JOURNAL OF GEOSPACE SCIENCE

Vol. 6 No. 2 (2026)

E-ISSN : 2413-6093
https://jogss.org

Bayesian Fusion of CPTu Dissipation and DMT Stress Indices for Clay History Classification

Ye-Jin Moon, Ha-Neul Jeon

School of Mechanical Engineering, Pusan National University, Busan, Republic of Korea

ABSTRACT

The accurate classification of clay stress history is a foundational requirement in geotechnical engineering, directly influencing the design, safety, and economic viability of infrastructure projects. Traditional deterministic methods often rely on isolated in-situ tests, such as the Piezocone Penetration Test with pore pressure measurement or the Flat Dilatometer Test, which can yield conflicting interpretations due to inherent soil variability and measurement uncertainties. This paper presents a comprehensive framework for the Bayesian fusion of dissipation metrics derived from the Piezocone Penetration Test and horizontal stress indices obtained from the Flat Dilatometer Test to classify clay history. By leveraging Bayesian inference, the proposed model systematically integrates the complementary strengths of both testing modalities while rigorously quantifying the epistemic and aleatory uncertainties associated with site characterization. Extensive field data from multiple well-documented clay deposits are utilized to calibrate the probabilistic model. The fusion approach demonstrates a significant improvement in classification accuracy for normally consolidated, lightly overconsolidated, and heavily overconsolidated clay profiles compared to single-sensor interpretations. The integration of dissipation decay characteristics with horizontal stress parameters provides a multidimensional decision boundary that mitigates false positive classifications in transitional soil layers. This research offers a robust, probabilistically sound methodology that enhances the reliability of geotechnical site investigations and provides engineers with a quantifiable measure of confidence in soil behavior predictions.

KEYWORDS

Bayesian Inference, Piezocone Penetration Test, Flat Dilatometer Test, Clay Stress History, Geotechnical Fusion

1. Introduction

1.1 Motivation and Background in Geotechnical Site Characterization

The mechanical behavior of cohesive soils is fundamentally governed by their stress history, which is typically quantified by the overconsolidation ratio. This ratio, defined as the maximum past effective stress divided by the current in-situ effective stress, dictates the compressibility, shear strength, and

permeability characteristics of clay deposits. Accurate determination of the overconsolidation ratio is paramount for predicting settlement under structural loads, assessing slope stability, and designing deep foundations. Historically, engineers have relied heavily on the extraction of high-quality undisturbed soil samples followed by extensive laboratory testing, most notably one-dimensional consolidation tests, to ascertain the stress history. However, the retrieval of truly undisturbed samples is notoriously difficult, particularly in sensitive or highly structured clays, and the laboratory processes are time-consuming, expensive, and subject to disturbances associated with stress relief and sample handling. Consequently, the geotechnical industry has increasingly transitioned towards in-situ testing methods to evaluate soil properties in their natural state [1]. Among the most widely adopted techniques are the Piezocone Penetration Test, commonly referred to as CPTu, and the Flat Dilatometer Test, known as DMT. While both methods offer continuous or near-continuous profiles of soil stratigraphy and empirical correlations to mechanical properties, they interact with the soil matrix in fundamentally different ways. The CPTu induces large strain, primarily vertical and radial displacements, providing continuous measurements of tip resistance, sleeve friction, and penetration pore water pressure. Furthermore, pausing the penetration allows for the measurement of pore pressure dissipation over time, which offers invaluable insights into the consolidation characteristics and hydraulic conductivity of the formation [2]. Conversely, the DMT is a lateral expansion test that introduces minimal initial disturbance due to its blade-like geometry. The subsequent expansion of a flexible membrane provides measurements that are highly sensitive to the lateral stress state and the stiffness of the soil, making it particularly well-suited for evaluating the horizontal stress index and, by extension, the stress history [3]. Despite their individual merits, reliance on a single testing modality often leads to ambiguous classifications, especially in geologically complex environments where physical properties overlap across different overconsolidation categories.

