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ANALYSIS OF CONTINUOUS SNOW TEMPERATURE PROFILES FROM AUTOMATIC WEATHER STATIONS IN AOSTA VALLEY (NW ITALY): UNCERTAINTIES AND APPLICATIONS

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Abstract

Continuous measurements of snow temperature profiles may be a valuable tool to investigate occurrence and persistence of thermal conditions promoting strengthening or weakening of the snow structure, with potentially important consequences on avalanche release. In this paper, automatic measurements of snow temperature profiles are analysed based on an extensive dataset (67 site-years) in Aosta Valley, Italy. The aims of this work are: (1) to highlight issues and uncertainties on the data and show appropriate data filtering that may be implemented by similar measurement networks; (2) to assess the impact of data filtering on temperature gradient calculation and, (3) to quantitatively describe the occurrence and duration of strong temperature gradients at the base of the snowpack and close to the snow surface that may lead to snowpack instability.

Three main sources of uncertainty were identified and corrected: (1) errors in the data logging; (2) drifts in temperature measurements; (3) a large bias in spring measurements due to snow melting and lack of contact between the sensor and the surrounding snow.

We estimated that strong temperature gradients may account for as much as 25% of total gradients and the duration of these may be as long as 35 days. The frequency of strong gradients was significantly higher at the snow surface than at the snowpack base. Hence, it is highlighted the importance of surface faceted crystals as potential weak layers in alpine snowpacks. *Keywords:* data filtering, snow temperature gradient, depth hoar, near-surface faceted crystals, snowpack instability, snow/soil interface

1 1. Introduction

Temperature distribution in the snowpack is a consequence of the snow-2 atmosphere interactions at the surface and of ground heat fluxes at the lower 3 boundary (or base) of the snowpack. Hence, snow temperatures are strictly 4 related to the energy balance of the snowpack and are commonly used to cal-5 culate temperature gradients. In turn, temperature gradients are responsible 6 for the snow metamorphism which can lead the snowpack towards stability 7 or instability conditions. After depositing on the ground, the seasonal snow 8 cover continues to change due to differences in vapor pressure within the ice 9 lattice. It is primarily the temperature gradient, along with the snow struc-10 ture, that drives differences in vapor pressure resulting in crystal metamor-11 phism. In particular, the metamorphism is of interest because it can indicate 12 strengthening or weakening of the grain structure (Shea et al., 2012). 13

Therefore, it is common among the Avalanche Warning Services to periodically measure, beside other physical properties, the snow temperature profile

in specific locations, in order to predict the possible evolution of snowpackstructure.

In some cases, snow temperatures are continuously registered from automatic weather stations (AWS) or are calculated by models, which are able to describe the snowpack structure on the basis of only few snow and meteorological data, such as for example air temperature, solar radiation, and surface snow temperature (Brun et al., 1989; Morland et al., 1990; Jordan et al., 1991; Lehning et al., 1999).

When using data from manual snow profiles, the temperature gradient of 24 the entire snowpack is calculated considering the snow surface temperature, 25 the ground surface temperature and the snow depth. However, surface snow 26 temperature varies greatly during the day (Fierz, 2011). Diurnal temperature 27 fluctuation within the top portion of the snowpack is the result of the net 28 energy balance at the snow surface, which includes different contributions. 29 Among them the most relevant are the radiation fluxes: short wave radiation 30 flux and net long wave radiation flux (Gray and Male, 1981). McClung and 31 Sharer (2006) suggested that short wave radiations can penetrate within the 32 snowpack to a depth of 10-20 cm. Higher values were reported by Fierz 33 (2011) and Ohara and Kavvas (2006): the thickness of what they call active 34 layer, where the snow temperature shows diurnal variation, reached about 35 50 and 60 cm, respectively. However, the depth of short wave penetration is 36 strictly related to the properties of the surface snowpack layers (Bakermans 37 et al., 2006). 38

Birkeland (1998) reports that the temperature 0.30 m below the surface changes little, if at all, on a daily basis, and represents a sort of diurnal ⁴¹ average. The temperature difference between the cooling and warming snow
⁴² surface and the relatively consistent temperature at 0.30 m below the snow
⁴³ surface results in strong temperature gradients in the near-surface layers
⁴⁴ which might lead to the formation of near-surface faceted crystals.

At the other end of the snowpack, close to the ground surface, kinetic metamorphism is promoted by the high vapor pressure, as snow temperatures are generally close to 0 °C, with the formation of depth hoar (Giddings and LaChapelle, 1962; Colbeck, 1983).

