Available *online* at: http://journal.unj.ac.id

Jurnal Pensil Pendidikan Teknik Sipil

Journal homepage: http://journal.unj.ac.id/unj/index.php/jpensil/index

EVALUATION OF THE CORRELATION BETWEEN CONE RESISTANCE VALUES (qc) AND N-SPT VALUE USING STATISTICAL METHODS IN COASTAL AREAS AROUND THE SEI PERCUT RIVER, NORTH SUMATRA

Bayu Wintoro[1*], *Amirah Zakiyyah*[2], *Anna Dewi*[3]

[1,2,3] Civil Engineering Department, Politeknik Negeri Bandung, Jalan Gegerkalong Hilir, Kec. Parongpong, West Bandung Regency, West Java, Indonesia

[*1]bayu.wintoro@polban.ac.id, [2]amirah.zakiyyah@polban.ac.id, [3]anna.dewi@polban.ac.id

P-ISSN: 2301-8437
E-ISSN: 2623-1085

ARTICLE HISTORY
Accepted:
23 Januari 2026
Revision:
18 Mei 2026
Published:
31 Mei 2026

ARTICLE DOI:
10.21009/jpensil.v15i2.65872

Abstract

When designing the substructure of a building or infrastructure, it is essential to use soil parameters obtained from both laboratory and field investigations. These parameters help assess actual ground conditions and estimate reliable bearing capacity on-site. Two common field tests used for this purpose are the Cone Penetration Test (CPT) and the Standard Penetration Test (SPT). This study explores the correlation between the results of these two methods, aiming to achieve more efficient and cost-effective soil analysis. The analysis draws on data from a total of 16 points of field investigation—8 from SPT and 8 from CPT—conducted across the research area. The statistical testing show that both the correlation coefficient (R) and the coefficient of determination (R^2) are close to 1, indicating a strong relationship. Specifically, the linear model produced values of 0.931 for R and 0.866 for R^2; the quadratic model yielded 0.932 and 0.868; and the cubic model gave 0.950 for R and 0.903 for R^2. The t-test results also indicate that the N-SPT is statistically significant influence on the qc across all models. The derived correlation equations between N-SPT and qc are as follows: Linear model: N-SPT = 0.208 qc + 1.004, Quadratic model: N-SPT = 0.0002 qc^2 + 0.1859 qc + 1.205, and Cubic model: N-SPT = 0.00001 qc^3 - 0.036 qc^2 + 0.4018 qc + 0.1323.

Keywords: Correlation, N-SPT Value, qc-CPT, Statistical Test

Introduction

Soil serves as the foundational support for any construction project, playing a critical role in bearing the load transmitted by the structure's foundation (Alielahi et al., 2023; Bowles, 1997; Kar & Ansary, 2023; M.Das, 2002). In planning a substructure, it is essential to obtain detailed information about soil parameters, which are derived from both field and laboratory investigations (Felić et al., 2025; Marzouk et al., 2023; Pinto et al., 2025). These parameters are necessary to calculate the bearing capacity of the soil at the construction site (Fauzi et al., 2025; Güner & Özgan, 2025; Pande et al., 2025). To ensure the accuracy and completeness of this data, a thorough geotechnical investigation must be conducted—one that relies not on a single type of test, but incorporates multiple methods of analysis (Arisandi et al., 2017). Soil is formed through various natural processes, including mechanical and chemical weathering of different types of rock (Amran & Permadi, 2021; Lee & Sino, 2024; Metboki, 2024). These actions produce various sedimentation patterns and formations (Jarushi & Cosentino, 2015).

In the process of planning and designing building structures, particularly foundations, soil investigation plays a critical role that cannot be overlooked (Karthik et al., 2025; Temitope et al., 2023). The varying soil conditions from one location to another have encouraged other researchers to conduct research on site-specific correlation from field tests to other soil parameters (Jarushi et al., 2025; Mangidi et al., 2023; Okodugha et al., 2025; Paul et al., 2025). In Indonesia, two of the most commonly used methods for assessing soil characteristics at a construction site are the Cone Penetration Test (CPT), often referred as the Sondir Test, and the Standard Penetration Test (SPT) (Miranda et al., 2025). Due to its simplicity, the SPT is the most used field investigation test around the world (Paul et al., 2025; Wadi et al., 2025). It provides information about the resistance and properties of soil (Arifuzzaman & Anisuzzaman, 2022; Ifat & Rahman, 2024; Izzo & Miletić, 2019). Also, with different soil properties there are many correlations of the SPT-N value (Alam et al., 2018; Costa et al., 2016; Faivre et al., 2023; Feda Aral & Gunes, 2017; Geotechnics et al., 2014; Jarushi & Cosentino, 2015; Nabila et al., 2023; Shahgholian et al., 2022; Sudjatmiko, 2022; Zhou et al., 2021). On the other hand, CPT are more reliable alternative to SPT due to its repeatability, standardization, and reliability (Nabila et al., 2023).

