



HAL
open science

Improving the Spatial Distribution of Snow Cover Simulations by Assimilation of Satellite Stereoscopic Imagery

César Deschamps-Berger, B. Cluzet, M. Dumont, M. Lafaysse, E. Berthier, P. Fanise, S. Gascoin

► **To cite this version:**

César Deschamps-Berger, B. Cluzet, M. Dumont, M. Lafaysse, E. Berthier, et al.. Improving the Spatial Distribution of Snow Cover Simulations by Assimilation of Satellite Stereoscopic Imagery. *Water Resources Research*, 2022, 58 (3), 10.1029/2021WR030271 . hal-03602822

HAL Id: hal-03602822

<https://hal.science/hal-03602822>

Submitted on 9 Mar 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1
2 **Improving the spatial distribution of snow cover simulations by**
3 **assimilation of satellite stereoscopic imagery**
4

5 **Deschamps-Berger C.^{1,2}, Cluzet B.¹, Dumont M.¹, Lafaysse M.¹, Berthier E.³, Fanise P.²,**
6 **Gascoin S.²**
7

8 ¹ Université Grenoble Alpes, Université de Toulouse, Météo-France, Grenoble, France, CNRS,
9 CNRM, Centre d'Etudes de la Neige, 38000 Grenoble, France.

10 ² Centre d'Etudes Spatiales de la Biosphère, CESBIO, Univ. Toulouse,
11 CNES/CNRS/INRA/IRD/UPS, 31401 Toulouse, France.

12 ³ Centre National de la Recherche Scientifique (CNRS-LEGOS), 31400 Toulouse, France.

13 Corresponding author: César Deschamps-Berger (cesar.deschamps-berger@protonmail.com)

14 **Key Points:**

- 15 ● Assimilation of one satellite snow depth map corrects bias in precipitation and improves
16 the modeled spatial variability of the snow depth
17 ● In the case of a large bias in precipitation, assimilation of a single snow depth map can
18 modify incidentally the way the SWE and snowpack bulk density are modeled
19 ● This approach, which combines satellite data for assimilation and validation, could be
20 transferred to unmonitored basins
21
22
23
24
25
26
27
28
29
30
31
32
33

34 **Abstract**

35 Mountain snow cover is highly variable both spatially and temporally and has a tremendous
36 impact on ecosystems and human activities. Numerical models provide continuous estimates of
37 the variability of snow cover properties in time and space. However, they suffer from large
38 uncertainties, for instance originating from errors in the meteorological inputs. Here, we show
39 that the snow depth variability at 250 m spatial resolution can be well simulated by assimilating
40 snow depth maps from satellite photogrammetry in a detailed snowpack model. The assimilation
41 of a single snow depth map per snow season using a particle filter is sufficient to improve the
42 simulated snow depth and its spatial variability, originally poorly represented due to missing
43 physical processes and errors in the precipitation inputs. Assimilation of snow depth only is
44 nevertheless not sufficient for both compensating for strong bias in precipitation and for
45 selecting the most appropriate representation of the physical processes in the snow model.
46 Combined assimilation of snow depths maps and other snow observations is thus a promising
47 avenue for accurate simulations of mountain snow cover.

48

49 **Plain language summary**

50 Snow in mountains is critical as it controls water availability for ecosystems and human
51 societies, when it is most needed. In the mountains the snow depth is both hard to map due to its
52 spatial variability and crucial to estimate water resources. Nowadays, the best estimations of the
53 snow depth distribution combine models and spatially distributed snow depth measurements. In
54 this work, we build upon this approach by combining a recently developed snow depth mapping
55 method with a state-of-the-art model through assimilation. The assimilation of snow depth maps
56 derived from satellite photogrammetry corrects bias in the precipitation and improves the spatial
57 variability of the simulated snow depth. The workflow presented can be transferred to any
58 mountain range, showing a promising way to study water resources in remote areas.

59

60 **1 Introduction**

61 The seasonal snowpack in mountain regions controls the seasonality of streamflow, vegetation
62 growth, soil and river temperature (Bard et al., 2015; Choler, 2018; Dedieu et al., 2016; Luce et
63 al., 2014). Accurate knowledge of the spatial distribution of the snowpack properties is necessary
64 to describe the timing and extent of these effects (Freudiger et al., 2017; Hedrick et al., 2018;

65 Margulis et al., 2019; Revuelto et al., 2016). However, a major challenge is the lack of a direct
66 method to estimate the spatial distribution of snow water equivalent (SWE) in mountain regions
67 (Dozier et al., 2016). Modeling is often used but is limited by the availability of accurate gridded
68 meteorological forcing (Raleigh et al., 2015). The spatial interpolation of meteorological
69 variables (e.g., air temperature, precipitation quantity and phase, and wind) is hampered by the
70 absence of meteorological stations at high elevations (Rasmussen et al., 2012) and by the high
71 spatial variability of meteorological processes in mountain environments due to the complex
72 topography (Barry, 2008). Snowpack models are also prone to errors due to uncertainties in
73 parameter values, the form of parameterizations and the lack of some physical processes
74 (Ménard et al., 2021). Assimilation of gridded data in a snowpack model is key to overcoming
75 these challenges (Giroto et al., 2020; Largeron et al., 2020). It enables taking advantage of the
76 profusion of remotely sensed data, especially satellite data, and improving model outputs by a
77 balanced combination of model states and observations as a function of their estimated
78 uncertainties. Maps of the snow cover area (SCA) are widely available and therefore have been
79 predominantly assimilated to improve the simulation of SWE and snowmelt runoff (e.g.,
80 Andreadis & Lettenmaier, 2006; Rodell & Houser, 2004; Thirel et al., 2011; Margulis et al.,
81 2015; Baba et al., 2018). Other gridded products were assimilated, such as SWE maps derived
82 from passive microwave images (Andreadis & Lettenmaier, 2006) or surface reflectance maps
83 (Dumont et al., 2012). But the SCA is only indirectly related to SWE and the low spatial
84 resolution of passive microwave images is limiting, fostering the need for assimilation of other
85 types of data.

86 HS is a key snowpack variable for hydrological applications, as it can be combined with bulk
87 density to obtain the SWE. Recently, the development of new methods to retrieve snow depth
88 (height of snow, HS) based on lidar or photogrammetric measurements from airborne, drone or
89 satellite platforms has presented new opportunities to better constrain snowpack models. Vögeli
90 et al. (2016) and Brauchli et al. (2017) used an HS map to distribute solid precipitation in a Swiss
91 Alps catchment. They corrected an initial field of precipitation with a multiplicative factor per
92 point based on the ratio of the HS at the point and the average HS of the area. The HS was
93 extracted from a single map measured close to the date of peak SWE by airborne
94 photogrammetry. This computationally simple method increased the spatial variability of the
95 simulated HS and improved the simulated discharge of the basin. Another simple method to

96 benefit from HS maps is the direct insertion of the HS map in the model. Revuelto et al. (2016)
97 showed that direct insertion of HS maps derived from terrestrial laser scans improved the spatial
98 distribution of modeled HS and the timing of snow melt in a Spanish Pyrenees catchment.
99 However, the area covered with terrestrial laser scans is at best a few square kilometers and was
100 less than 1 km² in that study (Deems et al., 2013). Shaw et al., (2020) used an HS map derived
101 from satellite stereo-imagery to initialize a hydrological model of a 102 km² high-Andean
102 catchment. This improved the simulation of the runoff compared with initialization with a
103 modeled HS map. Lidar measurements of the Airborne Snow Observatory (ASO, Painter et al.,
104 2015) campaigns enabled experiments of direct insertion of HS maps on a larger scale in a
105 mountainous environment (>1000 km²) (Hedrick et al., 2018). Insertion of a dozen HS maps
106 from approximately 1st April and throughout the melt season improved the spatial distribution of
107 modeled HS in several catchments in the western USA (Hedrick et al., 2018). However, the
108 direct insertion of any observed variable can lead to an unrealistic state of the snowpack
109 variables that are not observed (e.g., density and temperature), resulting in a rapid loss of its
110 added value (Viallon-galinier et al., 2020). In addition, grid cells where the model predicts no
111 snow, although the observation indicates that snow is present, require the estimation of the
112 vertical profile of all snow physical properties (e.g. density, temperature). More generally, direct
113 insertion assumes that observations are perfect, which is unrealistic. To avoid this assumption,
114 other methods consider and balance the uncertainties of the observation and of the model. For
115 instance, the particle batch smoother method is applied to ensemble simulations by weighting the
116 ensemble members (the particles) based on their distance to the observation. With the same data
117 as Hedrick et al. (2018), this approach improved the HS spatial distribution up to 75 days after
118 assimilation of a single HS map (Margulis et al., 2019). The particle filter method is similar to
119 the particle batch smoother but can easily be combined with a forecast system. It is well adapted
120 to nonlinear detailed snow models with variable numbers of layers (Cluzet et al., 2021). A
121 particle filter assimilation scheme has been used for point simulations of snowpack either with
122 synthetic (Charrois et al., 2016; Cluzet et al., 2021) or real data (Magnusson et al., 2017; Smyth
123 et al., 2019; Smyth et al., 2020) but, to our knowledge, has never been used with gridded data.

124 These studies are promising and show how HS maps can improve the simulation of the spatial
125 distribution of snowpack properties. Except for Shaw et al. (2020), these studies relied on highly
126 accurate airborne and terrestrial measurements with standard errors smaller than 0.2 m. This

127 level of accuracy can only be reached by ground, drone or airborne measurements, which require
128 direct access to, or close to, the field. However, the assimilation of data artificially degraded to
129 lower accuracy still improved point simulation of the snowpack (Smyth et al., 2020). Very high-
130 resolution stereoscopic satellites such as Pléiades or Worldview provide HS maps with a lower
131 accuracy (~0.7 m) than ground, drone or airborne methods but with less logistical constraints and
132 less cost for the end user (Marti et al., 2016; Shaw et al., 2020; Deschamps-Berger et al., 2020;
133 Eberhard et al., 2021). With this method, HS maps are calculated by differencing two digital
134 elevation models derived from stereoscopic images with and without snow. The typical footprint
135 of a single image (20 km x 20 km for Pléiades) is larger than ground and drone products but
136 smaller than airborne products. Pairs or triplets of stereoscopic images are acquired on-demand
137 contrary to optical satellites with a fixed revisit time (e.g. MODIS, Landsat, Sentinel).
138 Multiannual time series of HS maps from satellite photogrammetry have never been used to date
139 for assimilation in a snowpack model.

140 In this work, we investigate if satellite photogrammetric HS maps can be used to improve snow
141 cover simulations. To this aim, we ran ensemble simulations of the SAFRAN-Crocus snowpack
142 modeling chain (Vernay et al., 2021) in a pilot catchment in the Pyrenees Mountains (France) for
143 five hydrological years at a 250 m spatial resolution. Several processes directly influence the HS
144 such as the amount of precipitation, the density of the fresh snow and the compaction of the
145 snowpack. The uncertainties of these processes are accounted for by using an ensemble of
146 meteorological forcings (e.g. uncertainty of the precipitation) and a multiphysical model (e.g.
147 density of the fresh snow, compaction). A multiphysical model is an ensemble modelling
148 framework in which ensemble members are calculated with different physical parameterizations
149 of most uncertain processes represented in the model (Essery et al., 2013; Lafaysse et al., 2017).
150 We calculated a multiannual time series of six HS maps from stereoscopic images from the
151 Pléiades satellites and assimilated one HS map per year with a particle filter scheme (Cluzet et
152 al., 2021).

153 Therefore, we tackle two main questions:

154 1. Is the accuracy of satellite photogrammetric HS maps sufficient to improve the spatial
155 distribution of the HS in a detailed model?

156 2. In case of improvement, does assimilation of the HS correct errors in the meteorological
157 forcings, in the physical parameterizations of the model, or both?

