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Rock temperature prior to failure: analysis of 209 rockfall events in the Mont Blanc massif (Western European Alps)

A. Legay¹, F. Magnin¹, L. Ravanel¹

¹ EDYTEM Lab, Université Savoie Mont Blanc, CNRS, Le Bourget-du-Lac, France

Corresponding author: Florence Magnin [florence.magnin@univ-smb.fr]

Key words: rockfall, alpine rockwall, thermal modeling, permafrost, Mont Blanc massif

1 ABSTRACT

2 Periglacial rockwalls are affected by an increase in rockfall activity attributed to permafrost
3 degradation. While recent laboratory testing has asserted the role of permafrost in bedrock
4 stability, linking experimental findings to field applications is hindered by the difficulty to assess
5 bedrock temperature at observed rockfall locations and time. In this study, we simulated bedrock
6 temperature for 209 rockfalls inventoried in the Mont Blanc massif between 2007 and 2015 and
7 209 000 random events artificially created at observed rockfall locations. Real and random events
8 are then compared in a statistical analysis to determine the results significance. Permafrost
9 conditions (or very close to 0 °C) were consistently found for all events with failure depth > 6 m,
10 and for some events affecting depths from 3 to 6 m. Shallower events were likely not related to

11 permafrost processes. Surface temperatures were significantly high up to at least 2 months prior to
12 failure with the highest peaks in significance 1.5 to 2 months and 1 to 5 days before rockfalls.
13 Similarly, temperature significances at scar depths were significantly high, but steadily decreasing,
14 1 day to 3 weeks before failure. The study confirms that warm permafrost areas (> -2 °C) are
15 particularly prone to rockfalls, and that failures are a direct response to extraordinary high bedrock
16 temperature in both frozen and unfrozen conditions. The results are promising for the development
17 of a rockfall susceptibility index but uncertainty analysis encourages to use a greater rockfall
18 sample and a different sample of random events.

19

20 **1. Introduction**

21

22 Rockwalls can be affected by significant gravity-related transfers of material throughout rockfall,
23 defined here as the detachment of a mass of rock with a volume exceeding 100 m^3 from a series
24 of discontinuities, and its transportation downslope on variable distance¹. Rockfall is one of the
25 most hazardous geomorphological processes in Alpine massifs and can threaten mountain
26 infrastructure²⁻⁵, tourism^{6,7} and valley floors in case of major events⁸⁻¹². Periglacial rockwalls have
27 been increasingly affected by rockfalls¹³⁻¹⁸, notably during summer heatwaves^{19,20} and permafrost
28 degradation is thus thought to be one of the main factors responsible for these increasing bedrock
29 destabilizations²¹⁻²⁵. With the projected degradation of alpine permafrost²⁶, these hazards will
30 likely become a major threat for mountain communities and a better understanding of the thermal
31 context leading to periglacial rockwall failure is therefore crucial.

32 Laboratory experiments conducted over the past two decades have extensively contributed to
33 understand how thawing bedrock may become unstable. In a first stage, Davies et al.²⁷ have

34 demonstrated that besides the normal stress, the strength of an ice filled rock joint is a function of
35 its temperature. It decreases with warming and reaches a minimal value at $-0.5\text{ }^{\circ}\text{C}$. Then, Mamot
36 et al.²⁸ have refined this analysis showing a decrease of ice-filled joint resistance by a range of 64
37 - 78 % when the bedrock warms from -10 to $-0.5\text{ }^{\circ}\text{C}$. Those studies agree with former
38 investigations combining field observations and heat conduction modeling to explain the link
39 between the thawing front propagation and boulder fall in periglacial rockwalls²⁹. However,
40 Krautblatter et al.²⁴ have lately explained that the rupture of ice filled joints may only occur at
41 depth < 20 m while, deeper, warming provokes slow deformation along rock-rock contact,
42 meaning that the rupture of ice-filled joints may only explain relatively shallow events. In addition,
43 laboratory experiments have also pointed out that ice-filled joint alteration may also result of
44 enhanced erosion provoked by water percolation and related advective heat transfer³⁰. This is
45 supported by field investigations at rockwall sites showing thawing corridors through geophysical
46 soundings³¹ or sudden temperature increase in borehole³². Water infiltration and circulation may
47 also cause hydrostatic pressure in ice-sealed fractures that could contribute to rockfall
48 triggering^{24,25,33,34} as suggested by observations of water together with massive ice in rockfall
49 scars²⁰⁻²². However, determining the role of hydraulic processes in alpine rockfall triggering is
50 challenging because of the lack of fully coupled thermo-hydro-mechanical numerical models and
51 data for parameterization³³.

52 Despite these limits, the link between rock slope failures and permafrost conditions was confirmed
53 for various events using transient heat conduction models for specific rockfalls^{21,22} or through
54 comparison of permafrost map³⁵ and rockfall inventory²⁶. Statistical analysis of climate variables
55 or rock surface temperature evolution also showed a strong link between air temperature anomaly
56 and rockfall occurrence in high mountain³⁶⁻³⁸, while various studies explain that strong thermal

57 oscillations and related cyclic thermal stress or thermal expansion related to heating may cause
58 rockfall in non-periglacial environments³⁹⁻⁴¹.

59 Despite these advances, observations are generally too sparse or inhomogeneous to draw robust
60 statistical analysis of thermal conditions at depth of bedrock failure, which limits the understanding
61 of the link between rockfall and rockwall thermal dynamics and therefore our capacity to predict
62 rockfalls.

63 Our study proposes to investigate bedrock thermal dynamics prior to rockfall occurrence for 209
64 inventoried events during the period 2007-2015 in the Mont Blanc massif. It uses a 1D transient
65 thermal model⁴² simulating temperature-depth profiles at a daily time step. Absolute temperatures
66 simulated at the rock surface and at the depths of rockfall scars prior to failures are presented but
67 the main part of the analysis is based on a statistical approach in order to minimize biases in results
68 interpretation. Our study addresses the following research questions:

- 69 - Which bedrock temperature conditions or dynamics are the most prone to rockfall
70 occurrence?
- 71 - Is bedrock temperature experiencing exceptionally high value prior to failure?
- 72 - Is there a statistical relationship between bedrock temperature and rock slope
73 destabilization?

74 The study aims at verifying the hypotheses that the observed rockfalls are a direct reaction to the
75 intense and exceptional summer heatwaves that occurred over the past summers⁴³⁻⁴⁵, and that
76 thawing permafrost (close to 0 °C) areas are the most prone to rockfalls. In this way, it intends to
77 better define the time-lag between the air temperature signal and the bedrock failure and to explore
78 a possible statistical relationship between air temperature, rock temperature dynamics and failure
79 occurrences that would help to predict such events with weather forecast.

