Report on CESBIO's contribution to the ACLIMO project

Théo Rétif, Laura Sourp, Camille Rogeaux, Simon Gascoin

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France – Italia ALCOTRA

Report on CESBIO's contribution to the ACLIMO project

High-resolution snow water equivalent modeling in French-Italian alpine parks

Authors : Théo Rétif[1], Laura Sourp[1,2], Camille, Rogeaux[3], Simon Gascoin[1]

[1] Univ Toulouse, CNES, CNRS, INRAE, IRD, CESBIO, Toulouse, France

[2] Magellium, Toulouse, France

[3] Parc national de la Vanoise, Chambéry, France

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I. Introduction

In the Alps, the snowpack is a natural seasonal water reservoir upon which fauna, flora, and humans depend for a multitude of uses. Within the framework of the ACLIMO project, funded by the European Interreg ALCOTRA program, Cesbio has implemented a tool for estimating the snow water equivalent (SWE) across the territory of seven natural parks[1] in France and Italy.

- Mercantour National Park
- Vanoise National Park
- Écrins National Park
- Gran Paradiso National Park
- Cozie Alps Protected Area
- Maritime Alps Protected Area
- Alpi Liguri Natural Park

This tool stems from research conducted at Cesbio (Sourp et al., 2025, 2026). It can simulate the snow water equivalent at high resolution (100 m), in near real-time (5-10 days latency) without in situ data. For this work, it is adapted and re-evaluated within the territory of the ACLIMO project's parks over the period 2015-2025. The computed SWE is further aggregated by catchment of interest defined by ACLIMO partners. A visualization platform is also developed to present the results at a monthly time step as a demonstrator for a service that could be operational in the future. This report presents the model setup, the evaluation results and discusses the limitations of the approach.

[1] Gesso e Stura River Park, although a partner of the ACLIMO project, was excluded due to the absence of a significant seasonal snow cover.

II. Data

This work combines several datasets to (i) run the snowpack model and (ii) evaluate its performance. The modeling framework relies on topographic information, land cover data, and atmospheric forcing to drive the snowpack simulations. In addition, satellite observations are integrated through a data assimilation procedure to constrain the simulated snow distribution. Sentinel-2 snow cover products are assimilated within the modeling framework, while independent datasets including MODIS snow cover observations and in-situ measurements are used for model evaluation.

1. Sentinel-2 Snow Cover Observations

Within the ACLIMO framework, Sentinel-2 snow cover observations are assimilated into a snowpack model to correct potential biases in the meteorological forcing and therefore improve the representation of snow cover dynamics. We use the Theia Snow collection, which provides operational snow cover area maps derived from Sentinel-2 (Gascoin et al., 2019). This dataset provides snow cover information at a spatial resolution of 20 m, with pixels classified into categories such as snow, no snow, cloud, or no data. An estimation of the snow cover fraction is provided for every snow pixel based on a linear scaling of the Normalized Difference Snow Index (Salomonson and Appel, 2004). Owing to the spatial detail and 5 day revisit of Sentinel-2, these products are particularly well suited for monitoring snow distribution in complex alpine environments but are only available since 2015.

2. MODIS Snow Cover Area

Park-scale snow cover simulations are evaluated using the daily snow cover product MOD10A1 derived from MODIS satellite observations. This dataset provides the Normalized Difference Snow Index (NDSI) of snow pixels at a spatial resolution of approximately 500 m since 2000.

3. In-Situ Measurements

Ground-based observations are used to independently evaluate the snow simulations. These measurements include snow depth, snow water equivalent, air temperature, and precipitation collected from several monitoring networks distributed across the study area.

French snow depth observations are obtained from the BDCLIM database (METEO France), which provides historical measurements from meteorological stations located above 450 m elevation across France, covering the 1950–2024 period. Additional snow depth observations in the Italian Alps are provided by regional monitoring networks operated by ARPA Piemonte and ARPA Valle d'Aosta. In total, snow depth data were collected from 20 stations distributed across France (5) and Italy (15) (Table 1). These datasets provide long-term information on snowpack variability and constitute an important reference for evaluating simulated snow depth.

Snow water equivalent observations provided by EDF (Électricité de France) are derived from manual snow surveys conducted at snow stakes, as well as from cosmic ray snow gauges (NRC). These NRC sensors provide direct and continuous estimates of the water stored within the snowpack and are particularly valuable for validating simulated SWE fields. Overall, data from 16 snow stakes and 5 cosmic ray snow gauges are used in this study (Table 2).

Meteorological observations, including air temperature and precipitation, are also provided by EDF monitoring stations. These measurements describe local atmospheric conditions and allow comparisons with the downscaled meteorological forcing used to drive the snow simulations. The dataset includes observations from 10 precipitation stations and 7 temperature stations.

Together, these in-situ datasets provide point-scale observations of snowpack and meteorological conditions at daily, monthly, or irregular temporal resolutions over the study period and are used to assess the performance of the simulations. While satellite observations offer spatially distributed information on snow cover, ground-based measurements enable detailed comparisons between observed and simulated variables at specific locations.

Station	Park	Longitude	Latitude	Elevation (m)
Le Selle	Alpi Cozie	6.91722	45.05444	1984
Melosa	Alpi Liguri	7.68429	43.99091	1554
Valdieri	Alpi Marittime	7.26806	44.20472	1397
Diga Del Chiotas	Alpi Marittime	7.33417	44.16111	2009
Entracquechiotas	Alpi Marittime	7.33389	44.16806	1980
Entracquelago Piastra	Alpi Marittime	7.38833	44.22694	964
Entracque Casermette	Alpi Marittime	7.38389	44.25056	875
Palanfre	Alpi Marittime	7.48861	44.19333	1648
Valle Pesio	Alpi Marittime	7.66000	44.23333	941
Locana Telessio	Gran Paradiso	7.37278	45.48361	1926
Locana Val Soera	Gran Paradiso	7.39556	45.48667	2411
Locana Eugio	Gran Paradiso	7.44250	45.45889	1898
Cogne Grand Crot	Gran Paradiso	7.36744	45.58800	2275
Valsavarenche Orvieille	Gran Paradiso	7.19196	45.57990	2169
Valsavarenche Pont	Gran Paradiso	7.20093	45.52680	1956
Rougnous Prapic EDFNIVO	Écrins	6.42250	44.66967	2486
Cezanne EDFNIVO	Écrins	6.41517	44.91733	1878
Les Écrins NIVOSE	Écrins	6.34617	44.93683	2932
Entraunes Estenc	Mercantour	6.75300	44.25583	2213
Sanguiniere EDFNIVO	Mercantour	6.77433	44.25250	2062
Boreon	Mercantour	7.28333	44.11667	1615
Sous les Barmes EDFNIVO	Vanoise	7.07533	45.45400	2329

Table 1 : Snow depth observation stations used for model evaluation. Coordinates are given in WGS84 and elevations are expressed in meters above sea level.

Station	Park	Longitude	Latitude	Elevation (m)
Barre de la Cabane	Écrins	6.41079	44.66020	2315
Cezanne	Écrins	6.41390	44.91739	1870
Chapelle la Saulce	Écrins	6.38845	44.67220	1790
Crouzat	Écrins	6.18171	44.86606	2200
Glacier Noir	Écrins	6.38788	44.91721	2360
Rougnous Prapic	Écrins	6.42433	44.66807	2480
Gorgias	Mercantour	6.78433	44.24273	2280
Le Lac d'Allos	Mercantour	6.70998	44.24020	2260
Petite Cayolle	Mercantour	6.73932	44.25558	2440
Plateau du Laus	Mercantour	6.70059	44.24261	2120
Sanguinières	Mercantour	6.77435	44.25291	2050
Chalet de la Grassaz	Vanoise	6.85260	45.47518	2330
Charvet	Vanoise	6.94165	45.41179	2420
Grand Fond	Vanoise	7.14046	45.39945	2600
La Plagne 4	Vanoise	6.84913	45.47898	2310
La Sétéria Deux	Vanoise	6.71233	45.26946	2329
Notre Dame d'Août	Vanoise	6.65710	45.28914	2500
Plan de la Gorme	Vanoise	6.71099	45.27625	2411
Plan du Lac	Vanoise	6.83543	45.34113	2375
Sources Supérieures	Vanoise	7.14337	45.40182	2680
Sous les Barmes	Vanoise	7.07828	45.45358	2350

Table 2 : Snow water equivalent observation stations used for model evaluation. Coordinates are given in WGS84 and elevations are expressed in meters above sea level.

4. Digital Elevation Model

Topographic information is derived from the GLO-30 Copernicus DEM at 30 m spatial resolution (European Space Agency and Airbus, 2022). This dataset provides a consistent representation of terrain elevation and forms a key input for the snow modeling framework.

5. Land Cover Dataset

Land cover information is derived from the Copernicus Global Dynamic Land Cover (2016 version) provided by the Copernicus Land Monitoring Service (Buchhorn et al., 2020). This dataset provides global land cover maps describing the land cover characteristics of the Earth's surface based on satellite observations.

The product includes several land cover classes such as forests, croplands, grasslands, wetlands, water bodies and built-up areas.

In this study, land cover information is used as an input to SnowModel to characterize surface land covers that influence snowpack processes. Vegetation type and ground cover affect mechanisms such as surface albedo or snow interception by vegetation, which ultimately influence snow accumulation and melt dynamics.

6. ERA5 Climate Reanalysis

Atmospheric forcing is derived from ERA5. It is produced by the Copernicus Climate Change Service and developed by the European Centre for Medium-Range Weather Forecasts.

ERA5 provides a global reconstruction of past atmospheric conditions by combining numerical weather prediction models with a wide range of observational data. The dataset provides hourly estimates of numerous atmospheric variables, including near-surface air temperature, precipitation, wind speed and humidity.

ERA5 data are available on a regular latitude–longitude grid with a spatial resolution of 0.25° (approximately 31 km at the Alps latitude) and cover the period from 1940 to the present. In this study, ERA5 variables are used as meteorological forcing inputs for the snowpack model after downscaling to 100 m spatial resolution (Section III).

7. Summary Table

The datasets used in this study are summarized in Table 3.

Dataset	Purpose	Spatial resolution	Temporal coverage
Sentinel-2 Snow Cover (Theia Snow Collection)	Assimilation into snowpack model to correct biases and improve snow distribution; derive fractional snow cover	20 m, resampled to 100 m	2015–present
MODIS Snow Cover (MOD10A1)	Evaluation of simulated snow cover at catchment scale	∼500 m	2000–present
Snow Depth Observations (BDCLIM, ARPA)	Validation of simulated snow depth	Point scale	1950–present
SWE Observations (EDF)	Validation of simulated SWE	Point scale	∼2015–present
Meteorological Observations (EDF)	Validation of temperature and precipitation forcing	Point scale	∼2015–present
Copernicus Digital Elevation Model (DEM)	Input topography for SnowModel; downscaling of meteorological forcing; controls snow accumulation/melt	30 m input, resampled to 100 m for SnowModel	Current
Copernicus Global Dynamic Land Cover	Characterize surface land cover influencing snowpack (forests, croplands, grasslands, wetlands, water bodies, and urban areas)	100 m, global annual	2015–2019
ERA5 Climate Reanalysis (C3S / ECMWF)	Hourly meteorological forcing for SnowModel (temperature, precipitation, wind, humidity)	∼0.25° (∼31 km), downscaled to 100 m	1940–present

Table 3 : Datasets used for snowpack modeling, assimilation, and evaluation.

III. Methods

This section describes both the method to simulate the snowpack and the method to evaluate the model output. The modeling approach referred to as the ERA5-SnowModel-Pipeline (ESP) relies on the SnowModel framework forced by ERA5 atmospheric reanalysis data (Sourp et al., 2025). It also uses satellite-based snow cover observations through a data assimilation scheme (Sourp et al., 2026).

First, the configuration of ESP is presented, including the parameters used for the simulation, the data assimilation settings, and the perturbation strategy applied to the model inputs. Second, the spatial aggregation of model outputs is described. To support operational applications for water resource management, model results were aggregated at the catchment scale using catchments delineated from a digital elevation model and a set of points of interest provided by local managers. Finally, the evaluation of the simulation performance is presented. Model outputs were compared with independent observations derived from both in-situ measurements and satellite products. Statistical metrics were computed to quantify the agreement between simulated and observed snow variables at both point scale and regional scale.

1. SnowModel

The snowpack simulations were performed using the SnowModel (Figure 1), a physically based and spatially distributed modeling system designed to simulate snow accumulation and melt processes (Liston and Elder, 2006). SnowModel integrates four submodules that represent processes controlling snowpack evolution, including meteorological downscaling, snowpack energy and mass balance, and snow–vegetation interactions.

Within SnowModel, meteorological forcing is spatially distributed using the MicroMet module, which interpolates atmospheric variables across the model domain based on terrain characteristics and predefined lapse rates. MicroMet accounts for topographic influences such as elevation, slope, and exposure in order to redistribute meteorological forcing fields from coarse-resolution datasets to the high-resolution simulation grid. In this case the meteorological forcing being sourced from ERA5, this amounts to a spatial downscaling of ERA5 data from 31 km to 100 m.

The snowpack evolution itself is simulated using the EnBal and SnowPack modules within SnowModel, which computes the temporal evolution of snow water equivalent, snow depth, and related snowpack properties by solving mass and energy balance equations with a multi-layer representation of the snowpack. The model represents processes such as snowfall accumulation, compaction, melt, sublimation, and interactions with vegetation canopies. Vegetation influences are parameterized through land cover information, which controls processes including canopy interception, snow unloading, and radiation exchanges. The snow cover fraction in every model cell was computed using the SSNOWD parameterization (Liston, 2004).

In this study, SnowModel was used to simulate the spatial and temporal evolution of snowpack conditions across the study area over the 2015–2025 period. Simulations were conducted at high spatial resolution (100 meters) and forced by atmospheric reanalysis data distributed using MicroMet. The model outputs are written at the daily timestep and include snow variables relevant for hydrological and environmental applications, such as snow water equivalent, snow depth, and snow cover area.

These simulations provide the prior estimates of snowpack conditions used in the subsequent data assimilation framework. Satellite observations of snow cover derived from Sentinel-2 are then assimilated using a particle-based approach in order to constrain the model simulations and improve the representation of snow cover dynamics.

