Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

Quantitative GSI–RMR_str Relationship for Rock Masses of the Central Alborz, Iran: A Field-Derived Empirical Model

Bizhan Shirdel*

Association of Official Judicial Experts of North Khorasan Province, Bojnord, Iran

Article Info

Received 7 December 2025
Received in Revised form 23 August 2026
Accepted 29 September 2026
Published online 29 September 2026

DOI: 10.22044/jme.2026.17283.3423

Keywords

Discontinuity Characterization
Joint Condition
Structural Parameters
Monte Carlo Simulation
External Validation

Abstract

Rock mass characterization is essential for safe and economical design in mining, tunneling, and slope engineering. The Geological Strength Index (GSI) and Rock Mass Rating (RMR) are among the most widely used empirical rock mass classification systems. However, existing quantitative correlations remain limited by geological variability and inconsistent parameter definitions, reducing their transferability across different geological settings. This study develops an empirical relationship between GSI and the structural component of Rock Mass Rating, hereafter termed RMR_str, for carbonate and clastic rock masses in the Central Alborz geological zone. RMR_str was defined using only the structural parameters common to both systems, excluding intact rock strength and groundwater ratings. The study surveyed 134 field stations across the Elika, Lar, and Shemshak formations, recording the discontinuity parameters required to determine GSI and calculate RMR_str. Regression analysis produced the correlation GSI = 1.73696 × RMR_str − 9.54120 (R^2 = 0.9993), which remained stable under cross-validation, Monte Carlo simulation, and sensitivity analysis. To evaluate the model beyond the calibration dataset, it was independently tested using field data from the Bukan bauxite mine, where it demonstrated acceptable predictive performance. The resulting equation enables quantitative GSI estimation from routinely available RMR_str data, with a typical uncertainty of ±3.1 GSI units (1σ) within the validated range (25 ≤ RMR_str ≤ 50). Because GSI and RMR_str share common structural descriptors, part of the reported coefficient of determination reflects mathematical coupling rather than independent predictive capability. Consequently, application outside the Central Alborz geological zone requires independent validation.

1. Introduction

Reliable rock mass characterization forms the foundation of geotechnical decision-making in mining, tunneling, slope engineering, and underground construction. Because rock masses exhibit considerable geological and structural variability, their engineering behavior cannot be evaluated solely from intact rock properties. Empirical rock mass classification systems provide practical frameworks for characterizing rock mass quality, predicting rock mass behavior, and communicating field observations in a consistent manner. These systems support the assessment of rock mass strength, deformability, excavation stability, and support requirements throughout the design and construction process. Hence, accurate and practical rock mass characterization remains essential for achieving safe, economical, and efficient rock engineering projects.

The Rock Mass Rating (RMR) system introduced by Bieniawski [1] has become one of the most widely adopted empirical rock mass classification systems for engineering design. Hoek and co-workers [2–4] subsequently developed the Geological Strength Index (GSI) to characterize rock mass structure and discontinuity conditions and to provide input for the Hoek–Brown failure criterion. Although both systems are derived primarily from field observations, they were

* Corresponding author: b.shirdel@nkhioe.ir (B.Shirdel(

developed for different engineering purposes and therefore are not directly interchangeable. In engineering practice, site investigations frequently provide RMR data, whereas many analytical and numerical design methods require GSI values. This practical mismatch has motivated numerous studies aimed at establishing quantitative relationships between the two systems. Hoek and Brown [2] initially proposed the widely cited approximation GSI = RMR89 − 5. Subsequent investigations demonstrated that the relationship varies substantially with lithology and geological conditions. Somodi et al. [5] reported slopes ranging from 0.79 to 0.88 for granite, siltstone, sandstone, and quartzite, whereas Zhang et al. [6] and Khan and Zaman [7] likewise showed that lithology-specific correlations generally outperform universal equations. Together, these studies demonstrate a clear evolution from simple empirical approximations toward lithology-specific and structurally constrained correlations, highlighting the growing recognition that geological context strongly influences the relationship between RMR and GSI and that no single correlation can adequately represent the diversity of geological conditions encountered in rock engineering. A further challenge concerns the estimation of GSI itself: traditional chart-based assessment relies heavily on engineering judgement and may introduce significant inter-observer variability. Marinos and Carter [8] noted that many published RMR–GSI correlations combine structural and non-structural RMR components despite GSI being fundamentally controlled by rock mass structure and discontinuity surface condition. Taken together with the lithology-dependent findings, this observation points to the same underlying gap. Although RMR–GSI correlations have progressively evolved toward more quantitative and geologically informed approaches, none has simultaneously isolated the structural components shared by both systems and determined GSI using a fully quantitative formulation. This methodological limitation is particularly relevant to the Central Alborz geological zone, where the Elika, Lar, and Shemshak formations constitute the principal rock units encountered in mining and civil engineering projects. Previous investigations in the Jajarm mining district have applied empirical rock mass classification methods to related engineering problems without establishing the quantitative structural relationship investigated in the present study. Field-based RMR and GSI assessments were used independently to determine final wall slopes at the Golbini mines [9,10], while UAV-based structural mapping was employed to identify geomechanically critical zones [11]. A subsequent study compared field-traversing and discontinuity-survey approaches for rock mass classification [12], whereas borehole-derived geomechanical parameters were applied to slope design at Golbini 7 [13]. Although these studies improved local geotechnical characterization, none isolated the structural components common to GSI and RMR or established a quantitatively validated correlation between them. Consequently, existing RMR databases cannot be directly converted into quantitative GSI estimates with demonstrated reliability. To address these limitations, the present study develops and evaluates an empirical relationship between GSI and RMR_str in two complementary stages. First, an analytical model derives the theoretical relationship purely from the mathematical structure of the two classification systems by evaluating all permissible combinations of the structural RMR components together with the quantitative GSI formulation proposed by Hoek et al. [3]. Second, this relationship is calibrated and validated using 134 independent field observations collected from the Elika, Lar, and Shemshak formations, where RMR_str was calculated exclusively from RQD, joint spacing, and joint condition ratings. The field-derived relationship is subsequently evaluated through cross-validation, Monte Carlo simulation, mixed-effects regression, robust regression, sensitivity analysis, and independent external validation using data from the Bukan bauxite mine.

