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A Particle Filter scheme for multivariate data assimilation into a point-scale snowpack model in Alpine environment

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Abstract. The accuracy of hydrological predictions in snow-dominated regions deeply depends on the quality of the snowpack simulations, whose dynamics strongly affects the local hydrological regime, especially during the melting period. With the aim of reducing the modelling uncertainty, data assimilation techniques are increasingly being implemented for operational purposes. This study aims at investigating the performance of a multivariate Sequential Importance Resampling - Particle Filter scheme designed to jointly assimilate several ground-based snow observations. The system, which relies on a multilayer energy-balance snow model, has been tested at three Alpine sites: Col de Porte (France), Torgnon (Italy), and Weissfluhjoch (Switzerland). The implementation of a multivariate data assimilation scheme faces several challenging issues, which are here addressed and extensively discussed: (1) the effectiveness of the perturbation of the meteorological forcing data in preventing the sample impoverishment; (2) the impact of the parameters resampling on the filter updating of the snowpack state; (3) the system sensitivity to the frequency of the assimilated observations.

1. Introduction

Snow-dominated areas play a distinctive role in water supply in terms of soil moisture, runoff, and groundwater recharge (Vivoroli et al., 2007; Dettinger, 2014). The knowledge of the spatio-temporal distribution of snow cover is therefore of critical importance to several applications (Viviroli et al., 2011; Fayad et al., 2017). When dealing with hydrological predictions in mountain regions, the modelling of snow dynamics is a challenging issue due to complex interactions among site-dependent factors, namely the meteorological forcing (Bormann et al., 2013; Luce et al., 2014), local topography (Molotch and Meromy, 2014; Revuelto et al., 2014), the presence of vegetation and the wind-induced phenomena (Gascoin et al., 2013; Zheng et al., 2016; Quéno et al., 2016).

Recently, an increasing interest focuses on investigating the potentials of Data Assimilation (DA) schemes in consistently improving the model simulations by assimilating ground-based measurements or remotely sensed snow-related observations (Bergeron et al., 2016; Dziubanski and Franz, 2016; Griessinger et al., 2016; Huang et al., 2017).

Several DA methodologies have been developed, each one characterized by different performances according to its degree of complexity. The sequential DA techniques are widely used for real-time applications, since they allow to process the observational data as it becomes available and sequentially update the model state. The most basic approaches rely on the direct insertion (Liston et al., 1999; Rodell and Houser, 2004; Malik et al., 2012) and the optimal interpolation schemes (Brasnett,1999; Liston and Hiemstra, 2008). Even though these conceptually simple DA schemes are attractive methods, their implementation within complex, multi-layered snow model is not straightforward, mainly because of possible model shocks resulting from physical inconsistencies among state variables (Magnusson et al., 2017). More advanced are the Cressman scheme (Cressman, 1959; Drusch et al., 2004; Dee et al., 2011; Balsamo et al. 2015) and the nudging method (Stauffer and Seaman, 1990; Boni et al. 2010), allowing to take into account the observational uncertainty, which is a priori defined. At a higher level are the Kalman filters, which are among the most commonly used sequential DA techniques (Kalman, 1960). The standard version of the Kalman Filter (KF) (Gelb, 1974), which relies on the system linearity assumption, was upgraded to the Extended Kalman Filter (EKF) (Miller et al., 1994) allowing to deal with nonlinear dynamic models through a linearized statistical approach (Sun et al., 2004; Dong et al., 2007). With the aim of overcoming the inaccuracy of the linearization procedure affecting the filter performance due to possible strong model nonlinearities (Moradkhani, 2008), the Ensemble Kalman Filter (EnKF) has been developed (Evensen, 1994). Unlike the KF and EKF schemes, this method does not require a model linearization since the error estimates are evaluated from an ensemble of possible model realizations using the Monte Carlo approach (Evensen, 2003). In the recent past, an increasing number of studies on snow hydrology have contributed to confirm the EnKF as a well-performing technique enabling to enhance the accuracy of hydrological simulations by consistently updating model predictions through the assimilation of snow-related observations (Andreadis and Lettenmaier, 2005; Durand and Margulis, 2006; Clark et al., 2006; Slater and Clark, 2006; Su et al., 2008; Durand and Margulis, 2008; Su et al., 2010; De Lannoy et al., 2012; Magnusson et al., 2014; Griessinger et al., 2016; Huang et al., 2017).

Even though the EnKF scheme provides a flexible framework to explicitly handle both observational and modelling uncertainties (Salamon and Feyen, 2009), some constraining assumptions hinder filter performance (Chen, 2003). Firstly, in Kalman filtering the analysis step relies on the second-order moments (Moradkhani et al., 2005). However, because the state variables in stochastic-dynamic systems are modelled as random variables, the involved probability distributions are not supposed to follow a Gaussian distribution (Weerts and El Serafy, 2006). Thus, in strongly nonlinear systems the first two moments are not likely to be sufficient to properly approximate the posterior probability distributions, whose estimates require the tracking of higher-order moments (Moradkhani et al., 2005). Secondly, the EnKF is limited to the linear updating procedure with significant simplification affecting the filter performance. Recently, Piazzi et al. (2017) investigated the main limitations in implementing a multivariate EnKF scheme to assimilate ground-based and remotely-sensed snow data in the framework of snow modelling.

In order to overcome these limiting issues, filter methods for non-Gaussian, nonlinear dynamical models have been developed. These sequential Monte Carlo techniques, also known as Particle Filter (PF) (Gordon et al., 1993), have the main advantage of relaxing the need for restrictive assumptions on the form of the probability distributions, since the full prior density is used within the updating procedure (Arulampalam et al., 2002). Thanks to their suitability to better succeed in handling systems nonlinearities, PF schemes are currently garnering a growing attention for snow modelling applications. Leisenring and Moradkhani (2011) compared the performances of common sequential EnKF-based DA methods and PF variants at assimilating synthetic SWE measurements to improve its seasonal predictions and to estimate some sensitive parameters in a small-scale snowpack model. The results suggested that all the DA techniques succeeded in enhancing the SWE dynamics. Even though PF-based techniques generally revealed a higher accuracy, the resulting bias was comparable with the Kalman filters one. Dechant and Moradkhani (2011) evaluated the PF performance in assimilating remotely sensed microwave radiance data to update the states of a snow model. The results showed that the DA scheme allowed to improve simulations of SWE as well as discharge forecasts. Thirel et al. (2013) investigated the implementation of the PF technique to assimilate MODIS SCA data into a physical distributed hydrological model, in order to enhance snowmelt-related stream flow predictions. Both synthetic and real experiments showed clear improvements of model discharge simulations, especially for intermediate values of observation error. Margulis et al. (2015) tested a newly-proposed PF approach to improve SWE estimates when assimilating historical Landsat-derived observations of fractional snow-covered area into a land surface model. This technique has been recently applied by Cortés et al. (2016). Charrois et al. (2016) investigated the performances of the Sequential Importance Resampling PF (SIR-PF) scheme in assimilating MODIS-like synthetic data of optical reflectance into a detailed multilayer snowpack model. The study assessed the impact of the assimilation, which well succeeded in reducing RMSE values on both snow depth and SWE with a resulting reduction of the uncertainty on the snow melt-out date. An even larger bias reduction was achieved by updating the model assimilating synthetic snow depth observations, except for thin snowpack. However, they proved that the joined assimilation of remotely sensed reflectance and measurements of snow depth can be the best combination to provide a significant improvement of the model simulations. Magnusson et al. (2017) found that the assimilation of daily snow depth measurements within a multi-layer energy-balance snow model through the PF scheme resulted in an improvement of the simulations of SWE and snowpack runoff over the whole analysis period. However, model daily runoff dynamics did not substantially benefit from the snow depths assimilation, except during the melt-out period.

In view of the promising performances of PF-based schemes in snow-related univariate DA applications, this study aims at contributing to this research field by addressing the potential of this technique in performing multivariate DA. The goal focuses on investigating how the PF scheme succeeds in consistently updating the system state by jointly assimilating several in-situ snow-related point data in a snow dynamic model. Section 2 firstly describes the analyzed case studies and the modelling system consisting of a multilayer energy-balance model and the DA scheme, whose main features are discussed. After sketching the experimental design, Section 3 explains the development of the PF-based DA scheme. The main issues hindering the filter efficiency are thoroughly discussed by analyzing the impact of the meteorological perturbation, the uncertainty of model parameters and the use of an additional snow density model to reduce the system sensitivity to the in-situ measurement frequency. Lastly, conclusions are outlined in Section 4.

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2. Materials and methods

2.1 Case studies

With the aim of testing the snow modelling system at a point-scale, the selection of the case studies has been restricted among pilot experimental sites, where automated weather stations supply meteorological and snow-related measurements of high quality and completeness. This choice has allowed to reliably investigate the filter performance regardless of possible inconsistent measures, since generally the in-situ observations are extensively verified through a quality control and data gaps filling (Morin et al., 2012; Essery et al., 2013; Lafaysse et al., 2017). Since the strategic requirements conditioning the placement of the test sites entail slightly impacting local features affecting the spatial snow distribution (e.g. wind-induced phenomena, slope, exposure) (Wever et al., 2015), the instrumental biases have been deemed as properly representative of the observational uncertainties. Moreover, with the purpose of investigating the snow model sensitivity to various meteorological conditions, measurement sites located at different elevations have been chosen. Moreover, the selection has been limited over the domain of interest, namely the Alpine region. Among the Alpine measurement sites, three snow experimental sites, meeting all the requirements, have been selected: Col de Porte (France), Weissfluhjoch (Switzerland) and Torgnon (Italy).

