial characterisation is important, as it quantifies the spatial variation of the ground. Such information provides essential data for informing geotechnical models that are critical for design. Spatial characterisation also facilitates simulation of the ground, which enables risk and reliability analyses to be performed. An example of such an analysis is provided at the end of the paper.

3 STATISTICAL UNCERTAINTY

Statistical uncertainty arises from the fact that site investigations almost exclusively sample and test a very limited volume of the ground and, hence, errors occur from deriving properties of the site based on these limited observations. It is beyond the scope of this paper to treat this aspect in detail. However, the interested reader is referred to Chapter 2 of the now dated, but nonetheless valuable, textbook entitled *Geotechnical Engineering* by Lee et al. (1982), which provides an excellent, accessible and practical treatise on soil variability and the use of statistics in geotechnical engineering. To illustrate the relevance of statistical uncertainty to geotechnical engineering practice, a relatively simple example is provided below.

Example:
Four undrained triaxial tests were performed on samples of a stiff clay. The corresponding measurements of undrained shear strength, s_u, were: 102, 98, 95 and 109 kPa. Determine the minimum number of samples of clay that should be taken so that the average in situ undrained shear strength value will be within 5% of the mean test result, with a 95% degree of confidence.

Solution:
In order to solve such problems, Student's *t* distribution is generally used [see Lee et al. (1983), p69, or any basic statistics textbook], particularly when the number of samples, *n*, is less than 30, which is often the case in geotechnical engineering. Hence, for the four samples taken and tested above, using the basic statistical relationships [e.g. Lee et al. (1983), p60] the mean, μ = 101 kPa and the standard deviation, σ = 6.06 kPa.

For Student's *t* distribution, the number of degrees of freedom, ν = *n* – 1 = 3. Since *p* = 95%, then *t* = 2.35 (from the *t*-distribution table).

Using the central limit theorem, for a specified level of confidence, μ must lie within the range of values $\mu \pm t(\sigma/\sqrt{n})$. Hence, for this situation, the limits are: $101 \pm 2.35(6.06/\sqrt{4})$ = 93.9 to 108.1 kPa. This is 7% either side of the mean. Hence further samples are needed.

Try 5 samples:
ν = 4, p = 95%, t = 2.13
The updated limits are: $101 \pm 2.13(6.06/\sqrt{5})$ = 95.23 to 106.77 kPa. This is 5.7% either side of the mean. Again, further samples are needed.

Try 6 samples:
ν = 5, p = 95%, t = 2.02
The updated limits are: $101 \pm 2.02(6.06/\sqrt{6})$ = 96.0 to 106.0 kPa. This is 5% either side of the mean. Hence, 6 samples in total are needed.

4 TESTING UNCERTAINTY

Testing uncertainty is the collective term that is the combination of three individual uncertainties: equipment, procedural and random errors. Equipment errors account for inaccuracies associated with effects such as electrical drift, non-linearities, out-of-calibration errors, and equipment irregularities. For example, in relation to the SPT, equipment errors also include excessive wear of the cutting shoe of the split-spoon sampler, equipment manufacturing defects, and inconsistencies with the drop weight trip mechanism.

Procedural errors are variabilities associated with limitations in existing test standards and between different operators. Again, with reference to the SPT, procedural errors also include the drop weight not conforming to the test standard, the variation in SPT-*N* as a result of energy loss at the tip of the split-spoon sampler due to friction between the drop weight and the guide rod, as well as drilling rod vibration. In terms of laboratory testing, such as the triaxial test, procedural errors also include sample disturbance. Finally, procedural errors also incorporate variations in the way a test is conducted between different operators.

Random errors are the variation of test results which cannot be directly attributed to spatial variability, equipment or procedural errors. Random errors are quantified by performing many tests under identical conditions, and are assumed to have a mean of zero, thus affecting test results equally, and without bias. Kulhawy and Trautmann (1996) provided a model for combining these separate uncertainties into a single testing error, which is expressed in terms of a coefficient of variation, $\mathrm{COV}_{(\mathrm{tot})}$:

$$\mathrm{COV}_{(\mathrm{tot})} = \sqrt{\mathrm{COV}^2_{(\mathrm{equip})} + \mathrm{COV}^2_{(\mathrm{proc})} + \mathrm{COV}^2_{(\mathrm{rand})}} \quad (6)$$

Equation (6) has two important assumptions: (i) all of the sources of uncertainty can be considered as additive; and (ii) each source of measurement error is considered to be independent, or uncorrelated.

