ASEAN
Journal of Scientific and Technological Reports
Online ISSN:2773-8752

Research article

Process Capability Assessment Using SPC and Cpk in the Analysis of Clay Soil Atterberg Limits: A Case Study in Pathum Thani Province

Pattaraporn Nueasri[1], and Rattanachot Thongpong[1*]

[1] Faculty of Industrial Technology, Valaya Alongkorn Rajabhat University under The Royal Patronage, Pathum Thani Province, 13180, Thailand
* Correspondence: rattanachot.thong@vru.ac.th

Citation:
Nueasri, P.; Thongpong, R. Process capability assessment using SPC and Cpk in the analysis of clay soil atterberg limits: a case study I Pathum Thani Province *ASEAN J. Sci. Tech. Report.* **2026**, *29*(2), e260404. https://doi.org/10.55164/ajstr.v29i2.260404.

Article history:
Received: July 14, 2025
Revised: October 9, 2025
Accepted: November 15, 2025
Available online: January 21 2026

Abstract: This study evaluated the consistency and capability of the testing process for the Plasticity Index (PI) of fine-grained soils, a parameter critical for soil classification and geotechnical design, particularly in compaction and foundation analyses. Statistical Process Control (SPC) was applied using X–MR control charts to monitor process stability, while process capability was assessed through Cp and Cpk indices under specification limits of LSL = 2.00 and USL = 10.00. Trend analysis and uncertainty evaluation were also conducted to strengthen the assessment framework. Results showed that the PI testing process was statistically stable, with all data points within control limits. However, process capability indices (Cp = 0.702, Cpk = 0.616) were below the benchmark value of 1.33, indicating insufficient performance due to inherent variability. Linear regression revealed no significant time-related trend ($R^2 = 0.1\%$, $p = 0.864$), confirming temporal consistency. Uncertainty analysis yielded an expanded uncertainty of ±0.537 at 95% confidence, equivalent to 9.7% of the mean PI. Such uncertainty suggests possible misclassification of results near specification thresholds. In conclusion, although the PI testing process was under statistical control and free of time-related drift, it exhibited substantial variability and high uncertainty. These findings emphasize the need to reduce variation and incorporate uncertainty into quality management practices, providing a more reliable basis for decision-making in geotechnical engineering applications.

Keywords: Plasticity index; statistical process control; capability; soil compaction

1. Introduction

Soil is a natural material that plays a fundamental role in civil engineering, serving as the foundation for essential infrastructure such as buildings, roads, dams, and other load-bearing structures. The geotechnical suitability of local soil properties is a decisive factor influencing structural stability and safety, particularly in rapidly urbanizing regions such as Pathum Thani Province, located within the Bangkok Metropolitan Region. The predominant clay soils in this area are highly sensitive to fluctuations in moisture content; variations in water can induce swelling or shrinkage, thereby affecting load-bearing capacity and potentially compromising structural integrity. Therefore, accurate and reliable soil characterization is imperative for effective infrastructure planning and design. A widely accepted approach for evaluating the behavior of fine-grained soils involves determining the Atterberg Limits, which include the Liquid Limit (LL), Plastic Limit (PL), and Plasticity

Index (PI). These parameters are essential for classifying clay types and predicting soil performance under varying moisture conditions and applied loads [1]. However, the results of Atterberg Limit tests often exhibit variability due to differences in operator expertise, equipment calibration, sample preparation, and environmental factors, which may undermine data reliability and reproducibility.

To address such inconsistencies, researchers have recently introduced Statistical Process Control (SPC) and the Process Capability Index (Cpk) from industrial engineering as systematic tools for assessing the stability and performance of laboratory testing processes. For example, Hasan and Abuel-Naga [2] applied electrochemical techniques to improve the precision of PI measurements, enabling more reliable process capability assessments. Marušić and Jagodnik [3] demonstrated that the fall cone method produces more consistent LL results compared to the conventional Casagrande apparatus. Likewise, Rosas et al. [4] and Knadel et al. [5] emphasized the potential of integrating machine learning and spectroscopy techniques to reduce measurement bias and enhance test accuracy. Despite these advancements, most previous studies have focused primarily on improving individual testing methods rather than evaluating the overall process capability and measurement uncertainty of soil characterization procedures. Furthermore, the application of SPC and Cpk analysis to geotechnical testing, particularly for Atterberg Limits of clay soils, remains limited, especially within the ASEAN region, where heterogeneous soil conditions and diverse laboratory practices can lead to inconsistent results. Accordingly, the present study aims to analyze the PI of clay soils in Pathum Thani Province and to evaluate the consistency and capability of the testing process through the application of SPC and Cpk methodologies. The ultimate objective is to systematically quantify data reliability and process stability, thereby ensuring that the test results are robust and suitable for incorporation into geotechnical design frameworks in rapidly developing urban environments.

2. Theoretical Framework and Related Research

The evaluation of soil properties, particularly the Atterberg Limits of clayey soils, is fundamental in civil engineering as it influences the design and long-term stability of infrastructure [1–3]. The Liquid Limit (LL), Plastic Limit (PL), and Plasticity Index (PI) are essential parameters for soil classification and for predicting deformation behavior under variable moisture and load conditions. However, traditional testing methods often face variability stemming from operator technique and equipment inconsistencies, which may compromise data reliability [6]. To improve precision and consistency, industrial engineering approaches such as Statistical Process Control (SPC) and the Process Capability Index (Cpk) have been integrated into soil testing [4,7]. Recent studies have explored alternative measurement techniques, including electrical resistivity modeling [8], diffuse reflectance spectroscopy [9], and machine learning-based estimations [10], aiming to reduce human-induced errors and enhance rapid analysis. Moreover, the inherent variability of geotechnical properties significantly affects design safety, highlighting the importance of robust statistical evaluations [6]. The strong correlation between Atterberg Limits and compaction characteristics further emphasizes PI as a key predictor for field performance [11]. Additionally, chemical and electrochemical stabilization techniques have proven effective in modifying soil plasticity in tropical soils [12]. These integrated approaches underscore the necessity of combining advanced measurement techniques and process control strategies to enhance data reliability and structural safety in geotechnical engineering.

