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Study on spatial variability of soils and load-bearing capacity of drilled shafts in lateritic ground

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Article

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Abstract

The natural variability of soil, influenced by weathering, human activity, and geological formation processes, is a critical factor in geotechnical engineering. This variability introduces significant uncertainty, particularly in the design of deep foundations, where the complex interaction between soil and structures, combined with varying geological conditions, complicates the prediction of structural behavior. However, focusing on deep foundations, this study examines soil property variability in southern Brazil. Standard penetration tests and slow static load tests were conducted to estimate pile load-bearing capacities. A reliability assessment method was employed to evaluate the accuracy of different prediction techniques, with results compared against load-settlement test data. Findings reveal significant discrepancies between prediction methods, with longer piles satisfying safety requirements, while shorter piles showed higher variability and did not meet the same safety standards. This research highlights the importance of incorporating soil variability and probabilistic analysis into foundation design to enhance reliability and safety.

1. Introduction

The soil can be considered a material that naturally exhibits variability inherent to its properties, attributed to the formation process and ongoing processes that alter them, like weathering, chemical transformations, the incorporation of foreign substances, and, in certain situations, human involvement (Phoon et al., 2006). This variability leads to spatial differences in geotechnical properties across various locations, representing a significant uncertainty source (Baecher & Christian, 2003). Principal sources of geotechnical uncertainty include inherent soil variability, where geological processes continuously modify the soil mass in its original location, measurement error resulting from equipment and operational procedures, and transformation uncertainty (Phoon & Kulhawy, 1999).

Layers of soil that are relatively homogeneous may present variation in geotechnical properties from point to point, a phenomenon referred to as inherent or spatial variability (Forrest & Orr, 2010). From this perspective, Phoon et al. (2016) indicates that characterizing geotechnical variability is critical in the reliability-based design process. Furthermore, Phoon & Tang (2019) suggest that this condition is associated with two key features: (1) coefficient of variation (COV) and (2) multivariate correlation. According to Phoon & Kulhawy (1999), the COV values reported in technical literature may significantly exceed the true inherent variability of soil due to four potential issues: mixing soil data from different geological units, inadequate equipment and procedure controls, failure to remove deterministic trends in soil data, and soil data collection over an extended period. The second key feature indicates that the reduction of transformation uncertainty of a specific geotechnical parameter, whether rock or soil, can be explored through multivariate correlation (Ching & Phoon, 2012).

Given the inherent complexity of geotechnical parameters, there is a noticeable trend toward the increased use of probabilistic analyses in cases involving field tests (Han et al., 2022; Lu et al., 2022), shallow foundations (Han et al., 2023; Shin et al., 2023; Fenton et al., 2007; Papaioannou & Straub, 2017), and deep foundations (Cherubini & Vessia, 2010; Crisp et al., 2022; Klammler et al., 2011; Nanazawa et al.,

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2019; Wang & Cao, 2013). This article focuses on evaluating deep foundations, where the complexity of predicting structural behavior is emphasized due to intricate soil-structure interactions, highly variable geological conditions, and the impacts of construction processes (Phoon & Tang, 2019).

Two main approaches can be identified in the context of load-carrying capacity predictions based on field test results (Abu-Farsakh & Titi, 2004). The direct approach involves directly utilizing field test data to evaluate bearing capacity. In contrast, the indirect approach depends on semi-empirical or theoretical methods to estimate soil strength parameters, subsequently used to determine the pile's unit end-bearing resistance and skin friction. Various empirical and semi-empirical methods have been developed to address the challenges associated with the indirect approach. These methods often incorporate conservative assumptions and simplify physical and geometric factors to facilitate analysis (Dithinde et al., 2016).

Abu-Hejleh et al. (2015) emphasize three elements for an enhanced foundation design: (1) analysis of geotechnical parameters in the database, (2) proper evaluation of load test trials, and (3) comparison of measured and predicted load capacity. The first topic is intricately linked to geotechnical investigation and the determination of site variability, which arises due to the presence of subsurface soil or rock deposits that vary geologically across the project site in terms of layer thickness, loading history, and geotechnical properties (Abu-Hejleh et al., 2010). The second topic is referred to as load testing, a direct method for assessing the ultimate load capacity of a foundation element; it presents some inherent uncertainties, such as the testing procedure (e.g., slow loading, dynamic testing), measurement techniques, and interpretation of results (Lesny et al., 2017). These uncertainties directly impact the performance of specific geotechnical structures. Consequently, by incorporating these sources into the calculation procedure, it becomes feasible to quantify the reliability index (β) and, consequently, the Probability of Failure (*PF*).

This study aimed to characterize the variability of theoretically homogeneous soil in Cruz Alta, southern Brazil. Standard Penetration Test (SPT) assays were conducted over a 79 km^2 area, covering the urban zone of the city. It is noteworthy that soil profiles are typically assessed through SPT (Santos et al., 2022; Santos & Coutinho, 2023). Additionally, slow static load testing was performed on bored pile foundations with 3- and 6-meters lengths. The predicted load-bearing capacity was obtained using semi-empirical methods that utilize input data derived from the SPT assay. Subsequently, this paper applies the First-Order Reliability Method (FORM) to determine the β values of bored pile foundations using different criteria for estimating load-bearing capacity derived from load-settlement curves obtained from slow static load testing. The application of the FORM is well-founded, as it has consistently proven to be a highly effective approach for probabilistic design in geotechnical engineering practice (Giacon Junior et al., 2019; Golafzani et al., 2020a; Nogueira et al., 2022).

2. Characteristics of the studied area

Cruz Alta encompasses an area of approximately 1360.55 square kilometers, with an estimated population of 58,913 habitants, according to the Brazilian Institute of Geography and Statistics (IBGE, 2024). Geologically, Cruz Alta is situated at the boundary between the Tupanciretã and Serra Geral formations, the latter represented by the Gramado Facies. The predominant soil type is Red Latosol, which has developed through the weathering of rocks from the Serra Geral Formation. In essence, the subsurface composition of the municipality primarily consists of basalt rock, which has contributed to the formation of this Latosol. Basalt is a volcanic-origin rock rich in primary minerals such as iron, calcium, and magnesium. The strength of the lateritic soil deposits in Cruz Alta was assessed using the SPT, with a total of 43 tests performed between 2013 and 2023. Figure 1 illustrates the study area's location map and the borehole sites. It is noted that most tests were concentrated in the municipality's central region. The geographic grid utilized is sourced from the website of the Brazilian Institute of Geography and Statistics (IBGE, 2024).