The CPT is a soil exploration method performed without drilling, where a steel cone is driven into the ground with constant rate by hydraulic force. During penetration, the equipment records two key parameters: tip resistance and sleeve friction. These values can estimate soil bearing capacity based on empirical formulas, identify vertical changes in soil layers, and detect soft or hard layers at specific depths (Nahesson et al., 2022; Sudjatmiko, 2022). One of the main advantages of this method is its speed in collecting continuous data, making it especially useful for obtaining a comprehensive subsurface profile. A key application of the CPT is the determination of soil stratigraphy and soil type.

The SPT is carried out by drilling into the ground. At certain depths, a sampler is driven into the soil by repeatedly dropping a heavy hammer. The number of hammer blows needed to push the sampler 300 mm into the ground is recorded as the N-value. This value gives an indication of how dense or stiff the soil is and helps estimate its strength and ability to support loads. Additionally, soil samples retrieved during the test can be visually examined to determine soil type, texture, and colour—important factors in constructing an accurate geotechnical profile (Haifani, 2021; Ifat & Rahman, 2024).

These two methods are often used together in a single site investigation program, as they complement each other. CPT provides fast and continuous data without requiring soil samples, while SPT offers descriptive insights supported by physical samples. By combining results from both tests, it can develop a more reliable understanding of subsurface conditions, leading to foundation designs that are safe, efficient, and tailored to the specific characteristics of the site. SPT and CPT are commonly applied in both preliminary and detailed soil investigations, as well as in construction quality control, depending on project requirements (Lee & Sino, 2024; Zhou et al., 2021). Consequently, establishing correlations between SPT N-values and CPT tip and sleeve friction resistances is essential to optimize the utilization of both datasets (Sudjatmiko, 2022).

Numerous studies have employed statistical methods to develop correlations for estimating cone resistance (qc) and friction resistance (fs) from across a wide range of soil types SPT data (Costa & Cunha, 2016). However, many researchers have examined the SPT–CPT correlations to local soil conditions and found that previous correlations often lacked geological considerations and did not clearly address the statistical methods used in the analyses (Faivre et al., 2023).

Research Methods

Topographically, the site is characterized by relatively flat terrain. The land use in the area is predominantly oil palm plantations, with portions consisting of former fishponds and mangrove-like forest ecosystems near the coastal region. The figure below presents an overview of the location and the mapping area of field investigations.

Figure 1. Soil investigation locations

Table 1. Field investigations data for SPT and CPT Tests

Depth (m)	N-SPT	CR (kg/cm2)	N-SPT	CR (kg/cm2)	N-SPT	CR (kg/cm2)	N-SPT	CR (kg/cm2)	N-SPT	CR (kg/cm2)	N-SPT	CR (kg/cm2)	N-SPT	CR (kg/cm2)	N-SPT
	BH1	**S2**	**BH2**	**S4**	**BH3**	**S3**	**BH4**	**S5**	**BH5**	**S6**	**BH6**	**S7**	**BH7**	**S9**	**BH8**
2.45	1	2	1	2	1	2	1	1	1	2	1	3	1	1	1
4.45	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6.45	1	1	1	5	1	2	1	2	1	3	1	1	1	2	1
8.45	1	5	1	1	1	3	1	2	1	2	1	2	1	1	1
10.45	1	8	1	4	1	6	2	2	2	3	1	3	2	2	1
12.45	1	5	2	8	1	6	2	3	1	6	2	3	2	2	1
14.45	2	10	3	7	2	14	2	3	2	6	2	3	3	4	2
16.45	2	8	5	20	3	11	2	7	8	13	3	8	4	15	3
18.45	4	12	7	34	11	20	10	49	20	53	4	13	9	47	10
20.45	5	46	18	40	18	42	16	67	20	56	2	15	12	81	14
22.45	9	42	22	91	22	30	12	82	22	81	5	20	14	78	16
24.45	16	103	27	156	22	117	20	116	28	124	8	26	19	91	53

In order to correlate the SPT and CPT results, the closest (in plan) CPT point to each SPT borehole was selected, defining a SPT-CPT pair (Shahgholian et al., 2022b). To achieve the objectives of the subsurface investigation, a total of 8 points of deep boring and 8 points of CPT were carried out within the study area.

The tools used in this study are the SPSS program and Microsoft Office to process the selected secondary data from the study location. The steps of the research are presented in the following flowchart.

