Integration of homogeneous structural region identification and rock mass quality classification

Qingfa Chen1,2,† and Tingchang Yin1,2,†

1College of Resources, Environment and Materials, Guangxi University, Nanning, Guangxi 530004, People’s Republic of China
2State Key Laboratory of Geomechanics and Geotechnical Engineering, Institute of Rock and Soil Mechanics, Chinese Academy of Sciences, Wuhan 430071, People’s Republic of China

In rock engineering projects, professionals assess the overall rock mass qualities using a sole value. However, the true qualities of partial rock masses are incompatible with such a value. To address this problem, the idea of regionally classifying rock mass qualities is proposed and the associated procedure presented. To achieve this goal, the probabilistic and deterministic joints within the study area were determined, and a three-dimensional joint network model was created. Then, the three-dimensional joint network model was discretized into interlocking subdomains, and the modified blockiness index \( MBi \) was used to finely identify the homogeneous structural regions, together with the \( k \)-means algorithm and the sum of squared errors (SSE). A synthetic model comprising homogeneous structural regions was developed and validated with respect to the extracted cross-sections. Next, an improved rock mass rating system \( RMR_{MBi} \) was introduced, and the viability of \( RMR_{MBi} \) was supported through a significant amount of theoretical cases and several real cases. Finally, visualization of regional \( RMR_{MBi} \) classification results was performed. Results show that: (i) the homogeneous structural regions are finely demarcated in three dimensions, and (ii) the proposed idea can overcome the problem of rock mass quality classification using the conventional approach often leading to ‘overgeneralization’.

1. Introduction

Rock mass quality classification is an auxiliary tool frequently used as an indicator for rock engineering, in which various rock materials and/or rock mass properties are quantified and subsequently combined using addition and subtraction [1], multiplication and division [2], etc., and therefore, the overall quality of a given rock
mass can be numerically assessed. A major benefit of such a classification system is that it can provide empirical guidance for designing rock engineering structures (e.g. excavation spans) [3] and also enable the estimation of rock mass mechanical properties, e.g. rock mass strength and rock mass deformation modulus [4].

Typically, rock mass quality classification results cannot be elaborated to a metre range [3], e.g. a rock mass rating (RMR) value always summarizes the average quality of the rock masses in a segment of the surrounding tunnel. For rock engineering projects (e.g. a rock dam or underground opening), engineers often assess the overall rock mass quality using a sole value, which, as in this case, may be problematic as the true qualities of the partial rock masses are incompatible with such a value. Some investigations have been undertaken to address this problem, e.g. Shang et al. [6] regionalized rock masses through engineering geological rock groupings in conjunction with lithologies and then conducted rock mass quality ratings in different regions. However, lithological regionalization does not consider rock mass structure, and even if the lithologies are identical or similar, rock mass qualities vary with different degrees of rock mass jointing. Objectively, a guideline should be followed when rock mass quality classification is conducted, i.e. regionalizing rock masses and then classifying rock mass qualities. Because lithological regionalization is slightly insufficient, the authors believe that the homogeneous structural region [7] (a further geological zoning) may be more appropriate, i.e. identifying rock mass homogeneous structural regions then classifying rock mass qualities.

Many existing identification methods of homogeneous structural regions zone engineer rock mass from a two-dimensional perspective, i.e. a rock outcrop, and use the joint data measured in daylighting rock masses, including joint orientation and joint density, to divide a given rock mass into different domains together with statistical knowledge. These existing methods mostly focus on small-scale joints (a trace length of approx. 4 m or shorter) [8,9], which are widely used in hydraulics, particularly the creation of a discrete fracture network (DFN) model and the subsequent seepage analysis. However, in these existing methods, some large-scale joints (e.g. incipient discontinuities, minor faults and bedding planes) are always ignored or defined as the presumptive boundaries of a homogeneous structural region [10,11]. Therefore, the existing methods cannot consider the implications of large-scale joints.

Additionally, some traditional rock mass quality classification systems, such as RMR [1], are limited in terms of quantification of the degree of jointing, i.e. the incorporation of rock quality designation (RQD) [12], which is frequently used in the rock engineering field but has some drawbacks as follows [13,14]: (i) RQD only counts the core pieces longer than 100 mm and fails to consider the effect of block size [15], and (ii) the RQD value is sensitive to orientation (i.e. orientation bias). Lowson & Bieniawski [4] recommended replacing the combined use of RQD and joint spacing with a sole use of joint frequency in the RMR system and stated that the limitations associated with the use of RQD can be removed. This stance is very controversial [16], and joint frequency is also orientation-dependent.