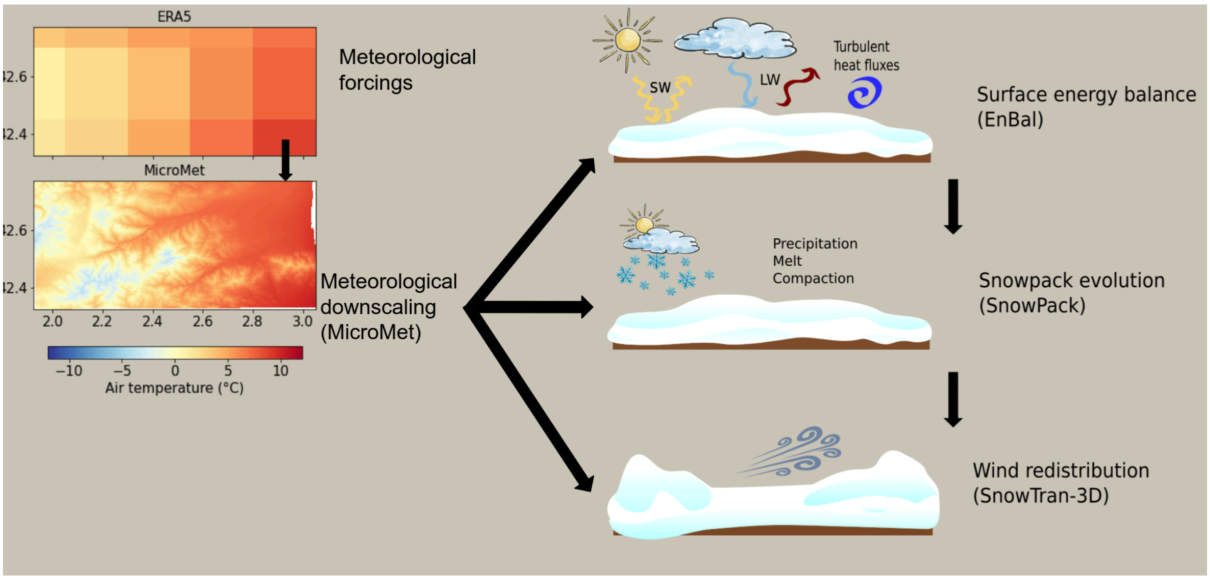

Figure 1 : SnowModel workflow illustrating the downscaling of ERA5 meteorological forcing by MicroMet and the simulation of surface energy balance, snowpack evolution, and wind-driven snow redistribution.

2. ESP Configuration

I. Deterministic simulations

Snowpack simulations were performed for each park individually using a JSON-based chain configuration that defines model inputs, outputs, and simulation parameters.

Topography is represented using a Digital Elevation Model (DEM), which is divided into sub-tiles to enable parallelization of the simulations. Sub-tiles that do not intersect the park geometry are removed in order to optimize computational efficiency. The DEM is used within the MicroMet module to distribute meteorological variables across the modeling domain and to derive terrain characteristics such as elevation, slope, and exposure. These topographic variables influence the spatial redistribution of atmospheric forcing fields including temperature, precipitation, and wind, which in turn control snow accumulation and melt processes within the different SnowModel submodules.

For the SnowModel simulations, the modeling grid is defined at a spatial resolution of 100 m. Meteorological forcing is provided exclusively by ERA5 reanalysis data at an hourly temporal resolution. The forcing is downscaled to the 100 m simulation grid using MicroMet. Vegetation is characterized using the PROBA-V global land cover map, which is used to parameterize snow–vegetation interactions, including canopy interception, unloading, and sublimation processes.

Snow transport by wind is deactivated in the current configuration, as evaluation showed it did not significantly improve model performance while increasing computational cost. Snow maximum density is imposed at a fixed value of 350 kg m^{-3} (Sourp et al., 2026).

II. Assimilation Framework

a. Ensemble generation

To account for uncertainties in meteorological forcing, an ensemble of snow simulations is generated by perturbing the input meteorological variables. In the present study, perturbations are applied to precipitation forcing. Precipitation perturbations are applied multiplicatively using a log-normal distribution, ensuring strictly positive values while preserving the statistical properties of precipitation. A coefficient of variation (CV) of 0.15 is used to characterize precipitation uncertainty, with a mean perturbation factor centered on zero in logarithmic space.

A total of 100 ensemble members are generated, each corresponding to a plausible realization of meteorological forcing conditions. Perturbation factors are randomly drawn once for each ensemble member and remain constant throughout the simulation period, thereby preserving temporal consistency within each simulation.

The perturbed meteorological forcings are then propagated through the SnowModel framework to generate an ensemble of prior snow states, including snow depth, snow water equivalent, and snow cover fraction fields. These ensemble simulations constitute the prior distribution used within the data assimilation framework.

b. Observation operator

The snow model simulates snow depth at each grid cell. To enable comparison with satellite observations of fractional snow cover, simulated snow depth was converted to snow cover fraction using an empirical parameterization (Sourp et al., 2026) .

$$SCF = \frac{HS}{HS + 0.11}$$

where HS is the simulated snow depth in meters and SCF is the snow cover fraction.

This relationship describes the progressive transition from full snow cover to bare ground as snow depth decreases and has been shown to provide realistic estimates of fractional snow cover at high spatial resolution during the melt season.

c. Satellite snow cover observations

Sentinel-2 snow cover fraction was first reprojected to the model grid using GDAL average resampling. For each grid cell, the observed SCF was then compared to the SCF derived from model simulations through the observation operator described above.

Observation errors were assumed to be Gaussian and uncorrelated in space and time. A constant observation error variance was used, corresponding to a standard deviation of 0.25 in fractional snow cover following a previous error assessment study (Gascoin et al., 2020).

Data assimilation was performed during the January–August period, corresponding to the main snow accumulation and melt season in the study area. Restricting the assimilation window to this period allows the assimilation procedure to focus on the seasonal evolution of the snowpack, particularly during spring melt, when snow conditions have a strong influence on water availability and hydrological processes.

d. Particle Batch Smoother assimilation

Satellite observations were assimilated using a Particle Batch Smoother (PBS) (Margulis et al., 2015). The PBS is a batch formulation of the particle filter that assimilates all available observations simultaneously. Each ensemble member is interpreted as a particle representing a possible realization of the snowpack evolution.

For each particle, the likelihood of the observations is computed assuming Gaussian observation errors:

$$w_i = e^{-(y-H(x_i))^2/(2R)}$$

where

- y is the observed snow cover fraction,
- $H(x_i)$ is the simulated SCF derived from ensemble member i,
- R is the observation error variance,
- w_i is the posterior weight assigned to particle i.

Posterior weights are normalized so that their sum equals one. These weights represent the probability of each ensemble member given the satellite observations.

The effective ensemble size is monitored using:

$$N_{eff} = \frac{1}{\sum_i w_i^2}$$

which provides an estimate of ensemble degeneracy.

e. Posterior snowpack estimation

Posterior estimates of snow variables, including snow depth, snow water equivalent, and snow cover fraction, were obtained as weighted averages across the ensemble members using the posterior particle weights. This approach allows the integration of satellite snow cover information while preserving physically consistent snowpack simulations produced by the snow model (Figure 2).

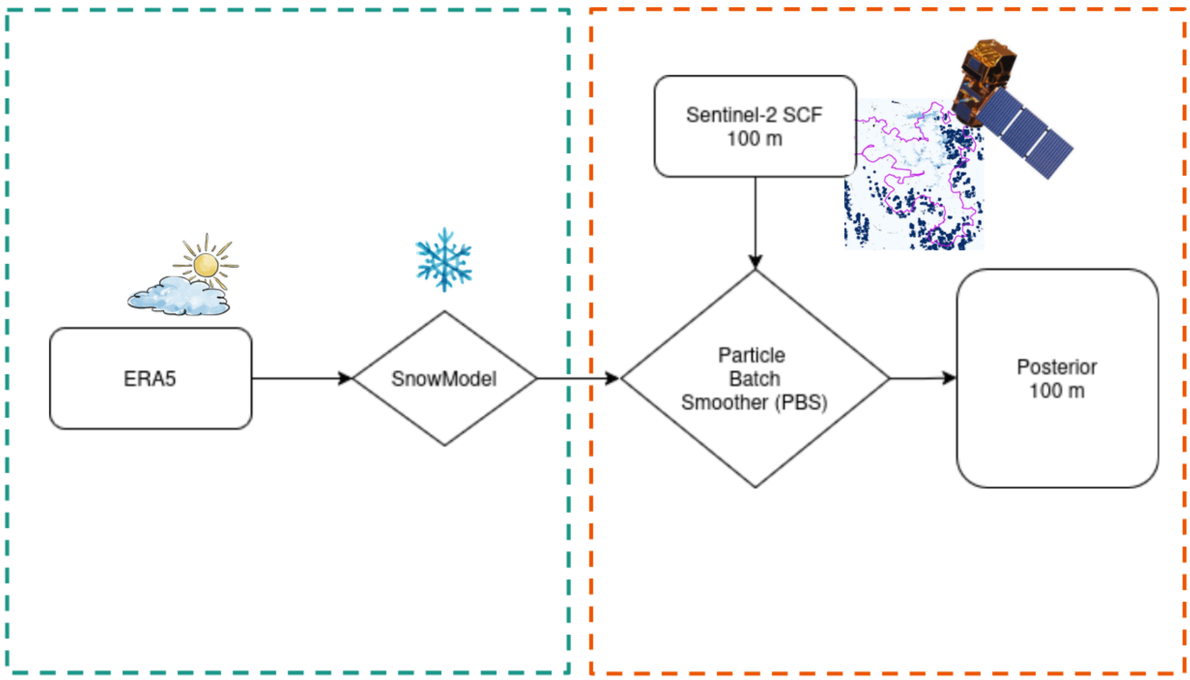

Figure 2 : Data assimilation workflow combining ERA5-driven SnowModel simulations with Sentinel-2 snow cover fraction observations through a Particle Batch Smoother.

f. Summary table

The configuration parameters used in this study are summarized in Table 4.

Parameter	Deterministic simulation	Assimilation experiment
Simulation period	Example: 2023-09-01 to 2024-08-31	Example: 2023-09-01 to 2024-08-31
Simulation domain	Each park simulated independently	Each park simulated independently
Spatial resolution	100 m	100 m
Meteorological forcing	ERA5 reanalysis	ERA5 reanalysis
Meteorological time step	1 h	1 h
Topography	Copernicus DEM, split into sub-tiles for parallelization	Copernicus DEM, split into sub-tiles for parallelization
Land cover	PROBA-V global land cover map	PROBA-V global land cover map
Snow transport	Disabled	Disabled
Maximum number of snow layers	6	6
Snow maximum density	Fixed value: 350 kg m^{-3}	Fixed value: 350 kg m^{-3}
Main saved variables	Snow depth (SNOD), snow water equivalent (SWED), snow cover area (SCA)	Snow depth (SNOD), snow water equivalent (SWED), snow cover area (SCA)
Averaged variables	Air temperature	Air temperature
Summed variables	Precipitation, runoff	Precipitation, runoff
Output frequency	Daily output	Daily output
Output compression	Enabled	Enabled
Chunk size	`nt = 12, nx = 20, ny = 20`	`nt = 12, nx = 20, ny = 20`
Precipitation perturbation	Disabled	Enabled, multiplicative log-normal perturbation
Precipitation CV	Not used	0.15
Temperature perturbation	Disabled	Disabled
Number of ensemble members	Not used	100
Assimilated observation	None	Sentinel-2 snow cover fraction
Observation variable	None	snow cover fraction
Observation error variance	None	0.0625 ($\sigma = 0.25$)
SCF computation	Disabled	Enabled using the SCF parameterization proposed by Sourp et al. (2026)
Assimilation season	None	January to August
Assimilation method	None	Particle Batch Smoother

Table 4 : Summary of the main SnowModel configuration parameters used for deterministic and assimilation simulations.

3. Catchment Delineation and Aggregation

To analyze snowpack dynamics at the hydrological unit scale, the study areas were subdivided into catchments defined from a set of points of interest corresponding to potential catchment outlets. These points were provided by the partner managers involved in the project and correspond to locations of operational or ecological relevance. The dataset used on June 2026 version includes 1,677 points associated with different types of sites, such as drinking water intakes, alpine pastures, pastoral cabins, hydropower infrastructures, lakes, natural environments, mountain refuges, springs, hydrometric stations, and wetlands.

Catchments were delineated from the Copernicus Digital Elevation Model using the multiple flow direction algorithm implemented in the `r.watershed` and `r.water.outlet` tools of the GRASS GIS software (GRASS Development Team et al., 2026). The outlet points were first snapped to the nearest drainage network derived from the DEM in order to ensure hydrological consistency, using a maximum snapping distance of 30 m. This procedure resulted in the generation of 1,677 individual catchments across the study area.

The resulting catchments exhibit a wide range of spatial extents. Without applying a minimum area threshold, the 1,677 catchments have a median area of 0.44 km² and a mean area of 9.21 km², reflecting the presence of numerous small mountain catchments.

For each catchment and each time step, snow water equivalent values simulated at the pixel scale were spatially averaged over all grid cells contained within the catchment. This approach provides an operational perspective by directly linking snowpack simulations to hydrological units relevant for water resource management and local decision-making.

The resulting catchment-scale SWE time series can be used to support multiple environmental and operational applications, including monitoring of water resources, assessment of snow availability for hydropower and pastoral activities, and evaluation of snow conditions in natural ecosystems such as wetlands or alpine lakes.

4. Model Evaluation

The performance of the snow simulations was evaluated by comparing model outputs with independent observations derived from both ground-based measurements and satellite products. The evaluation focuses on key snowpack variables including snow depth, snow water equivalent, and snow cover fraction.

Ground-based observations were used to assess simulated snow depth and SWE at the point scale. Model outputs were collocated with observation sites by extracting values from the nearest model grid cell. The agreement between simulated and observed time series was quantified using standard statistical metrics, including the root mean square error (RMSE) and the mean absolute error (MAE).

Snow depth observations allow evaluation of the model's ability to reproduce the temporal evolution of snow accumulation and melt at local scale. Snow water equivalent measurements, obtained from both cosmic-ray snow gauges (NRC) and manual snow surveys (stakes), provide a more direct estimate of the water stored within the snowpack and are therefore particularly relevant for hydrological applications. Simulated SWE from deterministic and assimilated simulations was compared with in-situ observations in order to assess both the seasonal evolution of snow water storage and the contribution of data assimilation.

At the regional scale, simulated snow cover was evaluated using the MODIS snow cover product. MODIS observations were processed in Google Earth Engine to derive continuous daily SCF time series over each study area. Missing observations caused by cloud cover were first filled using linear interpolation in order to obtain gap-free daily datasets (Gascoin et al., 2022). The interpolated NDSI values were subsequently converted into snow cover fraction following the empirical relationship proposed by Salomonson and Appel (2004), similarly to the approach used for Sentinel-2 observations. Finally, the SCF values were spatially aggregated over each park area to compute snow cover area (SCA) time series, expressed in km², which were then compared with the corresponding simulated snow cover dynamics.

The evaluation was performed for both open-loop simulations (without assimilation) and simulations incorporating Sentinel-2 snow cover assimilation, allowing the impact of data assimilation on snowpack estimation to be quantified. In addition to the statistical metrics, time series analyses and graphical comparisons were used to assess the temporal evolution of snow conditions at both local and regional scales.

IV. Results

This section presents the results of the snowpack simulations across multiple spatial scales and variables. The performance of the deterministic (open-loop) simulations and the simulations including data assimilation are compared against independent observations. The analysis is conducted at the park scale and the point scale in order to assess both the spatial and temporal consistency of the model outputs.

1. Park-scale Evaluation

I. Snow Cover Area (SCA)

Simulated snow cover area time series were compared with MODIS observations for a selection of representative park–year combinations.