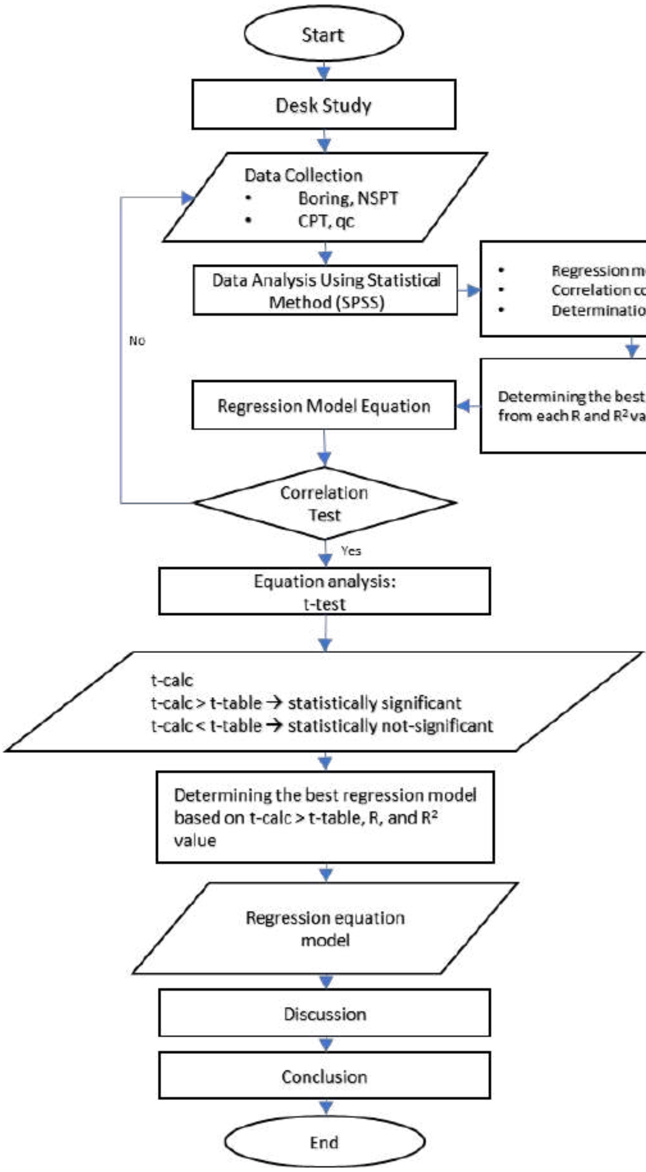

Figure 2. Flowchart for the research

Regression analysis serves as a statistical approach to quantitatively model the relationship of two or more variables, wherein the dependent and independent variables are clearly defined. The resulting regression equation represents the line that characterizes the nature of this relationship. This analytical framework includes both simple linear regression (LR) and non-linear regression (NLR) techniques, where it depends on the complexity of the data and the underlying patterns observed.

In a LR model, two variables are considered: an independent variable (α) and a dependent variable (γ). The regression relationship between these variables can be expressed in the following general form:

$$Y = \mathrm{a} + \mathrm{b}\,\alpha + \varepsilon$$

Where:
- γ = dependent variable
- α = independent variable
- a = intercept
- b = regression coefficient (slope)
- ε = error term

NLR models is used to estimate the relation dependent and/or independent variables when the pattern of association is not adequately represented by a linear function. This method often yields greater accuracy compared to linear regression, as it utilizes iterative algorithms to estimate model parameters.

There are two commonly applied forms of NLR models: the quadratic regression model and the cubic regression model.

The general equations of the quadratic regression model (Jarantow et al., 2023) is:

$$\gamma = \mathrm{a} + \mathrm{b}\,\alpha + \mathrm{c}\,\alpha\,2$$

And the general equations of the cubic regression model (Jarantow et al., 2023) is:

$$\gamma = \mathrm{a} + \mathrm{b}\,\alpha + \mathrm{c}\,\alpha\,2 + \mathrm{d}\,\alpha\,3$$

Where:
- γ = dependent variable
- α = independent variable
- a, b, c, d = model coefficients

The fundamental assumption tested in this both (LR and NLR) analysis is the assumption of normality. A normality test is conducted to check whether the data follow a normal distribution or not. Data that are normally distributed exhibit a symmetric and standardized pattern of spread. This distribution is characterized by two parameters: the mean and the standard deviation. Specifically, a standard normal distribution has a mean of 0 and a standard deviation of 1. When visualized in a graph, the curve of a normal distribution takes the shape of a symmetrical bell-shaped curve. There is ongoing debate regarding the importance of the normality assumption, as it is rarely fully met and its influence diminishes with increasing sample size (Gelman & Hill, 2006). Spearman's rank correlation is a non-parametric statistical technique used to measure how strongly two variables are related and to identify whether their relationship follows a consistent increasing or decreasing trend. Rather than relying on the actual numerical values, this method is based on the ranked positions of the data, which makes it suitable for analyzing relationships that are monotonic but not necessarily linear. Spearman's rank correlation does not depend on the assumption that the data are normally distributed. As a result, it can be effectively applied to data measured on ordinal, interval, or ratio scales, particularly when the data contain outliers or exhibit non-normal behavior. This flexibility makes Spearman's method especially useful in practical and engineering-related studies where ideal statistical assumptions are often difficult to satisfy.