3. Characterization of N value

3.1 Spatial variability

The spatial variability of soil represents a significant source of uncertainty within geotechnical engineering (Baecher & Christian, 2003; Guo et al., 2023). Considering this premise, spatial variability becomes essential. The spatial variability of SPT results was evaluated. Figure 2 presents the values of *N* (penetration resistance index) at different depths. Given the quantity of available data, the *N* values were estimated in locations where data were unavailable through interpolation using a spatial correlation technique known as kriging. This approach is a weighted moving average interpolation procedure aimed at minimizing the estimated variance of the interpolated value by weighting the average of the values of its neighbors (Phoon et al., 2006). The input data for the geostatistical calculation consisted of the *N* values at each depth and their corresponding spatial locations. It is pertinent to mention that the contour lines shown correspond to the municipality's urban grid. The soil in question is affiliated with a red latosol, or lateritic soil, prevalent throughout the analyzed region (Falcão et al., 2023). Generally, at a depth of 1 meter, the *N* values remain below 3, barring select locations where this figure drops below five blows. As depth increases, *N* values tend to rise, particularly in regions characterized by lower elevations, where they exhibit diminished *N* values. At a depth of 9 meters, the *N* values remain relatively low, not exceeding

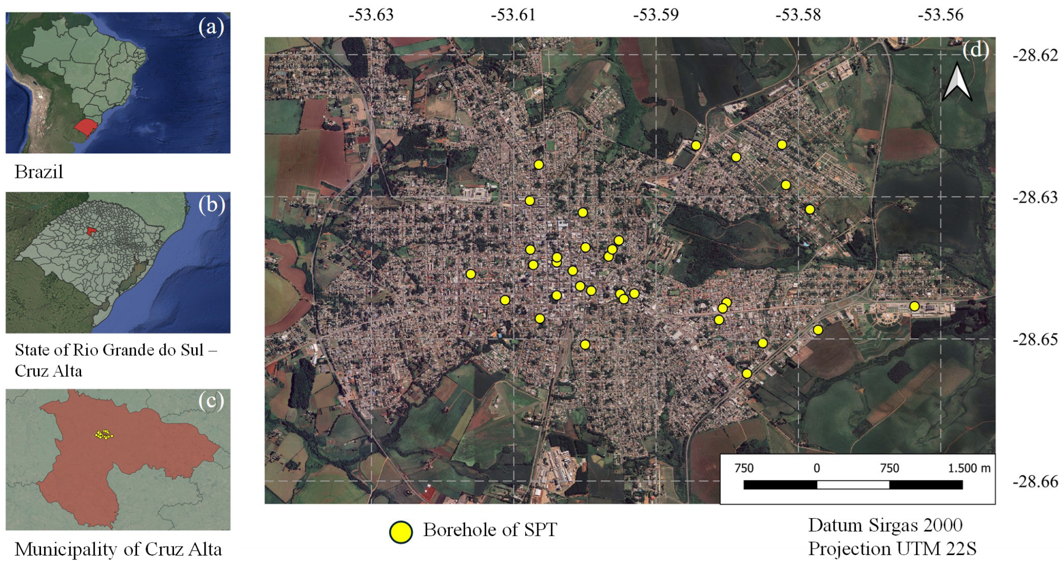

Figure 1. Location and spatial distribution of the SPT boreholes in Cruz Alta. (a) Brazil highlighting the state of Rio Grande do Sul; (b) Rio Grande do Sul highlighting the municipality of Cruz Alta; (c) Administrative boundaries of Cruz Alta with indication of the study area; (d) Satellite image of Cruz Alta showing the SPT borehole locations (yellow dots).

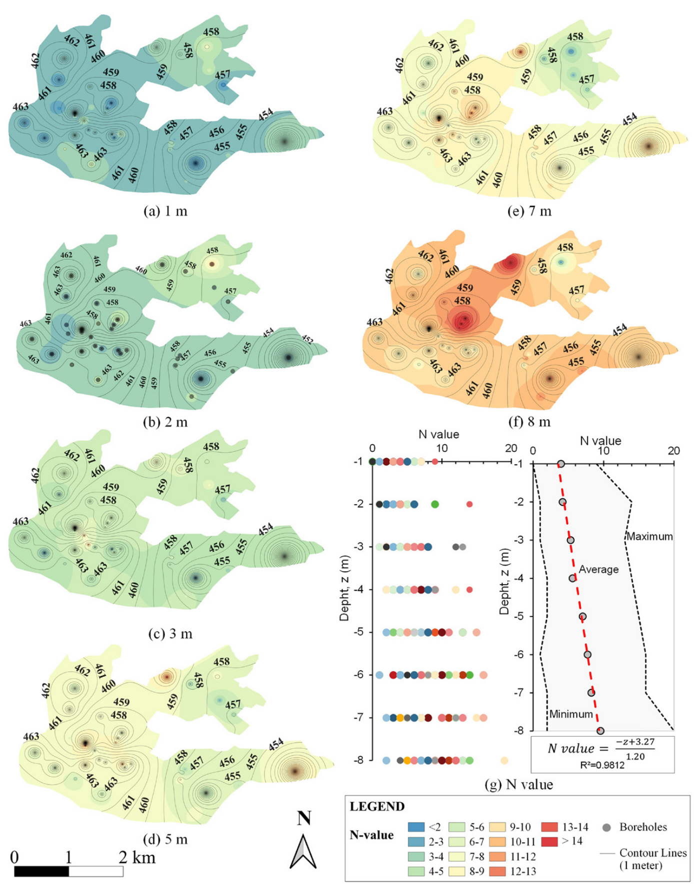

Figure 2. Spatial and vertical distribution of SPT N-values in Cruz Alta. (a)–(f) Interpolated N-value maps at depths of 1 m, 2 m, 3 m, 5 m, 7 m, and 8 m, respectively, generated by kriging. (g) Depth profile of N-values: left – discrete values per borehole; right – minimum, average (red dashed line), and maximum values with depth.

15 blows. In all borehole reports, the soil was classified as reddish clayey through tactile-visual identification. There is a high dispersion of data; however, it is notable that *N* values are relatively low in the initial meters of depth, indicating a low bearing capacity of the soil under these conditions.

Additionally, an examination of the average *N* values was performed. For this condition, there is a clear trend of linear growth in the average *N* value with depth, with an R^2 value of 0.9812 obtained through linear regression. It should be noted that the coefficient of determination (R^2) indicates the proximity of the measured points to the regression line fitted by the model. Given that the R^2 value was close to 1.00, the analysis supports the theory that there is a statistical relationship among the data.

