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1 **Temperature distribution in a permafrost-affected rock**
2 **ridge from conductivity and induced polarization**
3 **tomography**

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15

16 **Key points:** 1. Understanding the temperature distribution in a high Alpine rock ridge is a
17 crucial step for hazard assessment. 2. Electrical conductivity and normalized chargeability are
18 very sensitive to temperature in freezing conditions. 3. Electrical conductivity and induced
19 polarization tomography can be used to provide temperature tomograms of a permafrost-
20 affected rock ridge.

21 **Keywords:** high-Alpine rock ridge; electrical conductivity; freezing curve; permafrost.

22

23

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24

25 **Abstract.** Knowledge on the thermal state of steep alpine rock faces is crucial to assess
26 potential geohazards associated with the degradation of permafrost. Temperature
27 measurements at the rock surface or in boreholes are however expensive, invasive, and
28 provide spatially-limited information. Electrical conductivity and induced polarization
29 tomography can detect permafrost. We test here a recently-developed petrophysical model
30 based on the use of an exponential freezing curve applied to both electrical conductivity and
31 normalized chargeability to infer the distribution of temperature below the freezing
32 temperature. We then apply this approach to obtain the temperature distribution from
33 electrical conductivity and induced polarization field data obtained across a profile extending
34 from the SE to NW faces of the lower Cosmiques ridge (Mont Blanc massif, Western
35 European Alps, 3613 m a.s.l., France). The geophysical datasets were acquired both in 2016
36 and 2019. The results indicate that the only NE face of the rock ridge is frozen. To evaluate
37 our results, we model the bedrock temperature across this rock ridge using CryoGRID2, a 1D
38 MATLAB diffusive transient thermal model and surface temperature time series. The
39 modelled temperature profile confirms the presence of permafrost in a way that is consistent
40 with that obtained from the geophysical data. Our study offers a promising low-cost approach
41 to monitor temperature distribution in Alpine rock walls and ridges in response to climate
42 change.

43

44 **1. Introduction**

45

46 Permafrost is defined as ground materials with temperature permanently below or equal
47 to the freezing temperature, which is typically around 0°C (Dobinski, 2011). Permafrost in
48 mid latitude mountain areas is currently strongly affected by climate change (e.g., Biskaborn
49 et al., 2019; PERMOS, 2019). In turn, permafrost degradation (warming and thawing of the
50 ice content) is known to have serious consequences on the mechanical properties of the rock
51 slopes (Gruber & Haeberli 2007; Krautblatter et al., 2013), resulting in an increasing rockfall
52 frequency and magnitude that affects high mountain rock walls (Haeberli & Beniston, 1998;
53 Ravanel & Deline, 2011; Ravanel et al., 2017). A precise knowledge of the thermal state of
54 permafrost in rock walls and rock ridges is therefore crucial in assessing the safety and
55 reliability of mountain infrastructures (Haeberli et al., 2010; Krautblatter et al., 2012), and to
56 prevent or limit their damages or disturbances (Duvillard et al., 2019).

57 Rock wall temperature can be directly determined and monitored by the mean of
58 temperature sensors installed at the rock surface or in boreholes (e.g., Magnin et al., 2015a).
59 Since these data are local (point or line measurements), there are commonly used to fit
60 statistical models explaining the rock surface temperature (e.g., Boeckli et al., 2012). They
61 can be also used to parameterize or validate physic-based models (i.e., based on solving the
62 heat equation) to infer the spatial distribution and evolution of rock wall permafrost and
63 temperature when direct measurements are missing (e.g., Gruber et al., 2004; Magnin et al.,
64 2017a; Magnin et al., 2019). However, the accuracy of the models is limited because of (i) a
65 lack of consideration of important parameters driving the energy balance at the rock surface
66 (e.g., variability in solar radiation or snow deposit), (ii) the rock material characteristics (e.g.,
67 the thermal conductivity, porosity, specific heat storage coefficient) are generally defined
68 upon standard values, considered as homogenous and isotropic, and finally because (iii)

69 complex heat transfer processes such as heat advection in bedrock fractures resulting of air
70 circulation or water infiltration are neglected. That said, simplified thermal models have been
71 shown to be reliable to estimate the permafrost characteristics at a given time period at
72 depth > 8 m, and to estimate its changes over pluriannual time scales (Magnin et al., 2017).

73 To overcome some of the limits of direct temperature measurements and numerical
74 modelling, electrical conductivity and induced polarization tomography can provide an
75 alternative and complementary way to estimate the extent of permafrost and temperature
76 distribution below the freezing temperature. In the past, electrical conductivity tomography
77 has been broadly used to detect and monitor mountain permafrost (e.g., Kneisel, 2006;
78 Krautblatter & Hauck, 2007; Supper et al., 2014; Mollaret et al., 2019) including in steep rock
79 walls (Magnin et al., 2015b; Keuschnig et al., 2017). Indeed, the much lower electrical
80 conductivity of frozen rocks with respect to unfrozen materials (see, for instance, Scott et al.,
81 1990; Maurer & Hauck, 2007; Kneisel et al., 2008). The advantages of these geophysical
82 methods are their low cost, their non-invasive character, and the fact that they provide 2D or
83 3D tomograms/images of the subsurface.

84 Krautblatter et al. (2010) and Magnin et al. (2015b) have been used laboratory
85 experiments to distinguish frozen from unfrozen rocks based on their electrical conductivity.
86 Currently, there is however an absence of a rigorous protocol to infer the temperature
87 distribution from electrical conductivity tomography. To our knowledge, these limitations are
88 due to the lack of a precise petrophysical-based methodology to infer temperature fields from
89 electrical conductivity tomograms. The conversion of electrical conductivity into temperature
90 distribution has however been successfully accomplished for other geological contexts than
91 permafrost such as, for instance, active volcanoes (Revil et al., 2018). A similar strategy is
92 followed in the present work.

93 In addition to electrical conductivity tomography, another geophysical method called
94 induced polarization can be used to infer the presence of permafrost (e.g., Duvillard et al.,
95 2018; Abdulsamad et al., 2019). Induced polarization refers to the reversible storage of
96 electrical charges in a porous material under a low-frequency varying (applied) electrical field
97 (e.g., Seigel, 1959; Kemna et al., 2012; Weller et al., 2013). In absence of metallic particles
98 and in presence of moisture in a porous or fractured rock, induced polarization is related to the
99 properties of the electrical double layer coating the surface of the grains (Revil, 2012, 2013;
100 Leroy et al., 2017). Recently, the dynamic Stern layer concepts developed by Revil (2012,
101 2013) have been extended to freezing conditions (Duvillard et al., 2018; Coperey et al., 2018;
102 Abdulsamad et al., 2019; Revil et al., 2019a). One of the advantages of induced polarization is
103 that it can be measured with the same equipment as the one used for electrical conductivity
104 data acquisition (Kemna et al., 2012).

105 The recent establishment of a unified petrophysical model describing both electrical
106 conductivity and induced polarization (normalized chargeability) of rocks in freezing
107 conditions provides the opportunity to convert electrical conductivity to temperature in areas
108 affected by permafrost. Our study proposes to investigate the potential of these geophysical
109 measurements and such petrophysical model tested on rock samples from outcrops to assess
110 the temperature field patterns of a high-Alpine rock ridge. Then, we apply our approach to
111 electrical conductivity and induced polarization data measured across the permafrost-affected
112 lower Cosmiques ridge (3613 m a.s.l.), in the Mont Blanc massif (Western European Alps,
113 France), below a refuge damaged by a 600-m³-rockfall in August 1998 (Ravanel et al., 2013).
114 To evaluate the results from the geophysical data, we use the rock surface temperature time
115 series collected on each side of the ridge (from July 2016 to September 2019 on the north face
116 and from July 2016 to April 2020 on the south face) to force a non-linear 1D heat conduction
117 model simulating the temperature across a profile crossing the ridge. This modelling exercise

118 is performed to see if the frozen portion of the ridge is consistent with the prediction from
 119 geophysics.

120

121 **2. Petrophysics**

122

123 **2.1. Electrical conductivity - temperature relationship**

124 Above the freezing temperature, the change in the electrical conductivity of a rock with
 125 temperature is controlled by the temperature dependence of the ionic mobilities, which is in
 126 turn controlled by the temperature dependence of the dynamic viscosity of the pore water. In
 127 these conditions, the temperature dependence of the electrical conductivity $\sigma(T)$ at
 128 temperature T (in S m^{-1}) is given by Revil et al. (2018):

$$129 \quad \sigma(T) = \sigma(T_0)[1 + \alpha_T(T - T_0)], \quad (1)$$

130 where $\alpha_T = 0.021 \text{ } ^\circ\text{C}^{-1}$ (i.e., the temperature dependence of the conductivity is roughly 2 %
 131 per degree Celcius, independent of the water content of the rock), the reference temperature is
 132 $T_0 = 25^\circ\text{C}$, and $\sigma(T_0)$ denotes the conductivity of the rock at the reference temperature. The
 133 conductivity of a rock represents the ability of the rock to conduct an electrical current under
 134 the application of an electrical field. It comprises two contributions: a bulk contribution
 135 associated with conduction in the bulk pore space and a surface conductivity associated with
 136 conduction in the electrical double layer coating the surface of the grains. Usually, in a
 137 shallow temperature field above freezing conditions, the spatial variability associated with
 138 equation (1) (2% change per degree Celsius) is much smaller than the variability associated
 139 with the spatial variations in porosity, texture, and surface conductivity. It follows that above
 140 the freezing temperature, a single snapshot of the electrical conductivity distribution cannot be
 141 used to infer the temperature distribution.

142 In freezing conditions, part of the liquid pore water of a rock is progressively transformed
 143 into ice so there is also an additional effect associated with the change of the water content
 144 itself. Since the salt remains segregated in the liquid pore water, the salinity of the liquid pore
 145 water increases with the decrease of temperature. These effects imply a strong impact of the
 146 temperature on the electrical conductivity, an impact that is much stronger than above the
 147 freezing temperature. To quantitatively assess these effects, few ingredients are required. The
 148 most important is the expression of a freezing curve describing the relationship, for a given
 149 porous material, between the liquid water content θ (dimensionless) and the temperature T
 150 (in °C). In Duvillard et al. (2018) and Coperey et al. (2019), the following exponential
 151 freezing curve was proposed and validated:

$$152 \quad \theta(T) = \begin{cases} (\phi - \theta_r) \exp\left(-\frac{T - T_F}{T_C}\right) + \theta_r, & T \leq T_F, \\ \phi, & T > T_F \end{cases}, \quad (2)$$

153 where θ_r (dimensionless) denotes the residual water content when $T \ll T_F$, T_F denotes the
 154 liquidus or freezing point/temperature, T_C denotes a characteristic temperature controlling the
 155 transition between the unfrozen state and the frozen state, ϕ (dimensionless) denotes the
 156 (connected) porosity, and $\phi - \theta_r$ denotes the maximum volumetric ice content at low
 157 temperatures. Equation (2) is somehow equivalent to the capillary pressure curve in drainage
 158 and imbibition studies and the temperature T_C is somehow associated with the broadness of
 159 the pore size distribution.

160 In freezing conditions, the conductivity of the rock is given by Duvillard et al. (2018):

$$161 \quad \sigma = \theta^{m-1} \frac{\sigma(T_0)}{\phi} [1 + \alpha_r (T - T_0)], \quad (3)$$

162 where m (dimensionless) denotes the cementation (porosity) exponent entering into Archie's
 163 law between the formation factor F and the porosity ϕ , i.e., $F = \phi^{-m}$. A typical value of m is

164 close to 2 and a typical range is between 1.5 and 2.5 (e.g., Coperey et al., 2019, and references
 165 therein). In equation (3), we do not have to make any assumption regarding the importance of
 166 surface conductivity associated with the cation exchange capacity of the rock (see Duvillard et
 167 al., 2018; Coperey et al., 2019, for details regarding this contribution). The effect of
 168 temperature below freezing conditions upon the electrical conductivity is therefore very
 169 strong, much stronger than changes associated with porosity and surface conductivity spatial
 170 changes in a given lithology (Coperey et al., 2019).