Moreover, within the snowpack, conditions favorable to the growth of 49 faceted crystals can be present, especially close to ice crusts (Colbeck and 50 Jamieson, 2001; Adams and Brown, 1983). Laboratory experiments by 51 Greene et al. (2006) have shown that, under a constant uni-directional strong 52 temperature gradient, increased bonding and greater mechanical strength oc-53 cur on the warm side of the ice lense while the cold side stay or become weak. 54 Depending on the orientation of the temperature gradient, the weak layer can 55 be on the top or on the bottom of the crust. 56

Hence, the study of partial gradients, even if measured at relatively coarse 57 stratigraphic scale (i.e. 20 cm increments), may give insight on local occur-58 rence of conditions that could promote snowpack instability. Near-surface 59 faceted crystals and depth hoar are examples of temperature-gradient meta-60 morphism near the surface or extending down through the base of the snow-61 pack. For example, Birkeland (1998) found that 59% of avalanches released 62 on faceted crystals formed near the surface before being subsequently buried. 63 Not only the strength of the gradient is important to the formation of weak 64 layers, but also its duration plays a key role. In a recent study, Marienthal et 65

al. (2012) found that different avalanche cycles occurred on depth hoar during the 2012 winter in south-west Montana. Schweizer and Jamieson (2001)
reported that 70% of 186 skier-triggered avalanches were released due to weak
layers of persistent grain types (i.e. surface hoar, faceted crystals, and depth
hoar).

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Mechanisms and processes affecting thermal properties of snow are well described in literature (Gray and Male, 1981; Jones et al., 2001; Kaempfer et al., 2005; Fierz, 2011) and it is not among the objectives of this paper to add new findings on this topics. Instead, we analyzed an existing extensive dataset (67 site-years) of continuous snow temperature profiles at 6 sites in Aosta Valley, NW-Italy, in order to:

(1) highlight issues and uncertainties on the data and show appropriate data
filtering that may be implemented by similar measurement networks,

(2) calculate snow temperature gradient and assess the impact of data filtering on gradient calculation, and

(3) quantitatively describe the occurrence and duration of strong temperature gradients at the base of the snowpack and close to the snow surface that
may promote snowpack instability.

85 2. Materials and methods

86 2.1. Study Area

Automatic weather stations (AWS) used in this study are located in the North-western portion of Aosta Valley (Fig.1, table 1). Aosta Valley surface area is 3262 km², the mean altitude is 2106 m a.s.l., with more than 80%

of its territory above 1500 m a.s.l.. Mean annual air temperature (T_{air}) at 90 2000 m a.s.l. ranges from -0.2 to 3.1 °C. The climate of the region is strongly 91 affected by the presence of surrounding high mountains, resulting in a typical 92 inner alpine continental climate (Mercalli et al., 2003). Topography in this 93 region exerts a major influence on several meteorological variables, as for 94 example on the precipitation: while on the south-eastern boundary of the 95 region the external mountain side receives as much as 2000 mm y $^{-1},$ about 96 70% of the region receives less than 1000 mm y^{-1} precipitation with minima 97 of less than 500 mm in the most inner part (Mercalli et al., 2003). 98



Figure 1: Location of the study sites. Dots represent AWS used in this study. The grey scale in the upper-right panel represents elevation (m ASL).

	Long (°)	Lat (°)	Elevation (m)	Period
Ferrache	7.02	45.86	2290	2001-2009
Saxe	6.98	45.81	2076	1992-2009
Grande T \hat{e} te	6.91	45.68	2430	1998-2009
Lavancher	7.02	45.80	2842	1992-2009
Plan Praz	6.95	45.76	2044	1999-2009
Orvieille	7.19	45.58	2170	2005-2009

Table 1: Main characteristics of the 6 study sites.

99 2.2. Data collection

Aosta Valley's meteorological network consists of 91 AWS. Beside mea-100 suring the classical meteorological parameters (such as precipitation, T_{air} , 101 wind speed and direction), 40 AWS also measure snow depth and six mea-102 sure snow temperatures (T_{snow}) . In this work we analyzed the data recorded 103 by these six AWS (Fig.1, Tab.1). T_{snow} was measured at 20 cm increments 104 between 0 and 400 cm from the soil surface with a sampling frequency of 4 105 hours. The array of the T_{snow} sensors is mounted on a white-painted, 4-m-106 height mast, located few meters apart from AWS. 107

Each weather station recorded snow depth by means of snow sensors, shielded T_{air} , barometric pressure, wind speed and direction at 30-min intervals. Total radiation was measured at the same intervals in 5 of the 6 AWS, since one of them (Orvieille) was not equipped with the radiometer. Published accuracies for the snow depth sensors and the termometers were 1 cm and $0.2 \,^{\circ}$ C, respectively. All instruments have been manufactured and installed ¹¹⁴ by CAE (Bologna, Italy), and operated and maintained by Centro Funzionale¹¹⁵ Regionale, Regione Autonoma Valle d'Aosta.