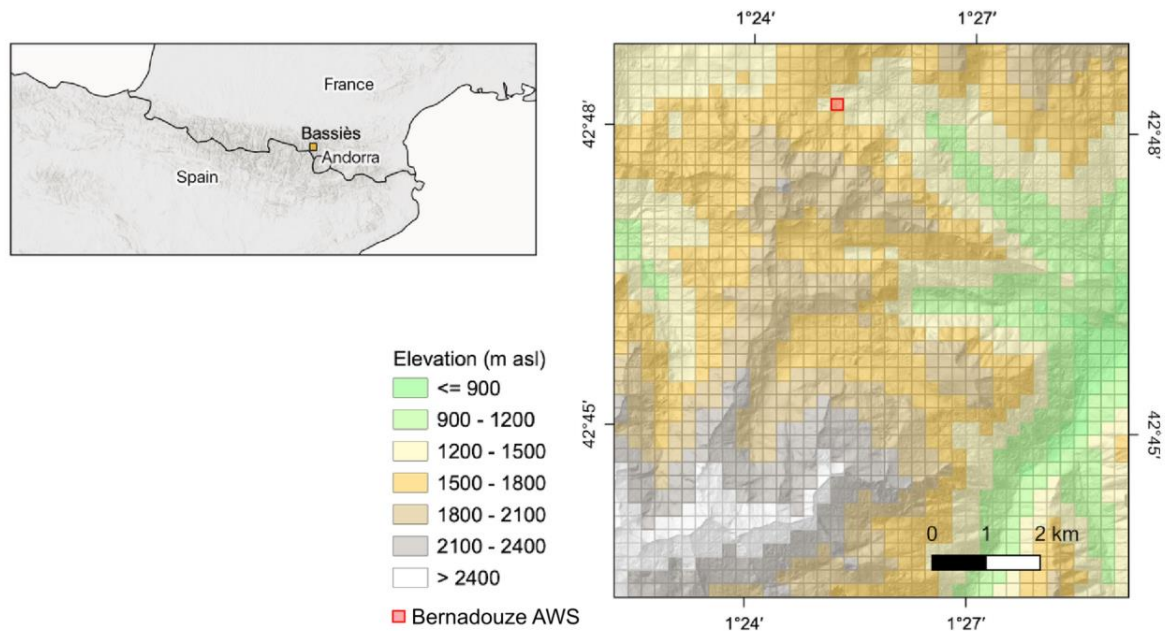
158 The impact of assimilation was evaluated with various independent data: a Pléiades HS map not
159 assimilated, Sentinel-2 and Landsat 8 snow melt-out date (SMOD), MODIS SCA and in situ HS
160 from an automatic meteorological station (Question 1). The impact of the assimilation is also
161 evaluated by comparing the meteorological forcings and the physical parameterization associated
162 with the ensemble members selected by the filter (Question 2).

163

164 **2 Study area**

165 The study site is a 100 km² mountainous area in the Upper Vicdessos Valley in the Pyrenees
166 (Figures 1 and 2), where elevation ranges between 1000 m a.s.l. and 2700 m a.s.l. (Szczypta et
167 al., 2015; Marti et al., 2016). The vegetation is subalpine pine and beech forest and alpine
168 grassland above the tree line at approximately 1800 m a.s.l. (Figure 3 of Vacquie et al., 2016).
169 Small portions of the area contain human infrastructures with a small city (Auzat, <0.5 km²) and
170 a few roads. Ponds and two man-made reservoirs for hydropower production cover
171 approximately 0.3 km². Seasonal snowpack typically sets in November-December and melts
172 between April and June. The study period encompasses five water years (1 September to 31
173 August, WY) from WY 2014-2015 to WY 2018-2019. This period provides various snow
174 conditions as shown by the winter precipitation of the nearby automatic weather station (AWS)
175 between 2000 and 2019. WY 2018-2019 and WY 2016-2017 had among the lowest winter
176 precipitation (rank number 19 and 17 respectively) while WY 2017-2018 had high winter
177 precipitation (rank number 3). WY 2014-2015 and WY 2015-2016 were close to the median
178 winter precipitation with rank 7 and 11.

179



180

181 **Figure 1.** The simulation area in the Upper Vicdessos valley, Pyrenees. The coloured map shows
182 the surface elevation at the resolution of the simulation grid (250 m). The background image is a
183 hillshade view of the topography at high-resolution (3 m).

184



185

186 **Figure 2.** Photographs taken from Col de la Serrette near the geographic center of the study area
187 (left: 26 October 2014, right: 11 March 2015).

188

189 **3 Data and methods**

190

3.1. Model and assimilation scheme

191 The Crocus model simulates snowpack as a stack of 3 to 50 snow layers that exchange mass and
192 energy between them and at their upper and lower boundaries. Here, the model was used in a
193 distributed geometry in a regular grid (Revuelto et al., 2018). There was no energy or mass
194 transfer between the points, which indicates that wind drift, horizontal heat transfer and
195 avalanches were not modeled. However, shading due to topography was considered in the
196 incident shortwave radiation. We used the multiphysics version ESCROC-E1, which is an
197 ensemble of 575 sets of parameterizations of eight physical processes implemented in the model
198 (Lafaysse et al., 2017). The parameterization of the density of the new snow and of the
199 compaction rate are expected to have the largest impact on HS. As in Cluzet et al. (2021), a set of
200 120 parameterizations was randomly drawn once and used for all WY and experiments.

201 The density and mass of each layer are prognostic variables in the model. Thus, assimilating HS
202 can result in modifying the SWE, the density or both. The SMOD was defined as the end of the
203 longest period with continuous snow cover. At each time step and for each grid point, the
204 modeled median HS map was converted to an SCA map with a threshold determining the
205 presence or lack of snow. The optimum HS threshold was chosen among six values in the 0.02
206 m-0.50 m range so that it minimizes the mean and standard deviation of the SMOD residual
207 (SMOD Crocus minus SMOD Sentinel-2/Landsat 8). Based on these criteria, the optimal
208 threshold was 0.20 m (Figure S1), which is close to the threshold of 0.15 m that maximizes the
209 agreement between MODIS SCA (500 m resolution) and in situ HS in the Pyrenees (Gascoin et
210 al., 2015).

211 The snowpack was simulated over five WY (WY 2014-2015 to WY 2018-2019) on a regular
212 grid of points separated by 250 m with a 15 min time step (Figure 1). An ensemble of 120
213 simulations was obtained by stochastic perturbations of the SAFRAN reanalysis and the use of
214 different physical parameterizations of the Crocus model (Lafaysse et al., 2017) (Figure 3). Once
215 per hydrological year, an HS map was assimilated with the particle filter of the data assimilation
216 scheme CrocO (Cluzet et al., 2021). The filter was applied independently to each grid point
217 where observations were available using only the observation at that grid point, following the
218 *rlocal* approach (Cluzet et al., 2021). The particle filter works in two steps. First, the ensemble
219 members (i.e. particles) are assigned a weight which is proportional to their distance to the
220 observation and is relative to the observation error. The observation error is assumed to be

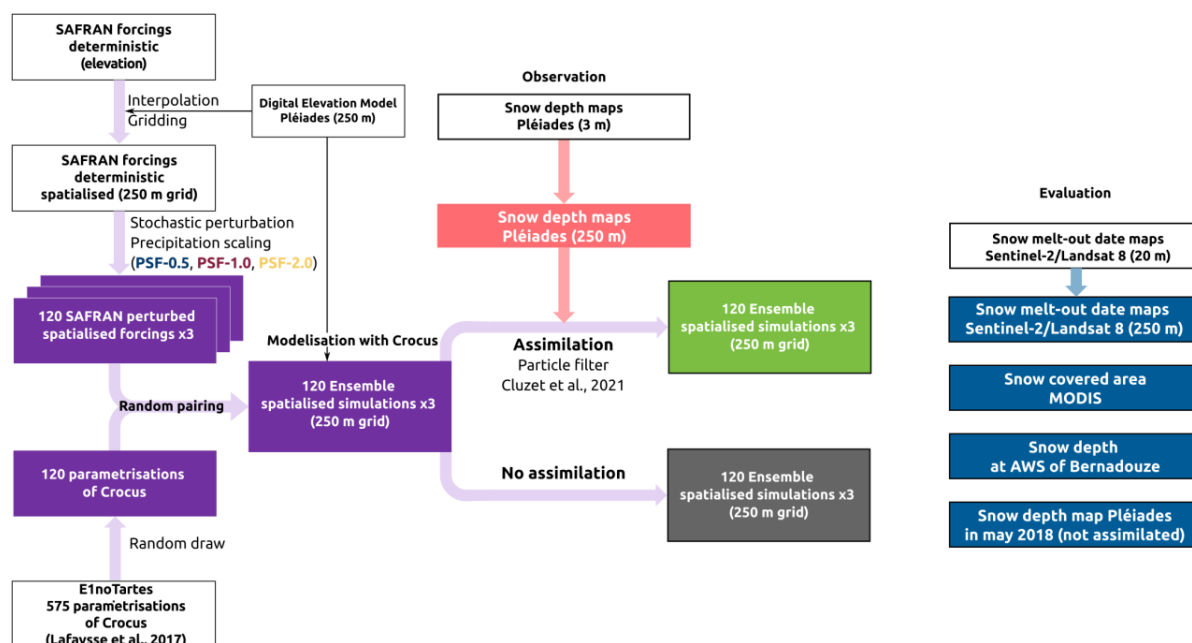
221 normally distributed with a defined standard deviation. Then, the particles are resampled (i.e.
222 eliminated or duplicated) based on their weight following Kitagawa (1996). Each particle results
223 from a meteorological forcing and a parameterization of the model. The particle filter only
224 resamples state vectors and has no influence on the forcing-model couples before or after the
225 assimilation. Nevertheless, we compare the meteorological forcings and the model
226 parameterizations associated with the particles selected by the filter (i.e. with assimilation) with
227 the one of the ensemble without assimilation.

228

229 3.2. Simulation grid and boundary conditions

230 The topography of the simulation grid was the snow-free digital elevation model (DEM)
231 calculated from the October 2014 Pléiades images. It was aggregated from its initial horizontal
232 resolution (3 m) to the simulation grid resolution (250 m) with an average block filter. The soil
233 and vegetation conditions were extracted at each grid point from the Harmonized World Soil
234 Database (FAO/IIASA/ISRIC/ISS-CAS/JRC, 2012) and Ecoclimap-2 data sets (Faroux et al.,
235 2013), respectively. The interaction between snowpack and forest was not accounted for because
236 the implementation of this complex coupling in SURFEX-Crocus is still in progress and not
237 sufficiently mature at the moment (Vincent et al., 2018) and because HS cannot be retrieved in
238 forest with satellite photogrammetry. The soil state (temperature and water/ice content) was
239 initialized with ten iterations of a one-year spin-up simulation with the meteorological conditions
240 of WY 2014-2015. All grid points were snow free on the last day of the spin-up simulations.

241



242
 243 **Figure 3.** General setup of the assimilation experiments. Pléiades HS maps (pink box) are
 244 assimilated with a particle filter in Crocus ensemble simulation (purple box). The ensemble
 245 results from perturbation of the meteorological forcings and different physical parameterizations
 246 of the Crocus model (purple boxes left). The assimilation run (green box) is evaluated by
 247 comparison with the run without assimilation (grey box) and with independent dataset (blue
 248 boxes).

249

250 3.3. Satellite photogrammetric snow depth maps

251 A time series of seven triplets of stereoscopic images (i.e. three almost synchronous images of
 252 the study area from different points of view) was acquired by the Pléiades satellites between
 253 October 2014 and March 2019 (Gleyzes et al., 2012) (Table 1). The terrain was snow free in
 254 October 2014, which provided a reference snow-off observation. The other acquisitions occurred
 255 once every winter in March or April (snow-on) close to the date of peak SWE. During winter
 256 2017-2018, two acquisitions were taken in February and May. Each acquisition provided a triplet
 257 (front, nadir, and back) of panchromatic images at a resolution of 0.5 m and a triplet of
 258 multispectral images (red, green, blue, and near-infrared) at a resolution of 2 m. The images were
 259 processed using a workflow that calculates a DEM from the panchromatic images and a land-

260 cover map from the multispectral images for each acquisition (Deschamps-Berger et al., 2020).
261 The difference between a snow-on and snow-off DEM provided an elevation difference map for
262 each snow-on acquisition. The land-cover map was labeled with the following classes: snow,
263 snow in shade, stable terrain, stable terrain in shade, forest, forest in shade and lakes. The stable
264 terrain is the area where no elevation changes are expected between the acquisitions (i.e., free of
265 snow) and where the elevation is constant in the DEM (i.e., free of forest). The HS map was
266 calculated by taking the elevation difference of snow-covered pixels and setting the HS to zero
267 over stable terrain pixels. The HS maps had an initial horizontal resolution of 3 m and were
268 aggregated using an average block filter of 250 m by 250 m centered on the simulation grid
269 points. HS were set to no-data if more than 90% of the pixels were no-data. This means that
270 more than 10^3 m² of HS are averaged, decreasing the error by a factor of two (Figure 10 in
271 Deschamps-Berger et al. (2020)). No-data pixels correspond to portions of the panchromatic
272 images that were saturated, covered with forest or with clouds. HS maps were also filtered to
273 exclude HS values out of the [-0.5 m; 30 m] range, which can occur due to local artifacts in
274 DEMs in shaded or forested areas in the snow-off DEM.

