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Assessment of the spatial variability of a Croatian flood embankment using the cone penetration test

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ABSTRACT: Understanding how soil varies spatially is necessary in order to accurately quantify the reliability of geotechnical infrastructure. For long linear infrastructure such as flood embankments, incorporating vertical and horizontal scales of fluctuation can have a significant impact on stability assessments. This paper presents preliminary results and discussion from a field test designed to determine the vertical and horizontal scales of fluctuation of a Croatian flood embankment. A series of 15 CPTUs were carried out over a 200m length of the embankment with a Multi-channel Analysis of Surface Waves (MASW) survey done on the same section. CPT spacing was designed specifically to determine horizontal variation with multiple CPTs carried out in close proximity to each other. There was significant variation in soil stratigraphy over the embankment section with pockets of increased strength and stiffness showing up in the MASW and CPT results. This paper discusses dealing with horizontal correlation in challenging deposits and presents initial findings from the underlying sand layer.

1 INTRODUCTION

Soil properties vary as a function of space and time. Quantifying exactly how they vary is of upmost importance in determining the capacity of geotechnical structures(De Gast, Vardon and Hicks, 2020). This is particularly important for aged linear infrastructure, which underwent less rigorous design than its modern counterparts and has a lower safety margin as a result (Reale *et al.*, 2016; Reale, Xue and Gavin, 2017). It is infeasible and inadvisable to replace such infrastructure en-masse, moreover it is likely unnecessary given that the structures have remained stable so far. Instead, a better approach is to quantify the uncertainties present in the material in order to accurately assess the risk of failure. Such an approach could be applied consistently with a risk-based decision methodology to decide which assets to improve or replace (Reale, Xue and Gavin, 2016).

Random field theory considers soil properties at a given location as random variables. Within a zero mean stationary random field, the spatial variation between one point and another in the same structure can be described by their correlation structure. Statistically modelling spatial variability presumes a stationary random field. Such an assumption may be hard to achieve in reality given that soil is not really stochastic but it is convenient to model it as such, as information is limited(Phoon, 2008). If a dataset is not stationary, then estimation of soil statistics may be subject to bias. To prevent this, the dataset should undergo transformation to achieve stationarity, data decomposition is frequently adopted to this end. Phoon et al (2003) describe a modified Bartlett hypothesis test that can be used to check stationarity.

If one is concerned about the average properties within some volume of soil (e.g. the average shear strength or average resistance of a material) then areas of high value balance areas of low value so that the variance of the average goes down as the volume of soil mobilised becomes larger. Point variations such as those listed by (Phoon & Kulhawy, 1999) are typically much higher than spatially averaged variations. Spatial averaging therefore reduces uncertainty. The net result of which is lower failure rates which are more consistent with those observed in reality (Phoon, 2008). Depending on the scale of fluctuations involved spatial averaging can have a significant impact on the stability of linear infrastructure.

Random field theory has been successfully used to generate one dimensional, two dimensional and three dimensional geological models (Zhu and Zhang, 2013; Lloret-Cabot, Fenton and Hicks, 2014) and applied to various geotechnical

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problems such as bearing capacity of foundations (Fenton and Griffiths, 2003; Srivastava and Babu, 2009),water flow (Renato et al., 2006), two dimensional slope stability (Srivastava, Babu and Haldar, 2010; Santoso, Phoon and Quek, 2011; Tabarroki, Ahmad and Banaki, 2013; Li *et al.*, 2014), three dimension slope stability (Hicks and Spencer, 2010), scour (Prendergast, Reale and Gavin, 2018) and suction caisson design (Remmers *et al.*, 2019).

This study describes the initial findings from a series of CPTs investigating the horizontal and vertical variability of a flood embankment in Croatia, the findings will be utilised in a wider study to investigate the stability of the flood defenses and to assess their potential for liquefaction.

2 METHODOLOGY

Decomposition can be used to investigate a CPTs underlying spatial correlation structure where a trend function is fitted to and extracted from a dataset using least squares or some similar approach. This removes any underlying trend from the data leaving behind some fluctuating component. The correlation structure of this fluctuating component can then be determined.

After removing any discernible trend, the soil property (in this case q_c) for a normal distribution can be described by Equation 1.

$$q_c = \mu + \sigma\,\mathbf{G} \tag{1}$$

where μ is the mean value described at some depth z using Equation 2, σ is the standard deviation at the same depth and $\mathbf{G}$ is a matrix containing n spatially correlated normal random processes of zero mean and unit variance which account for the spatial correlation structure of the soil.

$$\mu(z) = a_i + b_i z \tag{2}$$

where a_i is the mean trends value at the beginning of the *ith* layer, b_i is the slope of the trendline in question and z is the depth.

