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Clay-content-dependent hydro-mechanical evolution of sand–clay mixtures: Experimental characterization and data-driven analysis

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Abstract

The clay content appears to govern the transition from granular to cohesive behaviour in sand–clay mixtures; however, this transition is often described using isolated property correlations. In this study, a controlled laboratory programme was combined with sparse-data modelling to characterise the physical, hydraulic, and mechanical responses of 11 mixtures containing 0–100% clay at 10% intervals. The laboratory programme comprised particle-size analysis, specific gravity, Atterberg limits, Standard Proctor compaction, falling-head permeability, direct shear, and unconfined compression. Clay content was treated as the single composition coordinate because sand content is its exact complement. Linear regression, second-order polynomial regression, support vector regression, random forest, and Gaussian process regression (GPR) were evaluated using leave-one-out cross-validation; permeability was modelled in $\log_{10}$ space, and GPR was additionally used for uncertainty and sensitivity assessment. Increasing clay content was associated with increases in the liquid limit from 14% to 88%, plasticity index from 5% to 57%, and optimum moisture content from 12.3% to 17.2%, while maximum dry density decreased from 17.9 to 13.9 kN/m³. Permeability appears to have decreased from 3.65×10^{-4} to 4.07×10^{-7} m/s. Friction angle appears to have decreased from 41.22° to 14.28°, whereas cohesion appears to have increased from 0 to 34.033 kPa. The unconfined compressive strength was non-monotonic, reaching 157.2 kPa at 40% clay and remaining near the maximum across the intermediate-clay range. These results suggest that model suitability may be property-specific and that sparse modelling is most useful when interpreted together with experimental evidence and restricted to the measured composition domain.

Keywords: sand–clay mixture; clay content; Gaussian process regression; leave-one-out cross-validation; hydro-mechanical behavior

1. Introduction

Binary mixtures of coarse and fine particles may constitute relatively simple laboratory systems through which the transition from granular to cohesive soil behaviour can be elucidated. Although their simplicity may appear deceptive, a small change in fines content can alter the load-transfer skeleton, pore geometry, water retention, plasticity, and stress-transfer mechanism (Simpson and Evans 2015) and (Wang et al. 2025), and may consequently cause several engineering properties to evolve at different rates. In practice, this compositional dependence may be relevant to earth fills, liners, embankments, foundation soils, and other compacted geomaterials in which natural or processed sand and clay coexist. Therefore, the central engineering question is not merely whether clay changes soil behaviour, but how a controlled change in the clay fraction reorganises the coupled physical, hydraulic, and mechanical response of the mixture.

A useful interpretation of sand-clay mixtures may need to recognise that the clay content is not an ordinary independent soil index when the material is prepared as a binary composition. The sand and clay percentages are complementary; increasing one necessarily decreases the other. This closure may establish a direct compositional pathway from a sand-dominated skeleton to a clay-dominated matrix. (Simpson and Evans 2015) suggested that sand-kaolinite mixtures can exhibit behavioural thresholds associated with packing-state transitions and percolation-type changes in force-chain continuity. (Deng et al. 2016) suggested that the hydro-mechanical behaviour changes as the sand skeleton evolves

from absent to partial, and then to complete. These observations consequently suggest the value of analysing a complete composition sweep rather than a narrow range selected for a specific application.

The hydraulic response appears to be particularly sensitive to the fine fraction because the flow is governed by pore size and pore connectivity. Clay can occupy void space between larger grains, reduce the effective flow channels, and increase the tortuosity. Studies on compacted clay-sand and sand-bentonite systems have repeatedly suggested that hydraulic conductivity depends strongly on clay mineralogy, clay fraction, compaction state, and pore structure (Ebina et al. 2004). For this reason, permeability often spans several orders of magnitude and may be analysed on a logarithmic rather than an ordinary linear scale when it is used as a regression target.

The mechanical response may evolve through competing mechanisms. Sand contributes interparticle friction, dilation potential, and a load-bearing granular skeleton, whereas clay contributes plasticity, surface forces, and apparent cohesion to the mixture. Direct shear studies, therefore, commonly show decreasing friction angles and increasing cohesion with higher clay content, although the detailed transition depends on mineralogy, density, water content, and stress state (Wibisono et al. 2018). Compressive strength may exhibit a non-monotonic response, with apparent cohesion contributing substantially to the strength of high-plasticity mixtures (Bouchemella and Taibi 2022). A study that measures the hydraulic, compaction, and strength properties on the same composition path may elucidate these competing mechanisms more clearly than separate single-property experiments.

Data-driven modelling may provide an additional means of quantifying composition–property responses; however, small laboratory datasets present a methodological challenge. Flexible machine-learning algorithms may fit small laboratory datasets very closely, but may nevertheless generalise poorly (Li et al. 2022). Consequently, training accuracy alone may not be a meaningful measure of predictive value. Recent data-centric geotechnical research appears to emphasise the integration of data analysis with the geotechnical context, physical constraints, interpretability, and uncertainty, rather than the application of algorithms as black boxes. (Zhang et al. 2022) showed that sparse geotechnical datasets benefit from models that incorporate prior knowledge and prediction uncertainties. (Tian and Wang 2024) emphasised the interpretability of site-specific machine learning, and demonstrated that geotechnical domain knowledge can materially improve data-driven predictions under sparse observations.

This study adopts a deliberately modest interpretation of machine learning. The experimental program is the principal evidence. Computational models were used to test whether the observed composition trends could be reproduced under leave-one-out validation, to identify where nonlinear models add value, to quantify uncertainty through Gaussian process regression (GPR), and to derive sensitivity along the measured composition coordinate. No synthetic observations were generated, and no interpolation points were treated as new experimental data. This distinction may be consequential because the study's information content may be understood as being determined by the 11 physically tested compositions, not by the number of points that can be plotted on a fitted curve.

The study may be understood as making four linked contributions: First, it may provide a unified experimental dataset for physical, plasticity, compaction, hydraulic, and mechanical properties over the full 0–100% clay content range. Second, it may introduce a composition-aware sparse-data modelling workflow in which mixture closure is enforced by using only clay content as the independent composition coordinate, and permeability is transformed according to its order-of-magnitude behaviour. Third, it may combine leave-one-out model comparison with GPR uncertainty and derivative-based sensitivity to distinguish monotonic responses from genuine transition behaviour. Fourth, it may translate the multi-property dataset into transparent application-specific rankings under perturbations of criterion weights, thereby separating the best tested composition under defined objectives from any claim of a universal engineering optimum.

The resulting framework is intended to address two questions simultaneously: How does clay content alter the engineering behaviour of a specific sand-clay system, and what additional insights can data-driven modelling provide

without overstating the predictive capacity of a sparse laboratory dataset? The emphasis throughout is therefore on physical consistency, cross-validated evidence, and transparent limits of inference.



Fig. 1 Experimental and domain-guided data-driven workflow used in this study

2. Materials and experimental programme

2.1. Soil source and binary mixture design

The soil materials used in the original experimental programme were collected from the Purbachal New Town Project area in Bangladesh, covering parts of Rupganj in Narayanganj District and Kaliganj in Gazipur District between the Balu and Sitalakhya river systems. The samples were prepared for characterisation through sieving and dispersion before the sand and clay fractions were combined in controlled proportions. Because soil mineralogy and particle characteristics are source-dependent, the present results are interpreted as material-specific laboratory relationships rather than universal properties of all sand-clay systems.

Eleven compositions were investigated from 0% to 100% clay in 10% increments. Thus, the composition series included two end members, pure sand and pure clay, and nine true binary mixtures. For each point on the composition path, the sand content was 100% minus the clay content. This closure relation was enforced in the data-driven analysis by retaining the clay content as the sole independent composition variable. The end members were retained in the material-property modelling because they defined the complete experimental transition; however, they were excluded from the application-specific optimisation so that the latter compared only actual sand-clay mixtures.

The testing programme comprised particle-size characterisation, hydrometer analysis, specific gravity, liquid and plastic limits, Standard Proctor compaction, falling-head permeability, direct shear, and unconfined compression. The particle-size distribution of the fine fraction followed ASTM D7928-21e1 (Committee 2021), liquid and plastic limits followed ASTM D4318-17e1 (Committee 2017), and unconfined compression followed ASTM D2166/D2166M-16 (Committee 2016). The remaining procedures followed the laboratory protocols documented in the original experimental records. Standard Proctor compaction provided the optimum moisture content (OMC) and maximum dry density (MDD), falling-head testing provided hydraulic conductivity, and direct shear provided the reported strength parameters.

Table 1 Consolidated experimental dataset used for the final analysis

Clay (%)	Sand (%)	G _s	LL (%)	PL (%)	PI (%)	MDD (kN/m ³)	OMC (%)	k (m/s)	φ (°)	c (kPa)	UCS (psi)
0.0000	100.00	2.6500	0.0000	0.0000	0.0000	17.9000	12.3000	3.65×10 ⁻⁴	41.2200	0.0000	0.0000
10.0000	90.0000	2.6800	14.0000	9.0000	5.0000	17.6500	12.5500	1.850×10 ⁻⁴	35.6700	0.9317	2.3000
20.0000	80.0000	2.6900	18.0000	11.0000	7.0000	17.4500	12.9000	9.371×10 ⁻⁵	32.3000	2.9362	14.3000
30.0000	70.0000	2.6900	25.0000	12.0000	13.0000	16.9000	13.1000	4.747×10 ⁻⁵	29.9900	4.3567	20.7000
40.0000	60.0000	2.6900	27.0000	13.0000	14.0000	16.5000	13.9100	2.405×10 ⁻⁵	26.3100	6.2613	22.8000
50.0000	50.0000	2.7000	29.0000	15.0000	14.0000	15.6700	14.5100	1.218×10 ⁻⁵	24.2250	8.9950	22.6000
60.0000	40.0000	2.7000	37.0000	18.0000	19.0000	15.1900	15.5500	6.173×10 ⁻⁶	22.7600	12.3210	22.5000
70.0000	30.0000	2.7100	49.0000	22.0000	27.0000	14.9100	15.7900	3.127×10 ⁻⁶	19.3200	14.8420	21.6000

Clay (%)	Sand (%)	G _s	LL (%)	PL (%)	PI (%)	MDD (kN/m ³)	OMC (%)	k (m/s)	φ (°)	c (kPa)	UCS (psi)
80.0000	20.0000	2.7100	53.0000	24.0000	29.0000	14.4100	16.3000	1.584×10 ⁻⁶	17.6400	17.5280	20.5000
90.0000	10.0000	2.7100	55.0000	25.0000	30.0000	14.2200	16.7000	8.026×10 ⁻⁷	15.4350	22.4160	18.8000
100.00	0.0000	2.7200	88.0000	31.0000	57.0000	13.9240	17.2200	4.066×10 ⁻⁷	14.2800	34.0330	16.5000

2.2. Physical and consistency characterization

The experimental characterization appears to have been retained at a level sufficient to elucidate the physical formation of the binary mixture rather than treating the clay percentage as an abstract model input. The coarse fraction appears to have been characterized by sieve analysis, whereas the fine fraction appears to have been characterized by sedimentation/hydrometer procedures, as reported in the thesis. Across the controlled composition sweep, the gradation curves appear to shift progressively toward the fine-particle domain as the clay replaces the sand (Fig. 2). This observation may provide the first direct experimental link between composition and later changes in the pore structure, water demand, and strength.