275 We defined a unique standard error for the measured HS, which is considered in the particle
276 filter. The standard error of the HS at a resolution of 250 m is lower than the standard error at a
277 resolution of 3 m due to the decrease in the random spatially-correlated error. A random error of
278 0.3 m was measured for a 250 m x 250 m averaging area at a mountainous site in California
279 (Figure 10 in Deschamps-Berger et al., 2020). A systematic error of 0.2 m was also typically
280 observed with similar data in several other studies (Table 4 in Deschamps-Berger et al., 2020).
281 We added these two error estimates to consider the uncertainty of how error can be transferred
282 from one site to another. Thus, the standard error of the HS at 250 m is 0.5 m.

283

284 3.4. Meteorological forcings

285 The meteorological variables needed as inputs in Crocus are air temperature, solid and liquid
286 precipitation, near-surface specific humidity, direct and diffuse shortwave radiation, longwave
287 radiation, and wind speed. The meteorological forcings were provided by the SAFRAN
288 reanalysis (Vernay et al., 2021) at an hourly resolution. SAFRAN provides meteorological data

289 for different elevation levels at a 300 m resolution within predefined regions of homogeneous
290 climate of approximately 1000 km², the so-called “Couserans massif” in this study. The forcings
291 were interpolated on the simulation grid according to their elevation (Revuelto et al., 2018).
292 Solar radiation was projected according to local slopes and shading effects computed in
293 dedicated routines of the SURFEX platform as in Revuelto et al. (2018).

294 The initial gridded forcing was perturbed stochastically to produce ensembles of 120 forcings.
295 Perturbation of the forcings aims to generate an ensemble of forcings with a dispersion among
296 the forcings matching their uncertainty. The stochastic perturbation was spatially constant and
297 temporally correlated following an updated version of the Charrois et al. (2016) method (see
298 Text S1). Perturbation of each meteorological variable was defined by two parameters, its
299 amplitude and its temporal correlation. All variables were perturbed with the parameters defined
300 in Charrois et al. (2016) at the Col de Porte site (Alps), except for precipitation because we found
301 that the uncertainty of annual cumulative precipitation was severely underestimated by Charrois
302 et al. (2016). Therefore, the temporal correlation of precipitation was increased from 15 hours to
303 1500 hours. This increases the dispersion of the annual cumulative precipitation among the
304 forcings and of the resulting average HS among the simulations in a magnitude more
305 representative of the typical known errors for both variables. In addition, three different sets of
306 forcings were calculated with three spatially and temporally uniform precipitation scaling factors
307 (PSF) to emulate precipitation biases that are typically observed in global reanalyses (Beck et al.,
308 2019). The reference experiment was run with a PSF of 1.0 (referred to as PSF-1.0) and was
309 compared with experiments in which precipitation was halved (PSF-0.5) or doubled (PSF-2.0).

310

311 3.5. Evaluation products and metrics

312 First, the impact of assimilation on the modeled snowpack was observed on the HS, SWE, bulk
313 density and runoff by comparison of the simulation with assimilation and the simulation without
314 assimilation. Then, the benefits of assimilation was measured by comparing the modeled HS
315 with the following independent observations:

316 - for WY 2017-2018 with a Pléiades HS map in May 2018, which was not assimilated

317 - a time series of HS at the Bernadouze AWS

318 - a time series of SCA derived from MODIS images

319 - a time series of SMOD maps calculated from Sentinel-2 and Landsat 8 images.

320 Note that we do not have observations of SWE or runoff on this area.

321 For each variable, X , describing the snowpack (i.e., HS, SWE, density, and runoff), a simulated
 322 ensemble was characterized by its mean, the first and third quartiles and its dispersion. These
 323 metrics were calculated for each time step (t) and each point of the grid (i,j). The mean is:

$$324 \quad \overline{X(l,j,t)} = \frac{1}{N} \sum_{n=1}^N \overline{X(l,j,t,n)} \quad (1)$$

325 where N is the size of the ensemble ($N=120$). The spread of the ensemble is

$$326 \quad \sigma(i,j,t) = \sqrt{\frac{1}{N} \sum_{n=1}^N (X(i,j,t,n) - \overline{X(l,j,t)})^2} \quad (2)$$

327 The mean is used to make a point-by-point comparison of the simulated ensemble with a
 328 reference map (HS and SMOD). It is used to compute the absolute bias between the ensemble
 329 and observation at a given point. However, it is not adapted to characterize the complete
 330 distribution of the ensemble. The continuous ranked probability score (*CRPS*) is a probabilistic
 331 score measuring the distance between the ensemble and observations (Hersbach, 2000). It
 332 compares the cumulative distribution function of the ensemble, $Fens$, with the observation, $Fobs$:

$$333 \quad CRPS(i,j,t) = \int_{-\infty}^{+\infty} [Fens(i,j,t,x) - Fobs(i,j,t,x)]^2 dx \quad (3)$$

334 where $Fobs$ is a step function defined by the observation value $Xobs$:

$$Fobs(i,j,x) = 1 \text{ if } x > Xobs ; 0 \text{ otherwise}$$

335 The higher the *CRPS*, the more the modeled ensemble is different from the observation. Thus,
 336 the assimilation aims at reducing the *CRPS* of the model compared to independent observations.

337 If not specified, the metrics were spatially averaged over grid points where observations were
 338 available. For the MODIS SCA and Bernadouze HS time series, the RMSE was calculated

339 between the modeled and observed variables from the assimilation date to the end of the WY.
340 The spatial variability of the modeled and observed HS maps was measured with semivariance
341 (Blöschl, 1999; Deems et al., 2006).

342 3.7. Snow melt-out date from Sentinel-2 and Landsat 8 images

343 We obtained every snow cover product available from the remote sensing products distribution
344 platform Theia between September 2016 and September 2019 (Gascoin et al., 2019). These snow
345 cover products were derived from Sentinel-2 and Landsat 8 images and provide a classification
346 of the surface as snow, no snow or cloud (including cloud shadow) at 20 m (Sentinel-2) or 30 m
347 (Landsat 8). Landsat 8 data were resampled to the Sentinel-2 20 m resolution grid by using
348 nearest neighbor interpolation. When Sentinel-2 and Landsat 8 data were available on the same
349 day, both products were merged by giving priority to Sentinel-2 on a pixel basis, i.e., Landsat 8
350 observations were used only if the Sentinel-2 pixel was classified as cloud. This time series was
351 linearly interpolated along the time dimension to produce a daily, gap-free time series of snow
352 absence and presence at a 20 m resolution between 1 September 2016 and 1 September 2019.
353 Maps of the SMOD were calculated from the snow cover time series following the same
354 definition as the simulated SMOD. The SMOD maps were aggregated with an average block
355 filter of 250 m by 250 m centered on the simulation grid points. The SMOD was set to no-data if
356 more than 90% of the initial pixel was covered with forest. The standard error of the SMOD
357 measurement was estimated at 6 days based on the revisit time between successive acquisitions
358 (~2.5 days) and the possible confusion with clouds.

359 3.8. Snow cover maps from MODIS

360 We used a collection of six Terra MODIS snow products (MOD10A1.006) to compute the SCA
361 of the model domain. The snow cover fraction (SCF) of each MODIS pixel (approximately 500
362 m) was derived from the “Snow cover NDSI” field using the formulae of Salomonson and Appel
363 (2004). Prior to computing the SCF, the missing values (approximately 50% of the data, mostly
364 due to cloud cover) were linearly interpolated to generate a gap-free, daily time series as above
365 with the Theia snow cover products. For every day between 1 September 2015 and 1 September
366 2019, a daily continuous SCA time series was thus obtained by summing the area-weighted
367 average of the SCF of each pixel within the study domain.

368 3.9. Bernadouze meteorological station

369 The Bernadouze automatic meteorological station is located in a clearing at 1420 m a.s.l. north of
 370 the study area (42.80°N, 1.42°E, Figure 1). HS is measured bihourly with an acoustic sensor with
 371 a centimetric accuracy (Gascoin & Fanise, 2018).

372 **Table 1.** Summary of the data used in this study.

373

Type	Source	Date	Horizontal resolution
Digital elevation model	Satellite photogrammetry (Pléiades)	2014-10-01	3 m
Snow depth map	Satellite photogrammetry (Pléiades)	2015-03-11	3 m
		2016-04-11	3 m
		2017-03-15	3 m
		2018-02-15	3 m
		2018-05-11	3 m
Snow melt-out date	Sentinel-2/Landsat 8 images	WY 2016-2017	20 m
		WY 2017-2018	
		WY 2018-2019	
Snow cover area	MODIS	all WY	500 m
Snow depth	Bernadouze AWS	all WY	

374

375

376 **4 Results**

377 4.1. Impact of the assimilation on the simulated snow depth on the assimilation date

378 Figure 4 shows the maps of the difference between the mean modeled HS and Pléiades HS
379 observations on all assimilation dates, for the different Precipitation Scaling Factor values (PSF).
380 Assimilation increased, on average, the modeled HS (PSF-0.5 and PSF-1.0) or decreased the
381 modeled HS (PSF-2.0) (Figure 4, Table S1). In all experiments and for all assimilation dates,
382 assimilation increased the similarity between the spatial distribution of the modeled and observed
383 HS, as expected. The semivariogram analysis indicates that the spatial variability of the modeled
384 HS was increased by the particle filter (Figure 5). The differences between the ensemble without
385 assimilation and the Pléiades observations were larger at high elevations for PSF-0.5 and PSF-
386 1.0 and rather homogeneous at all elevations for PSF-2.0 (Figure 6 and S2). The modeled HS
387 was largely inferior to observed HS in the southern part of the area prior to assimilation,
388 independent of the elevation for PSF-0.5 and PSF-1.0 (WY 2014-2015, WY 2016-2017, Figure
389 6). This difference was even observed in PSF-2.0 despite the HS being increased by the doubling
390 of precipitation. The mismatch between observed and modeled HS in WY 2018-2019 could be
391 related to spatially structured errors in the Pléiades HS map (see 5.5).

392 Figure 7 presents the evolution of the spatial average of the mean absolute difference between
393 the observations and the model, the ensemble spread, the CRPS and the Pearson correlation for
394 assimilated Pléiades observations (solid line). As expected, the distance between the assimilated
395 observations and the model, shown by the CRPS and the mean absolute difference, is always
396 reduced by the particle filter compared to the runs without assimilation. The CRPS and the mean
397 absolute bias reduction were larger for PSF-0.5 and PSF-2.0 without assimilation than for PSF-
398 1.0, but the values were reduced by the assimilation and close to each other for all experiments.
399 For all years and experiments, the Pearson correlation between the modeled and observed HS
400 increased to ~ 0.99 after assimilation.

401 4.2. Impact of the assimilation on the simulated SWE, density, and runoff

402 On the date of the assimilation, the assimilation of the HS maps had different impacts on the
403 modeled bulk density and the SWE depending on the experiment (Figure 8). The increase (PSF-
404 0.5 and PSF-1.0) and decrease (PSF-2.0) in HS were associated with similar modifications of the
405 SWE. Density was also modified to a lesser extent, typically $\pm 25 \text{ kg m}^3$. Density was
406 diminished for PSF-0.5 and some WY of PSF-1.0. Conversely, density was increased for PSF-
407 2.0.

408 The change in SWE on the date of the assimilation also resulted in modification of the melt
409 runoff amplitude and duration throughout the end of the snow season (Figure S4). Total melt
410 runoff increased from 20% to 30% for PSF-0.5, by 10% or less for PSF-1.0 and decreased by
411 10% or less for PSF-2.0. The end of the melt period was extended by up to 10 days for PSF-0.5
412 and not modified for PSF-2.0.