171 Assuming that the cementation exponent m is close to 2, an explicit relationship is
 172 obtained between the measured conductivity below the freezing point, $\sigma(T)$, and temperature,
 173 T :

$$174 \quad \sigma(T) \approx \left[(\phi - \theta_r) \exp\left(-\frac{T - T_F}{T_C}\right) + \theta_r \right] \frac{\sigma(T_0)}{\phi} [1 + \alpha_T (T - T_0)]. \quad (4)$$

175
 176 Equation (4) will be used to connect electrical conductivity to temperature in field conditions.
 177 Below the freezing temperature, temperature spatial variations are expected to be mimicked,
 178 to some level, by the electrical conductivity distribution.

179 **2.2. Normalized chargeability - temperature relationship**

180 In the present paper, induced polarization is characterized by a single parameter called
 181 the normalized chargeability, which can be either obtained from the frequency dispersion of
 182 the conductivity data (for instance measured at two distinct frequencies, the so-called
 183 frequency effect) or from time-domain induced polarization by looking at the decay of the
 184 secondary voltage after the shut-down of the primary current (Kemna et al., 2012). Above the
 185 freezing temperature, the change in the normalized chargeability M_n (in S m^{-1}) of a rock with
 186 temperature is controlled by the temperature dependence of the ionic mobilities, which is in
 187 turn controlled by the temperature dependence of the dynamic viscosity of the pore water.
 188 Like for the electrical conductivity, we have therefore (Revil et al., 2012):

189
$$M_n(T) = M_n(T_0)[1 + \alpha_T(T - T_0)], \quad (5)$$

190 where $\alpha_T = 0.021 \text{ } ^\circ\text{C}^{-1}$, the reference temperature is $T_0 = 25^\circ\text{C}$, and $M_n(T_0)$ denotes the
 191 normalized chargeability of the rock at the reference temperature. Using the model developed
 192 in Duvillard et al. (2018), the dependence of the normalized chargeability in freezing
 193 conditions is given by:

194
$$M_n(T) \approx \left[(\phi - \theta_r) \exp\left(-\frac{T - T_F}{T_c}\right) + \theta_r \right] \frac{M_n(T_0)}{\phi} [1 + \alpha_T(T - T_0)]. \quad (6)$$

195 Therefore, in freezing conditions, the temperature dependence of the normalized chargeability
 196 and the temperature dependence of the electrical conductivity are strictly the same. This is
 197 because of the specific dependence of the conductivity with the water content in freezing
 198 conditions related to the segregation of salt in the liquid water phase. Thus, at the opposite of
 199 what can be done in hydrothermal systems (Revil et al., 2019b), we cannot combine here the
 200 normalized chargeability and electrical conductivity tomography to obtain independently the
 201 liquid water content.

202 Interestingly however, the ratio of the normalized chargeability by the conductivity
 203 appears to be independent of temperature and, from equations (4) and (6), we have:

204
$$\frac{M_n(T)}{\sigma(T)} \approx \frac{M_n(T_0)}{\sigma(T_0)}. \quad (7)$$

205 According to the dynamic Stern layer model developed by Revil (2012) and for conditions
 206 implying that the salt remains segregated into the liquid pore water, the normalized
 207 chargeability and the conductivity are related to the water content θ by

208
$$M_n(T_0) \approx \theta^{m-1} \rho_g \lambda \text{CEC}, \quad (8)$$

209
$$\sigma(T_0) \approx \theta^{m-1} \sigma_w + \theta^{m-1} \rho_g B \text{CEC}, \quad (9)$$

210 respectively. Therefore, the ratio between the normalized chargeability and the conductivity is
 211 given by

$$\frac{M_n(T)}{\sigma(T)} \approx \frac{\rho_g \lambda \text{CEC}}{\sigma_w + \rho_g \text{BCEC}}. \quad (10)$$

213 When the conductivity of the rock is dominated by surface conductivity along the surface of
 214 the grains (i.e., $\sigma_w \ll \rho_g \text{BCEC}$), this ratio is exactly given by $R = \lambda / B = 0.10$, independent
 215 of the water content and temperature (Duvillard et al., 2018). When we have $M_n(T) / \sigma(T) < R$,
 216 this means that the bulk contribution of electrical conductivity (related to the pore water
 217 conduction σ_w) cannot be neglected.

218

219 3. Test site

220 The lower Cosmiques ridge is located at 600–1000 m SSW of the Aiguille du Midi (3842
 221 m a.s.l.), on the northwestern side of the Mont Blanc massif (Figure 1a), which spreads
 222 between France, Italy and Switzerland, and belongs to the Alpine external crystalline massifs.
 223 The ridge develops horizontally, on the French side of the massif, over a length of 400 m
 224 (Figure 1bc) in the Mont Blanc granite from the Hercynian metamorphic series (Bussy and
 225 von Raumer, 1994). The extension of the SE face is 50-m-high and stands above the Glacier
 226 du Géant. It is about 75° steep and has a rather smooth surface. It is sometimes partially
 227 covered by the snow that takes support on the glacier below. The NW face is about 350-m-
 228 high, 55° steep, and is highly rugged, allowing heterogeneous snow accumulation during a
 229 part of the year. The Mean Annual Rock Surface Temperature (MARST), modeled for the
 230 steep slopes of the Mont Blanc massif for the period 1961-1990 (Magnin et al., 2015c), is
 231 around -4°C in the NW face, and -1°C in the SE face of the lower Cosmiques ridge. A refuge
 232 was built during the period 1989 - 1991 on the top of the ridge (3613 m a.s.l.). It represents a
 233 popular location (hosting about 7000 people a year) since it is located along one of the main
 234 climbing route to reach the summit of the Mont Blanc. In August 1998, a 600 m³-rockfall

235 occurred right below the refuge and partly destabilized the infrastructure, which was closed
236 for 8 months for reinforcement work (Figure 1d; Ravanel et al., 2013).

237

238 **4. Methods**

239 **4.1. Geophysical measurements**

240 *4.1.1 Field investigations*

241 The geophysical field survey was performed both in October 2016 and September 2019.
242 It extends from the foot of the SE face to the upper 64 m of the NW face, running below the
243 refuge anchors and building (Figure 2). Two 64-m-long cables (128-m-long profile) and a
244 total of 64 electrodes (2-m-spacing) were connected to a resistivity meter (ABEM Terrameter
245 SAS-4000 in 2016 and ABEM LS2 in 2019). We used 10-mm-thick and 120-mm-long
246 stainless steel electrodes for both surveys. Warm salty water, conductive metallic grease, and
247 bentonite were used to improve the electrical contacts between the electrodes and the ground
248 (Krautblatter & Hauck, 2007; Magnin et al., 2015b). The Wenner configuration was used
249 because of its best signal-to-noise ratio thanks to its particular electrode configuration since
250 the voltage electrodes MN are located in-between the current electrodes AB (e.g., Dahlin and
251 Zhou, 2004; Kneisel, 2006). During the surveys, only two electrodes had to be excluded due
252 to their high contact resistances (Table 1). Topography along the profile was extracted from a
253 terrestrial laser scanning point cloud acquired in 2016 for the SE face and from a
254 photogrammetric model acquired with a drone in 2019 on the both faces of the ridge. The data
255 were inverted with the RES2DINV-3.54.44 software using a smoothness-constrained least-
256 squares method and the standard Gauss-Newton method (see Loke and Barker, 1996, for
257 details). The inversion was stopped at the 3rd iteration when the convergence criterion was
258 reached (i.e., the difference in the root-mean square error of the data misfit function is below a
259 target value).

260

261 **4.1.2. Laboratory experiments**

262 In order to test the petrophysical model discussed in Section 2, we performed an
263 electrical conductivity experiment on a rock sample collected in the field from an outcrop.
264 The sample (labeled PAS1 below) was immersed in a temperature-controlled bath following
265 the same protocol as in Duvillard et al. (2018). Sample PAS1 was cut to get a 5-cm large
266 cube. Sample PAS1 (granite) was characterized by a porosity $\phi = 0.028$, a cation exchange
267 capacity $\text{CEC} = 0.80 \text{ meq}/100 \text{ g}$, and a formation factor $F = 499$ (for more details, see sample
268 labelled COS in Coperey et al., 2019). Before to perform the laboratory measurements in the
269 laboratory, the sample was dried during 24 hours then saturated under vacuum with degassed
270 water from melted snow taken on the field. The sample was left several weeks in the solution
271 to reach chemical equilibrium before to perform the laboratory measurements. The water
272 conductivity at 25°C and at equilibrium was 0.0257 S m^{-1} .

273 In addition, we used the laboratory data determined by Magnin et al. (2015b).
274 This second sample (labeled G1 below) was collected in the same geological unit and
275 saturated with tap water. Four non-polarizing Ag-AgCl_2 electrodes were placed on the
276 sample: two current electrodes (A and B) on the end-faces of the sample. Two voltage
277 electrodes (M and N, separated by a distance of 3.5 cm) were placed on the external side of
278 the core sample.

279 The sample holder was installed in a heat-resistant insulating bag immersed in a
280 thermostat bath (KISS K6 from Huber; $210 \times 400 \times 546 \text{ mm}$; bath volume: 4.5 L). The
281 temperature of this bath was controlled with a precision of 0.1°C . Glycol was used as heat
282 carrying fluid and the complex conductivity measurements were carried out with the
283 impedance-meter. The conductivity measurements were reported here at 1 Hertz. The
284 experimental data together with a fit of the data with equation (1) (for temperatures above the

285 freezing temperature) and with equation (4) (for temperatures below the freezing temperature)
286 are shown in Figure 3. We see that the model proposed in Section 2 is able to fit the data
287 above and below the freezing temperature and provides therefore a bridge to connect
288 electrical conductivity to temperature.

289 Induced polarization measurements were done in time domain with the sample core I.P.
290 tester from GDD Inc. and using sample Sample PAS1. We used the four electrodes approach,
291 i.e., current electrodes A and B are attached on the end faces of the cylindrical core while the
292 potential electrodes M and N are fixed on the external side of the sample. In order to avoid
293 drying and short circuits at the electrodes, the sample was covered with insulating adhesive
294 tape except at the position of the electrodes. Then, the sample was brought to different
295 temperatures thanks to a thermally-controlled bath (Kiss K6 from Huber; see Figure 5 in
296 Coperey et al., 2019). The periods of the primary current injection were 1.0, 2.0 and 4.0
297 seconds. The decay curve was recorded using 20 windows distributed in a “Cole-Cole”
298 configuration. More details about time-domain induced polarization measurements can be
299 found in Kemna et al. (2012) and Revil et al. (2018). The results are shown in Figure 4 and
300 are fitted by equations (5) and (6). We see that the model is able to fit the data very well.

301 In our analysis, from Figure 3, we have $M_n(T_0) = 5.9 \times 10^{-7} \text{ S m}^{-1}$ and from Figure 4 we
302 have $\sigma(T_0) \approx 9 \times 10^{-5} \text{ S m}^{-1}$. This yields $M_n(T)/\sigma(T) = 0.007 \ll R$, which means in turn that
303 surface conduction is not the dominating conduction mechanisms controlling the electrical
304 conductivity of these rocks. Unaltered granite rock samples are usually characterized by a low
305 specific surface areas and CEC, which could explain this observation.

