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Research article

Engineering properties of peat: a data-driven approach

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Abstract: Peat is a highly variable organic soil that presents major challenges for geotechnical engineering. In Finland, where peatlands cover one-third of the land area, infrastructure often intersects deep deposits that are difficult to characterise and costly to improve. Conventional practice relies on conservative assumptions or large-scale replacement, which can be expensive and carbon intensive. In this study, we compiled a harmonised database of over 250 datapoints from Finnish, Nordic, and Western European sources, focusing on compressibility, yield stress, and undrained shear strength. Regression analyses were benchmarked against Random Forest machine learning models. The results confirmed that the compression index is well predicted from water content, whereas yield stress and undrained shear strength display high variability under regression. Random Forest models provided modest improvements over conventional regression for strength-related parameters, while compressibility remained well captured by empirical correlations. Cross-parameter estimators offer additional tools where direct strength testing is unavailable. The findings underline the complementary roles of regression and machine learning in peat characterisation. Moreover, a hybrid workflow is proposed: regressions for early screening and conservative design, and machine learning for refined, site-specific assessment, supporting more sustainable infrastructure development on peatlands.

Keywords: peat; database; compressibility; shear strength; machine learning; correlations

1. Introduction

Peatlands are globally widespread, covering approximately 3–4% of the Earth's land surface [1]. In Finland, they occupy 33.5% of the national land area, making peat one of the most common ground conditions encountered in infrastructure development [2]. While ecologically valuable, peat deposits pose numerous challenges for civil engineering. Roads, railways, pipelines, and energy installations frequently come across peatlands, particularly in central, western, and northern Finland, where deposits may extend several metres in depth. Such projects are often associated with high construction costs, continuous maintenance needs, and significant environmental impacts [3,4].

Peat differs fundamentally from mineral soils in composition and behaviour. It is formed of partially decomposed plant remains accumulated under waterlogged conditions and subsequently fossilised [3,5]. Peaty soils are organic soils that are typically fibrous and are classified as materials with more than 75% organics by dry mass [6]. Finnish peat deposits commonly exhibit water contents ranging between 300–2000% and bulk densities between 600–1200 kg/m^3 [2]. Their fibrous structure imparts tensile resistance and facilitates water flow but also introduces pronounced mechanical anisotropy. In situ consolidation processes generate structural cross-anisotropy, further complicating laboratory testing and parameter determination. Peat layers are usually stratified, with fibrous, undecomposed peat forming the acrotelm at the surface, and more decomposed, waterlogged peat forming the catotelm at depth. Gases produced by ongoing biochemical degradation (e.g., CO_2, H_2S, and CH_4) may prevent full saturation even below the water table [5].

Mechanically, peat exhibits frictional behaviour with relatively high effective friction angles and small cohesion compared to mineral soils [5]. Its low effective stress environment contributes to poor bearing capacity, excessive settlement, high creep potential, and complex rate-dependent deformation [7]. Peat is also subject to biological and chemical degradation, adding to its long-term instability [8]. These factors make peat one of the most problematic geomaterials in civil engineering.

Peat classification systems are central to engineering practice. The Von Post scale [9] remains widely used in Finland, while the European Standard SFS-EN ISO 14688-1 [10] distinguishes fibrous, pseudo-fibrous, and amorphous peat types based on a manual squeezing test. While consistency limits can be determined for amorphous peat, they are not applicable to fibrous varieties [11]. Research also highlights the importance of documenting parent vegetation type (e.g., moss peat and grass peat) in addition to index properties, as genesis has a strong influence on mechanical behaviour [5].

Historically, Finnish infrastructure projects have managed peat by avoidance, replacement, preloading, or chemical stabilisation. Although effective, these strategies are costly, carbon-intensive, and not aligned with sustainability goals of modern infrastructure [4]. Given this, there is a need for predictive models that can capture peat behaviour without relying on conservative overdesign. While some peat-specific approaches exist, they are often simplistic, site-specific, or based on limited datasets. Data-driven modelling may therefore provide a valuable way forward.

Despite decades of study, empirical and constitutive models for peat are poorly calibrated to Finnish conditions, rely heavily on subjective indices such as the Von Post scale, and show weak predictive power for key engineering properties such as compressibility and shear strength. Data-driven approaches, including regression models developed from large experimental datasets, have proven effective in other regions (e.g., [12]) but remain underdeveloped for Finnish peats. Furthermore, Machine Learning (ML) has not been systematically explored in peat engineering.

In this paper, we address these gaps by:

- Compiling a database of Finnish peat properties, complemented with international references.
- Evaluating how well conventional data-driven regression methods can predict engineering properties such as compressibility and shear strength.

- Exploring the potential of ML techniques, particularly Random Forest (RF) regression, to improve predictive accuracy.
- Comparing model outputs with Finnish design guidelines to assess their alignment and conservatism.
- Demonstrating how combined data-driven and ML approaches can support more sustainable, reliable, and carbon-efficient geotechnical design on peatlands.

2. Engineering background

2.1. Engineering properties of peat in everyday practice

The behaviour of peat has been studied for decades, yet it remains one of the most problematic geomaterials in civil engineering. Two properties are especially critical in everyday design: compressibility, which governs settlement, and shear strength, which controls stability. Compressibility is commonly expressed through the compression index C_c and yield or preconsolidation stress σ'_p. Shear strength is usually quantified in practice by the undrained shear strength s_u, even though drainage might occur in peat during loading because of its fibrous nature. Therefore, although it may be more appropriate to talk about the "shear strength" of peat, in practice, it is interpreted under a total stress framework.

Early studies emphasised the influence of fibre content and sample disturbance on both properties [13–15]. Hobbs [16] proposed a classification framework based on botanical origin and decomposition, which helped explain the variability observed between peats from different regions. A key milestone was the empirical relationship proposed by Mesri and Ajlouni [3], linking water content w directly to the compression index $C_c = w/100$. Despite its simplicity, this correlation remains widely used for settlement prediction. Later, the researchers in [17] and [12] expanded the empirical basis through large compilations of laboratory data from Ireland, the Netherlands, and the UK, which continue to serve as benchmarks for statistical modelling of peat properties.

In Finland, however, there is lack of a proper validation of international correlations. This aspect is crucial considering that local peats may differ in climate, vegetation, decomposition, and microstructure. As a result, national practice has relied on simplified approaches. The Von Post decomposition scale (H1–H10), originally developed for ecological classification, is widely used to characterise peat in the field. Finnish Transport Infrastructure Agency (Väylävirasto) guidelines [18] combine Von Post class H with w to estimate s_u, primarily for embankment stability analysis. While ensuring safety, this reliance on subjective, site-dependent indices limits reproducibility and integration with modern design workflows. Moreover, in Finland, in-situ strength of peat is determined through a Field Vane Test (FVT), where the measured strength is reduced by a factor of 2.0 [18]. Literature [12] shows that the vane correction factor may vary between 1 and 6, decreasing with increasing degree of decomposition, thus implicating that FVT tests in peat may give misleading and, in some cases, non-conservative results and should be treated cautiously.

Other European countries employ more quantitative systems. For instance, Dutch practice often uses cone penetration test (CPT) results, calibrated against laboratory testing, to dynamically estimate shear strength and settlement. For instance, Zwanenburg and Jardine [19] observed s_u of peat in line with undrained triaxial compression test results from full-scale failure tests, along with a positive correlation between s_u and the overconsolidation ratio OCR.

Finnish studies have begun to fill this gap. Oedometer tests performed by Sillanpää [20] yielded valuable data on compressibility and yield stress, while direct simple shear (DSS) and triaxial (TX) tests by Sainio [21] examined strain-dependent shear strength across decomposition states and stress paths. Furthermore, the researchers in [21] explored the calibration of CPTU in Finnish peat, suggesting a cone factor $N_{kt} \approx 15$ based on corrected FVT results. This is in line with the findings of Zwanenburg and Jardine [19] for Dutch peat. These contributions provide a foundation for more quantitative and reproducible models of Finnish peat behaviour.

2.2. Role of artificial intelligence in geotechnical engineering

While empirical and regression-based correlations remain central to practice, they often lack accuracy and generalisability. Data-driven methods, which rely on statistical analysis of large datasets, offer an opportunity to capture behavioural trends and reduce dependence on subjective indices.

Building on this foundation, artificial intelligence (AI) and particularly Machine Learning (ML) enable the modelling of complex, non-linear, multivariate relationships that traditional regression cannot easily represent. Algorithms such as Random Forests (RF) and Neural Networks (NN) have shown promising results in geotechnical engineering, including applications to the prediction of soil properties, where they offer advantages in handling non-linearity, outliers, and incomplete data [22–25]. AI approaches are also adaptable: models can be retrained as new data become available, making them well-suited for the highly variable and heterogeneous nature of peat.

Despite these advantages, applications of AI to peat remain rare. Most researchers continue to rely on empirical correlations or guideline-based estimates. Systematic application of AI to peat could provide more reliable predictions of compressibility, yield stress, and shear strength, while enabling back-calculation and gap filling in practical datasets. This would not only modernise Finnish practice and align with the digitalisation of geotechnics but also support more sustainable and carbon-efficient design of infrastructure on peatlands.