Figure 3 presents histograms of *N* values with depth. At certain depths, such as 1 m, the *N* value exhibited very low variability, with a high frequency of identical readings. This condition limits the applicability of the lognormal model, which requires positive-valued, right-skewed continuous data with some degree of dispersion. Nonetheless, the lognormal distribution was also fitted to the data at each depth, allowing for comparison with the normal distribution model. The variability observed in the dataset is partly attributed to the predetermined criteria for test termination. Up to a depth of 6 meters, data from 43 borehole logs were analyzed. This number decreases to 29 to 7 meters and further reduces to 28 to 8 meters. *N* values across the analyzed depth range were relatively low, with minimum values ranging from 0 to 2 blows and maximum values from 9 to 39 blows. This behavior is consistent with typical lateritic soils, which tend to exhibit low *SPT-N* values in the upper layers due to their high porosity (Conciani et al., 2023). Analysis of the sample standard deviation (Std Dev) revealed substantial variability, with coefficients of variation (*COV*) ranging from 47.70% to 60.91%. According to Phoon et al. (2006), the typical *COV* range for *N* values lies between 25% and 50%, which is lower than the values obtained in this study. Given the low stratigraphic heterogeneity observed in the SPT results, the variability in N values is likely attributable to human factors and to the temporal conditions under which the tests were performed, as they were conducted over ten years (2013 to 2023). According to Carvalho & Gitirana Junior (2021), in unsaturated soils, temporal factors play a significant role, as variations in moisture content—and consequently in soil behavior—are common over time.

Figure 4 shows the groundwater level identified during the SPT investigations, as well as the estimated values at locations without direct measurements, obtained through

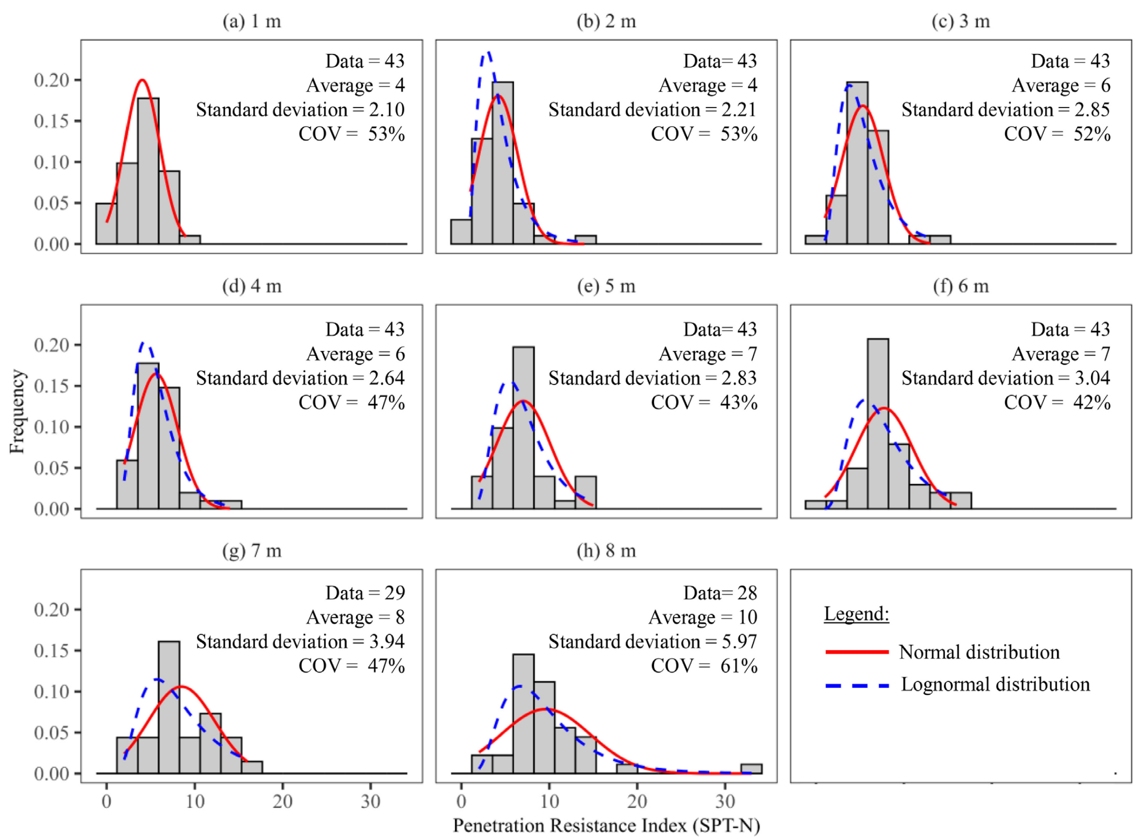

Figure 3. Histograms of *SPT-N* values at different depths, with fitted probability distributions. (a)–(h) Frequency distributions of N-values at depths from 1 m to 8 m, respectively. Each plot shows the histogram of observed data, along with the fitted normal distribution (red solid line) and lognormal distribution (blue dashed line).

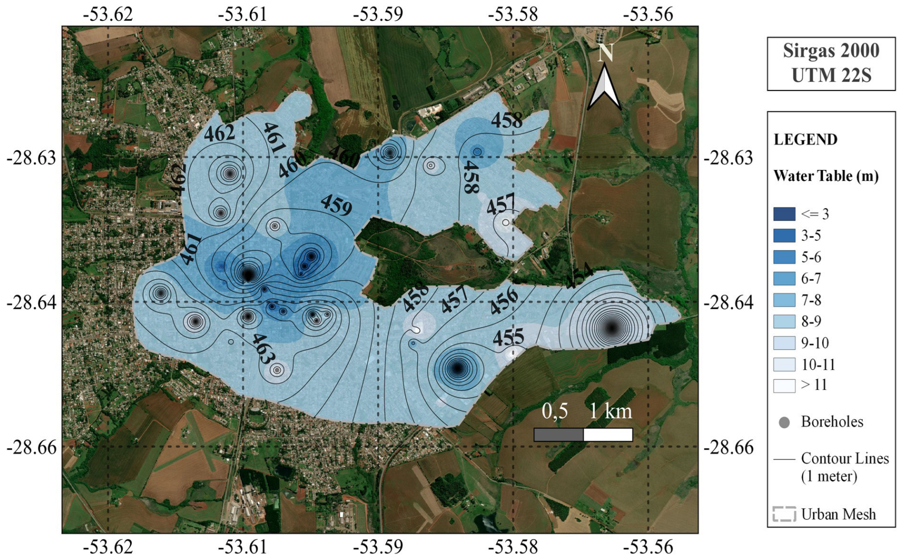

Figure 4. Spatial distribution of groundwater level in the study area.

spatial correlation techniques. The groundwater depth ranged from 3 to 11 meters, with most values concentrated between approximately 8 and 10 meters. In certain areas, however, the water table was identified at shallower depths, between 3 and 5 meters. It is important to note that the water level is directly influenced by local topographic elevation, which helps to explain part of the observed spatial variability. Figure 4, by illustrating the spatial variability of the groundwater level, supports the interpretation of the *N*-value dispersion shown in Figure 3. Before analyzing this dispersion in detail, it is important to highlight that Falcão et al. (2023) conducted SPTs with and without water circulation in soils from the same region and observed that the addition of water during testing resulted in lower *N*-values. This behavior helps to explain the broader range of variability found in the present study, which exceeds the typical dispersion commonly reported for SPT data. Sales et al. (2023) also confirmed that increased moisture content in lateritic soils tends to reduce *N*-values, further supporting this interpretation. Even so, significant differences are reported in the literature. For example, Uzielli et al. (2007) reported a *COV* of approximately 30%, Harr (1987) indicated a range between 15% and 45%, and Kulhawy (1992) suggested typical values between 25% and 50%.