In this study, to overcome the aforementioned problems, a modified blockiness index (MBi) [17] was introduced, and attempts were made to finely demarcate the homogeneous structural regions in the study area (i.e. an underground mining stope). Subsequently, an improved RMR system (RMRmbi), in which the combined use of RQD and joint spacing was replaced with MBi, was adopted to three-dimensionally assess rock mass qualities. This study provides robust guidance for underground mine support and numerical simulation of rock mass behaviour (e.g. the discrete element model).

2. Material and methods

As described in §1, professionals always evaluate the overall rock mass qualities using a sole value, and this approach is often one of ‘overgeneralization’. To address this problem, an idea of regionally classifying rock mass qualities, i.e. identifying rock mass homogeneous structural regions then classifying rock mass qualities, is proposed. Based on this idea, the associated procedure was established and can be outlined as follows: (i) using an existing identification method of homogeneous structural regions and considering the implication of large-scale joints, the given rock mass was finely regionalized using the MBi index, and (ii) a visualization of overall rock mass qualities differentiated by RMRmbi values was performed. The flowchart for regionally classifying rock mass qualities is shown in figure 1, and details can be found in §§3–6.

3. Study area

The Zinc-polymetallic Mine is in Tongkeng, Guangxi Province, in Southwest China, and is rich in tin, lead, zinc, antimony and indium. It is also a large production base of non-ferrous metals in China.
Faults are well developed in the Zinc-polymetallic Mine, and the ore bodies mainly occur in marlstone, calcareous marl, shale and so on. An underground mining stope (with a size of approximately 60 × 100 × 50 m) was selected as the testing area (figure 2a), and the field observation was carried out (figure 2b).

3.1. Determination of the distribution parameters of probabilistic joints

The existing identification method of homogeneous structural regions mostly focuses on examining the homogeneous degree of joints between two sites, and the tested joints are always small-scale (i.e. mechanical joints with a trace length of approximately 4 m or shorter) and intersect inside the rock mass in a significant amount. The geometrical parameters of small-scale joints can always be said to have a probabilistic distribution, and hence, when a joint network model is created, a large number of small-scale joints are randomly generated via a distribution function, which corresponds to the in situ conditions examined, and are termed ‘probabilistic joints’ [18]. Regarding that, the small-scale joints in the four cross-cut galleries were measured, and the orientation data are shown in figure 3. Sufficient samples were obtained in the criss-crossed galleries, which enabled a test to determine the homogeneous degree of all the observed small-scale joints. The method proposed by Li et al. [7] was employed to test such a degree. It can be concluded that all the statistical p-values calculated are greater than 0.05, and hence no significant difference exists between these samples, which indicates that the small-scale joints in the test area are statistically homogeneous.

Overall small-scale joint data are presented in figure 4, and the probabilistic distribution parameters of these joints were determined as shown in table 1, which can be used to generate probabilistic joints.
3.2. Identification of the deterministic joints and their geometrical properties

Some joints have been observed that are greater than the gallery scale. Investigation shows that these joints mostly belong to incipient discontinuities, minor faults, bedding planes, etc. Because the quantity is relatively small, these large-scale joints can be defined as ‘deterministic joints’ [19].

It is possible to define the diameter of a large-scale joint as infinite (note that the disc-joint model is used for creating a joint network). However, if all the observed joints that are greater than the gallery scale are generated as an infinite plane, the computer calculation is very time-consuming, and the intensity of jointing will be overestimated because the majority of large-scale joints may be connected. Therefore, a determination method for connected joints was employed, which enables the identification of the connected large-scale joints in an underground mining stope. In this method, the connectivity degree of large-scale joints can be examined with respect to joint categorization, mechanical property, coplanar condition, etc. (more details are provided in the electronic supplementary material).

Following the determination method of connected joints, the connectivity degrees of large-scale joints were investigated, and a total of 42 deterministic joints were identified. Most of them are incipient discontinuities, minor faults and bedding planes, with lithologies of limestone and silicite. The fillings are mainly calcite, and the joint wall is smooth or rough. The groundwater conditions are completely dry. The deterministic joints can be generated using five input parameters: \(x, y, z, \alpha, \) and \(\beta\). (\(x, y, z\))

Figure 2. (a) Location of the study area; and (b) field observation.
denotes the coordinate of the disc-model centre, $a$ is the dip direction, and $b$ is the dip. The deterministic joint network is shown in figure 5.

