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ORIGINAL ARTICLE

A series of regression models to predict the weathering index of tropical granite rock mass

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Abstract

In the recent past, several weathering indicators have been developed to describe its state of weathering. The state of rock weathering is a useful indicator to estimate the integrity of tropically weathered rock material and mass which weatherability plays an important role in a tropical region. Through a ground assessment tool, the strength and durability of the rock mass could be estimated and complex or adopted to simplify the early prediction of the complex engineering parameter. This paper presents several models of the Weathering Index (WI) using selected significant parameters using statistical analysis. For this purpose, several sites have been chosen to represent granitic rock mass. Forty (40) numbers of samples were collected and tested comprising from four (4) sites in Malaysia. Several laboratory tests have been conducted such as Point Load Index ($Is_{(50)}$), dry density, Slake Durability 1 (SD1), Slake Durability 2 (SD2) and moisture content. The field and laboratory data sets are used to determine the WI by using simple regression and MLR analysis Significant parameters found to be useful in determining the WI are selected namely SD1, dry density, $Is_{(50)}$, and block volume. These parameters were selected based on stepwise analysis using Statistical Package for the Social Sciences (SPSS). Following the models' implementation, the models were evaluated and the best prediction model was selected after considering statistical coefficients, such as coefficient of determination (R2), variance account for (VAF), and root mean squared error (RMSE), as well as utilizing a straightforward ranking approach. The findings of this study could contribute to the more accurate prediction of WI using a more simplistic field and laboratory parameters. Therefore, the WI is useful during the initial stages and planning of rock excavation work and provides a good description of weathering grade and rock mass properties, which will affect excavatability in granitic areas.

Keywords Granite weathered rock · Bedded · Non-bedded rocks · Multiple linear regression

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Introduction

Weathering is a natural process that occurs and changes the physical, biological, mechanical, and chemical properties of rocks, which is reported by all scholars as a problem for rock structures in the construction of infrastructure such as roads and tunnels. Each of these properties is used to determine the grade of weathering that varies according to the type of rock (Irfan and Dearman 1978a, b; Rocchi et al. 2017; Leão et al. 2019; Tran et al. 2019; Jaques et al. 2020). In this regard, engineers need to consider the level of weathering, especially in physical and mechanical properties because its effect is very significant in rock engineering. However, most engineers are currently inclined toward mineral and chemical weathering (Udagedara et al. 2017; Perri 2020; Román-Sánchez et al. 2021). The effects of weathering caused by physical, mineralogical, and geomechanically processes can be seen in terms of changes in the properties of the material rock index. Studying the effect of weathering processes on all rock types' physical and mechanical properties in a tropical environment is crucial (Tugrul and Gurpinar 1997; Ghiasi et al. 2009; Abad et al. 2015; Tran et al. 2019). Therefore, changes during weathering are important to determine quantitatively. In the case study, the determination of the WI determined based on parameters consisting of rock mass and rock material properties for non-bedded rocks in tropical region was discussed.

The engineering properties of rock have the most important role, allowing engineers to make precise assessments of geotechnical design and construction (Afrazi et al. 2022). In this study, an attempt has been made to estimate the essential parameters of the rock mass and material properties that are widely used in geotechnical projects, which are point load index, slake durability, dry density and block volume (Riazi et al. 2023). Besides that, an attempt to get the best equation of the WI by using significant parameters based on previous studies and related to the background of the study. Durability is an essential parameter that must be considered in the rock's ability to resist degradation and long-term problem prediction, and is a key parameter for classifying rock weathering in an excavatability system (Ceryan et al. 2008a; Arman et al. 2019). Rock durability is also associated with texture (i.e., crystal interlocking, shape and size, area, and perimeter length). Based on the evaluation of the existing excavation system, strength is one of the mechanical characteristics of rock materials that are always considered one of the important factors in determining excavatability (Heidari et al. 2013; Pour et al. 2022; Liang et al. 2015). On the other hand, the vital study of observations on the granite strength affected by moisture content was conducted by Mohamad et al. (2011, 2015), Hasan et al. (2019) in various weathering grades. Although granite is one of the strongest and most durable rocks, it is no exception to the weathering process and effects of moisture content. In recent years, there has been an increasing amount of literature on block size. From the literature review conducted by several scholars, most of them report that the measurement and characteristics of joints in the rock mass is difficult. This is because the continuities found in the rock are irregular and have variations in size and length. Therefore, the block size is more difficult to determine, especially for tropical areas where the weathered rock mass has experienced greater weathering. Blocks of rock found in a rock mass are usually separated and limited by the intersection of several joints. The size of the blocks in the rock mass depends on several factors including the number of discontinuity sets, spacing and persistence that separates the blocks (Palmstrom 2005). Instead, density is a physical property that is commonly used and important as an engineering characteristic of rock mass, affecting mechanical properties (Udagedara et al. 2017). They correlate using a combination of chemical, physical and mechanical in their study, considering the significance of parameters $Is_{(50)}$, Id_2, and density. There are similarities between the attitudes expressed by Leão et al. (2019) in this study which described that density is important in the study of rock mineralogy and is greatly influenced by physical weathering. Baiyegunhi et al. (2014) reported that density is affected by many factors such as mineralogical, porosity, and pore pressure. However, researchers rarely reported this behavior, even though these parameters significantly affect the weathering process (Momeni et al. 2017). The research conducted by Anikoh et al. (2015), investigated the physical–mechanical properties including density, porosity, and strength of granite in their study. Density, degree of weathering, rock quality designation (RQD), cavities, porosity, water absorption, Is(50), and blastability index (BI) are important factors for categorizing rock weathering in an excavatability system.

Over the past 30 years, many researchers have been conducted to study the excavatability of rock mass by considering significant parameters of excavatability. During surface excavation works, indirect methods are more difficult to obtain than direct methods due to the limitations of each. Although extensive research has been conducted on excavatability, no single study exists that adequately covers all important parameters in the tropics. Previous research has established that only one or two parameters are not enough to classify the level of rock weathering in an excavatability classification system (Ceryan et al. 2008a; Gurocak and Yalcin 2016; Jaques et al. 2020). A diggability index was first presented by Karpuz (1990) and considers five classification parameters: weathering, mean of joint spacing, seismic wave velocity (Vp), Schmidt Hardness value, and UCS using regression analysis. This index provides information about the equipment used in the excavation process as well as a rock quality indicator. Considering the diggability, which considers the rock characteristics and the efficiency of the equipment employed, the system is also incredibly thorough. Existing assessments have used various methods including regression analysis and soft computing methods. Basarir et al. (2007) has recommended a rippability system based on Schmidt Hammer parameters, Js, UCS and sonic velocity, by using the fuzzy inference system (FIS) method. The integrated rippability classification system considers both professional judgment and the combined use of the rock and equipment qualities. The main reason fuzzy set theory was chosen is that it effectively handles variable selection uncertainty. On the other hand, the "Diggability Index," which (Iphar and Goktan 2006) developed, took into account the weathering, rock strength, joint spacing, and bedding spacing of the ground. The fundamental ideas of fuzzy set theory were explained, and then the Mamdani fuzzy algorithm was used to apply the fuzzy set theory to one of the traditional classification methods.

Recently, Dagdelenler et al. (2020) created a flexible excavation evaluation (EXCASS) method that involved the two metrics GSI and $Is_{(50)}$ in a study using a combination of statistical-based evaluation. Bhatawdekar Ramesh Maulidhar (2020), researched granite. Tropical weathered rock masses are divided into three categories: massive, blocky, and fractured rock, to make the assessment of development blasting performance easier. The strength qualities, porosity, and water absorption of rocks are the basis for the introduction of the WI. On the other hand, the Block Weathering Index (BWI) is developed using computational models and fictitious values from exploration data. Vidana Pathiranagei et al. (2023) have also created a classification system using the parameters ($I_{s(50)}$), slake durability index (Id_2), density, mineralogy, and microstructure. The engineering attributes of granitic rocks in Iran can be predicted by new weathering classes based on Brazilian tensile strength, porosity, p-wave velocity, strength retention index, and $Is_{(50)}$ (Heidari et al. 2013). Therefore, there is a critical need for researchers today to continue to work on creating a flexible and explicit model to evaluate rock excavatability.

