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Correlation Analysis of RMR and Q Systems in Himalaya Rock Mass Conditions: A Case Study of Seti-khola Hydropower Project, Nepal

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Abstract

Rock mass classification systems such as Q, Rock Mass Rating (RMR), and Geological Strength Index (GSI) are widely applied in Himalayan tunneling to assess excavation and support requirements. This study aims to establish an empirical relationship between RMR and Q values based on 934 field observations collected from the 3.1 km-long headrace tunnel of the Seti Khola Hydropower Project (22 MW) in western Nepal. Multiple regression models—linear, logarithmic, exponential, and power—were applied to the categorical and overall dataset, and their performance was assessed using standard statistical indicators (R^2, MAE, RMSE, and MAPE). The logarithmic model emerged as the most suitable, revealing a moderate but meaningful correlation that better captures the non-linear scaling behavior between Q and RMR. These findings offer improved compatibility and cross-interpretability between classification systems in Himalayan geological settings.

Keywords: *Q-system, Rock mass, RMR.*

1. Introduction

Rock mass classification methods like the NGI-index Q system (Barton et al., 1974), Rock mass rating (RMR) (Bieniawski, 1989), and Geological Strength Index (GSI) (Hoek et al., 1995) are famed approaches in underground space industries for figuring out the rock mass parameters and tunnel support work. In the context of Nepal Himalaya, Q and RMR systems have been most frequently used and practiced in underground excavation design and support work (Shrestha & Panthi, 2013).

Most existing classification systems were developed from civil engineering case histories adopted from Europe, America, and Oceania (Palmström & Broch, 2006). The attention to detail is that various classification systems take on multiple factors, and the rating levels for these parameters vary from one classification system to another. Due to the varying nature of the classification system, at least two methods should be used at any site during the early stages of a project. Classification by two approaches yields in lucid picture of the rock mass characteristics and its properties. This guides tunnel engineers/ geologists in safe excavation methods and support systems in tunnel construction by predicting the behavior of the rock mass. On the other hand, understanding the rock's quality helps estimate the volume of reinforcement and support needed. Classifying rock masses helps identify potential hazards like rock falls, collapses, or deformation, enabling preventive measures (Hoek & Brown, 1997). Reinforcement strategies like bolting, shortcrete, or concrete lining, and challenging environments associated with these measures are better rectified (Barton, 2002). Due to the clinical uses of the classification system, it has always proven to be a means of consistent communication between engineers, geologists, and contractors.

In general, a link between the Rock Mass Rating (RMR) and the Q-system is needed for consistency, comparison, and real-world use in rock engineering. Although they have different approaches, specifications, and uses, both systems are frequently employed for classifying rock masses. The correlation of these systems makes better comprehension, interoperability, and decision-making in underground or subsurface projects possible.

2. Project Features and Geology

The Seti Khola Hydropower Project is a 22 MW run-of-river plant designed to generate 133.43 GWh annually using a 40 m^3/s flow and 68 m gross head. Water is diverted at 585 m elevation into desanders, then carried through a 3.1 km headrace tunnel to a surge tank and penstock, leading to a powerhouse at 518 m elevation. Three horizontal Francis turbines generate power, which is evacuated via a 1.5 km, 132 kV LILO transmission line to the Lekhnath–Damauli grid.

The Pokhara Valley, situated in the Midlands of the Lesser Himalaya, is bordered by hill formations primarily made up of low-grade metamorphic rocks assigned to the Kuncha Formation—one of the most ancient geological units in the Lesser Himalaya. These rocks mainly consist of variable phyllites, quartzites, and meta-sandstones, reflecting differing degrees of metamorphism. Roughly 19 km to the north, the Main Central Thrust (MCT) passes near Hemja and Karkineta, while the Main Boundary Thrust (MBT) lies about 45 km to the south of the area. The geological setting at the site features intensely deformed and foliated rock masses, with prominent structural patterns such as nappe formations and klippen (Panthi & Basnet, 2023).