Therefore, the theoretical foundation of this study is built upon the integration of geotechnical testing principles with industrial quality management methodologies. By combining the deterministic nature of soil mechanics (through Atterberg Limits and classification) with statistical control concepts (SPC, Cp, Cpk) and uncertainty quantification, the framework provides a holistic approach to assess both the accuracy and consistency of soil property testing. This integration is particularly novel in the ASEAN context, where laboratory variability often challenges the reliability of soil classification for design and construction.

2.1 Atterberg Limits and Soil Classification

Atterberg Limits are quantitative indices used to describe the consistency and moisture-related behavior of clay soils. These limits provide systematic insight into strength, shrinkage potential, and plasticity under varying water contents [13]. Standardized testing procedures follow ASTM D4318–17 [1] and comprise:

- Liquid Limit (LL): The moisture content at which soil transitions from a plastic to a liquid state.
- Plastic Limit (PL): The moisture level at which soil shifts from semi-solid to plastic behavior.
- Shrinkage Limit (SL): The lowest moisture content at which further drying does not result in volume reduction. Soil classification based on the PI is derived using the equation 1.

$$PI = LL - PL \tag{1}$$

This index allows the classification of soils according to the Unified Soil Classification System (USCS), where the Plasticity Index (PI) and Liquid Limit (LL) thresholds define the soil type and its expected engineering behavior. The USCS categorizes fine-grained soils based on LL and PI values using the Casagrande Plasticity Chart, which delineates soil boundaries through the empirical A-line relationship, as shown in equation 2.

$$PI = 0.73(LL - 20) \tag{2}$$

This relationship helps differentiate clay and silt behavior and is widely applied in geotechnical engineering practice for soil classification purposes.

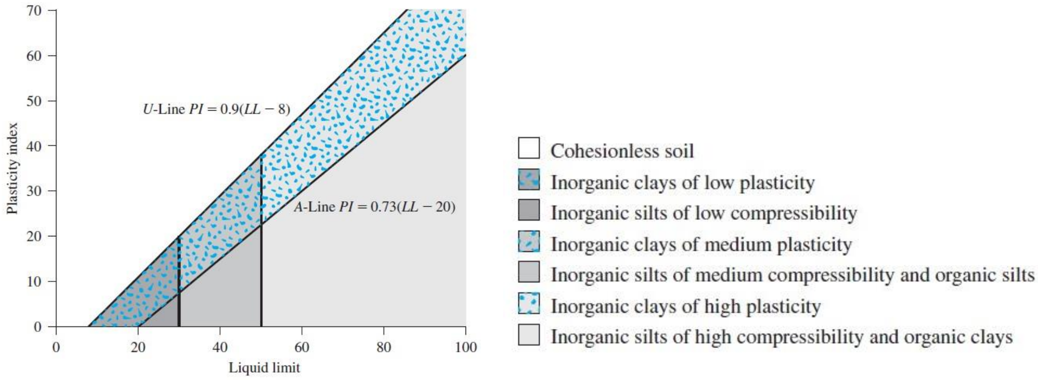


Figure 1. Casagrande plasticity chart showing classification of fine-grained soils based on LL and PI [14].

The A-line separates silts (ML/MH) from clays (CL/CH), with plasticity and liquidity thresholds guiding the classification [14]. Soil groups are interpreted not only by index values but also by their geotechnical behavior in construction and load-bearing scenarios.

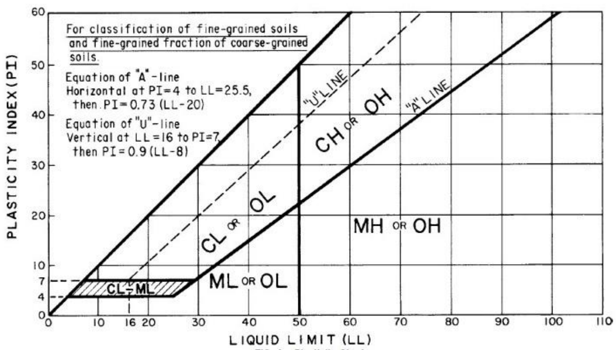


Figure 2. Plasticity chart for the USCS classification according to ASTM D4318-17 [1]

Table 1. Soil classification criteria according to USCS

Soil Group (USCS)	LL (%)	PI (%)	Key Characteristics
CL – Clay, Low Plasticity	LL ≤ 50	PI below A-line and PI < 7 (or ~7–17: medium)	Acceptable settlement; easily compacted
CH – Clay, High Plasticity	LL > 50	PI above A-line and PI > 17	High shrink–swell potential; requires stabilization (e.g., lime/cement)
ML / MH – Silt (Low/High Plasticity)	varies with LL	PI below A-line	Low shear strength; easily saturated and flow-prone

Recent advancements in soil characterization have introduced alternative methods to assess Atterberg Limits with improved precision and reproducibility. These approaches range from spectroscopic techniques to machine learning models and geotechnical interrelationships.

This study introduces a process-oriented framework for Atterberg Limits evaluation by integrating Statistical Process Control (SPC), process capability indices, and uncertainty assessment. Unlike previous works that emphasized prediction, correlation, or material characterization, this approach bridges geotechnical testing with quality management tools, providing a new perspective on the reliability, stability, and interpretive confidence of soil property testing, as summarized in Table 2.