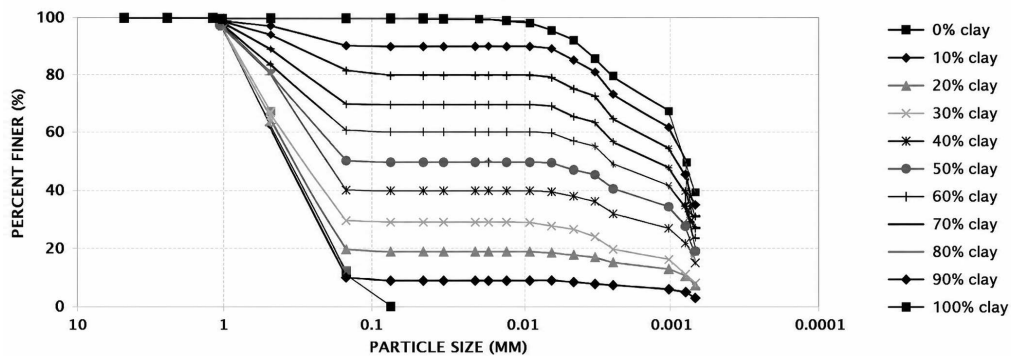


Fig. 2 Grain-size distribution of the investigated sand-clay compositions

The specific gravity was determined by the pycnometer method for the same composition sequence.

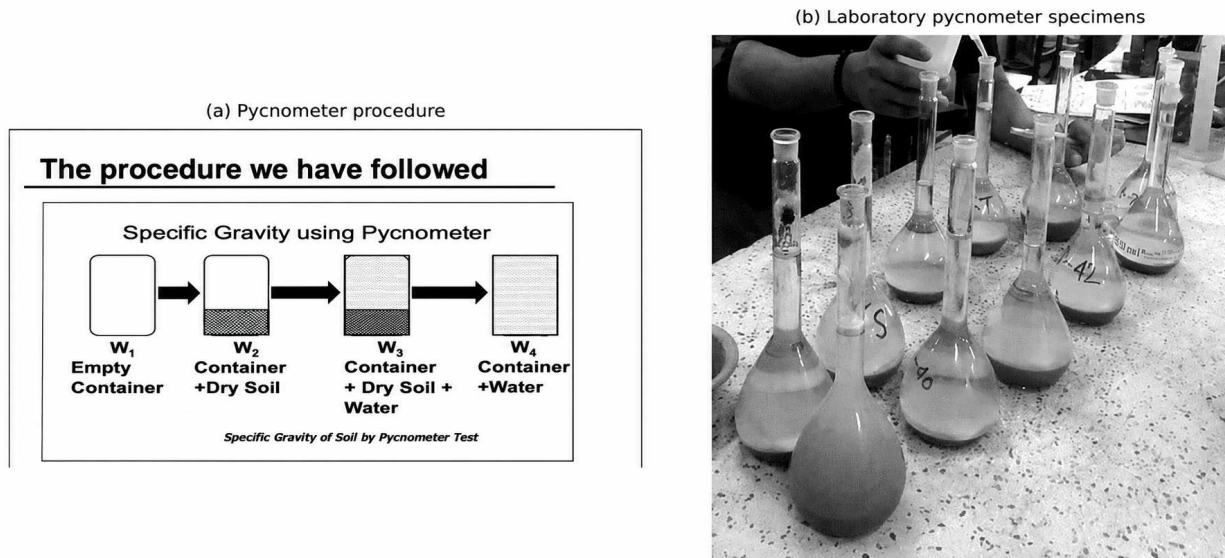


Fig. 3 Specific-gravity testing by pycnometer: (a) procedure documented in the experimental records and (b) representative laboratory pycnometer specimens

The specific-gravity determination across the composition series could serve as an index of the soil solids' relative density. The resulting variation appeared limited compared with the changes observed in the hydraulic and mechanical responses but could provide an internally consistent indication of the gradual shift in the solid-phase composition. The Atterberg limits were determined using the Casagrande apparatus and thread-rolling procedures documented in this

study. The zero-percent clay end member was non-plastic and was represented by zeros in the consolidated modeling table; therefore, the plasticity analysis was focused, in practical terms, on the clay-containing mixtures, even though the numerical composition sweep included the sand end member for continuity.

The liquid limit (LL), plastic limit (PL), and plasticity index (PI) are retained as separate response variables because they may encode different aspects of moisture-dependent consistency. Their systematic evolution may also provide a useful check on the internal order of the composition series. A model that predicts oscillatory plasticity in a clearly monotonic composition sweep may be physically implausible, even if a high training score is obtained. This is one reason why the later sensitivity analysis is interpreted together with the raw experimental points rather than in isolation.

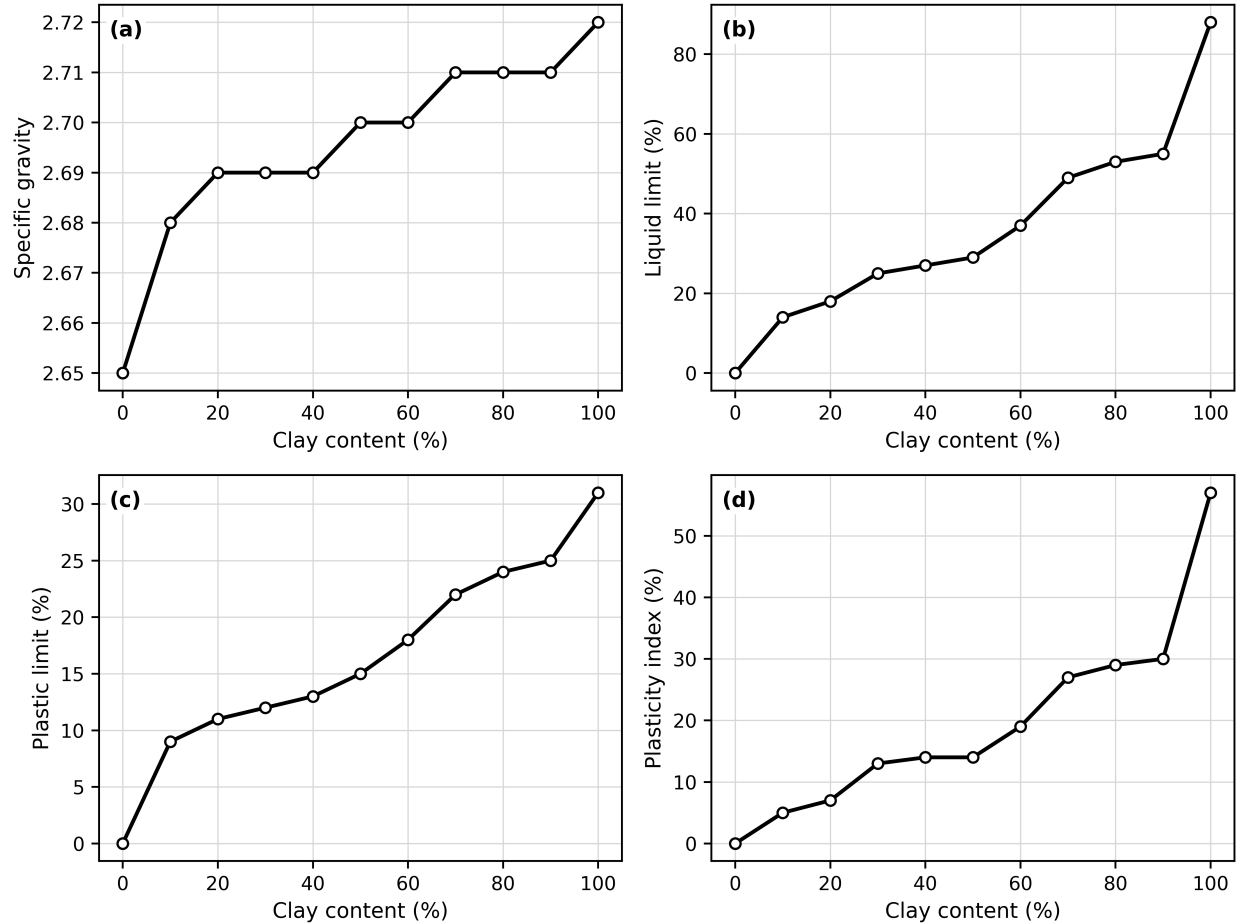


Fig. 4 Experimental evolution of (a) specific gravity, (b) liquid limit, (c) plastic limit and (d) plasticity index with clay content

2.3. Compaction and hydraulic tests

The laboratory program also incorporated visual documentation of the hydraulic, compaction, and unconfined-compression procedures. Figure 5 summarizes the falling-head configuration, laboratory permeability cell, Standard Proctor apparatus geometry, and representative specimens from the unconfined-compression (UCS) tests after testing.

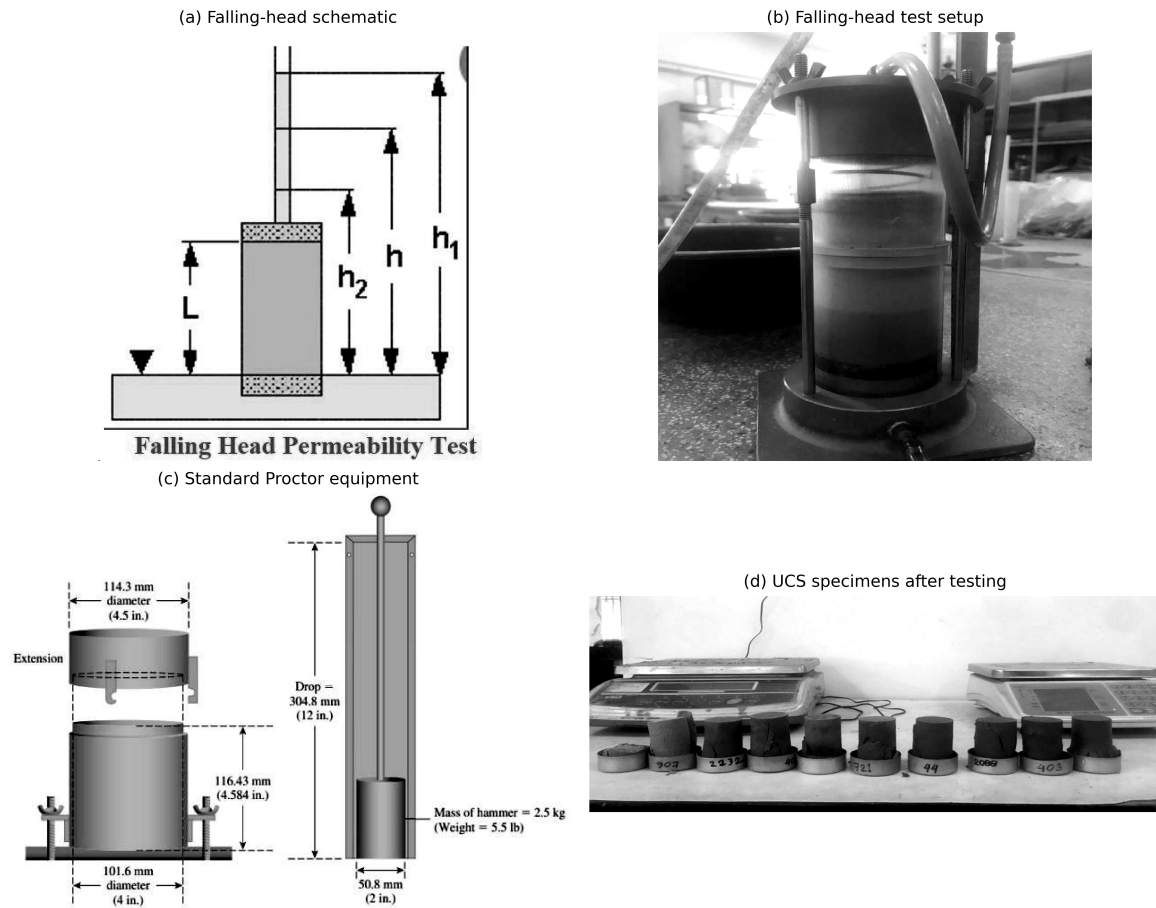


Fig. 5 Representative experimental arrangements: (a) falling-head permeability schematic, (b) falling-head test setup, (c) Standard Proctor equipment and (d) UCS specimens after testing

Standard Proctor testing was conducted to determine the optimum moisture content (OMC) and maximum dry density (MDD) for each mixture. These two properties were interpreted jointly because they represent competing aspects of the compaction response: additional clay generally increases the water demand required to achieve compaction while reducing the maximum dry unit weight attainable under a fixed compactive effort (Kafle et al. 2024). These parameters were analysed together to evaluate how the compaction response evolved across the composition sweep.