3. Materials and methods

This study is based on a dataset of laboratory data from Finnish, Nordic, and Western European peatlands. The final dataset comprises more than 250 datapoints covering multiple test types and sites. The primary Finnish contributions are the oedometer testing programme reported by Sillanpää [20], which covered four domestic sites as well as samples from Norway and Sweden, and the DSS and TX testing carried out by Sainio [21] on fibrous peat from central Finland. These were supplemented by the large empirical datasets of [12,17], which include deformation and strength properties of peat from Ireland, the Netherlands, and the UK from oedometer and DSS tests. Table 1 provides an overview of the datasets.

We focused on a set of key geotechnical parameters. Water content w was used as the primary independent variable. Compressibility was described using the compression index C_c, the creep index $C_{\alpha\varepsilon}$, the yield stress σ'_p, the constrained modulus M_0 at the in-situ vertical effective stress σ'_{v0}, and the normally consolidated modulus number m'. Shear strength was represented by the undrained shear strength s_u.

Four empirical functional forms were tested between w and each target parameter: a linear model, an inverse model, a power model, and a logarithmic model. Model performance was assessed through the coefficient of determination R^2, the root mean squared error $RMSE$, and the coefficient of variation COV. Fitting was carried out using least-squares optimisation, and the preferred regression function for each variable was selected based on statistical performance and engineering interpretability.

Table 1. Overview of peat datasets used in this study.

Properties	N. sites	N. points	Source
Deformation properties (oedometer)	15 sites (Ireland n.10, Norway n.2, The Netherlands n.3)	59	Boylan & Long [12]
Strength properties (DSS)	16 sites (Ireland n.13, Scotland n.1, The Netherlands n.2)	106	Long & Boylan [17]
Strength properties (DSS, TX)	1 site (Finland)	14	Sainio [21]
Deformation properties (oedometer)	11 sites (Finland n.4, Norway n.2, Sweden n.5)	76	Sillanpää [20]

In addition to the single-variable regressions, multivariable linear regression models were developed for σ'_p, M_0, C_c, m', and $C_{\alpha\varepsilon}$ to examine whether additional index properties could improve predictive performance. Undrained shear strength s_u was excluded from this stage because the database contained only paired (w, s_u) values, preventing meaningful multivariable analysis. Numerical predictors were retained only when at least ten joint observations with the target existed. Occasional isolated missing predictor values were replaced by the median of the remaining data to avoid discarding otherwise valid rows, while predictors with substantial missingness were excluded. Model performance was quantified using fitted R^2, $RMSE$, COV, and five-fold cross-validated coefficient of determination (R^2_{CV}).

To benchmark the potential improvement from nonlinear and interacting effects, the same predictor sets were subsequently used to train multivariable RF models.

To capture non-linear interactions and cross-variable effects, RF was applied to the dataset. RF constructs multiple decision trees from bootstrapped samples and averages their predictions to reduce variance. The models used 500 trees with unrestricted depth, mean squared error as the split criterion, and random feature selection at each split. Model performance was evaluated using out-of-bag (OOB) estimates as an internal validation metric and K-fold cross-validation for external validation. A conventional 80/20 train–test division was adopted, without stratification, as the response variables were continuous. A brief sensitivity check was carried out for the number of trees (100–1500) and the maximum tree depth (5–unrestricted). The cross-validated performance stabilised beyond approximately 300 trees, and no benefit was observed from restricting the depth. For this reason, the models were run with 500 trees and unlimited depth.

To interpret the behaviour of the RF models and quantify the relative contribution of individual predictors, SHAP (SHapley Additive exPlanations) [26] analysis was performed for all target variables except s_u. SHAP beeswarm and bar plots were used to visualise the dominant influences on the predicted properties, including the relative importance of water content, density, void ratio, humification, and other descriptors. In addition to standard SHAP, SHAP-IQ (SHAP Interaction Quantification) [27] was applied to capture pairwise interactions between predictors, which are particularly relevant where properties often act jointly rather than independently.

In practice, s_u is not always available for site investigations. To address this, supplementary cross-parameter models were developed to estimate s_u from other measured properties, including m', M_0, C_c, and σ'_p. For example, s_u was correlated with σ'_p using the relationship $s_u = \alpha\sigma'_p$ widely applied in clays, e.g., [28–30], but with a derived α coefficient, reflecting the fibrous structure and partial drainage of peat. These estimators were intended not as replacements for direct testing but as practical tools for filling data gaps and validating site models.

4. Results

4.1. Single-variable regressions

The first phase of analysis involved developing regression-based correlations between w and the target parameters. This approach could be seen as the standard in geotechnical practice, where simple functional forms were valued for their interpretability and ease of use during preliminary design stages. Linear, inverse, power, and logarithmic functions were tested, and the best-fitting models were selected based on a combination of statistical fit and engineering judgement.

Table 2. Regression correlations between water content and key peat parameters, with R^2, $RMSE$, and COV as performance metrics.

Parameter	Correlation type	N. points	Formula	R^2	$RMSE$	COV
m'	Inverse	127	$m' = 3330/w$	−0.020	2.91	0.52
M_0	Inverse	82	$M_0 = 161.3/w$	0.003	0.21	0.87
C_c	Power	98	$C_c = 0.255(w/100)^{1.5}$	0.86	1.31	0.21
$C_{\alpha\varepsilon}$	Logarithmic	63	$C_{\alpha\varepsilon} = 0.013\ln(w) - 0.06$	0.13	0.02	0.63
σ'_p	Inverse	110	$\sigma'_p = 10005/w$	0.38	8.67	0.61
s_u	Inverse	120	$s_{uDSS} = 4973/w$	0.10	4.47	0.58

The regression analysis produced a range of outcomes, which are summarised in Table 2. Among the parameters considered, C_c displayed the clearest trend, showing a strong dependence on w (Figure 1). This relationship was consistent with the well-established correlation proposed by Mesri and Ajlouni [3], which has long been regarded as a benchmark in peat settlement analysis. Moreover, the power correlation was consistent with that reported by the researchers in [31] for Finnish and Danish clays, silts, and organic soils. Statistically, the fit was robust ($R^2 = 0.86$) and logically aligned with the physical nature of organic soils: higher water contents typically reflected looser structures and greater compressibility. In contrast, regression models were less successful in describing the remaining deformation and strength-related properties. Weak trends were also observed for $C_{\alpha\varepsilon}$ (Figure 2), M_0 (Figure 3), and m' (Figure 4). The undrained shear strength s_u (Figure 5) exhibited only a weak inverse correlation with water content ($R^2 = 0.10$), despite its popularity in Finnish geotechnical practice. A similar picture emerged for σ'_p (Figure 6), where values varied considerably even at comparable water contents, limiting the usefulness of the regression despite a modest correlation ($R^2 = 0.38$). These outcomes underline the limitations of simple single-variable regressions when applied to soils with highly non-linear and heterogeneous behaviour.

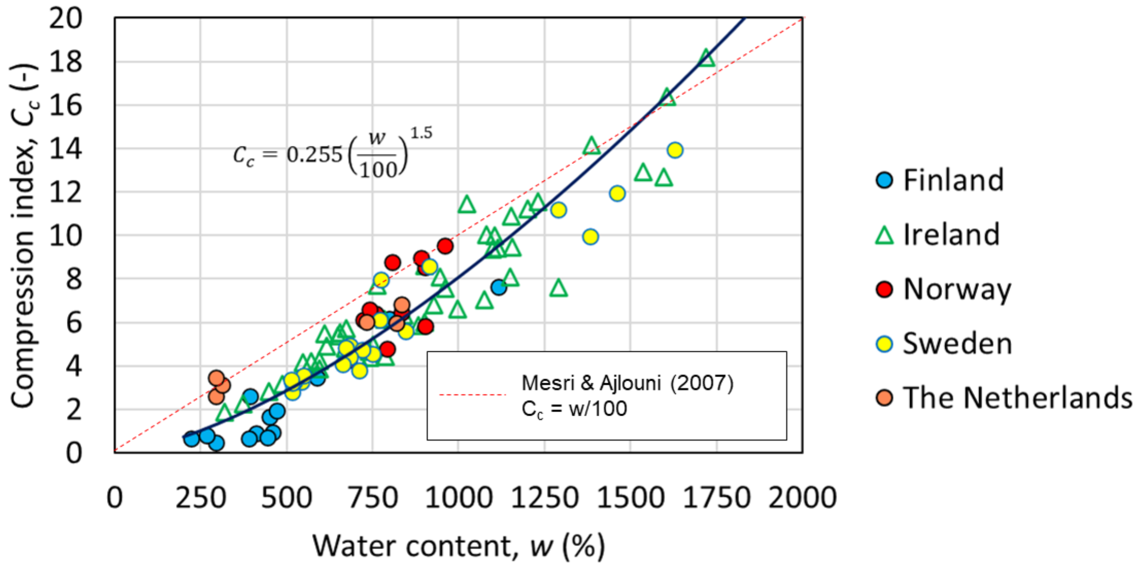

Figure 1. Compression index C_c versus water content w.