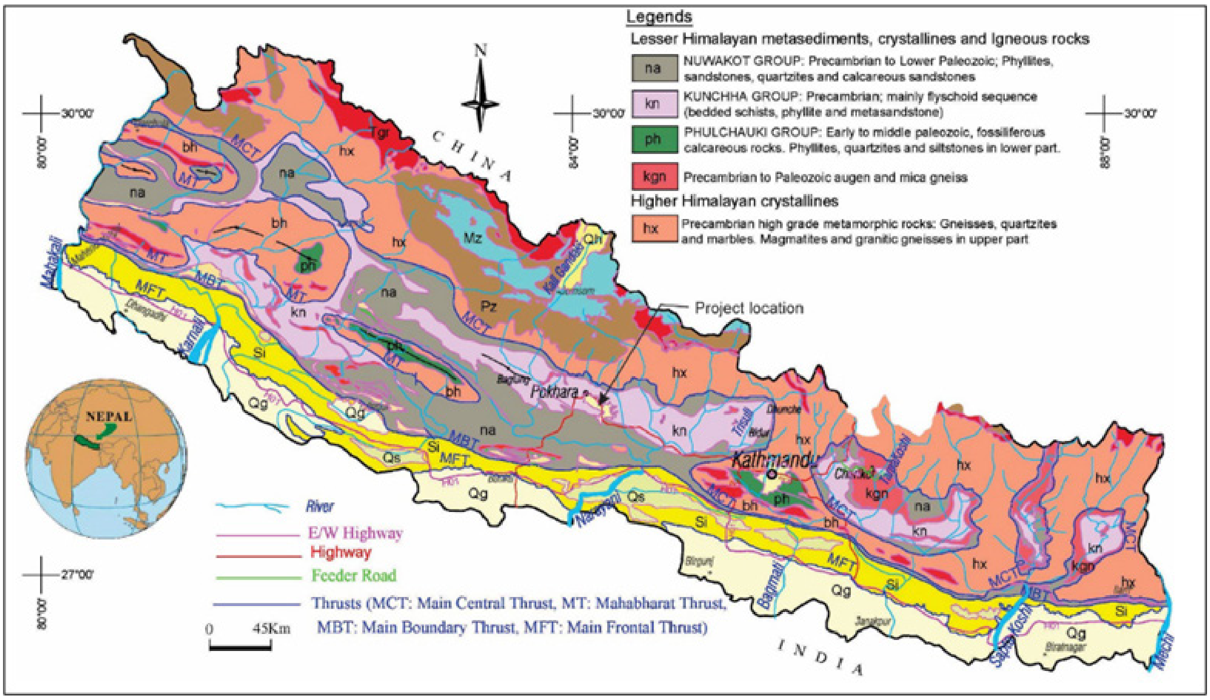

Figure 1: Geological location of the project (Panthi & Basnet, 2023)

3. Literature Review

3.1 Rock Mass Classification

Q System

The Q-value describes the rock mass stability of an underground opening in jointed rock masses. High Q-values indicate good stability, and low values mean poor stability (Barton, Lien, & Lunde, 1974). There are six parameters in the Q-system, and these are used to calculate the Q-value of the rock mass. The equation of the Q-system is:

$$Q = \frac{RQD}{jn} * \frac{jr}{ja} * \frac{jw}{SRF}$$

RQD Rock quality designation

Jn = Joint set number

Jr = Joint roughness number

Ja = Joint alteration number

Jw = Joint water reduction factor

SRF Stress reduction factor

RMR-System

This engineering classification system, which was developed by Bieniawski in (1973, 1989) utilizes the following six rock mass parameters:

i. Uniaxial compressive strength of intact rock material.
ii. Rock quality designation (RQD).
iii. Spacing of discontinuities
iv. Condition of discontinuities (Length/persistence, Separation, Smoothness, Infilling, and Alteration/Weathering)
v. Groundwater conditions.
vi. Orientation of discontinuities.