The complete moisture-density response may be more informative than the extracted OMC and MDD values alone. The original compaction curves for the composition series, shown in Fig. 6, suggested a systematic downward shift of the dry-unit-weight envelope and a rightward movement of the optimum-moisture region as the clay content increased. The subsequent summary plots of the OMC and MDD may therefore be understood as summaries derived from these measured curves, rather than as independently generated values. This trend aligns with typical soil behavior, where increasing clay fractions necessitate higher water contents to reach peak compaction efficiency while concurrently restricting the achievable maximum dry density due to the altered mineralogical structure (Wang and Yin 2020; Bachirou et al. 2025).

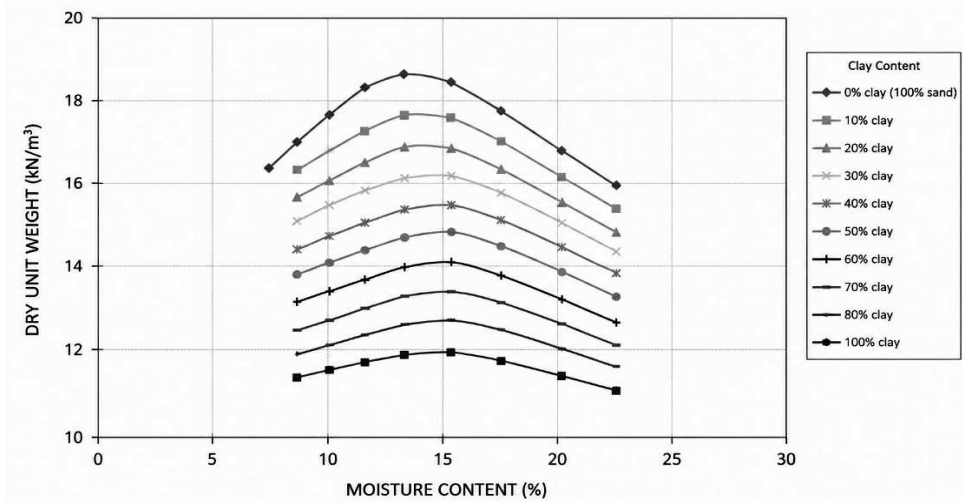


Fig. 6 Standard Proctor compaction curves for the investigated clay contents

Hydraulic conductivity was determined using falling-head permeability testing. The final consolidated permeability series ranged from 3.65095×10^{-4} m/s for the sand end member to 4.06634×10^{-7} m/s for the clay end member. Because this response spans nearly three orders of magnitude, $\log_{10}(k)$ may provide the appropriate modelling target. The plotted experimental values remain in engineering units on a logarithmic ordinate so that both high- and low-conductivity mixtures are visible.

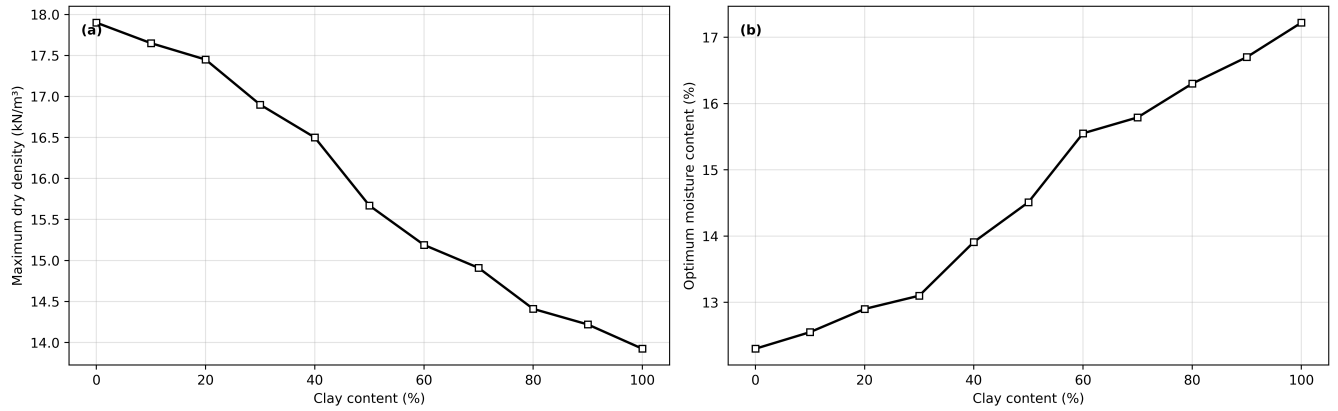


Fig. 7 Effect of clay content on (a) maximum dry density and (b) optimum moisture content

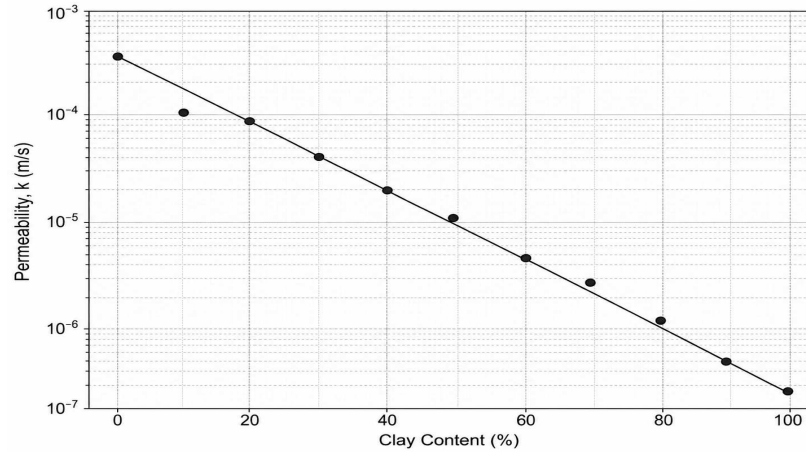


Fig. 8 Experimental permeability as a function of clay content

2.4. Mechanical tests

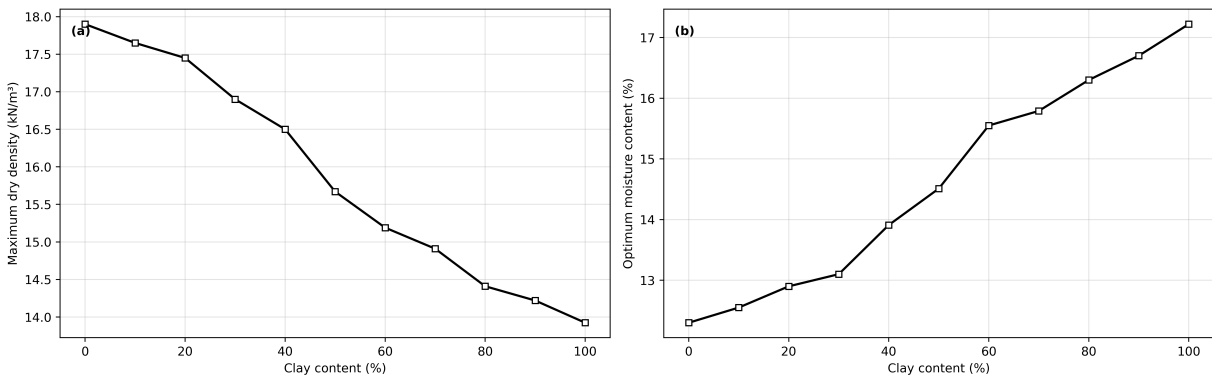


Fig. 7 Experimental effect of clay content on (a) maximum dry density and (b) optimum moisture content

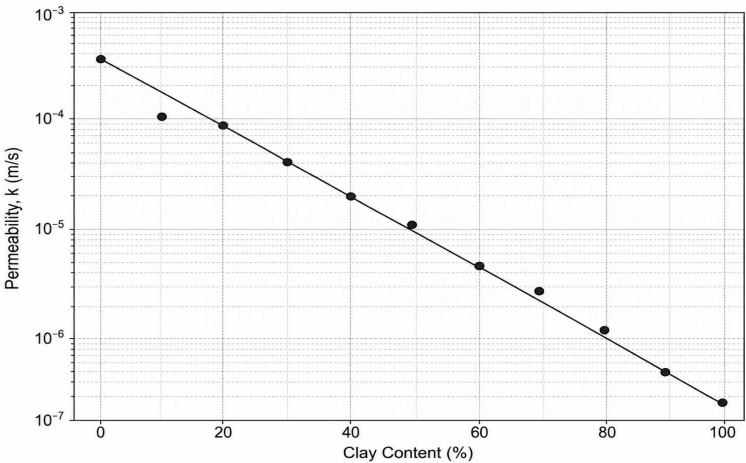


Fig. 8 Experimental permeability as a function of clay content

2.4. Mechanical tests

The interpretation of the mechanical program proceeded from the raw-response level toward higher-order interpretation. The direct-shear program used three normal-stress levels for each composition. Fig. 9 appears to show the resulting shear stress versus normal-stress response for the complete clay content series. The progressive flattening of the envelopes with increasing clay content appears to be consistent with the simultaneous decrease in friction angle and increase in cohesive intercept (Wibisono et al. 2018).

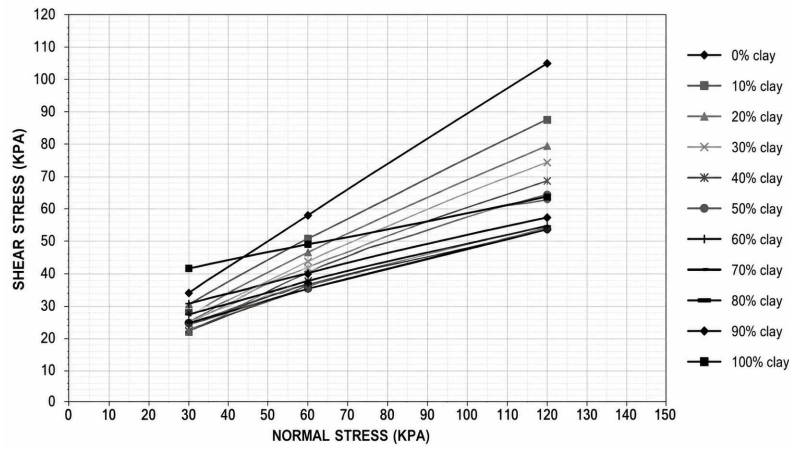


Fig. 9 Shear stress versus normal stress for all investigated clay contents

Unconfined compression testing was conducted on cylindrical specimens prepared under the mixture-specific optimum moisture condition. Rather than relying only on the peak unconfined compressive strength (UCS), Fig. 10 appears to present the complete compressive stress–strain responses within the chart. The curves appear to show both the rapid strengthening associated with the initial clay addition and the broad intermediate-clay strength plateau that subsequently emerges in the peak-UCS summary.