2. Materials and Methods

2.1. Field Data Collection and Parameter Determination

Engineering geological field investigations were conducted at 134 survey stations distributed across the Elika, Lar, and Shemshak formations in the Central Alborz geological zone of northern Iran. At each station, discontinuity characteristics, Rock Quality Designation (RQD), joint spacing, joint condition, intact rock strength, and groundwater conditions were systematically recorded following the recommendations of the RMR (1989) system [1]. Although intact rock strength and groundwater were measured during field investigations, they were excluded from the structural rock mass rating (RMR_str) because they are not included in the quantitative formulation of GSI proposed by Hoek et al. [3]. All measurements were collected using standardized engineering

geological mapping procedures to ensure consistency and repeatability throughout the dataset.

Rock Quality Designation (RQD): Field teams measured RQD along 30–50 m scanlines using the linear scanline method. The adjustment relationships proposed by Celada and Bieniawski (2020) [15] then corrected the measured RQD values for scanline orientation effects. Other researchers have also proposed alternative approaches for RQD adjustment in anisotropic rock masses [16].

Joint Spacing and Condition: Joint spacing was measured in the field, and true spacing was subsequently calculated by accounting for joint orientation and discontinuity geometry. This study assigned joint condition ratings based on five sub-parameters—persistence, aperture, roughness, infilling, and weathering—strictly following the guidelines and rating tables of the RMR (1989) system [1].

Uniaxial compressive strength (UCS) and groundwater conditions were recorded but intentionally excluded from RMR_str to ensure that the proposed relationship was based exclusively on structural rock mass characteristics.

Calculation of Structural Rock Mass Rating (RMR_str): This study calculated RMR_str as the sum of the ratings for RQD, joint spacing, and joint condition:

$$RMR_str = R_RQD + R_Spacing + JCond_{89}. \quad (1)$$

Quantitative Determination of Geological Strength Index (GSI): To minimize subjectivity, this study adopted the quantitative method proposed by Hoek et al. (2013) [3]. This study calculated GSI using the analytical equation derived from the quantified GSI chart:

$$GSI = 1.5 \times JCond_{89} + RQD/2 \quad (2)$$

where $JCond_{89}$ represents the joint condition rating defined in the RMR (1989) system [1].

2.2. Geological Setting and Study Sites

The investigated rock masses are located within the Jajarm mining district in the Central Alborz structural zone of northern Iran. Field investigations covered representative engineering geological conditions developed in three major lithostratigraphic units that are frequently encountered in mining and civil engineering projects in the region.

The **Elika Formation (Upper Triassic)** consists predominantly of thick-bedded to massive dolomite and dolomitic limestone and forms the footwall of the Jajarm bauxite horizon. Twenty-eight survey stations were investigated within the Golbini (Mines 1–8) and Zo (Mines 1–4) bauxite mines.

The **Lar Formation (Middle–Upper Jurassic)** is composed mainly of massive to thick-bedded limestone and represents the host rock of the Tangeh Gazi limestone mine. Twenty-six field stations were investigated within this formation.

The **Shemshak Formation (Lower–Middle Jurassic)** comprises interbedded sandstone, siltstone, and shale and forms the hanging wall of the bauxite deposits. Eighty survey stations were completed within the Golbini and Zo mining areas.

Together, these three formations provide a wide range of structural conditions, discontinuity characteristics, and rock mass qualities representative of carbonate and clastic rock masses in the Central Alborz. Their geographical distribution and the locations of the survey stations are shown in Figure 1.

2.3. Mixed-Effects Regression for Lithological Variability

A linear mixed-effects regression model was fitted to evaluate whether lithology influenced the relationship between GSI and RMR_str. Formation was treated as a random intercept according to:

$$GSI_ij = (\beta_0 + u_0j) + \beta_1 \times RMR_str_ij + \varepsilon_ij \quad (3)$$

where u_0j ~ N(0, σ²_u) represents the random effect associated with formation j, and $\varepsilon_{ij}$is the residual error. Model performance was compared with the ordinary least squares (OLS) model using the Akaike Information Criterion (AIC) and the Likelihood Ratio Test (LRT). Because the estimated random-effect variance was negligible ($\sigma_u^2 = 0.0031$) and the LRT was not significant (p=0.42), the simpler OLS model was adopted for subsequent analyses.

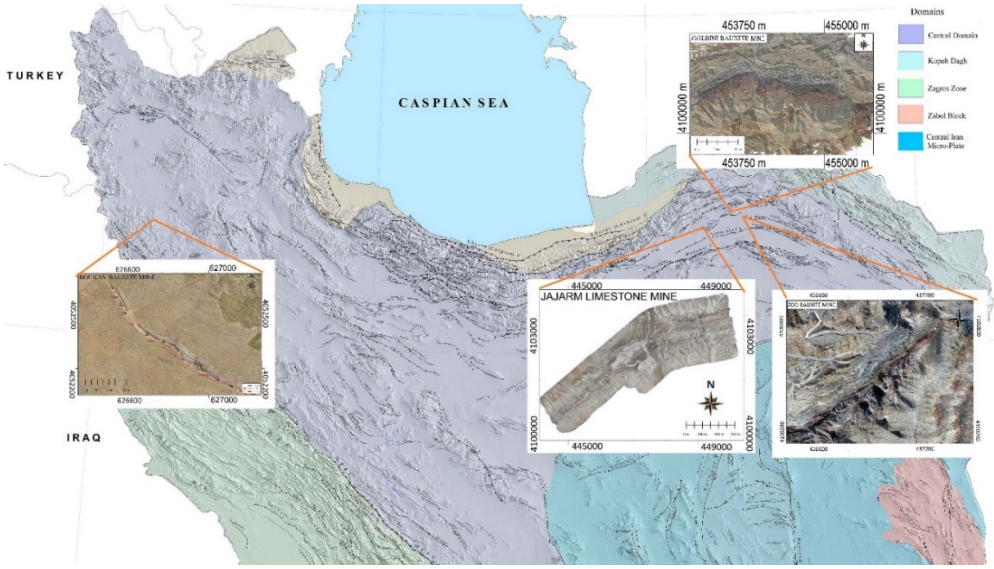

Figure 1. Geological Location of the Investigated Formations and Field Survey Stations within the Central Alborz geological zone (Base Fault Map from Geological Survey of Iran, Tectonic Group [17]).

