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P.-A Duvillard, Florence Magnin, André Revil, A Legay, Ludovic Ravanel, F Abdulsamad, A Coperey

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

4 P.-A. Duvillard<sup>1,2,3</sup>, F. Magnin<sup>1</sup>, A. Revil<sup>1</sup>, A. Legay<sup>1</sup>, L. Ravanel<sup>1</sup>,  
5 F. Abdulsamad<sup>1</sup>, and A. Coperey<sup>1</sup>

6  
7 1. EDYTEM, Univ. Savoie Mont-Blanc, Univ. Grenoble Alpes, CNRS, 73000 Chambéry, France.

8 2. PACTE, Univ. Grenoble Alpes, CNRS, 38000 Grenoble, France.

9

10 **Corresponding author:** André Revil ([andre.revil@univ-smb.fr](mailto:andre.revil@univ-smb.fr))

11

12 **Emails:** [pierre-allain.duvillard@univ-smb.fr](mailto:pierre-allain.duvillard@univ-smb.fr); [florence.magnin@univ-smb.fr](mailto:florence.magnin@univ-smb.fr);

13 [andre.revil@univ-smb.fr](mailto:andre.revil@univ-smb.fr); [ludovic.ravanel@univ-smb.fr](mailto:ludovic.ravanel@univ-smb.fr); [feras.abdul-samad@univ-smb.fr](mailto:feras.abdul-samad@univ-smb.fr).

14 [antoine.coperey@univ-smb.fr](mailto:antoine.coperey@univ-smb.fr); [legay.alexandre@gmail.com](mailto:legay.alexandre@gmail.com)

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

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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-m<sup>3</sup>-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  $\text{S m}^{-1}$ ) 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  $\theta$  (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  $\theta_r$  (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,  $\phi$  (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  $\phi$ , 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  $\text{S m}^{-1}$ ) 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  $\theta$  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

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

212 When the conductivity of the rock is dominated by surface conductivity along the surface of  
 213 the grains (i.e.,  $\sigma_w \ll \rho_g \text{BCEC}$ ), this ratio is exactly given by  $R = \lambda / B = 0.10$ , independent  
 214 of the water content and temperature (Duvillard et al., 2018). When we have  $M_n(T) / \sigma(T) < R$ ,  
 215 this means that the bulk contribution of electrical conductivity (related to the pore water  
 216 conduction  $\sigma_w$ ) 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 m<sup>3</sup>-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 3<sup>rd</sup> 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 CEC = 0.80 meq/100 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<sup>-1</sup>.

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<sub>2</sub> 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 × 400 × 546 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 1<sup>st</sup> and 2019 September 18<sup>th</sup>. 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  $10^{-4} \text{ S.m}^{-1}$  and  $10^{-5} \text{ S.m}^{-1}$ ) or normalized chargeability  
381 values (between  $10^{-6} \text{ S.m}^{-1}$  and  $10^{-7} \text{ S.m}^{-1}$ ) 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  $25^\circ\text{C}$  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,  $-1.7^\circ\text{C}$   
410 in 2016, then  $-1^\circ\text{C}$  in 2019; sample PAS1,  $-10^\circ\text{C}$  in 2016, then  $-6^\circ\text{C}$  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  $-3.7^\circ\text{C}$  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 1<sup>st</sup> to 2019 September 18<sup>th</sup>. They  
419 show a depth of the permafrost in the NW face around -15 m with temperature between  $-2/-$   
420  $3^\circ\text{C}$  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  $0^\circ\text{C}$ ) 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  $2.2^\circ\text{C}$  (sample PAS1 saturated with snowmelt; Figure 3a) suggests that the bedrock  
434 temperature is between  $-2^\circ\text{C}$  and  $-4^\circ\text{C}$  in 2016 and 2019 at a depth of 10 m in the NW face  
435 while the temperatures simulated with the numerical model is  $-2^\circ\text{C}$ . The determination of the  
436 temperature distribution assuming  $T_c = -0.36^\circ\text{C}$  (Figure 3b) suggests a bedrock temperature of  
437  $-0.5^\circ\text{C}$  at 10 m depth in 2016 and 2019 while the numerical simulation suggests  $-2^\circ\text{C}$ .  
438 Therefore, the numerical modeling shows that the NW face of the rock ridge is frozen  
439 (permafrost conditions) with a temperature around  $-2^\circ\text{C}$ ; 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  $-2^{\circ}\text{C}$ , 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

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## Tables

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

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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

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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.