Col de Porte site

The Col de Porte observatory (CDP) is located near Grenoble, in the Chartreuse massif (45°30’ N, 5°77’ E) at an elevation of 1325 m a.s.l.. This pilot site is placed in a grassy meadow surrounded by a coniferous forest on the eastern side. Snow cover is usually present from December to April, on average (Lafaysse et al., 2017). Nevertheless, during the winter season surface melt and rainfall events can frequently occur at the relatively low altitude of the experimental site. In-situ meteorological data, at the hourly resolution, include measurements of 2-m air temperature and relative humidity, 10-m wind speed, incoming short- and longwave radiations and precipitation rates. Precipitation phase is manually assessed using all possible ancillary information (Lafaysse et al., 2017). Snow-related observations are provided both at daily and hourly resolution. Weekly manual snow pits enable to collect internal snowpack information (e.g. snow temperature, density profiles, liquid water content). Furthermore, hourly records of temperature and height of vertically-free settling disks are available. Along with weekly manual SWE measurements, since the season 2001-2002 SWE is automatically measured on a daily basis by a ground-based cosmic rays counter. Hourly snow albedo data are estimated through the radiation sensors, as the ratio between incoming and reflected shortwave radiation (Morin et al., 2012). Moreover, measurements of snow surface and soil temperatures are hourly available. Snowmelt runoff is hourly estimated through two lysimeters, as well.

Weissfluhjoch site

The Weissfluhjoch site (WFJ) (46.82°N, 9.80°E) is located at an altitude of 2540 m a.s.l. in the Swiss Alp, near Davos, Switzerland (WSL Institute for Snow and Avalanche Research SLF, 2015b). This snow experimental site is placed in an almost flat area of a south-easterly oriented slope. At WFJ the snow season generally starts in October/November and lasts until June/July (Weveret al., 2015). An automated weather station provides a comprehensive multiyear dataset including

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measurements of air temperature and relative humidity, wind speed and direction, incoming and outgoing short- and longwave radiation, snow/ice surface temperature, temperature of soil at its interface with the snowpack, snow depth and precipitation (Schmucki et al., 2014). Snow temperatures are measured at 50, 100 and 150 cm above the ground surface. From September 2013 onwards, soil temperatures are measured at 50-, 30- and 10-cm depth. Additionally, snowpack runoff data are supplied by a snow lysimeter. The rain gauge and snow lysimeter measure at an interval of 10 min, whereas most other measurements are done at 30-min intervals. Lastly, an upward-looking ground-penetrating radar provides 30-min data on liquid water percolation allowing to monitor the progress of the meltwater front (Schmid et al., 2014). Every two weeks, generally in early and in the middle of each month depending on weather conditions, a manual full-depth snow profile is performed in order to provide measurements of snow temperature and snow density (WSL Institute for Snow and Avalanche Research SLF, 2015a). Snow density and SWE are also manually measured through snow cores.

Torgnon site

The Torgnon site (TGN) (Tellinod, 45°50’ N, 7°34’ E) is located in Aosta Valley, a mountain region in northwestern Italian Alps. The experimental site is subalpine grassland, at an elevation of 2160 m a.s.l. (Filippa et al., 2015). The area slopes lightly (4°) and it is characterized by a typical intra-alpine semi-continental climate, with an average annual temperature of around 3°C and a mean annual precipitation of 880 mm (Galvagno et al., 2013). On average, the snow season lasts from the end of October to late May, when the test site is covered by a thick snow cover (90-120 cm). Since 2008, an automatic weather station provides 30-min averaged records of different meteorological parameters, including air and surface temperatures (HMP45, Vaisala, SI-111 and therm107, Campbell Scientific), incoming and outgoing short- and longwave radiations, and surface albedo (CNR4, Kipp&Zonen), precipitation (OTT Pluvio2, Weighing Rain Gauge), soil water content (CS-616, Campbell Scientific), snow depth (SR50A-L, Campbell Scientific) and wind speed and direction (WINDSONIC1-L, Campbell Scientific). Furthermore, SWE in-situ measurements are available with a sampling resolution of 6 hours for the snow seasons 2013-2014 and 2015-2016 (CS725, Campbell & Scientific). The sensor provides comprehensive SWE measures over a sizeable area of 50-100 m^2, with a resulting lower impact of several local factors (e.g. snow drifting, vegetation). Bi-weekly manual measures of snow density (snow pits) are available during the winter season (3-4 measurements per month, on average).

According to the in-situ meteorological observations, the selected experimental sites are characterized through two of the most ruling climate forcing, namely air temperature and snowfall rate (Lòpez-Moreno and Nogués-Bravo, 2005), together with the snow depth trend (Figure 1).

2.2 Snow model

The snow model relies on a multilayer scheme consisting of two layers of both soil and snowpack. The model provides an estimate of several snow-related variables describing the snowpack state by simulating the main physical processes (i.e. accumulation, density dynamics, melting and sublimation processes, radiative balance, heat and mass exchanges). The explicit energy and mass balances framework requires several input forcing meteorological data: air temperature, wind

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velocity, relative air humidity, precipitation and incident shortwave solar radiation. While a full description of model is extensively explained in Piazzi et al. (2017), some details on model parameterizations are given below.

- *Precipitation phase*: When total precipitation rate is provided, the partitioning between rain- and snowfall is based on both air temperature and relative humidity, according to the approach proposed by Froidurot et al. (2014).
- *Snow compaction*: Snow density is updated considering both the compaction and the destructive thermal metamorphism according to the physically-based parameterization proposed by Anderson (1976).
- *Fresh snow density:* In case of snowfall, the fresh snow density is evaluated as a function of the air temperature (Hedstromand and Pomeroy, 1998).
- *Snow albedo:* With respect to the original version of the model scheme described in Piazzi et al. (2017), the empirical snow albedo parameterization proposed by Douville et al. (1995) has been introduced. Following this formulation, the surface albedo (α) is predicted as prognostic variable:

  Albedo for cold snow: $\alpha_s(t+\delta t) = \alpha_s(t) - {\tau_\alpha}^{-1}\delta t$ (1a)

  Albedo for melting snow: $\alpha_s(t+\delta t) = [\alpha_s(t) - \alpha_{min}]\exp(-{\tau_m}^{-1}\delta t) + \alpha_{min}$ (1b)

  Albedo update (snowfall event): $\delta\alpha_s = (\alpha_{max} - \alpha_s)\frac{S_f\delta t}{S_0}$ (1c)

  where:

  S_f is the snowfall rate [kg m^{-2}]; $\alpha_{max} = 0.85$; $\alpha_{min} = 0.5$; $S_0 = 10$ kg m^{-2}; $\tau_\alpha = 10^7$ s; $\tau_m = 3.6 \cdot 10^5$ s .

  The albedo dynamics is described by a linear decay over time under cold snow conditions (Eq. 1a) and an exponential decay in the presence of melting snow (Eq. 1b). When a snowfall event occurs, the albedo is consistently updated (Eq. 1c).
- *Turbulent heat fluxes:* Sensible and latent heat fluxes are evaluated following the bulk formulation. The atmospheric stability is evaluated as a function of the Richardson Bulk number, according to the empirical scheme of Caparrini et al. (2004).

2.3 Particle filter data assimilation scheme

The PF technique relies on the Monte Carlo approach to solve the Bayesian recursive estimation problem. Consider the state vector(X_t) including all the prognostic variables

$$X_t = M[X_{t-1}, \theta, U_t, \Omega_t] \quad (2)$$

where M is the dynamic model operator, which calls for the model input vector (U_t), the vector of model parameters (θ), and the model error (Ω_t). Whenever a set of observations is available, the analysis procedure allows to update the a priori state according to the observation vector (Y_t), which requires an observation operator (H) enabling to generate the model equivalents of the observations:

$$Y_t = H[X_t, \Psi_t] \quad (3)$$

where Ψ_t is the observational noise, which is generally assumed to be Gaussian and independent of the model error.

The sequential filtering problem aims at finding the maximum of the conditional probability density function (pdf) of the model state $P(X_t|D_t)$, where $D_t = \{Y_t; t = 1, \dots, t\}$ encompasses all the available observational information on the time step t.

Given the posterior pdf at time *t-1* $p(X_{t-1}|D_{t-1})$, it is possible to obtain the pdf of the current state $p(X_t|D_t)$ in two stages, namely the prediction of the prior density $p(X_t|D_{t-1})$ (Eq. 4) and the update of the forecast pdf according to new observations (Eq. 5).

$$p(X_t|D_{t-1}) = \int p(X_t|X_{t-1}) p(X_{t-1}|D_{t-1})\, dX_{t-1} \tag{4}$$

$$p(X_t|D_t) = p(X_t|Y_t, D_{t-1}) = \frac{p(Y_t|X_t)p(X_t|D_{t-1})}{\int p(Y_t|X_t)p(X_t|D_{t-1})dX_t} \tag{5}$$

where $p(X_t|X_{t-1})$ is the known transition pdf, $p(Y_t|X_t)$ measures the likelihood of a given model state with respect to the observations.

When dealing with high dimensional and nonlinear systems, an analytical solution of the problem is unfeasible (Moradkhani et al., 2005). The implementation of ensemble methods using a Monte Carlo sampling allows to fully approximate the posterior density $p(X_t|D_t)$ through a set of N independent randomly drawn samples, called particles (Arulampalam et al., 2002; Moradkhani et al. 2005; Weerts and El Serafy, 2006):

$$p(X_{0:t}|Y_{1:t}) \approx \sum_{i=1}^{N} W_t^i \delta\left(X_{0:t} - X_{0:t}^i\right) \tag{6}$$

where $\{X_t^i, W_t^i\}$ denote the ith particle drawn from the posterior distribution and its associated weight, $\delta(\cdot)$ is the Dirac delta function. Particles $\left(X_t^i\right)$ are drawn from a known proposal distribution $q\left(X_{0:t}^i|Y_{1:t}\right)$, according to the Sequential Importance Sampling (SIS) approach (Moradkhani et al., 2005; Guingla et al., 2012). The importance weights of the particles are recursively defined according to the following formula:

$$W_t^i \propto W_{t-1}^i p\left(Y_t|X_t^i\right) \tag{7}$$

A well-known common issue with SIS-PF is the sample degeneracy, which prevents particles from properly approximating the posterior distribution. Arulampalam et al., (2002) explained that whenever the effective number of particles (N_{eff}) falls below a fixed threshold value, the impact of the degeneracy needs to be mitigated by increasing the number of particles, where:

$$N_{eff} \approx \frac{1}{\sum_{i=1}^{N} W_t^i} \tag{8}$$

Since this approach is often unfeasible due to the increase in computational demand (Salamon and Feyen, 2009), a resampling procedure is frequently introduced to restore the sample variety through a Markov chain chaotic Monte Carlo (Moradkhani et al., 2005).

