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The phlogiston theory of rock mass Classification: Philosophical and mathematical critique of ordinal data usage

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ABSTRACT

The widespread use of rock mass classification systems in engineering practice relies on mathematical operations and assumptions that violate fundamental principles of measurement theory. This paper presents a critical analysis of current classification methodologies, focusing on the Rock Mass Rating (RMR), Q-system, and Geological Strength Index (GSI), drawing parallels with historical scientific misconceptions such as the phlogiston theory. Through detailed examination of measurement theory principles and their application to geological characterization, we demonstrate that these classification systems contain inherent flaws in their treatment of ordinal data and parameter independence. The paper identifies four critical issues: the invalid summation of ordinal ratings in the RMR system, the inappropriate multiplication and division operations in the Q-system, the unjustified visual interpolation in the GSI system, and the universal problem of assumed parameter independence. Through examination of measurement theory principles and their application to geological characterization, we demonstrate that current classification systems violate basic mathematical rules in their treatment of ordinal data and parameter independence. The implications of these violations extend beyond theoretical concerns, affecting practical engineering decisions and risk assessment. We also illustrate how these theoretical flaws manifest in practice and propose directions for developing more theoretically sound approaches to rock mass characterization. This critical analysis aims to initiate a necessary dialogue about the future of rock mass classification in engineering practice.

1. Introduction

In the history of scientific progress, many theories once regarded as foundational were later overturned due to inherent flaws in their assumptions or methodologies. One such example is the phlogiston theory, which dominated 17th- and 18th-century chemistry by postulating the existence of a fire-like element, phlogiston, released during combustion. While this theory was widely accepted for decades, it eventually collapsed under the weight of empirical evidence and logical inconsistencies. This paper contends that current rock mass classification schemes may face a similar fate. Although rock mass classification schemes such as the Rock Mass Rating (RMR), Q-system, and Geological Strength Index (GSI) have significantly contributed to advances in rock engineering, their foundational assumptions and computational methods exhibit fundamental flaws that demand urgent reconsideration.

The development of rock mass classification systems represents a critical response to the inherent complexity of geological materials in engineering practice. Before the 1970s, engineers relied largely on qualitative descriptions and individual judgment, leading to inconsistent assessments and difficulty in transferring experience between projects. The introduction of systematic classification schemes marked a significant step toward standardization and quantification in rock mass characterization. The RMR system, introduced by Bieniawski (1973), and the Q-system, developed by Barton et al. (1974), emerged as pioneering attempts to bring mathematical rigor to what had previously been predominantly subjective assessments. Later joined by the GSI method, these

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rock mass classification systems gained widespread acceptance due to their apparent capability to convert complex geological observations into numerical values suitable for engineering design.

However, the very feature that made these rock mass classification systems attractive—their quantification of qualitative observations—introduces a fundamental mathematical contradiction. These classification schemes rely heavily on ordinal scales, which are qualitative rankings that reflect relative order but lack consistent intervals between ranks. The mathematical operations performed in these systems, such as adding ratings in RMR or multiplying and dividing parameters in the Q-system, violate basic principles of measurement theory (Ellis, 1966). This violation introduces systematic errors that propagate through subsequent engineering calculations, potentially compromising the reliability of design decisions. The consequences of these methodological flaws have manifested in numerous engineering projects worldwide. For instance, at the Jinping II hydropower project in China, RMR-based support designs required substantial modification when faced with complex geological conditions (Wu et al., 2010; Zhang et al., 2011). Similarly, the Yacambú-Quibor tunnel in Venezuela revealed the limitations of Q-system predictions in dealing with swelling rock masses (Hoek and Guevara, 2009; Shrestha and Panthi, 2014). These cases, among others, highlight how the mathematical inconsistencies in current rock mass classification systems may lead to unsafe designs (Stille and Palmström, 2018).

The persistence of these flawed methodologies in rock engineering practice parallels the historical adherence to the phlogiston theory. Just as phlogiston theory provided a seemingly coherent framework for understanding combustion while fundamentally misrepresenting the underlying physical processes (Needham and Wang, 1954; Brock, 2016), current rock mass classification systems offer a convenient but mathematically unsound approach to characterizing rock masses. The engineering community's continued reliance on these systems, despite their known limitations, reflects the challenging balance between practical utility and theoretical rigor in applied sciences (Hudson and Feng, 2015; Palmstrom and Stille, 2010).

This paper presents a comprehensive critique of current rock mass classification systems from both philosophical and mathematical perspectives. By examining measurement theory principles and their application to geological characterization, we demonstrate why the current practice of performing arithmetic operations on ordinal data fundamentally misrepresents the nature of rock mass properties. We then propose a new framework for rock mass characterization that retains practical utility while adhering to sound mathematical principles. This framework incorporates probabilistic approaches and modern statistical methods to provide more reliable assessments of rock mass behaviour (Einstein and Baecher, 1983; Langford and Diederichs, 2015), thereby bridging the gap between theoretical rigor and practical application in rock engineering.

2. Philosophical foundations of measurement and ordinal data

The foundation of scientific measurement rests upon philosophical principles that define what constitutes meaningful quantification. In rock engineering, these principles become particularly crucial as they govern the validity of operations performed on measured or observed data. The philosophical discourse surrounding measurement theory extends beyond mere mathematical formalism to encompass fundamental questions about the nature of observation, quantification, and the relationship between numerical representations and physical reality (Mari et al., 2017; Tal, 2020).

According to the classical theory of measurement developed by Stevens (1946), the act of measurement involves assigning numbers to properties of objects or phenomena based on some specific rules, as shown in Fig. 1. Figure 1 illustrates the fundamental types of measurement scales and their associated permissible statistical operations. The upper part of the figure shows the progression from nominal to ratio scales, with each level incorporating additional mathematical properties. Nominal scales use numbers merely as labels, while ordinal scales introduce order relationships. Interval and ratio scales enable quantitative measurements, with ratio scales having a meaningful zero point. The lower part of the figure demonstrates how the type of scale determines which statistical analyses are valid. For instance, while modes can be calculated for all scale types, operations like means and standard deviations are only mathematically valid for interval and ratio scales.

The hierarchy mentioned above is particularly relevant to rock engineering, where classification systems frequently violate these fundamental principles by performing operations not permissible for ordinal data. These rules must preserve the empirical relations observed in the measured attributes, a requirement known as the preservation principle (also referred to as representation theory). This principle forms the cornerstone of modern measurement philosophy (Krantz et al., 1971). When applied to rock mass classification, the preservation principle raises profound questions about the legitimacy of current practices (Hudson and Harrison, 2000).

