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# Predictive capabilities of 2D and 3D block propagation models integrating block shape assessed from field experiments

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1 **Predictive capabilities of 2D and 3D block propagation**  
2 **models integrating block shape assessed from field**  
3 **experiments**

4 **Franck Bourrier · Vincent Acary**

5  
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7 **Abstract** Block propagation models have been used for years for rockfall hazard  
8 assessment. However, the calibration of model parameters that allow the simula-  
9 tions to accurately predict rockfall trajectories for a given study site remains a key  
10 issue.

11 This research aims at investigating the predictive capabilities of block propa-  
12 gation models after a preliminary calibration phase. It is focused on models inte-  
13 grating the shape of blocks since, despite their sound physical bases, they remain  
14 less used than lumped-mass approaches due to their more recent popularisation.

15 Benefiting from both a recently built model integrating block shape, usable  
16 in 2D and 3D, and from recent experimental results at the slope scale, we first  
17 performed a calibration based on the use of the 2D model, and then we evaluated  
18 the predictive capabilities of the calibrated model in 2D and in 3D using the  
19 remaining part of the experimental results.

20 The calibrated model simulations predict the main characteristics of the propa-  
21 gation, that is the preferential deposit zones and the ranges of velocities at specific  
22 locations. Good matches between simulations and experimental results in both the  
23 calibration and validation phases emphasizes the wide applicability of the model:  
24 after a calibration phase on a sufficient number of different soil types, the model  
25 may be used in a predictive manner. The good match between 2D and 3D simula-  
26 tions also highlights the ease-of-use of the model for field applications, as the 2D

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27 model produces sufficiently accurate results while also being easier and faster to  
28 calibrate.

29 As classically observed for block propagation models, the model is not sufficient  
30 to predict the details of the velocity and stopping points but provides accurate  
31 predictions of the global ranges of these quantities, in particular of the extreme  
32 values. To lift these limitations in terms of predictive capabilities, more advanced  
33 calibration procedures based on optimization techniques constitute a promising  
34 path forward.

35 **Keywords** Rockfall · Model · Propagation · Fields experiments · Calibration

## 36 1 Introduction

37 Block propagation analysis is a key element in the process of rockfall hazard as-  
38 sessment. Although empirical approaches remain in use, block propagation is gen-  
39 erally quantitatively analysed using process-based models (Volkwein et al., 2011).  
40 Among these, classical 2D lumped-mass models are still extensively used. They  
41 consider the block as a moving material point that propagates in interaction with  
42 the terrain, modelled as a 2D profile. Several levels of complexity exist regarding  
43 the modeling of the interaction between the block and the terrain, allowing mod-  
44 els to account for the effects of both terrain and block properties (Dorren, 2003;  
45 Volkwein et al., 2011; Bourrier and Hungr, 2013). Despite the historical preemi-  
46 nence of 2D lumped-mass models, an increase in the use of more complex mod-  
47 els has been observed for approximately twenty years. Several 3D lumped-mass  
48 models (e.g. Guzzetti et al., 2002; Dorren, 2003; Crosta and Agliardi, 2004; Lan  
49 et al., 2007) have been developed and are widely used. Models explicitly integrat-  
50 ing block shape (e.g. Descoedres and Zimmermann, 1987; Koo and Chern, 1998;  
51 Leine et al., 2014; Toe et al., 2018) have been more recently applied for practical  
52 case studies. Such models have existed for several decades (Falcetta, J.L., 1985;  
53 Descoedres and Zimmermann, 1987), but their practical use has only been en-  
54 abled by the recent increase in computational capabilities. The relatively recent  
55 interest in these models entails that the research results related to them (e.g. Toe  
56 et al., 2018; Lu et al., 2019, 2020; Garcia et al., 2020; Yan et al., 2020) are sub-  
57 stantially less numerous than those related to lumped-mass models, in particular  
58 concerning their calibration and use in practice.

59 Although block propagation models have been used for years, the settings of  
60 the model parameters to guarantee the predictive capabilities of the simulations  
61 for a given study site remains difficult. As the number of existing rockfall events  
62 on the site of interest is usually very small, even sometimes nil, these settings  
63 cannot only be based on the comparison to these events. Most practitioners favor

64 settings based on the use of typical ranges of parameter values depending on the  
65 soil type, obtained from back analysis of simulations on several sites or given by  
66 the model developers. These values may be adjusted depending on the experience  
67 of the practitioner and on the observed deposited blocks and previous events on  
68 the site. Generally, the predictive capabilities of the simulations cannot directly  
69 be assessed, because of limited events on the site. Consequently, it relies on the  
70 quality of the block propagation model and of the associated calibration.

71 The calibration process complexity mainly depends on the characteristics of  
72 the propagation model. The use of models based on sound physical approaches  
73 simplifies the calibration process since such models are generally robust and in-  
74 volve parameters with clear physical meanings. The number of model parameters  
75 should also remain limited to its minimum because the assessment of the relative  
76 influence of the parameters is simplified and because it reduces the amount of data  
77 required for calibration. The questions of the amount of data required for a correct  
78 calibration and of the type of data required remain open. As mentioned above,  
79 the quantity of experimental data required for the calibration strongly depends on  
80 the robustness of the model and on the number of parameters. Both data at the  
81 rebound scale (Labiouse and Heidenreich, 2009; Bourrier et al., 2012; Asteriou and  
82 Tsiambaos, 2018; Lu et al., 2019) and at the slope scale (Giani et al., 2004; Dorren  
83 et al., 2006; Spadari et al., 2012; Hu et al., 2017; Volkwein et al., 2018; Caviezel  
84 et al., 2019; Williams et al., 2020) may be used. Finally, the calibration procedure  
85 should remain practically feasible. This question is crucial, especially for models  
86 that require large computational efforts, such as the propagation models explicitly  
87 integrating block shape.

88 The objective of this research work is twofold. We aim to: i) investigate the  
89 predictive capabilities of block propagation models that integrate the shape of  
90 blocks and ii) define a practice-oriented calibration procedure that requires mod-  
91 erate computational and field measurement effort. For that purpose, we made use  
92 of both a recently built model integrating block shape usable both in 2D and 3D  
93 and from recent experimental results at the slope scale.

94 The propagation model used is based on nonsmooth mechanics (Moreau, 1988;  
95 Brogliato, 2016), following recent research results in the field (Leine et al., 2014).  
96 The nonsmooth approach is a sound modeling framework to obtain a robust nu-  
97 merical method, which satisfies the threshold phenomena (friction, contact) and  
98 the dissipation properties of the model in discrete time, in particular impact dissi-  
99 pation and energy properties (Acary, 2015). In this article, the novel contribution  
100 is to include Coulomb-type rolling friction in addition to more standard phenom-  
101 ena such as frictional, plastic and impact dissipation processes at the interface  
102 between the soil and the block. Introducing rolling resistance to accurately model

103 the interaction was already shown to be efficient in (Bourrier et al., 2012; Garcia  
104 et al., 2020). The experimental dataset used in this article consists of data on  
105 two propagation paths with similar soil types. It provides sufficiently exhaustive,  
106 diversified, and detailed data to i) calibrate the model on the first path, and ii)  
107 assess its predictive capabilities on the second path. In addition, the extensive data  
108 related to block properties and trajectories on both sites, and the large number of  
109 blocks released, constitutes a substantial advantage for both the calibration and  
110 the assessment of predictive capabilities.

111 For the purpose of the study, we developed a practice-oriented calibration  
112 procedure. We first performed a calibration based on the use of the 2D model and  
113 of the experimental data on the first experimental path. Second, we evaluated the  
114 predictive capabilities of the calibrated model in 2D and in 3D using the remaining  
115 part of the experimental results. This work specifically investigates two key issues:  
116 i) the capacity of 2D models to reproduce block propagation trajectories calculated  
117 in 3D and ii) the existence of model parameters, associated with given soil types,  
118 suitable for both 2D and 3D models and for any site.

119 The field experiments and the modeling approach are respectively presented  
120 in Section 2 and Section 3. The results obtained are then detailed in Section 4,  
121 focusing first on the calibration of the model (Section 4.1) and, then, analysing  
122 the relevance and robustness of the simulation results (Section 4.2) as well as the  
123 predictive capabilities of the model (Section 4.3). Section 5 concludes the article  
124 with a detailed discussion of the results.

## 125 **2 Field experiments**

126 The field experiments used in this study for the calibration of the model and as-  
127 sessment of its predictive capabilities were collected with the objective of providing  
128 experimental data of block propagation for the assessment of various models pre-  
129 dictive capacities for configurations where propagation simulations are potentially  
130 problematic (Bourrier et al., 2020).

131 The experiments, carried out in a quarry (Authume, France, owned by Pernot  
132 S.A), consisted in the successive release of more than one hundred blocks on two  
133 propagation paths. The first path, referred to as path A (Fig. 1), is characterized  
134 by an upper gentle slope section, made of newly deposited quarry waste, mixing  
135 sand, clay, and limestone fragments. This upper slope is overhanging a subvertical  
136 rock cut made of compact limestone rock and, at the toe of this wall, an horizontal  
137 track, made of compact quarry waste. A second rock cut, with the same character-  
138 istics as the first one, separates this track from the quasihorizontal platform, also  
139 made of compact quarry waste, acting as the terminal deposit area. The second

140 path, referred to as path B (Fig. 2), is characterized, in its upper section, by an  
141 inclined slope made of medium soft quarry waste, mixing sand, clay, and limestone  
142 fragments. This slope is bordered, at mid-distance, by a rock cut on one side and  
143 by a talus on the other, which creates a so-called corridor. The intermediate sec-  
144 tion of path B is characterized by two successive tracks, made of compact quarry  
145 waste, and separated by a short slope, made of medium soft quarry waste. The  
146 second track is followed by an inclined slope also made of medium soft quarry  
147 waste, terminated by a globally horizontal deposit area, made of compact quarry  
148 waste. For both paths, the altitude difference between the top and the bottom of  
149 the path is approximately  $45m$ .