1.2 Limitations of Current In-Situ Testing Methods

The interpretation of in-situ test data relies heavily on empirical or semi-empirical correlations derived from specific geologic formations. When these correlations are extrapolated to new sites with different depositional environments, mineralogy, or diagenetic processes, the predictive accuracy frequently deteriorates. For instance, the estimation of overconsolidation ratio from CPTu data is heavily dependent on the net cone resistance and the excess pore water pressure generated during penetration [4]. However, the generation of pore pressure is highly complex, influenced by the partial drainage conditions during penetration, the rigidity index of the soil, and the degree of soil structure or cementation. Dissipation tests, while providing a direct measure of the coefficient of consolidation, are often underutilized for stress history classification due to the non-linear and sometimes non-monotonic decay curves observed in heavily overconsolidated clays [5]. On the other hand, the DMT horizontal stress index is widely recognized as one of the most reliable indicators of overconsolidation ratio, as it reflects the in-situ lateral earth pressure coefficient which increases during unloading processes [6]. Nevertheless, the DMT is a point-in-time measurement taken at specific depth intervals, lacking the high-resolution continuous profiling capability of the CPTu. Furthermore, both methods are subject to measurement noise, equipment compliance issues, and operator-induced variabilities [7]. When engineers evaluate data from both tests side-by-side, they often encounter conflicting classifications. A soil layer might exhibit a CPTu signature indicative of a normally consolidated clay due to low tip resistance, while simultaneously displaying a high DMT horizontal stress index suggestive of overconsolidation. These discrepancies force practitioners to rely on subjective engineering judgment, effectively discarding the objective value of the collected data. The deterministic frameworks currently prevalent in geotechnical engineering lack a formal mechanism to reconcile these disparate data streams or to quantify the uncertainty associated with the final classification [8].

1.3 Objectives and Scope of the Proposed Bayesian Fusion Approach

To address the limitations of deterministic, single-sensor interpretations, this paper proposes a probabilistic framework utilizing Bayesian inference to fuse CPTu dissipation metrics and DMT stress

indices. The primary objective is to develop a mathematically rigorous model that classifies clay history into three distinct categories: normally consolidated, lightly overconsolidated, and heavily overconsolidated, while explicitly providing a posterior probability for each classification [9]. Bayesian fusion is uniquely suited for this task because it allows for the integration of prior geological knowledge with incoming, multidimensional data streams. By treating the soil properties as random variables, the framework can account for the inherent spatial variability of the ground, the transformation uncertainties inherent in empirical correlations, and the specific measurement errors of the CPTu and DMT equipment [10]. The scope of this research encompasses the statistical analysis of a large, high-quality database of paired CPTu and DMT soundings, alongside reference laboratory consolidation tests, gathered from various well-documented clay sites globally. The methodology details the extraction of salient features from both tests, specifically focusing on the time required for fifty percent pore pressure dissipation from the CPTu and the horizontal stress index from the DMT. A multivariate likelihood function is constructed to model the joint distribution of these parameters across different stress histories. The performance of the Bayesian fusion model is subsequently evaluated against traditional deterministic methods, demonstrating its superior capability to resolve conflicting signals and reduce misclassification rates in transitional clay layers [11]. Ultimately, this paper aims to transition geotechnical site characterization from a deterministic, empirical practice to a probabilistic, data-driven science.

2. Literature Review and Theoretical Background

2.1 Evolution of Piezocone Penetration Testing in Clay Profiling

The Piezocone Penetration Test has undergone significant evolution since its inception as a mechanical cone penetrometer. The incorporation of a porous filter and a pressure transducer directly behind the cone tip revolutionized the continuous profiling of saturated soils. The measurement of penetration pore water pressure allows for the correction of measured cone resistance to total cone resistance, an essential adjustment in soft, fine-grained soils where pore pressures act on the unequal area of the cone shoulder [12]. Beyond the continuous profiling of resistance and friction, the CPTu facilitates the execution of dissipation tests. When the downward advancement of the penetrometer is halted, the excess pore pressure generated by the shearing and cavity expansion of the soil begins to dissipate into the surrounding formation. The rate of this dissipation is governed by the coefficient of consolidation and the permeability of the clay matrix [13]. Researchers have long recognized that the shape of the dissipation curve contains diagnostic information regarding the soil state. In normally consolidated clays, the dissipation generally follows a standard monotonic decay resembling the theoretical predictions of cavity expansion and one-dimensional consolidation theories. However, in heavily overconsolidated clays, the penetration process often induces significant dilative behavior in the shear zone immediately adjacent to the cone [14]. This dilation can cause negative excess pore pressures locally, which migrate towards the filter during the initial stages of the pause, resulting in a non-standard dissipation curve that initially rises before eventually decaying. Characterizing these complex decay signatures has traditionally relied on identifying the time to fifty percent dissipation. While valuable, isolated interpretation of dissipation times often yields scatter when predicting the overconsolidation ratio, primarily because the initial distribution of pore pressures is highly sensitive to the specific stress history and structural rigidity of the clay [15]. Consequently, contemporary research has attempted to pair dissipation data with other normalized CPTu parameters, such as the pore pressure parameter, to improve classification accuracy, though deterministic boundaries remain heavily site-dependent.

