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Introduction to ROCK/10/4025 database

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ABSTRACT

This short communication is introducing ROCK/10/4025, an incomplete multivariate rock database containing 10 rock parameters, namely: porosity (n), unit weight (γ), Schmidt hammer hardness (L-type), Block Punch Index (BPI), Brazilian tensile strength (σ_{bt}), Point Load strength index, ($Is_{(50)}$), P-Wave velocity (V_p), Uniaxial compressive strength, (σ_c), Young's modulus, (E) and Hoek-Brown constant m_i. The structure and data organisation are presented through summary statistics and cross-correlation plots. The Excel file that contains the ROCK/10/4025 database can be downloaded from the following Mendeley link: https://data.mendeley.com/datasets/vk9vs574sk/1

Introduction

The mechanical properties of intact rock, uniaxial compressive strength (σ_c), and Young's modulus (E) are essential parameters for several rock engineering design applications (Gomez-Heras et al., 2020; Nefeslioglu, 2013). The direct determination of mechanical properties is often a time- consuming, costly process, while the acquisition and formulation of suitable samples can be demanding and non-sustainable (Gomez-Heras et al., 2020). Although the uniaxial compressive strength σ_c of intact rock is an essential parameter for the design of surface and underground excavations, it is always challenging to obtain a representative value (Nefeslioglu, 2013). Nonetheless, laboratory based direct compressive strength measurements may be problematic, as obtaining fresh, high-quality core samples can be a challenge due to budget constraints, especially at the preliminary design stage of a project. To address this and provide a reliable and representative value for uniaxial compressive strength, a plethora of transformation models have been proposed in the past decades (Brady & Brown, 2006; Tsiambaos, G. & Sabatakakis, N., 2004; Mishra, D.A. & Basu, A., 2013). Yet these transformation models usually fail to account for aleatory uncertainty resulting from intrinsic variability, and epistemic uncertainty due to measurement errors, the scatter in σ_c measurements, limitations in modelling data, and testing methods, and thus, may have implications in the prediction of uniaxial compressive strength σ_c, (Goodman, 1989). Furthermore, scale effect and sample size limitations in σ_c estimation can vary significantly between laboratory-scale and in situ rock samples, making probabilistic or geostatistical methods (Hudson & Harrison, 1997) more suitable than single point deterministic values. Besides fracture density, orientation, and persistence can lead to significant deviations from laboratory measurements, suggesting stochastic modelling to be more suitable in σ_c prediction. Mineral composition, crystal particle size, the degree of interlocking and angularity, the fabric that infers the degree of anisotropy, porosity, fractures, weathering, and several site-specific ground conditions are factors that control the value of mechanical properties. Transformation models are not 100 % accurate, and their transformation uncertainty (Phoon & Kulhawy, 1999) may be significant. Moreover, most models are "generic" because they are calibrated by generic (e.g., global) data; hence, they may not provide an unbiased prediction for a particular site due to the site's uniqueness (Ching et al., 2018). A plausible solution to improve confidence in uniaxial compressive strength σ_c and Young's modulus E estimates stems from combining multiple data sources, (laboratory test and literature databases), (Brady & Brown, 2006), using Bayesian updating and geostatistical methods, to refine σ_c estimates, by integrating site specific data with larger data sets. Big data and machine learning can improve σ_c estimations, (Elmo, D. & Stead, D., 2020; Muzamhindo & Ferentinou, 2023), and strengthen digital transformation models, using artificial intelligence (AI) tools and machine learning (ML) methods to improve σ_c and E predictions. Table 1 presents some transformation models for σ_c.

The current short communication aims to present a rock database named ROCK/10/4025 (Muzamhindo & Ferentinou, 2023) that contains data on σ_c and E index properties, (porosity (n), unit weight (γ), Schmidt hammer hardness (L-type), Block Punch Index (BPI), Brazilian tensile strength (σ_{bt}), Point Load strength index, $Is_{(50)}$, P-Wave velocity (V_p), and Hoek-Brown constant m_i of real rock records compiled from the literature from several sites, and use it to inform σ_c estimation when laboratory tests are absent or limited. The database name follows a widely adopted naming convention for a soil/rock database proposed

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Table 1
Some transformation models for σ_c.