116 2.3. Data processing

Data quality check is pivotal for automatically-operated, only periodically-117 maintained sensors, such the ones we have analyzed. A first quality check 118 was done in order to detect data affected by wrong acquisition, i.e. erroneous 119 data, most commonly a constant series of -30 °C readings for a long period. 120 This was done by quantitatively evaluating the relationship between T_{snow} 121 and T_{air} data. We first calculated the difference between T_{air} and T_{snow} at 122 each level. We then applied a threshold on the difference of -20 and +30 °C 123 respectively and removed all data falling outside that interval. The temper-124 ature thresholds are not physically based but were set arbitrarily after an 125 exploratory analysis. Hence, since we cannot a priori exclude that real data 126 may have been removed, the temperature gradient analysis was also run on 127 the unfiltered dataset, with the same results, indicating that even if real tem-128 perature records may have been removed, these data were probably for the 129 snow free period or for heights above the snowpack. Based on that analysis, 130 a small number of records (about 3% of the total) was removed. 131

One major issue in the dataset was detected in springtime data. When the snow melts, the mast (although white painted) conducts much heat and allows the surrounding snow to melt faster than it would occur under natural conditions. This occurrence results in free space around the sensors similar to that found around tree stems during snowmelt. In terms of measured temperatures, this resulted in positive temperatures at heights that were supposed to be inside the snowpack. A careful analysis showed that this feature

occurred systematically each spring at all sites and across all depths. We 139 therefore decided to assume that all positive temperatures occurring within 140 the snowpack were indicative of a melting snowpack, and substituted all pos-141 itive temperatures with 0 °C values. By this procedure an average across all 142 sites of 30% data were replaced. This substantial data filling was necessary in 143 order to get reliable snow temperature profiles and subsequent temperature 144 gradients. In the results section we will show how this correction affected the 145 computation of temperature gradients. 146

A second issue was represented by drifts in the sensors. Thermometers were 147 calibrated by the manufacturer before installation, but after that any further 148 inter-calibration was not performed or, if performed by manufacturer, it was 149 not tracked. To check the inter-comparability of temperatures measured at 150 different heights within one site we performed the following analysis. From 15: the complete 4-hour time series of a given site we selected snow-free (HS=0 152 cm), nighttime (total radiation less than 20 W m⁻², Papale et al. (2006)) 153 data in order to exclude the effect of solar radiation. We then further subset 154 the data to get a sample of well mixed atmospheric conditions (wind speed 155 higher than 0.5 m s^{-1}), i.e. when the air column on the whole 4-m array is 156 well mixed and therefore unlikely to show air stratification and consequently 157 a temperature gradient. For each temperature profile we calculated the de-158 viation from the profile mean and used a contour plot analysis to show shifts 159 in the sensors that could be caused by drifts. 160

Fig.2 shows one example of this analysis (about 2000 profiles from site Grande $T\hat{e}te$). A consistent departure from the mean temperature profile at a given height (as at 200 cm in fig.2) may represent a drift in the sensor measure-

ment. However, those drifts are not consistent through the whole period,
probably due to a manufacturer's recalibration of the sensors that was not
tracked by the operators. To take into account this source of uncertainty we
applied two different filters.

(1) For each 4-hour vertical temperature profile we computed the difference 168 in temperature from each adjacent sensor. If this difference was higher than 169 $10 \,^{\circ}\text{C}$ (i.e., leading to a temperature gradient of $50 \,^{\circ}\text{C/m}$ or higher), the 170 record was discarded. Discarded data were then gap-filled by linear inter-171 polation. The 50 °C/m threshold was chosen according to published values 172 of partial gradients (Hood et al., 2005; Birkeland, 1998). These studies re-173 port near-surface temperature gradients much higher than $50 \,^{\circ}\text{C/m}$ only very 174 close to the snow surface and at very small vertical increments (e.g. 5 cm 175 increments). The magnitude of those surface gradient decrease exponentially 176 with depth, so that at 15-20 cm from the snow surface values of partial gradi-177 ent exceeding $50 \,^{\circ}\text{C/m}$ were not reported. Based on these values, and given 178 the relatively coarse vertical resolution of our thermistor array we assume 179 that values higher than $50 \,^{\circ}\text{C/m}$ can hardly be measured by our experimen-180 tal setup. 181