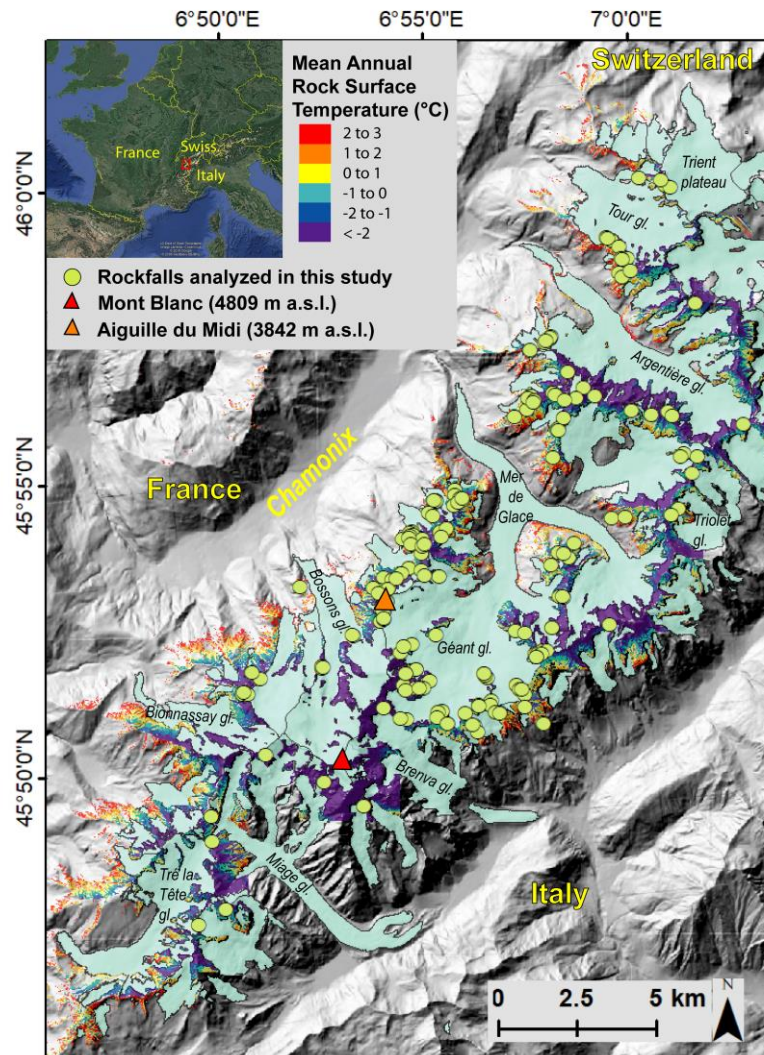
80 2. Study area and rockfall database

81 The Mont Blanc massif (MBM; Fig. 1), with its highest point at 4809 m a.s.l., is a crystalline
82 massif that extends over an area of 550 km² in the Western Alps. It presents two main lithological
83 units: a Variscan metamorphic series in the W and SW of the massif, and an intrusive late-Variscan
84 granite in the central and eastern parts, crosscut by three main sets of shear zones and faults⁴⁷.
85 27 % of the massif was covered by glaciers in the 2000s⁴⁸, and 7-12 % of the MBM area are
86 permafrost-affected rockwalls⁴⁹. Permafrost is largely present above 2600 and 3200 m a.s.l. on
87 north- and south-facing slopes, respectively⁴⁹.

88 In the MBM, infrastructures (cable cars, mountain huts, rack railways³) and mountaineers⁷ are
89 exposed to rockfall. Rockfalls are surveyed since 2007 by a network of observers⁵⁰ focused on the
90 central part (57 %) of the MBM. First based on the use of reporting sheets, the transmission of
91 information is now done more directly (oral communication, telephone, mail) or by using an app.
92 The network of observers is reactivated annually (through articles, meetings, forums, mailing-lists)
93 while amateur climbers are also solicited through posters installed in huts or articles in the
94 specialized press and forums. During each fall, extensive fieldwork is routinely carried out to
95 verify the observations from the network and/or to complete them with further data. In little-visited
96 areas of the mountain range, fieldwork is carried out at locations that were not reported by the
97 network, but identified by correlative deposits. Finally, for each event, the date of occurrence (or
98 observation of the deposit), the precise location of the scar, topographic parameters of the
99 destabilized area (altitude, orientation, slope), the fallen volume, and an estimate of the depth of
100 detachment are documented.

101 Among all the events inventoried between 2007 and 2015, we selected the 209 rockfalls with all
102 required input data for modeling: coordinates, scar depth, date of failure and MARST (Mean

103 Annual Rock Surface Temperature). The MARST was extracted at rockfall locations from the 4-
 104 m-resolution map created by Magnin et al.³⁵. This map is based on a statistical model calibrated
 105 by Boeckli et al.⁵¹ using MARST measurements from the European Alps, computed potential
 106 incoming solar radiation and modeled air temperature.



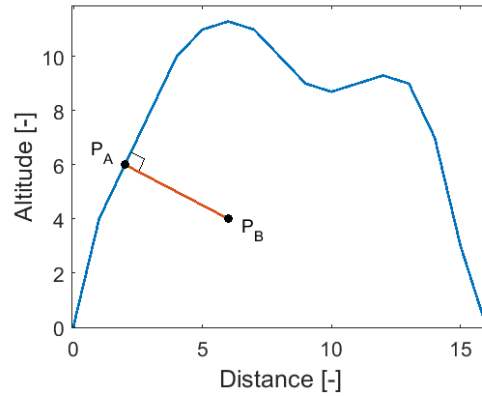
107
 108 **Figure 1.** The Mont Blanc massif, the MARST distribution and the location of rockfalls analyzed in this study.
 109

110 Summary characteristics of this rockfall database are displayed in Table 1 and their distribution
111 displayed in Figure 1. The detailed characteristics are provided in Table S1. About 5% of the
112 rockfalls (10 events) have a MARST > 2 °C, meaning that they are likely in non-permafrost
113 conditions. Indeed, according to Hasler et al.⁵², permafrost might be found below MARST up to
114 3 °C due to the cooling effect of shallow snow cover and air ventilation into fractures. But since
115 the MARST map is built upon mean air temperature for the period 1961-1990 which was about
116 1 °C cooler than the recent period³⁵, we assume that permafrost may exist below MARST up to
117 2 °C. In addition, 23 events (11%) have MARST between 0 and 2 °C and are thus likely in
118 discontinuous and/or warm permafrost conditions.

119

120 **3. Methods**

121 The goal of our research was to model a temperature-depth (T_z) profile at rockfall locations in
122 order to assess the thermal conditions prior to failure. The simulations were conducted in 1D and
123 intended to represent bedrock temperature perpendicular to the rock surface (Fig. 2). In steep alpine
124 rockwalls, temperature at depth is partly driven by lateral heat fluxes induced by the topographical
125 settings which provoke high surface temperature variability⁵³. Thus, we developed an algorithm
126 which accounts for possible lateral heat fluxes in order to correct the modeled T_z profile. In this
127 section, we introduce the so-called CryoGRID2 model (sect. 3.1) that we used to simulate heat
128 transfer, the forcing data and bottom heat flux correction algorithm (sect. 3.2), the model fitting
129 approach (sect. 3.3), the uncertainty calculations (sect. 3.4), and the model implementation at each
130 rockfall location (sect. 3.5).



131
 132 **Figure 2.** Simplified sketch illustrating the modeled T_z profiles. The blue line represents a topographical profile. P_A
 133 is the surface point where the rockfall occurred. P_B is the bottom point of the profile. The red line is the profile where
 134 the temperature was calculated at chosen spatial and temporal steps. Altitude and distance are in arbitrary units.

135

136 3.1. Heat diffusion modeling with CryoGRID2

137 We used CryoGRID2 for simulating T_z profiles, a MATLAB diffusive transient thermal 1D model
 138 developed by Westermann et al.⁴² solving a nonlinear diffusion equation over time. Initially
 139 developed for permafrost issues, it solves the conductive heat transfer by taking into account rock
 140 properties, air content, water/ice content, and related thawing/freezing processes through latent
 141 heat consumption and release. The top of the profile was forced by a surface temperature time
 142 series (Dirichlet condition). At the bottom, the profile was forced by a thermal flux (Neumann
 143 condition). At every time step, the profile at time $n-1$ was used as an input for calculating spatial
 144 derivatives. At the first time step, we derived an initialization profile by taking the steady state
 145 approximation of the equation with the mean of the surface temperature time series for the
 146 Dirichlet condition and the first thermal flux for the Neumann condition. This first thermal flux is
 147 derived by assuming that the temperature of the profile bottom is equal to the mean of the surface
 148 temperature time series (sect. 3.2). CryoGRID2 can handle snowpack at the rock surface.
 149 However, since it is almost impossible to construct or obtain such data in steep alpine rockwalls

150 where snow depth is highly variable, snow was neglected in the present study. A summary of the
151 CryoGRID2 principal input parameters and outputs are available in Supplements (Table S2).

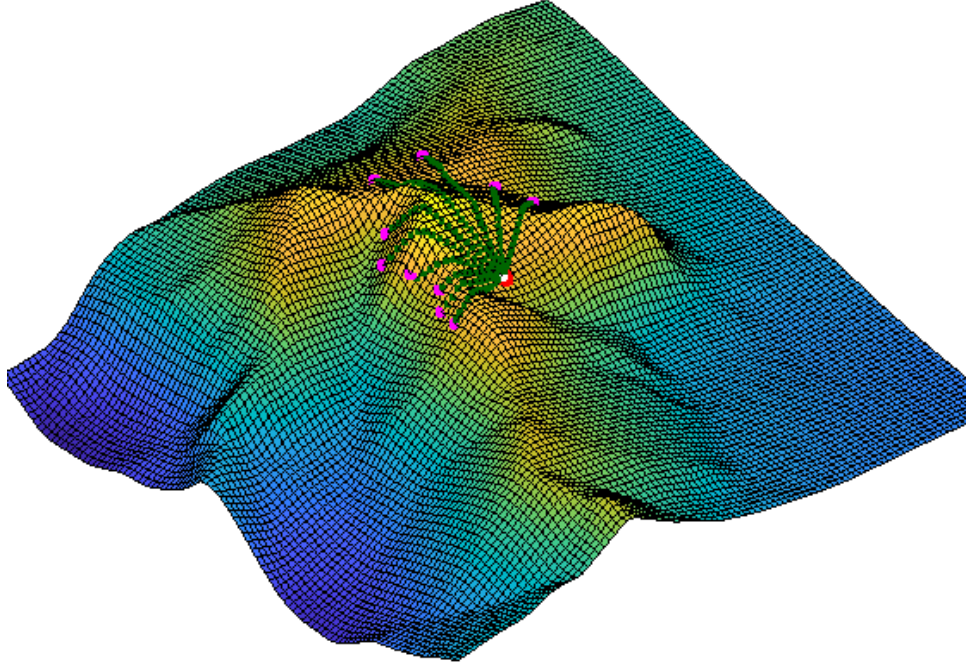
152

153 3.2. Forcing data and correction heat flux

154 The top of the T_z profiles was forced with Rock Surface Temperature (RST) time series derived
155 from the summation of an air temperature anomaly to the MARST extracted at rockfall locations
156 (sect. 2). The air temperature anomaly was calculated in comparison to the 1961-1990 mean air
157 temperature used to derive the MARST map (sect. 2) and from the daily air temperature recorded
158 by *Météo France* at Chamonix (1042 m a.s.l.) since 1993 (beginning of hourly air temperature
159 records), similarly to Magnin et al.²⁶.