Literature	Transformation model	Remark / Country
Basu and Kamran (2010)	$\sigma_c = 11.103(Is_{(50)}) + 37.659$	schist / Pakistan
Bieniawski (1975)	$\sigma_c = 24Is_{(50)}$	Sandstone, quartzite, norite, / South Africa
Fakir et al. (2017)	$\sigma_c = 15.939Is_{(50)} + 37.235$	Granitoid rocks / South Africa
Kahraman (2001)	$\sigma_c = 4\ 10^{-10}\ Is_{(50)}{}^{5.87}$	Dolomite, sandstone, limestone, marl, diabase, serpentine, hematite / Turkey
Ulusay et al. (1994)	$\sigma_c = 19.5Is_{(50)} + 12.7$	Mixed / Turkey

by Ching and Phoon (2014), which follows: (soil type)/ (number of parameters of interest)/ (number of data points). By making this database available to the public, the cross-correlation behaviors between (σ_c, E) and index properties can be investigated at both generic site-specific levels, or by considering the lithology factor, or a combination of the previous criteria. It is anticipated that this database sharing will contribute to research in data-driven site characterization (Phoon et al., 2022). In GEOAI first editorial (Phoon et al., 2025) communication articles are encouraged to inform the GEOAI community on databases, which will be fulfilled by this short communication article. This article also hopes to contribute to the encouragement of more authors to share theoretical breakthroughs, algorithms, databases, and case histories through a short communication format in a timely way to accelerate machine learning and AI research in geotechnics. For the sharing of a database, the proposed format in this paper is: (1) introduction, (2) physical background of the database, (3) exploratory data analysis. This format is aligned with the three core elements of data-centric geotechnics: data centricity, fit for (and transform) practice, and geotechnical context (Phoon et al., 2022).

Multivariate database ROCK/10/4025

A generic global database ROCK/10/4025 is compiled from published data sets and includes 9 measured intact rock parameters, and a 10th parameter, the Hoek-Brown constant m_i, which was estimated for all the data, to indirectly include the lithology in the dataset. Hoek-Brown constant m_i was estimated, using Hoek and Brown's proposed guidelines for determining m_i values for determining rock types, which can be used for preliminary design when triaxial tests are not available. The current database is labeled, (material type) / (number of parameters of interest) / (number of data points) following generic databases compiled for clays (2014), sands (Ching. et al 2017), rocks (Ching et al., 2018), and rock mass (Ching et al. 2021).

The rock database comprises igneous, metamorphic, and sedimentary rocks of 40 various lithologies. The geographical extent of the database covers 23 countries, including Algeria, Brazil, Chile, Croatia, Denmark, Egypt, France, Greece, India, Iran, Iraq, Israel, Italy, Jordan, Malaysia, Nigeria, Pakistan, Portugal, South Africa, Spain, Turkey, Ukraine, USA and expands, across five continents.

ROCK/10/4025 is populated with 54.8 % sedimentary, 35.4 % igneous, 9.2 % metamorphic, and 0.6 % unclassified samples. The index parameters of intact rock samples are unit weight (γ: 4.41 - 35.41kN/m^3), porosity (n: 0.06 % - 37.8 %), Schmidt Hammer Hardness (R_L: 10.0 – 72.0), Point Load Index ($Is_{(50)}$: 0.05 – 30.55) MPa, P-wave velocity (V_p: 0.38 – 9.91 km/s), Brazilian tensile strength (σ_{bt}: 0.48 – 49.24 MPa), Block Punch index (BPI: 1.89– 38.98 MPa), Hoek Brown constant (m_i: 6 – 33), Young's modulus (E: 0.03 – 183.30 GPa), and (σ_c: 0.27 – 560.31 MPa). The values of σ_c cover the full range of weak (σ_c <20 MPa), to medium (20<σ_c<100 MPa), and strong rocks (σ_c>100 MPa), based on classification by (Kulhawy et al. 1991). Most of the specimens have σ_c values ranging from 50MPa-250 MPa, corresponding to strong and very strong. Only a few samples have σ_c ⟨5 MPa and σ_c ⟩ 250 MPa, which are very weak, extremely weak, and extremely strong samples. Most of the test samples are cylindrical in diameter in the range (30–75) mm, and a few are cubical (253 – 753) mm^3.