Table 2. Summary of Recent Studies on Atterberg Limits and Identified Research Gaps

Reference	Atterberg Limits Focus	Spectroscopy / Indirect Estimation	Machine Learning (ML)	Correlation / Empirical Analysis	Soil Structure	SPC / Process Capability	Uncertainty & Guard Band
Knadel, Rehman et al. [5]	LL, PL, PI	x					
Rosas et al. [4]	LL, PL, PI		x				
Bhavya & Nagaraj [10]	LL, PL, PI				x		
Karakan et al. [15]	LL, PI			x			
Dehghanian & İpek [16]	PI				x		
This Study	LL, PL, PI					x	x

As summarized in Table 2, most previous studies focused on improving test precision or correlation analysis but rarely quantified process capability and uncertainty. This identified gap forms the foundation of the present study.

2.2 Statistical Process Control (SPC)

Statistical Process Control (SPC) refers to a set of statistical tools used to monitor, analyze, and control variability within testing or production processes. In this study, the primary SPC tool applied is the Individual Control Chart, also known as the X-MR Chart, which consists of two components [17].

*2.2.1. **X-Chart (Individual Value Chart)*** is used to monitor the central tendency of measured data.

- Mean of the data series:

$$\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{3}$$

- Control limits for the X-Chart:

$$\mathrm{UCL_X} = \bar{X} + 2.66 \cdot \overline{MR}, \quad \mathrm{LCL_X} = \bar{X} - 2.66 \cdot \overline{MR} \tag{4}$$

Where :

$\bar{X}$ = Mean of the data series

n = Number of samples

X_i = Individual measurement

$\overline{MR}$= Average moving range

$\mathrm{UCL_X}$ = Upper control limit

$\mathrm{LCL_X}$ = Lower control limit

2.2.2 *The MR-Chart (Moving Range Chart)* is used to assess short-term variability between successive measurements.

- Moving range for each data pair:

$$MR_i = |X_i - X_{i-1}| \tag{5}$$

- Mean of the moving ranges:

$$\overline{MR} = \frac{1}{n-1}\sum_{i=2}^{n} MR_i \tag{6}$$

2.2.3 Process Capability Index (Cpk)

The Process Capability Index (Cpk) is a quantitative metric used to evaluate how well a process can produce outputs within predefined specification limits. It considers both process variability and the location of the process mean relative to the specification range.

The standard formula is:

$$\mathrm{Cpk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right) \tag{7}$$

Where:

USL = Upper Specification Limit

LSL = Lower Specification Limit

μ = Process mean

σ = Standard deviation of the data

Common interpretation criteria include:

Cpk < 1.00, meaning the process is incapable or poorly controlled

Cpk = 1.00, meaning marginally acceptable

Cpk > 1.33, meaning the process exhibits high capability and statistical control

Integrating Cpk into the evaluation of soil properties, such as PI, enables a quantitative link between geotechnical characteristics and the ability to maintain testing consistency and quality. This approach supports data-driven decision-making in soil classification and construction design.

3. Research Framework

This study is grounded in an integrative framework combining concepts from civil engineering and industrial engineering. Its primary focus is the assessment of clay soil properties using Atterberg Limits, specifically the LL, PL, and PI. These parameters are essential for classifying clay soils according to the USCS and for predicting soil behavior under real-world conditions, such as mechanical loading and moisture variation. The data obtained from laboratory tests are subsequently analyzed statistically to evaluate process consistency and quality through the application of SPC and the computation of the Cpk [18]. The independent variables in this study include the Atterberg Limit values (LL, PL, PI) and fundamental soil sample characteristics such as sampling location and initial moisture content, which directly influence soil behavior. The dependent variables are the Cp and Cpk indices, which reflect the capability of the testing process. A Cpk

≥ 1.33 is typically required for high capability relative to specification limits; values between 1.00–1.33 indicate marginal capability as shown in Figure 3.

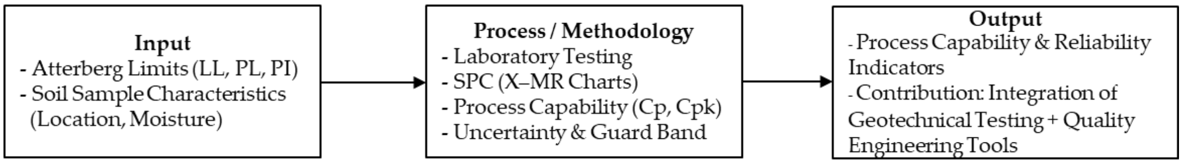


Figure 3. Research framework for Atterberg Limits testing with SPC, Cp/Cpk, and uncertainty analysis.

4. Methodology

4.1 Study Area and Soil Sampling

This study was conducted in Pathum Thani Province, located in the lower Chao Phraya River basin. The region's predominant soil type is moisture-saturated clay, which is particularly sensitive to environmental fluctuations. A total of 50 soil samples were collected across diverse subzones with varying environmental conditions to ensure a broad representation of local variability. Samples were gathered in their natural moisture state, stored in sealed containers, and subsequently transferred to the laboratory for formal testing.

4.2 Soil Property Testing

The collected soil samples were subjected to standard laboratory tests to determine their Atterberg Limits, including Liquid Limit (LL), Plastic Limit (PL), and Shrinkage Limit (SL), in accordance with ASTM D4318-17 [1]. Following the completion of these tests, the Plasticity Index (PI) was calculated using the equation. The complete test results are summarized in Table 3, providing a statistical foundation for subsequent analysis of process stability and capability.