4. Existing Relationship

The Rock Mass Rating (RMR) system and the Q-system are two widely used empirical classification methods in rock engineering for assessing the quality of rock masses. Since both systems are used to evaluate similar characteristics of rock masses, researchers in the past have tried to establish empirical relationships between them to allow for easier comparison and interoperability between projects using different systems. The existing relationship between RMR and Q has been presented below in Table 1

Table 1: Existing relationship between RMR and Q (Source: Chaulagain & Dahal, 2023)

Existing Correlation	Proposed by
RMR = 5.37lnQ + 40.48	Hashemi et al.
RMR = 6.4lnQ + 49.6	Kumar et al.
RMR = 3.7lnQ + 53.1	Sari and Pasamehmetoglu
RMR = 2.8lnQ + 45.19	Cosar
RMR = 4.2 InQ + 50.6	Asgari
RMR = 6.1 InQ + 53.4	Rawlings et al.
RMR = 7lnQ + 36	Tugrul
RMR = 15lnQ +50	Barton

Existing Correlation	Proposed by
RMR = 7lnQ +44	El-Naqa
RMR = 12.11lnQ +50.89	Choquet and Hadjigogiu
RMR = 9lnQ +49	Al-Harthi
RMR = 6.8 InQ+42	Sheorey
RMR = 8.7lnQ + 38	Kaiser and Gale
RMR = 5.3InQ +50.81	Udd and Wang
RMR = 43.89–9.19InQ	Celada Tamames
RMR = 10.5InQ +41.8	Abad et al.
RMR = 7.5InQ +42	Baczynski
RMR = 5InQ +60.8	Cameron-Clerke and Budavari
RMR = 5.4lnQ +55.2	Moreno
RMR = 9InQ +44	Bieniawski

5. Research Methodology

The entire dataset was collected from tunnel face mapping conducted at a drill-and-blast excavated tunnel spanning 2.1 km (Chaulagain & Dahal, 2023). During the face mapping, Rock Mass Rating (RMR) and Q-values were calculated using their respective parameters along the tunnel length. To develop improved correlations and establish geology-specific relationships, the general geological conditions of the tunnels were considered in the analysis. The total length of tunnels was subdivided into two main geological categories, as detailed in the accompanying tables 3 and 4. Different algebraic forms—including linear, exponential, logarithmic, and power equations—were then explored to determine the most appropriate equation demonstrating the strongest correlation and lowest prediction error between RMR and Q values for categorical and overall datasets.

Model accuracy and performance were rigorously evaluated using statistical indices such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2) (Thapa, Ghimire & Bhusal, 2024). Finally, the regression model with the highest coefficient of determination and best overall performance was identified for both datasets, and only the overall dataset was compared against previously published equations from other researchers to validate its applicability within the geological context of this study.

6. Database Study

The descriptive statistics for the dataset, which includes 956 observations, provide insight into the overall quality of the rock mass based on two commonly used classification systems: the Q value and the Rock Mass Rating (RMR). The Q value ranges from 0.01 to 4.17, with a mean of 0.79 and a median of 0.56. These values indicate that the majority of the rock masses fall within the poor to fair quality category, as Q values typically range from around 0.001 (very poor) to 1000 (excellent). The standard deviation of 0.78 suggests a wide spread in rock quality, and the fact that the mean is higher than the median indicates a right-skewed distribution — a few samples have relatively higher Q values, which raise the average.

Similarly, the RMR values in the dataset range from 10 to 60, with a mean of 33.46 and a median of 35. These values also point to predominantly poor rock quality, as per the RMR classification system, where scores between 20 and 40 are considered poor and those between 40 and 60 are considered fair. The standard deviation of 9.55 shows moderate variability in rock mass quality across the dataset.

Overall, both the Q value and RMR statistics suggest that the dataset primarily comprises rock masses in poor condition, with only a limited number of samples exhibiting better quality.

Table 2: Statistical summary of the overall datasets

RMC System	Count	mean	std	min	25%	50%	75%	max
Q	934	0.79	0.78	0.01	0.22	0.56	0.97	4.17
RMR	934	33.46	9.61	10	25	35	41	60

Table 3: Statistical summary of category 1 datasets

Category 1:	RMC System	Count	mean	std	min	25%	50%	75%	max
	Q	636	0.96	0.84	0.01	0.41	0.66	1.1	4.1
Metasandstone/ Slate/Phyllite	RMR	636	34.82	9.51	15	30	36	43	56

Table 4: Statistical summary of category 2 datasets

Category	RMC System	Count	mean	std	min	25%	50%	75%	max
2:Quartzite	Q	140	0.3	0.26	0.03	0.1	0.17	0.5	1.33
	RMR	140	31.64	8.96	10	25	30	35	60

