Session Report

Application of Statistical Techniques

Prof. Mark Jaksa
University of Adelaide, Australia

Overview of Presentation

- Background
  - Modelling Spatial Variability
  - Artificial Neural Networks

- Papers (9)
  - Reliability (3)
  - Spatial variability (5)
  - ANNs (1)

- Presentations at 1:45 – 3:15 pm in the Coolangatta Rooms 1 & 2

Modelling Spatial Variability

Mathematical techniques focus on stochastic methods:

- Regression analysis
- Random field theory
- Geostatistics
- Fractal theory

- Regression analysis is too simplistic;
- Fractal theory is useful but no modelling tools are available.

Random Field Theory (RFT)

- 3D extension of time series analysis.
- Applied to geotechnical engineering by Prof. Eric VanMarcke (MIT, Princeton) in late 1970s, early 1980s.

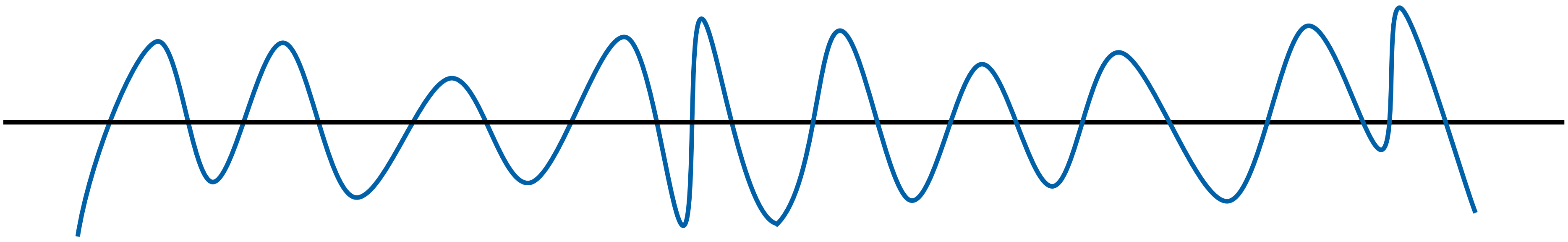
Spatial variability is expressed by 3 parameters:

1. Mean (average);
2. Variance, Standard deviation, Coefficient of variation;
3. Scale of fluctuation (uses autocorrelation function).

Scale of Fluctuation

- The scale of fluctuation, SOF, is a measure of the distance over which soil properties are highly correlated.

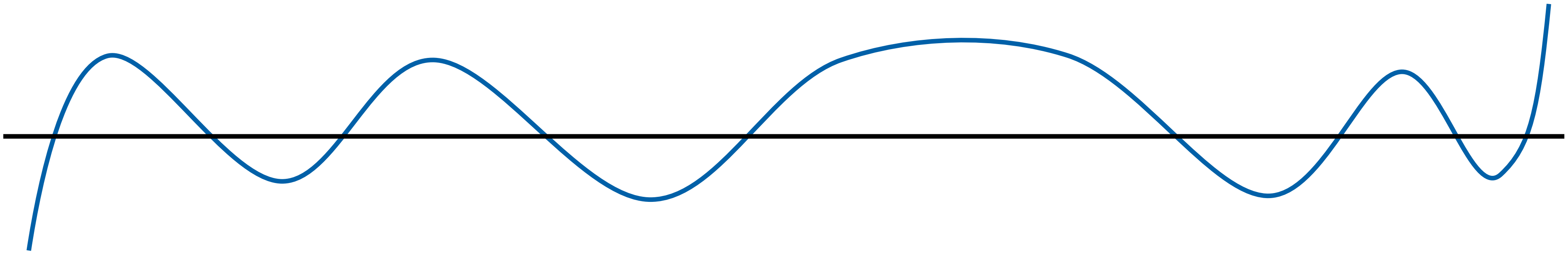
- Small values of SOF imply rapid fluctuations about the mean.



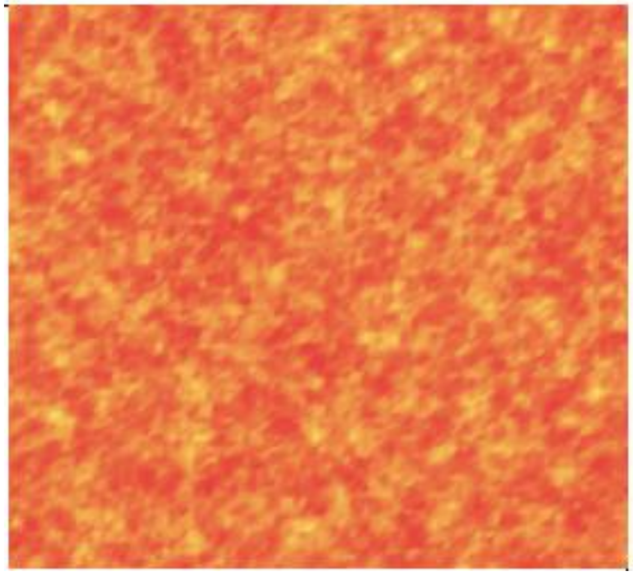
Scale of Fluctuation

- The scale of fluctuation, SOF, is a measure of the distance over which soil properties are highly correlated.

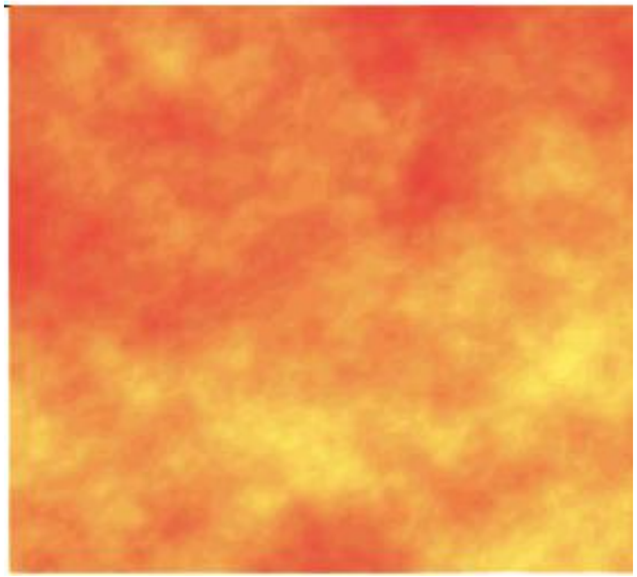
- Large values suggest a slowly varying property, with respect to the mean.