2.3.1 Sequential Importance Resampling

Gordon et al. (1993) proposed the Sequential Importance Resampling (SIR) technique, which introduces a resampling procedure within the SIS procedure. At each time step, the additional resampling step discards particles having low importance weights while replicating particles having high importance weight, while the total number of particles N is maintained unchanged. As exhaustively explained by Weerts and Serafy (2006), the SIR algorithm relies on the generation of an empirical cumulative distribution (cdf) of the particles according to their weights W_t^i and the projection of a discrete set of N samples $\{X_t^i, i = 1, \dots, N\}$ with probabilities $\{W_t^i, i = 1, \dots, N\}$ uniformly drawn within the domain of the distribution. The resulting set contains replications of the particles having high importance weight, which are the most likely to be drawn (Figure 2).

2.3.2 Likelihood function

When dealing with a multivariate SIR-PF scheme, it is necessary to take into account the different uncertainty affecting each observed variable. Therefore, the likelihood function is a N_{obs}-dimensional normal distribution, where N_{obs} is the varying number of the effectively assimilated variables. The likelihood function is therefore defined as:

$$p(Y_t|X_t) = N\{(Y_t - X_t^i), \mu, R\} \tag{9}$$

where μ and R are respectively the null mean vector and the error covariance matrix of observations characterizing the multivariate Gaussian distribution. Thus, at each assimilation time step the particles weights are updated according to the following equation:

$$W_t^i = \frac{exp\left(-\frac{1}{2R}\left[Y_t - H\left(X_t^i\right)\right]^2\right)}{\sum_{i=1}^{N} exp\left(-\frac{1}{2R}\left[Y_t - H\left(X_t^i\right)\right]^2\right)} \tag{10}$$

2.4 Generation of ensemble particles

2.4.1 Perturbation of meteorological input data

Meteorological forcings are one of the major sources of uncertainty affecting snowpack simulations (Raleigh et al., 2015). Therefore, an ensemble of possible model realizations is generated by perturbing the model inputs, namely precipitation, air temperature and relative humidity, solar radiation, wind speed. The ensemble of perturbed inputs allows to take into account a well-representative range of weather conditions at the experimental sites, which result in an ensemble of possible snowpack states standing for the uncertainty of model predictions (Charrois et al., 2016). A meteorological ensemble of 100 members is generated by perturbing the in-situ meteorological data with an additive stochastic noise applied at each time step (i.e. 15 minutes). Following the methodology proposed by Magnusson et al. (2017), the random perturbations are provided through a first-order autoregressive model in order to guarantee a physical consistency and a temporal correlation of the time-variant forcings. Perturbations are generated considering the error statistics evaluated at the CDP site (Table 1) (Magnusson et al., 2017), which result from the comparison between SAFRAN reanalysis data (Vidal et al., 2010) and the observations supplied by the French station (Charrois et al., 2016). The main limitation of this procedure is the lack of correlations among the perturbed forcing variables, which does not ensure their physical consistency (Charrois et al., 2016). It is also noteworthy that the same error statistics specifically derived from the observations supplied by the CDP station are used for the generation of the meteorological ensembles at all the snow experimental sites. As highlighted by Magnusson et al. (2017), this approach is likely to reduce the filter performance at the Italian and Swiss sites.

2.4.2 Model parameters resampling and perturbations generation

Since the introduction of stochastic noise plays a major role in reducing the effect of the sample impoverishment (Moradkhani et al., 2005), the uncertainty of model parameters is supposed to significantly contribute to restore the ensembles spread between two following assimilation time steps. Following the methodology proposed by Moradkhani et al. (2005), the resampling procedure is carried out both in the parameters and the state variables spaces. Therefore, at each assimilation time step, after the particles resampling the parameters are perturbed before being used at the successive time step. Following Salamon and Feyen (2009), the parameters variance is restricted between upper and lower limits in order to avoid model instabilities and to also assure a minimum process noise, in order to prevent any variance collapse. The variance ranges are set according to the results of several tests carried out by varying their limits and evaluating the impact on filter performance. Unlike the study of Moradkhani et al. (2005), who applied the dual SIR-PF scheme to estimate model parameters, in this case the main aim is to succeed in enlarging the parameters ensemble to ensure a significant spread of the particles. Therefore, tuning parameters are properly set to guarantee a significant variance of the parameters distribution.

2.5 Experimental setup

2.5.1 Snow data

The multivariate DA scheme has been designed to consistently update the system state by jointly assimilating ground-based observations of surface temperature, albedo, snow depth, SWE and snow density. Table 2 lists the datasets of the experimental sites.

Automatic in-situ measurements of surface temperature, albedo, and snow depth are supplied on an hourly or sub-hourly basis by all the selected stations throughout the whole datasets.

Even though direct SWE measurements are generally widely lacking, the snow experimental sites are one of the main sources of consistent measures of this variable. Daily automatic measures are provided at CDP since the winter season 2001/02. With a lower measurement frequency, at WFJ SWE observations are available every two weeks over the whole dataset period. Unlike these two sites, the TGN station supplies in-situ 6-hrs automatic SWE measurements during the snow seasons 2013/14 and 2015/16. In order to be able to properly use these measures within the analysis of simulations on seasonal/annual scale, the raw observational data have been smoothed from possible inconsistent oscillations and anomalies (e.g. rain-on-snow events) through their daily average (Table 3).

Although an exhaustive knowledge of snow density is needed to properly define the snowpack state and its dynamics, direct continuous observations of snow density are generally lacking. An exception is the TGN site, where biweekly manual measurements provide useful information throughout the whole dataset period. However, thanks to the relation among snow

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depth, SWE and snow density (Jonas et al., 2009), observations of at least two of these variables are enough to indirectly estimate the third one with a roughly tolerable degree of uncertainty. According to this approach, at both the Swiss and the French sites bi-weekly and daily snow density measurements have been derived, respectively (threshold value at 550 kg/m^3). At TGN daily snow densities have been indirectly estimated during the two winter seasons when SWE measures are available. Conversely, bi-weekly SWE estimates have been derived during the other two snow seasons, when snow densities measurements are otherwise supplied. Because the two sensors measuring snow depth and SWE can be not located at exactly the same point, however, it is noteworthy that possible inconsistencies can arise due to the spatial variability in snow cover, especially under shallow snow conditions (Essery et al., 2013; Lafaysse et al., 2017).

2.5.2 Evaluation metrics

The results of this study are shown and discussed in terms of SWE, snow depth and surface temperature. The SWE is one of the most relevant snow-related quantities from a hydrological point of view, since its accuracy in estimate strongly impacts discharge simulations (Zappa et al., 2003). Along with this variable, the assessment of snow depth simulations allows to indirectly evaluate the model dynamics of snow density (Jonas et al., 2009). Furthermore, the impact of the filter updating on the system energy balance is analyzed by considering the simulations of the surface temperature.

In order to assess the filter performance, each analysis is evaluated through the following statistical metrics by considering the whole datasets of measurements (snowless periods are neglected):

Correlation coefficient: $R = \frac{cov(Obs, Exp)}{\sigma_{obs} \cdot \sigma_{exp}}$ (11)

Root Mean Square Error: $RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(Obs_k - Exp_k)^2}$ (12)

Normalized Error Reduction (Chen et al., 2011): $NER = \left(1 - \frac{RMSE_{Exp}}{RMSE_{OL}}\right) \cdot 100$ (13)

Assimilation efficiency (Brocca et al., 2012) : $Eff = \left(1 - \frac{\sum_{k=1}^{N}(Exp_k - Obs_k)^2}{\sum_{k=1}^{N}(OL_k - Obs_k)^2}\right) \cdot 100$ (14)

where OL are the Open Loop simulations (without DA) of the control run.

3. RESULTS AND DISCUSSION

3.1 Multivariate DA with perturbed meteorological input data

3.1.1 Impact of the meteorological uncertainty on ensemble simulations without DA

After verifying that the introduction of the stochastic noise does not affect the observed inputs on average at any site, firstly the aim is to assess the impact of the meteorological uncertainty on the ensemble snowpack simulations, without considering the assimilation of snow data. Indeed, since the strong system nonlinearities make the model response to the inputs perturbation hardly predictable, it is important to verify that no spurious trends occur with respect to the deterministic control run. To investigate the impact of the meteorological stochastic perturbations, 100-ensemble snowpack simulations forced by as many different meteorological conditions are analyzed. For the sake of concision and clarity, a representative winter season is shown for each site (Figure 3).

The ensembles spread reveals possible over- and underestimation of the ensemble model simulations as direct consequence of the perturbation of the forcing data. Nevertheless, the time series of the deterministic control run (i.e. open loop simulations) are generally included within the ensemble envelop.

The variance of the mass-related ensembles is generally the largest at the end of the winter season, when the perturbation of energy-related forcing variables (i.e. air temperature, shortwave radiation) leads to well-spread melt-out scenarios resulting from the difference in melt timing (i.e. some particles have just started to melt and some others have already disappeared). During the winter season, the spread of SWE ensembles is increased whenever a snowfall event occurs due to the uncertainties in the precipitation rates allowing to provide the mass balance of each model realization with different input of snowfall rate. Of course, sites climatology (e.g. frequency of snowfall events) strongly impacts the resulting ensemble variance. A significant variance of the surface temperature ensembles is ensured by its high sensitivity to the inputs uncertainty, namely the perturbation of the air temperature and shortwave radiation, which directly impacts the snowpack energy balance. However, it is important to consider that some threshold processes involved within the snow dynamics model (e.g. disappearance of the surface snow layer, limitation of state variable within physical ranges) can be counter-productive in enlarging the ensembles spread.