After removing the linear depth trend of each q_c profile in the dataset, the standard deviation of the detrended tip resistances can be calculated. Dividing an individual detrended tip resistance by its respective standard deviation transforms the tip resistance variation into the standard normal space. i.e. it produces normal random fields with a mean of zero and a standard deviation of 1. Variations within these normal random fields can be used to estimate the spatial correlation structure $\widehat{\rho}(\tau_j)$ of the tip resistance with depth or horizontal distance, see Equation 3.

$$\widehat{\rho}(\tau_j) = \frac{1}{\sigma^2(n-j)} \sum_{i=1}^{n-j} (X_i - \mu)(X_{i+j} - \mu) \tag{3}$$

where $j = 0,1,\ldots, n\text{-}1$ with n being the number of data points, $\tau_j = j\Delta\tau$ is the lag distance between the two points in question where $\Delta\tau$ is the distance between two adjacent points, μ is the estimated mean, σ is the standard deviation and X is the random soil property in this case tip resistance. A Markov correlation function (Lloret-Cabot, Fenton and Hicks, 2014; Kasama and Whittle, 2015) was used to approximate the spatial correlation structure, see Equation 4. It is important to note, that many correlation functions exist and the choice of correlation function will depend on the goodness of fit achieved with the underlying correlation structure. The scale of fluctuation θ, is varied until the correlation structure obtained from Equation 3 is described by the correlation function i.e. until the difference between $\hat{\rho}(\tau)$ and $\rho(\tau)$ is negligible.

$$\rho(\tau_j) = \exp\left(\frac{-2|\tau_j|}{\theta}\right) \tag{4}$$

For horizontal spatial variation the Equation 4 holds except there is a greater distance between measurement points and the spacing between points is unlikely to be uniform. In practice this complicates the process as it becomes difficulty to determine when like is being compared with like. The authors compared the top of the sand layer in each CPT as if they occurred at the same depth and determined horizontal correlations across CPT using a 1m moving window therein.

3 TEST SITE

The CPT test location is located next to a embankment in central Croatia, in Orle Municipiality, around 25 km from Zagreb. The embankment is part of a flood defence network which protects the wider area from the influence of the Odra and Sava rivers. CPTs were performed over a 200m length at the following spacings [0 m, 2 m, 5 m, 10 m, 25 m, 50 m, 75 m, 100 m, 125 m, 150 m, 175 m, 190 m, 195 m, 198 m, 200 m], see Figure 1, to a depth of 15 m. The first soil layer at the site was a clay of variable thickness, with deeper deposits of between 7m and 8m found on either end of the 200m test length. Layer thickness reduced to approximately 2m in the middle of the test length. Underneath the clay was a dense sand deposit to great depth. The full set of CPT traces demonstrated a lot of variability, particularly within the sand layer and at transition depths, see Figure 2.

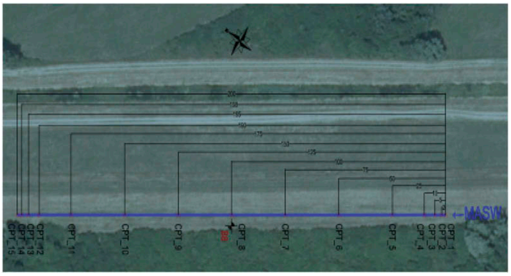

Figure 1. CPT traces and MASW were performed along the blue line adjacent to the embankment.

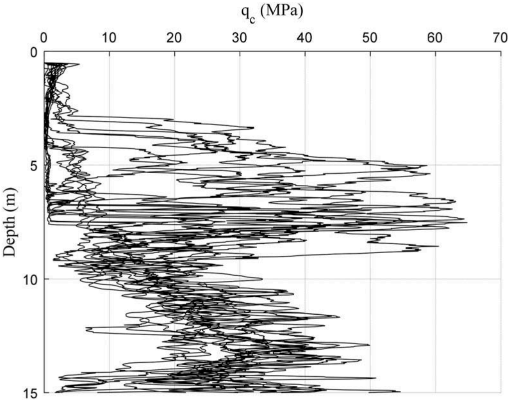

Figure 2. 15 CPT traces across the site.

Multi-Channel Analysis of Surface Waves (MASW) was also performed at the site, see Figure 3, which corroborated the assumed stratigraphy showing deeper deposits of low shear wave velocity at either end of the test length. The presence of localized deposits of increased stiffness can also be seen within the sand layer, demonstrating the variability of the material.

Due to the complex layering present in the upper clay layer the initial spatial variability interrogation is focused in the lower sand layer from a depth of 10 to 15m where the soil behaves more consistently across the site, see Figure 4.

