

1 **Response to the Editor**

2

3 Dear Martin,

4

5 Thank you for your comments.

6

7 In Figure 1, we have modified the caption to indicate that the needle probes were at 14, 24, 34  
8 and 44 cm above the ground-lichen interface.

9

10 In Figure 4b, the temperatures never gets close to  $-50^{\circ}\text{C}$ . You may have mixed up the  
11 temperature and wind speed curves. The temperature curve is in red, and the minimum  
12 temperature was  $-38^{\circ}\text{C}$ , so we believe that the scale lower limit of  $-50^{\circ}\text{C}$  is adequate.

13

14 We change “snow height differ” to “snow heights differ” (Figure 5 caption).

15

16 The title of the reference Payette et al. (2001) has been fixed.

17

18 Thank you for your careful reading.

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21 Florent Domine, on behalf of all authors.

22

23

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25

1 **Automatic monitoring of the effective thermal conductivity**  
2 **of snow in a low Arctic shrub tundra**

3  
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15

16 **Abstract**

17 The effective thermal conductivity of snow,  $k_{eff}$ , is a critical variable which determines the  
18 temperature gradient in the snowpack and heat exchanges between the ground and the  
19 atmosphere through the snow. Its accurate knowledge is therefore required to simulate snow  
20 metamorphism, the ground thermal regime, permafrost stability, nutrient recycling and  
21 vegetation growth. Yet, few data are available on the seasonal evolution of snow thermal  
22 conductivity in the Arctic. We have deployed heated needle probes on low Arctic shrub  
23 tundra near Umiujaq, Quebec, (N56°34'; W76°29') and monitored automatically the  
24 evolution of  $k_{eff}$  for two consecutive winters, 2012-2013 and 2013-2014, at 4 heights in the  
25 snowpack. Shrubs are 20 cm-high dwarf birch. Here, we develop an algorithm for the  
26 automatic determination of  $k_{eff}$  from the heating curves and obtain 404  $k_{eff}$  values. We evaluate  
27 possible errors and biases associated with the use of the heated needles. The time-evolution of  
28  $k_{eff}$  is very different for both winters. This is explained by comparing the meteorological  
29 conditions in both winters, which induced different conditions for snow metamorphism. In

1 particular, important melting events in the second year increased snow hardness, impeding  
2 subsequent densification and increase in thermal conductivity. We conclude that shrubs have  
3 very important impacts on snow physical evolution: (1) shrubs absorb light and facilitate  
4 snow melt under intense radiation; (2) the dense twig network of dwarf birch prevent snow  
5 compaction and therefore  $k_{eff}$  increase; (3) the low density depth hoar that forms within shrubs  
6 collapsed in late winter, leaving a void that was not filled by snow.

7

## 8 **1 Introduction**

9 Snow on the ground acts as a thermally insulating layer which limits ground cooling in  
10 winter. This has large scale and far-reaching implications concerning for example the  
11 recycling of soil nutrients and their availability for the subsequent growing season (Saccone et  
12 al., 2013; Sturm et al., 2005) and the thermal regime of permafrost (Zhang, 2005). An  
13 essential variable to quantify snow thermal effects is its effective thermal conductivity,  $k_{eff}$   
14 (Calonne et al., 2011; Sturm et al., 1997), defined as:

$$15 \quad F = -k_{eff} \frac{dT}{dz} \quad (1),$$

16 with  $F$  the heat flux in  $\text{W m}^{-2}$  and  $dT/dz$  the vertical temperature gradient in  $\text{K m}^{-1}$  through the  
17 layer. The variable is termed “effective” because besides the fact that it is meant to represent  
18 the conductive behaviour of snow as a porous medium made of ice and air, which already  
19 makes it an effective property, it also implicitly includes processes such as heat transfer by  
20 latent heat exchanges caused by sublimation and condensation during snow metamorphism  
21 (Sturm et al., 1997).

22 The snowpack is made up of layers of different properties, and the insulating properties of a  
23 whole snowpack may be described by its thermal resistance  $R_T$  (Domine et al., 2012; Liston et  
24 al., 2002; Sturm et al., 2001), which sums up the properties of all the layers:

$$25 \quad R_T = \sum_i \frac{h_i}{k_{eff,i}} \quad (2)$$

26 where  $h_i$  is the thickness of layer  $i$ .  $R_T$  thus has units of  $\text{m}^2 \text{K W}^{-1}$ . Under steady state  
27 conditions, this variable relates the upward heat flux through the snowpack  $F$  to the  
28 temperature difference between its surface and its base,  $T_{top}-T_{base}$ :

1 
$$F = -\frac{T_{top} - T_{base}}{R_T} \quad (3)$$

2 However, while  $R_T$  gives a useful and intuitive indication of the snowpack properties,  
3 representing a complex layered snowpack as a single homogeneous layer characterized by  $R_T$   
4 can lead to very large errors in simulated soil temperature, because steady state conditions are  
5 seldom reached in nature. The detailed thermal structure of the snowpack must therefore be  
6 known for a proper simulation of the ground thermal regime (Ekici et al., 2014), and how it  
7 will evolve with global warming.

8 Sturm et al. (2005) and Gouttevin et al. (2012) have shown that snow-vegetation interactions  
9 could accelerate permafrost thawing in a climate warming context. The general idea is that  
10 warming-induced shrub growth on Arctic herb tundra leads to snow trapping. Shrubs then  
11 shelter snow from wind erosion and compaction, facilitating the formation of insulating depth  
12 hoar layers at the expense of more heat-conductive wind slabs. This results in reduced soil  
13 winter cooling. Gouttevin et al. (2012) illustrated the effect of vegetation by examining the  
14 extreme case where herb tundra would be replaced by taiga.  $R_T$  values increase from about 3  
15  $\text{m}^2 \text{K W}^{-1}$  for herb tundra to values at least 4 times higher for taiga, resulting in soil warming  
16 reaching 12 K. Since permafrost thawing could lead to the microbial mineralization of soil  
17 carbon, with the release of greenhouse gases  $\text{CO}_2$  and  $\text{CH}_4$ , (Koven et al., 2011; Schuur et al.,  
18 2008), this example demonstrates the importance of snow-vegetation interactions to  
19 understand snow thermal conductivity and the ground thermal regime.

20 Improving the description of thermal conductivity in snow and land surface models requires,  
21 in addition to model improvements, the acquisition of in-situ data in various environments. In  
22 particular, very little data are available on the thermal conductivity of Arctic and subarctic  
23 snow as it evolves through the winter, especially as a function of vegetation type. Indeed,  
24 interactions between snow and vegetation are believed to play a strong role on the time  
25 evolution of the physical properties of snow (Liston et al., 2002). Winter-long monitoring of  
26 snow thermal conductivity has rarely been done, and these few studies are limited to taiga  
27 (Sturm and Johnson, 1992) and Alpine snow (Morin et al., 2010).

28 The purpose of this work is twofold. First, we test a method for the continuous monitoring of  
29 snow thermal conductivity in northern regions and for the automatic analysis of the data.  
30 Second, we obtain two years of data on the evolution of snow thermal conductivity, and these  
31 are the first such time series for snow on shrub tundra. We therefore discuss these data and in

1 particular two aspects where the new time series differ from existing ones: the impact of  
2 shrubs and of melt-freeze events on the evolution of  $k_{eff}$ .

