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1 **Toward objective rockfall trajectory simulation using a stochastic impact model**

2

3 **Franck Bourrier <sup>a\*</sup>, Luuk Dorren <sup>b</sup>, François Nicot <sup>a</sup>, Frédéric Berger <sup>a</sup> and Félix Darve <sup>c</sup>**

4

5 *a Cemagref - 2, rue de la Papeterie - BP 76 - 38 402 Saint Martin d'Hères Cedex – France*

6 *b Federal Office for the Environment FOEN - Hazard Prevention Division - 3003 Bern - Switzerland*

7 *c L3S-R - INPG, UJF, CNRS - Domaine Universitaire - BP 53 - 38 041 Grenoble Cedex 9 - France*

8 *\*Corresponding author. Tel.: +33 4 76 76 27 27; Fax: +33 4 76 51 38 03; E-mail:*

9 *franck.bourrier@cemagref.fr.*

10

11 **Abstract:**

12 The accuracy of rockfall trajectory simulations depends to a large extent on the calculation of the rebound  
13 of falling boulders on different parts of a slope where rockfalls could occur. The models commonly used  
14 for rebound calculation are based on restitution coefficients, which can only be calibrated subjectively in  
15 the field. To come up with a robust and objective procedure for rebound calculation, a stochastic impact  
16 model associated with an objective field data collection method was developed and tested in this study.  
17 The aims of this work were to assess the adequacy of this approach and to evaluate the minimum amount  
18 of field data required to obtain simulation results with a satisfactory level of predictability. To achieve  
19 these objectives, the rebound calculation procedure developed was integrated into a three-dimensional  
20 rockfall simulation model, and the simulated results were compared with those obtained from field  
21 rockfall experiments. For rocky slopes, the simulations satisfactorily predict the experimental results. This  
22 approach is advantageous because it combines precise modelling of the mechanisms involved in the  
23 rebound and of their related variability with an objective field data collection procedure which basically  
24 only requires collecting the mean size of soil rocks. The approach proposed in this study therefore  
25 constitutes an excellent basis for the objective probabilistic assessment of rockfall hazard.

26

27 Keywords: 3D simulations; field experiments; restitution coefficients; rockfall rebound; stochastic  
28 modelling; Rockyfor3D.

## 29 **1. Introduction**

30 As shown by the recent accidents occurring in March 2006 in the French Alps and June 2006 on the  
31 Gotthard highway in Switzerland, rockfall is one of the main natural hazards that pose risks to residential  
32 areas, infrastructures, and populations in the Alps. Rockfall is generally defined as the removal of  
33 individual boulders from a cliff face (Varnes, 1978; Whalley, 1984; Selby, 1993; Cruden and Varnes,  
34 1996). This study focuses on single falling rocks with a volume up to 1.3 m<sup>3</sup>. In rockfall hazard  
35 assessment, trajectory simulation models are increasingly used for designing protective measures such as  
36 nets and dams (Descoeurdes, 1997; Peila et al., 1998; Nicot et al., 2001, 2007) or for making hazard maps  
37 (Kobayashi et al., 1990; Evans and Hungr, 1993; Guzzetti et al., 2002; Chau et al., 2004; Jaboyedoff et  
38 al., 2005; Bourrier et al., 2008b; Frattini et al., 2008).

39 The most difficult process to simulate in such trajectory models is the rebound, which describes the  
40 impact of the falling boulder on the slope surface. To calculate such a rebound, a wide range of  
41 algorithms is currently available, which are summarised in Guzzetti et al. (2002), Dorren (2003), and  
42 Heidenreich (2004). Rebound deterministic modelling remains highly speculative since the information  
43 available on the mechanical and geometrical properties of the soil is not sufficient to perform a relevant  
44 deterministic prediction of boulder rebound. In particular, the characterisation of the spatial distributions  
45 of the parameters required for rebound calculation generally result from a field survey which, for practical  
46 reasons, cannot be exhaustive. Stochastic approaches have therefore been proposed (Paronuzzi, 1989;  
47 Pfeiffer and Bowen, 1989; Azzoni et al., 1995; Dudt and Heidenreich, 2001; Guzzetti et al., 2002;  
48 Agliardi and Crosta, 2003; Jaboyedoff et al., 2005; Bourrier et al., 2007, 2008b; Frattini et al., 2008) to  
49 account for the variability of the rebound. Most of these approaches are based on two parameters, both  
50 called restitution coefficients, which proved to partially represent the complexity of the rebound (Wu,

51 1985; Bozzolo and Pamini, 1986; Chau et al., 1998; Ushiro et al., 2000; Chau et al., 2002; Heidenreich,  
52 2004). The problem is that stochastic variation of the restitution coefficients only account for the  
53 variability related to terrain characteristics. Variability due to the kinematics of the falling boulder is not  
54 accounted for. In addition, estimating the values of these two parameters in the field is a difficult task  
55 mainly based on literature values that are associated with certain surface characteristics of the slope.  
56 Overviews of commonly used values for restitution coefficients are given in (Paronuzzi, 1989; Pfeiffer  
57 and Bowen, 1989; Azzoni et al., 1992; Azzoni and De Freitas, 1995; Chau et al., 2002; Agliardi and  
58 Crosta, 2003; Scioldo, 2006). Most models are very sensitive to the values of these restitution  
59 coefficients. In addition, the values in the literature vary significantly for identical surface characteristics.  
60 The resulting subjectivity in the choice of these parameter values therefore partly explains the large  
61 variation in the results obtained when applying different models, or even the same model used by  
62 different operators, at the same site (Interreg IIc, 2001; Berger and Dorren, 2006).  
63 To overcome these difficulties, a more objective rebound calculation procedure based on a stochastic  
64 impact model was developed. This procedure models the variability associated with the rebound and only  
65 requires collecting a very limited set of field parameters: the size of the falling boulder and the sizes  
66 characterising the rocks composing the slope surface. Our first objective was to test and validate the  
67 procedure developed. The second objective was to evaluate the minimum amount of field data required to  
68 obtain simulation results with a satisfactory level of predictability.  
69 This paper first explains the rebound calculation procedure developed and its integration into a three-  
70 dimensional rockfall trajectory simulation model. Then the simulation results are compared with those  
71 obtained from field rockfall experiments and discussed.

## 72 **2. Full-scale rockfall experiments on a mountain slope**

73 Full-scale rockfall experiments were carried out in an avalanche track in the Forêt Communale de  
74 Vaujany in France (N. 45°12', E. 6°3'). The study area covers an Alpine slope ranging from 1200 to 1400  
75 m above sea level with a mean gradient of 38°. The experimental site is part of a hillslope that is formed

76 by a postglacial talus slope (Fig. 1), downslope from rock faces consisting of the “Granite des Sept  
77 Laux”, which belong to the crystalline Belledonne massif. The talus cone mainly consists of rock  
78 avalanche, snow avalanche, and rockfall deposits. The study site is ~ 100 m wide and 570 m long  
79 (distance between the starting point and the lower forest road, measured along the slope). Between the  
80 starting point and the lower forest road, it has the shape of a channel with a maximum depth and width of  
81 2 and 10 m, respectively. Since avalanches occur every year in this channel, it is denuded of trees.

82

83 Fig. 1.

84

85 The protocol was identical for all rockfall experiments. Before each boulder release, the volume of the  
86 boulder was measured and the boulder was coloured with biodegradable paint so that it left traces after  
87 rebounding on the slope. The volume was estimated by measuring the height, width, and depth along the  
88 three most dominant boulder axes and by assuming that the boulders were rectangular. A total of 100  
89 boulders were released individually, one after the other. The mean volume was  $0.8 \text{ m}^3$ , and the standard  
90 deviation  $0.15 \text{ m}^3$  (Fig. 2).

91

92 Fig. 2.

93

94 A front shovel was used to release the boulders down the slope, starting with a free fall of 5 m. As soon as  
95 the boulder stopped, the impact locations and stopping points were captured with an Impulse LR 200 laser  
96 distance meter manufactured by Laser Technology, Inc. (Centennial, CO, USA). In addition, the rockfall  
97 trajectories were filmed by five digital cameras, which were placed so that the camera planes were  
98 perpendicular to the channel, which is the preferred rockfall path, and 30 m away (Fig. 1). The cameras  
99 were fixed at a height of 10 m in trees. Additional details on the experiments are given in Dorren et al.  
100 (2006).

101 The digital films of the 100 rockfall trajectories were analysed using image processing software called  
102 AviStep 2.1.1 (developed by M. Delabaere, St. Denis de la Réunion, France). This program extracts the  
103 position and the velocity of a moving particle for each individual image in a digital film using the  
104 following principle. First, in the first image of each film, the field-measured rebound distances are  
105 identified. Second, soil surface detection is conducted by linking the successive impact points in the films  
106 assuming that soil surface is linear between two impact points. Third, the two-dimensional trajectory of  
107 each falling boulder was analysed using a sequence of movie images (Fig. 3). Finally, the analysis of the  
108 movie images provided the rebound heights, i.e., the maximum vertical distance between the centre of the  
109 boulder and the slope's surface, as well as the position of the boulder for every image (every 0.04 s). This  
110 makes it possible to determine the velocity.

111 Since the resolution of the movie images did not allow for a precise measurement of the rotational  
112 velocity, only the translational kinetic energy  $E_{trans}$  was calculated to reduce the uncertainty in the results.

113 The translational kinetic energy  $E_{trans}$  of a falling boulder is calculated as:

$$114 \quad E_{trans} = \frac{1}{2} m_b V^2 \quad (1)$$

115 where  $m_b$  is the mass, and  $V$  is the translational velocity of the boulder.

116 The experimental results therefore do not provide information on either the rotational kinetic energy  $E_{rot}$   
117 or the total kinetic energy  $E_{tot}$ , which are defined as follows:

$$118 \quad E_{rot} = \frac{1}{2} I_b \omega^2 \quad (2)$$

119 and

$$120 \quad E_{tot} = E_{trans} + E_{rot} \quad (3)$$

121 where  $I_b$  is the moment of inertia, and  $\omega$  is the rotational velocity of the boulder.

