Quantifying uncertainty in rock mass properties: Implications for GSI, RMi, and RMR assessments

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Abstract

Probability-based empirical methods were employed as an alternative approach to predicting uncertainties associated with rock mass properties. The focus was on developing probabilistic spreadsheets to forecast rock mass classification indexes. Histograms were constructed to describe the best distribution in predicting rock mass properties. The developed models also offer utility in predicting the impact of discontinuities within the rock mass on rock strength and rock mass classification systems. Statistical analyses identified volumetric joint count, joint spacing, joint frequency, and rock strength as the most influential parameters. Moreover, the statistical analysis revealed varying degrees of correlation among different rock mass properties. While some properties demonstrated significant correlations suitable for modelling, others did not align well with any correlation model. The results highlight the need for a comprehensive approach to rock mass characterization, considering multiple factors beyond volumetric joint count. Geological complexities, including tectonic activity and weathering processes, may obscure direct correlations. These results emphasize the importance of empirical modelling and detailed site investigations for accurate assessment of rock mass quality and stability in the Himalaya.

Keywords

rock mass classification, probability, spreadsheet, correlation

Introduction

A rock mass comprises two distinct aspects: intact rock and discontinuities, each exerting significant influence on the overall strength and deformability of the rock mass. Furthermore, the extent of weathering is widely acknowledged to have a substantial impact on the in-situ engineering characteristics of rocks (Park and West, 2001). Therefore, accurate assessments of strength and deformability are crucial for rock mass characterization. Although the structural characteristics and degree of weathering of the rock mass have the greatest influence on near-surface mine workings, the characteristics of rock formations encountered in mining vary widely, both geographically and randomly, and they are rarely predictable with certainty (Abbas et al., 2023; Qin et al., 2024).

Preliminary design research must adequately explain the random characteristics of natural materials like soil and rock. since they are inherently diverse and unpredictable (Abbas et al., 2024; Sari, Karpuz, and Aydaya, 2010). Currently, a stochastic system is preferred to deterministic variation in rock mass properties (Sari, Karpuz, and Aydaya, 2010). In a stochastic estimation, it is possible to take into account all available information regarding a certain random quality. Probability distributions, which provide both the possible range of values for the variable and the relative frequency of each value within that range, make this simple to accomplish (Evans et al., 2011). In earlier studies, statistical and probabilistic techniques were applied to calculate the minimum number of specimens needed for rock mechanics laboratory testing or to estimate the strength and deformability of rocks from laboratory experiments (Gill, Corthésy, and Leite, 2005; Sari and Karpuz, 2006).

The variability of the mechanical characteristics of a rock mass is challenging to experimentally assess (Abbas et al., 2023). When there is a lack of site data, rock engineers commonly use empirical methods to determine rock mass attributes (Barton et al., 1974; Hoek and Bray, 1981).

The Himalayan rocks present a unique complexity stemming from a history of intense tectonic activity, yet there is a notable lack of studies concerning rock mass classification in this region (Abbas et al, 2022). Existing classifications are utilized for assessing slope and tunnel stability; however, a significant source of uncertainty lies in the analysis of discontinuities within jointed rock masses. Despite the critical importance of understanding this uncertainty for ensuring infrastructure safety and stability in the Himalayas, research in this area has garnered limited attention. Consequently, there is a pressing need for deeper study of uncertainty associated with jointed rock masses in the Himalayas to enhance comprehension and management of geological hazards in this region.

In this study we investigate uncertainty in the computation of key rock engineering indices such as the Geological Strength Index (GSI), Rock Mass Index (RMI), and Rock Mass Rating (RMR). To achieve this objective, data has been gathered from ongoing tunnelling projects traversing the Himalayas in northern Pakistan. Leveraging existing statistical models, this research aims to identify the most influential parameters affecting GSI, RMI, and RMR. We present empirical correlations of rock mass parameters specifically for the challenging geological conditions of the Himalayan region. These correlations are designed to enhance the understanding of rock mass behaviour and stability assessment in this unique and complex terrain.