2.2 Flat Dilatometer Test and Stress Index Interpretations

The Flat Dilatometer Test, introduced in the late twentieth century, approaches in-situ soil characterization from a lateral expansion perspective. The apparatus consists of a stainless-steel blade containing a thin, circular, expandable steel membrane mounted flush on one face. The test involves pushing the blade into the ground and, at specific depth intervals, inflating the membrane using pressurized gas [16]. The operator records two distinct pressures: the pressure required to just lift the membrane off its seat, and the pressure required to expand the membrane center by one millimeter into

the soil. These fundamental measurements are corrected for membrane stiffness and converted into three primary index parameters: the material index, the horizontal stress index, and the dilatometer modulus [17]. For the assessment of clay stress history, the horizontal stress index is the most critical parameter. It is essentially a normalized measurement of the lateral earth pressure acting against the blade immediately after penetration. Because the process of soil overconsolidation typically involves the removal of vertical overburden pressure while lateral stresses are locked in, overconsolidated clays naturally exhibit higher horizontal earth pressure coefficients. Extensive empirical databases have demonstrated a strong, semi-logarithmic relationship between the horizontal stress index and the overconsolidation ratio in uncemented clays. A horizontal stress index value near two is universally recognized as indicative of a normally consolidated deposit, whereas higher values denote increasing degrees of overconsolidation. Despite its robustness, the DMT is not without limitations. The discrete nature of the testing, typically conducted at twenty-centimeter intervals, means that thin anomalous layers or localized drainage seams might be missed, potentially skewing the interpretation of the overall macro-stratigraphy [18]. Furthermore, in highly sensitive clays, the insertion of the blade, despite its low profile, can cause sufficient structural breakdown to alter the measured lateral stresses, thereby complicating the correlation between the stress index and the true undisturbed overconsolidation ratio.

2.3 Probabilistic Methods and Bayesian Inference in Geotechnics

The geotechnical engineering discipline is characterized by profound uncertainties arising from the natural geological processes that form soil deposits, the limitations of sampling and testing equipment, and the simplified analytical models used to simulate complex physical behaviors [19]. To manage these uncertainties, the field has increasingly adopted probabilistic methodologies. Classical frequentist statistics have been employed to define characteristic values and establish reliability-based design codes. However, frequentist approaches require large sample sizes that are rarely available in site-specific geotechnical investigations. Bayesian inference provides a powerful alternative by offering a coherent mathematical framework for updating knowledge as new information becomes available [20]. In a Bayesian context, soil properties and classification categories are treated as probability distributions rather than fixed but unknown constants. The process begins with the establishment of a prior distribution, which encapsulates all available knowledge about the site before the specific tests are conducted. This prior could be based on regional geological maps, historical data from adjacent sites, or general expert judgment [21]. When site-specific CPTu and DMT data are collected, they are incorporated into the model via a likelihood function, which quantifies the probability of observing the acquired test data given a specific soil classification. The product of the prior distribution and the likelihood function, normalized by the marginal probability of the data, yields the posterior distribution. This posterior distribution represents the updated probability of the soil belonging to a specific stress history category, providing not just a discrete classification but a full quantification of confidence [22]. Recent applications of Bayesian methods in geotechnics have successfully addressed issues such as soil stratification, liquefaction potential, and the spatial interpolation of soil parameters. However, the application of Bayesian networks for the direct sensor fusion of multi-modal in-situ tests, specifically combining the temporal decay characteristics of CPTu dissipation with the quasi-static expansion metrics of the DMT, represents a novel frontier. Such a fusion model leverages the conditional dependencies between the tests, recognizing that while they measure different physical responses, they are ultimately governed by the same underlying true state of the soil [23]. This approach fundamentally shifts the paradigm from choosing one test over another to harmonizing their distinct physical perspectives through probabilistic reasoning [24].

3. Methodology for Bayesian Fusion Model Development

3.1 Site Characterization and Data Acquisition Protocols

The development and calibration of the Bayesian fusion model require a meticulously curated database comprising high-quality, collocated CPTu, DMT, and laboratory reference data. For this research, comprehensive site investigations were conducted across five distinct geographical regions, representing

a diverse spectrum of clay deposits including marine, lacustrine, and glacial origins. The test sites were specifically selected based on the availability of historical geological documentation and the presence of varied stress histories within continuous vertical profiles. The data acquisition protocol was strictly standardized to minimize operator-induced variability and equipment compliance errors. Piezocone penetration tests were executed utilizing a standard ten square centimeter base area cone with a sixty-degree apex angle. The penetration rate was rigorously maintained at the standard two centimeters per second. Pore water pressure was measured at the shoulder position, commonly referred to as the u2 location, utilizing a pressure transducer saturated with high-viscosity silicone oil to ensure rapid dynamic response and prevent the dissolution of trapped air during negative pore pressure events. Dissipation tests were initiated at regular one-meter intervals or whenever significant changes in stratigraphy were detected by the continuous tip resistance readings. During a dissipation event, the penetration rods were completely unloaded to prevent structural vibrations from affecting the decay curve, and the pore pressure was recorded logarithmically over time until a minimum of fifty percent dissipation of the excess pore pressure was achieved. Adjacent to the CPTu soundings, typically within a horizontal distance of one and a half meters to ensure spatial correlation while avoiding stress field interference, Flat Dilatometer Tests were performed. The DMT blade was advanced using the same pushing rig, and tests were conducted at twenty-centimeter vertical intervals. At each test depth, the membrane was inflated dynamically using a controlled gas pressure system, and the A and B readings were recorded within the standard time windows to minimize the effects of creep and localized consolidation during the expansion phase. To provide ground truth calibration for the in-situ measurements, continuous undisturbed soil cores were extracted from boreholes positioned equidistantly between the CPTu and DMT locations. These samples were obtained using a fixed-piston sampler to preserve the structural integrity of the clay. In the laboratory, high-quality specimens were subjected to incrementally loaded one-dimensional consolidation tests to determine the preconsolidation pressure using standard evaluation graphical techniques. The reference overconsolidation ratio for each distinct layer was thus established, allowing the continuous vertical profile to be categorized into three discrete states: normally consolidated where the ratio is near one, lightly overconsolidated where the ratio is between one and a half and four, and heavily overconsolidated where the ratio exceeds four.