There are 4025 records in the database stored in an Excel worksheet that consists of a set of values measured for the same intact rock sample. The resulting database is not a complete multivariate database in the way that all 10 parameters are populated for all the rows in the worksheet (i.e., each row is not in full, completed with values). The percentage of completeness, of the data base is defined as the "(number of filled values)/ [(number of parameters) x (number of rows)]. The percentage of completeness is 50 % for ROCK/10/4025.

The parameters of interest were categorised into the following groups:

1. Index properties: porosity (n), unit weight (γ), L-type Schmidt hammer hardness (RL), and Block Punch Index (BPI). The Schmidt rebound hammer is a practical non-destructive test method for the evaluation initially of rock strength and, subsequently, rock quality (Kolaiti & Papadopoulos, 1993). The surface hardness of rock is measured using a portable device with a non-destructive application called the Schmidt rebound hammer (Kurtulus et al., 2018). The ISRM has standardized the recommended test procedure for the Schmidt rebound hammer test. Researchers have indicated that the Schmidt rebound hammer could be a good indicator for determining the σ_c of rock (Kolaiti & Papadopoulos, 1993; Kurtulus et al., 2018). There are two types of Schmidt hammer: L-type and N-type. In ROCK/10/4025, R_L data dominate (96 %) because the L-type hammer is recommended for rocks as per (ISRM, 2007). There are studies where both R_L and R_N were measured (Ayadin and Basu (2005), Basu et al. (2009), but in ROCK/10/4025, only R_L was included.
2. Strength parameters: Brazilian tensile strength (σ_{bt}), point load strength index ($Is_{(50)}$), and uniaxial compressive strength (σ_c). Index tests like the $Is_{(50)}$, σ_{bt}, have helped researchers develop models to predict the uniaxial compressive strength of rocks because they are easier to perform, require smaller or irregular-shaped specimens, and are more practical in the field or preliminary assessments. Grasso et al. (1992) state that despite the limitations associated with index tests, when coupled with experienced judgment, they provide initial estimates of rock properties required at the feasibility and preliminary design stage. The point load index has long been used as the most suitable intermediary for the σ_c estimation (Kahraman et al., 2005). It is evident from published research that the equations exhibit a wide range of equation forms from linear to quadratic and power laws, but the issue is that there is no agreement between authors on a specific conversion factor (Ferentinou & Fakir, 2017). The strength parameters of rock depend on specimen size, sample geometry, and loading rate. $Is_{(50)}$ is size dependent, it is customary to correct $Is_{(50)}$ to a standard diameter of 50 mm (Franklin, 1985) because point load testing can be conducted over a wide range of diameters. Prakoso (2002)did not observe an effect of sample diameter on the coefficient of variation (COV) of rock strengths (σ_c, σ_{bt}, and $Is_{(50)}$), therefore, sample size correction is not adopted for σ_c parameter or σ_{bt} in the compiled database ROCK/10/4025.
3. Stiffness: Young modulus (E). The database contains average values of E. ISRM, suggested methods to determine tangent, secant, and average modulus. Ching et al. (2018) report that the difference between the tangent modulus at 50 % (Et_{50}) and the average modulus for the linear portion of the stress-strain curve (E_{av}) is not significant compared to the transformation uncertainty. Thus, average values of Young's modulus are recorded in the database.
4. Dynamic property: P-wave velocity (V_p), also known as P-wave velocity, is determined by using ultrasonic pulse or sound tests. This is