Statistical analysis of rock mass: Past studies

In the literature, there are a limited number of studies that consider uncertainty in RMR, RMI, and GSI. Monto Carlo (MC) simulation has been used to incorporate uncertainty in GSI from Kizikaya and New Zealand greywacke (Sari, 2015), leading to the conclusion that the MC method is a viable tool for assessing the variability of rock mass properties. A probabilistic method to characterize the mechanical behaviour of rock mass has been presented by Kim and Gao (1995). Doyuran, Ayday, and Karahanoglu (1993) looked into the most suitable frequency distributions for aperture, persistence, and spacing of discontinuities in andesite, marble, and peridotite. Recent studies have investigated correlations of rock mass classification systems specifically for underground excavations in the Himalayas (Abbas et al., 2023). Statistical analysis revealed that within a single rock mass, the degree of weathering and the orientation of discontinuities significantly influence the frequency distributions of discontinuity parameters.

Research methodology

The GSI (Hoek, Kaiser, and Bawden, 2000) and RMR (Bieniawski, 1973) are frequently used in surface and subsurface geotechnical investigations. Through their extensive usage and validation across diverse geological settings, the GSI and RMR frameworks have earned recognition as indispensable resources in the field of rock mechanics and engineering geology.

The first parameter of the RMR, the joint compressive strength (JCS) (ISRM, 1978), is given by

$$JCS = 10^{(0.00088\gamma R+1.01)} \quad [1]$$

where γ is the unit mass of rock material (expressed in kN/m^3) and R is the representative rebound, i.e. the mean of the five higher measured values on a set of ten measurements for each tested discontinuity.

The second parameter used to determine RMR has been indirectly derived by Palmstrom (1982), who suggested that when cores are not available, the RQD may be estimated from the number of joints per unit volume, by summing the number of discontinuities per metre for each joint. The conversion formula for clay-free rock masses is

$$RQD = 115 - 3.3Jv \quad [2]$$

where *Jv* is the volumetric joint count, which represents the total number of joints within a unit volume of rock mass and can be derived from the average spacing of each discontinuity.

When RQD = 0 for $Jv > 35$, and RQD = 100 for $Jv < 4.5$,

$$Jv = \frac{1}{s1} + \frac{1}{s2} + \frac{1}{s3} + \cdots \quad [3]$$

Here *s*1, *s*2, and *s*3 are the joint set spacings. Random joints can be included by assuming a random spacing (sr) for each of these. Experience indicates that this can be set to *sr* = 5 m, thus, the volumetric joint count can be generally expressed as

$$Jv = \frac{1}{s1} + \frac{1}{s2} + \frac{1}{s3} + \cdots \frac{Nr}{5} \quad [4]$$

The condition of discontinuities includes the following properties:

Persistence describes the discontinuity length

Aperture has been measured using ISRM classes (ISRM, 1978).

The roughness of surfaces, The Joint Roughness Coefficient (JRC) is probably the most commonly used measure of the roughness of rock joint surfaces. The JRC is evaluated by visual comparison of measured profiles against a set of standard JRC profiles produced by Barton and Choubey (1977).

The fifth parameter of the RMR classification takes into account the occurrence of water along discontinuities.

The frequency distribution of data is shown in Figure 1.

The GSI has been empirically correlated with RMR and jointing parameter (JP). The jointing parameter, which expresses the reduction of intact strength of a rock mass, is calculated as

$$JP = \ 0.2 \times JC^{0.5} \times Vb^{D} \quad [5]$$

Here JP is joint parameter, *Vb* is block volume, and JC is the joint condition factor, including roughness and size of the joints, while the exponent D is 0.37 ×JC$^{-0.2.}$ It varies from 0.2 to 0.6. In common conditions JC = 1.75.

The GSI chart proposed by Hoek considered only two parameters: block volume and weathering conditions. However, Hoek, Marinos, and Benissi (1998) suggested the following relationship between GSI and RMR.

$$GSI = RMR - 5 \quad [6]$$

Cai and Kaiser (2006) incorporated the jointing condition factor (JC) and the block volume (*Vb*) and suggested the following relationship.

$$GSI = (26.5 + 8.79lnJC + 0.79lnVb)/(1 + 0.015lnJC - 0.025lnVb) \quad [7]$$

Russo (2009) considered the jointing parameter and suggested the following equation for GSI:

$$GSI = 153 - 165/\left(1 + \left(\frac{Jp}{0.19}\right)\right)^{0.44} \quad [8]$$