3.3. Three-dimensional joint network model coupling probabilistic and deterministic joints

Typically, when the small-scale joints show a statistically homogeneous feature, the tested samples (galleries) can be treated as identical homogeneous structural regions. However, the large-scale joints should not be ignored, and thus, a further identification of homogeneous structural regions should be conducted. Before proceeding with this further identification, a three-dimensional joint network model coupling probabilistic and deterministic joints (with a size of $60 \times 100 \times 50$ m) was developed (figure 6). Note that the generated range of probabilistic joints was $80 \times 120 \times 70$ m, because there are some joints whose disc-model centres are outside the model but intersect the model, i.e. boundary effects were eliminated.

4. Three-dimensionally fine identification of homogeneous structural regions

4.1. Selection of the identification index and rationality

Generally, various geometrical parameters, including joint orientation, trace length and joint density, can be used to identify structural region boundaries. In this study, the given rock masses were finely regionalized.
in three dimensions using the MBi index. The MBi index is defined as the ratio of the volume of rock blocks, which are fully enclosed by joints, to the total rock mass volume, and it can be calculated as follows:

\[
MB_i = B_1 + \frac{1}{2}B_2 + \frac{1}{3}B_3 + \frac{1}{4}B_4 + \frac{1}{5}B_5, \tag{4.1}
\]

where \(B_1, B_2, B_3, B_4\) and \(B_5\) are the block percentages of the volumes in five intervals \((0–0.008, 0.008–0.03, 0.03–0.2, 0.2–1.0\) and greater than \(1.0\) m\(^3\), respectively. A higher MBi value indicates a more fractured rock mass and vice versa.

Over the years, joint orientation has typically been used to evaluate homogeneous structural regions, though it is not a prerequisite [20]. For example, Kulatielake et al. [21] used the box fractal dimension as a measure of a statistically homogeneous rock mass; they also reported that block sizes are primarily controlled by joint persistence and density.

The MBi index is a three-dimensional measurement of block size and degree of jointing that can capture the effects of joint persistence and density [22,23]. Meanwhile, the MBi value is produced by
the joint network, which can be exactly adopted for structural region identification based on the
three-dimensional joint network model coupling the probabilistic and deterministic joints.

4.2. Discretizing the three-dimensional joint network model into subdomains

Before discretizing the three-dimensional joint network model (figure 6) into subdomains, the size of the subdomain needs to be determined. Referring to the concept of representative elementary volume (REV) [23], the optimal size of the subdomain was derived via the following steps: (i) the children models of the gradually increasing sizes were generated inside the parent model, as shown in figure 7, (ii) the $MB_i$ values of all the children models were calculated using equation (4.1), and (iii) the optimal size of 20 m was determined using the coefficient of variation ($C_v$), as shown in figure 8. It is noted that the deterministic joints are temporarily excluded in the parent model, because if the deterministic joints are considered, the whole joint network model is no longer statistically homogeneous and the determined REV size is meaningless [18].

Figure 5. Three-dimensional joint network generated via deterministic joints.

Figure 6. Three-dimensional joint network generated by the coupling of probabilistic and deterministic joints.
The interlocking subdomains that are partially overlapping each other were generated within the three-dimensional joint network model, and the distance between the two adjacent subdomains is 1 m (figure 9). Additionally, to measure the MBi values of the model boundaries, all the deterministic and probabilistic joints were generated and accommodated in a space of 80 × 120 × 70 m, and the true model size was 60 × 100 × 50 m. The MBi values of all subdomains were determined, as shown in figure 10, and have a normal distribution with parameter μ of 0.2703 and σ² of 0.2721.

4.3. Finely identifying homogeneous structural regions using k-means and sum of squared errors

Cluster analysis is a process that partitions objects into k groups, and the yielded groups are generally called clusters. Objects in the same cluster are more similar, in some sense, to each other than to those

---

**Figure 7.** A two-dimensional hypothetical example to illustrate the children models. Children models of increasing sizes were developed along the geometrical centre of the parent model.