7. Results and Discussion

7.1 Regression analysis for categorical dataset

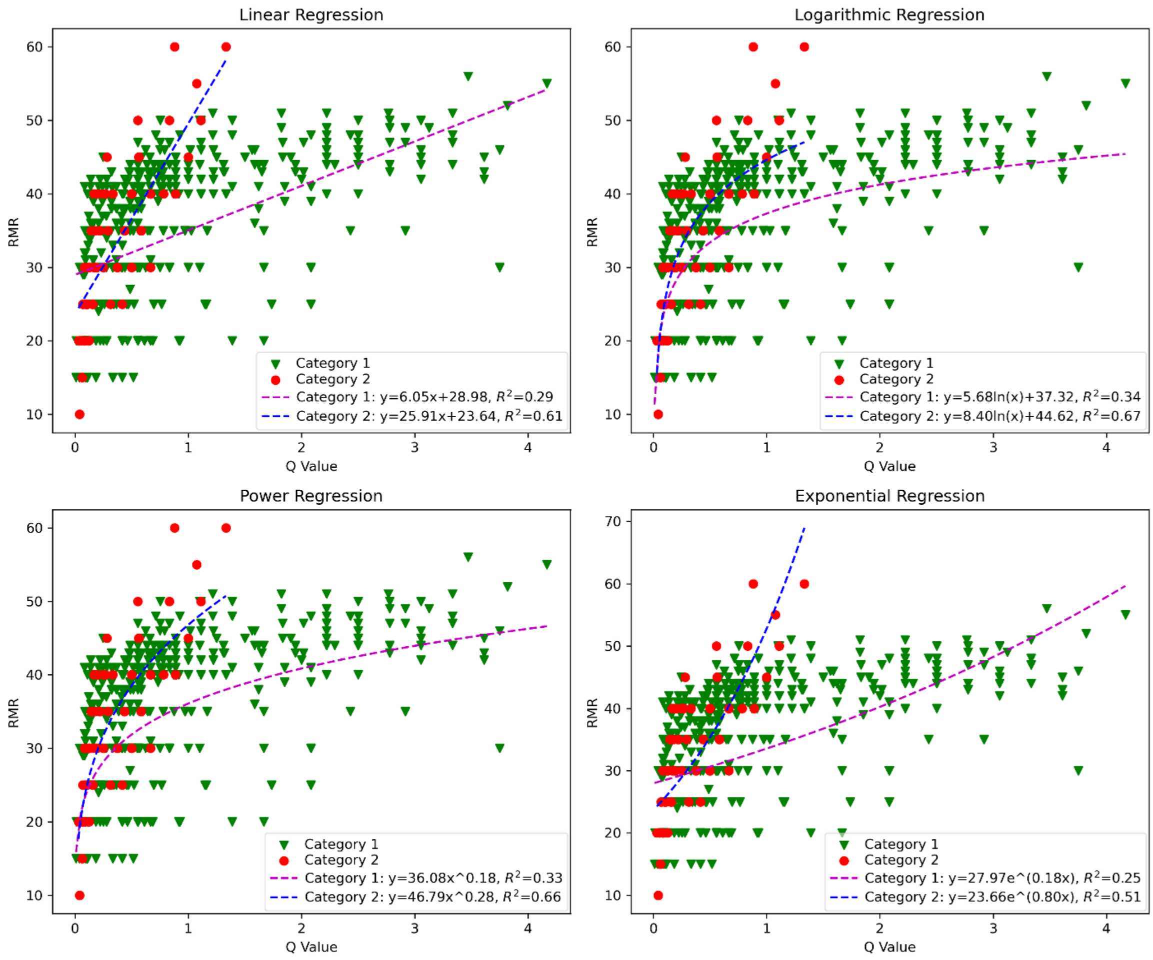

Figure 2: Comparison of regression models in categorical data

Figure 2: presents a comparative analysis of four regression models—linear, logarithmic, exponential, and power—used to assess the relationship between Q Value and Rock Mass Rating (RMR) across two distinct geological categories. The data were divided into Category 1 and Category 2, and regression lines were fitted separately for each. The results reveal significant differences in model performance between the two categories. For Category 1, the linear model demonstrated the best performance, with a relatively high coefficient of determination (R^2 = 0.61) and low error metrics (MAE and RMSE), suggesting that a linear relationship is more appropriate for this group. In contrast, Category 2 showed better alignment with non-linear models. Among these, the logarithmic regression provided the strongest fit (R^2 = 0.67), closely followed by the power model (R^2 = 0.66). Although both non-linear models exhibited higher mean absolute percentage errors (MAPE), they were effective in capturing the overall trend of the data. The exponential model, while producing visually smooth curves, was less reliable due to its tendency to over predict RMR at higher Q values: an outcome that may not be realistic in actual geotechnical conditions. Visual inspection of the plots further supports these findings, showing that for the same Q value, Category 2 tends to have higher RMR values than Category 1, highlighting the influence of geological differences. Additionally, the logarithmic and power models display a tapering effect, where RMR increases at a decreasing rate as Q increases, aligning more closely with expected rock mass behavior. Overall, the analysis underscores the importance of using non-linear models-particularly logarithmic and power functions-when modeling the Q-RMR relationship and highlights the benefits of treating geological categories separately to improve accuracy and interpretability in rock mass classification and engineering applications.

Table 5: Comparison of statistical indices in categorical datasets for different regression models.

Approach	R2	MAE	RMSE	MAPE	Remarks
Linear	0.29	6.68	8	23.02%	Category 1
Logarithmic	0.34	31.57	32.59	89.58%	