160 We created a correction flux applied at the profile bottom (Neumann condition) to account for
161 possible lateral heat fluxes coming from surrounding rock faces by using the MARST map (Fig.
162 1), the 4-m-resolution DEM used to map the MARST and the Chamonix air temperature anomaly
163 time series. We first searched for all surrounding rock faces that may influence the heat fluxes at
164 P_B (see Fig. 2 for P_B) as detailed in the Supplement S1 to obtained N points $(P_i)_{i \in [1:N]}$ at similar
165 altitude than P_A and which were assumed to influence the lower part of the modeled T_z profile
166 (Fig. 3).

167



168

169 **Figure 3.** Illustration of the searching method. The 4-m-resolution DEM is represented on a 200×200 m square that
 170 contains a 200 m radius circle research limit. The white dot in the center is the surface point P_A (see Fig. 2 for P_A)
 171 which is the top of the T_z profile. The red dots surrounding P_A represent all the directions eliminated at the first r-step
 172 (see Supplement S1). The green dots represent the research directions. Finally, the magenta dots are the selected points
 173 for the correction heat flux calculation. Units and the scale are intentionally hidden to lighten the figure. Likewise,
 174 only 20 different directions are plotted (instead of 100 used in this study) to help the readability.

175

176 We then applied thermal fluxes coming from the selected points. For every point P_i , the MARST
 177 at P_i location ($MARST_i$) is extracted from the map and distance d_i between P_i and the bottom point
 178 P_B of the modeled T_z profile was calculated. For calculating the i^{th} flux, we separated two cases
 179 according to d_i ($>$ or $<$ to 30 m) as detailed in the Supplement S1.

180 We thus determined the thermal flux $j_{Q,i}(t)$ of all P_i and calculated the global $j_Q(t)$ as follows:

$$j_Q(t) = c_{exp} \frac{\sum_{i=1}^N j_{Q,i}(t)}{100} \quad (1)$$

181 We divided by 100 because we explored 100 directions, the final flux being an equivalent of a
182 discrete integral. All the fluxes had different directions and different application surfaces. However,
183 we applied all of them at P_B . For considering that, we corrected the final flux by an experimental
184 coefficient c_{exp} . This coefficient was fitted at the same time as the other model parameters (sect.
185 3.3).

186

187 3.3. Model fitting

188 The simulated transient temperature fields are affected by a set of parameters related to bedrock
189 properties and model characteristics (Table S2). Principal parameters are listed below and have
190 been fitted by running a host of test values until a minimal difference between simulated and
191 measured temperature profiles into boreholes was achieved.

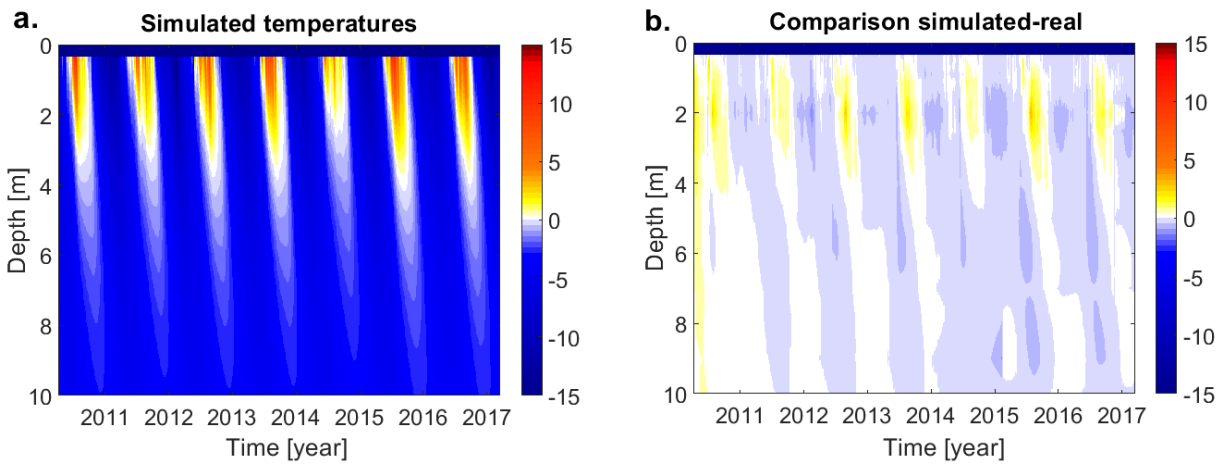
- 192 • The rock thermal conductivity ($k_{bedrock}$), the rock volumetric heat capacity ($c_{bedrock}$), the
193 porosity (ϕ) and the total water content ($\theta_{w,tot}$), which can be assimilated to the bedrock
194 saturation, all change the soil thermal diffusivity, *i.e.* the time needed for the rock to reach
195 thermal equilibrium.
- 196 • Van Genuchten parameters (S2) θ_r , α and n change the (θ_{sat}, T) curve. The exact influence is
197 not detailed here but, for example, a higher α will impact the dynamics by requiring a higher
198 temperature for melting all the ice.
- 199 • c_{exp} changes the magnitude of the lateral heat fluxes (sect. 3.2). For example, the higher is c_{exp} ,
200 the stronger is the cooling effect of opposite north faces on south faces and *vice versa*.
- 201 • Spin-up parameters change the accuracy of the results during the first years of simulation. Tests
202 we performed showed that three years of spin-up are enough for limiting errors under 0.1 °C
203 the first year of simulation and that this error quickly decreases over time.

204 Borehole temperature measurements used for model fitting were collected at the Aiguille du Midi¹⁵
205 (ADM; 3852 m a.s.l.; Fig. 1). Three 10-m-deep boreholes have been drilled in 2009 in SE, NE and
206 NW-exposed rock faces with varying slope conditions (55 ° to sub-vertical) and snow deposits
207 (from continuous and rather thick to discontinuous and thin snow cover, or very local snow
208 deposit). The NE and NW exposed boreholes (respectively BH_E and BH_N) have been equipped
209 with 15 thermistor-chains spread between 0.3 and 10 m depth, while the SE exposed borehole
210 (BH_S) has 14 sensors spread between 0.14 and 9.64 m depth. They have been recording
211 temperature since December 2009 (except BH_E: April 2010) at a 3-hour time interval. Model
212 fitting was performed at a daily time step using temperature time series at the shallowest depths as
213 forcing temperature time series at the top of the model domain. The simulated T_z profiles were
214 then compared with measured temperatures in the boreholes.

215 Minimization of the Root Mean Square Error (RMSE) between simulations and boreholes time
216 series were obtained with parameter values displayed in Table 2. Figure 4a displays a simulated
217 T_z profile for a 9 years period with the best-fitted bedrock properties while Figure 4b displays the
218 difference between the measured and the modeled temperature (interpolated between sensors).