Table 3. Atterberg Limits of Clay Soil Samples from Laboratory Testing

Sample No.	Liquid Limit (LL, %)	Plastic Limit (PL, %)	Shrinkage Limit (SL, %)	Plasticity Index (PI, %)	VLL	VPL	VSL
1	60.65	57.52	33.57	3.13	0.9	0.46	0.07
2	52.06	46.47	32.24	5.6	0.88	0.75	0.4
3	61.52	57.99	28.22	3.52	0.98	0.59	0.47
4	40.29	35.26	23.95	5.03	0.8	0.65	0.06
5	48.46	40.76	27.08	7.7	0.89	0.74	0.48
6	47.84	43.1	26.39	4.74	0.75	0.59	0.41
7	51.87	45.64	26.12	6.23	0.8	0.68	0.51
8	48.45	39.34	29.27	9.11	0.93	0.44	0.32
9	59.83	53.79	33.99	6.04	0.82	0.4	0.28
10	50.14	44.68	34.02	5.46	0.99	0.86	0.46
...	...	...	...	...	...	...	...
48	56.51	51.64	41.32	4.87	0.83	0.57	0.15
49	53.56	49.37	31.4	4.19	0.75	0.52	0.25
50	42.03	36.33	26.91	5.7	0.74	0.42	0.31

*Note: Table 3 shows selected samples for illustration. Full results are included in the Supplementary Appendix.

The relationship between moisture content and the volume ratio of soil samples (n = 50) exhibits a consistently convex upward trend. This pattern reflects the expansion behavior of clayey soil mass as moisture increases, a characteristic attributable to its high-water adsorption and retention capacity. In the low moisture range (below 20%), the volume ratio remains relatively stable within 0.2–0.4, indicating that the soil remains in a semi-solid state with preserved internal structure and limited deformability. When moisture rises to approximately 25–40%, the volume ratio increases noticeably, suggesting a transition into the plastic state where the soil demonstrates enhanced deformability without fracturing. This behavior aligns with the defined thresholds of PL and LL, as described by Atterberg [19]. Beyond 45% moisture content, the graph shows a rapid increase in volume ratio, indicating entry into the liquid state. In this condition, the soil loses its shape-retention capacity, and interparticle bonding weakens significantly. Such moisture levels exceed the LL and can adversely affect the structural integrity of geotechnical applications, including foundations and compacted fills.

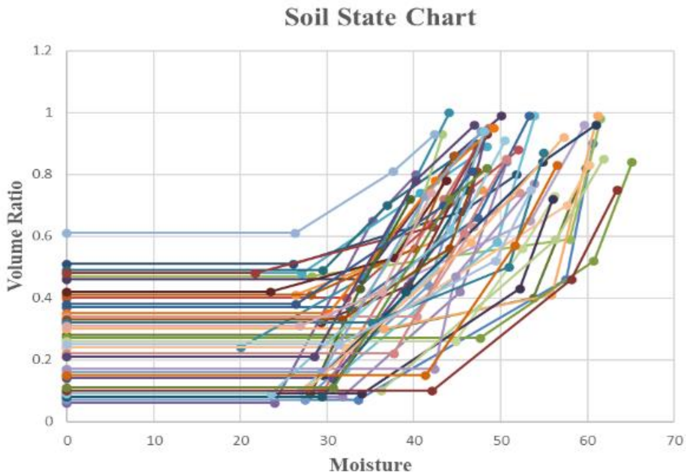


Figure 4. The relationship between moisture content and the volume ratio of soil samples

Figure 4 illustrates this volumetric transition clearly. The slope of the curve across different intervals also suggests sample-specific responses to moisture variation. Notably, soils with higher PI values tend to exhibit greater expansion, potentially due to differences in clay mineral composition. These PI values are consequently used as key indicators for evaluating soil behavior and serve as the basis for statistical process analysis in subsequent research stages.

Table 4. Statistical Analysis of Atterberg Limit Variables

Variable	N	Mean	SE Mean	StDev	Minimum	Q1	Median	Q3
LL	50	51.454	0.917	6.484	39.600	47.080	50.325	56.330
PL	50	45.944	0.988	6.987	33.770	40.627	44.750	51.785
SL	50	31.184	0.821	5.806	20.030	27.365	29.835	33.995
PI	50	5.510	0.269	1.902	2.170	4.250	5.335	6.230

The statistical analysis of 50 clay soil samples revealed Atterberg Limit values that reflect distinctive geotechnical characteristics of the study area in Pathum Thani Province. Specifically, the average LL was 51.45%, with a standard deviation of 6.48, indicating that local soils exhibit a broad moisture transition range from liquid to plastic states. Liquid Limit values exceeding 50% suggest that most samples belong to high water-retention clays with pronounced plasticity behavior. The PL had an average of 45.94% and a median of 45.77%, reflecting a symmetrically distributed dataset and indicating that most soils transition from semi-solid to plastic form at relatively high moisture levels. This range aligns with favorable workability for foundation and compaction applications. Shrinkage Limit (SL) values averaged 31.18%, suggesting that the minimum moisture level at which volume reduction ceases remains relatively high. This behavior is typical of deep-layer clays with fine-grained structures capable of preserving volumetric stability upon drying. The Plasticity Index (PI), defined as the difference between LL and PL, averaged 5.51% with a range of 2.17–10.75%, classifying the soil samples within the low to medium plasticity range based on USCS criteria. The concentration of PI values within a narrow bandwidth indicates a high degree of consistency in soil characteristics across the sampled region. This observation aligns with initial control chart results (X-MR), which confirmed process stability. The statistical data suggest that clay soils in Pathum Thani exhibit low to moderate plasticity, making them suitable for compaction work with manageable moisture sensitivity. These findings provide a sound foundation for subsequent process capability evaluation using the Cpk index and SPC methodology.

5. Results

5.1 Process Consistency Evaluation of Plasticity Index Testing

The consistency of the Plasticity Index (PI) testing process was assessed using an Individual Control Chart (X-MR Chart), which includes two components: the Individual Value Chart (X-Chart) and the Moving Range Chart (MR-Chart). These charts evaluate both central tendency and short-term variability across successive measurements of PI values. The statistical control parameters derived from the test data are summarized in Table 5.