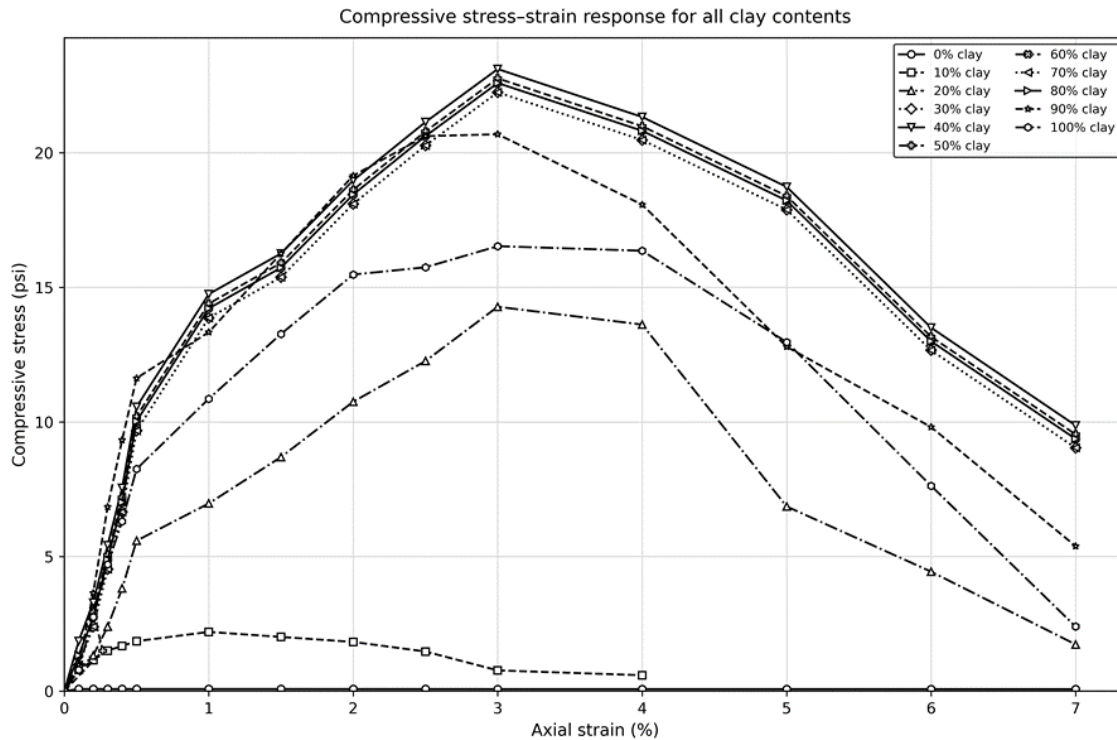


Fig. 10 Compressive stress–strain response for the investigated sand–clay compositions

The direct-shear results were reduced to two conventional strength parameters reported in this study: the internal friction angle and cohesion. These parameters are not interpreted as independent fundamental constants of the mixture; rather, they may summarize the observed shift in the strength mechanism under the test conditions. The progression

from high friction and negligible cohesion at low clay content to lower friction and higher cohesion at high clay content appears to be a key mechanistic trend used to interpret the UCS response.

Unconfined compressive strength was evaluated across the full composition range. Among the reported UCS values, the maximum of 22.8 psi corresponds to approximately 157.2 kPa. Unlike plasticity, compaction, and direct-shear parameters, UCS appears to be strongly non-monotonic (Nagaraj 2016). Accordingly, it may provide a particularly informative response for assessing whether nonlinear data-driven methods may identify a broad optimum region rather than merely reproduce a monotonic slope.

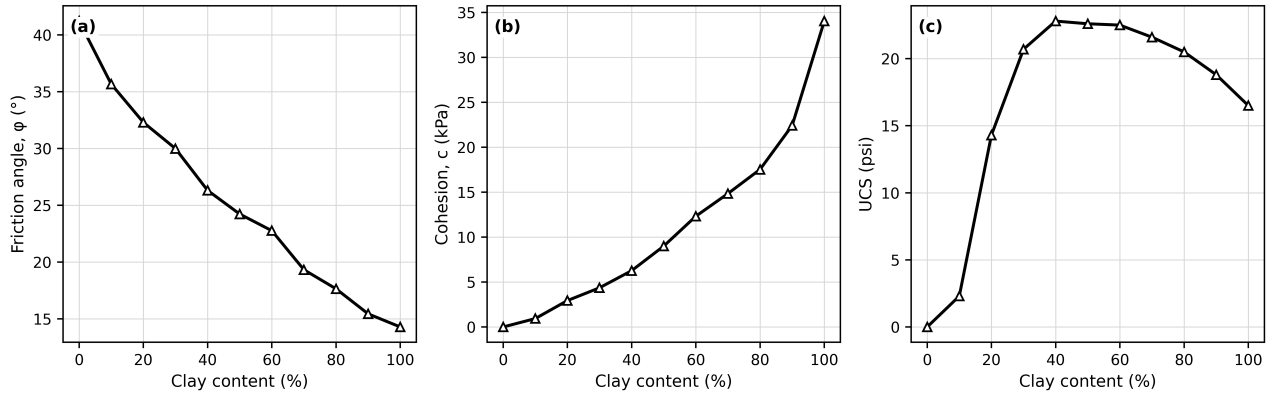


Fig. 11 Experimental evolution of (a) friction angle, (b) cohesion and (c) unconfined compressive strength with clay content

3. Domain-guided sparse-data modelling framework

3.1. Composition coordinate and response variables

The modelling objective was deliberately aligned with the experimental objective: quantifying the effect of clay content on each measured engineering property. Therefore, the clay and sand percentages were not entered as two separate predictors. In a binary mixture, their sum is fixed at 100%; therefore, using both could duplicate the same compositional information and induce perfect collinearity in linear models. Clay content C , ranging from 0% to 100%, was used as the single composition coordinate, whereas each engineering property was treated in turn as a response variable.

This one-dimensional design may differ from multi-feature geotechnical machine-learning studies in which several independent site or state variables are used simultaneously (Letif et al. 2024). Consequently, feature-importance analyses, including Shapley additive explanations (SHAP), may not be central to the present work: with one independent predictor, such analyses would largely restate the fitted association between clay content and the response. More informative quantities may be the cross-validated prediction error, uncertainty along the composition axis, and the derivative of a smooth response model with respect to clay content.

3.2. Candidate regression models

Five regression families were compared in this study. Linear regression provides the simplest baseline and tests whether the composition response is adequately represented by a first-order trend. Second-order polynomial regression adds one degree of curvature while remaining interpretable. Support vector regression (SVR) with a radial-basis-function kernel was included because it may represent smooth nonlinear relationships in small datasets (Pan et al. 2023). The implementation used $C=100$, $\gamma=\text{'scale'}$, and $\epsilon=0.05$ after standardising the input. Random forest regression, using 500 trees with a maximum depth of three and a fixed random seed, was used as a non-parametric ensemble benchmark (Breiman 2001). Gaussian process regression (GPR) may provide a smooth probabilistic response and predictive standard deviation, making it particularly useful for sparse experiments (Quoilin and Schrouff 2016).

The Gaussian process regression (GPR) kernel combines a constant kernel, radial-basis-function kernel, and white-noise term. The response was normalised internally, and the optimiser was restarted ten times from different initial positions using a fixed random seed. These models were not intended to identify a universally superior algorithm; rather, the comparison was intended to assess the extent to which model complexity could be supported by eleven independent compositions and whether the cross-validated pattern appeared consistent with the experimentally observed response.

3.3. Permeability transformation

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3.4. Leave-one-out validation and performance metrics

A random train-test split would be unstable for only 11 observations because the test set would contain only a few compositions, and the apparent performance would depend strongly on which points happened to be selected (An et al. 2021). Accordingly, leave-one-out cross-validation (LOOCV) was adopted as the primary validation strategy. Each composition was excluded once, the model was fitted to the remaining 10 points, and the excluded response was predicted. The 11 out-of-sample predictions were then combined to calculate the coefficient of determination (R^2), root-mean-square error (RMSE), and mean absolute error (MAE).

The training R^2 was also retained, although its interpretive role was restricted to diagnostic assessment. The difference between the training R^2 and the LOOCV R^2 was used as a simple generalisation-gap indicator; large positive gaps suggest that a model fits the 11-point series substantially better than it predicts the omitted compositions. The model selection for each response was based on the lowest LOOCV RMSE on the modelling scale, rather than the largest training R^2 . The analysis was conducted using Scikit-learn (PedregosaFabian et al. 2011).

3.5. Uncertainty and composition sensitivity

After model comparison, Gaussian process regression (GPR) was fitted to each complete response series to derive a common smooth response representation and an approximate 95% prediction band. This use of GPR was separate from the best-model selection. Even when GPR did not yield the lowest root-mean-square error (RMSE), its probabilistic response could provide a consistent basis for visualising where the fitted relation was tightly or weakly constrained by the sparse data. The band may be interpreted as model-based uncertainty conditional on the chosen kernel and data; it does not purport to encompass all sources of laboratory, sampling, or mineralogical uncertainty.

Composition sensitivity was calculated numerically as the gradient of the GPR mean response with respect to the clay content. For permeability, the derivative was taken in $\log_{10}(k)$ space so that the sensitivity represented an order-of-magnitude change rather than an absolute m/s change. A persistent sign of the sensitivity may support a monotonic experimental trend; a sign reversal may indicate a maximum or minimum. Because smooth GPR curves can exhibit small oscillations in sparse data, only broad and experimentally supported transition regions were interpreted physically. The unconfined compressive strength (UCS) maximum may therefore warrant emphasis, whereas minor derivative sign changes in otherwise monotonic plasticity curves need not be treated as separate physical thresholds.

3.6. Application-specific mixture screening

A multi-criteria desirability analysis was used as the final engineering screening step in this study. Each property included in a scenario was min-max normalised across the nine true binary mixtures (10–90% clay), thereby permitting comparison across criteria. The benefit criteria were oriented such that larger normalised values were preferred, and the cost criteria were oriented such that smaller values were preferred. A weighted sum was used to generate a composite suitability score. The weights were explicit scenario assumptions, not code or standard requirements; therefore, they were reported transparently rather than hidden in the optimisation.

Four scenarios were considered. High-strength screening assigned a weight of 0.80 to unconfined compressive strength (UCS) and 0.10 each to cohesion and friction angle. Compacted-fill/embankment screening assigned 0.35 to maximum dry density (MDD), 0.30 to UCS, 0.20 to friction angle, and 0.15 to lower optimum moisture content (OMC). Low-

permeability-barrier screening assigned 0.75 to low log-permeability and 0.25 to high cohesion. Drainage/permeable-fill screening assigned 0.60 to high log-permeability, 0.25 to high friction angle, and 0.15 to low plasticity index (PI). The compacted-fill results may therefore be interpreted as comparative screening outcomes rather than pavement or subgrade design classifications because California Bearing Ratio, swelling, durability, and project-specific acceptance limits are absent from the dataset.

Weight robustness was evaluated by perturbing each base weight independently by $\pm 20\%$, renormalizing the weights to sum to one, and repeating the ranking 5,000 times. The fraction of simulations in which each mixture ranked first may provide a transparent measure of the reported recommendation's stability under modest changes in engineering priorities.