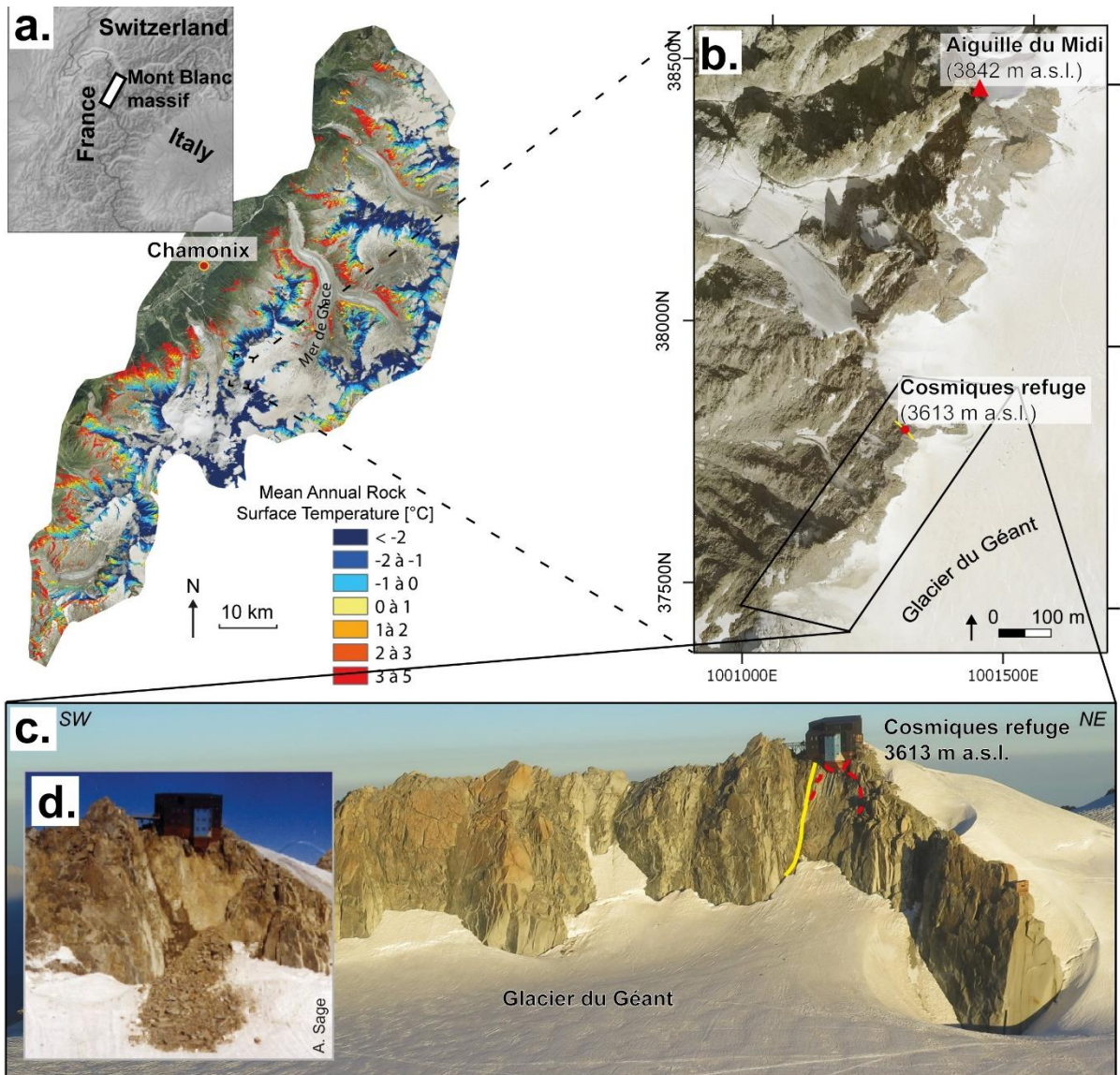
Parameter	Value
Thermal conductivity	$3.3 \text{ W K}^{-1} \text{ K}^{-1}$
Porosity	0.01
Volumetric heat capacity	$2.10^6 \text{ J m}^{-3} \text{ K}^{-1}$

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## Figures

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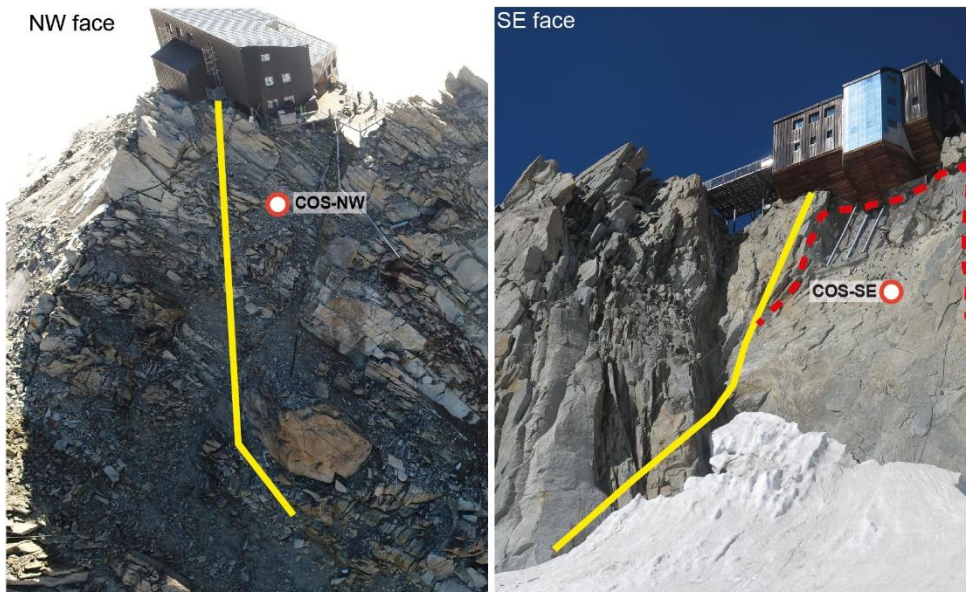


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670 **Figure 1.** The Cosmiques refuge on the lower Cosmiques rock ridge (Mont Blanc massif,  
 671 Western European Alps, France). **a.** The Mont Blanc massif (here, the French side) is largely  
 672 affected by the permafrost (Magnin et al., 2015a). **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 ( $\sim 600 \text{ m}^3$ ).