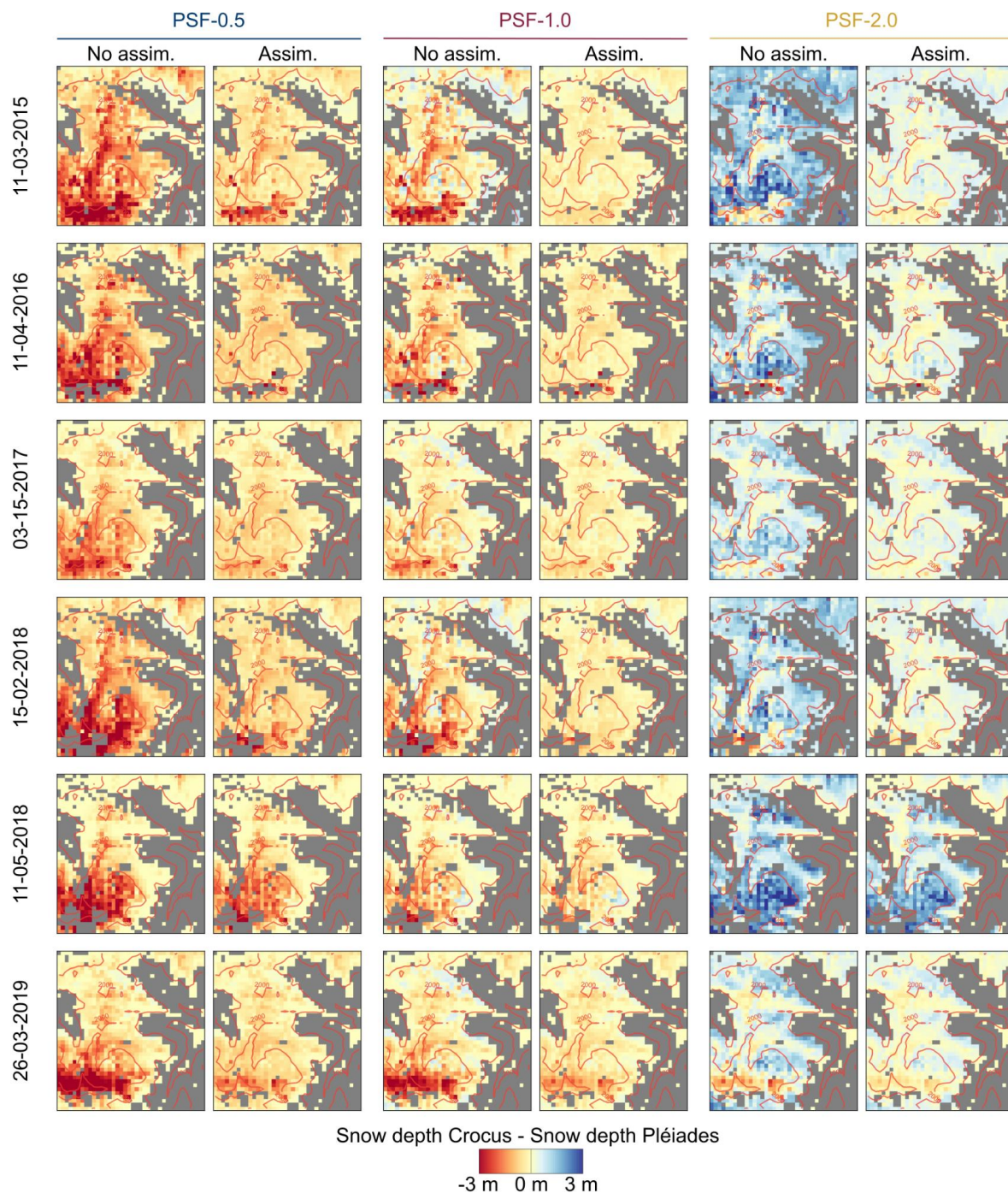
413

414 4.3 Selection of the particles based on their meteorological forcing and their model
415 physical parameterization

416 The HS of ensemble members that are selected by the particle filter may be more appropriate due
417 to their meteorological forcing, their physical version of the Crocus model, or both. Figure 9
418 shows the mean precipitation until the assimilation date of WY 2014-2015 associated with all the
419 particles of the ensemble (gray) and associated with the particles selected by the filter (green).
420 Particles with higher precipitation rates were selected for PSF-0.5 and PSF-1.0 in agreement with
421 the observed increase in SWE due to assimilation for these two experiments. Particles with lower
422 precipitation rates were selected for PSF-2.0, again in agreement with the associated SWE
423 reduction. Distribution of the other meteorological variables was not modified by assimilation.

424 Figure 10 shows the versions of the compaction modeling in Crocus associated with all the
425 particles of the ensemble with and without assimilation. No version of the compaction was
426 excluded by the assimilation, but some were preferentially selected. The compaction version
427 from Anderson (1976) was preferred at the expense of the version from Teufelsbauer (2011) in
428 the PSF-0.5. The opposite preferential selection occurred in PSF-2.0. No clear impact of

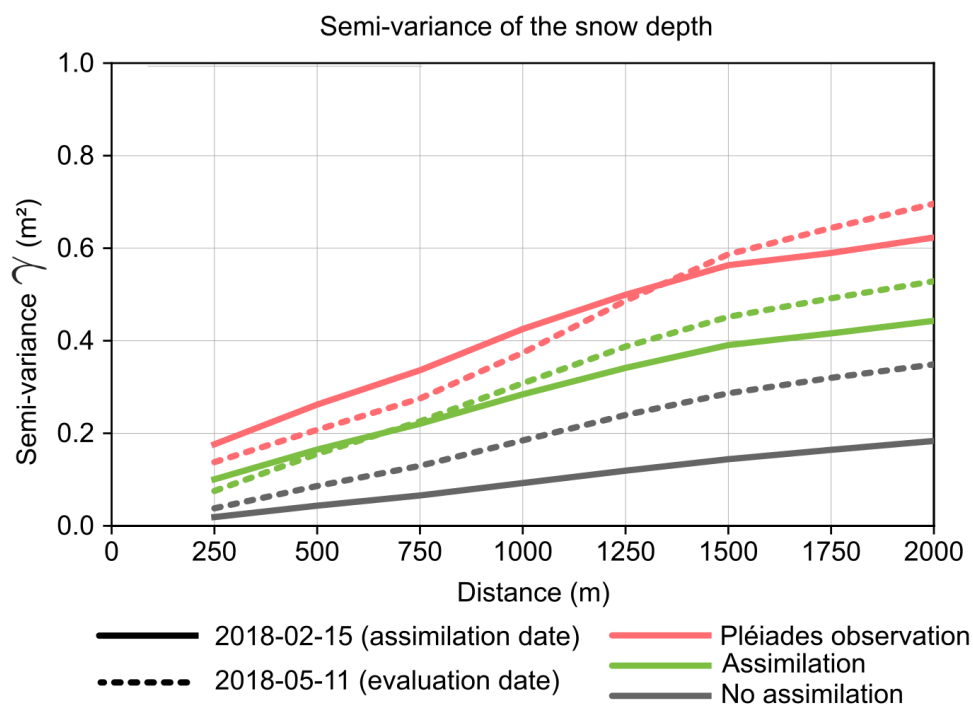
429 assimilation was observed for PSF-1.0 or for other physical laws impacting snowpack density
 430 (i.e., density of fresh snow and snow grain metamorphism).



431
 432 **Figure 4.** Differences of snow depth maps (Crocus minus Pléiades) without assimilation (left
 433 column for a given PSF) and with assimilation (right column for a given PSF). The rows show

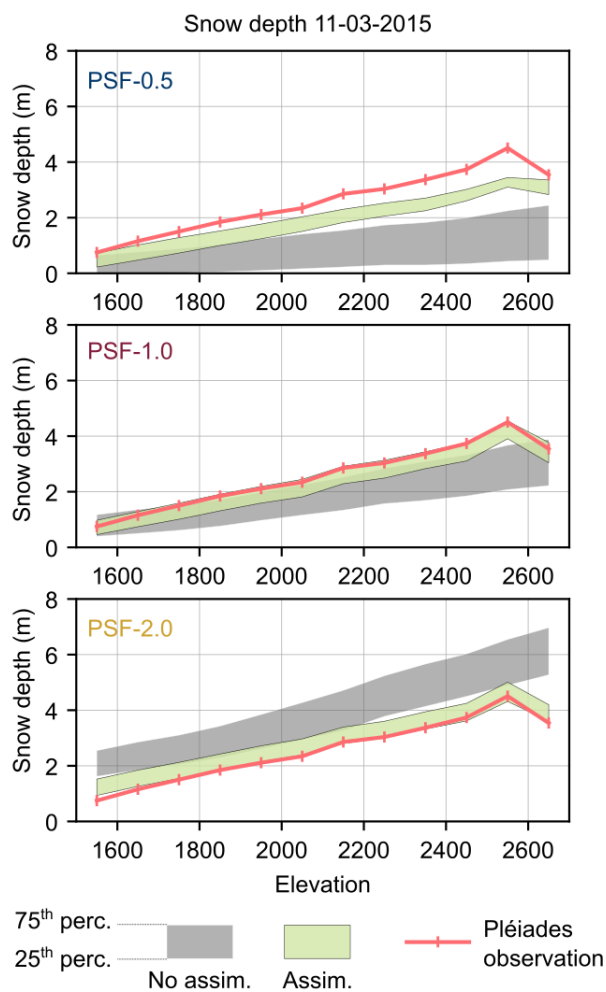
434 the different acquisition dates. The differences are always smaller in the assimilation run, even
 435 on 11 May 2018, 85 days after the assimilation date.

436



437

438 **Figure 5.** Semi-variogram of the snow depth modeled without assimilation (grey), with
 439 assimilation (green) and in the Pléiades snow depth maps. The thick solid lines show the 15
 440 February 2018 semi-variance (assimilation date) and the thick dashed lines show the 11 May
 441 2018 semi-variance (evaluation date). The assimilation increased the spatial variability of the
 442 modeled HS at the assimilation date. This improvement remains 85 days after the assimilation on
 443 11 May 2018.



444

445 **Figure 6.** Envelopes of the snow depth ensemble without assimilation (grey) and with
 446 assimilation (green) as a function of elevation. The envelope shows the first and third quartile of
 447 the ensemble distribution. The rows show the three precipitation scaling experiments, from top to
 448 bottom: PSF-0.5, PSF-1.0, PSF-2.0. The snow depth measured with Pléiades (red) is identical in
 449 all plots.