4. Experimental results and physical interpretation

4.1. Gradation, specific gravity and plasticity evolution

The grain-size curves in Fig. 2 suggest that the experimental variable represents a substantive and progressive alteration in particle-size composition. Sand-rich mixtures retain a coarse load-bearing behavior (Simpson and Evans 2015), whereas increasing clay content progressively shifts more material into the fine fraction. This gradational change may constitute the physical origin of the subsequent changes in water retention, compaction behaviour, hydraulic conductivity, and mechanical response. The pycnometer documentation in Fig. 3 further suggests that the specific gravity was measured across the same prepared mixture sequence rather than inferred from constituent proportions.

The specific gravity increased gradually from 2.65 for pure sand to 2.72 for pure clay. The total change was approximately 2.6%, which may indicate that the pronounced changes in the hydraulic and mechanical behaviour cannot be attributed solely to a substantial alteration in solid-phase density. Instead, the dominant changes appear to arise from particle size, fabric, surface activity, and water interaction. Therefore, the stepped yet monotonic pattern may support the use of a simple linear model as an initial benchmark for this property. The consolidated index property trends are summarised in Fig. 4.

The Atterberg limit results suggested a stronger compositional effect on the plasticity index. Although the sand end-member was nonplastic, the 10% clay mixture exhibited a liquid limit (LL), plastic limit (PL), and plasticity index (PI) of 14%, 9%, and 5%, respectively, whereas the corresponding values at 100% clay content were 88%, 31%, and 57%, respectively. However, this increase was non-uniform. The LL and PI increased particularly strongly at the clay-rich end, suggesting that the consistency response is increasingly governed by the clay matrix once the fine phase dominates the mixture (Kim et al. 2018). This qualitative transition is compatible with the general idea of skeleton changes in coarse-fine mixtures reported by (Simpson and Evans 2015), although the precise threshold is material-specific.

The monotonic ordering of LL, PL, and PI may provide a useful physical verification for data-driven models. The Spearman correlation coefficients were essentially +1 for all three response types. Accordingly, a highly flexible model that generates repeated large reversals between adjacent measured compositions may not provide credible information. In the final analysis, linear regression was selected using leave-one-out cross-validation (LOOCV) for LL, PL, and PI, suggesting that the sparse dataset may not have justified a more complex predictor, even though the raw response contained a local curvature.

4.2. Compaction

The full compaction curves (Fig. 6) may provide a more informative experimental characterisation than the OMC and MDD endpoints. With increasing clay content, the moisture density envelopes shifted downward, and their peaks moved toward higher water contents. This systematic migration is consistent across the composition series and may support the interpretation of the extracted increase in optimum moisture content (OMC) and decrease in maximum dry density (MDD) as linked consequences of increasing fine-particle surface area and water demand.

The maximum dry density (MDD) decreased continuously from 17.9 to 13.9 kN/m³ as the clay content increased, while the optimum moisture content (OMC) increased from 12.3% to 17.2%. These two trends appear mechanically consistent. Increasing the fine fraction may increase the specific surface and the water required for lubrication and rearrangement during compaction (Alnmr and Ray 2021), while the lower-density clay-rich fabric may reduce the dry unit weight. Figure 7 summarises the extracted MDD and OMC trends. The decline in MDD became steepest through the intermediate composition range, whereas OMC showed its greatest model-based sensitivity around the middle of the sweep.

The cross-validated models for these responses appeared highly stable within the present domain. Gaussian process regression (GPR) produced leave-one-out cross-validation (LOOCV) R^2 values of approximately 0.991 for MDD and 0.983 for OMC, with generalisation gaps close to zero. These high values may arise from the smooth controlled

composition sweep and should not be extrapolated to natural soils with additional variables. However, within the present laboratory domain, the major compaction trends appear to be well-resolved by the available observations.

4.3. Hydraulic response

Permeability appeared to show the largest relative change of any measured property. The value decreased from 3.65095×10^{-4} m/s at 0% clay to 4.06634×10^{-7} m/s at 100% clay, corresponding to an approximately 900-fold reduction. Even at intermediate compositions, the response was strong. Figure 8 displays the full composition trend on a logarithmic ordinate $\times 10^{-6}$ m/s. This decrease appears physically consistent with the progressive restriction of interconnected flow paths as the fine fraction increases.

The results also illustrate why hydraulic conductivity modelling may need to account for scale. On a linear ordinate, the low-conductivity half of the dataset collapses visually near zero, whereas on a logarithmic ordinate, the composition response across the full range appears to remain visible. Within the modelling representation, the final consolidated series appears nearly log-linear. This regularity is useful: although a simple log-linear relation represents the supplied 11-point permeability sequence exceptionally well, the fit does not demonstrate a broadly generalisable machine-learning (ML) model (Zhang et al. 2023); rather, it indicates the adequacy of the log-linear representation for the supplied sequence. Independent replicate permeability tests and additional soil sources are required to quantify the experimental scatter and transferability.

The observed hydraulic trend was qualitatively consistent with previous compacted clay–sand studies. Ebina et al. (2004) showed that hydraulic conductivity is highly sensitive to clay characteristics in compacted clay–sand specimens, whereas (Deng et al. 2016) linked the hydro–mechanical behaviour to the evolution of the sand skeleton and fine-phase interaction. The present experiment may extend this qualitative understanding across a complete composition range for the investigated materials.

4.4. Transition from frictional to cohesive shear resistance

The raw failure envelope representation in Fig. 9 appears to reveal the transition between mechanisms before the reduction in the friction angle and cohesion. At the sand-rich end, the shear stress increased steeply with normal stress, and the intercept was negligible. As the clay content increased, the envelope slope decreased, whereas the intercept appeared to increase. Accordingly, the two fitted strength parameters may be interpreted as encoding an apparent repartitioning of the shear resistance rather than representing independent trends.

The direct shear parameters appear to have changed in the opposite direction. The friction angle continuously decreased from 41.22° at 0% clay to 14.28° at 100% clay. The cohesion increased from approximately zero to 34.033 kPa. The paired response may provide direct evidence that the dominant strength mechanism changes with composition, where particle interlocking and friction are progressively replaced by fine-particle bonding and cohesive resistance. Similar clay-content effects have been observed in clay–sand shear testing, with the balance between the frictional and cohesive contributions depending on the clay fraction and test state (Kim et al. 2018). A composition-dependent summary is shown in Fig. 11

The decline in the friction angle appears steepest at the sand-rich end of the GPR sensitivity curve and becomes more gradual as the clay content increases. Cohesion appears to behave in the opposite manner, with the largest model-based sensitivity toward the clay-rich end. These response shapes suggest that engineering trade-offs may be unavoidable. A high-clay mixture may provide strong cohesive resistance and very low permeability; however, it simultaneously sacrifices the friction angle, density, and drainage capacity (Bouchemella and Taibi 2022).

4.5. Non-monotonic UCS and the intermediate-clay strength region

The complete stress–strain responses shown in Fig. 10 suggest that the compositional effect is not limited to the peak stress. Pure sand and materials with very low clay content appear to provide limited unconfined resistance, whereas the curves increase sharply as clay is introduced. The 30–60% clay mixtures developed the highest stress levels over a comparable strain range, after which the response weakened as the clay content increased further. This raw-response evidence independently supports treating the 40–60% region as a broad strength plateau rather than assigning significance only to the single numerical maximum at 40% clay.

The UCS appears to provide the clearest evidence of the optimum composition. The response increases from approximately zero for pure sand to 2.3 psi at 10% clay and 14.3 psi at 20% clay, then increases to 20.7 psi at 30% clay, and a measured maximum of 22.8 psi at 40% clay. Values from 40% to 60% clay remained tightly clustered between 22.5 and 22.8 psi before decreasing to 16.5 psi at 100% clay. Accordingly, the results suggest a broad favorable intermediate-clay strength zone rather than a mathematically sharp universal optimum at a specific percentage.

The initial strength increase may reflect the combined benefit of fines filling the sand skeleton and increasing cohesive resistance, while sufficient coarse particles remain to contribute interlocking and load transfer. Beyond the intermediate range, continued clay addition may reduce the frictional skeleton and increase plasticity; the gain in cohesion may no longer be sufficient to offset the loss in granular contribution. (Simpson and Evans 2015) provide a broader framework for this type of transition through changes in coarse-fine skeleton participation; however, the exact mechanisms and threshold fractions may depend on particle properties and test conditions.

The non-monotonic shape also suggests that linear regression may be inadequate for UCS. Its LOOCV R^2 appeared comparatively low relative to those of nonlinear alternatives. SVR was selected based on the lowest LOOCV RMSE, with an LOOCV R^2 of approximately 0.906 and MAE of 1.385 psi. The GPR sensitivity curve suggests the strongest positive response at low-to-intermediate clay content and a gradual negative response after the broad maximum, which appears consistent with the experimental points.

5. Data-driven results

5.1. Cross-validated model comparison

Table 2 Best model for each engineering property selected by minimum LOOCV RMSE. Permeability metrics are evaluated in $\log_{10}(k)$ modelling space

Property	Model	Train R^2	LOOCV R^2	LOOCV RMSE	LOOCV MAE	Generalization gap	Spearman rho
Specific gravity	Linear regression	0.8327	0.6844	0.0103	0.0070	0.1483	0.9793
Liquid limit (%)	Linear regression	0.9097	0.8320	9.4759	6.8333	0.0777	1.0000
Plastic limit (%)	Linear regression	0.9523	0.9139	2.4464	1.9596	0.0384	1.0000
Plasticity index (%)	Linear regression	0.8475	0.7097	8.1436	5.6305	0.1378	0.9977
Maximum dry density (kN/m^3)	GPR	0.9964	0.9907	0.1346	0.1137	0.0058	-1.0000
Optimum moisture content (%)	GPR	0.9936	0.9825	0.2240	0.1644	0.0110	1.0000
Permeability, k (m/s)	Linear regression	1.0000	1.0000	4.983e-07	4.187e-07	1.079e-13	-1.0000
Friction angle, ϕ ($^\circ$)	Polynomial regression (degree 2)	0.9948	0.9862	0.9729	0.7090	0.0086	-1.0000
Cohesion, c (kPa)	SVR	0.9973	0.9312	2.5943	1.2051	0.0661	1.0000
UCS (psi)	SVR	0.9826	0.9059	2.3700	1.3845	0.0768	0.3273

The model comparison suggests that complexity may be property-specific rather than uniformly imposed. Linear regression was used for specific gravity, liquid limit (LL), plastic limit (PL), and plasticity index (PI). These variables appear to exhibit monotonicity and sufficient smoothness; consequently, the 11-point dataset may not require additional flexibility under LOOCV. Second-order polynomial regression was selected for the friction angle, where a slight curvature improved the omitted-point predictions. GPR was selected for MDD and OMC, and SVR was selected for cohesion and UCS. For permeability, linear regression in log space appears to provide an almost exact representation of the final consolidated data.

The strongest cross-validated results were obtained for MDD, friction angle, permeability, and OMC. Specific gravity and PI had lower LOOCV R^2 values despite clear monotonic trends, partly because their absolute changes were small

or the end-member curvature had a disproportionate effect on R^2 . This suggests that generalization should include RMSE and MAE, in addition to R^2 . A lower R^2 does not necessarily indicate the absence of a physical trend; it may reflect limited variance or a few influential composition points (Martínez-Mayorga et al. 2024).

The generalisation gaps associated with the selected models appear small for the major hydraulic, compaction, and strength responses. The largest gap among the selected models appears to occur for the specific gravity, while the nonlinear UCS model retains a moderate gap. These results do not appear to remove the fundamental limitation imposed by $n = 11$: LOOCV tests interpolation across the measured composition domain, rather than transfer to a different sand mineralogy, clay mineralogy, compaction energy, or stress history (Hargreaves et al. 2023).