The Spearman rank correlation coefficient, commonly denoted by the symbol ϱ (rho), takes values within the range of –1 to +1. A value close to +1 reflects a strongly increasing monotonic association between two variables, whereas a value near –1 represents a strongly decreasing monotonic association. A coefficient around zero suggests that there is no consistent monotonic pattern linking the variables. Unlike parametric correlation measures, Spearman's coefficient is derived from the ranked order of the observations rather than their actual numerical magnitudes. This rank-based approach allows the method to remain effective even when the relationship between variables is non-linear or when the data deviate from a normal distribution. Consequently, Spearman's correlation is particularly well suited for analyzing datasets that violate common parametric assumptions or contain irregular distributions (Lobo & Guntur, 2018).

Hypothesis testing in the regression model is conducted using the t-test. A statistically significant result implies that the discerned relationship is unlikely to have take place by random chance and is therefore generalizable to the broader population. In this context, significance is typically assessed using a predetermined significance level (e.g., $\alpha = 0.05$), with p-values indicating the probability of observing the given result under the null hypothesis, when the p-value $< \alpha$ level, the hypothesis is rejected, suggesting that the independent variable has a meaningful impact on the dependent variable (Arisandi et al., 2017).

Research Results and Discussion

In statistical analysis, scatter plots are used to illustrate the relationship between two variables, and Pearson's correlation is frequently employed to quantify this relationship through the correlation coefficient (Wadi et al., 2022). Spearman's or Kendall's correlation does not assume any specific data distribution and is more appropriate when:

- The given data is not normally distributed
- The relationship between variables is non-linear
- Outliers are present

Based on the Spearman correlation test conducted on both data sets (N-SPT values and cone resistance/qc from the CPT test), a Spearman correlation coefficient of 0.892 was obtained, marked with two asterisks (**), indicating that the p-value is less than 0.01. Furthermore, a p-value of less than 0.05 indicates that the data sets are statistically significant, confirming a strong association between the N-SPT results and the qc values from the CPT test.

Table 2. Nonparametric correlations (Spearman) test result

			qc	**N-SPT**
Spearman's rho	qc	Correlation Coefficient	1.000	0.892**
		Sig. (2-tailed)		0.000
		N	96	96
	N-SPT	Correlation Coefficient	0.892**	1.000
		Sig. (2-tailed)	0.000	
		N	96	96

** Correlation is significant at the 0.01 level (2-tailed)

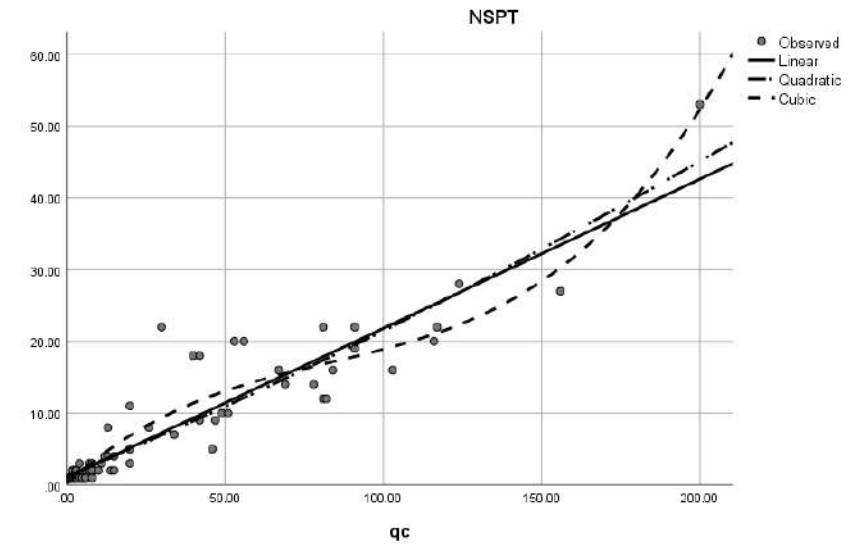

Figure 3. Linear, Quadratic, and Cubic Regression Line of N-SPT vs qc using SPSS

Linear Model

The linear regression equation for this model is N-SPT = 0.208 qc + 1.004. From Table 3, the R value of 0.931 demonstrates a very strong positive relationship of the independent variable, cone resistance (qc), with the dependent variable, N-SPT value. This high correlation indicates that increases in qc are closely associated with increases in N. In addition, the R^2 obtained from the analysis is 0.866, indicating that a substantial portion of the variation observed in the dependent variable is accounted for by the proposed model. In practical terms, this result means that approximately 86.6% of the changes in the dependent variable can be explained by the relationship captured in the regression equation. This high R^2 value reflects the strong explanatory performance of the model in representing the underlying data. The remaining 13.4% of the unexplained variation is likely influenced by other factors not considered in the analysis, such as inherent variability in soil conditions, measurement uncertainty, or additional parameters beyond the scope of the current study.