306

307 **4.2 Rock surface temperature measurement and temperature modeling**

308 Rock surface temperature (RST) measurements allow to locally assessing the presence of
309 permafrost by continuously measuring temperature for at least one full year (Gruber et al.,

310 2004; Magnin et al., 2015a). Three RST sensors Geoprecision PT1000 with M-Log5W
311 loggers (resolution: 0.01°C, accuracy +/- 0,1°C with temperature recorded every 3 hours)
312 were installed at a depth of 10 cm in July 2016 in the SE and NW faces and near the refuge
313 foundation. The latter is not used in this study. The SE face sensor was installed 15 m below
314 the refuge (at 3595 m a.s.l.), in the 1998 scar, and the NW face sensor was installed below the
315 terrace of the refuge (at 3603 m a.s.l.) in a massive slab (Figure 2). The NW face sensor was
316 installed in a snow-free location, but the one on the SE face was installed on a rock wall on
317 which snow accumulates in winter, covering the sensor. These sensors recorded RST at an
318 hourly time step until September 2018 yielding time series > 2 years. The MARSTs allow a
319 first approximation of the presence/absence of permafrost, negative values indicating the very
320 likely presence of permafrost while values up to 3°C might also indicate possible permafrost
321 presence (Hasler et al., 2011). Such data can also be used to simulate permafrost evolution at
322 depth by forcing a heat conduction model (e.g., Hipp et al., 2014).

323 To evaluate the occurrence of permafrost obtained from field electrical conductivity
324 measurements, we simulate the bedrock temperature evolution during the years prior to
325 measurements in order to assess the thermal state at the day of geophysical investigations in
326 2016 and 2019. To do so, we first reconstruct a time series of the daily RST (January 1993 to
327 July 2016) at the SE and NW loggers locations by fitting a linear regression model between
328 the measured RST and local air temperature records (data from *Météo France*). We tested the
329 model fit with air temperature records from Chamonix (1042 m a.s.l.) and the Aiguille du
330 Midi (3842 m a.s.l.). The best correlation between daily RST and daily air temperature was
331 obtained with the Chamonix time series for the NW sensor (0.88) and with the Aiguille du
332 Midi time series for the SE sensor (0.77 against 0.63 for the Chamonix time series). Lower
333 correlation between air temperature and RST on at the SE sensor is due to the presence of

334 snow during winter and the stronger variability in incoming solar radiation than at the NW
335 sensor.

336 We then used air temperature time series best correlated with the RST to reconstruct the
337 RST prior to and after RST measurements by using the fitted regression model coefficients.
338 Since the Aiguille du Midi weather records only start in February 2007 and because they are
339 affected by several gaps during the period 2007-2019, data from the Chamonix time series,
340 which are continuous over time, were used to fill the gaps when reconstructing the RST time
341 series on the SE face. Two RST time series are thus created for the NW and SE logger
342 locations, starting in January 1993 (beginning of the continuous air temperature
343 measurements by *Météo France* in Chamonix) and ending in September 2019, with the
344 measured values between July 2016 and September 2018 and the reconstructed values before
345 and after. These time series were used to force a MATLAB diffusive transient thermal model,
346 the so-called Cryogrid 2 model (Westerman et al., 2013).

347 We solve a 1D nonlinear diffusion equation over time by taking into account rock
348 properties, air content, water/ice content, and related thawing/freezing processes through
349 latent heat consumption and release. Our goal is to determine the temperature distribution
350 along a quasi-horizontal profile crossing the ridge with a length of 32.75 m. In the original
351 approach by Westerman et al. (2013), Cryogrid2 is used to model the temperature distribution
352 in a vertical section with only the upper surface that has been exposed to air. Therefore, a RST
353 time series is used to impose the boundary condition at the top of the column (corresponding
354 therefore to a Dirichlet boundary condition) and a thermal flux at the bottom (corresponding
355 to a Neumann boundary condition).

356 Our model is however different from the modeling used in Westerman et al., (2013) since
357 we model the temperature distribution across a ridge and we need to apply two RST time
358 series (the SE and NW temperature time series) at both ends of the profile. In other words, in

359 our case, we apply a Dirichlet boundary condition at each end of the 1D profile to estimate the
360 temperature distribution by solving the heat equation with Cryogrid2.

361 The equations are solved with a spatial resolution of 10 cm near the two end-points (i.e.,
362 from 0 to 1 m and from 31.75 to 32.75 m). We use a discretization of 20 cm in the remaining
363 part of the profile (i.e., from 1 to 31.75 m). The simulation is performed between 1993
364 January 1st and 2019 September 18th. Physical rock parameters were fitted using temperature
365 time series in three 10-m-depth boreholes at the Aiguille du Midi (Magnin et al., 2015a). They
366 are reported in Table 2 and provide reasonable estimates for granites.

367 Legay et al. (submitted) have calculated model uncertainty (standard deviation) of 0.55°C
368 according to the error distribution (difference between the modeled and measured temperature
369 values in the boreholes). In addition, uncertainties of the inputs of the model must be
370 considered; the loggers give an uncertainty of $\Delta_{95\%} = 1.1^\circ\text{C}$ for the measured temperatures
371 time series (NW and SE series).

372

373 **5. Results**

374 **5.1. Electrical conductivity and normalized chargeability tomograms**

375 Electrical conductivity tomograms acquired in 2016 and 2019 show a vertical distribution
376 of the conductivities with rather low conductivity values ($< 10^{-4} \text{ S m}^{-1}$) below the NW face
377 and higher values below the SE face ($> 10^{-4} \text{ S m}^{-1}$). The chargeability tomograms acquired in
378 2019 show a similar vertical distribution between the NW face and SE face with lower values
379 in the NW face compared to 2016 ($> 10^{-6} \text{ S.m}^{-1}$). The two color scales are adjusted with 0°C
380 value to the conductivity values (between 10^{-4} S.m^{-1} and 10^{-5} S.m^{-1}) or normalized chargeability
381 values (between 10^{-6} S.m^{-1} and 10^{-7} S.m^{-1}) observed during the laboratory experiments (Figures
382 3 and 4). This suggests that permafrost presence is restricted to the NW face with a vertical
383 permafrost limit below the hut and the absence of permafrost below the SE face (Figures 5

384 and 6). At this stage, only a semi-quantitative interpretation of the profiles is possible, as
 385 previously carried out in previous studies analyzing electrical conductivity tomograms in rock
 386 walls (Krautblatter & Hauck, 2007; Magnin et al., 2015b; Keuschnig et al., 2017). This is, at
 387 the current stage, not possible to assess how close to the thawing point the permafrost is.

388

389 **5.2. Petrophysical modelled temperature distribution in the ridge**

390 In order to convert the electrical conductivity distribution into temperature fields, we
 391 consider the following values of the model parameters entering equations (4): $T_c = -0.36^\circ\text{C}$, $\phi =$
 392 0.028 , $\theta_r = 0.006$, $T_F = 0^\circ\text{C}$ based on the experimental data (Figure 3). In addition, we
 393 consider the characteristic temperature entering equation (4) in the range
 394 $-2.2^\circ\text{C} \leq T_c \leq -0.4^\circ\text{C}$ based on our experimental data. The last step is to determine the value
 395 of the conductivity of the rock at the reference temperature, i.e., $\sigma(T_0)$. We first determine the
 396 value of $\sigma(T_F = 0^\circ\text{C})$ from the electrical conductivity distribution resulting from the electrical
 397 conductivity tomogram. This value is obtained as follows. Because of the change of slope in
 398 the conductivity versus temperature curve, the distribution of the conductivity values should
 399 be marked by a minimum, which is clearly identified in Figures 7 and 8 for both laboratory
 400 and field data, acquired in 2016 and 2019. This yields $\sigma(T_F = 0^\circ\text{C}) = 5 \times 10^{-5} \text{ S.m}^{-1}$ for the field
 401 data. Then, this value is converted to the reference temperature of 25°C to be used in equation
 402 (4). Using equation (1), we obtain $\sigma(T_0) = 8 \times 10^{-5} \text{ S m}^{-1}$, therefore in excellent agreement with
 403 the values determined independently from the curve fitting shown in Figure 3 ($\sigma(T_0) =$
 404 $8.8 \times 10^{-5} \text{ S.m}^{-1}$ for sample G1 and $\sigma(T_0) = 9.3 \times 10^{-5} \text{ S.m}^{-1}$ for sample PAS1). This indicates
 405 that the two samples are representative of the rock below the Cosmiques refuge since the
 406 value of this conductivity is consistent between laboratory and field data.

407 With these values, two temperature distributions are shown in Figure 9 for
408 $T_c = -2.2^\circ\text{C}$ and $T_c = -0.4^\circ\text{C}$, respectively. These results show a relative increase of the
409 lowest temperature between 2016 and 2019, according to the two sample (sample G1, -1.7°C
410 in 2016, then -1°C in 2019; sample PAS1, -10°C in 2016, then -6°C in 2019), suggesting
411 permafrost degradation (warming) within this 3 year period.

412

413 **5.3 Measured and modelled bedrock temperature**

414 The MARST during the measurement period (from August 15, 2016 to August 15,
415 2018) was -3.7°C on the NW face and $+2.4^\circ\text{C}$ on the SE face. This is in agreement with
416 suggestion from the petrophysical models which displays permafrost conditions below the
417 NW face but not below the SE face. Temperatures simulated at depth with CryoGRID2 are
418 presented in Figure 10 for the period from 2009 January 1st to 2019 September 18th. They
419 show a depth of the permafrost in the NW face around -15 m with temperature between $-2/-$
420 3°C during the ERT and IP acquisition in October 2016 and September 2019. This simulation
421 indicates warm permafrost in the NW face, probably in thawing phase.

422

423 **6. Discussion**

424 **6.1 Comparison between geophysics and numerical modeling**

425 When we compare the negative temperature converted from the geophysics
426 (petrophysical model only used under 0°C) with temperature simulated with the numerical
427 model, we observe that the NW face of the rock ridge is frozen with both methods, in 2016
428 and 2019. We recall that the geophysical data can only be used to assess the temperature in
429 the frozen portion of the ridge; above the freezing temperature, the effect of heterogeneity is
430 stronger than the effect of temperature regarding their effects on the conductivity field. Figure
431 9 confirms a good correlation between the frozen and unfrozen part of the ridge between the

432 geophysical prediction and the numerical modeling. The temperature distribution with $T_c = -$
433 2.2°C (sample PAS1 saturated with snowmelt; Figure 3a) suggests that the bedrock
434 temperature is between -2°C and -4°C in 2016 and 2019 at a depth of 10 m in the NW face
435 while the temperatures simulated with the numerical model is -2°C . The determination of the
436 temperature distribution assuming $T_c = -0.36^\circ\text{C}$ (Figure 3b) suggests a bedrock temperature of
437 -0.5°C at 10 m depth in 2016 and 2019 while the numerical simulation suggests -2°C .
438 Therefore, the numerical modeling shows that the NW face of the rock ridge is frozen
439 (permafrost conditions) with a temperature around -2°C ; which is very consistent with the
440 interpretation of the geophysical data from the sample PAS1 (with $T_c = -2.2^\circ\text{C}$, see Figure 9).