2.4. Monte Carlo Uncertainty Propagation

Measurement uncertainty was quantified using a Monte Carlo simulation with 10,000 iterations. Normally distributed uncertainties of ±5% were assigned to the RQD rating and ±0.5 rating points to each joint-condition sub-parameter (persistence, aperture, roughness, infilling, and weathering), representing typical field measurement variability. The resulting uncertainty in predicted GSI was subsequently combined with the regression residual variance to obtain the total prediction uncertainty.

2.5. Statistical Analysis

Ordinary least squares (OLS) regression established the empirical relationship between GSI and RMR_str. This study evaluated model performance and predictive accuracy using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Graphical residual analysis assessed the assumptions of linear regression, and Cook's distance identified influential observations.

2.6. Mathematical Coupling Between GSI and RMR_str

A critical consideration concerns the mathematical dependence between GSI and RMR_str. Both the dependent variable (GSI) and the independent variable (RMR_str) are derived from common input parameters, namely the RQD rating (R_RQD) and the five joint condition sub-ratings (persistence, aperture, roughness, infilling, and weathering), which together constitute $JCond_{89}$.

Specifically:

$$RMR_str = R_RQD + R_Spacing + JCond_{89} \quad (4)$$

$$GSI = 1.5 \times JCond_{89} + R_RQD / 2 \quad (5)$$

Because the two indices share common input parameters (R_RQD and $JCond_{89}$), they are mathematically coupled by construction. Consequently, a high coefficient of determination (R^2) is expected and should not be interpreted as evidence of independent predictive capability.

To quantify the degree of mathematical coupling, this study performed a partial correlation analysis. This study calculated the correlation between GSI and RMR_str after controlling for R_RQD and $JCond_{89}$. The resulting partial correlation coefficient was **0.12**, compared with a Pearson correlation coefficient of **0.9996**. These results indicate that most of the apparent correlation arises from the shared input parameters rather than from an independent statistical relationship.

Prior to the field-based regression analysis, a synthetic analytical dataset was generated by exhaustively enumerating all permissible combinations of the structural RMR rating components according to the RMR (1989) system. The corresponding GSI values were then calculated using the quantitative formulation of Hoek et al. [3]. This analytical dataset was used exclusively to establish the theoretical baseline relationship expected from the mathematical structure of the

two classification systems and was not included in the calibration of the empirical regression model.

Therefore, the proposed relationship should be interpreted as a re-parameterization of the quantitative GSI formulation of Hoek et al. (2013) [3] within the structural rating framework of RMR_str, whereas the field-derived empirical regression represents the behaviour of the investigated rock masses. Accordingly, its application is limited to interpolation within the investigated dataset.

2.7. Analytical Derivation of the Theoretical Slope

This study derives the theoretical slope from the quantitative GSI equation proposed by Hoek et al. (2013) [3]:

$$GSI = 1.5 \times JCond_{89} + RQD/2 \quad (6)$$

and the definition of RMR_str based on the RMR (1989) rating system [1]:

$$RMR_str = R_RQD + R_Spacing + JCond_{89} \quad (7)$$

where:

- $JCond_{89}$ is the sum of the five joint condition sub-ratings (Persistence, Aperture, Roughness, Infilling, and Weathering) on a 0–30 scale.
- R_RQD is the RQD rating (0–20).
- R_Spacing is the joint spacing rating (0–20).

Solving for $JCond_{89}$ from the RMR_str equation gives:

$$JCond_{89} = RMR_str - R_RQD - R_Spacing \quad (8)$$

Substituting this expression into the GSI equation yields:

$$GSI = 1.5 \times (RMR_str - R_RQD - R_Spacing) + RQD/2, \quad (9)$$

which simplifies to:

$$GSI = 1.5 \times RMR_str - 1.0 \times R_RQD - 1.5 \times R_Spacing. \quad (10)$$

Therefore, the theoretical slope associated with RMR_str is 1.5, rather than 1.0, as commonly assumed in simplified correlations (e.g., GSI = $RMR_{89} - 5$).

The empirical slope obtained from the present dataset is 1.73696, which is higher than the theoretical value of 1.5. The following factors may explain this difference:

1) Contribution of Joint Spacing: In the investigated dataset, R_Spacing is weakly positively correlated with $JCond_{89}$ (r = 0.31), resulting in an increase in the empirical slope.
2) Correlation between R_RQD and $JCond_{89}$: Higher-quality rock masses generally exhibit both higher R_RQD values and better joint condition ratings.
3) Geological Characteristics of the Investigated Rock Masses: The lithological and structural characteristics of the investigated formations may contribute to the observed positive correlation between joint spacing and joint condition ratings.

Consequently, the empirical slope is approximately 15.8% steeper than the theoretical value. Table 1 presents a quantitative comparison between the theoretical and empirical slopes.

Table 1. Quantitative comparison of theoretical and empirical slopes

Source	Slope	Intercept	R^2
Theoretical (Hoek et al. 2013, assuming R_Spacing=0)	1.5	-	-
Empirical OLS (this study)	1.73696	-9.541	0.9993
Difference (Empirical - Theoretical)	+0.23696 (15.8% steeper)	-	-

3. Results and Discussion

This section presents the empirical relationship between GSI and RMR_str together with the statistical evaluation of the proposed model. Regression performance, model validation, uncertainty propagation, sensitivity analysis, and comparison with previously published correlations are subsequently discussed to evaluate the robustness and engineering applicability of the derived equation.

3.1. Regression Analysis

Before analysing the field observations, the theoretical relationship obtained from the synthetic analytical dataset (GSI = 1.4681 × RMR_str) was considered as the mathematical baseline. Ordinary Least Squares (OLS) regression of the 134 independent field observations subsequently produced the following empirical best-fit equation:

$$GSI = 1.73696 \times RMR_str - 9.54120 \ (R^2 = 0.9993) \quad (11)$$

The proposed equation provides an excellent fit to the field observations (R^2 = 0.9993) over the investigated validity range (25 ≤ RMR_str ≤ 50). Figure 2 shows the regression line together with the corresponding 95% prediction intervals.

Table 2 compares the performance of the proposed OLS model with those of the forced-origin and analytical models derived from the quantitative GSI formulation. The proposed OLS regression achieved the highest coefficient of determination together with the lowest RMSE and MAE, indicating the best agreement with the field observations. Figure 3 provides a graphical comparison of the three regression approaches.