Table 5. Control Chart Parameters from X-MR Analysis of PI Data

Process Mean	Mean Moving Range	Upper Control Limit X Chart	Lower Control Limit X Chart	Upper Control Limit MR Chart	Lower Control Limit MR Chart
5.51	2.426	11.96	-0.94	7.925	0

The analysis revealed that the average Plasticity Index (PI) from 50 test samples was 5.51%, with a standard deviation of 1.90. Based on the Individual Value Chart, all data points were found within the statistical control boundaries. Upper Control Limit (UCL) = 11.96 and Lower Control Limit (LCL) = –0.94 with no observations falling outside the acceptable range. This indicates the absence of special cause variation or systematic irregularities. Similarly, the Moving Range Chart showed an average moving range ($\overline{MR}$) of 2.43, and no individual MR values exceeded the UCL of 7.93. These results confirm that the PI testing process was statistically stable and consistent across the entire dataset, as shown in Figure 5.

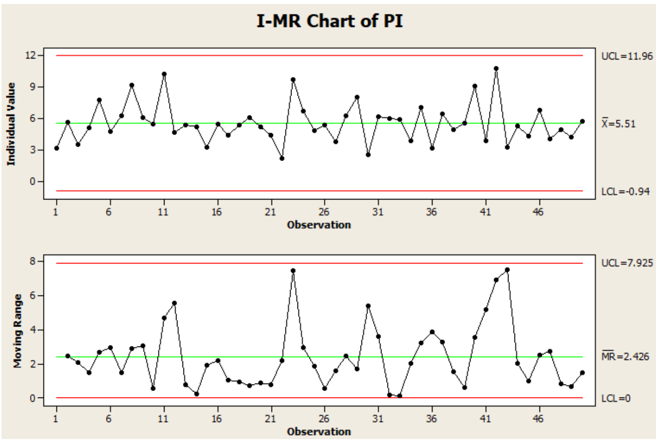


Figure 5. X-MR Control Chart of Plasticity Index

Upon examining the data distribution, no systematic bias or directional drift was observed, and the variation appeared random throughout the dataset. This confirms that the PI testing process was statistically "in control," in accordance with the principles of Statistical Process Control (SPC) [17]. There were no signs of abnormal behavior caused by process shifts or external disturbances. As such, the test results from all 50 samples can be considered sufficiently reliable, serving as a strong foundation for evaluating the process capability index (Cpk) in the subsequent section.

5.2 Process Capability Assessment of Plasticity Index Testing.

The capability of the Plasticity Index (PI) testing process was evaluated using the Cp and Cpk indices under predefined specification limits: a Lower Specification Limit (LSL) of 2.00 and an Upper Specification Limit (USL) of 10.00. This specification range is grounded in geotechnical engineering considerations. A PI value below 2.00 generally indicates non-plastic material, which is unsuitable for compaction applications due to poor deformation capacity. Conversely, PI values exceeding 10.00 suggest highly plastic clays that may cause structural instability, such as shrinkage upon drying or excessive swelling when exposed to moisture. This rationale aligns with the classification criteria defined by the Unified Soil Classification System (USCS), which categorizes clays into three ranges: Low plasticity: PI < 7**,** Medium plasticity: 7 ≤ PI ≤ 17, and High plasticity: PI > 17**.** Therefore, selecting a specification range of 2–10 effectively encompasses materials within the "low to medium plasticity" category, consistent with the characteristics of Pathum Thani clay soils observed in this study. These threshold values support the engineering suitability of the materials for foundational and fill applications while setting boundaries that protect against undesirable behaviors under field conditions, as presented in Figure 6.

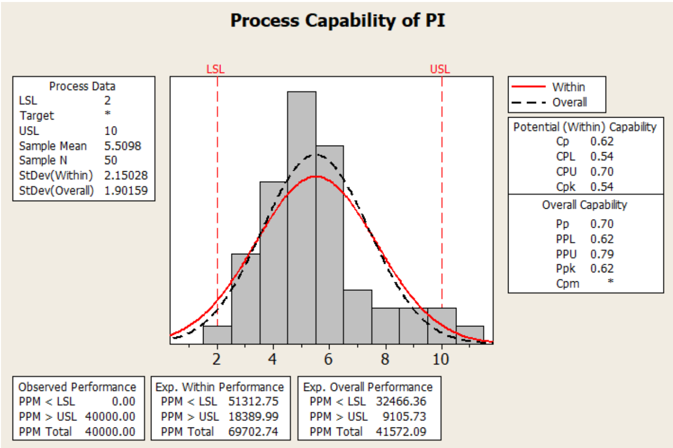
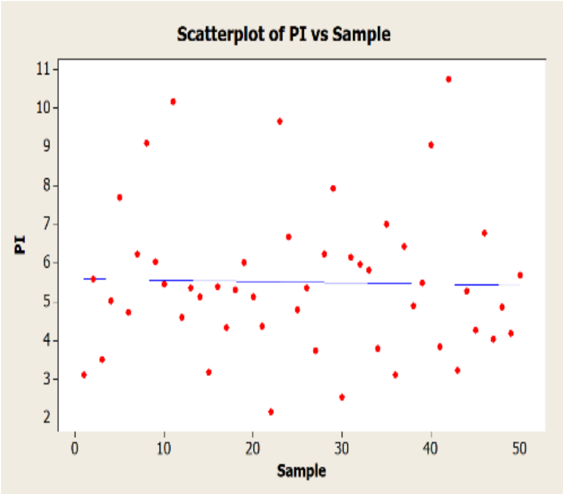