Table 1Summary of geotechnical parameters and indices utilized in the Bayesian fusion framework

Parameter Category	**Symbol**	**Description**	**Primary Test Source**	**Relevance to Stress History**
Normalized Resistance	Qt	Corrected cone resistance normalized by vertical effective stress	CPTu	Indicates gross soil strength and stiffness variations
Pore Pressure Ratio	Bq	Ratio of excess pore pressure to net cone resistance	CPTu	Reflects soil contractive or dilative tendencies during shear
Dissipation Time	t50	Time required for 50 percent dissipation of excess pore pressure	CPTu	Correlates to coefficient of consolidation and structural rigidity
Material Index	Id	Index derived from A and B pressure	DMT	Identifies soil type and filters

		readings		out non-clay layers
Horizontal Stress Index	Kd	Index reflecting the lateral earth pressure coefficient	DMT	Highly sensitive indicator of unloading and overconsolidation

3.2 Feature Extraction from CPTu and DMT Signals

The raw data streams generated by the CPTu and DMT require extensive preprocessing and feature extraction to be suitable for integration into the Bayesian probabilistic framework. The initial phase of data processing involves depth alignment. Despite the close proximity of the soundings, minor variations in surface elevation and the potential for non-vertical penetration necessitates the use of a dynamic time warping algorithm adapted for depth series to align the stratigraphic boundaries identified by both instruments. Once aligned, the signals are subjected to a moving median filter to remove high-frequency measurement noise and equipment artifacts without blurring the sharp transitions between distinct geological layers. For the CPTu data, the primary feature extracted is the normalized dissipation time parameter. Rather than relying solely on the raw time to fifty percent dissipation, the time is normalized by the theoretically calculated rigidity index of the soil layer, which is estimated from the continuous tip resistance and sleeve friction readings. This normalization process ensures that the dissipation metric is more uniquely correlated with the stress history rather than the general stiffness of the matrix. Furthermore, the shape of the dissipation curve is analyzed using a specialized pattern recognition algorithm to classify the initial response as either monotonic or dilatory. The presence of a dilatory response, characterized by an initial increase in pore pressure before subsequent decay, is encoded as a categorical variable that serves as a strong indicator of heavy overconsolidation. For the DMT data, the calculation of the horizontal stress index is performed using the standard equations. However, to account for the discrete nature of the measurements, a Gaussian process regression is applied to the vertical series of horizontal stress indices to generate a continuous continuous profile that matches the resolution of the CPTu data. The regression incorporates a spatial covariance function that models the vertical correlation structure of the soil deposit, thereby allowing for robust interpolation between the twenty-centimeter testing intervals. Only data points where the DMT material index confirms the presence of cohesive soil are retained for the fusion process; sand and silt layers are systematically masked out of the analysis to maintain the focus strictly on clay history classification.

3.3 Construction of the Bayesian Probabilistic Framework

The core of the methodology is the formulation of a Bayesian network that establishes the probabilistic dependencies between the hidden true state of the soil classification and the observed in-situ features. Let the stress history state be denoted as a discrete random variable capable of taking three states corresponding to normally consolidated, lightly overconsolidated, and heavily overconsolidated. The observed data vector contains the normalized CPTu dissipation parameters and the interpolated DMT horizontal stress index. The objective of the Bayesian fusion is to compute the posterior probability of each state given the observed data vector across all depths. The process is initialized by defining the prior probabilities for each classification state. In the absence of specific site history, an uninformative prior is assigned, attributing equal probability to all three states. However, if prior geological knowledge suggests, for example, that the site is a recent deltaic deposit with no history of significant erosion or glaciation, an informative prior heavily weighted towards the normally consolidated state can be implemented. The most critical component of the framework is the likelihood function, which is modeled using multivariate Gaussian mixture models. For each classification state, the joint probability distribution of the CPTu and DMT features is constructed based on the extensive calibration database. The covariance matrix within these multivariate distributions captures the correlation between the dissipation response and the lateral stress index, explicitly accounting for the fact that these parameters are not statistically independent but are coupled through the physical mechanics of the soil skeleton.