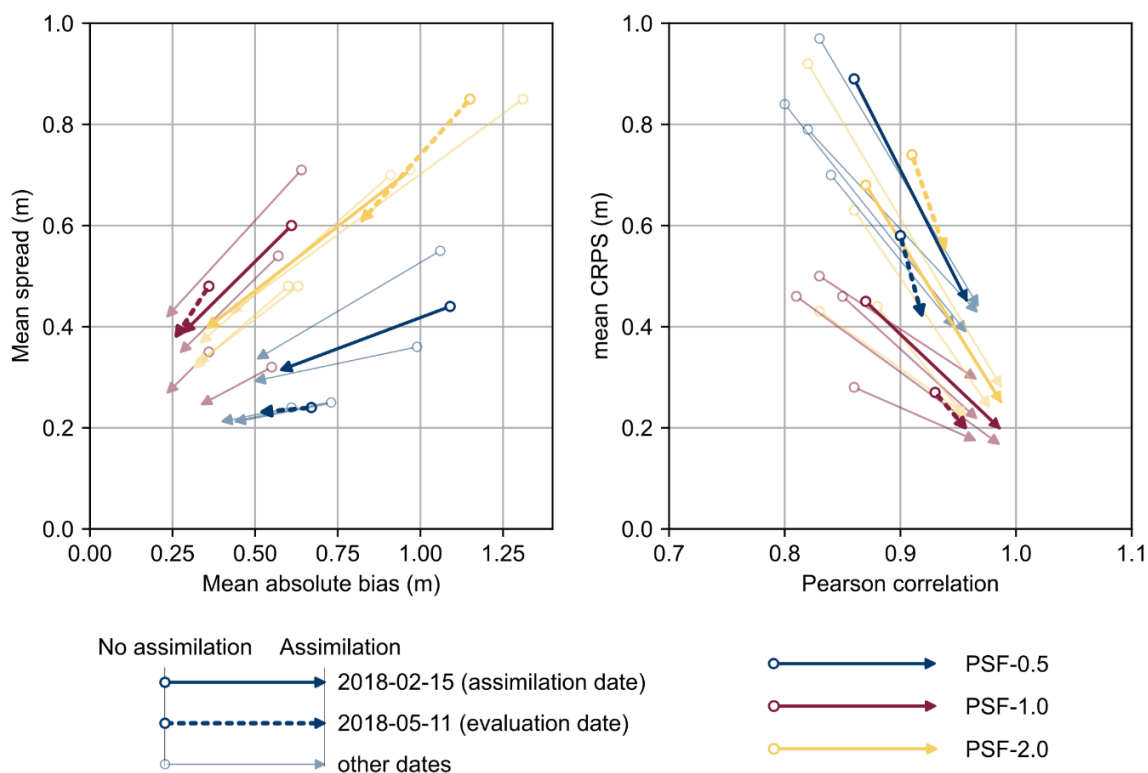
450

451

452

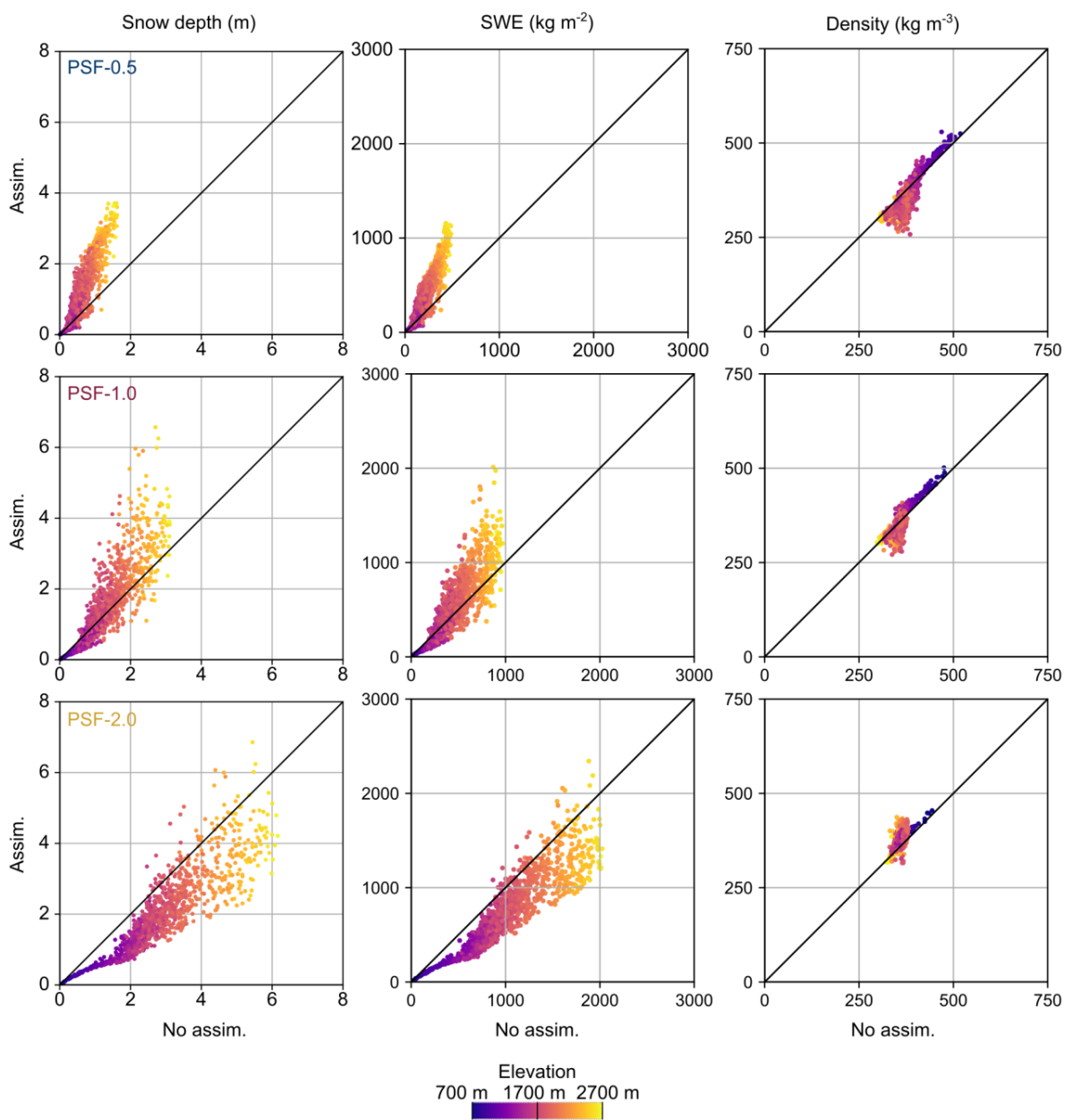
453

454

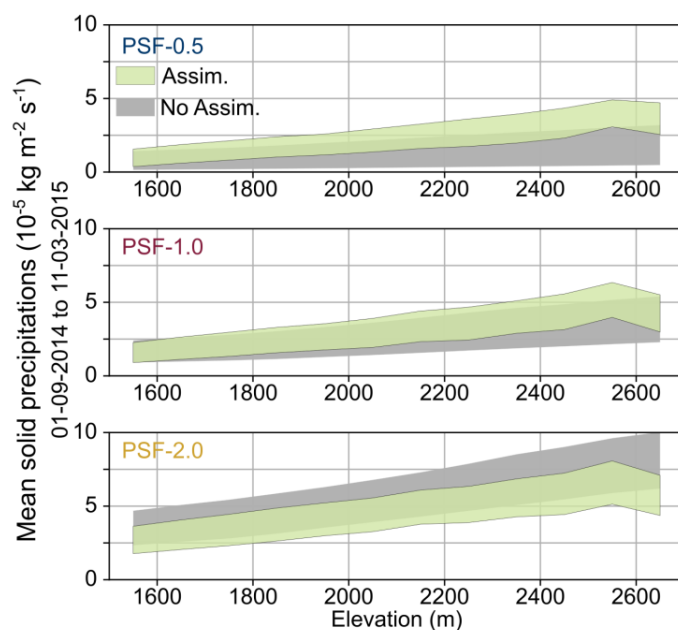


455

456 **Figure 7.** Impact of the assimilation on the modeled snow depth at the assimilation date (solid
 457 line) and on the evaluation date (dashed line) compared to Pléiades snow depth maps. Left plot
 458 shows the ensemble spread and the mean absolute error. Right plot shows the CRPS and the
 459 Pearson correlation. Each arrow shows the statistic for a single date with the metrics without
 460 assimilation at the base of the arrow and the metrics with assimilation at the head of the arrow.
 461 February and May 2018 arrows are in full colors while other dates are slightly transparent. The
 462 arrow color shows the precipitation scaling factor. The assimilation reduced the spread of the
 463 ensemble, the bias between the modeled HS and the observation, the mean CRPS and increased
 464 the correlation between the modeled HS and the observation. This is expected at the assimilation
 465 date but the fact that it subsists on 11 May 2018 shows the long-lasting benefit of the
 466 assimilation.

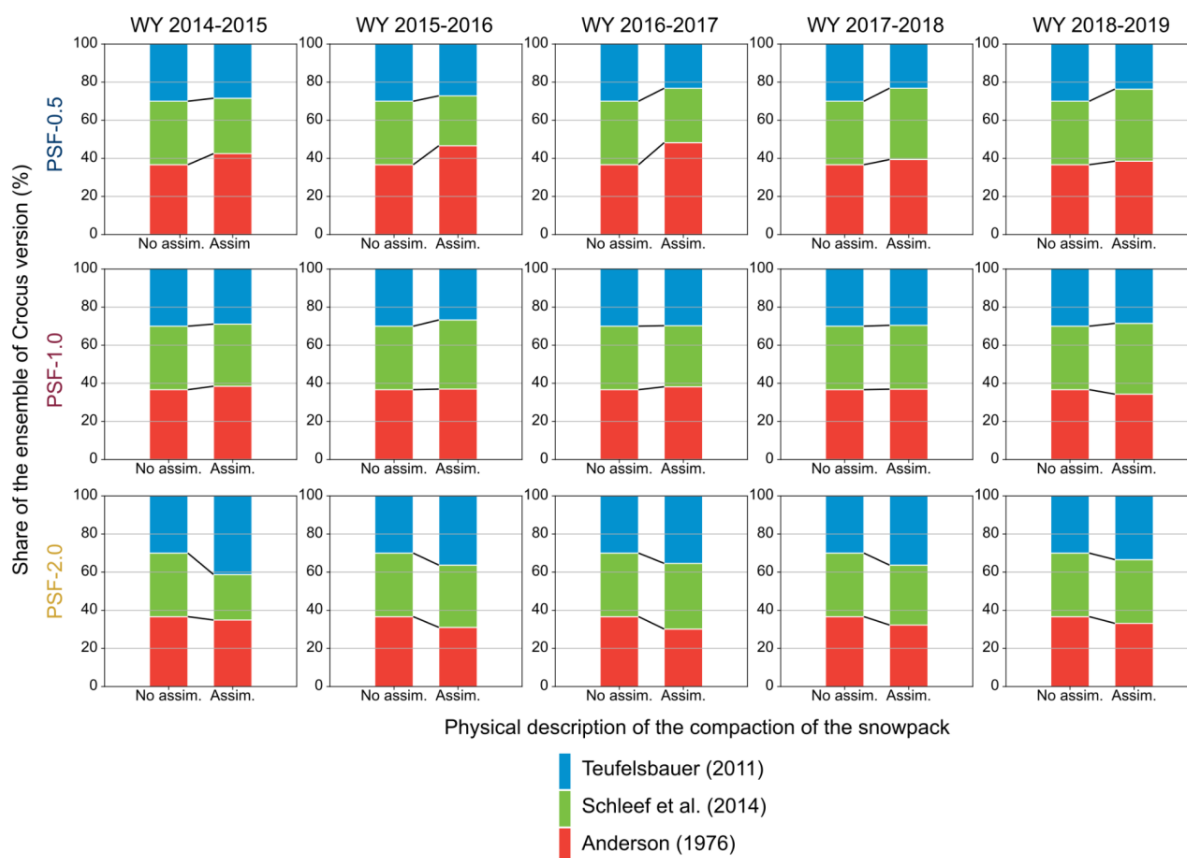


467
 468 **Figure 8.** Impact of the particle filter on snow depth (left), SWE (middle) and density (right) on
 469 11 March 2015 (assimilation date). Each dot represents the mean value of a simulation grid point
 470 with the color showing the elevation of the point. The rows show the different precipitation
 471 scaling experiments, from top to bottom: PSF-0.5, PSF-1.0, PSF-2.0.



473

474 **Figure 9.** Solid precipitation rate per elevation between 1 September 2014 and 11 March 2015
 475 (assimilation date). Green envelope shows the precipitation of the particles selected by the
 476 assimilation (the first and third quartile). Grey envelope shows the precipitation of all the
 477 particles (i.e. no assimilation). The assimilation selected members with mean precipitations
 478 compensating the bias introduced by PSF-0.5 and PSF-2.0.