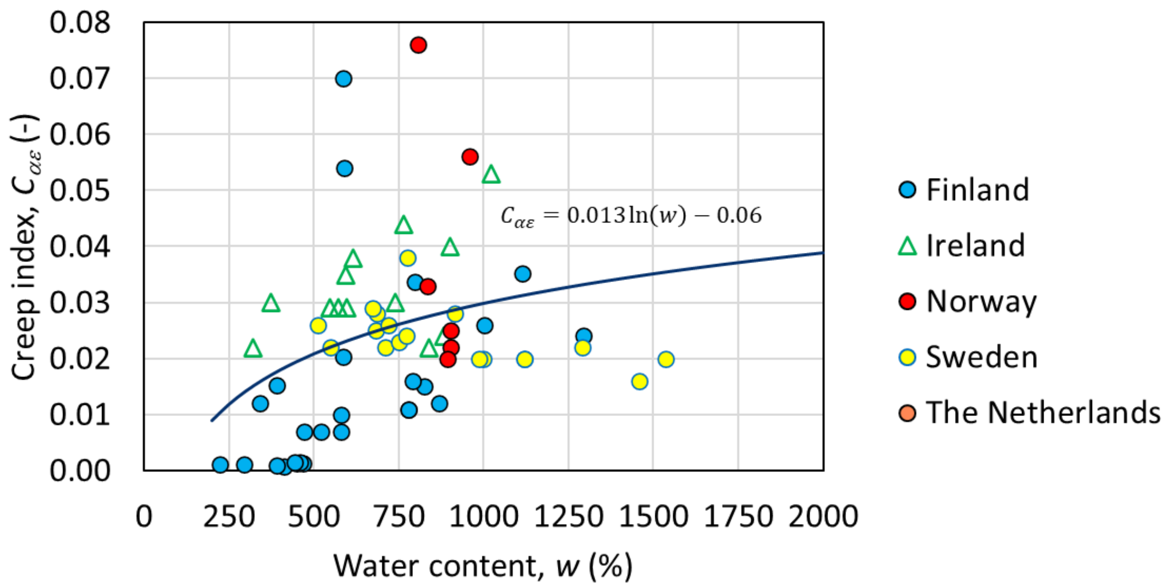

Figure 2. Creep index $C_{\alpha\varepsilon}$ versus water content w.

The ratio between the creep index and compression index provided a useful way to benchmark long-term deformation behaviour. In the compiled dataset, values of C_α/C_c generally fell within or close to the empirical range of 0.06 ± 0.01 reported by Mesri and Ajlouni [3] (Figure 7). Irish and Norwegian peats tended to show a large variability, while Finnish peat data were within the empirical band. Swedish peats were closer to or slightly below the lower boundary. This suggested that regional differences in decomposition state and fibre content influence secondary compression. Overall, the findings support the continued use of the Mesri and Ajlouni [3] band as a practical guideline for peat but also highlight that national datasets may cluster at different levels within that range.

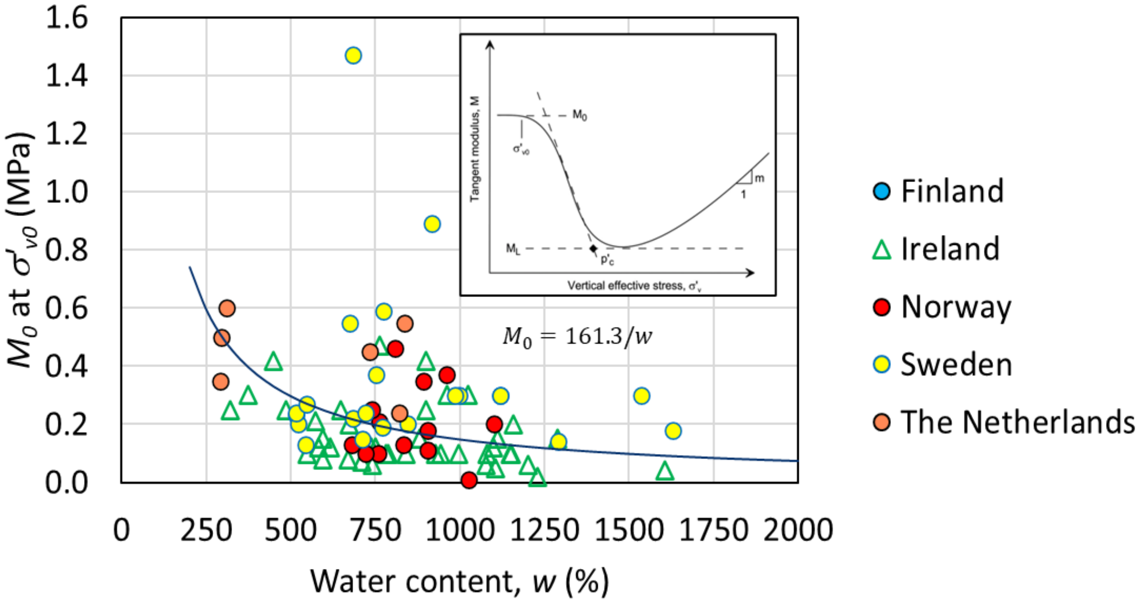

Figure 3. Constrained modulus M_0 at σ'_{v0} versus water content w, with schematic illustration of modulus definition.

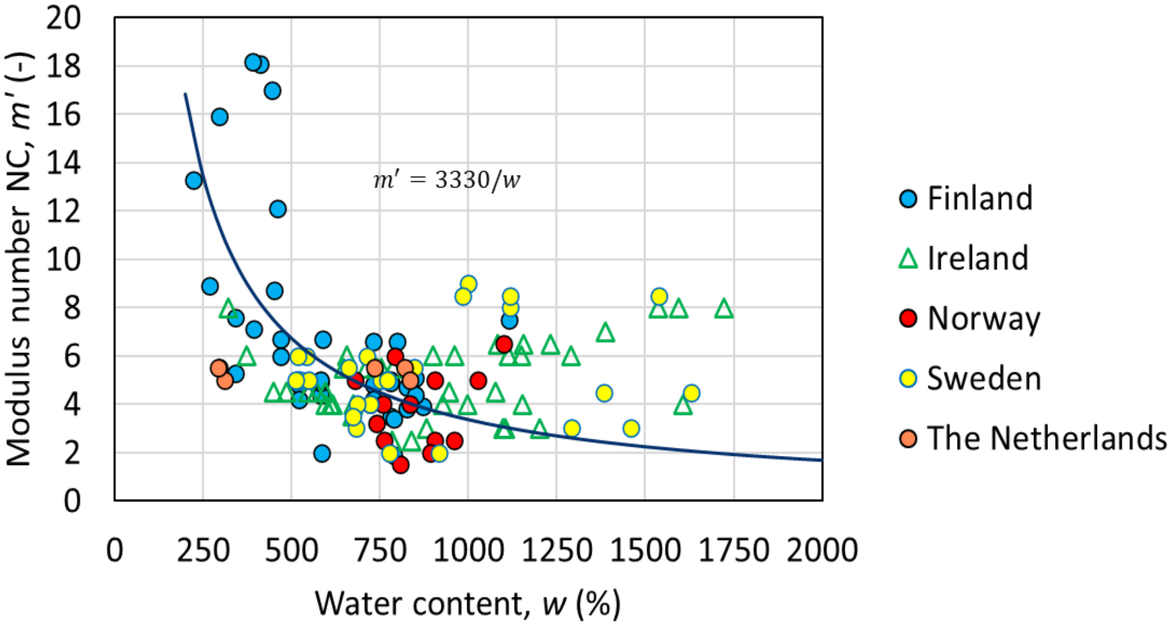

Figure 4. Modulus number m' versus water content w.

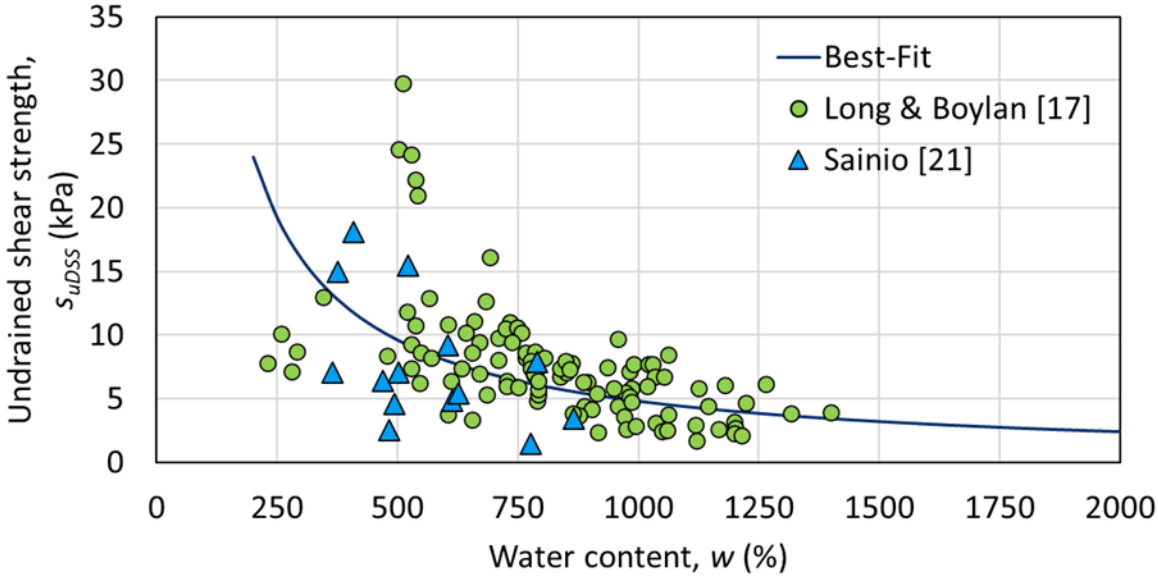

Figure 5. Undrained shear strength s_u versus water content w.