**Figure 8.** Determination of the optimal size of the children model (i.e. subdomain).
in the other clusters. Cluster analysis is essentially similar to homogeneous structural region identification. To measure the similarity degree between different subdomains, a $k$-means algorithm was used to cluster the $MB_i$ values of all the subdomains.

The $k$-means algorithm is a widely used clustering procedure. Before the $k$-means algorithm is executed, the cluster number should be determined. A classical $k$-means algorithm can be performed via the following steps: (i) randomly distribute the sample $\{x_1, x_2, \ldots, x_n\}$ to $k$ clusters and calculate the initial centre of each cluster $\{z_1, z_2, \ldots, z_k\}$ using equation (4.2) as follows:

$$Z_i = \frac{1}{n} \sum_{x_i \in S_i} x_i,$$  

(4.2)

where $n$ is the number of objects in cluster $i$ and $S_i$ denotes cluster $i$; (ii) compute the distances between the object $x_i$ and $Z_i (i = 1, 2, \ldots, k)$, and allocate this object to its nearest cluster; (iii) update the centre of the $k$ cluster using equation (4.2); and (iv) calculate the $D$ value using equation (4.3) as follows:

$$D = \sum_{i=1}^{n} \left[ \min_{z_1, z_2, \ldots, z_k} d(x_i, z_i)^2 \right],$$  

(4.3)

and (v) end the algorithm if the $D$ values converge, and if not, return to step (ii).
In this section, the sum of squared error (SSE) was adopted to determine an optimal cluster number, which can be calculated as follows:

\[
SSE = \sum_{i=1}^{k} \sum_{x \in S_i} d(x, z_i)^2.
\]  

When the cluster number increases, the number of objects in a cluster will decrease, and the distances between the objects and the corresponding centres of the clusters will shorten. In this circumstance, SSE values will decrease. However, when the decrease degree of SSE values lessens, i.e. the slopes of the curve (SSE versus cluster number) insignificantly vary, a conclusion can be reached that increasing the cluster number can no longer improve the clustering qualities, and the corresponding data point can be deemed the turning point in the curve. Thus, the associated cluster number can be regarded as optimal. A scatter plot of SSE and cluster number was developed as shown in figure 11, indicating that the optimal cluster number is six. Therefore, a k-means algorithm with a cluster number of six was executed, and six clusters were yielded as follows: [0.02747%, 0.14986%], [0.14987%, 0.28447%], [0.28448%, 0.47531%], [0.47532%, 0.68421%], [0.68422%, 0.96486%] and [0.96487%, 1.91390%]. These concurrently suggest that the data values in the same cluster are highly similar, and the associated subdomains can be grouped into a homogeneous structural region.

### 4.4. Synthetic model of homogeneous structural regions and its verification

Pre-processing of subdomains was performed: all the subdomains were contracted into elements (or say, sub-subdomains) of 1 × 1 × 1 m along the centres of the subdomains, as shown in figure 12. In turn, the model (figure 6) was discretized again into elements. Subsequently, these elements were stained different colours according to their associated \(MB_i\) values, i.e. \(MB_i\) values in the same cluster were highlighted with an identical colour, as shown in figure 13. The histogram of the rock mass volumes in different homogeneous structural regions is shown in figure 14.

As can be seen in figures 13 and 14, the vast majority of rock masses in the study area fall into the intervals [0.002747%, 0.14986%] and [0.014987, 0.28447%]. If the joint network model of the study area is entirely built by probabilistic joints, the \(MB_i\) values of the children models range from 0.033% to 0.045% (as shown in figure 8), which falls into the interval [0.014987, 0.28447%]. Thus, it can be concluded that the \(MB_i\) values of the whole study area are majorly affected by probabilistic joints. However, it is improper to evaluate the overall study area as a homogeneous structural region, because the \(MB_i\) values of the children models in the probabilistic joint network vary within a narrow interval. Figure 14 shows that a substantial proportion of subdomains have higher \(MB_i\) values than the children models of the REV sizes, and this is a result of a large number of deterministic joints that
enhance the degree of jointing. Nevertheless, the existing identification method of structural regions is limited in this respect.

Cross-sections were extracted along the three-dimensional joint network model (figure 6) and synthetic model of the homogeneous structural regions (figure 13) at half length, half width and half height, and comparisons were conducted to validate the accuracy of the fine identifications of homogeneous structural regions (figure 15). Visual inspections were performed, based on the dense degree of joints; as shown in the closed red (dashed) wireframes in figure 15, where the dense degree of joints is high, the $MB_i$ value is high. In short, this synthetic model of homogeneous structural regions can capture the differences in joint densities between subdomains, and its accuracy is supported.