Another important rock mass classification unit is RMI. Palmstrom (1996) proposed the following equation for RMI by incorporating the uniaxial compressive strength (σc) and the jointing parameter:

$$RMi = \ \sigma c \times Jp \quad [9]$$

Kumar, Samadhiya, and Anbalagan (2004) developed an empirical relationship between of RMI and *Q* for rocks mass along the Himalayas.

$$RMi = 0.5Q^{0.93} \quad [10]$$

The RMR is another rock mass index frequently used in geotechnical projects. Bieniawski (1984) developed the following equation to derive RMR from *Q*:

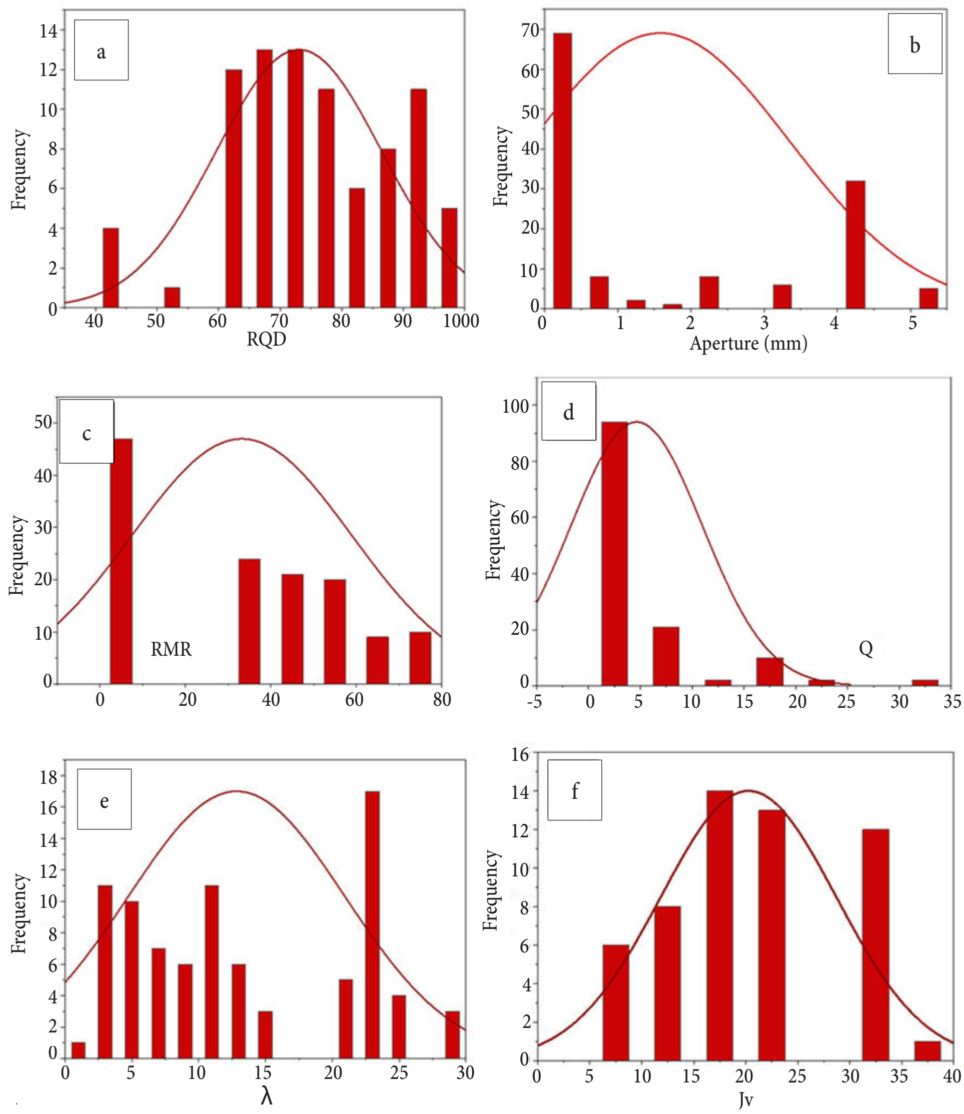

Figure 1—Frequency distributions of rock mass properties

$$RMR = 9lnQ + 44 \quad [11]$$

Rutledge and Perston (1978) suggested the following relationship:

