

Interpretation of CPTU Tests with Statistical and Geostatistical Methods

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Abstract. In the paper statistical methods for the interpretation of CPT data for the definition of subsoil stratigraphy have been applied to a subsoil CPTU data set of the Italian Center of Aerospace Research (CIRA) in Capua (Italy). Results obtained by following the method proposed by Wickremesinghe and Campanella (1991) have been compared with those obtained by a geostatistical method recently proposed by Spacagna (2014), based on the spatial variability analysis of CPTU data. The latter results showed a more detailed definition of the transitions between different subsoil layers along the investigated vertical axes.

Keywords. CPTU, geostatistical analysis, soil classification.

1. Introduction

The identification of homogeneous soil layers is a fundamental step for geotechnical characterization of soil. The operation is based on the interpretation of data coming from different sources, being the comparison between borehole logs and cone penetration test results one of the most diffused and sound. Nevertheless, this deterministic approach suffers the subjectivity of the interpretation of available data.

The statistical analyses developed over the years allow a less subjective interpretation of subsoil data. In cone penetration testing the continuous measurements of cone resistance q_c , sleeve friction f_s , and pore pressure u with depth allow a statistical treatment of results finalized to the identification of lithological discontinuities and the reconstruction of the stratigraphic profiles (Lo Presti et al., 2009). The test proposed by Wickremesinghe and Campanella (1991), based on the introduction of the intraclass correlation coefficient, has been used by several authors (Herzagy et al., 1996; Zhang and Tumay, 1996). Phoon, Quek, and An (2003) proposed a statistical method based on the modified Bartlett test and

introduced the spatial correlation of data. Kurup and Griffin (2006) proposed the use of artificial neural networks for soil classification while Jung, Gardoni, and Biscontin (2008) suggested a probabilistic based approach. Recently Wang et al. (2013) developed a Bayesian method. Uzielli (2008) studied the range and coefficient of variation of the normalized cone resistance Q_t , the ratio between the cone resistance and the normalized lateral resistance F_r , and the ratio of pore pressures B_q (Robertson and Cabal, 2010).

In the paper the subsoil data of the site of the Italian Center of Aerospace Research (CIRA) situated in Capua, Italy, have been analyzed by means of two different methods, namely the statistical method proposed by Wickremesinghe and Campanella (1991) and a geostatistical method proposed by Spacagna (2014). The latter method provides a more accurate interpretation of the cone penetration tests taking into account the spatial correlation of the measured values. The results arising from the two approaches have been finally compared and discussed in detail.