3.2 Outliers

In geotechnical datasets, extreme values that deviate significantly from the general trend—referred to as outliers—are often encountered. These values may affect statistical modeling by introducing bias in parameter estimation and can result from human error, equipment limitations, or natural variability (Phoon & Tang, 2019). For geotechnical applications, literature reviews recommend robust detection methods such as box plots based on the interquartile range (IQR) and median-based rules, rather than approaches based on standard deviation, due to data skewness and small sample sizes (Dastjerdy et al., 2023).

In the present study, outliers were identified using the box plot shown in Figure 5. The data at 2 m and 3 m depths exhibit approximately symmetric distributions, with the median located near the center of the box. At 1 m and 8 m, the distributions are positively skewed, as the median lies closer to the upper quartile. Conversely, from 4 m to 7 m, the data exhibit slight negative skewness, with the median approaching the lower quartile. Outliers were identified at all depths except 7 m, with the most extreme deviations occurring at 6 m—both below the lower whisker and above the upper whisker.

Considering the large number of valid measurements and the known influence of temporal variability and execution conditions on SPT results, these outliers were interpreted as part of the natural variability of the dataset rather than measurement errors. However, for the probabilistic bearing capacity analysis, they were excluded to improve statistical consistency and avoid distortions in parameter estimation. This procedure is consistent with statistical best practices, which recommend trimming or winsorizing outliers when they reflect genuine variability but may adversely affect model performance (Kwak & Kim, 2017). Moreover, Dastjerdy et al. (2023) highlight that IQR-based approaches, such as box plot fences, are more reliable than conventional parametric tests when applied to geomechanical data.

3.2.1 Normality tests

Normality tests are statistical procedures used to assess whether a dataset follows a Gaussian distribution. These tests return a p-value, which represents the probability of

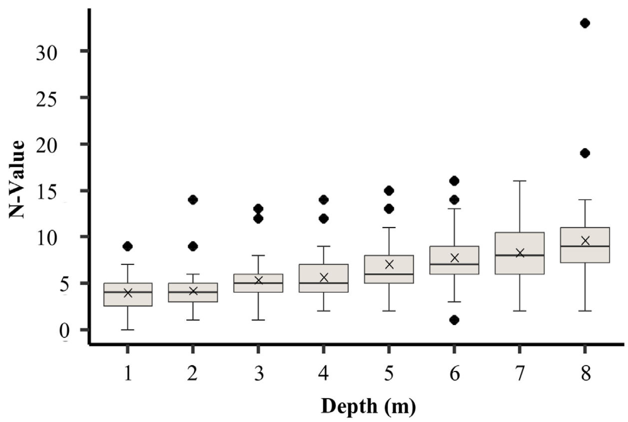

Figure 5. Analysis of outliers derived from the N value along the depth.

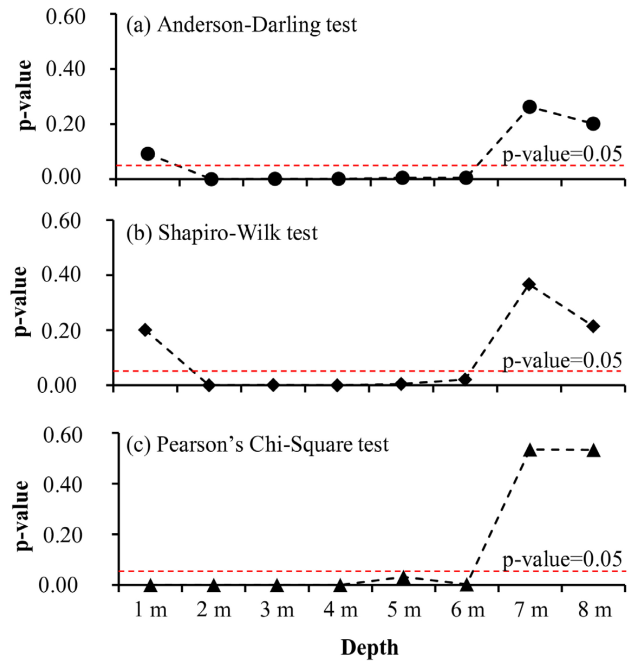

Figure 6. p-values using the Anderson-Darling test (a), Shapiro-Wilk test (c), and Pearson's Chi-Square test.

observing the data under the assumption that it follows a normal distribution. A high p-value (typically $p > 0.05$) indicates that there is no statistical evidence to reject the null hypothesis of normality. Conversely, a p-value less than or equal to 0.05 ($p \leq 0.05$) suggests that the data significantly deviates from a normal distribution.

In this study, the normality of N-values at each depth was evaluated using three statistical tests: the Anderson–Darling test (Anderson & Darling, 1954), the Shapiro–Wilk test (Shapiro & Wilk, 1965), and Pearson's Chi-Square test (Pearson, 2009). The results are summarized in Figure 6. At a depth of 1 metre, the results were partially conflicting. The Chi-Square test produced a p-value ≤ 0.05, indicating non-normality. However, both the Shapiro–Wilk and Anderson–Darling tests yielded p-values greater than 0.05, suggesting that the data do not significantly deviate from normality. This interpretation is supported by the visual inspection of the corresponding histogram (Figure 3a), which shows that the data closely follow the fitted normal curve. Therefore, the data at this depth were considered to follow a normal distribution, with greater emphasis given to the more robust tests for small sample sizes and continuous data.

Between depths of 2 m and 6 m, all tests returned p-values below 0.05, consistently indicating that the data do not follow a normal distribution. In contrast, for the 7 m and 8 m depths, all three tests yielded p-values above 0.05, supporting the assumption of normality. This interpretation is further confirmed by the histograms at these depths (Figure 3g and 3h), in which the data appear to align well with the fitted normal distribution curve.

4. Static load test

An experimental geotechnical engineering field site was established in lateritic soils in southern Brazil (Falcão et al., 2023; Masutti et al., 2023). This study examined the behavior of conventional piles with lengths of 3.00 m and 6.00 m, each with a diameter of 0.30 m. The assessment of these pile foundations utilized the slow load static test (SML). According to Fellenius (2024), the static analysis of the axial response of a pile involves assessing both sustained (permanent) and transient (live) loads applied at the pile head, which are subsequently transmitted to the soil via the resistance offered by both the shaft and the tip.

