3-D image-based numerical computations of snow permeability: links to specific surface area, density, and microstructural anisotropy

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Abstract

We used three-dimensional (3-D) images of snow microstructure to carry out numerical estimations of the full tensor of the intrinsic permeability of snow ($K$). This study was performed on 35 snow samples, spanning a wide range of seasonal snow types. Because the permeability is related to a characteristic length, we introduced a dimensionless tensor $K^* = K/r_{es}^2$, where the equivalent sphere radius of ice grains ($r_{es}$) is computed from the specific surface area of snow (SSA) and the ice density ($\rho_i$) as follows: $r_{es} = 3/(SSA \times \rho_i)$. Values of $K^*$, the average of vertical and horizontal components of $K^*$, were plotted vs. snow density ($\rho_s$) and compared to analytical models and data from the literature, showing generally a good agreement. The 35 values of $K^*$ were fitted to $\rho_s$ and provide the following regression: $K^* = 2.94 \times \exp(-0.013\rho_s)$, with a correlation coefficient of 0.985. This indicates that permeability, if assumed isotropic, can be reasonably determined from SSA and $\rho_s$, which are both easily measurable in the field. However, the anisotropy coefficient of $K$, induced by the snow microstructure, ranges from 0.74 to 1.66 for the samples considered. This behavior is consistent with that of the effective thermal conductivity obtained in a previous work.

1 Introduction

Once fallen on the ground, snow forms a complex porous material made of ice, air, water vapor and sometimes liquid water. The amount of these quantities, and their geometrical arrangement at the grains scale, referred to as the microstructure, strongly influence the physical properties of snow. Among them, the intrinsic permeability tensor of snow $K$ (m$^2$) links the pressure gradient $\nabla p$ (Pa m$^{-1}$) and the discharge per unit area $q$ (m s$^{-1}$) through the Darcy’s law $q = -(1/\mu)K\nabla p$, where $\mu$ is the dynamic viscosity of the fluid (kg m$^{-1}$ s$^{-1}$).

The intrinsic permeability is of particular interest to better understand the transport properties of snow and firn, such as wind pumping (Colbeck, 1989, 1997), convection
(Akitaya, 1974; Powers et al., 1985; Brun and Touvier, 1987; Sturm and Johnson, 1991; Albert et al., 2004) and liquid water flow (Colbeck, 1975, 1976; Waldner et al., 2004; Katsushina et al., 2009; Yamaguchi et al., 2010). It is a key variable for a wide number of applications such as atmospheric and firn chemistry (Freitag et al., 2002; Neumann, 2003; Grannas et al., 2007) or snow-firn metamorphism (Albert, 2002; Hörhold et al., 2009). Recently, permeability has also been proposed as a means of characterization for quantitative snow classification (Arakawa et al., 2009).

The first quantitative data on snow permeability are attributed to Bader (1939). Shimizu (1970), Sommerfeld and Rocchio (1993), and Jordan et al. (1999) realized extensive experiments on seasonal snow and proposed parametrizations depending on grain size and density. However, these studies are characterized by a significant scatter in the results, which seems mainly due to experimental reasons (Sommerfeld and Rocchio, 1993). More recently, the availability of 3-D images of snow and firn from X-ray tomography (Brzoska et al., 1999; Coléou et al., 2001; Freitag et al., 2004; Schneebeli and Sokratov, 2004; Kaempfer et al., 2005) opened the way to numerical simulations. Courville et al. (2010) computed one component of the permeability of firn samples using Lattice-Boltzman modeling and Zermatten et al. (2011) performed direct pore-level simulations on five snow samples. While these numerical computations seem particularly promising, the obtained results show only a relative agreement with previous experimental studies and theoretical models.

To try to better understand the origin of the scatter observed in the literature and the impact of the snow microstructure, we carried out numerical simulations of the intrinsic permeability \( K \) on 35 3-D images of snow obtained from microtomography. Computations were performed with the software Geodict (Thoemen et al., 2008; Koivu et al., 2009; Calonne et al., 2011) and are based on the periodic homogenization method (Auriault et al., 2009). This work follows the pioneering developments of Courville et al. (2010) and Zermatten et al. (2011). The main differences lie in the fact that our study considers a wide range of snow types and samples, uses the periodic homogenization method and evaluates the anisotropy of \( K \). In addition, detailed comparisons to
the main datasets and analytical laws available in the literature are provided and discussed.