5. A rock mass quality classification system: $RMR_{mbi}$

The failure to accurately assess rock mass qualities may be a result of an unreliable measurement of block size [13]. Some drawbacks of the simultaneous use of $RQD$ and joint spacing in the $RMR$ system have been widely acknowledged as follows: (i) both $RQD$ and joint spacing are anisotropic, (ii) the $RQD$ concept ignores the block size effect [15], (iii) joint persistence is neglected, and (iv) the simultaneous use repeatedly calculates the joint density [25].

In this instance, the $RMR_{mbi}$ was introduced, in which the simultaneous use of $RQD$ and joint spacing is replaced with $MB_i$ and the other input parameters remain unchanged. The $RMR_{mbi}$ has several advantages compared to the $RMR$ [17,23] as follows: (i) $MB_i$ is a three-dimensional quantification of jointing degree and is not anisotropic, (ii) $MB_i$ counts blocks of all sizes, (iii) joint persistence is
considered, and (iv) the $RMR_{mbi}$ does not repeatedly calculate the joint density. The rating of $MB_i(R_M)$ can be determined using a continuous function as follows:

$$R_M = 40 - 0.4 \times MB_i.$$  \hfill (5.1)

The higher the $MB_i$ value, the higher the degree of jointing, and the poorer the rock mass quality.

5.1. Preliminarily analysing the viability of $RMR_{mbi}$ based on theoretical discrete fracture network (DFN) models

As described in this section, a significant amount of theoretical DFN models were created to preliminarily analyse the viability of $RMR_{mbi}$. Because the degree of jointing (or block size) is primarily influenced by joint spacing and persistence [23,26], 20 joint spacing values and 10 joint persistence values were chosen (table 2) and then cross-joined, and in this manner, 200 combinations of joint spacing and persistence were obtained. Additionally, the other input parameters of DFN models were fixed, as shown in

Figure 14. Histogram of the rock mass volumes in different homogeneous structural regions.

Figure 15. Graphical comparison test. (a–c) denote the cross-sections extracting along the three-dimensional joint network model (figure 6) and the synthetic model of homogeneous structural regions (figure 13) at half length, half width and half height.
Table 3. Based on the 200 combinations and the fixed parameters, 200 theoretical DFN models were established (figure 16).  

Table 2. Selected representative values of joint spacing and persistence.

| joint spacing classification [23] | extremely wide | very wide | wide | moderate | close | very close | extremely close |
|----------------------------------|----------------|-----------|------|----------|-------|------------|-----------------|
| selected value (m)               | 7              | 4, 5      | 0.9, 1.3, 0.3, 0.4, 0.5, 0.09, 0.13, 0.03 | 0.01 | 0.01 and 6 |
|                                  | and 6          | 1.7       | 0.6  | 0.17     | 0.02  | 0.02 and 2 |
|                                  |                |           |      | and 0.2  | 0.04  |            |

| joint persistence classification [23] | very high | high | medium | low | very low |
|--------------------------------------|-----------|------|--------|-----|---------|
| selected value (m)                   | 30 and 40 | 15 and 20 | 5 and 10 | 2 and 3 | 0.5 and 1 |
|                                      |           |       |        |     | 20      |

Table 3. Distribution of the joint parameters of the theoretical DFN Model.

| joint set no. | set 1 | set 2 | set 2 |
|---------------|-------|-------|-------|
| distribution type of joint persistence | uniform | uniform | uniform |
| distribution type of joint orientation | uniform | uniform | uniform |
| κ for Fisher | 0 | 0 | 0 |
| average dip direction/dip (°) | 0/90 | 90/0 | 90/90 |

Table 3. Based on the 200 combinations and the fixed parameters, 200 theoretical DFN models were established (figure 16).  