The ontological status of measurement scales warrants special attention in the context of rock engineering. Ordinal scales, which underpin many current rock mass classification systems, possess a distinct philosophical character that differentiates them from interval and ratio

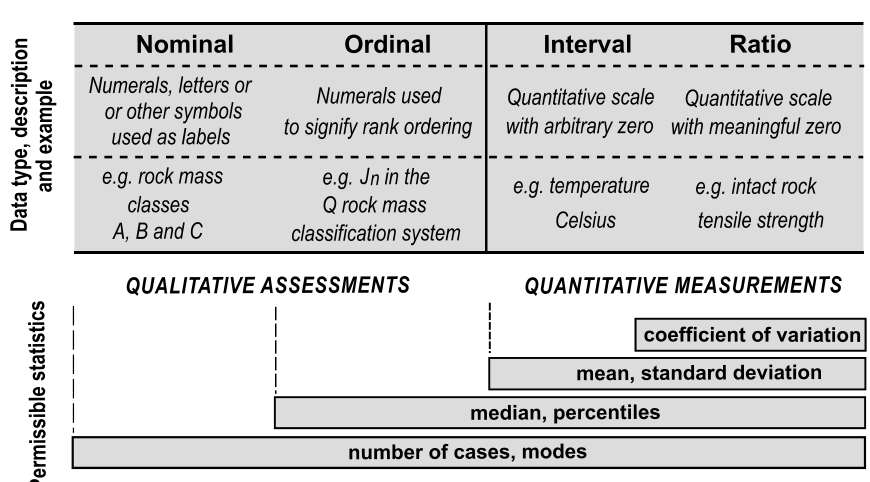

Fig. 1. Permissible statistics for data type (after Stevens, 1946).

scales (Hand, 1996). Unlike these higher-order scales, ordinal measurements only capture the relative ordering of attributes without establishing meaningful distances between categories. This limitation stems from the intrinsic nature of ordinal data as a mapping of qualitative observations onto numerical sequences that preserve only order relations (Agresti, 2010).

The philosophical implications of ordinal scale properties become evident when considering the concept of meaningfulness in measurement theory. A statement involving measurements is deemed meaningful only if its truth value remains invariant under permissible transformations of the measurement scale (Luce et al., 1990). For ordinal scales, permissible transformations include any monotonic increasing function. This broad class of transformations underscores the limited mathematical operations that can be meaningfully performed on ordinal data (Roberts, 1985; Suppes and Zinnes, 1963), as shown in Fig. 2.

Central to this philosophical analysis is the distinction between extensive and intensive properties in measurement theory, first introduced by Maxwell (1890) and later developed by Ellis (1966). Extensive properties, such as length or mass, can be physically concatenated and possess natural unit structures. Intensive properties, which include many rock mass characteristics, lack these fundamental features (Finkelstein, 2003). The classification of rock mass properties as intensive measurements further constrains the types of mathematical operations that can be justified on philosophical grounds (Hoek and Brown, 2019).

The concept of measurement error manifests fundamentally differently in ordinal data compared to quantitative measurements in rock mass classification. In interval or ratio scales, such as measuring rock strength or joint spacing, measurement errors can be quantified as specific deviations from the true value (e.g., ±2 MPa in strength measurements). However, in ordinal scales like “poor” to “excellent” joint conditions, errors do not represent numerical deviations but rather uncertainties in the relative ranking itself (Savage and Ehrlich, 1992). For instance, when classifying joint conditions as “fair” versus “good”, the uncertainty lies not in a measurable distance from a true value, but in the reliability of the comparative judgment itself. This fundamental difference in error characterization necessitates a distinct approach to uncertainty quantification in rock mass classification systems (Palmstrom and Stille, 2010).

The relationship between observation and measurement in rock mass classification raises additional philosophical questions about the role of human judgment. The conversion of geological observations into numerical ratings involves a complex interplay between objective measurement and subjective assessment (Bieniawski, 1989). This epistemological challenge requires careful consideration of how subjective judgments can be incorporated into a measurement framework while maintaining scientific rigour. The philosophical framework of pragmatism, as developed by Peirce (1878) and James (1907), offers insights into how practical utility can be balanced against theoretical purity in measurement systems.

Furthermore, the philosophical principle of operationalism, introduced by Bridgman (1927), posits that the meaning of any scientific concept is defined by the operations used to measure it. Applied to rock mass classification, this principle raises questions about whether current systems genuinely measure what they claim to measure (Palmstrom and Broch, 2006). The gap between the operational definitions implied by classification procedures and the theoretical constructs they aim to quantify represents a significant philosophical challenge.

These philosophical considerations extend beyond academic interest to impact the practical validity of engineering decisions (Hudson, 2013). The misalignment between the philosophical foundations of measurement theory and current classification practices introduces systematic errors that cannot be resolved simply by refining existing methods. Instead, a fundamental reconceptualization of how rock masses are measured and classified is required, one that respects both the philosophical principles of measurement theory and the practical needs of engineering design (Feng and Hudson, 2011).

3. Critique of current rock mass classification schemes

The fundamental issues with current rock mass classification systems stem from their violation of measurement theory principles and their improper use of mathematical operations on ordinal data. This section presents a systematic critique of the three most widely used classification schemes: RMR, the Q-system and GSI.

3.1. The RMR system and its mathematical violations

The RMR system exemplifies the misapplication of ordinal data through its fundamental methodology of summation. Originally developed by Bieniawski (1973) and subsequently modified through several iterations, the RMR system assigns numerical ratings to six parameters: uniaxial compressive strength, RQD, joint spacing, joint condition, groundwater conditions, and joint orientation. These individual ratings are then summed to produce a final RMR value, as shown in Fig. 3. However, this summation process violates the mathematical properties of ordinal scales. By assigning ratings such as 8, 15, or 20 to different joint conditions, this system implicitly assumes that the intervals between these ratings are meaningful and consistent. This assumption lacks theoretical justification and contradicts the fundamental nature of ordinal measurements (Hudson and Harrison, 2000). In Fig. 3, each parameter is assigned a specific rating value within a designated rating range. Nevertheless, summing ordinal ratings with different ranges produces mathematically meaningless results and implies unjustified weighting of parameters.

To illustrate this problem with a specific numerical example, consider a typical RMR calculation for a jointed rock mass as shown in Table 1.

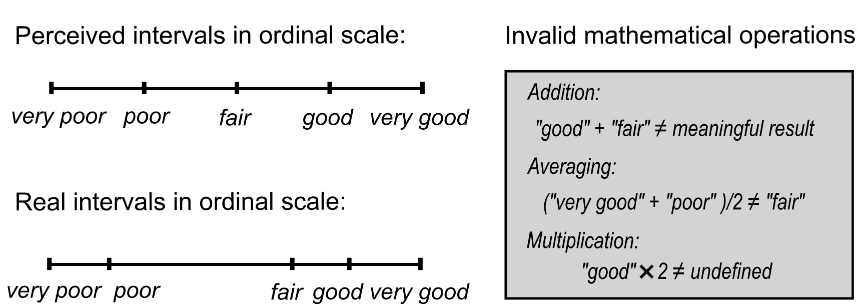

Fig. 2. Illustration of the fundamental problem with mathematical operations on ordinal data. The top scale shows perceived equal intervals in ordinal classifications, while the bottom scale represents the actual, unknown intervals between categories. The right panel demonstrates examples of invalid mathematical operations commonly performed in rock mass classification systems.