Figure 6. Process Capability Analysis of Plasticity Index

The analysis revealed that the process capability index values were Cp = 0.702 and Cpk = 0.616, both below the commonly accepted benchmark of 1.00 or higher for quality control. A Cp value less than 1.00 indicates that the process variation exceeds the tolerance defined by the specification limits. In addition, the Cpk value of 0.616 confirms that the process mean is not centered within the specification range. This conclusion is supported by the observation that the upper capability (CPU) exceeds the lower capability (CPL), which indicates that the process distribution is skewed toward the Lower Specification Limit (LSL). Cp reflects the theoretical capability of the process, assuming perfect centering. The low value suggests substantial internal variation. On the other hand, Cpk considers the position of the process mean, and the resulting value reveals that the process average deviates from the midpoint of the specification range. Such misalignment may introduce performance risks under field conditions. The Parts Per Million (PPM) analysis showed that approximately 4 percent of the results exceeded the Upper Specification Limit (USL), which is equivalent to 40,000 PPM. Although no values fell below the LSL, the presence of high-side outliers negatively affects overall process conformity. According to structural engineering standards, a Cpk value of at least 1.33 is typically required to ensure reliable performance. The observed Cpk falls short of this requirement, even when material-specific variability is taken into account. In conclusion, while the PI testing process demonstrates statistical stability, the overall capability remains low. To address this issue, it is recommended to improve moisture control, enhance sample preparation procedures, and refine measurement techniques. These adjustments can help reduce process variation and increase the Cpk value to meet engineering reliability standards more effectively.

5.3 Trend Analysis

Trend analysis of the Plasticity Index (PI) values across 50 test samples revealed a randomly distributed pattern, with no observable upward or downward trend throughout the testing sequence. The corresponding sample sequence chart confirms that the data remained statistically stable over time. This indicates that the testing process did not experience time-based drift or variation induced by external factors, such as environmental fluctuations or procedural inconsistency during sample handling, as shown in Figure 7.



Regression Analysis: PI versus Sample

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The regression equation is
PI = 5.59 - 0.0032 Sample


Predictor       Coef  SE Coef      T      P
Constant      5.5923   0.5515  10.14  0.000
Sample      -0.00323  0.01882  -0.17  0.864


S = 1.92070   R-Sq = 0.1%   R-Sq(adj) = 0.0%


Analysis of Variance

Source          DF       SS     MS     F      P
Regression       1    0.109  0.109  0.03  0.864
Residual Error  48  177.077  3.689
Total           49  177.186
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Figure 7. Trend Analysis of the Plasticity Index (PI)

To investigate the temporal behavior of the PI and determine whether a systematic trend exists across the sequence of measurements, a Linear Trend Analysis was performed using Minitab 16. The dataset consisted of PI values from 50 consecutively measured soil samples. The results were visualized through a scatterplot with an overlaid linear trend line to assess directional movement. The analysis indicated that PI values were distributed across the range of approximately 2 to 11, without exhibiting any clear upward or downward trajectory. The linear trend line displayed an extremely shallow slope, suggesting no significant temporal change in PI values throughout the testing sequence. If evaluated using a regression model, the coefficient of determination (R^2) was found to be lower than 0.10, implying that linear trends explain only a minimal portion of the observed variability. This finding supports the interpretation that the PI testing process is temporally stable and free from progressive drift or systematic deviation. The absence of trend-related anomalies aligns with the results from the X-MR control chart, which demonstrated that the process operates within statistically stable conditions. Therefore, there is no indication of abnormal variation at any specific point in the sample sequence. The trend-free nature of the data reinforces earlier SPC results and confirms that the testing process was conducted under controlled and repeatable conditions, without interference from special causes. The estimated linear regression equation, using Sample Order as the independent variable and PI as the dependent variable, is expressed as:

$$\widehat{PI} = 5.5923 - 0.0032 \cdot \text{Sample}$$

This equation further illustrates that the slope is nearly zero, and the process mean remains consistent throughout the sample order.

Table 6. The regression analysis results

Slope	R-Squared (R^2)	P-Value	Residual Standard Deviation
−0.0032	0.1%	0.864	1.9207

Based on the regression analysis results, the slope of −0.0032 indicates a slight negative trend in PI values as sample order increases. However, the associated p-value of 0.864 demonstrates that this trend is not statistically significant. The coefficient of determination (R^2) equals just 0.1%, meaning that the linear trend line explains only 0.1% of the variation in PI values. This suggests that the trend has virtually no influence on the overall behavior of the dataset. Accordingly, it can be concluded that the PI testing process does not exhibit a clear temporal pattern across the sample sequence. This finding supports the earlier X-MR chart analysis, which confirmed the statistical stability of the testing process and the absence of systematic time-dependent changes.

5.4 Uncertainty Analysis

The uncertainty of the mean PI was evaluated using a 95 % confidence interval to assess the reliability and precision of the testing results. The computed mean PI was 5.51, with a 95 % confidence interval ranging from 5.08 to 5.94, indicating a relatively narrow dispersion and confirming the stability of the dataset. This narrow range reflects good measurement precision and supports confidence in the reliability of soil quality assessments. According to the statistical summary presented in Table 3, the descriptive values are as follows: Mean = 5.51, Standard Deviation = 1.90, and 95 % Confidence Interval of the Mean = [5.08, 5.94]. Subsequently, the expanded uncertainty was determined using the following equation 8.

$$U = k \cdot \frac{\sigma}{\sqrt{n}} \tag{8}$$

Where:

U = Expanded Uncertainty
k = Coverage factor (for 95% confidence, typically k = 2)
σ = Standard deviation
n = Sample size

This expanded uncertainty offers a quantitative expression of the range within which the true mean value is expected to fall with high confidence. A relatively low uncertainty indicates high reproducibility and test consistency.

$$U = 2 \cdot \frac{1.90}{\sqrt{50}}$$
$$\text{by } k = 2 \text{ (95\% confidence interval)}$$
$$= \pm 0.537$$

The expanded uncertainty of ±0.537 represents the confidence interval of the true process mean, not the deviation of individual test results. This indicates that the estimated mean PI lies within this range at a 95% confidence level. This becomes especially critical when considered alongside specification limits. For instance, if a measured PI value approaches the Upper Specification Limit (USL) of 10.00 such as 9.5 units the inclusion of uncertainty may result in values exceeding the allowable threshold. Therefore, caution is advised when interpreting PI results, and it is recommended to evaluate uncertainty in conjunction with specification criteria to minimize engineering risk. On the other hand, a narrow confidence interval reflects the consistency of the testing process and reduces the likelihood that the results will deviate substantially from standard thresholds. This reinforces the reliability of the PI measurements and supports their use in process capability evaluation.