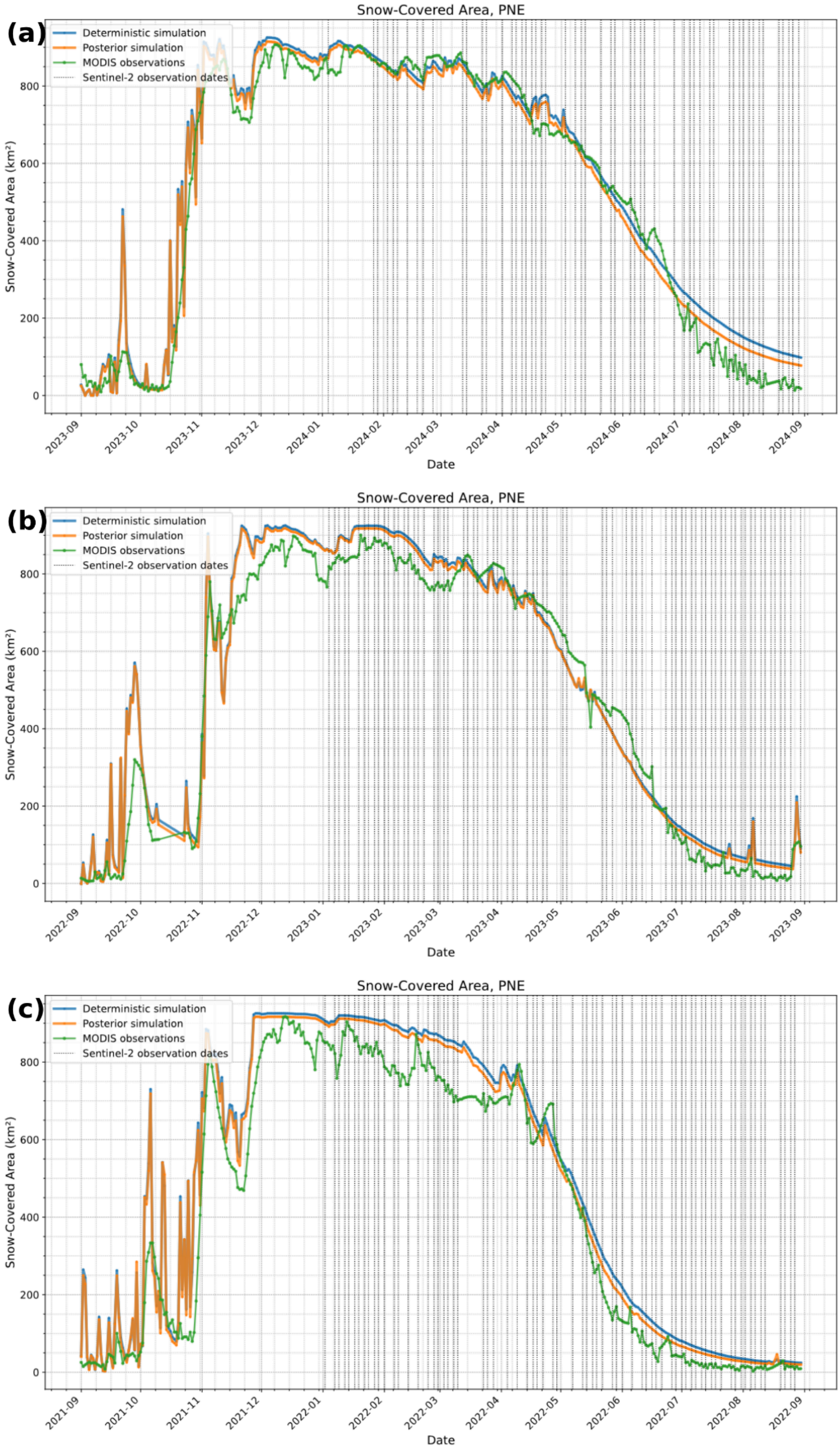

Figure 3 : Interannual evolution of snow-covered area (SCA) in the Écrins park (2021–2024), comparing deterministic and assimilated simulations with MODIS observations.

Regarding the Écrins over the three hydrological years 2021-2022, 2022-2023 and 2023-2024, the simulations successfully reproduce the main seasonal dynamics of snow cover, including the onset of accumulation, the winter maximum, and the overall timing of the melt period (Figure 3). The magnitude of peak SCA is generally well captured, confirming the model's ability to represent large-scale snow evolution.

A slight overestimation of snow-covered area is observed during winter, which remains consistent across years. Differences become more pronounced during the melt period, where simulations tend to maintain snow cover longer than observed. Despite the availability of Sentinel-2 observations, the impact of data assimilation remains limited, with only minor differences between deterministic and assimilated simulations.

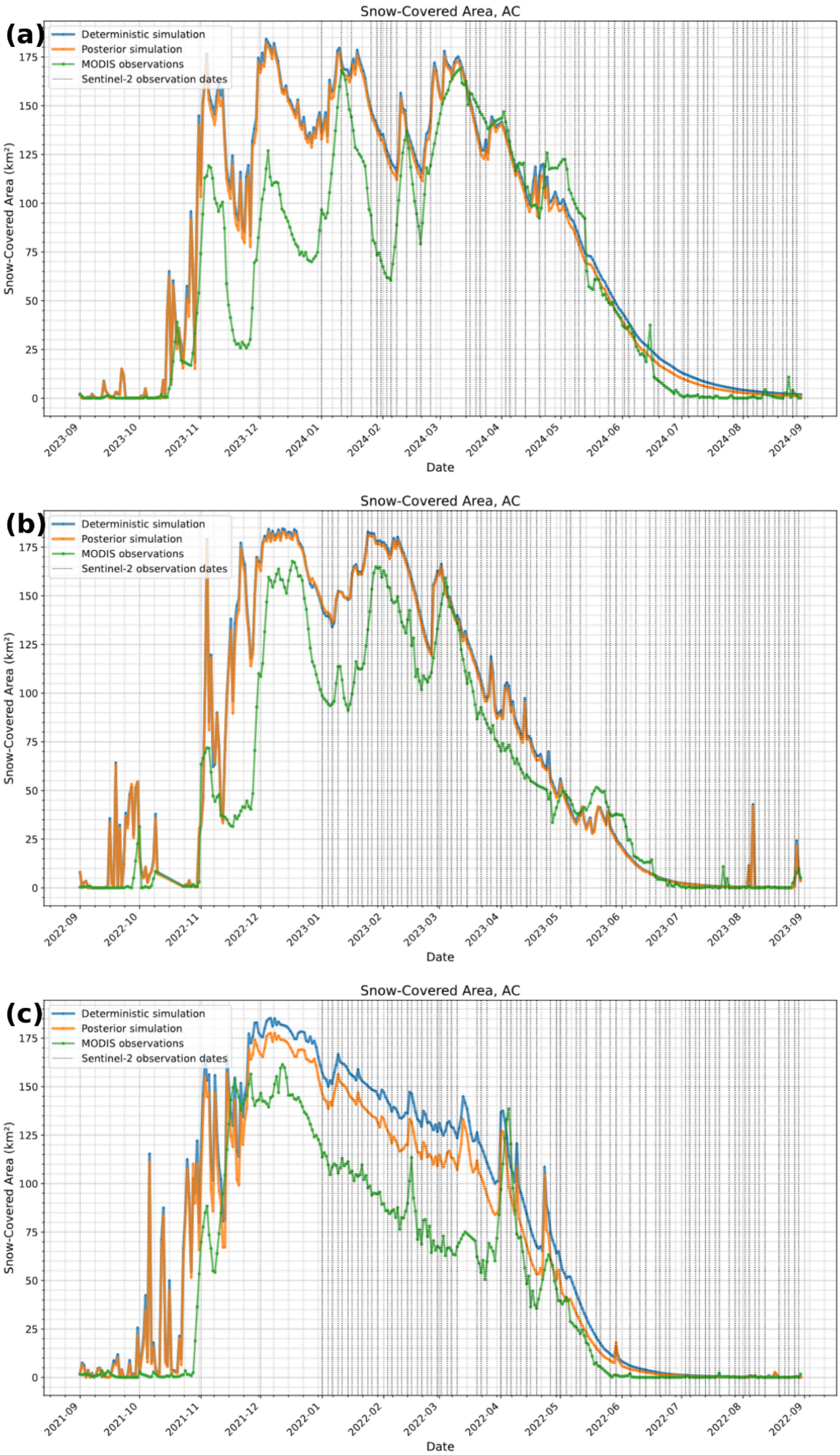

Figure 4 : Interannual evolution of snow-covered area (SCA) in the Alpi Cozie park (2021–2024), comparing deterministic and assimilated simulations with MODIS observations.

In the Alpi Cozie park, the model also reproduces the seasonal evolution of snow cover with good consistency, with a generally satisfactory agreement with MODIS (Figure 4). The timing of accumulation, peak snow cover, and melt is well captured. As in the previous case, the contribution of data assimilation remains limited, with only marginal improvements during transition periods.

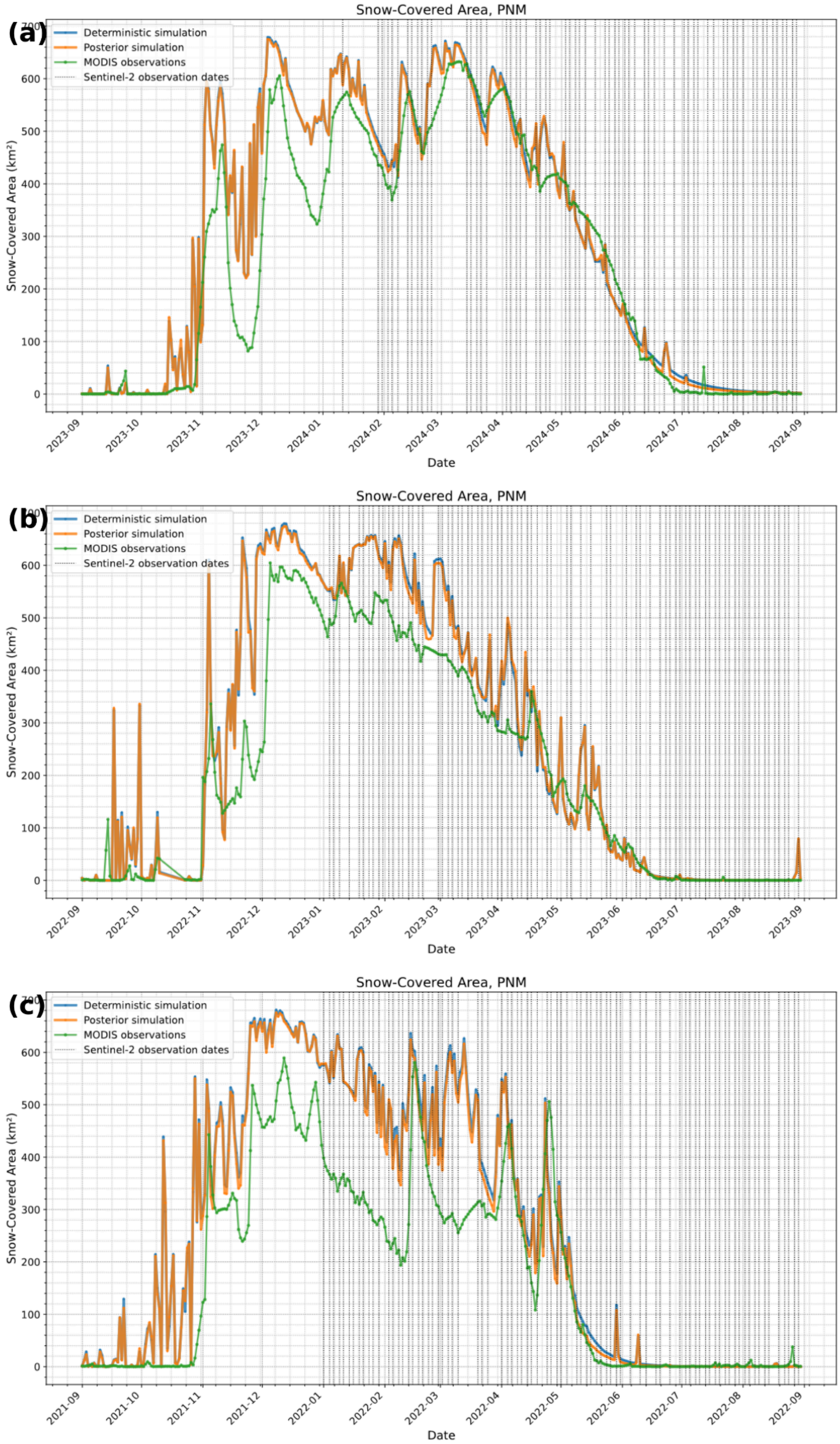

Figure 5 : Interannual evolution of snow-covered area (SCA) in the Mercantour park (2021–2024), comparing deterministic and assimilated simulations with MODIS observations.

The results over the Mercantour confirm the overall robustness of the modeling framework, with a good representation of the seasonal snow cycle and a satisfactory agreement with MODIS observations (Figure 5).

Compared to the previous sites, a higher temporal variability is observed, both in simulations and observations. This reflects the influence of complex topography and strong spatial heterogeneity, as well as the occurrence of rapid accumulation and melt events. While these short-term variations are not fully captured by the model, the overall seasonal dynamics remain well represented.

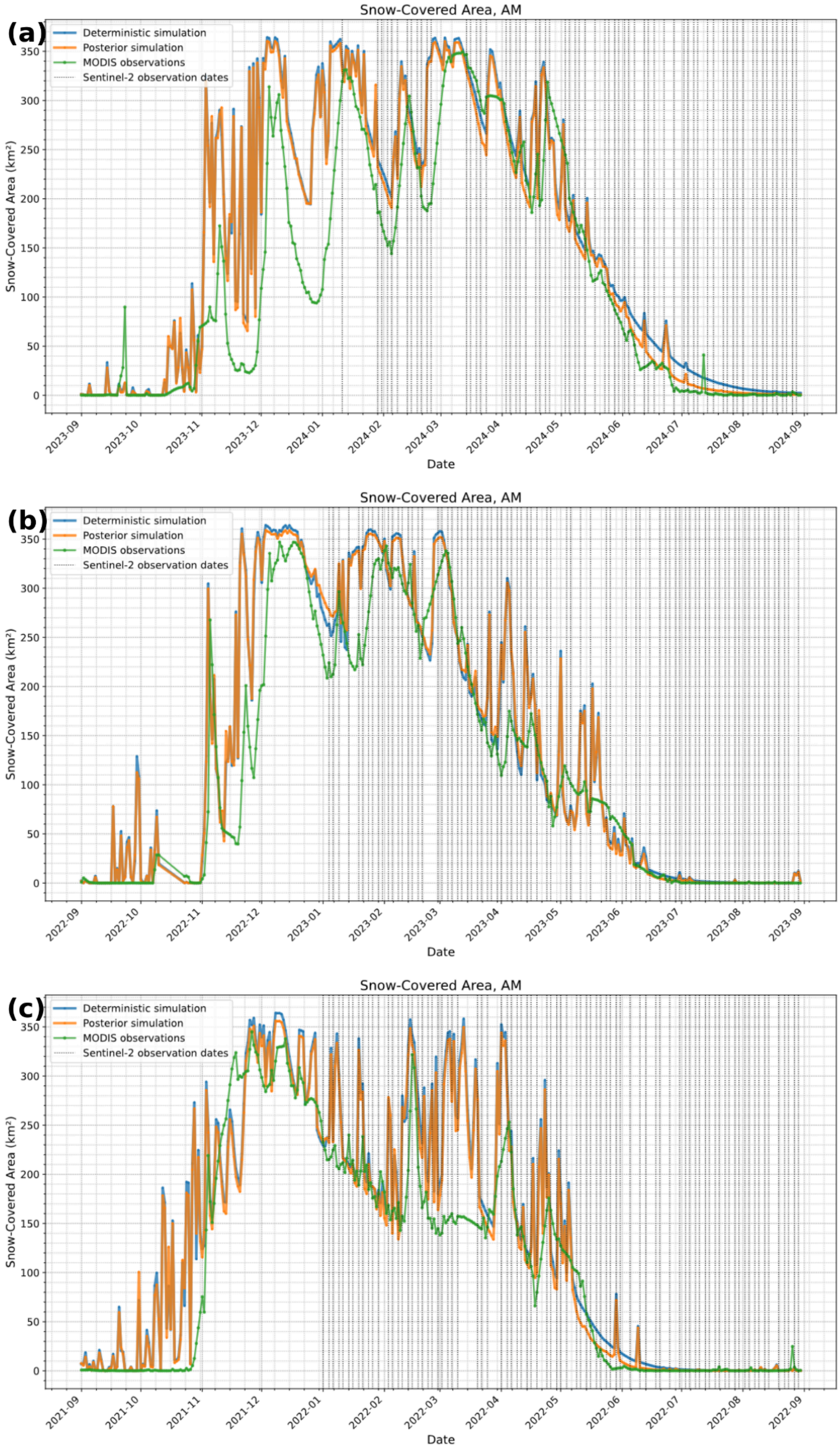

Figure 6 : Interannual evolution of snow-covered area (SCA) in the Alpi Marittime park (2021–2024), comparing deterministic and assimilated simulations with MODIS observations.