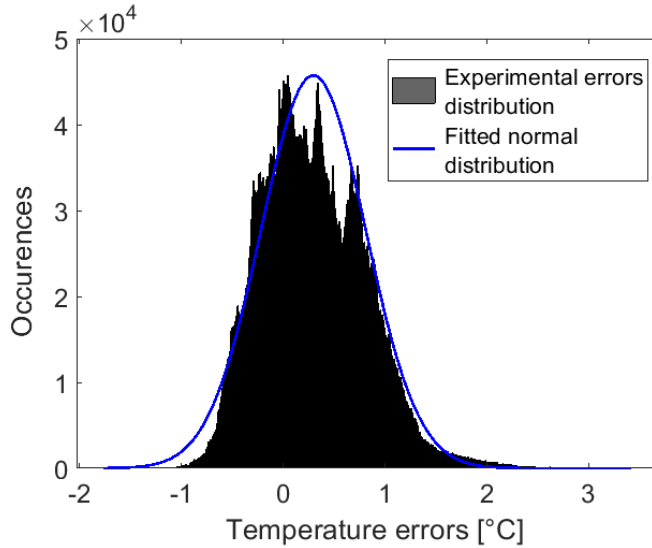
219 Figure 5 presents the error distribution obtained with the parameters displayed in Table 2. All the
220 normality tests (Anderson Darling, Kolmogorov Smirnov, Lilliefors...) rejected the hypothesis
221 that this distribution came from a normal distribution at a 5 % significance level. However, the
222 number of points was abnormally high because all the points at every depth and every time were
223 considered in the three cases (more than 5 million points in total). But in reality, there were only
224 three “real” points of comparison (*i.e.*, the three boreholes). The Kolmogorov Smirnov statistic
225 was 0.039 and the critical value corresponding at three data points at a 5 % significance level was
226 0.71, while the critical value with all the points was 10^{-4} order of magnitude. Therefore, in this

227 context of three “real” points of comparison, the test could not reject the hypothesis that the data
 228 came from a normal distribution. Thus, for working with Gaussian uncertainties, we assumed this
 229 hypothesis of Gaussian errors and we used the mean error of 0.295°C and the standard deviation
 230 (σ) of 0.515°C (Fig. 5) for our analysis. Based on these results, we systematically removed 0.3°C
 231 (upper bound of 0.295°C) to the final modeled temperatures and a standard deviation value
 232 $\sigma_{\text{Cryogrid}} = 0.55^{\circ}\text{C}$ (upper bound of 0.515°C) was considered for uncertainty (as a reminder, σ
 233 corresponds to a 68 % reliable level and 2σ to a 95 % reliable level for Gaussian data).
 234



235
 236 **Figure 4. a.** BH_E borehole simulation realized with parameters detailed in Table 2. Input surface temperatures were
 237 extracted from the borehole real values. The 0.3 m spatial shift at the top of the profiles is due to the depth of the first
 238 temperature value recorded in the borehole. **b.** Comparison between BH_E borehole simulation and real BH_E
 239 borehole values. RMSE can then be displaced from these values (e_i) $_{i \in [1:N]}$ by the following formula: $RMSE = \sqrt{\frac{\sum_{i=1}^N e_i^2}{N}}$.

240



241

242 **Figure 5.** Fit of the temperature errors by a normal distribution. Errors are defined as the difference between the
 243 simulated borehole temperatures (BH_S, BH_E or BH_N) and the real borehole temperatures. The fit gave a mean of
 244 0.295 °C and a standard deviation of $\sigma = 0.515$ °C.

245 3.4. Uncertainty analysis

246 In addition to the uncertainty associated with model parameters, the uncertainty of the forcing RST
 247 time series must be considered. RST time series being created as the summation of a MARST and
 248 anomaly values (see sect. 3.2.), we consider two terms for this uncertainty, one for the MARST
 249 and one for the anomalies. For the MARST, the standard deviation of 1.616 °C is reported in the
 250 study from Boeckli et al.⁵¹ that describes the statistical model on which is based the initial MARST
 251 used in our study (displayed in Fig. 1). We thus kept the upper bound of this value to determine
 252 $\sigma_{\text{MARST}} = 1.7$ °C. For the anomalies, the uncertainty results from the only consideration of the air
 253 temperature changes in Chamonix to create RST anomalies while daily RST variations may also
 254 result of the varying lapse rate, which is typical of alpine environments⁵⁴, as well as the varying
 255 incoming solar radiation and possible snow accumulation⁴⁹ which are neglected. We calculated
 256 the uncertainty for RST anomalies, referred as σ_{anomaly} , by using a set of measured RST time series

257 at 5 sensors installed at the top of the ADM in sub-vertical S (2 sensors), N, E, and W exposed
 258 rock faces, at a depth of 0.03 m⁴⁹.

259 One of the two S-exposed sensors is located right above a ledge where snow accumulates during
 260 winter which lowers the MARST by about 1°C compared to snow-free conditions for similar sun-
 261 exposure⁴⁹. RST have been recorded continuously at an hourly time step from 2007 to 2010. The
 262 MARST for the years 2007 to 2010 were then calculated for each sensor and were adjusted to the
 263 1961-1990 period by applying the air temperature anomaly between 1961-1990 and the years of
 264 measurements (2007 to 2010). Then, the adjusted MARST of each sensor was subtracted to the
 265 measured daily RST to obtain daily temperature anomalies at sensor locations.

266 Comparison between the daily air temperature anomalies measured in Chamonix and the RST
 267 anomalies calculated from the 5 RST sensors resulted in Gaussian errors with a standard deviation
 268 of $\sigma_{\text{anomaly}} = 4$ °C.

269 To sum up, the uncertainties were as follows:

- 270 • $\sigma_{\text{Cryogrid}} = 0.55$ °C
- 271 • $\sigma_{\text{MARST}} = 1.7$ °C
- 272 • $\sigma_{\text{anomaly}} = 4$ °C

273 Then, for surface temperature series, the total uncertainty was:

$$\sigma_{\text{surf}} = \sqrt{\sigma_{\text{MARST}}^2 + \sigma_{\text{anomaly}}^2} \quad (2)$$

274 Numerically, it gave: $\sigma_{\text{surf}} = 4.4$ °C.

275 In the next part of the study, the temperature at the depth of the rockfall scar was analyzed (referred
 276 hereafter as “scar temperature”). With most scar depth > 1 m (Tab. 1), these temperatures were not
 277 significantly affected by daily surface temperature changes. Thus, σ_{anomaly} was neglected when
 278 dealing with scar temperatures and total uncertainty for scar temperature was therefore:

$$\sigma_{\text{scar}} = \sqrt{\sigma_{\text{Cryogrid}}^2 + \sigma_{\text{MARST}}^2} \quad (3)$$

279 Numerically, it gave: $\sigma_{\text{scar}} = 1.8 \text{ }^\circ\text{C}$.

280 To analyze the results, we also used temperature percentiles (sect. 4). A X % temperature
 281 percentile is defined as a value which is warmer than X % and colder than (100-X) % of some
 282 chosen reference temperatures which were defined as explained in section 4. To estimate modeled
 283 temperature percentile uncertainties, simulations were done for the three boreholes, using the
 284 MARST map (Fig. 1) and the air temperature anomaly to generate the forcing surface temperature
 285 time series. Percentiles of the modeled temperature values were then calculated for the full
 286 borehole time series and compared with the real temperature percentile values. Gaussian errors
 287 were obtained, with $\sigma_{\text{surf prct}} = 13.8 \%$ and $\sigma_{\text{scar prct}} = 10.7 \%$. This approach of considering all the
 288 uncertainty sources at once was less precise but sufficient in that case with long and complex
 289 calculations.

290

291 *3.5. Approach for simulating the temperature dynamics at rockfall locations*

292 To analyze bedrock thermal dynamics prior to rockfalls, the following protocol was used
 293 for every event:

- 294 • The rock surface temperature time series was created as described in section 3.2.
- 295 • The CryoGRID2 simulations were run between 1st January 1993 and 31st December 2015,
 296 with the bedrock parameters determined after fitting (Tab. 2). Given that the fitting step
 297 showed that a spin-up period of 3 years is sufficient, we assumed that the years 1993-1996
 298 were the spin-up years while rockfalls are only documented since 2007. The simulated T_z
 299 profiles were 20.5 m long, which is 5 m deeper than the deepest scar depth (Tab. 1). This

300 5 m buffer permitted to lower the errors in the deeper part of the profiles where the
301 correction thermal flux was applied (see sect 3.3).

302 This process was entirely automated in Bash language and MATLAB programs on the Univ.
303 Savoie Mont Blanc - CNRS/IN2P3 MUST computing center. Then, all the simulations could be
304 started at the same time on different calculation resources.