150 The study site offers significant complexity and variability in terms of topog-  
151 raphy and surface characteristics. The combinations of gentle slopes and soft soils,  
152 involving block motion almost analogous to rolling, and the complex topographies  
153 with rapid changes in slope inclination and/or orientation favor challenging-to-  
154 model block trajectories. However, both the size of the propagation paths and the  
155 types of soils involved, in particular the soft soils made of quarry waste, are rather  
156 particular and obviously not representative for the variety of sites encountered  
157 when doing block propagation analyses.

158 A Digital Terrain Model (DTM - resolution:  $0.2m$ ) was built in order to perform  
159 analyses of block trajectories. The DTM was generated from a set of images, taken  
160 from a UAV and from the ground. The images were treated using photogrammetry  
161 techniques (specifically the software Agisoft V1.2.6). A set of 20 control points  
162 covering the site, and located in a local coordinate system using a theodolite  
163 (Leica TS02), was used in the building process. Two GPS points and one geodesic  
164 point were also recorded to georeference the DTM.

165 Approximately fifty blocks were successively released on each propagation path  
166 using a power shovel. A release zone ( $4m \times 4m$  horizontal area) was delimited at  
167 the top of each path. The vertical release heights were set at  $4m$  for path A and  
168  $2m$  for path B.

169 The blocks used in the experimental campaign were visually selected to obtain  
170 block volumes approximately ranging between  $0.1$  and  $0.75m^3$ . The range of block  
171 volumes is rather restricted compared to the wide range potentially encountered  
172 in rockfall events. Consequently, the block-terrain interactions observed in the  
173 experiments are potentially not representative for all the processes involved in  
174 block propagation.

175 Each block was weighed and three principal lengths ( $L_1$ ,  $L_2$ , and  $L_3$ , with  
176  $L_1 > L_2 > L_3$ ) were measured for each block. These lengths characterize the  
177 minimal parallelepiped that incorporates the block. No additional measurements

178 of block shapes, such as their reconstruction using photogrammetry for example,  
179 have been made during the experimental campaign.

180 The quantitative analysis of block kinematics focused on measurements at spe-  
181 cific locations of the site, called *Evaluation Screens (ES)* (Figures 1 and 2), using  
182 cameras with shooting range focused on the *ES*. For path A, the first evaluation  
183 screen (*ES1 – A*) was located at the end of the uphill gentle slope, just before the  
184 first rock cut, and the second one (*ES2 – A*) at the top of the downhill rock cut.  
185 For path B, *ES1 – B* is the contour line at the elevation of the corridor beginning  
186 while *ES2 – B* was located at the downstream extremity of the first sloping track.

187 The blocks velocities were measured at the *ES*. For these measurements, two  
188 positions of the block at the slope surface before and after the *ES* and the duration  
189 taken by the block to travel this distance were first measured from projections of  
190 the video footage images on the DTM of the site. Second, the velocity at the *ES*  
191 was calculated assuming either free flight or rolling of the block. In the first case,  
192 the block positions just before and just after the evaluation screen correspond  
193 to successive impact points and the velocity at the *ES* was calculated assuming  
194 a parabolic trajectory of the block. Details of this calculation can be found in  
195 Bourrier et al. (2012). In the second one, the velocity at the evaluation screen was  
196 assimilated to the mean velocity between the two positions. The error in terms  
197 of velocity measurement is mainly due to errors on the visual positioning of the  
198 points on the DTM. This error is estimated around  $0.5m$ , inducing errors on the  
199 velocity around  $1m/s$ .

200 Complementary, precise determination of the blocks' stopping points locations  
201 were conducted after each series of five blocks released. The theodolite used for  
202 this purpose (Leica TS02) provided measurements with an estimated accuracy of  
203  $0.1m$ , mainly resulting from uncertainties associated with the visual assessment of  
204 blocks' centers of gravity. In the case of breakage of the block, the stopping point  
205 considered was the stopping point of the largest resulting fragment, if it could be  
206 identified, or the last impact point before breakage, if the block broke into several  
207 small pieces.

208 Further details about the study site, the experimental protocol, and the mea-  
209 surements can be found in Bourrier et al. (2020).

210 As the experimental dataset consists of data on two propagation paths with  
211 similar soil types, it is very well adapted for, firstly, calibrating a propagation  
212 model on one path and, secondly, assessing the predictive capabilities of the model  
213 on the second one. In addition, the number of different types of soils remains  
214 limited (medium compacted quarry waste, compacted quarry waste, and compact  
215 rock), which simplifies the calibration phase, and the type of soils are similar  
216 on both paths, which is crucial for a calibration on one path, followed by an

217 assessment of predictive capabilities on the second one. Finally, the extensive data  
 218 related to block properties and trajectories on both sites and the large number of  
 219 blocks released constitutes a substantial advantage for both the calibration and  
 220 the assessment of predictive capabilities.

### 221 **3 Block propagation modeling**

#### 222 3.1 Propagation model description

223 The propagation model was developed using the Siconos software (Acary et al.,  
 224 2019)<sup>1</sup>. Siconos is an open-source scientific software primarily targeted at modeling  
 225 and simulating nonsmooth dynamical systems.

226 The propagation model allows the simulation of the 3D propagation of a block  
 227 modelled as a convex facetized rigid body interacting with a terrain, modelled as  
 228 a triangulated surface. In 2D, the block is a polygon, and the surface a polyline.  
 229 As classically done in block propagation models, successive releases of blocks with  
 230 different initial conditions are simulated to quantify the variability of the block  
 231 propagation process. For each block, the propagation modeling is a time-stepping  
 232 process. At each time step, the occurrence of an interaction between the block and  
 233 the surface is checked. In the case of an interaction, an impulse is applied to the  
 234 block. The propagation stops when the block reaches its static equilibrium.

##### 235 *3.1.1 Propagation of a block*

In a three-dimensional configuration, the position of the block center of mass is denoted  $x_g \in \mathbb{R}^3$ , and the block orientation is characterized by the rotation matrix  $\mathbf{R} \in \mathbb{R}^{3 \times 3}$  of the body-fixed frame with respect to a given inertial frame. The rotation matrix is parametrized by a unit quaternion  $\mathbf{q} \in \mathbb{R}^4$ ,  $\|\mathbf{q}\| = 1$  such that  $\mathbf{R} = \Phi(\mathbf{q})$ ,  $\dot{\mathbf{q}} = \Psi(\mathbf{q})\Omega$  where  $\Omega \in \mathbb{R}^3$  is the angular velocity of the body expressed in the body-fixed frame. Formulae for  $\Phi$  and  $\Psi$  can be found in standard textbooks on multi-body dynamics (Géradin and Cardona, 2001). We denote by  $q$  the generalized coordinate vector of the block, and by  $v$  the associated generalized velocity vector:

$$q := \begin{bmatrix} x_g \\ \mathbf{q} \end{bmatrix}, \quad v := \begin{bmatrix} v_g \\ \Omega \end{bmatrix}. \quad (1)$$

The relation between  $v$  and the time derivative of  $q$  is

$$\dot{q} = \begin{bmatrix} \dot{x}_g \\ \Psi(\mathbf{q})\dot{\mathbf{q}} \end{bmatrix} = \begin{bmatrix} I_3 & 0 \\ 0 & \Psi(\mathbf{q}) \end{bmatrix} v := T(q)v \quad (2)$$

---

<sup>1</sup> <http://github.com/siconos/siconos>



236 with  $T(q) \in \mathbb{R}^{7 \times 6}$ , and  $I_3$  the identity matrix. Note that the generalized velocity  
237 vector  $v$  is not directly the time derivative of the generalized coordinate vector.

The Newton-Euler equation in compact form may be written as:

$$\begin{cases} \dot{q} = T(q)v, \\ M\dot{v} = F(q, v) \end{cases} \quad (3)$$

$M \in \mathbb{R}^{6 \times 6}$  is the total inertia matrix

$$M := \begin{pmatrix} mI_3 & 0 \\ 0 & I \end{pmatrix}, \quad (4)$$

238 where  $m > 0$  is the mass,  $I \in \mathbb{R}^{3 \times 3}$  is the matrix of moments of inertia around  
239 the center of mass and the axis of the body-fixed frame.

The vector  $F(q, v) \in \mathbb{R}^6$  collects all the forces and torques applied to the body

$$F(q, v) := \begin{pmatrix} f(x_g, v_g, \mathbf{q}, \Omega) \\ I\Omega \times \Omega + t(x_g, v_g, \mathbf{q}, \Omega) \end{pmatrix}. \quad (5)$$

240 where the vectors  $f(\cdot) \in \mathbb{R}^3$  and  $t(\cdot) \in \mathbb{R}^3$  are the total forces and torques applied  
241 to the body, respectively. The term  $I\Omega \times \Omega$  represents the gyroscopic forces.

242 Among the other forces and torques applied to the body, those induced by the  
243 contact between the slope surface and the block are essential. In the model, these  
244 forces are considered as unilateral constraints applied to the block. The distance  
245 between the block and the surface is associated with a gap function  $g(q)$  and  
246 the block is subjected to the unilateral constraint  $g(q) \geq 0$ , that prevents the  
247 penetration of the block into the ground. The unilateral constraint generates a  
248 generalized reaction force applied to the body defined by  $R \in \mathbb{R}^6$ .

The value of  $R$  is characterized using an impact law that governs the interaction  
between the block and the slope surface. Impact laws are classically expressed in  
local contact frames. For that reason, the local relative velocity  $u$  and the local  
reaction  $p$  are expressed in terms of generalized variables with linear relations for  
a given  $q$  as:

$$\begin{aligned} u &= G^\top(q)v \\ R &= G(q)p. \end{aligned} \quad (6)$$

249 where  $G^\top(q)$  is the operator relating local variables to global ones.

In the simple case of  $m$  frictionless unilateral constraints, the Newton-Euler equations can thus be written as:

$$\begin{cases} \dot{q} = T(q)v, \\ M\dot{v} = F(q, v) + R \\ u = G^\top(q)v, \quad R = G(q)p \\ 0 \leq g(q) \perp p \geq 0. \end{cases} \quad (7)$$

250 where  $u \in \mathbb{R}^m, p \in \mathbb{R}^m$  and  $G(q) \in \mathbb{R}^{6 \times m}$ . The inequalities involving vectors are  
 251 understood to hold component-wise and the  $x \perp y$  symbol means that  $y^\top x = 0$ .  
 252 The last line of (7) is the contact law, also known as the Signorini condition.