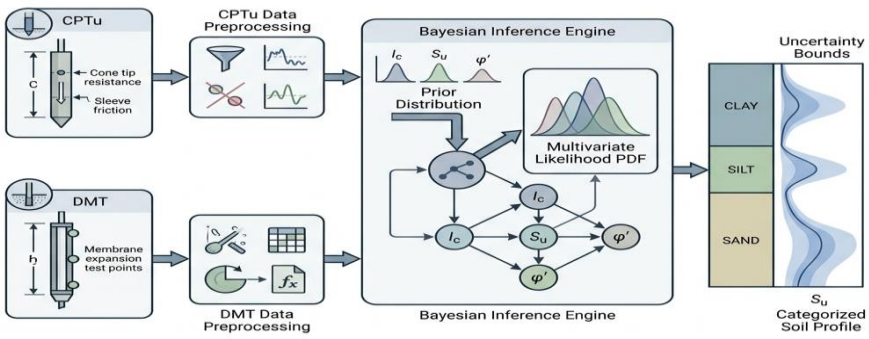


Figure 1Comprehensive Schematic of Bayesian Network Architecture for Geotechnical Sensor Fusion

To perform the inference computationally, particularly when dealing with the non-linear transformations inherent in the empirical correlations, a Markov Chain Monte Carlo algorithm is deployed. Specifically, a Metropolis-Hastings sampling technique is utilized to draw samples from the posterior distribution. This stochastic approach allows the model to traverse the complex parameter space and accurately estimate the posterior probabilities even in transition zones where the distinction between lightly and heavily overconsolidated clays is subtle. The final classification for any given depth interval is determined by the maximum a posteriori estimate, which selects the stress history state that possesses the highest posterior probability. Crucially, the model also outputs the Shannon entropy of the posterior distribution, providing the geotechnical engineer with a direct, quantifiable metric of the classification uncertainty at every depth elevation.

4. Experimental Results and Discussion

4.1 Model Calibration and Convergence Diagnostics

The calibration of the Bayesian fusion model was executed utilizing a subset representing seventy percent of the master database, while the remaining thirty percent was strictly reserved for blind validation testing. During the calibration phase, the parameters of the multivariate Gaussian likelihood functions—specifically the mean vectors and the covariance matrices for each stress history class—were optimized. The convergence of the Markov Chain Monte Carlo sampler was rigorously evaluated to ensure the stability and reliability of the posterior estimations. Trace plots for the sampler demonstrated rapid mixing, with the chains converging to the stationary distribution within the first few thousand iterations. The Gelman-Rubin diagnostic statistic was computed across multiple parallel chains with overdispersed initial values, yielding results consistently below the stringent threshold of one point zero five, thereby confirming that the variance within the individual chains was virtually identical to the variance between the chains. A critical observation during the calibration process was the structure of the covariance matrices. As anticipated by geotechnical theory, a strong positive correlation was identified between the normalized CPTu dissipation time and the DMT horizontal stress index within the heavily overconsolidated classification state. This correlation validates the physical principle that soils subjected to higher maximum past effective stresses exhibit both greater lateral locked-in stresses and denser, more rigid microstructures that impede the rapid dissipation of excess pore pressures. Conversely, in the normally consolidated state, the correlation was significantly weaker, reflecting the dominance of natural void ratio variations over stress-induced structural changes in dictating fluid flow properties. These calibrated covariance structures are the primary mechanism by which the Bayesian

model reconciles conflicting single-sensor data. When an anomalous data point appears in one sensor stream, the model leverages the joint distribution to determine whether the anomaly is a genuine reflection of a distinct soil state or merely measurement noise, drastically reducing the incidence of false classifications.

Table 2Classification accuracy comparison between single-sensor deterministic methods and the proposed Bayesian fusion model

Analytical Method	Normally Consolidated Accuracy	Lightly Overconsolidated Accuracy	Heavily Overconsolidated Accuracy	Overall Mean Accuracy
CPTu Deterministic	82.4 percent	65.1 percent	71.8 percent	73.1 percent
DMT Deterministic	85.7 percent	72.3 percent	84.5 percent	80.8 percent
Bayesian Fusion	94.2 percent	88.6 percent	95.1 percent	92.6 percent