A similar behavior is observed in the Alpi Marittime park, where the model captures the main phases of the snow season with a satisfactory agreement at the seasonal scale (Figure 6). However, as in the Mercantour, the region is characterized by strong temporal variability, particularly during accumulation and transition periods.

This variability is linked to highly dynamic meteorological conditions, including intermittent snowfall and rapid melt events, which are only partially reproduced by the model. Simulations tend to slightly overestimate snow-covered area during winter, suggesting a persistent bias in snow accumulation or melt processes. Nevertheless, the timing of snow disappearance is generally well captured.

Consistent with the other sites, the contribution of data assimilation remains limited, with only minor differences between deterministic and assimilated simulations.

2. Point-scale Evaluation

I. Snow Depth (HS)

Simulated snow depth time series were compared with in-situ observations for a selection of representative station–year combinations across the study area.

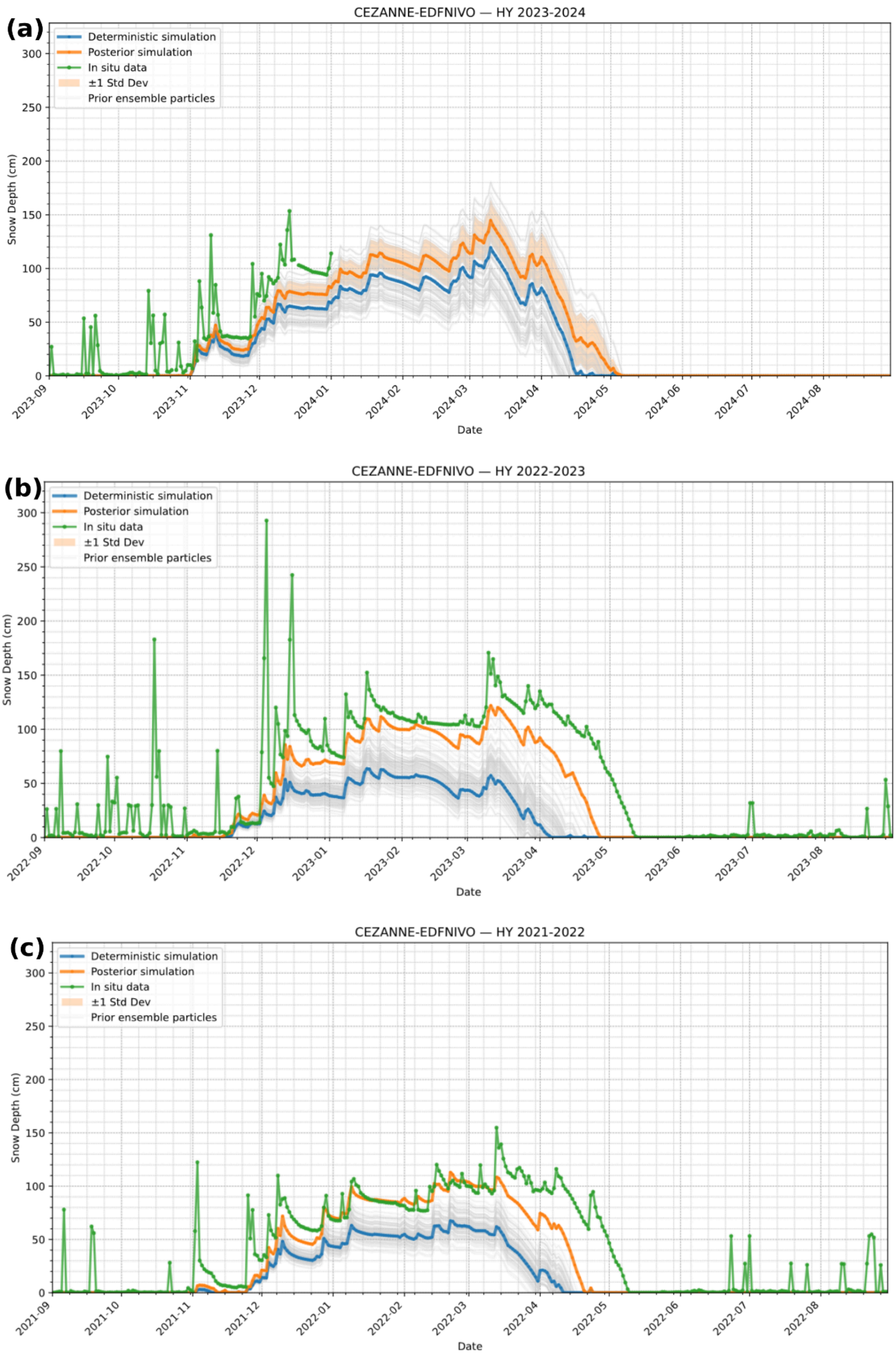

Figure 7 : Interannual evolution of snow depth at the Cezanne-EDFNIVO (PNE) station (2021–2024), comparing deterministic and assimilated simulations with in-situ observations.

At the station scale, the model reproduces the main temporal dynamics of snow depth in a satisfactory manner, including the onset of accumulation, the evolution of the snowpack during winter, and the timing of melt (Figure 7). The seasonal cycle is therefore well captured, highlighting the consistency of the model even at local scale.

Differences are nevertheless observed in terms of magnitude, with both deterministic and assimilated simulations generally underestimating snow depth compared to in-situ observations, particularly during peak accumulation periods. These discrepancies likely reflect limitations in the representation of snowfall, snow compaction processes, or the intrinsic mismatch between point measurements and grid-scale simulations.

The ensemble spread, represented by the prior standard deviation, remains relatively limited and does not fully encompass the observed variability. This suggests that the perturbation strategy does not generate sufficient dispersion to represent the full range of possible snow conditions, which in turn constrains the impact of data assimilation.

Despite these limitations, data assimilation contributes to improving the agreement with observations. Posterior simulations are generally closer to in-situ measurements than deterministic simulations, especially during the accumulation phase. However, this improvement remains moderate and does not fully correct the underestimation of snow depth.

During the melt period, the timing of snow disappearance is reasonably well reproduced, further confirming the model's ability to represent the seasonal evolution of the snowpack.

Overall, these results indicate that, despite some biases in magnitude, the model provides a satisfactory representation of snow depth dynamics at the station scale, with consistent temporal behavior and a moderate but positive contribution of data assimilation.

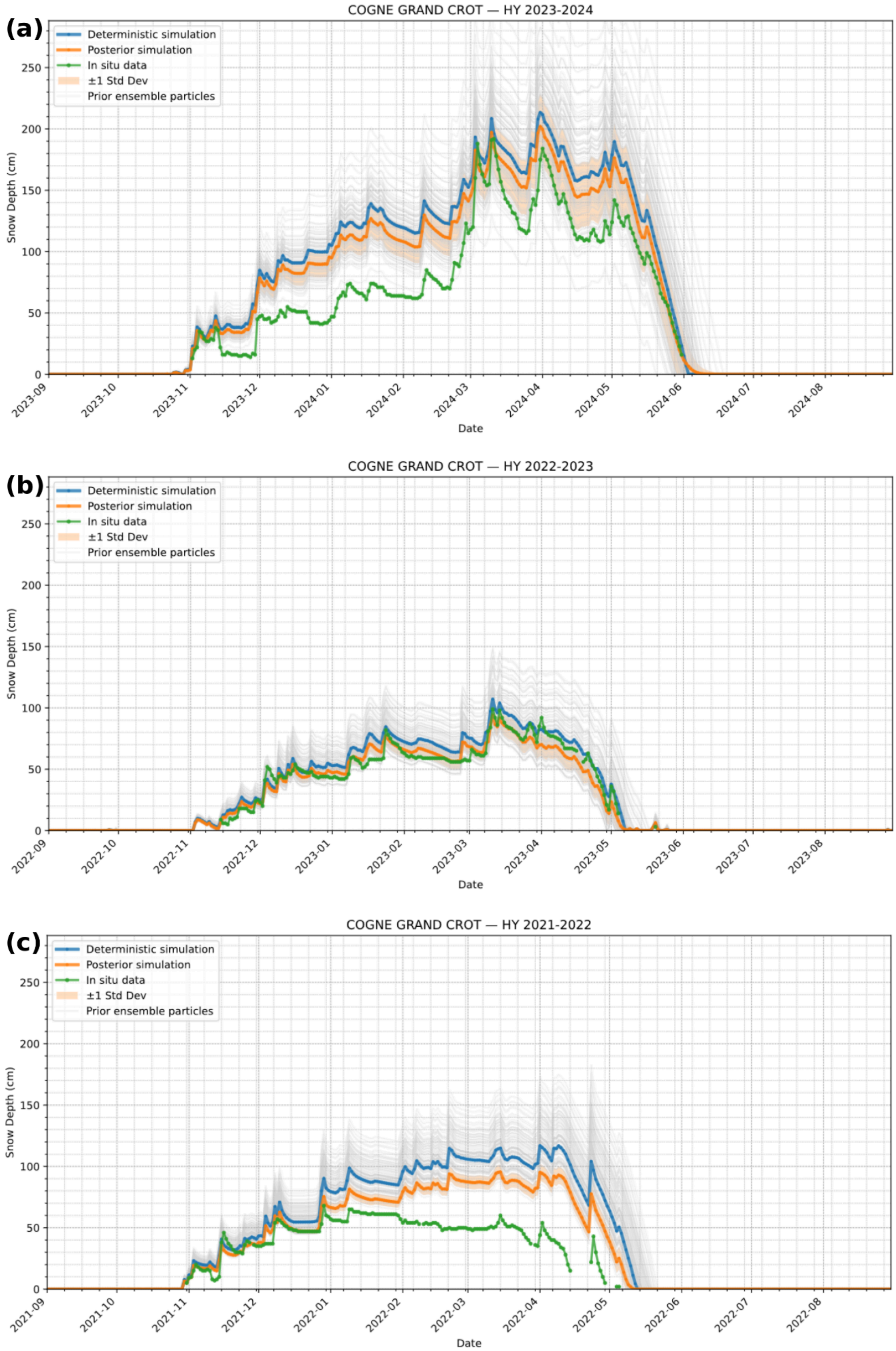

Figure 8 : Interannual evolution of snow depth at the Cogne Grand Crot (GP) station (2021–2024), comparing deterministic and assimilated simulations with in-situ observations.

The simulations at the Cogne Grand Crot station scale reproduce the overall temporal evolution of snow depth in a consistent and satisfactory manner over the three hydrological years (Figure 8). The timing of snow accumulation, the progression during winter, and the onset of melt are generally well captured, demonstrating the robustness of the model at local scale.

In terms of magnitude, both deterministic and assimilated simulations tend to overestimate snow depth compared to in-situ observations, particularly during the winter period and around peak accumulation. This bias is more pronounced in some years and may be related to an overestimation of snowfall or to limitations in the representation of snow compaction processes. Despite this, the temporal dynamics remain well aligned with observations.

The ensemble spread shows a reasonable range of possible snow states, although it does not always fully encompass the observed variability. This indicates that, while uncertainty is partially represented, the ensemble remains somewhat constrained, which limits the capacity of the assimilation to strongly adjust the simulations.

Data assimilation contributes to a moderate improvement of the results. Posterior simulations are generally closer to observations than deterministic runs, particularly during the accumulation and early melt phases. However, as observed at other sites, this improvement remains limited and does not fully correct the positive bias in snow depth.

The melt period is overall well reproduced, with a good agreement in the timing of snow disappearance across the different years. This confirms the ability of the model to capture the main seasonal transitions of the snowpack.

Overall, despite a tendency to overestimate snow depth, the model provides a satisfactory representation of snowpack dynamics at this station, with coherent temporal behavior and a consistent, albeit moderate, contribution of data assimilation.

II. Snow Water Equivalent (SWE)

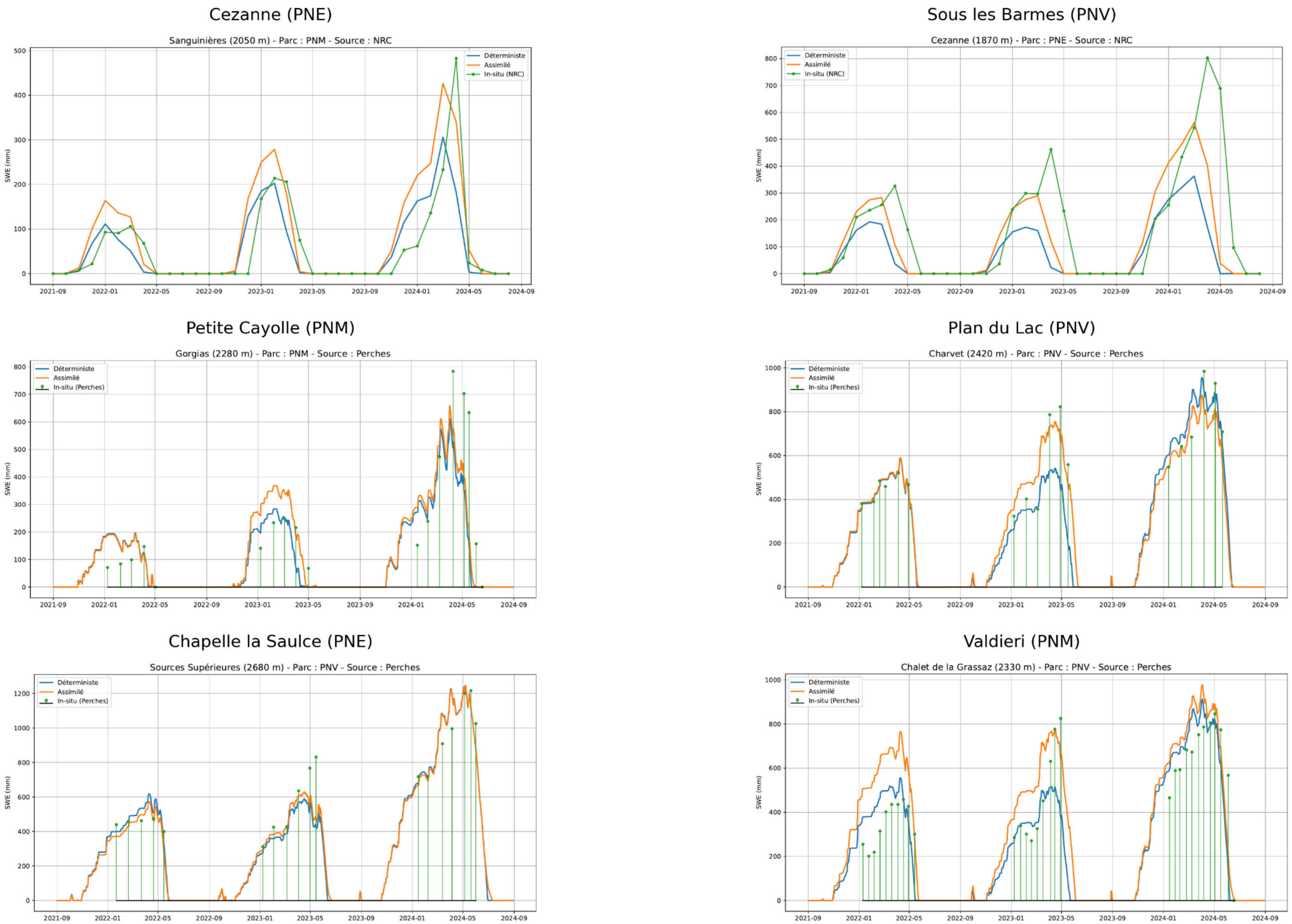

Figure 9 : Seasonal evolution of snow water equivalent (SWE) at selected stations (2021–2024), comparing deterministic and assimilated simulations with in-situ observations.