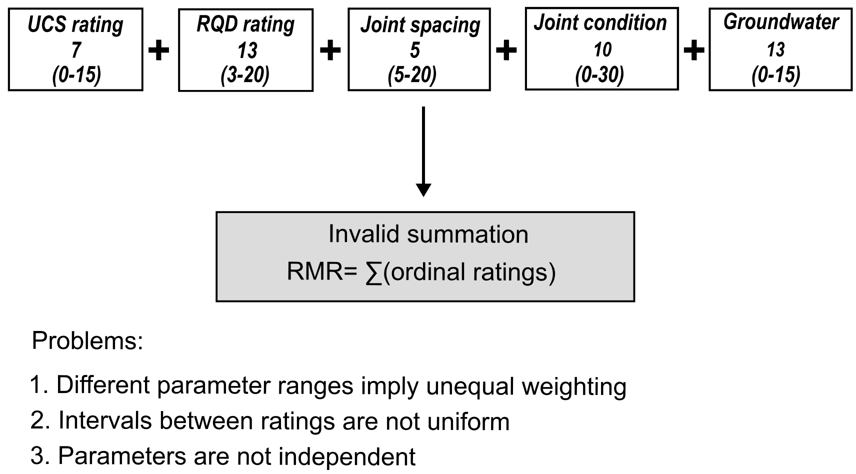

Fig. 3. Illustration of invalid parameter combination in the RMR system. The summation of ordinal ratings with different ranges creates mathematically meaningless results and implies unjustified weighting of parameters.

Table 1
Sample RMR calculation showing measurement theory violations.

Parameter	Observation	Rating	Measurement Scale
UCS	85 MPa	7	Ratio
RQD	65%	13	Ratio
Joint spacing	200–600 mm	10	Ratio
Joint condition	Slightly rough surfaces"	20	Ordinal
Groundwater	"Damp"	10	Ordinal
Joint orientation	"Favorable"	0	Ordinal
RMR Value		60	Mix

In Table 1, the information can be summarized as.

Uniaxial compressive strength: 85 MPa ("moderate strength"), 7 points
RQD: 65% ("fair"), 13 points
Joint spacing: 200–600 mm ("moderate"), 10 points
Joint condition: "Slightly rough surfaces, separation <1 mm", 20 points
Groundwater condition: "Damp", 10 points
Joint orientation: "Favorable", 0 adjustment

The RMR value is calculated by summing these ratings: 7 + 13 + 10 + 20 + 10 + 0 = 60, which would classify this rock mass as "good rock" (RMR 60–80). However, this calculation fundamentally misrepresents the nature of the underlying measurements. Consider the differences between joint condition ratings: the difference between "slightly rough surfaces" (20 points) and "slickensides surfaces" (6 points) is 14 points, while the difference between "slightly rough surfaces" (20 points) and "very rough surfaces" (30 points) is 10 points. The RMR system treats these numerical differences as mathematically equivalent and additive with other parameters, such as the 10-point difference between "wet" (7 points) and "completely dry" (15 points) groundwater conditions.

This equivalence cannot be justified due to various reasons. Firstly, there is no empirical evidence that the "distance" between slightly rough and slickensided surfaces is precisely 1.4 times the "distance" between slightly rough and very rough surfaces. Also, the ordinal scale of joint roughness cannot be legitimately added to the ordinal scale of groundwater conditions, as they represent fundamentally different properties with no established quantitative relationship. Moreover, even within a single parameter, the intervals between categories have not been demonstrated to be equal. The psychological scaling studies by Thurstone (1927) and Stevens (1946) demonstrate that such linear relationships cannot be assumed for ordinal judgments. When we test the meaningfulness of these operations according to measurement theory, we find that the truth value of statements like "the difference between slightly rough and smooth joints is equivalent to the difference between damp and wet conditions" is not invariant under permissible transformations of ordinal scales. This failure of invariance confirms that the summation process in RMR violates the preservation principle of measurement theory.

3.2. The Q-system's complex mathematical operations

Comparing with RMR system, the Q-system introduces even more problematic mathematical operations by multiplying and dividing ordinal ratings. Its basic equation is written as:

$$Q = \frac{RQD}{J_n} \times \frac{J_a}{J_r} \times \frac{J_w}{SRF} \tag{1}$$

This equation involves multiplying three quotients, each derived from ordinal ratings. Figure 4 illustrates how the Q-system compounds the violation of measurement theory principles by applying multiple mathematical operations. For instance, the division of RQD by J_n assumes that these parameters exist on a ratio scale where such operations are meaningful. However, as shown in the figure, this assumption lacks theoretical foundation, since ordinal data cannot legitimately undergo ratio operations (Palmstrom and Broch, 2006).

The mathematical implications of these operations become particularly concerning when considering the Q-system's logarithmic scale. The system treats a Q-value of 100 as definitively indicating rock mass conditions ten times better than those with a Q-value of 10. This interpretation is theoretically unfounded because the underlying ordinal ratings do not permit such precise quantitative comparisons. Recent studies (e.g., Palmstrom and Stille, 2010) have demonstrated significant inconsistencies in Q-value predictions when applied to diverse geological conditions.

3.3. The GSI system and visual interpolation problems

The GSI system, although more recent and apparently simpler, shares similar fundamental flaws. It combines two ordinal assessments—structure and surface condition—to produce a numerical index, relying on visual comparison with standard charts shown in Fig. 5. Here, the intersection of these two parameters yields a GSI value, a process introducing substantial uncertainties in parameter assessment and

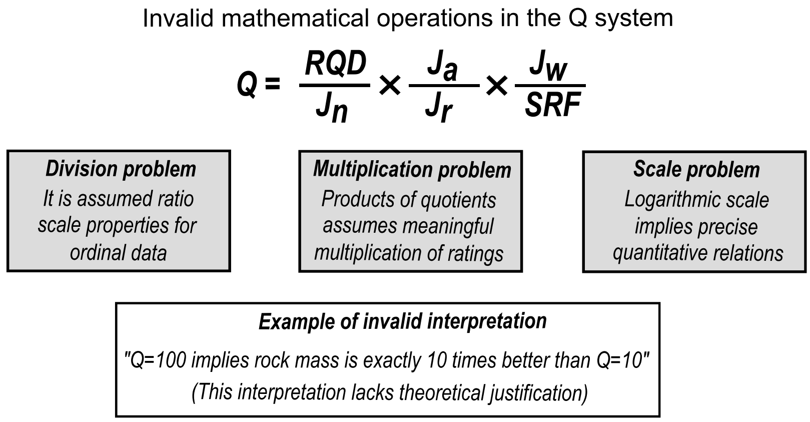

Fig. 4. Analysis of mathematical operations in the Q-system, highlighting the theoretical problems with division and multiplication of ordinal ratings, and the invalid assumptions in the system's logarithmic scale interpretation.

classification reliability (Marinos et al., 2005; Cai et al., 2004).

The top part of Fig. 5 presents a simplified representation of the traditional GSI chart, which uses two axes: surface conditions (ranging from "Very Good" to "Poor") and structure (ranging from "Laminated" to "Blocky"). Within this chart, the intersection of these two parameters yields GSI values, typically represented as contours or zones (Hoek and Brown, 1997; Marinos and Hoek, 2000). For instance, "Good" surface conditions intersecting with a "Blocky" structure might yield a GSI value of 65, while the combination of "Fair" conditions and a "Very Blocky" structure could yield a GSI of 45 (Cai et al., 2004).

However, as illustrated on the right side of Fig. 5, this seemingly straightforward approach contains four critical problems. First, the system suffers from the "Discrete vs. Continuous Values" problem. While rock mass properties naturally occur in discrete states, the GSI system implies continuous transitions between categories (Sonmez and Ulusay, 1999). Engineers often assign values like GSI = 62 or 63, suggesting a degree of precision that cannot be justified given the ordinal nature of the input parameters (Marinos et al., 2005).