305

306 4. **Approach for result analysis**

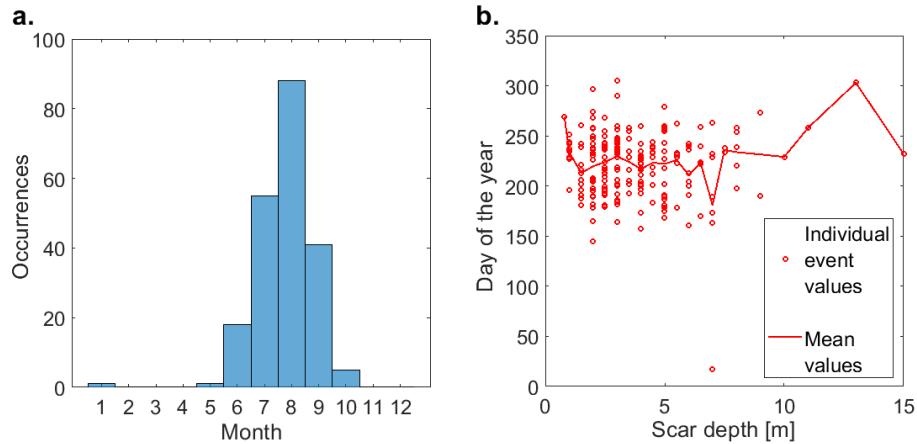
307 *4.1. Model output processing and analysis*

308 Four rock temperature variables were analyzed: the (i) scar and (ii) surface temperatures, and the
309 (iii) scar and (iv) surface temperature percentiles. They were all examined through 11 different
310 temporalities: 1 day, 3 days, 5 days, 1 week, 10 days, 2 weeks, 17 days, 3 weeks, 1 month, 45 days
311 and 2 months. The surface temperature was simply extracted at the uppermost depth of the T_z
312 profile (0.05 m). The scar temperature was extracted at the scar depth specified in the rockfall
313 database for each event (Tab. 1). For temporality of 1 day, surface temperature percentiles were
314 calculated by comparing the simulated surface temperature at the day of rockfall occurrence with
315 all the daily surface temperatures of the simulated time series (1st January 1996 - 31st December
316 2015). For other temporalities of n days prior to rockfall occurrence, the reference temperatures
317 were calculated by averaging the temperature between a day $d1$ which is, by turns, each day in the
318 temperature time series, and a day $d0$ which is the first day of the averaging period prior to $d1$,
319 defined as $d0 = d1 - n + 1$. Then, the average temperatures for the various temporalities prior to
320 failure were compared with the respective reference temperatures. At this step, we had only
321 absolute values of surface and scar temperatures, and absolute values of surface and scar

322 temperature percentiles. We then aimed at answering if this temperature value was abnormally
323 high for the current period.

324 To do so, 1000 dates were drawn randomly and the 4 studied variables were extracted for the 11
325 different temporalities at each rockfall location. The choice of the number of random events was
326 based on a compromise between the calculation resources and the potential to reduce the
327 uncertainty. The scar depths of the 1000 random dates of a specific event location were chosen
328 equal to the scar depth of this event. To remove sources of biases, dates of the random events were
329 drawn: a) after 2007 and b) with the same monthly distribution as the 209 rockfalls events. Reason
330 for a) was to remove biases linked to the recent decades of atmospheric warming as the rockfall
331 database starts in 2007. If artificial rockfall events would have been drawn in the full period 1996-
332 2015, extracted temperatures at the beginning of the time series would have been expected to be
333 lower and it would have been impossible to determine if a significance of warmer temperatures
334 for rockfall events was real or just related to the atmospheric warming contribution. Reason for b)
335 is that rockfalls mostly occurred between June and October (with an attendance peak in August,
336 Fig. 6a) and these months were, on average, warmer than other months of the year. If random
337 events would have been drawn in the full year, a significance of warmer temperature for real events
338 could have been simply interpreted as the reflection of this reason and not as an extraordinary
339 thermal state of the rock before the failure. Thus, random events were drawn according to the same
340 monthly distribution as the 209 real events (Fig. 6a). Figure 6b shows that the temporal distribution
341 of rockfall events is not dependent on the scar depth, that is why the same monthly distribution is
342 taken for every scar depth and that no scar depth groups were created. Likewise, no relationship
343 was found with the elevation, the slope angle or the sun-exposure (Fig. S1).

344



345

346 **Figure 6. a.** Histogram illustrating the distribution of the 209 rockfalls throughout the year that was used as a basis to

347 draw random events dates. **b.** Plot illustrating the distribution of the events throughout the year in comparison to the

348 scar depths. The absence of relationship between scar depth and rockfall timing was considered to not draw the

349 monthly distribution of random events according to depth. The same is true for elevation, slope angle and sun-exposure

350 (Fig. S1). Means of 0.8 m, 9 m, 10 m, 11 m, 13 m and 15 m scar depths must be observed carefully because they are

351 represented by one or two points only.

352

353 4.2. Determining results significance

354 For searching significant results, real rockfalls temperatures and temperature percentiles were

355 compared with those of random events. Firstly, a simple comparison of the means for every scar

356 depth and every temporality was realized. Then, the comparison was done for every temporality

357 without regarding the scar depth. Uncertainties were derived by dividing the uncertainty of the

358 variable (σ_{surf} , σ_{scar} , $\sigma_{\text{surf prct}}$ or $\sigma_{\text{scar prct}}$) by the square root of the total number of points used for

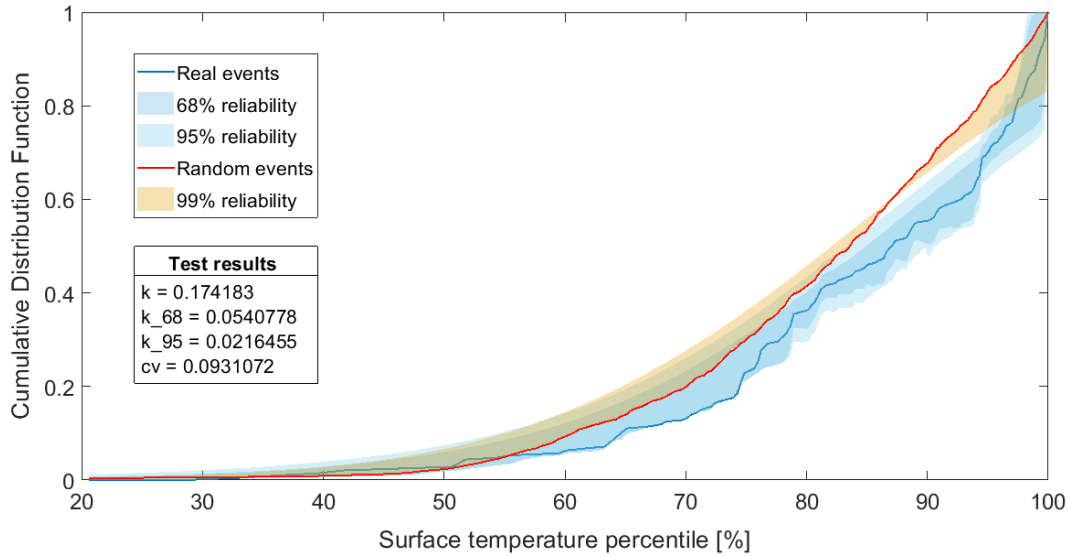
359 calculating the mean. Since 209 000 random events were considered, uncertainties of the means

360 of random events variables were small and almost impossible to see when plotted against the real

361 events uncertainty.

362 A Kolmogorov Smirnov test (KS test) was then performed for assessing if the real rockfalls sample
363 could have been drawn from the random events distribution. It was calculated by determining the
364 highest ordinate difference between the Cumulative Distribution Functions (CDFs) of the real
365 rockfalls and the random events series. This statistic was then compared with tabulated critical
366 values for obtaining the result of the test. This test was chosen because it is non-parametric, which
367 is important since the temperature percentiles are clearly not Gaussian (Anderson Darling,
368 Kolmogorov Smirnov and Lilliefors tests reject this hypothesis with a 5 % significance level), and
369 because it was possible to consider the uncertainty values while performing the test. This second
370 point is, astonishingly and unfortunately, uncommon for statistical tests. The only feasible rough
371 uncertainty incorporation is generally to present upper and lower bounds of the test by realizing it
372 with the high and low values of the data points. Here, for surface or scar temperature percentiles,
373 the uncertainties were included as explained in the Supplement S2.

374 An example of CDF represented with the uncertainties and resulting KS test is displayed in Figure
375 7 for one specific variable (surface temperature percentile) and one specific temporality (1 day).
376 The KS statistic must be compared with the critical value (cv). If the statistic is higher, the test
377 rejects the hypothesis that the experimental data (real events) comes from the model (random
378 events) with a 5 % significance level. Here, the test rejected the hypothesis that the experimental
379 data (real events) came from the model (random events) in the normal case with a 5 % significance
380 level, but could not reject this hypothesis when considering the uncertainties.