## 3 **2 General methods**

4 Our study site was near Umiujaq, on the eastern shore of Hudson Bay, Quebec, Canada, N:  
5  $56^{\circ}33'31''$  W: $76^{\circ}28'56''$ . Vegetation types there include herb tundra, shrub tundra with dwarf  
6 birch and willows, 20 cm to 1 m height, and forest tundra (i.e. forest patches on tundra,  
7 (Payette et al., 2001). Bare basalt outcrops are also frequent. Umiujaq is just north of the tree  
8 line, as the boreal open forest can be found about 40 km to the east and south. The  
9 experimental system discussed here was deployed in shrub tundra dominated by dwarf birch  
10 (*Betula glandulosa*). The ground under the birch was entirely covered with cladonia, a thick  
11 ( $\approx 5$  to 10 cm) white lichen of very low density that formed a highly insulating layer on top of  
12 the ground. Measured  $k_{eff}$  valued in the cladonia were around  $0.025 \text{ W m}^{-1} \text{ K}^{-1}$ , essentially the  
13 value of air. The system deployed consisted of 4 TP02 heated needle probes (NPs) from  
14 Hukseflux, fixed horizontally in holes drilled in vertical poles at heights 14, 24, 34 and 44 cm  
15 measured from the base of the lichen in August 2012. These heights were selected to focus on  
16 the impact of shrubs on snow properties. In August 2012, the dwarf birch at the study site  
17 were 20 cm high at most. In October 2014, the shrubs had grown to 30 to 35 cm high (Figure  
18 1). The heights cannot be determined with a precision better than 4 cm. Because of the  
19 continuum between lichen and litter, the vegetation-ground interface cannot be located  
20 accurately. In fact, heights measured in October 2014 were 3 cm less. Pt1000 temperature  
21 sensors are integrated into the base of each probe. The pole supporting the NPs were placed in  
22 August 2012. Due to logistical difficulties, the NPs were not available at that time and they  
23 were inserted on 14 February 2013. A block of snow was carefully removed, the probes were  
24 inserted horizontally and the block was rapidly replaced, with minimal perturbation to the  
25 snowpack. Measurements were started on 16 February 2013 until the end of the snow season  
26 in late April, and a second winter of measurements was recorded for the whole 2013-2014  
27 winter.

28 The heated NP method has been discussed in detail by Sturm and Johnson (1992) and Morin  
29 et al. (2010). Briefly, the needle comprises a 10 cm heated zone, which is heated at constant  
30 power ( $q=0.4 \text{ W m}^{-1}$ ). The temperature is monitored at the center of the heated zone. Heat  
31 dissipation depends on the effective thermal conductivity of the medium. By plotting the  
32 temperature of a thermocouple located at the center of the needle heated zone as a function of

1  $\ln(t)$ , where  $t$  is time, a linear curve is theoretically obtained, whose slope is inversely  
2 proportional to  $k_{eff}$ .

3 Besides conductive and latent heat exchange processes, air convection in the snowpack can  
4 contribute to heat transfer (Sturm et al., 1997). Convection in snow is not an intrinsic property  
5 of the snow, as it depends among other factors on the temperature gradient in the snow, so our  
6 data analysis will need to detect its possible occurrence and avoid resulting perturbations in  
7 the measurement of  $k_{eff}$ .

8 Thermal conductivity in snow is often anisotropic (Calonne et al., 2011) with the vertical  
9 component either greater or smaller than the horizontal one depending on snow type.  
10 Horizontal NPs therefore measure a mixture of both components while the relevant variable  
11 for soil to atmosphere heat transfer is the vertical component. The impact of this aspect will  
12 be addressed in the discussion section.

13 The heating time used was 150 s. A temperature reading was recorded every second during  
14 heating, and every second for 150 s during the subsequent cooling stage. The variable  $k_{eff}$  can  
15 be independently determined from the heating and cooling curves, but using the heating curve  
16 gives more accurate values (Morin et al., 2010; Sturm and Johnson, 1992), so that using the  
17 cooling curve did not improve the determination of  $k_{eff}$ . Our work therefore focused on  
18 treating the heating curve. Our setup and methods are similar to those of (Morin et al., 2010),  
19 who estimate the accuracy of the measurement to be better than 5% or  $0.005 \text{ W m}^{-1} \text{ K}^{-1}$ ,  
20 whichever is larger.

21 The TP02 probes were automated by a Campbell Scientific CR1000 data logger, powered by  
22 batteries and a solar panel. Since snow thermal conductivity evolved fairly slowly, a  
23 measurement was performed every 2 days at 5:00, when the air temperature was lowest to  
24 minimize the risk of melting. This frequency of measurement minimizes perturbation to the  
25 snow's natural evolution caused by the heating: typically, the temperature rises by about  $1^\circ\text{C}$   
26 for less than one minute every other day, totalling about 90 minutes of very moderate heating  
27 during the whole winter. For each probe, the data logger program verified that the snow  
28 temperature was below  $-2.0^\circ\text{C}$  before starting the heating cycle. This was to avoid snow  
29 melting, which would have irreversibly perturbed the snow structure.

30 Even though heating curves are in principle linear, many perturbations can take place,  
31 resulting in parts of the plots that are curved so that a time range must be selected to derive  
32  $k_{eff}$ . Given the amount of data obtained, manually selecting the correct interval can be very

1 time consuming and an automated procedure was sought. An important objective of this work  
2 is to validate this automatic procedure, so that it can be applied reliably to other similar  
3 systems that are being deployed in the Arctic.

4 In addition to snow thermal conductivity, we also deployed many instruments to monitor  
5 environmental variables required to simulate the evolution of snow physical properties.  
6 Measurements were recorded hourly. These included an air temperature and relative humidity  
7 sensor model HC2S3 from Rotronic, a cup anemometer, both at 2.3 m height, a SR50A  
8 acoustic snow height gauge, a CNR4 radiometer from Kipp & Zonen that measured  
9 downwelling and upwelling shortwave and longwave radiation. The radiometer was ventilated  
10 with a CNF4 heated fan to reduce the risk of frost build up and snow accumulation. The  
11 CNF4 was operated 5 minutes every hour just before the hourly measurements. Likewise, the  
12 HC2S3 sensor was placed in white ventilated U-shaped tubing whose fan was run for 5  
13 minutes before measurement. Furthermore, thermistors were placed in the snow at heights  
14 above ground of 0, 4, 8, 16, 24, 30 and 38 cm.

15 In addition to automatic measurements, field measurements were done in February 2013 and  
16 January and February 2014. Each time, 10 to 15 snow pits were dug to investigate snow  
17 spatial variability. The stratigraphy was examined and profiles of density and thermal  
18 conductivity were measured. Snow density was measured with a 100 cm<sup>3</sup> box cutter (Conger  
19 and McClung, 2009) and a field scale. This proved difficult when ice layers were present, as  
20 breaking ice layers cleanly is delicate. We estimate that when thick ice layers were present,  
21 density underestimates of about 20% were possible, but the exact error in this case is very  
22 difficult to evaluate.

23

### 24 **3 Treatment of the heating curves**

25 The treatment of the heating curves has been detailed in Sturm and Johnson (1992) and Morin  
26 et al. (2010). Ideally, after an initiation period of about 20 s where the “linear” equation does  
27 not apply, the heating curves obtained with the NP method should be linear (strictly speaking,  
28 the plots are logarithmic, but are called linear because of their aspect on graphs) and the  
29 thermal conductivity extracted from any time interval should yield a unique value, assuming  
30 that the needle is in perfect thermal contact with the medium which is further assumed to be  
31 homogeneous (Morin et al., 2010). Riche and Schneebeli (2010) have raised the issue of the  
32 imperfect contact between the needle and the snow, caused by damage to the snow during  
33 needle insertion, which modifies thermal conductivity around the needle. However, the

1 impact of such effects are generally limited to short heating times as demonstrated by Morin  
2 et al. (2010), which corresponds to the period of time which needs to be discarded from the  
3 analysis anyway. Furthermore, in our case the needles are left in place and are not inserted for  
4 each measurement. As a result, the snow structure forms and evolves around the needle, and  
5 there is no perturbation caused by the insertion. In most cases, apart from the initial period of  
6 about 20 s, the heating curves are linear as shown in Figure 2a.