(2) For each vertical temperature profile, we first increased the resolution
from 20 to 0.2 cm, by linearly interpolating (using a cubic spline) between
points. We then computed a moving average with a 40 cm resolution window
resulting in smoothed, reconstructed temperature profiles in the snowpack.
The drift analysis was then performed on the filtered datasets, and resulted
in a general increase in data quality (Fig. 2). In the result section we will
show how this correction affect the computation of temperature gradients in

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Figure 2: Contour plot of absolute deviations from the mean temperature profile (°C) showing potential drifts in the sensors for site Grande Tête for PST dataset (a), DA dataset (b), and MAA dataset (c). To stretch values in the low range, values higher than 5° C were set at 5° C

In summary, the three filtering steps lead to four different datasets: (1) unfiltered data (RAW), (2) data filtered for positive T_{snow} (PST), (3) data filtered for drifts with the Difference Approach (DA), and (4) data filtered for drifts with the Moving Average Approach (MAA).

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196 2.4. Temperature gradient analysis

The snow temperature gradients ($^{\circ}C/m$) were computed as the difference in temperature between the lower of two adjacent thermistors and the upper one divided by the vertical distance (0.20 m). A partial gradient is considered within the snowpack when the upper thermometer is covered by at least 10 cm of snow.

For some of the analyzes that we will present, among the whole array of partial gradients in the snowpack, we focused on two remarkable ones: the basal gradient (BG, calculated between 0 and 20 cm), and the surface gradient (SG, the gradient calculated approximately at the snow surface). The basal gradient is of interest to investigate the occurrence of depth hoar, whereas the surface gradient for near-surface faceted crystals.

In order to test the possibility to predict temperature gradients based on environmental parameters, we investigated the relationship between BG, SG and snow depth, T_{air} , solar radiation, and wind speed.

All data have been analyzed using R software for statistical computing (R
development core team, 2010).

213

214 3. Results

Main characteristics of the study sites for the measurement period are reported in table 1, and basic meteorological data are represented in Fig. 3. T_{air} exhibits a linear decrease with elevation, with Lavancher (2842 m a.s.l.) being the coldest site. Average monthly snow depths are consistently higher in Saxe and Lavancher. The latter shows furthermore a different timing in the seasonal distribution of the snowpack, with delayed snowmelt compared to other sites, as a consequence of higher elevation.



Figure 3: Monthly average air temperatures and snow depths at the six investigated sites. Error bars represent confidence intervals.

222 3.1. Snow temperatures

The seasonal course of vertical profiles of T_{snow} are shown by means of contour plots (Fig.4). The depth of the snowpack affects snow temperatures during the course of the winter. While episodic cold periods and the resulting low air temperatures can lower snow temperature close to the surface (as in the period from January to March in Fig.4, when minimum recorded T_{snow} were close to -20 °C), snow temperature at the snow/soil interface remains close to 0 °C for the whole winter (Pomeroy and Brun, 2000). Starting from the beginning of April, the melting snowpack becomes consistently isothermal.

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Figure 4: Seasonal course of mean daily snow temperatures for Saxe in winter 2002-2003. Dataset: PST.

Fig.4 reports an example of relatively warm and deep snowpack occurring in a warm winter. To illustrate the behavior of snow thermal properties in a cold and less snowy winter (e.g. 2004-2005), we show the contour plot of the site located at highest elevation (Lavancher, Fig.5). A long period of cold air temperatures in the period from mid February to mid March results in a cold front in a relatively shallow snowpack that penetrates down to the snow/soil interface. Note that at the end of the cold period, the snowpack gradually warms from the surface, driven by higher air temperatures, whereas at the snow/soil interface temperature remains lower, resulting in a negative surface gradient.





Figure 5: Seasonal course of daily snow temperatures for Lavancher in winter 2004-2005. Dataset: PST.

244 3.2. Temperature gradients

Fig. 6 shows an example of seasonal course of hourly partial gradients in the snowpack.

At this site, positive gradients in the snowpack occur throughout winter and
early spring. Strong positive gradients at the snow surface between February

and March coexist with lower positive gradients in the lower portion of the
snowpack. At the snow surface, the diurnal alternation between positive and
negative gradients is evident.



Figure 6: Seasonal course of hourly partial gradients for Plan Praz in winter 2004-2005. The black solid line depicts snow depth. a) RAW dataset, b) PST dataset.