122

123 Fig. 3.

124

### 125 **3. Trajectory simulation using a stochastic rebound algorithm**

126 The simulation model used is the 3D rockfall trajectory model Rockyfor3D, which has been developed  
127 since 1998 (Dorren et al., 2006). This model simulates the rockfall trajectory in 3D by calculating  
128 sequences of parabolic free fall through the air and rebounds on the slope, as well as impacts against  
129 trees, if specified. Rolling is represented by a sequence of short-distance rebounds and sliding is not  
130 modelled. Falling boulders are represented in the model by spheres using a hybrid approach. This means  
131 that, during parabolic free fall, the falling sphere is represented by a single point (lumped mass) and,  
132 during the rebound calculation, by a real sphere. The three major components of Rockyfor3D are 1) the  
133 parabolic free fall calculation and its intersection with the topography, 2) the rebound calculation, and 3)  
134 the fall direction calculation after rebound.

#### 135 *3.1. Parabolic free fall*

136 The parabolic free fall is calculated with a standard algorithm for a uniformly accelerated parabolic  
137 movement through the air. This calculation determines the position and the normal (with respect to the  
138 local slope)  $V_n^{\text{in}}$ , tangential  $V_t^{\text{in}}$ , and rotational  $\omega^{\text{in}}$  velocities at the intersection with the slope topography,  
139 represented by a Digital Elevation Model (DEM). As such, Rockyfor3D simulates a 3D trajectory by  
140 calculating the displacement of the boulder position along the  $x$ -,  $y$ -, and  $z$ -axes (Fig. 4). Here, the  $z$ -axis  
141 corresponds to its vertical position, the  $x$ -axis to the east–west direction, and the  $y$ -axis to the north–south  
142 direction (Fig. 4A). By its  $x$  and  $y$  coordinates, the 3D trajectory is linked to a set of raster maps with a  
143 resolution between 1 and roughly 20 m. For this study, however, the raster resolution was 2.5 m. The  
144 raster maps provide information on the topography (DEM), the slope surface characteristics, and the  
145 release points (for this study, only one release raster cell was defined).

146 Knowing the position of the rebound and the slope surface characteristics defined by the raster maps at  
147 this position, as well as the velocities before rebound, the rebound calculation using the stochastic impact  
148 model can be initiated.

149

150 Fig. 4.

151

### 152 3.2. Stochastic impact model

153 The rebound calculation determines the normal  $V_n^{\text{out}}$ , tangential  $V_t^{\text{out}}$ , and rotational  $\omega^{\text{out}}$  velocities after  
154 rebound based on the velocities before rebound, called incident velocities, and on the parameters  
155 determining the energy loss during the rebound. The rebound model initially integrated in Rockyfor3D  
156 (Dorren et al., 2006) was replaced by a stochastic impact model that calculates the velocity vector after  
157 rebound  $\mathbf{V}^{\text{out}}$  from the velocity vector before rebound  $\mathbf{V}^{\text{in}}$  following the expression:

$$158 \quad \mathbf{V}^{\text{out}} = \mathbf{A}\mathbf{V}^{\text{in}} \quad \text{with} \quad \mathbf{V}^{\text{out}} = \begin{bmatrix} V_t^{\text{out}} \\ V_n^{\text{out}} \\ \omega^{\text{out}} \end{bmatrix}, \quad \mathbf{A} = \begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ a_7 & a_8 & a_9 \end{bmatrix}, \quad \mathbf{V}^{\text{in}} = \begin{bmatrix} V_t^{\text{in}} \\ V_n^{\text{in}} \\ \omega^{\text{in}} \end{bmatrix} \quad (4)$$

159 This means that each of the three velocities after rebound ( $V_t^{\text{out}}$ ,  $V_n^{\text{out}}$ , and  $\omega^{\text{out}}$ ) is calculated with the three  
160 incident velocity components ( $V_t^{\text{in}}$ ,  $V_n^{\text{in}}$ , and  $\omega^{\text{in}}$ ) and three coefficients of matrix  $\mathbf{A}$ .

161 For example, the tangential component of the velocity after rebound  $V_t^{\text{out}}$  is expressed as follows:

$$162 \quad V_t^{\text{out}} = a_1 V_t^{\text{in}} + a_2 V_n^{\text{in}} + a_3 \omega^{\text{in}} \quad (5)$$

163 The coefficients  $a_i$ , as well as the correlations between them, are characterised by normal probability  
164 distribution functions. These allow the model to account for the high variability of the local slope surface  
165 characteristics and the kinematics of the rebounding sphere. Specific information can be found in Bourrier  
166 et al. (2007, 2008b).

167

168 Fig. 5.

169

170 Because of the defined inter-relationships between the outgoing and incident velocity components, the  
171 stochastic impact model differs completely from classical rebound algorithms. Most of these only use a  
172 tangential  $R_t$  and a normal  $R_n$  restitution coefficient for different slope surface types (see Guzzetti et al.,



173 2002; Dorren, 2003), which are defined by the user but are not related to all three incident velocity  
174 components. Many authors have already revealed that this approach introduces errors in rebound  
175 calculations. The  $R_t$  and  $R_n$  coefficients are defined as follows:

$$176 \quad R_t = \frac{V_t^{out}}{V_t^{in}} \quad (6)$$

$$177 \quad R_n = -\frac{V_n^{out}}{V_n^{in}} \quad (7)$$

178 Contrary to classical models, the restitution coefficients  $R_t$  and  $R_n$  that can be recalculated from the  
179 velocities before and after rebound as predicted by the stochastic impact model are not constant values.  
180 They both depend on all the incident kinematic parameters and the terrain characteristics. Figure 6 shows  
181 an example of the effect of the incident angle on the mean restitution coefficients  $R_t$  and  $R_n$  predicted by  
182 the stochastic impact model.

183

184 Fig. 6.

185

186 The values of the coefficients  $a_i$  defined in matrix  $\mathbf{A}$  are derived from the statistical analyses of a large  
187 data set obtained from numerical simulations of impacts (Bourrier et al., 2007, 2008a, 2008b). These  
188 numerical simulations of impacts were previously calibrated from laboratory experiments of the impact of  
189 a 10-cm spherical rock on a coarse soil composed of gravels ranging from 1 cm to 5 cm (Bourrier et al.,  
190 2008b). The adequate agreement between the laboratory experiments and the numerical simulations of  
191 impacts proves that the impact simulations, and consequently the stochastic impact model, satisfactorily  
192 express the energy transfers occurring during the impact of a boulder on a coarse soil. Although the  
193 calibration of the numerical model of impacts was satisfactory, one limitation could stem from the  
194 differences in the size of the impacting and soil rocks during calibration and during application in this  
195 study. However, the influence of the scale change effects was proved to be small by comparing the results  
196 of the numerical simulations of impacts at different scales (Bourrier, 2008).

197 For this study, the parameters of the stochastic impact model were determined for five fixed ratios, which  
198 have the values 1, 2, 3, 4, and 5, between the radius of the falling boulder  $R_b$  and the mean radius of the  
199 particles constituting the slope surface  $R_m$ . For each  $R_b/R_m$  ratio, a fixed set of model parameters was  
200 calculated. For larger ratios, the model has not yet been calibrated, which means that it is currently not  
201 suitable for rebounds of large boulders on fine soils.

### 202 3.3. Calculation of the fall direction

203 The fall direction in the  $x$ - $y$  plane is primarily determined by the slope topography at the rebound position  
204 and is calculated by a probabilistic algorithm. During each subsequent rebound, the model allows the  
205 sphere to deviate from its direction before rebound towards the direction of the aspect of the raster cell in  
206 which the boulder rebounds (Figs. 5 and 7). The aspect is the downslope direction of the maximum rate of  
207 change in value from each cell in a raster to its neighbouring ones and represents the steepest slope  
208 direction. The deviation angle  $\delta$  (Fig. 5) is determined by a random number that defines whether the  
209 boulder is deviated between 0 and 22.5° from its original direction, or 22.5–45°, or 45–50°. The first case  
210 has a 72% probability of occurrence, the second one has a 24% probability, and the third one a 4%  
211 probability (Fig. 7). These deviation angles and their related probabilities are based on the experimental  
212 results presented in Dorren et al. (2005). If the sphere moves upslope, a maximum deviation of 22.5° is  
213 allowed for both directions lateral to the direction before rebound. If the boulder enters a depression in the  
214 DEM, the direction before and after rebound remains unchanged.

215

216 Fig. 7.

217

### 218 3.4. Input data

219 The DEM used for the experimental site covers an area from the release point to the opposite river bank  
220 in the valley bottom. The DEM was created using inverse distance-weighted interpolation (see for

221 instance Weber and Englund, 1992) of, on average, three  $x$ ,  $y$ ,  $z$  points per DEM cell. These points were  
222 collected in the field with a detailed topographical survey using a laser distance meter and a compass. The  
223 topographical survey was conducted so that a mean density of 1 point/m was available in all directions.  
224 We created this DEM because, due to the surrounding forest cover, GPS measurements are not accurate  
225 on the study site and a high-resolution, photogrammetric or LiDAR-derived DEM was not available.  
226 Verification with an available 10-m DEM and an orthophoto showed that the accuracy of the created  
227 DEM was about 1 m in the  $x$ - $y$  plane and 0.5–1.5 m in the  $z$ -direction.

228 At the release point, boulders were dropped from a height of 5 m. The simulated boulders were assumed  
229 to be spherical, and the distribution of their volumes was identical to the experimental distribution (Fig.  
230 2). The errors associated with volume estimation were therefore the same in the experiments and in the  
231 simulations. Volume estimation errors were reduced as much as possible by choosing the released  
232 boulders in a quarry so that they were as spherical as possible.

233 The slope surface characteristics were determined in the field by identifying homogenous zones that are  
234 represented as polygons on a map (Fig. 1). Each polygon defines the size of the material covering the  
235 slope. To represent the size of the surface material in this polygon map, we used two different  
236 approaches. The first one, which is called method A (“size classes”), describes the surface with three size  
237 probability classes according to Dorren et al. (2006). The second one, called method B (“mean size”), is a  
238 more simplified description, which is based only on the mean radius  $R_m$  of the material covering the  
239 slope. Method A aims at giving a precise description of the size of the surface material and its variation.

240 The method uses three roughness classes  $Rg_{70}$ ,  $Rg_{20}$ , and  $Rg_{10}$ . These classes represent the diameter of the  
241 obstacle, corresponding to rocks covering the soil surface, encountered by a falling boulder during 70%,  
242 20%, and 10%, respectively, of the rebounds in a homogenous zone. For method A, the field survey  
243 therefore consists of estimating the equivalent diameter of the rocks covering the soil surface  
244 corresponding to the three classes  $Rg_{70}$ ,  $Rg_{20}$ , and  $Rg_{10}$  in each homogenous zone on the study slope.