Furthermore, the results presented in Table 4 show a t-value of 24.683, which is significantly higher than the critical t-value of 2.262 at a 5% level of significance. This result confirms that the independent variable has a statistically significant influence on the dependent variable. Therefore, the relationship between qc and N is not only strong but also statistically reliable, supporting the validity of the developed model.

Table 3. Output of correlation coefficient and determination coefficient for linear model

R	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
0.931	0.866	0.865	3.183

The independent variable is qc.

Table 4. Output of Linear Regression Equation

	Unstandardized B	**Coefficients Std. Error**	**Standardized Coefficients Beta**	**t**	**Sig.**
qc	0.208	0.008	0.931	24.683	0.000
(Constant)	1.004	0.388		2.590	0.011

Quadratic Model

The quadratic regression equation for this model is N-SPT = 0.0002 qc^2 + 0.1859 qc + 1.205. This form of regression suggests that the increase in N-values changes with increasing qc, reflecting the complex behavior of soil resistance as measured by CPT and SPT methods. Such a nonlinear relationship is reasonable, considering variations in soil density, stress conditions, and material properties at different depths.

From in Table 5, the R value of 0.932 demonstrates a very strong positive relationship in the qc and the N-value. This high correlation confirms that qc is closely associated with changes in N-values. In addition, the R^2 is 0.868. This slightly higher explanatory power compared to a linear model suggests that the quadratic form provides a better representation of the relationship in qc and N-SPT.

Furthermore, the t-test results shown in Table 6 reveal a calculated t-value of 8.661, which is significantly greater than the critical t-value of 2.262 at the 5% significance level. This result confirms that the qc has a statistically significant influence on the N-SPT. Therefore, the proposed quadratic model is not only statistically significant but also reliable for predicting N-values from cone resistance (qc) within the range of data analyzed.

Table 5. Output of Correlation Coefficient and Determination Coefficient for Quadratic Model

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.932	0.868	0.865	3.178

The independent variable is qc.

Table 6. Output of Quadratic Regression Equation

	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
qc	0.186	0.021	0.832	8.661	0.000
qc ** 2	0.000	0.000	0.108	1.121	0.265
(Constant)	1.205	0.427		2.825	0.006

Cubic Model

The cubic regression equation for this model is N-SPT = 0.00001 qc^3 - 0.036 qc^2 + 0.4018 qc + 0.1323. From Table 7, the R value of 0.950 indicates a very strong positive relationship between the qc and the N-SPT. This high correlation suggests that variations in qc are closely and consistently associated with changes in N-values, highlighting the strong interdependence between the two parameters. Such a strong relationship reflects how the model to capture the underlying soil behavior measured by both CPT and SPT methods.

Moreover, the R^2 is 0.903, indicating that about 90.3% of the variation in the N-SPT is accounted for by the model. This strong explanatory ability tells that the model fits the observed data very well, with only a small proportion of the variability in N-values attributed to factors outside the model. When compared to earlier models, this outcome reflects improved accuracy and greater reliability in prediction.

Additionally, the t-test results presented in Table 8 show a computed t-value of 9.551, which is much higher than the critical t-value of 2.262 at the 5% significance level. This demonstrates that the qc has a statistically significant effect on the N-SPT. Therefore, the relationship described by the model is both strong and statistically sound, confirming its appropriateness for estimating N-values from cone resistance (qc) data within the context of this study.

Table 7. Output of Correlation Coefficient and Determination Coefficient for Cubic Model

R	R Square	Adjusted R Square	Std. Error of the Estimate
0.950	0.903	0.900	2.745

The independent variable is qc.

Table 8. Output of Cubic Regression Equation

	Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
qc	0.402	0.042	1.797	9.551	0.000
qc ** 2	-0.004	0.001	-2.295	-5.357	0.000
qc ** 3	1.438E-5	0.000	1.572	5.716	0.000
(Constant)	0.132	0.413		0.320	0.750

The study demonstrates that empirical correlations are best applied within the regions and soil conditions under which they were developed. If used outside these contexts, they should be treated as indicative only, and supplementary in-situ testing is advised (Zhou et al., 2021). The strong correlation obtained in this study is consistent with several previous studies that reported a significant relationship between SPT and CPT parameters in geotechnical investigations. Previous researchers generally found that qc values tend to increase proportionally with N-SPT values, particularly in granular and stiff-cohesive soils, although the degree of correlation may vary depending on local geological conditions, soil type, groundwater conditions, and testing procedures. Compared to earlier empirical correlations, the correlation coefficient obtained in this study ($r = 0.892$) indicates a relatively high level of agreement, suggesting that the soil conditions at the study site exhibit consistent behavior between penetration resistance measured by SPT and cone resistance measured by CPT.