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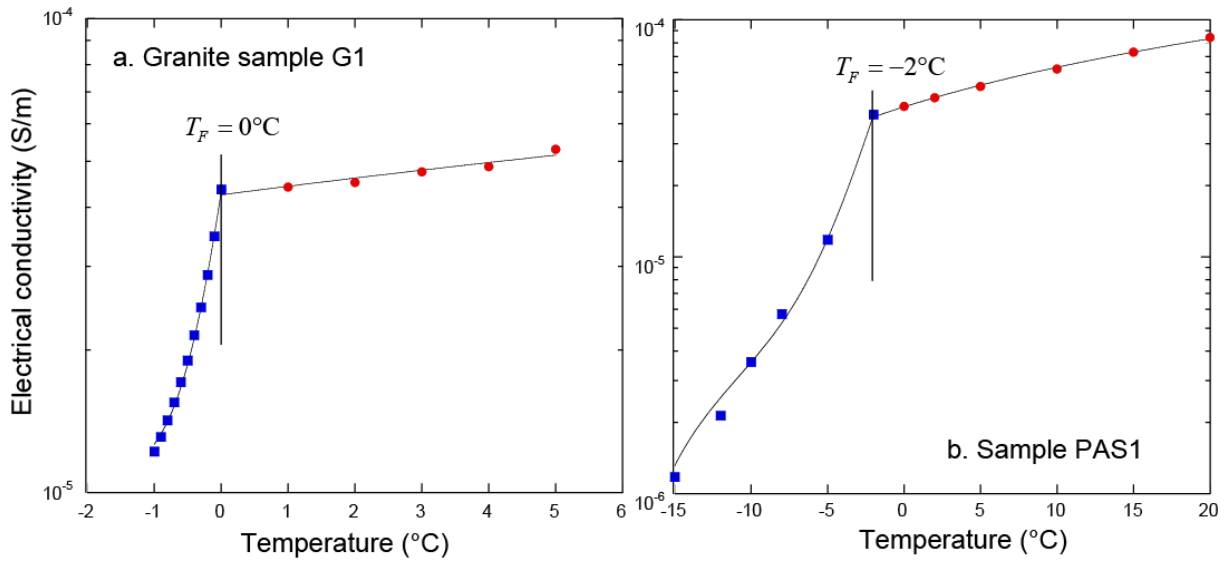
677 **Figure 2.** Location of the temperature sensors and the ERT profile below the Cosmiques  
678 refuge. The labels COS-NW and COS-SE denote the position of the temperature sensors.