Table 7. Summary of Expanded Uncertainty (±U) and Percent Error

Summary	Value	Description
PI (μ)	5.51	Based on the Plasticity Index results from 50 soil samples
(σ)	1.90	Calculated using Minitab statistical analysis
Factor (k)	2	Corresponds to a 95% confidence level
Uncertainty (±U)	±0.537	$U = 2 \cdot \frac{1.90}{\sqrt{50}}$
% Uncertainty of Mean	9.74	$\frac{U}{\mu} \times 100 = 0.537 \div 5.51 \times 100$

To enhance decision reliability near specification boundaries, a Guard Band was established based on the expanded uncertainty (±0.537). This approach is especially critical when assessing Plasticity Index (PI) values that approach the Lower Specification Limit (LSL = 2.00) or Upper Specification Limit (USL = 10.00).

Table 8. Guard Band Assessment for Specification-Based Decision-Making

Specification Limit	Value	Guard Band (±U)	Cautionary Interpretation
Lower Spec Limit	2.00	2.00 + 0.537 = 2.537	PI ≤ 2.537 should be considered near the LSL boundary.
Upper Spec Limit	10.00	10.00 – 0.537 = 9.463	PI ≥ 9.463 should be considered near the USL boundary.

Values falling within the range of 2.537 to 9.463 are considered to lie within the compliance zone, representing acceptable conformity to the specification limits. However, PI values approaching either limit should be interpreted with engineering caution, as measurement uncertainty may influence the classification outcome. For instance, a sample yielding a PI of 9.2 lies within the upper cautionary zone. Considering the expanded uncertainty of ±0.537, the true value could potentially exceed the Upper Specification Limit (USL = 10.00) in practice. Therefore, such borderline cases should be treated conservatively and not be conclusively classified as within specification, particularly in quality control applications such as soil compaction or fill material evaluation. Incorporating guard bands into process capability evaluation enhances the robustness and reliability of engineering decisions near specification boundaries. This approach helps reduce false acceptance or rejection risks, ensuring more dependable quality assurance under conditions of measurement uncertainty.

6. Discussion

In the process capability analysis using Statistical Process Control (SPC), the X–MR charts for Liquid Limit (LL), Plastic Limit (PL), and Plasticity Index (PI) demonstrated that all test results were within control limits, confirming statistical stability and the absence of abnormal variation. This outcome indicates that the testing procedure is consistent and reliable for laboratory practice. Process capability indices were recalculated for PI with respect to the specification limits (LSL = 2.00, USL = 10.00). The results showed Cp = 0.702 and Cpk = 0.616, both lower than the Automotive Industry Action Group benchmark of 1.33. These findings reveal that although the process is statistically stable, its capability remains limited, reflecting moderate internal variability. Compared with the initially reported values, the corrected indices suggest that the process is closer to acceptable levels, but further improvements are still necessary. Enhancements in operational parameters, particularly moisture regulation, sample preparation, and instrument calibration, could help reduce variability and improve performance toward capability benchmarks. The corrected uncertainty analysis provided additional insights. The expanded uncertainty was calculated as ±0.537, equivalent to approximately 9.7% of the mean PI value (5.51). This is substantially lower than previously reported and demonstrates that the measurement system has reasonable precision. Considering guard band adjustments, this uncertainty improves the reliability of decisions regarding specification compliance. These results align with prior studies by Hasan and Abuel-Naga [2] and Abdallah et al. [7], which emphasized the value of statistical indices in geotechnical testing. Overall, the findings indicate that while the current process is not fully capable, it remains stable, reasonably precise, and suitable for preliminary geotechnical assessments.

7. Conclusion

This study aimed to evaluate the consistency and capability of the soil property testing process, with emphasis on the Plasticity Index (PI), a key parameter for classifying clay soil based on the Unified Soil Classification System (USCS). Plasticity Index serves as a critical indicator in geotechnical engineering applications, such as compaction assessment and subgrade stability analysis. The research methodology integrated Statistical Process Control (SPC), Process Capability Index (Cpk) evaluation, trend analysis, and uncertainty analysis to provide a comprehensive view of temporal stability, process reliability, and data limitations. The analysis demonstrated that the X-MR Control Chart, comprising the X Chart and Moving Range Chart, effectively captured process stability. All 50 PI data points were located within control limits, with no sign of abnormal patterns or systemic interference, confirming statistical stability of the measurement process. Process capability was assessed using Cp and Cpk indices under specified limits: Lower Specification Limit (LSL) = 2.00 and Upper Specification Limit (USL) = 10.00. Results showed Cp = 0.702 and Cpk = 0.616, both falling below the industry-accepted benchmark of 1.33 for quality assurance. These values indicate that although the process is statistically stable, it remains incapable of fully meeting specification requirements due to internal variability, particularly in relation to results near the upper limit of the specification range. Trend analysis using linear regression revealed no statistically significant time-based drift in PI values (R^2 = 0.1%, p-value = 0.864), reinforcing the stability of the process over sequential measurements. No embedded anomalies or directional bias were detected, corroborating findings from SPC. Uncertainty was quantified using a Type A evaluation based on actual test data. The corrected expanded uncertainty (±U) was ±0.537, representing approximately 9.7% of the mean PI value (5.51). This relatively moderate level of uncertainty indicates that the measurement system is more precise than previously reported, providing higher confidence in results even when values approach specification boundaries. When integrated with Guard Band considerations, this level of uncertainty improves interpretive safety and reduces decision-making error in material quality control for engineered fill. In summary, the PI testing process demonstrated temporal stability and statistical control. However, limited process capability (Cpk = 0.616 < 1.33) underscores the need for stricter control of influencing factors such as moisture regulation, sample preparation, and measurement precision. Furthermore, the corrected uncertainty analysis highlights the importance of including measurement uncertainty as an integral component of engineering judgment when interpreting PI results near specification limits.