Power	0.33	10.12	11.58	27.50%	
Exponential	0.25	6.91	8.23	22.92%	
Linear	0.61	4.45	5.60	16.28%	Category 2
Logarithmic	0.67	29.72	30.87	93.97%	
Power	0.66	22.92	23.58	74.58%	
Exponential	0.51	4.79	5.90	17.09%	

7.2 Regression analysis for overall dataset

The figure 3: illustrates four different regression models: linear, logarithmic, power, and exponential-used to analyze the relationship between Q Value and RMR (Rock Mass Rating) for overall datasets. Each model attempts to describe how RMR changes as a function of Q Value, with varying degrees of accuracy.

The linear regression model assumes a constant rate of change, described by the equation RMR=7.00 Q+27.93. It explains 32% of the variability in RMR (R2=0.32), indicating a moderate but not very strong linear relationship. Similarly, logarithmic regression model, given by RMR=5.75 ln (Q) +37.76, assumes that the increase in RMR slows down as Q increases, fitting the data better with an R2 of 0.44. This suggests that improvements in rock mass quality result in diminishing returns in RMR.

The Power Regression model, represented by RMR=3.61Q0.19, also performs well with an R2 of 0.44, implying a non-linear scaling relationship between Q and RMR, often seen when both variables follow a logarithmic or proportional growth pattern. In contrast, the Exponential Regression model, expressed as RMR=3.29e0.22Q, assumes that RMR increases at an accelerating rate with Q, but it fits the data poorly with an R2 of only 0.27.

Among the tested regression models, the logarithmic model emerged as the most suitable for describing the relationship between Q-value and RMR, exhibiting the highest R^2 (0.44) and lowest MAE (5.75). While the power model showed a slightly lower MAPE, the logarithmic model consistently performed better across most key metrics, indicating stronger explanatory power and predictive accuracy.

These findings suggest that the relationship between Q and RMR is not strictly linear or exponential, but rather follows a curvilinear (scaling) trend. This is particularly important in practical rock engineering applications, where converting between Q and RMR systems is often necessary for design decisions and stability assessments. Adopting a logarithmic approach allows for a more reliable and realistic representation of this empirical relationship under varying geological conditions.