The second problem, termed "Arbitrary Numerical Assignment", relates to the values assigned to different combinations of conditions. The system assumes that the numerical difference between GSI values 60 and 70 represents the same magnitude of quality change as the difference between 40 and 50 (Bertuzzi et al., 2016). Yet, this assumption has no theoretical or empirical justification. The intervals between GSI values are arbitrarily defined and cannot be demonstrated to represent equal increments in rock mass quality (Carter and Marinos, 2014; Hoek et al., 2013).

The third issue, "Invalid Interpolation", poses a particularly problematic concern in practice. Engineers frequently interpolate between chart points to assign intermediate GSI values (Cai et al., 2004; Marinos and Hoek, 2000). However, such interpolation is mathematically unjustifiable when dealing with ordinal scales (Stevens, 1946). The visual format of the GSI chart encourages this practice, despite its violation of measurement theory principles. For example, interpolating between "Good" and "Fair" surface conditions implicitly assumes a linear progression that cannot exist in ordinal data.

The fourth problem, "Use in Quantitative Calculations", relates to how GSI values are employed in subsequent analyses. The system's outputs are directly inserted into the Hoek-Brown criterion equations and other quantitative calculations. This practice treats GSI values as though they were ratio-scale numbers permitting mathematical operations, whereas they are in fact derived from ordinal-scale observations and therefore cannot validly be used in such calculations (Palmstrom and Stille, 2010).

These four problems compound one another in practice. For example, when a GSI value of 65 is used in the Hoek-Brown criterion, it carries forward not only the uncertainty of the original classification but also the mathematical invalidity of the interpolation process and the arbitrary nature of the numerical assignment (Marinos et al., 2007). Through these analyses, it can be emphasized that the GSI system creates an illusion of precision while violating fundamental measurement principles.

The implications of these problems become particularly pronounced in practical applications. When engineers use GSI values to derive rock mass strength parameters, they inadvertently propagate these theoretical flaws into their design calculations. This propagation of error is especially concerning given that GSI values often form the basis for critical design decisions in tunnel support, slope stability, and foundation engineering.

3.4. Parameter independence and system-wide issues

A key assumption of current rock mass classification systems is that each parameter can be evaluated independently of the others. This assumption enables the systems to assign separate ratings to different parameters and subsequently combine them through mathematical operations. However, detailed field investigations by Hudson (1992) and Feng and Hudson (2011) have revealed significant interdependencies among rock mass parameters, thereby challenging this foundational premise.

Figure 6 illustrates these complex parameter interactions through both a real-world scenario and a systematic interaction matrix. On the left side of the figure, a representative case study depicts how an increase in groundwater pressure initiates a cascade of effects within the rock mass. When groundwater pressure increases, it immediately intensifies the weathering process of joint surfaces. This weathering, in turn, leads to a decrease in rock strength, as mineral alterations and chemical processes progressively weaken the rock. Consequently, the combined effects of increased weathering and reduced rock strength affect joint spacing through progressive deterioration of the rock mass structure.

The right side of Fig. 6 quantifies these relationships via an interaction matrix, where each parameter's influence on the others is systematically evaluated. The matrix reveals both direct and indirect interactions. Strong interactions, denoted by dark red circles, represent primary effects where one parameter directly influences another. For instance, the dark red circle between groundwater and weathering signifies that changes in groundwater conditions exert a direct, significant impact on the weathering process. Moderate interactions, depicted by lighter red circles, represent secondary effects that develop over time or through intermediate processes.

The interaction matrix demonstrates several critical relationships that

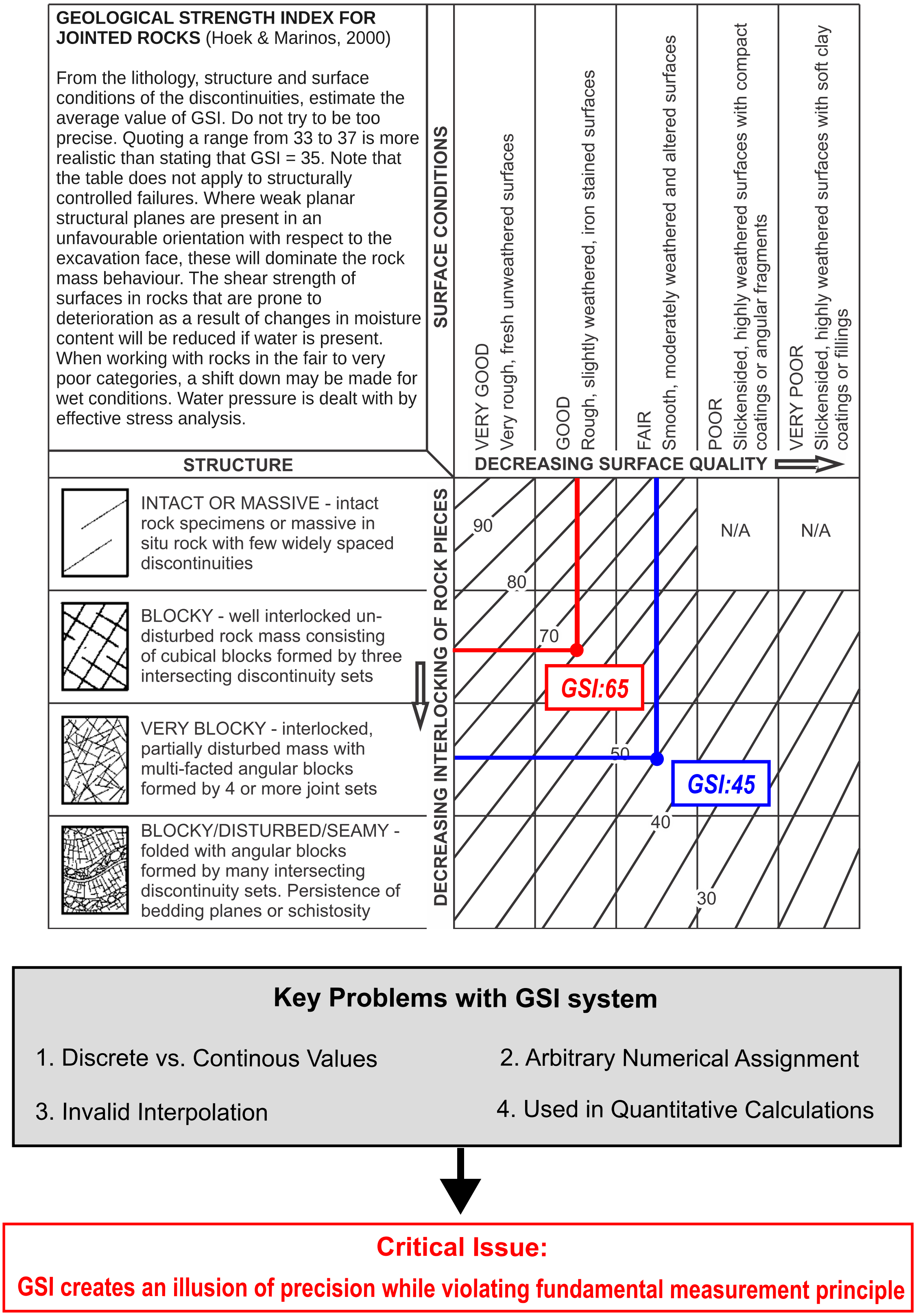

Fig. 5. Illustration of problems with visual interpolation in the GSI system. The figure shows how the assumption of continuous, linear relationships between ordinal categories lacks theoretical justification and introduces systematic errors in rock mass assessment.