Overall, the results are satisfactory and indicate that the model reliably reproduces the main seasonal dynamics of SWE across most stations (Figure 9). The timing of accumulation, the winter build-up, and the spring depletion are generally well captured, as illustrated for example at stations such as Cezanne (PNE), Sous les Barmes (PNV) and Plan du Lac (PNV). The deterministic simulations already provide a coherent baseline representation of SWE across contrasted station locations.

In terms of magnitude, however, some site-dependent biases persist. Simulated peak SWE tends to be overestimated at some snow-survey stations such as Valdieri (PNM) and Petite Cayolle (PNM), whereas the agreement is closer at stations such as Plan du Lac (PNV) and Chapelle la Saulce (PNE). Despite these biases, the timing of melt is generally well reproduced, even when peak values are less accurate.

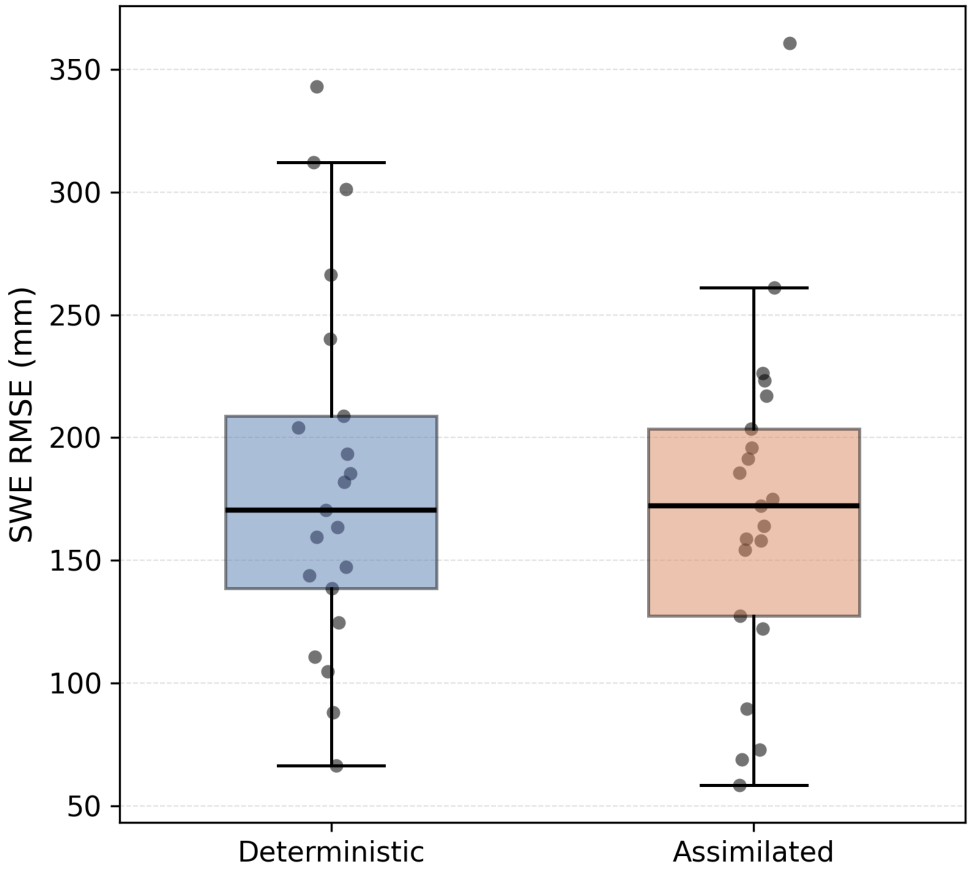

Figure 10 : Distribution of snow water equivalent (SWE) RMSE (mm) values for deterministic and assimilated simulations over the 2021–2024 period. Individual points correspond to station-scale evaluations.

Station	Source	Altitude (m)	Park	$RMSE_{det}$	MAE_{det}	$RMSE_{assim}$	MAE_{assim}	ΔRMSE
Sanguinières	NRC	2050	PNM	66	33	69	41	+3
Sous les Barmes	NRC	2350	PNV	312	179	261	136	-51
Notre Dame d'Août	NRC	2500	PNV	209	132	204	131	-5
Cezanne	NRC	1870	PNE	193	99	159	79	-35
Rougnous Prapic	NRC	2480	PNE	204	114	191	123	-13
Le Lac d'Allos	Stake	2260	PNM	144	89	122	84	-22
Plateau du Laus	Stake	2120	PNM	88	61	73	62	-15
Gorgias	Stake	2280	PNM	170	113	158	116	-12
Petite Cayolle	Stake	2440	PNM	266	212	172	125	-94
Plan de la Gorme	Stake	2411	PNV	343	315	361	338	+18
Charvet	Stake	2420	PNV	147	96	90	69	-58
Grand Fond	Stake	2600	PNV	182	129	154	106	-28
Sources Supérieures	Stake	2680	PNV	138	97	127	89	-11
La Plagne 4	Stake	2310	PNV	185	114	164	107	-21
Plan du Lac	Stake	2375	PNV	125	108	175	150	+50
Chalet de la Grassaz	Stake	2330	PNV	160	114	196	171	+36
La Sétéria Deux	Stake	2329	PNV	164	135	186	154	+22
Chapelle la Saulce	Stake	1790	PNE	111	75	58	46	-52
Glacier Noir	Stake	2360	PNE	301	200	223	190	-78
Crouzat	Stake	2200	PNE	240	191	217	177	-23
Barre de la Cabane	Stake	2315	PNE	105	83	226	189	+122

Figure 11 : Station-scale evaluation of snow water equivalent (SWE) simulations over the 2021--2024 period. RMSE and MAE are given in mm for deterministic and assimilated simulations.

The impact of assimilation is generally positive but heterogeneous (Figure 10). SWE assimilation reduces RMSE at 15 out of the 21 evaluated stations (Figure 11), with clear improvements at several sites such as Sous les Barmes (312 to 261 mm), Cezanne (193 to 159 mm), Petite Cayolle (266 to 172 mm), Chapelle la Saulce (111 to 58 mm), and Glacier Noir (301 to 223 mm). These results highlight the capacity of the assimilation framework to improve SWE estimates. However, this improvement is not systematic. At some stations, assimilation has limited effect or even degrades the results, confirming that its performance strongly depends on local conditions and on the spread and realism of the prior ensemble.

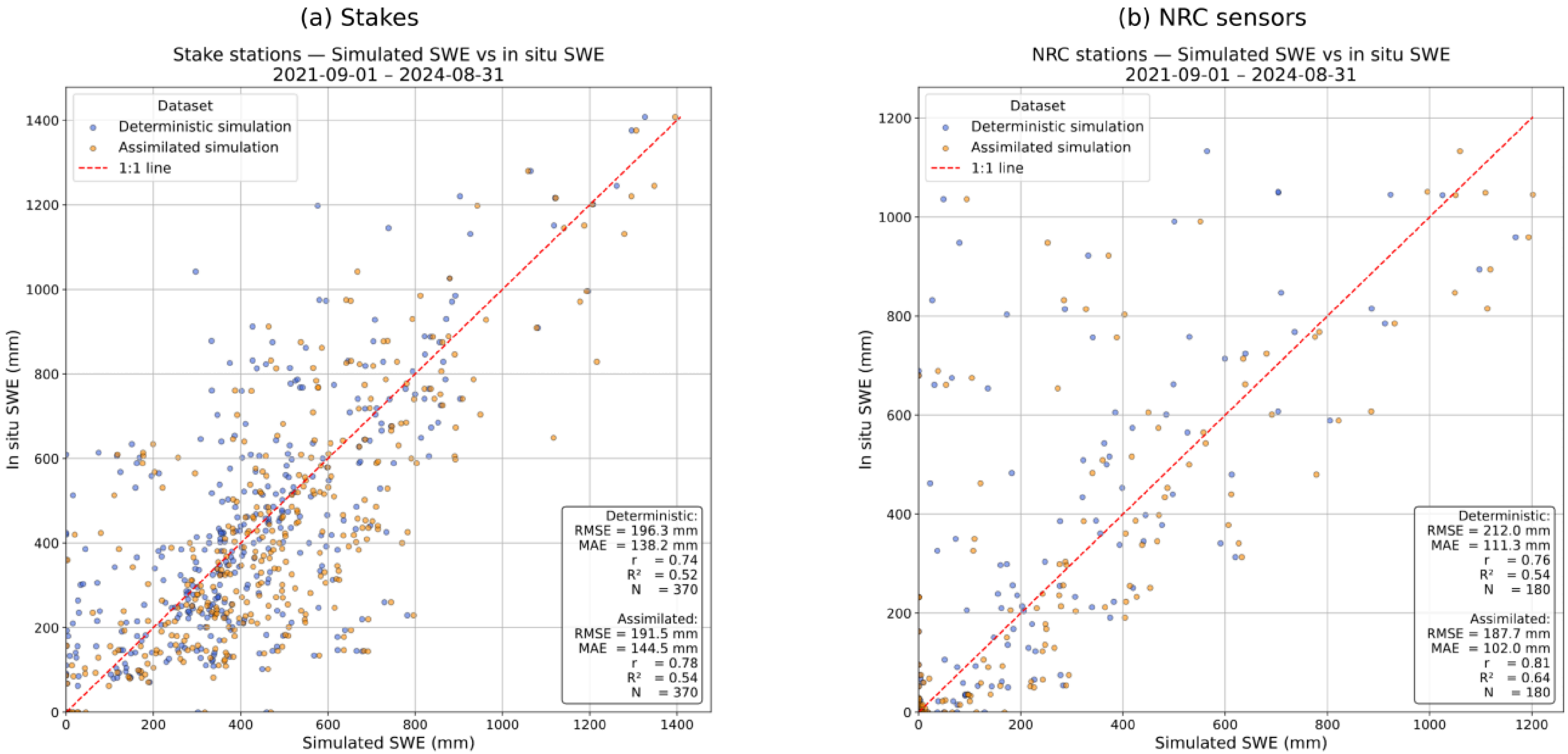

Figure 12 : Comparison between simulated and observed snow water equivalent (SWE) for stakes (a) and NRC sensors (b) over the 2021–2024 period.

This overall behavior is further illustrated in the figure above (Figure 12), which compares simulated and observed SWE across all stations for both snow stakes and NRC datasets. In both cases, a positive correlation is observed, with most points distributed around the 1:1 line, confirming the model's ability to capture the overall magnitude of SWE. The deterministic simulations already show a consistent relationship with observations, reinforcing their robustness. Assimilation generally leads to a slight improvement, particularly for NRC stations, where correlation increases (from 0.76 to 0.81) and RMSE decreases (from 212 to 188 mm). For snow stakes, improvements are more moderate and sometimes mixed, in line with the station-based analysis.

3. Synthesis

Snow Cover Area

Across all study areas, the model demonstrates a consistent ability to reproduce the main features of the seasonal snow cycle, including the timing of accumulation, peak snow cover, and melt. While systematic biases persist—such as a slight overestimation of snow-covered area during winter and occasional delays in snowmelt—the agreement with MODIS observations remains satisfactory.

The comparison between sites highlights the influence of local conditions on model performance. Glacierized areas introduce additional biases at the end of the season, while non-glacierized regions allow a clearer attribution of discrepancies to forcing and model parameterization. Regions such as the Mercantour and Alpi Marittime further illustrate the challenges associated with highly variable snow conditions.

Despite the integration of Sentinel-2 observations, the impact of data assimilation remains limited in the current configuration. Overall, the results indicate that deterministic simulations already provide a robust representation of large-scale snow dynamics.

Snow Depth

At the point scale, the evaluation based on in-situ observations shows that the model provides a satisfactory representation of snow depth dynamics across a wide range of stations and climatic conditions (Figure 13).

The deterministic simulations (open-loop) reproduce well the temporal evolution of snow depth, with RMSE values ranging from about 10 to 40 cm, depending on the site and year. This confirms the ability of the model to capture the main processes of snow accumulation and melt at local scale, despite inherent uncertainties in meteorological forcing and sub-grid variability.

The impact of data assimilation is contrasted across stations and years. In some cases, assimilation leads to a reduction of errors, with RMSE decreases of up to 30–50% (e.g., Cogne Grand Crot 2021–2022, Palanfre 2022–2023), demonstrating its potential to improve local snow estimates. In other cases, however, the assimilation has a limited or even negative impact, with increased errors compared to the deterministic simulations (e.g., Diga Del Chiotas or some Gran Paradiso stations).

This variability reflects the sensitivity of the assimilation framework to:

- the quality and representativeness of observations,
- the spread of the ensemble,
- and the complexity of local snow processes.

Overall, the ensemble spread partially captures the uncertainty in snow depth, but remains insufficient in some situations, limiting the efficiency of the Particle Batch Smoother and occasionally leading to suboptimal corrections.

Despite these limitations, the results remain consistent and reliable, with the deterministic simulations already providing a solid baseline. Data assimilation, while not systematically improving the results, shows promising performance in specific contexts, particularly when the ensemble adequately represents the variability of the system.