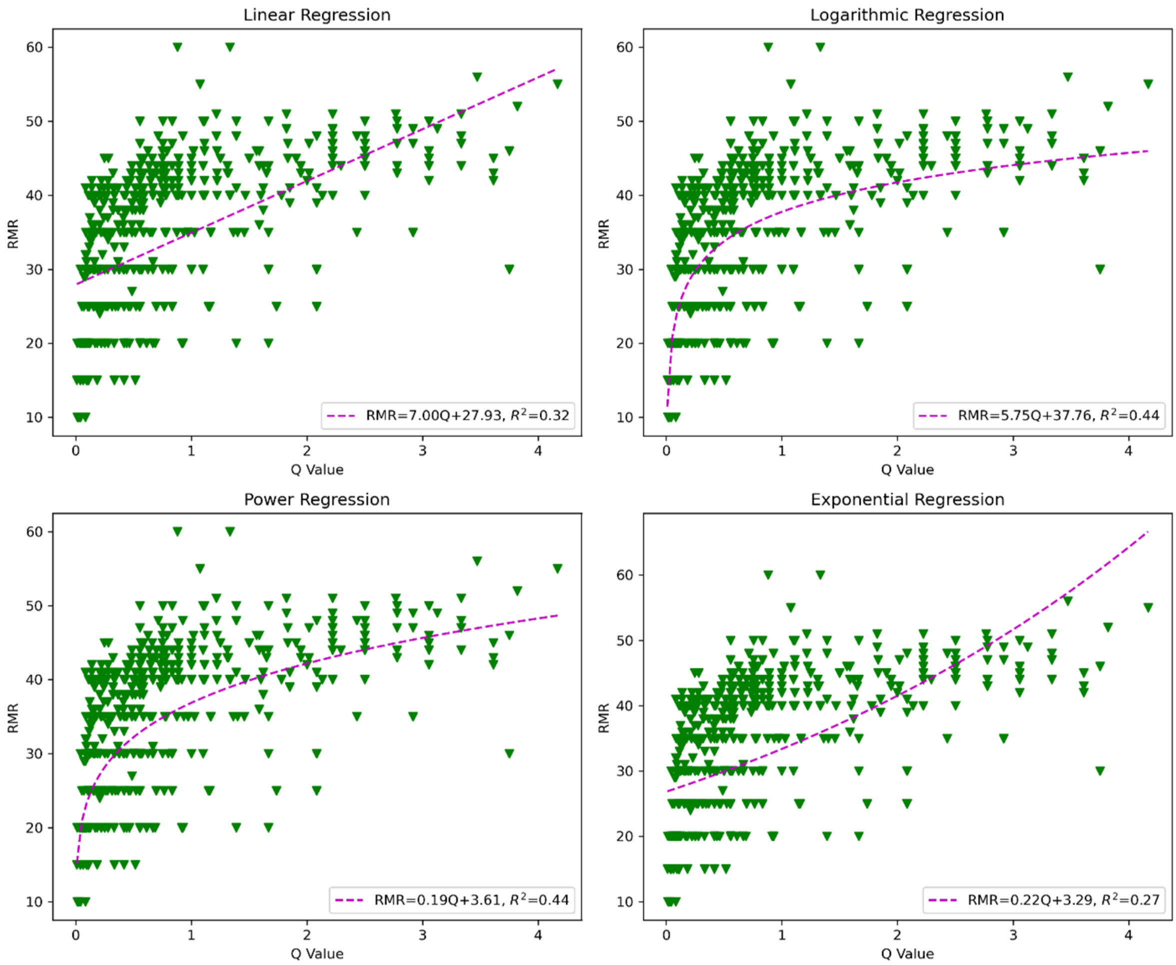

Figure 3: Comparison of regression models in overall data

Table 6: Comparison of statistical indices for different regression models

Regression Model	R^2	MAE	RMSE	MAPE
Linear	0.33	6.45	7.0	23.69%
Logarithmic	0.44	5.75	7.17	20.34%
Power	0.44	5.85	7.28	20.10%
Exponential	0.26	6.80	8.27	23.65%