Fig. 6b shows data corrected for positive spring temperatures, whereas Fig. 6a shows the same data uncorrected. Negative gradients at the base of the snowpack in spring are an artifact due to the unrealistic above-zero temperatures in the snowpack.

256 3.3. Strong temperature gradients in the snowpack: occurrence and duration

Particularly relevant to snowpack stability are temperature gradients higher 257 than $20 \,^{\circ}\text{C/m}$. The 4-hour dataset was used to compute the relative number 258 of weak ($<5 \,^{\circ}C/m$), medium (between 5 and 20 $^{\circ}C/m$) and strong ($>20 \,^{\circ}C/m$) 259 gradients. Gradients were taken as absolute values for this analysis, because 260 heat fluxes may be responsible for constructive metamorphism both upwards 261 and downwards. Fig. 7 reports the frequency histograms for basal gradi-262 ent (BG) and surface gradient (SG), averaged across all sites and separated 263 for the three datasets, computed over the entire study period. There is a 264 common pattern across all datasets and snowpack portions, with generally 265 more than 60% of gradients being classified as weak, and a decreasing oc-266 currence of medium and strong gradients. The frequency of strong gradients 267 is significantly higher in SG compared to BG for all datasets. Correspond-268 ingly, the frequency of weak gradients is significantly lower in SG compared 269 to BD. Comparing the different datasets, the highest number of strong gra-270 dients was found in the unfiltered dataset (RAW, Fig. 7a). Data filtered 271 for positive T_{snow} (PST) feature a higher number of weak gradients and a 272 lower number of medium gradients compared to RAW, with no difference 273 on strong gradients. The effect of the difference-approach filtering (DA) was 274 very similar to that of PST. The moving-average-approach (MAA) resulted 275 in an increase in weak gradients, and in a decrease in both medium and 276

strong gradients compared to RAW data. To give an estimate of the relative number of negative and positive temperature gradients, these were computed on the DA dataset for surface gradients (the gradients that are expected to show the largest number of negative gradients). Averaged across all sites positive strong gradients were about 80% of total strong gradients.



Figure 7: Relative number of temperature gradients according to classes weak, medium and strong in two portions of the snowpack (BG, basal gradient; SG, surface gradient), for the raw data (a, RAW), the data filtered for positive T_{snow} (b, PST), data filtered for drifts using the difference approach (c, DA), and data filtered for drifts using the moving average approach (d, MAA).

Table 2 reports the relative number of strong partial gradients at the

base of the snowpack for each site, according to different filters applied. As
shown also in Fig. 7 strong gradients decrease from RAW to highly filtered
data at all sites, even if strong differences exist across sites. This difference is
associated to the different snow patterns of those sites, in particular Ferrache,
Grande Tête and Orvieille show lower snow depths compared to Lavancher,
Saxe and Plan Praz. Instead, surface temperature gradients appear to be
positively related to elevation (cfr. Table 1).

Table 2: Relative number (%) of strong partial gradients at the base of the snowpack and at the snow surface for each site according to the different filters applied.

			BG			SG		
Site	RAW	\mathbf{PST}	DA	MAA	RAW	\mathbf{PST}	DA	MAA
Ferrache	16.7	8.5	7.1	0.5	27.9	14.3	13.3	5.9
Saxe	1.5	1.1	1.0	0.1	16.9	10.0	9.6	6.7
Grande T \hat{e} te	10.9	9.1	7.3	0.4	36.7	27.5	23.5	14.4
Lavancher	7.3	4.5	4.3	0.2	23.8	12.6	11.6	7.0
Plan Praz	2.4	1.7	1.6	0.1	6.0	4.5	4.0	2.4
Orvieille	14.8	13.7	12.6	1.6	26.0	22.1	20.3	10.5

To evaluate the duration of strong gradients in the snowpack, we calculated the number of consecutive days with strong gradients, and for each site we computed the maximum number of consecutive days with strong gradients (Table 3). For this analysis, we used the daily partial gradients (absolute values). The maximum number of consecutive days was found at site Grande Tête in the RAW dataset, with as much a 154 consecutive days with a temperature gradient higher than 20 °C/m. In general, there is a good agreement ²⁹⁷ between dataset PST and DA, except for Ferrache and Grande Tête. RAW
²⁹⁸ data lead to highest number of consecutive days with strong gradients for all
²⁹⁹ sites except Ferrache, whereas the MAA filtering procedure always resulted
³⁰⁰ in the lowest number of consecutive days.