Scale of Fluctuation – 2D



Small SOF



Large SOF

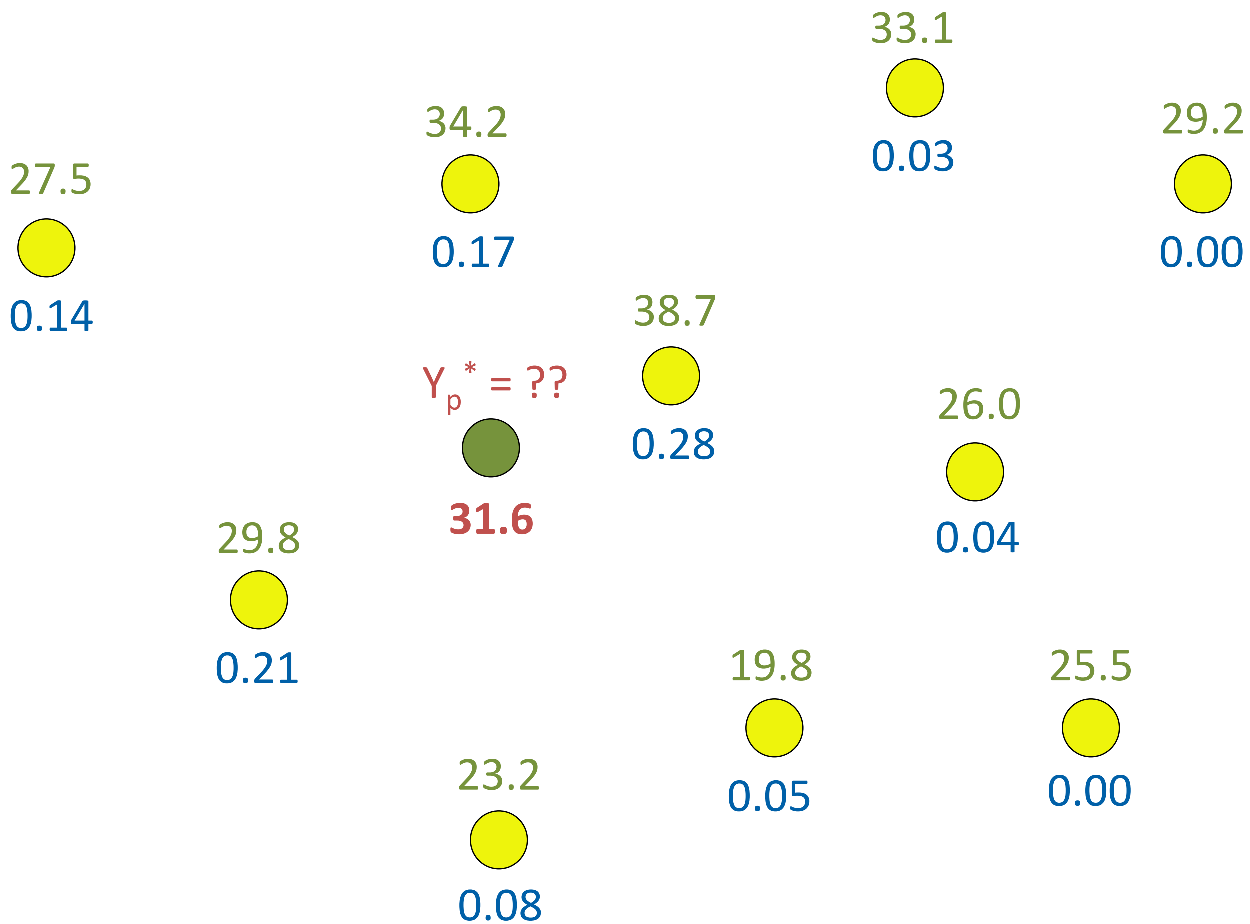
Geostatistics

- Geostatistics was developed to assist in the estimation of changes in ore grade within a mine and is largely a result of the work of D. Krige and G. Matheron in the early 1960s.
- Geostatistics has been applied to many disciplines including: groundwater hydrology; hydrogeology; surface hydrology; earthquake engineering and seismology; pollution control; geochemical exploration; and geotechnical engineering.

Geostatistics

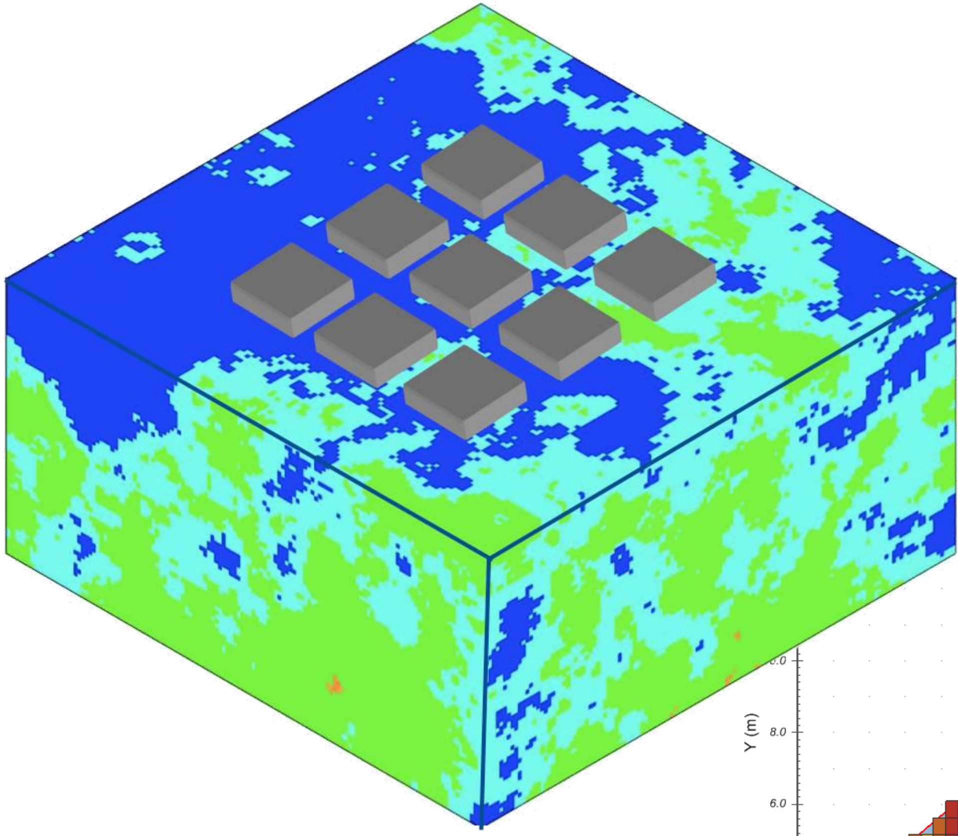
- Geostatistics can be applied to any natural phenomena that are spatially or temporally associated.
- Geostatistics is based on the regionalised variable, that is, one that can be represented by random functions, rather than independent random variables (classical approach).
- Makes use of the semivariogram.