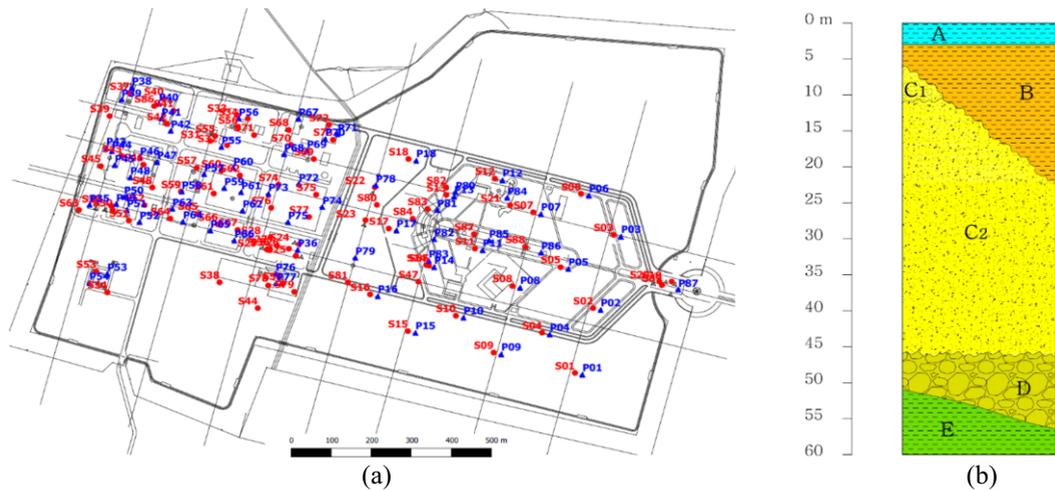


Figure 1. a) Plan of the investigations performed at CIRA site (Boreholes: S, CPT/CPTU: P), b) Litho-stratigraphic column: (A) alluvial sandy silt; (B) clayey silt and peat; (C1) volcanic sand (eruption of Neapolitan Yellow Tuff); (C2) Ash and pumice (eruption of Campanian Ignimbrite); (D) Sand and gravel, (E) marine silty sand.

2. Case of Study

The Italian Center of Aerospace Research (CIRA) situated in Capua (Italy) is a flat area of approximately 2 km² located in the plain of the Volturno River, at the edge of the great tectonic depression of the Campania Plain. Several volcanic events have modified the structure in the last 50,000 years, affecting the topography and relief within the area. The main products of the volcanic activity are the Ignimbrite Campana (32,000 years ago) and the Neapolitan Yellow Tuff (18,000 years ago), as indicated in the formation C₁ and C₂ in Figure 1.b. The marshy environment formed later was gradually drained from the Volturno River, which has generated a sedimentation with an ever greater energy, locally covering the area by recent alluvial materials, referred to as A and B formations in Figure 1.b.

A large campaign of in situ investigations was performed at the design stage for the subsoil characterization of the large area (Figure 1.a). 88 boreholes, 56 CPT and 15 CPTU were executed aimed at investigating strata within about 45 meters from the ground surface. The large number of data available favoured the application of statistical methods for the stratigraphic analysis of the subsoil model.

3. Statistical Method (Wickremesinghe and Campanella, 1991)

The method proposed by the Authors is based on the Student test aimed to the verification of equality of the means, according to the procedure shown in Figure 2. With reference to the relevant parameters of CPTU test (cone resistance, q_c , lateral resistance, f_s and pore pressure, u) along the vertical axis, a window W_{d_0} is centered around the point d_0 . The depth where the point d_0 is located has been hypothesized as the transition between two different lithological layers. The opening of the window W_{d_0} includes two subsets of data, namely Ω_1 and Ω_2 , with size respectively equal to n_1 and n_2 , average \bar{Q}_1 and \bar{Q}_2 and variance σ_1^2 and σ_2^2 .

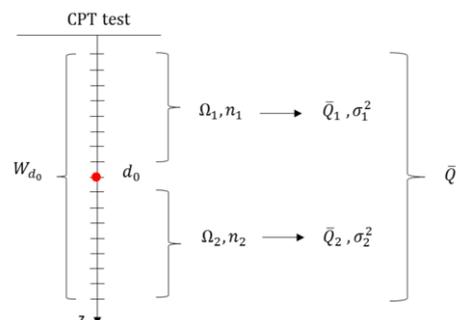


Figure 2. Definition of the two subsets of relevant parameters along the vertical axis of CPTU test