2 Methods

2.1 Snow samples

Numerical computations were performed on 35 tomographic images obtained from previous experiments or field sampling, spanning most snow types of seasonal snow, i.e. Precipitation Particles (PP), Decomposing and Fragmented precipitation particles (DF), Rounded Grains (RG), Faceted Crystals (FC), Depth Hoar (DH) and Melt Forms (MF), according to the International Classification for Seasonal Snow on the Ground (ICSSG) (Fierz et al., 2009).

Two-thirds of the snow samples come from controlled cold-room experiments: a first series (PP, DF and RG) was obtained by subjecting deposited natural snow to isothermal conditions at 271 K (Flin et al., 2004). Another RG sample was obtained under similar conditions, but after sieving. A second series (RG, FC and DH) was obtained under a temperature gradient of 43 K m$^{-1}$ at 269 K and corresponds to various stages of metamorphism of the initial sieved snow (RG) into FC then DH. Two others similar experiments, with a gradient of 16 and 100 K m$^{-1}$ at 268 and 270 K, provided two samples (FC and DH) (Coléou et al., 2001; Flin and Brzoska, 2008). A series of MF samples was obtained by grain coarsening in water-saturated snow using the method of Raymond and Tusima (1979) followed by draining of their liquid water content (Coléou et al., 2001; Flin et al., 2011).

The remaining snow samples were directly collected in the field: 10 snow specimens (PP, DF and RG) were sampled at increasing depths in the snowpack of the Girose glacier (Écrins, French Alps) (Flin et al., 2011). Another PP sample was collected at Col de Porte (Chartreuse, French Alps).
Additional information about the snow samples are indicated in Table 1 of the auxiliary materials available online.

2.2 Computation of snow permeability

Physical phenomena in heterogeneous systems such as porous media can be modeled by an equivalent continuous macroscopic description, provided that the condition of separation of scales is satisfied (Auriault, 1991; Auriault et al., 2009). This fundamental condition may be expressed as $\varepsilon = l/L << 1$, in which $l$ and $L$ are the characteristic lengths of the heterogeneities at the pore scale and of the macroscopic sample or excitation, respectively. This condition implies the existence of a Representative Elementary Volume (REV) of size $l$ of the material and the physical phenomena. The REV constitutes the smallest fraction of the sample volume from which a variable representative of the whole can be determined. Assuming that this condition is fulfilled, the main results concerning the derivation of Darcy’s law from the physics at the pore scale using the homogenization method for periodic structures (Ene and Sanchez-Palencia, 1975; Auriault, 1991), are presented.

Without loss of generality (Auriault, 2011), we consider a rigid porous matrix which is periodic with period $\Omega$, i.e. the size of the REV, and which is fully saturated by an incompressible Newtonian fluid of density $\rho$ and viscosity $\mu$. $\Omega^s$ and $\Omega^f$ are the domains occupied by the solid and the fluid, respectively. The common boundary of $\Omega^s$ and $\Omega^f$ is denoted $\Gamma$. The porosity is defined as $\phi = |\Omega^f|/|\Omega|$. At the pore scale, the steady state flow is described by:

$$\mu \nabla v - \nabla p = \rho (v \cdot \nabla) v, \quad \nabla \cdot v = 0, \quad \text{within } \Omega^f, \quad \text{with } v = 0 \text{ on } \Gamma$$

(1)

where $v$ and $p$ are the velocity and the pressure of the fluid, respectively. Using the homogenization method, it can be shown that the corresponding macroscopic description strongly depends on the order of magnitude of the pore Reynolds number, $R_{el} = |\rho (v \cdot \nabla) v|/|\mu \Delta v| = O(\rho v_c l / \mu)$ where $v_c$ is a characteristic value of fluid velocity.
When $R_{el} < \mathcal{O}(1)$, the macroscopic flow is described by Darcy’s law, otherwise non-linearities appear at the macroscopic scale (Mei and Auriault, 1991). In what follows, it is assumed that $R_{el} < \mathcal{O}(1)$, which is typically the case for example if we consider airflow through snow and firn induced by moderate winds ($< 6 \text{ m s}^{-1}$) over the snowpack surface (Albert, 2002). Under such conditions, the macroscopic description is written:

$$\langle \mathbf{v} \rangle = -\frac{\mathbf{K}}{\mu} \nabla p, \quad \nabla \cdot \langle \mathbf{v} \rangle = 0, \quad \text{with } \langle \mathbf{x} \rangle = \frac{1}{\Omega} \int_{\Omega} \mathbf{x} \, d\Omega$$