7 In low density snow with large grains such as depth hoar, plots can be curved at long heating  
8 times, as shown in Figure 2b . Sturm and Johnson (1992) attribute this change of slope to the  
9 onset of convection, which by adding an extra heat transfer process, reduces the needle  
10 heating rate. Since we are interested in conductive and latent heat transfer processes only, the  
11 correct value for us is obviously that of the steepest part of the plot after the initiation period,  
12 here between 20 and 50 seconds, which gives a  $k_{eff}$  value of  $0.053 \text{ W m}^{-1} \text{ K}^{-1}$ . Using the  
13 interval 90-140 s to extract  $k_{eff}$  would have yielded a value of  $0.115 \text{ W m}^{-1} \text{ K}^{-1}$ . Choosing the  
14 adequate part of the plot to extract the correct thermal conductivity value is thus critical.

15 In order to develop an algorithm capable of accurately and automatically extracting thermal  
16 conductivity values from heating curves, we first analyzed our data manually from the 2012-  
17 2013 and 2013-2014 winters. This was done visually by examining the linearity of the plot  
18 and selecting the best possible linear section of the plot. This proved to be very easy, as a  
19 change of slope of about 5% is easily detected visually. In all cases, convection was easy to  
20 detect. In the absence of convection, a large time interval from 20 or 30 s to over 100 s, was  
21 often found to have a very good visual linearity. This produced a set of reliable values against  
22 which to compare those obtained by our algorithm. The main condition controlling the choice  
23 of the interval was the presence or the absence of convection. Thus, we tried to detect when  
24 convection occurred and to select the best time interval corresponding to both types of heating  
25 curves.

26 The analysis of 404 measurements showed that convection always occurred when the  
27 maximum heating,  $\Delta T_{max}$ , at 100 s time and with a heating power of  $0.4 \text{ W m}^{-1}$ , was greater  
28 than  $1.18^\circ\text{C}$ , and never occurred when  $\Delta T_{max}$  was less than  $1.07^\circ\text{C}$ . We obtained only 2 cases  
29 where convection took place for  $\Delta T_{max} < 1.18^\circ\text{C}$ , with  $\Delta T_{max}$  values of  $1.13$  and  $1.15^\circ\text{C}$ . We  
30 also found 7 measurements without convection for  $1.07 \leq \Delta T_{max} < 1.18^\circ\text{C}$ . To detect whether  
31 convection happened for cases within this  $\Delta T_{max}$  interval, we ran a routine to compare the  $k_{eff}$   
32 values yielded by two intervals, at short and at long heating times. If the value extracted from

1 the long heating time was higher by >5%, then we considered that convection occurred, as  
2 observed in Figure 2b. If not, we concluded there was no convection.

3 We then divided our heating curves into 2 classes, depending on their  $\Delta T_{\max}$  values: the class  
4 without convection ( $\Delta T_{\max} < 1.07^{\circ}\text{C}$ ), and the class with convection ( $\Delta T_{\max} \geq 1.18^{\circ}\text{C}$ ). When  
5  $\Delta T_{\max}$  is in-between, both behaviors could be found and the class of the heating curve was  
6 determined according to the additional procedure. For both classes, we tested various time  
7 intervals which we used to calculate  $k_{\text{eff}}$ . These values calculated automatically (hereafter  
8 “automatically calculated values”) for selected intervals were then compared to the values,  
9 hereafter “manually calculated values”, obtained using a manually selected time interval.  
10 Results are shown for both winters in Tables 1 and 2.

11 When convection was detected, the time interval giving the lowest mean quadratic difference  
12 (RMSE) and the lowest algebraic error is 20-50 s for both years. We will then retain this  
13 interval when convection takes place. In the absence of convection, essentially all time  
14 intervals tested yielded values close to the manual ones, and selected an interval is here a  
15 second order optimization. The optimal interval is 40-100 s in 2013-2014. In 2012-2013, the  
16 lowest RMSE came from the 50-110 s interval, and the lowest mean algebraic error from the  
17 40-100 s one. However, in 2012-2013, the number of measurements without convection was  
18 only 34, while it was 189 in 2013-2014. Moreover, results for the 40-100 s interval in 2012-  
19 2013 are not significantly different from those of the 50-110 s interval for RMSE, and give a  
20 better algebraic error. When convection is absent, we thus selected the 40-100 s time interval.

21 Finally, we applied a last check to ensure measurement quality. Despite the programming of  
22 the  $-2^{\circ}\text{C}$  temperature threshold, we observed a few cases where snow was close to melting.  
23 Heating curves were then irregular, even showing decreases in temperature, presumably  
24 because of local melting. This only happened three times in spring, after the onset of snow  
25 melt, so we discarded these measurements anyway. We also encountered 10 cases of irregular  
26 heating curves with very large  $\Delta T_{\max}$  ( $\geq 2.89^{\circ}\text{C}$ ), presumably due to an intense and unstable  
27 convection (Figure 2c). Still, we successfully managed to extract the  $k_{\text{eff}}$  values because the  
28 irregularities appeared after the 20-50 s time interval. This nevertheless showed us that poor  
29 quality heating curves could be obtained. To reject those, we set a threshold value on the  
30 quality of the linear fit. Thus, when the squared correlation coefficient  $R^2$  was below 0.97, the  
31 measurement was deemed unreliable and discarded.

1 From this analysis, we conclude that with a constant heating power of  $0.4 \text{ W m}^{-1}$ , a heating  
2 time of 100 s is sufficient. Heating until 150 s does not lead to any gain in data quality and  
3 increases the risk of melting the snow, irreversibly modifying its structure. Our automatic  
4 treatment procedure is then as follows:

5 1. Determine the maximum heating of the measurement at 100 s,  $\Delta T_{\max}$ , to detect whether  
6 convection was likely to have taken place. The convective threshold is  $1.18^\circ\text{C}$ . Below  
7  $1.07^\circ\text{C}$ , convection is absent.

8 2. Based on the class of the measurement, a time interval is selected. We selected 40-100 s  
9 when the heating is below the  $1.07^\circ\text{C}$  threshold (no convection), and 20-50 s when it is  
10 above the  $1.18^\circ\text{C}$  threshold (convection).

11 3. For  $\Delta T_{\max}$  between both thresholds, both behaviours are considered. Two  $k_{\text{eff}}$  values from  
12 both time intervals are extracted and compared. If the value from the higher interval is  
13 greater than that from the lower interval by more than 5%, then convection took place and  
14 the 20-50 s interval is selected. Otherwise, the interval 40-100 s is used.

15 4. The  $k_{\text{eff}}$  value obtained is kept only if the squared correlation coefficient is equal to or  
16 greater than 0.97.

17 A schematic of the algorithm is shown in Figure 3. In Tables 1 and 2, we also reported the  
18 maximum difference between the  $k_{\text{eff}}$  values determined manually and automatically, and  
19 analyzed the cases where large errors were observed, in order to detect possible flaws in the  
20 algorithm. For the 2012-2013 winter, measurements without convection show a mean relative  
21 algebraic error of 0.44% for the interval 40-100s, with a largest algebraic error of -4.78%. For  
22 errors below 5%, the calculation is deemed acceptable and no further investigation was made.