Single- and multivariable regression analysis is a component of conventional statistics, but artificial neural networks (ANN), fuzzy logic, and adaptive neuro-fuzzy inference systems (ANFIS) are the core components of soft computing. Since soft computing techniques are so powerful, they are preferred in many engineering applications. Soft computing technology is widely used in mining to solve uncertainty and imprecision in a variety of domains, such as equipment selection, rock mechanics, rock blasting, and mining method selection (Jang and Topal 2014). Relationships among the geotechnical and geological properties were established using statistical methods such as single regression (Entwisle et al. 2005; Fener et al. 2005; Buyuksagis and Goktan 2007; Kahraman and Gunaydin 2009; Khandelwal and Singh 2009; Sharma et al. 2010; Kahraman 2014; Karaman and Kesimal 2015; Verma et al. 2012; Alemdag et al. 2015), Multiple Regression Analysis (MRA) (Karaman et al. 2015; Manouchehrian et al. 2012; Monjezi et al. 2012; Kumar et al. 2011; Yesiloglu-gultekin et al. 2013a, b; Karakus and Tutmez 2006) and soft computing. Soft computing includes artificial neural network (ANN), (Singh et al. 2005; 2012a, b; Karaman et al. 2015; Manouchehrian et al. 2012; Monjezi et al. 2012; Yesiloglu-gultekin et al. 2013a, b; Yesiloglu-gultekin et al. 2013a, b; Sharma et al. 2017a, b; Pappalardo and Mineo 2022; Aladejare et al. 2021) adaptive neuro-fuzzy inference system (ANFIS) (Karakus and Tutmez 2006; Sezer et al. 2014; Jalalifar et al. 2011; Singh et al. 2012a, b, 2013a, b; Yesiloglu-gultekin et al. 2013a, b; Kainthola et al. 2015; Asrari et al. 2015; Kumar et al. 2018) and combination of ANN and Fuzzy Systems (Singh et al. 2005; Firat et al. 2012; Singh et al. 2013a, b; Jahed Armaghani et al. 2014; Khajevand 2022, 2023; Ceryan et al. 2021; Jang and Topal 2014; Mishra et al. 2015; Sharma et al. 2017a, b; Mahdiyar et al. 2019; Abdi 2020).

The development of a new classification that employs a quantitative methodology and takes into account the geological and geotechnical features, as well as their association with the degree of weathering in this tropical region, is imperative, according to the study's findings. As reported by Ceryan et al. (2008a), quantitative weathering classification into four groups, including empirical formula and statistical analysis. In this study, an excavation evaluation system was developed for non-bedded rocks by using the WI and production rate obtained from the direct method carried out at the study site. This study uses input parameters that are significant to the assessment of excavation, namely PLT, durability, dry density, block volume and moisture content, the combination in this assessment is based on statistical methods, namely simple regression and MRA. Khajevand (2022) developed some predictive models to estimate the slake durability index of rocks in a comparative sense. He found that porosity, Schmidt hardness, P-wave velocity, and UCS are the best parameters for determining the durability of rocks, according to experimental equations derived by MRA. Arman (2021) The generated empirical equations are sufficiently accurate for the initial stages of structural design and can be used to estimate UCS values from ITS and Id_2 values within a specific correlation coefficient, R. Recently, Khajevand (2023) reported that MLR, ANN, and ANFIS were used to examine the correlations between UCS and a few geotechnical characteristics, such as dry density, porosity, UPV, PLS, BTS, and BPS. It is discovered that all of these techniques can be used to accurately forecast the UCS of rocks. Jahed Armaghani et al. (2014) tested some rocks to set as model inputs of dry density, ultrasonic velocity, quartz content, and plagioclase in the advance of the predictive models. The objective of his research is to use an ANFIS to present two prediction models of UCS and E for granite. It has been demonstrated that ANFIS has many advantages since it combines the best features of FIS and ANN approaches to show a high prediction ability in challenging, multivariate, nonlinear engineering situations.

Both statistical methods and soft computing methods have their strengths and weaknesses, and their suitability depends on the specific problem at hand, the nature of the data, and the goals of the analysis. However, for this study, it is emphasized that the most appropriate statistical method to achieve the objective is to use simple regression and multiple regression methods. MRA allows the inclusion of multiple independent variables simultaneously, which can help capture the combined effects of these factors on the weathering process. One often-used statistical tool is regression analysis, which is used to extract the relationship between several variables. With the use of a regression function, this method systematically ascertains the link between the dependent variable (output) and the independent variable (predictor) (Aladejare et al. 2021). Statistical methods often provide more interpretable results because they are based on clear mathematical models with clear assumptions. This can be important in areas where understanding the underlying relationships is important. Statistical methods often involve simpler algorithms and calculations compared to some soft computing methods, making them more computationally efficient for certain types of analysis, especially with large data sets. For civil engineering problems, soft computing approaches offer flexible computational procedures with a high degree of accuracy; yet, the majority of published studies omit to present the necessary details and the mathematical framework (Mirrashid and Naderpour 2020). The choice between statistical methods and soft computing may also depend on the expertise available in a particular domain. Some researchers may have a stronger background in statistical methods and feel more comfortable using them. The potential advantages of probabilistic and soft computing techniques in engineering geology research and application are highlighted in this special issue, along with opportunities for further advancement and promotion (Li et al. 2016).

Through the discussion of this literature, it can be seen the production of weathering and excavatability class models and classifications for the field of engineering geology. This study attempts to fill the gap by introducing an accurate classification system by using the most significant rock mass and material properties. This study is expected to be able to relate the influence of weathering to excavatability. The results of this study are described and discussed in the next section. This research is an attempt to estimate the essential parameters including block size in classifying the degree of rock weathering, which is rarely discussed. Based on the objectives of this research, geotechnical characteristics have been obtained by conducting several laboratory tests on rocks following ISRM standards. The innovation of this research is in providing a more comprehensive classification for prediction model for non-bedded rock, by using statistical methods approaches namely MLR. The obtained model is used and its performance is analyzed by using statistical methods such as coefficient of correlation (R2), Root Mean Square Error (RMSE), Variance Account For (VAF), and Performance Index (PI). Next, it evaluated so by reviewing all methods and comparing them to each other and previous research. The results of this study are described and discussed in the next section.

Geological setting

To accomplish the objective of this study, several ripping experiments were carried out on granite rocks that had varying degrees of weathering, ranging from completely weathered to completely fresh. Several locations in the states of Johor, Negeri Sembilan, and Perak have been selected to carry out the test, the location shown in Fig. 1. The selection of this site is the excavation work being carried out during the study. Therefore, the measurement work of ripping performance can be easily measured. But there is also a need to carry out trial excavation using different machines. Therefore, the machine was brought to the study site to conduct a trial excavation.

The site in Perak, Malaysia is in the Kledang Range area and borders the Granitic Main Range, a massive and homogenous rock body. Granite typically has an age of 200–230 Ma. It serves as Peninsular Malaysia's "backbone.", with the 400 km-long Main Range batholith and the 40 km-long Kledang Range (Cobbing et al. 1986). These two batholiths form high mountains that have high-angle faults and steep sides. The mountains are composed of granite, with quartz's dominant mineral content. There is also a limestone deposition and forming bedrock, with karstic formation features such as pinnacles and throughs. These massive bodies are commonly highly fractured (Choong et al. 2014).

The second site's geology, located in Nilai, Negeri Sembilan consists of an intrusion of Main Range Granite. Referred to (Cobbing et al. 1986), the intrusive age of the Main Range Granite is 200 -230 Ma and mainly emplaced of Ordovician to Devonian age. Granite is identified as biotite granite and muscovite, which are medium to coarse-grained. One of the Klang Gates Quartz Ridge series is the main fault on this property. At roughly 14 km in length, it is thought to be the world's longest quartz ridge. With a small amount of felspar,