For sites Plan Praz and Orvieille the highest number of consecutive days was consistently found at the snow surface for all datasets. The mean duration (in days) of a persistent strong gradient (all depths mediated) was fairly constant across sites and datasets, ranging between 1 and 2.5 days, except for site Grande Tête in RAW dataset, which was much higher.

Table 3: Average(\pm SD) and maximum number of consecutive days with mean daily gradient higher than 20 °C/m for all sites and all datasets. For maximum, depth and year of occurrence are also indicated.

Site	Dataset	N days (mean)	N days (max)	Depth (max)	Year (max)
Ferrache	RAW	$1.9{\pm}0.8$	21	40-60 cm	2009
	\mathbf{PST}	$1.9{\pm}0.7$	23	$0\text{-}20 \mathrm{~cm}$	2005
	DA	$1.6{\pm}0.5$	14	60-80 cm	2009
	MAA	$1.1{\pm}0.3$	5	$60-80 \mathrm{~cm}$	2009
Saxe	RAW	$1.6{\pm}0.5$	12	$0-20~\mathrm{cm}$	1999
	\mathbf{PST}	$1.5 {\pm} 0.5$	12	0-20 cm	1999
	DA	$1.4{\pm}0.4$	12	0-20 cm	1999
	MAA	$1.2{\pm}0.3$	5	$100\text{-}120~\mathrm{cm}$	2005
Grande T \hat{e} te	RAW	$8.1{\pm}14.1$	154	80-100 cm	2001
	\mathbf{PST}	$1.9{\pm}1.5$	21	Surface	2001
	DA	$1.6{\pm}1.0$	16	0-20 cm	2006
	MAA	$2.4{\pm}3.0$	5	$0-20~\mathrm{cm}$	2006
Lavancher	RAW	$2.3{\pm}1.4$	117	40-60 cm	2008
	\mathbf{PST}	$2.0{\pm}0.9$	35	$40\text{-}60~\mathrm{cm}$	2008
	DA	$2.0{\pm}0.7$	35	$40\text{-}60~\mathrm{cm}$	2008
	MAA	$1.3{\pm}0.6$	8	Surface	2007
Plan Praz	RAW	$1.6{\pm}0.6$	8	Surface	1999
	\mathbf{PST}	$1.7{\pm}0.8$	8	Surface	1998
	DA	$1.7{\pm}0.7$	8	Surface	1998
	MAA	$1.4{\pm}0.6$	5	Surface	2005
Orvieille	RAW	$1.9{\pm}1.4$	15	Surface	2005
	\mathbf{PST}	$2.0{\pm}1.5$	15	Surface	2006
	DA	$2.0{\pm}1.4$	15	Surface	2006
	MAA	$1.1 {\pm} 0.1$	2	Surface	2006

306 3.4. Relationship between temperature gradients and environmental variables

We hypothesized a strong relationship between snow depth, T_{air} and the 307 snow temperature gradients. As an example, this relationship is illustrated 308 in Fig. 8 for 4-hour partial gradients from the PST dataset. As expected, 309 absolute values of partial gradients at the base of the snowpack are higher 310 with lower snow depths and gradually get closer to 0 °C/m with increasing 311 snow depth. The same pattern can be seen at the surface, but with increasing 312 scatter, suggesting that other factors exert a major influence at the snow 313 surface. 314



Figure 8: Scatter plot between hourly partial gradients (positive in black, negative in red), air temperature and snow depth, for all sites and years, dataset: PST.

Table 4: Pearson correlation coefficient between snow temperature gradients (separated between positive and negative gradients, column 'sign'), snow depth and air temperature for different datasets (all coefficients are significant at p<0.001, except those denoted by *).

Gradient	Dataset	Sign	Snow depth	T_{air}	Total radiation	Wind speed
BG	RAW	+	-0.33	-0.14	-0.03	-0.09
		-	0.25	-0.24	-0.23	0.00*
SG		+	-0.18	-0.27	0.05	-0.03
		-	0.07	-0.15	-0.36	0.05
BG	\mathbf{PST}	+	-0.44	-0.30	-0.12	-0.10
		-	0.06	-0.08	-0.10	-0.09
SG		+	-0.19	-0.44	-0.14	-0.03
		-	0.06	0.08	-0.16	0.09
BG	DA	+	-0.47	-0.31	-0.13	-0.10
		-	0.16	-0.06	-0.12	-0.10
SG		+	-0.18	-0.45	-0.16	-0.02
		-	0.06	0.10	-0.15	0.09
BG	MAA	+	-0.46	-0.34	-0.13	-0.12
		-	0.42	-0.16	-0.14	0.03
SG		+	-0.08	-0.38	-0.03	-0.01*
		-	-0.01*	-0.19	-0.30	0.00*