23 When convection was detected in 2012-2013, we obtained a mean error of 3.33% from the  
24 interval 20-50s. The highest errors, between 5% and 6.1%, came from 11 measurements  
25 where convection took place early, before 45 seconds. The linear regression applied between  
26 20 and 50 seconds therefore leads to a slight overestimation of  $k_{\text{eff}}$ , giving a maximum error of  
27  $0.008 \text{ W m}^{-1} \text{ K}^{-1}$ . In any case, it is likely that the early onset of convection makes a precise  
28 determination of  $k_{\text{eff}}$  delicate, and the error in the manual determination is probably increased  
29 in this case. Taking the manual measurement as the correct reference is probably not ideal and  
30 the value obtained in this case inevitably carries a larger uncertainty than usual. Thus, the  
31 interval 20-50 s remains the best compromise to obtain the lowest error for measurements  
32 with convection.

1 For the 2013-2014 winter, cases where convection was detected are fewer than the previous  
2 winter, and  $k_{eff}$  extracted from the interval 20-50 s resulted in more accurate results, with a  
3 mean algebraic error of -0.42% and a maximum quadratic error of 4.63%.

4 In the absence of convection in 2013-2014,  $k_{eff}$  values determined automatically from the time  
5 interval 40-100 s show a satisfactory mean relative algebraic error of -0.03%. The largest five  
6 errors, around 10%, all came from the 24 cm needle. On those measurements, the slope of the  
7 heating curve was decreasing over time, which means that  $k_{eff}$  is increasing probably because  
8 of heterogeneities in the snow. During our field work, we observed a lot of melt-freeze forms  
9 in the snowpack, especially at the height of this probe where we noticed several ice layers.  
10 These observations are consistent with the calculated  $k_{eff}$  values, around  $0.25 \text{ W m}^{-1} \text{ K}^{-1}$   
11 (Sturm et al., 1997), and the shape of the curve reflects the heterogeneities observed. When  
12 the heating wave reaches a dense conductive layer, more heat is dissipated and heating is  
13 reduced. In these curved plots, it is difficult to select the most suitable interval, and the error  
14 largely reflects the arbitrary character of the manual determination.

15 We also obtained 11 errors between 5 and 7% from the 14 cm needle. On these  
16 measurements, we found the opposite behavior than previously, with  $k_{eff}$  decreasing after 50  
17 seconds. Given that the height of this probe corresponds to the basal depth hoar layer, we can  
18 attribute this change of slope to air-filled volumes in the snow. The absence of convection can  
19 be explained by the relatively high  $k_{eff}$  values, around  $0.18 \text{ W m}^{-1} \text{ K}^{-1}$ , which reduces heating.  
20 These results are consistent with our field observations of a hard depth hoar layer at the same  
21 height.

22 In summary, using our algorithm with the time interval 20-50 s when convection is detected,  
23 and 40-100 s otherwise, gives values within 5% of measured ones in 90.6% of cases. In 8.2%  
24 of cases, the difference is between 5 and 10%. Errors above 10% were encountered only 5  
25 times out of 404 values, and a physical explanation can be proposed in all cases. The most  
26 difficult determinations are probably for heterogeneous snow with melt-freeze structures.  
27 Based on this analysis of more than 400 heating curves, we therefore conclude that our  
28 algorithm is reliable with an overall RMSE of 3.27% and a maximum error of 11.4%.

29

#### 30 **4 Results**

31 Figure 4 shows the effective thermal conductivity values measured during the 2012-2013  
32 winter. To facilitate discussion, we also show the evolution of air temperature and wind speed

1 at 2 m height and of snowpack thickness. Figure 5 shows data for the 2013-2014 winter.  
2 Thermal conductivity data does not start at the onset of the snow cover, because the snow  
3 temperature was too warm for the measurement to proceed. Figure 6 shows snow  
4 stratigraphies and density profiles in February of each year within about 50 m of our thermal  
5 conductivity NP location.

6 First of all, we must stress the fairly large spatial variation of snow properties. The ground  
7 surface was not flat and the snow redistribution by wind was important. This resulted in  
8 highly variable snowpack thickness. The dwarf birch cover was also highly variable. Within  
9 100 m of our site, the ground could be covered with just white lichen (cladonia) or by dwarf  
10 birch bushes 20 to 80 cm high. Dwarf birch twigs absorb light and modify the local energy  
11 budget. All these variations resulted in variations in snow property at the meter scale,  
12 noticeable in the degree of melting, the amount, density and grain size of depth hoar, the  
13 thickness and hardness of wind slabs, etc. Such variations are usual in the Arctic and  
14 elsewhere, as illustrated in detail in e.g. (Domine et al., 2012), see their Figure 1. Strict  
15 correspondence between the data of Figures 4 and 5 on the one hand, and Figure 6 on the  
16 other hand should therefore not be sought.

17 Both winters had fairly similar meteorology regarding temperature and wind speed. Yet, in  
18 2013-2014, there were much more extensive signs of melting in the snowpack. In February  
19 2013, we observed only slight signs of melt-freeze cycling in the snow, and the depth hoar  
20 was for the most part very soft and of low density ( $<250 \text{ kg m}^{-3}$ , sometimes even lower than  
21 150). In February 2014, signs of melt-freeze cycling were extensive and the depth hoar was  
22 mixed with melt/refreeze clusters and was thus hard and of high density ( $>250 \text{ kg m}^{-3}$ ,  
23 sometimes even higher than 350) (Figure 6).

24 Differences between both winters also show up when the  $k_{eff}$  evolutions are examined. In  
25 2012-2013,  $k_{eff}$  values at 34 and 44 cm increased significantly and more than doubled. On the  
26 contrary, values at 14 and 24 cm showed only small increases, with the values at 14 cm even  
27 showing a sudden drop from 0.07 to 0.03  $\text{W m}^{-1} \text{K}^{-1}$  between 28 and 30 March 2013. In 2013-  
28 2014,  $k_{eff}$  values remained essentially constant, apart from 3 events: the initial increase at 44  
29 cm, the initial decrease at 34 cm, and again a sudden drop at 14 cm from 0.17 to 0.13  $\text{W m}^{-1}$   
30  $\text{K}^{-1}$  between 9 and 11 April 2014.

31

## 1 5 Discussion

### 2 5.1 Suitability of the method

3 Methods currently used to determine snow thermal conductivity are the heated NP, the heat  
4 flux plate (HFP) and simulations based on microtomographic images (SIM) (Calonne et al.,  
5 2011; Riche and Schneebeli, 2013). Briefly, for the HFP method, a known temperature  
6 gradient is established across a snow sample and the heat flux is measured. Equation (1)  
7 allows the determination of  $k_{eff}$ . For simulations, a 3-D microstructural image, typically with a  
8 resolution of 10  $\mu\text{m}$ , is obtained for the snow sample. A finite element simulation is then  
9 performed, taking into account conduction through the ice and air. Latent heat fluxes are not  
10 considered in these simulations, because they are calculated to represent about 1% of heat  
11 transfer at  $-16^\circ\text{C}$  (Riche and Schneebeli, 2013). Both the HFP and SIM methods are not suited  
12 for the continuous monitoring of snow thermal conductivity in remote and inaccessible  
13 regions. Calonne et al. (2011) and Riche and Schneebeli (2013) have compared results from  
14 the three methods. Both studies conclude that the NP method has two weaknesses: (1) it does  
15 not take into account snow anisotropy; (2) it seems to systematically give values that are too  
16 low by about 35%.