In addition, the regression trend observed in this study demonstrates a similar pattern to previously developed empirical models, where higher cone resistance values correspond to greater SPT blow counts. However, slight deviations from previous regression equations may occur due to differences in soil stratification, soil density, fines content, and regional geological characteristics. These findings reinforce the applicability of CPT data as a reliable predictor for estimating SPT values in preliminary site investigations, particularly when rapid and continuous subsurface profiling is required. Therefore, the regression relationship developed in this study can provide a useful local empirical reference for geotechnical characterization and foundation design in areas with similar soil conditions (Shahgholian et al., 2022b; Sudjatmiko, 2022b).

Conclusion

The statistical analysis revealed strong correlations between the N-SPT and qc values across all tested regression models. The correlation coefficient (R) and coefficient of determination (R^2) approached values close to 1, indicating a high degree of fit. Specifically, the linear model yielded $R = 0.931$ and $R^2 = 0.866$, the quadratic model showed $R = 0.932$ and $R^2 = 0.868$, while the cubic model produced $R = 0.950$ and $R^2 = 0.903$. Furthermore, t-test results confirmed that the qc variable has a statistically significant effect on the N-SPT variable in all three models. The regression equations derived from the analysis are as follows: Linear model: N-SPT(linear) = 0.208 qc + 1.004, Quadratic model: N-SPT(quadratic) = $0.0002\ qc^2 + 0.1859\ qc + 1.205$, and Cubic model: N-SPT(cubic) = $0.00001\ qc^3 - 0.036\ qc^2 + 0.4018\ qc + 0.1323$. These results suggest that all three regression models provide a strong basis for estimating N-SPT from qc, with the cubic model offered a slightly better fit, albeit with marginal improvement over the quadratic and linear models.

The strong statistical relationship observed in this study also highlights the practical advantages of integrating CPT and SPT data in geotechnical investigations. By establishing a reliable correlation between qc and N-values, engineers can reduce reliance on extensive SPT drilling in certain conditions, thereby improving efficiency in both time and cost. This approach is highly beneficial for large-scale projects or sites with limited accessibility, where CPT testing can provide continuous subsurface information more rapidly. Despite these advantages, the applicability of the developed correlation remains dependent on local soil conditions and testing consistency. Variations in soil composition, stress history, and depositional environment may influence the relationship between qc and N-values. As such, calibration using site-specific data is recommended when applying the correlation to new locations. This ensures that the estimated parameters remain representative of actual field conditions and reduces the risk of misinterpretation.

Future studies may further improve the reliability of SPT–CPT correlations by incorporating additional variables such as soil classification, fines content, and effective overburden stress. Expanding the database with more test results across different soil types and geological settings would also help refine the model and broaden its applicability. Such efforts would contribute to more robust and versatile correlations for use in geotechnical design and site investigation practices.

Acknowledgement

The appreciation goes to the commissionaire board of the company for their invaluable resources and support. Appreciation is also extended to fellow colleagues for the insightful discussions that inspired and strengthened this research. Their patience and readiness to assist had a significant role in bringing this research to completion. Lastly, sincere thanks are conveyed to the field technical staff for their expertise and professionalism in carrying out the field investigations. Their continued support and willingness to assist were crucial to the successful completion of this research

References

Alam, M., Aaqib, M., Sadiq, S., Mandokhail, S. J., Adeel, M. B., Maqsood-Ur-Rehman, & Kakar, N. A. (2018). Empirical SPT-CPT correlation for soils from Lahore, Pakistan. IOP Conference Series: Materials Science and Engineering, 414(1). https://doi.org/10.1088/1757-899X/414/1/012015

Alielahi, H., Mousavi, D., & addin Nadernia, Z. (2023). Statistical Assessment of Bearing Capacity of Cast-In-Situ Bored Piles Using Direct CPT and SPT Methods: A Case Study. Indian Geotechnical Journal, 53(3), 698–714. https://doi.org/10.1007/s40098-022-00690-4

Amran, Y., & Permadi, I. (2021). Analisis Perubahan Sifat Mekanis Tanah Gambut pada Stabilisasi Tanah Secara Kimiawi Menggunakan Difasoil Stabilizer dan Semen. TAPAK: Teknologi Aplikasi Konstruksi, 10(2). https://doi.org/10.24127/tp.v10i2.1585

Arifuzzaman, & Anisuzzaman, M. (2022). An initiative to correlate the SPT and CPT data for an alluvial deposit of Dhaka city. International Journal of Geo-Engineering, 13(1). https://doi.org/10.1186/s40703-021-00170-3

Arisandi, D., Apriyanti, Y., & Fahriani, F. (2017). Analisis Korelasi Nilai NSPT Dengan Nilai Tahanan Konus Sondir Menggunakan Metode Statistika. Jurnal Teknik Sipil Fakultas Teknik Universitas Bangka Belitung, 5, 1–10.