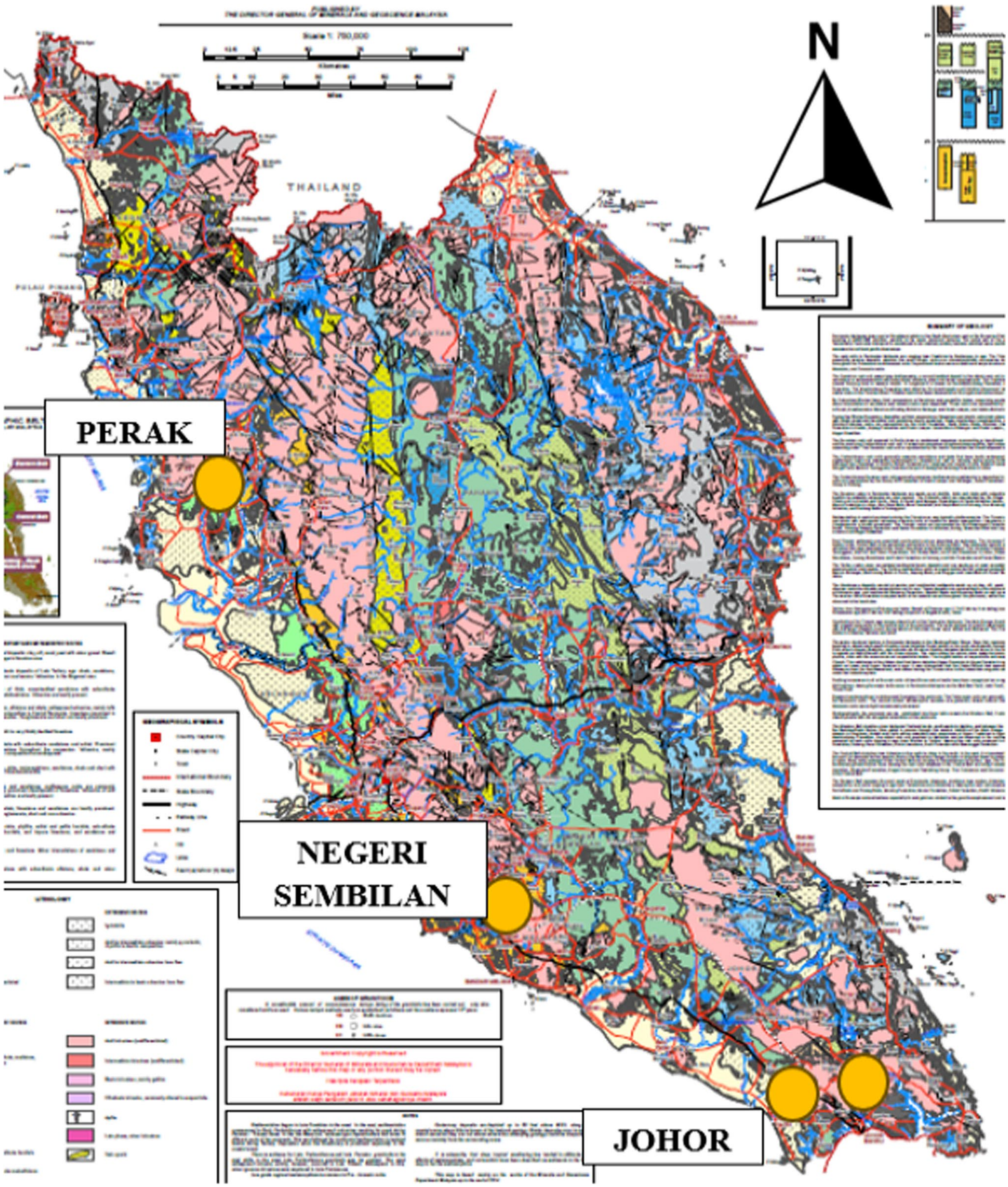

Fig. 1 Site Location

quartz predominates in the quartz vein. There are at least three phases of vein intrusion or more than that. This quartz vein was formed when the rest of the magma crystallized and consolidated in the vertical slab of the trench. Then this quartz vein is formed through large linear fissures in the massive granite rock structure. Based on observation, there

Table 1 Descriptive Statistics for the Investigated Properties of Rocks in the Database

Parameter	No of data	Minimum	Maximum	Mean	Standard Deviation
Fresh (Grade 1)					
Uniaxial Compressive Strength (UCS) (MPa)	10	139.63	188.02	162.5`	27.75
Point Load Index, $Is_{(50)}$ (MPa)	10	5.8	7.4	6.8	1.1564
Schmit Rebound Hammer, R	10	60	63	61	2.154
Dry Density (kg/m^3)	10	2607.11	2666.5	2629.5	55.98
Slake Durability Index, $I_{d(1)}$	10				
Slake Durability Index, $I_{d(2)}$	10				
Moisture Content (%)	10	0.40	0.61	0.5	0.1327
Joint Spacing (m)	10	0.9	2.0	1.3	0.559
Block Volume	10	0.6875	2.000	1.60	0.7909
Resistivity (ohm.m)	10	4000	4000		
Seismic, P-wave (m/s)	10	3200	3200		
Slightly Weathered Rock (Grade 1I)					
Uniaxial Compressive Strength (UCS) (MPa)	10	88.90	112.16	101.0	15.68
Point Load Index, $Is_{(50)}$ (MPa)	10	3.7	4.63	4.2	0.6534
Schmit Rebound Hammer, R	10	54	60	55.9	6.008
Dry Density (kg/m^3)	10	2363.26	2604.08	2468.7	140.28
Slake Durability Index, $I_{d(1)}$	10	94.65	96.97	71.7	1.5084
Slake Durability Index, $I_{d(2)}$	10	91.46	95.65	93.4	2.0489
Moisture Content (%)	10	0.4 3	2.56	1.5	1.074
Joint Spacing (m)	10	0.6	1.3	1.0	0.51
Block Volume	10	0.78	1.470	1.00	0.520
Resistivity (ohm.m)	10	2000	2400		
Seismic, P-wave (m/s)	10	2500	4000		
Moderately Weathered Rock (Grade III)					
Uniaxial Compressive Strength (UCS) (MPa)	10	32.69	75.68	52.2	24.26
Point Load Index, $Is_{(50)}$ (MPa)	10	1.36	3.15	2.2	1.0109
Schmit Rebound Hammer, R	10	30	36	34	4.176
Dry Density (kg/m^3)	10	2166.14	2344.0	2251.0	126.72
Slake Durability Index, $I_{d(1)}$	10	83.74	88.5	85.8	3.084
Slake Durability Index, $I_{d(2)}$	10	79.14	86.27	97.0	14.641
Moisture Content (%)	10	1.51	4.57	3.0	1.598
Joint Spacing (m)	10	0.3	1.0	0.6	0.508
Block Volume	10	0.0293	0.875	0.500	0.4967
Resistivity (ohm.m)	10	2500	4000		
Seismic, P-wave (m/s)	10	2000	2400		
Highly Weathered Rock (Grade 1 V)					
Uniaxial Compressive Strength (UCS) (MPa)	10	9.22	18.62	16.1	11.125
Point Load Index, $Is_{(50)}$ (MPa)	10	0.38`	0.78	0.7	0.4635
Schmit Rebound Hammer, R	10	17	20	18	2.622
Dry Density (kg/m^3)	10	1958.98	2102.76	2043.5	137.09
Slake Durability Index, $I_{d(1)}$	10	28.2	38.3	33.8	6.627
Slake Durability Index, $I_{d(2)}$	10	9.99	30.6	21.8	10.869
Moisture Content (%)	10	2.57	6.55	4.4	1.93
Joint Spacing (m)	10	0.1	0.5	0.4	0.3246
Block Volume	10	0.01	0.088	0.100	0.1703
Resistivity (ohm.m)	10	500	2500		
Seismic, P-wave (m/s)	10	800	2000		
Completely Weathered Rock (Grade V)					
Uniaxial Compressive Strength (UCS) (MPa)	10	1.69	7.61	4.3	3.286

Table 1 (continued)

Parameter	No of data	Minimum	Maximum	Mean	Standard Deviation
Point Load Index, $Is_{(50)}$ (MPa)	10	0.07	0.32	0.2	0.1369
Schmit Rebound Hammer, R	10	0	17	6.2	8.749
Dry Density (kg/m^3)	10	1702.96	2060.27	1901.50	179.5
Slake Durability Index, $I_{d(1)}$	10	8.26	10.09	10.3	4.984
Slake Durability Index, $I_{d(2)}$	10				
Moisture Content (%)	10	5.93	8.02	7.3	1.053
Joint Spacing (m)	10	0.18	0.43	0.3	0.199
Block Volume	10	0.006	0.048	0.0	0.028
Resistivity (ohm.m)	10	500	500		
Seismic, P-wave (m/s)	10	750	800		

are three phases of intrusions that can be identified. The first phase is considered the major phase of intrusion. Based on observation, there are three phases of intrusions that can be identified. The first phase is considered the major phase of intrusion.

The third site location is in Johor, Malaysia. The area consists of acid intrusive rocks that consist of granite that are excavated for quarry purposes. The lithology of the studied site consists of plutonic igneous rock from Muntahak Pluton (Cobbing et al. 1986). This region's granitic rock is categorized as medium-grained granite. The majority of the rocks have medium to coarse grains and colors that range from nearly pink to pinkish gray. Gray and pink granite with fine to coarse grains makes up the majority of the ground beneath the Muntahak Mountain area. The predominant rock types in this region's granite include quartz, plagioclase, and k-felspar. Minerals like hornblende and biotite can also occasionally be found.

Statistical assessments of field test

The database consists of rock mass and material characteristics such as density, moisture content, strength, Schmidt Hammer, UCS, seismic velocity, and SD1. The characteristics of granite with different weathering grades and the total number of samples. The data obtained involves granite rocks with different weathering grades. Overall, the rock samples in this database have been used for statistical analysis. Table 1 shows that the survey line is composed of low P-wave velocities ranging from 500 to 3200 m/s.

Apart from the parameters mentioned above, tests such as UCS, Schmidt Rebound Hammer, dry density, and P wave velocity of rock samples are also determined. Analysis of mineralogical composition and grain size is also carried out. All parameters were evaluated statistically based on weathering grade. Therefore, only the most appropriate parameters are selected and will be used to help develop the

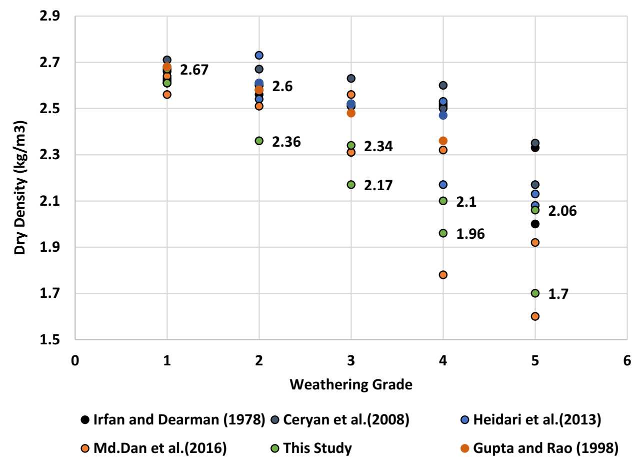

Fig. 2 Dry Density

classification. Based on the effects of weathering on rock mass and rock material properties that have been studied so deeply since the last decade, several classification systems have been proposed by several scholars. However, the research conducted is focused on certain characteristics, namely chemical, mineralogical (Ceryan et al. 2008a, b), and geomechanically (Gupta and Seshagiri Rao 2000; Arel and Tugrul 2001; Gupta and Rao 2001; Lan et al. 2003; Orhan et al. 2006). There is also a new initiative to provide classification based on the combined index (Lan et al. 2003; Ceryan 2015). The boundaries between different weathering grades are determined based on the rock mass and rock material properties data obtained from this study, where the data is compared with previously published data. This means that the points obtained for each grade of weathering are located within the boundaries of the same type of weathering grade, as shown in Fig. 2.