479

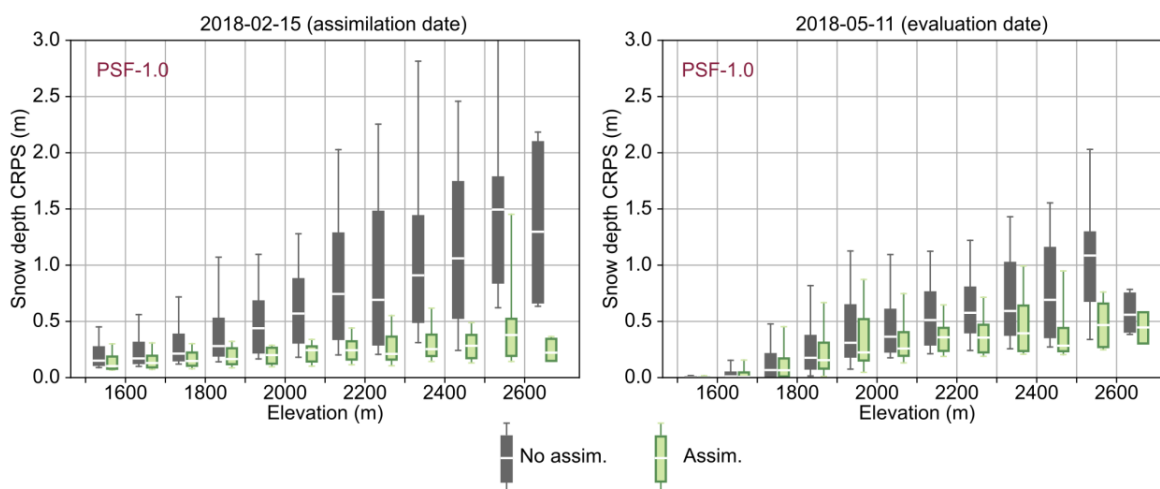
480 **Figure 10.** Distribution of the physical parameterizations of the snowpack compaction of all the
 481 particles (i.e. no assimilation, left bar) or of the particles selected by the assimilation (right bar).
 482 Each column shows the distribution for a WY and each row shows the distribution for the
 483 precipitation scaling experiments, from top to bottom: PSF-0.5, PSF-1.0, PSF-2.0. The
 484 assimilation selected and eliminated preferentially some physical parameterizations of the PSF-
 485 0.5 and PSF-2.0 experiments.

486 4.4. Independent evaluation of the impact of assimilation

487 A Pléiades HS observation is available on 11 May 2018, 85 days after the assimilation date of 15
 488 February 2018, enabling us to assess the impact of the assimilation on the modeled snowpack
 489 with independent data. The mean bias and spread of the ensemble were reduced in the
 490 assimilation run on this date (dashed arrows in Figure 7). The mean CRPS was smaller in May in
 491 the assimilation run than without assimilation for all elevation levels (Figure 11). The spatial
 492 variability introduced by assimilation was also conserved in May (dashed line in Figure 5).

493 HS measured at the Bernadouze AWS was 1.17 m and 0.82 m on the assimilation dates of WY
 494 2014-2015 and WY 2017-2018, respectively (Figure S5). It was null or close to null (i.e., <0.3
 495 m) on all other assimilation dates both in Pléiades and at the AWS. HS at the closest grid point
 496 was improved (i.e., decreased) from ~0.3 m to 0.5 m by assimilation for PSF-2.0. It was slightly
 497 improved by ~0.1 m (i.e., increased) for PSF-0.5 for WY 2014-2015 and WY 2017-2018, which
 498 were WY with the thickest snowpack during the study period. The impact was null or weak for
 499 other assimilation dates of PSF-0.5 and PSF-1.0 due to the lack of snow or good agreement
 500 between the model and Pléiades observation prior to assimilation.

501 After assimilation, the modeled SMOD was delayed by typically 15 days for PSF-0.5 compared
 502 with the modeled SMOD without assimilation. This improved the modeled SMOD by the same
 503 duration, as shown by the map of the difference between modeled and SMOD observed by
 504 Sentinel-2/Landsat 8 (Figure 12). Conversely, the modeled SMOD was advanced and generally
 505 improved by approximately 5 days for PSF-2.0. However, assimilation locally degraded the
 506 modeled SMOD in the southern part of the zone in WY 2017-2018 and WY 2018-2019. The
 507 impact of assimilation on the SMOD was null on average for PSF-1.0. The modeled SCA was
 508 improved by assimilation compared with MODIS SCA (Figure S6). The RMSE of SCA was
 509 reduced by ~20% for PSF-1.0 and PSF-2.0, and ~30% for PSF-0.5 (not shown).



510

511 **Figure 11.** Distribution of the snow depth CRPS against elevation on 15 February 2018
 512 (assimilation date) and 85 days later on 11 May 2018 (evaluation date). The CRPS is calculated
 513 from the modeled snow depth without assimilation (grey), with assimilation (green) and a

517 **Figure 12.** Impact of the assimilation on the modeled SMOD in days. Blue areas show
518 improvement of the modeled SMOD while red areas show worsening of the modeled SMOD by
519 the assimilation. Modeled SMOD in the yellow areas was not modified by the assimilation.
520 SMOD was improved by the assimilation in PSF-0.5 and to a lesser extent in PSF-2.0.

521 **5 Discussion**

522 5.1. Correction of errors in the meteorological forcings

523 The mean precipitation of the particle selected by the particle filter differed from the mean
524 precipitation of all particles (Figure 9). This was observed in PSF-0.5 and PSF-2.0 which
525 emulate bias in precipitation observed in global reanalyses (Beck et al., 2019) and also in PSF-
526 1.0 which provides a reference run to compare HS observations from Pléiades with those from
527 the SAFRAN-Crocus chain. HS was underestimated in PSF-1.0 without assimilation of snow
528 observations, especially at elevations above 2000 m a.s.l. The discrepancy was typically 10% to
529 20%. This bias had the same sign and similar magnitude than those previously reported by
530 comparing SAFRAN-Crocus simulations with HS measurements in this part of the Pyrenees
531 (Quéno et al., 2016). The strong precipitation gradient with elevation is difficult to reproduce for
532 an analysis system without any observation at high elevation, explaining the increasing bias of
533 HS with elevation (Vionnet et al., 2019). As the assimilation improved the modeled HS (Figure
534 4, 7, and 11), SMOD (Figure 12), and SCA (Figure S5) in PSF-0.5 and PSF-2.0, we conclude
535 that errors in precipitation can be reduced by the assimilation of Pléiades HS in case of large
536 bias. In case of smaller bias (e.g. PSF-1.0), we conclude that the assimilation of Pléiades HS map
537 benefits by improving the modeled spatial variability of HS (Figure 5).

538 The assimilation had no clear impact on the other meteorological variables. This likely results
539 from the short correlation time of the applied perturbation, which did not sufficiently
540 differentiate the particles. A short correlation time of the perturbation (i.e., 15 h) results in an
541 ensemble of forcings with a random distribution at each time step but a similar yearly mean.
542 Smyth et al. (2019) found that the perturbation of radiative forcing and of precipitation produced
543 assimilation results similar to those of the perturbation of precipitation only. Increasing the
544 correlation time of the perturbation of the temperature could be relevant in evaluating the impact

545 of a large bias in temperature, as it controls the precipitation phase partition during precipitation
546 events.

547

548

549 5.2 Correction of errors in the physical parameterization

550 Density of the snowpack was also modified by assimilation. Density could be modified as a
551 consequence of SWE modification; more SWE due to more precipitation should lead to more
552 compaction and denser snowpack on average. However, the sign of density modification was not
553 consistent with this hypothesis (e.g. PSF-0.5 in Figure 8). The densification law from Anderson
554 (1976) favored in PSF-0.5 leads to slower densification than the law from Teufelsbauer (2011),
555 depreciated by the assimilation. This indicates that the increase in HS for PSF-0.5 also resulted
556 from a slower densification and the decrease in HS for PSF-2.0, resulted from a faster
557 densification. This is not necessarily a good reason, as the bias of the HS is related to
558 precipitation errors by construction in the PSF-0.5 and PSF-2.0 experiments.

559 The same phenomenon was observed when assimilating synthetic punctual HS in a two-layer
560 model (Smyth et al., 2019). While Smyth et al. (2019) concluded that the modeled density was
561 improved by assimilation thanks to SWE and HS measurements, we lack in situ measurements to
562 perform similar evaluations. Our experiments suggest that assimilation can compensate for
563 meteorological errors by the selection of different physical parameterizations. As a result, an
564 improvement of the simulated SWE can not be systematically guaranteed through HS
565 assimilation. Including different observed variables in the assimilation scheme should help avoid
566 these equifinality issues in the future.

567

568 5.3. Evolution of the snowpack after the assimilation date

569 Satellite-based data (Pléiades, MODIS, Sentinel-2, and Landsat 8) provided independent spatial
570 information to evaluate assimilation performance (Figure 4, 5, 7, 11, and 12). Impact of
571 assimilation on the SMOD was only evident for PSF-0.5 and PSF-2.0 because the modeled

572 SMOD was largely degraded before the assimilation and the HS increment due to assimilation
573 was large. No positive impact of assimilation in PSF-1.0 was visible in the SMOD comparison,
574 probably because the limited HS assimilation increments likely resulted in SMOD changes that
575 were too small to be captured by the daily to biweekly resolution of the Sentinel-2/Landsat 8
576 SMOD products. In addition, several physical processes shaping the snowpack between the
577 assimilation date and SMOD are not taken into account in this version of Crocus (e.g., wind drift,
578 avalanche deposits, multiple reflections from surrounding surfaces, and light-absorbing
579 particles). For instance, the impact of light-absorbing particles was considered through the
580 decrease in visible albedo with snow age, and the parameterization was calibrated at the Col de
581 Porte site in the Alps (Brun et al., 1992). This does not represent the spatial and temporal
582 variability of the light-absorbing particles present in the modeled snowpack. The TARTES
583 module, which explicitly represents the impact of the light-absorbing particles, was not used
584 because it requires many more computational resources and additional forcing data (Tuzet et al.,
585 2017). The explicit modeling of the light-absorbing particles leads to faster melting and a ~6-day
586 advance of the SMOD in this region compared with the Crocus version used here (Réveillet et
587 al., in review). The impact is larger at high elevations and could partially explain the local
588 worsening of the modeled SMOD at high elevations in PSF-1.0 and PSF-2.0. In this area,
589 assimilation increased the HS, which delayed the SMOD, but the SMOD was already
590 overestimated without assimilation.

591

592 5.4. Perspective on the assimilation scheme

593 Ensemble simulations provide an estimate of the uncertainty of the modeled variables of
594 interest (e.g. SWE, density) by the way of the ensemble spread. In theory, assimilation should
595 reduce the spread to the magnitude of observation error but should not underestimate the residual
596 uncertainty by a too selective particle filter leading to ensemble collapse (i.e., selection of a
597 single particle). Here, assimilation reduced the spread of the ensemble of modeled HS in the
598 range to the observation error (Figure 7). This suggests that the spread of the ensemble of HS
599 prior to assimilation, the bias between the ensemble prior to assimilation and observation, and
600 the observation error were consistent. However, assimilation did not modify the ensemble for

601 points at low elevation for PSF-0.5, where all members of the ensemble had no snow. The
602 multiplicative perturbation of precipitation used here cannot produce an ensemble of the HS with
603 a sufficiently large spread where snow falls are low and snowpack is thin. A way to address this
604 issue would be to introduce a spatially variable perturbation of precipitation and to increase the
605 perturbation amplitude in areas of thin snowpacks (i.e., low elevation and strong wind erosion)
606 or to use additive perturbation of the precipitation (Magnusson et al., 2017).

607 5.5. Snow depth mapping methods

608 Higher resolution and more accurate products can be generated from airborne surveys (Brauchli
609 et al., 2017; Hedrick et al., 2018). The higher accuracy reached with airborne lidar or
610 photogrammetry reduces the need to aggregate HS maps and allows higher resolution
611 simulations. In particular, satellite photogrammetry DEM can suffer from errors in the estimation
612 of the satellite attitude which results in erroneous undulations in the HS maps, so called “jitter”
613 (Deschamps-Berger et al., 2020). The magnitude and the spatial distribution of the difference
614 between modeled and observed HS on 26 March 2019 suggest that the corresponding winter
615 DEM is affected by jitter. The jitter is a spatially structured error whose magnitude depends on
616 the image and varies within an image. The largest negative anomaly of modeled HS in the south
617 of the study site on 26 March 2019 is likely due to an undulation of large amplitude. To our
618 knowledge, there is no way to correct for jitter without significant areas of stable terrain which is
619 the case here. Despite this error in the assimilated HS, assimilation improved the modeled
620 SMOD for PSF-0.5 but notably degraded the modeled SMOD in the south for PSF-2.0, where
621 the error due to jitter is believed to be the largest. Despite these errors, the strong asset of satellite
622 photogrammetry is the ability to acquire images in any place of the globe. The typical coverage
623 of a Pleiades image (20 km by 20 km) is too small to cover a whole mountain range like airborne
624 methods could do (Painter et al., 2015). It remains much larger than UAV or terrestrial based
625 methods (Eberhardt et al., 2020).