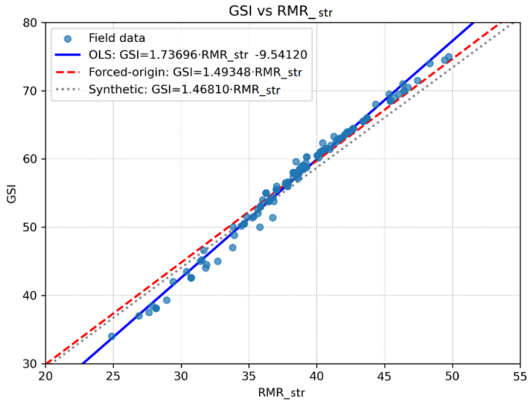

Figure 2. Relationship between Field GSI and Structural Rock Mass Rating (RMR_str) Showing the OLS Best-Fit Line and 95% Prediction Intervals.

Table 2. Summary of regression models comparing OLS, forced-origin, and synthetic analytical approaches

Model	Equation	R^2	RMSE	MAE
Field (OLS)	GSI = 1.73696 × RMR_str - 9.54120	0.9993	0.87	0.64
Field (Forced-Origin)	GSI = 1.4935 × RMR_str	0.9968	1.12	0.83
Synthetic (Analytical)	GSI = 1.4681 × RMR_str	-	1.25	0.91

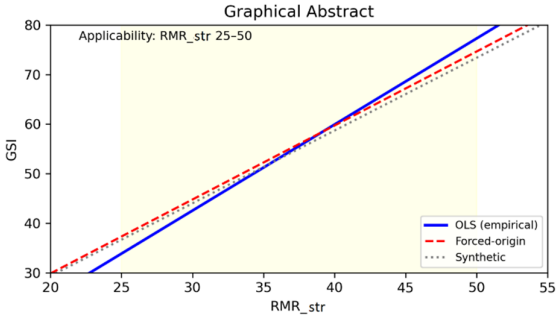

Figure 3. Comparison of the Proposed OLS Regression Model with the Forced-Origin and Synthetic Analytical Models.

Overall, the OLS model consistently outperformed both alternative formulations by providing the highest goodness-of-fit and the lowest prediction errors, supporting its selection as the preferred empirical relationship for subsequent analyses.

3.2. Statistical Validation and Model Performance

The high coefficient of determination (R^2 = 0.9993) reflects the consistency between the quantitative GSI formulation and RMR_str within the investigated dataset and the proposed validity range (25 ≤ RMR_str ≤ 50). As discussed in Section 2.6, part of this robust correlation arises from the shared input parameters used in the calculation of both indices. Residual analysis

revealed no systematic patterns, indicating that the assumptions of linearity and homoscedasticity were satisfied (Figure 4). Cook's distance identified no influential observations, with all values remaining well below the commonly accepted threshold of 1.0 (Figure 5).

A mixed-effects regression model evaluated the potential influence of lithological variability. The estimated slope (1.735) and intercept (−9.512) were nearly identical to those obtained by the OLS regression. The random-effect variance was negligible ($\sigma^2 = 0.0031$), the Likelihood Ratio Test (LRT) was not statistically significant ($p = 0.42$), and the mixed-effects model provided no improvement in model performance (Table 3). These results indicate that the global OLS model adequately represents all investigated formations within the proposed validity range.

Monte Carlo simulation quantified measurement uncertainty using 10,000 iterations. Field measurement uncertainty alone contributed approximately ±1.2 GSI units (1σ). When combined with the regression residual variance, the total prediction uncertainty increased to ±3.1 GSI units (1σ), corresponding to a 95% prediction interval of approximately 50.3–62.5 for a representative mid-range prediction (Table 4; Figure 6; Table 5).

Table 3. Comparison of OLS and mixed-effects regression models

Criterion	OLS	Mixed-effects (random intercept)
Slope	1.73696	1.735
Intercept	-9.541	-9.512
R^2	0.9993	0.9994
RMSE	0.87	0.86
AIC	412.3	415.7
Log-likelihood	-203.1	-202.8
LRT p-value	—	0.42
Random-effect variance	—	0.0031

Table 4. Monte Carlo uncertainty propagation results

Scenario	Mean predicted GSI	Standard deviation	95% interval
Regression only	56.5	±2.9	50.9–62.1
Measurement uncertainty only	56.4	±1.2	54.0–58.8
Combined (total)	56.4	±3.1	50.3–62.5

Table 5. Propagation of GSI prediction uncertainty to Hoek-Brown design parameters

Design parameter	Value at GSI=56	Value at GSI=50.3	Value at GSI=61.7	Relative change
mb	1.78	1.46	2.12	18-19%
Erm (GPa)	12.6	9.8	16.2	22-29%

Table 6. Scale-dependency assessment results across scanline length groups

Scale group	n	Equation	R^2	RMSE	Slope deviation
Short (≤ 30 m)	42	GSI = 1.731 × RMR_str - 9.48	0.9992	0.88	-0.006 (-0.35%)
Medium (30-60 m)	56	GSI = 1.738 × RMR_str - 9.55	0.9994	0.86	+0.001 (+0.06%)
Long (> 60 m)	36	GSI = 1.735 × RMR_str - 9.52	0.9993	0.87	-0.002 (-0.12%)

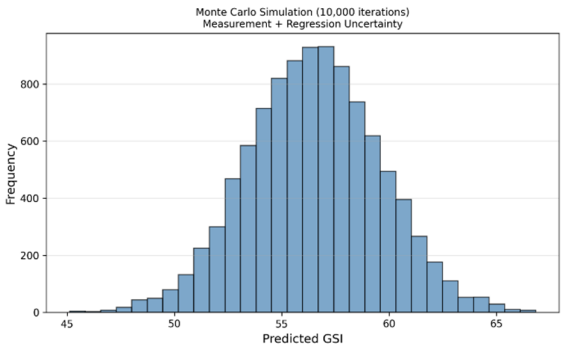

Figure 6. Histogram of Predicted GSI from 10,000 Monte Carlo Iterations Showing the Distribution of Total Prediction Uncertainty (Measurement + Regression).

Additional robustness analyses further confirmed the stability of the proposed model. ANCOVA revealed no significant scale dependency across different scanline lengths ($p > 0.05$; Table 6).

