https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Distributed snow modeling across contrasting climatic regimes: Forcing sensitivity and regime-dependent assimilation

Mevlüthan Sakallı[1,2], Francesco Avanzi[2], A.Arda Şorman[1], Simone Gabellani[2], Aynur Şensoy[1]

[1] Eskişehir Technical University, Dept. of Civil Eng., 26555 Eskişehir, Türkiye
[2] CIMA Research Foundation, Savona, 17100, Italy

Correspondence to: Aynur Şensoy (asensoy@eskisehir.edu.tr)

Abstract. Mountain snowpacks regulate seasonal water availability in climatically diverse headwater basins, yet long-term distributed snow observations remain sparse in complex mountainous terrain. This study investigates snow regime characteristics, forcing sensitivity, multi-source snow mapping consistency, and data assimilation effectiveness across contrasting climatic conditions over the 2003-2024 period in two hydrologically important basins in Türkiye: the Mediterranean-continental transition Seyhan Basin and the continental Upper Euphrates (Karasu) Basin. The spatially distributed S3M model was driven by three alternative meteorological forcing configurations (station observations, ERA5-Land, and MSWX-Past) and evaluated against ground measurements together with independent reanalysis and satellite products, including CERRA-Land, MODIS, and C-SNOW. Results demonstrate that forcing uncertainty primarily affects snow magnitude (snow water equivalent and snow depth), whereas snow-covered area (SCA) remains comparatively robust across forcing configurations (NSE 0.82-0.91). MSWX-Past consistently outperformed ERA5-Land, particularly in representing precipitation, substantially reducing systematic snow overestimation and improving agreement with independent snow observations. Spatial and long-term analyses further reveal an increasing prevalence of negative snow anomalies after 2013, accompanied by episodic decoupling between snow magnitude and persistence. Data assimilation exhibited pronounced regime-dependent behavior. In the transient Seyhan Basin, assimilation substantially improved local snow dynamics by correcting timing errors and premature melt cycles, increasing station-scale performance from KGE 0.28 to 0.61. In contrast, assimilation in the continental Karasu Basin primarily reduced large-scale accumulation biases through spatially coherent adjustments, while point-scale improvements remained spatially variable. Overall, the results demonstrate that forcing uncertainty primarily affects snow magnitude, whereas the effectiveness of data assimilation is strongly governed by snow-regime characteristics. These findings provide a transferable framework for distributed snow monitoring and demonstrate the operational potential of S3M for hydrological forecasting in climatically heterogeneous, data-scarce mountain basins.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

1 Introduction

Mountain snowpacks function as natural reservoirs in snow-dominated basins, accumulating during winter and releasing water gradually through melt in spring and early summer, thereby regulating streamflow during dry periods (Barnett et al., 2005). In recent decades, substantial changes in snow regimes have been observed globally in response to climate warming, with widespread declines in snow accumulation, earlier melt onset, and reduced snow persistence, particularly in mid-latitude and mountainous regions (Legg, 2021; Pulliainen et al., 2020, Musselman et al., 2018). In regions such as Türkiye, where snowmelt contributes significantly to agriculture, hydropower generation, and municipal water supply exceeding 50% of annual runoff in eastern basins (Şorman et al., 2009) these changes pose serious challenges for water resource reliability and long-term planning. Accurate snow monitoring and modeling are therefore essential under increasing hydro-climatic uncertainty (Beniston et al., 2018; Sospedra-Alfonso & Merryfield, 2017). Beyond its role as seasonal storage, snowpack variability directly controls runoff timing, peak discharge, groundwater recharge, and interannual water availability, affecting flood risk, reservoir operations, and drought resilience.

In mountainous terrain, accurate representation of key snow variables snow water equivalent (SWE), snow depth (HS), and snow-covered area (SCA) is critical for hydrological forecasting and projections (Andreadis & Lettenmaier, 2006; Essery, 2015). Snow processes exhibit pronounced spatial and temporal variability, affecting applications ranging from avalanche forecasting (Bartelt & Lehning, 2002) and snow albedo dynamics (Pedersen & Winther, 2005) to SWE estimation (Raleigh & Lundquist, 2012; Rutter et al., 2009) and snowmelt-driven runoff modeling (Stewart, 2009). To address these diverse applications, snow models of varying complexity have been developed, ranging from temperature-index approaches to multilayer energy balance models. Representative examples include SRM (Martinec et al., 1998), SNOWPACK (Bartelt & Lehning, 2002; Lehning et al., 2002), ALPINE3D (Lehning et al., 2006), SNOW-17 (Anderson, 2006), and S3M (Avanzi et al., 2022). Among these, S3M has been specifically designed for distributed cryospheric applications with computational efficiency and data assimilation capability and has been implemented in operational and semi-operational hydrological forecasting contexts in Alpine regions. Its hybrid energy-temperature structure and flexible assimilation framework make it particularly suitable for data-scarce mountainous basins where high-complexity multilayer models may be computationally demanding.

Despite extensive model development, no universal relationship between model complexity and performance has been established (Rutter et al., 2009; Essery et al., 2013; Magnusson et al., 2015; Avanzi et al., 2016; Terzago et al., 2020). Model performance depends strongly on forcing quality, parameterization choices, and regional characteristics. Snow regimes differ substantially between Mediterranean- transition and continental mountain climates. Mediterranean regimes are typically characterized by fragmented snow cover, frequent melt–refreeze cycles, and strong mid-season variability, whereas continental regimes exhibit deeper, more persistent, and spatially coherent snowpacks. These structural differences are expected to influence both snow dynamics and model behavior across regions, affecting model sensitivity to forcing errors and the effectiveness of data assimilation schemes. Mountainous regions, often characterized by sparse observational

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

networks, present particular challenges for high-complexity models that require extensive input data (Avanzi et al., 2021). Multi-model intercomparison studies further suggest that models of moderate complexity can perform comparably to more sophisticated frameworks under suitable conditions (Essery et al., 2013; Finger et al., 2015; Magnusson et al., 2015; Terzago et al., 2020).

In addition to model structure, the quality of meteorological forcing exerts a first-order control on simulated snow states. Errors in precipitation phase partitioning, temperature, and radiation propagate nonlinearly into snow accumulation magnitude and melt timing, particularly in elevation-driven mountain systems. However, the extent to which forcing sensitivity interacts with climatic regime characteristics remains insufficiently quantified.

In data-limited mountainous environments, numerical snow models provide essential spatial and temporal estimates yet remain subject to structural and forcing uncertainties. Data assimilation provides a mechanism to reduce these uncertainties by integrating observational information into simulated snow states (Helmert et al., 2018; Leisenring & Moradkhani, 2011; Saloranta, 2016). Assimilation approaches vary depending on the observational variable used, including SCA (Andreadis & Lettenmaier, 2006; Clark et al., 2006; Deschamps-Berger et al., 2022; Hou et al., 2021), SWE (De Lannoy et al., 2012; Gan et al., 2022; Micheletty et al., 2022), and HS (Girotto et al., 2024; Helmert et al., 2018; Liu et al., 2013; Magnusson et al., 2017). While assimilation approaches based on SCA, SWE, and HS have been widely explored, their effectiveness is not uniform and is likely influenced by snowpack characteristics such as persistence, magnitude, and spatial coherence. However, comparative evaluations of assimilation performance across contrasting snow regimes remain limited.

Despite these advances, limited attention has been given to jointly evaluating how forcing uncertainty, climatic regime variability, and data assimilation interact in distributed snow modeling. In particular, it remains unclear whether forcing uncertainties primarily affects snow magnitude while leaving spatiotemporal indicators more robust and whether assimilation effectiveness varies systematically across regimes. This gap is critical in Mediterranean–continental transition zones, which represent especially challenging, underrepresented environments due to strong intra-seasonal variability and precipitation phase sensitivity. Türkiye provides a unique natural laboratory where these contrasting regimes coexist within short distances, allowing for a controlled comparison of regime-dependent snow dynamics. Specifically, it remains to be seen how the performance of operational, computationally efficient assimilation approaches is constrained by differences in snow persistence and spatial coherence across these distinct regimes.

This study contributes to the literature by explicitly linking forcing uncertainty, snow regime characteristics, and the effectiveness of data assimilation within a unified distributed modeling framework. Rather than proposing a new assimilation methodology, the study evaluates how a computationally efficient, operationally applicable assimilation scheme performs under contrasting snow-regime conditions.

The objectives of this study are to (i) characterize snow dynamics across contrasting climatic regimes, (ii) quantify the sensitivity of snow magnitude and spatiotemporal indicators to alternative meteorological forcing datasets, and (iii) evaluate the extent to which multi-source data assimilation reduces model uncertainty. This perspective allows us to assess not only

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

model sensitivity to forcing uncertainty but also the conditions under which assimilation can meaningfully improve snow simulations.