Geostatistics – Kriging

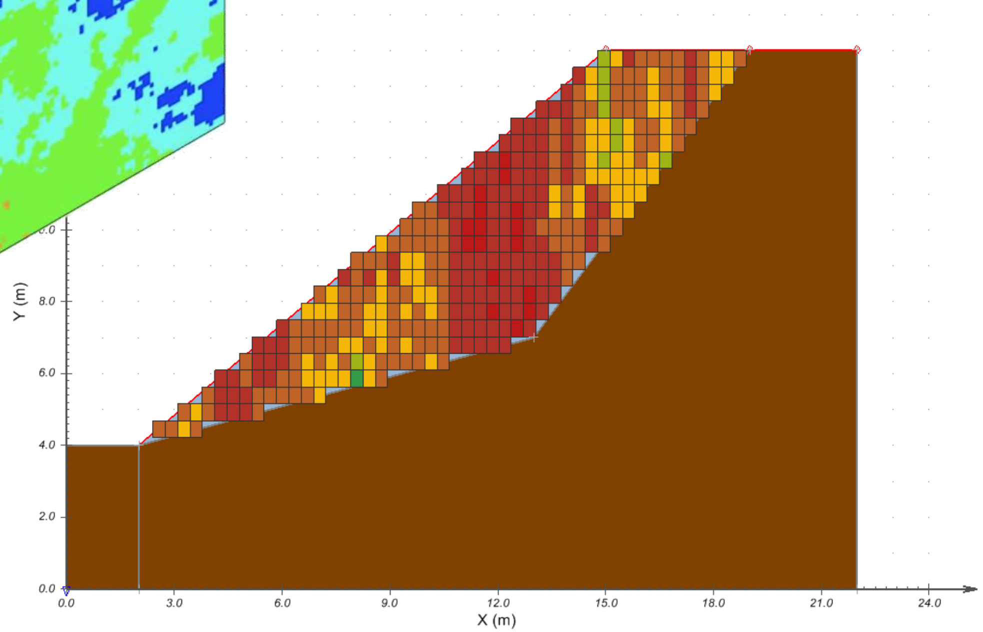


$$Y_p^* = 0.28 \times 38.7 + 0.21 \times 29.8 + 0.17 \times 34.2 + \cdots$$

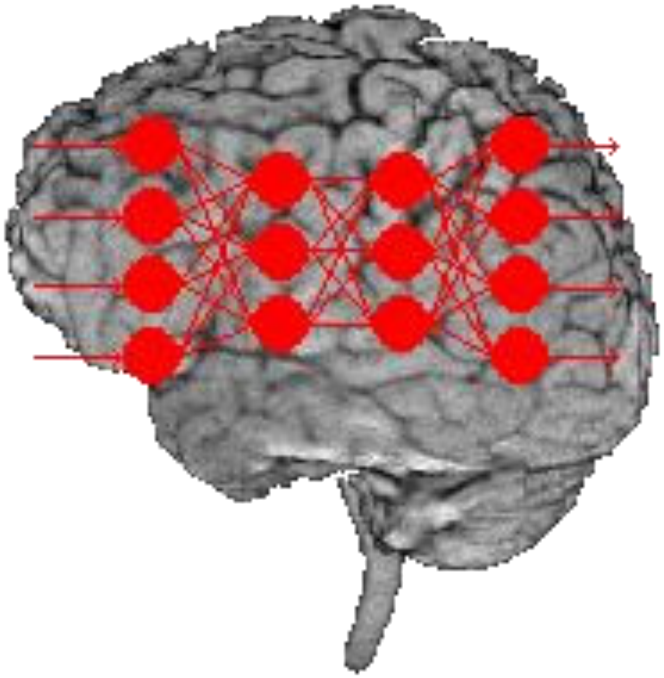
RFT and Geostatistics – Simulation

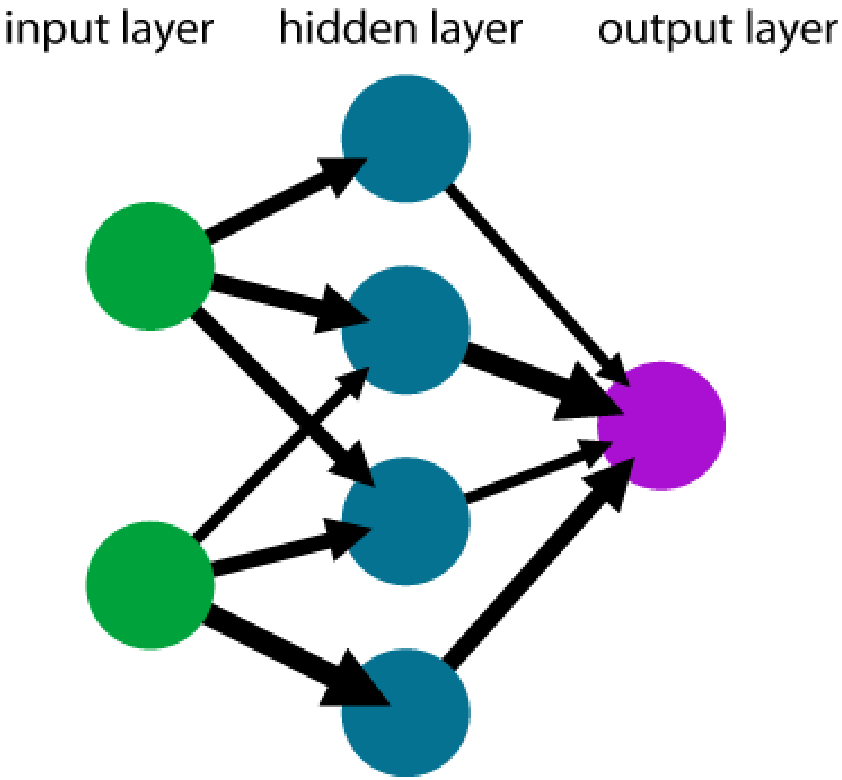


SVSlope



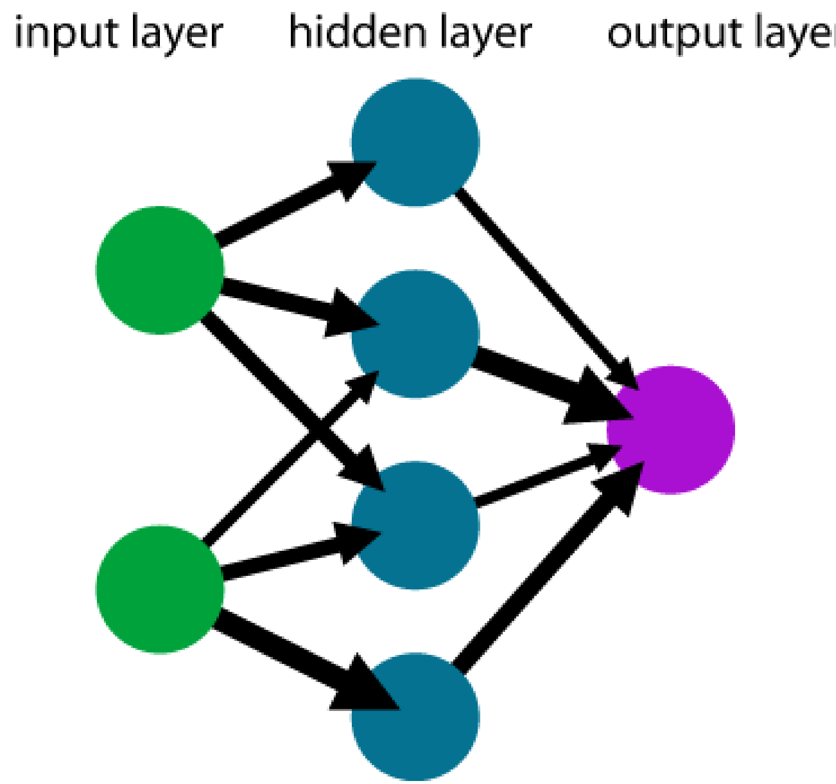
Artificial Neural Networks (ANNs)





Artificial Neural Networks (ANNs)

- ANN developed using data.
- Weights between nodes are optimised with successive iterations until the error is minimised.
- Aim: To develop accurate predictions of the output variable(s) from the input variables.



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- Papers (9)
  - **Reliability (3)**
  - Spatial variability
  - ANNs

Foti & Passeri

Reliability of soil porosity estimation from seismic wave velocities

S. Foti & F. Passeri

Politecnico di Torino, Italy

Aim:

- To investigate the reliability of porosity estimation from shear wave velocities using error propagation theory.

Foti & Passeri

$$n = \frac{\rho^s - \sqrt{(\rho^s)^2 - \dfrac{4\,(\rho^s - \rho^w)\,K^w}{V_p{}^2 - 2\left(\dfrac{1-\nu_{sk}}{1-2\,\nu_{sk}}\right)V_s{}^2}}}{2\,(\rho^s - \rho^w)}$$

- Porosity, n, is a function of density of the soil solids, ρ^s, and pore water, ρ^w, bulk modulus of pore water, K^w, dilatational and shear wave velocities, V_p and V_s, and the Poisson's ratio of the soil skeleton, ν_{sk}.

Foti & Passeri

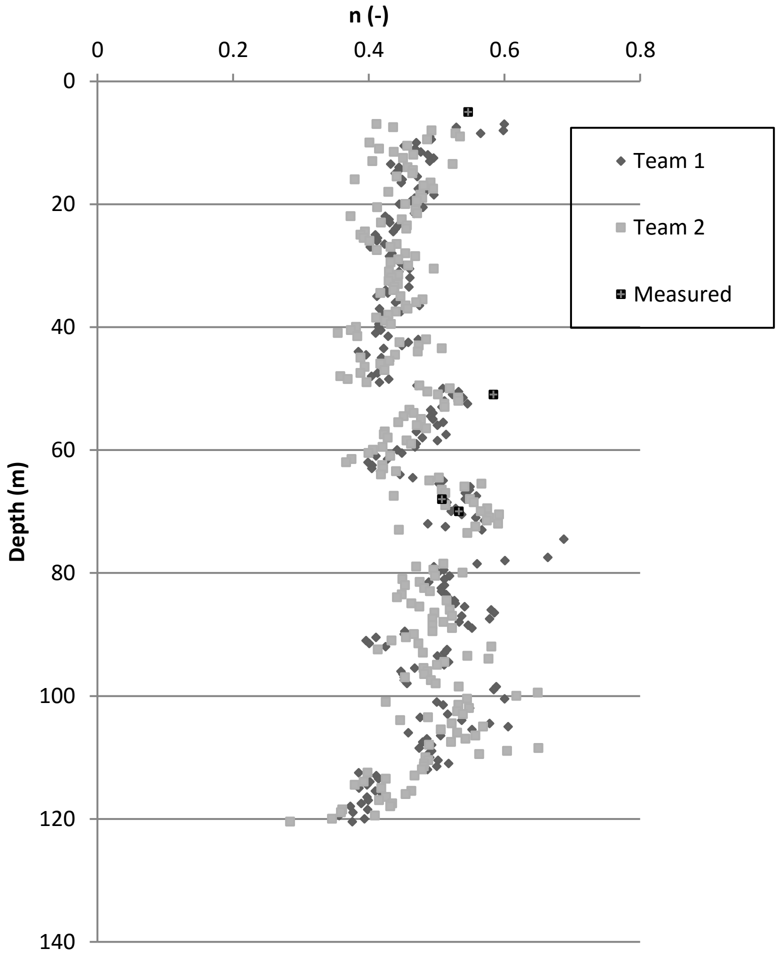
- Consider: $n = f\,(\rho^s, \rho^w, K^w, V_p = d/t_p, V_s = d/t_s, v_{sk})$, where d is the travel distance and t is the travel time.

- Assumed that each variable is normally and randomly distributed and independent.

Foti & Passeri – Case Studies

Presented two case studies:

- Site of Zelazny Most tailings dam (Poland);
- A site in the Italian town of Mirandola.



Foti & Passeri – Conclusions

- In particular, for cross-hole tests, the distance between boreholes is significant.
- Travel times have a minor influence.
- The effect of P-waves is significant.
- The effects of the velocity of compressional waves in water and the Poisson's ratio of the soil skeleton also affect the estimate of n.

Huang et al.