253 A specific impact law involving Coulomb friction with rolling resistance at the  
 254 contact was implemented in the model. This law involves a standard Coulomb  
 255 friction law which is a set-valued force law that generates a resistive force to  
 256 sliding, *i.e.* opposite to the sliding velocity. The Coulomb-type rolling friction law,  
 257 considered in this article, is also a set-valued force law that generates a resistive  
 258 moment to rolling, *i.e.* opposite to the rolling velocity. This rolling friction model  
 259 has been developed in Acary and Bourrier (2021) and only the main features are  
 260 recalled in a three-dimensional setting, but the following formulation can be easily  
 261 specified for a 2D configuration.

As mentioned previously, the formulation of the impact law requires the definition of local variables at contact. Let us assume that we can uniquely define an orthonormal contact frame at the contact point  $C$  denoted by  $(C, \mathbf{N}, \mathbf{T}_1, \mathbf{T}_2)$ , where  $\mathbf{N} \in \mathbb{R}^3$  defines an outward unit normal vector to the block at point  $C$  and  $\mathbf{T}_1 \in \mathbb{R}^3, \mathbf{T}_2 \in \mathbb{R}^3$  are unit tangent vectors. The reaction force exerted by the block on the surface is denoted by  $r \in \mathbb{R}^3$ . It can be decomposed in the contact frame as

$$r := r_N \mathbf{N} + r_{T_1} \mathbf{T}_1 + r_{T_2} \mathbf{T}_2, \quad \text{with } r_N \in \mathbb{R} \text{ and } r_T := [r_{T_1}, r_{T_2}]^\top \in \mathbb{R}^2, \quad (8)$$

where  $r_T$  is the tangent reaction, that will be used to model Coulomb friction. The relative velocity at contact  $u \in \mathbb{R}^3$  is used as natural way to formulate friction. It is also decomposed as

$$u := u_N \mathbf{N} + u_{T_1} \mathbf{T}_1 + u_{T_2} \mathbf{T}_2 \quad \text{with } u_N \in \mathbb{R} \text{ and } u_T = [u_{T_1}, u_{T_2}]^\top \in \mathbb{R}^2, \quad (9)$$

where  $u_T$  is the sliding relative local velocity. In order to formulate the Coulomb-type rolling friction at contact, we also introduce the relative angular velocity  $\omega_R \in \mathbb{R}^2$  and the rolling friction reaction torque  $m_R \in \mathbb{R}^2$  at contact. To obtain a compact formulation of the impact model, we denote the local variables at contact

by:

$$p := \begin{bmatrix} r_N \\ r_T \\ m_R \end{bmatrix} = \begin{bmatrix} r \\ m_R \end{bmatrix} \quad \text{and} \quad y := \begin{bmatrix} u_N \\ u_T \\ \omega_R \end{bmatrix} = \begin{bmatrix} u \\ \omega_R \end{bmatrix}. \quad (10)$$

At the velocity level, the Signorini condition is written

$$\begin{cases} 0 \leq u_N \perp r_N \geq 0 & \text{if } g(q) \leq 0 \\ r_N = 0 & \text{otherwise.} \end{cases} \quad (11)$$

The motion of the block is expected to be nonsmooth since impacts occur when the block hits the ground. The model must be completed by an impact law that will define the post-impact velocity  $u_N^+$  with respect to, at least, the pre-impact velocity  $u_N^-$ . The simplest choice is to use the Newton impact law that can be written as

$$u_N^+ = -e_c u_N^-, \quad (12)$$

where  $e_c \geq 0$  is the coefficient of restitution. If impact occurs, the reaction  $p$ , and its components,  $r$  and  $m_R$  are no longer homogeneous to forces but to impulses. As is usually done in impact mechanics (Moreau, 1988; Brogliato, 2016), the contact law with unilateral constraints and friction is written in terms of local relative velocities and impulses. The Newton impact law can be included in the complementary condition at the velocity level as

$$0 \leq \bar{u}_N \perp r_N \geq 0 \text{ if } g(q) \leq 0, \quad (13)$$

262 with  $\bar{u}_N := u_N^+ + e_c u_N^-$  and  $r_N$  is the normal reaction impulse. For  $g(q) > 0$ , we  
 263 trivially have  $p = 0$ . For  $g(q) \leq 0$ , the Coulomb friction model with unilateral  
 264 contact and rolling resistance is defined in all modes, following the work in Acary  
 265 and Bourrier (2021):

– take-off:

$$p = 0, \bar{u}_N \geq 0, \quad (14)$$

– sticking and no-rolling:

$$p \in K_r, u = 0, \omega_R = 0, \quad (15)$$

– sliding and no-rolling:

$$p \in K_r, \bar{u}_N = 0, \|r_T\| = \mu_c r_N, \|m_R\| < \mu_{r,c} r_N, \|r_T\| u_T = -\|u_T\| r_T, \omega_R = 0, \quad (16)$$

– sticking and rolling:

$$p \in K_r, \bar{u}_N = 0, \|r_T\| < \mu_c r_N, \|m_R\| = \mu_{r,c} r_N, \|m_R\| \omega_R = -\|\omega_R\| m_R, u_T = 0, \quad (17)$$

– and sliding and rolling:

$$p \in \partial K_r, \bar{u}_N = 0, \|r_T\| = \mu_c r_N, \|m_R\| = \mu_{r,c} r_N, \quad (18)$$

$$\|r_T\| u_T = -\|u_T\| r_T, \quad \|m_R\| \omega_R = -\|\omega_R\| m_R,$$

where the extended friction cone  $K_r$  is defined as the cone of admissible reaction forces and torques, by

$$K_r = \{p \in \mathbb{R}^5 \mid \|r_T\| \leq \mu r_N, \quad \|m_R\| \leq \mu_{r,c} r_N\} \subset \mathbb{R}^5, \quad (19)$$

and its boundary is given by

$$\partial K_r = \{p \in \mathbb{R}^5 \mid \|r_T\| = \mu r_N, \quad \|m_R\| = \mu_{r,c} r_N\} \subset \mathbb{R}^5. \quad (20)$$

266 Although the model of the interaction between the block and the soil does  
 267 not allow the soil deformation to be explicitly accounted for during impact, it  
 268 integrates block energy losses due to plasticity, viscosity and wave propagation by  
 269 means of the restitution coefficient  $e_c$ . The frictional processes at the interface are  
 270 also accounted for using  $\mu_c$ . Finally, the rolling friction coefficient  $\mu_{r,c}$  quantifies  
 271 cratering and resistance of the soil to block rolling around the contact point.

272 Some details on the numerical implementation of the complete rolling fric-  
 273 tion model can be found in Acary and Bourrier (2021). In this work, the sim-  
 274 ulations have been done with the Moreau-Jean time-stepping scheme (Jean and  
 275 Moreau, 1987; Acary and Brogliato, 2008) based on a  $\theta$ -method for the smooth  
 276 terms and the projected Gauss-Seidel method for the discrete frictional contact  
 277 problems (Jourdan et al., 1998; Acary et al., 2018). The numerical methods are  
 278 implemented in the Siconos software (available as a free open-source software) and  
 279 the version v4.3.0 is used in this article.

280 The  $\theta$  parameter is set equal to 1/2 to avoid the numerical dissipation of energy  
 281 due to the time-stepping scheme (Acary, 2015). The time step and the error toler-  
 282 ance of the projected Gauss-Seidel solver are set at  $10^{-3}$  s and  $10^{-4}$ , respectively.  
 283 Under these simulation conditions, the computational effort to compute the prop-  
 284 agation of 50 blocks on path A or B is typically a few minutes for 2D simulations  
 285 and a few hours for 3D ones on a personal laptop, provided that the numerical  
 286 model is not optimized.

### 287 3.1.2 Simulation of the blocks propagation

288 In total, the simulation of block propagation requires the definition of the terrain,  
289 as a triangulated surface or a polyline, of the block geometry, as a meshed polyhe-  
290 dron or polygon, of the soil properties at all points of the site, by means of three  
291 parameters ( $e_c$ ,  $\mu_c$ ,  $\mu_{r,c}$ ), and of the initial release conditions (block location and  
292 orientation).

293 The block size, global shape (characterized by the three dimensions of the  
294 minimal parallelepiped including the block), and initial release conditions (initial  
295 location and orientation) can be either defined as **a**) single values, if a specific  
296 unstable rock compartment is identified, or **b**) variables quantities, if different  
297 block sizes, shapes and initial release conditions, have been identified in a field  
298 survey. It is also possible to set the initial block velocity at a non-null value, as  
299 sometimes done in propagation models to reproduce specific release conditions.  
300 However, in this paper, block velocity is set at nil value in accordance with the  
301 experimental procedure.

302 Global homogeneous zones in the site are defined and associated with different  
303 soil properties, i.e. with deterministic values of  $e_c$ ,  $\mu_c$ ,  $\mu_{r,c}$ . We assume that the  
304 variability of the soil properties in a homogeneous zone is a relatively minor cause  
305 of block trajectory variability.

306 Finally, the detailed block shape and initial orientation are randomly set for  
307 each block release, assuming that these quantities are the main causes of the  
308 variability of the block propagation process.

### 309 3.2 Simulations of the experiments

310 For the 3D simulations of the experiments, a  $1m$  resolution DTM was built from  
311 the resampling of the  $0.2m$  resolution DTM generated. The decrease in DTM  
312 resolution is required because, as the model of the interaction between the block  
313 and the soil does not explicitly integrate soil plastic strains, a  $0.2m$  resolution  
314 DTM would model local topography details that are suppressed in real impacts  
315 due to cratering. One can note that the decrease in DTM resolution also drastically  
316 decreases computational time.