2 Study area

Seasonal snowpack is a dominant control on runoff generation in Türkiye's mountainous regions. To evaluate distributed snow dynamics across contrasting hydro-climatic regimes, two snow-dominated basins were selected: the Seyhan Basin, representing a Mediterranean–continental transition system, and the Upper Euphrates (Karasu) Basin, a high-elevation continental headwater. Although both basins exhibit comparable topographic complexity and elevation gradients, they differ markedly in temperature regime and precipitation phase. This contrast provides a robust framework for evaluating snow accumulation and melt processes under distinct climatic controls using the distributed S3M model.

The Seyhan Basin, located in southern Türkiye, covers an area of 21,890 km² and extends from the Taurus Mountains to the Mediterranean Sea (Fig. 1). Elevations range from 0 to 3,707 m, with a mean elevation of 1,500 m, resulting in strong climatic gradients. The basin represents a transition between Mediterranean and continental climates, with mild, humid winters in the lowlands and colder, more continental conditions in the mountainous regions. The mean annual temperature is about 12°C, and the mean annual precipitation is approximately 553 mm. Snow accumulation is primarily confined to higher elevations and exhibits strong spatial variability and intermittent persistence. The Seyhan Basin plays a crucial role in Türkiye's agricultural productivity. Furthermore, its topographic and climatic diversity offers significant potential for renewable energy production, particularly hydropower and solar energy development.

In contrast, the Karasu Basin (10,250 km²), located in eastern Türkiye, forms a high-elevation headwater of the Euphrates River (Fig. 1). Elevations range from 1,125 to 3,538 m, with a mean elevation of 1,983 m. The climate is cold and continental, with a mean annual temperature of 4.9°C and annual precipitation of about 410 mm, most of which falls as snow. The basin is characterized by a snow-dominated hydrological regime, with deeper, more persistent, and spatially coherent snowpack compared to Seyhan.

Together, these basins provide a natural contrast between transient and persistent snow regimes, enabling systematic evaluation of forcing sensitivity and assimilation performance under differing snow conditions.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

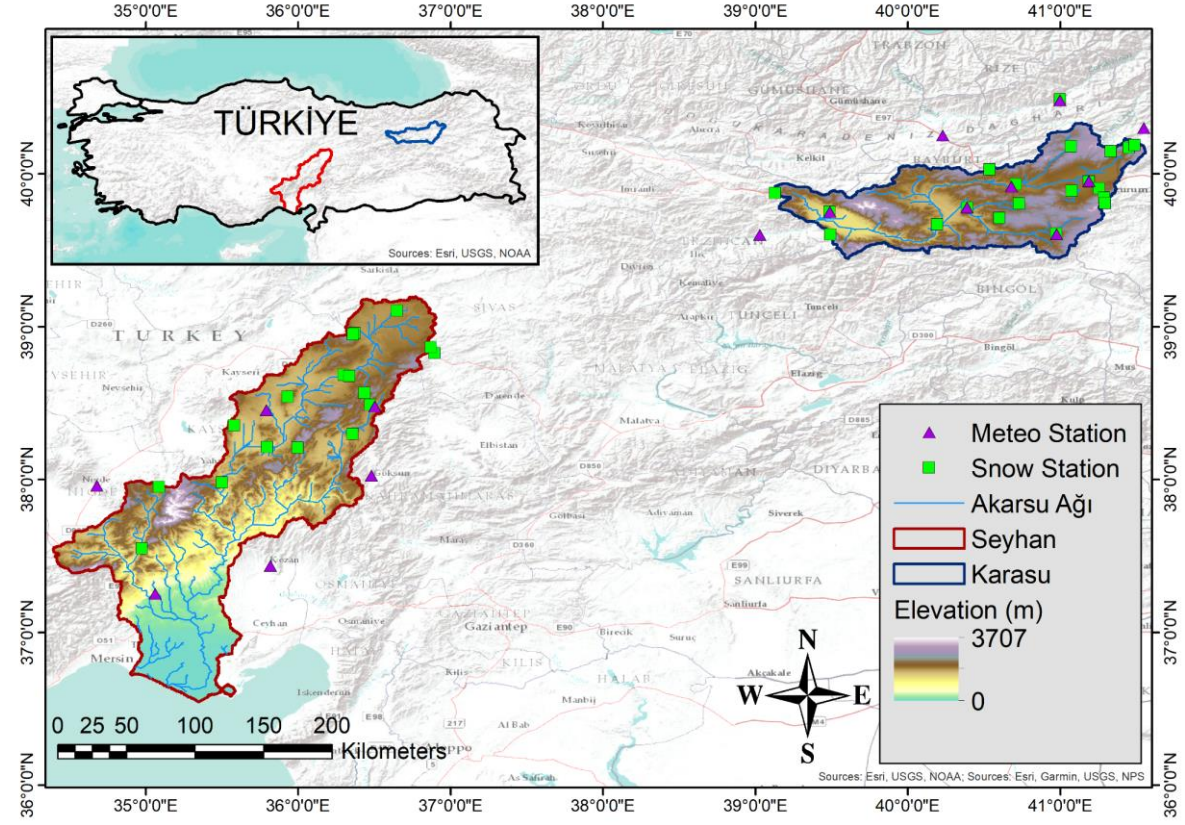


Figure 1. Pilot catchments and observation network. Sources: Esri, USGS, NOAA, Garmin, NPS | Powered by Esri.

3 Data

Despite their hydrological importance and complex mountain topography, both basins lack long-term, spatially distributed snow observations. To address this limitation, a comprehensive multi-source dataset was compiled, including in situ measurements, satellite products, and atmospheric reanalysis data. The S3M model was forced with alternative datasets and evaluated against independent observations, enabling systematic assessment of forcing sensitivity and model uncertainty.

In data-scarce mountainous environments, the limited spatial representativeness of ground observations introduces uncertainty into model forcing and evaluation (Günther et al., 2019; Levin et al., 2023; McMillan et al., 2018). This limitation is particularly critical for snow processes, which exhibit strong elevation-dependent variability and rapid temporal dynamics (Clark et al., 2011; Dozier, 2011; Margulis et al., 2015). Reanalysis and satellite products therefore play a key role by providing spatially continuous datasets that better capture these dynamics.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

3.1 Ground-based meteorological and snow observations

Ground-based observations provide the primary reference for model evaluation. Two networks were used: Automated Weather Observing Systems (AWOS) and snow monitoring stations comprising both manual and automated measurements. A total of 12 AWOS stations per basin provided temperature and precipitation data for the 2003-2024 period.

Snow observations from more than 20 stations were used for independent validation and for the implementation of the data assimilation framework. These stations provide snow depth (HS) measurements through manual surveys and automated telemetry systems comparable to SNOTEL-type installations.

3.2 Reanalysis data

Three gridded datasets were used: ERA5-Land (ERA5-L), MSWX-Past (MSWX-P), and CERRA-Land. The ERA5-Land (Muñoz-Sabater et al., 2021) dataset, released in 2019 by the European Centre for Medium-Range Weather Forecasts (ECMWF) under the Copernicus Climate Change Service (C3S), provides global land-surface variables at 0.1° resolution. The MSWX-Past (Beck et al., 2022) dataset, combining ERA5 with additional gridded products and applying statistical bias correction and downscaling procedures, provides variables at 0.1° resolution. CERRA-Land is a regional reanalysis at 5.5 km resolution, based on the SURFEX land-surface model and incorporating surface observations through the MESCAN analysis system.

ERA5-L and MSWX-P were used as alternative meteorological forcings for S3M, including precipitation, air temperature, relative humidity, and shortwave radiation. Snow depth (HS) and snow water equivalent (SWE) from ERA5-L and CERRA-Land were used for independent evaluation of simulated snow states, while snow-covered area (SCA) was obtained exclusively from ERA5-L.

3.3 Satellite data

Satellite-based snow products were used to evaluate model outputs and support data assimilation. MODIS (500 m) and IMS (4 km) products were used for snow-covered area (SCA) analysis, while SEVIRI provided high-frequency observations under clear-sky conditions. The satellite-based snowmelt equivalent (SWE) and snow depth (HS) products are SWE-E (~25 km) and C-SNOW (~1 km), respectively. SWE-E provides important information in the validation step of the model results, while C-SNOW serves as high-resolution input data for the assimilation structure. These datasets were used for independent validation of simulated snow states and, where applicable, within the data assimilation framework.

The MODIS (MODerate Resolution Imaging Spectroradiometer) snow product (Collection 6) was used in its Cloud-Gap Filled (CGF) version (Hall et al., 2019; Hall & Riggs, 2021). The CGF approach reduces cloud-induced data gaps by incorporating information from adjacent days, enabling temporally consistent snow-covered area (SCA) analysis in mountainous regions where cloud contamination is frequent. The Interactive Multisensor Snow and Ice Mapping System (IMS) (Helfrich et al., 2007) integrates multiple satellite observations and ancillary data through an operational analysis

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

framework. SEVIRI (Spinning Enhanced Visible and Infrared Imager) is a sensor onboard the Meteosat Second Generation (MSG) satellites. The SE-D SEVIRI (H10/H34) snow product derived from the Meteosat Second Generation (MSG) platform provides observations at a 15-minute temporal frequency.