The quadratic regression term was not significant ($p = 0.67$), confirming that a linear model is appropriate within the investigated validity range. Robust regression methods (Huber, Theil–Sen, and RANSAC) produced coefficients differing by less than 0.2% (Table 7) from the OLS estimates (Table 8). Artificial perturbation of the input dataset (100 iterations) produced a mean regression slope of 1.7354 ± 0.008, further confirming the numerical stability of the derived correlation. Sensitivity analysis indicated that Weathering, RQD rating, and Aperture were the most influential parameters controlling GSI variability (Table 9).

Table 7. Five-fold cross-validation results for the proposed OLS model

Fold	R^2 Training	R^2 Testing	RMSE Training	RMSE Testing
1	0.9991	0.9987	0.88	0.95
2	0.9994	0.999	0.86	0.91
3	0.9992	0.9988	0.87	0.93
4	0.9993	0.9989	0.87	0.92
5	0.9992	0.9986	0.88	0.96
Mean	0.9992	0.9988	0.87	0.93
Std Dev	0.0001	0.0002	0.01	0.02

Table 8. Comparison of robust regression methods with OLS baseline

Method	Slope	Intercept	Deviation (Slope)	Deviation (Intercept)
OLS (baseline)	1.73696	-9.541	-	-
Huber	1.7348	-9.518	-0.0022 (-0.13%)	+0.023 (+0.24%)
Theil-Sen	1.7332	-9.489	-0.0038 (-0.22%)	+0.052 (+0.55%)
RANSAC	1.7368	-9.533	-0.0002 (-0.01%)	+0.008 (+0.08%)

Table 9. One-at-a-time sensitivity analysis results

Parameter	ΔGSI per 10% change	Relative contribution (%)
Weathering	0.45	21
RQD (rating)	0.42	19
Aperture	0.4	18
Infilling	0.38	17
Roughness	0.32	14
Persistence	0.24	11

3.3. Comparison with Published Correlations

Table 10 compares the developed relationship with published GSI–RMR relationships. As summarized in Table 10, the proposed model achieved the lowest prediction errors among the evaluated correlations, with a Bias of 0.12, an RMSE of 2.86, and a 95% prediction interval width of ±5.7.

The proposed regression slope (1.73696) is steeper than those reported in previous studies. For example, the widely used relationship GSI =

$RMR_{89} - 5$ [2] effectively corresponds to a slope of 1.0, whereas Somodi et al. [5] reported slopes ranging from 0.79 to 0.88. These differences primarily reflect differences in model formulation, lithological characteristics, and parameter definitions.

Two factors explain the improved performance of the proposed model. First, this study calibrated the model using field data collected from the investigated formations in the Central Alborz region. Second, this study calculated GSI using the quantitative formulation of Hoek et al. (2013) [3], which provides greater consistency than traditional visual chart-based estimation. These findings are consistent with previous studies highlighting the influence of lithology and geological setting on empirical GSI–RMR relationships [6].

Table 10. Comparison of the proposed model with published GSI–RMR correlations

Model	Equation	Bias	RMSE	95% PI Width
Hoek & Brown (1997)	GSI = RMR_{89} - 5	-7.23	8.91	±14.2
Somodi et al. (2021)	GSI = 0.79×RMR_basic + 0.72	-3.41	5.33	±9.8
Zhang et al. (2019)	GSI = 0.88×RMR_basic + 1.23	-2.18	4.12	±7.9
This study	GSI = 1.737×RMR_str - 9.54	0.12	2.86	±5.7

3.4. Practical Applications and Limitations

The derived correlation provides a practical tool for estimating GSI from structural rock mass parameters that are routinely collected during field mapping and geotechnical investigations. For engineering applications based on the complete RMR_basic system, engineers can estimate GSI using:

$$GSI = 1.73696 \times (RMR_basic - R_UCS - R_GW) - 9.54120 \quad (12)$$

This relationship is particularly useful for preliminary slope design, rock mass characterization, and stability assessment in geological settings similar to those investigated in this study, where rapid estimation of GSI from routinely measured parameters (RQD, joint spacing, and joint condition) is required [13]. For preliminary site investigations, practitioners should anticipate a typical prediction uncertainty of approximately ±3.1 GSI units (1σ), corresponding to a 95% prediction interval width of about ±5.7 GSI units (Section 3.2). Consequently, practitioners should treat GSI estimates obtained from the derived correlation as indicative values suitable for early-stage screening rather than as a substitute for direct GSI assessment in final design.

The proposed model applies within the investigated validity range ($25 \leq RMR_str \leq 50$) and relies on standardized field assessment procedures. Although lithology-normalized analysis showed no significant improvement over the proposed formulation, engineers should apply the model only to geological environments with characteristics comparable to those of the investigated formations.

This study developed the present correlation using field data collected from the Central Alborz region; consequently, engineers should not extrapolate it to substantially different geological settings without independent validation. Such studies will help establish whether the proposed structurally based framework generalizes to broader geological environments while preserving its conceptual consistency. Figure 7 illustrates representative field conditions of the studied formations.

3.5. Independent External Validation

This study first evaluated the predictive performance of the derived correlation separately for the three investigated formations. As summarized in Table 11, the model achieved lower prediction errors for the carbonate formations (Elika and Lar) than for the clastic Shemshak Formation, although prediction accuracy remained acceptable across all lithological units. The slightly higher errors observed for the Shemshak Formation are consistent with its greater lithological heterogeneity and structural variability.