The results for the dry density parameters obtained through this study are compared with previous studies in a range (Gupta and Rao 1998; Iran and Dearman 1978a,

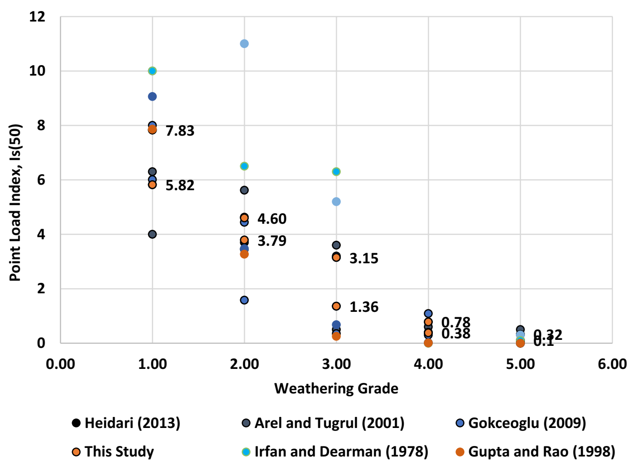

Fig. 3 Point Load Index, Is(50)

1978b; Ceryan 2008; Heidari et al. 2013; Md Dan 2016). The classification of non-bedded rocks is a good attempt that can be used in areas that experience physical weathering. Therefore, one of the methods that can be used is to compare the results obtained from this study with the results obtained presented in other international journals. This comparison is made against different weathering conditions but can support the applicability of the classification proposed in this study. As reported by Ramesh Murlidhar et al. (2022), apart from density, several other parameters such as RQD, GSI, Shmidt Hammer Number, Is(50), porosity, and Blastibility Index, BI are useful for the evaluation of rock mass classification for blastibility against non-bedded rocks in tropical areas. They believed that rock density has a direct impact on blastability.

The research value of the $Is_{(50)}$ obtained in this study was compared first with the results obtained by Gupta and Rao (1998), Gupta and Seshagiri Rao (2000), Heidari et al. (2013), Arel and Tugrul (2001), Gokceoglu et al. (2009), Iran and Dearman (1978a; b). The comparison made shows a small overlap located in moderately weathered granite (Grade III). While a more significant level of overlap occurs in highly weathered granite (Grade IV). Therefore, in this regression analysis, this parameter is suitable for making predictions about weathering grade. The comparison made (Fig. 3) shows that the data obtained in this study is parallel and reasonable to the data of studies that have been done for the past three centuries until now.

Material and methods

All the procedures, practices, and assessment methods employed in this research are based on the International Society of Rock Mechanics (ISRM) guidelines (ISRM, 1978) (ISRM, 1988) (ISRM, 2007). According to Little's (1969) proposal, the degree of rock weathering is represented by six classes and zones. Residual soil makes up grade VI. Fresh rock is grade I, moderately weathered rock is grade II, heavily weathered rock is grade IV, and completely weathered rock is grade V.

Studied areas and testing procedure

The overall results of fieldwork and laboratory investigations are shown in Table 1. In this section, the data found in this table is used for simple and multiple regression analysis. The process of testing is mainly based on the standard descriptions of ISRM, 2007. The following laboratory tests were conducted in the study:

(a) Moisture Content.
(b) Point Load Index ($I_{s(50)}$).
(c) Slake Durability Index (I_{d1}).
(d) Dry Density.

Moisture content

A minimum of 10 lumps with a mass of 50 g or a minimum dimension of ten times the maximum grain size, whichever is larger, is chosen to serve as a representative sample. One measures the weight of the dried and cleaned container, A. A minimum dimension of ten times the maximum grain size, or a minimum of ten lumps weighing fifty grams each, was required for a representative sample. The weight B is obtained by measuring the weight of the sample inside the container. The sample is allowed to cool in a desiccator for 24 h after being dried to a consistent mass in an oven at 105 °C. The grain mass, C, is then calculated using the weight of the container and the dried sample. This equation could be used to determine the moisture content:

$$w = \frac{Mcms - Mcds}{Mcds - Mc} \times 100 = \frac{Mw}{Ms} \times 100$$

where w is water content (%), $Mcms$ is the mass of the container and moist specimen (g), Mc is the mass of container (g), Mw is the mass of water (g) and Ms is the mass of oven-dry specimen (g).

Point Load test

During excavations at the research location, fifty rock samples were collected from various weathering zones. Each sample that is tested in the Point load test has a shape and size that affects the test results and determines the rock efficiency rating. Nonetheless, the more appropriate rocks are those that are square or rectangular because core samples are not available at the location. To avoid the sample falling during the test, it should be made sure to have flat and parallel properties. A point load tester was used to evaluate these samples. Consequently, for every sample with varying levels of weathering, the point load strength value for the rock was determined. A tape measure was used to measure the rock samples' dimensions, which were then entered into a test form. A load was applied to the rock sample until it failed, at which point the load was recorded before the sample was recovered. When calculating the point load, the resistive load of the sample strength that is put between two loading cones or bits is added to the sample strength. To the uncorrected point load strength (Is) equation, a correction factor (F) is added as follows:

$$I_s = \frac{P}{D_e^2} \tag{1}$$

$$I_{s(50)} = F \times I_s \tag{2}$$

where P is the failure load (N) and $D_e{}^2$ is 4A/π which is the equivalent diameter of the lump sample.

Where $F = (D_e/50)^{0.45}$.

Slake durability test

Ten randomly chosen rock lumps, weighing 40–60 g apiece, make up the sample, which has a mass of 450–600 g overall. With a hammer or other compression tool, larger rock blocks are easily broken into the necessary aggregate size. The biggest size of the lump should not exceed 30 mm. Roughly spherical lump sizes and rounded corners should be the result of processing. Samples with known dry weights are poured into the barrel in batches. After a few hours in the oven to dry, the barrel was properly weighed before testing. Initially, the mass (A) plus the drum were recorded. The slake test, which involves spinning the sample barrel at 200 revolutions per minute (20 rpm), takes around 10 min to finish. The rock sample in the barrel is dried in an oven for a few hours after the test is over, and its dry weight is recorded. Following the initial cycle, measurements were taken of the drum's mass and the sample's cooled retained component (B). It was the same process all over again. Following the second cycle, the drum and sample mass that were kept were recorded as C. Ultimately, the mass of the clean, brushed drum was determined to be D. This is the sample weight following the initial cycle. The test could be repeated in the second cycle for softer rocks (high slaking index).

Based on the test, ten sample specimens were used to generate concise recommendations. To put it briefly, the samples were baked to dryness. They then rotated in a partially saturated state inside a slake durability drum for five minutes. Once the drum was removed, it was left to dry at 105 degrees Celsius for sixteen hours. Subsequently, the weight of the specimen that was retained was registered. Some of the formulas that could be used to define the slake durability indices are as follows:

$$I_{d1} = \frac{B - D}{A - D} \times 100 \tag{3}$$

$$I_{d2} = \frac{C - D}{A - D} \times 100 \tag{4}$$

where I_{d1} is the initial slake durability index (%), I_{d2} is the slake durability index for the second cycle (%), A is the mass of the drum and oven-dried sample that was retained before the first cycle (g), B is the mass of the drum and oven-dried specimen that was retained after the first cycle (g), C is the mass of the drum and oven-dried specimen that was retained after the second cycle (g), and D is the mass of the drum and oven-dried sample that was retained after the cycle (g).

A greater number of refined materials were able to pass through the net and into the water bath while the test was being conducted. Id1, also known as the slake durability index, was the percentage of the drum's initial dry weight. The table proposed by Franklin and Chandra (1972) is used to show the division of the Slake Durability Scale, and represent surviving rock fragments after the second cycle.

Weathering index

Next, this section will give the steps taken in obtaining the WI. Quantitative methods are used in estimating changes and classification of weathering and are explained in detail, using statistical analysis. To develop a model to estimate the WI for the studied rocks, data obtained from field and laboratory tests were analyzed using simple regression and MRA.

Regression analyses

Regression analysis is a set of statistical processes in statistical modeling to obtain the relationship between the dependent variable and the independent variable. From studies conducted in geological and rock engineering, regression analysis is also used to create predictive models for rock properties. In this study, both moderate and multiple regression analyses were carried out to develop a prediction model for the WI by using parameters that have been identified as significant to the excavatability of non-bedded rock.

