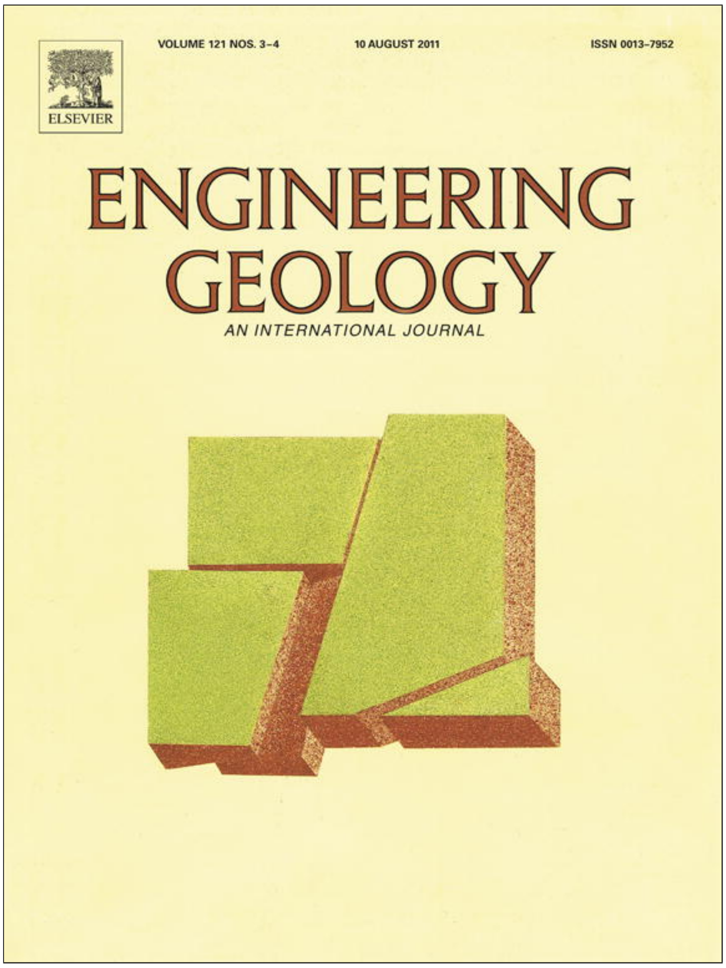
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A linear classifier for probabilistic prediction of squeezing conditions in Himalayan tunnels

R. Jimenez [a,*], D. Recio [a,b]

[a] ETSI Caminos, Canales y Puertos, Technical University of Madrid, Spain
[b] Acciona Infraestructuras I+D+i, Madrid, Spain

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ABSTRACT

Rock squeezing is a time-dependent process associated to the plastic flow (creep) of rock masses subjected to pressures exceeding a limiting shear stress. It usually produces large convergences that can have a significant negative influence on the budget and time needed to successfully complete a tunneling project. We propose a novel empirical method for prediction of squeezing conditions in rock tunnels which is based on the application of the theory of linear classifiers to an extensive database of well-documented squeezing case histories from tunnels in the Himalayas and Himalayan foothills that has been compiled from the literature. Our method allows us to propose new class-separation lines to estimate the occurrence of squeezing conditions (squeezing vs no-squeezing), and it also allows to compute probabilities of squeezing for different combinations of tunnel depth and rock mass quality. Results show that, as expected, the probability of squeezing significantly increases with depth and also that the quality of the rock mass has a crucial influence on squeezing probability, with probabilities of squeezing changing by significant amounts given a single-step variation within the Q system. They also show that our newly proposed squeezing class-separation line presents good results that improve the predictive capabilities of previously available criteria.

1. Introduction

Rock squeezing is produced by plastic flow (creep) of rock masses subjected to stresses that exceed a limiting shear stress, leading to material failure, and typically producing large convergences around tunnels that could continue for long periods of time (Barla, 1995; Dalgic, 2002). Such large convergences are commonly associated to difficulties during (and after) construction that normally require non-standard excavation and support methods; re-excavation of specific sections where excessive convergences reduce the section below minimum acceptable limits; or both (Schubert, 1996; Hoek, 1999; Dalgic, 2002; Hoek and Guevara, 2009; Barla, 2010). They could also produce long term problems associated to floor heave or support failures (Barla and Pelizza, 2000); or even, in extreme circumstances, the abandonment of the tunnel project. In addition, squeezing ground conditions are an important factor for TBM design (Robbins, 1997; Ramoni and Anagnostou, 2010), and squeezing can also produce the entrapment of TBMs (Shang et al., 2004; Hoek and Guevara, 2009), especially if they are forced to stop due to mechanical breakdowns or to insufficient thrust capabilities.

The term squeezing, however, has been often vaguely-defined in the literature (Panet, 1996); for instance, Barla (2001) presents a review with nine different definitions of squeezing available in the rock mechanics literature, and other definitions have been proposed as well (Einstein, 1996; Panet, 1996; Dalgic, 2002). In general, definitions of squeezing include the ideas of (i) non-elastic time-dependant behavior (see e.g., Gioda and Cividini, 1996); (ii) failure of the rock mass due to concentration of stresses around the excavation; and (iii) large convergences, or large loads on the support, or both (Kovari and Staus, 1996; Panet, 1996). Conceptually, the term squeezing is different from swelling; volume increase of the ground due to water absorption or to other physical–chemical processes (Terzaghi and Terzaghi, 1946; Einstein, 1996). However, since both processes often occur simultaneously in real cases (Einstein, 1996), alternative definitions of squeezing that make no distinction on the nature of the motion have been proposed as well (Aydan et al., 1996).

The threshold for "large" convergences has not always been defined in a consistent way either, although a normalized convergence value of 1% is commonly considered to be the threshold for squeezing occurrence, as proposed by several authors and verified by field data (Sakurai, 1983; Chern et al., 1998). Such deformation level usually corresponds to a limited plastic radius around the excavation (Goel et al., 1995b; Chern et al., 1998; Hoek, 2001) so that, in most cases, the tunnel does not suffer problems associated to excessive deformations. In any case, convergences larger than 1% should only be considered as an indicator of the initiation of likely construction

* Corresponding author at: ETSI Caminos, Canales y Puertos (Geotecnia) C/ Profesor Aranguren s/n, 28040 Madrid, Spain. Tel.: +34 913366710x107; fax: +34 913366774.
E-mail address: rafael.jimenez@upm.es (R. Jimenez).