17 Snow is indeed anisotropic, as readily revealed for example by the cursory observation of  
18 columnar depth hoar. For the study of heat transfer through the snowpack, the relevant  
19 variable is the vertical thermal conductivity,  $k_z$ . In Arctic snow, NPs have to be inserted  
20 horizontally, because the heated region is 10 cm long, and this is very often much larger than  
21 the thickness of an Arctic snow layer, so that what is measured by a horizontal NP,  $k_{NP,h}$ , is a  
22 mix between  $k_z$  and the horizontal thermal conductivity  $k_h=k_x=k_y$ , (Riche and Schneebeli,  
23 2013):

$$24 \quad k_{NP,h} = \sqrt{k_h k_z} \quad (4)$$

25 Anisotropy can be quantified by the ratio  $k_z/k_h=\alpha$  (Riche and Schneebeli, 2013) so that we  
26 have:

$$27 \quad k_z = \sqrt{\alpha} k_{NP,h} \quad (5)$$

28 Over half of the values of  $\alpha$  are close to 1 (between 0.8 and 1.2) (Calonne et al., 2011; Riche  
29 and Schneebeli, 2013) so that measuring  $k_{NP,h}$  to obtain  $k_z$  will often only cause a small error  
30 due to anisotropy. However, over 90% of  $\alpha$  values range between 0.7 to 1.45 (Calonne et al.,

1 2011), and values as high as 2 have been observed, so that anisotropy on average creates an  
2 uncertainty of about 20% on  $k_z$  from  $k_{NP,h}$  measurements.

3 In available studies, NP gives systematically lower results than HPF and SIM. While HPF and  
4 SIM are not perfect and can have systematic errors, as detailed by Riche and Schneebeli  
5 (2013), these imperfections are probably not sufficient to explain the low values found by the  
6 NP method. Of particular interest is the observation that, while NP gives results similar to  
7 HFP in homogeneous isotropic materials such as polystyrene and wax, it gives lower values  
8 in granular materials such as salt grains and snow (Riche and Schneebeli, 2013). Thus the  
9 granular nature of the material may be related to the cause of the underestimation of  $k_{eff}$  by  
10 NP. Riche and Schneebeli (2013) explore several possibilities to explain the underestimation.  
11 These are (i) the high contact resistance. This would not apply in our case as the needle is not  
12 inserted each time and the medium perturbation is minimal. (ii) The heterogeneity in the  
13 temperature field. From the measurement of the dielectric properties, it is known empirically  
14 that the radius of curvature of the electrode must be much larger than the snow grain diameter  
15 (Matzler, 1996). This conditions would not be fulfilled for snows such as depth hoar, as well  
16 as for the salt grains studied by Riche and Schneebeli (2013). (iii) The thermal field is too far  
17 from homogenous conditions for such a thin NP to apply the theory developed for transient  
18 methods (Blackwell, 1954; Matzler, 1996).

19 In any case, no definite understanding has been reached today. Calonne et al. (2011) analyzed  
20 their NP heating curve in a simple manner, using always the same 30-80 s time interval  
21 regardless of the curve shape. We reanalyzed NP data from Calonne et al. (2011) (both their  
22 one published value and other unpublished values that they supplied us with) with the  
23 algorithm of Figure 3, and this on average increased their value by 10%. Their published  
24 value in their Figure 1 increased by 9%, from 0.156 to 0.170 W m<sup>-1</sup> K<sup>-1</sup>. We therefore come to  
25 the conclusion that, even though NP data is lower than SIM data, reanalyzed data is probably  
26 only about 10% lower than SIM data.

27 Riche and Schneebeli (2013) analyzed their NP heating curve using the constant 30-100 s  
28 time interval. Since they performed measurements both with a vertical and a horizontal  
29 needle, they could determine  $k_h$  and  $k_z$  from their NP measurements and compared those with  
30 similar data obtained from SIM. Based on 8 snow samples, they conclude that NP data were  
31 “systematically lower by 10-35%” than SIM values. We did not re-evaluate the NP data of  
32 (Riche and Schneebeli, 2013). Based on our analysis of the data of Calonne et al. (2011) and

1 on the data of Riche and Schneebeli (2013), we estimate that NP data, taking into account  
2 anisotropy, probably underestimates  $k_z$  by about 20% on average.

3 In summary, errors in our monitoring data amount to a random error of 20% due to anisotropy  
4 if the snow type is not known, and a low systematic error that is on average 20%. Additional  
5 random errors are that due to the NP method (5%) and that due to our algorithm (3%), leading  
6 to a total error of 29%, deduced from the square root of the sum of the squares of all errors..

7 Given that snow thermal conductivity varies in the range 0.025 to 0.7 W m<sup>-1</sup> K<sup>-1</sup> (Sturm et al.,  
8 1997), i.e a factor of almost 30, the data obtained are still very useful, despite the errors.

9 Corrections can be proposed to reduce the errors. To begin with, NP data can be increased by  
10 20% to remove the systematic error and limit the uncertainty to its random component, 21%.

11 Second, corrections can be suggested for anisotropy. Lower Arctic snow layers are usually  
12 made up of depth hoar, with  $k_z > k_h$ , while upper layers are usually made up of wind slabs with  
13  $k_z < k_h$ . Based on equation (5) and on a mean anisotropy of 20%, our data at 14 and 24 cm  
14 could be increased by 20% and those at 34 and 44 cm decreased by 20%. These tentative  
15 corrections can be refined when the difference between NP and SIM measurements are better  
16 understood. At the moment, the comparison is based on 2 studies totalling less than 10  
17 measurements and little theoretical understanding of the processes, so there is room for a lot  
18 of improvements. Future detailed simulations of the snowpack energy balance may also  
19 produce a valuable comparison between observations and models, which may help reduce  
20 uncertainties. However, our current ability to model snow on shrub tundra is probably  
21 insufficient to reach the accuracy required for such comparisons.

22

## 23 **5.2 Thermal conductivity of snow in shrub tundra**

24 Our study site is a low Arctic one, in shrub tundra near the tree line. Relevant climatic  
25 characteristics include fairly cold weather with temperatures as low as -36°C both years,  
26 above freezing episodes in autumn, a fairly low latitude that ensures significant insolation all  
27 winter (typically 50 to 150 W m<sup>-2</sup> daily maximum, during the 120 days centred the winter  
28 solstice), and the presence of shrubs that can act as radiation absorbers above and within the  
29 snow. To our knowledge, the time series of snow thermal conductivity presented here are the  
30 only ones available for shrub tundra. The conditions encountered here were significantly  
31 different from those in similar previous studies. Sturm and Johnson (1992) worked in interior  
32 Alaska on a spot with no erect vegetation. Winters there were colder than at our site, with no

1 melting events. The thin snowpack, combined with the cold temperatures, generated extreme  
2 temperature gradients in the snow, reaching  $300 \text{ K m}^{-1}$ , and almost all the snow cover  
3 transformed into depth hoar (Sturm and Benson, 1997). Morin et al. (2010) worked in an  
4 unvegetated high Alpine area with high snow accumulation ( $\sim 2 \text{ m}$ ). Air temperatures were  
5 moderate, fluctuating mostly between  $0$  and  $-15^\circ\text{C}$ , and signs of melting were not readily  
6 observed. Originalities of our site include the important occurrence of melting and the  
7 presence of shrubs with a dense network of twigs. We focus our discussion on both these  
8 aspects, and also investigate the difference in the evolution of  $k_{eff}$  between both winters  
9 studied.

10 Our data suggest that both meteorological conditions and snow metamorphism contributed to  
11 the difference between both years. In 2012, continuous snow cover started on 8 November,  
12 and in 2013 on 26 October. Between the start of the permanent snow cover and 31 December,  
13 the average temperature was  $-9.3^\circ\text{C}$  in 2012 and  $-11.9^\circ\text{C}$  in 2013, which does not explain the  
14 melt signs difference in both years. There were more warm spells in the second year, which is  
15 more consistent with observations. In 2012-2013, the amount of air temperature above  $0^\circ\text{C}$   
16 after permanent snow cover was  $51^\circ\text{C hour}$  until February, and in 2013-2014, the value was  
17  $96^\circ\text{C hour}$ . Of course, air temperature alone is insufficient to estimate the intensity of melting.  
18 Also relevant is the intensity of solar radiation. While in autumn 2012, incident solar radiation  
19 after the onset of permanent snow cover exceeded  $200 \text{ W m}^{-2}$  only once (on 18 November) it  
20 exceeded that value on seven days in autumn 2013, even reaching  $336 \text{ W m}^{-2}$  on 28 October,  
21 when the snowpack was about 25 cm high. Even though the air temperature only reached  $-$   
22  $1.4^\circ\text{C}$  on that day, light absorption by the snow, increased by the widespread presence of  
23 dwarf birch twigs, doubtless produced significant melting.