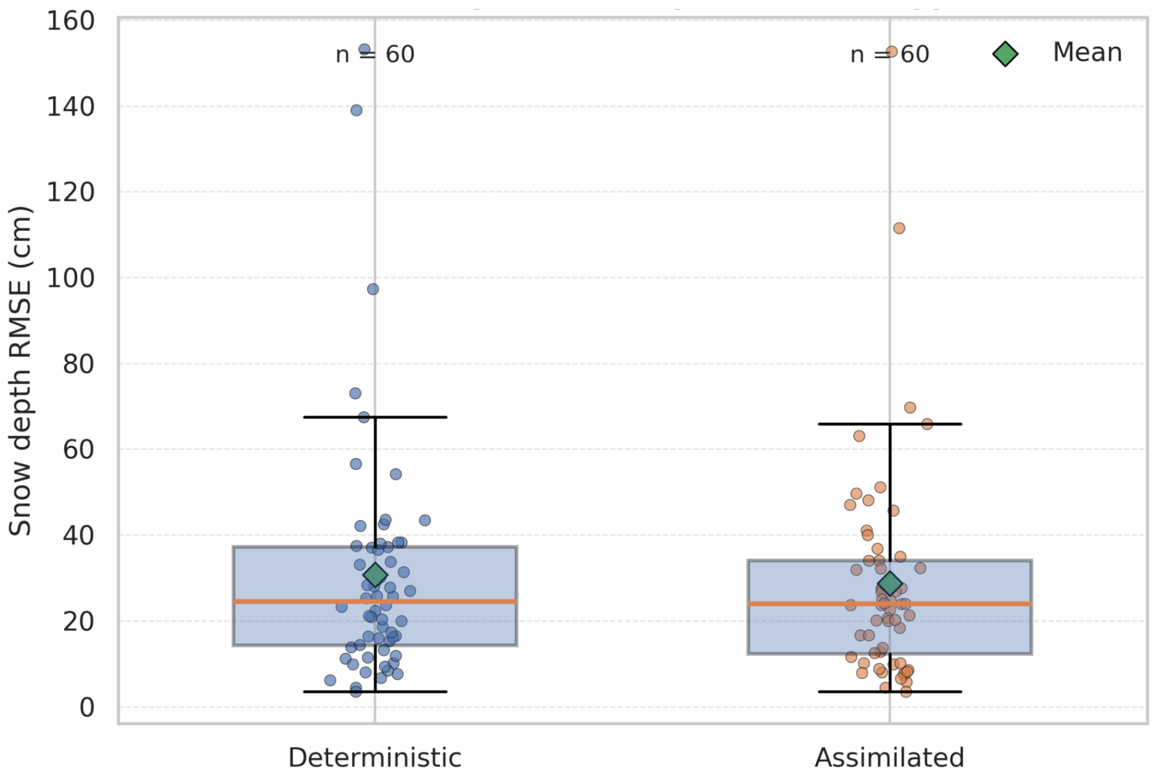

Figure 13 : Distribution of snow depth RMSE (cm) values for deterministic and assimilated simulations over the 2021–2024 period. Individual points correspond to station-scale evaluations.

Station	2015–2016	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2021–2022	2022–2023	2023–2024
AC___LE SELLE	10.2	15.7	15.9	15.9	19.3	5.1	18.7	13.9	25.7
AL___MELOSA	15.1	16.4	20.3	12.2	7.1	11.1	7.6	6.2	11.3
AM___DIGA DEL CHIOTAS	16.1	18.0	25.8	18.0	30.1	37.5	16.1	16.5	22.3
AM___ENTRACQUE - CASERMETTE	21.7	27.2	51.0	16.9	15.8	34.1	4.5	16.5	10.1
AM___ENTRACQUECHIOTAS	39.9	31.7	35.0	21.2	22.3	25.4	25.9	19.9	23.7
AM___ENTRACQUELAGO PIASTRA	16.9	13.2	25.1	13.1	12.4	22.0	3.5	13.3	9.9
AM___PALANFRE	23.1	19.1	48.8	10.7	23.1	20.3	11.8	28.1	20.8
AM___VALDIERI	34.3	36.5	92.8	28.9	37.8	46.0	14.4	31.3	37.2
AM___VALLE PESIO	38.1	37.5	71.9	28.5	19.8	51.4	8.0	28.4	8.5
GP___COGNE GRAND CROT	15.8	10.5	35.4	54.2	75.1	29.9	42.6	9.4	43.6
GP___LOCANA EUGIO	26.0	31.8	69.3	48.8	75.2	33.7	43.4	25.3	67.4
GP___LOCANA TELESSIO	21.4	16.8	20.2	40.9	55.2	22.2	37.6	15.4	38.3
GP___LOCANA VAL SOERA	40.7	57.0	30.4	101.5	122.6	64.0	97.4	56.7	139.0
GP___VALSAVARENCHE ORVIEILLE	15.4	14.8	44.8	54.7	67.3	22.9	33.8	16.3	37.2
GP___VALSAVARENCHE PONT	16.3	15.5	69.6	37.4	77.5	20.0	33.2	6.7	36.6
PNE___CEZANNE-EDFNIVO	–	66.8	83.6	37.0	70.6	46.2	38.0	54.2	30.3
PNE___LES ECRINS-NIVOSE	38.4	67.6	77.0	41.7	80.6	31.0	17.3	29.5	20.3
PNE___ROUGNOUS PRAPIC-EDFNIVO	–	37.3	22.9	26.1	33.6	31.5	27.8	23.4	11.5
PNM___SANGUINIERE-EDFNIVO	–	54.2	44.7	29.7	31.5	203.1	153.2	42.1	21.2
PNV___SOUS LES BARMES-EDFNIVO	–	61.7	53.2	21.0	24.9	40.7	27.0	73.1	38.3

Table 5 : RMSE (cm) of deterministic snow depth simulations for each station and hydrological year (2015–2024).

Snow Water Equivalent

The model reproduces the main seasonal dynamics of SWE across most stations, with deterministic simulations already providing a good representation. Some site-dependent biases remain, particularly an overestimation of peak SWE at several snow-survey stations.

The impact of Sentinel-2 assimilation is generally positive but heterogeneous. RMSE is reduced at most stations, with notable improvements at sites such as Sous les Barmes, Petite Cayolle, and Glacier Noir, although some stations show limited or negative impacts. Assimilation provides moderate improvements while deterministic simulations already capture the main SWE dynamics consistently.

4. Catchment-scale results visualisation

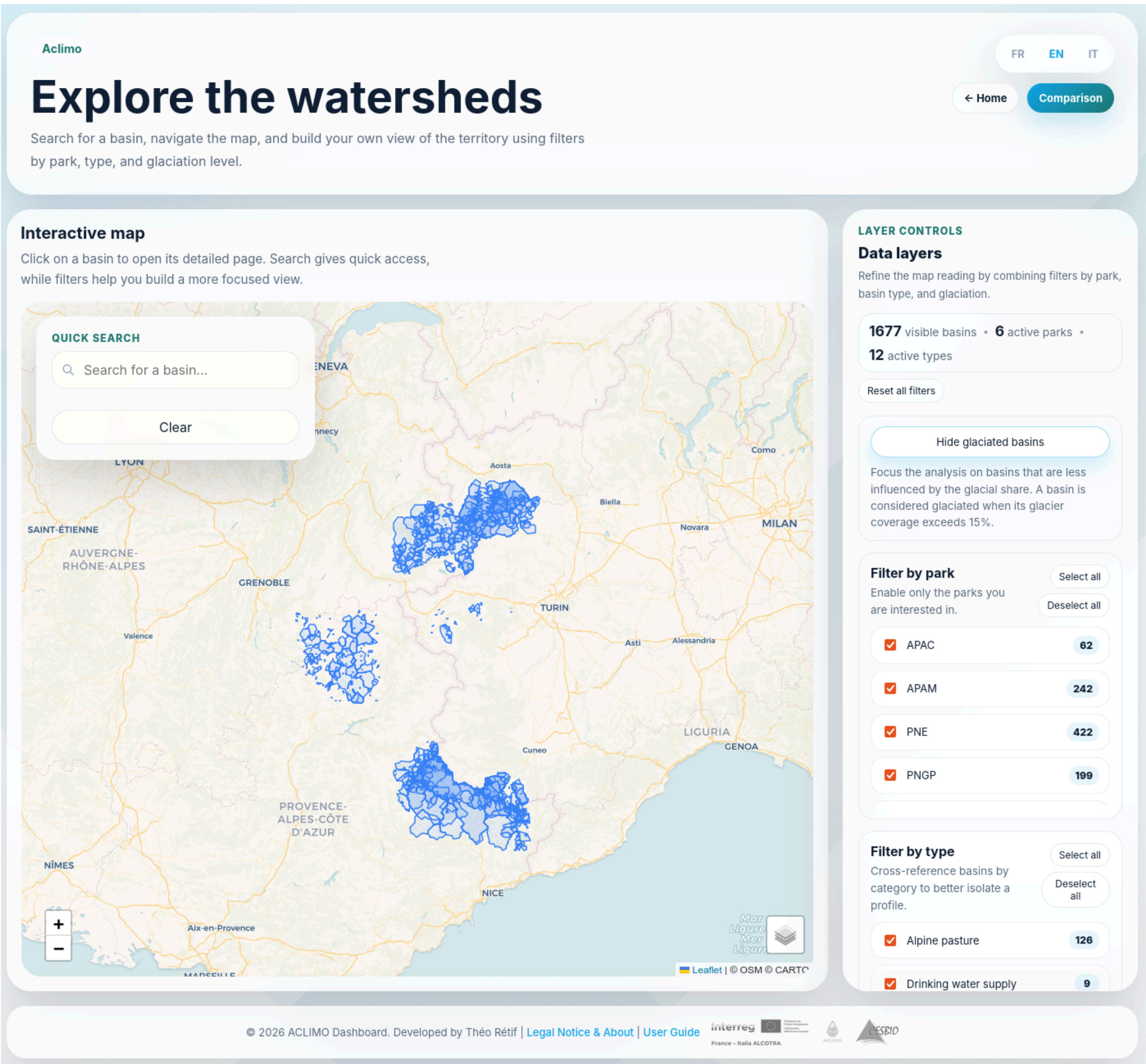

Figure 14 : Screenshot (June 2026) of the ACLIMO webpage, map page

The catchment-scale SWE time series are made available through an interactive web platform developed within the project[2], which allows users to visualize and explore snow water equivalent dynamics across delineated catchments (Figure 14). Through this interface, stakeholders can access temporal trajectories of SWE, compare different years and catchments, and identify critical periods of water availability or deficit (Figure 15). Catchments with a glacierized fraction above 15% of their total area are explicitly flagged on the platform, allowing users to account for the potential influence of glaciers when interpreting SWE dynamics. This facilitates the interpretation of model outputs in a decision-oriented context, for applications such as anticipating water shortages for mountain refuges, managing pastoral resources, or supporting hydropower planning. This approach enables a more integrated understanding of snow-driven water resources in mountain environments, while also highlighting the potential of such tools for supporting climate adaptation strategies at the local scale.

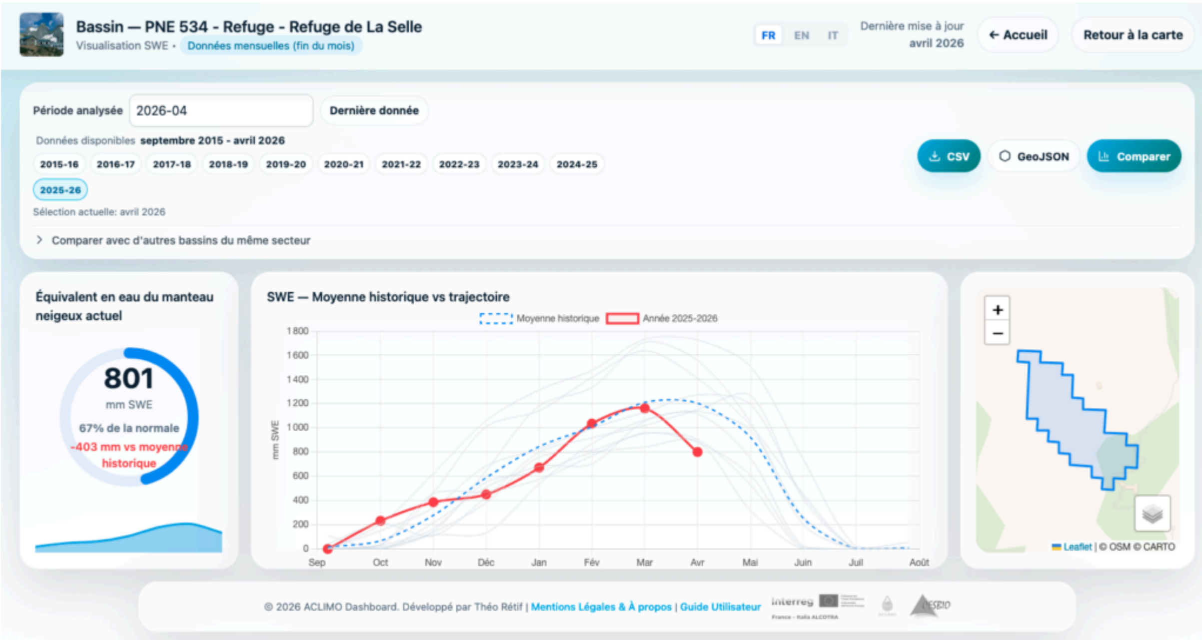

Figure 15 : Screenshot (May 2026) of the ACLIMO webpage for Refuge de la Selle (Écrins)

[2] https://flask.sedoo.fr/aclimo

V. Discussion

This work presents an assessment of snowpack simulations across multiple spatial scales, combining physically based modeling, satellite data assimilation, and in-situ validation datasets. The results demonstrate that the ERA5–SnowModel framework provides a robust and consistent representation of snow dynamics across contrasted alpine environments, while also highlighting the strengths and limitations of the Sentinel-2 data assimilation approach.

1. Model performance across scales

At the park scale, the model successfully reproduces the main seasonal dynamics of snow cover area, including accumulation onset, peak snow extent, and melt timing. The agreement with MODIS observations indicates that the combination of ERA5 forcing and MicroMet downscaling captures the patterns of snow variability despite the complexity of alpine terrain.

Nevertheless, some systematic biases remain. Simulations tend to slightly overestimate snow-covered areas during winter and occasionally delay snow disappearance during the melt season. These discrepancies are likely related to uncertainties in precipitation forcing, the absence of an explicit glacier representation in the model, and limitations in the parameterization of snowpack processes such as snow density evolution and albedo changes.

At the point scale, comparisons with snow depth and snow water equivalent observations confirm the ability of the model to reproduce the temporal evolution of the snowpack. The timing of accumulation and melt is well represented, but differences in magnitude vary among sites. These discrepancies reflect a combination of uncertainties in meteorological forcing, model parameterization, and representativeness differences between point measurements and 100 m grid-cell simulations.

Thus, deterministic simulations already provide a solid baseline and demonstrate the robustness of the framework across a wide range of climatic and topographic conditions.

2. Impact and limitations of data assimilation

The assimilation of Sentinel-2 snow cover observations produces mixed results. Improvements are observed at several stations, particularly for snow water equivalent, but the impact remains limited and is not systematic across variables, locations, or years.

At the park scale, assimilated and deterministic simulations often show very similar snow cover dynamics. At the station scale, assimilation can reduce errors in some cases, but may also have little influence or even degrade the results. This indicates that the deterministic simulations already capture a large part of the observed variability and leave limited room for correction through snow cover assimilation alone.

Several factors may explain this behaviour. First, Sentinel-2 observations provide information on snow cover extent rather than directly on snow mass. Second, the conversion from simulated snow depth to snow cover fraction through an empirical relationship introduces additional uncertainty. Finally, the temporal availability of Sentinel-2 observations remains constrained by cloud cover and revisit frequency, limiting the number of effective assimilation updates.

The limited ensemble spread may also reduce the efficiency of the Particle Batch Smoother. The ensemble does not always encompass the full range of observed snow conditions, restricting the capacity of the assimilation framework to significantly adjust model states.