The SWE-E (H13) product provides daily SWE estimates at ~0.25° spatial resolution using passive microwave observations and the HUT retrieval algorithm (Lemmetyinen et al., 2010).

C-SNOW was developed to provide radar-based measurements in mountainous regions of the Northern Hemisphere using the C-band SAR sensor of Sentinel-1. Furthermore, by combining observations from Sentinel-1A and Sentinel-1B, the product effectively reduced the temporal resolution from 12 days to 6 days.

Together, these datasets enable a multi-source evaluation framework in which meteorological forcing, snow magnitude, and spatial snow dynamics can be assessed consistently across scales and data types.

4 Methodology

4.1 Modeling framework

The aim of this study is to evaluate snow dynamics at daily time steps using multiple forcing and observation datasets in two climatically contrasting, snow-dominated basins through the S3M snow model. The overall workflow of the study is illustrated in Fig. 2.

S3M is a spatially distributed, physically based, single-layer snow model designed to simulate dry- and wet-snowpack dynamics with limited input requirements while maintaining computational efficiency (Avanzi et al., 2022). The model is driven by precipitation, air temperature, relative humidity, and incoming shortwave radiation, and represents precipitation phase partitioning (snowfall and rainfall), accumulation, melt, refreezing, liquid water retention, and glacier contributions through a simplified process-based framework. Snowmelt is computed using a hybrid formulation combining explicit shortwave radiation with a temperature-index approach. The model also incorporates an efficient nudging-based data assimilation framework in which snow depth observations are internally converted to snow water equivalent before updating the model state. Given that the present study focuses on forcing sensitivity and data assimilation rather than model development, only a brief description is provided here; a comprehensive description of the model physics and governing equations is provided by Avanzi et al. (2022).

4.2 Data assimilation framework

To integrate observations into the distributed simulations, S3M incorporates a computationally efficient nudging assimilation scheme (Avanzi et al., 2022). This framework progressively reduces discrepancies between model states and observations, thereby avoiding abrupt corrections and preserving mass balance consistency. Crucially, the assimilation is performed directly on the core state variable, snow water equivalent (SWE), rather than snow depth (HS). When independent HS

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

observations are introduced, they are dynamically converted to SWE using the model's internal time-dependent snow density formulations to ensure consistency before relaxation is applied.

While advanced, ensemble-based sequential assimilation techniques such as the Ensemble Kalman Filter (EnKF) offer dynamic background error covariance structures, their mathematical efficiency remains heavily dependent on accurately defining initial forcing error distributions and model structural covariances. In data-scarce, highly complex alpine regions where spatial meteorological networks are sparse and terrain-induced micro-climatic gradients are steep, explicitly parameterizing these covariance matrices often introduces profound statistical over-fitting and sampling errors. Under these highly unconstrained operational conditions, a deterministic nudging framework provides a mathematically stable alternative. By utilizing a continuous relaxation timescale, the scheme bypasses the need for explicit background covariance calculations while effectively acting as a robust spatial mass-balancer and temporal tracking stabilizer. This balance delivers a highly reliable, physically bounded state estimation without the structural vulnerabilities and prohibitive computational overhead inherent to complex stochastic ensemble filters in data-limited domains.

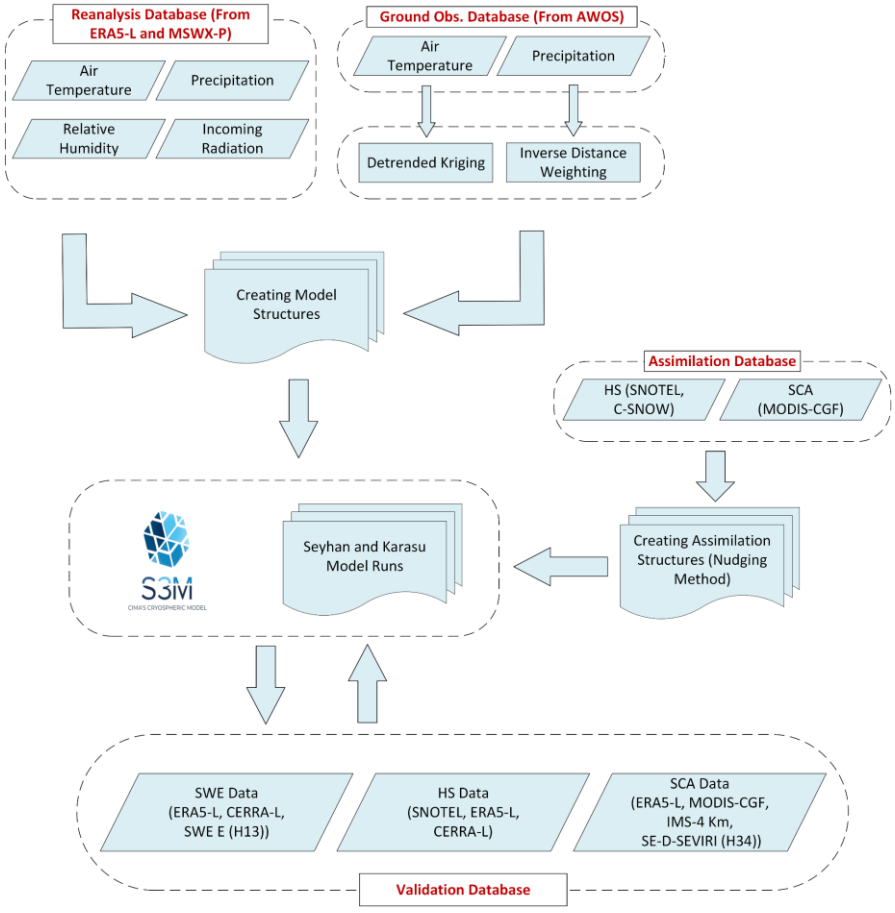


Figure 2. Workflow of the study

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

4.3 Experimental design and model configurations

Three alternative forcing configurations were developed using ERA5-L, MSWX-P, and in situ meteorological observations for the 2003-2024 water years in both the Seyhan and Karasu basins. For reanalysis-driven configurations (ERA5-L and MSWX-P), model runs were performed daily on a uniform 5 km spatial grid, which preserves the native resolution and structural uncertainty of the atmospheric products; the ground-observation baseline was executed on a 1 km grid due to limited station network.

For reanalysis-driven simulations, precipitation, air temperature, relative humidity, and downward shortwave radiation were directly extracted from ERA5-L and MSWX-P. Prior to model implementation, forcing variables were evaluated against ground observations to assess bias characteristics. For the in situ-based configuration, precipitation and temperature were derived from meteorological stations per basin. Spatially distributed fields were generated using Inverse Distance Weighting (IDW) for precipitation and detrended kriging for temperature to account for elevation-dependent gradients. Due to limited availability of relative humidity and shortwave radiation measurements at the station level, these variables were supplemented using MSWX-P data.

Model outputs (SWE, HS, and SCA) were evaluated against independent reanalysis, satellite, and ground-based datasets as described in Section 5. Assimilation experiments were conducted using both HS and SCA observations.

4.4 Performance metrics

Continuous snow variables were evaluated using standard hydro-meteorological metrics (RMSE, NSE, KGE, and Pearson r), while spatial snow cover dynamics were assessed using grid-based categorical indices (POD, FAR, CSI, HR, and SMR) derived from standard contingency tables.

5 Results and discussion

5.1 Meteorological forcing validation

The performance of ERA5-L and MSWX-P was evaluated against daily observations from 24 meteorological stations distributed across the Seyhan and Karasu basins, spanning strong elevation gradients (Fig. 3).

Temperature was consistently better represented by MSWX-Past in both basins, with KGE, NSE, and R^2 values generally exceeding 0.60 and often approaching 1.0. In contrast, ERA5-L exhibited greater variability, particularly in the Karasu Basin, where performance occasionally deteriorated to near-zero efficiency. Temperature skill was slightly higher in Seyhan than in Karasu, likely reflecting lower climatic severity and elevation variability.

Precipitation showed substantially lower and more heterogeneous performance. Although MSWX-Past generally outperformed ERA5-L, both datasets exhibited reduced skill compared to temperature, with KGE values rarely exceeding

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

0.60. ERA5-L frequently produced negative efficiency scores, particularly in the Karasu Basin, indicating limited reliability in capturing precipitation variability.

Overall, MSWX-Past provides a more consistent representation of meteorological forcing across both basins. The better performance of MSWX-Past, particularly for precipitation, is important because precipitation uncertainty propagates directly into simulated snow accumulation.

Previous studies have shown that errors in precipitation forcing generally dominate snow model uncertainty in complex mountain terrain, whereas temperature errors mainly affect the timing of melt rather than seasonal accumulation (Raleigh et al., 2015, Sun & Margulis, 2026). Our results support this understanding across two contrasting climatic regimes and further demonstrate that the benefits of improved forcing are considerably larger in the continental Karasu basin, where larger seasonal snow storage amplifies precipitation-related errors.