The test results are illustrated in Figure 7. The analysis compared piles with lengths of 3.00 m (P1, P2 and P3), shown in Figure7-a, and 6.00 m (P3, P4 and P5), depicted in Figure7-b. In both cases, the piles exhibited a final settlement of 50 mm, limited by the deflection gauge's capacity. The findings revealed a 149% increase in load-bearing capacity, doubling the pile's length. When comparing piles of 3.00 m and 6.00 m lengths, three distinct behaviors were identified:

- initial soil stiffness;
- transition to a plastic phase with increased loading;
- absence of elastic recovery during the unloading phase.

As depicted by the load-settlement curves, irrespective of the pile length, the resistance stabilizes after a slight initial movement, indicating a plastic response of the system. Therefore, it is expected to assume a final value independent of movement for analysis under ultimate conditions (Fellenius, 2024).

The load capacity for 3.00 m length piles varied from 70 to 120 kN, whereas for 6.00 m length piles, it ranged from 200 to 220 kN, indicating more significant variability in the shorter piles. Increasing the pile length resulted in a reduction in the variability of the ultimate load capacity. Variability in load capacity can be attributed to the geotechnical properties of the soil. As the length of the pile increases, the resistance provided by lateral friction also increases, resulting in more homogeneous outcomes. The variability in short piles is linked

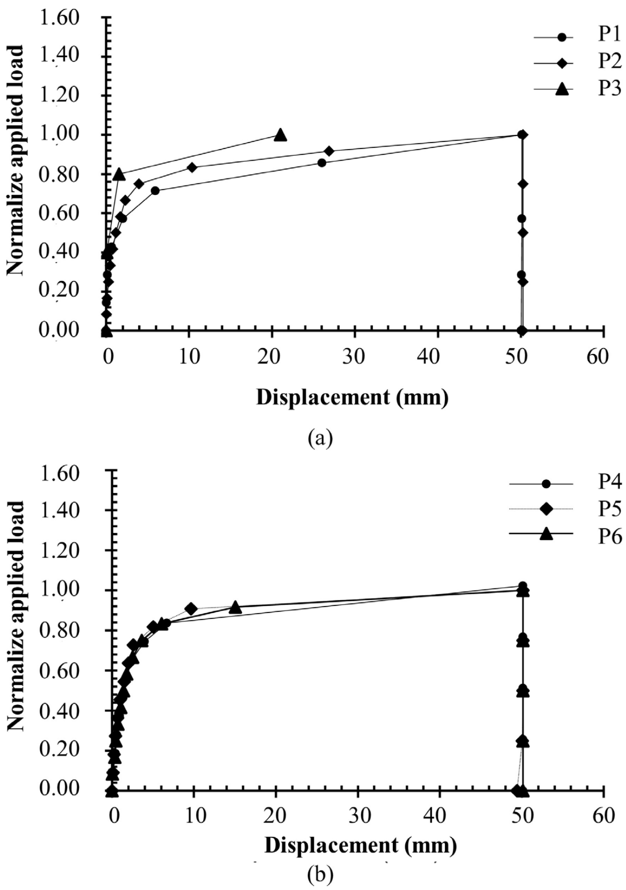

Figure 7. Results of the static load test: (a) piles with a length of 3 meters; and (b) piles with a length of 6 meters.

to the pile diameter, embedded length, soil properties (e.g., saturation), and moisture content, which impact lateral load capacity and behavior in clayey soil (Aljanabi & Bazaz, 2020).

Although only six load tests were performed in the present study, the results obtained are in close agreement with values reported in experimental campaigns conducted under similar geotechnical conditions, thereby reinforcing the representativeness of the data. For example, at the experimental field of the University of Brasília (UnB), manually excavated bored piles with a diameter of 15 cm and a length of 5 m were tested in lateritic soils, yielding ultimate load capacities on the order of 70 kN (Sales et al., 2023). Similarly, Cavalcante et al. (2007) reported results from tests conducted at the experimental site of the State University of Londrina (UEL), involving manually excavated piles with a diameter of 25 cm and a length of 3 m, constructed using plain concrete and soil-cement, and subjected to mixed loading conditions. The average ultimate load capacities observed were 49 kN for concrete piles and 60 kN for soil-cement piles. These values are compatible with those obtained in the present study for 3 m long piles, which ranged from 70 to 120 kN, thus supporting the interpretation of the load–settlement behavior despite the limited number of tests. Therefore, while acknowledging the statistical limitations, the similarity with results from other studies in lateritic soils lends credibility and practical applicability to the findings.

5. Evaluation of axial load capacity of piles

According to AASHTO (2007), the axial load capacity of piles can be determined through static or dynamic analyses. This discussion will focus exclusively on static analyses, as the available data do not encompass dynamic analysis. The load applied at the top of the pile is transmitted to the soil through lateral friction and toe resistance. Consequently, the static analysis addresses both sustained (dead) and transient loads (Fellenius, 2024). Static analysis is categorized into direct and indirect methods. Direct methods are based on results from in situ tests (e.g., Standard Penetration Test and Cone Penetration Test). In contrast, indirect methods are derived from load capacity equations designed to describe pile behavior under compression or uplift. Nonetheless, these methods exhibit a degree of empiricism (Phoon & Tang, 2019).

Pile testing, including static load tests, dynamic tests, and bidirectional tests, is conducted to validate and calibrate these methods. Accurately determining the ultimate load capacity of piles is intrinsically challenging due to the variability inherent in the estimation methodology (e.g., adjustment coefficients). The axial load capacity of piles can be estimated through statistical analyses, load tests, methods based on in-situ tests, and values suggested by codes and manuals (Obeta et al., 2018). Field-testing methodologies are increasingly applied as laboratory-based approaches may have limitations, with field tests providing a more precise understanding of soil behavior at depth (Eslami & Gholami, 2006).

The semi-empirical methodology for determining pile load capacity is viable because it relies on empirical correlations with in situ test data (Nogueira et al., 2022). In this context, field test-based methods, such as the SPT, are justified for estimating the axial load capacity of bored piles, with the N-value often used as a critical input parameter. Semi-empirical methods based on SPT and cone penetration test (CPT) are utilized to estimate the load-bearing capacity of pile foundations(Golafzani et al., 2020a, b; Heidari & Ghazavi, 2021; Lin et al., 2022; Nogueira et al., 2022). However, to assess the variability in the axial load capacity of bored piles, the methods of Aoki & Velloso (1975), Meyerhof (1976), and Décourt & Quaresma (1978) were employed. Table 1 outlines these methodologies and summarizes their respective methodologies, including the specific parameters and equations used.