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problems, as many tunnels have been successfully completed after allowing strains much higher than 1% (Hoek, 2001).

Squeezing problems are particularly common in relatively deep tunnels in weak rock, although significant convergences can also occur in shallower tunnels within very weak or over-stressed rock masses due to, for instance, tectonic or topographic effects (Shrestha and Broch, 2008; Hoek and Marinos, 2010; Hudson, 2010). Deep excavations in hard rock, on the other hand, tend to produce problems associated to rock bursting (Hoek, 2001; Hoek and Marinos, 2010), although significant time-dependant behavior and squeezing (Malan and Basson, 1998; Malan, 1999) have also been observed in some cases.

It is therefore clear that squeezing can have a significant negative influence on the budget and time needed to successfully complete a tunneling project. For that reason, there have been significant efforts to develop tools for squeezing prediction and for estimation of convergences in tunnels considering rheological and time-dependant models. For instance, Sulem et al. (1987) presented an analytical solution for prediction of (future) time-dependent displacements in tunnels that consider the rheological effects of the rock mass and also the effects of the rate of face advance. Such solution has been later employed to anticipate changes in geological conditions ahead of the face (Sellner and Steindorfer, 2000; Schubert and Grossauer, 2004), as well as to estimate the relative importance of the rheological behavior of the rock with respect to the rate of advance of the tunnel face (Kontogianni et al., 2006).

Analytical solutions to compute creep deformations in squeezing rock have also been proposed and, for instance, (Fritz, 1984) presented a solution for axisymmetric tunnels in elasto-viscoplastic media. Similarly, there has been a recent strong interest on the application of time-dependant constitutive models to model tunnel behavior. Sterpi and Gioda (2009) employed a visco-elasto-plastic constitutive model to account for the influence of tertiary creep on tunnel closure (and, hence, on squeezing behavior); whereas Debernardi and Barla (2009) proposed a stress-hardening elastic-viscous-plastic constitutive law which has been shown to reproduce well the squeezing behavior of real tunnels (Barla, 2010). Other rheological laws have also been proposed; for instance, Phienwej et al. (2007) employed hyperbolic and power creep laws to predict time-dependent closure of circular tunnels considering the effect of support types and installation location, whereas Guan et al. (2008) present the implementation of a rheological model that considers the degradation of Mohr–Coulomb parameters (damage) with time and as function of a stress coefficient that indicates "distance to failure".

Such methods, however, often rely on the "up-scaling of properties" therefore introducing significant uncertainties into the analysis (they are calibrated from laboratory tests, which are not always representative of rock mass conditions; (Sterpi and Gioda, 2009)). They may also need complex calibration procedures (Guan et al., 2009) that, in addition, are based on convergence data that is only available after tunnel construction (Zhifa et al., 2001; Boidy et al., 2002). This aspect, in conjunction with the complexity of the models involved, greatly reduces the a-priori capabilities for squeezing prediction of such methods and, in addition, it makes their application difficult prior to tunnel construction and reducing their usefulness during the planning stage. Furthermore, and despite the rapid advances in numerical tools available to the average tunnel designer, they are probably still not robust enough (and validated enough) to be routinely employed in real tunneling projects (Hoek and Marinos, 2010).

Based on the above, and due to their simplicity and ease of use, empirical methods still play a crucial role for squeezing prediction (Shrestha, 2005), although alternative methods for uncertainty analysis based on Monte Carlo simulation have also been proposed (Panthi and Nilsen, 2007). (See below for a review of empirical methods for squeezing prediction.) In this paper, we propose a novel empirical method for prediction of squeezing conditions in rock tunnels in the Himalayas and Himalayan foothills. Our method relies on the statistical analysis (using the theory of linear classifiers) of an extensive database of well-documented Himalayan case histories that has been compiled from the literature, which allows us to estimate the occurrence of squeezing conditions (squeezing vs no-squeezing) and also to compute probabilities of squeezing for tunnels in such conditions.

The main factors of the squeezing definitions presented above have been considered for the construction of the database employed in our analysis, so that squeezing occurrences predicted by our method would be expected to correspond to situations in which relatively large deformations (say, more than 1% for an unlined tunnel) could occur, therefore producing problems during or after (from weeks to a few years) construction, unless special construction methods are employed to cope with squeezing ground. Note, however, that no intention is made to model the time-dependant aspect of the problem or, in other words, to compute the evolution of convergences with time.

2. A review of empirical methods for squeezing prediction

Many methods for empirical squeezing prediction are based on the definition of *competence factors* that relate (some indicators of) rock mass strength and stress at the tunnel depth. For instance Jethwa et al. (1984) and Hoek and Marinos (2000) predicted tunnel squeezing based on the ratio between rock mass uniaxial strength, σ_{cm}, and lithostatic stress, $\sigma_0 = \gamma_r H$; as an example, Hoek (2001) proposes that values of $\sigma_{cm}/\sigma_0 < 0.35$ are likely to produce squeezing (as defined by normalized convergences of more than 1% in unsupported tunnels).

Other empirical methods for squeezing prediction are based on the use of geomechanical classifications (RMR or Q systems). Such classifications have a long tradition of application in rock tunneling, and it is therefore usual to record RMR or Q values at the face as the tunnel advances; such records, in conjunction to observations of squeezing occurrence (or not occurrence), can be used to develop empirical relations for squeezing prediction. In that sense, for instance, Singh et al. (1992) presented a well-known empirical correlation to anticipate squeezing conditions based on the *Q*-value of the rock mass, in which tunnels deeper than $H = 350Q^{1/3}$ (with *H* in meters) could be expected to present squeezing. Similarly, given the practical difficulties for prediction of the Stress Reduction Factor (SRF) in the *Q* system, Goel et al. (1995b) eliminated the influence of *SRF* on *Q*, and, to that end, they defined a Rock Mass Number as $N = (RQD/J_n)(J_r/J_a)J_w$. (Note that *N* is equal to *Q* when $SRF = 1$). They also incorporated the influence of tunnel dimensions by considering the product $HB^{0.1}$, where *H* is the tunnel depth and *B* is the tunnel width (both in meters). (For an in-depth review of these and other methods for empirical squeezing prediction; see Singh et al., 1997 and Shrestha, 2005.)