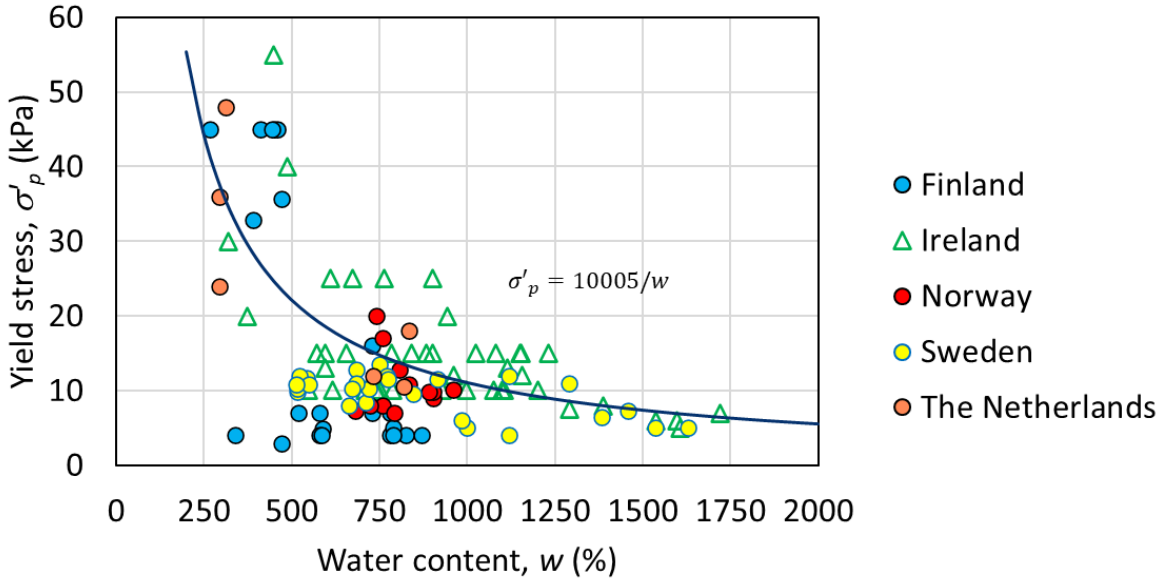

Figure 6. Yield stress σ'_p versus water content w.

The scatter observed in the regression analyses could partly be attributed to geographic differences. Irish peats occupied the highest water content range in the compiled dataset, often exceeding 1500%, whereas Finnish peats clustered between approximately 220% and 1300%. Smaller datasets from Sweden, Norway, and The Netherlands showed overlapping ranges, generally below 1200%. These regional contrasts highlight that while the compression index–water content relationship is robust across sites, correlations for stiffness and strength might be influenced by depositional environment and require local calibration.

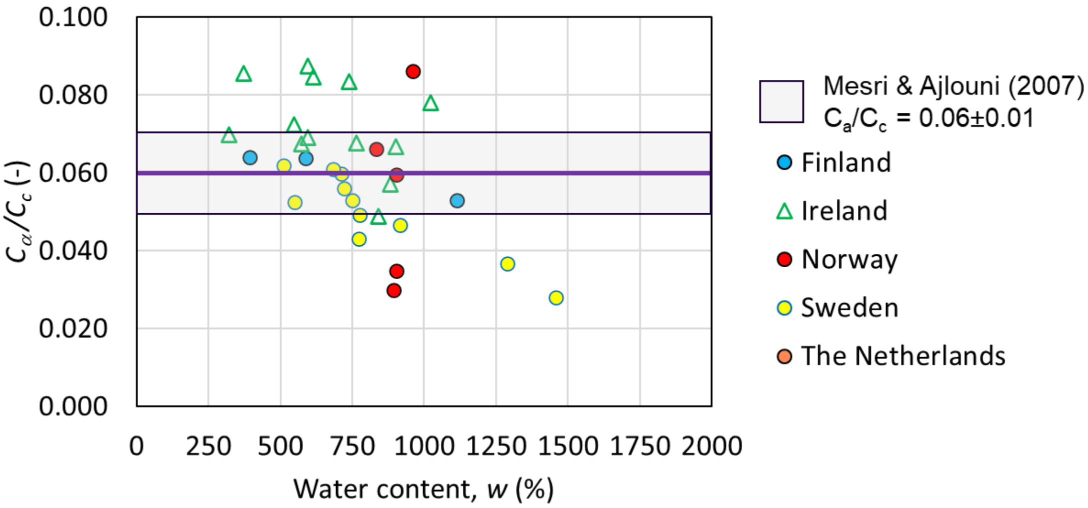

Figure 7. Ratio of creep index to compression index C_α/C_c versus water content w.

Table 3. Random Forest performance metrics R^2, $RMSE$, and COV for out-of-bag (OOB) estimates and K-Fold cross-validation (CV).

Parameter	N. points	R^2_{OOB}	$RMSE^2_{OOB}$	COV^2_{OOB}	R^2_{CV}	$RMSE_{CV}$	COV_{CV}
m'	127	0.16	2.64	0.48	0.25	2.49	0.45
M_0	82	-0.30	0.24	1.00	-0.33	0.24	1.01
C_c	98	0.83	1.48	0.24	0.84	1.42	0.23
$C_{\alpha\varepsilon}$	63	0.11	0.00	0.63	0.02	0.00	0.67
σ'_p	110	0.52	7.60	0.54	0.52	7.63	0.54
s_u	120	0.21	4.18	0.55	0.23	4.13	0.54

To complement the single-variable regressions, RF regression was applied using w as the sole predictor (Figure 8). The results in Table 3 show that non-linear models can extract additional information from the same variable. For s_u, the RF model achieved R^2_{OOB} of approximately 0.21, with a similar cross-validated performance, indicating an improvement over the regression fit. A comparable pattern was observed for σ'_p, with $R^2_{OOB} \approx R^2_{CV} = 0.52$, confirming that part of the unexplained variability can be captured by non-linear interactions even when only one descriptor is available.

For C_c, the RF model achieved $R^2_{OOB} \approx 0.83$, which was comparable to the strong linear regression ($R^2 = 0.86$), indicating little added benefit from non-linear modelling. Cross-validated performance remained close to the OOB estimate, suggesting that the model generalises well despite the limited input space. For $C_{\alpha\varepsilon}$, M_0, and m', both R^2_{OOB} and R^2_{CV} values were modest, consistent with the weak physical signal carried by w for these stiffness- and creep-related parameters.

Overall, the RF results showed that w alone can support moderately improved predictions when analysed through a non-linear framework, particularly for strength- and yield-related parameters. The close agreement between OOB and CV metrics suggests limited overfitting in the single-variable case. However, the performance remained constrained by the lack of additional physical descriptors, reinforcing the need for multivariable modelling to capture the underlying behaviour of peat more reliably.

A complementary set of cross-parameter models was developed to estimate s_u from other measurable properties. Relationships with m', M_0, C_c, and σ'_p were tested, with σ'_p emerging as the most reliable predictor. The derived equations are listed in Table 4. Among these, the σ'_p-based estimator deserves attention. This model relates to a well-known empirical correlation for clay, where s_u is often approximated as 22–25% of σ'_p [30]. However, the coefficient in peat (0.5) was significantly higher, likely reflecting its fibrous structure, partial drainage, and strain-rate effects.