Author Contributions: Conceptualization, P.N. and R.T.; methodology, P.N. (industrial engineering) and R.T. (civil engineering); software, P.N.; validation, P.N. and R.T.; formal analysis, P.N. (industrial engineering) and R.T. (civil engineering); investigation, P.N.; resources, R.T.; data curation, P.N.; writing—original draft preparation, P.N.; writing—review and editing, R.T.; visualization, P.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] ASTM D4318-17. *Standard Test Methods for Liquid Limit, Plastic Limit, and Plasticity Index of Soils*; ASTM International: West Conshohocken, PA, USA, **2017**.

[2] Hasan, M. F.; Abuel-Naga, H. Determining Liquid Limit and Plastic Limit of Clay Soils by Electrical Surface Conduction and Diffuse Double Layer Thickness. *Minerals* **2024**, *14*3), 210. https://doi.org/10.3390/min14030210

[3] Marušić, D.; Jagodnik, V. Determination of the Atterberg Limits Using a Fall Cone Device on Low Plasticity Silty Sands. *Min. Geol. Pet. Eng. Bull.* **2023**, *38*(3), 133–145. https://doi.org/10.17794/rgn.2023.3.11

[4] Rosas, D. A.; Burgos, D.; Branch, J. W.; Corbi, A. Automatic Determination of the Atterberg Limits with Machine Learning. *DYNA* **2022**, *89*(224), 102619. https://doi.org/10.15446/dyna.v89n224.102619

[5] Knadel, M.; Rehman, H. U.; Pouladi, N.; de Jonge, L. W.; Moldrup, P.; Arthur, E. Estimating Atterberg Limits of Soils from Reflectance Spectroscopy and Pedotransfer Functions. *Geoderma* **2021**, *402*, 115300. https://doi.org/10.1016/j.geoderma.2021.115300

[6] Phoon, K. K.; Kulhawy, F. H. Characterization of Geotechnical Variability. *Can. Geotech. J.* **1999**, *36*(4), 612–624.

[7] Abdallah, A.; Russo, G.; Cuisinier, O. Statistical and Predictive Analyses of the Strength Development of a Cement-Treated Clayey Soil. *Geotechnics* **2023**, *3*(2), 465–479. https://doi.org/10.3390/geotechnics3020026

[8] Alsharari, N.; Olenko, A.; Abuel-Naga, H. Modeling of Electrical Resistivity of Soil Based on Geotechnical Properties. *arXiv* **2019**, arXiv:1911.06501. https://arxiv.org/abs/1911.06501

[9] Weber, P.; Knadel, M.; Arthur, E. Diffuse Reflectance Spectroscopy for Rapid Estimation of Soil Atterberg Limits. *Geoderma* **2018**, *361*, 114083. https://doi.org/10.1016/j.geoderma.2018.07.018

[10] Bhavya, K.; Nagaraj, T. Influence of Soil Structure and Clay Mineralogy on Atterberg Limits. *Sci. Rep.* **2025**, *15*, 11292. https://doi.org/10.1038/s41598-025-98729-y

[11] Prasanna, H. S.; Harshitha, D. Correlation of Compaction Characteristics of Fine-Grained Soils Using Atterberg Limits. *Int. J. Eng. Res. Technol.* **2017**, *6*(6). https://doi.org/10.17577/IJERTV6IS060051

[12] Ayodele, A. L.; Pamukcu, S.; Agbede, O. A. Plasticity Modification of a Tropical Laterite by Electrochemical Stabilization. *Electrochim. Acta* **2020**, *341*, 136047. https://doi.org/10.1016/j.electacta.2020.136047

[13] Holtz, R. D.; Kovacs, W. D.; Sheahan, T. C. *An Introduction to Geotechnical Engineering*, 2nd ed.; Prentice Hall: Upper Saddle River, NJ, **2011**.

[14] Das, B. M.; Sobhan, K. *Principles of Geotechnical Engineering*, 8th ed., SI Version; Cengage Learning: Stamford, CT, **2014**.

[15] Karakan. Comparative Analysis of Atterberg Limits, Liquidity Index, Flow Index, and Undrained Shear Strength in Binary Clay Mixtures. *Appl. Sci.* **2022**, *12*, 8616. https://doi.org/10.3390/app12178616

[16] Dehghanian, K.; İpek, S. Ö. A Survey on the Relationships between Compression Index, Coefficient of Consolidation, and Atterberg Limits. *J. Sustain. Constr. Mater. Technol.* **2022**, *7*(4). https://doi.org/10.47481/jscmt.1161504

[17] Abdallah, A.; Russo, G.; Cuisinier, O. Statistical and Predictive Analyses of the Strength Development of a Cement-Treated Clayey Soil. *Geotechnics* **2023**, *3*(2), 465–479. https://doi.org/10.3390/geotechnics3020026

[18] Montgomery, D. C. *Introduction to Statistical Quality Control*, 7th ed.; John Wiley & Sons: Hoboken, NJ, USA, **2019**.

[19] Terzaghi, K.; Peck, R. B.; Mesri, G. *Soil Mechanics in Engineering Practice*, 3rd ed.; John Wiley & Sons: Hoboken, NJ, **1996**.

[20] Saied, E.; Besees, A. Y.; Wazeer, A.; Abd-Eltwab, A. A. Process Performance Analysis in Cement Industry. *Int. J. Sci. Technol. Res.* **2020**, *9*(6), 844–860.