441

442 **6.2 Uncertainty**

443 In the previous section, we made a qualitative comparison between the prediction of
444 the geophysical data using the petrophysical model discussed in Section 2 and the 1D
445 numerical model. We avoided a direct comparison because, in our opinion, both approaches
446 contain sources of uncertainties. For the numerical model, the main sources of errors are
447 associated with (1) uncertainties associated with the dimensionality of the numerical model,
448 (2) uncertainties in the value of the petrophysical parameters used in the heat equation, (3)
449 uncertainties in the boundary conditions, and (4) uncertainties in the numerical modeling
450 itself. Regarding the geophysical data, sources of errors are associated with (1) uncertainties
451 in the inversion of the geophysical data (choice of the regularization term in the cost
452 function), (2) uncertainties in the geophysical data, and (3) uncertainties in the parameters
453 entering in the petrophysical model. A complete analysis of the uncertainties associated with
454 the two approaches is out of the scope of the present paper. This being said, a future
455 investigation will focus on a temperature tomogram that will combine 2D numerical modeling

456 of the heat equation with the geophysical data to get a balance in terms of combining the two
457 types of information.

458

459 **6.3 Influence of surface conductivity**

460 In absence of metallic particles, the electrical conductivity of a rock sample has two
461 contributions: a bulk conductivity associated with the pore water in the connected pore space
462 and a surface (interfacial) conductivity associated with conduction in the electrical double
463 layer coating the surface of the grains. The third point we want to discuss is the influence of
464 this surface conductivity in the overall electrical conductivity of the rock ridge. With the
465 laboratory data, we already demonstrated that surface conduction is likely not dominant in
466 explaining the conductivity of the granite from the ridge. What about the field data? Figure 11
467 displays the field and laboratory data in terms of normalized chargeability versus
468 conductivity. It clearly shows that the slope ($0.016 \ll R = 0.10$) is such that the conductivity
469 is dominated with the pore water conductivity rather than by the surface conductivity. This is
470 an important point in interpreting electrical conductivity tomograms in field conditions.

471

472 **7. Conclusions**

473 Assessing permafrost distribution in steep high-Alpine rock walls and ridges is
474 challenging due to the highly variable temperature distribution, largely governed by the
475 micro- to meso-topographical settings and the related topoclimatic control. Point-scale
476 temperature measurements and temperature models are therefore limited. In this study, we
477 proposed to assess the 2D temperature distribution of a sensitive rock ridge (presence of a
478 refuge with 140 beds) by mean of an electrical conductivity tomography measurement and a
479 petrophysical model parameterized with calibrated freezing curves in laboratory. The
480 electrical conductivity data performed on two rock samples were used for these calibrations

481 and fitted with the petrophysical model developed in Duvillard et al. (2018). The
482 parameterized petrophysical model applied to electrical conductivity data performed over the
483 rock ridge provides realistic temperature fields for the lower Cosmiques ridge. Warm
484 permafrost is inferred right below the NW face and the absence of permafrost is inferred right
485 below the SE face and below the refuge. The resulting temperature extracted from geophysics,
486 with sample saturated with melted snow, advert temperature around -2°C , which is consistent
487 with the simulated temperature. This approach needs to be tested on other areas to better
488 assess the asset and limits of the proposed method. An in-depth analyzis of the relationship
489 between the conductivity and the normalized chargeability indicates that the conductivity is
490 dominated here by the bulk conductivity rather than by the surface conductivity associated
491 with conduction in the electrical double later coating the grains.

492
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504

505 **References**

506

507 Abdulsamad F., Revil A., Ghorbani A., Toy V., Kirilova M., Coperey A., Duvillard P.A.,
508 Ménard G. & Ravanel L., 2019. Complex conductivity of graphitic schists and
509 sandstones, *Journal of Geophysical Research*, **124**, 8223–8249,
510 doi:10.1029/2019JB017628

511 Biskaborn B.K., Smith S.L., Noetzli J., Matthes H., Vieira G., Streletskiy D.A., Schoeneich
512 P., Romanovsky V.E., Lewkowicz A.G., Abramov A., Allard M., Boike J., Cable W.L.,
513 Christiansen H.H., Delaloye R., Diekmann B., Drozdov D., Etzelmüller B., Grosse G.,
514 Guglielmin M., Ingeman-Nielsen T., Isaksen K., Ishikawa M., Johansson M., Johannsson
515 H., Joo A., Kaverin D., Kholodov A., Konstantinov P., Kröger T., Lambiel C., Lanckman
516 J.-P., Luo D., Malkova G., Meiklejohn I., Moskalenko N., Oliva M., Phillips M., Ramos
517 M., Sannel A.B.K., Sergeev D., Seybold C., Skryabin P., Vasiliev A., Wu Q., Yoshikawa
518 K., Zheleznyak M., Lantuit H., 2019. Permafrost is warming at a global scale. *Nature*
519 *Communications*, **10**, doi:10.1038/s41467-018-08240-4

520 Boeckli, L., Brenning, A., Gruber, S. & Noetzli, J., 2012. Permafrost distribution in the
521 European Alps: calculation and evaluation of an index map and summary statistics, *The*
522 *Cryosphere*, **6**, 807–820, doi:10.5194/tc-6-807-2012.

523 Bussy F., & von Raumer J.F. (1994). U-Pb geochronology of Paleozoic magmatic events in the
524 Mont-Blanc crystalline massif, Western Alps. *Swiss Bulletin of Mineralogy and*
525 *Petrology*, **74**: 514-515.

526 Coperey, A., Revil, A., Abdulsamad, F., Stutz, B., Duvillard, P.A, Ravanel, L., 2019. Low
527 frequency induced polarization of porous media undergoing freezing: preliminary
528 observations and modeling. *J. Geophys. Res.*, **124**, doi:10.1029/2018JB017015.

- 529 Dahlin, T. & Zhou, B., 2004. A numerical comparison of 2D resistivity imaging with 10
530 electrode arrays, *Geophysical Prospecting*, **52**, 379–398, doi:10.1111/j.1365-
531 2478.2004.00423.x.
- 532 Dobinski, W., 2011. Permafrost, *Earth Science Review*, **108**, 158–169,
533 doi:10.1016/j.earscirev.2011.06.007.
- 534 Duvillard, P.A., Revil, A., Qi, Y., Soueid Ahmed, A., Coperey, A. & Ravel, L., 2018.
535 Three-dimensional electrical conductivity and induced polarization tomography of a rock
536 glacier, *J. Geophys. Res.*, **123**, doi:10.1029/2018JB015965
- 537 Duvillard, P.-A., Ravel, L., Marcer, M. & Schoeneich, P., 2019. Recent evolution of
538 damage to infrastructure on permafrost in the French Alps, *Regional Environmental*
539 *Change*, **19**, 1281-1293, doi:10.1007/s10113-019-01465-z
- 540 Gruber, S. & Haeberli, W., 2007. Permafrost in steep bedrock slopes and its temperature-
541 related destabilization following climate change, *J. Geophys. Res.* **112**,
542 doi:10.1029/2006JF000547.
- 543 Gruber, S., Hoelzle, M. & Haeberli, W., 2004. Rock-wall temperatures in the Alps: modelling
544 their topographic distribution and regional differences, *Permafrost and Periglacial*
545 *Processes*, **15**, 299–307, doi:10.1002/ppp.501.
- 546 Haeberli, W. & Beniston, M., 1998. Climate change and its impacts on glaciers and
547 permafrost in the Alps, *Ambio*, **27**, 258–265.
- 548 Haeberli, W., Noetzli, J., Arenson, L., Delaloye, R., Gärtner-Roer, I., Gruber, S., Isaksen, K.,
549 Kneisel, C., Krautblatter, M. & Phillips, M., 2010. Mountain permafrost: development
550 and challenges of a young research field, *Journal of Glaciology*, **56**, 1043–1058.
- 551 Kemna, A., Binley, A., Cassiani, G., Niederleithinger, E., Revil, A., Slater, L., Williams,
552 K.H., Orozco, A.F., Haegel, F.-H., & Hoerdt, A., 2012. An overview of the spectral

- 553 induced polarization method for near-surface applications. *Near Surface Geophysics*, **10**,
554 453–468. doi:10.3997/1873-0604.2012027.
- 555 Keuschnig, M., Krautblatter, M., Hartmeyer, I., Fuss, C. & Schrott, L., 2017. Automated
556 electrical resistivity tomography testing for early warning in unstable permafrost rock
557 walls around Alpine infrastructure, *Permafrost and Periglacial Processes*. **28**, 158–171.
558 <https://doi.org/10.1002/ppp.1916>
- 559 Kneisel, C., 2006. Assessment of subsurface lithology in mountain environments using 2D
560 resistivity imaging, *Geomorphology*, **80**, 32–44, doi:10.1016/j.geomorph.2005.09.012.
- 561 Kneisel, C., Hauck, C., Fortier, R. & Moorman, B. (2008) Advances in geophysical methods
562 for permafrost investigations. *Permafrost Periglac. Process.*, **19**, 157–178.
563 doi:10.1002/ppp.616
- 564 Krautblatter, M. & Hauck, C., 2007. Electrical resistivity tomography monitoring of
565 permafrost in solid rock walls, *J. Geophys. Res.*, **112**, doi:10.1029/2006JF000546.
- 566 Krautblatter, M., Verleysdonk, S., Flores-Orozco & A., Kemna, A., 2010. Temperature-
567 calibrated imaging of seasonal changes in permafrost rock walls by quantitative electrical
568 resistivity tomography (Zugspitze, German/Austrian Alps), *J. Geophys. Res.*, **115**,
569 doi:10.1029/2008JF001209.
- 570 Krautblatter, M., Huggel, C., Deline, P. & Hasler, A., 2012. Research perspectives on
571 unstable high-alpine bedrock permafrost: Measurement, modelling and process
572 understanding, *Permafrost and Periglacial Processes*, **23**, 80–88, doi:10.1002/ppp.740.
- 573 Legay, A., Magnin, F., Ravanel L., submitted. Rock temperature prior to failure: analysis of
574 209 rockfall events in the Mont Blanc massif (Western European Alps), submitted to
575 *Permafrost and Periglacial Processes*

- 576 Leroy, P., S. Li, Jougnot D., Revil A. & Wu Y., 2017. Modeling the evolution of spectral
577 induced polarization during calcite precipitation on glass beads, *Geophysical Journal*
578 *International*, **209**(1), 123-140, doi:10.1093/gji/ggx001.
- 579 Loke, M.H. & Barker, R.D., 1996. Rapid least-squares inversion of apparent resistivity
580 pseudosections by a quasi-Newton method, *Geophysical Prospecting*, **44**, 131–152.
581 doi:10.1111/j.1365-2478.1996.tb00142.x
- 582 Magnin, F., Deline, P., Ravanel, L., Noetzli, J. & Pogliotti, P., 2015a. Thermal characteristics
583 of permafrost in the steep alpine rock walls of the Aiguille du Midi (Mont Blanc Massif,
584 3842 m a.s.l), *The Cryosphere*, **9**, 109–121, doi:10.5194/tc-9-109-2015
- 585 Magnin, F., Krautblatter, M., Deline, P., Ravanel, L., Malet, E. & Bevington, A., 2015b.
586 Determination of warm, sensitive permafrost areas in near-vertical rockwalls and
587 evaluation of distributed models by electrical resistivity tomography, *J. Geophys. Res.*,
588 **120**, 745–762, doi.org/10.1002/2014JF003351
- 589 Magnin, F., Brenning, A., Bodin, X., Deline, P. & Ravanel, L., 2015c. Modélisation
590 statistique de la distribution du permafrost de paroi: application au massif du Mont Blanc,
591 *Géomorphologie Relief Process. Environ.*, **21**, 145–162.
- 592 Magnin, F., Josnin, J.-Y., Ravanel, L., Pergaud, J., Pohl, B. & Deline, P., 2017a. Modelling
593 rock wall permafrost degradation in the Mont Blanc massif from the LIA to the end of the
594 21st century, *The Cryosphere*, **11**, 1813–1834, doi:10.5194/tc-11-1813-2017
- 595 Magnin, F., Westermann, S., Pogliotti, P., Ravanel, L., Deline, P., & Malet, E., 2017b. Snow
596 control on active layer thickness in steep alpine rock walls (Aiguille du Midi, 3842 m
597 a.s.l., Mont Blanc massif), *Catena*, **149**(2), 648–662, doi:10.1016/j.catena.2016.06.006.
- 598 Magnin, F., Etzelmüller, B., Westermann, S., Isaksen, K., Hilger, P. & Hermanns, R. L.,
599 2019: Permafrost distribution in steep rock slopes in Norway: measurements, statistical