Because the RMR_{mbi} and RMR only differ in the characterization of the degree of jointing, the RQD values and the joint spacing values of all theoretical DFN models were determined referring to [27], as shown in figures 17 and 18. Additionally, all the measured MBi values are shown in figure 19. Based on figures 17–19, the ratings of RQD plus joint spacing (R_{RQD,JS}) and MBi (R_M) were calculated, according to [28] and equation (5.1), respectively, as shown in figure 20. This figure shows that for the majority of theoretical DFN models, the R_{RQD,JS} and R_M share similar evaluation results, e.g. in the intervals of 10 to 30. However, for a number of theoretical DFN models, the two rating standards yield different results, which may be because of the implication of joint persistence on MBi. The correlation coefficient r [29] between R_M and R_{RQD,JS} was determined to be 0.93, which is very close to 1, and this suggests that (i) R_M and R_{RQD,JS} share a similar sensibility to distinguish rock mass structures, and (ii) the evaluation results of R_M are in close proximity to those of R_{RQD,JS}, which has been substantially applied, and therefore, R_M is potentially adoptable.

5.2. Assessing the viability of RMR_{mbi} based on several real data

As described in this section, some real data (including all the input parameters of RMR_{mbi} and RMR) collected from [30–33] were used to again support the viability of RMR_{mbi} and the final rating results.
Figure 17. Histogram of the RQD values (theoretical DFN models).

Figure 18. Histogram of the joint spacing values (theoretical DFN models).

Figure 19. Histogram of MBi values (theoretical DFN models).
are shown in figure 21. It can be seen that the fitting line is near the 1:1 line, suggesting that they have similar abilities to evaluate the qualities of real rock masses. However, the fitting line is under the 1:1 line, which indicates that most $RMR_{mbi}$ values are greater than those of $RMR$, and in turn, when appraising the rock mass qualities in the ‘Fair’ category or higher, the $RMR_{mbi}$ may not be as conservative, similar to $RMR$.

Overall, according to the results of the simulated experiments and real applications, it is considered that $RMR_{mbi}$ is a workable classification method with great application potential. $RMR_{mbi}$ not only overcomes the theoretical limitations of $RQD$ and joint spacing but also produces practical and reasonable rating results. Figures 20 and 21 imply that $RMR_{mbi}$ is slightly different from $RMR$, and this circumstance is inevitable because the subsystem of $RMR_{mbi}$ ($R_{Xb}$) can capture the influence of joint persistence on the degree of jointing.

6. Visualization of the regional rock mass quality classification results

As described in §4, the $MB_i$ values of all elements of the three-dimensional joint network model were obtained. Therefore, based on the synthetic model of homogeneous structural regions (figure 13), the
RMRmbi classification and its visualization can be effectively implemented. During the geological investigation, a large number of stations were sited in the main and cross-cut galleries, and the geological data were measured. The Kriging method [11] was used to estimate the RMRmbi values of the untouchable rock masses, based on geological data measured in galleries. Then, the visual model of RMRmbi classification was constructed, which was stained with different colours according to the RMRmbi values (figure 22).

As shown in figure 22, the rock masses of the study area are in Classes I, II and III, respectively. The volumes of the rock masses of the different classes were counted, as shown in figure 23. The great majority of rock masses are in Class II followed by Classes III and I as follows: $25.9857 \times 10^4$ m$^3$ (Class II), $3.4568 \times 10^4$ m$^3$ (Class III) and $0.5575 \times 10^4$ m$^3$ (Class I). The rock masses in the three classes differ greatly in volume, indicating that Class II is the dominant quality of the study area. Additionally, the rock mass qualities gradually decrease with an increase in depth.

7. Conclusion

To address the problem that rock mass quality classification is often one of ‘overgeneralization’ when a traditional evaluation approach is used, the idea of regionally classifying rock mass qualities, i.e. identifying rock mass homogeneous structural regions then classifying rock mass qualities, was proposed and the associated procedure presented. Visualizations of homogeneous structural region
Additionally, the development of RMRmbi is a new attempt. Although the conventional RMR system has some limitations, it has been successfully applied for more than 40 years. The experience of its application has been substantially accumulated, which is exactly what the RMRmbi of the current version lacks. Furthermore, completing a conventional RMR task requires a few minutes or an hour in a local area; however, to obtain a final RMRmbi value, professionals may spend more time constructing joint network models and calculating rock block sizes (maybe several hours or days). Therefore, future studies are needed to further verify the applicability of RMRmbi (e.g. applying the RMRmbi to more real cases and developing a method to rapidly determine the MBi value of jointed rock masses).

Ethics. Research ethics: We are not required to complete an ethical assessment prior to conducting our research. Because the research in this paper is a rock engineering problem, no ethical problem is related to this paper. Animal ethics: We are not required to complete an ethical assessment prior to conducting our research. No animal is used or related to this paper.