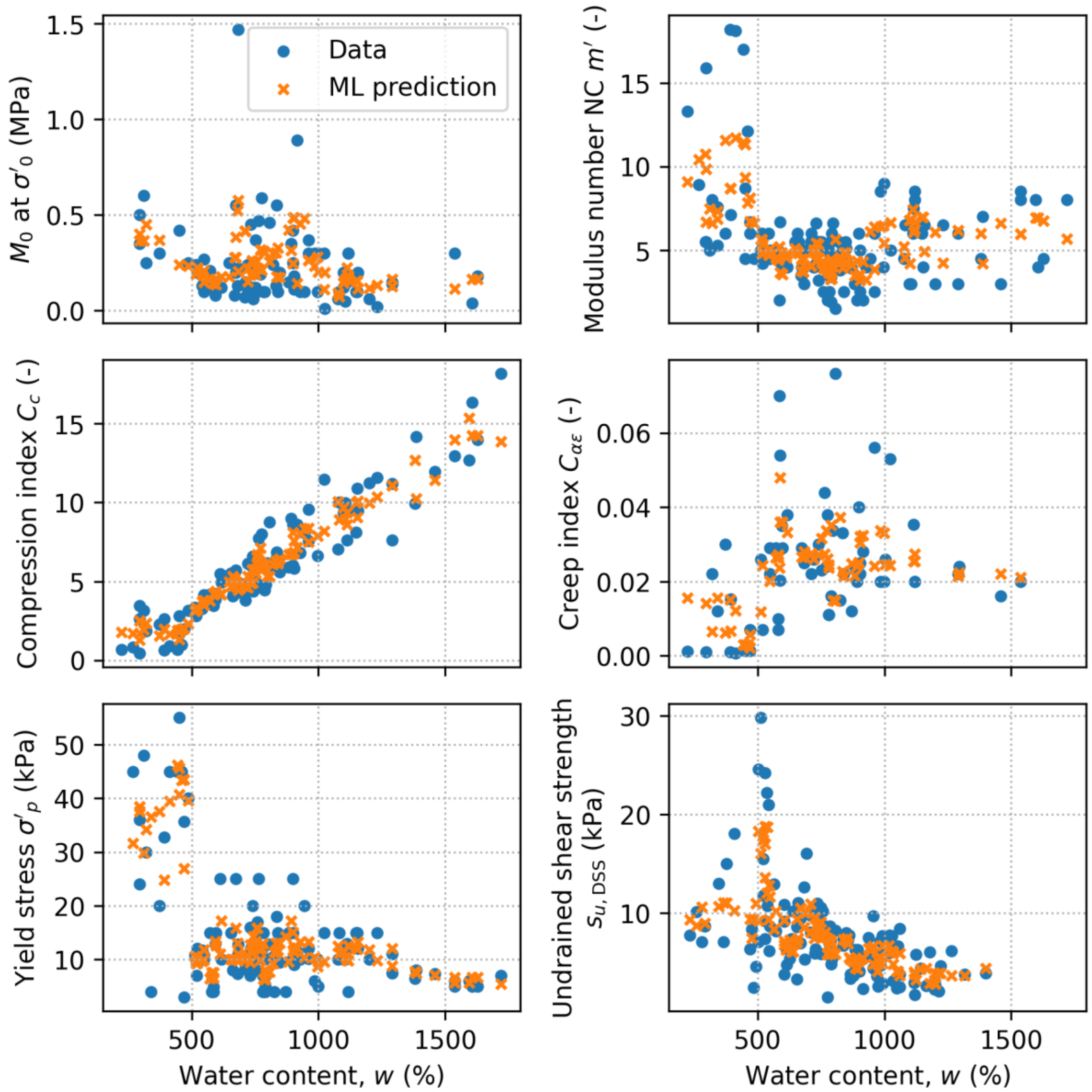

Figure 8. Comparison of measured peat properties (Data) and Random Forest (ML) predictions as a function of water content.

Finally, the predictive models were benchmarked against the empirical $s_u - w$ envelopes prescribed by the Finnish Transport Infrastructure Agency [18] (Figure 9). Regression-based predictions tended to align with the lower guideline envelope. RF outputs, by contrast, tracked the central trend of the dataset or slightly above, offering estimates that were potentially more realistic for well-characterised sites.

This comparison suggested that empirical guidelines and ML-based models can be used in tandem: the former providing a conservative safety baseline, and the latter offering refined predictions to optimise design. Overall, the results indicated that ML models can extend, rather than replace, empirical guidelines. By offering more accurate and site-specific predictions, these models may enable leaner designs, lower carbon footprints, and better use of testing resources, especially in the large-scale infrastructure projects that frequently encounter Finnish peatlands.

Table 4. Cross-parameter correlations for undrained shear strength s_u derived from other peat parameters m', M_0, C_c, and σ'_p.

Parameter	Formula	Substituted s_u formula	Best-fit s_u formula (k = 4973)
m' (-)	$m' = 3330/w$	$s_u = \frac{k \cdot m'}{3330}$	$s_u = 1.49\, m'$
M_0 (kPa)	$M_0 = 161300/w$	$s_u = \frac{k \cdot M_0}{161300}$	$s_u = \frac{M_0}{32.4}$
C_c (-)	$C_c = 0.255\left(\frac{w}{100}\right)^{1.5}$	$s_u = \frac{k}{100\left(\frac{C_c}{0.255}\right)^{2/3}}$	$s_u = \frac{49.73}{\left(\frac{C_c}{0.255}\right)^{2/3}}$
σ'_p (kPa)	$\sigma'_p = 10005/w$	$s_u = \frac{k \cdot \sigma'_p}{10005}$	$s_u = 0.5\, \sigma'_p$

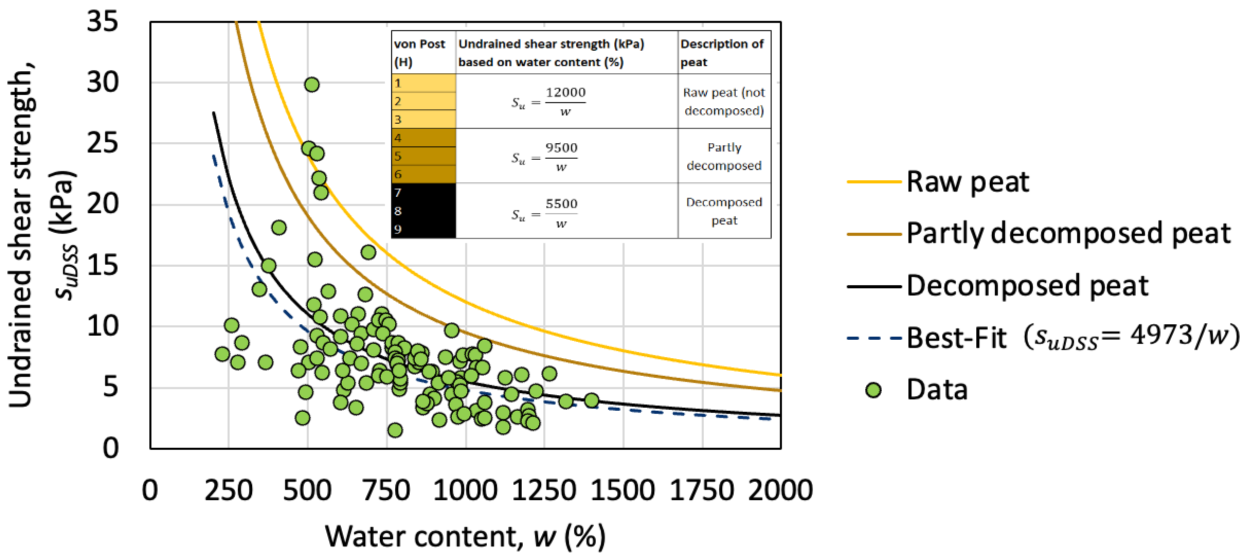

Figure 9. Scatter plot of undrained shear strength s_u versus water content w, including best-fit regression curve and empirical Finnish guideline [18] envelopes.

4.2. Multivariable regression

The w-based correlations provide useful first-order trends, particularly for compressibility. However, the large scatter observed in the stiffness- and strength-related parameters indicated that single-variable regressions cannot fully capture the complexity of peat. To assess whether additional index properties improve predictive performance, multivariable linear models were developed for σ'_p, M_0, C_c, m', and $C_{\alpha\varepsilon}$. Undrained shear strength s_u was excluded from this stage, as the database contained only paired (w, s_u) values and therefore did not support a meaningful multivariable analysis.

The resulting models (Table 5 and equations (1–5)) showed that multivariable regression performed very well for C_c ($R^2 = 0.93$) but more modestly for the remaining parameters. For σ'_p, the linear model yielded $R^2 = 0.60$. M_0 was poorly captured ($R^2 = 0.18$), while $C_{\alpha\varepsilon}$ performed better at 0.45 and m' reached a moderate R^2 of around 0.55.

Table 5. Multivariable linear regression results for σ'_p, M_0, C_c, m', and $C_{\alpha\varepsilon}$, including predictors used, number of valid rows, and fitted performance metrics.