- 600 modelling and implications for geomorphological processes, *Earth Surf. Dynam.*, **7**,
601 1019–1040, doi:10.5194/esurf-7-1019-2019
- 602 Maurer, H. & Hauck, C. (2007) Geophysical imaging of alpine rock glaciers. *Journal of*
603 *Glaciology*, **53**, 110–120. doi:10.3189/172756507781833893
- 604 Mollaret, C., Hilbich, C., Pellet, C., Flores-Orozco, A., Delaloye, R. & Hauck, C., 2019.
605 Mountain permafrost degradation documented through a network of permanent electrical
606 resistivity tomography sites, *The Cryosphere*, **13**, 2557–2578, doi:10.5194/tc-13-2557.
- 607 Noetzli, J., Gruber, S., Kohl, T., Salzmann, N. & Haeberli, W., 2007. Three-dimensional
608 distribution and evolution of permafrost temperatures in idealized high-mountain
609 topography, *Journal of Geophysical Research*, **112**(F2), doi:10.1029/2006JF000545.
- 610 PERMOS 2019. Permafrost in Switzerland 2014/2015 to 2017/2018. Noetzli, J., Pellet, C.,
611 and Staub, B. (eds.), Glaciological Report (Permafrost) No. 16-19 of the *Cryospheric*
612 *Commission of the Swiss Academy of Sciences*, 104 pp, doi:10.13093/permos-rep-2019-
613 16-1
- 614 Ravanel, L. & Deline, P., 2011. Climate influence on rockfalls in high-Alpine steep
615 rockwalls: The north side of the Aiguilles de Chamonix (Mont Blanc massif) since the
616 end of the ‘Little Ice Age’, *The Holocene*, **21**, 357–365. doi:10.1177/0959683610374887.
- 617 Ravanel, L., Deline, P., Lambiel, C. & Vincent, C., 2013. Instability of a high alpine rock
618 ridge: the lower arête des cosmiques, mont blanc massif, france, *Geogr. Ann. Ser. Phys.*
619 *Geogr.*, **95**, 51–66, doi:10.1111/geoa.12000.
- 620 Ravanel, L., Magnin, F. & Deline, P., 2017. Impacts of the 2003 and 2015 summer heatwaves
621 on permafrost-affected rock-walls in the Mont Blanc massif, *Sci. Total Environ.*, **609**,
622 132–143, doi:10.1016/j.scitotenv.2017.07.055.
- 623 Revil A., Razdan M., Julien S., Coperey A., Mao D., Abdulsamad F., Gasquet D., Sharma R.
624 & Rossi M., 2019a. Induced polarization response of porous media with metallic particles

- 625 – Part 9. Influence of permafrost, *Geophysics*, **84**(5), A43-W32, doi:10.1190/geo2019-
626 0013.1.
- 627 Revil A., Qi Y., Ghorbani A., Coperey A., Soueid Ahmed A., Finizola A. & T. Ricci, 2019b.
628 Induced polarization of volcanic rocks. 3. Imaging clay cap properties in geothermal
629 fields, *Geophysical Journal International*, **218**, 2, 1398–1427, doi:10.1093/gji/ggz207.
- 630 Revil A., Ghorbani A., Gailler L.S., Gresse M., Panwar N., & Sharma R., 2018. Electrical
631 conductivity and induced polarization investigations at Kilauea volcano, Hawai'i, *Journal*
632 *of Volcanology and Geothermal Research*, **368**, 31–50,
633 doi:10.1016/j.jvolgeores.2018.10.014.
- 634 Revil, A., 2013. Effective conductivity and permittivity of unsaturated porous materials in the
635 frequency range 1 mHz–1GHz, *Water Resources Research* **49**, 306–327,
636 doi:10.1029/2012WR012700.
- 637 Revil, A., 2012. Spectral induced polarization of shaly sands: Influence of the electrical
638 double layer, *Water Resources Research*, **48**, doi: 10.1029/2011WR011260.
- 639 Scott, W., Sellmann, P. & Hunter, J. (1990). Geophysics in the Study of Permafrost. in
640 Geotechnical and Environmental Geophysics Investigations in Geophysics, Vols 1-0,
641 355–384, *Society of Exploration Geophysicists*. doi:10.1190/1.9781560802785.ch13
- 642 Seigel, H.O., 1959. Mathematical formulation and type curves for induced polarization,
643 *Geophysics*, **24**, 547–565, doi:10.1190/1.1438625.
- 644 Supper, R., Ottowitz, D., Jochum, B., Römer, A., Pfeiler, S., Gruber, S., Keuschnig, M. & Ita,
645 A., 2014. Geoelectrical monitoring of frozen ground and permafrost in alpine areas: field
646 studies and considerations towards an improved measuring technology, *Surf. Geophys.*
647 **12**, doi:10.3997/1873-0604.2013057.

648 Weller, A., Slater, L., & Nordsiek, S., 2013. On the relationship between induced polarization
649 and surface conductivity: Implications for petrophysical interpretation of electrical
650 measurements, *Geophysics*, **78**, D315–D325. doi:10.1190/geo2013-0076.1.

651 Westermann, S, Schuler, TV, Gislås, K & Etzelmüller, B, 2013. Transient thermal modeling
652 of permafrost conditions in Southern Norway, *The Cryosphere*, **7**(2), 719-739,
653 doi:10.5194/tc-7-719-2013.

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655

656

Tables

657

658 **Table 1.** Information regarding the electrical resistivity and induced polarization surveys. ER
659 and IP stand for electrical resistivity and induced polarization, respectively.

660

Profile	ER2016	ER2019	IP2019
Date of survey	5 October	19 September	19 September
Electrode array type	Wenner 64XL	Wenner 64	Wenner 64
Number of data points	593	447	443
Number of inverted points	588	439	226
Root-mean-square error	29.5	19.2	14.2

661

662 **Table 1:** Parameters used for the numerical simulation of the ridge temperature according to
663 the model Legay et al. (submitted). The value of these petrophysical parameters have been
664 fitted using the temperature data measured in three shallow wells.

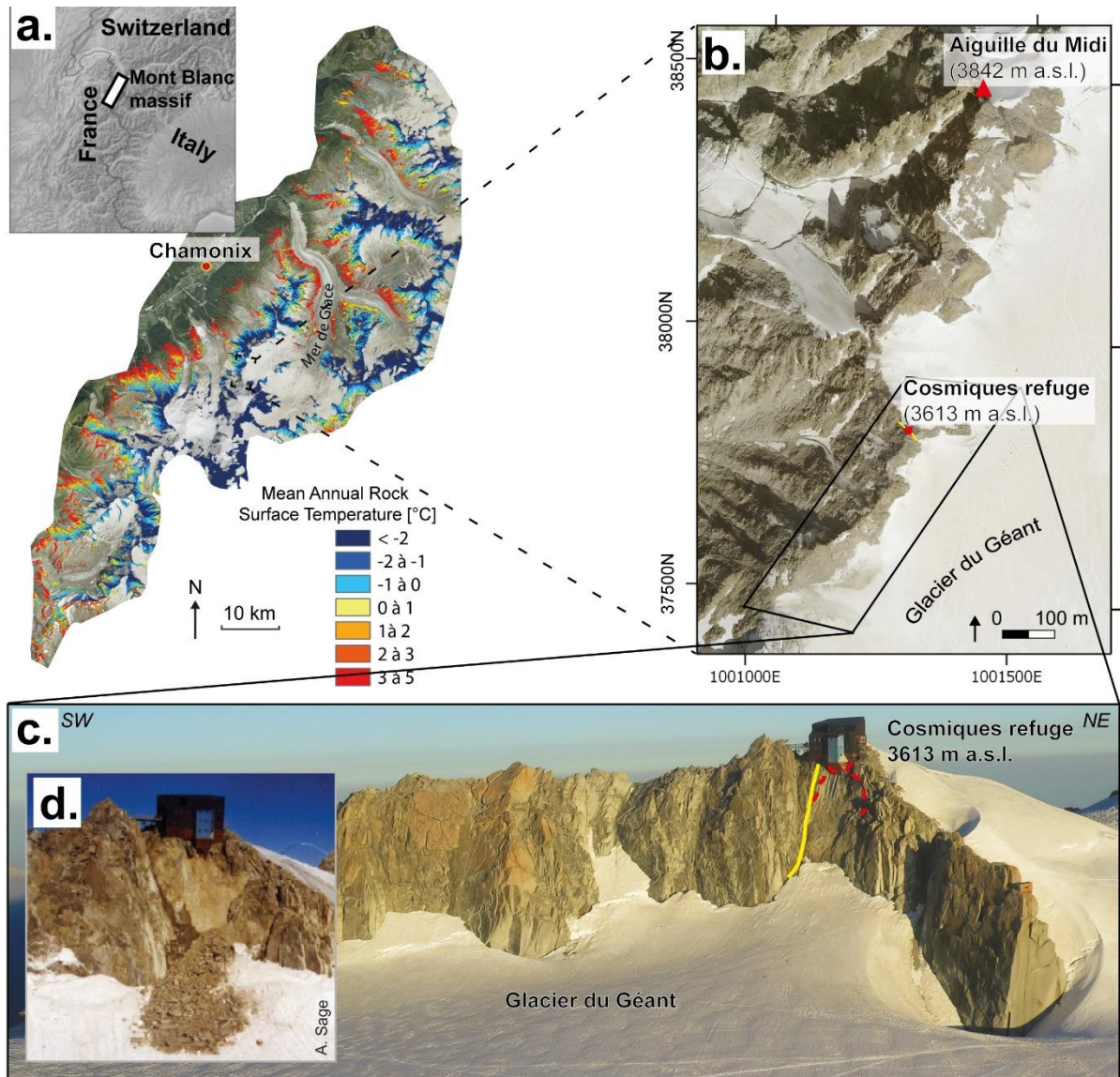
Parameter	Value
Thermal conductivity	$3.3 \text{ W K}^{-1} \text{ K}^{-1}$
Porosity	0.01
Volumetric heat capacity	$2.10^6 \text{ J m}^{-3} \text{ K}^{-1}$

665

Figures

666

667

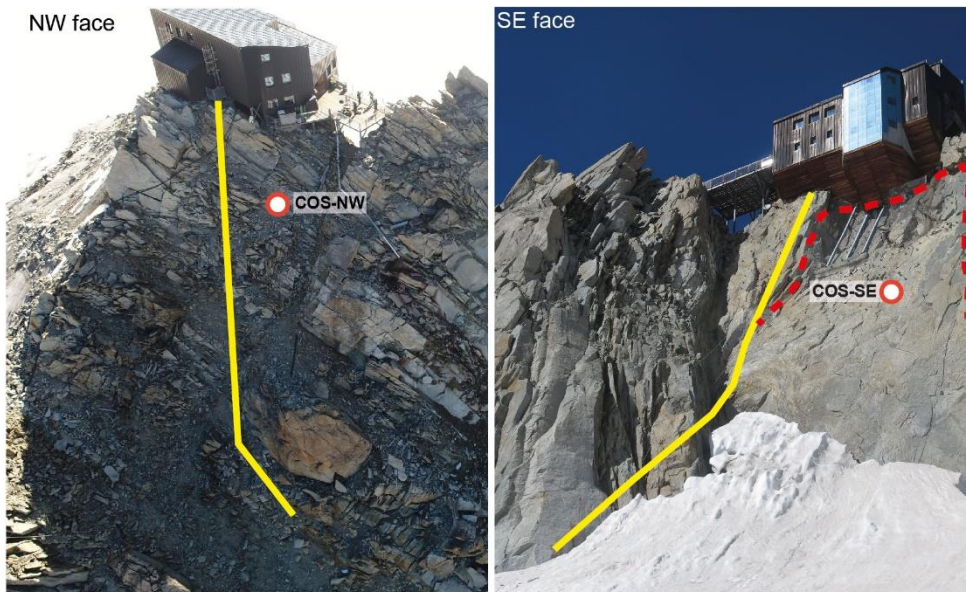


668

669

670 **Figure 1.** The Cosmiques refuge on the lower Cosmiques rock ridge (Mont Blanc massif,
 671 Western European Alps, France). **a.** The Mont Blanc massif (here, the French side) is largely
 672 affected by the permafrost (Magnin et al., 2015a). **b.** The lower Cosmiques ridge close to the
 673 Aiguille du Midi (3842 m a.s.l.). **c.** South-east face of the lower Cosmiques ridge seen from
 674 the glacier du Géant (Sept. 2016). **d.** The Cosmiques rockfall of August 1998 ($\sim 600 \text{ m}^3$).