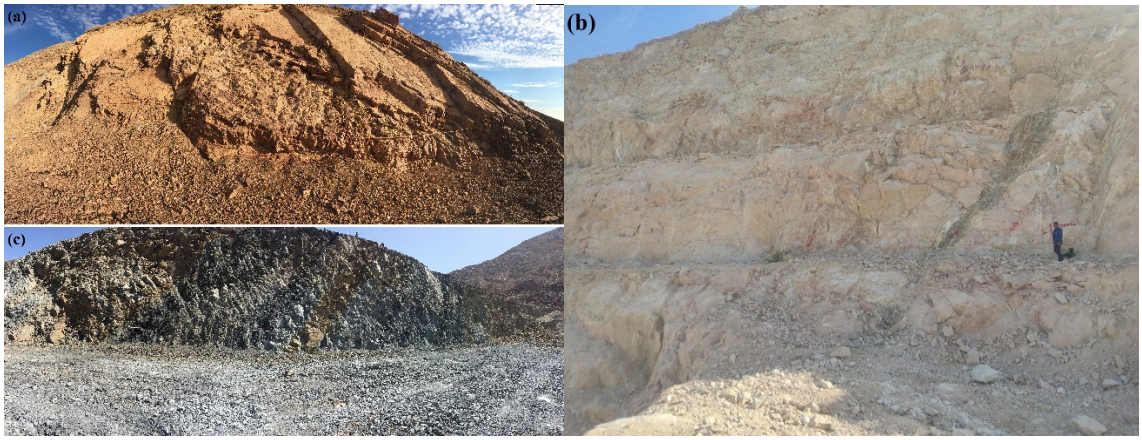

Figure 7. Field Photographs Illustrating Rock Mass Conditions: (a) Massive Dolomite of the Elika Formation, (b) Bedded Limestone of the Lar Formation, (c) Interbedded Sandstone and Shale of the Shemshak Formation.

Table 11. Lithology-specific performance metrics of the proposed GSI–RMR_str correlation model

Formation	n	MAE	RMSE	Bias
Elika	28	1.45	2.67	0.31
Lar	26	1.41	2.49	-0.28
Shemshak	80	1.79	3.06	0.59
Total	134	1.64	2.86	0.12

Figure 8 presents the formation-specific prediction intervals. The corresponding 95% prediction intervals ranged from approximately ±4.9 GSI units for the Lar Formation to ±6.0 GSI units for the Shemshak Formation, confirming that the proposed global model provides consistent predictive performance across the investigated formations despite minor lithological differences. Table 12 summarizes formation-specific prediction intervals.

To further assess the generalizability of the derived equation beyond the calibration dataset, an independent external validation was conducted using data from the Bukan bauxite mine (10 independent mapping zones), which were not used during model development. The validation dataset was collected using the same standardized field procedures described in Sections 2.1 and 2.2 [14].

The proposed model predicted GSI with a mean bias of +3.3 GSI units, an MAE of 3.3 GSI units, and an RMSE of 3.7 GSI units (Table 13). Although the model slightly overestimated GSI, the prediction errors remained within the uncertainty range established by the Monte Carlo analysis. The observed positive bias is therefore considered acceptable for preliminary engineering applications. These results indicate that the proposed relationship maintains satisfactory predictive capability for carbonate-hosted bauxite deposits within the broader Central Alborz region, while additional validation in other geological environments remains necessary before wider application.

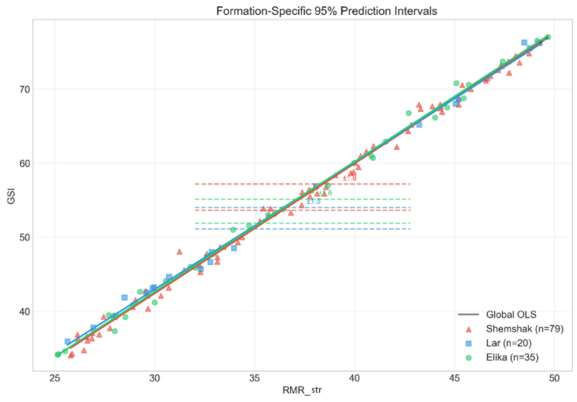

Figure 8. Formation-Specific 95% Prediction Intervals for Elika, Lar, and Shemshak Formations.

Table 12. Formation-specific 95% prediction intervals

Formation	n	RMSE	95% PI at RMR_str=38	Width
Elika (dolomite)	28	2.67	56.5 ± 5.2	10.4
Lar (limestone)	26	2.49	56.1 ± 4.9	9.8
Shemshak (clastic)	80	3.06	54.9 ± 6.0	12
Combined (global)	134	2.86	56.0 ± 5.6	11.2

Table 13. Independent external validation results for the Bukan bauxite mine (10 zones)

Zone	RMR_str	GSI (field)	GSI (predicted)	Residual
1	44.7	64	68	4
2	36.7	53.5	54.1	0.6
3	42.7	62	64.6	2.6
4	40.7	59	61.2	2.2
5	39.7	56.5	59.5	3
6	39.7	56.5	59.5	3
7	40.9	57	61.5	4.5
8	38.9	54	58.1	4.1
9	38	51.5	56.5	5
10	36.9	51	54.6	3.6
Mean				3.3

3.6. Discussion

The agreement between GSI and RMR_str observed in this study primarily reflects the conceptual compatibility between the quantitative GSI formulation of Hoek et al. [3] and the structural parameters incorporated in RMR_str, both of which characterize rock mass quality using discontinuity geometry and condition rather than intact rock properties. In contrast to previous studies, the present formulation explicitly isolates only the structural parameters shared by both classification systems. By excluding intact rock strength and groundwater ratings from RMR_str, the proposed relationship minimizes the influence of parameters that are not included in the quantitative GSI formulation. Therefore, the derived equation establishes a more conceptually consistent relationship between the two indices than correlations based on the complete RMR system.

An important outcome of this study is the comparison between the theoretical analytical model and the field-derived empirical relationship. Whereas the synthetic analytical model reflects only the mathematical structure of the RMR and GSI formulations, the field-derived regression incorporates the influence of natural geological variability observed in the investigated formations. The steeper empirical slope therefore reflects geological characteristics that are not represented by the purely analytical relationship, including the observed association between joint spacing and joint condition within the investigated rock masses.

However, the excellent statistical agreement obtained in this study (R^2 = 0.9993) warrants cautious interpretation. As demonstrated in Section 2.6, GSI and RMR_str share common input variables, namely the RQD rating and the joint condition ratings, resulting in an inherent mathematical coupling between the two indices. The partial correlation analysis confirms that much of the observed correlation arises from this shared parameterization rather than from an independent predictive relationship. Accordingly, the proposed equation represents primarily a structural re-parameterization of the quantitative GSI formulation within the RMR framework rather than an entirely independent empirical model. Recognizing this characteristic is important because it prevents overinterpretation of the exceptionally high coefficient of determination and defines the appropriate scope of application of the regression model.