6. Model uncertainty

Mathematical equations based on field tests are fraught with uncertainties, which may impact the method's efficiency (Phoon & Kulhawy, 2005). The model factor (λ_r) is used to

Table 1. Methods for evaluation of axial bearing capacity of bored piles.

Method	Ultimate bearing capacity
Aoki & Velloso (1975)	$Q_{ult} = Q_p + Q_s = \frac{KN_p A_b}{F1} + \frac{U}{F2}\sum_{i=1}^{n}\left(KN_L \Delta L\right)_i$ *K= 0.50 and α=2.80 (clayey silty sand)* *F1= 3 (bored pile) and F2= 2F1*
Meyerhof (1976)	$Q_{ult} = Q_p + Q_s = nN_t A_t + n\overline{N_s} A_s D$ m=120.10^3 N/m^2 and n=1.10^3 N/m^2 for bored piles
Décourt & Quaresma (1978)	$Q_{ult} = Q_p + Q_s = CN_p A_b + U\left(\frac{N_L}{3}+1\right)\Delta L$ α=0.85 and β= 0.80 (clayey)

quantify these uncertainties, referring to the ratio between the measured axial load capacity (Q_m) and the predicted capacity (Q_p). It should be noted that λ_r is a calibration parameter of the predictive model, quantifying the bias and variability of the model relative to actual field tests. In contrast, the safety factor is a code-based design margin that provides a buffer against all uncertainties. The model factor is presented through a box plot in Figure 8, considering piles of 3 and 6 meters in length. Data from 6 SMLs were used, with averages from approximately 43 SPT tests. In total, 258 combinations for each method were evaluated for each pile. The smallest interquartile range (IQR) was observed for the 3-meter piles compared to the 6-meter piles. The Décourt-Quaresma method, regardless of pile length, showed the lowest *IQR* among the methods compared. The *IQR* values for the 3-meter piles, considering the Aoki-Velloso and Meyerhof methods, are relatively similar, being 0.80 for the former and 0.70 for the latter. The *COV* values between the predictive methodologies are relatively close, ranging from 40% to 53% for the 3-meter piles and from 7% to 11% for the 6-meter piles; it is noted that the *COV* is approximately four times lower for the 6-meter piles. This phenomenon may be attributed to the increased variability of near-surface soils in shorter piles, resulting in a more heterogeneous transfer of lateral friction than in longer piles. A similar observation was made by Nogueira et al. (2022) in bored piles within residual soils, where the highest variability was detected near the soil surface, particularly in the shorter piles analyzed. Considering the mathematical assumptions of each axial load capacity prediction method, variability in their results is typical when compared (Golafzani et al., 2020a; Haldar & Sivakumar Babu, 2008; Giacon Junior et al., 2019; Nogueira et al., 2022). The *COV* ranged from 7% to 60%, not exceeding the typical range of 16% to 67% observed for drilled shafts in sand/clay (Tang et al., 2019). The mean and median values were relatively close, indicating that the data distribution is reasonably symmetrical and that outliers do not significantly affect the mean. Phoon & Tang (2019) adopted the variability levels for soil proposed by Phoon et al. (2003) and established the following classification based on *COV*: (1) low (*COV* < 0.3), (2) medium (0.3 ≤ *COV* < 0.6), (3) high (0.6 ≤ *COV* < 0.9), and (4) very high (*COV* ≥ 0.9). According to this classification, all prediction methods for the 3 m piles fall within the medium *COV* range, while the 6 m piles exhibit a low *COV*.

Figure 9 presents the probability plots of observed λ_r for normal and log-normal distributions. The log-normal distribution better aligns with the data; similar findings were reported by Phoon et al. Phoon & Kulhawy (2005) for rigid drilled shafts subjected to lateral loading. Golafzani et al. (2020a) also noted that regardless of the methodology, the ratio Q_m/Q_p followed a log-normal distribution of model uncertain for driven piles. Additionally, the results of Anderson & Darling (1954), Shapiro & Wilk (1965), and Pearson (2009) normality tests indicate *p*-values below 0.05, suggesting that the data do not fit the normal distribution regardless of the method or pile length. However, it is observed that the data also fit a normal distribution, albeit less effectively. This can be explained by Figure 8, in which the mean and median values are relatively close, indicating a reasonably symmetrical data distribution and minimal influence of outliers on the mean, consistent with the normal distribution.

7. Reliability index of pile bearing capacity

Reliability analysis is directly derived from the limit state design concept, which is widely applied in geotechnical engineering to assess the structural performance of deep foundations (Baecher & Christian, 2003; Lin et al., 2022). For a vertically loaded pile, the limit state function is mathematically expressed as $M = R - Q$, where R represents the pile's ultimate bearing capacity, and Q is the applied load. The safety margin M is defined as the difference between these two quantities. When R and Q follow a normal distribution, M will also be normally distributed with a mean μ_M and standard deviation σ_M; in this case, the β corresponds to the standard normal variate Z, which is related to the cumulative distribution function $\Phi(Z)$ of the standard normal distribution, evaluated

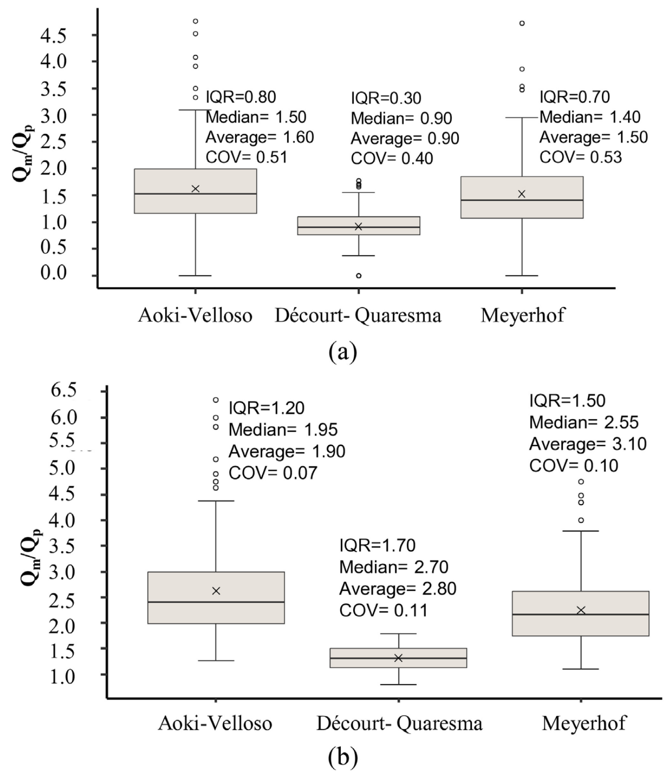

Figure 8. Box plot depicting the resistance bias factor (λ_r) derived from predictive methods: (a) piles with a length of 3 meters; (b) piles with a length of 6 meters.