3.1.2 Multivariate DA simulations

The SIR-PF scheme is implemented to jointly assimilate several observed snow data within the snow model (Sect. 2.4). The aim is to assess the performance of the multivariate DA system and investigate its efficiency in updating snowpack states.

The assimilation frequency is set to every 3 hours in order to ensure an efficient exploitation of the high frequency in-situ measurements supplied by the automatic stations at the analyzed snow experimental sites.

The resulting statistical scores (Figure 4) reveal the filter effectiveness in updating snow depth simulations, whose correlation and RMSE values are significantly improved with respect to the control run, especially at the French and Swiss stations. The update of SWE model predictions is more challenging. At the French and Italian sites, the assimilation of snow data actually leads to a worsening of the quality of the model simulations with respect to the deterministic control run, except for some sporadic winter seasons.

Conversely, a significant improvement is observed at the Swiss station, where the filter updating benefits from a larger spread of the SWE simulations ensured by a higher frequency of snowfall events, on average. Even though the filter well succeeds in enhancing the simulations of surface temperature at CDP and WFJ sites, the snowpack thermal state at TGN is adversely affected by the assimilation of snow data.

To better understand and properly assess the results, it is important to stress some key conditions exerting the most influence on the filter effectiveness.

One of the main ruling issues is the scale of the model ensemble spread. A well-spread ensemble makes the filter efficient in weighting the particles. When the ensemble is squeezed, the resampling procedure is more challenging since all the particles are close to each other with resulting similar likelihood values. In this undesired case, the filter might not succeed in well discriminating the more likely ensemble members since they all are assigned almost the same weight. On the other hand, if the particles are well spaced, their resampling is more straightforward since each particle is properly discriminated through a specific weight proportional to its likelihood.

Alongside this issue, it is of critical importance how the particles are placed on average with respect to their measures. The most conducive condition calls for well-spread ensembles enclosing their corresponding observations. In this situation, the filter is favoured in selecting the most likely particles and properly weighting them. However, the spread of the model ensembles turns out to be the overriding condition. Indeed, even if the model predictions are significantly biased, a large ensemble spread can allow to progressively stretch the simulations towards the observed system state through subsequent proper updates.

When dealing with a multivariate DA scheme, the fulfilling of these conditions is even more challenging. In such an application, the filter is designed to select the particles best describing the observed system state with respect to all the available observations at the assimilation time step. Therefore, with respect to an univariate DA scheme, here the filtering procedure is more heavily constrained, depending on how many observations are provided. Even though the effects of the ensemble degeneracy can be reduced through the resampling procedure, the perturbation of the meteorological data turns out to be not sufficient to prevent the sample impoverishment within two following assimilation time steps (e.g. SWE ensemble when no snowfall event occurs). It is noteworthy that a decrease in the ensemble spread, even just of one variable, can affect the overall resampling procedure. As previously explained, this limitation is even intensified by the physics of the snowpack model, whose threshold processes can weaken the effect of inputs perturbation.

Another further issue is the difference in the measurements frequency of the variables to assimilate. At each assimilation time step the Gaussian likelihood function is n-dimensional depending on the number of the observed variables. Thus, the particles weighting is carried out considering their likelihood in relation to the available measurements at that time. This dynamic entails that the resampling procedure can be more strongly conditioned by the observations having a higher measurement frequency (e.g. hourly or sub-hourly measurements of snow depth). Thus, possible misleading updates of the variables less frequently observed can occur, since they are updated without taking into account particles likelihood with respect to their own lacking observations (e.g. daily or bi-weekly measurements of SWE). For instance, when a measure of snow depth is provided, no observational information on SWE can be properly retrieved unless its indirect estimate if snow density data are available. Otherwise, the filter can fail in consistently updating the overall snow mass-related state, since a lot of possible combinations of SWE and snow density can well fit the observed snowpack depth. In terms of filter efficiency, this means that when only a snow depth observation is provided the filter looks for particles having the higher likelihood with respect to this snow quantity, regardless the SWE and snow density states. Nevertheless, it is not unlikely that several particles have the same likelihood because the combination of even strongly-biased values of SWE and snow

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density can well fit the observed snow depth through an offsetting effect among these variables. This is the main reason explaining the higher filter performance in terms of snow depth with respect to the SWE simulations.

The multivariate DA simulations allow to point out two main limitations of this application. Firstly, the ensemble spread needs to be enlarged in order to improve the filter efficiency in well weighting and resampling the ensemble particles. Moreover, the effect of the difference in measurements frequency of the assimilated variables has to be limited in order to consistently update the snow mass balance.

3.2 Multivariate DA with perturbed model parameters

With the aim of overcoming the sample impoverishment, the uncertainty of model parameters is introduced in order to succeed in enlarging the ensembles spread, whose size strongly impacts the filter performance. Therefore, along with the perturbation of meteorological inputs, each particle independently evolves according to its own specific set of parameters ruling the model physical dynamics, whose equations remain unchanged, however.

3.2.1 Sensitivity analysis of model parameters

When considering the uncertainty of model parameters, a preliminary sensitivity analysis is of critical importance for a twofold reason. Firstly, it is intended to properly identify the most ruling parameters affecting the model simulations. Secondly, an accurate selection accordingly enables to neglect those parameters whose perturbation would uselessly demand for a larger computational requirement. The sensitivity analysis is carried out by making the parameters vary within proper ranges and analyzing the impact on the model predictions. Parameters ranges are estimated in order to both avoid model numerical instabilities and comply with possible physical constraints. The criterion for selecting the model parameters is mainly focused on identifying those allowing to increase the ensemble spread of the state variables more slightly affected by the meteorological uncertainty, namely SWE, snow density and surface albedo. The sensitivity analysis allows to identify 5 model parameters listed in Table 4.

While the three albedo parameters are perturbed in order to guarantee a significant enlargement of the ensembles spread of this prognostic variable, the perturbation of snow roughness and snow viscosity strongly impacts the snowpack dynamics. Indeed, several analyses reveal a high sensitivity of model simulations to the resampling of these mass-related parameters, especially in terms of SWE and snow density. Snow roughness strongly affects the snowpack energy balance by ruling the turbulent heat fluxes. As a consequence, the perturbation of this parameter mainly impacts the SWE ensembles by providing each particle with different snow melting fluxes. The effects of the perturbation of snow viscosity are prominent on the snow density evolution, especially on the snow compaction dynamics.

Thanks to this approach, the degeneracy of the model ensembles is avoided via resampling and the sample impoverishment is prevented through the parameters perturbation (Figure 5).

3.2.2 Multivariate DA simulations with parameters resampling

As stated by Salamon and Feyen (2009), when dealing with parameters uncertainty it is important to consider that the model response to a change in parameters has not immediate effect on the simulated state. This issue can be overcome by giving the model a sufficiently large response time between following system updates. The assimilation frequency is therefore reduced to every 24 hours. This choice is intended to guarantee a higher model response time without omitting a large number of observed snow data.

Figure 6 shows the statistical metrics of the multivariate DA simulations resulting from the implementation of the model parameters resampling. With respect to the previous analysis considering the meteorological data as the only source of uncertainty (Sect. 3.1.2), the introduction of the parameters resampling allows to heavily increase the filter efficiency at updating the model SWE simulations at CDP site. It is noteworthy that the parameters resampling does not only ensure a sizeable enlargement of the ensembles spread but it also allows to better estimate the model parameters on average. Indeed, while the resampling of the state variables allows to consistently update the system state at the assimilation time step, the modelling of snowpack dynamics between two following assimilation time steps benefits from the parameters resampling, which enables to take better account of the parameters seasonality (e.g. melting period).

At the French site, the daily SWE measurement frequency ensures an effective resampling of the mass-related parameters, namely snow roughness and snow viscosity. Furthermore, the retention of satisfying performance of the filter in terms of snow depth on average suggests a beneficial impact on the snow density dynamics. Conversely, the introduction of the parameters resampling does not always result in a significant improvement of SWE simulations at the Swiss station. This limitation is mainly due to the lower biweekly frequency of the SWE measurements, with respect to the French case study.

At WFJ site, at the daily assimilation time steps when no SWE observation is available, the estimate of the particles likelihood cannot rely on observational information on the snow mass-related parameters (e.g. SWE, snow density). Therefore, it is not unlikely that the resampling procedure leads to suboptimal values of the mass-related parameters. Moreover, the enlargement of the ensembles spread ensured by the parameters resampling entails a higher probability of selecting particles having SWE values even farther from the actual state with respect to the simulations of the deterministic control run, when no direct SWE observed data are provided. This thesis is supported by the results obtained at the TGN site, where the multivariate DA scheme allows to consistently update the SWE simulations when the daily average SWE measurements are available, namely throughout the winters 2013-14 and 2015-16. During the other two snow seasons, when biweekly SWE observations are assimilated, the filter does not succeed in improving model predictions. The filter updating is not as effective for the simulation of surface temperature, especially at the Swiss and French sites. This suboptimal performance is mainly addicted to the concurrence of several factors. Firstly, the quicker dynamics of the daily thermal cycle make the temperature simulations more sensitive to the reduction in assimilation frequency, with respect to the other variables. Secondly, even though the filter succeeds in daily updating the system thermal state, the parameters values resulting from the resampling procedure do not ensure a long-lasting effect on the temperature trend between two following

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assimilation time steps. Indeed, since the parameters are resampled according to their representativeness at the assimilation time step, their values are not likely to be the optimal ones to well catch the succession of diurnal and nocturnal peaks. Although the parameters resampling ensures an enlargement of the ensembles spread, which is one of the constraining conditions to ensure the filter effectiveness, the quality of the multivariate DA simulations strongly depends on the reliability of the parameters resampling, which requires direct observational information to properly estimate the more likely parameters values.