The most common form of analysis is linear regression, which is the line that best fits and is close to the data through mathematical features. Linear and non-linear multiple regression are the two distinct types of multiple regression that are available. Detailed explanations of both types are provided in the following paragraphs. In the MLR analysis, the parameter values for the function are determined in such a way that the function provides the best possible match to a certain collection of data observations. In solving problems related to rock engineering and geotechnics, it was found that this MLR technique has been widely applied. The MLR equation is introduced by Heidari et al. (2013), Khanlari and Naseri (2016), Mohamad et al. (2017a), Hasanipanah et al. (2017), Vidana Pathiranagei et al. (2023), Mohamad et al. (2017a, b), Lee and Yoon (2017), Anikoh et al. (2015) to estimate certain parameters. Arıkan et al. (2007) has carried out simple and multiple regression analyses considering some of the most suitable geomechanically parameters and chemical properties. It includes porosity, indirect tensile strength, block punch strength, and P wave velocity, for predicting weathering classification for engineering purposes by considering all weathering grades.

Simple regression analysis

The accuracy of the regression model is influenced by the type of function and the quantity of data. Ceryan et al. (2021) reported that input selection methods for regression models can be implemented based on three categories, namely filter, embedded, and wrapper methods. At first, the relationship between variables was examined through bivariate correlation analysis. Pearson's Correlation was used to examine the relationship. Then, a simple linear regression was conducted to confirm the relationship.

Referring to Table 2, it was revealed that production rate has a significant negative correlation with all variables but positively correlated with moisture content. Slake durability was found to have the strongest correlation with production rate while the weakest correlation is between production rate and joint spacing.

In the field of rock engineering, one of the strategies that is utilized to develop an engineering model is the simple linear regression analysis. This technique involves the utilization of input parameters to estimate unknown indices or parameters. Regression methods in statistics include simple linear analysis and MLR. To achieve the objectives of this study, several steps have been carried out. The first stage is to conduct a simple regression analysis between independent variables, such as slake durability index, point load index, moisture content, and others (Table 2). Since there is a significant association between productivity rate and all predictor variables, it is necessary to determine which factors significantly influence the productivity rate. Therefore, MLR is carried out to meet this objective.

Simple bivariate regression is a type of regression in which there is just one independent variable and one dependent variable. It is possible to predict the dependent variable by considering the independent variable and applying the equation that is presented below:

$$Y = a + bx \tag{5}$$

where a indicates a constant, while x and y are independent and dependent variables, respectively. This equation can be further extended to various concept variables as shown in equation

$$y = a + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + bnxn \tag{6}$$

where x_1, x_2, x_3,…x_n shows various independent variables for the prediction of y.

As can be observed, the linear equation has given the best results in WI prediction through significant parameters. The results show that this relationship is statistically significant. However, to obtain the best model in WI predictions, multiple input parameters are required. Therefore, MRA was constructed and developed.

Charts to estimate properties of weathered rocks on material properties

Figure 4 shows the suggested correlation between weathering grade and rock characteristics that were important for excavatability. Although the relationship's findings are respectable and statistically significant, they are insufficient to determine the WI. Additionally, it indicates that other noteworthy inputs to excavatability would be required to forecast the WI for non-bedded rocks. As a result, the MRA modeling technique was created.

It shows a simple analysis of weathering grades with significant input parameters, namely SD1, $Is_{(50)}$, dry density, and block volume with weathering grade. Almost all graphs show a strong inverse linear relationship between weathering grade and input parameters. This diagram also shows that as the weathering grade increases, other parameters such as SD1, $Is_{(50)}$ and dry density decrease. It can also be seen that there is a very clear overlap in all weathering grade relationships with input parameters. This shows that the estimation of weathering class cannot only use one parameter, instead more inputs are needed. Therefore, a prediction model using several inputs has been proposed for this purpose. A total of 30% of the total data was used as training, used to check the standardization of the obtained model. This overall data is also used as a revision data set against the data set obtained from the literature. Figure 4 shows the increase in the slaking index with the change of rock from Weathering Grade 1–6, showing a high correlation coefficient of 0.8629. This test provides a good correlation ($r > 0.80$) which is suggested for the quantification of weathering of granite. Classification using the point load index shows a relatively large degree of overlapping

Table 2 Correlation matrix obtained from the parameters obtained from granite

	Production Rate	Slake Durability 1	Slake Durability 2	UCS	Point Load Test	Moisture Content	Joint Spacing	Block Volume	Seismic	Resistivity
Production Rate	1	– 0.904**	– 0.888**	– 0.734**	– 0.734**	0.706**	– 0.423**	– 0.573**	– 0.540**	– 0.516**
SlakeDurability 1		1	0.960**	0.842**	0.844**	– 0.725**	0.372**	0.565**	0.639**	0.472**
SlakeDurability 2			1	0.838**	0.840**	– 0.662**	0.407**	0.592**	0.647**	0.456**
Uniaxal Compressive Strength (UCS)				1	1.000**	– 0.643**	0.474**	0.701**	0.669**	0.715**
Point Load Test					1	– 0.644**	0.474**	0.701**	0.668**	0.715**
Moisture Content						1	– 0.219**	– 0.384**	– 0.191**	– 0.611**
Joint Spacing (m)							1	0.660**	0.410**	0.247**
Block Volume								1	0.576**	0.508**
Seismic									1	0.862**
Resistivity										1

*Significant at 0.01 significance level

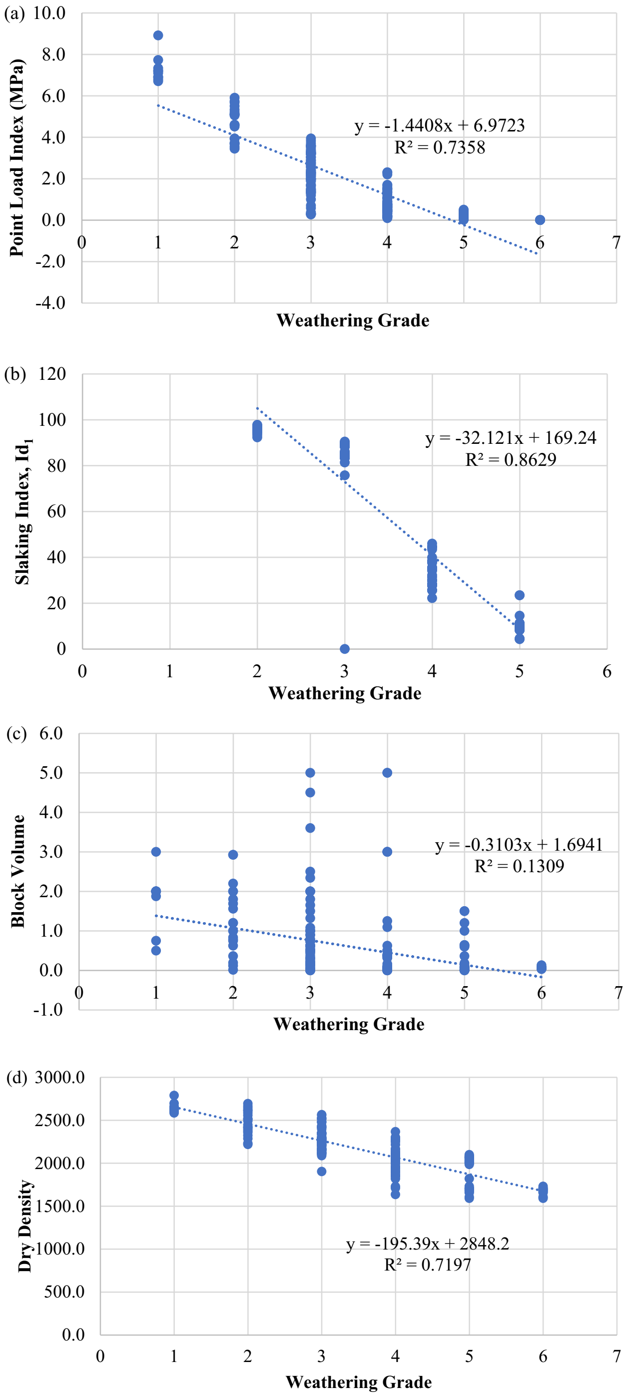

Fig. 4 Simple regression analyses results of **a** point load index $Is_{(50)}$—weathering degree; **b** SD1—weathering degree; **c** block volume – weathering degree; **d** dry density—weathering degree

between Grade III and Grade IV, making it difficult to determine the weathering grade. However, classification based on this parameter is easier because this test is easy to conduct and measure. This evaluation shows that using a value that depends on only one parameter is very impossible to apply. For this reason, in this study, three prediction models with four inputs and one output were built.

As shown in Fig. 4a, PLT which measures the strength of rock samples under the point load test shows a relationship with weathering grade. This is important in the evaluation of the mechanical properties and stability of rocks. Based on the graph above, there is a trend of decreasing $Is_{(50)}$ with increasing weathering grade. The graph shows the trend where more rock samples have lower PLT values compared to fresh and slightly weathered samples. However, there is a significant overlapping of up to 2 MPa between Weathering grades III and IV. This is due to the soil-rock characteristics that occur on granite. More weathering corresponds to a lower PLT value, reflecting rocks that are more susceptible to failure with weaker mechanical properties. Therefore, the relationship between these two parameters can be influenced by various factors such as environmental conditions and rock types. A higher PLT indicates greater strength, referring to the lower weathering grade which is weathering grades I and II. Therefore, strength was found to decrease with higher weathering grade. Overall, the relationship between these two parameters shows a progressive deterioration caused by weathering. This dominant trend is very similar to the scholarly findings by Tating et al. (2014), Gupta and Seshagiri Rao (2000), Awang et al. (2021).