$$RMR = 5.9lnQ + 43 \quad [12]$$

Results and discussion

The descriptive statistics of the rock mass classifications are given in Table I. The RQD is in the range of 40 to 95. The RMR value is 38 to 77. The mean values of RQD and RMR are 73 and 50 respectively. The probabilistic wanalysis of the RQD, RMI, and RMR is as follows. The probabilistic models of Equations [6–8] are shown in Figure 2. The distribution that best describes the data is Equation [6], since the GSI calculated from RMR using Equation [6] is more consistent and the data is less scattered compared to the other two equations. One of the drawbacks of Equation [8] is that the GSI calculated is close to or greater than 100, which is meaningless. The mean value of GSI is the same for all three equations; however, the GSI values calculated for the same rock mass are different.

The RMI calculated from Equations [9] and [10] is shown in Figure 3. Equation [10] (suggested by Kumar, Samadhiya, and Anbalagan) is more consistent and the data is less scattered compared to Equation [9]. Kumar, Samadhiya, and Anbalagan (2004) developed their correlation for the Himalayas. This is why the correlation is the most suitable for RMI, as the data used in this study was from a tunnelling project in that region. This shows that the empirical correlations are dependent on rock type and regional geology.

Table I

Descriptive statistics of rock mass properties

Parameter	Minimum	Maximum	Mean	Std. deviation
RQD	40.00	95	73.060	13.430
Vb	0.000135	7	0.426	1.122
Js	0.08	3	0.694	0.606
a	0.10	5	1.517	1.787
RMR	38.00	77	50.798	12.607
	0.50	34	6.283	7.332

Similarly, the RMR calculated from Equations [11] and [12] are dissimilar for the same rock mass (Figure 4). Equation [11] is more consistent than Equation [12]. Hence it can be said that the

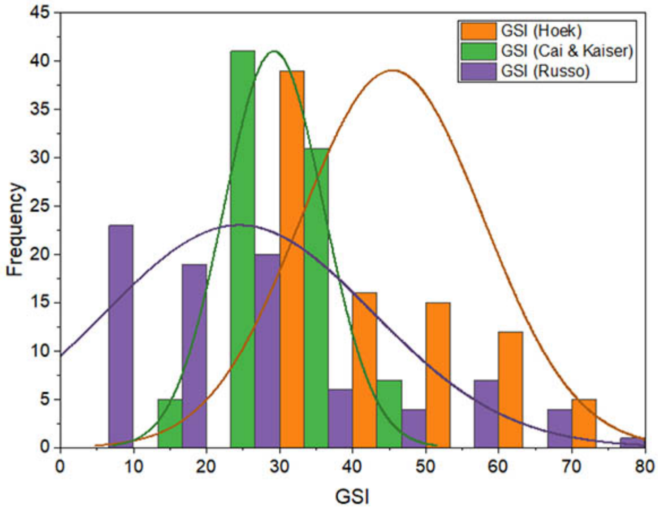

Figure 2—GSI frequency distribution for the Himalayas using three quantitative approaches

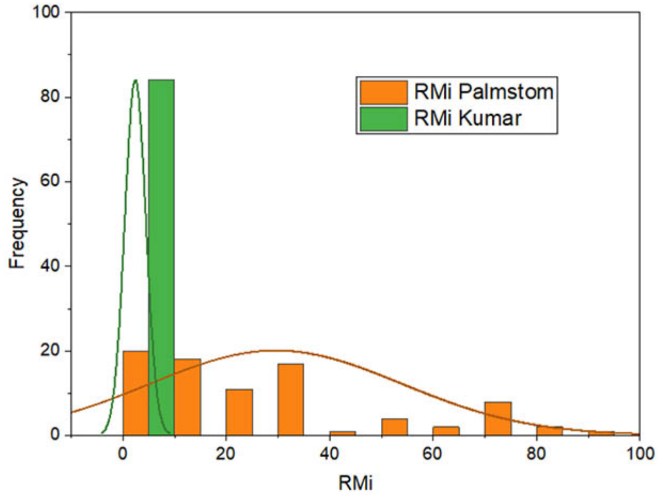

Figure 3—RMI frequency distribution for the Himalayas using two quantitative approaches