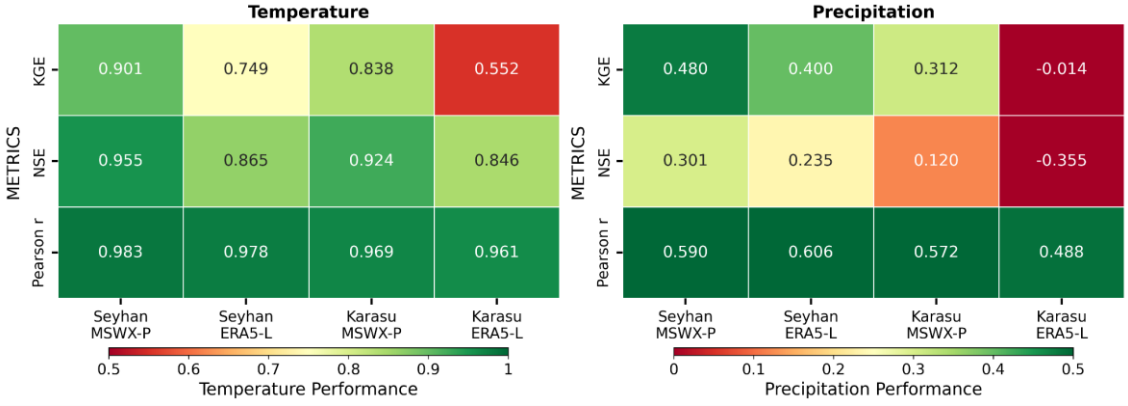


Figure 3. ERA5-L and MSWX-P data validation on the Seyhan and Karasu

5.2 Sensitivity of snow simulations to forcing choice

In this section, how alternative forcing configurations propagate into simulated snow states is evaluated by dividing the assessment into basin-averaged temporal dynamics and grid-scale spatial consistency.

5.2.1 Basin-averaged sensitivity and temporal dynamics

Following meteorological validation, S3M was forced with three alternative datasets (observations, ERA5-L, and MSWX-P) to quantify forcing-driven differences in simulated snow dynamics. Fig. 4 presents the daily median and interquartile range (IQR) distributions of SWE, HS, and SCA for the Seyhan and Karasu basins over the 2003–2024 period.

Forcing choice primarily controls snow magnitude, while its influence on seasonal snow cover dynamics is comparatively limited. ERA5-L–driven simulations generally produced higher SWE and HS values, particularly during accumulation and peak snow periods, whereas MSWX-P simulations were closer to the observation-driven configuration. These differences are more pronounced in the Karasu Basin, where larger snow accumulation amplifies forcing-related contrasts.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

In contrast, SCA is less sensitive to forcing. All configurations reproduce the main seasonal pattern of snow cover, although minor deviations occur during accumulation and melt transitions, especially in the more heterogeneous Seyhan Basin. This indicates that forcing uncertainty affects snow magnitude more strongly than the timing and spatial extent of snow cover. Basin-averaged time series for selected years (Fig. S1 in the Supplementary Materials) further support these patterns. In Seyhan, simulations show similar seasonal timing across forcings, with ERA5-L yielding slightly higher peak SWE during snow-rich years. In Karasu, differences between forcings become more pronounced, particularly under high-accumulation conditions.

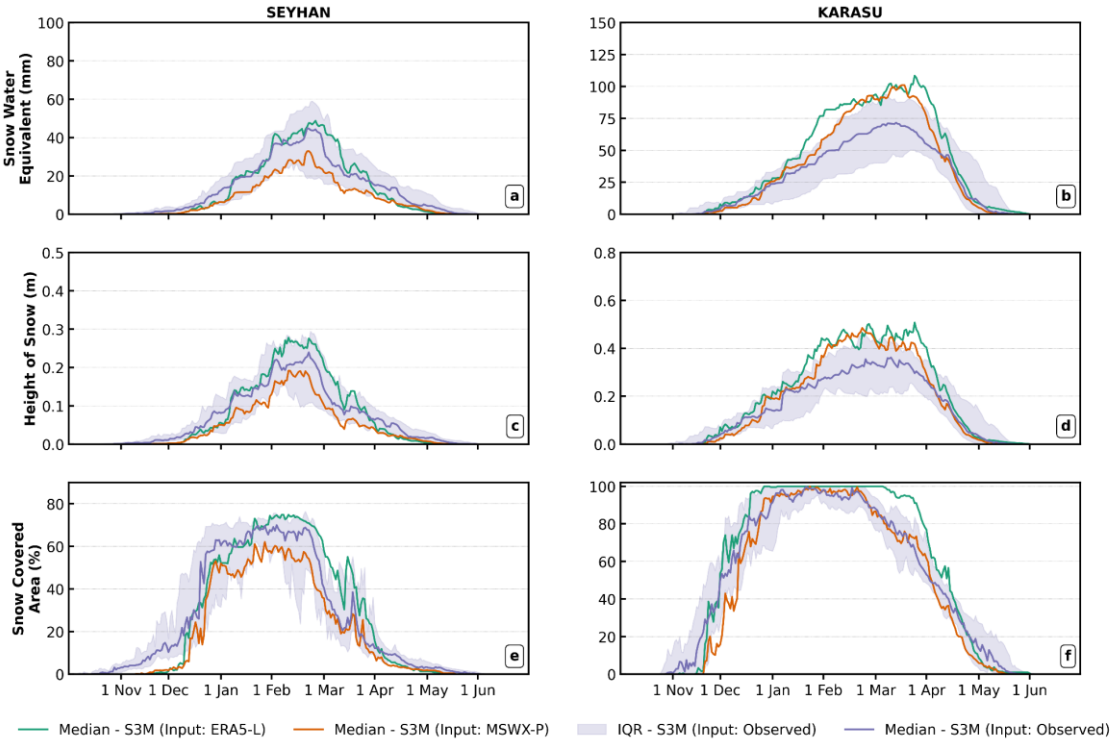


Figure 4. Daily median and interquartile range (IQR) distributions of simulated SWE, HS, and SCA for the Seyhan (left panels) and Karasu (right panels) basins over the 2003-2024 water years.

Figure 5a summarizes the basin-averaged performance metrics for the 2003-2024 water years. Given the lack of long-term, spatially distributed snow water equivalent (SWE) and snow depth observations, a common limitation in mountainous regions, CERRA-Land is utilized as a spatial benchmark for snow depth magnitude and variability. However, due to shared structural characteristics with reanalysis-based products, CERRA-Land does not provide a fully independent validation. To ensure a robust, independent evaluation, S3M simulations are concurrently validated against basin-averaged observational snow depth (Obs.(D)-HS) and MODIS-derived snow cover area (SCA).

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

The results reveal a strong dependency on the chosen validation reference. When evaluated against CERRA-Land, ERA5-L driven simulations exhibit the highest agreement, particularly in the Karasu basin. However, this performance shifts dramatically when compared against independent observations (Obs.(D)-HS). In the Seyhan basin, the ERA5-L simulation performance drops sharply. In contrast, the model driven by observed data demonstrates much greater stability and localized accuracy across both basins when verified against actual observations. The high agreement between ERA5-L driven runs and CERRA-Land is a classic artifact of internal model/reanalysis coupling (as both rely on shared ECMWF atmospheric boundaries). Across all forcing configurations, SCA metrics remain consistently high and less sensitive to forcing shifts, indicating that forcing uncertainty primarily impacts snow magnitude metrics rather than horizontal snow extent.

The heatmaps (Fig. 4) reveal that while temperature fields are exceptionally well-reproduced across both basins and datasets, precipitation metrics exhibit severe degradations and high inter-basin variability. In the Seyhan basin, MSWX-P provides slightly better representation of precipitation relative to ERA5-L, which directly translates to MSWX-P's higher performance in capturing independent observed snow depth (Fig. 5a). Conversely, in the Karasu basin, ERA5-L's precipitation metrics collapse entirely. This severe underperformance in capturing actual precipitation events explains why the ERA5-L-driven S3M model, despite artificially aligning well with the reanalysis-bound CERRA-Land benchmark, exhibits a noticeable performance drop when confronted with independent observational snow data. These findings underscore that precipitation forcing errors remain the primary driver of distributed snow modeling uncertainty in Türkiye's complex transition zones.