3. From snow modeling to operational applications

Beyond model evaluation, a major contribution of this work lies in the transformation of distributed snowpack simulations into operational indicators relevant for water-resource management.

More than 1,500 catchments were delineated from points of interest provided by project partners and used to aggregate simulated snow water equivalent. This approach makes it possible to translate pixel-scale snow information into indicators directly linked to hydrological units and stakeholder needs.

The resulting products are integrated into an interactive web platform that enables users to visualize snow water storage dynamics, compare catchments and years, and identify periods of potential water shortage. By connecting meteorological forcing, snowpack modeling, catchment-scale aggregation, and user-oriented visualization, the study demonstrates the feasibility of delivering operational snow information to support environmental management and climate adaptation in mountain regions.

4. Perspectives

Future developments could focus on improving the representation of uncertainty through more sophisticated ensemble generation strategies, including multi-variable and time-varying perturbations. Alternative data assimilation approaches and the integration of additional observation types, such as snow depth measurements, could also be investigated.

Finally, the results show that high-resolution deterministic simulations already provide a reliable representation of snowpack dynamics across the study area. While Sentinel-2 assimilation offers local improvements in some situations, its added value remains limited in the current configuration. Nevertheless, the study highlights the potential of combining physically based modeling, satellite observations, and catchment-scale indicators to support the monitoring and management of snow-dependent water resources.

VI. Conclusion

This study presented a high-resolution snow modeling framework developed within the ACLIMO project to support water-resource management in Alpine protected areas. Using ERA5 meteorological reanalyses, topographic and land-cover information, and the SnowModel modeling system, snowpack dynamics were simulated at 100 m spatial resolution across multiple mountain parks over the 2015-2025 period.

The evaluation against independent in-situ observations and satellite products demonstrates that the modeling framework provides a good representation of snow cover, snow depth, and snow water equivalent across a wide range of climatic and topographic conditions. Deterministic simulations successfully reproduce the main characteristics of the seasonal snow cycle and constitute a reliable baseline for snowpack monitoring applications.

The assimilation of Sentinel-2 snow cover observations using a Particle Batch Smoother was also investigated. Local improvements were observed for some stations and variables, but the impact remained limited and heterogeneous. These results suggest that, in the current configuration, the quality of the meteorological forcing and the representation of model uncertainties exert a stronger influence on simulation performance than the assimilation of snow cover observations alone.

Beyond model evaluation, the main contribution of this work lies in the transformation of distributed snowpack simulations into operational indicators relevant for territorial stakeholders. By aggregating snow information over more than 1,500 catchments delineated from partner-defined points of interest, the framework provides direct estimates of snow water storage at hydrologically meaningful scales. The integration of these products into an interactive web platform further demonstrates the potential of translating scientific modeling outputs into practical tools for environmental monitoring and water-resource management.

Future developments will focus on improving the representation of uncertainties, exploring alternative assimilation strategies, and extending the framework towards near-real-time applications. More broadly, this work illustrates how physically based snow modeling and Earth observation data can be combined to support climate adaptation and sustainable water management in mountain regions.

VII. Code availability

The modeling and data assimilation framework developed in this study is available through a Git repository[3]. The repository contains the implementation of the snow simulation chain, ensemble generation, and data assimilation procedures used in this work. It is a private repository due to SnowModel licensing restrictions. However, a public repository including code to prepare the data and perform the assimilation without SnowModel code is available (SOURP Laura / ERA_SnowModel_Pipeline · GitLab, 2024).

[3] https://src.koda.cnrs.fr/laura.sourp.1/esp_ssnowd

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IX. Appendices

Appendix A — Meteorological forcing evaluation

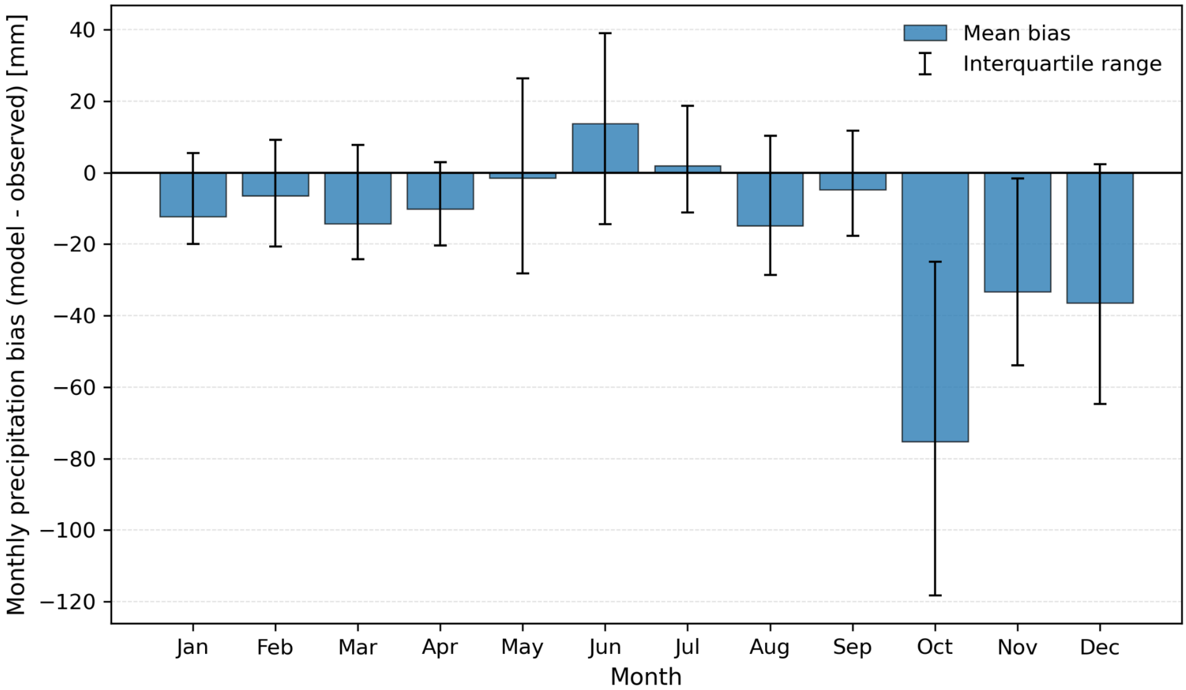

Figure A1 : Mean monthly bias between modelled and observed precipitation over the 2015–2024 period. Error bars indicate the interquartile range.

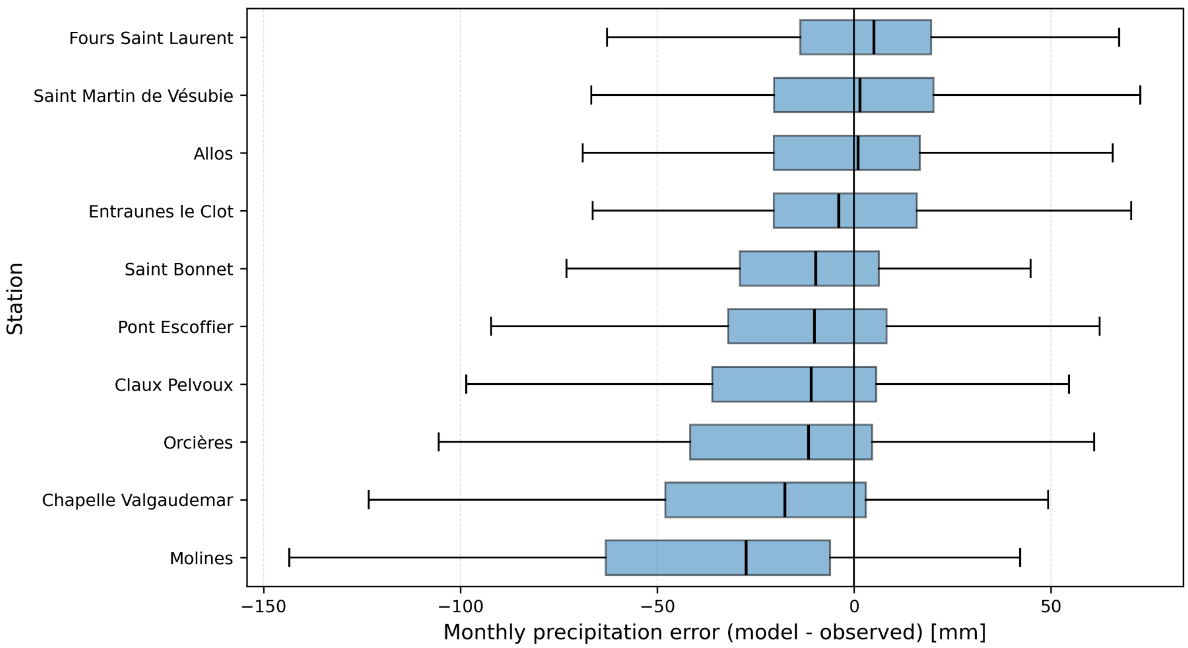

Figure A2 : Station-wise distribution of monthly precipitation errors, computed as modeled minus observed precipitation, for each EDF precipitation station.

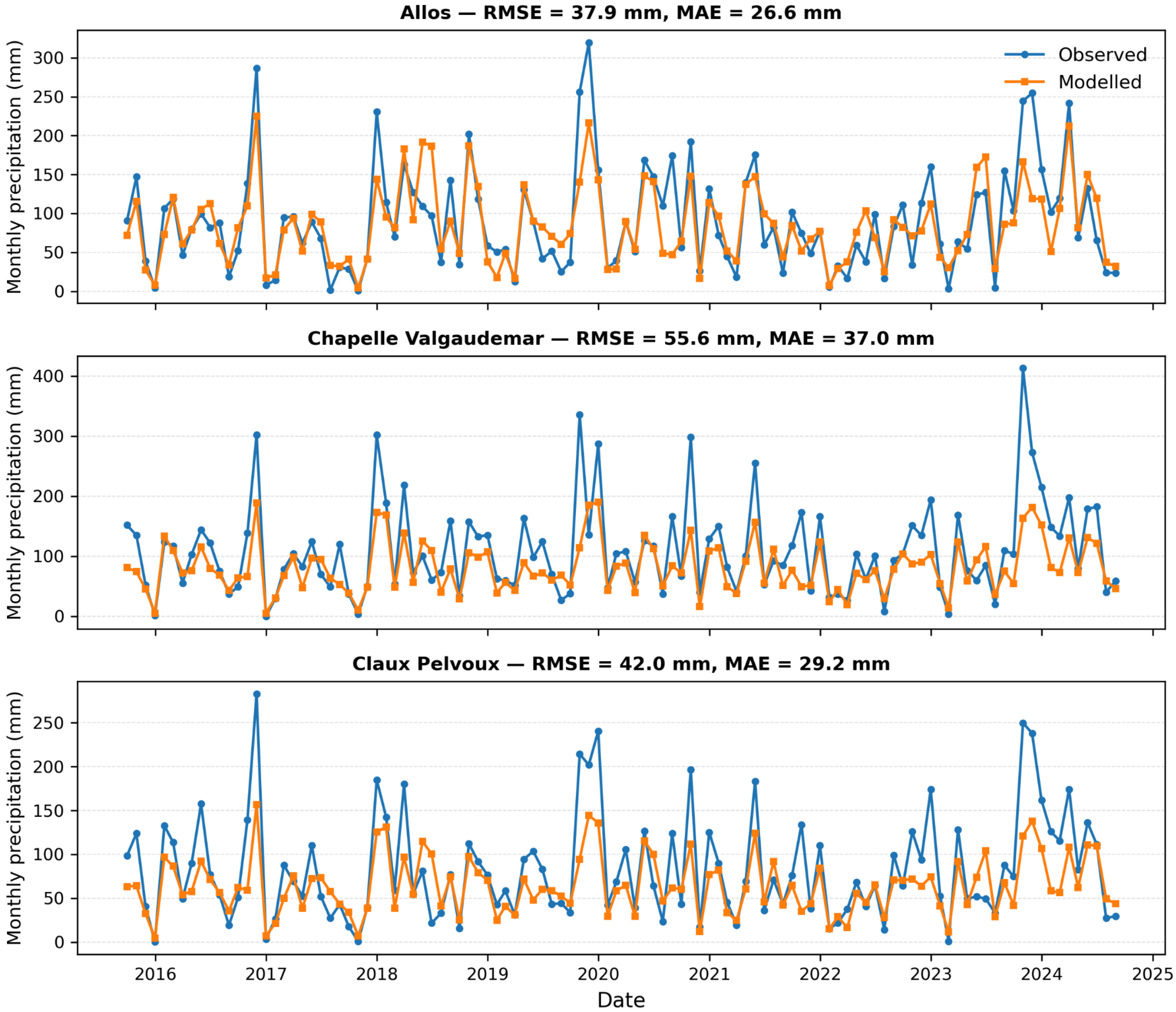

Figure A3 : Comparison between observed and modeled monthly precipitation for representative stations.

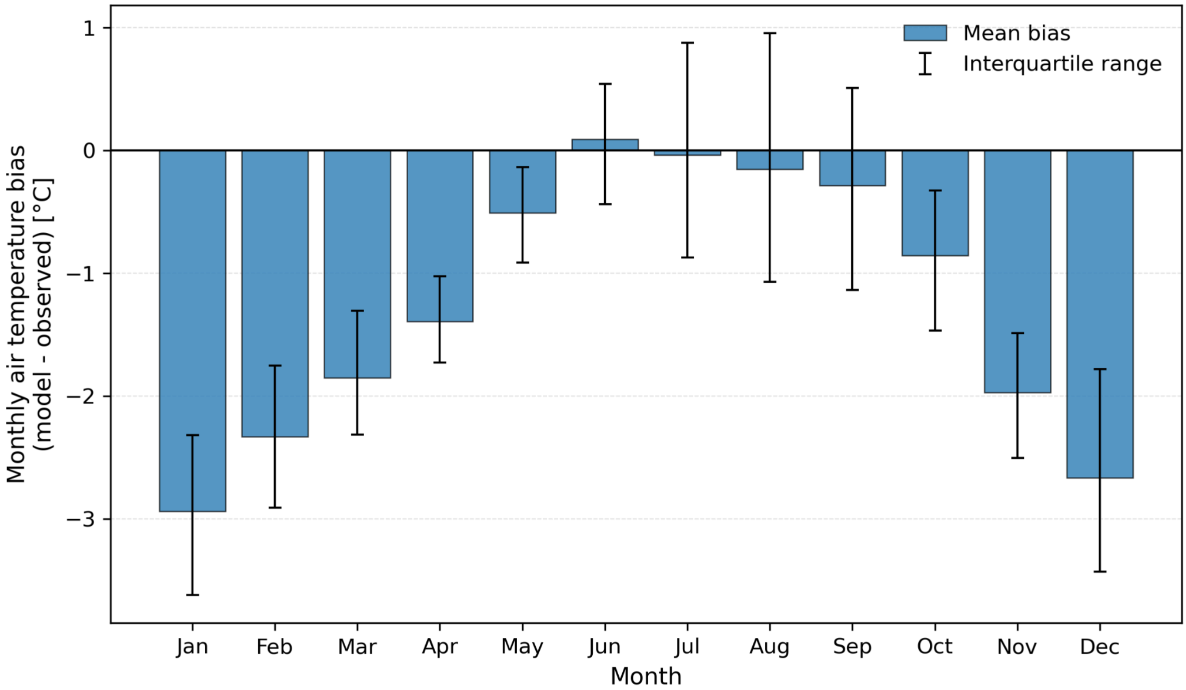

Figure A4 : Mean monthly bias between modeled and observed air temperature over the 2015–2024 period. Error bars indicate the interquartile range.