245 During each rebound calculation, the mean radius  $R_m$  of the material encountered by the impacting  
246 boulder was randomly chosen from the three material size values  $Rg_{70}$ ,  $Rg_{20}$ , and  $Rg_{10}$  given their

247 accompanying probabilities. In method B, only one mean radius  $R_m$  value represented the material size in  
248 each homogenous zone. Rebound was therefore calculated by considering  $R_m$  the mean radius of the rock  
249 encountered by the falling boulder in a given zone.

250 In the rebound model used, the value of the  $R_b/R_m$  ratio is rounded to the nearest integer with a maximum  
251 of 5. A set of rebound model parameters ( $a_i$  coefficients) was determined depending on the value of the  
252  $R_b/R_m$  ratio. Table 1 reports the values used for all the polygons defined and shown on the map in Fig. 1.

253

254 Table 1.

255

### 256 *3.5. Simulation scenarios*

257 Rockfall trajectory simulations were carried out using method A (“size classes”) and method B (“mean  
258 size”). For each method, 100, 1000, 2000, 5000, and 10000 falling boulders were simulated. For each set  
259 of simulations, the probability distribution functions of the velocity, translational kinetic energy, and  
260 passing height were compared with the corresponding experimental distributions at two “evaluation lines”  
261 (Figure 1). Evaluation line 1 (EL1) was located 185 m from the starting point, measured along the slope,  
262 directly in the centre of the viewing plane of camera 4. Evaluation line 2 (EL2) was located after 235 m,  
263 in the centre of the viewing plane of camera 5. In addition, the spatial patterns of the trajectories, the  
264 passing frequencies per raster cell, and the stopping locations of the simulated boulders were analysed.  
265 The latter were compared with stopping locations observed during the field rockfall experiments.

### 266 *3.6. Rebound analysis*

267 If the agreement between the experimental and simulated results is satisfactory, the simulations can  
268 collect additional information on the kinematics of the falling boulders, which cannot be measured during  
269 the full-scale field experiments. First, precise values of the rotational kinetic energy of the falling  
270 boulders at EL1 and EL2 can be obtained from simulations, whereas the rotation of the falling boulder

271 cannot be precisely measured from the experimental films. In the simulations, the rotational kinetic  
 272 energy of the falling boulder  $E_{rot}$  can therefore be compared with the translational kinetic energy of the  
 273 falling boulder  $E_{trans}$  and with the total kinetic energy of the falling boulder  $E_{tot}$ .  
 274 Information regarding the incident kinetic energy for all rebounds can also be collected, whereas this is  
 275 not possible from field experiments. In particular, for each rebound, the simulations provide information  
 276 on the distribution of the incident kinetic energy between the tangential, normal, and rotational incident  
 277 velocity components. Starting from Eqs. 1, 2, and 3, the incident kinetic energy  $E_{tot}^{in}$  is divided into  
 278 normal incident energy  $E_n^{in}$ , tangential incident energy  $E_t^{in}$ , and rotational incident energy  $E_{rot}^{in}$  defined  
 279 as follows:

$$280 \quad E_{tot}^{in} = E_t^{in} + E_n^{in} + E_{rot}^{in} \quad (8)$$

$$281 \quad E_t^{in} = \frac{1}{2} m_b (V_t^{in})^2 \quad (9)$$

$$282 \quad E_n^{in} = \frac{1}{2} m_b (V_n^{in})^2 \quad (10)$$

$$283 \quad E_{rot}^{in} = \frac{1}{2} I_b (\omega^{in})^2 \quad (11)$$

284 Finally, to compare the implemented rebound algorithm to classical rebound models based on the use of  
 285 restitution coefficients, the  $R_t$  and  $R_n$  values obtained during the simulations were computed using the  
 286 classical definition given in Eqs. 6 and 7.

## 287 **4. Results**

288 1000 rockfall simulations were required to provide stable predictions, meaning that the variation in the  
 289 means and standard deviations of the parameters measured on EL1 and EL2 became  $< 5\%$ . However, to  
 290 decrease the variation in the results as much as possible, 10000 simulations were executed for both  
 291 methods.

292 *4.1. Kinematic results at the evaluation lines*

293 The comparisons between the experimental and simulated results at EL1 and EL2 show that both the  
294 mean values and standard deviations were predicted accurately for boulder velocity, passing heights, and  
295 translational kinetic energy (Table 2). However, in most cases, the simulated mean values and standard  
296 deviations were slightly smaller than the experimental values. In addition, the predictions obtained using  
297 method B (“mean size”) were systematically closer to the experimental results than those obtained using  
298 method A (“size classes”). All relative errors (RE) (Table 3) are < 21% for method B, whereas they reach  
299 up to 32% for method A.

300 The shapes of the distributions of the simulated quantities were very similar for methods A and B (Fig. 8).  
301 These distributions were also similar to those obtained from the experimental results. On the contrary, the  
302 maximum values were overestimated by the simulations, irrespective of the method used (Table 3).

303 The statistical Kolmogorov-Smirnov test was performed to compare all the simulated distributions with  
304 the corresponding experimental distributions. If the result of the test is 0, it can be assumed that the  
305 simulated and experimental results are similar. If the result is 1, this is not the case. The similarity  
306 hypothesis is rejected if the p-value associated with the test is less than 0.05. The larger the p-value is, the  
307 more plausible the hypothesis that the two samples belong to the same distribution. The results of the  
308 Kolmogorov-Smirnov tests showed that method B (“mean size”) provided a better prediction of the  
309 experimental distributions because the similarity hypothesis was only rejected once out of 6 comparisons.  
310 For method A (“size classes”), it was rejected 4 times out of 6 comparisons. In addition, the p-value  
311 obtained when comparing the simulated distributions to the measured distributions were all between 0.01  
312 and 0.3 whatever method was used, which means that the simulated distributions were not significantly  
313 different from the experimental distributions. Both methods A and B can therefore be considered suitable  
314 to simulate the experimental results.

315

316 Table 2.

317

318 Table 3.

319

320 Table 4.

321

322 Fig. 8.

323

#### 324 *4.2. Rockfall trajectories*

325 The numbers of boulders deposited with decreasing altitude are presented in Fig. 9, for both the  
326 experimental and simulated results. The simulations, using methods A and B, provided values similar to  
327 the experimental values for the distribution of stopping points, especially for boulders reaching low  
328 altitudes. Interestingly, predictions using method A (“size classes”) resulted in a slight underestimation of  
329 the percentage of passing boulders with decreasing altitude. On the contrary, the simulations using  
330 method B (“mean size”) provided a slight overestimation. For boulders stopping just after the release  
331 point and for boulders reaching long distances from the release point ( $> 350$  m), both methods predicted  
332 larger percentages of passing boulders than the experimental results.

333

334 Fig. 9.

335

336 The comparison between simulated run-out zones and experimental stopping points (Fig. 10) showed  
337 that, first, the simulated run-out zone was larger than the one observed during the experiments. Second,  
338 discrepancies were observed for stopping points located below the forest road. In the experiments, two  
339 distinct deposit areas were observed, whereas the simulated passing frequencies only highlighted one of  
340 them located on the bottom left of the maps in Fig. 10.

341

342 Fig. 10.

343

344 *4.3. Information gathered from simulations*

345 Since we consider that the agreement between the experimental and simulated results is highly  
346 acceptable, we used the simulations to study kinematical parameters that could not be measured in the  
347 field, in particular the distribution of the rotational velocity of the falling boulder (Fig. 11). The mean  
348 value of the  $E_{rot}/E_{tot}$  ratio was 6% for EL1 and 8% for EL2. In addition, the associated standard deviation  
349 was 7% for EL1 and 8% for EL2.

350

351 Fig. 11.

352

353 Further, the simulated  $E_t^{in} / E_{tot}^{in}$  ratios (Fig. 12) showed that most of the incident energy was associated  
354 with the tangent-to-soil-surface component of the incident velocity. This result was confirmed by the  
355 distribution of the incidence angle (Fig. 13), which highlights the small values of this angle. Finally, the  
356 simulation results provided information on the distribution of  $R_t$  and  $R_n$  restitution coefficients for all  
357 rebounds, as shown in Fig. 14.

358

359 Fig. 12.

360

361 Fig. 13.

362

363 Fig. 14.

364



## 365 **5. Discussion**

### 366 *5.1. Comparison of the experimental and simulation results*

367 The comparisons of the experimental and simulated results, using methods A and B, showed that the 3D  
368 trajectory simulation could predict rockfall trajectories and kinematics. Reproducible simulation results  
369 were obtained from 1000 simulations onwards, which makes 3D trajectory simulation feasible. However,  
370 in this study, there were fewer sources of variability than in the daily practice of rockfall hazard  
371 assessment. In particular, the rockfall starting position and the boulder volumes were exactly known. In  
372 practice, the latter are not always easy to predict.

373 The differences between the observed and simulated distributions, the maximum values in particular,  
374 could stem from the fact that, in the experiments, the distributions were based on only 100 rockfall  
375 experiments. They therefore do not represent the full asymptotic distribution that would have been  
376 obtained from a very large number of experiments. However, the global shape of the distribution, such as  
377 the most probable value and the global distribution of the values, was satisfactorily represented. Thus, if  
378 only the global characteristics of the distributions are compared, the simulated distributions can be  
379 considered good predictions, which was confirmed by the results of the Kolmogorov-Smirnov test, in  
380 particular for method B (“mean size”).

381 The comparisons between the simulated and the experimental stopping points showed the capability of  
382 the rockfall model to predict run-out distances (Fig. 9). However, Fig. 9 shows that method B (“mean  
383 size”) approached the experimentally observed deposit pattern best. Neither method A nor B reproduced  
384 the number of boulders stopping in the upslope section of the test site. These blocks stopped within the  
385 first 20–40 m from the release point due to sliding on the side with the largest surface after the first  
386 rebound. Figure 9 shows that this accounted for ~ 5% of the released boulders. For large distances from  
387 the release point (350 m and farther), the differences between the simulated and the experimental  
388 maximum run-out distances (Fig. 9) resulted from the rebound algorithm not being adapted to the surface  
389 material consisting of soils composed of fine particles, which was found in the valley bottom (Fig. 10).