Data accessibility. We include all the joint data in Dryad Digital Repository: http://dx.doi.org/10.5061/dryad.7nh05k6 [34].

Authors’ contributions. Q.C. conceived of the study, helped draft the manuscript and reviewed the manuscript. T.Y. collected and analysed the data, constructed the models and wrote the manuscript. All authors gave final approval for publication.

Competing interests. The authors declare no competing interests.

Funding. This work was financially supported by the National Science Foundation for Young Scientists of China (grant no. 41402306) and the Open Research Fund of State Key Laboratory of Geomechanics and Geotechnical Engineering, Institute of Rock and Soil Mechanics, Chinese Academy of Sciences (grant no. Z016015).
Acknowledgements. The authors thank the two anonymous reviewers for their constructive comments. The authors would specifically like to thank Mr Shikang Qin (Guangxi University, China), Dr Hong Yin (Guangxi University, China) and Mr Yuan Gao (Guangxi University, China) for useful discussions during the preparation of this manuscript.

References

1. Bieniawski ZT. 1989 Engineering rock mass classifications. New York, NY: Wiley.
2. Bar N, Barton N. 2017 The Q-slope method for rock slope engineering. Rock Mech. Rock Eng. 50, 3307–3322. (doi:10.1007/s00603-017-1305-0)
3. Cerda B, Tardaguila I, Varona P, Bieniawski ZT. 2014 Innovating tunnel design by an improved experience-based RMR system. In Proc. World Tunn. Congr. 2014 — Tunnels a Better Life, Foz do Iguaçu, Brazil, 1–9.
4. Lawson AR, Bieniawski ZT. 2013 Critical assessment of RMR based tunnel design practices: a practical engineer’s approach. In Rapid Excav. Tunneling Conf., Washington, DC, 16.
5. Boldini D, Bruno R, Egger H, Stafisso D, Voza A. 2018 Statistical and geostatistical analysis of drilling parameters in the Brenner base tunnel. Rock Mech. Rock Eng. 51, 1955–1963. (doi:10.1007/s00603-018-1446-9)
6. Shang Y et al. 2013 Application comparison of engineering geological rock group and rock mass classification in rock engineering. Chin. J. Rock Mech. Eng. 32, 3205–3214.
7. Li Y, Wang Q, Chen J, Han L, Song S. 2014 Identification of structural domain boundaries at the Songta dam site based on nonparametric tests. Int. J. Rock Mech. Min. Sci. 70, 177–184. (doi:10.1016/j.ijrmms.2014.04.018)
8. Song S, Wang Q, Chen J, Cao C, Li Y, Zhou X. 2015 Demarcation of homogenic structural domains within a rock mass based on joint orientation and trace length. J. Struct. Geol. 80, 16–24. (doi:10.1016/j.jsg.2015.08.006)
9. Song S, Wang Q, Chen J, Li Y, Zhang Q, Cao C. 2015 A multivariate method for identifying structural domain boundaries in a rock mass. Bull. Eng. Geol. Environ. 74, 1407–1418. (doi:10.1007/s10064-014-0686-5)
10. Gao J, Yang C, Wang G. 2010 Discussion on zonning method of structural homogeneity of rock mass in Beishan of Gansu Province. Rock Soil Mech. 31, 588–592.
11. Escuder VJ, Carbonell R, Jurado MJ, Marti D, Perez-Estain A. 2001 Two-dimensional geostatistical modeling and prediction of the fracture system in the Alblaya Granitic Pluton, SW Iberian Massif, Spain. J. Struct. Geol. 23, 2011–2023. (doi:10.1016/S0191-8141(01)00026-8)
12. Deere DU. 1964 Technical description of rock cores for engineering purposes. Felsmech Ingenieurugn. 1, 16–22.
13. Palmstrom A. 2005 Measurements of and correlations between block size and rock quality designation (RQD). Tunn. Undergr. Sp. Technol. 20, 362–377. (doi:10.1016/j.tust.2005.01.005)
14. Pells PS, Bieniawski ZT, Hencher SR, Pells SE. 2017 Rock quality designation (RQD): time to rest in peace. Can. Geotech. J. 54, 825–834. (doi:10.1139/cgj-2016-0012)