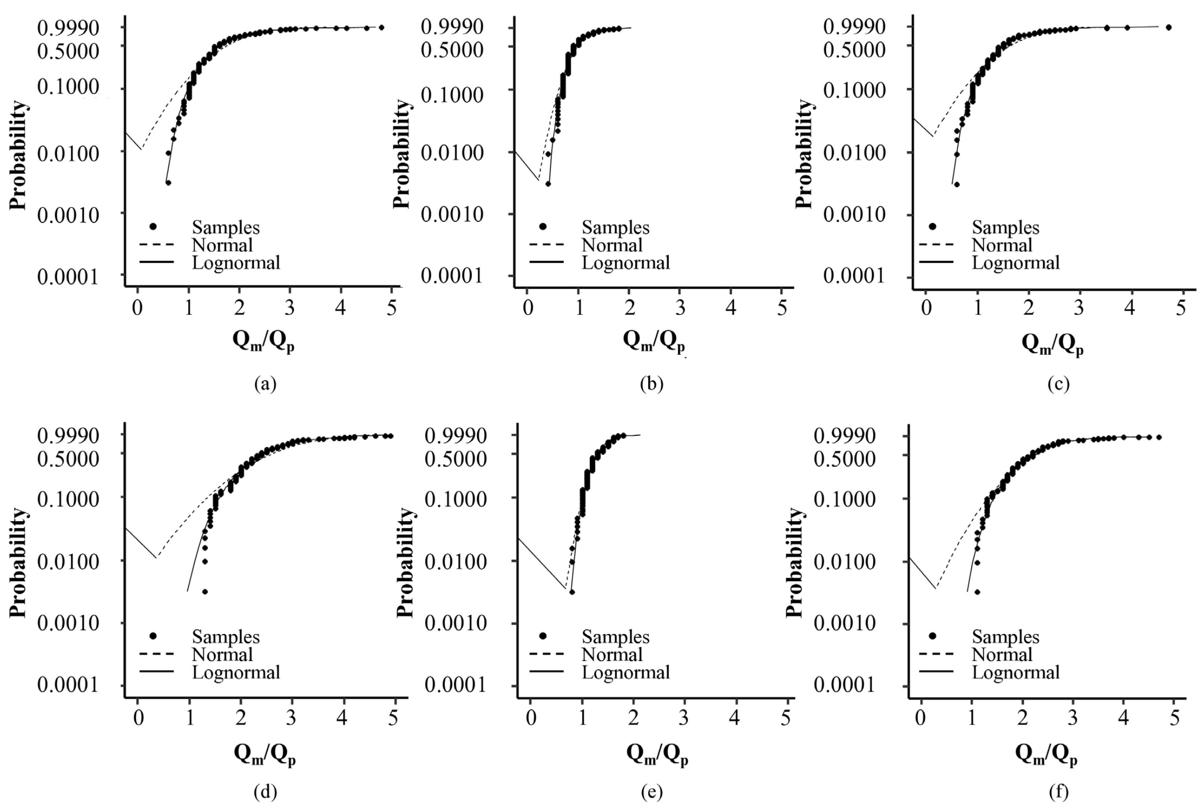

Figure 9. Probability plot for observed λ_r: (a) 3-meter piles using the Aoki-Velloso method; (b) 3-meter piles using the Decourt-Quaresma method; (c) 3-meter piles using the Meyerhof method; (d) 6-meter piles using the Aoki-Velloso method; (e) 6-meter piles using the Decourt-Quaresma method; (f) 6-meter piles using the Meyerhof method.

from $-\infty$ to positive values of Z. However, when considering the PF, the focus shifts to the integral distribution from $-\infty$ to negative values of Z, representing outcomes below the average. Owing to the symmetry of the normal distribution, the probability of failure can be expressed as $PF = 1 - \Phi(\beta)$, where $\Phi(-\beta)$ is the cumulative distribution function evaluated at $-\beta$. The safety factor (FS) is the ratio between R and Q; thus, failure occurs when FS equals 1. Therefore, the β can be defined by Equation 1 where $E[FS]$ expected FS values and σ_{FS} is FS's standard deviation.

$$\beta = \frac{E[FS]-1}{\sigma_{FS}} \tag{1}$$

The FORM method was applied for reliability analyses of isolated drilled shafts. The determination of R was achieved through semi-empirical methods (Aoki & Velloso, 1975; Décourt & Quaresma, 1978; Meyerhof, 1976). that estimate the axial load capacity based on the linear nature of the limit state function. The FORM is based on the following spatial equation: G(X) = R(X, U) - S(X, U) = 0. First, the variables are mapped using the FORM technique from the physical space (system X) into a conventional standard normal space (system Y). In this transformation, variables in the physical space, which may be correlated or non-standardized, are converted into a set of uncorrelated, standardized variables (with a mean of zero and a standard deviation of one) in the standard normal space. The reliability index β is then calculated in the standard normal space. This index represents the shortest distance between the failure surface, defined by G(Y) = 0, and the origin of the standard normal space (Hasofer & Lind, 1974). This distance is essentially a standardized measure of the system's distance from the failure condition.

8. Reliability-based assessment of predictive methods

In Figure 10, the β values are presented as a function of the FS. The calculation method used was FORM. It is observed that piles with a length of 3 m exhibit lower β values compared to the 6 m piles. As previously discussed, shorter piles show more significant spatial variability, confirmed by the variation in the results estimated by the prediction methods and, consequently, by the lower β values. Regarding FS, the values for the 3 m piles ranged between 1 and 2, with the Décourt & Quaresma (1978) showing the lowest FS and, consequently, the highest probability of failure (PF = 53.9%). The methods of Aoki & Velloso (1975), and Meyerhof (1976) resulted in higher FS values for the 3 m piles and, therefore, higher β values, with PFs of 15.9% and 18.9%, respectively. For the 6 m piles, the lowest FS and β were obtained using the Décourt & Quaresma (1978), resulting in a PF of 8.5%. On the other hand, the methods of Aoki & Velloso (1975) and Meyerhof (1976) presented the highest FS and β values. The Décourt & Quaresma (1978)

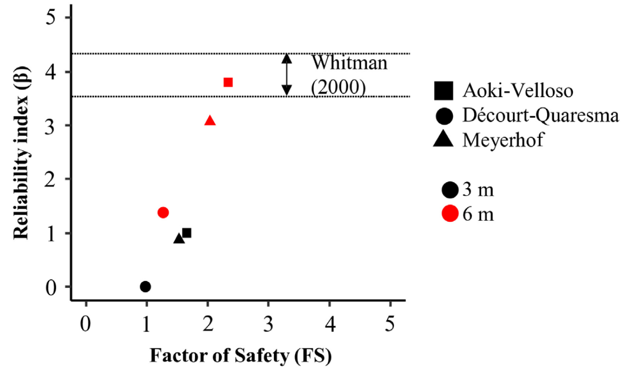

Figure 10. Reliability indices using FORM for various methods.

method yielded the lowest β values due to the proximity of its estimates to those obtained in SML tests. Vargas (2022) also observed that the Décourt & Quaresma (1978) method closely matches the values measured in SMLs for clay soils. The criterion proposed by Whitman (2000) for evaluating pile foundations based on β establishes a range of 3.70 to 4.20, corresponding to failure probabilities between 10^{-5} and 10^{-4}. β values within this range indicate an adequate safety level. It is noted that the 3 m piles fall below the adequate level, and that for the 6 m piles, only the Aoki and Velloso method falls within the acceptable range.