where $\langle \mathbf{v} \rangle = \mathbf{q}$ represents the Darcy’s velocity and $\mathbf{K}$ is the intrinsic permeability tensor of the porous media. This tensor, which is symmetric and positive, is defined as $K_{ij} = \langle k_{ij} \rangle$. The second order tensor $\mathbf{k}$ is solution of the following boundary value problem over the REV,

$$\mu \Delta \mathbf{v} - \nabla \tilde{p} - \nabla p = 0, \quad \nabla \cdot \mathbf{v} = 0, \quad \text{within } \Omega^f, \quad \text{with } \mathbf{v} = \mathbf{0} \text{ on } \Gamma$$

where $\mathbf{v} = -(1/\mu)\mathbf{k}\nabla p$, the pressure fluctuation $\tilde{p}$ (with $\langle \tilde{p} \rangle = 0$) are the periodic unknowns and $\nabla p$ is a given macroscopic gradient of pressure.

The components of the permeability tensor $\mathbf{K}$ were estimated by solving the above boundary value problem (3) on a REV extracted from tomographic images (see Sect. 3.4), using the software Geodict (http://www.geodict.de). It was previously ensured that the ratio between closed and open porosity is negligible, meaning that it is correct to consider that air can flow through the whole porosity of REVs. In the following, the non-diagonal terms of the tensor $\mathbf{K}$, about 50 times lower than diagonal terms, are not presented (the $x$, $y$ and $z$ axes of 3-D images correspond to the principal directions of the microstructure, $z$ being along the direction of the gravity). We note $K$ the average value of the three diagonal terms of $\mathbf{K}$, $K_z$ its vertical component and $K_{xy}$ the average of its two horizontal components.
2.3 Computations of microstructural properties

Snow porosity (\(\phi\)), and thus snow density (\(\rho_s = \rho_i (1 - \phi)\), in kg m\(^{-3}\), with the ice density \(\rho_i = 917\) kg m\(^{-3}\)), were estimated from 3-D images using a standard voxel counting algorithm.

The specific surface area (SSA, in m\(^2\) kg\(^{-1}\)) of a snow sample is defined as the ratio of the total surface area of the air/ice interface per unit mass. It was computed from 3-D images using a stereological method as described by Flin et al. (2011) where the SSA is obtained by averaging SSA estimations computed along 3 orthogonal directions (x, y, z).

The equivalent sphere radius of a snow sample (\(r_{es}\), in m) (Sommerfeld and Rocchio, 1993; Luciano and Albert, 2002), also called the optical radius (Picard et al., 2009), is a characteristic length of the ice grains at the microscopic scale. It corresponds to the radius of a collection of spheres having the same SSA value than the sample considered. \(r_{es}\) is related to SSA by \(r_{es} = 3/(\text{SSA} \times \rho_i)\).

3 Results and discussion

3.1 Dimensionless permeability vs. snow density

The permeability tensor \(K\), the density \(\rho_s\), and the SSA were computed on REVs. from the 35 3-D images. \(K\) exhibits values between \(4 \times 10^{-10}\) and \(6 \times 10^{-9}\) m\(^2\), while \(\rho_s\) and SSA range from 103 to 544 kg m\(^{-3}\) and from 4 to 56 m\(^2\) kg\(^{-1}\), respectively. For each sample, detailed values are provided in Table 2 of the auxiliary online materials.

The intrinsic permeability is strongly linked to a characteristic length of the microstructure of the medium considered (Boutin and Geindreau, 2010). Thus, \(K\) is often normalized by its characteristic length to the square, leading to a dimensionless tensor that we note \(K^*\). Because snow SSA is a well-defined variable which is quite easy to estimate experimentally (Gallet et al., 2009; Arnaud et al., 2011), and numerically using 3-D
images (Flin et al., 2011), we chose to use the equivalent sphere radius ($r_{es}$), directly given by the SSA computation, to normalize the components of $K$. In the following, $K^*$ is thus equal to $K/r_{es}^2$ and we keep the notation $K^*, K^*_z$ and $K^*_{xy}$ for the average, vertical and horizontal components of $K^*$, respectively. One can also choose to normalize $K$ by a characteristic length corresponding to the pore space and use the hydraulic radius ($r_h$), commonly applied to flow through pipes and open channels. This normalization is as good as that with $r_{es}$, since these two radii are linked by the simple relationship: $r_h = r_{es}(1 - \phi)/(3\phi)$ (Bear, 1972). Computing the granulometry is another method to determine a characteristic length (Zermatten et al., 2011). However, this parameter is less convenient because it can not be estimated experimentally but only numerically from 3-D images.