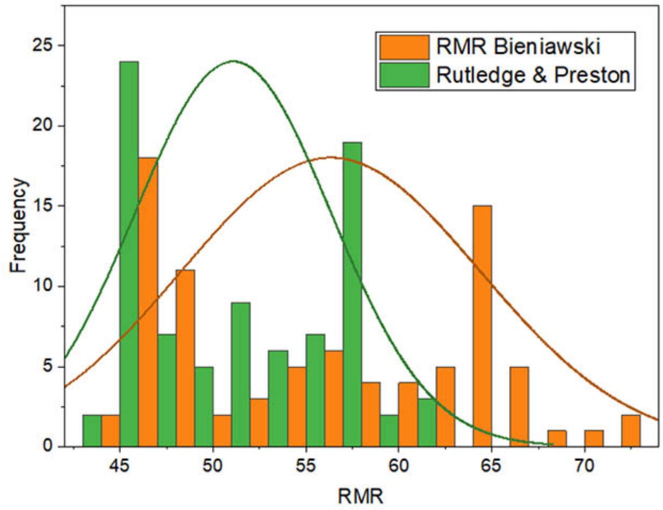

Figure 4—RMR frequency distribution for the Himalayas using two quantitative approaches

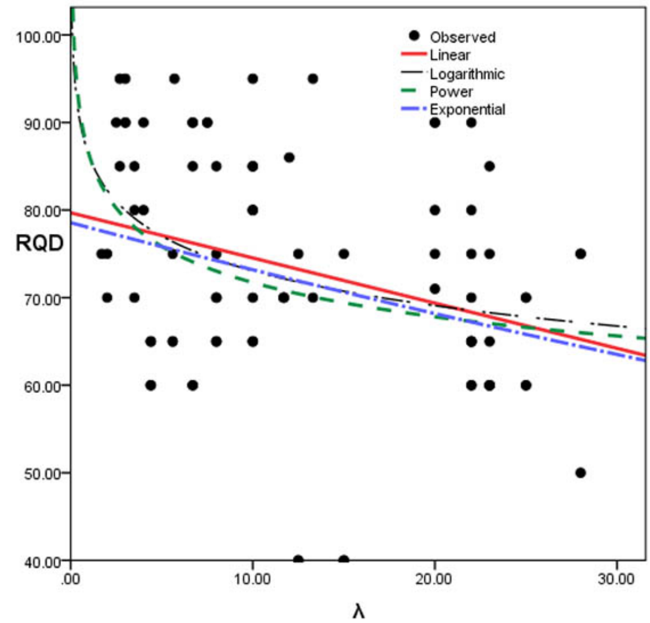

Figure 5— Correlation of RQD with joint frequency

rock strength and other parameters are rock-dependent and a single correlation between rock mass properties may not be representative for all rock types. It is recommended that more realistic correlations be used for different rock types based on regional geology.

A specific correlation of RQD from joint frequency for the Himalayas is presented in Equation [13]. Four statistical models (Figure 5) –linear, power, exponential, and logarithmic – were applied to the data. It was observed that the best fit model is exponential [Equation 13]. Here the data is less scattered with a strong correlation coefficient of 0.8 (Table III). Figure. 6 shows the correlation between volumetric joint count and RQD. No significant correlation was observed in any type of statistical model. None of the models are statistically significant as the correlation coefficients are less than 0.5 (Table IV).

$$RQD = 7.5e^{-0.007\lambda} + 78 \quad [13]$$

where λ is the average number of discontinuities per metre, λ = 1/(mean joint spacing). The distribution of spacing must be negatively exponential if the theoretical RQD is to be applied to a particular rock.

The correlation of different rock mass properties for a single rock type is shown in Table II. The RQD has a good correlation with V_b, joint spacing (J_s), and joint aperture (a), with correlation coefficients greater than 0.5. RQD is not significantly correlated with RMR. This suggests that RQD, reflecting the degree of rock mass integrity and fracturing, exhibits meaningful relationships with these specific geometric and structural characteristics of the rock mass. However, it is important to note that RQD does not exhibit a significant correlation with RMR. This discrepancy could stem from the broader scope of RMR, which incorporates additional factors beyond RQD, such as joint orientation, joint roughness, and groundwater conditions. Consequently, while RQD provides valuable informations into certain aspects of rock mass behaviour, its limited correlation with RMR highlights the need for a comprehensive approach to rock mass characterization, considering a range of parameters to accurately assess rock mass stability and engineering properties.