Other researchers have also proposed estimates of degrees of squeezing intensity based on estimates of tunnel deformations. For instance, Aydan et al. (1993) transformed the competence factor concept into a strains concept (based on the analogy between the stress–strain response of rock in the laboratory and within the rock mass around tunnels), and they proposed several levels of squeezing based on the ratio between the peak tangential strain at the tunnel boundary and the elastic strain. Similarly, Hoek and Marinos (2000) (see also (Hoek, 2001)) proposed several levels of squeezing based on the strains produced by the excavation of an unsupported tunnel in rock masses with different $\sigma_{cm}/p0$ values; Sakurai (1997) defined warning levels against excessive deformation based on the concept of critical strain; and Singh et al. (2007) have recently proposed the use of their squeezing index (defined as expected strain divided by critical strain) to predict levels of squeezing potential in tunnels.

In this work we propose new empirical equations for squeezing prediction (and for estimation of the associated uncertainties) that are based on the use of statistical classification. To that end, we have compiled an extensive database of well-documented case histories

Table 1
Iterative parameter estimates for the linear classifier model.

Iteration	θ_1	θ_2	θ_3
(a) logQ vs H model			
0	0	0	0
1	−2.452302453	−1.241844276	0.005546925
2	−4.170797469	−1.985885961	0.009685494
3	−5.23285435	−2.42153310	0.01227157
4	−5.52133196	−2.53690498	0.01296426
5	−5.53763677	−2.54334136	0.01300292
6	−5.53768493	−2.54336022	0.01300303
(b) logQ vs logH model			
0	0	0	0
1	−7.461548	−1.163881	2.773747
2	−15.290369	−1.964125	5.801055
3	−20.183303	−2.485557	7.679302
4	−21.759721	−2.653168	8.280635
5	−21.892405	−2.667128	8.331105
6	−21.893265	−2.667218	8.331431

from tunnels in the Himalayas and Himalayan foothills that are available from the literature. Starting from an original set of case histories, we filtered the data to obtain a total of 62 data points that were later employed in the statistical analysis. The reason to perform such filtering was to assure that the data are reliable (using only data from well-documented case histories published in prestigious sources); original (i.e., to avoid the use of the same case history several times); and independent (i.e., we only use data that is the product of direct measurement and/or estimation and, for instance, we avoid the use of published empirical correlations to obtain Q values from RMR—or vice versa). The complete database of case histories employed in this work is reproduced in Appendix A (Table 2).

3. Linear classifiers for squeezing prediction

Classifiers are commonly employed in statistics and machine learning to help with the labeling of observations; that is, given one observation (or occurrence) of a set of variables X for which the classifier is trained, they help to categorize such observation by assignment of a discrete-valued random variable Y ("class label"). Such classification can be performed in a probabilistic way, so that the label of each observation is assigned to the outcome of Y that maximizes the conditional probability of the class label given the observation (i.e., it maximizes $P(Y|X)$). Once that we have computed the conditional probabilities of each possible label considered, it is clear that such conditional probabilities can also be employed as a measurement of the uncertainties of the assignments, therefore providing additional information to the designer that could be useful, for instance, in tunnel risk analyses.

For the sake of completeness, here we present a brief introduction to the theory of classification, with a particular attention to discriminative models based on *logistic regression*. As we will see, this approach introduces linear decision boundaries between the different class labels, and it is therefore referred to as a "linear classifier". Our discussion below is mainly based on the work of Jordan (2003); additional useful references are Duda et al. (2001) and Mitchell (2005).

As mentioned above, given a set of random variables that compose the input vector of observations $X=(X_1,\ldots,X_n)$, we need to compute the conditional probabilities of the class labels Y given the observed data $P(Y=y|X=x)$. In the case of squeezing, we can model Y as a Bernoulli random variable (with values of 1 for occurrence of squeezing and 0 for no squeezing), with probability distribution given by (note that, for simplicity, we shorten the notation):

$$p(y|x) = \mu(x)^y(1-\mu(x))^{1-y}, \tag{1}$$

where $\mu(x)=p(Y=1|x)=E(y|x)$ is the parameter of the distribution. Note, however, that such parameter μ is itself a function of x, and we therefore need to compute it based on the values of the observed variables. To that end, we assume that μ depends on x via the linear transformation $\nu(x)=\theta^T x$ (θ is a parameter vector); and also that ν is transformed into a probability scale by means of the logistic function (see Figure 1.) That is, we have:

$$\mu(x) = \frac{1}{1+\exp(-\nu(x))}. \tag{2}$$

The parameter vector θ needs to be "learned" before we can use the classifier to predict the expected outcome (squeezing or not squeezing) of a specific case. To that end, we can use training datasets (as we do by means of the dataset of case histories presented in Appendix A) to compute maximum likelihood estimates of the parameter vector θ. (Maximum likelihood estimation is a common tool for calibration of models in statistics; its goal is to provide a set of parameters that maximizes the likelihood – in other words, the probability – that the model generates the observations that we actually have.)

Given a training dataset of observations of input parameters and outcomes, $\mathcal{D}=(x_n,y_n)\,;n=1,\ldots,N$, the likelihood of such N observations can be computed as:

$$p(y_1,\ldots,y_N|x_1,\ldots,x_N,\theta) = \prod_n \mu_n^{y_n}(1-\mu_n)^{1-y_n}, \tag{3}$$

and, taking logarithms for mathematical convenience,

$$l(\theta|\mathcal{D}) = \log(p(y_1,\ldots,y_N|x_1,\ldots,x_N,\theta)) = \sum_n \{y_n\log\mu_n + (1-y_n)\log(1-\mu_n)\}. \tag{4}$$

The log-likelihood in Eq. (4) can be maximized using a Newton–Raphson-type algorithm such as the Iteratively Re-weighted Least Squares Algorithm (IRLS) (Wasserman, 2004). Newton–Raphson algorithms are iterative algorithms in which the $i+1$-th estimation of parameters is based on the previous one, and also on the information about the first and second derivatives with respect to the (unknown) parameters. The general expression is given by:

$$\theta^{(i+1)} = \theta^{(i)} - H^{-1}\nabla_\theta l, \tag{5}$$

where l is the log-likelihood function to be optimized (see Eq. (4)), ∇_θ is the gradient vector with respect to the parameters, and H is the Hessian matrix.