Bowles, J. E. (1997). Foundation Analysis and Design International Fifth Edition. In Civil Engineering Materials.

Costa, Y. D., & Cunha, E. S. (2016). Correlations between SPT and CPT data for a sedimentary tropical silty sand deposit in Brazil. Geotechnical and Geophysical Site Characterisation 5. https://www.issmge.org/publications/online-library

Costa, Y. D., Cunha, E. S., Costa, C. L., & Pereira, A. C. (2016). Correlations Between SPT And CPT Data For Sedimentary Tropical Silty Sand Deposit in Brazil. International Society for Soil Mechanics and Geotechnical Engineering. https://www.issmge.org/publications/online-library

Faivre, Y., Mirzaghorbanali, A., Nourizadeh, H., Shokri, B. J., Mcdougall, K., & Aziz, N. (2023). SPT-CPT correlation in Southeast Queensland, Australia. Resource Operators Conference, 268–279. https://ro.uow.edu.au/coalhttps://ro.uow.edu.au/coal/884

Fauzi, A., Afif, A., Lastiasih, Y., & Wahyudi, H. (2025). Numerical Analysis of EPS Geofoam as Lightweight Embankment Fill on Soft Soil: Case Study of Patimban Access Toll Road, Package 3. Interdisciplinary Social Studies, 5, 540–553. https://doi.org/10.55324/iss.v5i1.1004

Feda Aral, I., & Gunes, E. (2017). Correlation of Standard and Cone Penetration Tests: Case Study from Tekirdag (Turkey). IOP Conference Series: Materials Science and Engineering, 245(3). https://doi.org/10.1088/1757-899X/245/3/032028

Felić, H., Marzouk, I., & Tschuchnigg, F. (2025). A Data-Driven Approach For Soil Parameter Determination Using Supervised Machine Learning. In L. Zhongqiang, J. Dai, & K. Robinson (Eds.), International Symposium on Geotechnical Safety and Risk (ISGSR) (pp. 729–733). https://doi.org/10.3850/GRF-25280825_isgsr-156-P210-cd

Geotechnics, O. G., Supervisor, G., Gudmund, :, & Eiksund, R. (2014). Correlation between SPT and CPT.

Güner, A. B. S., & Özgan, E. (2025). Statistical Analysis of Soil Parameters Affecting the Bearing Capacity and Settlement Behaviour of Gravel Soils. Applied Sciences (Switzerland), 15(10). https://doi.org/10.3390/app15105271

Haifani, A. M. (2021). Developing New Relationship between Standard Penetration, Cone Penetration Test and Sleeve Friction in Various Soil Type (Vol. 48, Number 4).

Ifat, Md. B. H., & Rahman, Md. A. (2024). Correlation Between SPT and CPT of Various Soil Types in Padma River at Mawa (Downstream Side) Near Padma Bridge. International Conference on Advances in CivilEngineering (ICACE2024), 1391–1398. https://icace2024.cuet.ac.bd

Izzo, M. Z., & Miletić, M. (2019). Sustainable improvement of the crack resistance of cohesive soils. Sustainability (Switzerland), 11(20). https://doi.org/10.3390/su11205806

Jarantow, S. W., Pisors, E. D., & Chiu, M. L. (2023). Introduction to the Use of Linear and Nonlinear Regression Analysis in Quantitative Biological Assays. Current Protocols, 3(6). https://doi.org/10.1002/cpz1.801

Jarushi, F., & Cosentino, P. (2015). A New Correlation between SPT and CPT for Various Soils. International Journal of Environmental, Ecological, Geological and Geophysical Engineering, 9, 101–107. https://doi.org/10.5281/zenodo.1099380

Jarushi, F., Hasan, M., Hammouda, S. S., & Kenshel, O. (2025). Comparison of Soil Properties obtained from In-Situ Tests and Laboratory: Case Study of shallow Foundation. World Congress on Civil, Structural, and Environmental Engineering. https://doi.org/10.11159/icgre25.160

Kar, A., & Ansary, M. A. (2023). Bearing capacity estimation of driven piles based on CPT and validated by static load tests. In Journal of Civil Engineering (IEB) (Vol. 51, Number 1).