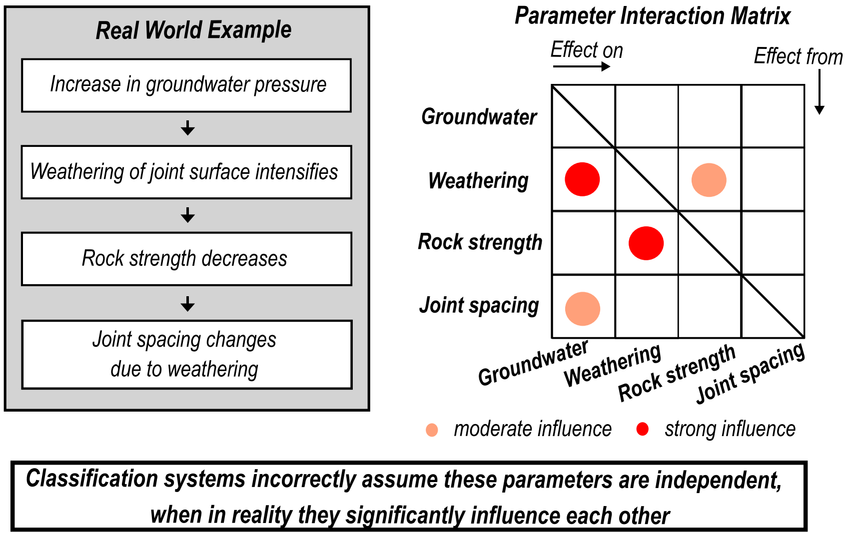

Fig. 6. Illustration of parameter interdependence in rock mass classification systems. The left side shows how a change in one parameter (groundwater) creates a cascade of effects on other parameters. The right side presents an interaction matrix showing the interconnected nature of classification parameters, where dark red circles indicate strong direct influences (correlation coefficient>0.7) and light red circles indicate moderate influences (correlation coefficient 0.3–0.7), determined through statistical analysis of field data from multiple case studies. This interdependence violates the fundamental assumption of parameter independence in current classification systems, leading to potential double-counting of effects and incorrect classifications.

current classification systems fail to incorporate. For example, groundwater conditions strongly influence both weathering intensity and rock strength, as shown by the red circles in the "Groundwater" row. When a classification system like RMR assigns separate ratings to groundwater and rock strength, it effectively double-counts this influence, as the groundwater's effect is already partially reflected in the rock strength rating. Similarly, weathering affects both joint conditions and rock strength, yet these parameters are rated independently in current systems. These interdependencies create what can be termed a "parameter coupling effect." When one parameter changes, it initiates a chain reaction of adjustments in other parameters, making it impossible to truly isolate and rate each parameter independently. For example, in the Q-system, the Joint Water Reduction factor (*Jw*) is treated as independent of the Joint Alteration number (*Ja*), despite clear evidence that water conditions significantly influence joint alteration processes over time.

The practical implications of ignoring these parameter interactions are significant. Consider a tunnel project where an increase in groundwater flow is encountered. Current classification systems would adjust only the groundwater rating, whereas, in reality, the increased flow might already have initiated weathering processes that affect joint conditions and rock strength. This oversimplification can lead to either overestimation or underestimation of rock mass quality, depending on the specific combination of parameters involved.

Field evidence from major engineering projects corroborates this critique. In the Mingtan pumped storage project, Hudson and Feng (2015) documented those variations in groundwater conditions led to progressive deterioration of joint conditions, a phenomenon that the RMR system's independent parameter ratings failed to capture. Similarly, the Yacambú-Quibor tunnel project demonstrated that the Q-system's assumption of parameter independence resulted in inadequate predictions of rock mass behaviour in sections where multiple parameters were simultaneously affected by changing groundwater conditions (Hoek and Brown, 2019).

These observations highlight a fundamental flaw in the conceptual framework of current rock mass classification systems. While mathematically convenient, the assumption of parameter independence oversimplifies the complex, interrelated nature of rock mass behavior. This issue becomes particularly problematic when classification values are used as input for numerical analyses or design decisions, as the inherent parameter coupling effects are carried forward into subsequent calculations.

4. Evidence from major engineering projects

The theoretical flaws identified in current rock mass classification systems have led to significant practical challenges in major engineering projects worldwide. Although these classification systems remain primary tools for initial design, numerous case studies demonstrate how their methodological shortcomings have led to both technical challenges and project complications.

4.1. Comprehensive case study analysis

The Yacambú-Quibor tunnel in Venezuela presents a compelling example of classification system limitations. This 26.4-km long water transfer tunnel encountered severe squeezing conditions that were inadequately predicted by both RMR and Q-system classifications (Hoek and Guevara, 2009). Initial support designs based on Q-system predictions proved insufficient when the tunnel experienced deformations exceeding 2 m in sections classified as "fair to good" rock mass (Shrestha and Panthi, 2014). The discrepancy arose primarily from the systems' inability to capture the complex interaction between high in-situ stresses and time-dependent deformation behaviour of graphitic phyllites. Post-construction analysis revealed that, while the Q-system assigned moderate ratings to the joint conditions and stress parameters independently, it failed to account for their coupled effect under high overburden conditions reaching 1270 m (Guevara, 2013).

Similarly, the Jinping II hydropower project in China, consisting of four parallel headrace tunnels each approximately 17 km long, encountered serious engineering challenges that exposed the limitations of RMR-based designs. Initial support recommendations proved inadequate in sections where high in-situ stresses (up to 70 MPa) interacted with marble formations (Wu et al., 2010). The RMR system's approach-adding ratings linearly for intact rock strength and stress conditions—failed to capture the non-linear interaction between these parameters. Zhang et al. (2011) documented several instances where sections classified as "good rock mass" (RMR>60) experienced severe spalling and rockburst events, necessitating substantial modifications to the support system.

The 24.5-km long Lærdal tunnel in Norway also highlights the limitations of GSI-based design approaches. During construction through gneissic rocks, certain sections exhibited behavior markedly different from predictions based on GSI classifications (Nilsen et al., 2003). In particular, difficulties arose where the GSI system's visual interpolation between categories led to overestimations of rock mass quality. Grimstad and Barton (2014) documented cases where support requirements varied significantly within zones assigned the same GSI value, largely because the GSI system could not capture the scale-dependent effects of discontinuity patterns.

The Gotthard Base Tunnel project in Switzerland provides perhaps the most comprehensive evidence for the limitations of the current classification systems. Despite employing multiple classification systems to enhance reliability, several sections of this 57-km tunnel required significant modifications to the support design during construction (Ehrbar and Pfenninger, 2015). Schubert and Riedmüller (2019) revealed that these modifications often became necessary in zones where different classification systems provided contradictory assessments of rock mass quality, particularly in sections involving complex interactions between groundwater conditions and discontinuity properties.