317 Profiles starting from the release zones were extracted from the  $1m$  DTM for  
318 the 2D simulations. The profiles were chosen from expert assessment of the main  
319 propagation corridors. For path A, the profile was generated along the steepest  
320 slope direction. For path B, a profile passing through the upper corridor, bordered  
321 by a rock cut and a talus, and following the steepest slope direction down this

322 corridor was built. At the crossing with the tracks, the profile crosses the track  
323 following the steepest slope direction of the above slope.

324 Each block propagation simulation set corresponds to the simulation of  $n$  block  
325 propagations. For each propagation simulation set, the stopping points of all blocks  
326 were stored as well as the velocities and heights of the blocks passing through the  
327  $ES$ .

328 For each block propagation, a set of four block properties (three block di-  
329 mensions  $L_1$ ,  $L_2$ ,  $L_3$ , and the block mass  $m_b$ ) was sampled among the quantities  
330 measured in the experiments. In 3D, a convex irregular polyhedron was generated  
331 so as to fit into a parallelepiped of dimensions  $L_1$ ,  $L_2$ ,  $L_3$ . Similarly, a convex irreg-  
332 ular polygon fitting into a rectangle was generated in 2D. The choice of the size of  
333 the rectangle, from the three block dimensions, is potentially crucial. Preliminary  
334 simulations showed that, as the experimental blocks were globally compact (Bour-  
335 rier et al., 2020) according to Sneed and Folk’s classification (Sneed and Folk,  
336 1958), i.e. with similar values for the three dimensions, this choice did not affect  
337 the simulations significantly enough to analyze the influence of this assumption.  
338 Consequently, we arbitrarily choose the dimensions  $L_1$  and  $L_2$ .

339 The polyhedron, or polygon, generation procedure consists of generating a  
340 point cloud, then identifying the points bordering the point cloud and, finally, cre-  
341 ating a convex envelope using these points (triangulated surface in 3D or polyline  
342 in 2D). The mass of the measured block is assigned to the body generated. The  
343 number of points of the convex envelope impacts the shape of the polyhedron or  
344 polygon. The shape of the convex polygons was controlled by means of the number  
345 of points of the initial point cloud used to generate the convex polygonal enve-  
346 lope: the larger the number of points in the point cloud, the larger the number  
347 of segments of the polygon. In the absence of experimental measurements of block  
348 shape, we set the parameters of the generation algorithm so that the mean num-  
349 ber of points of the convex envelope was around 50 in 3D and 20 in 2D. Given  
350 the arbitrary character of the block shape generation procedure, we performed  
351 additional analysis of the effect of block shape in 2D (see section 4.2). For these  
352 simulations, two other types of irregular polygon, with smaller (10 points - called  
353 *Sharp polygon*) and larger (40 points - called *Round polygon*) numbers of points of  
354 the convex envelope, were used. In addition, rectangular blocks and EOTA (rect-  
355 angles with "cut corners") blocks (EOTA, 2018) with the same slenderness as the  
356 experimental blocks were modelled.

357 The horizontal initial coordinates of the blocks were randomly chosen within  
358 ranges of values corresponding to the experiments. The initial vertical location of  
359 the block was defined so that the initial height of the block gravity center above the  
360 slope surface was equal to  $4m$  for path A, or  $2m$  for path B. Finally, the orientation

361 was randomly set using one random unit quaternion in 3D or one random angle in  
362 2D. Although some block propagation models allow the initial velocity to be set  
363 at a non-null value, we initialized block velocity at nil value, in accordance with  
364 the experimental procedure.

365 Homogeneous zones in terms of soil properties (Fig. 3) were determined by ex-  
366 pert knowledge with the objective of limiting the different types of soils. Assuming  
367 that the subvertical rock cuts are not impacted by blocks, only two different soil  
368 types were defined in the site: loose quarry waste, mixing sand, clay, and limestone  
369 fragments, encountered in slope zones, and compact quarry waste, corresponding  
370 to the tracks and terminal deposit areas. Fixed values of the three parameters  
371 associated with soil properties were set for each soil type.

372 Finally, for each simulation set (Fig. 4), the only physical unknown parameters  
373 are the soil properties that are set to match the results (calibration phase) or  
374 according to previous results (validation phase).

#### 375 **4 Calibration and assessment of the block propagation model**

376 The approach proposed is based on a practice-oriented calibration procedure. To  
377 limit the computational and field measurement efforts, we choose to use the 2D  
378 propagation model for the calibration, taking the risk that the values of parame-  
379 ters obtained from this calibration may not be suitable for 3D block propagation  
380 models. Indeed, 2D models limit the possible trajectories to a 2D profile. They  
381 also entail substantial assumptions in terms of block shape, interaction with the  
382 slope surface, and block behavior during the flight phase.

383 The experimental dataset available is well adapted to evaluate the relevance of  
384 this approach since the substantial amount of data on two different propagation  
385 paths having the same soil types allows the use of different data for the calibration  
386 of the model and for the assessment of its predictive capabilities. To this end, only  
387 the experimental data on path A were used for the calibration of the soil properties  
388 using 2D simulations so that the experimental results obtained for path B could  
389 be dedicated to validation only.

390 The experimental results available for both paths correspond to the propaga-  
391 tion of approximately fifty blocks along each path. We choose to perform calibra-  
392 tion using simulation sets of  $n = 50$  block releases to compare samples of the same  
393 size as in the experiments and to limit the simulation duration. As this limited  
394 amount of block release is probably not sufficient to assess the complete variabil-  
395 ity of the block propagation, we additionally compared different simulation results  
396 obtained with  $n = 50$  among each other and with results obtained for increasing  
397 numbers of block releases.

398 We used both the measurements of the stopping points and of the velocities  
399 for the comparisons between the experiments and the simulations. In 2D, the lo-  
400 cations of the stopping points cannot directly be used for such a comparison as  
401 the blocks do not necessarily propagate through the profiles chosen for the simula-  
402 tions. For that reason, instead of comparing the stopping distances, we compared  
403 the percentages of blocks located in experimentally identified preferential deposit  
404 zones (Fig. 5).

405 In the following, the calibration that allows the determination of the optimal  
406 soil properties is presented first. Then, the applicability and the robustness of the  
407 simulations are investigated. The repeatability of the simulation results and the  
408 influence of the number  $n$  of block propagations per simulation set were used to  
409 assess the applicability while the analyses of the influence of the modeling of blocks  
410 shape and of soil properties allowed the evaluation of the model robustness.

#### 411 4.1 Calibration using 2D simulations

412 The calibration phase consisted of iteratively selecting the values of the soil prop-  
413 erties that lead to the best match between the simulation and the experimental  
414 results. Although a more complex calibration procedure, based on optimization  
415 processes for example (Mollon et al., 2012), could have been more efficient, we  
416 chose a calibration procedure corresponding to the classical use of block propaga-  
417 tion models by practitioners.

418 The first step of the calibration consisted of setting values of the soil properties  
419 for Soil 1 (Fig. 3) that reproduce the experimental trajectories of the block along  
420 the uphill slope. In this part of the slope, the blocks propagated by successions  
421 of very small rebounds which induced low velocities, ranging between almost nil  
422 ones and  $7.5\text{m/s}$  (Fig. 6), at  $ES1 - A$ . Very few blocks were stopped in this part  
423 of the slope: 2% of the blocks were stopped in zone 1A and 2% in zone 2A.

424 The setting of parameters for Soil 1 is challenging because it requires finding  
425 sets of values that allow propagation of the block at low velocity until  $ES1 - A$   
426 and very few blocks stop in zones 1A and 2A. The best fit parameters (Table 1)  
427 result in very few block stops and similar velocity ranges to the experiments at  
428  $ES1 - A$  (Fig. 6). However, the parameters chosen entail slight overestimation of  
429 the block stopping in zones 1A and 2A. In addition, even if the velocity ranges are  
430 similar, we did not manage to find parameters that reproduce the experimental  
431 velocity distribution at  $ES1 - A$ , in particular the large number of blocks with  
432 small velocities. Consequently, the propagation of a large number of blocks with  
433 small velocities at  $ES1 - A$  seems not to be possible using this model.



434 Despite these differences, the parameter set chosen remains the most suitable  
 435 obtained from calibration. Other sets of parameters either yielded too many blocks  
 436 stopped before  $ES1 - A$  or too high velocities at  $ES1 - A$ .

437 The direct setting of parameters associated with Soil 2 at the same values  
 438 as for Soil 1 (Fig. 6 - 1 zone) provides simulation results that match well with  
 439 experimental results in terms of velocity ranges at  $ES2 - A$  and of relative distri-  
 440 butions between the blocks stopped in zones 3A and 4A. The predictions of both  
 441 quantities were improved (Fig. 6 - 2 zones) considering that Soil 2 leads to more  
 442 frictional dissipation (Table 1), i.e. larger values of both  $\mu_c$  and  $\mu_{r,c}$ , since it is  
 443 more compact.

444 In an attempt to improve the predictions of block propagation in the upper  
 445 part of the slope, a third zone, corresponding to the release zone of the blocks (Fig.  
 446 1) was defined.  $\mu_{r,c}$  was set at nil value in this zone to favor initial propagation  
 447 of the blocks (Fig. 6 - 3 zones). This change slightly improved the distribution of  
 448 block stopping points, since a smaller number of blocks were stopped in zones 1A  
 449 and 2A, but it did not improve the quality of the calibration in terms of matching  
 450 the experimental distribution of the velocities at  $ES1 - A$ .

451 It is worth noting that the calibration of the soil properties (Table 1) finally  
 452 lead to setting the restitution coefficient  $e_c$  at nil value for both soils. This setting  
 453 is in accordance with two qualitative experimental observations: i) the blocks do  
 454 not bounce when vertically impacting horizontal surfaces, ii) the velocity of the  
 455 impact point normal to the impacted surface seems very small compared to the  
 456 tangential one.

457 One can also note that the differences between the two latter simulations for  
 458 zones 1A and 2A as well as for  $ES1 - A$  illustrate the fact that using  $n = 50$  is  
 459 not sufficient for a complete assessment of the variability of the simulation results  
 460 due to different initial block shapes and orientations.