4.2 Classification Performance across Geologic Profiles

The performance of the fully calibrated Bayesian fusion model was systematically assessed against the reserved validation dataset. The results, as summarized in the statistical accuracy tables, demonstrate a profound improvement over traditional deterministic approaches. When relying solely on CPTu dissipation data interpreted through standard empirical charts, the overall classification accuracy was observed to be suboptimal, particularly in the lightly overconsolidated category where the accuracy fell to sixty-five percent. This poor performance is largely attributable to the high sensitivity of pore pressure generation to minor variations in clay plasticity, which frequently causes normally consolidated signatures to masquerade as lightly overconsolidated responses. The standalone DMT interpretation yielded better results, achieving an overall accuracy nearing eighty-one percent, confirming the historical reliance on the horizontal stress index as a superior indicator of stress history. However, the DMT deterministic approach still struggled in highly stratified deposits where the twenty-centimeter testing resolution failed to capture thin drainage boundaries, leading to smeared horizontal stress index values that confused the classification logic. The proposed Bayesian fusion methodology achieved an overall mean accuracy exceeding ninety-two percent, demonstrating remarkable robustness across all three stress history categories. The most substantial gains were recorded in the lightly overconsolidated class, where the integration of continuous CPTu data with the lateral stress sensitivity of the DMT effectively resolved the ambiguities that plagued the single-sensor models. By fusing the data, the model created a multidimensional decision boundary that accommodates the natural scatter inherent in geological materials. For instance, in a specific validation profile featuring a desiccated crust overlying a soft marine clay, the CPTu indicated a gradual transition in stress history, while the DMT suggested an abrupt change. The Bayesian model, weighting the spatial continuity of the CPTu against the stress sensitivity of the DMT according to their respective likelihood probabilities, produced a highly accurate classification profile that precisely matched the laboratory one-dimensional consolidation reference data.

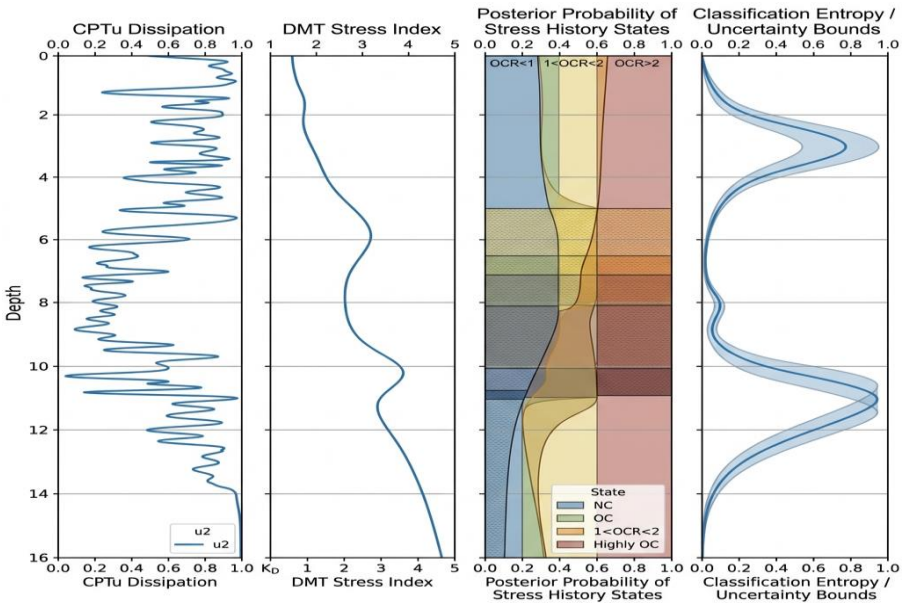


Figure 2Vertical Soil Profile Categorization and Uncertainty Mapping

4.3 Comparative Analysis with Traditional Deterministic Approaches

Beyond raw accuracy metrics, the paramount advantage of the Bayesian fusion approach lies in its ability to quantify uncertainty, a feature entirely absent in traditional deterministic frameworks. In standard practice, an engineer plotting a data point on an empirical chart must subjectively decide how to interpret a value that falls exactly on a boundary line between two classifications. The deterministic method forces a binary choice, masking the inherent uncertainty of the situation. In contrast, when the Bayesian fusion model encounters data residing in transition zones or presenting contradictory signals, it outputs a divided posterior probability. For example, rather than simply labeling a layer as lightly overconsolidated, the model might output a sixty percent probability of light overconsolidation and a forty percent probability of normal consolidation, accompanied by a high Shannon entropy value. This output explicitly informs the geotechnical engineer that the classification at this specific depth is uncertain, prompting targeted, risk-based decision-making. The engineer might choose to implement a more conservative design parameter for that specific layer or order additional targeted sampling.