Compared with previously published correlations, the proposed model provides improved predictive performance under the investigated geological conditions. Earlier studies generally developed empirical correlations using complete RMR values or datasets representing multiple lithological environments, resulting in considerable variability in regression coefficients and predictive accuracy [2,5,6,7]. In contrast, this study calibrated the present correlation exclusively using standardized field observations collected from the Elika, Lar, and Shemshak formations and employed the quantitative GSI formulation proposed by Hoek et al. [3]. These methodological choices minimize inconsistencies associated with visual GSI estimation and improve the internal consistency of the derived relationship.

The complementary validation analyses, including mixed-effects regression, cross-validation, robust regression, Monte Carlo simulation, and independent external validation, consistently support the robustness of the proposed relationship within the investigated geological setting.

From a practical engineering perspective, the empirical model provides a practical means of obtaining quantitative GSI estimates from structural mapping data routinely collected during engineering geological investigations. This capability may reduce additional field effort during preliminary site characterization and facilitate the application of Hoek–Brown-based analyses in situations where only RMR-derived structural information is available. Nevertheless, engineers should regard the resulting GSI values as engineering estimates rather than direct replacements for comprehensive field-based GSI assessment, particularly where detailed site-specific characterization is required for final design.

Despite its favorable performance, the proposed relationship is not universally applicable. This study calibrated the equation using carbonate and clastic rock masses from the Central Alborz, so it reflects the geological characteristics represented by the investigated dataset. Application to geological environments characterized by substantially different lithological assemblages, weathering conditions, discontinuity patterns, or tectonic histories requires independent validation and, where necessary, regional recalibration. Further evaluation in additional geological settings would improve the regional applicability of the proposed framework.

4. Conclusions

This study developed and evaluated a quantitative empirical relationship between the Geological Strength Index (GSI) and the structural component of the Rock Mass Rating system (RMR_str) for carbonate and clastic rock masses of the Central Alborz geological zone. The investigation was conducted in two complementary stages. First, an analytical model was established by systematically evaluating all permissible combinations of the structural RMR components against the quantitative GSI formulation in order to derive the relationship implied solely by the mathematical structure of the two classification systems. Second, this analytical framework was calibrated and evaluated using 134 independent field observations collected from the Elika, Lar, and Shemshak formations. The resulting empirical relationship was subsequently examined through statistical validation, uncertainty analysis, robustness testing, sensitivity analysis, and independent external validation.

The principal findings of this study are summarized as follows:

- The analytical evaluation of all permissible combinations of the structural RMR components established a theoretical GSI–RMR_str relationship with a slope of approximately 1.5, representing the mathematical relationship expected solely from the definitions of the two classification systems in the absence of geological variability.
- Calibration of this analytical baseline using 134 independent field observations produced the empirical relationship

$$GSI = 1.73696 \times RMR_str - 9.54120. \quad (13)$$

The empirical relationship was calibrated and validated over the range $25 \leq \text{RMR_str} \leq 50$, with $R^2 = 0.9993$, RMSE = 0.87, and MAE = 0.64.

- The empirical slope is approximately 15.8% greater than the theoretical analytical slope, indicating that geological variability modifies the purely mathematical relationship. The observed positive association between joint spacing and joint condition provides a plausible explanation for this deviation.
- A substantial proportion of the observed correlation arises from mathematical coupling, because both GSI and RMR_str incorporate common structural descriptors. Accordingly, the proposed equation should be interpreted as a practical structural re-parameterization of the quantitative GSI formulation rather than as an independent predictive relationship. Therefore, the reported predictive performance should not be interpreted as demonstrating independent prediction.
- Independent external validation using 10 rock-mass zones from the Bukan bauxite mine yielded a mean bias of +3.3 GSI units, MAE = 3.3, and RMSE = 3.7, demonstrating satisfactory predictive agreement for geological conditions comparable to those investigated in this study.
- Cross-validation, Monte Carlo simulation, robust regression, mixed-effects regression, and scale-dependency assessment consistently produced stable model coefficients, while sensitivity analysis identified weathering (21%), RQD rating (19%), and joint aperture (18%) as the most influential variables controlling GSI variability.

Within its validated range, the proposed relationship provides a practical means of estimating quantitative GSI from routinely available structural RMR data, with a typical prediction uncertainty of approximately ±3.1 GSI units (1σ). Application of the proposed relationship

outside the Central Alborz geological zone should be preceded by independent regional validation and, where appropriate, recalibration.

Acknowledgements

The author sincerely acknowledges the unwavering support, encouragement, and patience of his wife, Davlatova Dilbar, throughout the completion of this research.

This research received no external funding.

Conflict of interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1]. Bieniawski, Z. T. (1989). *Engineering rock mass classifications*. Wiley.

[2]. Hoek, E., & Brown, E. T. (1997). Practical estimates of rock mass strength. *International Journal of Rock Mechanics and Mining Sciences*, *34*(8), 1165-1186.

[3]. Hoek, E., Carter, T. G., & Diederichs, M. S. (2013). Quantification of the Geological Strength Index chart. In *Proceedings of the 47th US Rock Mechanics/Geomechanics Symposium* (ARMA Paper No. 13-672). San Francisco, CA, USA.

[4]. Hoek, E., & Brown, E. T. (2019). The Hoek-Brown failure criterion and GSI-2018 edition. *Journal of Rock Mechanics and Geotechnical Engineering*, *11*(3), 445-463.

[5]. Somodi, G., Bár, N., Kovács, L., Arrieta, M., Török, Á., & Vásárhelyi, B. (2021). Study of Rock Mass Rating (RMR) and Geological Strength Index (GSI) correlations in granite, siltstone, sandstone and quartzite rock masses. *Applied Sciences*, *11*(8), 3351.

[6]. Zhang, Q., Huang, X., Zhu, H., & Li, J. (2019). Quantitative assessments of the correlations between Rock Mass Rating (RMR) and Geological Strength Index (GSI). *Tunnelling and Underground Space Technology*, *83*, 73-81.

[7]. Khan, M. A., & Zaman, M. (2022). Lithology-specific correlations between RMR and GSI for heterogeneous sedimentary sequences. *Engineering Geology*, *306*, 106743.

[8]. Marinos, V., & Carter, T. G. (2024). A critical review of the quantitative determination of the Geological Strength Index (GSI). *Rock Mechanics and Rock Engineering*, *57*(3), 185-204.