Enhanced data interpretation: combining in-situ test data by Bayesian updating

J. Huang, R. Kelly & S.W. Sloan

ARC Centre of Excellence for Geotechnical Science and Engineering, The University of Newcastle, Australia

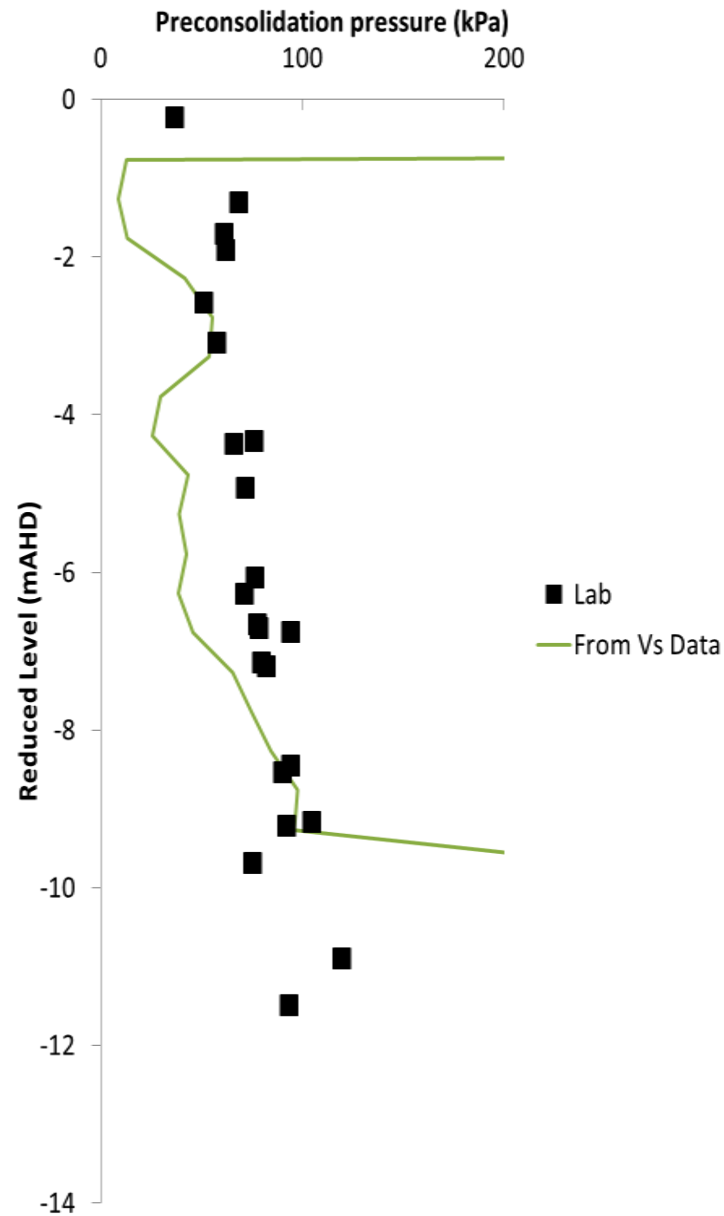
SMEC, Brisbane, Australia

Aim:

- To apply Bayesian updating to include laboratory testing and associated uncertainties to enhance the accuracy of seismic measurements.

Huang et al.

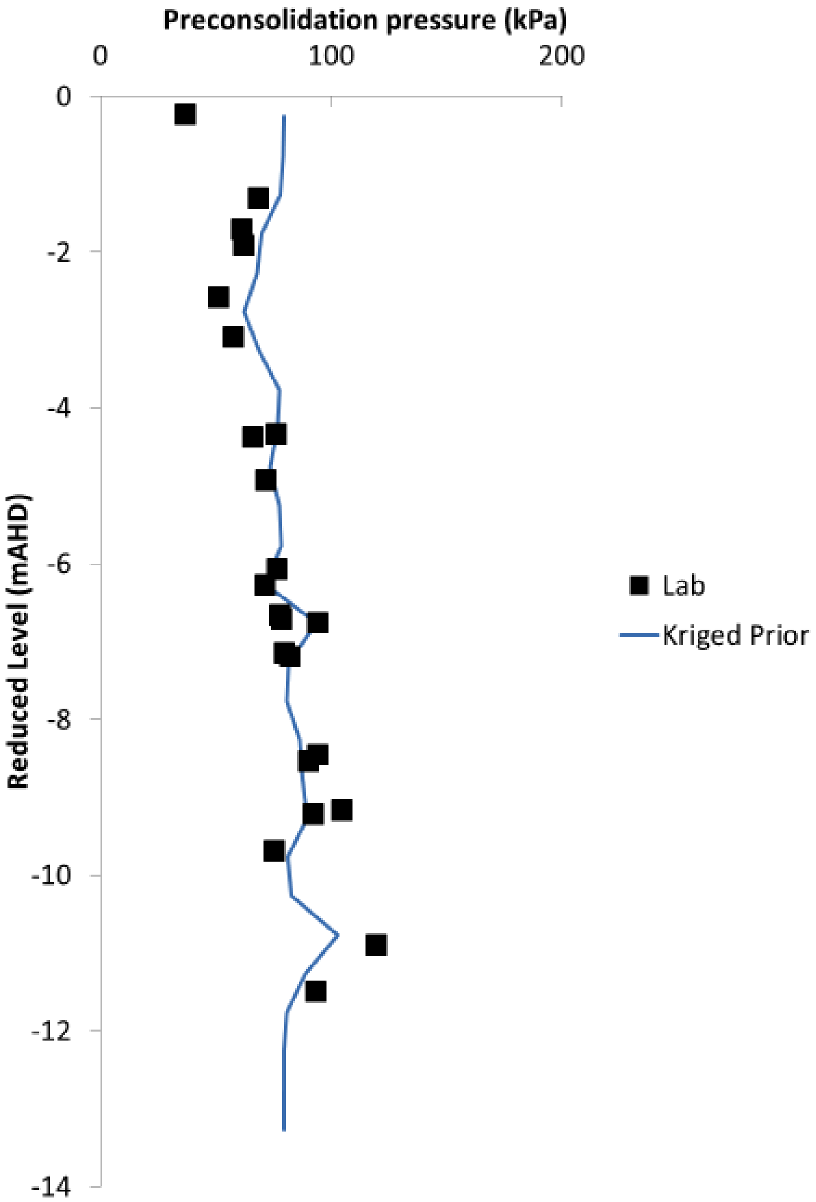
- Involves measurement of shear wave velocity, V_s, using the seismic DMT and supplemented with laboratory determined preconsolidation pressure data from constant rate of strain oedometer tests.



Huang et al.

- Empirical relationships between the preconsolidation pressure and shear wave velocity are first derived from the two sets of data (V_s and σ'_v).

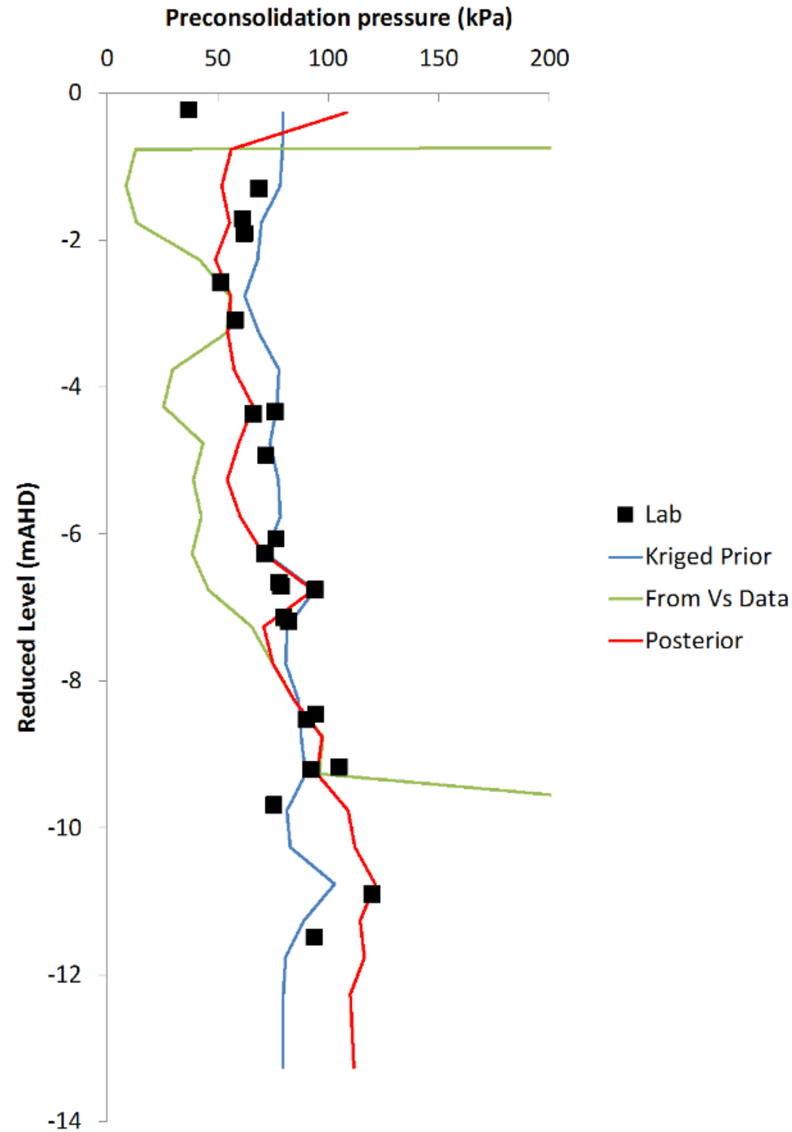
- Prior distribution of pre-consolidation pressures is obtained using a linear trend and kriging.



Huang et al. – Conclusions

- The uncertainties of pre-consolidation pressure can be significantly reduced by incorporating shear wave velocity measurements.