By examining data from many tests and projects, Kulhawy and Trautmann (1996) provided uncertainty estimates for five common in situ test methods, as shown in Table 1. Lee et al. (1983) and Phoon and Kulhawy (1999a,b) also provided similar guidance in relation to several laboratory and in situ tests and geotechnical parameters.

As can be seen from Table 1, both the CPT and DMT yield the lowest range of total measurement error; i.e. between 5 and 15%. Using both RFT and geostatistics, Jaksa et al. (1997) confirmed that the random measurement error associated with the CPT is indeed small, i.e. 3% or lower.

5 TRANSFORMATION UNCERTAINTY

As shown previously in Figure 1, transformation (or model) uncertainty is another important factor that contributes overall to geotechnical engineering uncertainty (Phoon and Kulhawy, 1999b). This error arises from the limitations of the model(s) used to transform the measurements, obtained in situ or in the laboratory, with the geotechnical parameters used in analysis and design. Again, using the SPT as an example, the single measurement obtained from this test is the SPT-*N* number. As is well understood, the SPT is a relatively crude test, which does not directly measure any geotechnical design parameter. This is also the case for most in situ tests, including the CPT and DMT. As a result, many researchers have developed transformation models correlating the SPT-*N* number with a wide range of geotechnical parameters, such as Young's modulus of elasticity, *E*; relative density, *RD*; and internal angle of friction, ϕ (Bowles, 1997). As stated by Wroth (1984), "the interpretation of data obtained from in situ tests is difficult, and for most tests it is both incomplete and imprecise." As a consequence, transformation models result in an added, sometimes significant, level of uncertainty in the site investigation and geotechnical engineering design processes.

Table 1. Uncertainty estimates for five common in situ tests (Source: Kulhawy and Trautmann 1996).

Test	Coefficient of Variation, COV (%)					
	Acronym	**Equipment**	**Procedure**	**Random**	**Total[a]**	**Range[b]**
Standard Penetration Test	SPT	5[c]–75[d]	5[c]–75[d]	12–15	14[c]–100[d]	15–45
Mechanical Cone Penetration Test	MCPT	5	10[e]–15[f]	10[e]–15[f]	15[e]–22[f]	15–25
Electrical Cone Penetration Test	CPT	3	5	5[e]–10[f]	8[e]–22[f]	5–15
Vane Shear Test	VST	5	8	10	14	10–20
Dilatometer Test	DMT	5	5	8	11	5–15
Pressuremeter Test (Pre-bored)	PMT	5	12	10	16	10–20[g]
Self-boring Pressuremeter Test	SBPMT	8	15	8	19	15–25[g]

[a] Determined from Equation (6).
[b] Because of limited data and judgement involved in estimating COVs, ranges represent probable magnitudes of field test measurement error.
[c,d] Best to worst case scenarios, respectively, for SPT.
[e,f] Tip and sleeve resistances, respectively, for CPT.
[g] Results may differ for p_0, p_f and p_1, but data are insufficient to clarify this issue.

Phoon and Kulhawy (1999b) used a correlation between the results of a pressuremeter test and the SPT to estimate transformation uncertainty associated with the SPT. The authors predicted that the transformation uncertainty in this case ranged between a COV value of 86% and 93%.

Another a striking example of the significance of transformation model uncertainty is evident in the relationship between in situ CBR and dynamic cone penetration test (DCP) results, an example of which is shown in Figure 9 (Austroads, 2017).

Drechsler (2011) presented the results of 249 unsoaked and 472 soaked CBR tests, along with DCPs performed adjacent to the sample locations. Bhowany et al. (2012) examined these data and compared them with several published CBR vs DCP transformation models, as shown in Figure 10, which includes Drechsler's data. It is clear that none of the relationships go anywhere close to modelling appropriately the measured data.

6 HUMAN UNCERTAINTY

Finally, human uncertainty is another factor which contributes to overall geotechnical engineering uncertainty. Swain (1989) defined human error as: "any member of a set of human actions or activities that exceeds some limit of acceptability, i.e. an out of tolerance action (or failure to act) where the limits of performance are defined by the system."