390 The algorithm was specifically developed for rocky surfaces and therefore will not produce realistic  
391 results for other soil types.

392 Although the simulated run-out zones were larger than the experimental run-out zones (Fig. 10), the 1%  
393 pass frequency limit, i.e., the limit passed by 1% of the boulders, correspond quite well to the  
394 experimentally observed stopping points only (Fig. 10), especially for method B.

395 The existence of two deposit areas was not reproduced by the simulations. The simulated passing  
396 frequency maps show two main trajectory paths upslope of the forest road, which converge into a single  
397 path in the downslope section. The experimental trajectories, however, also show two distinct paths in the  
398 downslope section. The difference between these experimental and simulated patterns resulted from an  
399 imperfect digital representation of the terrain in the DEM south-west of the middle forest road (Fig. 15).  
400 This local discrepancy induced slight changes in the pattern of the trajectory path and in the shape of the  
401 run-out zone associated with the 1/100 pass frequency (Fig. 10).

402

403 Fig. 15.

404

405 Finally, the comparison of the results obtained by method A and method B raises questions on how  
406 precise the parameter values estimated in the field must be. For methods A and B, the simulated  
407 distributions of velocities, rebound heights, and energies (Fig. 8) as well as the run-out zones (Fig. 9)  
408 were very similar. The detail of the description of the slope surface characteristics therefore only slightly  
409 influences the simulation results. Our experience shows, however, that in the field it is easier to estimate  
410 three size classes than a single one, as shown in Fig. 16. For example, on a slope covered with rather fine  
411 scree (< 5 cm), quite some rocks measured 10 cm in diameter, and 10% of the surface covered with 20-  
412 cm rocks, it is quite difficult to estimate a single, valid, mean particle size. The “size classes” method  
413 describes the mean size of the particles that cover 70%, 20%, and 10% of the surface, with 70% = 5 cm,  
414 20% = 10 cm, and 10% = 20 cm. Since method B (“mean size”) provided more accurate results, this

415 implies that method A (“size classes”) could be used in the field for a better estimate of the single mean  
416 particle size, so that method B (“mean size”) could be used in the simulation.

417

418 Fig. 16.

419

## 420 *5.2. Advantages and limitations of the approach*

421 An advantage of the approach presented here is that simulation can be used to gather information that  
422 cannot be obtained in the field (see section 3.6). First, the simulated distributions of the rotational kinetic  
423 energies compared to the total kinetic energy at EL1 and EL2 show that the translational velocity of the  
424 boulder mainly determines the total boulder kinetic energy (Fig. 11). One could note a slight trend toward  
425 a downhill increase in the  $E_{rot}/E_{tot}$  ratio, which may be due to the specific topography of the study site.  
426 Although the rotational energy was smaller than the translational energy, the knowledge of the  
427 distribution between these two energies is essential for designing effective protective structures. The  
428 translational kinetic energy mainly determines the design of the structure (structural strength  
429 performance), whereas the rotational kinetic energy determines the capability of the structure to prevent  
430 boulders from rolling over the structure (structure shape efficiency).

431 Another advantage of the approach presented is the insight obtained in the commonly used coefficients  $R_t$   
432 and  $R_n$ . The values of the  $R_t$  calculated from the simulated rebounds (Fig. 14) are in accordance with  
433 common values for talus slopes, but they show that the variability of  $R_t$  is even greater than assumed in  
434 the literature. In contrast, the values of the  $R_n$  coefficients (Fig. 14) are extremely high compared to the  
435 common values, which generally range from 0.25 to 0.65. The dependence of  $R_t$  and  $R_n$  recalculated from  
436 the stochastic impact model on the incidence angle explains this phenomenon (Fig. 6). For small  
437 incidence angles, which correspond to most of the rockfall impacts in the simulations (Fig. 13), the values  
438 of  $R_t$  depend only slightly on the incidence angle; they correspond to common values ( $R_t \approx 0.7$ ; Fig. 14).  
439 On the contrary, the values of  $R_n$  are very high ( $R_n > 1$ ) compared to common values (Fig. 14). However,

440 in the case of a vertical impact, the  $R_n$  values predicted by the stochastic impact model (Fig. 6) are in  
441 accordance with common experimental results ( $R_n \approx 0.4$ ). The main reason for these differences is that the  
442 common values of  $R_n$  are generally obtained from experimental campaigns conducted for boulders falling  
443 vertically on a slope surface. This does not correspond to the simulated impact cases because simulation  
444 incidence angles were, for the most part,  $< 50^\circ$ , as shown in Fig. 13. The high values of  $R_n$  in the  
445 simulations explain that, although the incident normal velocity  $V_n^{\text{in}}$  was small for impacts that were  
446 parallel to the slope's surface, the normal velocity of the boulder after a rebound can be very high because  
447 of the energy transfer from the rotational to the translational kinetic energy. This phenomenon is not  
448 accounted for in classical rebound algorithms, whereas it is included in the stochastic impact model.  
449 The values of  $R_n$  should therefore be chosen with caution when performing a rockfall trajectory analysis  
450 using classical rebound algorithms. However, the importance of  $R_n$  is generally subordinate to  $R_t$ . Indeed,  
451 properly modelling the transfer of the tangential incident energy between the falling boulder and the soil  
452 during a rebound is essential because Fig. 12 shows that the tangential incident energy is, in most cases,  
453 determinant for the total incident energy (93% of the calculated  $E_t^{\text{in}} / E_{\text{tot}}^{\text{in}}$  ratios are  $> 0.75$ ).

454 The two main points of interest in the rebound calculation procedure developed herein are, first, precisely  
455 modelling the mechanisms governing the rebound as well as their associated variability and, second, the  
456 more objective field data collection procedure. Both points are of great interest for rockfall hazard  
457 mapping, which demand a satisfactory prediction of the variability of both the stopping points and the  
458 kinematics of the falling boulders. Following the proposed approach, hazard mapping can be greatly  
459 improved because it allows the reliable spatial characterisation of the passing frequencies as well as of the  
460 mean and standard deviation values of the rockfall energies (intensity). Rockfall hazard mapping  
461 approaches based on combinations of intensity and probability, such as those developed in Switzerland  
462 (Raetzo et al., 2002; Jaboyedoff et al., 2005), can therefore be used with increased confidence.

463 However, this work is limited by the partial character of the validation. From a theoretical point of view,  
464 the amount of experimental data is not (and almost never is) sufficient to validate simulated rare events.

465 Since the performance and analysis of 1000 full-scale rockfall experiments would take roughly 10 years,  
466 one must rely on simulations to predict extreme events, even though they are not fully validated.  
467 Another limitation of this study is that the stochastic impact model developed can only be used on rocky  
468 slopes. However, similar approaches could be developed to characterise the rebound of a boulder on all  
469 types of soil provided that large data sets composed of reproducible and precisely defined impact tests are  
470 available for statistical analysis. To create these data sets, the direct use of laboratory or field experiments  
471 is not suitable. However, they can be generated from numerical simulations that have previously been  
472 calibrated using these experiments. That is exactly where the challenge lies.

## 473 **6. Conclusions**

474 This paper has investigated a newly developed stochastic impact model, which was implemented in an  
475 existing 3D rockfall trajectory model to calculate velocities of simulated boulders after a rebound on the  
476 slope. The first objective of this study was to assess the adequacy of the approach proposed. For this  
477 purpose, a full-scale experimental program made it possible to assess the predictive capacity of this tool.  
478 Comparisons between experimental and simulated results show very acceptable agreements. The second  
479 objective of the study was to evaluate the minimum amount of field data required to obtain accurate  
480 simulation results. The main advantages of the developed approach are the small number of parameters to  
481 be assessed in the field and the clear physical meaning of these parameters. Basically, only the mean size  
482 of the rocks covering the surface of the slope is required. This can be measured objectively in the field.  
483 The method developed does not work for boulders impacting fine soils. We believe, however, that a  
484 similar objective stochastic rebound model could be developed, based on a similar combination of  
485 numerical and laboratory experiments.  
486 The stochastic feature of this new approach is an excellent basis for continuing integrating probabilistic  
487 information in rockfall hazard management. As reliable spatially distributed probabilistic information on  
488 rockfall trajectories is provided, such as the passing heights and kinetic energy distributions as well as the

489 passing frequencies for each position on a slope, the proposed approach offers a complete data set for  
490 positioning and designing rockfall protective structures as well as for hazard zoning.

491

## 492 **References**

493 Agliardi, F., Crosta, G.B., 2003. High resolution three-dimensional numerical modelling of rockfalls.

494 International Journal of Rock Mechanics and Mining Sciences. 40, 455-471.

495 Azzoni, A., Rossi P.P., Drigo E., Giani G.P., Zaninetti A., 1992. In situ observations of rockfalls analysis

496 parameters Proceedings of the sixth International Symposium of Landslides. Balkema, Rotterdam, The

497 Netherlands, pp. 307-314.

498 Azzoni, A., Barbera, G.L., Zaninetti A., 1995. Analysis and prediction of rockfalls using a mathematical

499 model. International Journal of Rock Mechanics and Mining Sciences. 32, 709-724.

500 Azzoni, A., De Freitas, M.H., 1995. Experimentally gained parameters, decisive for rock fall analysis.

501 Rock Mechanics and Rock Engineering. 28 (2), 111-124.

502 Berger, F., Dorren, L.K.A., 2006. Objective comparison of rockfall models using real size experimental

503 data. Disaster mitigation of debris flows, slope failures and landslides. Universal Academy Press Inc.,

504 Tokyo, Japan, pp. 245-252.

505 Bourrier, F., Nicot, F., Darve, F., 2007. Rockfall modelling: Numerical simulation of the impact of a

506 particle on a coarse granular medium. Proc. 10th Int. Congr. on NUMERICAL MODEL in Geomechanics.

507 Balkema, Rotterdam, The Netherlands, pp. 699-705.

508 Bourrier, F. 2008. Modélisation de l'impact d'un bloc rocheux sur un terrain naturel, application à la

509 trajectographie des chutes de bloc. PhD thesis, Institut Polytechnique de Grenoble, France.

510 Bourrier, F., Nicot, F., Darve, F., 2008a. Physical processes within a 2D granular layer during an impact.

511 Granular Matter. 10 (6), 415-437.

512 Bourrier, F., Eckert, N., Bellot, H., Heymann, A., Nicot, F., Darve, F., 2008b. Numerical modelling of

513 physical processes involved during the impact of a rock on a coarse soil. Proc. 2nd Euro Med. Symp.