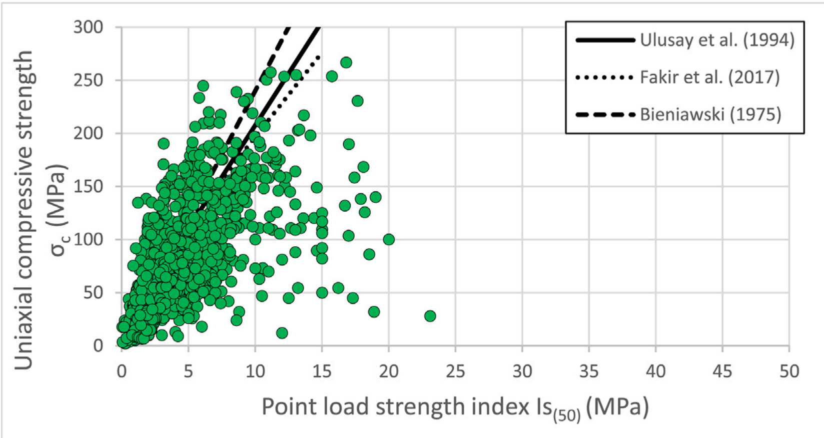

Fig. 1. Cross-correlation plot between σ_c and $Is_{(50)}$ in ROCK/10/4025, number of data points = 1138.

a non-destructive test as it emits low-amplitude waves whose stress is below the yield stress of rock (Mishra & Basu, 2013). The P-wave velocity of rock is affected by lithology, formation porosity, pore pressure, matrix, temperature, rock mass weathering, and alteration zones, bedding planes, and joint properties (Birch, 1960).

The constant m_i is a fundamental parameter essential for the Hoek-Brown failure criterion developed to estimate the strength of rock mass properties. Hoek-Brown constant parameter mi is estimated from a series of triaxial compression tests (Hoek & Brown, 1997). The constant m_i depends on the frictional characteristics of the component minerals in the intact rock, and it has a significant influence on rock strength, depending on grain size, and rock cementation, (Hoek & Marinos, 2000). The simplified method proposed by Shen and Karakus (2014) was used to estimate m_i for the common types of rocks (sandstone, limestone, marble, granite, and coal).

Connections to other databases

Ching et al. (2018) compiled a global rock database, labeled as ROCK/9/4069. The same authors compared the database, with previously existing proposed transformation models and found that the coverage of ROCK/9/4069 is wider than that of each model, which is usually site-specific. 14 out of 96 case studies are common in ROCK/9/4069 and ROCK/10/4025. These 82 original contributions are presented for the first time in Muzamhindo & Ferentinou (2023). ROCK/10/4025 database was compared to three existing transformation models (Fig. 1), which fit the average trend of ROCK/10/4025. The cross-correlation plot between σ_c and $Is_{(50)}$ in ROCK/10/4025 shows examples of previous transformation models, which are well covered by ROCK/10/4025 data cloud. The investigation of the named database (Muzamhindo & Ferentinou, 2023) suggested that most probably the proposed transformation models in the literature were not dependent on the rock type and that the models predicting, E as opposed to the models that predict σ_c suffer from smaller transformation uncertainties. It was also found that the $Is_{(50)}$ is the most effective parameter in predicting the σ_c, while S_h (shore scleroscope hardness) and V_p (shear wave velocity) are the most effective at estimating E.

Exploratory data analysis

The generic statistics of the 10 parameters are listed in Table 2. The statistics are the mean value, coefficient of variation (COV), minimum value (min), and maximum value (max). Note that the statistics in Table 2 are not for a specific site, but for the entire database that covers numerous sites. They should not be used for design, which requires statistics at the site level. The number of data points is further subdivided into the number of igneous, sedimentary, and metamorphic data points.

Table 2
Summary of generic statistics, for the ROCK/10/4025 database at global level, (all sites and lithologies combined (Source: Muzamhindo & Ferentinou, 2023).

Nr	Variable	# data	Mean	COV	Min	Max
1	γ (kN/m^3)	1918	23.85	0.16	4.41	35.41
2	n (%)	1371	7.55	1.26	0.06	37.8
3	R_L	2157	42.78	0.27	10	72
4	σ_{bt} (MPa)	582	8.69	0.73	0.48	49.24
5	$Is_{(50)}$ (MPa)	2348	4.05	0.80	0.05	30.55
6	BPI (MPa)	380	8.64	0.84	1.89	38.98
7	m_i	3994	17.25	0.54	6.00	32.00
8	σ_c (MPa)	3997	78.81	0.73	0.27	560.31
9	E (GPa)	953	68.95	1.24	0.03	183.30
10	V_p (km/s)	2366	4.30	0.36	0.375	9.814

* COV = coefficient of variation; Min = minimum; Max = maximum.