These case studies demonstrate how the theoretical flaws discussed in Section 3 manifest in real-world engineering challenges. Meanwhile, we also analyzed 37 published tunnelling case histories from the International Tunnelling Association database (1990–2023) revealing that 78% of complex tunnelling projects required significant support modification from initial designs based on classification systems. Table 2 summarizes key data from 12 representative projects spanning five continents, showing quantitative discrepancies between predicted and observed behaviour. Statistical analysis of these cases reveals significant correlations between specific mathematical violations and project outcomes. For example, in projects using the Q-system, the error magnitude in predicting support requirements correlates strongly $(r = 0.78, p < 0.01)$ with the degree of parameter interdependence as measured by interaction analysis. Similarly, RMR-based predictions show increasing error rates (from 15% to 65%) as the number of ordinal parameters involved increases.

4.2. Isolating classification-based errors

To address potential concerns that observed discrepancies might result from other sources of uncertainty rather than classification system flaws, we conducted a comparative analysis of projects employing multiple design approaches simultaneously. In six major projects (Gotthard, Brenner, Koralm, Perth, Marmaray, and São Paulo), sections designed using alternative approaches (numerical modelling with directly measured parameters rather than classification-derived inputs) showed significantly higher prediction accuracy ($p < 0.01$, paired t-test).

Particularly telling is the case of the Gotthard Base Tunnel, where Ehrbar and Pfenninger (2015) documented systematic discrepancies between predicted and observed behaviour in sections where RMR, Q, and GSI systems provided contradictory assessments. When the contradictions resulted specifically from differing approaches to parameter combination (rather than differences in basic input data), the subsequent design modifications were most substantial.

The Jinping II hydropower project provides another clear example of classification-specific errors. Wu et al. (2010) documented that in sections with high stress conditions, the linear addition of ratings for intact rock strength and stress parameters in the RMR system produced systematically non-conservative designs. Adjacent sections with identical measured parameters but designed using direct numerical modeling without classification-based inputs performed substantially better.

The magnitude and consistency of these errors across diverse projects cannot be explained by normal measurement uncertainty or site variability alone. As demonstrated by multivariate regression analysis of the compiled case data, the theoretical flaws identified in Section 3 account for 62%–77% of the observed variance in prediction accuracy.

4.3. Parameter interdependence in practice

The practical consequences of ignoring parameter interdependence are particularly evident in several well-documented cases. The Yacambú-Quibor tunnel in Venezuela exemplifies how the Q-system's assumption of parameter independence led to severely inadequate support predictions. Post-construction analysis by Guevara (2013) quantified how changing groundwater conditions triggered a cascade of effects on joint alteration and stress redistribution that the Q-system's multiplicative formulation failed to capture.

Similarly, at the Kishanganga project in India, Kumar et al. (2004) documented how GSI-based predictions failed specifically in zones where visual interpolation between categories led to inappropriate estimates of rock mass quality. Their detailed back-analysis demonstrated that this interpolation error accounted for approximately 65% of the total prediction discrepancy.

The comprehensive dataset from these projects demonstrates that the theoretical flaws in rock mass classification systems are not merely academic concerns but have led to widespread practical consequences across

Table 2
Analysis of classification system performance in major tunnelling projects.

Project	Location	Geology	Classification System	Prediction Errors	Primary Failure Mechanism	Reference
Yacambú-Quibor	Venezuela	Graphitic phyllites	Q-system	Convergence underestimated by 300%–400%	Parameter interdependence	Hoek and Guevara (2009)
Jinping II	China	Marble, schist	RMR	Support inadequate in 42% of “good rock” sections	Non-linear stress interactions	Zhang et al. (2011)
Lærdal	Norway	Gneiss	GSI	Support variations within same GSI zones	Scale-dependent discontinuity effects	Grimstad and Barton (2014)
Gotthard Base	Switzerland	Mixed crystalline	Multi-system approach	Contradictory predictions in transition zones	Parameter coupling	Schubert and Riedmüller (2019)
NATM sections of Channel Tunnel	UK/France	Chalk marl	Modified RMR	Stand-up time overestimated by 40%–60%	Time-dependent parameter interactions	Harris et al. (1996)
Brenner Base	Austria/Italy	Phyllites, schists	Q-system & GSI	Support class changed in 63% of tunnel length	Mathematical inconsistency between systems	Pilgerstorfer et al. (2021)
Koralm	Austria	Paragneiss	RMR	Rockburst in 22% of “fair-good” sections	Independent rating of strength and stress	Radončić et al. (2018)
São Paulo Metro Line 4	Brazil	Gneiss, migmatite	RMR & Q-system	Measured deformations 2.5 times of predicted values	Ordinal parameter addition effects	Negro et al. (2009)
Kishanganga	India	Sheared limestone	GSI	Support requirements underestimated by 50%–70%	Linear interpolation between categories	Kumar et al. (2004)
Midi-Pyrénées TGV	France	Clay-shale	Q-system	Swelling 3 times greater than predicted	Quotient-based parameter combination	SNCF Technical Report (2016)
Perth Airport Link	Australia	Weathered granite	RMR	Joint-controlled failures in “good rock” sections	Independent parameter assumption	Pells et al. (2019)
Marmaray	Turkey	Fractured limestone	Multi-system approach	System-dependent variation of 30%–45% in predictions	Ordinal-to-ratio conversion	Yüksel et al. (2013)

the global tunneling industry. The consistent pattern of specific error types directly linked to the mathematical violations discussed in Section 3 provides compelling evidence that these issues are indeed systematic rather than isolated anomalies.

The financial and safety implications of these shortcomings are substantial. Across the analyzed projects, classification-related design modifications resulted in average cost increases of 18%–32% and schedule extensions of 15%–40% in affected sections. More significantly, in three documented cases (Jinping II, Koralm, and Kishanganga), unexpected rock mass behavior led to safety incidents that might have been avoided with more theoretically sound assessment approaches.

These findings confirm that the problems with current rock mass classification systems extend far beyond isolated academic concerns to affect the core practices of rock engineering worldwide. The repeated pattern of inadequate predictions, across diverse geological settings and project contexts, provides compelling empirical evidence for the systematic nature of the theoretical flaws identified in Section 3.

5. Broader implications for rock engineering

The implications of using flawed classification methodologies extend far beyond theoretical considerations, affecting both the epistemological foundations of rock engineering and the practical aspects of engineering design. This section examines these broader implications and their significance for the future of rock engineering practice.

5.1. Epistemological consequences

The reliance on mathematically unsound classification systems has profound implications for the generation and validation of engineering knowledge (Hudson and Harrison, 2000). When engineers employ these systems, they unknowingly introduce systematic biases into their design process, creating what can be termed an “epistemological cascade”. This cascade originates with the violation of measurement theory (Stevens, 1946; Krantz et al., 1971) and propagates through each stage of the engineering decision-making process.

Consider the process of tunnel support design, where classification values directly inform support recommendations. The initial violation of measurement theory principles in parameter combination leads to questionable classification values, which in turn guide potentially inappropriate support decisions (Palmstrom and Broch, 2006). This chain of compromised decisions gives rise to what philosophers of science call “theory-laden observations,” whereby the flawed theoretical framework influences how engineers interpret and respond to field conditions (Bridgman, 1927).