The gradient vector can be computed taking derivatives of Eq. (4)

$$\nabla_\theta l = \sum_n (y_n-\mu_n)x_n = X^T(y-\mu), \tag{6}$$

and, taking second derivatives, we get the Hessian matrix as,

$$H = -\sum_n \mu_n(1-\mu_n)x_n x_n^T = -X^T W X, \tag{7}$$

where W is a diagonal matrix with weights that are a function of θ (therefore, they change from iteration to iteration—hence the name of iterative reweighted) and that are given by,

$$W = \mathrm{diag}\{\mu_1(1-\mu_1),\ldots,\mu_N(1-\mu_N)\}. \tag{8}$$

Going back to Eq. (5), and substituting the expressions for the gradient and Hessian given by Eqs. (6) and (7), we get:

$$\theta^{(i+1)} = \theta^{(i)} + \left(X^T W^{(i)} X\right)^{-1} X^T\left(y-\mu^{(i)}\right). \tag{9}$$

That is, from Eq. (9) we see that we can iteratively compute estimates of the parameters based on a set of observations. The Newton–Raphson is a second order algorithm that usually converges

Table 2
Database of case histories employed in this work.

No.	Tunnel	Location	Rock type	Span	Depth	Deformation	Geomechanical charact				Squeezing	Refs
				[m]	[m]	[%]	*Q*	*SRF*	*N*	*RMR*		
1	Khara hydro project	India	Clay conglomerate	6.0	150	0.42	0.400	5000	2000	35	0	Goel et al. (1995b) and Singh et al. (2007)
2	Khara hydro project	India	Clay conglomerate	6.0	200	0.75	0.400	5000	2000	30	0	Goel et al. (1995b) and Singh et al. (2007)
3	Lakhwar	India	–	6.0	250		8500	2500	21,250	61	0	Goel et al. (1995b)
4	Lakhwar	India	–	14.0	250		8500	2500	21,250	61	0	Goel et al. (1995b)
5	Maneri stage I	India	–	58	225		3600	2500	9000	51	0	Goel et al. (1995b)
6	Maneri stage I	India	–	5.8	550		4500	2667	12,000	55	0	Goel et al. (1995b)
7	Maneri stage I	India	–	5.8	550		3600	2500	9000	51	0	Goel et al. (1995b)
8	Maneri stage I	India	–	5.8	300		0.400	5000	2000	35	0	Goel et al. (1995b)
9	Maneri stage II	India	–	7.0	200		0.570	4386	2500	38	0	Goel et al. (1995b)
10	Maneri stage II	India	–	7.0	175		0.840	5000	4200	40	0	Goel et al. (1995b)
11	Maneri stage II	India	–	7.0	250		2710	2583	7000	50	0	Goel et al. (1995b)
12	Maneri–Bhali hydro project	India	Fractured quartzite	4.8	225	0.06	3600	2500	9000	51	0	Goel et al. (1995a) and Singh et al. (2007)
13	Maneri–Uttarkashi power	India	Sheared Metabasics	4.8	340	0.40	1800				0	Goel et al. (1995a)
14	Maneri–Uttarkashi power	India	Foliated Metabasics	4.8	550		5100				0	Goel et al. (1995a)
15	Salal	India	–	12.0	150		1.100	2727	3000	41	0	Goel et al. (1995b)
16	Tehri Dam project	India	Argilaceous phyllite	12.0	220	0.38	0.800	4375	3500	42	0	Goel et al. (1995b) and Singh et al. (2007)
17	Theri	India	–	12.0	300		6000	2500	15,000	59	0	Goel et al. (1995b)
18	Upper Krishna project	India	–	13.0	34		15,000	5000	75,000	68	0	Goel et al. (1995b)
19	Upper Krishna project	India	Banded schists	13.0	52	0.18	15,000	2500	37,500	65	0	Goel et al. (1995b) and Singh et al. (2007)
20	Chibro–Khodri	India	Schists	3.0	280	2.80	0.050	7500	0.375	14	1	Goel et al.(1995b) and Hoek (2001)
21	Chibro–Khodri	India	–	3.0	280	4.50	0.220	0.500	0.110	13	1	Goel et al. (1995b)
22	Chibro–Khodri	India	–	9.0	680	6.00	0.050	10,000	0.500	14	1	Goel et al. (1995b)
23	Chibro–Khodri	India	–	9.0	280	2.00	0.022	5000	0.110	13	1	Goel et al. (1995b)
24	Giri–Bata	India	–	4.6	240	5.50	0.120	5000	0.600	20	1	Goel et al. (1995b)
25	Giri–Bata	India	Slate	4.2	380	7.60	0.510	5000	2550	35	1	Goel et al. (1995b) and Hoek (2001)
26	Khimti 1 hydroproject A1 ch515	Nepal	Sheared schists	4.2	100	5.24	0.005	10,000	0.045	7	1	Shrestha (2005)
27	Khimti 1 hydroproject A4 ch1013	Nepal	Sericite schists	4.0	112	2.39	0.006	10,000	0.060	18	1	Shrestha (2005)
28	Khimti 1 hydroproject A1 ch580	Nepal	Sheared schists	4.3	111	1.50	0.008	10,000	0.080	7	1	Shrestha (2005)
29	Khimti 1 hydroproject A4 ch974	Nepal	Gneiss	4.0	112	0.40	0.008	10,000	0.080	23	0	Shrestha (2005)
30	Khimti 1 hydroproject A4 ch1045	Nepal	Clay–filled sheared gneiss	4.0	112	0.20	0.008	10,000	0.080	19	0	Shrestha (2005)
31	Khimti 1 hydroproject A3 ch220	Nepal	Schists	4.0	140	1.60	0.009	10,000	0.090	8	1	Shrestha (2005)
32	Khimti 1 hydroproject A1 ch500	Nepal	Sheared schists	4.2	100	7.63	0.010	10,000	0.100	17	1	Shrestha (2005)
33	Khimti 1 hydroproject A2 ch601	Nepal	Sericite schists	4.0	138	0.38	0.013	10,000	0.130	18	0	Shrestha (2005)
34	Khimti 1 hydroproject A2 ch1283	Nepal	Gneiss and sericite schists	4.4	212	0.05	0.040	2500	0.100	17	0	Shrestha (2005)
35	Khimti 1 hydroproject A3 ch345	Nepal	Gneiss and sericite schists	5.0	300	0.36	0.050	5000	0.250	20	1	Shrestha (2005)
36	Khimti 1 hydroproject A1 ch665	Nepal	Gneiss and schists	4.0	112	0.59	0.060	5000	0.300	20	0	Shrestha (2005)
37	Khimti 1 hydroproject A2 ch1730	Nepal	Gneiss	4.0	95	0.58	0.065	5000	0.325	20	0	Shrestha (2005)
38	Khimti 1 hydroproject A4 ch550	Nepal	Chlorite sericite gneiss	4.0	218	0.28	0.070	10000	0.700	27	0	Shrestha (2005)
39	Khimti 1 hydroproject A1 ch475	Nepal	Gneiss and sericite schists	4.0	98	1.55	0.080	3800	0.304	15	1	Shrestha (2005)
40	Khimti 1 hydroproject A3 ch235	Nepal	Gneiss	5.0	284	2.48	0.090	5000	0.450	19	1	Shrestha (2005)
41	Khimti 1 hydroproject A3 ch340	Nepal	Gneiss and sericite schists	5.0	300	0.56	0.090	2500	0.225	25	1	Shrestha (2005)
42	Khimti 1 hydroproject A2 ch1357	Nepal	Banded gneiss and chlorite schists	4.0	261	0.31	0.095	5000	0.475	21	0	Shrestha (2005)
43	Khimti 1 hydroproject A2 ch895	Nepal	Gneiss and chlorite schists	4.0	198	0.58	0.140	7500	1050	21	0	Shrestha (2005)
44	Khimti 1 hydroproject A4 ch503	Nepal	Gneiss and sericite schists	4.0	225	0.49	0.140	5000	0.700	28	0	Shrestha (2005)
45	Khimti 1 hydroproject A3 ch15	Nepal	Gneiss and schists	5.0	130	0.68	0.200	5000	1000	25	1	Shrestha (2005)