381

382 **Figure 7.** Illustration of a KS test result. The surface temperature percentiles were here considered at the rockfall

383 event day (temporality of 1 day). “k” represents the KS statistic between the CDFs without considering the

384 uncertainties. “k_68” represents the statistic between the 68 % reliable real events CDF and the 99 % reliable random

385 events CDF. “k_95” represents the statistic between the 95 % reliable real events CDF and the 99 % reliable random

386 events CDF. The 68 % and 95 % reliable random events CDFs are not presented because they were very close to the

387 99 % reliable one (the reason for this stability is that random events CDF is made of 209 000 points). “cv” is the 5 %

388 significance level critical value of the KS test in this context. To know the result of the test, the KS statistic must be

389 compared with the critical value. If the statistic is higher, the test rejects the hypothesis that the experimental data (real

390 events) come from the model (random events) with a 5 % significance level. Here, the test rejected the hypothesis in

391 the normal case but could not reject it when considering the uncertainties.

392

393 To show orders of magnitude of simulated temperatures, scar and surface temperature variables

394 were used in a first step. However, in a second step, only temperature percentile variables were

395 kept since they are better for finding statistical significance.

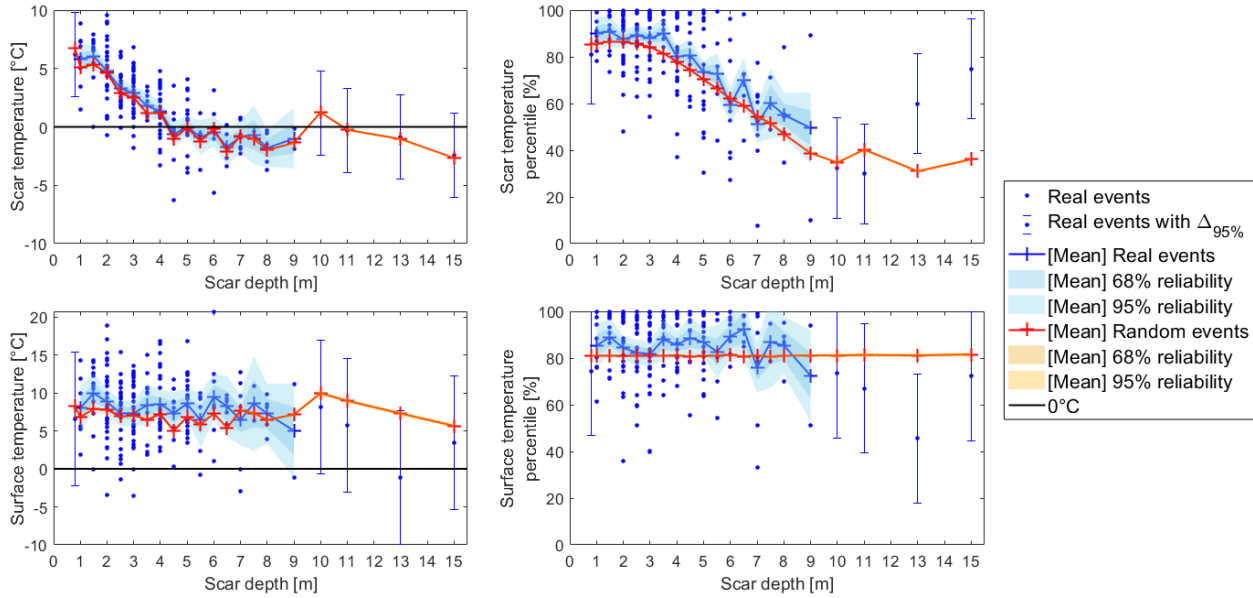
396

397

398 **5. Results**

399 When considering the uncertainties, none of the four variables (surface and scar depth
400 temperatures and temperature percentiles) could be distinguished from the random events values
401 when reasoning by scar depth. This finding is illustrated in Figure 8 for a temporality of 1 day
402 while other temporalities, showing similar patterns, are displayed in the Supplements (Fig. S2).
403 However, whatever the considered variable, the mean distributions were in most cases - except 6
404 and 7 m depths - higher than the random events. This was particularly pronounced for the
405 percentile variables. The four variables were strikingly scattered, but some notable patterns could
406 be distinguished. First, the closer to the surface, the warmer was the scar temperature, for both real
407 and random events. The average temperature became negative from 3-4 m depth downward (see
408 Fig. S2 also) but consistency in negative scar temperature was found for depths > 6 m only, despite
409 a few events showed positive and close to 0 °C conditions. Only 2 events had scar temperature <
410 -5 °C. The surface temperatures were mostly positive and no distinct pattern could be found
411 according to scar depths. Scar temperature percentiles scattering increased with depth and their
412 mean decreased from 90 to 50 % between 1 and 9 m depth while surface temperature percentiles
413 showed no obvious link with scar depths. When extending the temporalities (Fig. S2), very similar
414 patterns were found, with slightly smaller scattering, slightly higher surface percentiles and
415 slightly lower scar temperature percentiles.

416



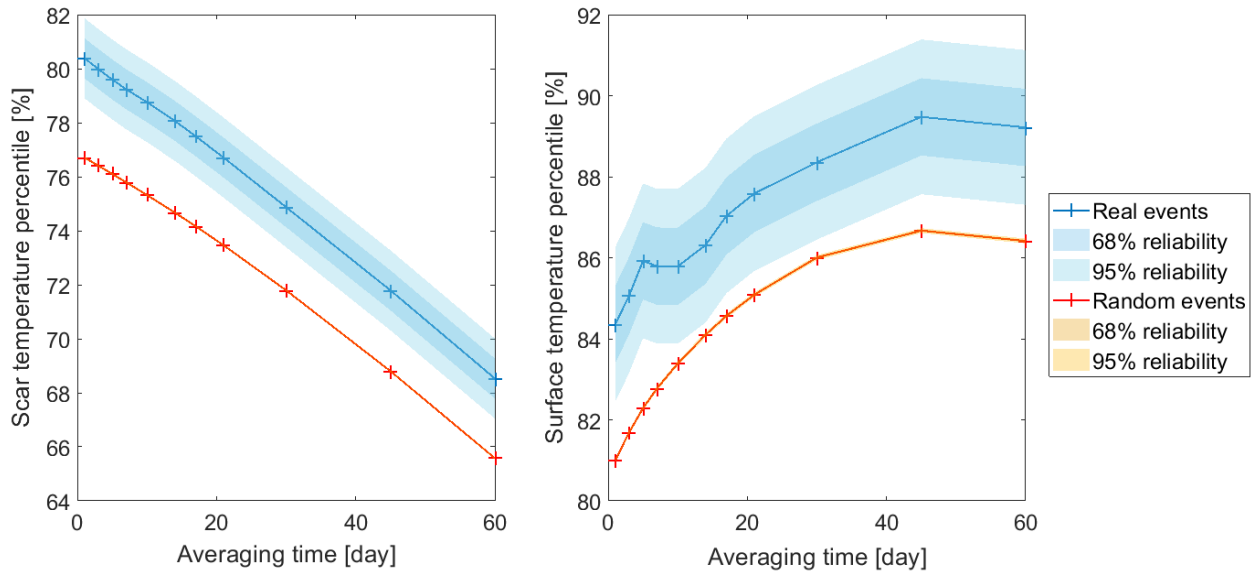
417

418 **Figure 8.** Comparison of the four studied variables between real and random rockfalls on the day of the event
 419 (temporality of 1 day). This comparison was done for every scar depth, all the events with the corresponding value of
 420 scar depth being used for calculating a mean. Ten other groups of figures like this one were done to verify our results
 421 for the 10 other temporalities (3 days, 5 days, 1 week, 10 days, 2 weeks, 17 days, 3 weeks, 1 month, 45 days and 2
 422 months) and four of them (1 week, 2 weeks, 1 month and 2 months) are presented in the Supplements (Figures S2).
 423 Uncertainties of random events variables cannot be seen because they were really low (order of magnitude of some
 424 degree tenths for temperature variables and some percent tenths for temperature percentile variables).

425

426 When looking at the results through the different temporalities, percentiles of scar and surface
 427 temperatures were, distinctively higher than the random events values, whatever the temporality
 428 (Fig. 9). For scar temperature percentiles, this difference was in order of magnitude of 3 % for
 429 mean values and at least 1.5 % for 95 % reliability values. For surface temperature percentiles,
 430 these percentages were nearly equal to 2.5 and 0.5 %.