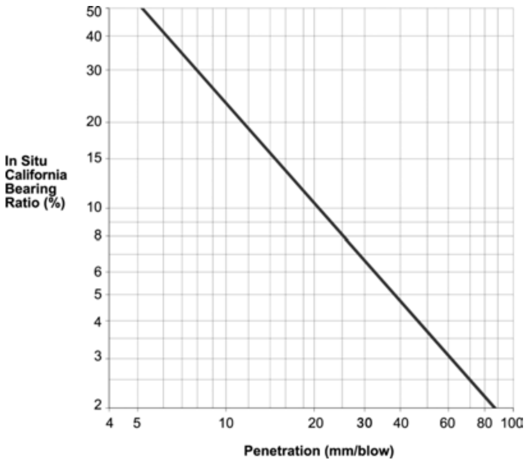

Figure 9. In situ CBR vs DCP transformation model (Austroads 2017)

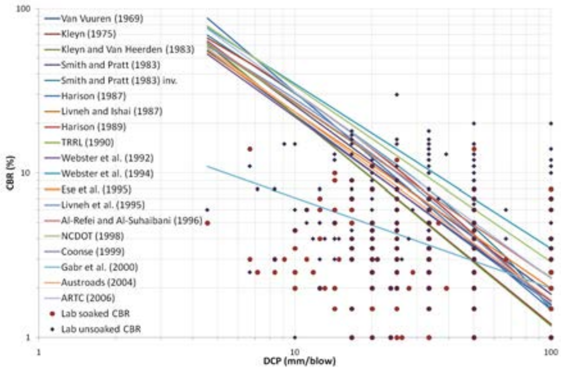

Figure 10. Laboratory measured CBR values plotted against the results of DCPs (Bhowany et al. 2012)

Given the fallibility of humankind, it is inevitable that errors occur. Kirwan (1994) stated that "human error is here to stay" and major system accidents, such as Three Mile Island, Chernobyl and Bhopal "have all been strongly influenced by human error." The literature abounds with unfortunate and occasionally distressing tales of engineering failures that were caused by poor decisions and processes, and sometimes sheer ineptitude. Some geotechnical engineering examples include the 1955 Fargo grain elevator failure (Nordlund and Deere, 1970) and the 1966 Aberfan (Kirwan, 1994; Johnes and McLean, 2006) and 1997 Thredbo (Mostyn and Sullivan, 2002) landslides.

Sowers (1993) documented the analysis of some 500 civil engineering failures and concluded that 58% originated in design, 38% in construction and 4% in operation. Approximately half of the problems that occurred during construction originated in design; the other half in construction. Three causes were identified: absence, ignorance and rejection of current technology. Absence of contemporary technology accounted for 12% of the failures, ignorance of contemporary technology was responsible for 33%, and rejection of technology was responsible for 55% of the failures. Of the total, 88% reflected human shortcomings that could have been reduced by acknowledging professional limitations, continuing education, modifying design and construction systems, and resisting the unbalanced pressures that impede good engineering.

Bea (2006) proposed a framework for extending traditional probability-based reliability and risk analyses to include human, organisational and knowledge related uncertainties in the geotechnical engineering context.

Simpson (2011) stated that significant geotechnical engineering failures rarely occur as a result of the reasonably expected statistical variation of parameters. Most often, they occur because (a) the ground conditions and geological features are significantly different from those expected, beyond the anticipated range of variation; (b) groundwater pressures are worse than expected; or (c) human error has led to mistakes in calculation or omission of an important factor, such as a likely extreme load or a failure mode (Simpson, 2011).

7 SPATIAL SIMULATION

This section presents two examples that demonstrate the potential benefits of applying probability and statistics to geotechnical engineering with the use of simulation of site investigations. The first involves recent work by the author's PhD student, Michael Crisp, examining the optimisation of site investigations. The second example presents research undertaken several years ago by Ferguson (1992), which explores the optimal borehole layout for intercepting subsoil contaminant hotspots.

7.1 Optimising Site Investigations

Crisp et al. (2019a,b) has recently undertaken spatial simulation of the ground in order to optimise site investigations. The authors used the local average subdivision method (Fenton and Vanmarcke, 1990) to generate realisations of the ground, incorporating multiple and variable soil layers, an example of which is shown in Figure 11.

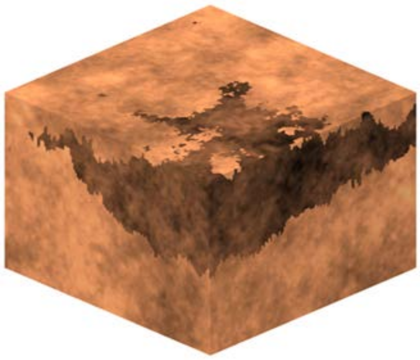

Figure 11. Simulated multi-layered, variable soil profile

Using Monte Carlo analysis, incorporating millions of realisations and the power of a supercomputer, Crisp et al. (2019a,b) examined the optimisation of site investigations using a variety of in situ and laboratory tests (i.e. CPT, DMT, standard penetration test and triaxial tests) to provide data for the design of pile foundations. Whilst it is beyond the scope of this paper to provide extensive treatment of these studies, a useful conclusion from this work is the recommended reduction method.