514 On Advances in Geomaterial and Structures. Publisher, location of publisher, pp. 501-506.

515 Bozzolo, D., Pamini, R., 1986. Simulation of rock falls down a valley side. *Acta Mechanica*. 63, 113-130.

516 Chau, K. T., Wong, R.H.C., Lee, C. F., 1998. Rockfall Problems in Hong Kong and some new  
517 Experimental Results for Coefficients of Restitution. *International Journal of Rock Mechanics and*  
518 *Mining Sciences*. 35(4-5), 662-663.

519 Chau, K.T., Wong, R.H.C., Wu, J.J., 2002. Coefficient of restitution and rotational motions of rockfall  
520 impacts. *International Journal of Rock Mechanics and Mining Sciences*. 39, 69-77.

521 Chau, K.T., Tang, Y.F., Wong, R.H.C., 2004. GIS based rockfall hazard map for Hong Kong.  
522 *International Journal of Rock Mechanics and Mining Sciences*. 41(1), 846-851.

523 Cruden, D.M., Varnes, D.J., 1996. Landslides types and processes : Chapter 3. In: Turner, A.K., Schuster,  
524 R.L., (Eds.), *Landslides: Investigation and Mitigation*. Transportation research board, Special report  
525 247, pp. 36-71.

526 Descoedres, F., 1997. Aspects géomécaniques des instabilités de falaises rocheuses et des chutes de  
527 blocs. *Publications de la société suisse de Mécanique des Sols et des Roches*. 135, 3-11.

528 Dorren, L.K.A., 2003. A review of rockfall mechanics and modelling approaches. *Progress in Physical*  
529 *Geography*. 27 (1), 69-87.

530 Dorren, L.K.A., Berger, F., Le Hir, C., Mermin, E., Tardif, P., 2005. Mechanisms, effects and  
531 management implications of rockfall in forests. *Forest Ecology and Management*. 215(1-3), 183-195.

532 Dorren, L.K.A., Berger, F., Putters, U.S., 2006. Real size experiments and 3D simulation of rockfall on  
533 forested and non-forested slopes. *Natural Hazards and Earth System Sciences*. 6, 145-153.

534 Dudt, J.P., Heidenreich, B., 2001. Treatment of the uncertainty in a three-dimensional numerical  
535 simulation model of rockfalls. *International Conference on Landslides*. pp. 507-514.

536 Evans, S.G., Hungr, O., 1993. The assessment of rockfall hazard at the base of talus slopes. *Canadian*  
537 *Geotechnical Journal*. 30, 620-636.

538 Frattini, P., Crosta, G.B., Carrara, A., Agliardi, F., 2008. Assessment of rockfall susceptibility by  
539 integrating statistical and physically-based approaches. *Geomorphology*. 94 (3-4), 419-437.

540 Guzzetti, F., Crosta, G., Detti, R., Agliardi F., 2002. STONE: a computer program for the three  
541 dimensional simulation of rock-falls. *Computer & Geosciences*. 28, 1079-1093.

542 Heidenreich, B., 2004. Small- and half-scale experimental studies of rockfall impacts on sandy slopes.  
543 PhD Thesis, Ecole Polytechnique Fédérale de Lausanne, Swiss.

544 Interreg IIC., 2001. Prévention des mouvements de versants et des instabilités de falaise - Confrontation  
545 des méthodes d'étude des éboulements rocheux dans l'arc alpin. Final report, Interreg IIC Program  
546 Méditerranée occidentale et Alpes Latines.

547 Jaboyedoff, M., Dudd, J.P., Labiouse, V., 2005. An attempt to refine rockfall zoning based on kinetic  
548 energy, frequency and fragmentation degree. *Natural Hazards and Earth System Sciences*. 5, 621-632.

549 Kobayashi, Y., Harp, E.L., Kagawa, T., 1990. Simulation of rockfalls triggered by earthquakes. *Rock  
550 Mechanics and Rock Engineering*. 23, 1-20.

551 Nicot, F., Cambou, B., Mazzoleni, G., 2001. From a constitutive modelling of metallic rings to the design  
552 of rockfall restraining nets. *International Journal for Numerical and Analytical Methods in  
553 Geomechanics*. 25, 49-70.

554 Nicot, F., Gotteland, P., Bertrand, D., Lambert, S., 2007. Multiscale approach to geo-composite cellular  
555 structures subjected to rock impacts. *International Journal for Numerical and Analytical Methods in  
556 Geomechanics*. 31, 1477-1515.

557 Paronuzzi, P., 1989. Probabilistic approach for design optimization of rockfall protective barriers.  
558 *Quarterly Journal of Engineering Geology and Hydrogeology*. 22, 175-183.

559 Peila, D., Pelizza, S., Sassudelli, F., 1998. Evaluation of behaviour of rockfall restraining nets by full  
560 scale tests. *Rock Mechanics Rock Engineering*. 31 (1), 1-24.

561 Pfeiffer, T.J., Bowen, T.D., 1989. Computer simulations of rockfalls. *Bulletin of the Association of  
562 Engineering Geology*. 26, 135-146.

563 Raetzo, H., Lateltin, O., Bollinger, D., Tripet, J., 2002. Hazard assessment in Switzerland – Codes of  
564 practice for mass movements. *Bulletin of engineering Geology and the Environment*. 61(3), 263-268.



- 565 Scioldo, G., 2006. User guide ISOMAP & ROTOMAP - 3D surface modelling and rockfall analysis.  
566 Geo&Soft International.
- 567 Selby, M. J., 1993. Hillslope materials and processes. Oxford University Press, Oxford.
- 568 Ushiro, T., Shinohara, S., Tanida, K., Yagi, N., 2000. A study on the motion of rockfalls on Slopes.  
569 Proceedings of the 5th Symposium on Impact Problems in Civil Engineering. pp. 91-96.
- 570 Varnes, D.J., 1978. Slope movement types and processes. In: Schuster, R.L., Krizek, R.J., (Eds.),  
571 Landslides, analysis and control. Transportation research board, Special report 176, pp. 11-33.
- 572 Weber, D., and Englund, E., 1992. Evaluation and comparison of spatial interpolators. Mathematical  
573 Geology. 24, 381-391.
- 574 Whalley, W.B., 1984. Rockfalls. In: D. Brunsten, D., Prior, D.B. (Eds), Slope instability. John Wiley and  
575 Sons, New York, pp. 217-256.
- 576 Wu, S.S., 1985. Rockfall evaluation by computer simulation. Transportation Research Record. 1031, 1-5.

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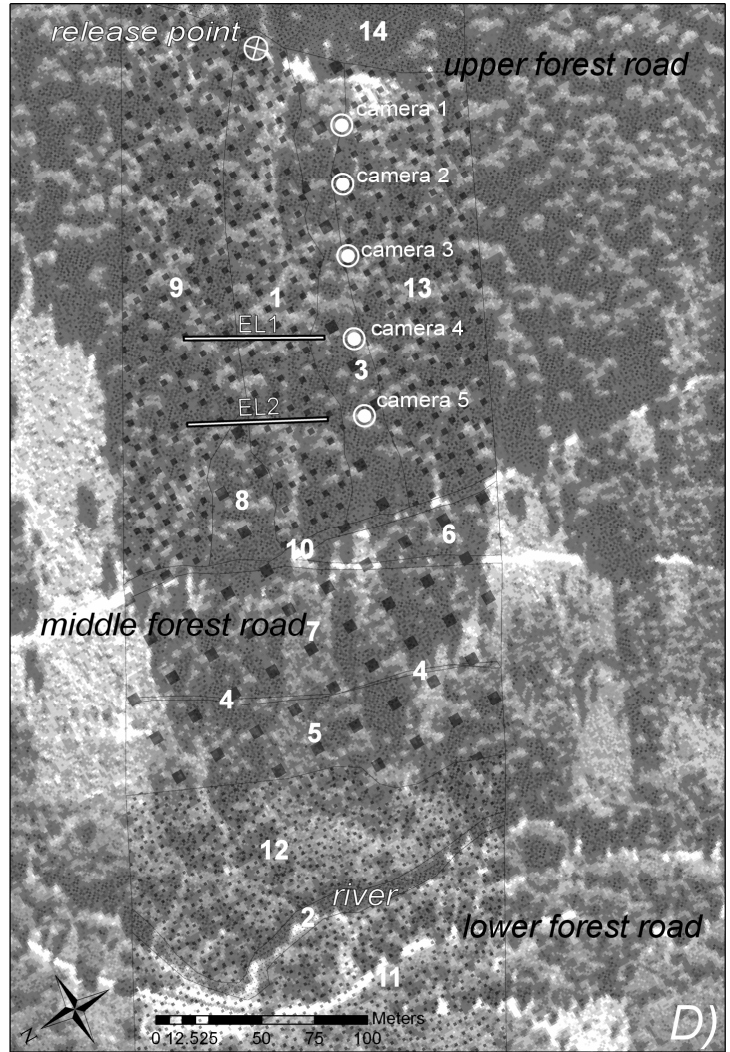
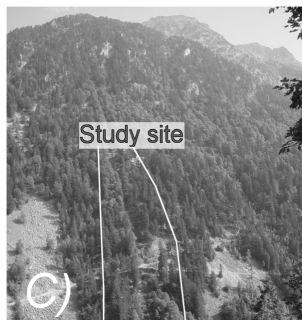
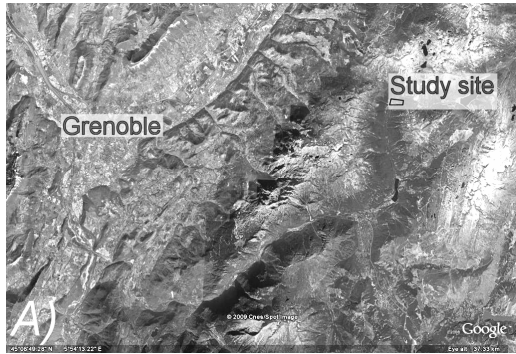
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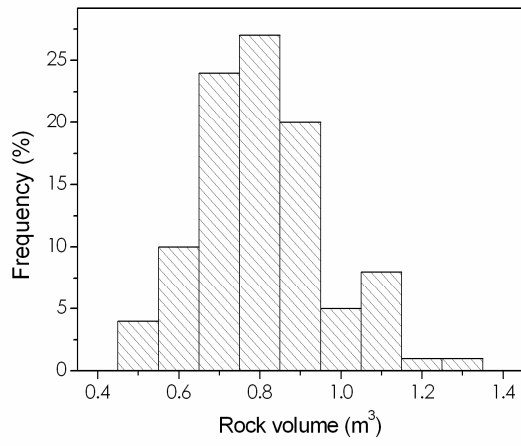
624 Table 4. Kolmogorov-Smirnov tests (KS tests) compared to experimental distributions after 10,000  
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626 Fig. 1.