Overall, the results indicate that forcing uncertainty primarily affects snow magnitude, whereas seasonal snow cover dynamics remain comparatively robust. Similar behavior has been reported in other mountainous regions (e.g., Günther et al., 2019; Magnusson et al., 2015), highlighting the importance of precipitation phase representation as a major source of uncertainty in distributed snow modeling. This distinction between snow amount and snow-covered area has important implications for operational applications. While snow-covered area remained comparatively robust across the different forcing datasets evaluated in this study, snow depth was considerably more sensitive to uncertainties in meteorological forcing, particularly precipitation. Previous studies have likewise shown that atmospheric forcing uncertainty is a major source of error in snow simulations, whereas satellite-derived snow-covered area provides a reliable representation of snow extent and is widely used in operational snow monitoring and snow data assimilation (Margulis et al., 2016; Largeron et al., 2020). Consequently, satellite-derived SCA may be sufficient for monitoring snow extent, whereas applications such as seasonal water-resource assessment, reservoir operation, and snowmelt forecasting require higher-quality meteorological forcing to accurately represent snow storage and meltwater availability (Li et al., 2019; Wang et al., 2020).

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

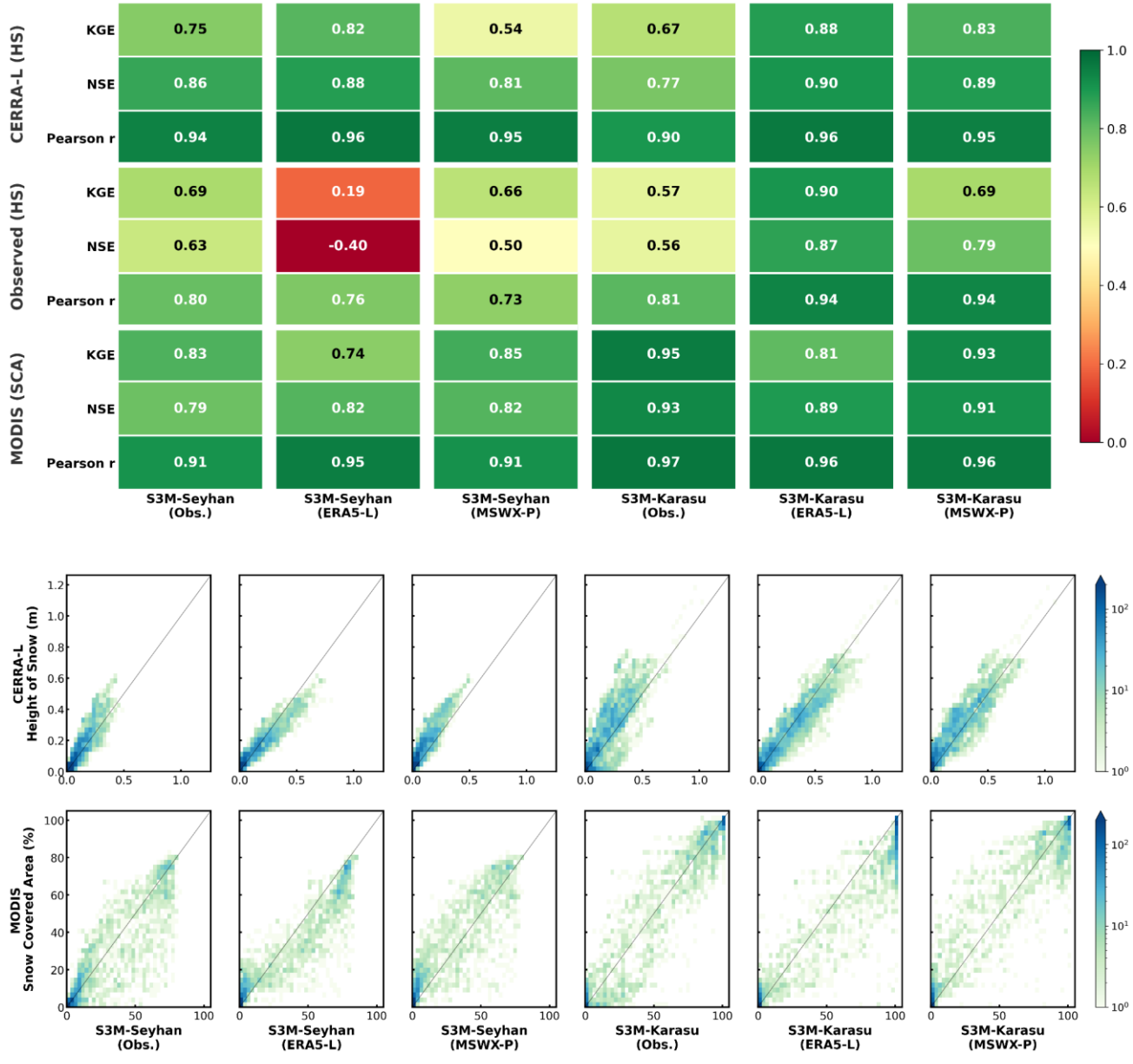


Figure 5. (a) Heatmap summarizing the performance of S3M simulations, (b) Grid-scale agreement between S3M simulations and independent reference datasets.

5.2.2 Spatial consistency and grid scale evaluation

To complement the basin-averaged statistics (Fig. 5a), Figure 5b illustrates grid-scale agreement between simulated and reference snow states. CERRA-Land comparisons reveal systematic underestimation at higher snow depths across all forcing configurations, with larger spatial dispersion in the continental Karasu Basin reflecting its deeper snowpacks and more complex terrain. In contrast, MODIS comparisons demonstrate consistently robust representation of snow-covered area

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

despite a slight positive bias. These results reinforce that meteorological forcing primarily influences snow magnitude, whereas spatial snow extent remains comparatively robust across forcing datasets.

Spatial comparisons under clear-sky conditions provide further insight into product consistency (Fig. S2 in the Supplementary Materials). In the Seyhan Basin, S3M reproduces the characteristic fragmented snow distribution confined to higher elevations, consistent with satellite and reanalysis products. Discrepancies are most evident during the ablation period, when rapid melt and patchy snow cover increase spatial uncertainty across all datasets. In the Karasu Basin, earlier accumulation onset and longer snow persistence are consistently captured. Spatial agreement between S3M and reference products is generally higher than in Seyhan, particularly during peak accumulation periods. Differences remain during the melt phase but are less pronounced, reflecting the basin's more spatially coherent snow cover. Overall, these results indicate that spatial agreement is strongest under stable snow conditions, while uncertainties increase during transitional periods such as accumulation onset and melt.

5.2.3 Contingency-based evaluation of snow detection

Pixel-based categorical performance indicates strong spatial detection skill across both basins (Fig. 6 and Fig. 7). Probability of Detection (POD) and Hit Rate (HR) remain consistently high, while False Alarm Ratio (FAR) is generally low, confirming reliable identification of snow-covered pixels.

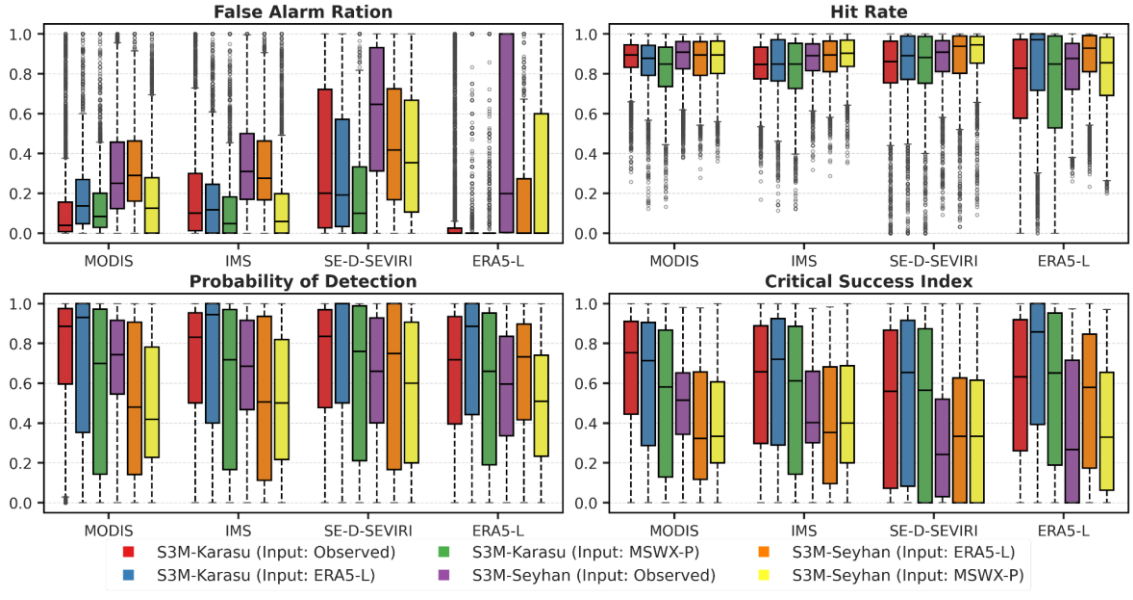


Figure 6. Pixel-based contingency table performance metrics for S3M simulations. Boxplots summarize spatial performance distributions over the 2003–2024 period.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Differences among forcing datasets were limited although MSWX-P and observation-driven simulations show more consistent performance, while ERA5-L driven exhibits marginally lower skill in some cases, particularly in the Karasu Basin. Detection performance also varies across reference datasets: FAR increases notably for SEVIRI and ERA5-L (>0.4), indicating higher uncertainty, whereas MODIS and IMS show more stable results.