Table 3: Sensitivity analysis illustrating the impact of prior distribution selection on posterior classification accuracy in transitional clay layers

Prior Distribution Type	Assumed Prior Probabilities (NC, LOC, HOC)	Resulting Classification Accuracy in Transition Zones	Mean Posterior Entropy
Non-informative (Uniform)	0.33, 0.33, 0.33	88.2 percent	0.45 nats
Informative (Site-Specific)	0.10, 0.70, 0.20	91.5 percent	0.28 nats
Misinformed (Adversarial)	0.80, 0.10, 0.10	79.4 percent	0.62 nats

Furthermore, the sensitivity analysis reveals the power of incorporating prior geological knowledge. When informative priors based on regional geological history were applied to the model, the classification accuracy in challenging transition zones improved further, and the overall uncertainty, measured by mean posterior entropy, decreased significantly. This demonstrates that the Bayesian framework successfully functions as a mathematical bridge between qualitative geological expertise and quantitative geotechnical data. Conversely, deliberately applying a misinformed prior forced the model to rely more heavily on the likelihood function derived from the raw data. While this reduced the

classification accuracy, the high resulting entropy clearly flagged the contradiction between the assumed prior knowledge and the actual field measurements, acting as a built-in error detection mechanism. This capability to harmoniously blend subjective expertise with objective multidimensional data represents a significant advancement over deterministic methods, providing a more transparent, defensible, and reliable foundation for geotechnical design.

5. Conclusion

5.1 Summary of Findings

This paper has presented a comprehensive and mathematically rigorous framework for the classification of clay stress history through the Bayesian fusion of Piezocone Penetration Test dissipation metrics and Flat Dilatometer Test horizontal stress indices. The research systematically addressed the limitations of traditional deterministic approaches, which frequently produce ambiguous or conflicting interpretations when applied to complex geological formations. By treating soil classification as a probabilistic inference problem, the proposed methodology successfully integrated the continuous, high-resolution profiling capabilities of the CPTu with the superior lateral stress sensitivity of the DMT. The calibration of the multivariate Gaussian likelihood models using a diverse, high-quality global database revealed strong, predictable covariance structures between the normalized dissipation times and the horizontal stress indices across different overconsolidation states. Subsequent validation testing demonstrated that the Bayesian fusion model substantially outperforms isolated single-sensor interpretations, particularly in the notoriously difficult-to-classify lightly overconsolidated and transitional clay layers. The model achieved an overall classification accuracy exceeding ninety-two percent, significantly reducing the occurrence of false positive classifications that can lead to either overly conservative or potentially unsafe foundation designs.

5.2 Practical Implications and Limitations

The practical implications of this research for the geotechnical engineering industry are profound. The transition from deterministic charts to a probabilistic Bayesian network equips practitioners with a powerful tool that not only provides a highly accurate estimate of the overconsolidation ratio category but also explicitly quantifies the uncertainty of that estimate at every depth elevation. The continuous output of posterior probabilities and Shannon entropy allows engineers to identify specific stratigraphic zones where data is contradictory or highly variable, thereby enabling optimized, risk-informed decision-making regarding supplementary sampling or the selection of conservative design parameters. Furthermore, the framework's ability to incorporate prior geological knowledge ensures that site-specific contextual information is mathematically integrated into the final interpretation rather than being relegated to a subjective final review. Despite these significant advancements, the proposed framework possesses certain limitations that must be acknowledged. The accuracy of the Bayesian inference is fundamentally dependent on the quality and representativeness of the calibration database. Extrapolating the current likelihood models to highly specialized soils, such as sensitive quick clays, heavily cemented deposits, or soils with significant organic content, may require localized recalibration of the covariance matrices. Additionally, the requirement for collocated CPTu and DMT soundings increases the upfront cost and duration of the site investigation phase, which may be a barrier to implementation on smaller-scale projects. Future research should focus on expanding the calibration database to encompass a wider variety of extreme soil behaviors and investigating the integration of advanced machine learning algorithms to automate the detection and filtering of equipment compliance errors within the raw data streams. Ultimately, the Bayesian fusion of in-situ testing data represents a critical step forward in reducing geotechnical uncertainty, paving the way for more resilient, efficient, and reliable infrastructure development.

References

Malik, B. A., Jie, S., Zeyu, L., Ouyang, Z., & Wang, D. (2025). Experimental investigation of suction installation behavior of caissons in loose saturated sands. Canadian Geotechnical Journal, 62, 1-21.