627

628 Fig. 2.



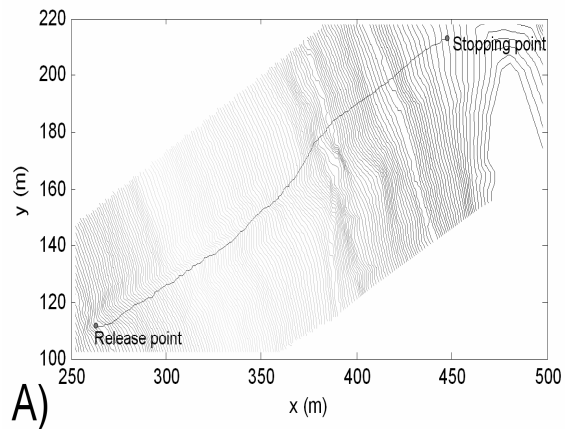
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630 Fig. 3.

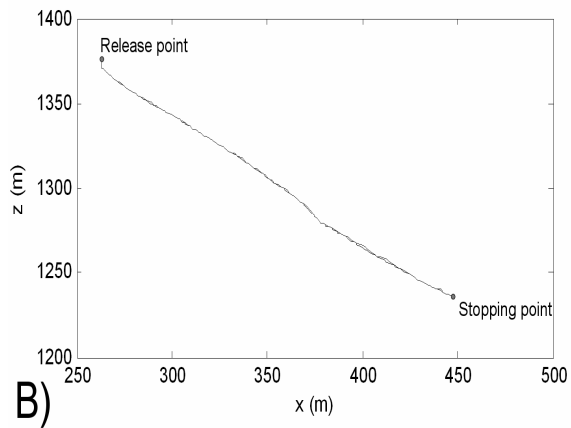


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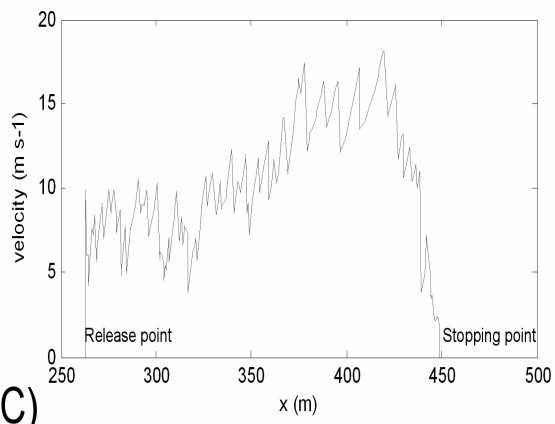
632 Fig. 4.



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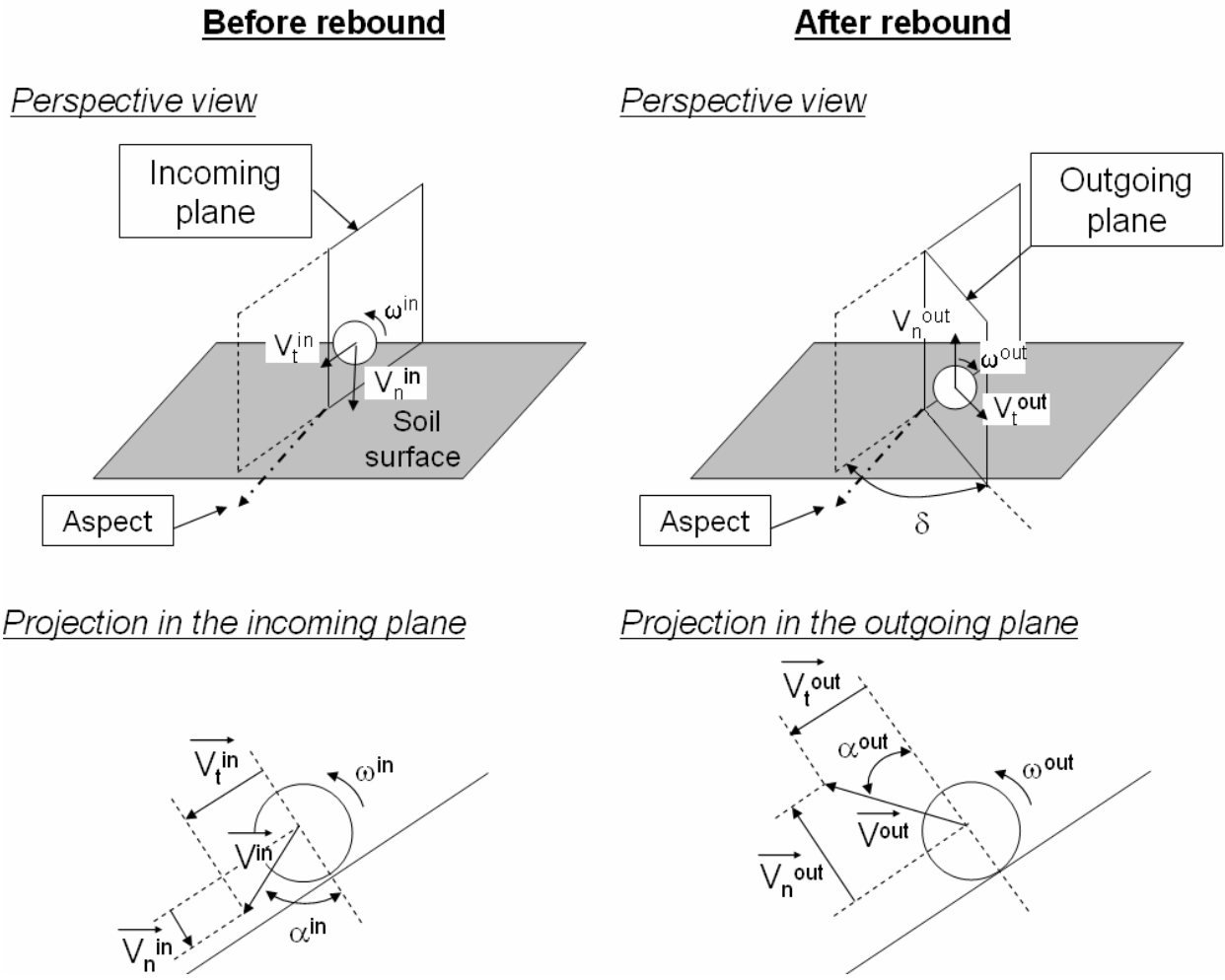


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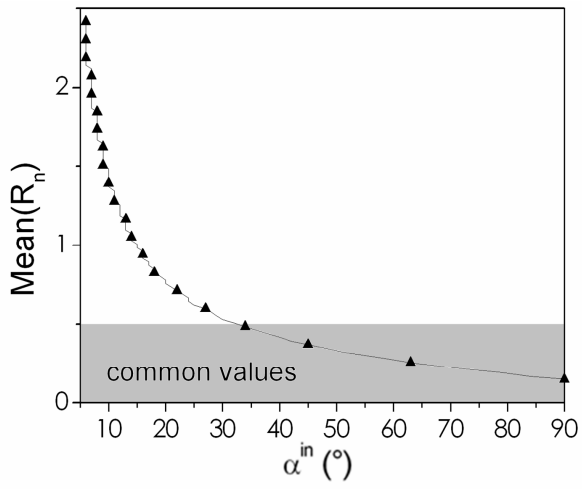
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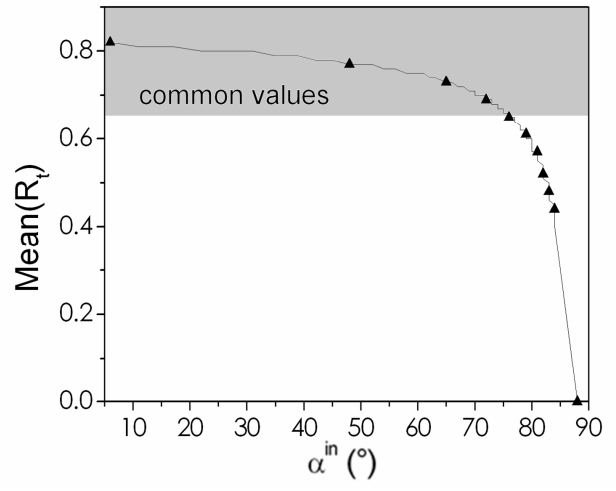




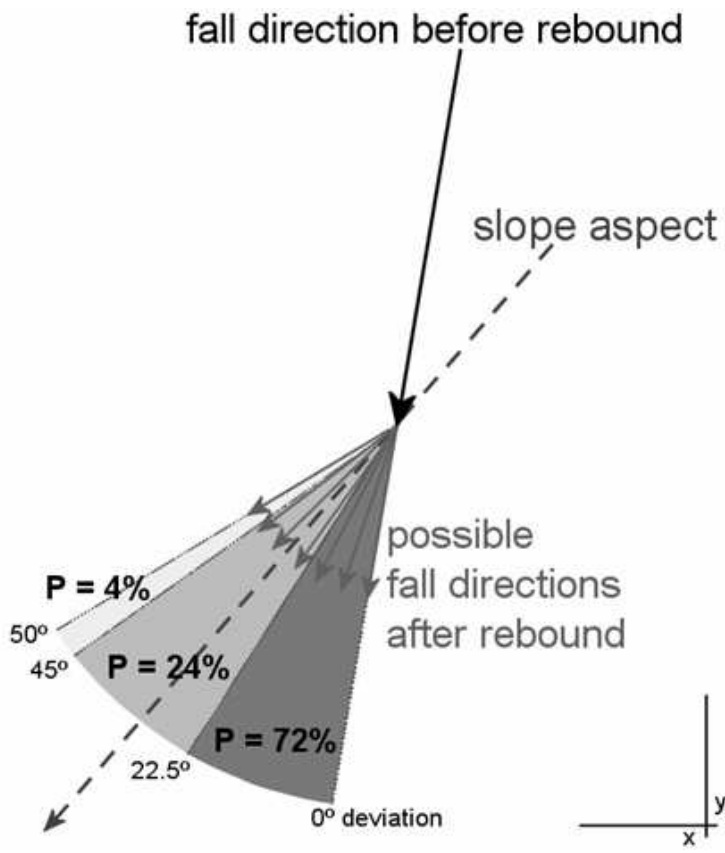
636 Fig. 6.