#### 461 4.2 Relevance and robustness of the simulations

462 The comparison between different simulation sets for  $n = 50$  (Fig. 7) allow the  
 463 quantification of the variability associated with these simulations. The results ob-  
 464 tained show that the different simulations are qualitatively similar in terms of  
 465 relative number of blocks stopped in the different zones and of velocity ranges at  
 466  $ES1 - A$  and  $ES2 - A$ . However, significant quantitative differences between the  
 467 simulation sets exist both in terms of percentages of blocks stopped in the different  
 468 zones and velocity distributions at  $ES$ .

469 The differences between the results tend to decrease, both in terms of stopping  
 470 points and velocities, for increasing values of  $n$  (Fig. 8). However, even between

471 large numbers of block releases ( $n = 500$  and  $n = 2000$ , for example), some  
472 differences remain. However, the smaller sample ( $n = 50$ ) is a good indicator of the  
473 general trends of the simulations for larger values of  $n$ . Consequently, simulation  
474 sets with  $n = 50$  were considered sufficient to provide representative numerical  
475 results.

476 Under the simulation assumptions described in section 3.2, the simulation pa-  
477 rameters that can influence the results are the initial orientation, the block shape  
478 and the soil properties. While the influence of the initial orientation was explored  
479 by making  $n$  block releases, the influence of the two latter parameters was analysed  
480 by comparing with the variability between the simulation sets for  $n = 50$  (Fig. 7).

481 Simulations with the best fit soil properties (Table 1) and different block shapes  
482 have been performed. Rectangular blocks, EOTA (rectangles with "cut corners")  
483 blocks (EOTA, 2018), and two convex polygons, made of smaller (*Sharp polygon*)  
484 and larger (*Round polygon*) numbers of segments, were modelled. These simula-  
485 tions (Fig. 9) showed that the influence of block shape is significantly larger than  
486 the variability observed for  $n = 50$  (Fig. 7) only for cubes and EOTA blocks. On  
487 the contrary, the shape of the random polygons exhibits influences of the same  
488 order of magnitude as the variability observed for  $n = 50$ . These results show  
489 that the influence of block shape modeling is important. In particular, the use  
490 of irregular polygons instead of regular shapes entails substantial differences. The  
491 assumptions of block shape modeling should thus be chosen cautiously.

492 The influence of soil properties was explored using constant soil properties on  
493 the study site and irregular block shapes with mean number of points of the convex  
494 envelope set at 20. In this analysis, initial values of the soil parameters were first  
495 defined. The restitution coefficient  $e_c$  was set at nil value, the friction coefficient  
496 was set  $\mu_c = 0.6$ , and the rolling friction coefficient  $\mu_{r,c}$  was set at nil value. The  
497 influence of each soil parameter was explored by varying each individually in turn.

498 The results obtained show significant influence of  $e_c$  (Fig. 11) and  $\mu_{r,c}$  (Fig.  
499 12) compared with differences in simulation sets for  $n = 50$  (Fig. 7), whereas the  
500 influence of  $\mu_c$  (Fig. 10) remains of the same order of magnitude as the variability  
501 observed for  $n = 50$ . These results show that the calibration of the parameters  
502 should focus on the choice of  $e_c$  and  $\mu_{r,c}$  since these parameters have a major  
503 influence. On the contrary, the setting of  $\mu_c$  is less crucial. One can also note that  
504 the increase in the velocities at *ES1 – A* for increasing values of  $e_c$  tends to confirm  
505 the relevance of choosing almost nil values of  $e_c$ .

506 As for the influence of block shape, the influence of soil parameters can be ex-  
507 plained from a physical point of view. Increases in  $e_c$  and decreases in  $\mu_{r,c}$  entail  
508 less energy dissipation and, consequently, more propagation and larger velocities.  
509 The influence of  $\mu_c$  is more complex to interpret since the influence of this param-

510 eter is less significant.  $\mu_c = 0.6$  seems to be in the vicinity of a threshold value.  
511 For  $\mu_c = 0.4$ , the blocks propagate preferentially by sliding with small frictional  
512 dissipation and thus travel further than for  $\mu_c = 0.6$ . For  $\mu_c = 0.8$ , the blocks tend  
513 to more preferentially roll and thus also propagate further than for  $\mu_c = 0.6$ .

#### 514 4.3 Predictive capabilities of the block propagation model

515 The soil parameters calibrated in 2D using the experimental results on path A  
516 (Table 1) have been used in 2D simulations to predict block propagation on path B.  
517 The predictions obtained provide relevant information concerning the preferential  
518 deposit zones, the mean velocities at  $ES1 - B$  and the velocity range at  $ES2 - B$   
519 (Fig. 13). However, the percentages of blocks stopped are underestimated for zone  
520  $1B$  and  $3B$  and overestimated for zones  $2B$  and  $4B$ . The extremely low and high  
521 values of velocities at  $ES1 - B$  are also not predicted. Finally, the details of velocity  
522 distribution at  $ES2 - B$  are not predicted. One can note that the variability of the  
523 results for different simulation sets is of the same order as for path A. Consequently,  
524 the soil parameters calibrated for path A provide the same level of accuracy in  
525 terms of block propagation prediction for path B.

526 The use of 3D simulations to predict block propagation on path B using soil  
527 parameters calibrated in 2D on path A improves the quality of the predictions  
528 (Fig. 14) in terms of velocity distribution prediction and relative order of the preferential  
529 deposit zones. Quantitatively, the same differences as for 2D simulations  
530 are observed. This result illustrates the fact that the parameters calibrated using  
531 a 2D model can provide the same level of accuracy when used to model block  
532 propagation in 3D in another propagation path.

533 Interestingly, simulations of block propagation in 3D on path A (Fig. 15) using  
534 the same soil properties as in 2D provide slightly better results in terms of velocity  
535 distribution prediction. However, the limitation concerning too many blocks  
536 stopping in the uphill part of the site remains.

537 Finally, the distribution of the block stopping points obtained from 3D simula-  
538 tions (Fig. 16) on path A exhibit similar lateral dispersion as in the experiments.  
539 As observed in Fig. 15, a significant over-representation of blocks are stopped on  
540 the uphill slope. For path B, although too many blocks are stopped on the uphill  
541 track compared to the ones stopped on the downhill one, the simulations predict  
542 well the substantial 3D deviations of the blocks from the main corridor.

## 543 5 Conclusion

544 The model proposed is based on a rigorous mechanical and numerical modeling of  
545 block propagation that focuses on the main parameters influencing the propaga-  
546 tion. The model allows the integration of the effects of topography, block shape,  
547 initial location and orientation in a detailed manner and a contact model is in-  
548 tegrated to reproduce the interaction between the soil and block. The contact  
549 model, based on sound mechanical bases, involves a limited number of parameters  
550 related with the main physical process. The restitution coefficient quantifies soil  
551 plasticity, viscosity and mechanical wave propagation, the friction at the interface  
552 is also implemented as well as a Coulomb-type rolling friction process which mod-  
553 els cratering and resistance of the soil to block rolling around the contact point.  
554 In total, only three parameters are required to define soil properties in terms of  
555 interaction with the block.

556 The modeling approach proposed is among the more complex and detailed  
557 ones in trajectory analyses. The model belongs to the class of “rigid body” models  
558 which are classically identified as more complex than “lumped mass” ones (Volk-  
559 wein et al., 2011). Compared to “lumped mass” models, “rigid body” models are  
560 based on more advanced mechanical concepts. In particular, instead of consider-  
561 ing the block as a material point and using rebound models involving changes of  
562 the block velocities at its center of gravity only, they explicitly model the block  
563 shape and the interaction at the contact scale. This increased complexity does  
564 not necessarily entail increases in the number of parameters and simplifies the  
565 physical interpretation of the results. Among the propagation models explicitly  
566 integrating block shape, the model proposed is based on nonsmooth mechanics  
567 which allows a modeling of the contact as an interaction between perfectly rigid  
568 bodies. All the dissipation processes are modeled in the interface, keeping the in-  
569 trinsic sticking feature of friction. In standard discrete element methods, Coulomb  
570 friction is generally regularized leading to non realistic viscous friction when stick-  
571 ing. The approach proposed in this paper does not require the introduction of  
572 local compliance at the contact scale which is usually difficult to measure exper-  
573 imentally, does not introduce damping, and allows the use of a more diversified  
574 range of numerical solving schemes. In particular, the numerical scheme used in  
575 this study allows the avoidance of artificial viscosity. Typically, artificial viscosity  
576 is added to ensure the numerical stability of the scheme, but results in unrealistic  
577 energy balances. The specificity of the modeling approach proposed will be crucial  
578 for several modeling improvements envisaged such as, for instance, coupling with  
579 other mechanical models (e.g. models of protection structures) or the modeling of  
580 block fragmentation during propagation. One can note that most of the model-

581 ing features presented in this paper are freely available in the open-source block  
582 propagation models platform Platrock<sup>2</sup> and its coupling with Siconos.

583 In addition, the simulation procedure proposed as well as the results obtained  
584 in terms of calibration of the models and assessment of their predictive capabilities  
585 constitute original outcomes of interest for the assessment of block propagation  
586 simulation quality.

587 The simulation procedure proposed allows the modeler to explicitly set the  
588 parameters that can be assessed in the field while the variability of the parameters  
589 that cannot be estimated (block shape and initial orientation, in this study) is  
590 explored statistically. This principle favors the practical usefulness of the procedure  
591 for practicing engineers. In the context of this study, the parameters set by the  
592 modeler were the global block properties (mass and sizes), the topography, and  
593 the release zone location, including the release height. The soil properties are also  
594 modeler-defined parameters but they are more difficult to set since they cannot  
595 directly be measured. In this study, they were calibrated and then used as input  
596 parameters to assess the predictive capabilities of the model.