Table 4 reports the correlation coefficients between snow temperature gradients and relevant environmental variables. Higher correlations were found between gradients, snow depth and T_{air} , whereas the relationship between gradients, solar radiation and wind speed was weaker. PST and DA filtering improves the correlation between either basal and surface positive tempera-

ture gradients, and snow depth and T_{air} , whereas MAA filtering results in 320 lower correlation between gradients and snow depth, but higher correlation 321 with T_{air} . The relatively weak relationship between partial gradients, snow 322 depth and T_{air} suggests that partial gradients cannot be predicted by means 323 of such simple environmental drivers. We performed a multiple regression 324 with T_{air} and snow depth as regressors and partial gradients (positive and 325 negative gradients separated) at all depths and found that none of them 326 could be properly predicted using any datasets. We furthermore tried to 327 include other environmental data (solar radiation, wind speed, air pressure, 328 etc.) as regressors when available, but with no substantial improve of the 329 model (data not shown). Multiple regression models showed \mathbb{R}^2 always lower 330 than 0.4. The pattern of \mathbb{R}^2 s across different datasets reflected the pattern 331 of correlation coefficients shown in table 4. 332

333 4. Discussion

334 4.1. The effect of data filtering on temperature gradient computation

An extensive dataset (67 site-years) of continuous measurements of T_{snow} 335 represents an invaluable tool to evaluate the occurrence and the duration 336 of strong temperature gradients at relatively small stratigraphic scale in the 337 snowpack owever, we have identified 3 sources of uncertainty on the data 338 that must be taken into account to get reliable information. Uncertainties 339 include erroneous data, positive T_{snow} in spring and drifts in the thermis-340 tors. Erroneous data were removed by evaluating the relationship between 341 T_{snow} and T_{air} , and this correction did not affect the computation of snow 342 temperature gradients. However, thresholds in this analysis were arbitrarily 343

chosen and dataset-specific. Therefore, they should be applied with cautionon other datasets.

Approximately 30% of positive temperatures in the snowpack were removed 346 and substituted by 0 °C. This correction resulted in more realistic tempera-347 ture gradients in the snowpack in spring (cfr. Fig. 6). The relative number 348 of gradient classes was also affected by the filtering as shown in Fig. 7. The 349 second filtering (DA) was intended to remove large sensors drifts, and showed 350 very similar results compared to PST. The MMA filtering was intended to 351 remove small drifts in the vertical temperature profile and resulted in a gen-352 eral smoothing of the partial gradients. Consequently, compared to RAW 353 and PST datasets, this filtering produced a higher number of weak gradi-354 ents, and a lower number of medium and strong gradients. The smoothing 355 effect of filtering was reflected also in the computation of consecutive days 356 with strong gradients (Table 3), with a decrease in duration towards subse-357 quent filtering steps. The unrealistic number of maximum consecutive days 358 with strong gradients calculated in Lavancher and Grande T \hat{e} te in the RAW 359 dataset is associated to positive T_{snow} and the difference between unfiltered 360 and filtered data in this analysis demonstrates the usefulness of PST filter. 361 Instead, the small difference found between PST and DA filtering suggests 362 that this latter correction only marginally affects the gradient calculation, 363 even if DA filter was effective in reducing the effect of sensor drifts (cfr. 364 Fig 2). Since the difference between PST and DA filtering is small, we also 365 confirm our preliminary assumption that gradients higher than $50 \,^{\circ}\text{C/m}$ can 366 hardly be measured by this experimental setup. 367

³⁶⁸ MAA filtering strongly reduces the occurrence and duration of strong gra-

dients, and fails in identifying inter-site differences in temperature gradients (discussed later). This is because MAA filtering resulted in an inordinate smoothing of temperature vertical profiles that in turn possibly lead to an underestimation of strong temperature gradients.

In summary, the combination of PST and DA filters significantly improves the dataset and may be applied to similar experimental setup. However, it must be noted that the gradient threshold of 50 °C/m should likely be increased in case of gradients measured at depth increments smaller than those used in this study (20 cm). In fact, gradients larger than 50 °C/m were reported by previous studies in small portions of the snowpack surfa to 10 cm increments (Hood et al., 2005; Birkeland, 1998; Greene et al., 2006).