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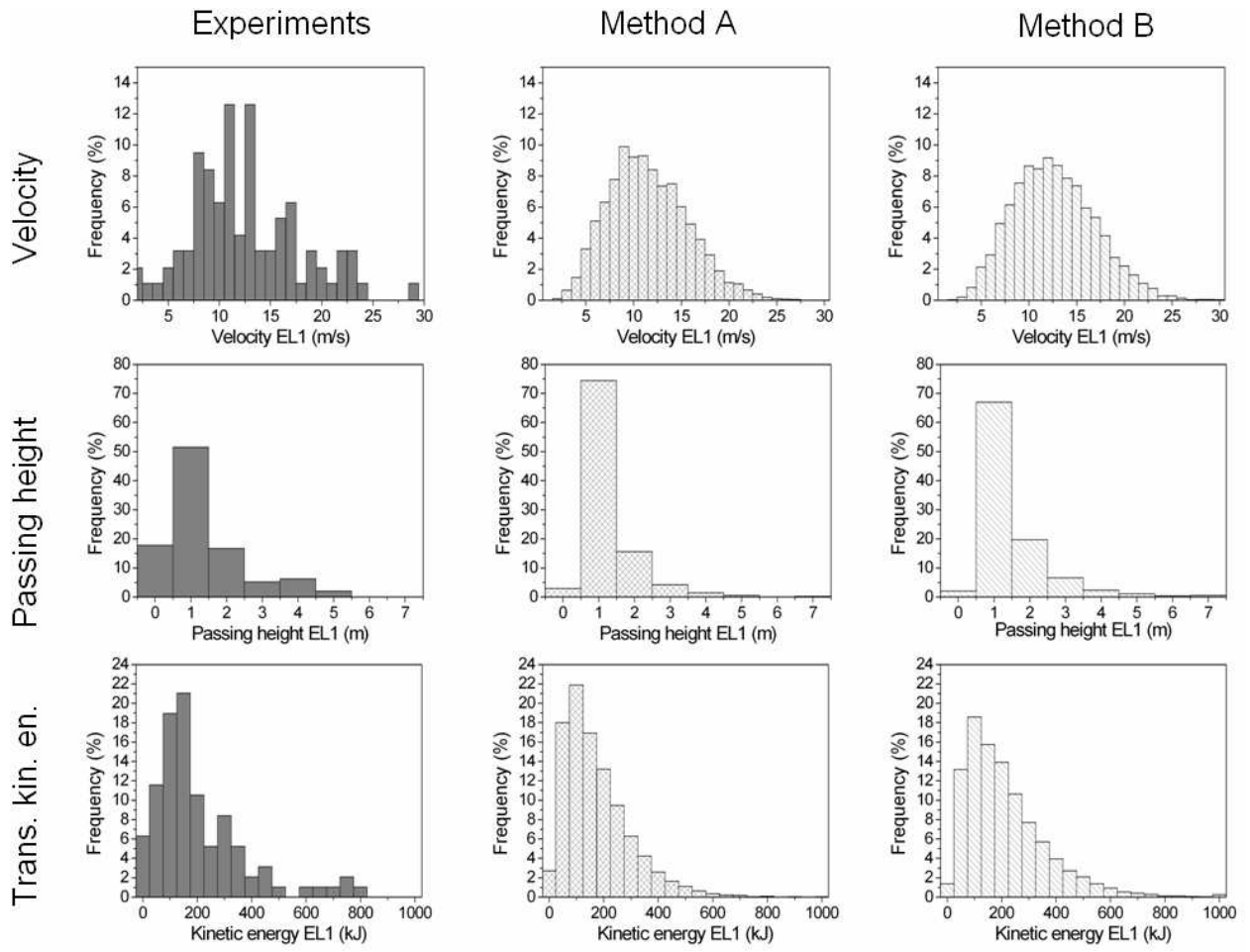


638 Fig. 7.



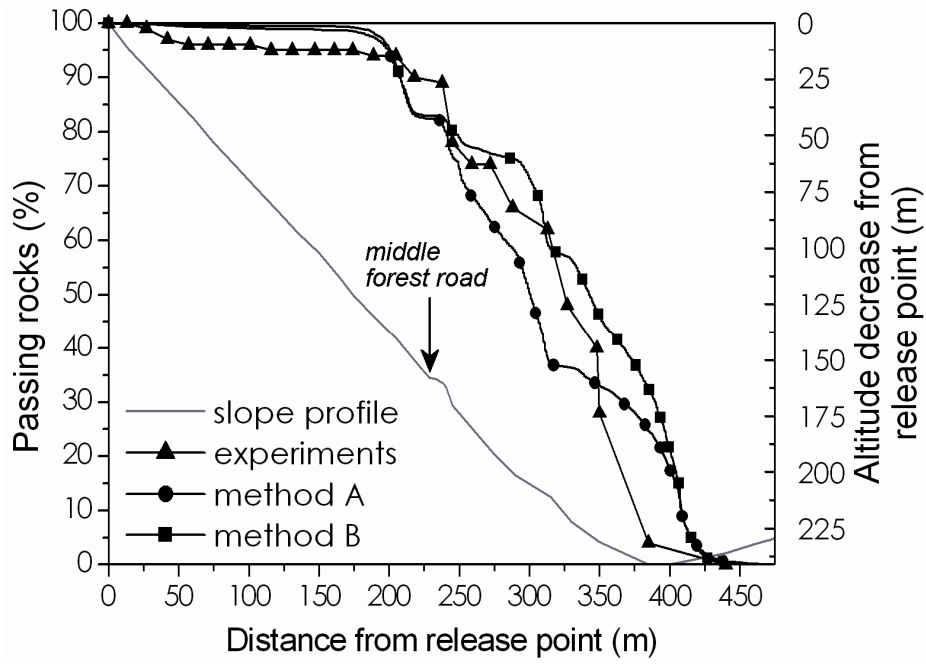
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640 Fig. 8.



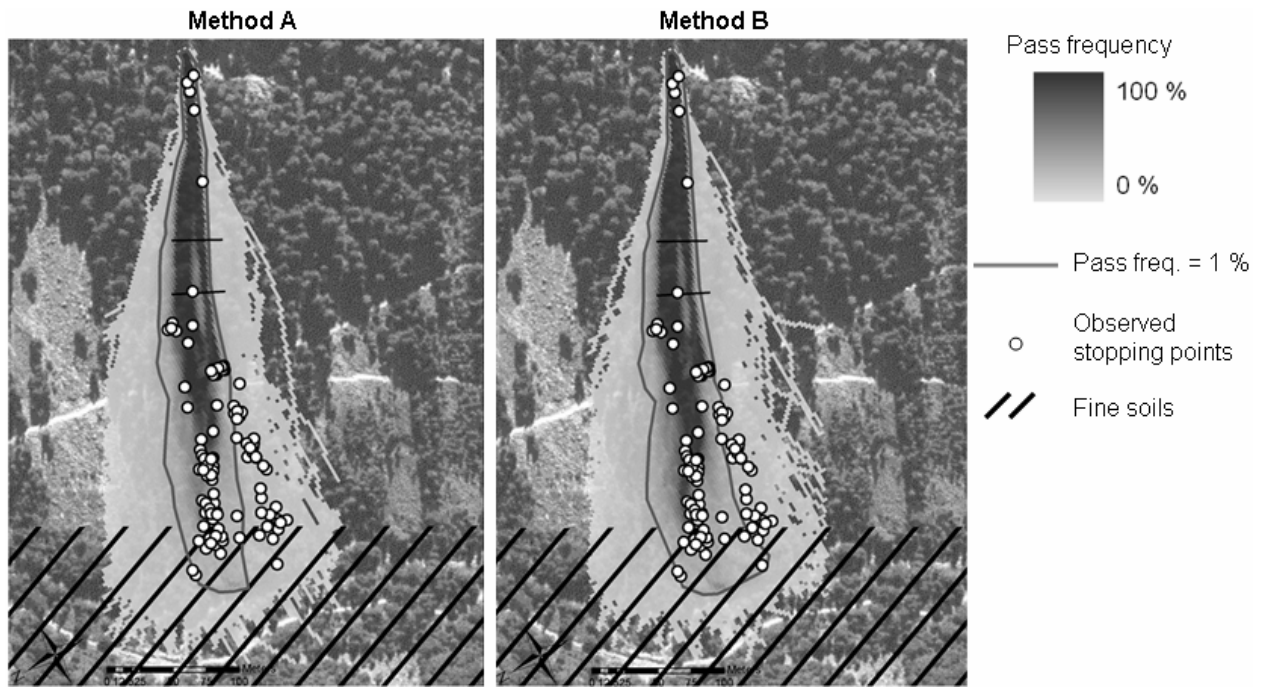
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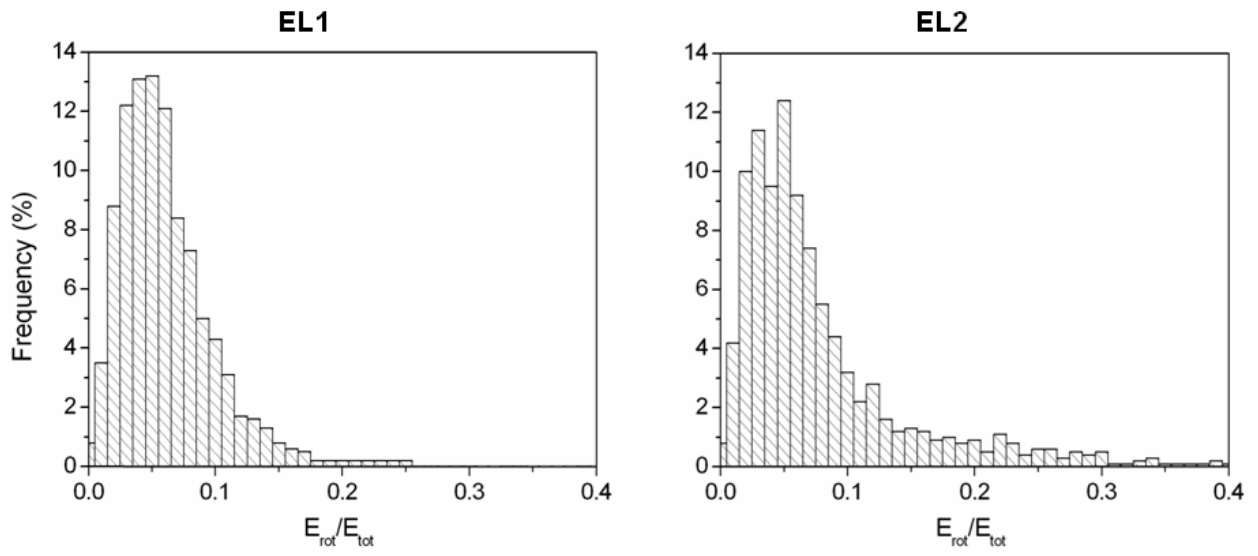


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644 Fig. 10.