When conducting a site investigation, data are obtained in order to characterise the geotechnical properties of the ground. For example, a site investigation might include several CPTs performed at different locations across a site. Hence, multiple values of q_c are obtained. A common consideration is deciding on the optimal method for reducing these multiple values to a single one that can be used for design. For example, should one use the simple arithmetic average, or perhaps a more complex method, such as the harmonic or geometric averages, or the minimum value or the first quartile, as shown in Table 1? Which method provides the most reliable result?

Table 1. Reduction methods

Reduction Method	**Relationship**
Standard Arithmetic Average	$\frac{1}{n}\sum_{i=1}^{n} x_i$
Harmonic Average	$\frac{1}{n}\left(\sum_{i=1}^{n}\frac{1}{x_i}\right)^{-1}$
Geometric Average	$\left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}}$
Minimum	$\min(x)$
1st Quartile	$\frac{1}{4}(n+1)^{th}\ value$
Inverse Distance	$\sum_{i=1}^{n}\frac{s_i}{s_{total}} x_i$
Inverse Distance Squared	$\sum_{i=1}^{n}\frac{s_i^2}{s_{total}^2} x_i$

Crisp et al. (2019b) proposed the *standard deviation* (SD) method, which results in a single, reduced value, X_{SD}, of a total of n samples, using the following relationships:

$$\mu_{ln} = \exp\left(\frac{1}{n}\sum_{i=1}^{n} ln(x_i)\right) \qquad (7)$$

$$\sigma_{ln} = \exp\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n} ln\left(\frac{x_i}{\mu_{ln}}\right)^2}\right)$$

$$X_{SD} = \frac{\mu_{ln}}{\sigma_{ln}}$$

The reduced value, X_{SD}, is one geometric standard deviation, σ_{ln}, below the geometric mean, μ_{ln}. Again, in relation to the CPT, x_i refers to a single q_c measurement.

7.2 Optimal Borehole Layout for Intercepting Contaminant Hotspots

Ferguson (1992) also used Monte Carlo simulation, in this case to examine the statistical efficiency of various borehole layouts to intercept a contaminant hotspot or anomaly. He investigated 5 patterns (shown in Fig. 12): (A) regular (square) grid; (B) stratified random; (C) stratified systematic unaligned; (D) simple random; and herringbone (Fig. 13). He assumed that an anomaly or contaminant was equally likely to occur at any position on the site. Stratified random is a location chosen randomly within each grid square, in contrast to simple random where each location is chosen completely at random. In the stratified systematic unaligned arrangement, the location in the lower left square (1,1) is generated randomly. Its Δx is used in each of the other squares on the bottom row, and only the Δy values are chosen randomly. The other squares in the left-most column use the Δy value of the bottom left square. The Δy value in (1,2) and the Δx value in (2,1) then determine the sampling location in square (2,2), and so on, as shown in Figure 12. The main disadvantage associated with this scheme is that it is difficult to set out on site.

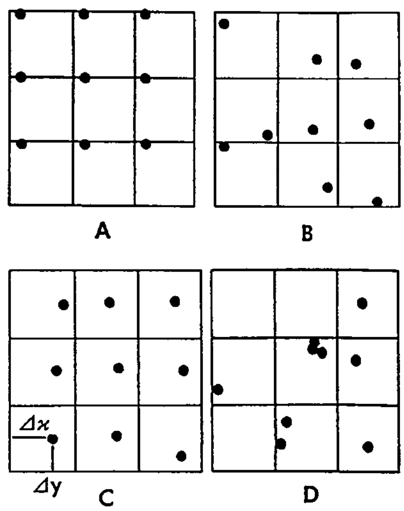

Figure 12. Borehole layouts: (A) regular grid; (B) stratified random; (C) stratified systematic unaligned; (D) simple random (Ferguson 1992)

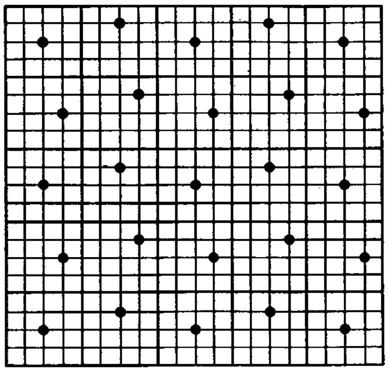

Figure 13. Herringbone layout.
Source: Ferguson (1992)

Ferguson (1992) examined 5 different contaminant shapes: a circle; square; rectangle; ellipse and plume. He explored the performance of the 5 borehole layouts by estimating the probability of finding a randomly located anomaly with a predetermined orientation. Each simulation involved 15,000 realisations to ensure a stable estimate of the success probability.