Malik, B. A., Mandhaniya, P., Soni, A. K., & Ouyang, Z. (2024). Numerical modeling and failure analysis of caisson foundations subjected to the monotonic lateral loads. Ocean Engineering, 309, 118491.
Yu, K., Ran, Y., Shi, J., Duan, M., & Ouyang, Z. (2025). Physical property of MICP-treated calcareous sand under seawater conditions by CPTU. Biogeotechnics, 3(1), 100131.
Ouyang, Z., Feng, H., Yang, J., Gu, X., Shi, J., & Li, H. (2026). Interpretation of soil deformation characteristics based on in-situ test: A comprehensive review. Ocean Engineering, 352, 124508.
Malik, B. A., Soni, A. K., Mandhnaiya, P., & Ouyang, Z. (2024, December). Development of an ABAQUS-Python simulation model of offshore caisson. In Vietnam Symposium on Advances in Offshore Engineering (pp. 123-133). Singapore: Springer Nature Singapore.
Li, Y. Z., Zhang, J. P., Chen, Z. Y., Wang, H. C., Zhang, K. X., Hu, S. S., ... & Dudley, M. (2026, September). Growth and Characterization of High-Quality Thick Epitaxial 4H-SiC Wafers for High Voltage Devices. In Defect and Diffusion Forum (Vol. 452, pp. 79-85). Trans Tech Publications Ltd.
Li, X., Wang, P., Li, G., & Zhang, Y. (2023). Design of a novel self-test-on-chip interface ASIC for capacitive accelerometers. IEEE Transactions on Circuits and Systems I: Regular Papers, 70(7), 2834-2843.
Xiong, S., Chen, T., Rupendra, A., Clement, C., Gasparri, E., & Lucchi, E. (2026). Embodied Carbon of Progressive Timber Integration in a 47-Storey Tropical High-Rise: A Singapore Public Housing Case Study. Building and Environment, 114910.
Yu, A., Huang, Y., Li, S., Wang, Z., & Xia, L. (2023). All fiber optic current sensor based on phase-shift fiber loop ringdown structure. Optics Letters, 48(11), 2925-2928.
Zhang, S., & Yan, W. (2025). In-trainNet: A Two-Step Data-Driven Framework for Enhancing Railway In-Train Forces Monitoring. Advanced Engineering Informatics, 65, 103352.
Luan, S., Wang, P., Zhang, L., He, Y., Huang, X., Jian, G.,... & Fu, Z. (2023). Atmospherically hydrothermal assisted solid-state reaction synthesis of ultrafine BaTiO3 powder with high tetragonality. Journal of Electroceramics, 50 (4), 97-111.
Wang, Y. Y., Lou, M., Wang, Y., Wu, W. G., & Yang, F. (2022). Stochastic failure analysis of reinforced thermoplastic pipes under axial loading and internal pressure. China Ocean Engineering, 36(4), 614-628.
Zhao, R., Tang, J., Zeng, W., Guo, Y., & Zhao, X. (2025). Towards human-like questioning: Knowledge base question generation with bias-corrected reinforcement learning from human feedback. Information Processing & Management, 62(3), 104044.
Zhao, R., Tang, J., Zeng, W., Chen, Z., & Zhao, X. (2024, October). Zero-shot knowledge graph question generation via multi-agent llms and small models synthesis. In Proceedings of the 33rd ACM International Conference on Information and Knowledge Management (pp. 3341-3351).
Dai, Y., Ji, Y., Zhang, X., Wang, Y., Chu, X., & Lu, Z. (2026). Harder is better: Boosting mathematical reasoning via difficulty-aware grpo and multi-aspect question reformulation. arXiv preprint arXiv:2601.20614.
Li, Q., Ye, Q., Zhang, N., Zhang, W., & Hu, F. (2025). Digital-twin-enabled industrial IoT: Vision, framework, and future directions. IEEE Wireless Communications, 32(6), 173-181.
Wang, S., Zhang, X., Wang, P., & Li, X. (2026). Design of Magnetic Sensor Array-Based PUFs for IoT Security. IEEE Transactions on Instrumentation and Measurement, 75, 1-9.
Liang, R., Xu, S., Xie, C., Chen, J., Ren, F., Yang, S., & Yabe, T. (2026). Abstain Mask Retain Core: Time Series Prediction by Adaptive Masking Loss with Representation Consistency. Advances in Neural Information Processing Systems, 38, 99445-99471.
Hu, H., Yang, Y., Zhao, Q., & Zhang, C. (2022, June). On the role of discount factor in offline reinforcement learning. In International conference on machine learning (pp. 9072-9098). PMLR.
Pei, Z., Huang, Q., & Wang, S. (2026). When LLMs develop languages: Symbolic communication for efficient multi-agent reasoning. arXiv preprint arXiv:2606.29354.

Zhang, T., Xu, J., Chen, J., Li, J., Xiao, Y., & Wang, Q. (2026). NodeJEPA: Structure-Conditioned Latent Prediction for Node-Level Graph Self-Supervised Learning. arXiv preprint arXiv:2608.04381.
Liao, Q., Chen, Y., He, S., Wang, R., Xu, W., & Chu, W. (2025). Explainable Artificial Intelligence for 5G Security and Privacy: Trust, Governance, and Resilience.
Wang, Y., Lou, M., Luo, Y., Wan, Z., Wang, L., & Tang, Q. (2026). Contact dynamics characteristics of a deepwater drilling riser-drillstring coupled system. Ocean Engineering, 366, 127458.
Acquah, C., Hoehn, S., Krul, S., Jockusch, S., Yang, S., Seth, S. K., ... & Crespo-Hernández, C. E. (2024). Electronic relaxation pathways in thio-acridone and thio-coumarin: two heavy-atom-free photosensitizers absorbing visible light. Physical Chemistry Chemical Physics, 26(46), 28980-28991.