- Whilst a 1D example is presented, the authors suggest that the technique is relevant to 2D and 3D.



Styler & Weemees

Quantifying and reducing uncertainty in down-hole shear wave velocities using signal stacking

M.A. Styler & I. Weemees

ConeTec Investigations, Ltd., Richmond, Canada

Aim:

- To quantify the improvement in the interpreted shear wave propagation time, in down-hole seismic testing, that can be realized through signal stacking of multiple traces.

Styler & Weemees

- Concerns down-hole seismic testing using a seismic piezocone (SCPTU).

The extensive paper demonstrates how to:

- calculate the noise in a set of down-hole seismic traces;
- quantify the SNR for a trace and for stacked signals; and
- evaluate the error in the propagation time when comparing two seismic traces.

Styler & Weemees – Conclusions

- SNR increases with signal stacking.

- The error in the propagation time decreases with higher SNR, and

- The decrease in SNR with depth can be countered by signal stacking.

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  - **Spatial variability (5)**
  - ANNs

Lehane et al.

Probabilistic assessment of laterally loaded pile performance in sand

B.M. Lehane, F. Glisic & J.P. Doherty

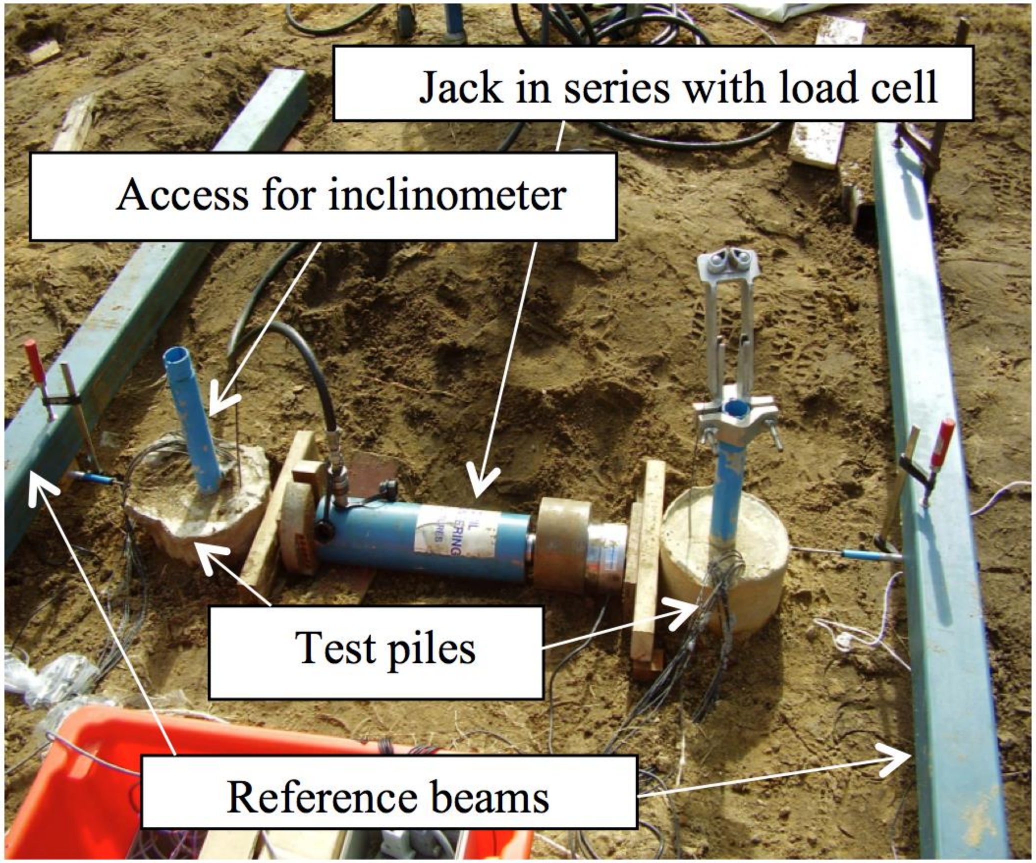
School of Civil, Environmental and Mining Engineering,
The University of Western Australia

Aim:

- To examine the effect of spatial variability of the ground on the performance of laterally loaded piles using a series of CPTs.

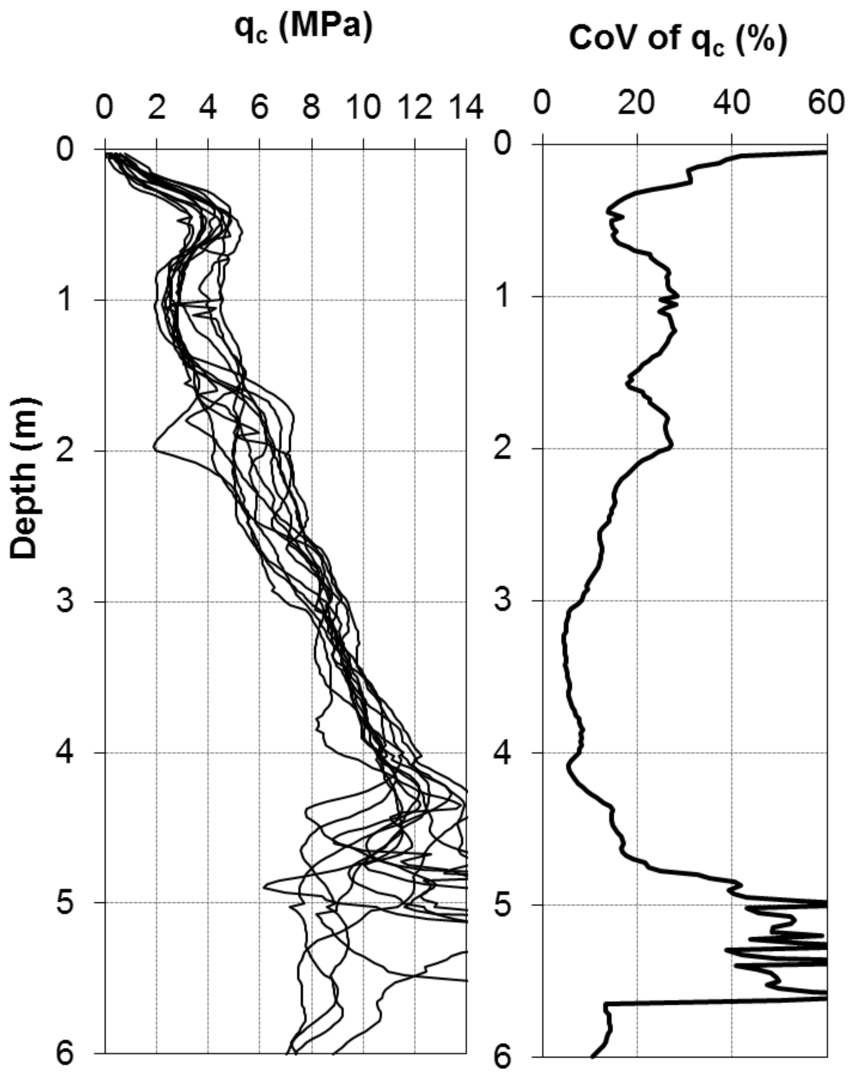
Lehane et al.

- Pile load testing carried out at Shenton Park, Perth, WA.
- Stratigraphy: 5 – 7 m siliceous dune sand overlying weakly cemented limestone.
- 2 × 225 mm diameter, 3.5 m long CFA piles.



Lehane et al.

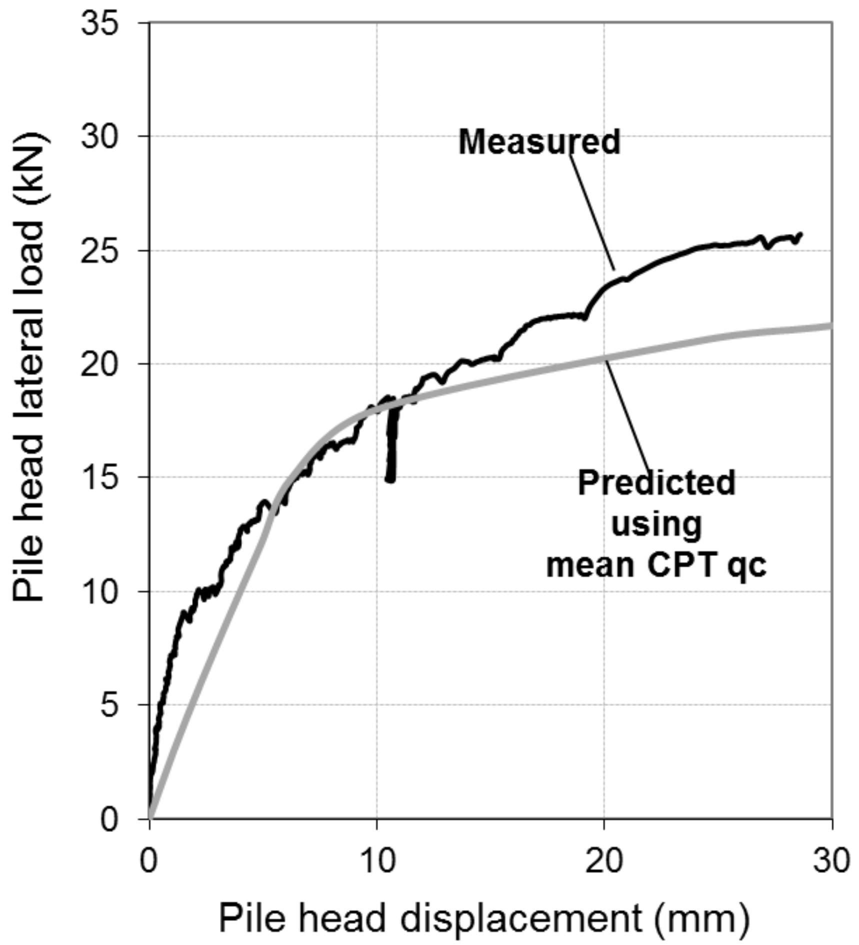
- 12 CPTs



Lehane et al.