Table 3
Summary statistics of ROCK/10/4025 for igneous intact rocks (Source: Muzamhindo & Ferentinou, 2023).

Nr	Parameter	Nr of data	Mean	COV	Min	Max
1	γ (kN/m^3)	709	22.7	0.17	7.95	29.43
2	n(%)	645	8.63	1.33	0.01	41.80
3	R_L	841	44.90	0.25	16.80	87.40
4	σ_{bt} (MPa)	312	5.93	0.50	0.90	34.40
5	$Is_{(50)}$ (MPa)	946	4.43	0.76	0.05	12.53
6	BPI (MPa)	63	14.54	0.77	1.30	38.98
7	m_i	1417	27.82	0.20	8.00	33.00
8	σ_c (MPa)	1402	90.77	0.66	2.09	459.17
9	E (GPa)	380	35.30	1.05	0.19	183.3
10	V_p (km/s)	753	4.62	0.32	0.85	9.81

Table 3 summarises the statistics according to the type of rock (sedimentary, igneous, metamorphic). To obtain meaningful second-order site-specific statistics, only sites with no least than 5 records are considered. Figs. 2 and 3 present the cross-correlation plots between some parameters in ROCK/10/4025. The cross-correlation plots are compared to some of the existing transformation models listed in Table 1. Fig. 4 presents the cross-correlation plot between σ_c and $Is_{(50)}$. The cross-correlation plot is compared to the rule-of-thumb $\sigma_c = 24Is_{(50)}$. Table 2 presents a summary of generic statistics for the entire database, while Tables 3–5 present summary statistics for igneous, sedimentary, and metamorphic intact rock types.

Value of database

ROCK/10/4025 is a global, comprehensive database that covers a wide range of lithologies and geographical locations. The database was originally compiled to improve the prediction of uniaxial compressive