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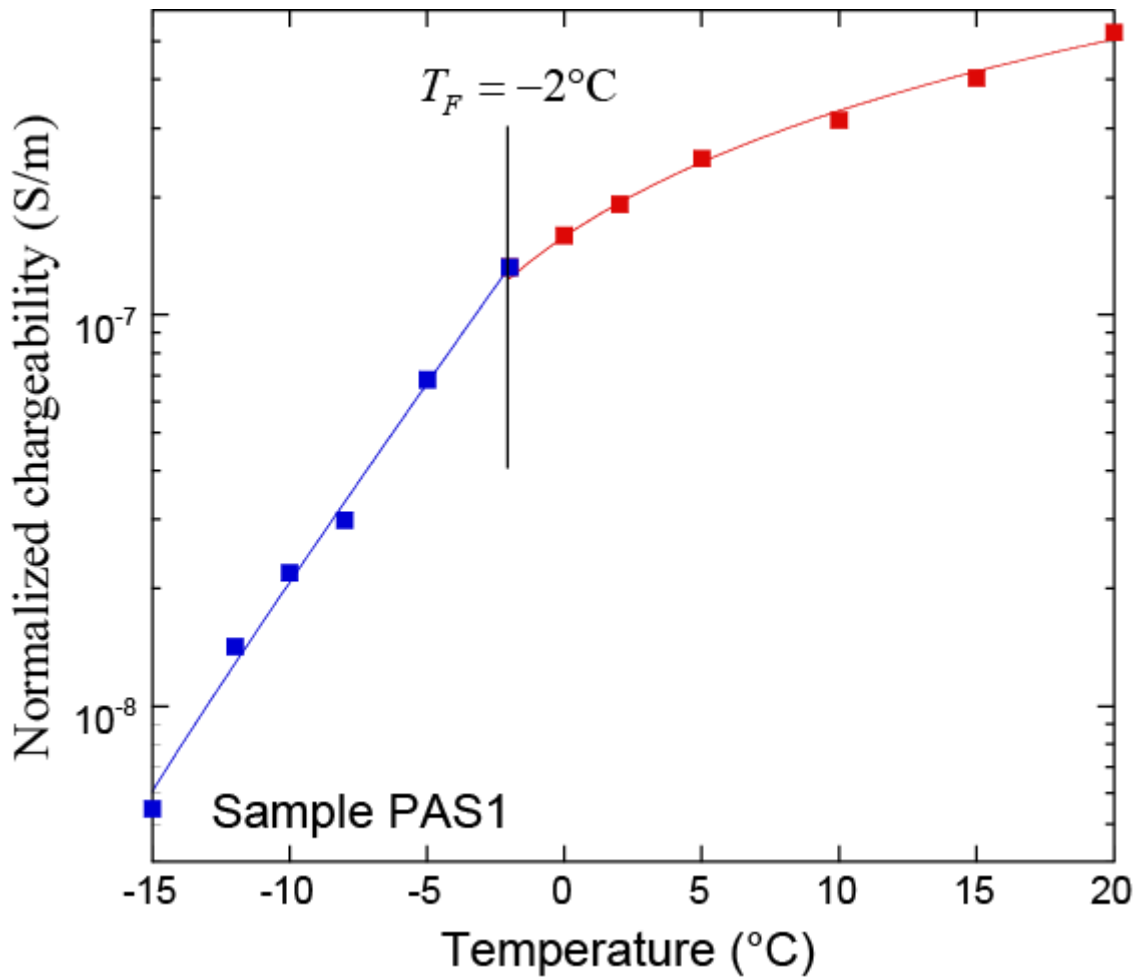
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684 **Figure 3.** Electrical conductivity data versus temperature for two granite core samples from  
 685 the Cosmiques rock ridge and fit of the data with the model from Duvillard et al. (2018). **a.**  
 686 Granite sample G1 between  $-1$  to  $+5^\circ\text{C}$  ( $T_F = 0^\circ\text{C}$ ). 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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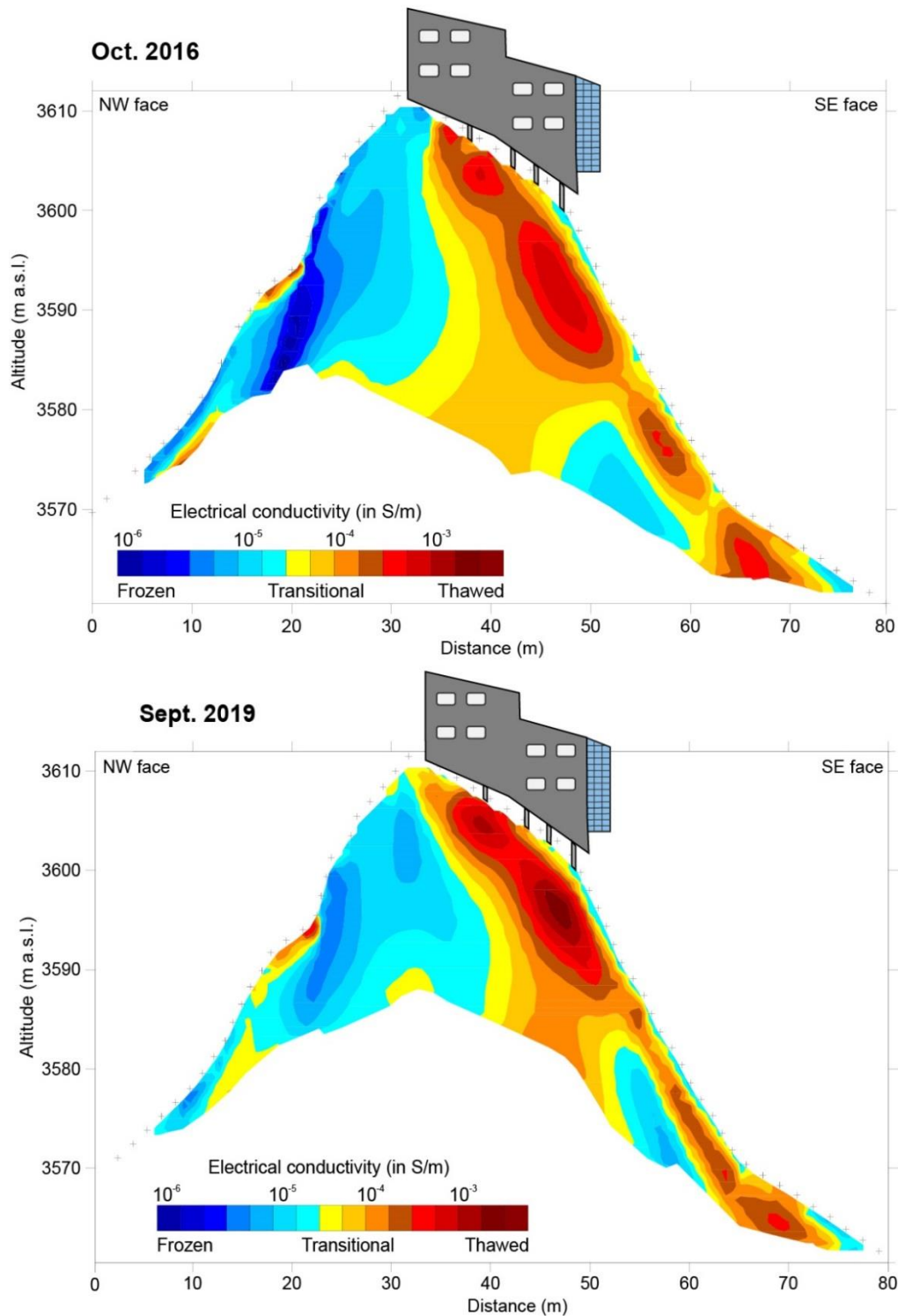