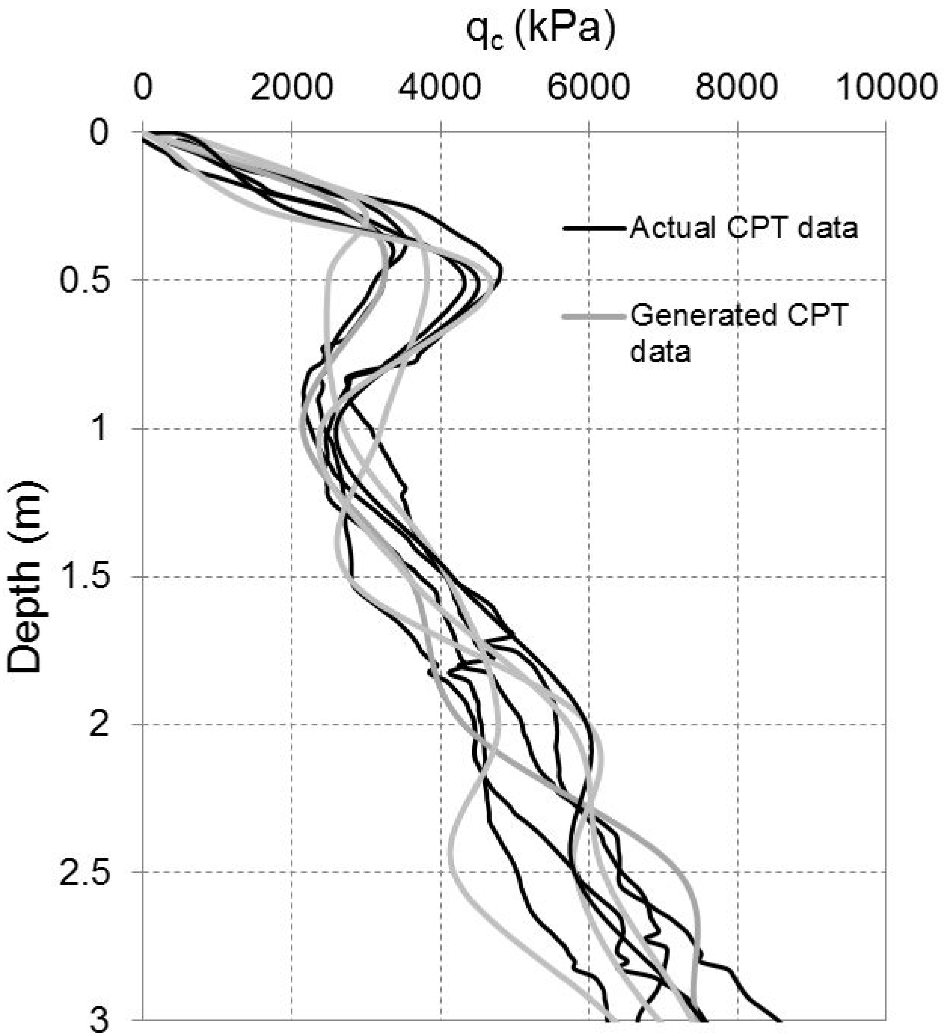
- Lateral load-displacement relationship predicted using LAP program incorporating the Suryasentana & Lehane (S&L) (2014, 2016) method.

- Good agreement between predicted and measured behaviour.



Lehane et al.

- 50 CPTs randomly generated
- Scale of fluctuation estimated 0.25 – 0.5 m



Lehane et al. – Conclusions

- The lateral load range likely to induce a given level of head rotation for a pile in sand is significantly lower than the range anticipated from the CPT q_c variability.
- The CPT-based S&L Method for laterally loaded piles provides good predictions for the lateral response of a test pile at a medium dense sand site.
- Predictions using the S&L and the API sand methods have a low sensitivity to randomly generated q_c or ϕ' profiles that are normally distributed at any given depth.

Krage et al.

Identification of geological depositional variations using CPT-based conditional probability mapping

C.P. Krage, J.T. DeJong & R.W. Boulanger
University of California, Davis, USA

Aim:

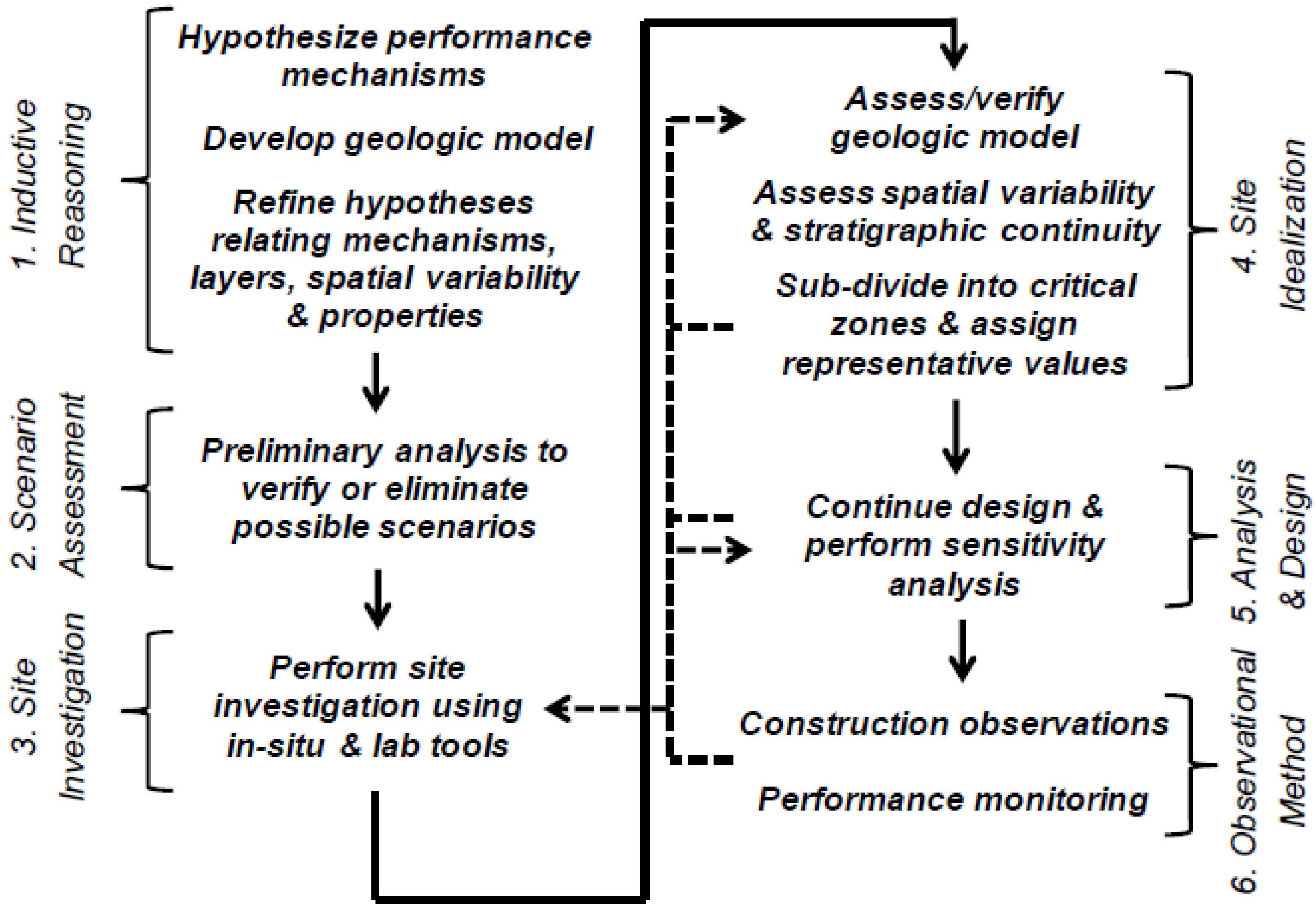
- To improve characterization and understanding of subsurface stratigraphy at a project site using transition probability geostatistics which is conditioned to CPT soundings and combined with geological information.