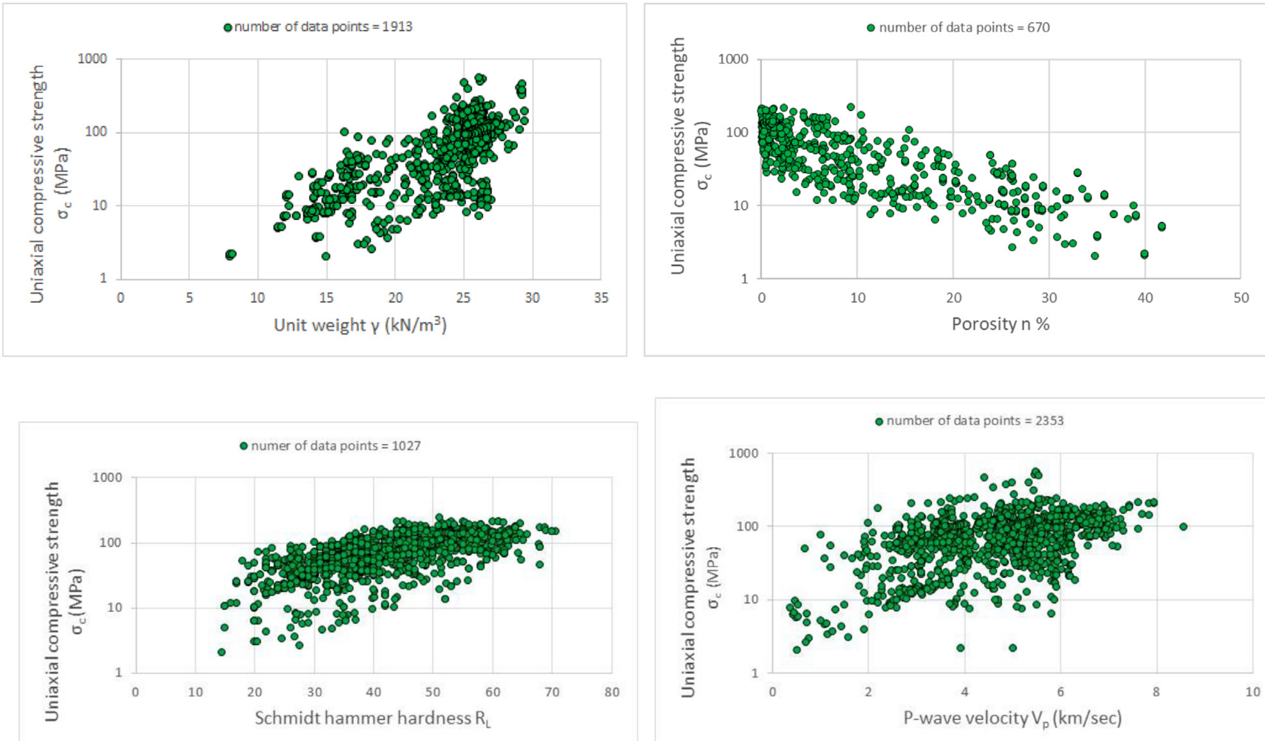

Fig. 2. Cross-correlation plots between σ_c and index properties in ROCK/10/4025.

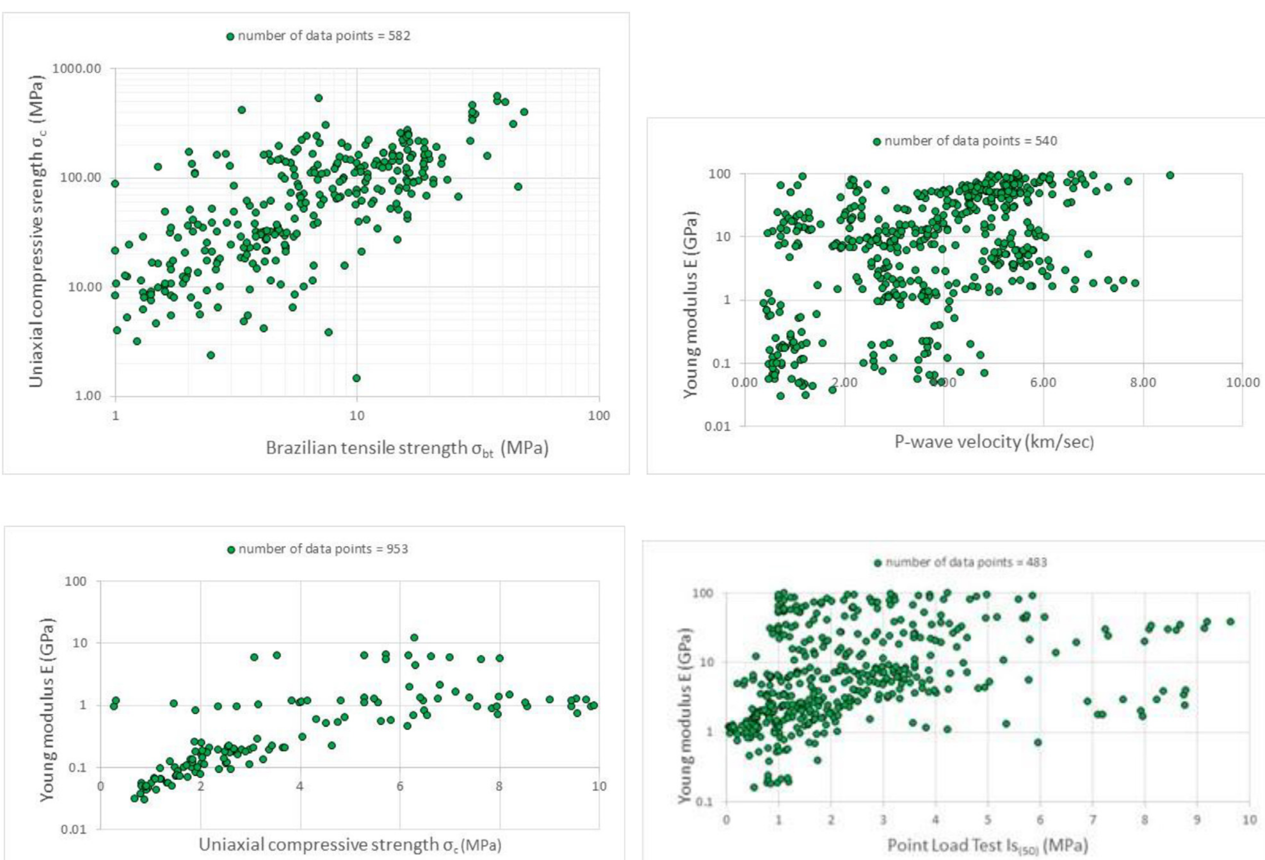

Fig. 3. Cross-correlation plots between σ_c, E and strength and dynamic properties in ROCK/10/4025.