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696 **Figure 4.** Normalized chargeability data versus temperature for the granite core sample PAS1  
 697 between -15 to +20°C ( $T_F = -2^\circ\text{C}$ ). The value of the model parameters are  $T_c = -5.4 \pm 0.7^\circ\text{C}$ ,  
 698  $\phi = 0.028$ ,  $\theta_r = 0.001$ ,  $M_n(T_0) = 5.9 \times 10^{-7} \text{ S m}^{-1}$ ,  $\alpha_T = 0.028 \pm 0.0007 \text{ }^\circ\text{C}^{-1}$ . 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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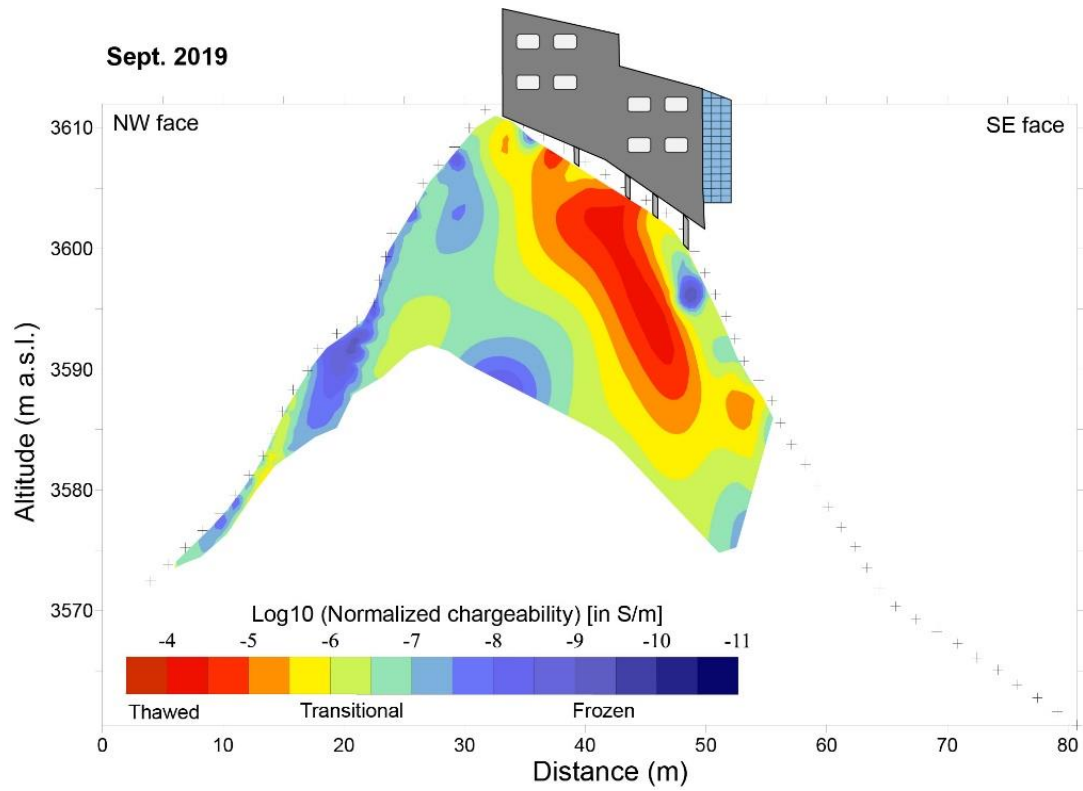
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704 **Figure 5.** Electrical conductivity tomography (in  $S\ m^{-1}$ ) of the rock ridge below the  
 705 Cosmiques refuge in 2016 and 2019. We use cold colors for the low conductivity values  
 706 presumed to correspond to the rock mass undergoing freezing conditions. The warm colors  
 707 corresponds to the rock mass above freezing conditions.

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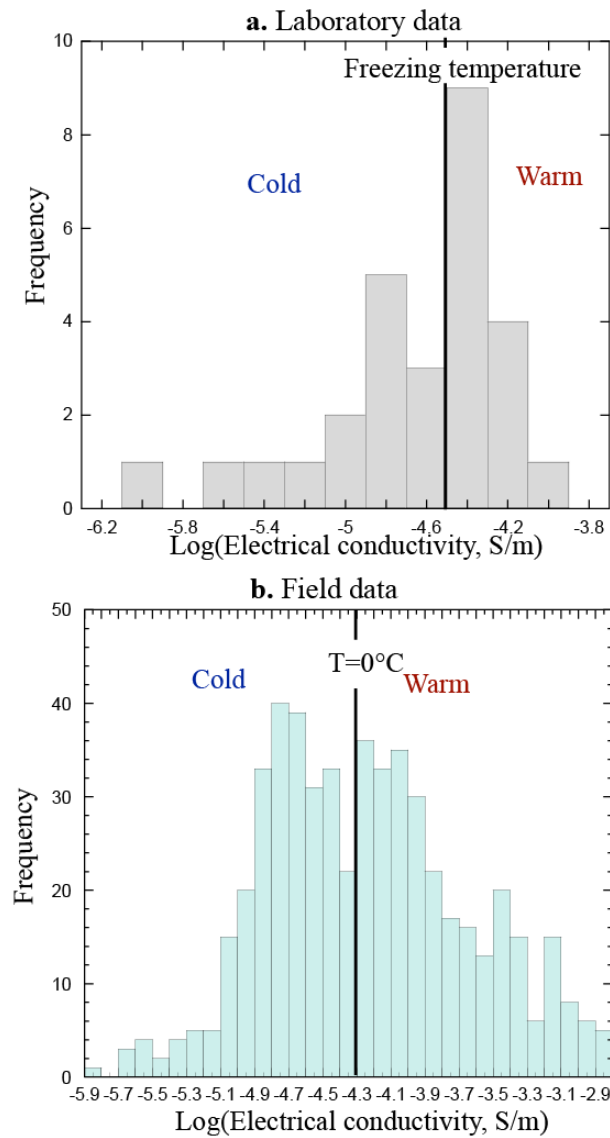


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711 **Figure 6.** Normalized chargeability tomograms (in  $S\ m^{-1}$ ) of the rock ridge below the  
 712 Cosmiques refuge in 2019. Tomogram is smaller in SE face due to the lack of inverted data  
 713 points.