626

627 5.6. Comparison to existing studies

628 Our results are in line with previous studies which concluded on the improvement of the
629 modeled spatial distribution of the HS through assimilation of a single HS map, with other
630 assimilation method, data source, data frequency and snowpack model (e.g. Revuelto et al.,
631 2016; Brauchli et al, 2017; Hedrick et al., 2018; Margulis et al., 2019; Shaw et al., 2020). The
632 observed improvement 85 days after the assimilation date in WY 2017-2018 is consistent with
633 the persistence of reduced error up to 100 days after the assimilation date in simulations
634 weighted with a particle batch smoother (Margulis et al., 2019). Our study confirms the
635 experimental results of Smyth et al. (2020) who found that HS measurements with uncertainty of
636 ~0.5 m, typical of satellite photogrammetry, are sufficient to significantly improve snowpack
637 simulations in mountainous regions.

638 The assimilation date of a single HS map is often found to be optimal close to peak SWE for
639 SWE estimation during the melt period (Brauchli et al., 2017; Hedrick et al., 2018; Margulis et
640 al., 2019). The assimilation of an HS map acquired 50 days after peak SWE was less beneficial
641 (Margulis et al., 2019). Here, the assimilation date was close to the basin peak SWE for WY
642 2014-2015, WY 2015-2016, and WY 2016-2017 but was ~40 days prior to the peak in WY
643 2017-2018 and ~50 days after the peak in WY 2018-2019. A third of the peak SWE mass
644 accumulated after the assimilation date for WY 2017-2018, and a quarter was lost before the
645 assimilation date for WY 2018-2019. However, the impact of assimilation on the SMOD (Figure
646 12) was similar for all WYs despite variable assimilation dates. This suggests that assimilation
647 can be beneficial even with a single observation more than a month before or after the peak
648 SWE.

649 **6 Conclusion**

650 Assimilation of a single HS map each year measured with satellite photogrammetry improved
651 simulation of the snowpack based on comparison of the modeled HS with an independent HS
652 map, independent satellite-derived maps of the SMOD and SCA. Assimilation corrected
653 erroneous precipitation gradients and partially compensated for processes lacking in the model
654 (e.g., wind redistribution) which improved the spatial distribution of modeled HS. The relatively
655 high standard error of the HS measurements (~0.70 m at a 3 m resolution) compared with other
656 remote sensing methods (e.g., drone or airborne) was reduced by aggregating the HS map at a

657 250 m resolution. Further work may evaluate the impact of assimilating HS maps from satellite
658 photogrammetry at higher resolutions (<250 m) to represent smaller-scale variability. Cross
659 validation dataset (airborne or terrestrial laser scan) would ease the measurement of the impact of
660 assimilation of satellite snow depth maps. The use of satellite photogrammetry is currently
661 limited by the footprint of the images (20 km x 20 km for Pléiades) and jitter errors. Variants of
662 the particle filter, could partly overcome these limitation by propagating information into
663 surrounding areas or erroneous areas by following correlation patterns in the ensemble (Cluzet et
664 al., 2021). Although it may be better constrained in the future by complementary assimilation
665 variables, the point-by-point particle filter used in this study already proved to be efficient and
666 should be easily transferable to other study sites. These results and the possibility of using the
667 particle filter several times per season when a new observation is available (sequential particle
668 filter) combined with meteorological forecasts suggest that this scheme is well suited to
669 operational applications (avalanche or flood forecasting). Assimilation had the largest impact on
670 simulations with degraded meteorological forcings, which are representative of global reanalyses
671 products. Combining satellite-derived snow depth observations, snowpack modeling and
672 globally available forcings may especially allow an improved estimation of the snow cover
673 properties in unmonitored mountain catchments (e.g., the Himalayas, Andes, and polar mountain
674 ranges).

675

676 **Acknowledgments**

677 This work has been supported by the CNES Tosca (APR MIOSOTIS) and the Programme
678 National de Télédétection Spatiale (PNTS; grant no. PNTS-2018-4). This work was cofunded by
679 the LabEx DRIIHM, French program "Investissements d'Avenir" (ANR-11-LABX-0010) which
680 is managed by the ANR (Observatoire Homme Milieu Pyrénées Haut Vicdessos). M.D. was
681 partially funded by ANR JCJC EBONI. Marie Dumont has received funding from the European
682 Research Council (ERC) under the European Union's Horizon 2020 research and innovation
683 programme (grant agreement no. 949516, IVORI). CNRM/CEN is part of Labex OSUG@2020.
684 Bernadouze weather station is supported by the Observatoire Spatial Régional (CNRS-INSU)
685 and the Observatoire Homme Milieu (CNRS-INEE). Thanks to R. Marti and B. Pirletta for the
686 pictures in figure 3. We thank Laura Sourp for useful discussions on the HS maps accuracy.

687

688 **Data**

689 The Pléiades images were obtained through DINAMIS (Dispositif Institutionnel National
690 d'Approvisionnement Mutualisé en Imagerie Spatiale) which allows cost-less Pléiades
691 acquisition for French research institutions. Otherwise Pléiades images can be ordered (i) at
692 reduced cost for European researchers also via DINAMIS or (ii) via Airbus Defense and Space
693 for non-EU researchers. The Pleiades snow depth maps used in this study are available at
694 <https://doi.org/10.5281/zenodo.4707494>. Meteorological forcings are available at
695 <https://doi.org/10.25326/37> (version 2019 was used in this study).

696 **Code**

697

698 **References**

699 Anderson, E. (1976). *A point energy and mass balance model of a snow cover*, NOAA Technical
700 *Report NWS 19*.

701 Andreadis, K. M., & Lettenmaier, D. P. (2006). Assimilating remotely sensed snow observations
702 into a macroscale hydrology model. *Advances in Water Resources*, 29, 872–886.
703 <https://doi.org/10.1016/j.advwatres.2005.08.004>

704 Baba, M. W., Gascoin, S., Jarlan, L., Simonneaux, V., & Hanich, L. (2018). Variations of the
705 snow water equivalent in the ourika catchment (Morocco) over 2000-2018 using
706 downscaled MERRA-2 data. *Water (Switzerland)*, 10(9).
707 <https://doi.org/10.3390/w10091120>

708 Bard, A., Renard, B., Lang, M., Giuntoli, I., Korck, J., Volken, D., Koboltschnig, G., & Janz, M.
709 (2015). Trends in the hydrologic regime of Alpine rivers. *Journal of Hydrology*, 529, 1823–
710 1837. <https://doi.org/10.1016/j.jhydrol.2015.07.052>

711 Barry, R. G. (2008). *Mountain weather and climate*. Cambridge University Press.

712 Beck, H. E., Pan, M., Roy, T., Weedon, G. P., Pappenberger, F., Dijk, A. I. J. M. Van, Huffman,
713 G. J., Adler, R. F., & Wood, E. F. (2019). Daily evaluation of 26 precipitation datasets
714 using Stage-IV gauge-radar data for the CONUS. *Hydrology and Earth System Sciences*,
715 23, 207–224. <https://doi.org/10.5194/hess-23-207-2019>

716

717 Blöschl, G. (1999). Scaling issues in snow hydrology. *Hydrological Processes*, 13(January),
718 2149–2175. [https://doi.org/10.1002/\(SICI\)1099-1085\(199910\)13:14/15<2149::AID-](https://doi.org/10.1002/(SICI)1099-1085(199910)13:14/15<2149::AID-)

719 HYP847>3.0.CO;2-8

720 Brauchli, T., Trujillo, E., Huwald, H., & Lehning, M. (2017). Influence of Slope-Scale Snowmelt
721 on Catchment Response Simulated With the *Alpine3D* Model. *Water Resources Research*,
722 1–17. <https://doi.org/10.1002/2017WR021278>

723 Brun, E., David, P., Sudul, M., & Brunot, G. (1992). A numerical model to simulate snow-cover
724 stratigraphy for operational avalanche forecasting. *Journal of Glaciology*, 38(128), 13–22.
725 <https://doi.org/10.1017/S0022143000009552>

726 Charrois, L., Cosme, E., Dumont, M., Lafaysse, M., Morin, S., & Libois, Q. (2016). On the
727 assimilation of optical reflectances and snow depth observations into a detailed snowpack
728 model. *The Cryosphere*, 10, 1021–1038. <https://doi.org/10.5194/tc-10-1021-2016>

729 Cholier, P. (2018). Perspectives in Plant Ecology , Evolution and Systematics Winter soil
730 temperature dependence of alpine plant distribution : Implications for anticipating
731 vegetation changes under a warming climate. *Perspectives in Plant Ecology, Evolution and*
732 *Systematics*, 30(November 2017), 6–15. <https://doi.org/10.1016/j.ppees.2017.11.002>

733 Cluzet, B., Lafaysse, M., Cosme, E., Albergel, C., & Meunier, L. (2021). CrocO _ v1 . 0 : a
734 particle filter to assimilate snowpack observations in a spatialised framework. *Geoscientific*
735 *Model Development*, 14, 1595–1614. <https://doi.org/10.5194/gmd-14-1595-2021>

736 Dedieu, J., Carlson, B. Z., Bigot, S., & Sirguey, P. (2016). On the Importance of High-
737 Resolution Time Series of Optical Imagery for Quantifying the Effects of Snow Cover
738 Duration on Alpine Plant Habitat. *Remote Sensing*, 8. <https://doi.org/10.3390/rs8060481>

739 Deems, J. S., Fassnacht, S. R., & Elder, K. J. (2006). Fractal Distribution of Snow Depth from
740 Lidar Data. *Journal of Hydrometeorology*, 7(2), 285–297.
741 <https://doi.org/10.1175/JHM487.1>

742 Deems, J. S., Painter, T. H., & Finnegan, D. C. (2013). Lidar measurement of snow depth : a
743 review. 59(215), 467–479. <https://doi.org/10.3189/2013JoG12J154>

744 Deschamps-Berger, C., Gascoin, S., Berthier, E., Deems, J., & Gutmann, E. (2020). Snow depth
745 mapping from stereo satellite imagery in mountainous terrain : evaluation using airborne
746 laser-scanning data. *The Cryosphere*, 2925–2940. <https://doi.org/10.5194/tc-14-2925-2020>

747 Dozier, J., Bair, E. H., & Davis, R. E. (2016). Estimating the spatial distribution of snow water
748 equivalent in the world’s mountains. *Wiley Interdisciplinary Reviews: Water*, 3(3), 461–
749 474. <https://doi.org/10.1002/wat2.1140>

750 Dumont, M., Durand, Y., Arnaud, Y., & Six, D. (2012). Variational assimilation of albedo in a
751 snowpack model and reconstruction of the spatial mass-balance distribution of an alpine
752 glacier. *Journal of Glaciology*, 58(207), 151–164. <https://doi.org/10.3189/2012JoG11J163>

753 Eberhard, L. A., Sirguey, P., Miller, A., Marty, M., Schindler, K., & Stoffel, A. (2021).
754 Intercomparison of photogrammetric platforms for spatially continuous snow depth