Table 2 (*continued*)

No.	Tunnel	Location	Rock type	Span	Depth	Deformation	Geomechanical charact				Squeezing	Refs
				[m]	[m]	[%]	*Q*	*SRF*	*N*	*RMR*		
46	Khimti 1 hydroproject A3 ch59	Nepal	Gneiss and schists	4.1	158	0.64	0.230	2500	0.575	30	0	Shrestha (2005)
47	Khimti 1 hydroproject A3 ch200	Nepal	Gneiss and shists	5.0	276	1.55	0.250	5000	1250	37	1	Shrestha (2005)
48	Khimti 1 hydroproject A3 ch210	Nepal	Gneiss and shists	5.0	276	1.13	0.280	5000	1400	25	1	Shrestha (2005)
49	Khimti 1 hydroproject A2 ch441	Nepal	Gneiss	4.0	126	0.07	0.300	2500	0.750	38	0	Shrestha (2005)
50	Khimti 1 hydroproject A4 ch852	Nepal	Banded gneiss	4.0	114	0.05	0.470	3800	1786	35	0	Shrestha (2005)
51	Khimti 1 hydroproject A4 ch876	Nepal	Banded gneiss	4.0	114	0.49	0.600	2500	1500	41	0	Shrestha (2005)
52	Loktak hydro	India	Schists	4.6	300	7.00	0.020				1	Hoek (2001) and Singh et al. (2007)
53	Loktak hydro	India	–	4.6	300	7.00	0.023	7500	0.173	15	1	Goel et al. (1995b)
54	Maneri Bhali stage I	India	Fractured quartzite	4.8	350	7.90	0.500				1	Goel et al. (1995a) and Hoek (2001)
55	Maneri Bhali stage II	India	Metabasite	2.5	480	2.50	0.800	5000	4000	35	1	Goel et al. (1995b) and Hoek (2001)
56	Maneri Bhali stage II	India	Metabasite	7.0	410	3.00	0.180	5000	0.900	24	1	Goel et al. (1995b) and Hoek (2001)
57	Maneri stage I	India	–	5.4	350		0.500	7500	3750	40	1	Goel et al. (1995b)
58	Maneri–Uttarkashi power	India	Laminated Metabasics	4.8	800	8.90	2500				1	Goel et al. (1995a) and Hoek (2001)
59	Nathpa Jhakri hydroproject	India	Schists	20.0	250	0.25	2700	5000	13,500		0	Bhasin et al. (1995) and Bhasin et al. (1996)
60	Uri project (tailrace) 0/300	India	Graphitic schists	90.4	500		0.030			12	1	Brantmark (1998)
61	Uri project (tailrace) 1/075	India	Metavolcanics	90.4	300		1900			50	0	Brantmark (1998)
62	Uri project (tailrace) 1/340	India	Graphitic schists	90.4	400		0.030			12	1	Brantmark (1998)

rapidly, so that a small number of iterations is usually enough to converge to a (the) solution of the parameter vector.

4. Results and discussion

We have implemented the algorithm described in Section 3 using the software for statistical analysis R (R Development Core Team, 2004). Following the work of previous authors (Singh et al., 1992; Hoek and Marinos, 2000; Hoek, 2001), we employ an input observations vector composed of two parameters related to "capacity" and "demand".

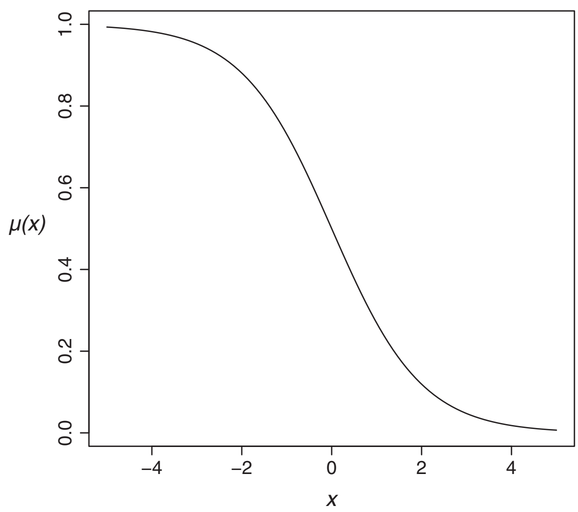

Fig. 1. The logistic function.

Capacity parameters could be related to rock mass strength as indicated by σ_{cm} (see e.g. Hoek, 2001) or by the Geological Strength index (Hoek and Brown, 1997); to rock mass characterizations given, for instance, by the RMR, Q, or RMi systems (for a review see Palmstrom and Stille, 2007); or even to some indicator of strain such as the elastic strain employed by Aydan et al. (1993) to define squeezing levels, or the critical strain employed by Singh et al. (2007) to define squeezing potential.