3.2.3 Sensitivity of parameters resampling to the SWE measurement frequency

The Italian case study provides evidence of the impact of the difference in SWE measurement frequency on the parameters resampling. In order to further investigate the system sensitivity, an experiment is performed at the CDP station with the aim of assessing how the reduction from daily to biweekly SWE observed data affects the 24-hours multivariate DA simulations. Obviously, a reduction in measurement frequency is expected to reduce the impact of the filter updating on the model simulations. However, when dealing with a multivariate DA scheme, the imbalance among the measurement frequency of the assimilated variables can lead to a further side-effect hindering the parameters estimate due to the largest impact of the more frequently observed variables (e.g. snow depth, surface temperature) on the particles weighting. Figure 7 shows the ensembles of snow viscosity and snow roughness resulting from the assimilation of daily and biweekly SWE observations throughout the winter season 2001-2002. A divergence between the two ensemble time series is clearly detectable on average, especially in terms of snow viscosity. The suboptimal estimate of the mass-related parameters based on biweekly SWE measurements leads to a worsening of model predictions with respect to the deterministic control run, as shown in Figure 8. Conversely, the filter effectiveness is not affected in terms of snow depth thanks to offsetting effects between SWE and snow density simulations.

3.3 Proxy information of snow mass-related variables

3.3.1 Additional snow density model

Even though the introduction of the parameters uncertainty well succeeds in enlarging the ensembles spread, the resampling procedure of both states and parameters turns out to be even counter-productive when it is not properly conditioned by observed data of ruling snow mass-related variables. Nevertheless, since SWE and snow density measurements are time-consuming and thus often not available for real-time applications, the aim is to reduce the system sensitivity affecting the filter performance by deriving indirect information on these snow variables. According to the methodology proposed by Jonas et al. (2009), an empirical snow density model is introduced in order to reliably determine indirect sampling of SWE state from snow depth measurements through a parameterization of snow density, depending on four main factors: seasonality, observed snow depth, site altitude and location. With the aim of evaluating the reliability of the resulting

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estimates, a qualitative comparison analysis is performed with respect to the observations available at the Swiss and Italian measurement sites, as shown in Figure 9.

Except for some sporadic winter seasons, generally the estimates of SWE and snow density well fit the observed snowpack dynamics, as demonstrated by a good agreement with the ground-based measurements.

However, it is noteworthy that the estimate of snow density features is more challenging for shallow snow depths, since a high variability can range from low-density new snow in early winter to high-density slush during springtime (Jonas et al., 2009).

3.3.2 Multivariate DA simulations with proxy information of snow mass-related variables

The implementation of the additional snow density model providing proxy information on the mass-related snow variables allows to significantly optimize the parameters resampling, as revealed by the outperforming statistical scores of the SWE simulations (Figure 10).

Generally, this approach allows for a consistent improvement of the snow depth predictions, as evidence of a proper estimate of snow density, except for the winter season 1999-2000 at the WFJ site. Conversely, no prominent effects are observed in terms of surface temperature.

The reduction in assimilation frequency necessarily leads to omitting large quantities of observed data. With the aim of preventing this limitation, the approach proposed by Salamon and Feyen (2009) has been tested. According to this method, each particle is assigned the median of the weights evaluated at all observation time steps within the 24-hrs response time interval. Although this approach allows to make full use of the available measurements, a more intensive use of proxy information on the snow mass-related variables makes the filter effectiveness more affected by the quality of the estimates, with resulting heterogeneous filter performance over the analyzed datasets.

4. CONCLUSIONS

This study investigated the potentials of a SIR-PF scheme for a multivariate assimilation of snow data at three experimental sites in the Alps. Even though PF technique proved its capability of properly handling the strong system nonlinearities of snow modelling, several challenging issues need to be addressed.

When dealing with a multivariate DA application, the sample impoverishment is more likely to occur with respect to the univariate case, since the filter is designed to strictly select the particles having the highest likelihood with respect to all the observed state variables. The perturbation of the meteorological forcing data has turned out not to be sufficient to restore the ensembles spread within two following 3-hrs assimilation time steps, with resulting poor filter performance, especially in terms of SWE.

In order to prevent this undesired condition, further stochastic noise has been introduced through the parameters resampling, with a reduction of the assimilation frequency to every 24 hours to ensure a sufficient model response time. Although this approach has succeeded to enlarge the model ensembles, the system has revealed a prominent sensitivity to the difference in measurement frequency of the assimilated variables, which hinders the filter effectiveness in consistently updating the modelled snow quantities. Indeed, the more frequently measured snow variables (e.g. snow depths) strongly condition the mass-related parameters resampling (i.e. snow viscosity and snow roughness), which can result in their possible suboptimal values.

The use of proxy information on snow mass-related variables supplied by an additional snow density model has allowed to improve the parameters resampling, which results in outperforming filter updating of snow depth and SWE predictions.

Nevertheless, several issues require further detailed analysis. The physical consistency of the meteorological ensembles needs to be improved. Indeed, the methodology does not take into account the correlations among the perturbed forcing variables and, moreover, the specific error statics characterizing the perturbations are to be specifically evaluated at each analyzed site. Even though the evaluation of the likelihood function for high-dimensional systems becomes more challenging (Margulis et al., 2015), the potential of using an empirical likelihood variants should be extensively investigated to assess the impact of using a Gaussian distribution (Leisenring and Moradkhani, 2011; Thirel et al., 2013). Furthermore, an interest is focused on testing other resampling techniques with the aim of analyzing how the resampling procedure affects the filter effectiveness (Moradkhani et al., 2005; Weerts and El Serafy, 2006; Salamon and Feyen, 2009).

Data availability

The snow and meteorological data from Col de Porte site are made freely available by Météo-France both on the PANGAEA depository (doi:10.1594/PANGAEA.774249) and on the public ftp server ftp://ftp-cnrm.meteo.fr/pub-cencdp/. The Weissfluhjoch dataset provided by the WSL Institute for Snow and Avalanche Research SLF can be obtained via IDAWEB (https://gate.meteoswiss.ch/idaweb) as well as from the Environmental Data Portal ENVIDAT (envidat.ch/dataset/10-16904-1). The dataset of Torgnon site is available on the European Fluxes Database (www.europe-fluxdata.eu/).

Author contributions.

This work is part of the G. Piazzi's PhD thesis, supervised by S. Gabellani, L. Campo. G. Thirel supervised the research activities during the visiting period of G. Piazzi at the Catchment Hydrology Research Group of the HBAN Unit (IRSTEA). All the authors have collaborated to the technical development of the modelling system and the manuscript writing.

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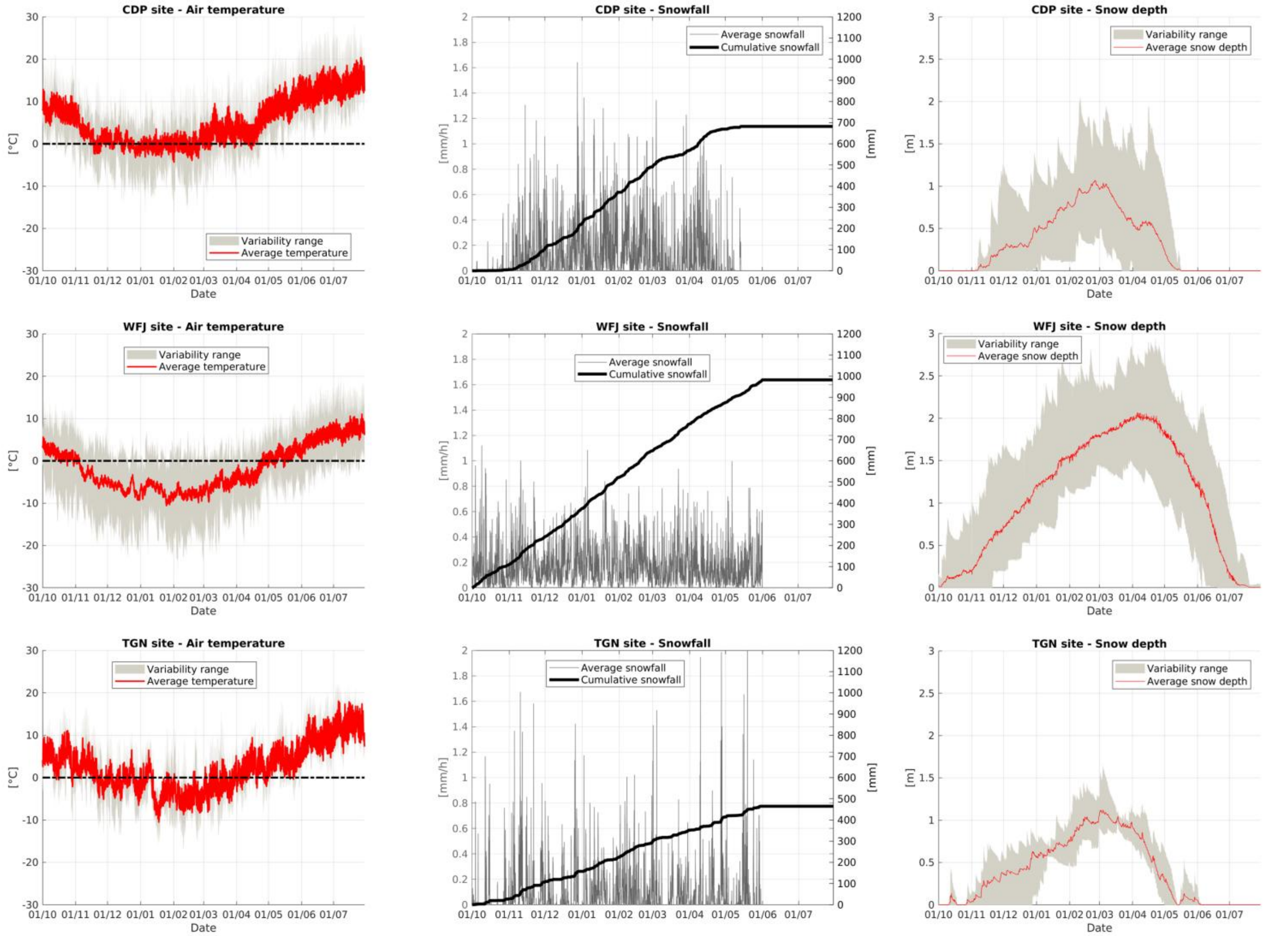

Figure 1: Meteorological characterization of CDP site (first row), WFJ site (second row), TGN site (third row) - Air temperature (left column), snowfall rates (middle column; at WFJ and TGN sites snowfall rates have been estimated according to Froidurot et al., 2014) and snow depth (right column) throughout an average snow season (early October – early July) throughout the overall datasets.