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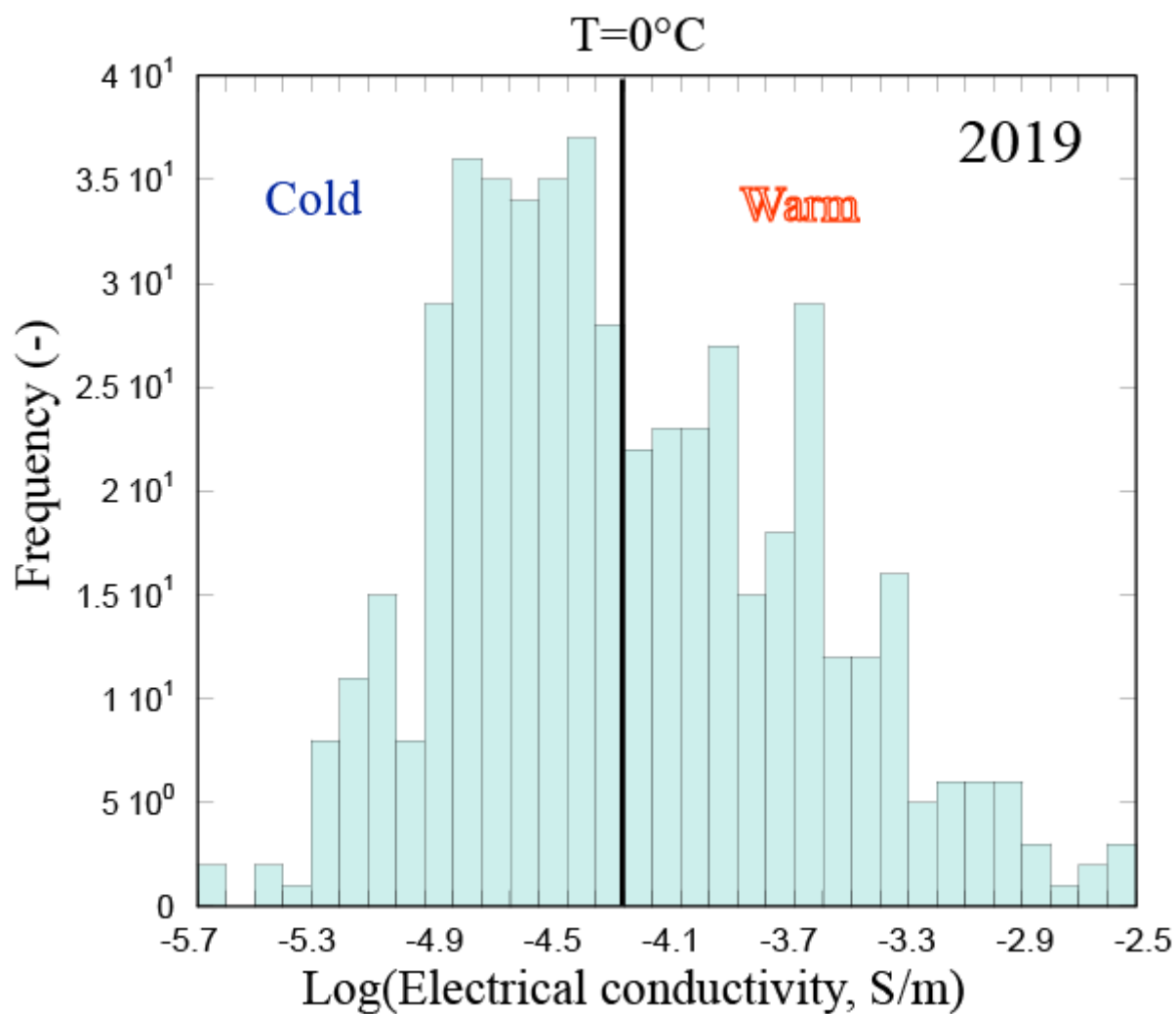