Clear basin contrasts are evident. The Karasu Basin, exhibits higher Critical Success Index (CSI ~0.6-0.9) and more stable performance, reflecting its persistent and spatially coherent snow cover. In contrast, the Seyhan Basin shows lower CSI values (~0.3-0.7) and greater sensitivity to forcing, consistent with its fragmented snow regime.

Seasonal analysis (Fig. 7) indicated reduced detection skill during accumulation and melt periods, while peak winter months showed higher performance under more stable snow conditions. These seasonal contrasts were more pronounced in the Seyhan Basin, consistent with its higher intra-seasonal variability.

Overall, snow detection skill was less sensitive to forcing selection than snow magnitude, suggesting that spatial snow presence is more robustly captured than snow amount. This behavior is consistent with previous studies indicating that SCA is generally more robust to forcing uncertainty than SWE or snow depth (Clark et al., 2011; Frei et al., 2012).

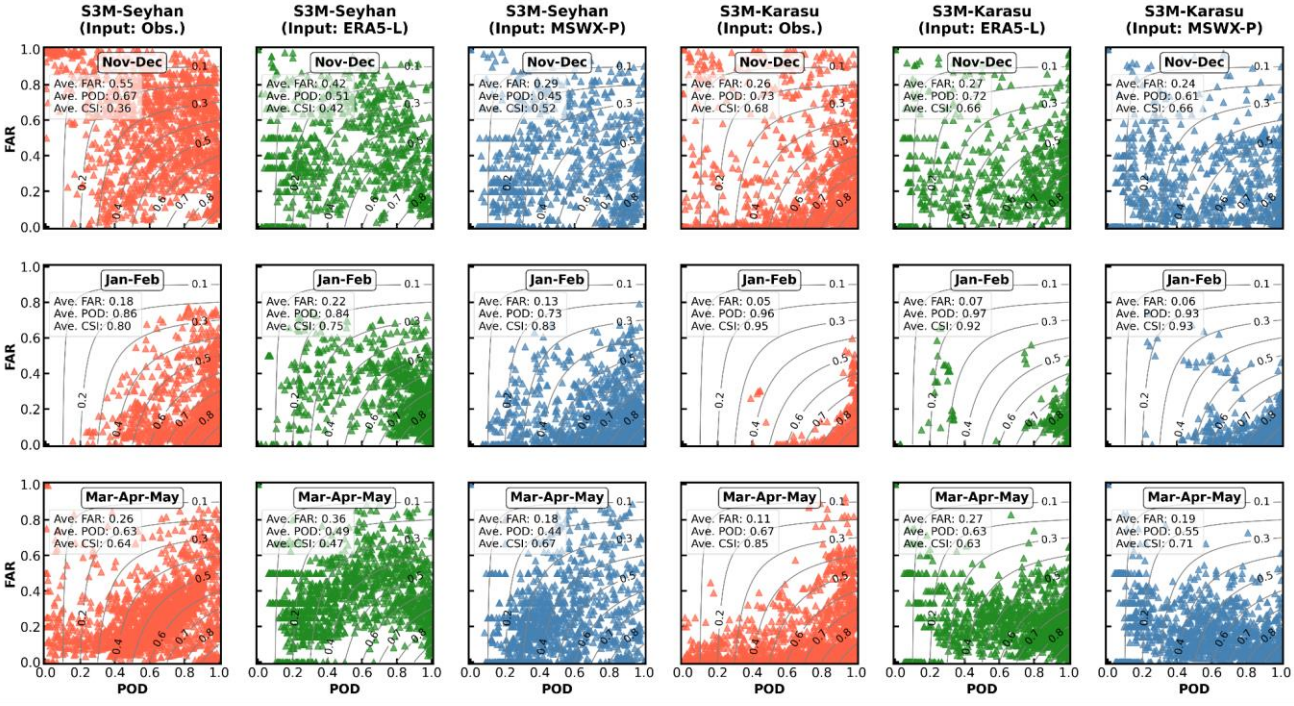


Figure 7. Seasonal mean False Alarm Ratio (FAR) and Probability of Detection (POD) evaluated against MODIS SCA data.

5.3 Ground-based snow validation

Ground-based snow observations provide a direct reference for evaluating simulated snow states. Station-level validation of S3M configurations was conducted using nine snow observation stations in each basin (Figure 8).

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

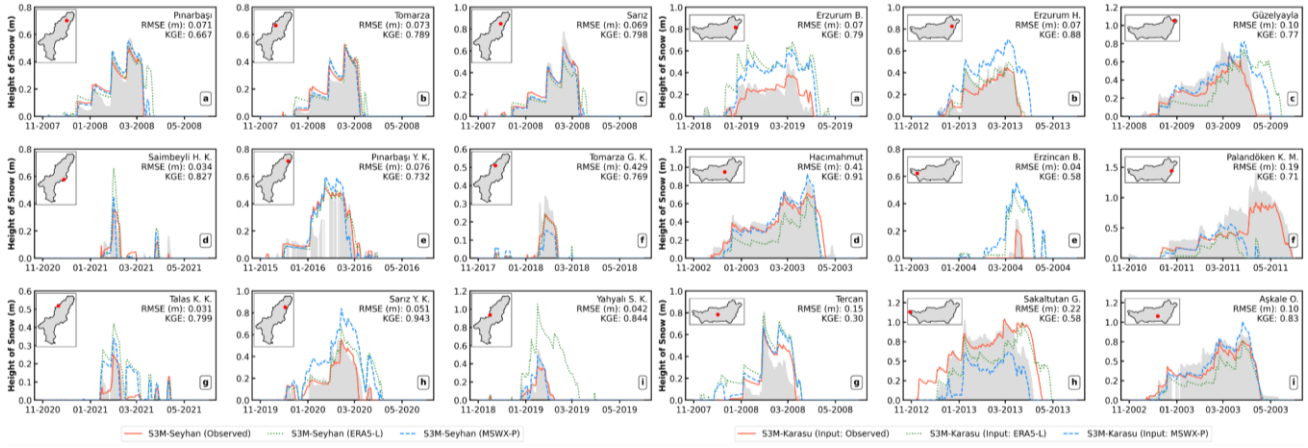


Figure 8. Station-level comparison of simulated and observed snow depth (HS) for selected water years.

In the Seyhan Basin, where stations are primarily located in upstream mountainous areas, model configurations exhibited broadly comparable performance; however, forcing-related differences were evident. ERA5-L–driven simulations generally produced higher snow depth estimates at several stations, with pronounced positive deviations at Yahyalı S.K., Saimbeyli H.K., and Talas K.K. In contrast, MSWX-P forcing yielded estimates more closely aligned with observation-driven simulations, indicating reduced systematic bias. Nevertheless, localized discrepancies remained, suggesting sensitivity to site-specific conditions and local variability.

In the Karasu Basin, characterized by higher and more persistent snow accumulation, deviations among configurations were more pronounced. Larger differences were observed across both low- and high-elevation stations, suggesting that forcing uncertainty affects snow simulations across the full elevation range. ERA5-L forcing generally produced higher snow depth estimates, while MSWX-P and observation-driven simulations showed more comparable behavior at several stations.

Aggregated station statistics (Fig. 9) support these patterns. The Seyhan Basin exhibited slightly higher mean performance (KGE ~ 0.66) compared to Karasu (~ 0.55), despite its lower overall snow accumulation. In Karasu, reduced performance was associated in part with stations having shorter records (e.g., Tercan) and greater variability in accumulation. High-performing stations in Seyhan (e.g., Talas K.K. and Pınarbaşı Y.K.) reached KGE values approaching 0.9, indicating strong local agreement.