597 A classical calibration procedure based on setting of the soil properties by  
598 trial and error was chosen in accordance with the engineering practices in the  
599 field of trajectory analysis. As this calibration uses 2D propagation models, it is  
600 feasible for use in engineering practice, given the computational efficiency of 2D  
601 models. To complement this point, the use of calibration data at the field scale,  
602 of block stopping points locations in particular, highlights the applicability of the  
603 procedure proposed since the latter data is more easily accessible to practitioners,  
604 compared to data at the rebound scale in particular. Finally, this study presents a  
605 calibration method based on comparisons with the complete distributions of sev-  
606 eral experimental measurements, and not only to global indicators (such as mean  
607 or maximum values) of these distributions, which is not typical in the literature.

608 The principle of the practice-oriented calibration procedure proposed was to  
609 use a 2D propagation model for the calibration to limit the computational and field  
610 measurement efforts, taking the risk that the values of parameters obtained from  
611 this calibration may not be suitable for 3D block propagation models. The propaga-  
612 tion simulations obtained in 2D and 3D, performed with the parameters calibrated  
613 in 2D, exhibit the same level match to the experimental results. Consequently, the  
614 proposed procedure is appropriate for an optimal parameter calibration. One can  
615 note that extensive Monte-Carlo 3D simulations, potentially using a coarser DTM,  
616 can constitute an alternative to such an optimal calibration procedure provided  
617 that sufficient computational resources are available.

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<sup>2</sup> <https://gitlab.com/platrock/platrock>

618 As is classically the case in trajectory analyses, the calibrated model simula-  
619 tions predict the main characteristics of the propagation, that is the preferential  
620 deposit zones and the range of velocities at specific locations, but not the quan-  
621 titative details of the stopping points and velocity distributions. In particular,  
622 significant differences are observed with regards to the detailed distribution of  
623 the velocities and block stopping points. The simulations performed with the cal-  
624 ibrated model on path B show the capacity of the model to predict the main  
625 characteristics of the propagation on path B. The level of experimental match is  
626 of the same order as in the calibration phase, i.e. for 2D simulations on path A.  
627 The similar level of experimental match in the calibration and validation phases  
628 highlights that rebound model parameters can be associated with soil types, at  
629 least on this example. This generic feature of the model setting is crucial in terms  
630 of industrial applicability since, after a calibration phase on a sufficient number of  
631 soil types, the model may be used in a predictive manner.

632 Although the results obtained in this specific context are promising, the mod-  
633 eling and calibration approaches still have to be adapted for a practical use since  
634 the conditions of the field experiments presented do not fully correspond to typ-  
635 ical practical conditions. In practice, the block release point, volume, shape and  
636 orientation are not fixed. They have to be assessed from field observations and, in  
637 most cases, release point locations and volumes have to be explored statistically in  
638 addition to block shape and orientation. In addition, in the absence of an exhaus-  
639 tive calibration of the model for a large range of soil types, additional calibrations  
640 will have to be performed which is a difficult task mainly because of the questions  
641 of the number and of type of data required for a correct calibration.

642 The results presented in this paper exhibit a level of experimental match that  
643 may not look sufficient for a quantitative design of protection structures or for  
644 precise hazard zone delineation. However, the results tend to show that the de-  
645 ficiencies are more in the details of the velocity distribution than in the global  
646 range of velocities. Consequently, it may be possible to design a structure on the  
647 basis of the predicted extreme quantities. In the same vein, differences in terms  
648 of block stopping points are mainly observed for small and medium propagation  
649 distances which is of smaller importance in practice than the blocks that demon-  
650 strate large propagation distances. In addition, the level of experimental match,  
651 although rather small, can be complemented with uncertainty assessment to pro-  
652 vide additional information that will increase awareness in the process of design  
653 or hard zone delineation.

## 654 **6 Conclusion**

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	Soil 1	Soil 2
$e_c$	0.	0.
$\mu_c$	0.5	0.6
$\mu_{r,c}$ (m)	0.04	0.05

Table 1: Soil properties obtained from calibration

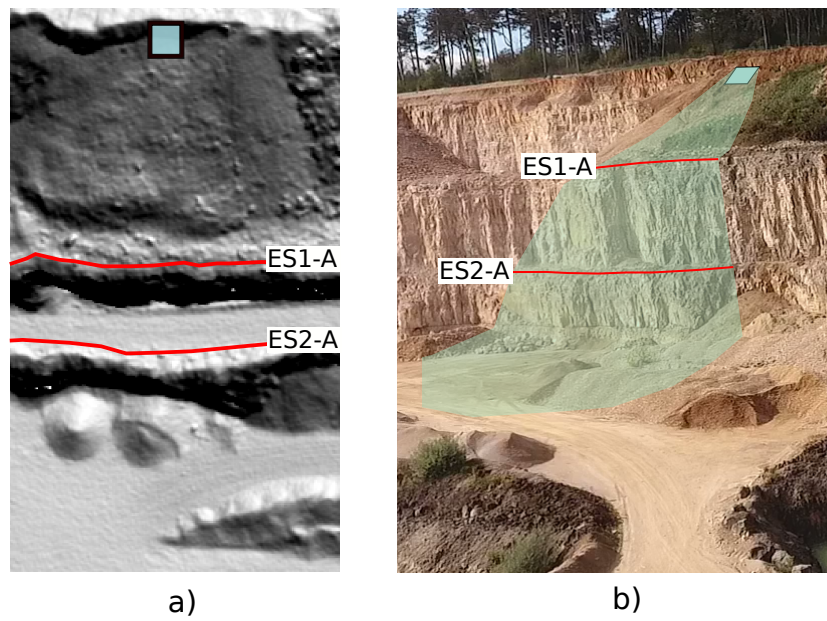


Fig. 1: Overview of path A (a: topview of a hillshade built from a 1m resolution DTM, b: general view) including the location of the Evaluation Screens ( $ES1 - A$  and  $ES2 - A$ ), of the release zone (green square), and of the potential propagation zone (light green zone).

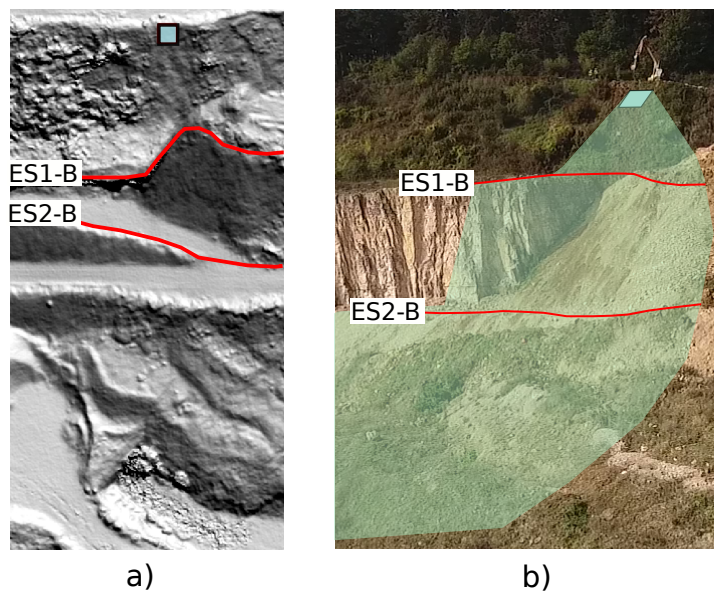


Fig. 2: Overview of path B (a: topview of a hillshade built from a 1m resolution DTM, b: general view) including the location of the Evaluation Screens ( $ES1 - B$  and  $ES2 - B$ ), of the release zone (green square), and of the potential propagation zone (light green zone).

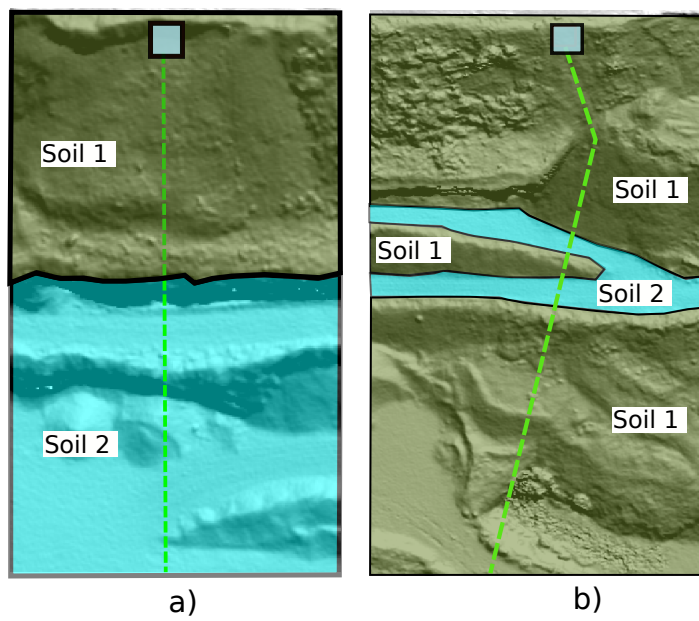


Fig. 3: Homogeneous zones in terms of soil properties determined by expert knowledge on the propagation paths A (a) and B (b). Two different soil types were defined at the site.

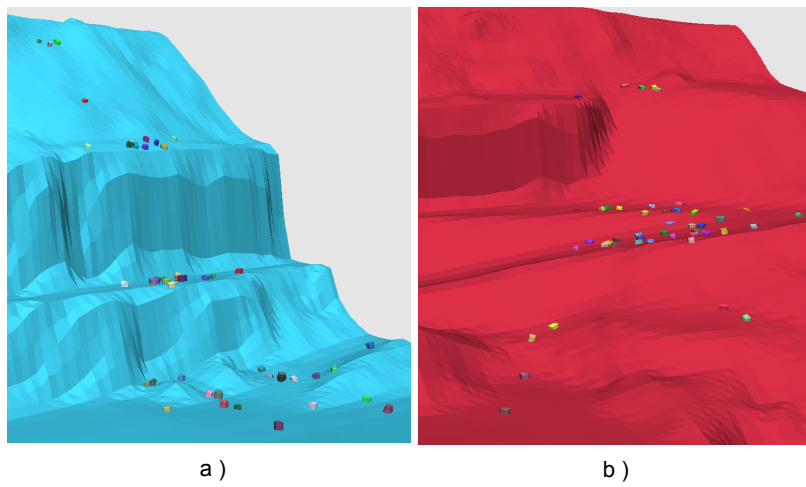


Fig. 4: Examples of block stopping points obtained from propagation simulations on path A (a) and path B (b).