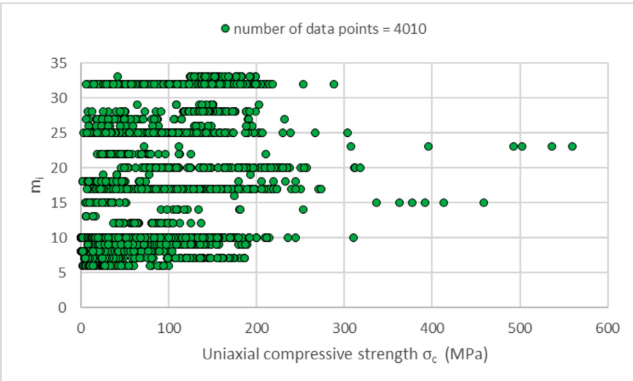

Fig. 4. Cross-correlation plot mi and σ_c in ROCK/10/4025.

Table 4
Summary statistics of ROCK/10/4025 for sedimentary intact rocks (Source: Muzamhindo & Ferentinou, 2023).

Nr	Parameter	Nr of data	Mean	COV	Min	Max
1	γ (kN/m^3)	1028	23.88	0.16	4.46	26.56
2	N (%)	647	7.28	1.01	0.06	34.79
3	R_L	1123	40.67	0.29	11.80	70.70
4	σ_{bt} (MPa)	252	7.03	1.05	0.48	49.24
5	$Is_{(50)}$ (MPa)	1180	3.43	0.84	0.02	30.55
6	BPI (MPa)	301	7.17	0.57	1.75	20.79
7	m_i	2207	10.81	0.33	6.00	32.00
8	σ_c (MPa)	2201	68.46	0.78	0.27	560.31
9	E (GPa)	555	15.91	1.28	0.03	99.9
10	V_p (km/s)	1339	4.11	0.39	0.38	7.84

Table 5
Summary statistics of ROCK/10/4025 for metamorphic intact rocks (Source: Muzamhindo & Ferentinou, 2023).

Nr	Parameter	Nr of data	Mean	COV	Min	Max
1	γ (kN/m^3)	181	26.38	0.14	23.64	30.31
2	n(%)	79	0.85	1.96	0.10	9.22
3	R_L	193	45.94	0.23	10.38	72.00
4	σ_{bt} (MPa)	18	8.76	0.59	2.41	19.70
5	$Is_{(50)}$ (MPa)	197	6.01	0.64	1.03	23.10
6	BPI (MPa)	16	13.08	0.46	4.61	27.05
7	m_i	370	15.73	0.48	9.00	33.00
8	σ_c (MPa)	369	97.83	0.60	8.00	288.20
9	E (GPa)	18	38.88	0.37	12.80	64.80
10	V_p (km/s)	259	4.58	0.32	1.47	7.94

strength σ_c by combining rock index properties, strength stiffness, dynamic properties, and Hoek-Brown constant m_i. This large database can introduce value in rock engineering, as it can enhance site-specific characterisation, support numerical modelling, and aid in benchmarking geomaterial behavior across different regions. It can also serve as a tool for more accurate rock mass classification, support data centered applications and improve risk assessment by capturing the variability in rock properties. A first step towards this direction is the development of machine learning models, which proved to be powerful tools that allowed for the reliable estimation or classification of σ_c (Muzamhindo & Ferentinou, 2023). Further steps could include the development of refined models suitable for site-specific predictions.

Data availability

The Excel file that contains the ROCK/10/4025 database can be downloaded from the following Mendeley link: https://data.mendeley.com/datasets/vk9vs574sk/1.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Maria Ferentinou: Conceptualisation, supervision, manuscript preparation. **Herbert Muzamhindo:** Investigation, Formal analysis, Data curation.

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