Karthik, N., Jeyapriya, S. P., & Rama, M. (2025). Large Language Model Based Prediction of SPT N value from Electrical Resistivity Correlations. Indian Journal Of Science And Technology, 18(46), 3640–3657. https://doi.org/10.17485/IJST/v18i46.1300

Lee, L. C., & Sino, H. (2024). A Critical Review of Soil Sampling and Data Analysis Strategies for Source Tracing of Soil in Forensic Investigations. Critical Reviews in Analytical Chemistry, 54(8), 3520–3558. https://doi.org/10.1080/10408347.2023.2253473

Mangidi, U., Minmahddun, A., Ngii, E., Sriyani, R., & Sulha. (2023). Prediction of SPT Value Based on Cone Penetration Test at Intake Water Project of Wolo River, Southeast Sulawesi. Indonesian Geotechnical Journal, 2(1). https://doi.org/10.56144/igj.v2i1.33

Marzouk, I., Oberhollenzer, S., & Tschuchnigg, F. (2023). An Automated System For Determining Soil Parameters: Case Study. Deformation Characteristics of Geomaterials, 3. https://www.issmge.org/publications/online-library

M.Das, B. (2002). Principles of Foundation Engineering. In McGraw-Hill handbooks.

Metboki, M. (2024). Pengujian Berdasarkan SNI Untuk Mengetahui Sifat Fisik dan Mekanis Tanah. Ahsana: Jurnal Penelitian Dan Pengabdian Kepada Masyarakat, 2(2), 40–43. https://doi.org/10.59395/ahsana.v2i2.337

Miranda, E. F., Sasongko, R. A., Cambodia, M., & Pratiwi, D. (2025). Characteristics of Soil Layers Based on Cone Penetration Test (CPT) for a Planned Villa Development (Case Study: Cisarua, Bogor). Journal of Civil Engineering and Planning, 6(2), 248–258. https://doi.org/10.37253/jcep.v6i2.11778

Nabila, A. T., Sayeed, N., Karim, R., Shahin, H. M., & Islam, S. (2023). Correlation of SPT-N & CPT Parameters of Dhaka Soil. World Congress on Civil, Structural, and Environmental Engineering. https://doi.org/10.11159/icgre23.111

Nahesson, P., Suhairiani, S., Enny, K. S., & Samuel, A. S. (2022). Distribution Pattern of Soil Bearing Capacity on the Island of Sumatra using Field Testing Data from Standard Penetration Test (SPT) Method. Journal of Physics: Conference Series, 2193(1). https://doi.org/10.1088/1742-6596/2193/1/012090

Okodugha, D. A., Omenaimen, I., Ikhazuagbe, O., & Aligamhe, V. I. (2025). Evaluating the Geotechnical Properties of Soil at Ughiole, Aviele, Edo State, Nigeria. European Journal of Advances in Engineering and Technology, 2025(3), 71–74.

Pande, P., Giri, J., Raut, J., Sabeur, H., Bhagat, R., & Azizi, M. (2025). Real-time prediction of soil bearing capacity in clayey soils using drilling parameters and statistical modeling. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-19767-0

Paul, I. K., Abedin, M. Z., & Saha, P. (2025). Penetration Test Parameters and Their Correlations for Different USCS Classes of Soil from Selected Locations of Bangladesh. Discover Civil Engineering, 2(1). https://doi.org/10.1007/s44290-025-00315-8

Pinto, J. M. R., Sert, S., & Arslan, E. (2025, December). Calibration of Undrained Parameters with Plaxis Soiltest Module based on Laboratory Triaxial Testing of a Fine-Grained Soil. EGE 14th International Conference on Applied Sciences.

Shahgholian, R., Ferreira, C., & da Fonseca, A. V. (2022). Correlation between SPT and CPT tests in liquefiable deposits. Cone Penetration Testing 2022 - Proceedings of the 5th International Symposium on Cone Penetration Testing, CPT 2022, 683–689. https://doi.org/10.1201/9781003308829-100

Sudjatmiko, E. T. (2022). SPT and CPT Correlation of Expansive Clay in Cikarang, Indonesia. Journal of the Civil Engineering Forum, 245–256. https://doi.org/10.22146/jcef.3458

Temitope, F. E., Blessing, B. O., & Olabanji, O. A. (2023). Geophysical And Geotechnical Pre-Foundation SiteInvestigation For Engineering Construction Purpose. IOSR Journal Of Applied Geology And Geophysics (IOSR-JAGG), 11. https://doi.org/10.9790/0990-1106012435

Wadi, D., Ahmed, H. E., Malik, I., Wu, W., & Fuad, A. (2025). Assessment of soil liquefaction potential using the standard penetration test at Port Sudan. University of Zawia Journal of Engineering Sciences and Technology, 3(1), 118–135. https://doi.org/10.26629/uzjest.2025.10

Zhou, H., Wotherspoon, L. M., Hayden, C., Mcgann, C. R., Stolte, A., & Haycock, I. (2021). Applicability of empirical SPT-CPT correlations for New Zealand soils. NZGS Symposium, 1–9.