The application of statistical models to analyse RQD derived from joint frequency data for the Himalayas is crucial for understanding the rock mass characteristics in this complex geological setting. The observation (Table III) that the exponential model provides the best fit suggests that the relationship between RQD and joint frequency in the Himalayas is nonlinear and exhibits exponential growth or decay. This result could be attributed to various geological factors influencing joint frequency and RQD (Deere, 1989). For instance, in regions with intense tectonic activity like the Himalayas, the distribution and density of fractures may follow complex patterns influenced by faulting, folding, and other structural features. Additionally, geological processes such as weathering and erosion may further alter the distribution of fractures, leading to nonlinear relationships between joint frequency and RQD (Abbas et al., 2022).

Moreover, the exponential model may better explain the diminishing returns or saturation effects observed in RQD as joint frequency increases. This phenomenon could reflect the decreasing proportion of intact rock at higher joint frequencies, where the fractures become increasingly interconnected, reducing the overall RQD value.

The lack of significant correlation between volumetric joint count and RQD, as depicted in Figure 6 and confirmed by the statistical analysis presented in Table IV, highlights an important aspect of rock mass characterization in the Himalayas. Despite efforts to explore potential relationships using various statistical models, including linear, power, exponential, and logarithmic models, none yielded statistically significant results, with all correlation coefficients below 0.5. The results suggests that in the context of the Himalayas, volumetric joint count alone may not be a reliable predictor of RQD, indicating the presence of additional factors influencing rock mass integrity and fracturing other than sheer volume of joints. Several factors could contribute to this lack

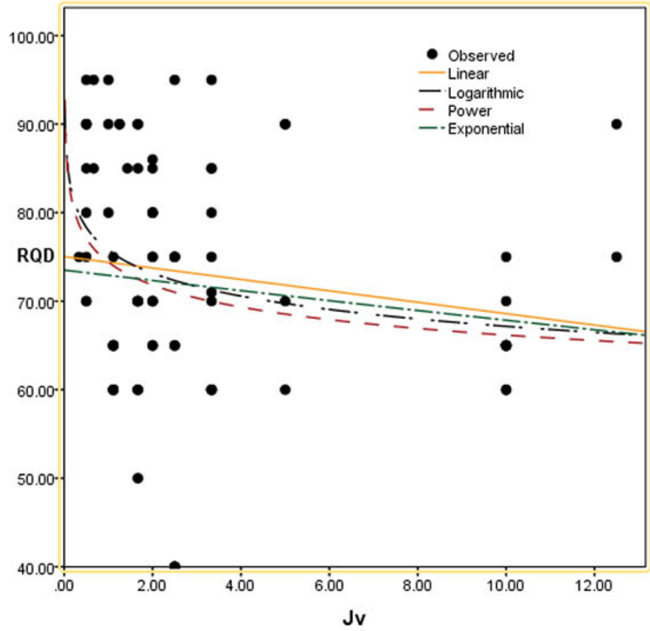

Figure 6—Correlation of RQD with volumetric joint count

Table II

Correlation among rock mass properties

		RQD	*Vb*	*Js*	*a*	RMR	Q
RQD	Pearson correlation	1	-0.623**	-0.777**	-0.800**	0.243*	.594**
	Sig. (2-tailed)		.000	0.000	.000	0.013	0.000
	Covariance	575.139	-69.831	-202.589	-251.943	140.058	99.876
Vb	Pearson correlation	-0.623**	1	0.830**	0.763**	-0.195*	-0.211*
	Sig. (2-tailed)	0.000		0.000	0.000	0.048	0.032
	Covariance	-69.831	21.878	42.209	46.895	-21.913	-6.919
Js	Pearson correlation	-0.777**	0.830**	1	0.933**	-0.180	-0.299**
	Sig. (2-tailed)	0.000	0.000		0.000	0.069	0.002
	Covariance	-202.589	42.209	118.223	133.327	-46.992	-22.773
a	Pearson correlation	-0.800**	0.763**	0.933**	1	-0.313**	-0.322**
	Sig. (2-tailed)	0.000	0.000	0.000		0.001	0.001
	Covariance	-251.943	46.895	133.327	172.564	-98.585	-29.650
RMR	Pearson correlation	0.243*	-0.195*	-0.180	-0.313**	1	0.408**
	Sig. (2-tailed)	0.013	0.048	0.069	0.001		0.000
	Covariance	140.058	-21.913	-46.992	-98.585	575.863	68.632
Q	Pearson correlation	0.594**	-0.211*	-0.299**	-0.322**	0.408**	1
	Sig. (2-tailed)	0.000	0.032	0.002	0.001	0.000	
	Covariance	99.876	-6.919	-22.773	-29.650	68.632	49.192
	N	103	103	103	103	103	103