Figure 14 presents the results for a circular anomaly, whose area was chosen as being 5% of the total area of the site. In this case, it is evident that the herringbone (H) layout performs best, followed by the, regular grid (G) and the stratified systematic unaligned (U) layouts. As can be seen, the random (R) and stratified random (S) layouts perform poorly.

Figure 15 shows the performance of the herringbone and regular grid layouts for each of the 5 shapes which occupy 5% of the total site area. It is evident that, in general, the herringbone pattern outperforms the regular grid, with about 30 samples needed to locate the anomaly with 95% probability of success.

The results of Ferguson (1992) have informed standards of practice in geoenvironmental engineering, including for example AS 4482.1, the Australian code of practice for investigation and sampling of sites with potentially contaminated soil (Standards Australia, 2005).

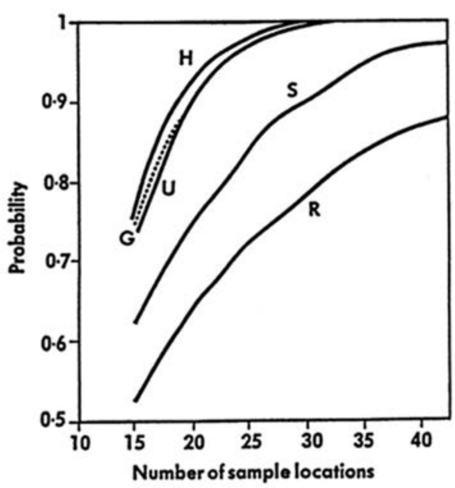

Figure 14. Performance of borehole layouts in detecting a circular anomaly occupying 5% of the total site area (Source: Ferguson 1992).

8 CONCLUSION

This paper has examined geotechnical uncertainty and unpacked it into its component parts, namely: spatial variability and statistical, testing, transformation and human uncertainties. Spatial variability is a key aspect of geotechnical uncertainty and the statistical measures and tools used to quantify this variability; i.e. the mean, variance and scale of fluctuation, have been presented. Testing uncertainty was shown to consist of three individual components: equipment, procedural and random errors. These, as well as transformation and human uncertainties, were shown also to be significant.

Finally, two examples were presented which highlight the power of statistics and simulation in the geotechnical engineering and site investigation contexts.

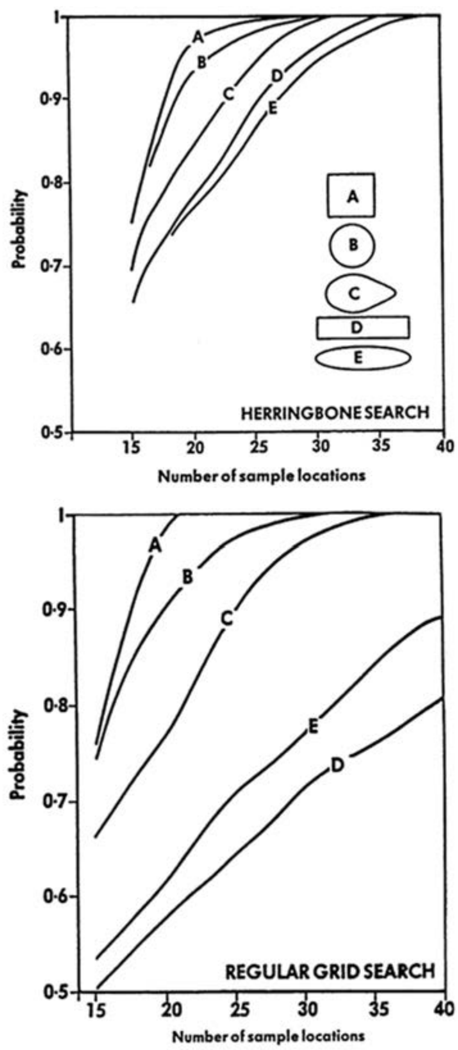

Figure 15. Performance of (a) herringbone and (b) regular grid layouts in detecting anomalies of different shapes, each occupying 5% of the total site area (Source: Ferguson 1992).

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