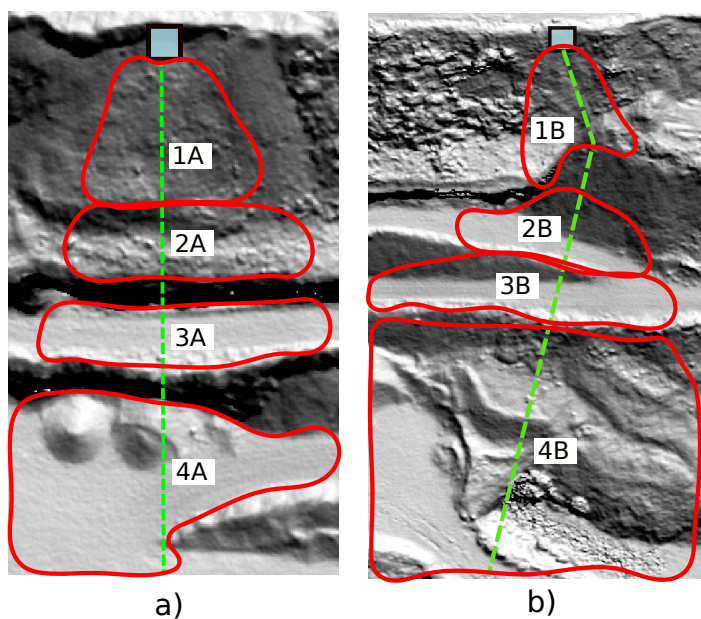


Fig. 5: Preferential deposit zones identified during the experimental campaign for path A (a) and path B (b) (Bourrier et al., 2020).

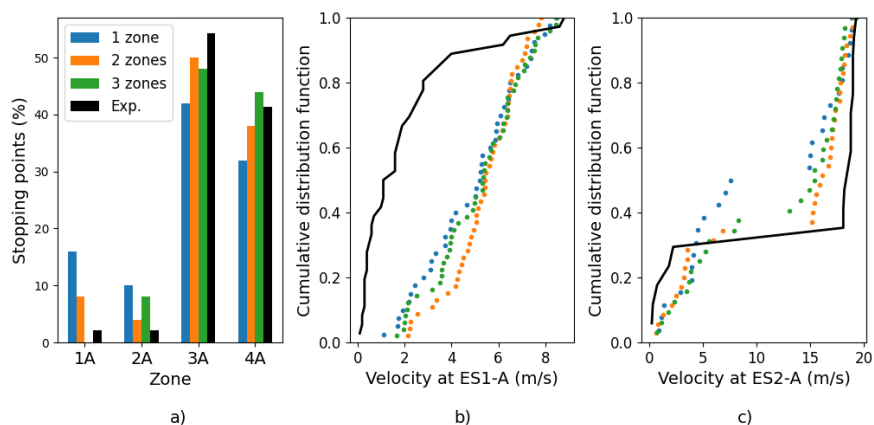


Fig. 6: Comparison between experiments and simulations results obtained for path A using the soil parameters associated with Soil 1 along the complete path (1 zone), or the best fit parameters for Soil 1 and 2 (2 zones), or the best fit parameters for Soil 1 and 2 and  $\mu_{r,c} = 0$  in the release zone of the blocks (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1-A$ , c: cumulative distribution function of block velocities at  $ES2-A$ ).

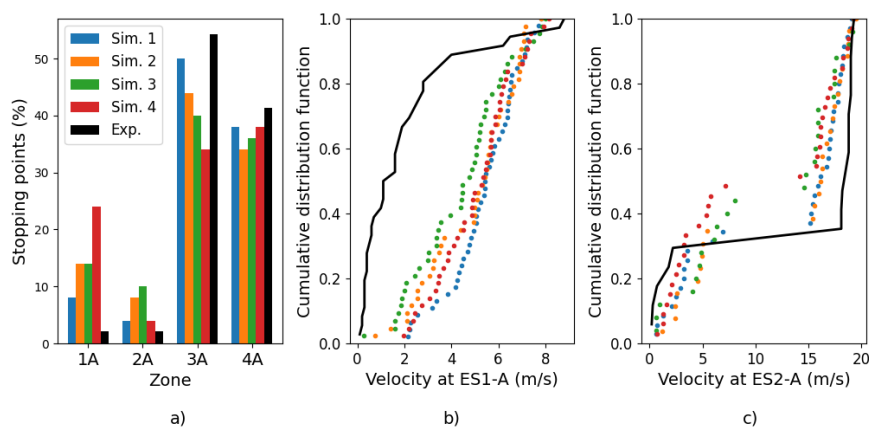


Fig. 7: Results obtained from different simulations of block propagation on path A using the calibrated parameters for soil properties and  $n = 50$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - A$ , c: cumulative distribution function of block velocities at  $ES2 - A$ ).

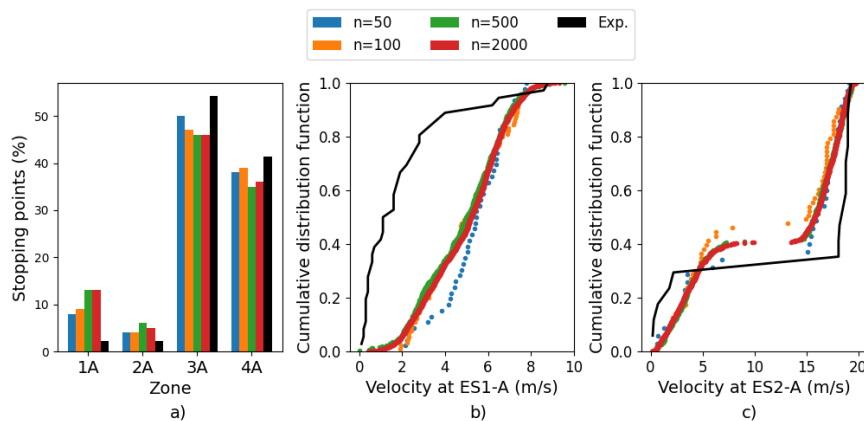


Fig. 8: Results obtained from different simulations of block propagation on path A using the calibrated parameters for soil properties and increasing numbers  $n$  of block releases (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - A$ , c: cumulative distribution function of block velocities at  $ES2 - A$ ).



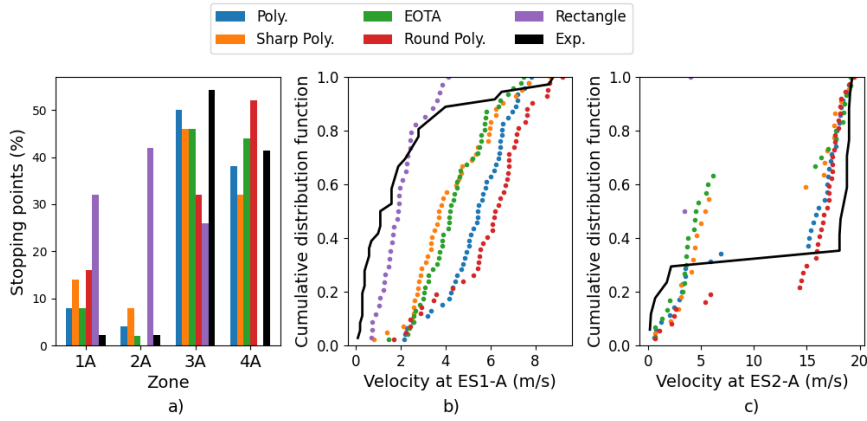


Fig. 9: Results obtained from different simulations of block propagation on path A using the calibrated parameters for soil properties and different block shapes (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - A$ , c: cumulative distribution function of block velocities at  $ES2 - A$ ).

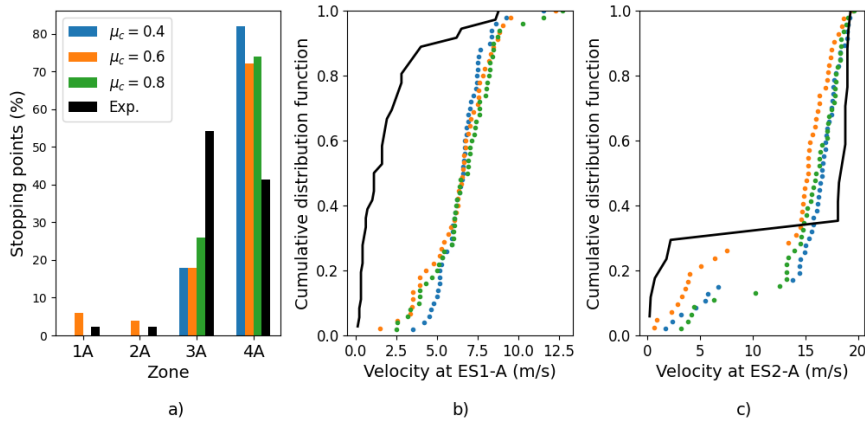


Fig. 10: Results obtained from different simulations of block propagation on path A using  $e_c = 0$ ,  $\mu_{r,c} = 0$  and different values of  $\mu_c$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - A$ , c: cumulative distribution function of block velocities at  $ES2 - A$ ).