Slake Index 1 gives an indication of the rock's susceptibility to disintegration when exposed to water. The graph (Fig. 4b) will probably show how the slaking index changes as the weathering grade of the rock increases. This graph showing Id_2 shows a clear trend with weathering grade. As weathering progresses, rocks become more susceptible to moisture breakdown due to structural weakness and mineral composition. The graph shows a positive correlation between weathering grade and rock's tendency for slaking, higher compared to more weathered ones. A higher slaking value indicates greater resistance to cracking, while a lower slaking value indicates a lower resistance is required to experience cracking. However, this graph does not show a large overlap between weathering grades. There is a point between the weathering grade that shows a transition zone that shows the rate of change of the slaking index increases or decreases. The results of this granite match the findings of the research done by Heidari et al. (2013), Momeni et al. (2017).

However, a weak inverse linear relationship can be observed between weathering levels and block volume, as shown in Fig. 4c. The diagram above shows the relationship between block volume and weathering grade for non-bedded rocks. This graph involves the understanding of non-bedded rocks reacting to different levels of weathering and how the block volume changes over time. Depending on the degree of weathering, different block sizes are present in varying amounts within the rock mass, and the distribution of block sizes varies according to weathering degree. The block size distribution shows different rates depending on the weathering grade, important to evaluate the nature and stability of the rock mass. In general, block volume decreases as the weathering grade increases. This result is in line with findings reported by Guan et al. (2001, Chiu and Ng (2014), Khalil Abad et al. (2014). When the rock sample grows from fresh to completely weathered, there is a significant change in the block size distribution. This happens because of the weathering process that takes place, which gradually breaks larger blocks of rock into smaller fragments. This can be seen in weathering grade I, block size is showing a larger value, which is a more noticeable condition on the rock surface. In this situation, fresh rock samples are harder and stronger and tend to have larger block sizes.

For weathering grade II, the block volume which is more significant on the surface is relatively less than in the rock mass according to depth. It shows that the block volume has gradually decreased but not significantly. This reduction in block volume occurs due to the beginning of the weathering process that occurs. In moderately weathered conditions, where the weathering grade continues to increase, the rate of block volume reduction is also getting faster. The increasingly significant weathering process breaks the granite blocks into smaller pieces. In a highly weathered state, the block volume state has reached a state where the block volume reduction becomes slower and more stable. In this phase, the weathering process has reached equilibrium with the environmental conditions. Finally, in a completely weathered state, the graph has reached a point where the degree of block volume reduction becomes slower and reaches a stable level. At this level, the existing rock blocks show a more consistent shape and appearance. At this level also shows the rate of lost volume becomes more consistent. The results obtained from this study are in line with the findings reported by Shang et al. (2008) and Jaques et al. (2023), block volume drastically decreased from slightly weathered to moderately weathered. Block size reduces as weathering grade increases, and a universal weathering-grade rock-mass categorization system is created for application in engineering properties (Irfan and Dearman 1978a; b).

In general, as shown in Fig. 4d there is an inverse relationship between dry density and weathering grade. The dry density decreases when the weathering grade increases. Fresh rock samples show higher dry density values compared to weathering grades II, III and IV. As the weathering grade increases (the rock undergoes more weathering), the dry density tends to decrease. This is because the weathering process often results in damage and fragmentation of rock material, which leads to a decrease in density. The weathering process can deteriorate the bonds between mineral grains, reducing the rock's ability to resist stress and load. As rocks undertake more extensive weathering, their mass per unit volume decreases due to the formation of cracks and segregation of mineral grains. However, the reduction that occurs between weathering grades is not very significant between weathering grades. On the other hand, there is an overlap between weathering grades. This trend suggests that there is a correlation between the weathering grade and the decrease in dry density. However, no point shows the transition zone between weathering grades. Because of this, the overlap that occurs is more significant for each weathering grade.

Multiple regression analysis

In rock engineering, multiple regression analysis has also been used by researchers to create a prediction model for the WI of rocks. Simple regression is extended upon by multiple regression. By utilizing the values of two or more extra variables, it is used to forecast the value of a variable. The possibility that a variable may be related to more than one variable is reflected in the idea of multiple regression. In this situation, estimating a dependent variable can be done by methodically combining all of the independent variables (Leech et al. 2003). MR is done typically as MLR, but it can use the same transformation technique that is used in similar models to construct more complex non-linear, multivariable models. However, this study will focus on the linear version. MRA was executed by IBM Statistical Package for the Social Sciences (SPSS) Statistics v. 26 (2019). MLR techniques can be achieved by manipulating input and output parameters. Regression in MRA illustrates the link between numerous independent variables (x_1, x_2, x_3,…, x_k) and a dependent variable (y), as seen in the formula below.

$$\breve{Y} = \alpha + b_1X_1 + b_2X_2 + \cdots + b_nX_n \tag{7}$$

where the term $\breve{Y}$ is the predicted value of Y (estimated from X*i*), α is the intercept, and b_1 is the partial regression coefficient.

Next, all data sets will be divided into five randomly selected data sets, and five (5) MLR equations will be created to obtain the WI. Then, the best and most accurate MLR equation from all the models produced will be chosen. The index results of the MLR model are shown in Table 4 for the training and test data sets. The equation obtained through the data set that has gone through this statistical analysis is the equation to get the WI. The R^2 values obtained are 0.78 and 0.79 for the testing and training sets, respectively. The database is divided into two data sets in forming regression models: testing and training. For this study, 20% of the data is testing and 80% of the data is divided into training. This finding is in line with the study by Basarir et al. (2014), using 80% of the data as train and 20% to validate the developed models. There is no specific rule in determining the minimum size necessary for this subset of data. However, from studies by previous researchers, there are several different recommendations in making the selection of test and training data. As a result, for this study, as much as 20%, i.e., 132 of the entire data set, were randomly selected for testing, while as much as 80% of the selected data, i.e., 528, were applied to training the models. This process has been repeated up to five times, using test and training pairs randomly chosen for each analysis.

Although the results show almost the same performance value between MLR in obtaining the WI. The parameters involved in the stepwise regression analysis are weathering grade, SD1 and 2, $Is_{(50)}$, UCS, moisture content, dry density, joint spacing, block volume, Schmidt hammer, seismic and resistivity. The dependent variable used is the production rate. The equation for the WI was obtained from the evaluation of parameters significant to excavatability by using a combination of regression equations. Before starting the stepwise regression process, an assessment is made of each rock mass property to obtain its influence on excavatability. To get a more accurate prediction, some literature and background studies on the issues involved with excavation are important. The evaluation of each existing excavatability assessment provides guidance and input to ensure that the selected parameters do not only depend on statistical analysis. The parameters that have been identified as significant are then used in regression analysis. Calculating RMSE and VAF allows for the control of the predictive power of the equations that are obtained from both simple and multiple regression models. It must be computed for each empirical equation that was obtained through the course of this investigation. This model is categorized as very good when the RMSE value is 0 and the VAF value is 100. The results for the models' performance indices which consist of R2, RMSE and VAF based on training and testing values are shown in Table 3.

In the MLR analysis, the parameter values for the function are determined in such a way that the function provides the best possible match to a certain collection of data observations. The following process is to develop a forecast equation to obtain the WI. Based on the data set that has been created, a total of five MLR equations have been developed to propose several WI sets as presented in Table 4. To develop this WI model, the model inputs involved are $Is_{(50)}$, SD1, dry density, and block volume. Therefore, a data set consisting of field and laboratory tests is prepared for the next step. For the present research, VAF, R^2, and RMSE were calculated in a method to control the capacity performance of all the developed models.

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(y - y'\right)^2}{\sum_{i=1}^{N} (y - \tilde{y})^2} \tag{8}$$

$$VAF = \left[1 - \frac{\operatorname{var}\left(y - y'\right)}{\operatorname{var}(y)}\right] \times 100 \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y - y')^2} \tag{10}$$

The variables y′ and y represent the anticipated and measured values, respectively. The symbol $\tilde{y}$ represents the mean of the y values, while the symbol N represents the total number of instances of the data. The model is considered as excellent if the parameters VAF = 100, $R^2 = 1$, and RMSE = 0. As shown in Fig. 4, the relationship between weathering grade and some parameters that are believed to affect the excavatability of related rocks. The results show that in ensuring this relationship can achieve the best model in combining rock mass and material properties in an index, significant parameter input is required. In this study, two modeling techniques namely MLR have been developed.

Result and discussion

Multiple regression and ANFIS models are based on mathematical equations. Attempts have been made several times to obtain a high-accuracy model. The steps to obtain the model have been illustrated in Fig.