Krage et al.

- The authors use geostatistics in two ways to augment site investigations to:

1. identify or estimate the soil type at unknown locations; and
2. estimate the engineering properties at these unknown spatial locations.

Krage et al. – Integrated Approach



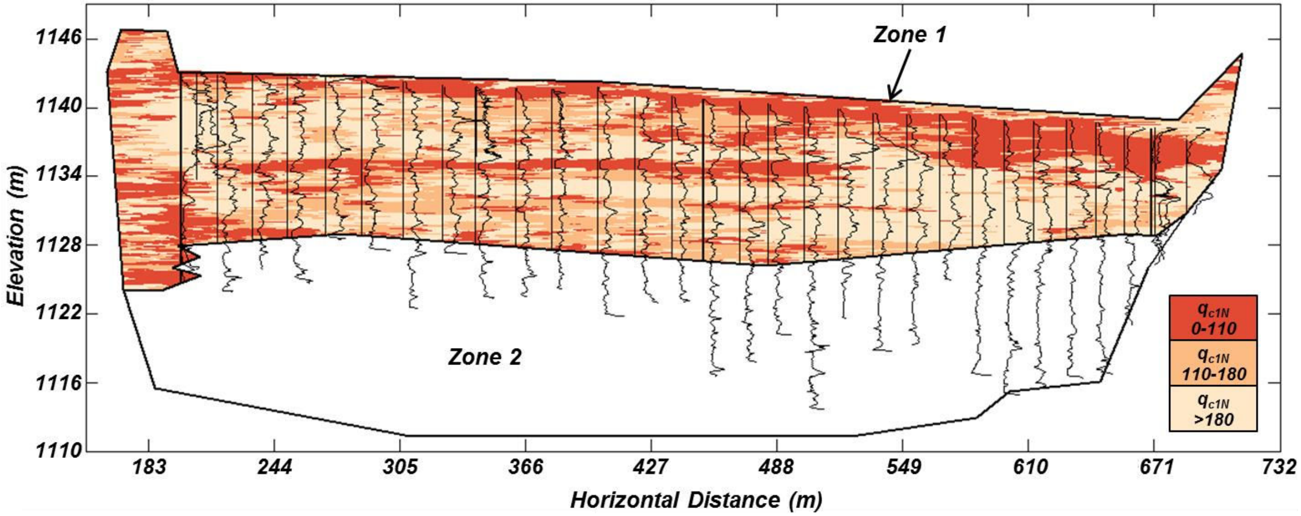
Krage et al. – Transition Probability

- Describes the likelihood of transitioning from one category (where categories are user defined; can be soil type or engineering property based) to another over some separation distance.

- The main advantage of this approach is the ability to model ordered systems (e.g. geologic facies environments)

Krage et al. – Example Case

- Site for a new 11 m high embankment dam with respect to liquefaction assessment.
- Geostatistical simulation was performed conditioned to CPTs taken along the dam wall alignment.



Krage et al. – Conclusions

- The simulations indicate liquefaction is expected to be most prevalent at shallow depths:
  - 1-2 m deep on the west side
  - to 4-6 m deep on the east side.

- Liquefaction is also expected at a larger depths.

Parida et al.

Stochastic waveform inversion for probabilistic geotechnical site characterization

S.S. Parida, K. Sett & P. Singla

University at Buffalo, New York, USA

Aim:

- To develop a stochastic inverse analysis methodology to estimate probabilistically Young's modulus from geophysical test measurements by accounting for uncertainties from spatial variability, measurement errors and limited data.

Parida et al. – Methodology

- Spectral analysis of surface waves (SASW)

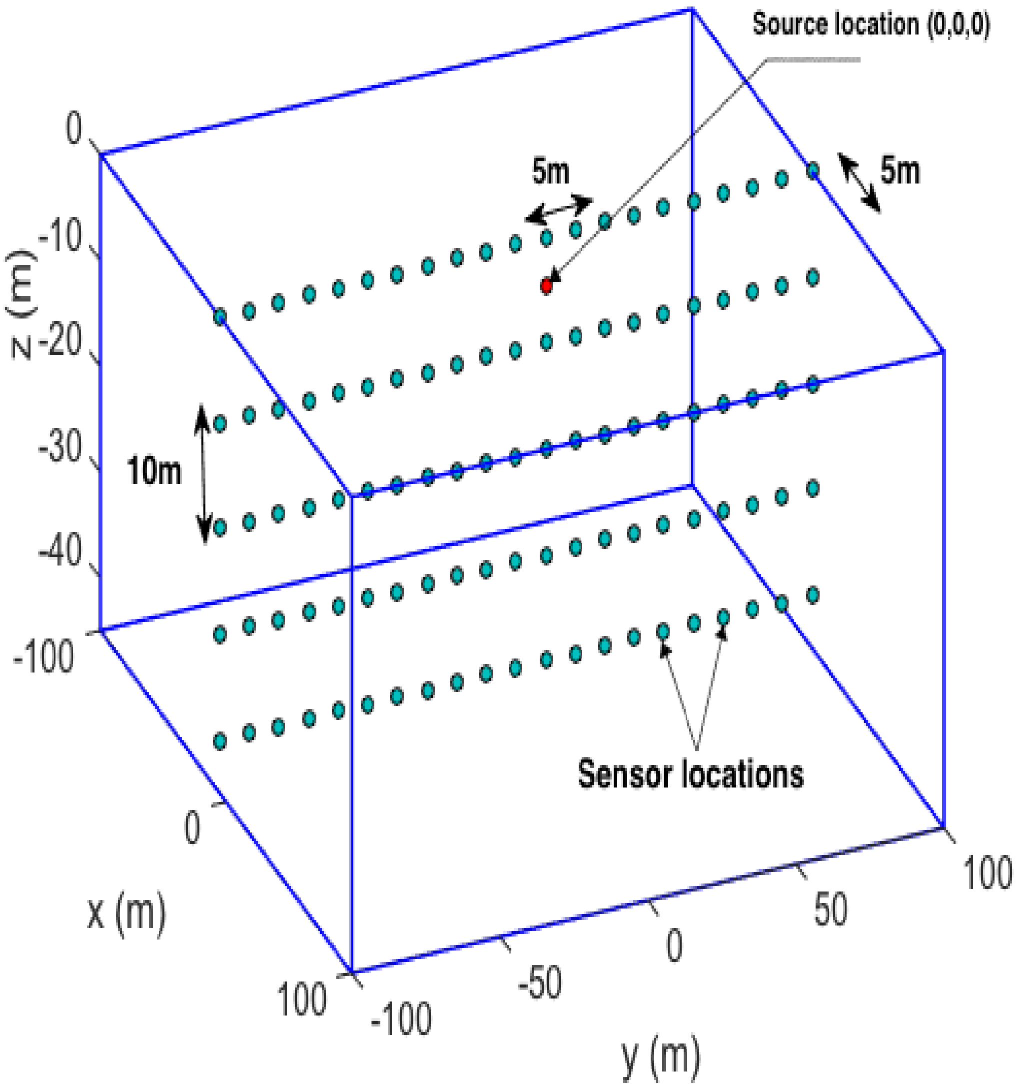
- Monte Carlo simulation

- Uses finite element method with the stochastic collocation approach to probabil-istically solve the forward problem for SASW.

Parida et al. – Virtual Site

- Used RFT to simulate ground profile.

- Excited the ground using a chirp signal.



Parida et al. – Conclusions

- The amount of information gained decreases with depth implying that the sensors towards the bottom contribute modestly to the inverse estimation process.

- The developed methodology is mathematically rigorous and computationally efficient, and is general enough to be extended widely.

Wierzbicki et al.

3D mapping of organic layers by means of CPTU and statistical data analysis

J. Wierzbicki, A. Smaga, K. Stefaniak & W. Wołyński

Adam Mickiewicz University, Poznań, Poland

Poznań University of Life Sciences, Poland

Aim:

- To examine selected methods of statistical data analysis to determine the spatial extent of organic soil layers using CPTU data.

Wierzbicki et al.

- Geotechnical characterisation undertaken at a site located 50 km from Poznań, Poland.
- Ground at the study area consists of glacial clay, layered sands and gravels, silts and organic soils.
- CPTU data were subjected to clustering analysis using the k-means method.
- Inverse distance weighting (IDW) method was used to develop 2D and 3D models.

Wierzbicki et al. – Conclusions

- Only simultaneous use of all available data allowed the detailed identification of the organic soil layer.

- The full 3D IDW model yielded unsatisfactory results.

- Future considerations:
  - Explore geostatistics (i.e. kriging).

Zou et al.