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table III

Model summary and parameter estimates

Equation	Model summary					Parameter estimates	
	R square	F	df1	df2	Sig.	Constant	b1
Linear	0.097	8.786	1	82	0.004	79.686	-0.516
Logarithmic	0.108	9.939	1	82	0.002	86.260	-5.734
Power	0.098	8.861	1	82	0.004	86.397	-0.081
Exponential	0.83	7.406	1	82	0.008	78.558	-0.007

Table IV

Model summary and parameter estimates

Equation	Model summary					Parameter estimates	
	R square	F	df1	df2	Sig.	Constant	b1
Linear	0.022	1.858	1	82	0.177	75.033	-0.645
Logarithmic	0.060	5.255	1	82	0.024	75.744	-3.730
Power	0.051	4.409	1	82	0.039	74.403	-0.051
Exponential	0.016	1.291	1	82	0.259	73.503	-0.008

of correlation. The complex geological history and tectonic activity in the Himalayan region may lead to complex fracture patterns and distributions that are not solely determined by volumetric joint count (Shah et al., 2023). Other factors such as joint orientation, spacing, and roughness, as well as the degree of weathering and rock type, may play significant roles in determining RQD. Furthermore, the influence of volumetric joint count o RQD may be offset by other factors that exert greater control over rock mass quality. For example, in heavily fractured rock masses with high volumetric joint count, the overall rock mass integrity and RQD may still be relatively high if the fractures are predominantly closed or filled, mitigating their impact on rock mass behaviour.

Conclusion

A probability-based analysis was performed to incorporate uncertainty in rock mass properties. The rock mass classification indexes GSI, RMR, and RMI were investigated using their proposed empirical equations. For GSI three equations were examined: a general equation proposed by Hoek, Marinos, and Benissi (1998) (Equation [6]), and relationships proposed by Cai and Kaiser (2006) and Russo (2009) (Equations [7] and [8]). The three suggested equations yield completely different values of GSI. In practical applications, the Hoek, Marinos, and Benissi equation is recommended for estimation of GSI along the Himalayas, as the data is less scattered compared to the other two equations.

In the case of RMI two equations (Equations [9] and [10]) were examined. Equation [10] (Kumar, Samadhiya, and Anbalagan, 2004) is more consistent and the data is less scattered compared to Equation [9], as the equation was developed using similar data along the Himalayas. Likewise, the RMR values calculated from Equations [11] and [12] are dissimilar for the same rock mass. Equation [11] is more consistent than Equation [12]. Hence it can be concluded that the rock strength and other parameters are rock-dependent and a single correlation between rock mass properties may not be representative for all rock types.

The results from the correlation analysis between volumetric joint count and RQD in the Himalayan region highlight the complexity of rock mass characterization in this geologically diverse and tectonically active area. Despite efforts to establish a relationship between volumetric joint count and RQD using various statistical models, none yielded statistically significant results, indicating a lack of strong correlation between these parameters. Geological complexities, such as varying fracture patterns influenced by tectonic activity and weathering processes, may obscure the direct relationship between volumetric joint count and RQD. Other factors such as joint orientation, spacing, roughness, and the degree of weathering may also have significantl influence on rock mass quality and behaviour, further complicating the correlation analysis.

The absence of a significant correlation between volumetric joint count and RQD emphasizes the importance of comprehensive site investigations and empirical modelling approaches in the Himalayan region.

Conflicts of Interest:

The authors declare no conflict of interest

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