675



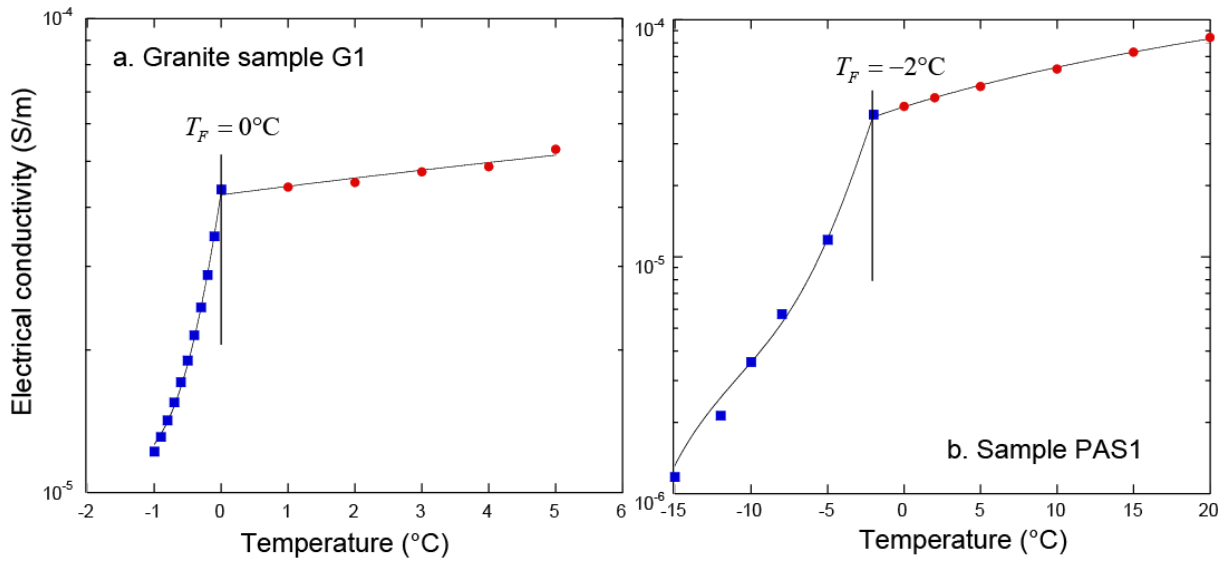
676

677 **Figure 2.** Location of the temperature sensors and the ERT profile below the Cosmiques
678 refuge. The labels COS-NW and COS-SE denote the position of the temperature sensors.

679

680

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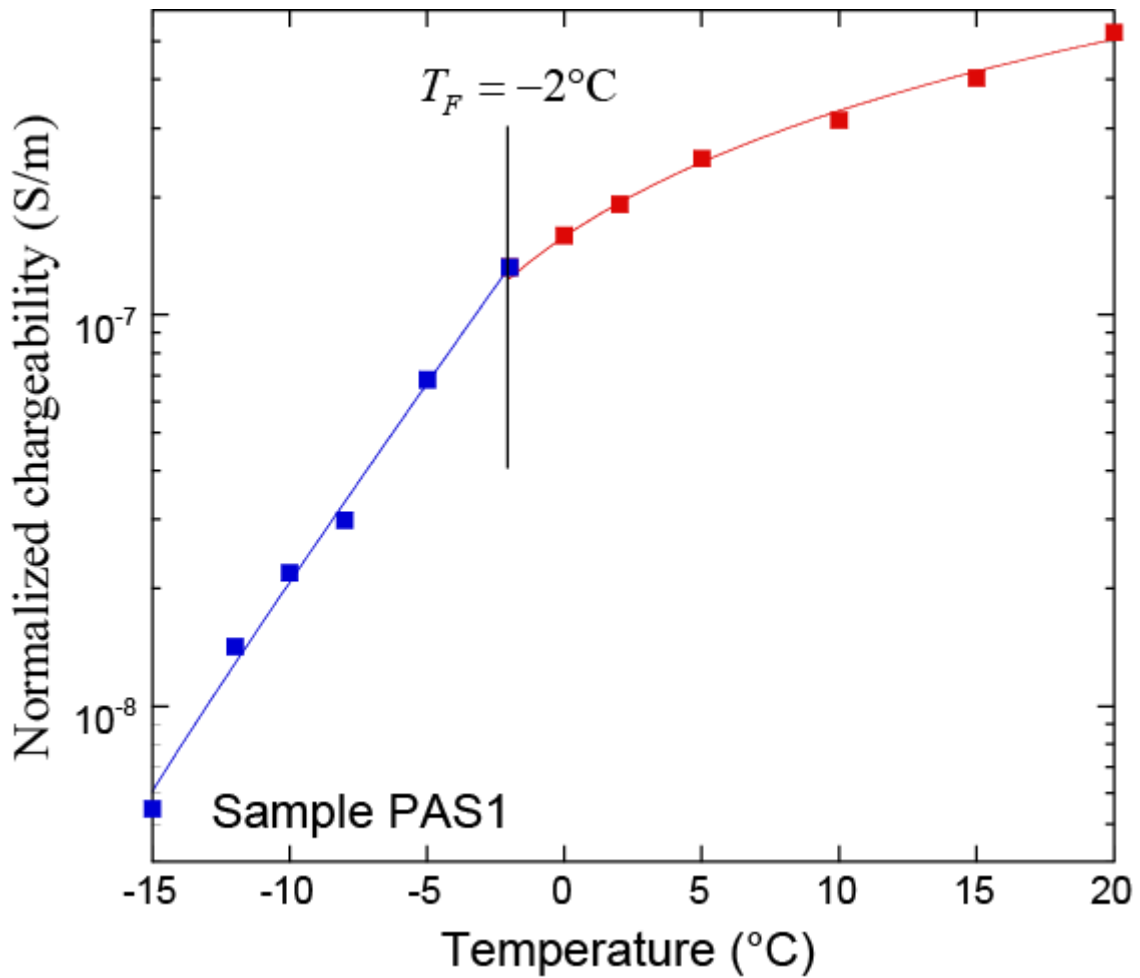
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684 **Figure 3.** Electrical conductivity data versus temperature for two granite core samples from
 685 the Cosmiques rock ridge and fit of the data with the model from Duvillard et al. (2018). **a.**
 686 Granite sample G1 between -1 to $+5^\circ\text{C}$ ($T_F = 0^\circ\text{C}$). The value of model parameters used to fit
 687 the measured data are $T_c = -0.36^\circ\text{C}$, $\phi = 0.028$, $\theta_r = 0.006$, and $\sigma(T_0) = 8.8 \times 10^{-5} \text{ S m}^{-1}$. **b.**
 688 Granite sample PAS1 between -15 to $+20^\circ\text{C}$ ($T_F = -2^\circ\text{C}$). The value of the model parameters
 689 are $T_c = -2.2^\circ\text{C}$, $\phi = 0.028$, $\theta_r = 0.005$, and $\sigma(T_0) = 9.3 \times 10^{-5} \text{ S m}^{-1}$. In both cases, the
 690 symbols denote the experimental data (red above the freezing temperature and blue below the
 691 freezing temperature) while the plain lines correspond to the fit of the model.

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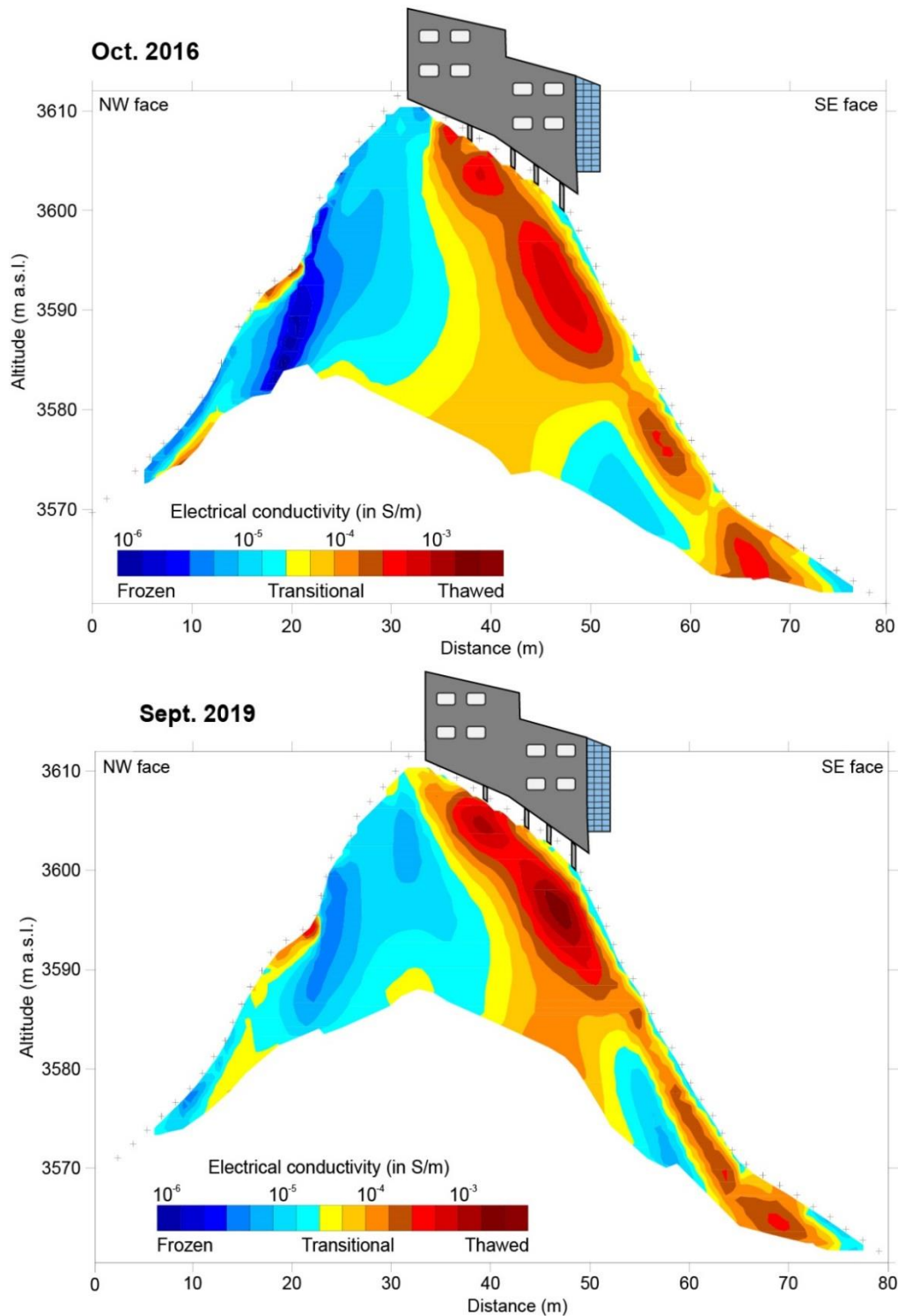


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696 **Figure 4.** Normalized chargeability data versus temperature for the granite core sample PAS1
 697 between -15 to +20°C ($T_F = -2^\circ\text{C}$). The value of the model parameters are $T_c = -5.4 \pm 0.7^\circ\text{C}$,
 698 $\phi = 0.028$, $\theta_r = 0.001$, $M_n(T_0) = 5.9 \times 10^{-7} \text{ S m}^{-1}$, $\alpha_T = 0.028 \pm 0.0007 \text{ }^\circ\text{C}^{-1}$. The symbols
 699 denote the experimental data (red above the freezing temperature and blue below the freezing
 700 temperature) while the plain lines correspond to the fit of the model.