7.3 Comparative Analysis of Logarithmic Models Relating RMR to Q Value

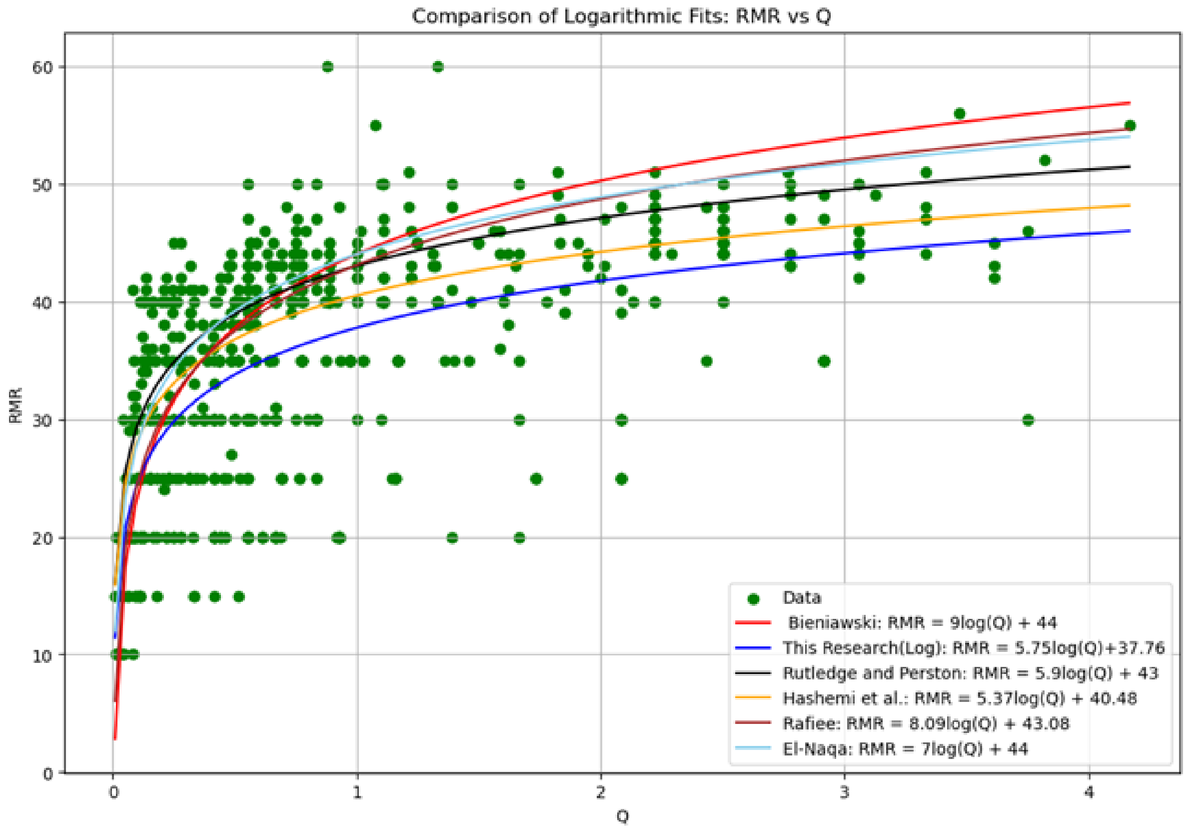

Figure 4: Comparison of the trendline of existing research work with previous research work

Figure 4 presents six logarithmic regression models showing the relationship between Rock Mass Rating (RMR) and Q value, overlaid on green circular data points representing observed measurements. The data show a general positive trend-higher Q values correlate with higher RMR-though with noticeable scatter, suggesting influence from other factors or measurement noise.

All models follow a logarithmic form, with RMR increasing quickly at low Q and tapering off at higher Q. The visual comparison shows that while all models follow the overall trend, none fit all points perfectly, suggesting potential for alternative models or inclusion of more variables. These relationships should be used cautiously in geological settings other than those examined in this study.

8. Conclusions

This study aimed to establish the meaningful correlation between RMR and Q-system from 934 datasets retrieved by tunnel face mapping of Seti hydro-electric project (22 MW). These field data collected were analyzed using linear, exponential, power and logarithmic regression model plotting best fit line that explains the variability in RMR and Q-value of rockmass.The statistical evaluation revealed that among the tested models, the logarithmic regression model provided the best fit for the dataset, with an R^2 value of 0.34 for category 1, R^2 value of 0.67 for category 2 and datasets, and R^2 value of 0.43 for overall datsets indicating that the variation in RMR can be explained by changes in the logarithm of Q . This suggests a moderate correlation between the two parameters, where RMR increases rapidly at lower Q values and then tapers off as Q increases- a typical behavior observed in logarithmic relationships.

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