- 755 mapping. *The Cryosphere*, 15, 69–94. <https://doi.org/10.5194/tc-15-69-2021>
- 756 Essery, R., Morin, S., Lejeune, Y., & Ménard, C. B. (2013). A comparison of 1701 snow models
757 using observations from an alpine site. *Advances in Water Resources*, 55, 131–148.
758 <https://doi.org/10.1016/j.advwatres.2012.07.013>
- 759 Freudiger, D., Kohn, I., Seibert, J., Stahl, K., & Weiler, M. (2017). Snow redistribution for the
760 hydrological modeling of alpine catchments. *Wiley Interdisciplinary Reviews: Water*, 4(5),
761 e1232. <https://doi.org/10.1002/wat2.1232>
- 762 Gascoïn, S., Hagolle, O., Huc, M., Jarlan, L., Dejoux, J. F., Szczypta, C., Marti, R., & Sánchez,
763 R. (2015). A snow cover climatology for the Pyrenees from MODIS snow products.
764 *Hydrology and Earth System Sciences*, 19(5), 2337–2351. [https://doi.org/10.5194/hess-19-](https://doi.org/10.5194/hess-19-2337-2015)
765 [2337-2015](https://doi.org/10.5194/hess-19-2337-2015)
- 766 Gascoïn, S., Grizonnet, M., Bouchet, M., Salgues, G. & Hagolle, O. (2019). Theia Snow
767 collection: high-resolution operational snow cover maps from Sentinel-2 and Landsat-8
768 data, *Earth System Science Data*. 11(2), 493–514. doi: 10.5194/essd-11-493-2019.
- 769 Giroto, M., Musselman, K. N., & Essery, R. L. H. (2020). Data Assimilation Improves
770 Estimates of Climate-Sensitive Seasonal Snow. *Current Climate Change Reports*, 81–94.
771 <https://doi.org/10.1007/s40641-020-00159-7>
- 772 Gleyzes, A., Perret L., Philippe Kubik, P. (2012). Pleiades system architecture and main
773 performances. *Int. Archives of Photogrammetry, Remote Sensing and Spatial Information*
774 *Sciences*, Vol. 39(1), pp. 537-542, Melbourne, Australia.
- 775 Hedrick, A., Marks, D., Havens, S., Robertson, M., Johnson, M., Sandusky, M., Marshall, H.-P.,
776 Kormos, P., Bormann, K., & Painter, T. (2018). Direct Insertion of NASA Airborne Snow
777 Observatory-Derived Snow Depth Time Series Into the iSnobal Energy Balance Snow
778 Model. *Water Resources Research*, 54, 8045–8063. <https://doi.org/10.1029/2018WR023190>
- 779 Hersbach, H. (2000). Decomposition of the Continuous Ranked Probability Score for Ensemble
780 Prediction Systems. *Weather and Forecasting*, 15, 559–570. [https://doi.org/10.1175/1520-](https://doi.org/10.1175/1520-0434(2000)015<0559:DOTCRP>2.0.CO;2)
781 [0434\(2000\)015<0559:DOTCRP>2.0.CO;2](https://doi.org/10.1175/1520-0434(2000)015<0559:DOTCRP>2.0.CO;2)
- 782 Kitagawa, G. (1996). Monte Carlo filter and smoother for non-Gaussian nonlinear state space
783 models, *J. Comput. Graph. Stat.*, 5, 1–25.
- 784 Lafaysse, M., Cluzet, B., Dumont, M., Lejeune, Y., Vionnet, V., & Morin, S. (2017). A
785 multiphysical ensemble system of numerical snow modelling. *Cryosphere*, 11(3), 1173–
786 1198. <https://doi.org/10.5194/tc-11-1173-2017>
- 787 Largeron, C., Dumont, M., Morin, S., Boone, A., Lafaysse, M., Metref, S., Cosme, E., Jonas, T.,
788 Winstral, A., Margulis, S. A., & Raleigh, M. (2020). Toward Snow Cover Estimation in
789 Mountainous Areas Using Modern Data Assimilation Methods : A Review. *Frontiers in*
790 *Earth Science*, 8(September). <https://doi.org/10.3389/feart.2020.00325>

- 791 Luce, C., Staab, B., Kramer, Ma., Wenger, S., Isaak, D., & McConnell, C. (2014). variability in
 792 the Pacific Northwest. *Water Resources Research*, 50, 1–16.
 793 <https://doi.org/10.1002/2013WR014329>.Received
- 794 Magnusson, J., Winstral, A., Stordal, A., Essery, R., & Jonas, T. (2017). Improving physically
 795 based snow simulations by assimilating snow depths using the particle filter. *Water*
 796 *Resources Research*, 53, 1125–1143. <https://doi.org/10.1002/2016WR019092>.Received
- 797 Margulis, S. A., Fang, Y., Li, D., Lettenmaier, D. P., & Andreadis, K. (2019). The utility of
 798 infrequent snow depth images for deriving continuous space-time estimates of seasonal
 799 snow water equivalent. *Geophysical Research Letters*, 2015, 2019GL082507.
 800 <https://doi.org/10.1029/2019GL082507>
- 801 Margulis, S. a., Giroto, M., Cortés, G., & Durand, M. (2015). A Particle Batch Smoother
 802 Approach to Snow Water Equivalent Estimation. *Journal of Hydrometeorology*, 16(May
 803 2015), 150504130725006. <https://doi.org/10.1175/JHM-D-14-0177.1>
- 804 Marti, R., Gascoin, S., Berthier, E., De Pinel, M., Houet, T., & Laffly, D. (2016). Mapping snow
 805 depth in open alpine terrain from stereo satellite imagery. *Cryosphere*, 10(4), 1361–1380.
 806 <https://doi.org/10.5194/tc-10-1361-2016>
- 807 Menard, C. B., Essery, R., Krinner, G., Arduini, G., Bartlett, P., Boone, A., Brutel-Vuilmet, C.,
 808 Burke, E., Cuntz, M., Dai, Y., Decharme, B., Dutra, E., Fang, X., Fierz, C., Gusev, Y.,
 809 Hagemann, S., Haverd, V., Kim, H., Lafaysse, M., Marke, T., Nasonova, O., Nitta, T.,
 810 Niwano, M., Pomeroy, J., Schädler, G., Semenov, V. A., Smirnova, T., Strasser, U.,
 811 Swenson, S., Turkov, D., Wever, N. and Yuan, H. (2021). Scientific and Human Errors in a
 812 Snow Model Intercomparison, *Bulletin of the American Meteorological Society*, 102(1),
 813 E61–E79. doi: 10.1175/bams-d-19-0329.1.
- 814 Quéno, L., Vionnet, V., Dombrowski-etchevers, I., Lafaysse, M., Dumont, M., Cnrs, F., Umr, C.,
 815 & Martin, S. (2016). Snowpack modelling in the Pyrenees driven by kilometric- resolution
 816 meteorological forecasts. *The Cryosphere*, 1571–1589. [https://doi.org/10.5194/tc-10-1571-](https://doi.org/10.5194/tc-10-1571-2016)
 817 2016
- 818 Raleigh, M. S., Lundquist, J. D., & Clark, M. P. (2015). Exploring the impact of forcing error
 819 characteristics on physically based snow simulations within a global sensitivity analysis
 820 framework. *Hydrology and Earth System Sciences*, 19(7), 3153–3179.
 821 <https://doi.org/10.5194/hess-19-3153-2015>
- 822 Rasmussen, R., Baker, B., Kochendorfer, J., Meyers, T., Landolt, S., Fischer, A., Black, J.,
 823 Thériault, J., Kucera, P., Gochis, D., Smith, C., Rodica, N., Hall, M., Ikeda, K., & Gutmann,
 824 E. (2012). How well are we measuring snow? *American Meteor*, June, 811–830.
 825 <https://doi.org/10.1175/BAMS-D-11-00052.1>
- 826 Revuelto, J., Jonas, T., & López-Moreno, J. I. (2016). Backward snow depth reconstruction at
 827 high spatial resolution based on time-lapse photography. *Hydrological Processes*, 30(17),
 828 2976–2990. <https://doi.org/10.1002/hyp.10823>

- 829 Revuelto, J., Lecourt, G., Lafaysse, M., Zin, I., Charrois, L., Vionnet, V., Dumont, M., Rabatel,
830 A., Six, D., Condom, T., Morin, S., Viani, A., & Sirguey, P. (2018). Multi-Criteria
831 Evaluation of Snowpack Simulations in Complex Alpine Terrain Using Satellite and In Situ
832 Observations. *Remote Sensing*, *10*(8), 1171. <https://doi.org/10.3390/rs10081171>
- 833 Rodell, M., & Houser, P. (2004). Updating a Land Surface Model with MODIS-Derived Snow
834 Cover. *Journal of Hydrometeorology*, *5*, 1064–1075. <https://doi.org/10.1175/JHM-395.1>
- 835 Salomonson, V. V., & Appel, I. (2004). Estimating fractional snow cover from MODIS using the
836 normalized difference snow index. *Remote Sensing of Environment*, *89*, 351–360.
837 <https://doi.org/10.1016/j.rse.2003.10.016>
- 838 Shaw, T., Caro, A., Mendoza, P., Ayala, Á., Gascoïn, S., & Mcphee, J. (2020). The Utility of
839 Optical Satellite Winter Snow Depths for Initializing a Glacio-Hydrological Model of a
840 High-Elevation , Andean Catchment. *Water Resources Research*.
841 <https://doi.org/10.1029/2020WR027188>
- 842 Smyth, E. J., Raleigh, M. S., & Small, E. E. (2019). Particle Filter Data Assimilation of Monthly
843 Snow Depth Observations Improves Estimation of Snow Density and SWE Water
844 Resources Research. *Water Resources Research*, *4*, 1296–1311.
845 <https://doi.org/10.1029/2018WR023400>
- 846
- 847 Smyth, E. J., Raleigh, M. S., & Small, E. E. (2020). Improving SWE estimation with data
848 assimilation: The influence of snow depth observation timing and uncertainty. *Water*
849 *Resources Research*, *56*. <https://doi.org/10.1029/2019WR026853>
- 850 Szczypta, C., Gascoïn, S., Houet, T., Hagolle, O., Dejoux, J. F., Vigneau, C., & Fanise, P.
851 (2015). Impact of climate and land cover changes on snow cover in a small Pyrenean
852 catchment. *Journal of Hydrology*, *521*, 84–99. <https://doi.org/10.1016/j.jhydrol.2014.11.060>
- 853 Teufelsbauer, H. (2011). A two-dimensional snow creep model for alpine terrain. *Natural*
854 *Hazards*, 481–497. <https://doi.org/10.1007/s11069-010-9515-8>
- 855 Thirel, G., Salamon, P., Burek, P., & Kalas, M. (2011). Assimilation of MODIS snow cover area
856 data in a distributed hydrological model. *Hydrology and Earth System Sciences*, *8*, 1329–
857 1364. <https://doi.org/10.5194/hessd-8-1329-2011>
- 858 Tuzet, F., Dumont, M., Lafaysse, M., Picard, G., Arnaud, L., Voisin, D., Lejeune, Y., Charrois,
859 L., Nabat, P., & Morin, S. (2017). A multilayer physically based snowpack model
860 simulating direct and indirect radiative impacts of light-absorbing impurities in snow. *The*
861 *Cryosphere*, *11*, 2633–2653. <https://doi.org/10.5194/tc-11-2633-2017>
- 862 Vacquie, L. A., Houet, T., Sheeren, D., Munnik, N. De, Roussel, V., & Waddle, J. (2016).
863 Adapting grazing practices to limit the reforestation of mountainous summer pastures : A
864 process-based approach. *Environmental Modelling and Software*, *84*, 395–411.
865 <https://doi.org/10.1016/j.envsoft.2016.05.006>

- 866 Vernay, M., Lafaysse, M., Hagenmuller, P., Nheili, R., Verfaillie, D., & Morin, S. (2019).
867 The S2M meteorological and snow cover reanalysis in the French mountainous areas (1958 -
868 present) [Data set]. AERIS. <https://doi.org/10.25326/37#2019>
- 869 [Vernay, M., Lafaysse, M., Monteiro, D., Hagenmuller, P., Nheili, R., Samacoïts, R., Verfaillie,
870 D., and Morin, S.: The S2M meteorological and snow cover reanalysis over the French
871 mountainous areas, description and evaluation \(1958–2020\), *Earth Syst. Sci. Data Discuss.*
872 \[preprint\], <https://doi.org/10.5194/essd-2021-249>, in review, 2021.](#)
- 873 Viallon-galinier, L., Hagenmuller, P., & Lafaysse, M. (2020). Forcing and evaluating detailed
874 snow cover models with stratigraphy observations. *Cold Regions Science and Technology*,
875 180. <https://doi.org/10.1016/j.coldregions.2020.103163>
- 876 Vincent, L., Lejeune, Y., Lafaysse, M., Boone, A., Le Gac, E., Coulaud, C., Freche, G., Sicart,
877 J.E. (2018). Interception of snowfall by the trees is the main challenge for snowpack
878 simulations under forests. *In Proceedings of ISSW*, 705-710
879 http://arc.lib.montana.edu/snow-science/objects/ISSW2018_O08.4.pdf
- 880 Vögeli, C., Lehning, M., Wever, N., & Bavay, M. (2016). Scaling Precipitation Input to Spatially
881 Distributed Hydrological Models by Measured Snow Distribution. *Frontiers in Earth*
882 *Science*, 4(December), 1–15. <https://doi.org/10.3389/feart.2016.00108>
- 883
- 884