In this paper, we employ the rock quality index Q as an indicator of capacity. The reason is that, despite the shortcomings indicated below, the Q system has been routinely employed during construction of Himalayan tunnels, therefore making it possible to compile an extensive database of case histories (see references in Appendix A). It also avoids the necessity to conduct laboratory tests (e.g., to estimate the values of m_i and σ_{ci} that are needed to compute σ_{cm}, or to estimate elastic or critical strains of the rock mass), therefore making it a convenient method for its application in real projects. (Laboratory tests are difficult to conduct in broken rocks prone to squeezing, and large-scale in situ tests are uncommon.) Similarly, it also avoids the need for advanced numerical models that may not be feasible at an early stage of a project. Furthermore, the use of Q will allow us to build on the work of Singh et al. (1992), and to compare our results with their widely employed Q-based squeezing criterion.

It has to be noted, however, that rock mass classifications could be unreliable in some cases when employed for squeezing prediction (Palmstrom and Stille, 2007), since rock squeezing is a complex phenomenon and they are only a limited approximation to the real ground behavior. (Other "behavioristic" methods, such as NATM, are based on monitoring the actual behavior of the ground in the tunnel and, therefore, they can only be employed after construction has started.) In that sense, for instance, the Q is expected to work better in fractured and "blocky" rock masses (Palmstrom and Stille, 2007) and, for squeezing prediction, could present difficulties associated to the assessment of the *SRF*, and to the lack of consideration of the compressive strength of the rock mass.

The difficulty with the *SRF* is that (as originally defined) *SRF* is itself a function of the degree of squeezing occurrence (Palmstrom and Broch, 2006). This shortcoming lead to the definition of the Rock Mass Number by Goel et al. (1995b); similarly, in more recent Himalayan projects (see e.g., Shrestha, 2005), the trend has been to define *SRF* based on the presence of weakness zones instead of on squeezing occurrence. Similarly, the *Q* system does not consider the compressive strength of the rock mass, although it could have an influence on stress-induced problems such as squeezing. (The expression $\sigma_{cm} \approx 5\gamma_{rock} Q_c^{1/3}$, with $Q_c = Q\sigma_c/100$, has been proposed by Barton (2000) to estimate the compressive strength of rock masses.)

The most common demand parameter is the stress level of the rock mass surrounding the tunnel, which depends on several factors such as tunnel depth, overall tectonic stress, and tunnel orientation with respect to the in-situ stress orientation. In this case, we use the depth of the tunnel *H* (in meters) as an indicator of demand; the reason is that depth can be employed (in a first approximation, and for rocks of similar density) to estimate the stress level in a tunnel constructed in a given tectonic region. (Note that, for instance, Hoek (2001) computes demand as $\sigma_0 = \gamma_{rock} H$, which mainly depends on *H* for rocks of similar density.) In addition, and although recent research (Heidbach et al., 2010) has shown that local stress sources (such as active faults systems) could control the short wave length (<200 km) of the stress pattern, it is expected that stresses will be heavily influenced by tectonic forces, so that they will be "similar" for tunnels with similar depth in the same tectonic region. (Figure 2 illustrates this point, and it shows that stress orientations are similar within the tectonic domain of the Himalayas and Himalayan foothills.)

Based on the above, we develop a linear classifier model that is given by the following the input observations matrix (note that *Q* has a logarithmic scale, and it is therefore convenient to perform the analysis working with *log Q*):

$$X = [1, X_1,\ X_2] = [1, \log Q, H], \tag{10}$$

where *X* is a $N \times 3$-dimensional matrix and 1 is a vector of ones that is used to provide an independent term in the regression. (Remember that *N* is the number of observations in the database of case histories employed.) We also construct a $N \times 1$-dimensional vector *Y* of squeezing observations, where we use the convention that $y = 1$ if the case corresponds to occurrence of squeezing and $y = 0$ otherwise.

Similarly, following the work of Singh et al. (1992), we can also develop a model in which the influence of *H* enters using a logarithmic scale; that is, we would have the following observations matrix:

$$X = [1,\ X_1, X_2] = [1, \log Q, \log H], \tag{11}$$

with its corresponding $N \times 1$-dimensional vector *Y* of squeezing observations.

The fast convergence of the IRLS algorithm to "learn" the vector of parameters, θ, (both in *log Q* vs *H* model and also in the *log Q* vs *log H* model) is illustrated by the different iterative estimates presented in Table 1. (A stopping criterion with tolerance of 1E-12 in log-likelihood values was employed.)

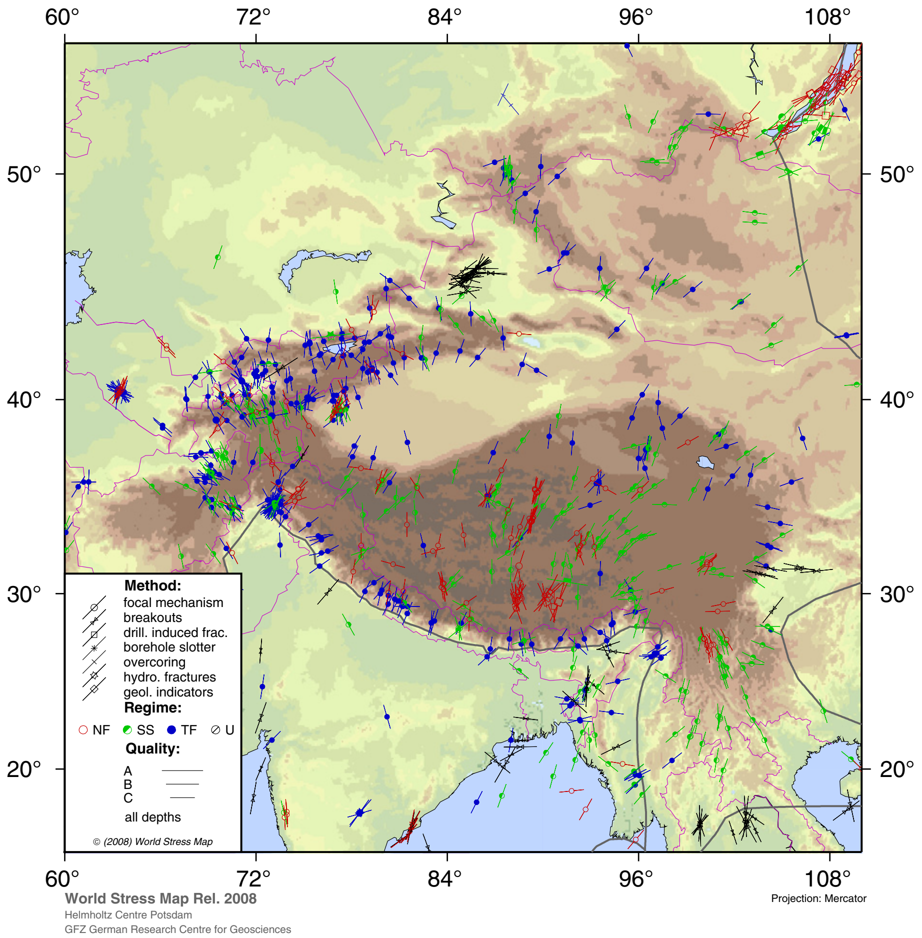

Fig. 2. Orientation of in-situ stresses in the Himalayan region (from World Stress Map project; Heidbach et al., 2008).