Overall, station-based validation supports earlier findings: ERA5-L forcing tends to produce higher snow magnitude estimates, whereas MSWX-P yields more balanced performance relative to observations. Performance variability is greater in the Karasu Basin. Bias patterns indicate systematic overestimation in ERA5-L simulations, whereas MSWX-P reduces these errors and achieves more consistent performance, as reflected in higher and more stable KGE values.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

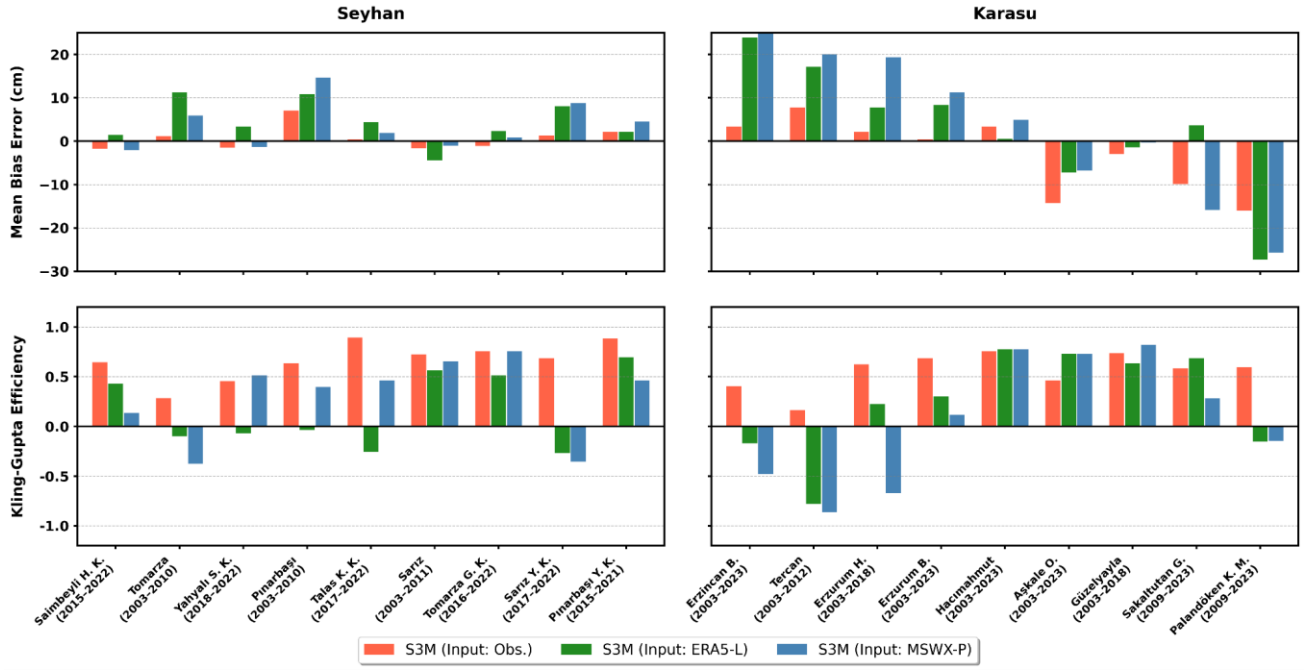


Figure 9. Station-level performance metrics for snow depth simulations aggregated across available water years.

5.4 Basin-scale snow regime characteristics

5.4.1 Interannual variability and anomaly patterns

Interannual variability in both snow magnitude (SWE) and persistence (snow-covered duration) reveals clear temporal shifts across the two basins (Fig. 10). Basin-averaged SWE anomalies indicate substantial year-to-year variability, with values ranging approximately between +40 - 50 mm and -40 - 60 mm. A noticeable shift toward more frequent negative anomalies occurs after ~2013 (Fig. 11). The magnitude of variability is generally higher in Karasu, reflecting its larger snow accumulation potential, whereas Seyhan exhibits more moderate but still pronounced fluctuations.

The increasing occurrence of negative snow anomalies after 2013 is consistent with reported warming trends and declining snow conditions across Türkiye and the eastern Mediterranean (Akyürek et al., 2023; Alexopoulos, 2026). Our results further suggest an emerging decoupling between snow amount and snow persistence, indicating that reductions in seasonal snow storage are not necessarily accompanied by proportional decreases in snow-covered duration. This behavior likely reflects the increasing influence of mid-winter melt events and more transient snowpack dynamics under a warming climate, consistent with broader observations of climate-driven changes in seasonal snow regimes (Pulliainen et al., 2020).

Snow-covered duration anomalies show a comparable range (approximately +30 - 40 days to -40 - 50 days), but with stronger intra-annual variability, particularly in Seyhan, while Karasu maintains relatively more stable and spatially coherent patterns.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

5.4.2 Decoupling between snow magnitude and persistence

The long-term interannual variability (2003–2024) reveals a near-perfect coupling between SWE and HS anomalies across both basins, indicating that physical snow depth remains the primary driver of regional water storage fluctuations (Fig. 11). A distinct regime-dependent climate sensitivity emerges: the continental Karasu basin exhibits highly amplified mass and depth anomalies compared to the milder, Mediterranean-transition Seyhan basin, reflecting its pronounced vulnerability to large-scale winter precipitation shifts. While both basins generally exhibit synchronized regional drought responses (e.g., 2007, 2014, 2018, and 2023), localized decoupling occurs in specific years (e.g., 2010, 2019), highlighting the complex atmospheric transition dynamics across Türkiye. Comparison of SWE and snow-covered duration anomalies reveals that changes in snow magnitude and persistence are not always synchronous (Fig. 11). For instance, years with near-neutral or slightly positive SWE anomalies can correspond to negative duration anomalies, indicating shorter but more concentrated snow accumulation periods. Conversely, some years exhibit modest SWE deficits but relatively stable snow duration. These inconsistencies suggest that snow magnitude and persistence may respond differently to climatic forcing, particularly under conditions of intermittent snowfall and mid-season melt events. For instance, a prolonged cold wave in 2012 triggered a synchronized, record-high spike in snow days despite moderate peak SWE. Crucially, the post-2019 period shows a progressive, multi-variable decline, culminating in a severe, synchronized collapse of snow duration and magnitude in 2023. This ongoing downward trend points to accelerated spring melt cycles, signaling a critical shift toward earlier runoff peaks and protracted summer dry periods in these snow-fed headwaters.

Overall, these results indicate that snow regime variability cannot be fully described by magnitude alone, and that temporal characteristics of snow cover play an important role, particularly in Mediterranean-transition environments.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

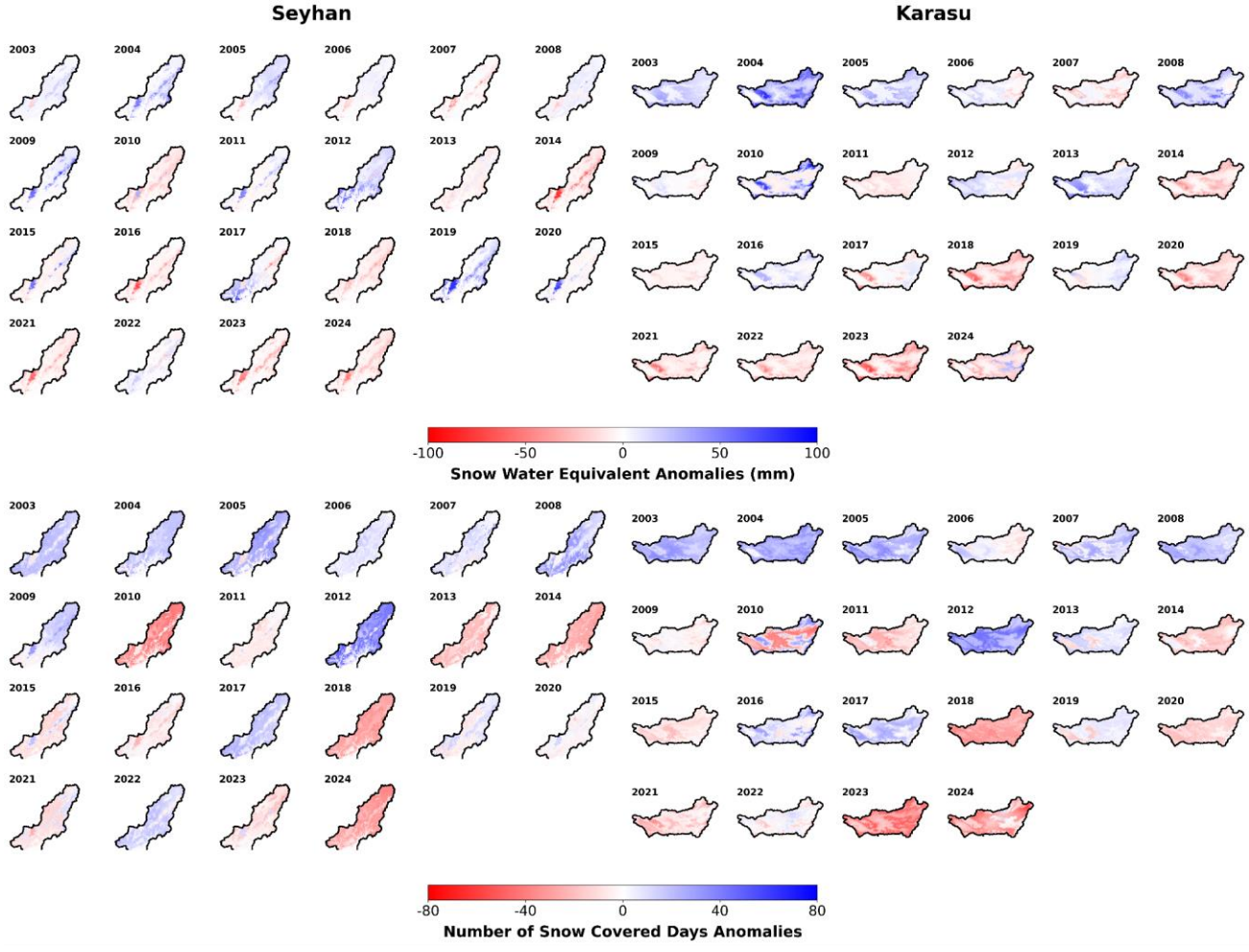


Figure 10. Interannual anomalies of SWE (top) and snow-covered duration (bottom) for the Seyhan and Karasu basins over the 2003-2024 period. Spatial maps show yearly deviations from basin-wide means, and time series represent basin-averaged anomalies.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