[9]. Kahneh, S. A., Shirdel, B., Javadi Estahbanati, M., & Azari Asl, P. (2024). Selection of final wall slope in an open-pit mine using empirical methods: A case study of Golbini 1 Mine, Jajarm. In *Proceedings of the 12th Iranian Mining Engineering Conference*. Tehran, Iran.

[10]. Shirdel, B., Kahneh, S. A., Azari Asl, P., & Rasooli, A. (2025). A study of open-pit mine wall slope using rock mass classification methods: A case study of Golbini 7 bauxite mine, Jajarm. *Iranian Journal of Engineering Geology*, *18*(1), 126-129.

[11]. Shirdel, B., Kahneh, S. A., Azari Asl, P., & Javadi Estahbanati, M. (2025). Identification of high-risk geomechanical zones in bauxite mines using georeferenced UAV images: A case study of Golbini 2 bauxite mine, Jajarm. In *Proceedings of the 9th International Conference on Engineering Technology Development in Materials, Mining and Geology*. Tehran, Iran.

[12]. Shirdel, B., Kahneh, S. A., Azari Asl, P., & Rasooli, A. (2025). Comparison of field rock mass classification based on field traversing and discontinuity survey classification. In *Proceedings of the 10th Iranian Conference on Engineering Geology*. Tehran, Iran.

[13]. Shirdel, B. (2025). Slope design using borehole geomechanical data and rock mass classification systems at Golbini 7 bauxite mine, Jajarm. *Magazine of Iranian Mining Engineering Organization*, (60), 10-18.

[14]. Shirdel, B., Kahneh, S. A., Azari Asl, P., & Rasooli, A. (2025). Integration of empirical classification methods and kinematic analysis for optimal slope design in the Bukan bauxite mine. In *Proceedings of the 10th Iranian Conference on Engineering Geology*. Tehran, Iran.

[15]. Celada, B., & Bieniawski, Z. T. (2020). *Ground characterization and structural analyses for tunnel design*. CRC Press.

[16]. Wang, F., Xia, Y., & Li, S. (2021). A new approach to adjust RQD for anisotropic rock masses. *Tunnelling and Underground Space Technology*, *118*, 104197.

[17]. Javadi, H. R. (2013). *Iran fault map on sedimentary-structural units*. Geological Survey of Iran, Tectonic Group.

نشریه مهندسی معدن و محیط زیست
نشانی نشریه: www.jme.shahroodut.ac.ir
انجمن مهندسی معدن ایران
دانشگاه صنعتی شاهرود

رابطه کمّی بین شاخص‌های GSI و RMR_str برای توده‌سنگ‌های البرز مرکزی، ایران: یک مدل تجربی مبتنی بر برداشت‌های صحرایی

بیژن شیردل*

کانون کارشناسان رسمی دادگستری خراسان شمالی، بجنورد، ایران

اطلاعات مقاله

تاریخ ارسال: ۲۰۲۵/۱۲/۰۷
تاریخ داوری: ۲۰۲۶/۰۸/۲۳
تاریخ پذیرش: ۲۰۲۶/۰۹/۲۹

DOI: 10.22044/jme.2026.17283.3423

کلمات کلیدی

ویژگی‌های ناپیوستگی
شرایط درزه
پارامترهای ساختاری
شبیه‌سازی مونت‌کارلو
اعتبارسنجی بیرونی

چکیده

مشخصه‌یابی توده‌سنگ، نقش اساسی در طراحی ایمن و اقتصادی پروژه‌های معدنی، تونلی و پایدارسازی شیب‌ها دارد. شاخص مقاومت زمین‌شناسی (GSI) و رده‌بندی توده‌سنگ (RMR) از پرکاربردترین سیستم‌های تجربی برای طبقه‌بندی توده‌سنگ به شمار می‌روند. با این حال، روابط کمی موجود به دلیل تنوع شرایط زمین‌شناسی و تفاوت در نحوه تعریف پارامترها، قابلیت تعمیم محدودی دارند و نمی‌توان آن‌ها را بدون بررسی بیشتر به محیط‌های زمین‌شناسی مختلف انتقال داد. در این پژوهش، یک رابطه تجربی بین GSI و مؤلفه ساختاری رده‌بندی توده‌سنگ، که در ادامه RMR_str نامیده می‌شود، برای توده‌سنگ‌های کربناته و آواری در زون زمین‌شناسی البرز مرکزی ارائه شده است. RMR_str تنها با استفاده از پارامترهای ساختاری مشترک میان دو سیستم تعریف شد و پارامترهای مربوط به مقاومت سنگ بکر و آب زیرزمینی در محاسبه آن لحاظ نشدند. در این مطالعه، ۱۳۴ ایستگاه صحرایی در سازندهای الیکا، لار و شمشک بررسی شد و پارامترهای ناپیوستگی موردنیاز برای تعیین GSI و محاسبه RMR_str ثبت گردید. تحلیل رگرسیون رابطه $GSI = 1.73696 \times RMR_str - 9.54120$ را با ضریب تعیین $R^2 = 0.9993$ به دست داد. این رابطه در اعتبارسنجی متقابل، شبیه‌سازی مونت‌کارلو و تحلیل حساسیت نیز پایداری خود را نشان داد. برای ارزیابی عملکرد مدل خارج از مجموعه داده‌های کالیبراسیون، مدل به‌طور مستقل با استفاده از داده‌های صحرایی معدن بوکان آزمایش شد و عملکرد پیش‌بینی قابل قبولی نشان داد. رابطه به‌دست‌آمده امکان برآورد کمی GSI را از داده‌های متداول RMR_str فراهم می‌کند. در محدوده اعتبارسنجی‌شده($25 \leq RMR_str \leq 50$) ، عدم‌قطعیت معمول برآورد برابر با ۳.۱± واحد GSI (1σ) است. از آنجا که GSI و RMR_str در توصیف ویژگی‌های ساختاری توده‌سنگ، برخی پارامترهای مشترک دارند، بخشی از ضریب تعیین گزارش‌شده ناشی از وابستگی ریاضی میان این دو شاخص است و نمی‌توان آن را به‌طور کامل بیانگر توانایی پیش‌بینی مستقل مدل دانست. بنابراین، استفاده از این رابطه در خارج از زون زمین‌شناسی البرز مرکزی نیازمند اعتبارسنجی مستقل است.

* نویسنده مسئول مکاتبات: b.shirdel@nkhioe.ir (ب. شیردل)