431

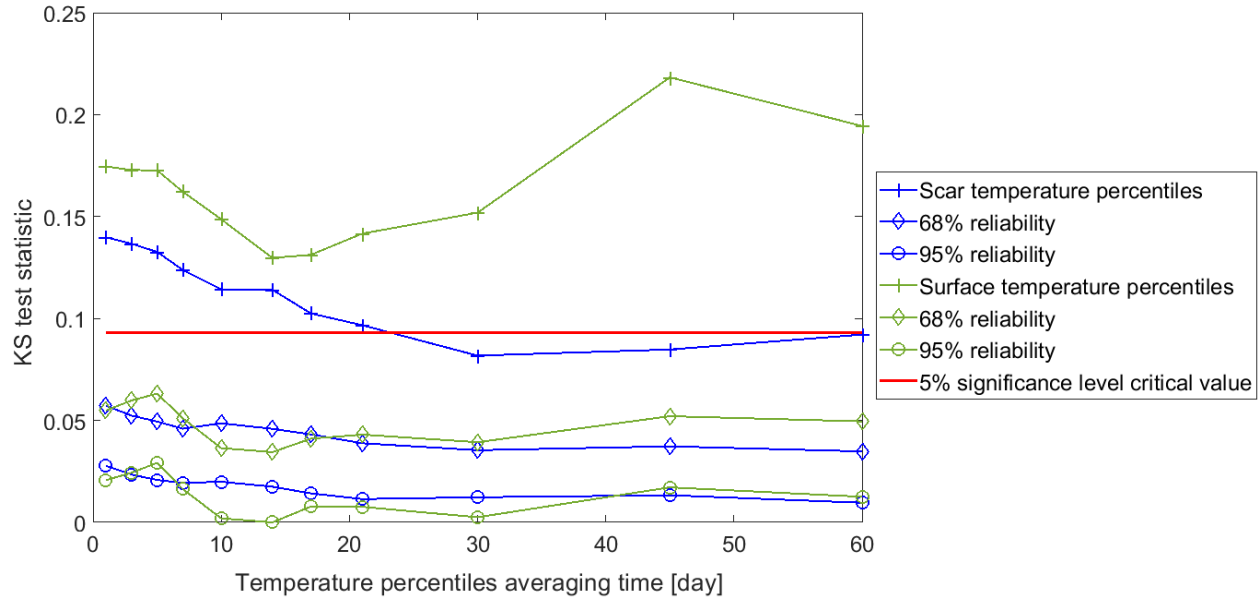


432

433 **Figure 9.** Comparison of the average temperature percentile variables between real and random rockfalls. Here, all
 434 scar depths were merged which explains a constant and rather low uncertainty (individual uncertainty divided by the
 435 square root of the total number of events, 209 for the real ones and 209 000 for the random ones). Every single point
 436 of this represents a full plot of Figure 8.

437

438 Implementation of the KS test showed that scar temperature percentiles for real events were
 439 significantly different from random events for temporalities between 1 and 21 days (Fig. 10). This
 440 significance decreases almost continuously with increasing temporality. Surface temperature
 441 significances varied with the different temporalities but were always well above the critical
 442 threshold. It reached its minimum value at about 14 days averaging time prior to failure and then
 443 increased continuously until 45 days averaging time prior to failure where it reached its maximum
 444 value. However, when considering the uncertainty, these results were not significant and it was
 445 therefore not possible to state whether the real events sample could have been drawn from the
 446 random events distribution. This points out the interest to work with a greater number of rockfalls.



447

448 **Figure 10.** Illustration of the significance of scar and surface temperature percentiles for every temporality. Every
 449 point of this plot corresponds to a KS test. For example, the three values “k”, “k_68” and “k_95” calculated in Figure
 450 7 are here represented by the green triplet of points (plus-sign marker, diamond marker and circular marker) at the 1-
 451 day abscissa.

452

453 6. Discussion

454 6.1. Strengths and limitations of the study

455 For this study, we have used a homogeneous rockfall inventory which ensures direct comparability
 456 of the results and a coherent statistical analysis. The relatively simple thermal modeling approach
 457 may appear as the main limitation since it lacks of consideration for solar radiation variability
 458 through time, precipitations and wind effects, or snow deposit controls. Energy balance approaches
 459 which have been commonly used in rockwall permafrost modeling^{19,55–57} would allow overcoming
 460 some of these limitations. However, by introducing a greater number of input parameters, energy
 461 balance models bear numerous sources of uncertainty, challenging its quantification⁵⁸. In this way,
 462 our simple modeling approach combined with the availability of bedrock temperature data into

463 boreholes has the main advantage to permit a detailed uncertainty analysis of our results. In
464 addition, our approach accounts for most important parameters which are an average value of
465 incoming short-wave solar radiation and air temperature (for the MARST calculation⁵⁹) at the
466 bedrock surface and the heat conduction at depth. Nevertheless, bedrock thermal parameters
467 (conductivity and heat capacity) have been calibrated with borehole temperature measurements
468 collected in the granitic part of the MBM while 18 (8.6 %) of the rockfalls occurred in the
469 metamorphic series. But since these series have in most cases very similar mineral composition as
470 the granitic unit⁴⁷, it is assumed that the results are marginally impacted, the variable anisotropy
471 which is not only related to lithology but also to site-specific fracturing possibly being the most
472 critical issue.

473 Another limit lies in snow deposits that may cool the bedrock surface and delay the thawing onset
474 during warm seasons^{57,60} when some rockfalls occurred. Thus, the greater statistical significance
475 of rather long time period of high surface temperature prior to rockfalls may partly depict the time
476 needed for snow melt for some events. But, in parallel, snow melt or rainfalls could also accelerate
477 the thawing through water percolation into bedrock fractures^{30,32}. The only possible reflection of
478 this overlooked effect in the results would be the events with rather low scar temperature
479 percentiles right before failure (Fig. 8). This means that the bedrock temperature didn't reach its
480 highest value when the failure occurred suggesting either that sudden heating is not the main
481 triggering factor or that other processes such as heat advection may have locally accelerated
482 bedrock warming. Such accelerated bedrock thawing was already suggested by former studies^{19,37}
483 to explain permafrost-related rockfalls. Despite these limits, our results allow discussing possible
484 thermal processes triggering rockfalls according to scar depth and climate signal characteristics.

485

486 *6.2. Results interpretation*487 *The role of thermal processes in rockfall triggering*

488 Variables comparison with scar depths (Fig. 8) has shown that it would have been irrelevant to
489 analyze the results based on scar depth groups. Such an analysis could have been attractive since
490 it could have been expected that scar temperature significance would have overweighted the one
491 of surface temperature. But the constantly low difference between random and real events
492 variables shows that the observed pattern is not specific to the real events and that the supposedly
493 link between scar depth and bedrock temperature pattern must be seen as the depiction of general
494 thermal conditions at rockfall locations. The decreasing average in scar variables (Fig. 8) must be
495 seen as the expected depth effect involving a delayed response to climate signals.

496 Temperature values at scar depths discriminate possible rockfall triggering processes with
497 permafrost degradation or frost-related processes strongly suggested for events > 6 m and for a
498 significant part of shallower events (3 to 6 m). On average, these events occurred in a range of
499 temperature between 0 and -2 °C and show noticeable agreement with experimental and theoretical
500 knowledge about reduced shear strength of ice-filled fractures within this temperature range^{24,27}.

501 In mountain environments, rockwalls are prone to instability because of extreme conditions with
502 large and sometimes sudden temperature variation, freeze and thaw cycles, as well as wet and dry
503 cycles throughout the year^{29,61-64}. Frost weathering processes related to ice segregation and
504 volumetric expansion, as well as repeated freeze and thaw cycles leading to bedrock fatigue are
505 well recognized mechanisms preparing to bedrock failures by breaking rock bridges and favoring
506 fracture propagation^{61,65-67}. Similarly, high thermal stress related to strong thermal oscillations is
507 also regarded as an essential factor favoring bedrock cracking due to repeated thermal contractions
508 and expansions that also affect non-periglacial rockwall, the warm days being particularly prone

509 to rockfall occurrence^{39,40,68,69}. The fact that many shallow events occurred at positive rock
510 temperature but also well higher than average rock temperatures as suggested by the temperature
511 percentiles, corroborates those studies.

512 In addition to the interpretation of possible processes acting in rockfall, percentiles reveal how air
513 temperature signals contribute to their triggering. Indeed, temperature values are suited for an
514 intrinsic comparison of the rockfall sample elements, while temperature percentiles rather inform
515 about the thermal dynamics specific to each location of the rockfall sample elements. In addition,
516 percentiles are better suited for determining statistical significance.