Using the “T”-shape symbols, Fig. 1 shows the $K^*_z$ and $K^*_{xy}$ components, in logarithmic scale, as a function of density. $K^*_z$, $K^*_{xy}$ and thus $K^*$ decrease with increasing $\rho_s$. PP samples exhibit the largest values of $K^*$ (1.05 for $\rho_s = 103$ kg m$^{-3}$), while the lowermost values are obtained for MF samples (2.16×10$^{-3}$ for $\rho_s = 544$ kg m$^{-3}$). Differences between $K^*_z$ and $K^*_{xy}$ values can be observed for several samples, FC and DH notably, and will be presented in Sect. 3.5. The 35 values of $K^*$ were fitted to $\rho_s$ and provide the following regression: $K^* = 2.94 \times \exp(-0.013\rho_s)$ (black curve in Fig. 1), with a correlation coefficient of 0.985. This high coefficient indicates a strong relationship between $K$, SSA and $\rho_s$. The permeability $K$ can thus be reasonably inferred from SSA and $\rho_s$ using the fit given above.

### 3.2 Comparisons between numerical computations, models and fit

In addition to our computed values and fit, Fig. 1 displays four curves of the dimensionless permeability vs. $\rho_s$ corresponding to the following regression, analytical formulas or numerical computations:

(i) The well-known Shimizu’s fit (Shimizu, 1970) is expressed as:

$$K = 0.077D^2 \times \exp(-0.0078\rho_s), \text{ with } D = 2r_{es}$$

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(ii) The self consistent (SC) estimate was obtained assuming that the porous medium is constituted of a bicomposite spherical pattern made of an internal spherical grain and an external fluid shell that ensures fluid connectivity. The morphology of the porous medium is reduced to the most basic information, i.e. the porosity and the grain size. Using the SC method, Boutin (2000) showed that the above porous media lead to the following estimate:

$$K = \left[ \frac{r_{es}^2}{(3\beta^3)} \right] \times \left[ -1 + \frac{(2 + \beta^5)}{(\beta(3 + 2\beta^5))} \right], \quad \text{where} \quad \beta = (1 - \phi)^{1/3}$$

(iii) In the Carman-Kozeny (CK) model, the medium is treated as a bundle of capillarity tubes of equal length. By solving the Navier-Stokes equations simultaneously for all the channels passing through a cross-section normal to the flow in the porous medium, the permeability is written as

$$K = \left( c \times \phi^3 \right) / \left( \text{SSA}_i \times (1 - \phi)^2 \right)$$

where SSA$_i$ is the specific surface area per unit of ice volume (SSA$_i$ = SSA$\times$$\rho_i$, in m$^{-1}$) and $c$ a coefficient which characterizes the geometry of the channels in the model. Empirically, $c$ is found to be equal to 0.2 for many types of porous media (Bear, 1972). The CK equation can thus be expressed as:

$$K = \left( 4r_{es}^2 \times \phi^3 \right) / (180(1 - \phi)^2)$$

(iv) Numerical values of permeability of a simple cubic packing of spheres (Boutin and Geindreau, 2010) were also reported in Fig. 1.

Estimates of SC and CK models correspond fairly well to the computed data for a wide range of snow density, despite their simplified geometry (see Fig. 1). For the MF samples, models fail to reflect the snow microstructure and overestimate the permeability. These results can be explained by the fact that at low density the airflow around a snow particle is little affected by flow around its neighbours. In contrast, at higher density, snow particles are close together and the flow around one of them disturbs the flow around the others. This last phenomenon is not captured by analytical models.
The Shimizu’s fit and our computations are not in good agreement. As pointed out by several studies (Sommerfeld and Rocchio, 1993; Jordan et al., 1999), we believe that this difference is largely due to the method used by Shimizu (1970) to estimate grain size. From snow cross-sections, he computed a grain diameter $D = 2r_{es} = \sqrt{6\rho_s/\pi \rho_i n}$, where $n$, the number of ice grains appearing in the cross section per a unit area, is estimated by a counting process described as: “a complicated-shaped grain having $m$ remarkable constrictions was counted as $m+1$ grains”. This visual method is subjective and may lead to erroneous estimates of $n$ and therefore of $K^*$.