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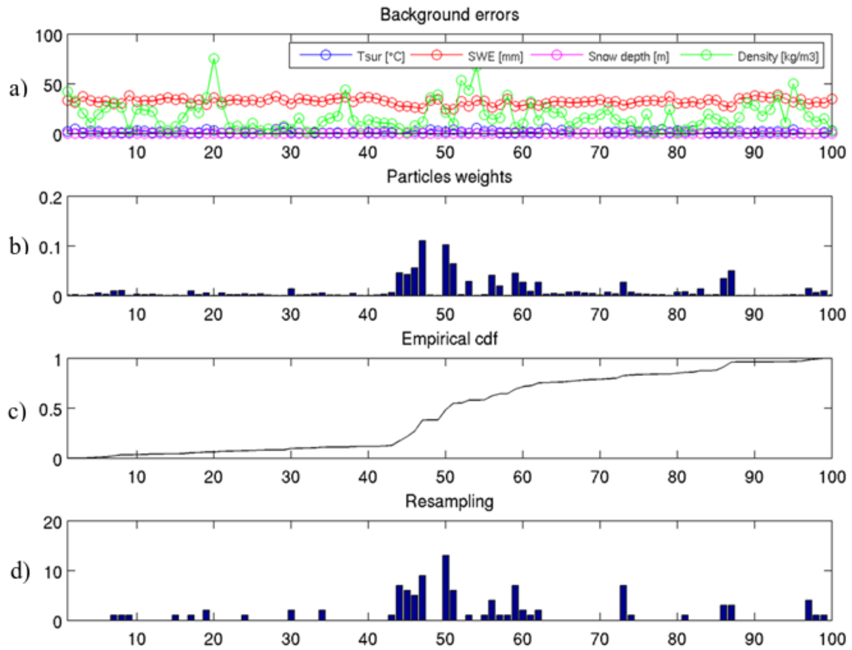

Figure 2: SIR-PF scheme for multivariate DA: (a) Open circles are the background errors forsurface temperature (in blue), SWE (in red), snow depth (in magenta) and snow density (in green). (b) Importance weights as a function of the particles indices. (c) Empirical cdf of the weights. (d) Number of resampled particles as a function of the particles indices.

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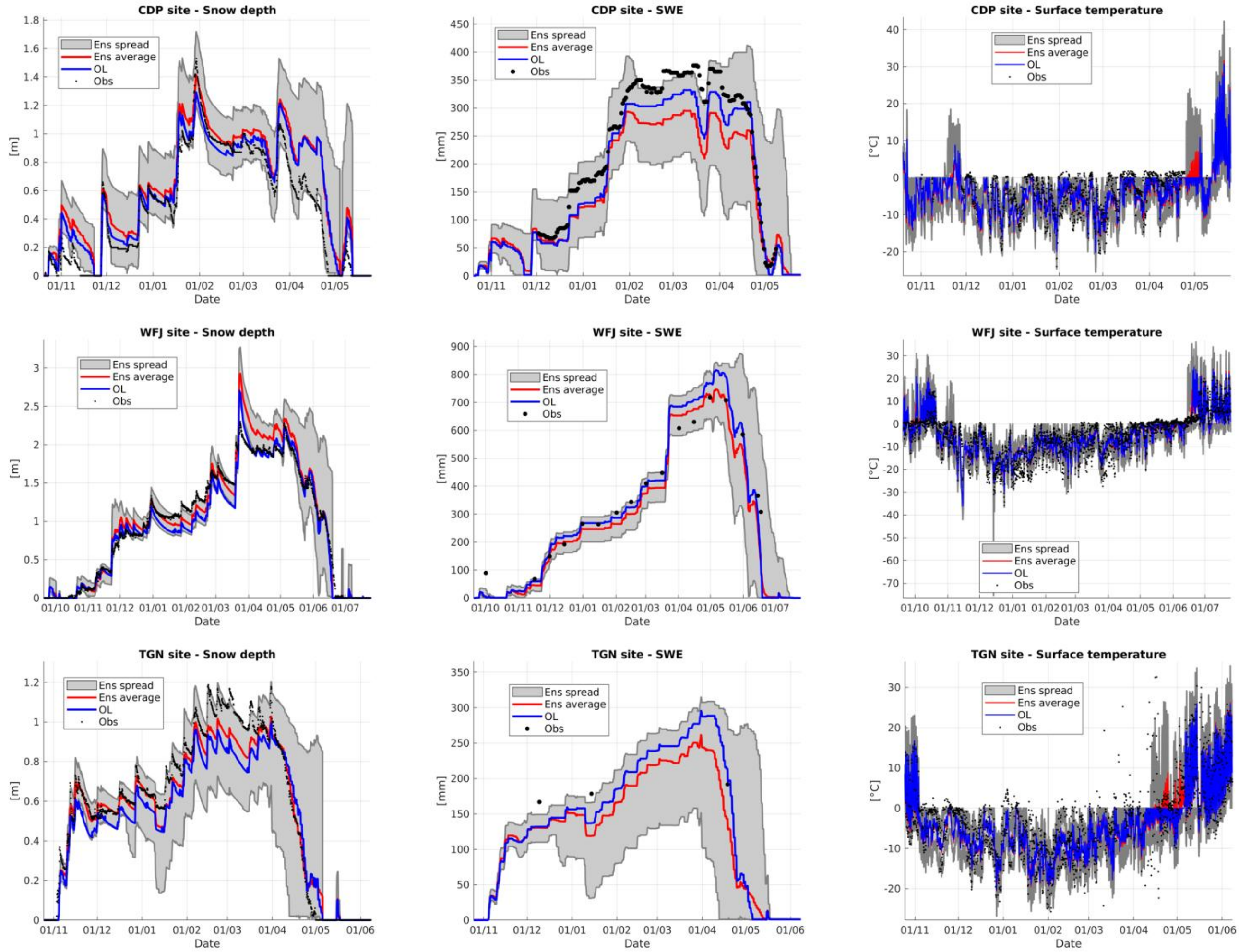

Figure 3: Impact of the meteorological uncertainty - Ensemble simulations of snow depth (left column),SWE (middle column), and surface temperature (right column) – CDP, winter season 2003-2004 (first row); WFJ, winter season 2001-2002 (second row); TGN, winter season 2014-2015 (third row).

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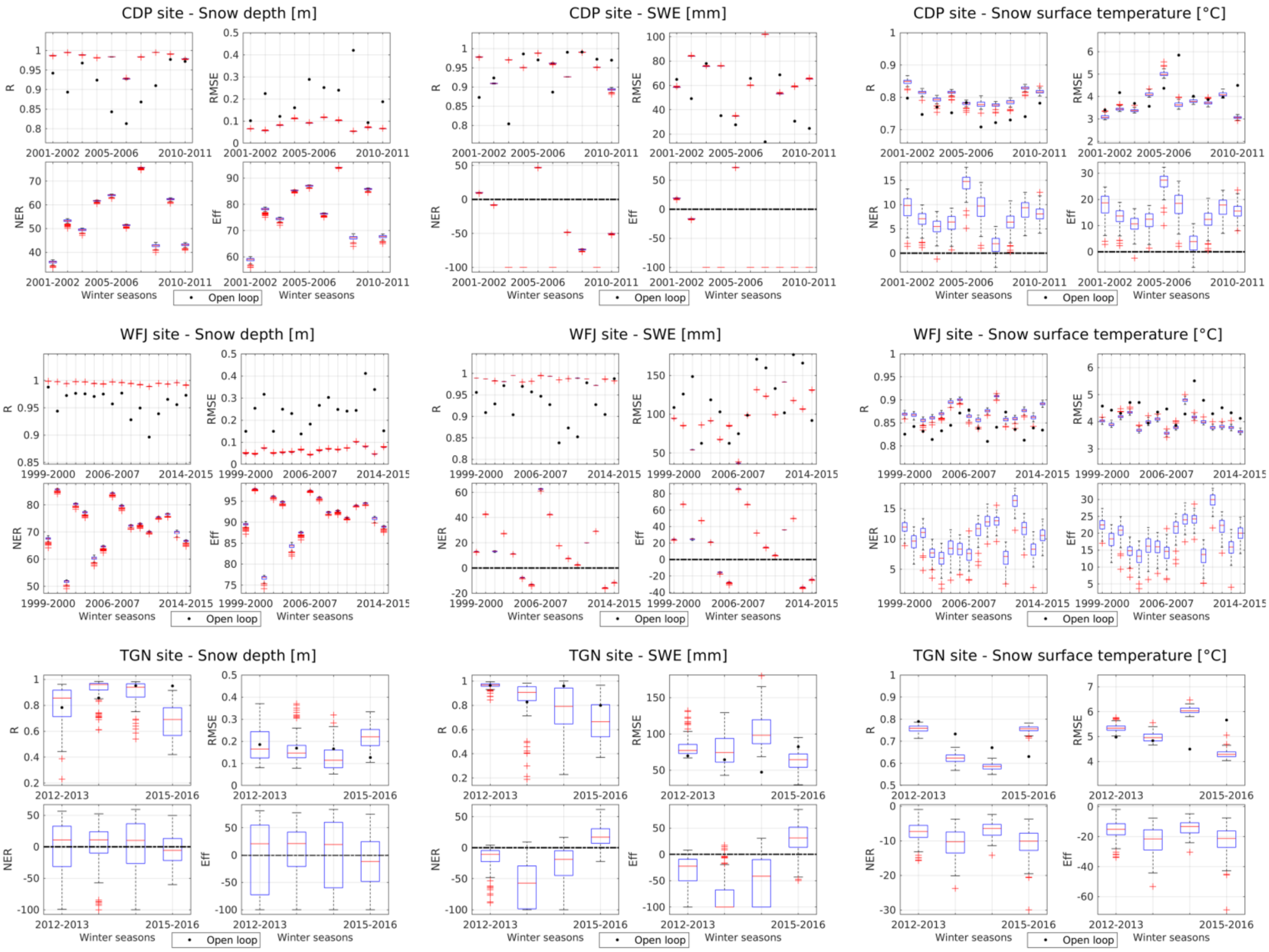

Figure 4: Multivariate DA scheme with perturbed meteorological data – Statistical scores of snow depth (left column), SWE (middle column) and surface temperature (right column). The bottom and top edges of each box indicate the 25th and 75th percentiles, respectively.