Target	Predictors used*	N	R^2	$RMSE$	COV
σ'_p	σ'_{v0}, ρ, w, e_0, H, LOI, M_0, m', C_c, $C_{\alpha\varepsilon}$	110	0.60	6.99	0.49
M_0	σ'_{v0}, ρ, w, e_0, H, LOI, σ'_p, m', C_c, $C_{\alpha\varepsilon}$	82	0.18	0.19	0.79
C_c	σ'_{v0}, ρ, w, e_0, H, LOI σ'_p, M_0, m', $C_{\alpha\varepsilon}$	98	0.93	0.91	0.15
m'	σ'_{v0}, ρ, w, e_0, H, LOI, σ'_p, M_0, C_c, $C_{\alpha\varepsilon}$	127	0.55	1.91	0.35
$C_{\alpha\varepsilon}$	σ'_{v0}, ρ, w, e_0, H, σ'_p, M_0, m', C_c	63	0.45	0.01	0.50

Note: *Legend: σ'_{v0} = in-situ vertical effective stress (kPa); ρ = density (t/m^3); w = water content (%); e_0 = void ratio (-); H = Von Post index H1-H9 (-); LOI = loss on ignition (%) M_0 = constrained modulus (MPa); m' = modulus number (-); C_c = compression index (-); and $C_{\alpha\varepsilon}$ = creep index (-).

Table 6. Random Forest regression performance for σ'_p, M_0, C_c, m', and $C_{\alpha\varepsilon}$ reported as fitted, out-of-bag, and five-fold cross-validated metrics.

Target	R^2_{fit}	$RMSE_{fit}$	COV_{fit}	R^2_{OOB}	$RMSE_{OOB}$	COV_{OOB}	R^2_{CV}	$RMSE_{CV}$	COV_{CV}
σ'_p	0.93	2.96	0.21	0.70	6.07	0.43	0.61	6.85	0.48
M_0	0.78	0.10	0.41	0.21	0.18	0.77	0.16	0.19	0.80
C_c	0.98	0.55	0.09	0.89	1.18	0.19	0.88	1.24	0.20
m'	0.93	0.74	0.13	0.71	1.53	0.28	0.67	1.64	0.30
$C_{\alpha\varepsilon}$	0.82	0.01	0.28	0.35	0.01	0.54	0.36	0.01	0.54

Although these results were statistically valid, their practical interpretation required caution. Many of the predictors included in the multivariable models (e.g., M_0, m', C_c, and $C_{\alpha\varepsilon}$) were descriptors of compressibility, stiffness, or time-dependent behaviour and were often derived from the same laboratory tests as the target parameters. Consequently, the regressions partially relied on variables that were physically and procedurally related to the quantity being predicted. While this improved goodness-of-fit, it limited the engineering usefulness of the resulting equations, particularly for early-stage characterisation where such parameters were typically unknown. In this sense, the multivariable regressions should be viewed primarily as consistency relationships within the database rather than standalone predictive tools.

RF models were trained using the same predictor sets to examine whether nonlinear and interacting effects could be captured. These models achieved very high fitting accuracy, as shown in Table 6. For example, $R^2 = 0.98$ for C_c and 0.93 for m' and σ'_p, although the cross-validated R^2 values were lower. This indicated that the apparent gains were primarily due to model flexibility rather than a robust underlying physical relationship, and that the linear and RF models showed limited ability to generalise unseen data within this dataset.

When comparing single-variable and multivariable models, improvements were parameter-dependent. For compressibility (C_c), multivariable regression achieved high accuracy ($R^2 = 0.93$), with RF offering only marginal gains ($R^2_{CV} = 0.88$). Yield stress σ'_p benefited most from RF, with fitted R^2 increasing from 0.60 to 0.93, although cross-validation showed a modest improvement (≈ 0.61). For stiffness and creep parameters (M_0, m', $C_{\alpha\varepsilon}$), regression and RF performed poorly, indicating that richer descriptors were needed. Taken together, these results confirmed that RF adds value for some properties but does not universally outperform regression.

$$\begin{aligned}\sigma'_p = -7.285 + 1.073\sigma'_{v0} + 34.98\rho - 0.02405w + 1.909e_0 + 1.159H - 0.3407LOI \\ + 2.66M_0 + 1.518m' - 0.5196C_c + 123C_{\alpha\varepsilon}\end{aligned} \tag{1}$$

$$\begin{aligned}M_0 = -0.275 + 0.002405\sigma'_{v0} + 0.7561\rho - 5.887 \cdot 10^{-5}w + 0.01248e_0 - 0.007934H \\ - 0.003333LOI + 0.001228\sigma'_p + 0.007m' - 0.003949C_c + 4.712C_{\alpha\varepsilon}\end{aligned} \tag{2}$$

$$\begin{aligned}C_c = -4.191 - 0.01961\sigma'_{v0} + 2.536\rho + 0.006443w + 0.2836e_0 + 0.03884H \\ - 0.01936LOI + 0.0135\sigma'_p + 0.285M_0 - 0.1367m' + 58.15C_{\alpha\varepsilon}\end{aligned} \tag{3}$$

$$\begin{aligned}m' = -1.492 - 0.1278\sigma'_{v0} + 3.475\rho + 0.002414w + 0.5065e_0 + 0.1048H \\ + 0.02187LOI + 0.07741\sigma'_p + 0.3452M_0 + 0.954C_c - 62.11C_{\alpha\varepsilon}\end{aligned} \tag{4}$$

$$\begin{aligned}C_{\alpha\varepsilon} = 0.1138 - 0.002307\sigma'_{v0} + 0.0525\rho - 8.069 \cdot 10^{-8}w + 0.001399e_0 \\ - 0.0004553H + 5.831 \cdot 10^{-5}\sigma'_p + 0.004491M_0 + 0.002237C_c \\ - 0.001507m'\end{aligned} \tag{5}$$

4.3. SHAP Analysis of predictor importance

To interpret the behaviour of the RF models and quantify the relative influence of each predictor, SHapley Additive exPlanations (SHAP) [26] analysis was performed for all targets except s_u. The beeswarm (Figure 10) and bar plots (Figure 11) show that water content w was the primary predictor for C_c, whereas C_c was the dominant predictor for σ'_p, with w and σ'_{v0} contributing second-level effects. For the remaining targets, the importance of individual predictors varied: e_0 influenced C_c, while LOI played a noticeable role for M_0. In contrast, density ρ and the Von Post index H show consistently low contributions across all models.

For stiffness and creep parameters (M_0, m', and $C_{\alpha\varepsilon}$), SHAP values were small for all predictors, consistent with the weak multivariable and cross-validated performance. This indicated that the dataset contained limited information for predicting these parameters, regardless of modelling technique.

Overall, the SHAP results highlight that although C_c and w drove most of the predictable variability, depending on the target, other basic index properties offered only marginal gains. Moreover, the poor predictability of stiffness and creep possibly reflects material variability rather than limitations of the modelling approach.

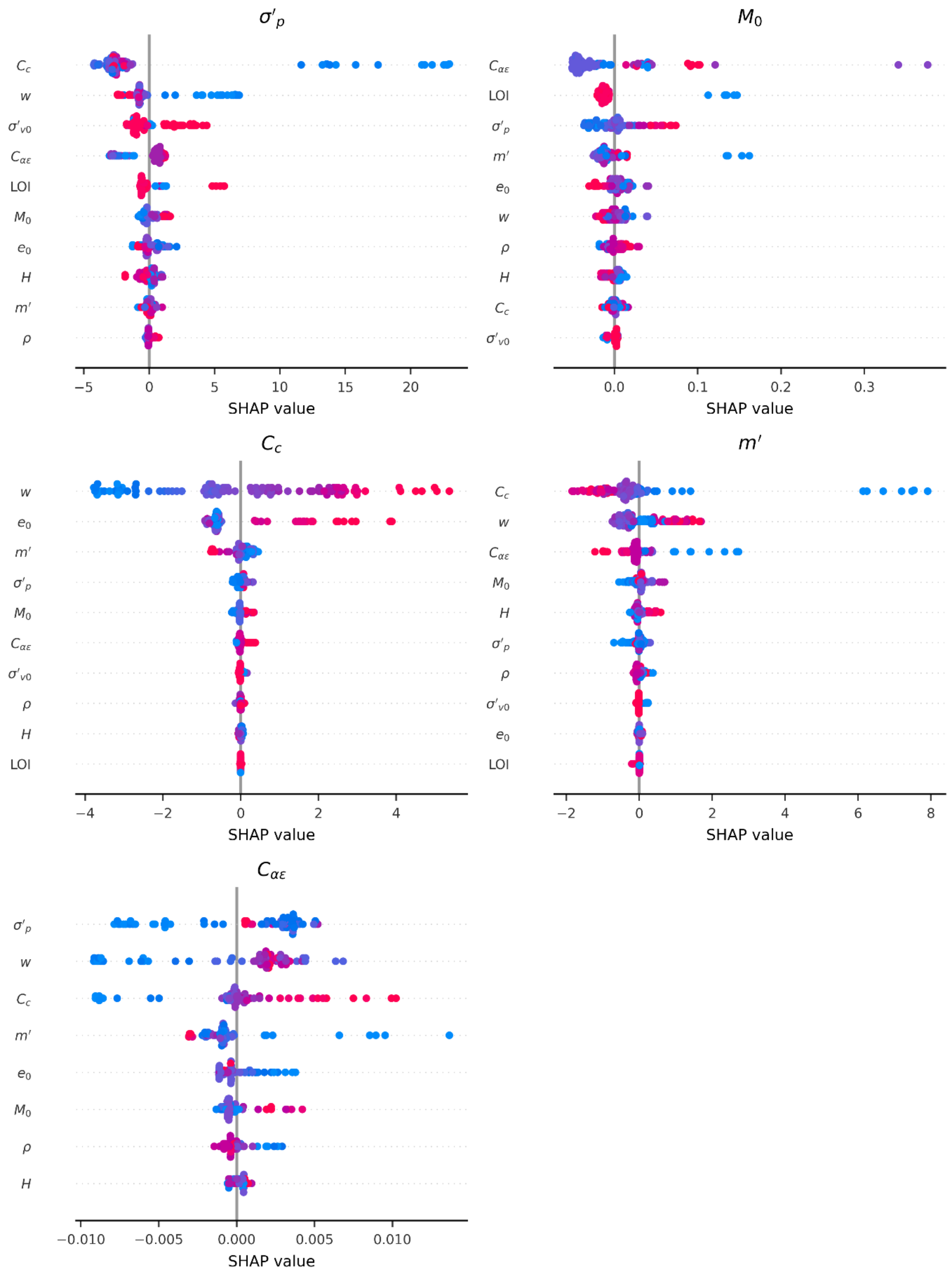

Figure 10. SHAP beeswarm plot showing feature contributions for the Random Forest model.