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717 **Figure 7.** Distribution of the electrical conductivity. **a.** Laboratory data. **b.** 2016-Field data  
 718 from the electrical conductivity tomogram. The observed minimum in the distribution is used  
 719 to define the value of the electrical 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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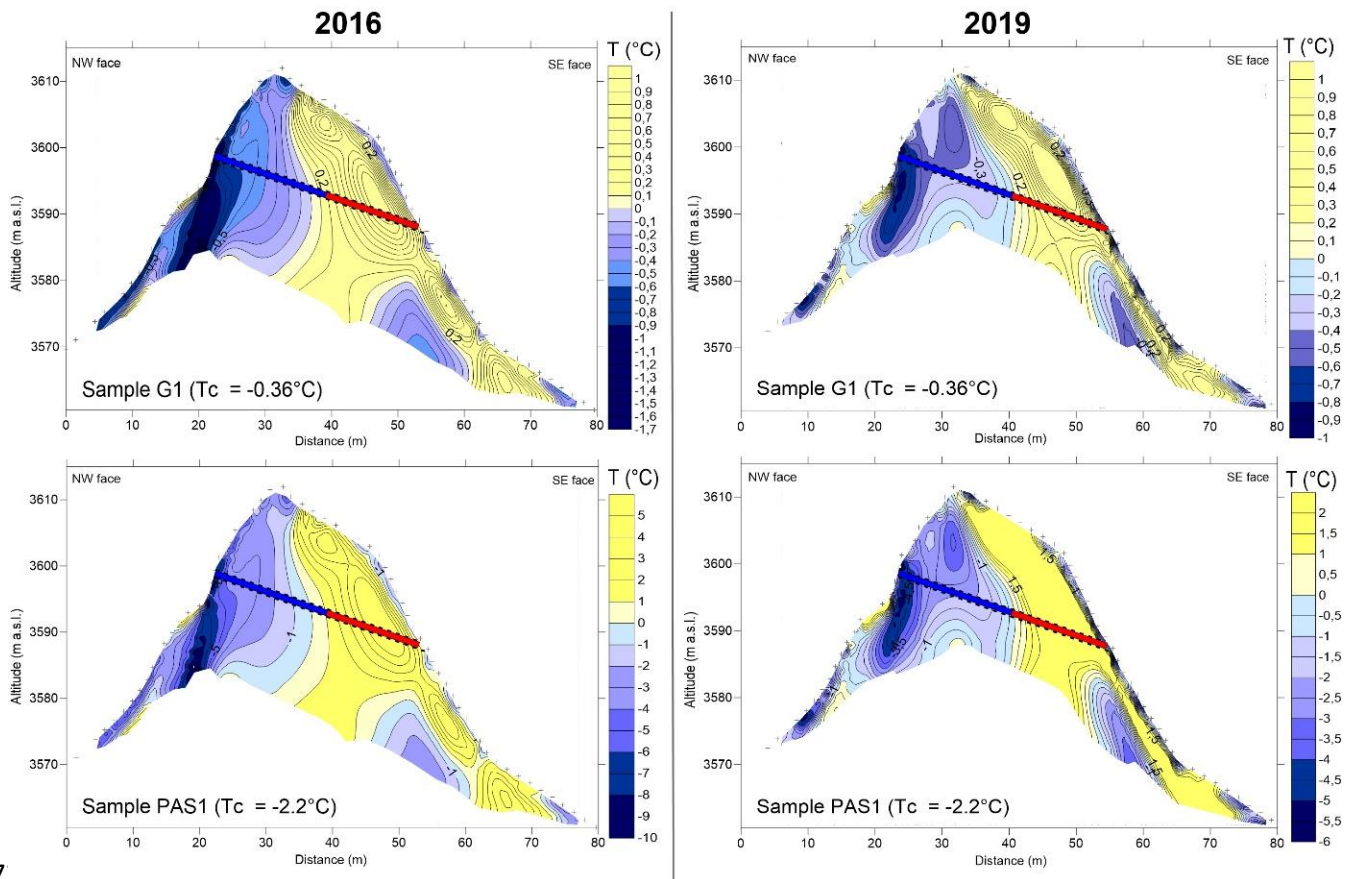


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725 **Figure 8.** Distribution of the electrical conductivity for the 2019 field data. We observe a  
 726 clear increase of the conductivity distribution with respect to 2016 (see Figure 7).