517

518 *Link between air temperature signals and rockfall triggering*

519 Comparisons of percentile means (Fig. 9) show that the real events have, in average, a warmer
520 temperature condition prior to failure than random ones, whatever the considered temporality,
521 from 1 day to 2 months (Fig. 8 and S2). However, the difference between the real rockfall events
522 and the random rockfall events can also be a statistical “sample effect” and the questions of
523 whether and to what extent the sample could have been drawn from the model persist. This
524 question is answered by the KS test and the significance study (Fig. 10). In the following, a high
525 significance must be interpreted as an approval of the previous results, namely that the real events
526 show warmer temperature conditions than usual and that this difference is not due to a “sample
527 effect”. The results show that the surface temperature percentiles between 1 day and 2 months
528 prior to failure are significantly higher than usual. More specifically, the highest significance for
529 these exceptionally high surface temperature percentiles is found 1.5 to 2 months prior to failure
530 and, in to a lesser extent, at an early time prior to the rockfall (1 to 5 days). In between these early
531 and late time periods, the statistical significance for the surface temperature percentiles decreases

532 and reaches a minimum at 2 weeks. This suggests that rockfall occurrences are favored by long-
533 lasting heatwaves (*i.e.* extended period of unusually high atmospheric heat) overtopped by a hot
534 spell (one or a few days of intense heat)⁷⁰. This early compound can thus be interpreted as a
535 triggering effect which only reinforces a long-term high surface temperature signal. The late
536 compound becomes more relevant in relation to the statistical significance of the scar temperature
537 temporalities. Indeed, high significances of scar temperatures for short time period (< 20 days) are
538 in some ways a corollary of high percentiles of surface temperature for at least a month due to the
539 delay needed for heat diffusion. But this would mean that bedrock failures are somewhat a direct
540 response to extraordinary high temperature at depth. Such results are partly in agreement with the
541 findings from Luethi et al.³⁷. This last study found that mid-sized rockfalls such as those we
542 investigated are a direct response to short-term periods of high surface temperature. The authors
543 attribute this fast reaction to accelerated bedrock thawing provoked by advective heat transfer from
544 water percolation. While this study was not accounting for the thermal dynamics at scar depth, our
545 study shows that scar depths were also affected by exceptionally high temperatures which are
546 explained by the only effect of heat conduction. It further demonstrates that this high temperature
547 at scar depth is likely a response to several weeks or months of high bedrock surface temperature.
548 It does not exclude effect of advective heat transport but suggests that heat conduction exerts a
549 predominant control. Such findings somehow remind the findings from Paranunzio et al.³⁶ which
550 pinpointed warm air temperature anomaly associated with a majority of rockfalls observed in the
551 Western Italian Alps. Finally, similarly to the study of Luethi et al.³⁷, it confirms that other thermal
552 processes than permafrost degradation are probably responsible for small size rockfalls,
553 supposedly high thermal stress due to intense temperature variation favoring bedrock failure
554 preparation.

555 These interpretations must be considered with caution since they are based on findings for which
556 the significance cannot be confirmed when considering the modeling approach uncertainty. This
557 limit draws some research outlooks that could lead to the definition of a susceptibility index of a
558 rockfall to occur according to the weather forecast.

559

560 *6.3. Outlooks*

561 Our study has shown that when considering model uncertainty, a part of our interpretation loses
562 significance as it is not clear whether the same results could have been drawn from a random
563 sample. For lowering these uncertainties and confirming/improving these results, two solutions are
564 possible.

565 The first one, which is the most challenging, is to lower the modeled temperature uncertainties
566 (σ_{Cryogrid} , σ_{MARST} or σ_{anomaly} ; see sect. 3.5). σ_{Cryogrid} could be improved by getting other borehole
567 data in order that CryoGRID2 parameters better represent the study area (boreholes in rockwalls
568 with other characteristics or in the metamorphic basement for example). σ_{MARST} could be tackled
569 by modeling the MARST with a RST sample collected in the study area rather than across the
570 entire European Alps^{35,51}. Finally, σ_{anomaly} could be improved by better defining the daily surface
571 temperature (see sect. 3.2.). RST anomaly time series could be created at the specific rockfall
572 locations by combining different meteorological parameters in a well-constrained energy balance
573 model.

574 The second solution for lowering the uncertainties would be to increase the sample size with a
575 higher number of rockfalls. This would lower the KS test critical values and the CDF uncertainties.
576 This second solution would be considered in the near future as the rockfall database will be
577 enriched with more recent events (2016-2020) which are currently under processing.

578 Additionally, with the method described in sect. 4, atmospheric warming and seasonal biases have
579 been ruled out. However, the bias linked with the rockfall locations persists. Indeed, the studied
580 locations were possibly particularly prone to instability (fracturing for example) as much as
581 rockfall dates were favorable for example. For removing this bias, random events should be chosen
582 in all the MBM, with characteristics (altitude, exposure, slope angle...) in accordance with the
583 rockfall sample characteristics. Such a study, in the continuation of this work, could result in the
584 development of a rockfall susceptibility index. This index would be defined with the values of the
585 four variables presented and, particularly, with their significances. This work of gathering all this
586 information could be done by machine learning or deep learning. Some of the real events will be
587 used in the learning process and the others for the testing step. Such a rockfall susceptibility index
588 could be a preliminary step towards a direct societal contribution of the past decade of permafrost
589 research, supporting risk mitigation and public awareness in a rapidly evolving environment.

590

591

592 **7. Conclusions**

593 In this paper, the thermal conditions and dynamics at and prior to rockfalls have been analyzed for
594 209 events inventoried in the MBM between 2007 and 2015 with 1D temperature modeling. Using
595 temperature measurements at five locations at the rock surface and into three 10-m-deep boreholes,
596 model uncertainty was quantified to refine model interpretation. Based on a random events
597 analysis approach, recent decades of atmospheric warming and seasonal biases have been
598 removed, and the statistical significance of our results was determined. The results were analyzed
599 through surface and scar depth temperature values to discriminate possible processes responsible
600 for rockfall triggering, as well as through temperature percentiles to analyze the statistical

601 significance and whether the rockfalls are a direct reaction to extreme air temperature signals.
602 Percentiles were defined in relation to 11 temporalities ranging from 1 day to 2 months. KS tests
603 were performed to determine whether our results could have been found from the random sample.

604 Our study draws the following conclusions:

605 • Permafrost degradation may be responsible for almost all events which scar depth was >
606 6 m, and for a significant part of events occurring between 3 and 6 m depth.

607 • For the 209 real events, the surface and scar temperature percentiles were, on average,
608 warmer than those of the random events. This difference is present for all the considered
609 temporalities. It is in order of magnitude of 3 % for scar temperature percentiles (1.5 % at least at
610 95 % reliability level) and 2.5 % for surface temperature percentiles (0.5 % at least at 95 %
611 reliability level).

612 • KS test shows significant relationships between rockfalls and surface temperature
613 percentiles at least up to 2 months prior to failure, and scar temperature percentiles up to 3 weeks
614 before the events. At the rock surface, temporalities > 1 month have the greatest significance and
615 those of 1-5 days are also remarkable. At scar depths, the closer to the event day, the greater the
616 significance.

617 • Significance results are interpreted as the effects of 1 to 5 days of extraordinary hot
618 weather (hot spell) acting as a triggering mechanism after > 1 month of exceptionally high air
619 temperature (long lasting heatwave), which result in high temperature at depth and sudden bedrock
620 failure.

621 • Decrease of the scar temperature percentiles significances suggests that rockfalls are a
622 direct reaction (lasting less than 3 weeks) to exceptionally high bedrock temperature.

623 • When considering 95 % reliability level, uncertainties are too high for concluding
624 anything about KS test significances (the three last points).

625 • Our study also points out the interest to apply such an approach with a greater rockfall
626 sample to better define the significance levels and appears promising to develop rockfall
627 susceptibility index using weather forecast.

628

629

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631

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636

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- 846

847 **Table 1.** Summary characteristics of the 209 rockfall events used in this study. MARST refers to the
 848 Mean Annual Rock Surface Temperature such as displayed in Figure 1.

	Altitude (m)	MARST (°C)	Volume (m ³)	Scar depth (m)	Slope angle (°)
Minimum	2175	-8.7	100	0.8	12*
Mean	3341	-2	1836	3	57
Median	3355	-2	400	3.8	57
Maximum	4085	4	60 000	15	82

849

850 **Table 1:** Optimum parameters for minimizing the RMSE between simulated and real borehole temperatures. * This
 851 low value is explained by the fact that the rockfall occurred from the top of a crest.

Parameter	Value
Bedrock conductivity (k_{bedrock})	3.3 W.m ⁻¹ .K ⁻¹
Bedrock porosity (ϕ)	1 %
Total water content ($\theta_{\text{w,tot}}$)	1 %
Bedrock volumetric heat capacity	2.10 ⁶ J.m ⁻³ .K ⁻¹
Profile resolution	From 1 to 3 m: 0.1 m From 3 to 10 m: 0.2 m From 10 m to 20.5 m: 0.5 m
Spin-up duration	3 years
C_{exp}	4

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