Finally, we find that a simple cubic packing of spheres appears to be sufficient to provide a relationship of $K^*$ vs. $\rho_s$ roughly consistent with our results in the whole range of density considered, and notably for the MF samples.

### 3.3 Comparison to experimental and numerical data

Figure 2 allows a comparison between our 35 values of $K^*$ (in black) and data from four previous studies (in color).

Sommerfeld and Rocchio (1993), Arakawa et al. (2009) and Courville et al. (2010) performed measurements of permeability using an air permeameter on fresh or equi-temperature snow, in south-eastern Wyoming (USA), on natural deposited dry snow in Hokkaido prefecture (Japan), and on polar firn (Antarctica), respectively. The SSA was estimated from photographs of snow section planes using a stereological method in the first two papers, while Courville et al. (2010) used tomographic images.

Numerical computations involving 3-D images were carried out in two recent studies: Courville et al. (2010) used Lattice-Boltzman modeling to compute the permeability in one direction on polar firn, and Zermatten et al. (2011) determined the vertical permeability for five snow samples using the direct pore-level simulations method. In both cases, SSA was estimated from the 3-D images.
Data from these four studies are overall well consistent with our computations and both analytical models, showing a similar relationship of dimensionless permeability with $\rho_s$.

Experimental values, especially those from Arakawa et al. (2009) which provided the bigger dataset, are nevertheless more scattered than computed values. This can be explained by the large number of experimental data but also by the difficulty to make reliable and reproducible measurements of permeability. A first source of errors may be the physical damage of the sample caused during its sampling or its handling (Sommerfeld and Rocchio, 1993). Shimizu (1970) and Sommerfeld and Rocchio (1993) also pointed out a bias linked to possible condensation/sublimation of the snow microstructure induced by the airflow imposed through the snow sample during the measurement.

The computations of Courville et al. (2010), Zermatten et al. (2011) and this study are in excellent agreement, although all three studies use different numerical methods and boundary conditions on the external faces of the sample. Zermatten et al. (2011) indicate significant differences between the CK model and their values, while Fig. 2 shows a good agreement between both: they apparently plotted an erroneous CK equation, using the specific surface area per unit of snow volume ($SSA_v$, in m$^{-1}$) in the expression of $K = \phi^3 / (5(1 - \phi)^2 SSA^2)$ instead of $SSA_i$ (see Sect. 3.2).

### 3.4 Representative elementary volume

The Representative Elementary Volume (REV) can be estimated by calculating values of a given variable from several sub-volumes of increasing sizes. It is reached as soon as values do not vary significantly when sub-volumes of computation increase. Note that the REV size depends on the variable and on the sample studied: REVs with respect to snow permeability are generally equal or larger than those for other variables, such as $\rho_s$, SSA or the effective thermal conductivity (Flin et al., 2011; Calonne et al., 2011). Thus, a special attention must be paid to ensure that computations are carried out on a sufficiently large volume.
Estimations of the REV were performed on one sample of each snow type and range from 2.5 mm$^3$ for the PP sample to 5.5 mm$^3$ for the MF sample (see auxiliary online materials), which corresponds to the total volumes of our 3-D images or less.

For 3 snow samples (RG, FC and MF), computations of $K$, SSA and $\rho_s$ were performed on total volumes and on sub-volumes of different sizes. Figure 3 shows the obtained values of $K^*$ as a function of $\rho_s$. By increasing the volume size of calculation (from volume 1 to 4 or 5 in Fig. 3), the result becomes closer to the previous one, which is consistent with the REV definition. Overall, our computed values are roughly consistent with our fit and the CK and SC model. Thus, we point out the fact that if $K$, SSA and/or $\rho_s$ are computed on a volume smaller than their REV, the final result, i.e. $K^*$ vs. $\rho_s$, remains in agreement with the evolution of $K^*$ proposed by our fit or analytical models. This observation highlights the robustness of the relationship between $K$, SSA and $\rho_s$.