The obtained reliability indices were compared with the indices recommended by the following standards: Eurocode (CEN, 1990), the Joint Committee on Structural Safety (JCSS, 2001), the Department of Defense Standard Practice for System Safety (MIL-STD-882) (US Department of Defense, 2012), and the US Army Corps of Engineers (USACE) Engineering Manual (ELT 1110-2-547, 1995). A reference period of 50 years and a medium-to-high consequence class were considered. According to the Eurocode, the reliability index for this condition ranges from 3.80 to 4.30. For JCSS (2001), the recommended range is between 3.80 and 4.40. MIL-STD-882 (2012) does not explicitly define β-values but characterizes reliability based on a risk classification system that considers the probability of occurrence and the severity of consequences. In this context, a remote probability of occurrence and catastrophic consequences were selected, corresponding to an acceptable reliability index of approximately 3.09 to 4.75. According to ELT 1110-2-547 (USACE, 1995), the recommended reliability indices are 3.00, 4.00, and 5.00 for structures with above average, good, and high-performance levels, respectively.

In this context, the β obtained by the Aoki and Velloso method for the 6-meter piles was the only one that met the requirements set forth by Eurocode (CEN, 1990), JCSS (2001), and MIL-STD-882 (US Department of Defense, 2012). According to the ELT 1110-2-547 standard (USACE, 1995), the performance level was above average but did not reach good or high. The 6 m piles assessed by Décourt and Quaresma and Meyerhof, as well as the 3 m piles, failed to meet the criteria of any of the examined international codes.

Brazilian standards do not explicitly guide the β. Barros et al. (2010) determined the reliability index for root pile foundations in a Brazilian construction case study. The authors identified β values ranging from 2.48 to 4.22, demonstrating that the higher the variability of the resistance, the lower the reliability index. The study highlights the importance of considering variability as a key parameter to ensure realistic and safe foundation designs.

9. Conclusions

Soil variability represents a substantial source of uncertainty in geotechnical engineering, particularly in predicting the load-bearing capacity of deep foundations. Given the importance of incorporating variability into the analyses, this study considered the variability of the *N*-value with depth and different empirical correlations. The observed variability is attributed to natural processes and local conditions, which can significantly affect the accuracy of geotechnical analyses. Methods employed to estimate pile load capacity demonstrated notable differences in results. Shorter piles exhibited more significant variability than longer piles, highlighting the complexity and heterogeneity of near-surface soils.

Among the analyzed methods, the Décourt-Quaresma method proved to be the most accurate, providing estimates closely aligned with field test results and exhibiting lower variability. In contrast, the Aoki-Velloso and Meyerhof methods showed more significant prediction variability, suggesting reduced accuracy relative to the actual soil conditions.

Regarding the results obtained using the FORM method, 6-meter piles met the recommended safety factors, according to Whitman (2000), whereas 3-meter piles did not achieve acceptable safety levels based on the analyzed methods' predictions. This finding underscores the importance of considering soil spatial variability and integrating probabilistic analyses into foundation design. Applying probabilistic methods is essential for enhancing prediction reliability and ensuring structural safety.

Furthermore, the investigation revealed that spatial variability and the quality of input data significantly impact the accuracy of load-bearing capacity estimates. Therefore, to improve geotechnical engineering practices, it is crucial to adopt approaches that integrate variability and probabilistic analyses, ensuring the accuracy of field data and the appropriateness of prediction methods. Integrating these factors will contribute to developing safer and more reliable designs.

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Declaration of interest

The authors have no conflicts of interest to declare. All co-authors have observed and affirmed the contents of the paper and there is no financial interest to report.

Authors' contributions

Patricia Rodrigues Falcão: conceptualization, data curation, writing – original draft. Dêreck Hummel Becher: conceptualization, methodology, writing – original draft. Angelo Dotto Ragagnim Prior: conceptualization, methodology, writing – original draft. Magnos Baroni: supervision, validation, writing – review & editing. Gustavo Corbelinni Masutti: conceptualization, writing – review & editing. Tiago de Jesus Souza: writing – review & editing.

Data availability

The datasets generated analyzed in the course of the current study are available from the corresponding author upon request.

Declaration of use of generative artificial intelligence

The use of artificial intelligence was not employed in this article.

List of symbols and abbreviations

A_t	Pile toe area
A_s	Unit shaft area
C	Characteristic soil coefficient (Décourt & Quaresma, 1978)
COV	Coefficient of variation
CPT	Cone penetration test
D	Embedment depth (Meyerhof, 1976)
E[FS]	Expected F values
F1 and *F2*	Correction factors (Aoki & Velloso, 1975)
FORM	First-Order Reliability Method
FS	Factor of Safety
IBGE	Brazilian Institute of Geography and Statistics
IQR	interquartile range
M	Safety margin
M	Toe coefficient (Meyerhof, 1976)
N	Penetration resistance index
N_p	Mean N value at the pile base level (Décourt & Quaresma, 1978)

N_L	Average N value for each soil layer (Décourt & Quaresma, 1978)
N_t	N value at the pile toe (Meyerhof, 1976)
N_s	Average N value along the pile shaft (Meyerhof, 1976)
PF	Probability of Failure
Q	Applied load
Q_m	Axial load capacity
Q_p	Ultimate base resistance
Q_s	Ultimate shaft resistance
R	Pile's ultimate capacity
R^2	coefficient of determination
SML	Slow load static test
Std. Dev.	Standard deviation
SPT	Standard Penetration Test
Z	Standard normal variation
α	Soil coefficient (Aoki & Velloso, 1975)
α	Soil coefficient (Décourt & Quaresma, 1978)
β	Reliability index
β	Coefficients based on pile and soil types (Décourt & Quaresma, 1978)
λ_r	Resistance bias factor
μ_M	Mean of safety margin
σ_M	Standard deviation of safety margin
Σ_f	Standard deviation of F
Φ	Cumulative distribution function

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