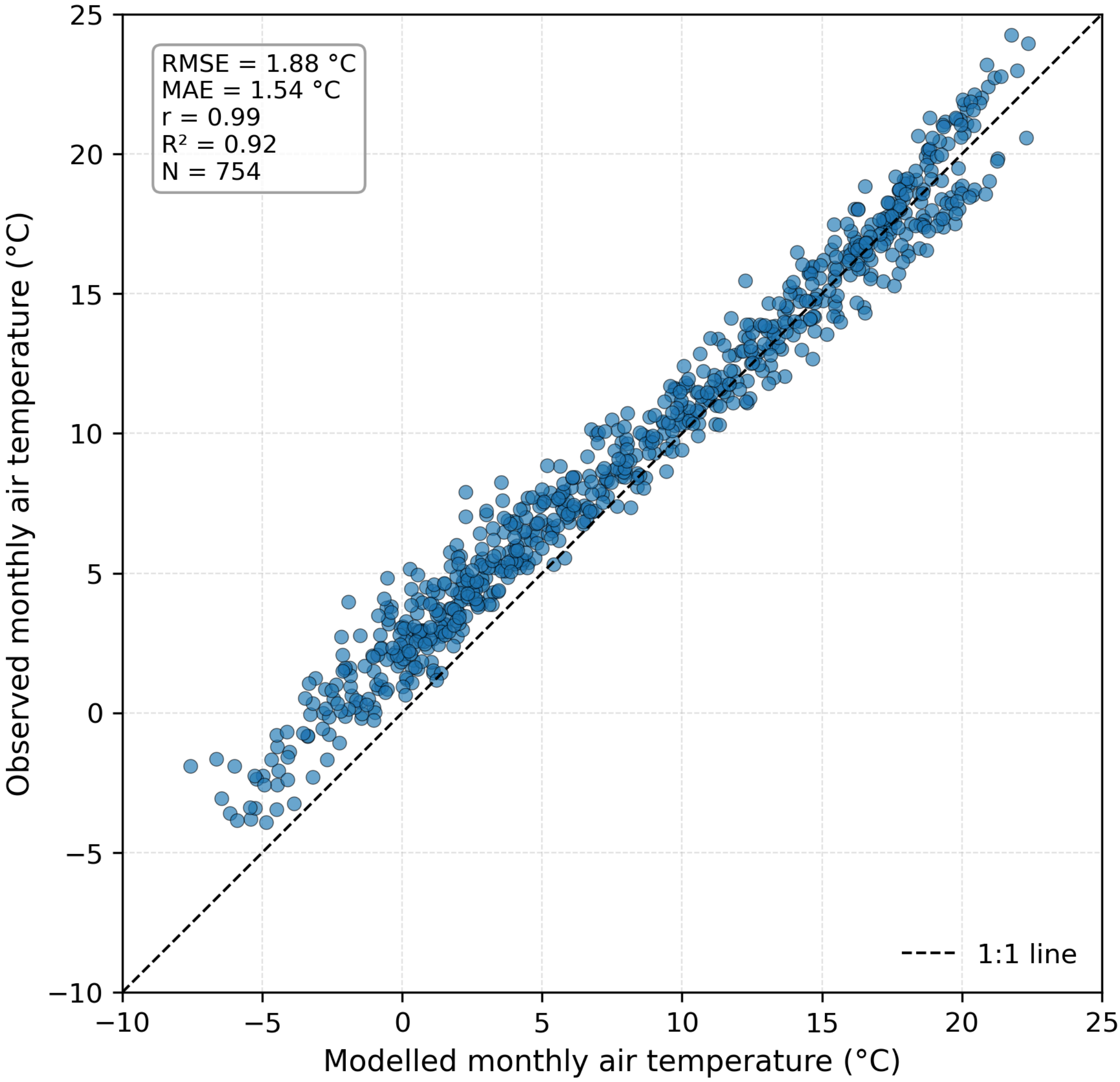

Figure A5 : Comparison between observed and modeled monthly air temperature values over the 2015–2024 period. The dashed line indicates the 1:1 relationship.

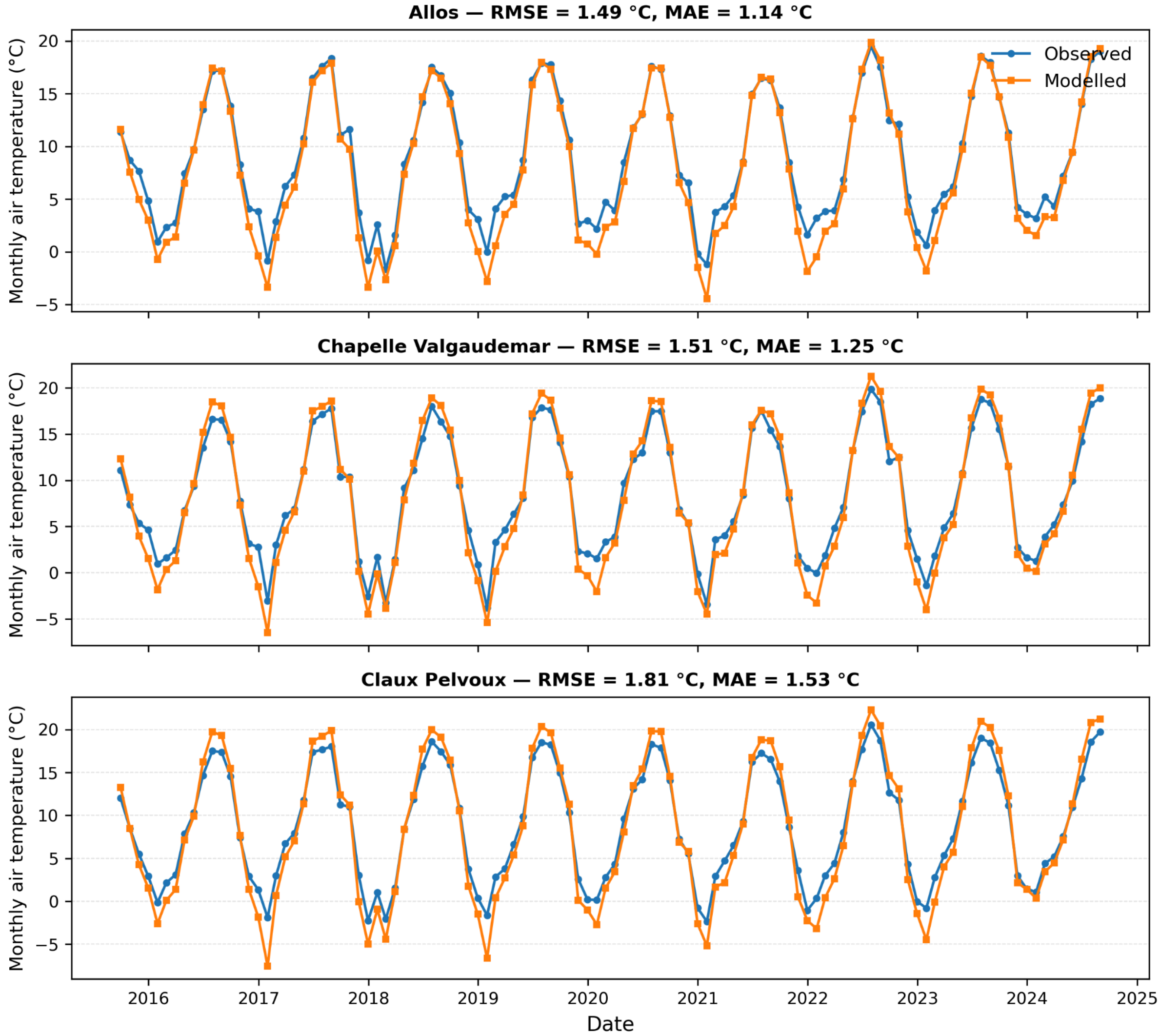

Figure A6 : Comparison between observed and modeled monthly air temperature for representative stations.

Appendix B — Snow water equivalent evaluation

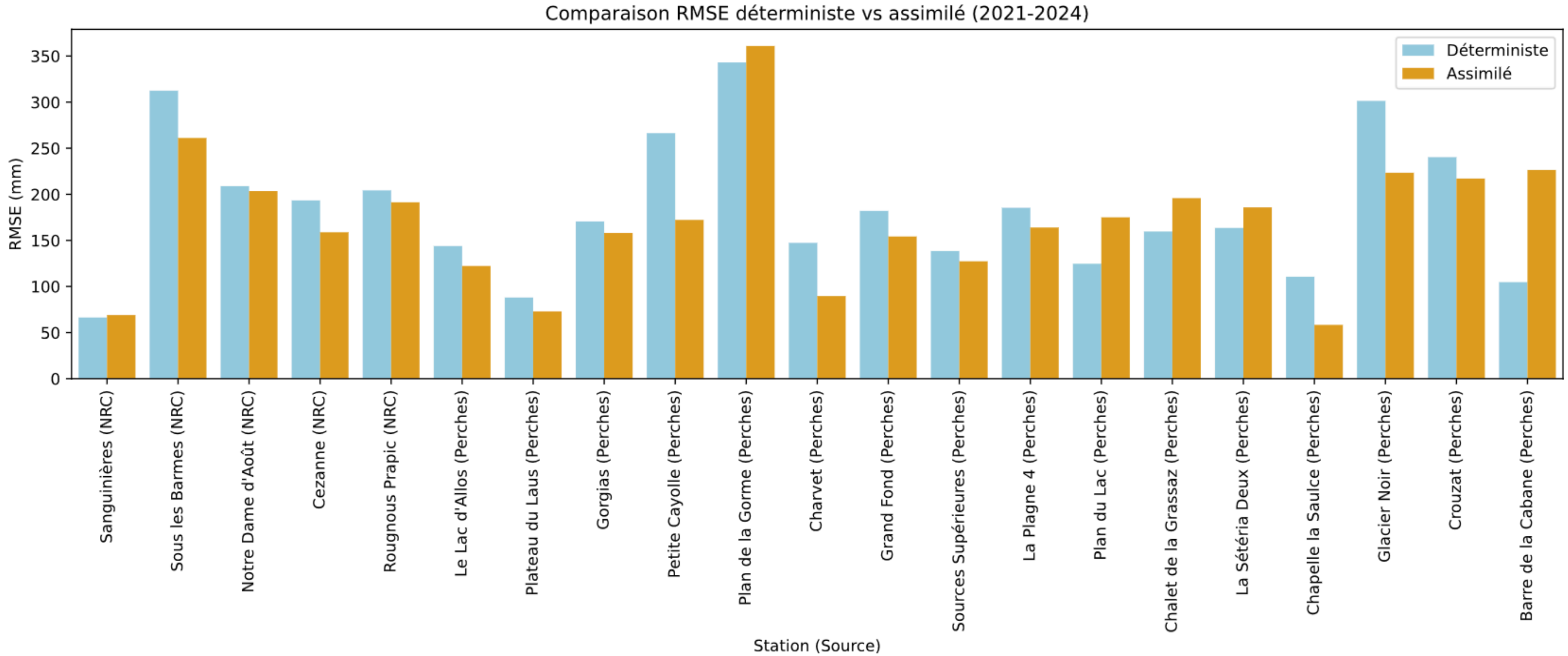

Figure B1 : Snow water equivalent RMSE (mm) values for deterministic and assimilated simulations over the 2021–2024 period for each station.

Appendix C — Catchment-scale analysis

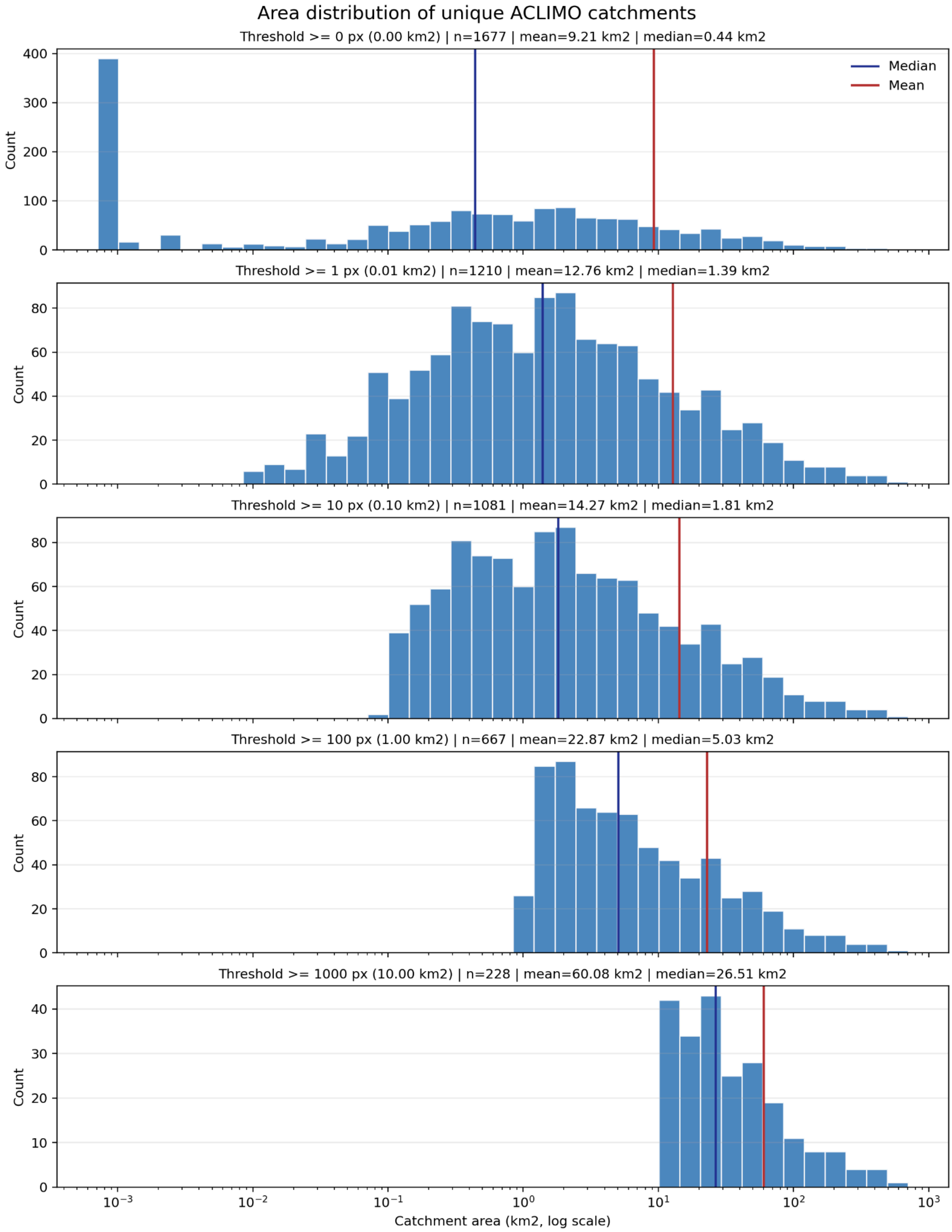

Figure C1 : Distribution of catchment areas for different minimum area thresholds.