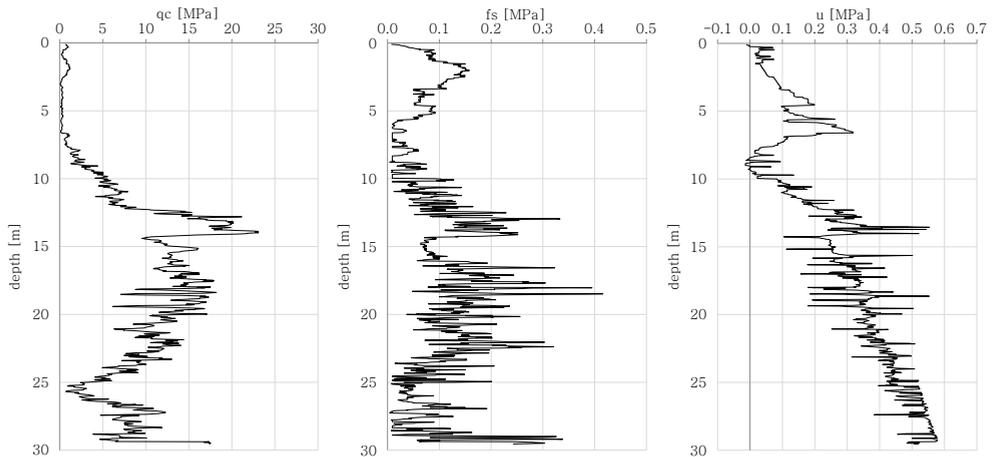


Figure 3. CPTU46: cone resistance q_c , sleeve friction f_s and pore pressure u

The value of the Student parameter T is defined in the Eq. (1), as suggested by Webster and Beckett (1968):

$$T = \frac{\bar{Q}_1 - \bar{Q}_2}{\gamma_w} \sqrt{\frac{n_1 n_2}{n_1 + n_2}} \quad (1)$$

where

$$\gamma_w = \frac{n_1}{n_1 + n_2 - 1} \sigma_1^2 + \frac{n_2}{n_1 + n_2 - 1} \sigma_2^2 \quad (2)$$

$$\sigma_1^2 = \frac{1}{(n_1 - 1)} \sum_{i=1}^{n_1} (Q_i - \bar{Q}_1)^2 \quad (3)$$

$$\sigma_2^2 = \frac{1}{(n_2 - 1)} \sum_{i=1}^{n_2} (Q_i - \bar{Q}_2)^2 \quad (4)$$

The intraclass correlation coefficient ρ_f is calculated using Eq. (5).

$$\rho_f = \frac{\gamma_b^2}{\gamma_b^2 + \gamma_w^2} \quad (5)$$

The variance between class γ_b^2 is defined by the Eq. (6):

$$\gamma_b^2 = \frac{1}{n_1 + n_2 - 1} \sum_{i=1}^{n_1+n_2} (Q_i - \bar{Q})^2 \quad (6)$$

where \bar{Q} is the average of the data Q_i belonging to the window w_{d_0} , with $i=1,2, \dots, (n_1 + n_2)$.

The defined parameters are calculated for each couple of subsets obtained by the translation of the window W_{d_0} along the vertical axis. For each point d_0 the value of the parameters T and ρ_f are then evaluated. Two new profiles are then available, namely the T and ρ_f profiles with depth. Along the new two profiles, higher values correspond to possible changes of the lithological strata.

The window W_{d_0} should contain possibly only one change of subsoil layer, and therefore its amplitude cannot be chosen arbitrarily. If W_{d_0} was too wide, more of one change of layer could be included in the selected window; on the opposite, a small amplitude of the window W_{d_0} does not provide enough data for a reliable statistical inference. Webster (1973) suggested a size of the window equal to two-thirds of the expected distance between different layers of the subsoil, while Wickremesinghe and Campanella (1991) considered the 2/3 of the spatial autocorrelation of the data as the reference amplitude of the window. In particular, the distance of autocorrelation is determined as the first relative minimum of the autocorrelation function.

Following the suggestions of the latter Authors, the statistical method has been applied to CPTU 46 results (Figure 3) of the CIRA site, in terms of the three relevant parameters q_c , f_s and u . The amplitude of the window W_{d_0} has been evaluated as equal to 1.32 m, that is 2/3 of the correlation distance of 2.00 m, being the

value as the minimum correlation distance evaluated from the autocorrelation functions q_c , f_s and u analyses shown in Figure 4. The results showed that the univocal choice of the minimum value of the autocorrelation function is not clear, therefore introducing a subjective evaluation in the choice of the correlation distance. In Figure 5 the profiles of the parameters T and ρ_l for q_c , f_s and u , have been showed with reference to the amplitude equal to 1.32 m of the window W_{d0} . The detection of the layer change is not straightforward, as highlighted by the results. Wickremesinghe and Campanella (1991) considered a transition between different layers only when the evaluated variable showed simultaneously a peak along the profile with depth. The mentioned condition is not occurring systematically from quantitative point of view, introducing then a subjective amount of judgment in the interpretation of the results.