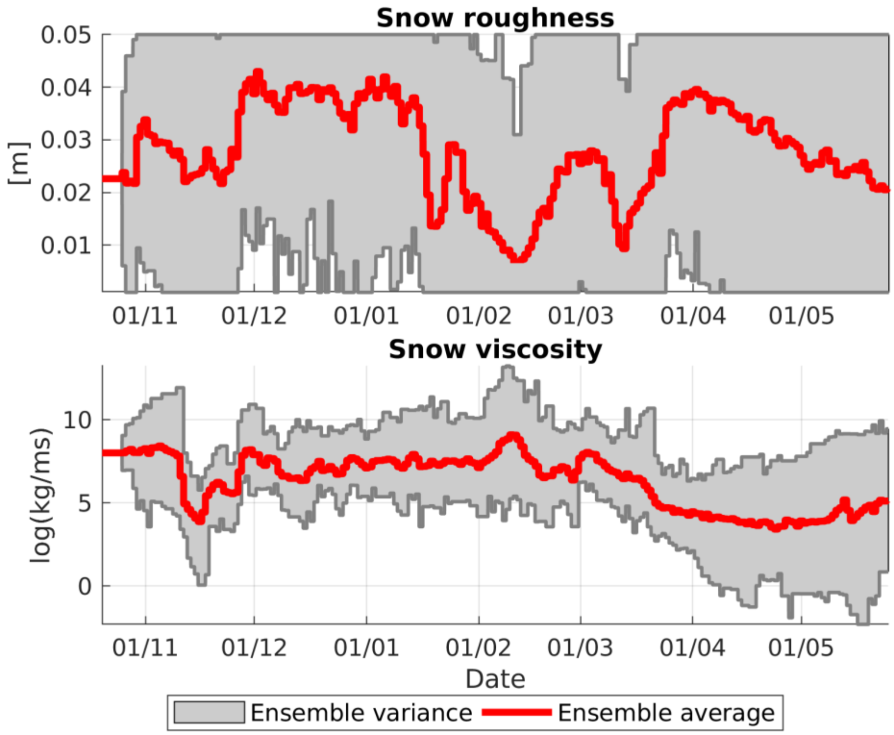

Figure 5: Uncertainty of model parameters – CDP site – Winter season 2010-2011. The panel shows the ensembles seasonality of snow roughness and snow viscosity.

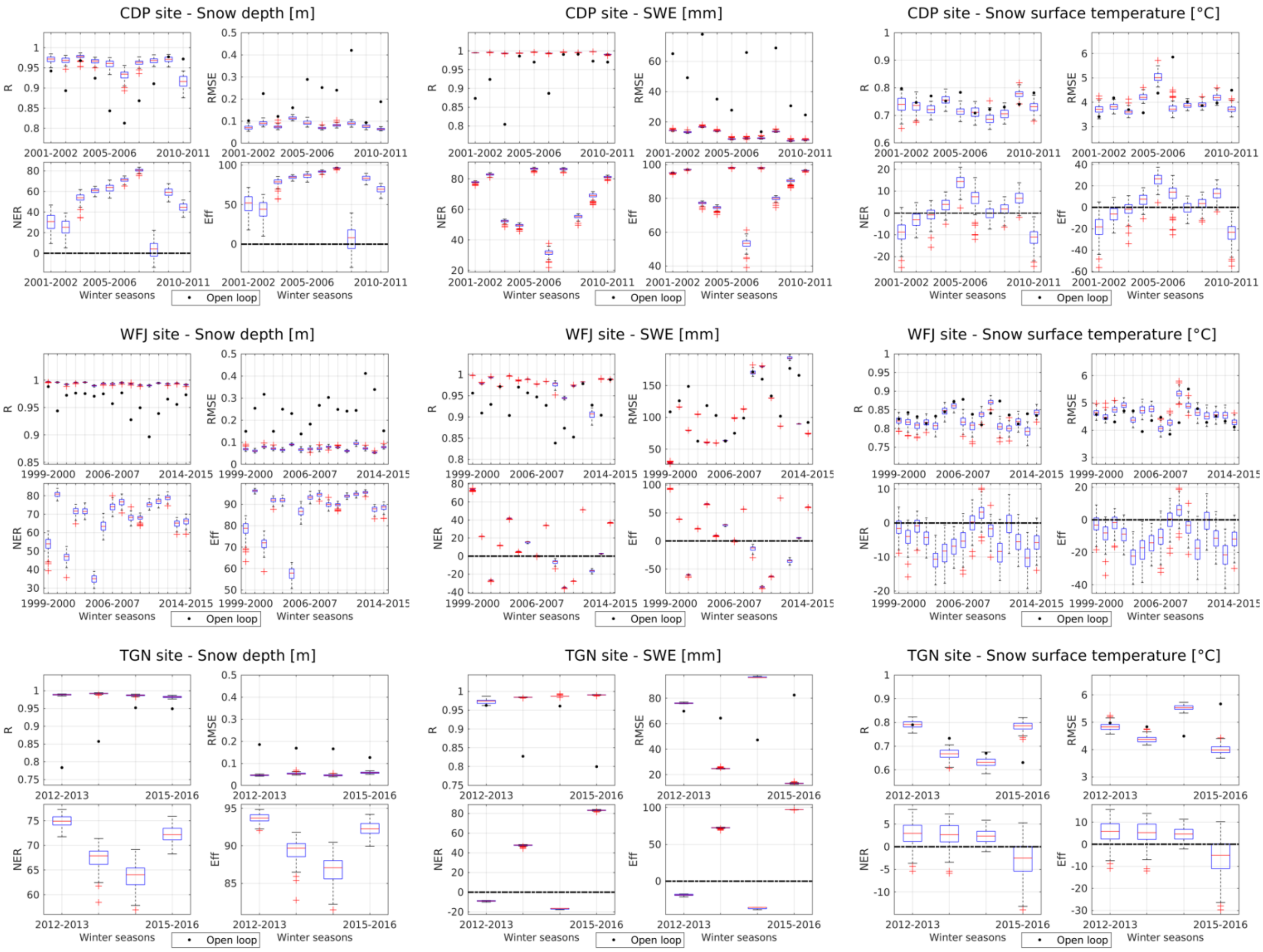

Figure 6: Multivariate DA scheme with perturbed meteorological data and model parameters resampling – Statistical scores of snow depth (left column), SWE (middle column) and surface temperature (right column) simulations – CDP site (first row); WFJ site (second row); TGN site (third row).

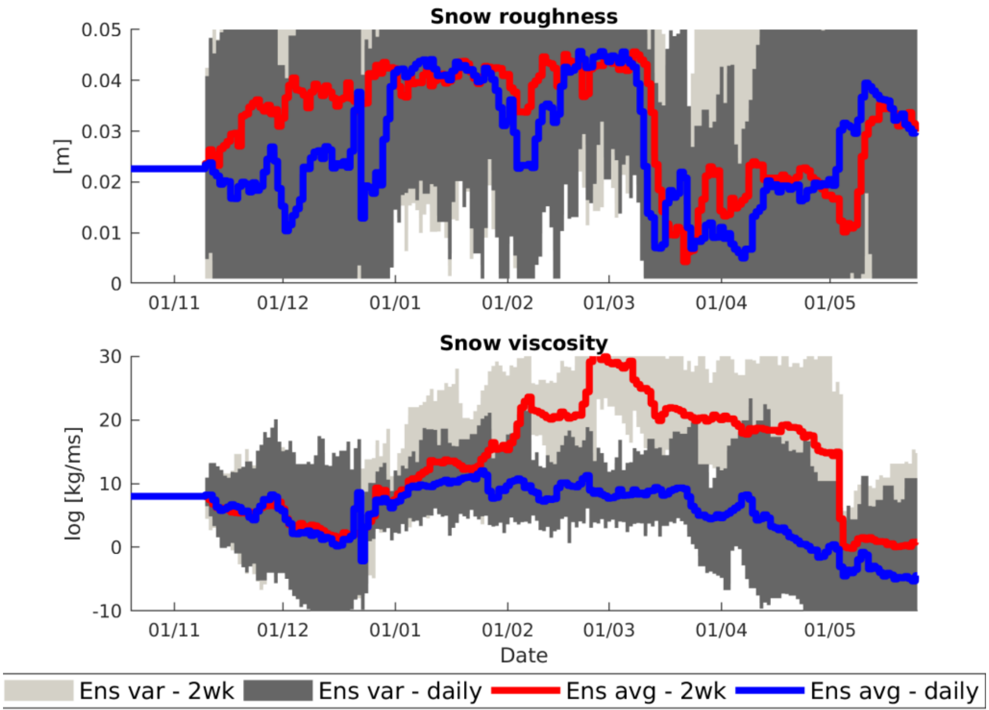

Figure 7: Sensitivity analysis of the multivariate DA scheme to SWE measurement frequency at CDP site, winter season 2001/02 – Parameters ensembles: snow roughness (on top) and snow viscosity (second row) resulting from the assimilation of daily (average trend in blue) and biweekly (red) SWE observations.