381 4.2. Magnitude of snow temperature gradients and variability across sites

Snowpack instability due to constructive metamorphism is usually asso-382 ciated to strong temperature gradients at the base of the snowpack and the 383 formation of depth hoar. However, strong surface gradients may promote 384 the formation of near-surface faceted crystals, which, if buried by new snow, 385 might also result in potential snowpack instability (Birkeland, 1998; Hood et 386 al., 2005). Here we show that the occurrence of strong temperature gradients 387 is significantly higher at the snow surface than at the snowpack base (Fig. 388 7), highlighting the importance of considering surface snow properties for 389 snowpack stability. 390

³⁹¹ Based on DA dataset we estimated that strong temperature gradients (i.e ³⁹² absolute gradients higher than $20 \,^{\circ}C/m$) account for between 1 and 13% of ³⁹³ total gradients at the base of the snowpack, and for between 4 and 24% at

the snow surface. With respect to snowpack stability, the first are associated 394 to full-depth avalanches, whereas the latter to surface slab avalanches, of-395 ten human-triggered (Schweizer and Jamieson, 2001; Schweizer and Lütschg, 396 2001). The mean duration of strong temperature gradients ranged from 1.4397 to 2 days, whereas the maximum duration varied across sites from 8 to 35 398 days. These time interval is sufficient for the development of faceted crystals 399 that might result in persistent weak layer (Birkeland, 1998). In two out of 400 six sites these long-lasting strong temperature gradients occurred at the snow 401 surface, whereas in two sites they occurred at the bottom of the snowpack. 402 These extreme gradients are not related to a specific, particularly cold or 403 snow-poor winter. 404

Although a strong relationship between snow depth, T_{air} and snow temperature gradients was not found, the occurrence and duration of these varied 406 across sites, primarily as a function of environmental drivers. The relative 407 number of strong partial gradients at the base of the snowpack reported in 408 table 2 was higher in Ferrache, Grande T \hat{e} te and Orvieille, which are also the 409 sites characterized by lower snow depths (Fig. 3), and lower in Lavancher 410 and Saxe. This pattern can be seen for all datasets, but only for PST the cor-411 relation between the relative number of strong gradients and the mean snow 412 depth was significant (r=-0.849, p<0.05). A similar behavior is also appar-413 ent for the duration of strong gradients (Table 3). Surface gradients are less 414 correlated with T_{air} and appear to be instead related to elevation. Eleva-415 tion is in turn related to solar radiation (positively) and to T_{air} (negatively) 416 and may therefore be seen as a number that integrates the two. However, 417 no direct relationship was found between occurrence or duration of surface 418

⁴¹⁹ gradients and radiation or T_{air} .

- 420 Even if in some cases synthesis data such as relative number and maximum
- duration of strong gradients showed a relationship with snow depth, T_{air}
- and elevation, the lack of such a clear relationship for 4-hourly and daily
- temperature gradients prevented us from modeling the seasonal course of
- ⁴²⁴ (temperature gradients based on simple environmental parameters.

425 5. Conclusions

The analysis of a large dataset of snow temperature profiles (about 3 mil-426 lions temperature records, from 67 site-years) has shown important features 427 related to the measurement of snow temperatures and the calculation of tem-428 perature gradient in the snowpack but also highlighted a number of issues 429 related to data quality. Data quality check has allowed to: (1) remove about 430 3% of the data likely associated with errors in the data logging; (2) identify a 431 substantial problem related to melting snow around the sensors during spring 432 which leads to positive snow temperatures; in order to solve this problem we 433 had to replace about 30% of fake, positive snow temperatures, assuming that 434 temperature was 0° C; and (3) identify a procedure based on the analysis of 435 snow-free, nighttime temperature profiles that allowed to identify drifts in 436 the sensors, corrected by means of two subsequent filtering procedures (DA 437 and MAA). 438

Filtering for (1) did not affect the snow gradient computation, whereas filtering for (2) substantially improved the data quality and the reliability of calculated snow temperature gradients. With respect to (3), DA filtering resulted in a small improvement of data, whereas MAA resulted in an inordinate smoothing of temperature vertical profiles that in turn possibly lead to
an underestimation of strong temperature gradients. Reliable snow temperature datasets may therefore be obtained by applying a filter for above zero
snow temperatures and a threshold for unrealistically high partial gradients.
This threshold must however be adjusted based on the vertical resolution of
temperature measurements.

Based on this extensive dataset, we estimated that strong temperature gradients may account for as much as 25% of total gradients and the duration of these may be as long as 35 days. The frequency of strong gradients is significantly higher at the snow surface than at the snowpack base. Therefore the formation of near-surface faceted crystals as potential weak layers must be taken into account when assessing snow stability in alpine snowpack

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