4. Geostatistical Approach

As the cone resistance q_c is related to the type of soil, it may be assumed that resistance values of the cone resistance measured at different depths within the same layer of soil present similar values. It is possible to define a spatial structure (i.e., dependency between value measured and position in space) of the measured variable with depth, to be analyzed by means of variograms (Chiles and Delfiner, 1999). Along the entire vertical profile of the CPTU the experimental variogram of cone resistance q_c was calculated, as shown in Figure 6.

Considering the variogram for couples of measure points at distance lesser than 3.00 m (Figure 6), it has been observed that the function is well interpolated by a spherical model characterized by a sill equal to 1.80 m

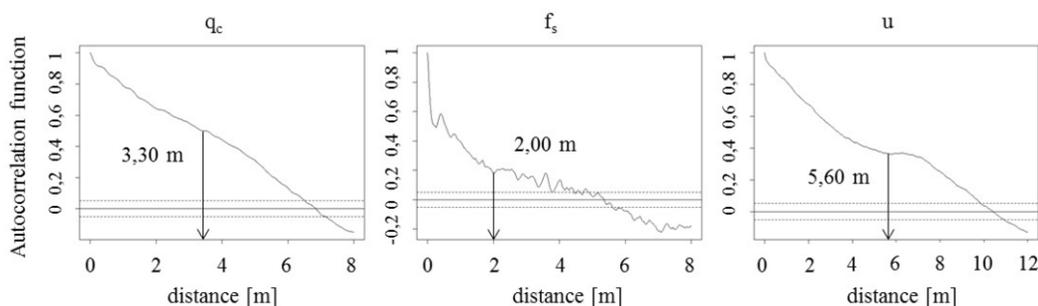


Figure 4. CPTU46: autocorrelation function of cone resistance q_c , sleeve friction f_s and pore pressure u

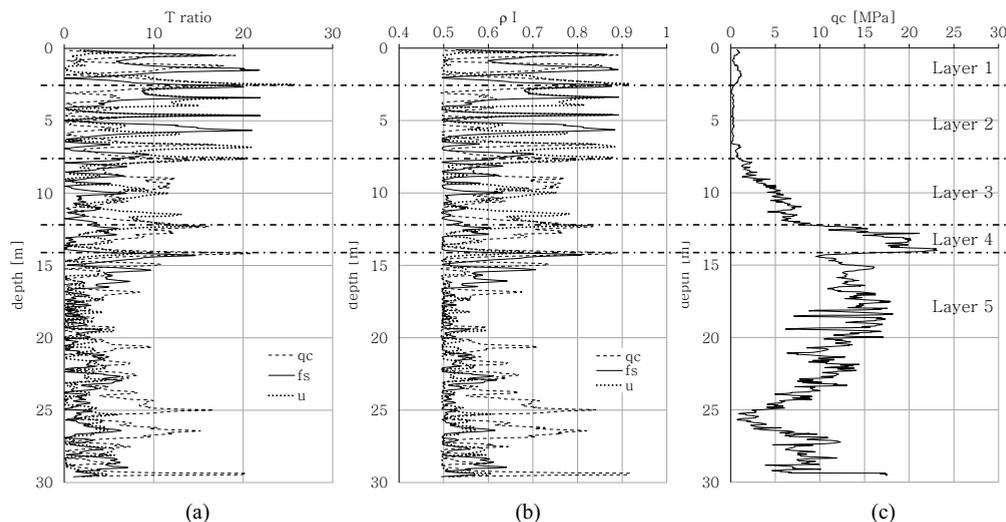


Figure 5. CPTU46: profiles of T ratio (a) of ρ_l (b), and q_c and interpretation of the results (c)

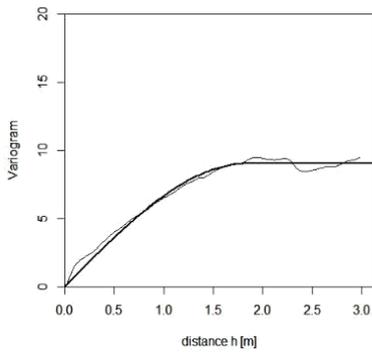


Figure 6. Experimental and theoretical variogram of the cone resistance q_c of CPTU 46.