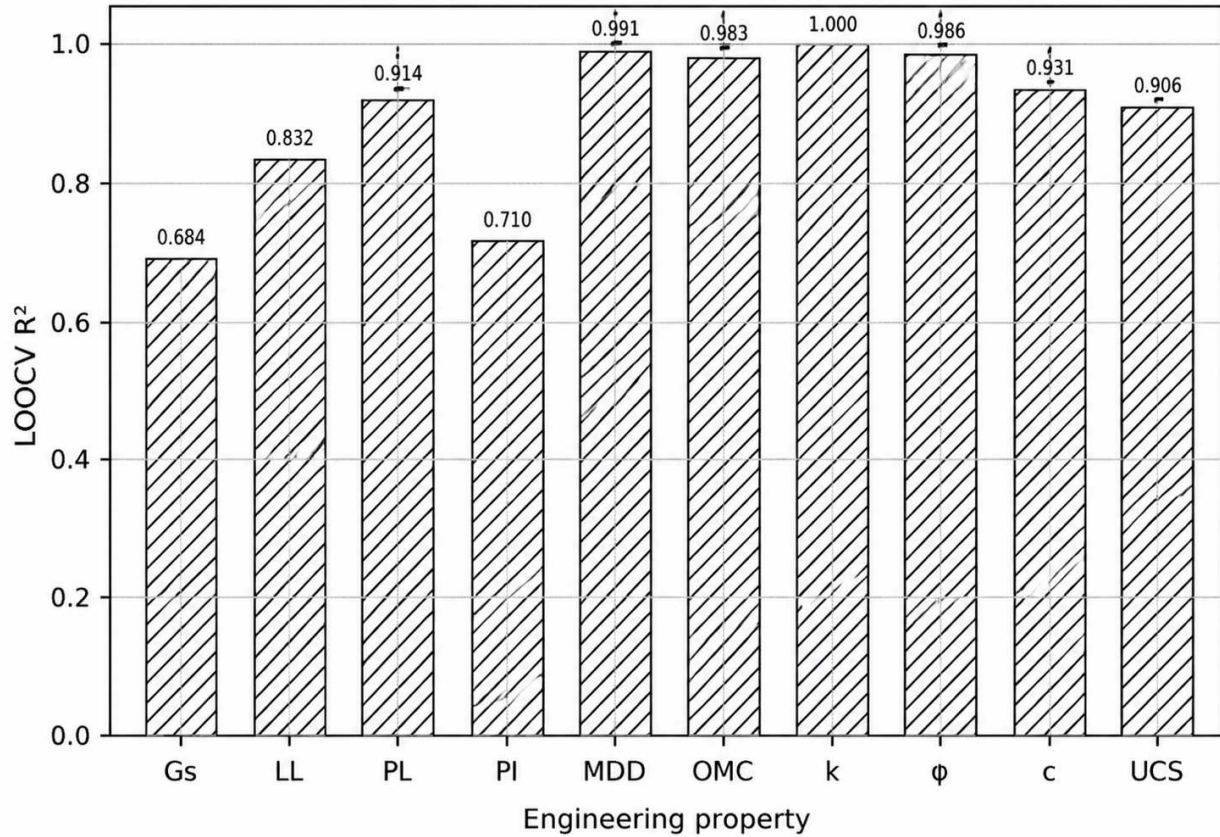


Fig. 12 Leave-one-out R^2 of the selected best model for each target property. Values quantify omitted-composition prediction within this 11-point laboratory series and do not represent validation on an independent soil source

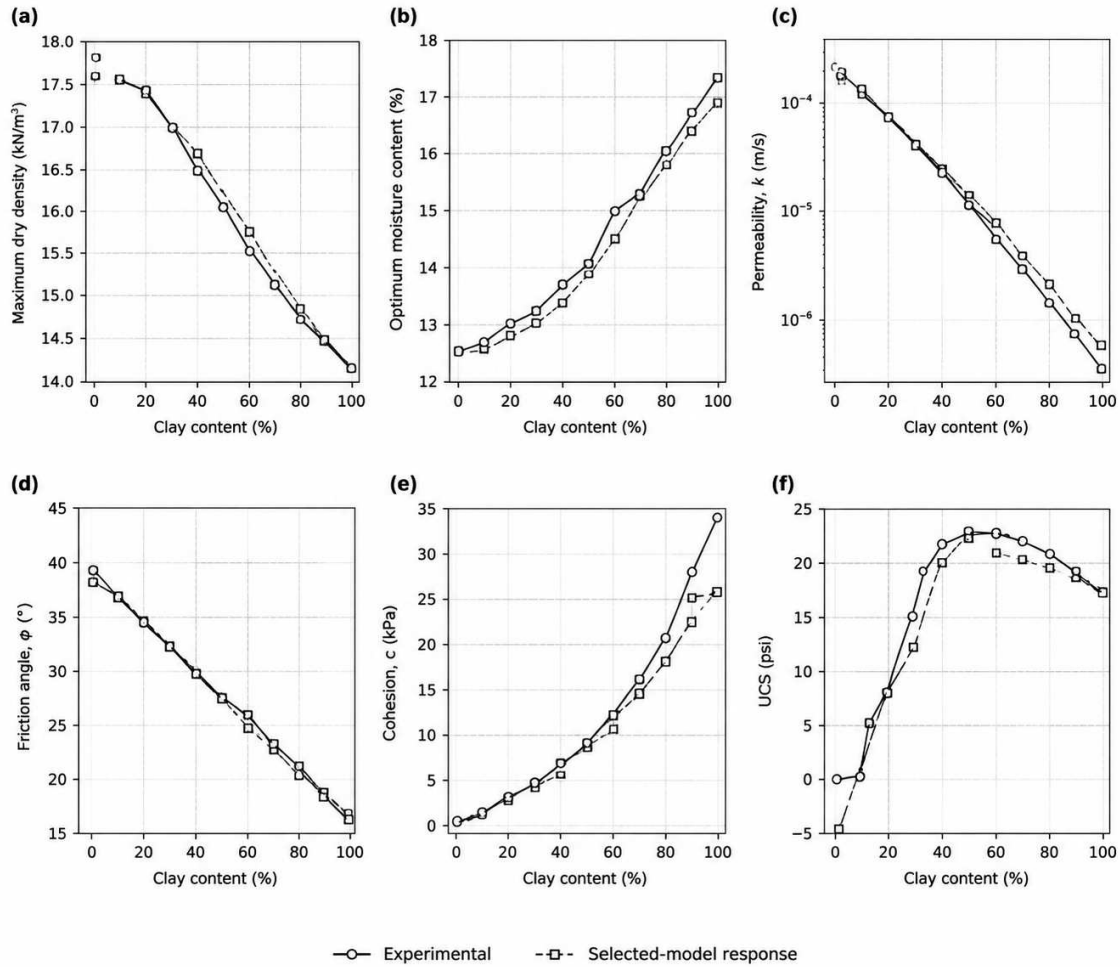


Fig. 13 Experimental observations and selected-model responses for key engineering properties. For GPR-selected MDD and OMC, the plotted curve is the full-data GPR mean; validation statistics are reported separately in Table 2. Permeability is shown on a logarithmic ordinate

5.2. GPR uncertainty and response smoothness

GPR response curves may provide a common, uncertainty-aware representation of composition sweeps. For the MDD, OMC, friction angle, and cohesion, the fitted mean appeared to follow the measured monotonic trend with relatively narrow bands throughout the interior of the dataset. Uncertainty generally appears to increase near boundaries and where the local curvature is less constrained, as expected for a smooth probabilistic regression (Rasmussen and Williams 2005) fitted to only 11 points.

For UCS, the GPR curve appears to resolve the rapid strength gain between approximately 10% and 30% clay, the broad plateau through the intermediate range, and the gradual decline at higher clay contents. The band is wider in the low-clay range, where UCS changes rapidly from near zero, and remains visibly finite across the plateau. This uncertainty representation may be more informative than the selection of the exact maximum of a smooth-fitted curve because several neighbouring compositions have experimentally similar strengths.

The GPR mean and band were plotted after back-transforming the permeability from log space. The response appeared approximately exponential in the engineering units. Because the final permeability series was unusually regular, the band appeared to reflect the assumed GPR noise/kernel structure rather than replicating the laboratory scatter. This suggests a need for future replicate testing if uncertainty in hydraulic conductivity is a primary research objective.

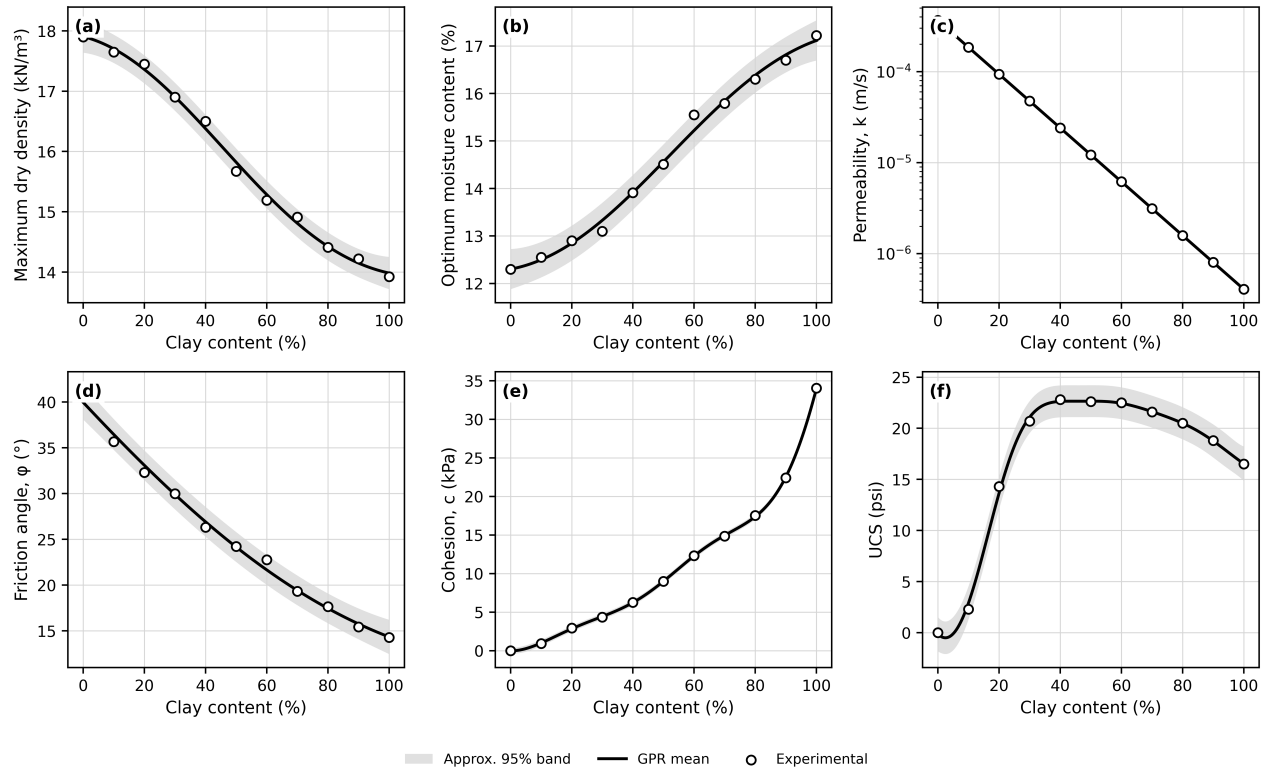


Fig. 14 GPR mean response and approximate 95% model-based uncertainty band for selected properties

5.3. Clay-content sensitivity and transition behaviour

Table 3 Selected GPR sensitivity indicators. Values quantify the fitted response and should be interpreted together with the experimental observations

Property	Clay at max sensitivity (%)	Maximum signed sensitivity	GPR predicted maximum at clay (%)	GPR predicted minimum at clay (%)	Monotonic agreement (%)
Maximum dry density (kN/m ³)	45.7500	-0.0559	0.0000	100.00	100.00
Optimum moisture content (%)	52.2500	0.0662	100.00	0.0000	100.00
Permeability, k (m/s)	17.5000	-0.0295	0.0000	100.00	100.00
Friction angle, ϕ (°)	0.0000	-0.3564	0.0000	100.00	100.00
Cohesion, c (kPa)	100.00	1.5064	100.00	0.2500	99.7506
UCS (psi)	16.5000	1.1471	50.5000	2.5000	45.1372

Sensitivity curves can elucidate the contrast between monotonic and non-monotonic responses. The sensitivity signs appear consistent across the measured properties: the MDD is negative throughout the composition range; the OMC is positive; the friction angle is negative; and the cohesion is positive. These signs are consistent with the experimental Spearman correlations and may provide an internal check on smooth GPR representation. The permeability sensitivity remained negative in the log space, suggesting a persistent order-of-magnitude decrease with clay content.