24 Furthermore, metamorphic conditions increased the difference between both years. Strong  
25 temperature gradient metamorphism can transform refrozen snow into depth hoar (Domine et  
26 al., 2009), therefore erasing the melting history. The thicker snow in 2013, by reducing the  
27 temperature gradient, certainly slowed down transformation into depth hoar. Figure 7 shows  
28 the temperature gradient in the bottom 30 cm of the snowpack. Between the establishment of  
29 the snowpack and 20 February, the mean value was  $22.5^\circ\text{C m}^{-1}$  in 2012-2013 and  $15.6^\circ\text{C m}^{-1}$   
30 in 2013-2014. Thus the larger amount of melting and the lower temperature gradient in 2013-  
31 2014 combined to produce a snowpack with more remaining signs of melting in the middle of  
32 winter.

1 Only very few studies have been devoted to the time-evolution of snow thermal conductivity  
2 over extended time periods in natural environments (Morin et al., 2010; Sturm and Johnson,  
3 1992), all dealing with the evolution of dry snow. Variables that play a role in this evolution  
4 include snow density and the temperature gradient in the snowpack. General observations in  
5 these studies are that in low density snow under high temperature gradient, metamorphism  
6 leads to depth hoar formation and  $k_{eff}$  shows little variations and values usually remain low  
7 ( $<0.1 \text{ W m}^{-1} \text{ K}^{-1}$ ) to moderate ( $<0.15 \text{ W m}^{-1} \text{ K}^{-1}$ ). In higher density snow under low  
8 temperature gradient, metamorphism favours sintering and the strengthening of bonds  
9 between grains, leading to increases in  $k_{eff}$  to values exceeding  $0.2 \text{ W m}^{-1} \text{ K}^{-1}$ . Laboratory  
10 experiments (Schneebeli and Sokratov, 2004) confirm this trend.

11 For the first winter studied,  $k_{eff}$  data starts on 16 February 2013. Between that date and 29  
12 April, the temperature gradient in the snow was low, with an average value of  $4.45^\circ\text{C m}^{-1}$   
13 between 0 and 30 cm (Figure 7). Intense precipitation in March with snow height exceeding  
14 120 cm (Figure 4) led to the build-up of a strong overburden that certainly densified the lower  
15 snow layers.  $k_{eff}$  values at 34 and 44 cm then increased rapidly, due to efficient sintering under  
16 these conditions. Layers at 14 and 24 cm showed a less marked increase, probably because the  
17 birch twig network prevented compaction, so that sintering in snow of lower density was less  
18 efficient. The sudden drop in  $k_{eff}$  at 14 cm is interesting. We observed that very low density  
19 depth hoar ( $<140 \text{ kg m}^{-3}$ ) could develop in the lower part of the birch shrubs, and this depth  
20 hoar often collapsed at the slightest contact. In places, voids were even present, presumably  
21 due to earlier spontaneous collapse. Our hypothesis is that between 28 and 30 March 2013,  
22 the depth hoar spontaneously collapsed and the NP found itself in a void within the depth  
23 hoar. Indeed, the  $k_{eff}$  value measured, around  $0.03 \text{ W m}^{-1} \text{ K}^{-1}$  in early April, is close to the  
24 value of air,  $0.023$ . Our value is slightly higher, possibly because some ice crystals may have  
25 formed on the needle during depth hoar formation, as the strong upward water vapor flux  
26 could have led to condensation on the needle. Indeed, during laboratory experiments, such  
27 crystal formation was observed (N. Calonne, personal communication, 2015).

28 In 2013-2014, an initial rapid increase is observed at 44 cm between 17 and 19 November,  
29 and an initial slower decrease is observed at 34 cm between 9 and 25 November. The 44 cm  
30 increase is due to a wind storm between 17 and 19 November, with wind speed exceeding  $22$   
31  $\text{m s}^{-1}$  at 2 m, which transformed recent precipitation into a wind slab. We propose that the 34  
32 cm decrease is due to the transformation of the snow layer into faceted crystals and possibly

1 depth hoar. Similar decreases have been observed by Sturm and Johnson (1992) and Morin et  
2 al. (2010), who interpreted it likewise.

3 Beside these initial processes and the April drop at 14 cm,  $k_{eff}$  values show little variations.  
4 Temperature gradients in the snow were overall lower than the previous winter, but values  
5 were more regular in particular at the end of the season. Values exceeding  $20^{\circ}\text{C m}^{-1}$  were  
6 observed until 5 March (compared to 9 February the previous winter) and the average  
7 gradient at 0-30 cm height between 16 February and 29 April 2013 was  $8.72^{\circ}\text{C m}^{-1}$  (Figure 7).  
8 We hypothesize that the melt-freeze layers formed a rigid 3-D network that prevented  
9 densification despite snowpack overburden in late winter. Since density and thermal  
10 conductivity are highly correlated (Domine et al., 2011; Sturm et al., 1997; Yen, 1981), it is  
11 not surprising that the lack of densification led to an absence of increase in  $k_{eff}$ .

12 The sudden slight drop in  $k_{eff}$  at 14 cm is puzzling. Given that post-drop values are around  
13 0.13, i.e. much larger than the air value, the complete collapse of the depth hoar cannot be  
14 invoked. We tentatively suggest that the snow structure was a mixture of depth hoar and melt-  
15 freeze crust, and the continuous weakening of this mixed structure during months of  
16 temperature gradient metamorphism led to its partial collapse. However, we are fully aware  
17 that additional observations are needed to test this suggestion.

## 18 **6 Conclusion**

19 This study demonstrates that NPs can be used in remote environments for the season-long  
20 monitoring of snow thermal conductivity. Of course, the NP method is not perfect, but even if  
21 in a worst case scenario, its error is 29%, the data obtained is still of great interest, given the  
22 range of variation of snow  $k_{eff}$ , and also given the fact that we knew nothing about the  
23 evolution of  $k_{eff}$  in low Arctic shrub tundra, and no data was available on the time-evolution of  
24  $k_{eff}$  of refrozen snow.

25 Noteworthy observations include the impact of dense shrubs on snow structure. Shrubs  
26 increase light absorption, and we postulated that this contributed to the significant melting in  
27 autumn 2013. This had a considerable effect on snow structure and on the evolution of  $k_{eff}$ .  
28 The other important effect of shrubs is to prevent compaction. This is readily observed at 14  
29 cm in Figure 4, where the increase in  $k_{eff}$  is moderate. This lack of compaction, combined with  
30 the upward loss of mass due to the temperature gradient, led to the postulated snow collapse  
31 in late March 2013. Also in winter 2013, the increase in  $k_{eff}$  at 24 cm is considerably less than  
32 at 34 and 44 cm, and we interpret this also as an effect of the shrubs. Finally, melt-freeze

1 episodes are also observed to limit snow compaction (and therefore increases in  $k_{eff}$ ) by  
2 forming a rigid network of melt-freeze clusters.