Assessment of ground improvement on silt based on spatial variability analysis of CPTU data

H.F. Zou, G.J. Cai, S.Y. Liu, J. Lin, T.V. Bheemasetti & A.J. Puppala

Southeast University, Nanjing, China

University of Texas at Arlington, Texas, USA

Aim:

- To examine the difference in spatial variability characteristics of silt before and after compaction.

Zou et al.

- A silt site located in the Jiangsu province, China, was improved using a new deep resonance compaction technique to increase the liquefaction resistance of the silt.
- CPTUs were performed before and after ground improvement to assess the efficacy of the technique.
- The study undertakes spatial variability analyses on the before and after CPTU data.

Zou et al.

- RFT was used to examine cone tip resistance.
- The mean, COV and SOF_v were examined prior to and after compaction.

Zou et al. – Conclusions

The results showed that:

- both mean and the SOF_v decreased immediately after compaction, but gradually increased with the strength and density recovery;
- COV consistently decreased after the compaction.

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  - **ANNs (1)**

Sastre et al.

Automatic methodology to predict grain size class from dynamic penetration test using neural networks

C. Sastre, M. Benz, R. Gourvès, P.Breul & C.Bacconnet

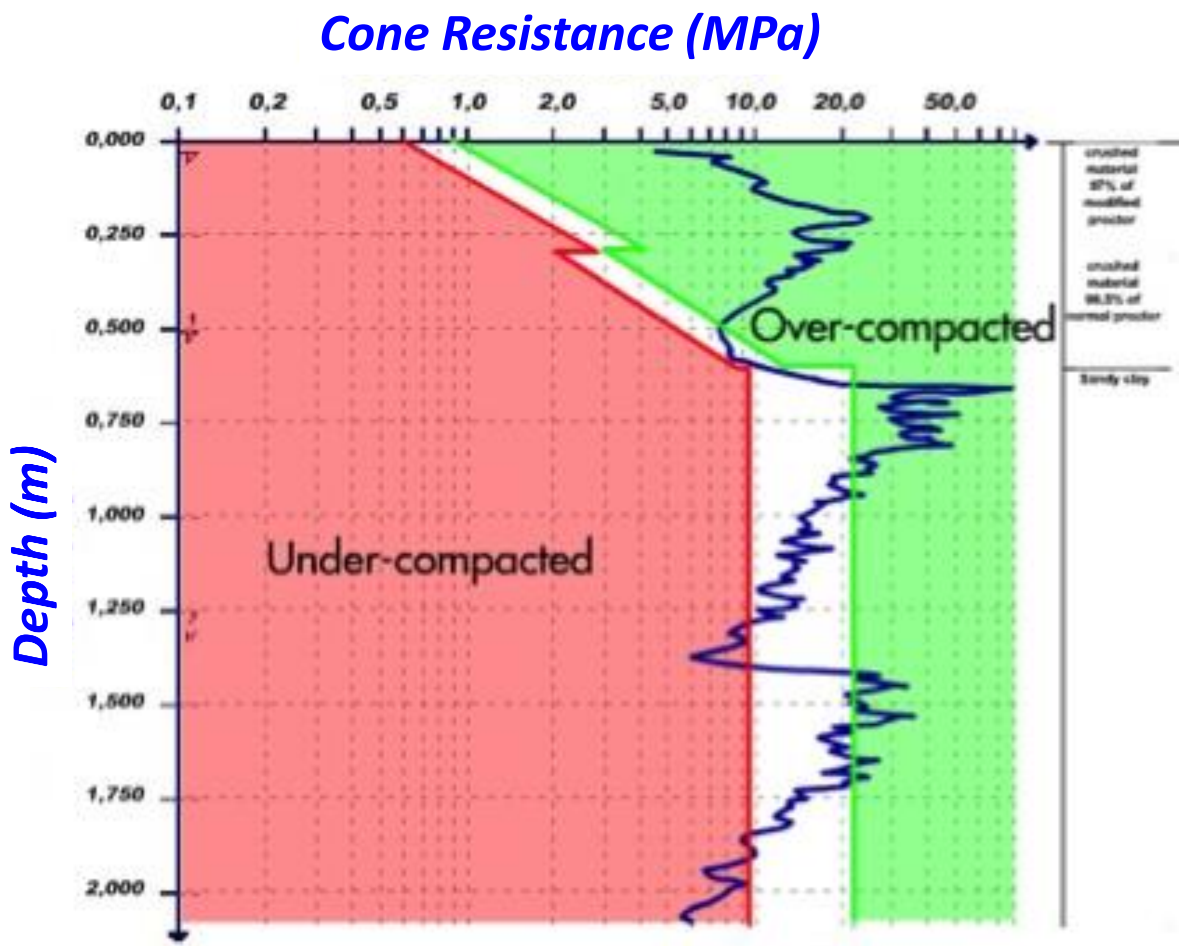
Sol Solution Géotechnique Réseaux, France

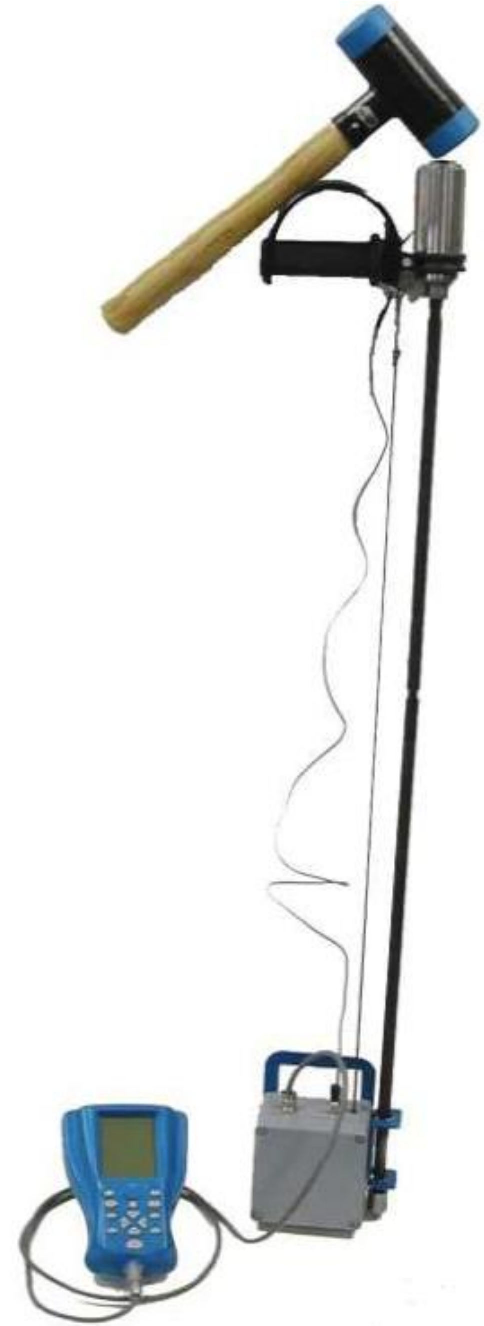
Université Blaise Pascal, Clermont-Ferrand, France

Aim:

- To develop an ANN to predict grain size class from Panda dynamic cone penetration test data.

Sastre et al. – Panda





Sastre et al. – Data

- The ANN model was developed using a database consisting of 218 Panda2 penetrograms incorporating:
  - 149 tests performed in a laboratory-based calibration chamber, and
  - 69 in situ tests carried out at various locations in France.

Sastre et al. – ANN Model Development

- Inputs: 26 (initially), reduced to 17:

1. q_d mean	10. q_d Shannon entropy
2. q_d median	11. q_d logarithm entropy range
3. q_d standard deviation	12. q_d skewness
4. q_d coefficient of variation	13. q_d slope changes
5. q_d variance	14. q_d waveform
6. q_d range	15. linear coeff. of linear trend
7. q_d interquartile range	16. independent coeff. of linear trend
8. q_d skewness	17. maximum spectral power
9. q_d kurtosis	

Sastre et al. – ANN Model Development

- Inputs: 26 (initially), reduce further?

1. q_d mean	10. q_d Shannon entropy
2. q_d median	11. q_d logarithm entropy range
3. q_d standard deviation	12. q_d skewness
4. q_d coefficient of variation	13. q_d slope changes
5. q_d variance	14. q_d waveform
6. q_d range	15. linear coeff. of linear trend
7. q_d interquartile range	16. independent coeff. of linear trend
8. q_d skewness	17. maximum spectral power
9. q_d kurtosis	

Sastre et al. – Optimal ANN Model

- Inputs: 17
- Hidden layers: 1
- Hidden layer nodes: 12
- Outputs: 1

Sastre et al. – Conclusions

- ANN Model performed well, with between 94% – 97% prediction accuracy.

- Future considerations:
  - Refine ANN model input parameters.
  - How will it be deployed?
  - Parsimonious model may lead to an equation.

Reminder

- Presentations at 1:45 – 3:15 pm in the Coolangatta Rooms 1 & 2