The UCS exhibits a distinct pattern: its sensitivity is strongly positive at low clay contents, approaches zero in the intermediate range, and becomes negative at higher clay contents. The fitted GPR maximum occurred near the middle of the composition sweep; however, the laboratory data suggested that 40%, 50%, and 60% clay had nearly indistinguishable strengths. For engineering purposes, the most defensible interpretation may therefore be an intermediate clay plateau rather than a single exact optimum inferred from a derivative zero crossing.

This cautious treatment may help avoid overinterpretation of small oscillations that can appear when a smooth probabilistic model is fitted to sparse data. Minor sign changes in an otherwise monotonic property were not considered as separate physical thresholds. Accordingly, the discussion is restricted to transitions that are visible in the experimental data and appear to have a plausible geotechnical mechanism.

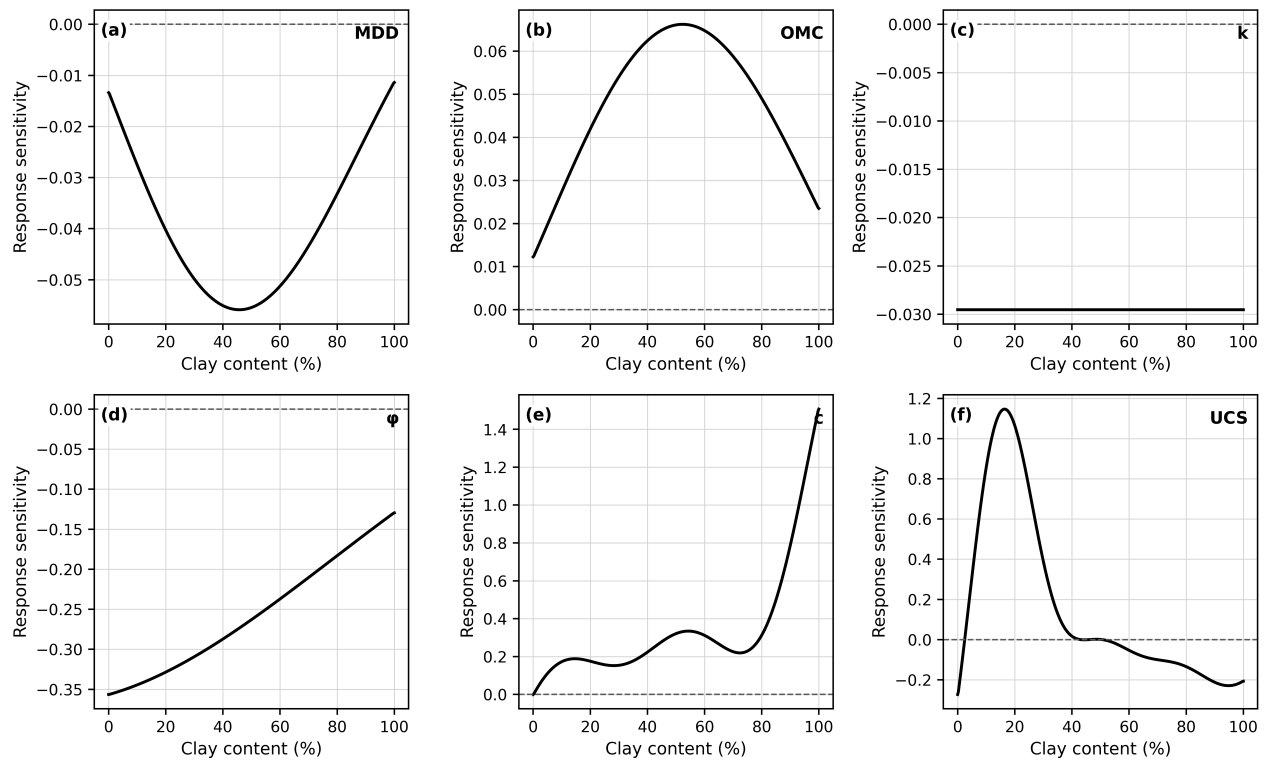


Fig. 15 GPR response sensitivity with respect to clay content for selected properties. For permeability, the derivative is evaluated in $\log_{10}(k)$ space; curves are used to identify broad response regimes rather than exact thresholds

6. Application-specific mixture screening

Table 4 Scenario definitions used in the transparent multi-criteria desirability analysis

Application	Criteria	Directions	Weights
High strength	UCS; Cohesion; Friction_Angle	benefit; benefit; benefit	0.80; 0.10; 0.10
Compacted fill / embankment screening	Dry_Density; UCS; Friction_Angle; OMC	benefit; benefit; benefit; cost	0.35; 0.30; 0.20; 0.15
Low-permeability barrier	Log10_Permeability; Cohesion	cost; benefit	0.75; 0.25
Drainage / permeable fill	Log10_Permeability; Friction_Angle; PI	benefit; benefit; cost	0.60; 0.25; 0.15

Table 5 Best-performing tested binary mixture under each application scenario

Application	Recommended mixture	Clay (%)	Sand (%)	Suitability score	UCS (psi)	Cohesion (kPa)	Friction angle (°)	Permeability (m/s)
High strength	40% clay - 60% sand	40	60	0.8786	22.8000	6.2613	26.3100	2.405e-05
Compacted fill / embankment screening	30% clay - 70% sand	30	70	0.8167	20.7000	4.3567	29.9900	4.747e-05
Low-permeability barrier	90% clay - 10% sand	90	10	1.0000	18.8000	22.4160	15.4350	8.026e-07
Drainage / permeable fill	10% clay - 90% sand	10	90	1.0000	2.3000	0.9317	35.6700	1.850e-04

The high-strength scenario appeared to favor 40% clay–60% sand, which attained a composite score of 0.87855. The next two candidates were 60% clay–40% sand (0.877505) and 50% clay–50% sand (0.873166), suggesting that the strength-oriented objective was nearly flat across the intermediate range. Under $\pm 20\%$ weight perturbation, 40% clay was selected first in 59.76% of the 5,000 simulations, and 60% clay was selected in 40.24% of the simulations. Accordingly, the result may be best reported as a robust intermediate clay strength region with 40% clay ranking first under the stated base weights, not as a universal 40% optimum.

The compacted-fill/embankment screening scenario selected 30% clay–70% sand, with a score of 0.816718, followed by 20% clay–80% sand at 0.809242 and 40% clay–60% sand at 0.740983. Weight perturbation selected 30% clay in 68.84% of the simulations and 20% clay in 31.16%. This result may reflect the trade-off between maintaining dry density and friction while obtaining a useful unconfined compressive strength (UCS). It should not be presented as a final subgrade design recommendation because the California B–g Ratio (CBR), swelling, cyclic behaviour, durability, and project-specific specification thresholds were not measured.

The hydraulic scenarios appeared more robust. Low-permeability-barrier screening appeared to select 90% clay and 10% sand across all weight-perturbation simulations, with 80% and 70% clay ranking second and third under the base weights. Drainage/permeable-fill screening appeared to select 10% clay–90% sand across all simulations, followed by 20% and 30% clay contents. These opposing results appear physically intuitive and may underscore the value of keeping application objectives explicit; the same property trend that benefits a barrier may be undesirable for drainage.

The screening analysis was intentionally limited to the experimentally tested compositions. Interpolation between 10% increments may be useful for hypothesis generation; however, the present study does not label untested compositions as experimentally optimised mixtures. Therefore, a practical follow-up would densify the experimental composition grid around the 20–60% range, where mechanical and compaction trade-offs may be most consequential.

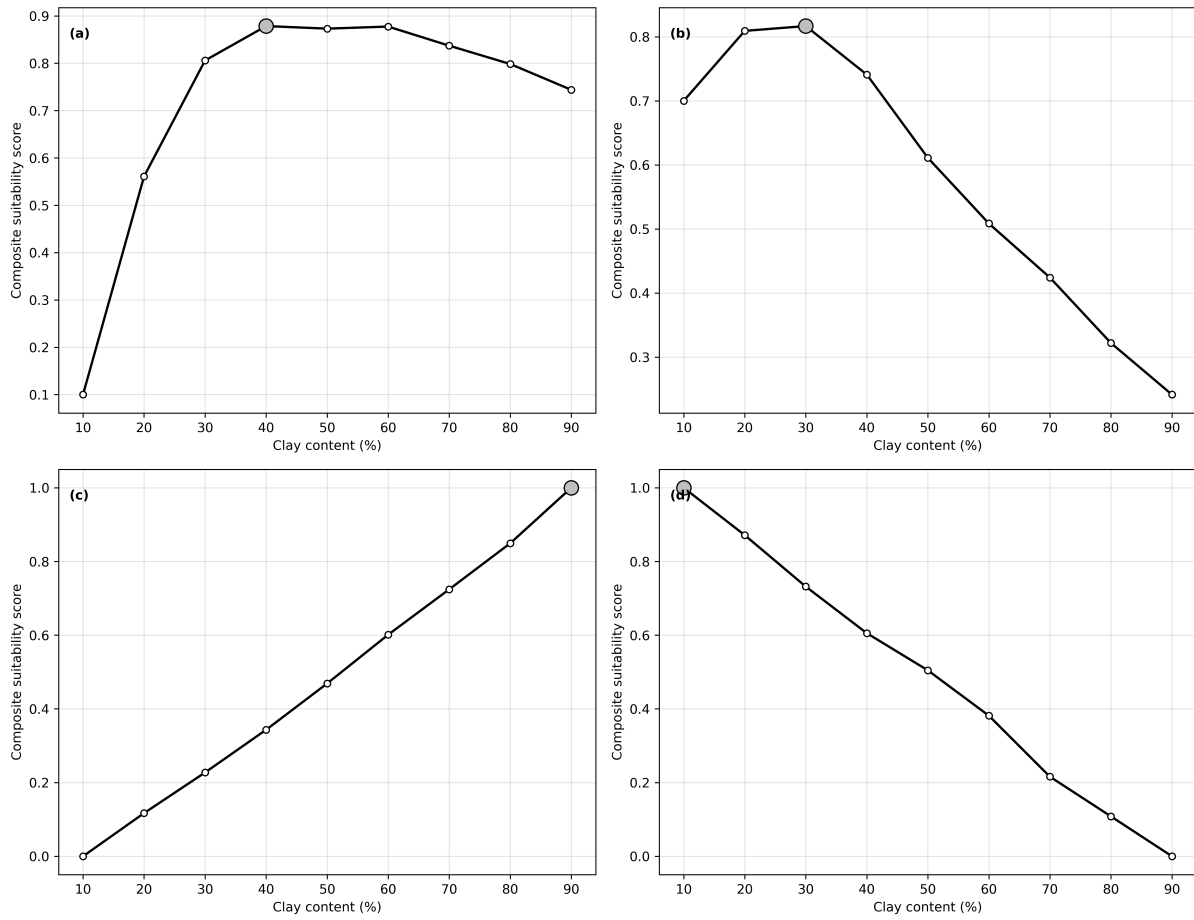


Fig. 16 Composite suitability score across the tested binary mixtures for (a) high strength, (b) compacted fill/embankment, (c) low-permeability barrier and (d) drainage/permeable fill screening