The measured variable is then spatially correlated if the measure points were distant not more than of 1.80 m. This distance allows the proper definition of the W_{d0} window of the statistical test proposed by Wickremesinghe and Campanella (1991).

The profiles of parameters T and ρ_I were then recalculated along the depth. The critical values of the parameters T and ρ_I allowing to identify possible changes of layer of soil were recalculated as well. The critical value of the parameter T was evaluated by performing goodness of fit tests (Kolmogorov-Smirnov test), in order to check the normality of the distribution. The critical value of the parameter

T was calculated as follows:

$$t_c = \mu_{T_{ratio}} \pm 1,65 \sigma_{T_{ratio}} \tag{7}$$

where $\mu_{T_{ratio}}$ and $\sigma_{T_{ratio}}$ are respectively mean and standard deviation of the normal distribution of the variable T. The critical value of the intraclass correlation coefficient ρ_I was also calculated using the relation (Eq. (8)) proposed by Herzagy, Mayne, and Rouhani (1996).

$$\rho_I^c = \mu_{\rho_I} \pm 1,65 \sigma_{\rho_I} \tag{8}$$

where μ_{ρ_I} and σ_{ρ_I} are respectively the mean and standard deviation of the normal distribution of the variable ρ_I .

Figure 7 shows the T and ρ_I profiles for the CPTU46 test as calculated for a width of the window W_{d0} equal to 1.80 m. The transition between different subsoil layers was identified for critical values of T and ρ_I respectively equal to 13.52 and 0.78.

The comparison between the results obtained by the method of Wickremesinghe and Campanella (1991) with the proposed method has been shown in Figure 8.a and b. The higher definition and frequency of the

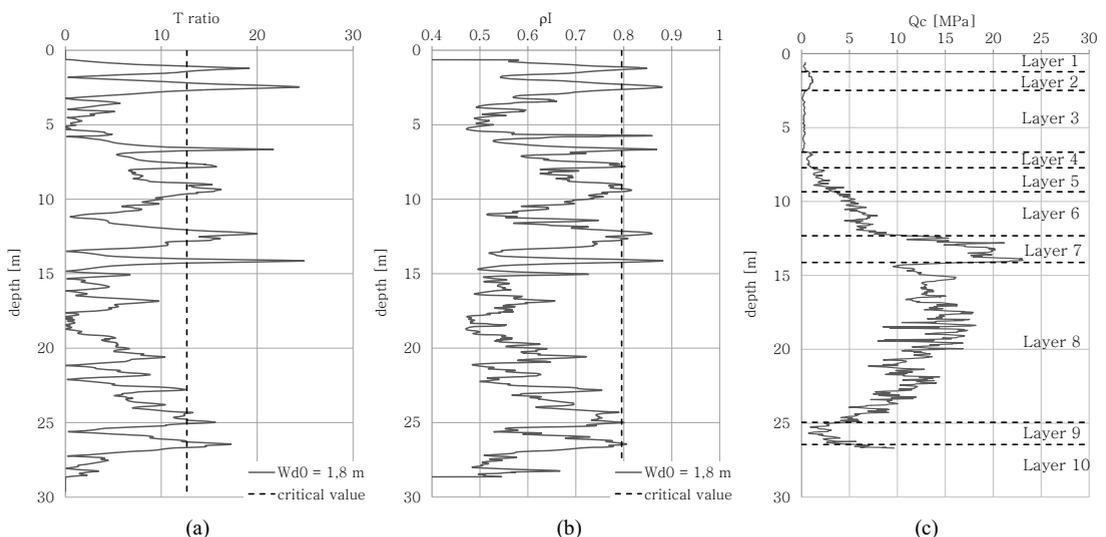


Figure 7. CPTU46: profiles of T ratio (a), ρ_I (b) and q_c and interpretation of the results (c) of the geostatistical approach