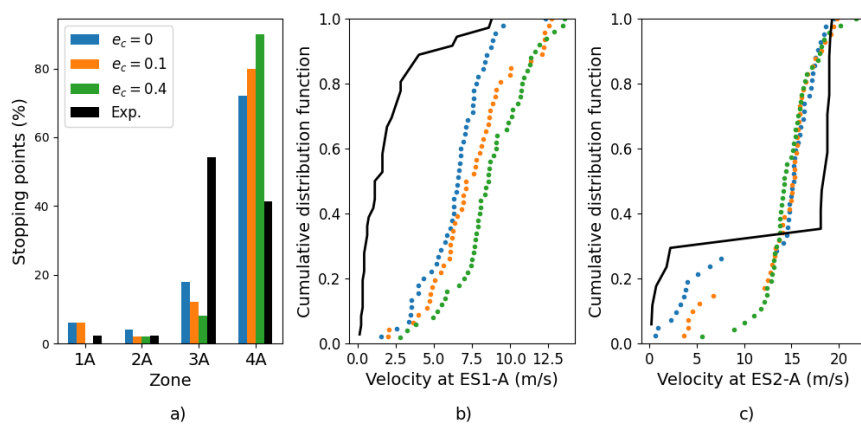


Fig. 11: Results obtained from different simulations of block propagation on path A using  $\mu_c = 0.6$ ,  $\mu_{r,c} = 0$  and different values of  $e_c$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1-A$ , c: cumulative distribution function of block velocities at  $ES2-A$ ).

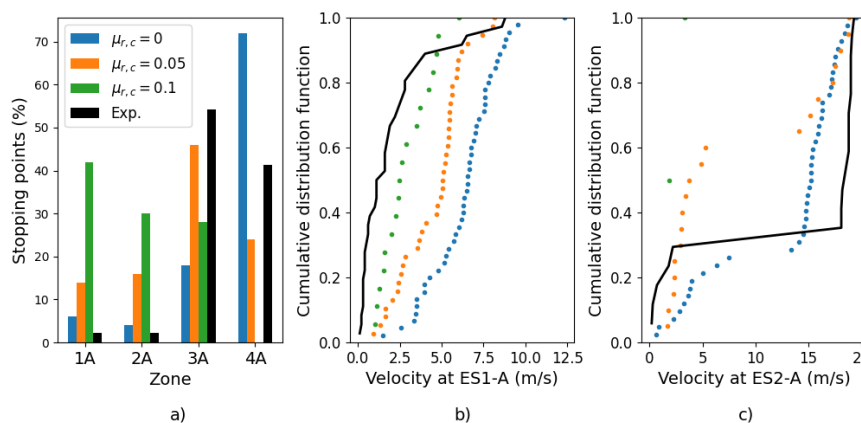


Fig. 12: Results obtained from different simulations of block propagation on path A using  $e_c = 0$ ,  $\mu_c = 0.6$  and different values of  $\mu_{r,c}$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1-A$ , c: cumulative distribution function of block velocities at  $ES2-A$ ).

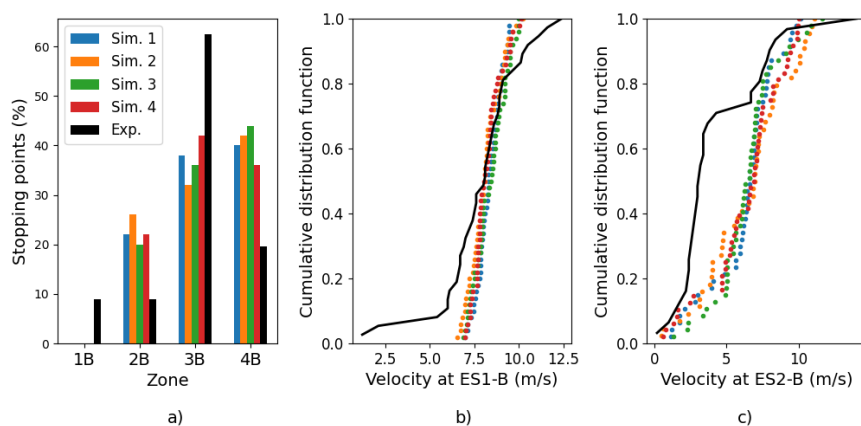


Fig. 13: Predictions of block propagation on path B obtained from 2D simulations with different simulation sets using the calibrated parameters for soil properties and  $n = 50$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - B$ , c: cumulative distribution function of block velocities at  $ES2 - B$ ).

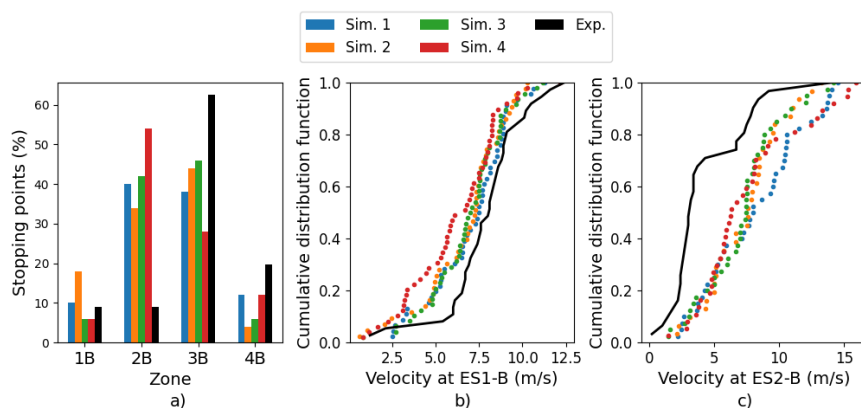


Fig. 14: Predictions of block propagation on path B obtained from 3D simulations with different simulation sets using the calibrated parameters for soil properties and  $n = 50$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - B$ , c: cumulative distribution function of block velocities at  $ES2 - B$ ).

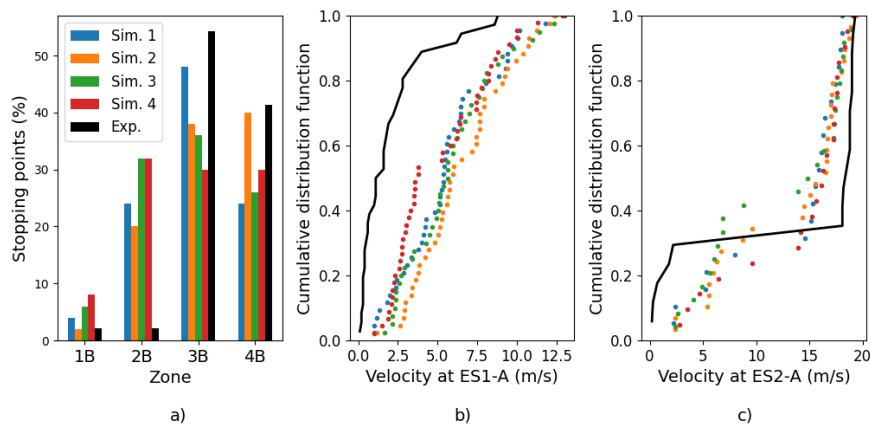


Fig. 15: Predictions of block propagation on path A obtained from 3D simulations with different simulation sets using the calibrated parameters for soil properties and  $n = 50$  (a: distribution of the stopping points between the preferential deposit zones, b: cumulative distribution function of block velocities at  $ES1 - A$ , c: cumulative distribution function of block velocities at  $ES2 - A$ ).

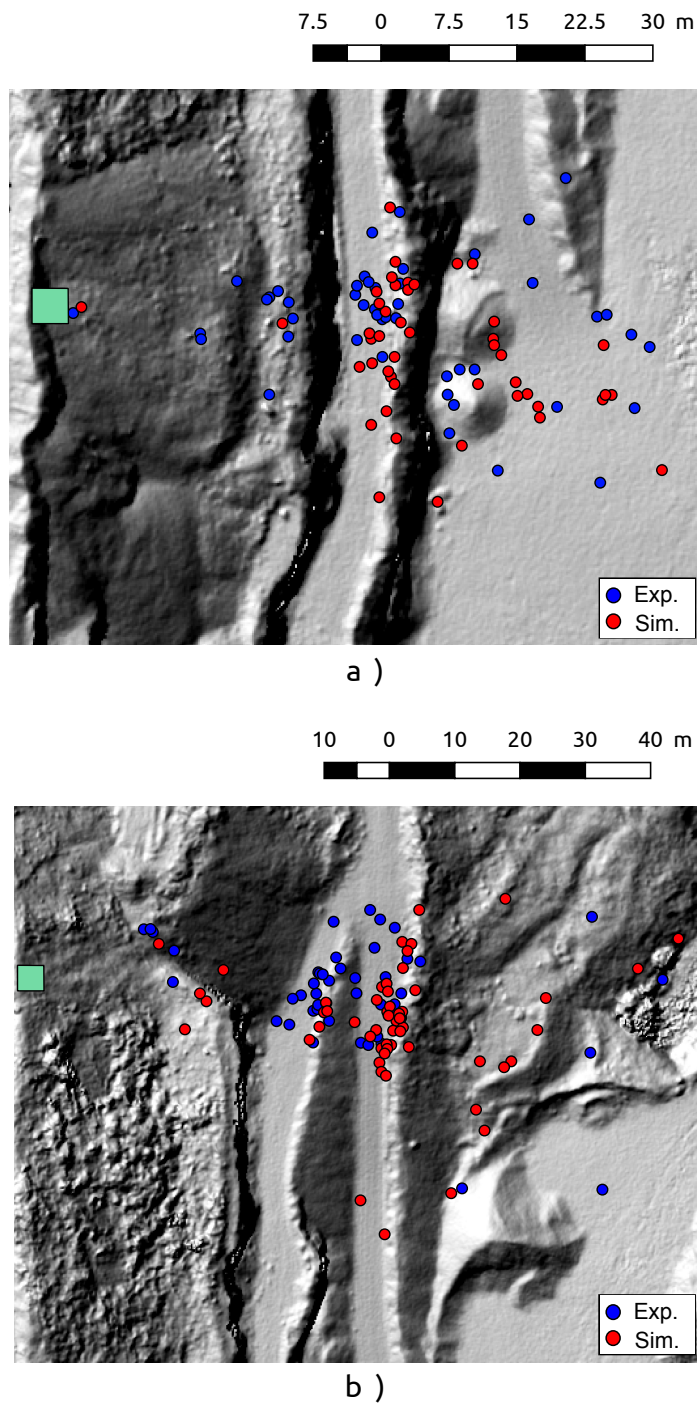


Fig. 16: Predictions of block stopping points on path A (a) and path B (b) obtained from 3D simulations with simulation sets using the calibrated parameters for soil properties and  $n = 50$ .