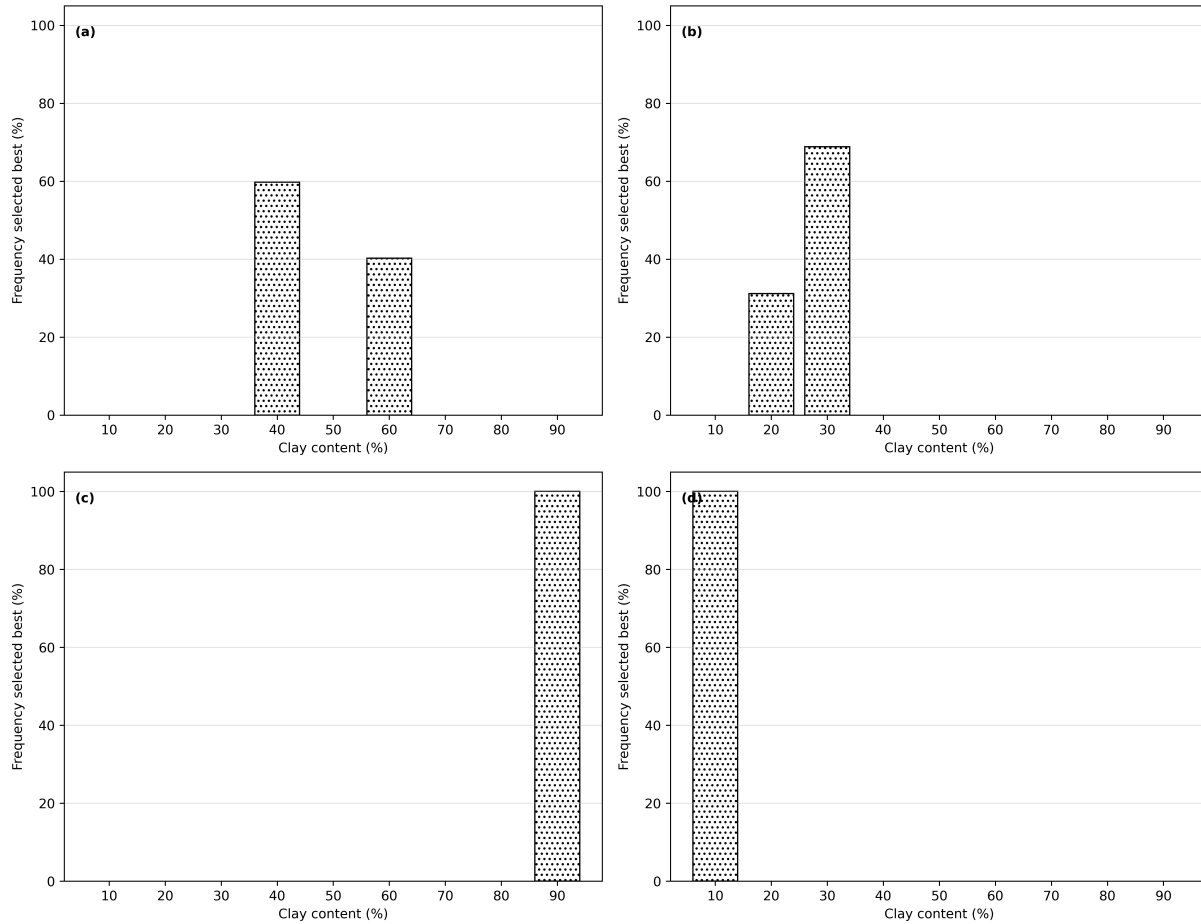


Fig. 17 Robustness of the application-specific rankings under 5,000 independent $\pm 20\%$ perturbations of criterion weights for (a) high strength, (b) compacted fill/embankment, (c) low-permeability barrier and (d) drainage/permeable fill screening

7. Discussion

Taken together, the experiments suggest a continuous transformation in material function rather than a single monotonic notion of “improvement” with clay addition. Sand-rich mixtures appear to preserve friction, density, and drainage; clay-rich mixtures appear to provide cohesion, plasticity, and hydraulic sealing; and intermediate mixtures may exploit both phases and yield the highest UCS. The composition most suitable for a given engineering application may therefore depend on the response being optimised and on the associated trade-offs deemed acceptable. Accordingly, an application-specific ranking appears more defensible than a single global optimum based on a potentially arbitrary average of unrelated properties.

The findings further suggest that small-data geotechnical machine learning warrants evaluation against simple baselines. Several responses appear to have been predicted more reliably by linear or low-order polynomial regression than by random-forest or nonlinear-kernel models under leave-one-out cross-validation (LOOCV). This result may be scientifically useful rather than indicative of machine-learning failure; it suggests that the information content of the controlled composition sweep is low-dimensional, and that a complex model is unnecessary for monotonic responses. The nonlinear contribution of support vector regression (SVR) becomes clearer for unconfined compressive strength (UCS) and cohesion, while Gaussian process regression (GPR) contributes uncertainty and sensitivity information even when it is not the nominal best predictor.

Accordingly, this study aligns more closely with data-centric experimental geotechnics than with a generic black-box prediction exercise. The computational workflow appears to incorporate three forms of geotechnical knowledge directly: binary-mixture closure, logarithmic treatment of hydraulic conductivity, and restriction of inference to the experimentally tested composition domain. It further avoids synthetic oversampling and reports uncertainty and omitted-point error. These choices appear responsive to the broader direction in data-driven geotechnics that calls for

a balance between data, domain knowledge, and engineering interpretation (Chen et al. 2024), (Tian and Wang 2024), (Zhang et al. 2023).

Nevertheless, the computational contributions should not be overstated; the models do not appear to constitute a new physics-informed neural network or a new constitutive law. Their value appears to lie in a transparent framework that extracts the response shape, uncertainty, sensitivity, and decision consequences from a sparse, but systematically designed laboratory series. This framing appears to be essential for reproducibility and honest comparison with more sophisticated physics-informed approaches

The mixture-response curves provide several testable hypotheses for future work: First, the UCS plateau between approximately 40% and 60% clay should be resolved with smaller composition increments and replicated specimens. Second, microstructural measurements can determine whether the observed changes correspond to a transition in coarse particle connectivity or progressive pore filling. Third, permeability replicates should be used to quantify the experimental variance because the final sequence used here appears unusually regular in log space. Fourth, additional performance variables, such as CBR, swelling pressure, consolidation, cyclic response, and durability, may be needed before converting comparative application rankings into design recommendations.

From a practical perspective, this study illustrates that laboratory planning and data analysis may need to be coupled in future studies. If the engineering objective is low permeability, a high-clay region may require finer resolution. If the objective is strength or compacted fill, the 20–60% region may be more informative because it contains a mechanical transition and ranking uncertainty. Therefore, a subsequent experimental campaign could use the current uncertainty and sensitivity results to allocate tests where they are most likely to change the engineering decisions.

8. Limitations and transferability

The primary limitation of this study was its small sample size. Eleven composition levels provide an unusually complete 0–100% sweep but may result in a comparatively sparse dataset for flexible statistical learning. LOOCV may use the available observations efficiently; however, it does not substitute for an independent external validation set (Kerns et al. 2015). Therefore, the reported R^2 values may be understood to quantify interpolation of the investigated material system and should not be interpreted as population-level predictive accuracy.

Second, the final modelling table contained one consolidated value per composition for each response. Where laboratory repeats existed in the broader study records, the final computational dataset supplied for this manuscript did not include replicate-level uncertainty. The GPR band therefore appears to represent model-based uncertainty rather than a direct experimental confidence interval. Future work could retain replicate measurements and propagate both measurement variance and model uncertainty.

Third, the study isolates composition, while other state variables are controlled or summarised. Natural soils may vary simultaneously in terms of mineralogy, gradation, particle shape, initial fabric, stress history, saturation, and chemistry (Chen et al. 2023). The models may not support extrapolation beyond 0–100% clay or transfer to another soil source without recalibration. The application rankings are similarly conditional on the selected material, test state, criteria, and weights.

Fourth, the mechanical dataset uses UCS reported in psi in the consolidated source. Although the maximum can be converted to approximately 157 kPa for context, the manuscript preserves the original numerical unit to avoid altering the underlying dataset. A future dataset could standardise all mechanical variables in SI units at acquisition.

Finally, application-specific results may function as screening tools rather than as code compliance checks. Additional tests and acceptance criteria are required, particularly for embankments or subgrade use. Nevertheless, the strength and hydraulic rankings may be useful for narrowing the composition range that should undergo additional tests.

9. Conclusions

A systematic sweep from 0% to 100% clay content suggested that composition may strongly control the physical, hydraulic, and mechanical behaviour of the investigated sand–clay system. The liquid limit increased from 14% at 10% clay to 88% at 100% clay, the plasticity index increased from 5 to 57, and the specific gravity changed only slightly from 2.65 to 2.72. The optimum moisture content increased from 12.3% to 17.2%, whereas the maximum dry density decreased from 17.9 to 13.9 kN/m³. The permeability decreased from 3.65095×10^{-4} to 4.06634×10^{-7} m/s and was nearly log-linear with clay content within the measured composition series. The shear strength response showed increasing cohesion from 0 to 34.033 kPa and decreasing friction angle from 41.22° to 14.28°, which may indicate a progressive transition from friction-dominated to cohesion-dominated behaviour.

The unconfined compressive strength (UCS) appeared to exhibit a non-monotonic response (Alnmr and Ray 2021). It increased rapidly with clay addition, reached a measured maximum of 22.8 psi (approximately 157.2 kPa) at 40% clay,

remained close to this maximum through the intermediate-clay range, and then decreased toward the clay-rich end. Accordingly, the data appear to support a broad intermediate clay strength region rather than a single sharply defined universal optimum. No single algorithm appeared to be optimal for every response: linear and second-order polynomial regressions were adequate for several smooth monotonic outputs; Gaussian process regression (GPR) performed well for the compaction-related variables and provided uncertainty and sensitivity information; and support vector regression (SVR) was selected for cohesion and UCS based on the minimum LOOCV RMSE.

The Gaussian process regression (GPR)-based sensitivity analysis separated persistent monotonic responses from the non-monotonic unconfined compressive strength (UCS) response without treating the fitted interpolation points as experimental observations. Under the stated screening criteria, the highest-ranked tested mixtures appeared to be as follows: 40% clay–60% sand for high strength, 30% clay–70% sand for compacted fill/embankment screening, 90% clay–10% sand for a low-permeability barrier, and 10% clay–90% sand for drainage/permeable fill. These are the top-performing tested mixtures under the specified screening assumptions and should not be interpreted as universal design optima. Overall, these findings suggest that systematically generated laboratory data can be combined with composition-aware sparse-data modelling, uncertainty assessment, and transparent engineering screening while preserving experimental observations as the primary scientific evidence.

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Data Availability: This data is from our undergraduate Thesis. It will be available upon request.