Relation between weathering indices and weathering degree

Regression analysis is easily assessed by considering the clear correlation between rock material parameters and rock mass properties with weathering grade. The set is based on a set of significant parameters as well as some parameters determined to be significant through literature review and the existing classification system. Therefore, this trial is done by obtaining the most accurate WI equation. Through single regression analysis, several parameters are found to have a significant correlation with the degree of weathering. However, it was found that there are parameters that are not significant in the simple regression showing the relationship between each other when combined in the MRA. It can be seen that as in the table, many equations are produced for each subset set through a set of significant parameters to form the WI. For all the weathering indexes involved, the setting first uses the highest R2 value. Although the evaluation is first made based on the highest R^2 value, it is

Table 3 Training and testing result

Type	Model	R2	RMSE	VAF	Rating for R2	Rating for RMSE	Rating for VAF	Rank Value
Non-Bedded All Parameter	Training 1	0.9443	0.0022	96.57	2	5	4	11
	Training 2	0.9896	0.0033	98.83	5	3	5	13
	Training 3	0.9863	0.003	94.55	4	4	3	11
	Training 4	0.9644	0.0211	83.08	3	1	2	7
	Training 5	0.7435	0.011	60.71	1	2	1	4
	Testing 1	0.9756	0.0133	97.95	4	1	4	9
	Testing 2	0.9920	0.0125	99.04	5	2	5	12
	Testing 3	0.9660	0.00315	93.129	3	5	3	11
	Testing 4	0.9401	0.0079	91.78	2	3	2	7
	Testing 5	0.8849	0.0074	84.78	1	4	1	6
Non Bedded All Parameter—Seismic, Js	Training 1	0.9097	0.002	95.40	1	1	2	5
	Training 2	0.9650	0.010	98.65	4	2	4	10
	Training 3	0.9649	0.001	96.59	3	5	3	11
	Training 4	0.950	0.002	89.45	2	4	1	7
	Training 5	0.9816	0.002	98.78	5	3	5	13
	Testing 1	0.9764	0.01	98.49	4	1	3	8
	Testing 2	0.9744	0.007	94.63	3	3	2	8
	Testing 3	0.9840	0.002	98.58	5	5	4	14
	Testing 4	0.9311	0.008	90.50	1	2	1	4
	Testing 5	0.9683	0.004	98.68	2	4	5	11
Non Bedded-with Js	Training 1	0.9461	0.001	97.17	2	3	4	9
	Training 2	0.9826	0.0017	99.37	4	2	5	11
	Training 3	0.9680	0.0008	96.75	5	4	3	12
	Training 4	0.9605	0.0202	84.89	3	1	2	5
	Training 5	0.6399	0.0006	56.45	1	5	1	7
	Testing 1	0.9764	0.0106	98.49	4	1	5	10
	Testing 2	0.9882	0.0015	99.44	5	4	4	13
	Testing 3	0.9235	0.0006	92.12	1	5	3	9
	Testing 4	0.9355	0.009	78.81	3	3	1	7
	Testing 5	0.9245	0.004	87.71	2	2	2	6
Non Bedded -Non BV	Training 1	0.9417	0.001	95.42	1	3	3	7
	Training 2	1.000	0.0023	97.61	5	1	4	10
	Training 3	0.9862	0.0014	91.99	4	2	1	7
	Training 4	0.9643	0.0005	94.77	3	4	2	9
	Training 5	0.9472	0.0001	98.45	2	5	5	12
	Testing 1	0.9758	0.005	97.35	4	1	4	9
	Testing 2	0.9876	0.003	96.14	5	3	3	11
	Testing 3	0.9700	0.005	95.52	3	2	2	7
	Testing 4	0.7221	0.0002	89.83	1	4	1	6
	Testing 5	0.9402	0.0001	98.13	2	5	5	12

not sufficient and practical to compare between equations. Therefore, the selection of this subset is based on the highest validation statistic, which uses R2, VAF, RMSE, and Performance Index (PI) values. As a result, all the selected equations have met the selection criteria for the WI, while the equations that do not meet the criteria have been excluded. From Table 3, it can be seen that the value of R^2 is from 0.7435 to 0.9896 for training, while 0.8849 to 0.992 for testing for the MR model test. Therefore, it can be concluded that there is only a small difference between the developed models. Analysis of simple regression and multiple regression using the regression method using Microsoft Excel.

Table 4 Total rank values for developed predictive techniques

Set	Model	Total Rank
All Parameter	1	20
	2	25
	3	22
	4	14
	5	10
Joint Spacing, Js	1	19
	2	24
	3	21
	4	12
	5	13
Seismic and Joint Spacing, Js	1	13
	2	18
	3	25
	4	11
	5	24
Non BV	1	16
	2	21
	3	14
	4	15
	5	24

After performing a simple regression analysis, it is seen that there is a need to obtain higher accuracy through the input of more than one parameter. Therefore, the ANFIS model has been developed for this purpose. All 52 datasets are divided into five datasets randomly. After that, this equation is developed using the data set that has been set. After that, the prediction performance of the developed model will be checked for the Training and test sets by considering the values of R^2, VAF, and RMSE. Table 3 shows the results obtained from R^2, RMSE, and VAF.

However, as seen in Table 4, the results obtained are more or less the same, causing difficulty in making the best model selection. Therefore, based on the method introduced by (Zorlu et al. 2008) which is a simple ranking method. This ranking value is done by making a count of each set of Training and tests, and then the best rating is given to the performance index that got the highest score. As shown in Table 5, the simplest example is Model 2 showing R^2 values for the training set which are 0.8221, 0.8131, 0.8662, 0.8876 and 0.8518. Therefore, the evaluation made is as 2, 1, 3, 5 and 4.

Based on the data presented in this table, it is clear that model 2 achieves the most favorable outcomes when compared to both MLR approaches. To gain a justification for the accuracy of the model that was constructed, many prediction performance indices, such as RMSE, VAF, and R^2, were determined for each model. An excellent prediction index for a statistical model is, in general, one hundred percent for VAF, zero for RMSE, and one for the R^2 for theory. By using these three parameters it is quite complicated to determine the most accurate model. (Yagiz et al. 2006) proposed a PI to obtain the accuracy of the model, and then make a comparison of the performance of the model that has been developed. The Performance Index (PI) used is as follows. Therefore, the highest PI value is the most accurate and reliable model. The PI value obtained for each model is shown in Table 5.

$$\mathrm{PI} = \left[\mathrm{R2} + \left(\frac{\mathrm{VAF}}{100}\right) - \mathrm{RMSE}\right] \tag{11}$$

Evaluation of the results

Proposed weathering classification for the granite

Next, the evaluation of the performance of the model that has been developed will be discussed to make the best prediction of the WI. (Frederick 2019) gives some suggestions on selecting the best input set, to reduce unnecessary input data. This is to obtain the most accurate regression model based on the quality and quantity of data involved in this analysis. The resulting model can be better interpreted and the ability to predict can be improved. (Ceryan et al. 2021) have also made input selections using the best regression analysis subset. Parameters such as porosity, seismic velocity and slake durability have been used to develop a predictive model in his study. Using the constructed datasets, four (4) MR equations were developed as shown in Table 6.

Figure 6 shows that all the parameters that are said to be significant and affect the WI equation are slaking durability 1, dry density, point load index, and block volume. The diagram shows the relationship developed in forecasting and actual WI using the MLR method. Figure 6 shows all the parameters that are said to be significant and affect the WI equation, namely slake durability 1, dry density, point load index, and block volume. The figure shows the relationship developed in the forecast and the actual WI using the MLR method. For diagram (a) the set consisting of all parameters namely SD1, dry density, $Is_{(50)}$ and block volume shows the best prediction model which is model 2 with R^2 values of 0.992 and 0.9896 respectively for testing and training data. The relationship that is developed next involves all the parameters with the connection distance as an additional parameter. It was found that model 2 is the best, which is testing showing 0.9882 and training showing 0.9826. The purpose of combining this parameter with joint spacing is to see the significant level of this parameter that affects excavatability.

Table 5 Total rank values for developed predictive techniques

Set	Model	PI
All Significance Parameters	Testing 1	1.9418
	Testing 2	1.9699
	Testing 3	1.8941
	Testing 4	1.850
	Testing 5	1.7197
	Training 1	1.9078
	Training 2	1.9746
	Training 3	1.9288
	Training 4	1.7741
	Training 5	1.3396
All Significance Parameter and Joint Spacing, Js	Testing 1	1.9507
	Testing 2	1.9811
	Testing 3	1.8441
	Testing 4	1.7146
	Testing 5	1.7976
	Training 1	1.9168
	Training 2	1.9746
	Training 3	1.9347
	Training 4	1.7892
	Training 5	1.2038
All Significance Parameters, Joint Spacing, Js and Seismic	Testing 1	1.9513
	Testing 2	1.9137
	Testing 3	1.9678
	Testing 4	1.8281
	Testing 5	1.9511
	Training 1	1.8617
	Training 2	1.9298
	Training 3	1.9415
	Training 4	1.8425
	Training 5	1.9674
All Significance Parameters excluding Block Volume, Bv	Testing 1	1.942
	Testing 2	1.9655
	Testing 3	1.898
	Testing 4	1.632
	Testing 5	1.755
	Training 1	1.905
	Training 2	1.985
	Training 3	1.929
	Training 4	1.774
	Training 5	1.5433

A relationship was developed as shown in Fig. 6c between the WI with seismic addition and joint spacing against a significant set of parameters, which were predicted and measured using the MR model for both the training and test sets. The R^2 values are 0.984 and 0.9649 for test and training, respectively. These results show values that are almost the same and lower than the set of significant parameters in the WI. This may be because block volume has been included as significant in the WI, therefore the presence of joint spacing does not have a significant effect because it only involves two dimensions compared to block volume which involves 3 dimensions of joint spacing.