3.5 Anisotropy

Numerical estimations of the permeability tensor allow to compute, for each sample, the anisotropy coefficient of $K$ such as $A(K) = K_z/K_{xy}$. As shown in Fig. 5, $A(K)$ ranges from 0.74 for a PP sample collected in the field, to 1.66 for a particularly evolved DH sample obtained in cold room. For this last sample, the velocity of the airflow along the vertical and horizontal directions is illustrated in Fig. 4 (see left and right hand side, respectively). The flow, constrained by the snow microstructure, is clearly more intense in the vertical than in the horizontal direction, leading to a high $K_z$ value. The value of 1.66 is of the same order of magnitude as the analytical coefficient of anisotropy for a network of vertical cylinders (Boutin, 2000). The range in $A(K)$ is consistent with the values between 0.75 and 1.9 measured by Luciano and Albert (2002) on firn collected from 1 to 13 m depth at Summit, Greenland.

Similarly, by defining the anisotropy coefficient $A(k_{\text{eff}})$ of the effective thermal conductivity tensor $k_{\text{eff}}$ provided in Calonne et al. (2011), one can compare $A(K)$ to $A(k_{\text{eff}})$.
for the same snow samples. According to Fig. 5, the anisotropy coefficients considered are in good agreement, showing that the microstructure influences similarly both variables. Nevertheless, some discrepancies can be observed depending on density, snow type and microstructure.

4 Conclusions

The intrinsic permeability tensor $K$ was computed on 35 tomographic images of various snow types by solving numerically on a REV a specific boundary value problem arising from the homogenization process. As the permeability is related to a characteristic length of the microstructure, we chose the equivalent sphere radius to reduce $K$ to a dimensionless tensor $K^*$. This variable is convenient because it is directly inferred from the specific surface area (SSA) of the snow sample which can be computed using 3-D images, as performed in this study, and also measured experimentally.

Values of $K^*$, average of vertical and horizontal components of $K^*$, plotted as a function of snow density ($\rho_s$), were presented and a fit was proposed, leading to two main observations: (i) Our relationship of $K^*$ vs. $\rho_s$ is fairly consistent with that of analytical models and data of the literature. (ii) $K^*$ and $\rho_s$ are strongly correlated. It leads to the major conclusion that the permeability of seasonal snow, if assumed isotropic, can be reasonably inferred from its $\rho_s$ and SSA field measurements using the proposed fit. This is particularly useful for numerical models able to simulate $\rho_s$ and SSA, allowing a straightforward estimate of snow permeability, with a great potential, e.g. for applications involving snowpack ventilation, such as air/snow chemical exchanges. Vertical and horizontal components of $K$ were used to compute the anisotropy coefficient of each sample. It was shown that anisotropy coefficients of $K$ and of the thermal conductivity tensor are consistent and allow to differentiate the DH and FC samples (highest values) from other snow types. This result suggests that the permeability may be helpful for quantitative classification of snow, as proposed by Arakawa et al. (2009),
provided that its anisotropy can be measured. However, the high coefficient of correlation found between $K$, SSA and $\rho_s$ seems to prevent the use of the permeability as an independent state variable of snow.

**Supplementary material related to this article is available online at:**
http://www.the-cryosphere-discuss.net/6/1157/2012/tcd-6-1157-2012-supplement.pdf.

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Fig. 1. Dimensionless permeability vs. snow density. “T” symbols indicate the computation values. Tips and horizontal bars of the “T” shapes represent the vertical and horizontal components of $K^*$, as computed in our study, respectively. Colors correspond to the ICSSG (Fierz et al., 2009). Analytical models, numerical computations and fits are also plotted.
Fig. 2. Dimensionless permeability vs. snow density. Our $K^*$ values (in black) are compared to results from other studies (in color). Symbols correspond to the ICSSG (Fierz et al., 2009), excepting stars which are used when firn is considered or when the snow type is not specified in the paper. Analytical models and fits are also plotted.
Fig. 3. Dimensionless permeability versus snow density for 3 snow samples. Symbols and colors correspond to the ICSSG (Fierz et al., 2009). For a given sample, each symbol represents a particular volume from which $K$, SSA and $\rho_s$ were computed. The largest volume corresponds to the total volume of the sample. Analytical models and fits are also plotted.
Fig. 4. Vertical cross section (plane (y,z)) of an evolved DH sample: Airflow velocity at the pore scale induced by a macroscopic gradient of pressure along the z (left) and y (right) direction. Ice grains are represented in gray. In the pores, colors indicate the velocity increasing from dark blue to red.
Fig. 5. $A(K)$ versus $A(k_{\text{eff}})$. Symbols and colors correspond to the ICSSG (Fierz et al., 2009).