Once that the classifier has been "learned", we can go back to the definition of $\nu = \theta_X^T$ and to the probability transformation given by the logistic function in Eq. (2) to compute lines with equal squeezing-probability for any probability values. For the *log Q* vs *H* classifier, we have:

$$\theta^T x = \ln\left(\frac{\mu(x)}{1-\mu(x)}\right), \tag{12}$$

$$\theta_1 \cdot 1 + \theta_2 \log Q + \theta_3 H = \ln\left(\frac{\mu(x)}{1-\mu(x)}\right), \tag{13}$$

where θ_i values are given by the converged solutions presented in Table 1(a).

In addition, from Eq. (12) we can obtain lines in *log Q* − *H* space with constant squeezing probability (for any value of probability given by μ). For instance, if we consider a line with 50% of squeezing probability, we obtain (working in Eq. (12) with $\mu = 0.5$):

$$H[\mathrm{m}] = 425.97 + 195.64 \log Q. \tag{14}$$

A similar discussion can be presented for the *log Q* − *log H* classifier model; the original equation of the classifier is:

$$\theta_1 \cdot 1 + \theta_2 \log Q + \theta_3 \log H = ln\left(\frac{\mu(x)}{1-\mu(x)}\right), \tag{15}$$

from where we can obtain the following class-separation line with a 50% of squeezing probability:

$$\log H[\mathrm{m}] = 2.6278 + 0.3201 \log Q. \tag{16}$$

The boundary line with 50% of squeezing probability can be, of course, plotted in a graph with the case histories employed, and it can also be used as a boundary line (50% decision line) to separate between squeezing and no-squeezing conditions. Such plot has been presented (both for the *log Q* vs *H* and for the *log Q* vs *log H* classifiers) in Fig. 3, where additional lines with other different squeezing probabilities (i.e., for $\mu = \{0.01, 0.10, 0.25, 0.50, 0.75, 0.90, 0.99\}$) have been presented as well. Similarly, and for comparison, Fig. 3 also presents the squeezing discrimination criterion proposed by Singh et al. (1992) based on their research on squeezing in tunnels in the Himalayas.

Based on the results presented in Fig. 3, we observe that, as expected, the newly proposed squeezing classifier shows an increase of squeezing probability as the depth of the tunnel increases and as the quality of the rock mass decreases. In particular, results indicate that tunnel depth can have a very important influence on the predicted values of squeezing probability, so that they could change from ≈10% for "shallow" tunnels in "bad" rock (i.e., $Q \approx 1$) to more than 90% for "deep" tunnels ($H > 600$ m) in the same rock mass. They also indicate that rock mass quality can have a very strong influence on squeezing probability, with probabilities of squeezing changing by a relatively large amount given a single-step classification change within the Q system. As an illustration, results in Fig. 3 indicate that the difference between having a rock mass at the boundary between a "extremely poor" and "very poor" classification (i.e., $Q \approx 0.1$), and at the boundary between "very poor" and "poor" classification ($Q \approx 1$) can be significant, with a change in squeezing probability of more than 50% in some cases.

In addition, we can use the observations within the dataset to assess the validity of the predictions. For instance, we observe (Figure 3(a)) that the 50% squeezing probability line (that, as mentioned, could be used as a hard-boundary for separation between squeezing and no-squeezing) presents a total of 13 (7-6) cases of miss-classification of observations in *log Q* vs *H* space, as seven observations are assigned a no-squeezing label when they actually presented squeezing, whereas six observations are assigned a squeezing label even though they did not present squeezing in reality; similarly (Figure 3(b)), it presents a total of eight (5-3) miss-classifications in *log Q* vs *log H* space. We also observe that, in both cases, such miss-classifications are (almost) balanced with respect to the 50% probability line; in other words, the linear classifier provides *unbiased* predictions of squeezing occurrence. Results also show that lines for other squeezing probability values provide reasonable results based on the evidence available and, for instance, cases of miss-classification tend to occur for cases in which the assignment is less certain (i.e., for assignment probabilities within the range of 10–75%).

By comparison, the squeezing criteria by Singh et al. (1992) (see Figure 3) present a total of 11 (2-9) miss-classifications with this database; note, however, that Singh's criteria seem to be (conservatively) "biased" toward assigning squeezing labels to cases in which no-squeezing occurred, as two observations are assigned a no-squeezing label when they actually presented squeezing, and nine observations are assigned a squeezing label but they did not present squeezing in reality. Similarly, it is observed that the newly developed model in *log Q* vs *log H* space provides a class-separation line that is almost parallel to the squeezing criterion proposed by Singh et al. (1992); in other words, the sensitivity of results to changes in rock quality and in tunnel depth is almost the same. In that sense, the reader should note that from Eq. (16) we obtain a class-separation line given by:

$$H[\mathrm{m}] = 424.4 Q^{0.32}, \tag{17}$$

which is very similar (but slightly less conservative) to the $H = 350Q^{1/3}$ proposed by Singh et al. (1992).

Finally, it is important to mention that the computed parameters cannot be considered as a "final solution" to the squeezing problem, and that they could (and should) be updated as more case histories of squeezing (or non-squeezing) tunnel performance become available. (Note that this is probably the reason why the squeezing criterion by Singh et al. (1992) seem to perform relatively worse in this case, as we have extended the original database that they employed in their work.) In addition, the reader should note that the newly proposed criteria for estimation of (probabilities of) squeezing occurrence is an empirical method and, therefore, it is only valid within the range of the variables for which there is data available. That means that, at least until more case histories can be included in the database, our empirical squeezing criterion should not be employed for tunnels deeper than, say, approximately 600–800 m, since that is the maximum depth range of reliable observations available within the database.