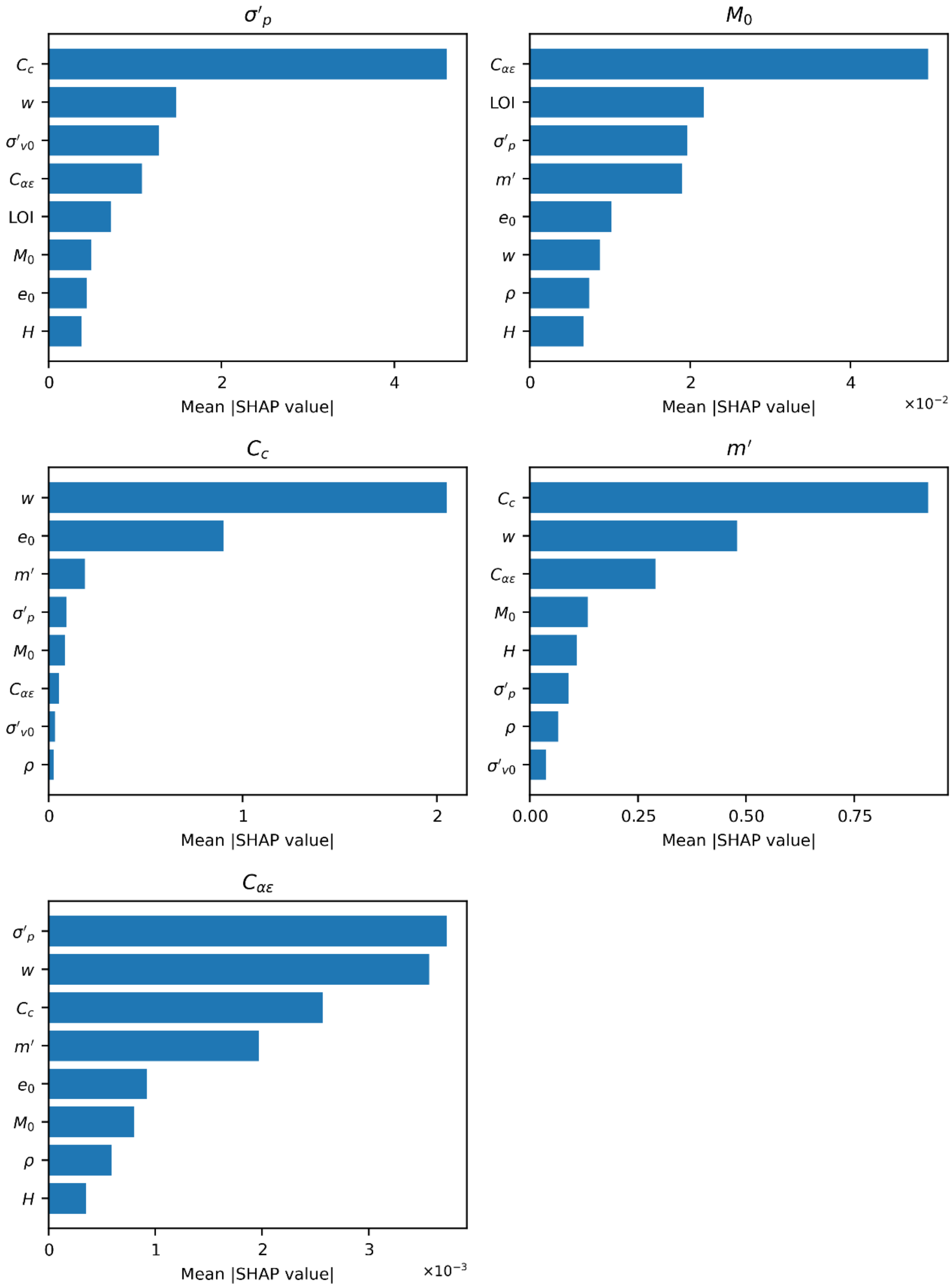

Figure 11. SHAP bar plot showing mean absolute SHAP values and feature importance.

However, standard SHAP captured only individual feature contributions and did not account for interaction effects, which are critical in soil mechanics where properties often act jointly. To address this, SHAP-IQ [27] analysis was performed to quantify pairwise interactions between predictors. SHAP-IQ decomposes the Shapley value into major effects and interaction terms, enabling the identification of nonlinear dependencies between features. Interaction strength was computed as the mean absolute SHAP interaction value across all samples and visualised using heatmaps for each target variable. The interaction heatmaps (Figure 12) reveal that the strongest dependencies occurred between

w and compressibility parameters (C_c, M_0), as well as between e_0 and C_c, particularly for σ'_p and C_c targets. These interactions indicated that soil behaviour is not purely additive; combined effects of moisture and compressibility dominate consolidation and stiffness responses. In contrast, creep-related parameter $C_{\alpha\varepsilon}$ showed negligible interactions, reinforcing its weak predictability. Overall, SHAP-IQ added a deeper interpretability layer by exposing nonlinear dependencies that standard SHAP could not capture, highlighting the importance of considering coupled soil properties in predictive models.

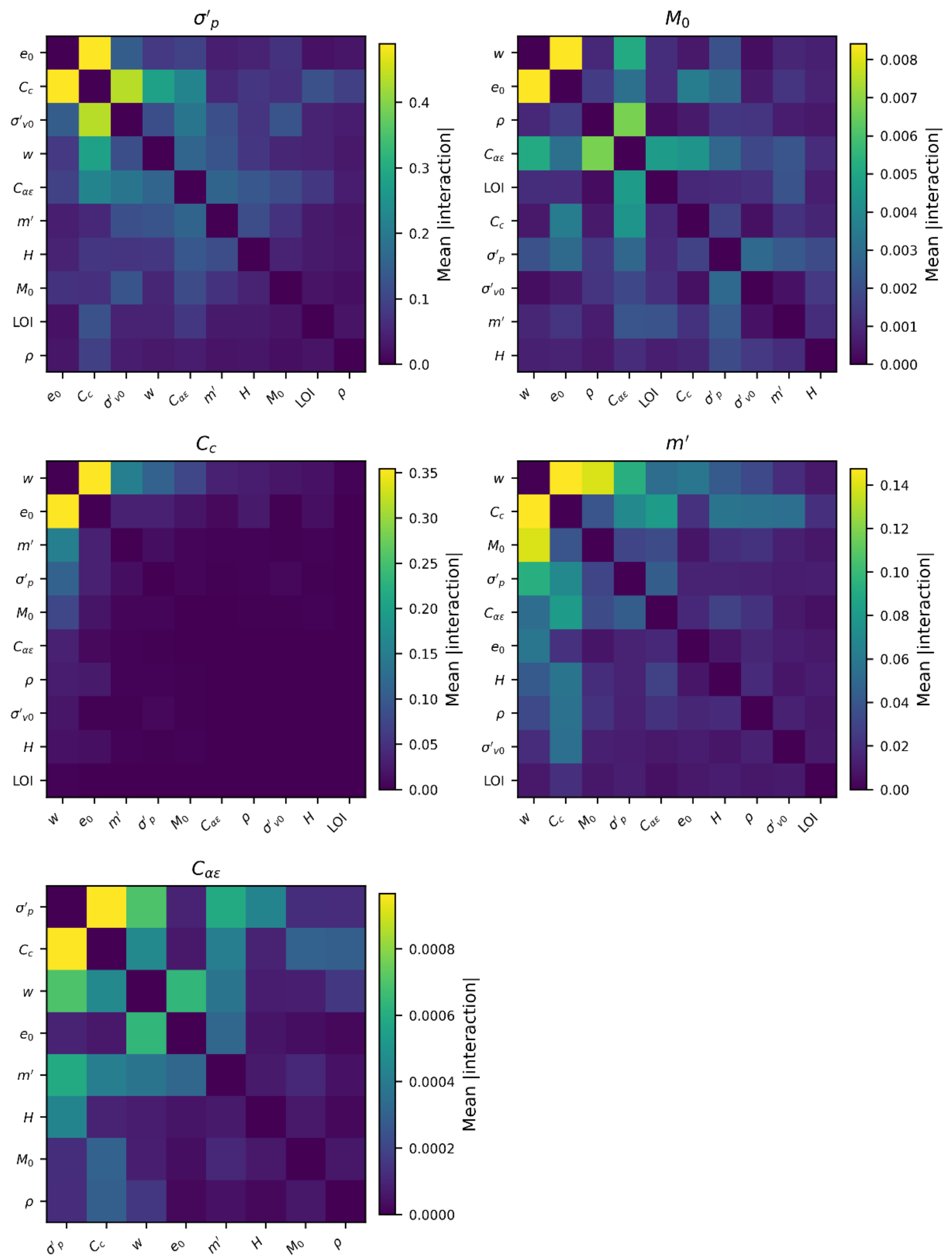

Figure 12. SHAP-IQ interaction heatmaps for selected target variables.