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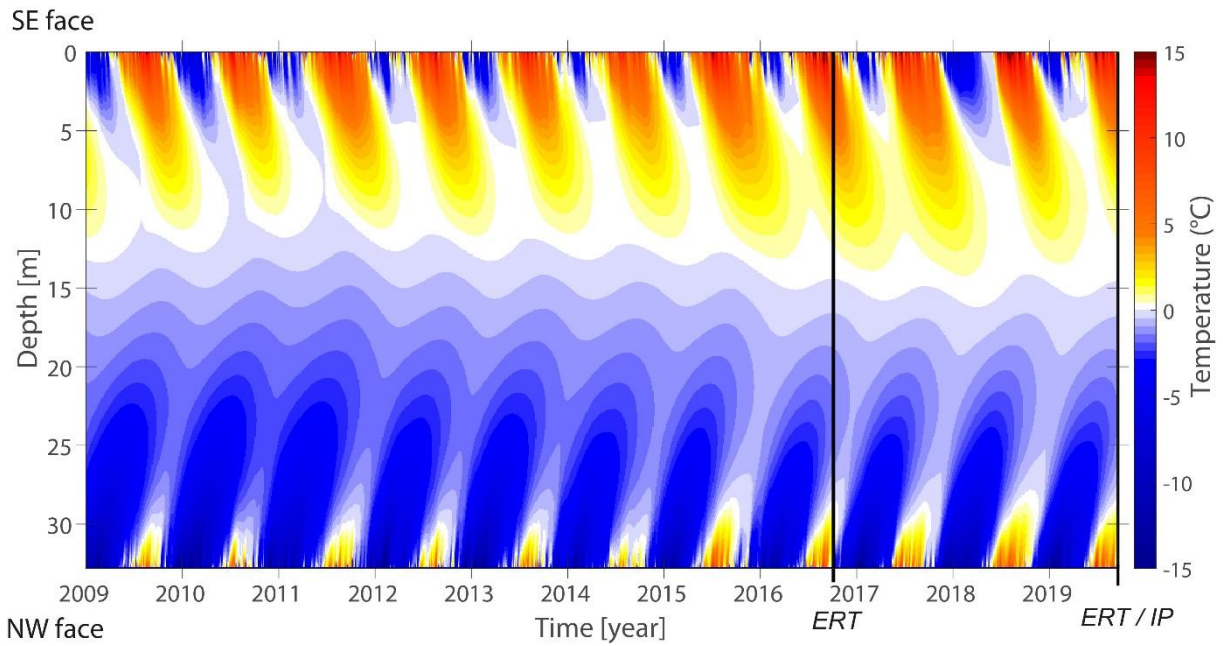
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730 **Figure 9.** Distribution of the temperature determined from the electrical conductivity  
 731 distribution for the 2016 and 2019 tomograms. **a.** Distribution obtained with the characteristic  
 732 temperature  $T_c = -0.4^\circ\text{C}$  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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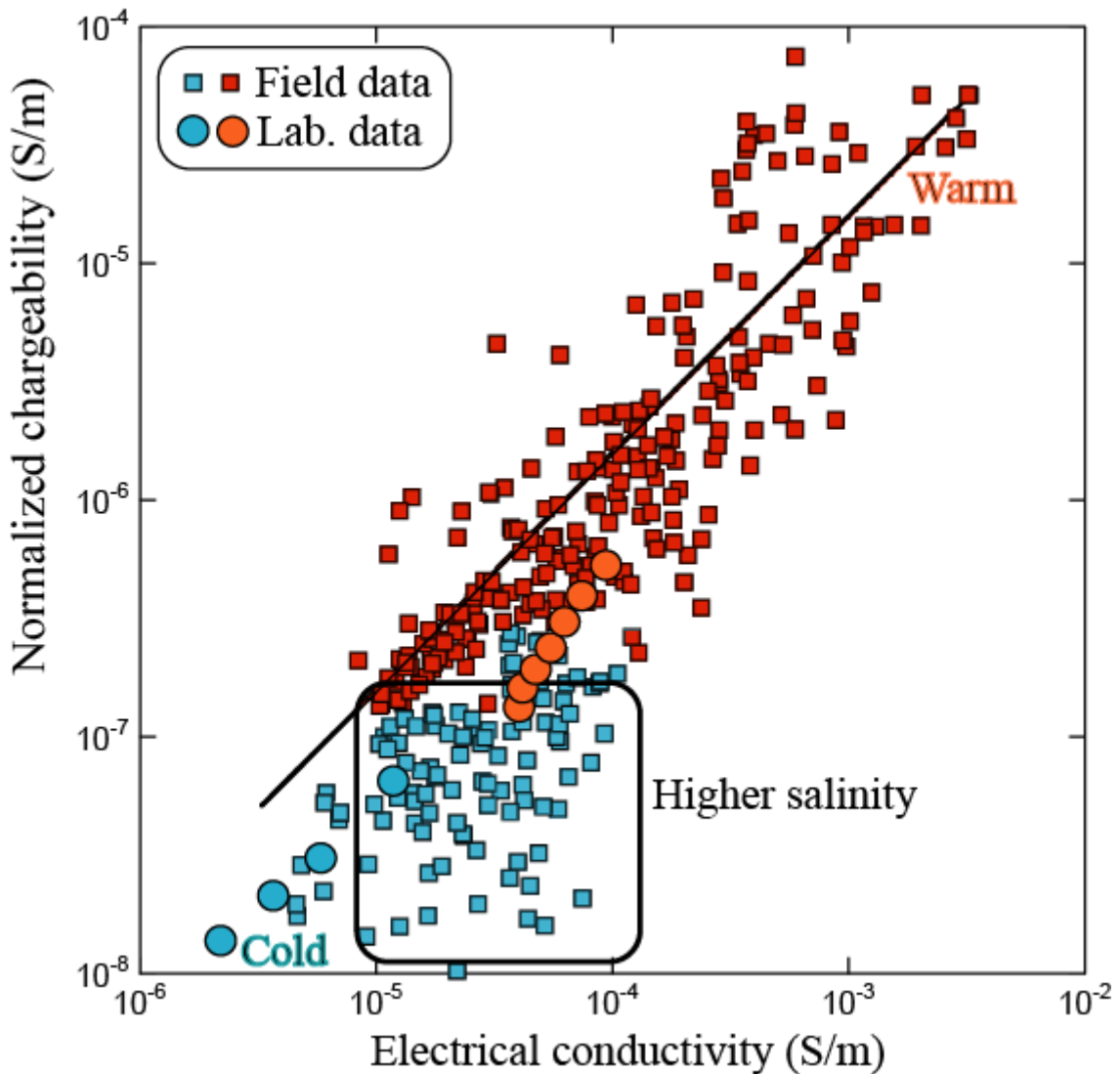
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743 **Figure 10.** Modelled daily rock temperature along a horizontal section of 32.75 m crossing  
 744 the ridge (as shown in Figure 9). The SE face of the rock ridge corresponds to the top of the  
 745 section while the NW face corresponds to the 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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