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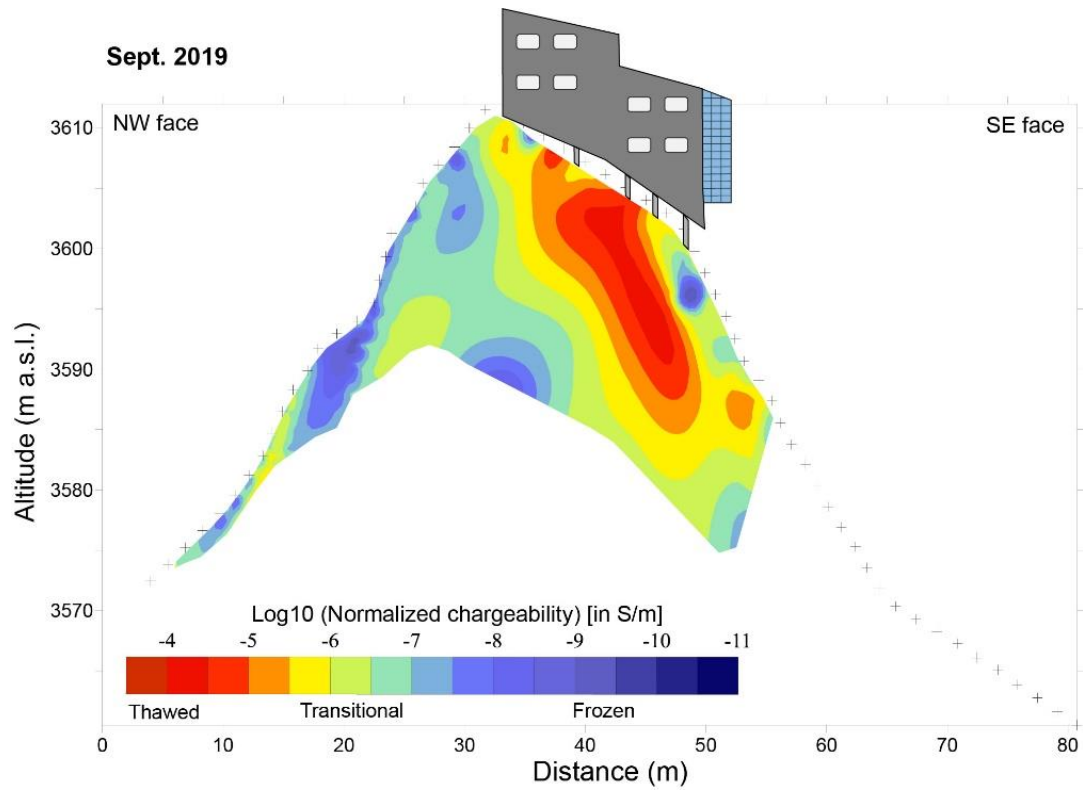
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704 **Figure 5.** Electrical conductivity tomography (in $S\ m^{-1}$) of the rock ridge below the
 705 Cosmiques refuge in 2016 and 2019. We use cold colors for the low conductivity values
 706 presumed to correspond to the rock mass undergoing freezing conditions. The warm colors
 707 corresponds to the rock mass above freezing conditions.

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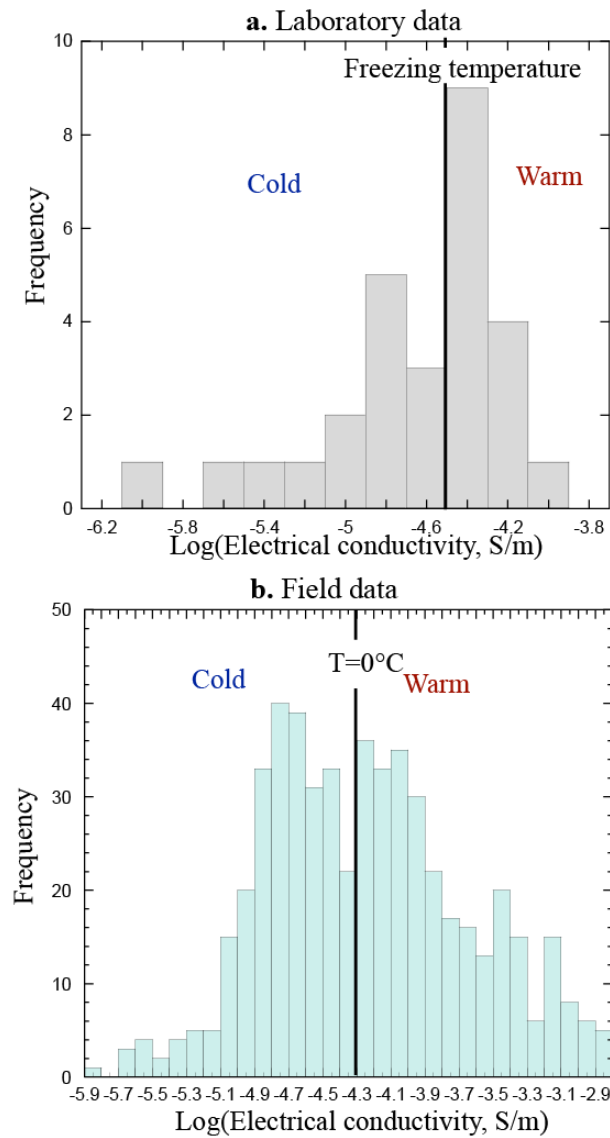


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711 **Figure 6.** Normalized chargeability tomograms (in $S\ m^{-1}$) of the rock ridge below the
 712 Cosmiques refuge in 2019. Tomogram is smaller in SE face due to the lack of inverted data
 713 points.

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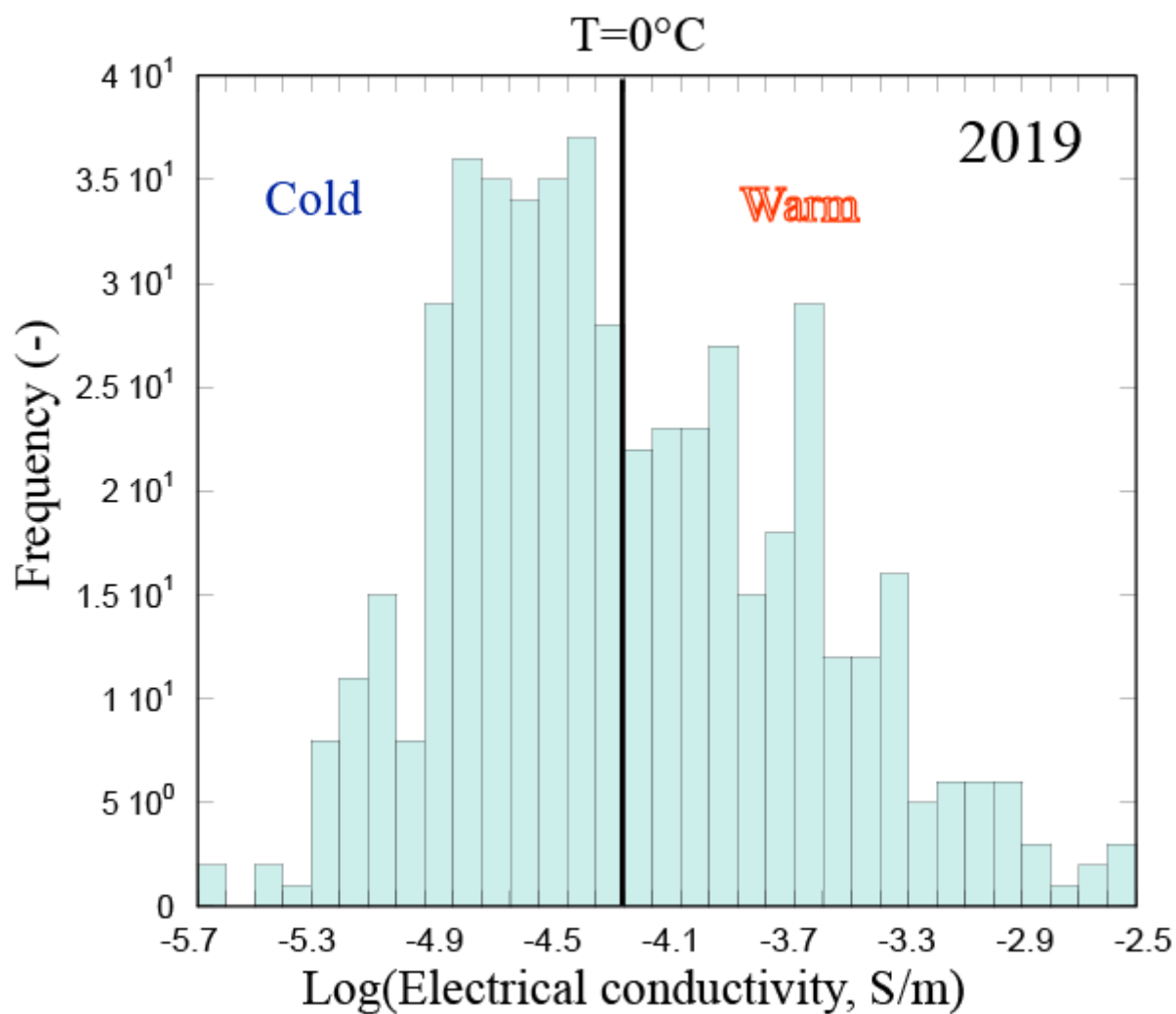


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717 **Figure 7.** Distribution of the electrical conductivity. **a.** Laboratory data. **b.** 2016-Field data
 718 from the electrical conductivity tomogram. The observed minimum in the distribution is used
 719 to define the value of the electrical conductivity of the material at the freezing temperature. In
 720 the field data, we obtain $\sigma(T_f = 0^\circ\text{C}) = 5 \times 10^{-5} \text{ S}\cdot\text{m}^{-1}$ (obtained from the vertical plain line
 721 associated with the minimum in the conductivity distribution).