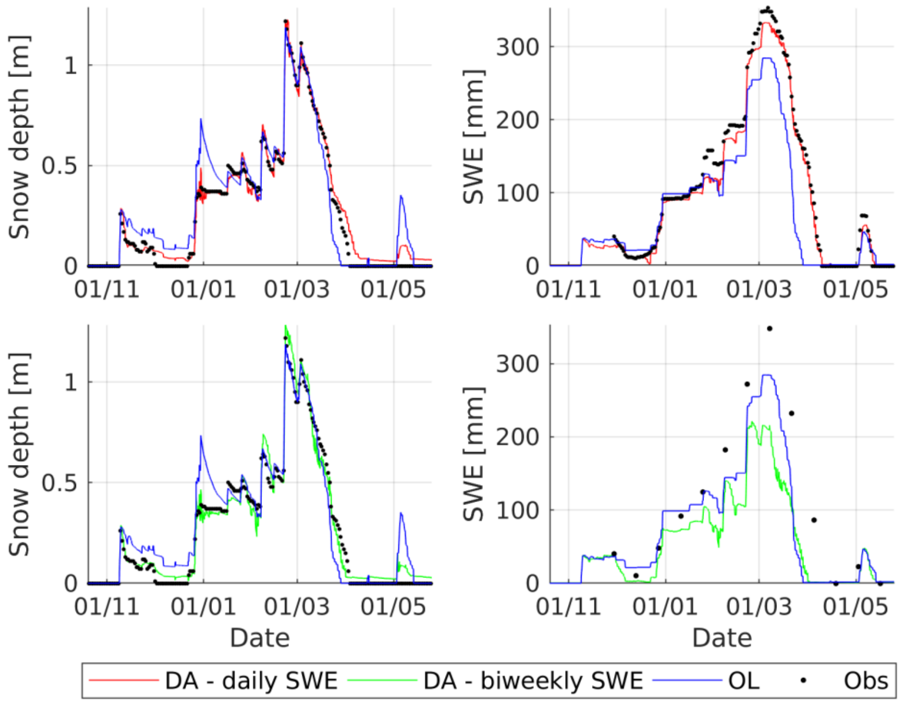

Figure 8: Sensitivity analysis of the multivariate DA scheme to SWE measurement frequency at CDP site, winter season 2001/02 – Simulations of snow depth (left column) and SWE (right column) for daily (first row) and biweekly (second row) SWE measurements.

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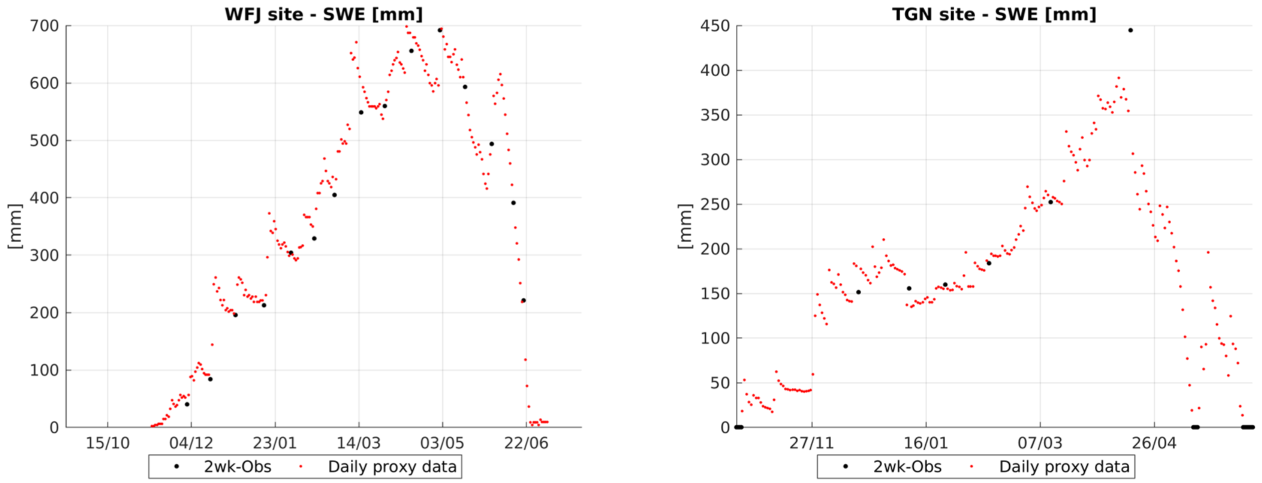

Figure 9: Additional snow density model –Comparison between SWE measurements and indirect proxy estimates - WFJ site, winter season 2005/06 (on the left); TGN site, winter season 2012/13 (on the right).

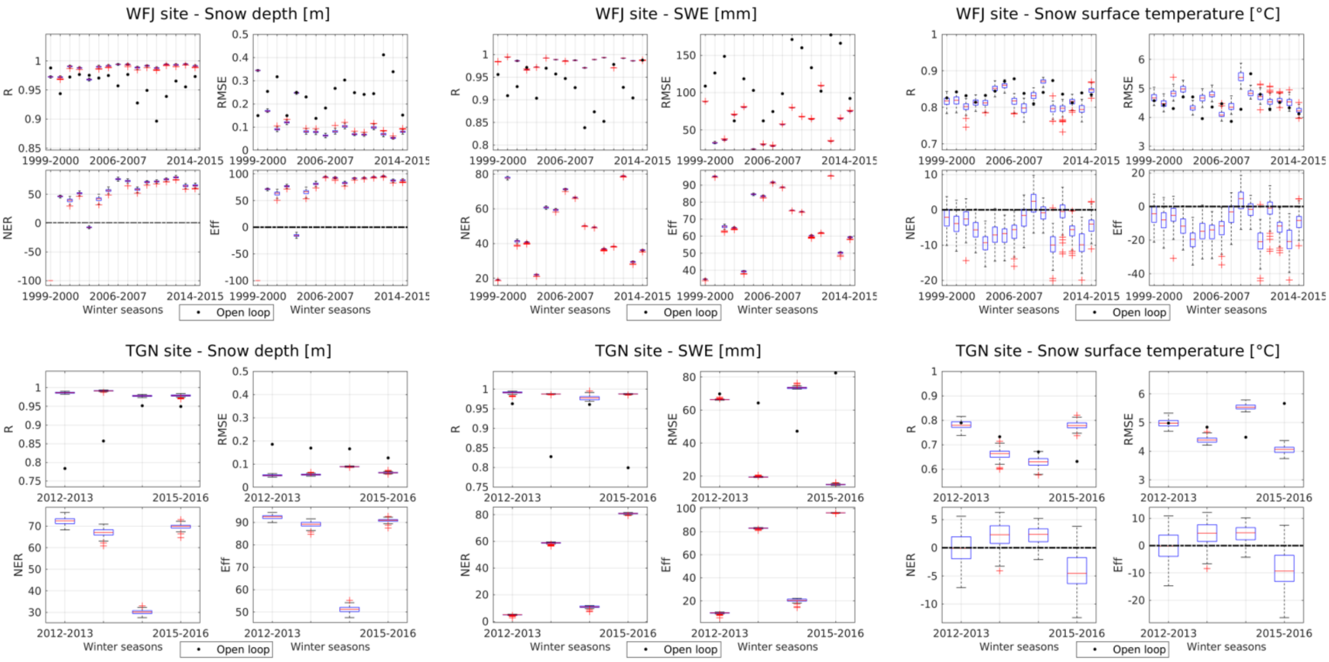

Figure 10: Multivariate DA scheme with auxiliary snow model - Statistical scores of snow depth (left column), SWE (middle column) and surface temperature (right column) simulations – WFJ site (first row); TGN site (second row).

Variable		Unit	Distribution	μ	σ	τ [h]	Lower limit	Upper limit
Air temperature	T_a	[°C]	Normal	0	0.9	4.8	-	-
Relative humidity	RH	[%]	Normal	0	8.9	8.4	0	100
Solar radiation	SW	[W/m^2]	Normal	0	min(SW, 109.1)	3.0	0	-
Precipitation	P	[mm]	Lognormal	-0.19	0.61	2.0	0	-
Wind speed	V	[m/s]	Lognormal	-0.14	0.53	8.2	0.5	25

Table 1: Error statistics for the generation of the meteorological ensembles (Magnusson et al., 2017).

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Site	Dataset size	Snow seasons from	Snow seasons to	Reference
CDP	10-years	2001/2002	2010/2011	Morin et al., 2012
WFJ	16-years	1999/2000	2014/2015	WSL Institute for Snow and Avalanche Research SLF, 2015b
TGN	4-years	2012/2013	2015/2016	Galvagno et al., 2013

Table 2: *Snow datasets.*

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Site	Assimilated variables T_{snow} [°C]	SWE [mm]	α [-]	*SD* [m]	ρ_{snow} [kg/m^3]
CDP	hourly	daily	hourly	hourly	**daily**
WFJ	30-min	bi-weekly	daily	30-min	**bi-weekly**
TGN	30-min	daily (2013/14, 2015/16); **bi-weekly (2012/13, 2014/15)**	daily (2012/13)	30-min	**daily (2013/14, 2015/16)**; bi-weekly (2012/13, 2014/15)

Table 3: Measurement frequency of the assimilated variables at each experimental site: snow surface temperature (T_{snow}), SWE, albedo (α), snow depth (SD) and snow density (ρ_{snow}) – Variables indirectly estimated are highlighted in bold.

	Parameter		Nominal value	Range
1.	Snow roughness	[mm]	0.0226	$[0.001 - 0.05]$
2.	Snow viscosity	[kg/ms]	10^8	$[7 \cdot 10^7 - 10^{12}]$
3.	Albedo parameter τ_α	[s]	10^7	$[0.52 - 1.55 \cdot 10^7]$
4.	Albedo parameter τ_m	[s]	$3.6 \cdot 10^5$	$[1.73 - 5.2 \cdot 10^5]$
5.	Albedo parameter S_0	[mm]	10	$[2 - 15]$

Table 4: Sensitivity analysis - Selected model parameters.