15. Hoek E, Diederichs MS. 2013 Quantification of the geological strength index chart. In 47th US Rock Mech/Geomech. Symp., San Francisco, CA, 23–26 June, p. 9.
16. Koutsofas DC. 2017 Discussion of ‘Rock quality designation (ROD): time to rest in peace’. Can. Geotech. J. 54, 1–9. (doi:10.1139/cgj-2017-0497)
17. Chen Q, Niu W, Zheng W, Liu J, Yin T, Fan Q. 2018 Correction of some problems in blockiness evaluation method in fractured rock mass. Rock Soil Mech. 39, 1–8.
18. Zhang Q, Wu A, Zhang L. 2014 Statistical analysis of stochastic blocks and its application to rock support. Tunn. Undergr. Sp. Technol. 43, 426–439. (doi:10.1016/j.tust.2014.06.005)
19. Wang S, Ni P, Guo M. 2013 Spatial characterization of joint planes and stability analysis of tunnel blocks. Tunn. Undergr. Sp. Technol. 38, 357–367. (doi:10.1016/j.tust.2013.07.017)
20. Fan L, Huang R, Ding X. 2003 Analysis on structural homogeneity of rock mass based on fracture density. Chin. J. Rock Mech. Eng. 22, 1132–1136.
21. Kulatilake PHSW, Fiedler R, Panda BB. 1997 Fractal dimension as a measure of statistical homogeneity of jointed rock masses. Eng. Geol. 48, 217–229. (doi:10.1016/S0013-7952(97)00045-8)
22. Zhang Q, Bian Z, Yu M. 2009 Preliminary research on rockmass integrity using spatial block identification technique. Chin. J. Rock Mech. Eng. 28, 507–515.
23. Xia L, Zheng Y, Yu Q. 2016 Estimation of the REV size for blockiness of fractured rock masses. Comput. Geotech. 76, 83–92. (doi:10.1016/j.compgeo.2016.02.016)
24. MacQueen J. 1967 Some methods for classification and analysis of multivariate observations. In Proc. Fifth Berkeley Symp. Math. Stat. Probab., Berkeley, CA, vol. 1, 281–297. Berkeley, CA: University of California Press.
25. Aydan pp. Ω, Ulusay R, Tokashiki N. 2014 A new rock mass quality rating system: rock mass quality rating (RMQR) and its application to the estimation of geomechanical characteristics of rock masses. Rock Mech. Rock Eng. 47, 1255–1276. (doi:10.1007/s00603-013-0462-z)
26. Shang J, West LJ, Hencher SR, Zhao Z. 2018 Geological discontinuity persistence: implications and quantification. Eng. Geol. 241, 41–54. (doi:10.1016/j.enggeo.2018.05.010)
27. Zhang W, Wang Q, Chen JP, Tan C, Yuan XD, Zou FJ. 2012 Determination of the optimal threshold and length measurements for RQD calculations. Int. J. Rock Mech. Min. Sci. 51, 1–12. (doi:10.1016/j.jrmms.2012.02.005)
28. Warren SN, Kallu RB, Barnard CK. 2016 Correlation of the rock mass rating (RMR) system with the unified soil classification system (USCS): introduction of the weak rock mass rating system (W-RMR). Rock Mech. Rock Eng. 49, 4507–4518. (doi:10.1007/s00603-016-1090-1)
29. Cohon J. 1988 Statistical power analysis for the behavioral sciences. 2nd edn, p. 567. (doi:10.1234/1245678)
30. Guangxi University, Huaxi Group. 2013 Classification for the jointed rock masses and optimization of the mining technology in Tongkeng Mine (a concluding report). (in Chinese).
31. Central South University, Huaxi Group, Liuzhou Huaxi Nonferrous Designing Institute. 2011 Assessment of the engineering rock mass quality in Xintongkuang Mine (a concluding report). (in Chinese).
32. Wang X. 2011 Analysis and simulation of fractured character in layer rockmass based on probabilistic: a case study of the dam of Jinping I hydropower station. Wuhan, Hubei, People’s Republic of China: China University of Geoscience. (in Chinese).
33. Pan H. 2012 Research on grouting uplifting mechanism of plinth of concrete facing dam. Chengdu, People’s Republic of China: Xiha University. (in Chinese).
34. Chen Q, Yin T. 2018 Data from: Integration of homogeneous structural region identification and rock mass quality classification. Dryad Digital Repository (doi:10.5061/dryad.76k6s56)