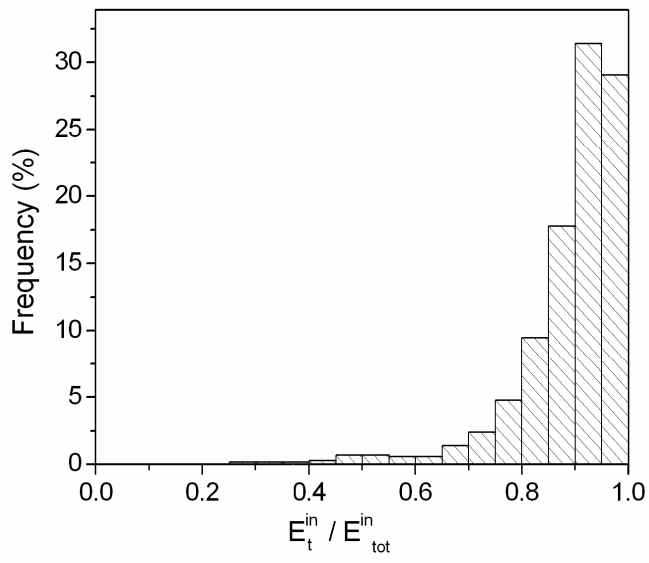


646 Fig. 11.



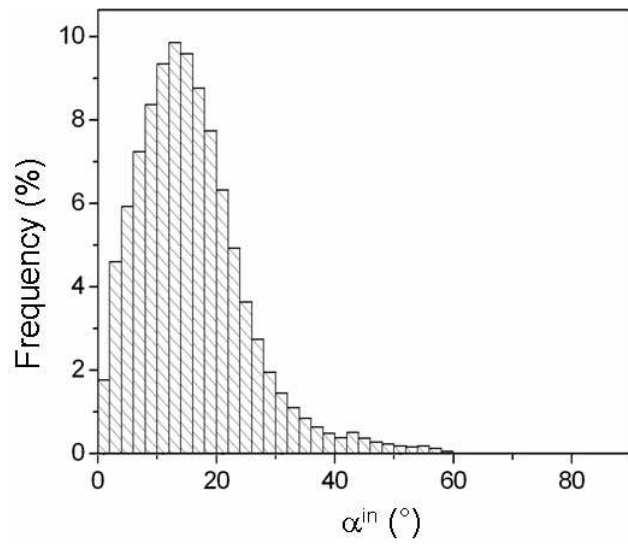
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648 Fig. 12.



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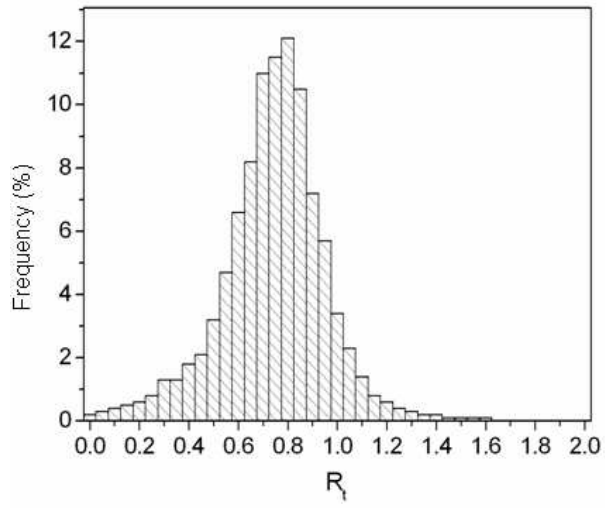
650 Fig. 13.



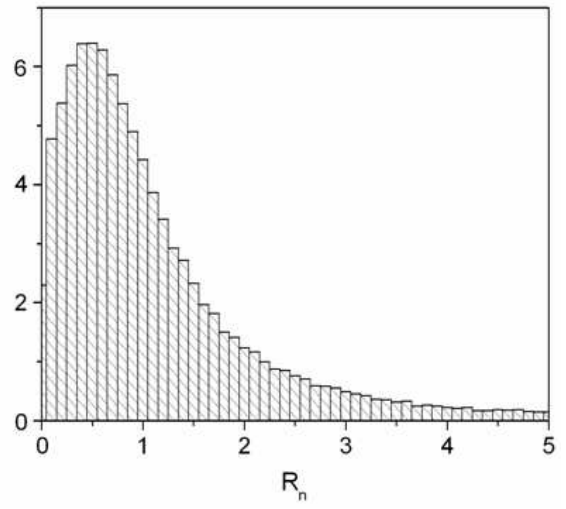
651



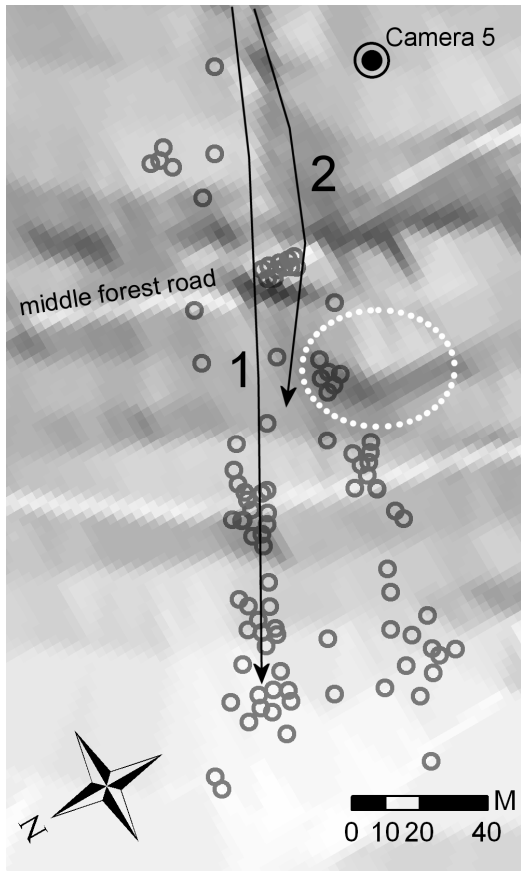
652 Fig. 14.



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654 Fig. 15.



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656 Fig. 16.



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658 Table 1.

<b>Zone</b>	$Rg_{70}$ (m)	$Rg_{20}$ (m)	$Rg_{10}$ (m)	$R_m$ (m)	Description
1	0.20	0.15	0.07	0.10	Inside the avalanche channel
2	Inf	Inf	Inf	Inf	River
3	0.30	0.10	0.45	0.18	Zone covered with talus alongside the channel
4	0.50	0.30	0.10	0.25	Old road on talus slope, covered with single blocks
5	0.40	0.20	0.10	0.25	Talus slope downslope of middle forest road
6	0.50	0.25	0.75	0.25	Rough talus slope downslope of middle forest road
7	0.50	0.28	0.90	0.25	Roughest part of the talus slope downslope of middle forest road
8	0.40	0.25	0.50	0.25	Small block accumulation
9	0.20	0.05	0.10	0.10	North-east forested part of talus slope
10	0.50	0.30	0.10	0.10	Irregular forest road on talus slope
11	0.05	0.05	0.05	0.05	Soils in valley bottom
12	0.02	0.05	0.10	0.03	Fine soils in valley bottom
13	0.25	0.15	0.10	0.10	South-west forested part of talus slope
14	0.10	0.20	0.30	0.10	Upper forest road

659 Table2.

	Velocity (m. s <sup>-1</sup> )			Passing height (m)			Trans. kin. en. (kJ)		
	Mean	Std. Dev.	Max.	Mean	Std. Dev.	Max.	Mean	Std. Dev.	Max.
EL1 <sup>a</sup> observed	12.5	5.2	28.1	1.4	1.1	5.0	205	169	786
EL1 method A	11.5	4.2	27.7	1.2	0.9	10.4	175	126	1081
EL1 method B	12.7	4.3	30.3	1.4	1.0	11.0	213	152	1332
EL2 observed	13.8	5.5	28.9	1.6	1.4	6.2	245	196	958
EL2 method A	10.9	4.7	29.6	1.2	1.0	15.5	167	139	1174
EL2 method B	12.1	5.1	31.8	1.4	1.1	12.7	207	173	1575

660 <sup>a</sup> EL = Evaluation line.

661

662 Table 3.

	RE velocity (%)			RE passing height (%)			RE Trans. kin. en. (%)		
	Mean	Std. Dev.	Max.	Mean	Std. Dev.	Max.	Mean	Std. Dev.	Max.
EL1 method A	-8	-19	-1	-14	-18	108	-15	-25	38
EL1 method B	2	-17	8	0	-9	120	4	-10	69
EL2 method A	-21	-15	2	-25	-29	150	-32	-29	23
EL2 method B	-12	-7	10	-13	-21	105	-16	-12	64

663 Table 4.

	Velocity		Passing height		Trans. kin. en.	
	KS test 0: not rejected 1: rejected	P-value	KS test 0: not rejected 1: rejected	P-value	KS test 0: not rejected 1: rejected	P-value
EL1 method A	0	0.2225	1	0.0385	0	0.1772
EL1 method B	0	0.2172	0	0.0570	0	0.1421
EL2 method A	1	0.0033	1	0.0224	1	0.0223
EL2 method B	0	0.1022	1	0.0366	0	0.2911

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