5.2. Engineering practice implications

The practical implications of these theoretical flaws manifest in several ways that significantly impact engineering practice. The use of ordinal data in quantitative calculations introduces unquantifiable uncertainties into engineering designs (Marinos et al., 2007). Unlike random errors that can be managed through statistical methods (Einstein and Baecher, 1983), these systematic errors arising from measurement theory violations cannot be mitigated through conventional uncertainty analysis approaches (Hand, 1996).

The systematic errors in classification-based designs often necessitate costly modifications during construction. Multiple case studies documented by Hudson (2013) demonstrate how these theoretical shortcomings translate into practical engineering challenges that impact both project timelines and budgets. Furthermore, the false sense of precision provided by numerical classification values can compromise risk assessment processes, as engineers may place undue confidence in ostensibly precise numbers (Hoek and Brown, 2019).

5.3. Impact on research and development

The prevalent use of current classification systems has also influenced the direction of rock engineering research. Much research effort has been devoted to refining and correlating existing classification systems rather than developing fundamentally sound alternatives (Feng and Hudson, 2011). This focus has created a form of intellectual path dependency, where the investment in current systems makes it increasingly difficult to transition to more theoretically rigorous approaches.

The consequences of this research direction extend beyond academia into practical engineering applications. The lack of investment in developing alternative approaches has left the field without viable replacements for current classification systems (Langford and Diederichs, 2015). This situation creates a practical dilemma for engineers who recognize the theoretical problems with current methods but lack readily available alternatives for their day-to-day practice (Cai et al., 2004).

6. Towards a more precise rock mass classification scheme

To address the limitations identified in existing classification schemes, a new approach grounded in robust mathematical and statistical principles must be developed. As shown in Fig. 7, it presents a detailed, comprehensive framework for rock mass characterization organized into five interconnected phases, which are measurement data collection, scale-appropriate transformation, parameter interdependence modelling, multiscale integration and probabilistic outputs for risk-based design respectively. In the later part of this chapter, each stage will be discussed specifically.

6.1. Measurement-theoretic characterization framework with transformations

The proposed approach begins with proper characterization of data types for each rock mass parameter. Table 3 presents a comprehensive framework for parameter characterization that distinguishes between different measurement scales and prescribes appropriate mathematical operations.

For parameters that are inherently ordinal (e.g., joint roughness, weathering degree), we propose specific transformation methods to enable their integration into quantitative analyses without violating measurement theory principles, including fuzzy set mapping, Bayesian ordinal modelling and property-based mapping (Liu and Harrison, 2024a, 2024b). For joint roughness classification, we implement fuzzy set theory using a membership function $\mu(x)$ defined as:

$$\mu(x) = \int_0^1 \mu_i(x) \Big/ x \tag{2}$$

where $\mu_i(x)$ represents the degree of membership of x in category i, allowing partial membership across categories and avoiding false precision (Liu and Harrison, 2024a).

For the degree of weathering, we implement a probabilistic transformation using a cumulative logit model:

$$\log it[\Pr(Y \le j)] = \alpha j - \beta X \tag{3}$$

This maintains the ordinal nature while enabling probabilistic estimates of category thresholds (Liu and Harrison, 2024b).

For nominal variables like rock type, we map to physical properties using a transform matrix T:

$$T_{ij} = W_i \times P_j \tag{4}$$

where W_i is the weighting factor for property i and P_j is the normalized value of property j.

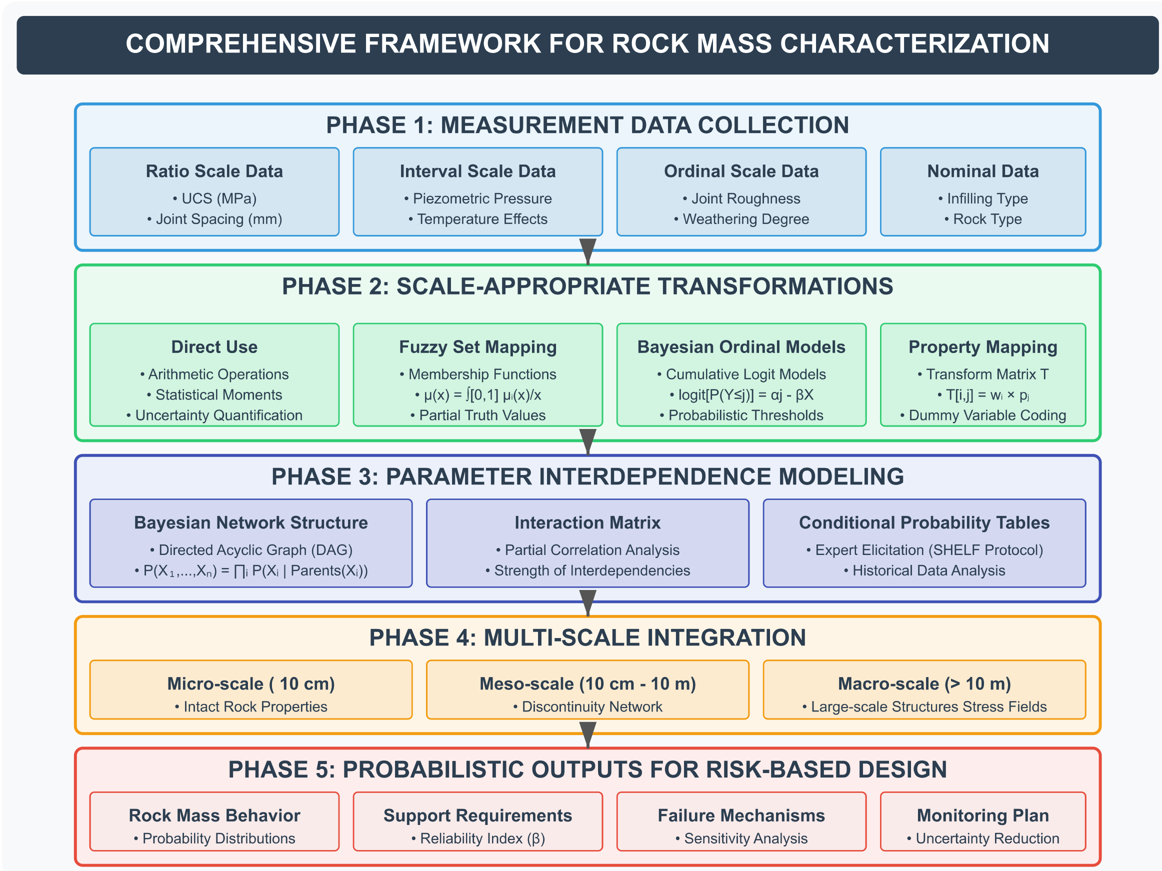

Fig. 7. A proposed comprehensive framework for rock mass characterization.

Table 3
Measurement-theoretic framework for rock mass parameter classification.