The relationship developed next is to use a set of significant parameters but eliminate one of the parameters, namely block volume. The relationships developed are

Table 6 Proposed MLR equations for 5 randomly selected datasets to predict the WI

Dataset no	Proposed equation	R^2 Training	R^2 Testing
Set 1—All significance parameters	– 0.00184 SD1 – 0.0023 DD– 0.2521 Is(50)-0.1062 Bv + 9.001	0.9443	0.9756
Set 2—All significance parameters with Joint Spacing, Js	– 0.00187 SD1 – 0.0021 DD– 0.2515 Is(50)-0.00946 Bv – 0.0439 Js + 9.0758	0.9896	0.992
Set 3—All significant parameters + Seismic + Joint Spacing	– 0.00184 SD1 – 0.0022 DD– 0.2428 Is(50)-0.0823 Bv – 0.0119 Js – 0.0000486 Vp + 8.9294	0.9863	0.966
Set 4—All significance parameters excluding Bv	– 0.00183 SD1 – 0.00192 DD– 0.289 Is(50)-0.1062 + 8.2184	0.9644	0.9401

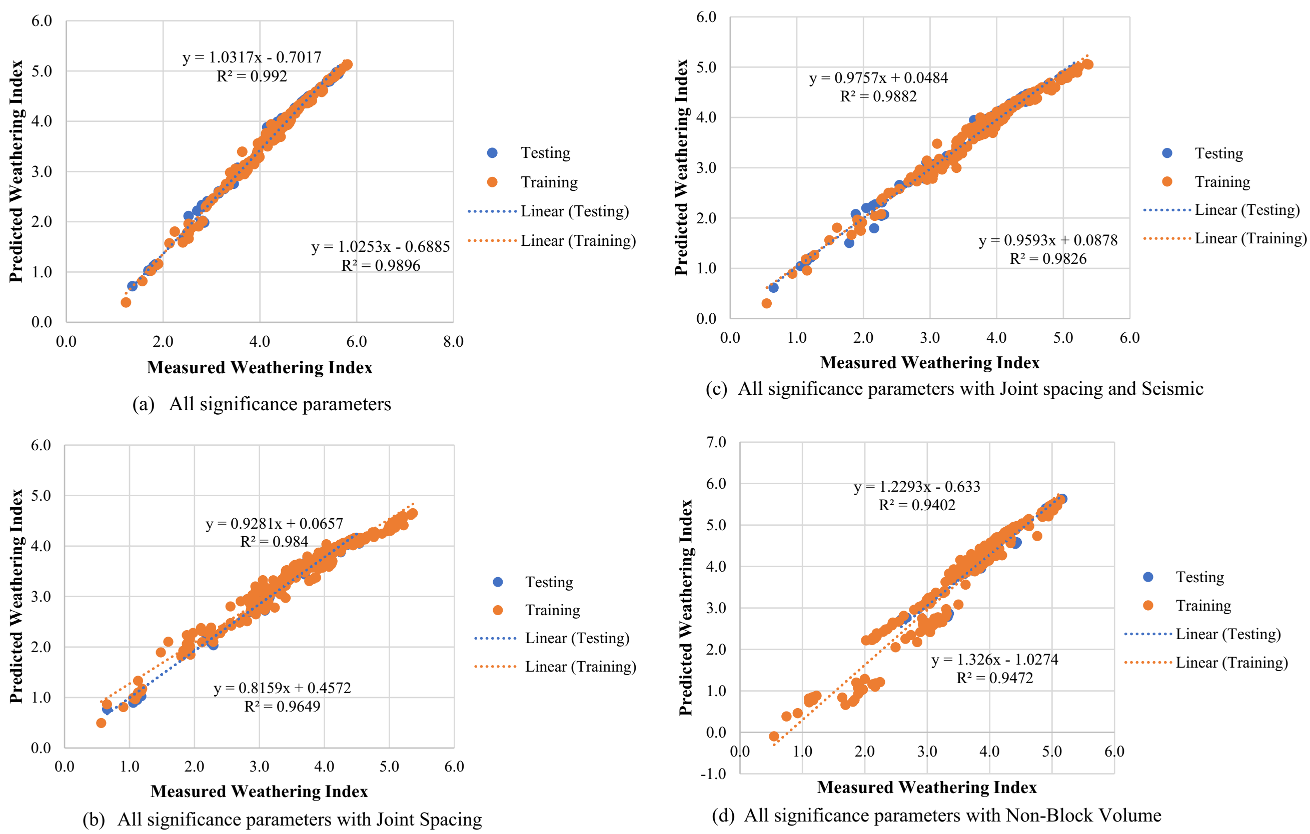

Fig. 6 **a** All significance parameters. **b** All significance parameters with joint spacing. **c** All significance parameters with joint spacing and seismic. **d** All significance parameters with non-block volume

between the weathering indices for both predicted and actual for the training and test sets. The selected model is model 3, showing the R^2 value for the test is 0.9402, while 0.9472 for Training. This result shows that block volume is one of the significant parameters and its removal in this equation influences the unification of parameters in the WI. The analysis of the graph resulting from this normalization method shows that the parameters removed from the WI may be correlated separately with the WI. In other words, separate data for this parameter can be used as an improvement to the existing index to be used in the interpretation of excavatability in tropical regions.

All significance parameters with Non-Block Volume.

Conclusion

Understanding the profile and its mechanical and chemical qualities is the goal of the categorization system for excavation purposes. The most crucial aspect of practical grading, nevertheless, is being able to identify the borders between Grade III and IV in terms of engineering at the rock-soil interface. In contrast to sedimentary rock, excavation work is simple in granite rocks. Geological mapping is crucial, especially for rock soil, which is defined as weathering grades III and IV where rock and soil make up the bottom surface and soil and boulders make up the top. There won't be as many engineering problems to solve and excavation work will be easier if the lines between grades III and IV can be drawn in the field. For Grades IV and V, on the other hand, just the interpretation is required (with more boulders and less boulders). On the other hand, changes in color and texture alone can be used to easily identify the leftover soil. There is just a crack without any dirt for Grade II. There is an opening for a crack and somewhat worn soil for grade III. However, the most crucial part—where a lot of people go wrong—is figuring out where the boundaries for III and IV are. The non-homogeneous material, which involves numerous locations and points along these rocks' limits, is the issue.

The point load strength index ($Is_{(50)}$), UCS, the spacing of discontinuities, and seismic velocities are the characteristics that are requested the most frequently and are considered to be the most desirable inputs. To a large extent, the Schmidt hammer test is among the most straightforward examinations that may be carried out on-site. However, there is a constraint that prevents it from being able to provide satisfactory results for samples that have been thoroughly weathered. As a result of this problem, the Schmidt test cannot be utilized as one of the inputs in the process of developing a categorization system. However, the current classification system only focuses on one type of rock and does not consider some parameters that are significant and unique to the tropics. For example, factors such as the effect of weathering, topography, lithology, moisture content, and the presence of interbedding are essential and need to be considered for sedimentary rocks. It is different for non-bedded rocks that have different lithology and characteristics. The scale of discontinuities is among the essential parameters in rock mass properties and is often ignored in existing assessments. These scales of discontinuities include bedding, joints, and blockiness of rock mass. The current literature and scenario in the construction industry also found that focus should be given to confirmation on rock soil characterization which usually involves class III and class IV weathering rocks, which is often a dispute among practitioners.

In this study, five properties of rock material consisting of block volume, $Is_{(50)}$, dry density, and Id1, are used as inputs to the classification system model developed to obtain WI values. After that, PI is introduced to get the accuracy of the developed model. This is to ensure the accuracy of the decision made is achieved. The model that has joint spacing as input along with four other parameters has the best average PI (testing 1.9811 and training 1.9746). Therefore, these results show that the model that uses a combination of all parameters with the addition of Joint spacing as an input variable has given the most accurate results. The model that uses joint spacing and seismic shows the lowest PI value. Therefore, this means that this seismic cannot be combined in a model that uses significant input of other parameters. It also shows that it is probable that seismic can be used as an independent parameter in forming a graphical method. As a result, the performance index obtained can be used as a good indicator in determining the most accurate model to develop. It also shows that the most effective parameter in predicting the WI is simple and multiple regression methods.

To produce a better classification system for weathered rock, the quantitative method is done with a combination of rock mass parameters and rock material properties considered. The rating system is based on physical and geomechanically parameters that are most affected by weathering and excavatability. Next, a rating system is used to give a score or grade to the weathering of rock materials based on the importance of its engineering features. Therefore, a statistical analysis was carried out using several parameters that were found to be significant on excavatability from different grades of weathering i.e. I to VI using simple regression and multiple regression analysis. Empirical correlations between block volume, $Is_{(50)}$, Dry density, and Id_1 have been reported and used to develop the WI and charts to make quick estimates of rock properties. The proposed WI based on rock mass and material properties, is used as an important factor to determine engineering problems related to weathering. The parameters involved show an overlap between weathering grades especially Vp and $Is_{(50)}$. Multiple regression analysis shows that this parameter shows a relatively high relationship with weathering grade in determining the WI.

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Data availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

Ethics approval The authors state that the research was conducted according to ethical standards.

Consent to participate/ publish Not applicable.

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