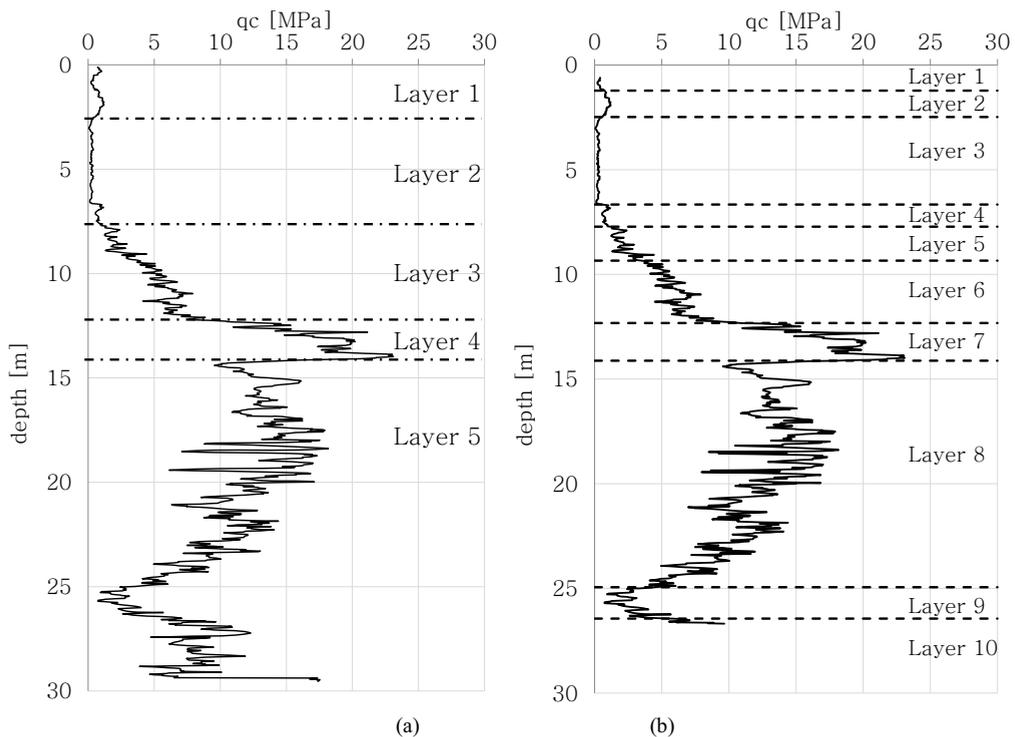


Figure 8. Interpretation of CPTU46: statistical approach (a), geostatistical approach (b)

transitions between layers of different lithology is evident for the proposed method, as highlighted by identification of 10 layers along the inspected depth instead of 5 layers identified by the statistical approach. The significance of this result is related to the range of the spatial correlation of the data. Significant results were also obtained for other CPTU tests available for the CIRA site (Spacagna, 2014).

5. Conclusions

In the paper a brief review of the statistical methods for the interpretation of CPT data for the definition of subsoil stratigraphy has been reported. The method proposed by Wickremesinghe and Campanella (1991) has been applied to a subsoil CPTU data set of the Italian Center of Aerospace Research (CIRA) in Capua (Italy). The results have been compared with those obtained by a geostatistical method recently proposed by Spacagna (2014), based on the spatial

variability analysis of CPTU data along the investigated vertical axes. The latter method showed a more detailed definition of the transitions between different subsoil layers. The detailed identification of different layers along the investigated vertical should be considered in the definition of subsoil geotechnical model for design purposes. The transition between layers, based on the variation of mechanical properties of the strata (i.e., cone resistance), add relevant and objective information to the investigated subsoil profile.

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