5. Discussion

5.1. Implications for geotechnical design practice

Our results show a noticeable difference in how regression and ML models perform on Finnish and Nordic peats. Compression-related parameters, such as the compression index C_c, are well captured by linear empirical models, confirming decades of established practice. By contrast, strength-related parameters, particularly undrained shear strength s_u and yield stress σ'_p, show considerable scatter under classical regressions. This divergence reflects the complex and heterogeneous nature of peat, which resists simple single-variable characterisation.

For practitioners, this implies that early-stage designs may continue to rely on regression-based estimators for settlement analysis, especially when only water content data are available. However, the weak performance of regressions for strength and stiffness highlights the risks of relying solely on empirical correlations: designs may become overly conservative, leading to unnecessary soil replacement or stabilisation or, more critically, unsafe if the lower-bound nature of peat strength is not accounted for.

The introduction of ML provides a powerful tool for geotechnical designers. The RF models offer some improvement for strength-related parameters, particularly σ'_p, but s_u remain difficult to predict. For compressibility, empirical correlations already achieve high accuracy, leaving little room for improvement. Overall, RF adds value for certain properties but does not universally outperform regression.

Taken together, the findings support a hybrid workflow: regression models for preliminary screening and feasibility, and machine learning tools for refined modelling and risk-sensitive applications such as critical infrastructure.

5.2. Sustainability and carbon impact

A key motivation for improving peatland geotechnical modelling lies in its climate implications. Traditional approaches, e.g., excavation, chemical stabilisation, or bypassing, are resource-intensive and carbon-heavy. By improving the accuracy of strength and settlement predictions, engineers can reduce conservative assumptions and thereby optimise the extent of ground improvement. This translates into lower material volumes, reduced emissions, and faster permitting in environmentally sensitive areas.

ML models, by supporting more tailored site-specific predictions, can help designs better reflect local conditions rather than relying solely on worst-case assumptions. While these benefits are conceptually clear, we do not provide quantitative estimates of carbon savings (e.g., excavation volume reductions or CO_2 emissions avoided). In future work, researchers should address this gap by linking improved prediction accuracy to measurable sustainability outcomes, such as tons of CO_2 saved under different design scenarios. Such analysis would help demonstrate the climate benefits of data-driven modelling and strengthen its role in achieving Finland's goal of carbon neutrality by 2035.

5.3. Methodological strengths and weaknesses

This study's main strength lies in its comprehensive, multi-source database, which integrates Finnish, Nordic, and European data under a consistent pre-processing framework. The inclusion of multiple test types and cross-regional comparisons enable robust benchmarking, while the dual application of regression and machine learning provides a rare side-by-side evaluation of traditional and emerging approaches.

Nevertheless, several limitations must be acknowledged:

- *Sample size:* Although the complete datapoints are sufficient to draw initial conclusions, the database remains modest compared to mineral soil datasets, e.g., [32.33]. Expanding the dataset would improve generalisability and enable testing of more advanced algorithms (e.g., gradient boosting and neural networks).
- *High variability:* Strength parameters remain strongly affected by differences in test procedure (DSS, TX), sample disturbance, and decomposition, introducing uncertainties that are difficult to quantify.
- *Lack of external validation:* Model performance is assessed through internal splits and out-of-bag errors. Independent validation on unseen datasets from other regions would provide stronger evidence of generalisability.
- *Poor predictive performance:* A critical observation is the poor predictive performance for certain parameters, as indicated by R^2 values close to zero or negative. Such values confirm that these models cannot provide accurate site-specific predictions. However, they capture the mean trend of the dataset and may offer limited value for preliminary screening or sensitivity checks, provided they are applied with caution and conservative assumptions. This reinforces the need for larger datasets and, possibly, additional descriptors.

5.4. Toward a smarter peat modelling framework

This study reinforces a key principle of modern geotechnical engineering: no single model is universally sufficient. Effective design instead requires a layered framework that combines transparent empirical rules with flexible data-driven tools. Such a framework enables practitioners to tailor model complexity to project risk, data availability, and sustainability goals.

In the Finnish peatland context, this translates to:

- Using regression models for rapid estimation and conservative design screening.
- Applying RF or other ML models for refined prediction of engineering properties, particularly in large-scale or high-risk projects.
- Employing cross-parameter estimators where direct strength measurements are unavailable.
- Continuously updating models as new data become available, ensuring adaptive learning over time.

Machine learning is unlikely to replace empirical knowledge, but it can complement it. In practice, it enables traditional expertise to be scaled and refined and perhaps shared more widely across projects.

6. Conclusions

In this study, we present a comprehensive data-driven investigation into the geotechnical behaviour of Finnish and Nordic peat, with particular emphasis on improving the prediction of compressibility, preconsolidation stress, and undrained shear strength. By compiling a harmonised dataset from published sources and laboratory studies, including the works of Sillanpää [20] and

Sainio [21], and applying regression and machine learning approaches, the study provides new insights into how peat behaviour can be more accurately estimated with limited site data.

Key findings:

- The compression index correlates strongly with water content, confirming the validity of classical empirical models. This supports the continued use of water content–based regressions for early settlement analysis.
- Yield stress and undrained shear strength exhibit higher variability and weaker regression fits compared to the compression index, highlighting the limited predictive value of single-variable estimation for strength parameters.
- Multivariable regressions improve predictive performance compared to single-variable models, particularly for the compression index, where they capture most of the explainable variability. For yield stress, they offer clearer interpretability even when accuracy remains moderate. However, their practical applicability is limited where the predictor set includes parameters that are alternative descriptors of the target property, reducing their usefulness for early-stage characterisation.
- RF models provide modest gains compared to conventional regression, mainly for yield stress, while undrained shear strength remains challenging (low R^2 even after ML). For compressibility, empirical correlations perform strongly, so RF adds little benefit. These results confirm that RF can complement traditional methods for site-specific modelling but should not replace direct testing or richer datasets.
- Model explainability (SHAP and SHAP-IQ) highlights the dominant role of water content across parameters and shows that only compressibility-related properties exhibit meaningful predictor interactions, whereas stiffness and creep parameters have consistently low feature influence, confirming their limited predictability from basic index properties alone.
- Cross-parameter estimators provide practical tools when direct strength testing is unavailable. While not a substitute for laboratory data, these formulas can support screening, back-calculation, and sensitivity analyses, although their statistical robustness varies, and they should be used with caution.
- Comparison with Finnish guidelines shows that regression-based predictions align with conservative envelopes, while RF outputs capture mean trends. This supports a hybrid strategy: conservative methods for screening and data-driven models for optimisation.

Improved prediction accuracy has the potential to reduce unnecessary soil replacement and associated carbon emissions. However, only compressibility is predicted with sufficient accuracy to meaningfully influence material optimisation; strength and stiffness parameters remain too uncertain for design reductions. While we do not quantify these savings, researchers should estimate excavation volumes and CO_2 reductions under different design scenarios to better demonstrate the climate benefits of data-driven modelling.

Additionally, researchers should further expand the dataset with more high-quality laboratory tests, especially from underrepresented Finnish regions, and incorporate additional descriptors such as fibre content, Von Post class, and organic matter composition. Comparative evaluation of advanced machine learning methods (e.g., XGBoost and neural networks) could provide insight into the trade-offs between accuracy and interpretability. Finally, while we include single-variable and multivariable models, future work could extend beyond deterministic prediction to probabilistic frameworks. For instance, approaches such as D-vine copulas [34] can flexibly capture nonlinear, asymmetric, and tail dependencies among properties, enabling joint probability modelling and more robust risk-based design.

Author contributions

Marco D'Ignazio: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing—original draft; Rasmus Sillanpää: Investigation, Methodology, Writing—original draft; Tim Länsivaara: Supervision, Validation, Writing—review & editing.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflicts of interest

The authors declare no conflicts of interest. Marco D'Ignazio and Tim Länsivaara are guest editors for AIMS Geosciences and were not involved in the editorial review or the decision to publish this article.

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