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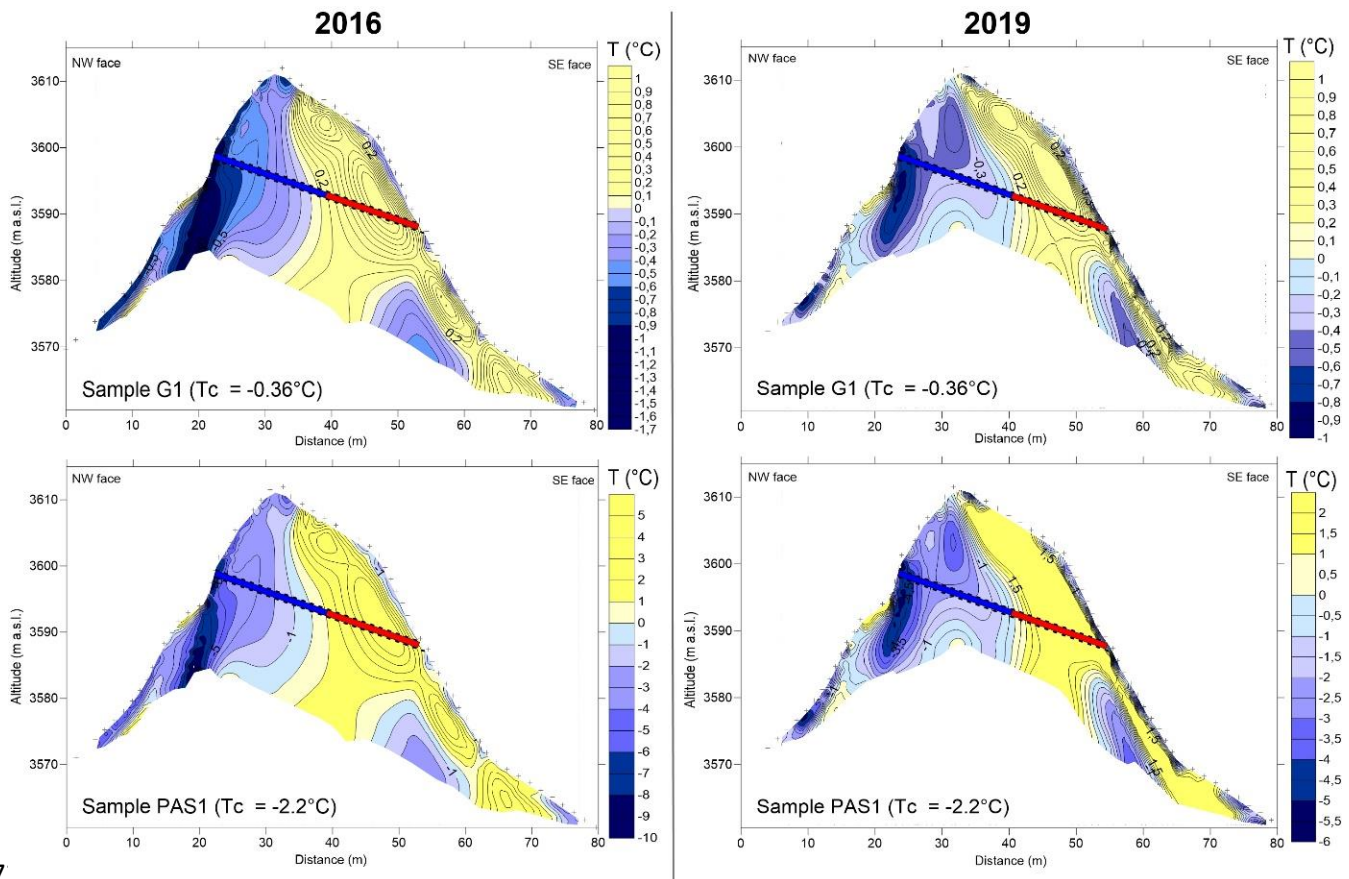


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725 **Figure 8.** Distribution of the electrical conductivity for the 2019 field data. We observe a
 726 clear increase of the conductivity distribution with respect to 2016 (see Figure 7).

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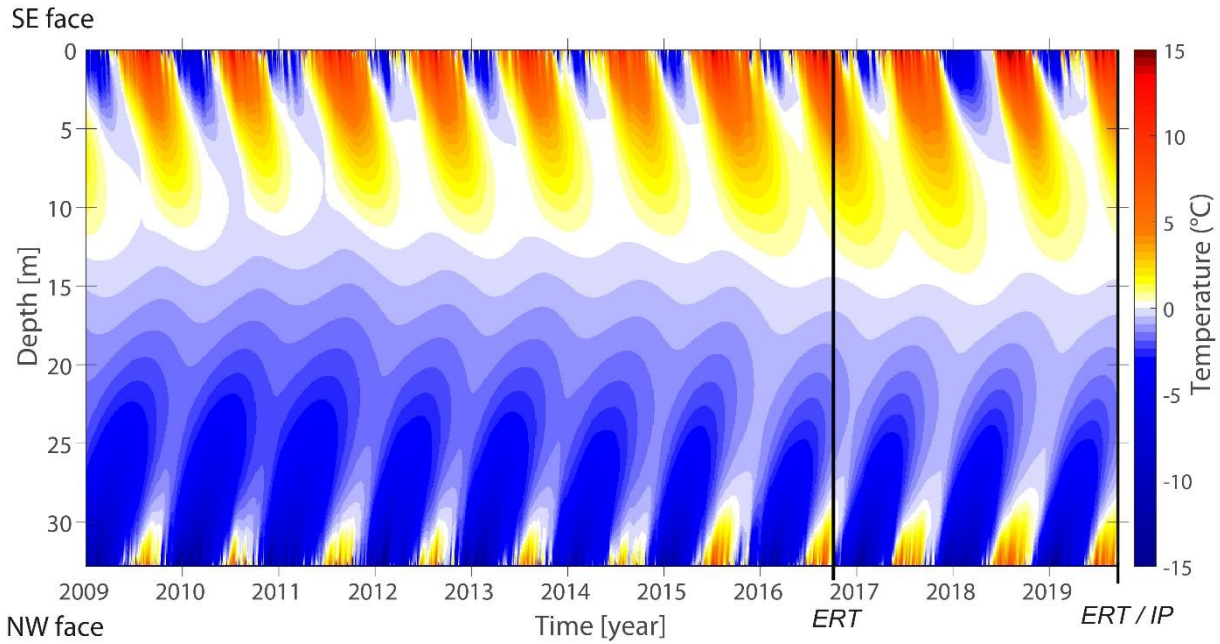
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730 **Figure 9.** Distribution of the temperature determined from the electrical conductivity
 731 distribution for the 2016 and 2019 tomograms. **a.** Distribution obtained with the characteristic
 732 temperature $T_c = -0.4^\circ\text{C}$ and $T_c = -2.2^\circ\text{C}$. Permafrost is inferred below the NW face of the
 733 rock ridge. We also show the pseudo-horizontal section of length 32.75 m crossing the ridge
 734 and used for the numerical modeling of the temperature field. The blue portion of this profile
 735 denotes the frozen section while the red portion indicates the zone above the freezing
 736 temperature. Note the excellent agreement between the geophysical prediction and the
 737 numerical model.

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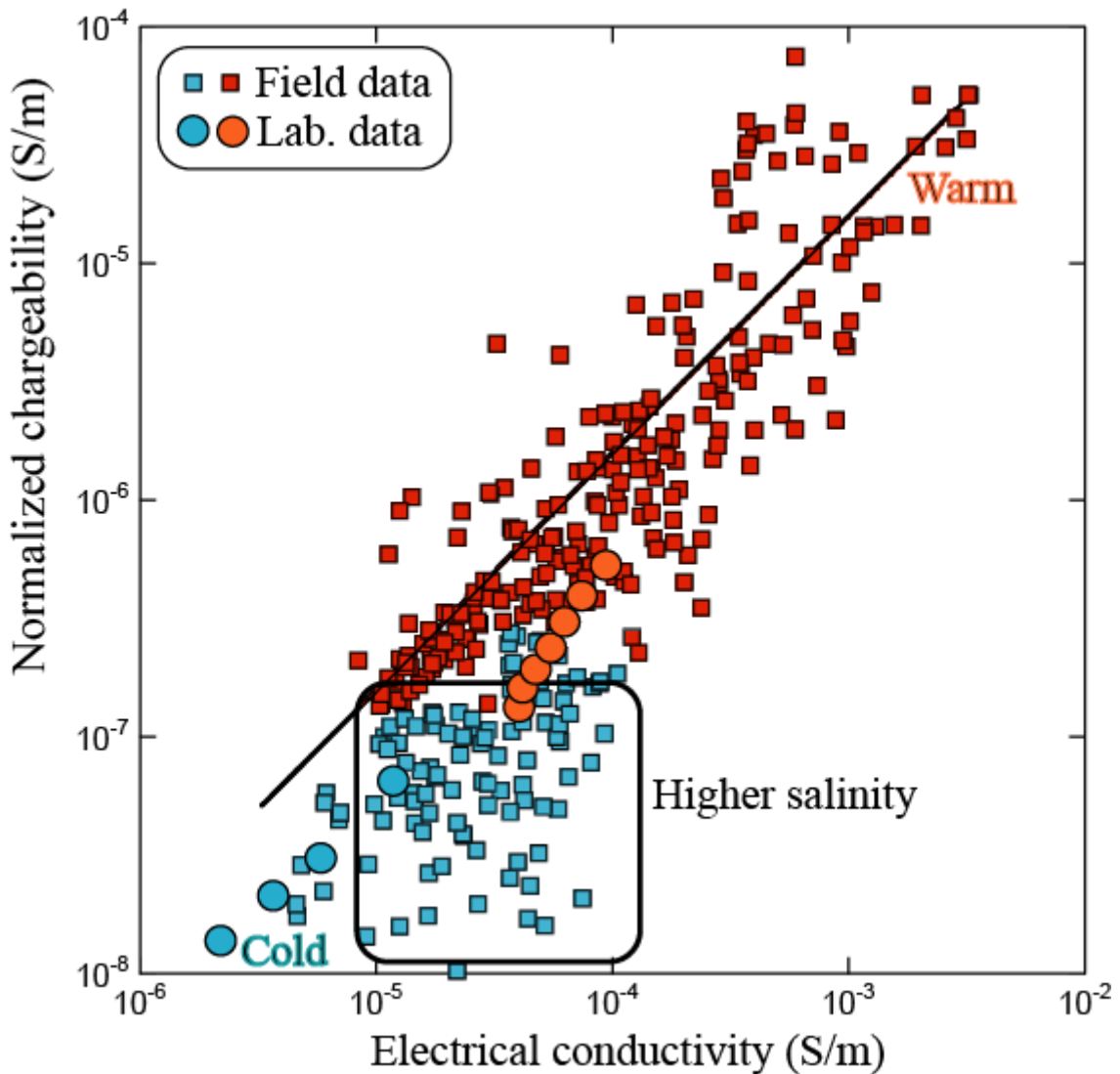
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743 **Figure 10.** Modelled daily rock temperature along a horizontal section of 32.75 m crossing
 744 the ridge (as shown in Figure 9). The SE face of the rock ridge corresponds to the top of the
 745 section while the NW face corresponds to the bottom part of the section. The temperature
 746 distribution is modeled by applying the observed thermal boundary conditions as explained in
 747 the main text. The two vertical lines correspond to the acquisition dates (in 2017 and 2019) of
 748 the geophysical data (ERT stands for electrical resistivity tomography while IP stands for
 749 induced polarization). We see that a large portion of the ridge is expected to be frozen.

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754 **Figure 11.** Normalized chargeability versus electrical conductivity. Comparison between the
 755 field and laboratory data (PAS1). The color code is blue for the cold values below the freezing
 756 temperature and red above the freezing temperature. The plain line corresponds to the best fit
 757 of the field data (with a slope of 0.016, $r = 0.69$). The small value of the slope (smaller than R
 758 = 0.10 indicates that conductivity is mostly dominated by the pore water contribution.

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