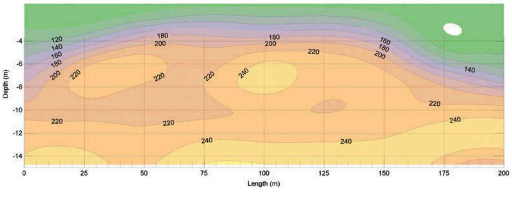

Figure 3. Shear wave velocities from MASW performed at the site, demonstrating the variability in the depth of the sand layer across the site.

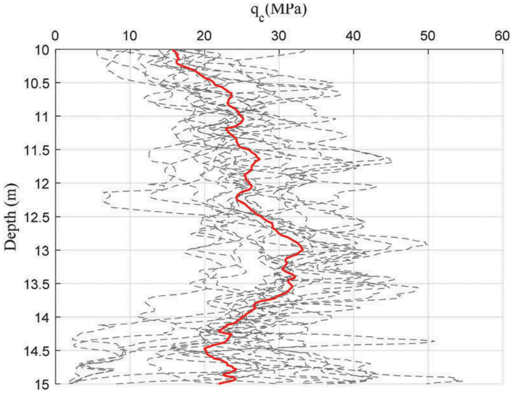

Figure 4. CPT traces from 10 to 15m with the mean qc profile shown in red.

4 RESULTS

The CPT traces in the lower sand layer were detrended, normalised and the underlying correlation structure was determined using the procedure described in section 2. Equation 4 was then fitted to the underlying structure by optimizing the scale of fluctuation. The vertical scale of fluctuation θ_V was found to be 0.82 m with the 95% confidence intervals ranging from 0.78 m to 0.85 m. A strong goodness of fit with achieved using the Markov correlation function with an R-square of 0.9358 and an RMSE of 0.0528.

The same procedure was followed for horizontal correlation with intermediate points interpolated to facilitate curve fitting. Initial results indicated that the horizontal scale of fluctuation was approximately 8.39 m with a 95% confidence interval range of 7.45 m to 9.33 m.

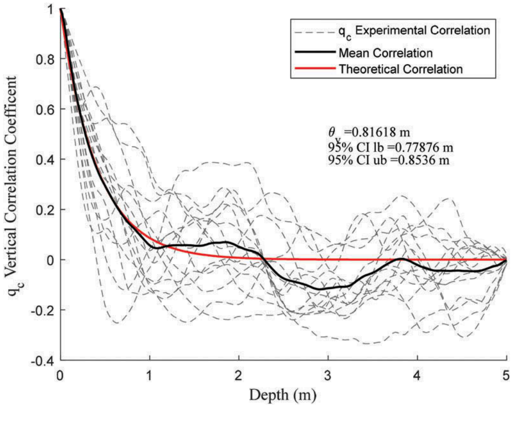

Figure 5. Vertical correlation structure found in the lower sand layer.

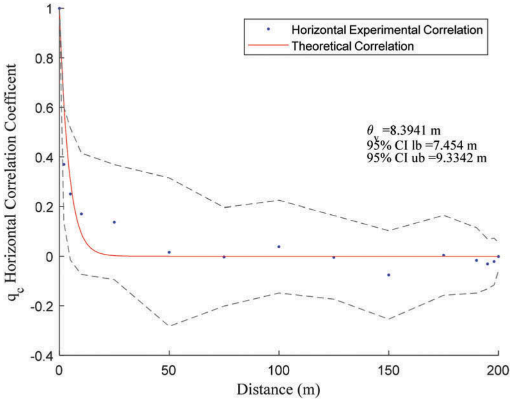

Figure 6. Initial horizontal correlation structure found in the lower sand layer.

5 DISCUSSION AND CONCLUSIONS

This paper presents initial results from a site investigation to investigate spatial variability in Croatia. Initial work was focused on the underlying sand layer which behaved more consistently than the finer surface deposits. Initial results suggest than horizontal variability is an order of magnitude greater than the vertical variability. However significant uncertainty exists in determining the horizontal correlation structure. One issue stems, from the variability in layer depth across the site, as the boundary of the sand layer is inclined. This makes it difficult to correlate “like with like” across the site as merely correlating CPTs at the same depth could result in correlating across layer boundaries. To overcome this the authors considered the top of the sand layer in each CPT as the start point of the analysis and used a moving window of 1m to determine horizontal correlations below those point. As there is no continuous measurement in the horizontal direction, there needs to be a methodology to ensure that the correct data is being used to determine the mean autocorrelation behavior horizontally. Different averaging procedures will be investigated, while different window sizes to determine the effect of sample size on scales of fluctuation. The analysis will also be rerun to consider the start point at intermediate CPT locations to check consistency across the site. Some consideration also needs to be paid to stationarity. This is difficult to ensure in the vertical direction, but much more so in the horizontal direction where there are much more limited discrete measurement points which makes the implementation of stationarity checks such as Bartlett statistics challenging. This will be investigated moving forward.

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