3 Further exploitation of these data will include their use for the adaptation of snow physics  
4 models to shrub tundra. Improved simulations of the snow and soil energy budgets may help  
5 improve our understanding of the errors in the NP measurement of snow  $k_{eff}$ . However, for  
6 snow model standards, a 29% uncertainty on  $k_{eff}$  is not large, and reducing it will require a  
7 very detailed description of the effect of shrubs on radiation and on snow compaction and  
8 metamorphism. These aspects are often overlooked by snow models today. The interest for  
9 such future developments is high, as for example this will lead to an improved ability to  
10 simulate the thermal regime of the ground and the fate of permafrost.

11

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1 Table 1. Comparison between  $k_{eff}$  values automatically ( $k_{eff\_auto}$ ) extracted from different  
 2 intervals, and values obtained from time intervals selected manually ( $k_{eff\_man}$ ), for the 2012-  
 3 2013 winter. Data for cases with and without convection are analyzed separately. RMSE is  
 4 the mean quadratic relative difference. Error is the mean relative algebraic error  $2(k_{eff\_auto} -$   
 5  $k_{eff\_man})/(k_{eff\_auto} + k_{eff\_man})$ . The maximum error observed is also shown. Bold values  
 6 correspond to the interval selected.

Interval, s	N without convection			N with convection		
	RMSE, % no convection	Error, % no convection	Error max,% no convection	RMSE, % convection	Error, % convection	Error max,% convection
20-50	3.52	3.18	7.64	<b>3.74</b>	<b>3.33</b>	<b>-6.12</b>
30-60	2.66	2.33	6.28	12.00	11.25	17.96
30-80	2.08	1.65	4.50	18.98	17.90	40.11
40-90	2.25	0.96	5.47	27.23	25.50	60.54
40-100	<b>1.85</b>	<b>0.44</b>	<b>-4.78</b>	29.83	28.01	60.45
50-110	1.69	-0.46	-5.21	37.15	34.59	71.31
60-120	2.35	-1.18	-6.52	42.09	39.03	68.89
90-140	3.48	-1.72	-8.02	53.66	49.08	97.37

7  
8  
9

1 Table 2. Same as Table 1, for the 2013-2014 winter.

Interval, s	N without convection			N with convection		
	RMSE, % no convection	Error, % no convection	Error max,% no convection	RMSE, % convection	Error, % convection	Error max,% convection
20-50	9.71	4.59	32.84	<b>1.89</b>	<b>-0.42</b>	<b>4.63</b>
30-60	6.75	3.27	21.92	3.13	1.69	13.14
30-80	4.75	1.95	14.27	5.90	4.29	22.02
40-90	3.78	0.47	12.18	8.94	7.48	26.68
40-100	<b>3.65</b>	<b>-0.03</b>	<b>11.44</b>	9.40	8.30	28.81
50-110	4.58	-1.05	12.71	13.09	11.94	34.95
60-120	5.93	-2.07	-19.72	16.14	15.05	39.21
90-140	9.39	-3.58	32.00	22.13	21.17	48.24

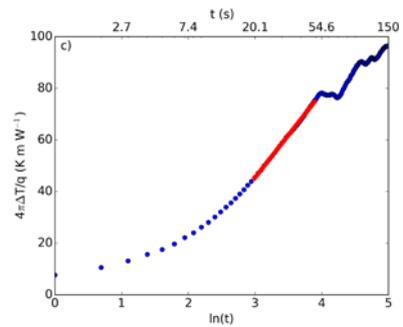
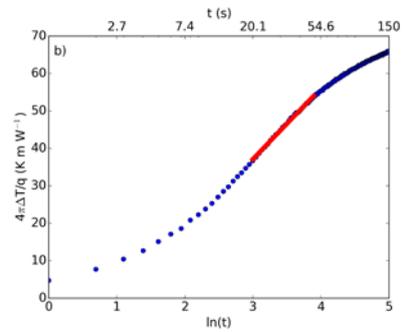
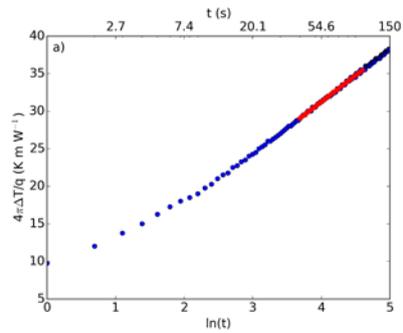
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Figure 1. Photograph of the four TP02 needle probes deployed in shrub tundra. The photo was taken on 6 October 2014, when the dwarf birch had grown to about 30 cm high. The needle probes are 14, 24, 34 and 44 cm above the ground-lichen interface.

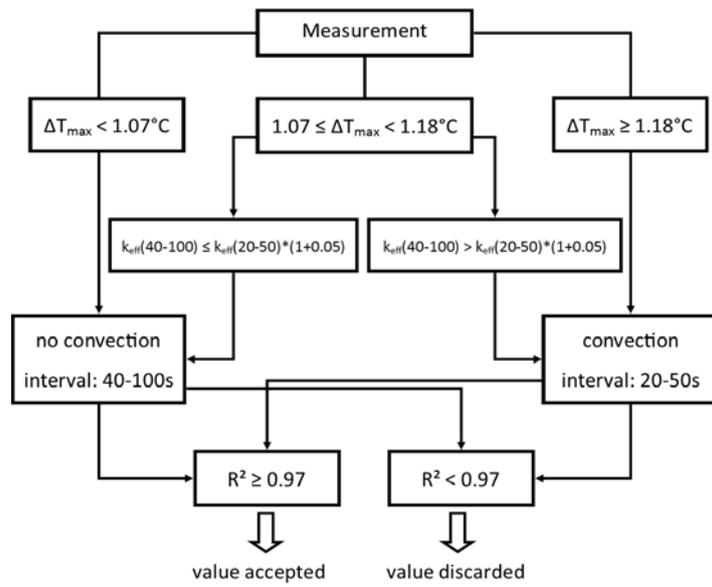


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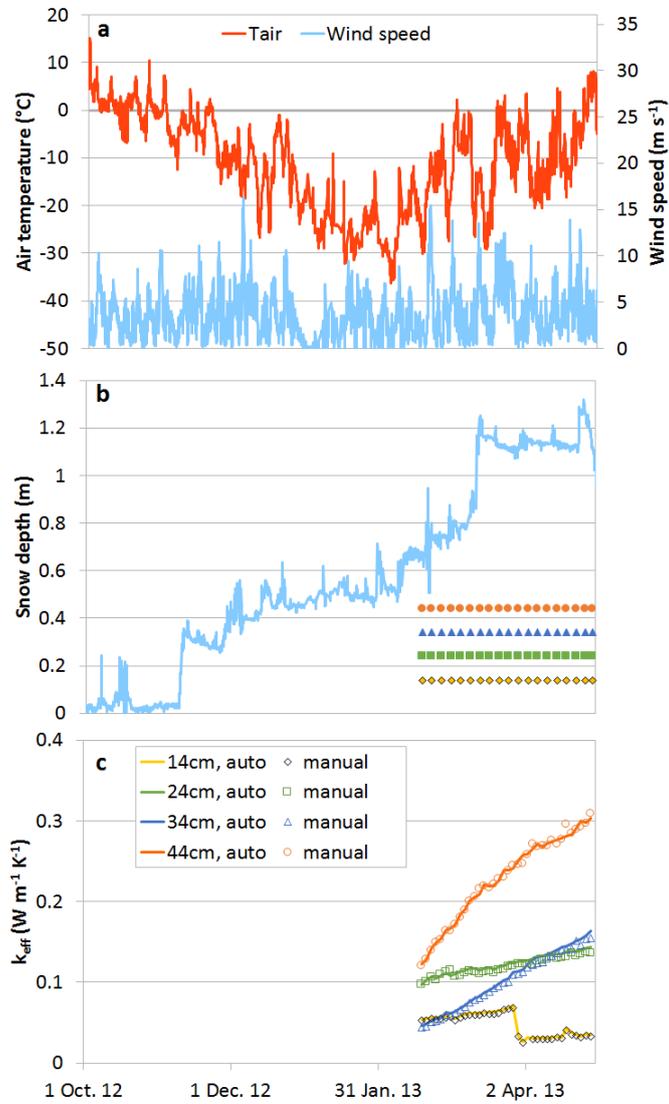
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4 Figure 2. Heating plots obtained with the needle probes of Figure 1. Red lines show the fit  
 5 using the selected time range. (a) Heating plot obtained on 22 February 2013 with the NP at a  
 6 height of 44 cm. After an initial period of less than 20 s when steady state does not apply, the  
 7 plot is linear. Time range used: 40-100 s. (b) Plot of 22 February 2013 with the NP at 34 cm.  
 8 The lower slope at long heating times is indicative of convection. Time range used: 20-50 s.  
 9 (c) Plot of 5 April 2013 with the needle probe at 14 cm.  $k_{eff}$  was  $0.037 \text{ W m}^{-1} \text{ K}^{-1}$  and  $\Delta T_{max}$   
 10 was  $3.5^\circ\text{C}$ , triggering intense and unstable convection. Time range used: 20-50 s.