5. Conclusions

Rock squeezing is a time dependant process that typically occurs in weak over-stressed rock masses and that could have a significant and negative influence on the budget and time needed for successful completion of a tunneling project. In this paper we present a novel method for probabilistic empirical prediction of squeezing conditions in rock tunnels, so that squeezing occurrences predicted by our method would be expected to correspond to cases in which relatively large deformations (more than 1% for an unlined tunnel) could occur, therefore producing problems during or after construction unless special construction methods are employed. To that end, we employ an extensive database of well-documented case histories of tunnels from the Himalayas and Himalayan foothills that has been compiled from the literature, and we apply the statistical theory of linear classification to develop a predictor of squeezing occurrence and to compute probabilities of squeezing that can be useful for risk analyses. No intention is made to model the time-dependant aspect of the problem or, in other words, to compute the evolution of convergences with time,

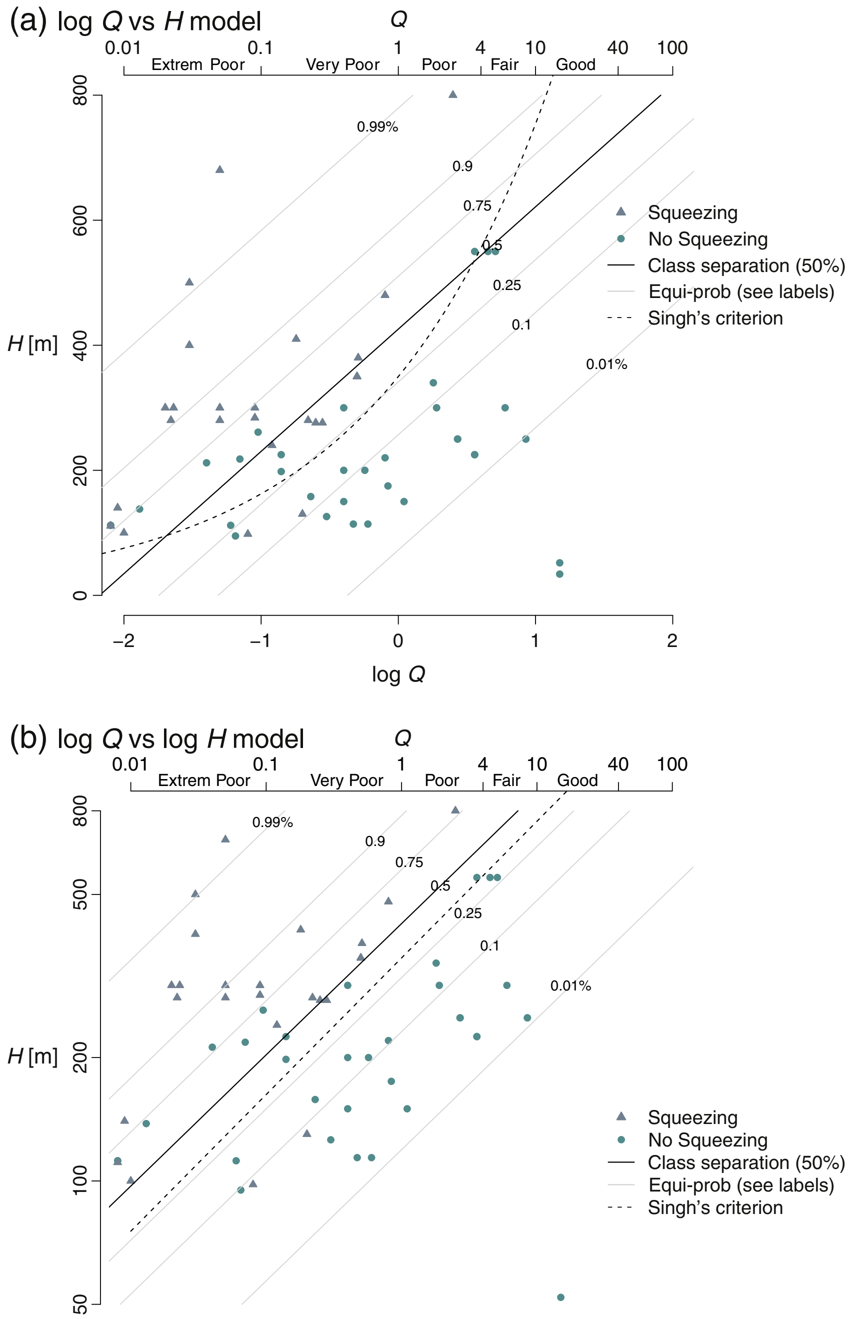

Fig. 3. Equi-probability lines for prediction of squeezing behavior.

although such analysis should probably be performed (using adequate methods, and after an adequate characterization of the rock mass) when squeezing occurrence is predicted with our model.

Our results show that, as expected, the newly proposed squeezing classifier shows a significant increase of squeezing probability as the depth of the tunnel increases, with probabilities of squeezing of "shallow" tunnels being significantly lower than for "deep" tunnels in a given rock mass. Similarly, it is also shown that the squeezing probability increases as the quality of the rock mass decreases; they also indicate that rock mass quality can have a very strong influence on squeezing probability, with probabilities of squeezing changing by a relatively large amount given a single-step classification change within the *Q* system.

Two linear classifier models (*logQ* vs *H* and *logQ* vs *logH*) have been proposed. Results show that the computed classifiers provide unbiased results in both cases (with approximately the same number of false positives and false negatives), and they also suggest that the *logQ* vs *logH* model has (slightly) better predictive capabilities. (This would suggest that the influence of tunnel depth on squeezing occurrence is a non-linear function.) In that sense, our newly presented model in *logQ* vs *logH* space for class-separation between squeezing and no-squeezing conditions suggests a similar sensitivity to depth and rock quality than the model by Singh et al. (1992) (both lines are parallel). However, it presents some improvements with respect to previously available criteria, as it presents fewer cases of miss-classification (hence improving the predictive capabilities of the approach) and also as it allows the estimation of probabilities that may be useful for decision-making under uncertainty.

Finally, it is important to emphasize that the presented solution could be further improved as more case histories of squeezing (or non-squeezing) tunnel performance are included in the training database. In addition, the reader should note that the newly proposed criterion for estimation of (probabilities of) squeezing occurrence is an empirical method and, therefore, it is only valid within the range of the variables for which there is data available. That means that, at least until more case histories can be included in the database, our empirical squeezing criterion should not be employed for tunnels deeper than, say, approximately 600–800 m, since that is the maximum depth range of observations available within the database.

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