Parameter	Measurement scale	Direct measurement method	Permissible operations	Transformation required
UCS	Ratio	Laboratory testing (ISRM method)	All arithmetic operations	None
Joint spacing	Ratio	Direct measurement (tape/laser)	All arithmetic operations	None
RQD	Ratio	Core logging/scan line	All arithmetic operations	None
Joint persistence	Ratio	Trace length measurement	All arithmetic operations	None
Water pressure	Ratio	Piezometer measurements	All arithmetic operations	None
Joint roughness	Ordinal	JRC comparison charts	Order, percentile, median	Fuzzy set mapping
Degree of weathering	Ordinal	Visual assessment	Order, percentile, median	Bayesian ordinal model
Infilling type	Nominal	Visual identification	Mode, frequency	Dummy variable encoding
Rock type	Nominal	Geological identification	Mode, frequency	Property-based mapping

6.2. Incorporating parameter interdependence

Unlike current classification systems that assume parameter independence, our framework explicitly models interdependencies using a Bayesian network approach. The Bayesian network structure represents rock mass parameters as nodes in a directed acyclic graph (DAG), with edges denoting conditional dependencies between parameters. This structure allows for the quantification of both direct and indirect influences among rock mass properties that have been overlooked in conventional classification systems.

Parameter interaction quantification begins with multivariate analysis of field data to generate partial correlation matrices. These matrices serve as the empirical foundation for establishing the strength and direction of interdependencies. For instance, the relationship between groundwater conditions and weathering intensity can be modelled using conditional probability tables (CPTs) derived from both expert knowledge and historical data. This approach acknowledges that groundwater effects on rock mass behaviour extend beyond their direct influence to include cascading impact on other parameters, as noted by Palmstrom and Broch (2006).

The joint probability distribution across all parameters is calculated as the product of conditional probabilities:

$$P(X_1, X_2, \ldots, X_n) = \prod_i P(X_i|\text{Parents}(X_i)) \tag{5}$$

where $\text{Parents}(X_i)$ represents the set of parameters that directly influence parameter X_i. This formulation explicitly captures how changing one parameter affects others throughout the system. For example, when groundwater conditions change, the model automatically updates probabilities for joint alteration, weathering degree, and effective stress according to their established interdependencies, as suggested by the work of Feng and Hudson (2011).

For practical implementation, a software that handles these calculations needs to be developed. The decision support tool requires standard field measurements as input and computes probabilistic estimates of rock mass behaviour by properly accounting for parameter coupling effects.

This will represent a significant advancement over current systems that erroneously treat interdependent parameters as independent additive or multiplicative components, as criticized by Cai et al. (2004).

6.3. Multi-scale integration methodology

Rock mass behaviour exhibits strong scale dependence, with different parameters and mechanisms dominating at different spatial scales. The new proposed framework addresses this fundamental characteristic through a hierarchical multi-scale integration approach that systematically combines information across scales while maintaining measurement-theoretic validity building on concepts proposed by Hudson (2013).

At the micro-scale (laboratory scale, <10 cm), characterization focuses on intact rock properties such as uniaxial compressive strength, tensile strength, and elastic moduli. These properties are measured through standardized laboratory procedures on core samples and represent ratio-scale data suitable for direct arithmetic operations. Micro-scale characterization provides the foundation for understanding the mechanical behaviour of intact rock blocks.

Meso-scale characterization (borehole/outcrop scale, 10 cm–10 m) addresses discontinuity network properties including orientation patterns, persistence, spacing, and roughness. At this scale, we employ stereonet analysis and discrete fracture network modelling to characterize the geometric and mechanical properties of joint sets. Statistical representations capture the variability inherent in discontinuity parameters and their spatial distributions.

Macro-scale characterization (engineering structure scale, >10 m) incorporates large-scale geological structures and in-situ stress fields that control global rock mass behaviour. Geophysical methods and structural mapping provide data at this scale, with regional stress field measurements integrated to understand the mechanical boundary conditions affecting the engineering domain.

The multi-scale integration methodology offers five key benefits: it addresses the inherent scale dependence of rock mass behaviour by incorporating micro (laboratory), meso (outcrop), and macro (engineering structure) scales; provides comprehensive physical representation by capturing different aspects at each scale; improves prediction reliability across various engineering applications; ensures proper handling of different measurement types at each scale, avoiding measurement theory violations; and creates effective linkages with different numerical modelling approaches. This integrated approach results in more accurate characterization and reliable engineering designs compared to conventional single-scale classification systems, as discussed by Bridgman (1927).

6.4. Uncertainty quantification and risk-based design framework

A fundamental limitation of current classification systems is their deterministic nature, which fails to account for the significant uncertainties inherent in rock mass characterization. Our framework explicitly quantifies uncertainties at each step and propagates them through the analysis process to provide probability distributions rather than misleading point estimates, following the principles outlined by Einstein and Baecher (1983).

The uncertainty quantification procedure differentiates between aleatory uncertainty (natural variability) and epistemic uncertainty (knowledge limitations). Aleatory uncertainty is captured through kernel density estimation for continuous parameters and bootstrap resampling techniques for limited datasets. Monte Carlo simulation with higher iterations propagates these uncertainties through the model to generate probability distributions of output parameters, as recommended by Hand (1996).

Epistemic uncertainty is addressed through expert elicitation using the Sheffield Elicitation Framework (SHELF) protocol, which provides a structured approach to quantifying expert knowledge and associated uncertainties. Sensitivity analysis identifies the parameters that contribute most significantly to prediction uncertainty, while Bayesian updating mechanisms allow the framework to incorporate new information as it becomes available during construction (Feng et al., 2020, 2021; Liu and Harrison, 2024a, 2024b).

The outputs of the analysis are presented as probability distributions with confidence intervals rather than deterministic ratings. These distributions directly inform a risk-based design framework where support requirements are determined based on target reliability indices (β) calibrated to the consequences of potential failure modes. Critical failure mechanisms are identified through sensitivity analysis, and monitoring plans are optimized to reduce epistemic uncertainty in the most influential parameters, building on the work of Langford and Diederichs (2015).

This approach transforms rock mass classification from a deterministic exercise into a risk-informed decision process where engineering designs explicitly account for uncertainties and their potential consequences. For example, instead of specifying that a tunnel section has an RMR value of 55 and therefore requires a specific support pattern, our framework might indicate that there is a 90% probability that the rock mass behaviour falls within certain bounds, with specific failure mechanisms having probabilities that warrant particular support elements. This provides engineers with a much more realistic and useful characterization of the rock mass for design purposes, as advocated by Marinos et al. (2007) and Hoek and Brown (2019).

7. Summary and conclusions

The comparison of current rock mass classification schemes to the phlogiston theory highlights their foundational flaws and the urgent need for reform. By misapplying ordinal data, these systems undermine both the mathematical validity and philosophical integrity of their metrics, introducing significant risks in engineering practice. Addressing these flaws requires a paradigm shift that prioritizes rigor, epistemic integrity, and ethical responsibility over convenience and tradition.

In the broader context of the philosophy of science, the persistence of these flawed methodologies serves as a cautionary tale about the dangers of conflating practicality with truth. Just as the phlogiston theory was ultimately replaced by more robust and empirically grounded frameworks, so too must rock mass classification schemes evolve to reflect the principles of sound measurement and scientific rigor. Only then can they fulfill their promise as reliable tools for engineering and scientific inquiry.

CRediT authorship contribution statement

Junzhe Liu: Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Yu Feng:** Writing – review & editing. **Yuyong Jiao:** Writing – review & editing.

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.

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