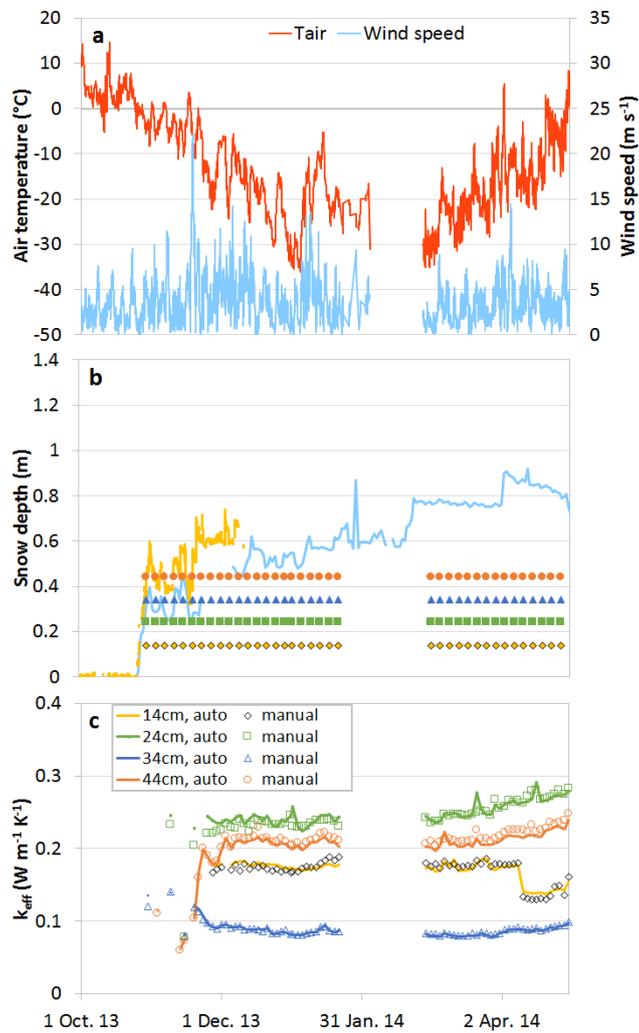


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 2 Figure 3. Schematic of the algorithm used to determine automatically the thermal conductivity  
 3 value from the heating curves.  $\Delta T_{\max}$  is the temperature difference measured after 100 s of  
 4 heating.  
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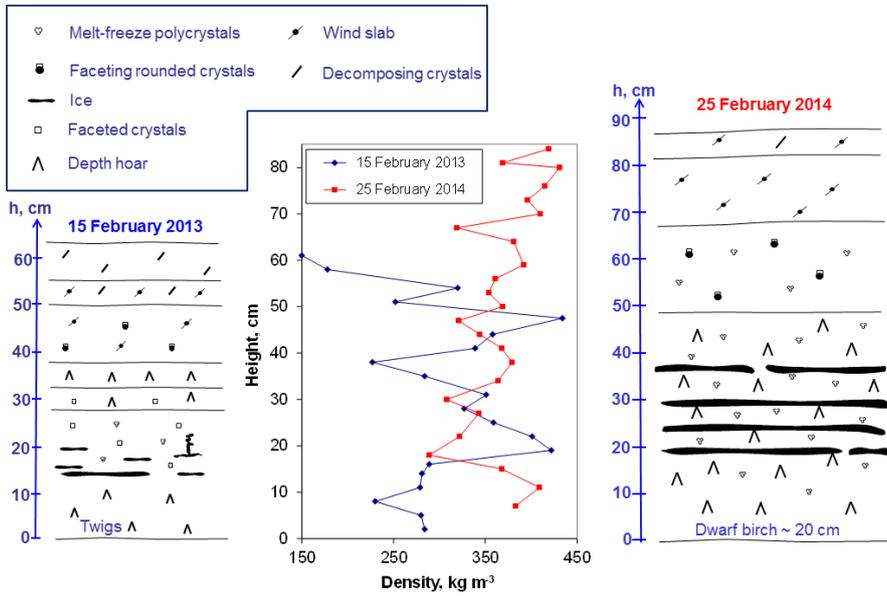


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 2 Figure 4. Meteorological and thermal conductivity data automatically recorded during the  
 3 winter 2012-2013. (a) Air temperature and wind speed; (b) snow height and NPs height; (c)  
 4  $k_{eff}$  time series. The snow gauge is about 6 m from the NPs, so that slight differences in snow  
 5 heights at both spots are possible.

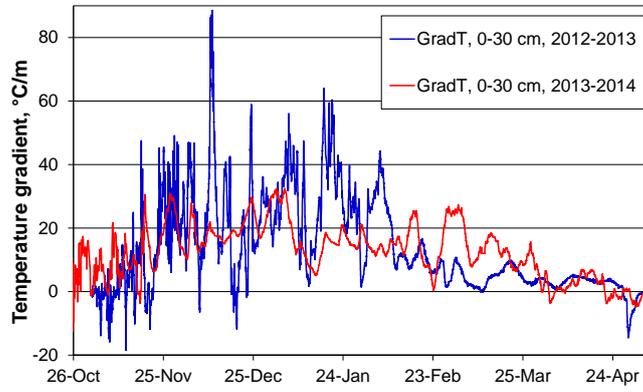
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 2 Figure 5. Meteorological and thermal conductivity data automatically recorded during the  
 3 winter 2013-2014. A battery failure caused the loss of meteorological data between 3 and 28  
 4 February and of the thermal conductivity data between 23 January and 28 February. (a) Air  
 5 temperature and wind speed; (b) snow height and NPs height. The snow gauge close to the  
 6 NPs (yellow line) broke. We therefore show data from another snow gauge located about 20  
 7 m from the NPs. Because of topography, the snow heights differ at both spots; (c)  $k_{eff}$  time  
 8 series.  
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 2 Figure 6. Stratigraphies and density profiles of the snow near our study site on 15 February  
 3 2013 (left) and 25 February 2014 (right). Snow crystal symbols are those detailed in (Fierz et  
 4 al., 2009). When ice layers were present, density measurements were difficult because the  
 5 clean sampling of ice layers was delicate. It was then easy to underestimate snow density,  
 6 possibly by as much as 20%. Because of lateral variations, these stratigraphies are not  
 7 necessarily identical to those present at the exact needle probe spot.  
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 2 Figure 7. Temperature gradient in the snowpack in the bottom 30 cm, calculated as  $(T_{0\text{cm}} -$   
 3  $T_{30\text{cm}})/0.3$ , for both winters studied.

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