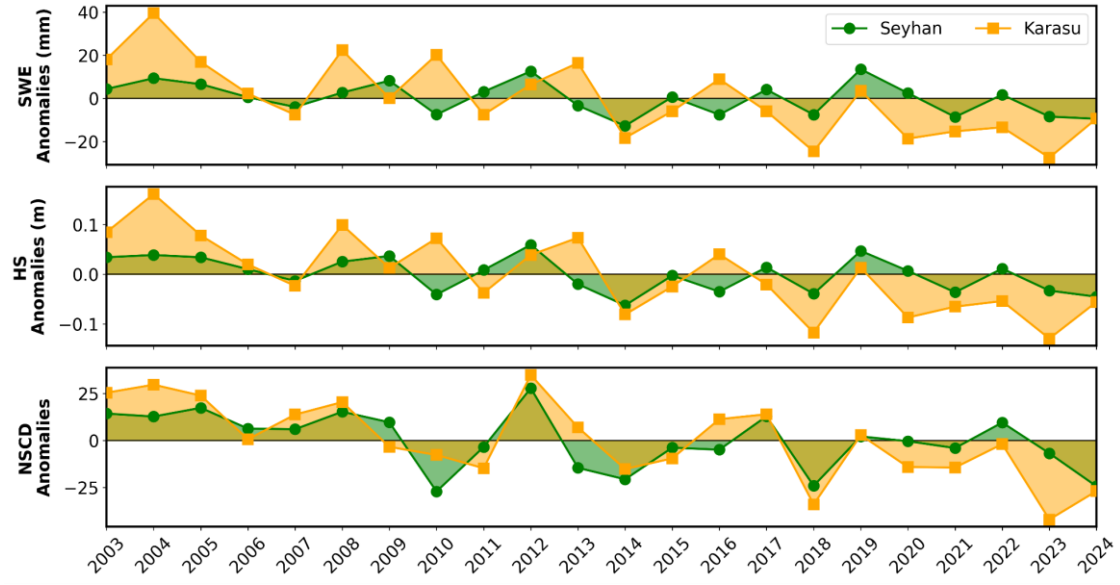


Figure 11. Yearly basin-averaged anomalies for Seyhan and Karasu basin over the 2003-2024 period.

5.5 Impact of data assimilation on snow simulations

5.5.1 Assimilation framework

Snow observations were assimilated into S3M using a nudging-based approach during the active season (November–May), prioritizing seven water years with optimal observational density. The scheme integrates distributed in situ snow depth (HS) and MODIS snow cover area (SCA) simultaneously as primary operational inputs. To evaluate the sensitivity of the system to alternative satellite-derived inputs, experimental runs were also conducted substituting in situ HS with the C-SNOW dataset. While C-SNOW provides high-resolution spatial coverage, its implementation is constrained by its inherent dry-snow masking threshold; the signal saturation and data masking caused by liquid water content during wet-snow phases limit its continuous applicability during crucial transitional melt periods.

While SCA primarily constrains the horizontal spatial extent of snow cover, HS directly scales the vertical snow mass. This dual-constrained approach allows us to evaluate whether the assimilation impact is driven by spatial correction, magnitude adjustment, or a combination of both. To ensure local representativeness across complex terrain, the station-based HS point observations were spatially interpolated using elevation-dependent lapse rates to account for the strong topographic gradients characteristic of the study basins.

5.5.2 Temporal and spatial impacts

Assimilation effects differed markedly between the two basins, both in magnitude and spatial coherence (Fig. 12). In the continental Karasu Basin, the assimilation framework introduces highly coherent, large-scale adjustments that address systematic model biases in a bi-directional manner. During years of severe underestimation (e.g. 2004), the scheme adds up

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

to +150 mm of SWE to high elevation accumulation zones (indicated in blue). Conversely, during high-snow years prone to model overestimation (e.g. 2009, 2019), it systematically dampens excess snow mass by up to -150 mm (indicated in red).

In contrast, assimilation impacts in the Mediterranean-influenced Seyhan Basin are visibly weaker and more fragmented. The spatial adjustments in Seyhan are highly heterogeneous and localized, with opposing positive and negative patches frequently coexisting within the same water year (e.g. 2017, 2019). This localized behavior reflects the basin's transient snow regime, where rapid melt cycles and limited snow persistence restrict the ability of assimilation to produce coherent large-scale corrections.

Across both basins, the assimilation effects were strongly elevation-dependent. Corrections were concentrated in high-elevation zones where snow accumulation dominates, while low-elevation areas showed minimal change. This indicates that assimilation does not introduce random perturbations but instead redistributes snow states in a physically consistent manner, aligned with orographic controls. Overall, these results demonstrate that assimilation primarily acts to constrain snow magnitude in regions of persistent accumulation, while its effectiveness diminishes in basins characterized by shallow and short-lived snowpacks.

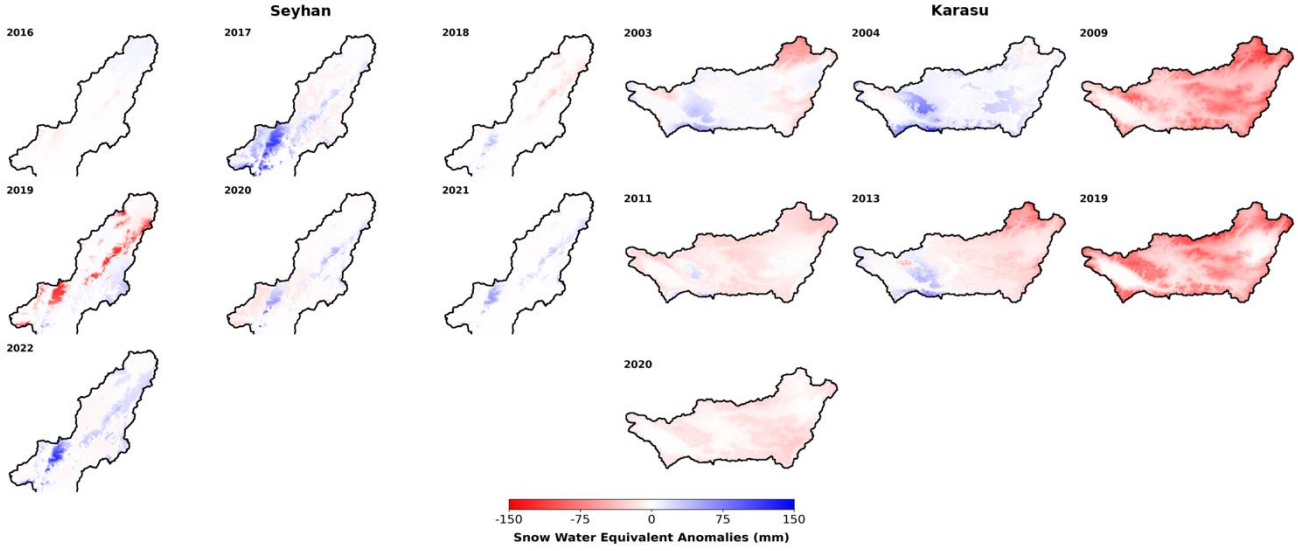


Figure 12. Interannual anomalies of SWE after data assimilation for the Seyhan and Karasu basins over the 2003-2024 period.

5.5.3 Different assimilation structures impacts

To evaluate how different data structures constrain regional snow states, we compared the distributed SWE anomaly fields resulting from the assimilation of satellite-derived C-SNOW against the baseline in situ framework (Fig. 13).

A stark contrast in spatial adjustment behavior emerges between the two data sources, highlighting their complementary strengths. The C-SNOW assimilation structure triggers intense, highly localized negative SWE anomalies (exceeding 200 mm) that sharply trace upper topographic boundaries across multiple water years. While this behavior reflects the product's strict dry/wet-snow masking threshold, it underscores C-SNOW's immense value as a high-resolution spatial constraint: it

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

455 excels at identifying precise, fine-scale snowline boundaries and high-altitude depletion zones that sparse station networks inherently smooth over.

Conversely, the ground-observation framework yields topographically continuous, bi-directional mass adjustments dynamically introducing widespread, moderate reductions during overestimating years (Karasu 2019) or injecting substantial mass (up to 200 mm) during underestimating seasons (Seyhan 2022). Ultimately, these results demonstrate that while point-
460 based observations offer high physical stability for basin-wide mass scaling, high-resolution radar products like C-SNOW provide an irreplaceable spatial tool for capturing complex, terrain-guided snow distribution margins.

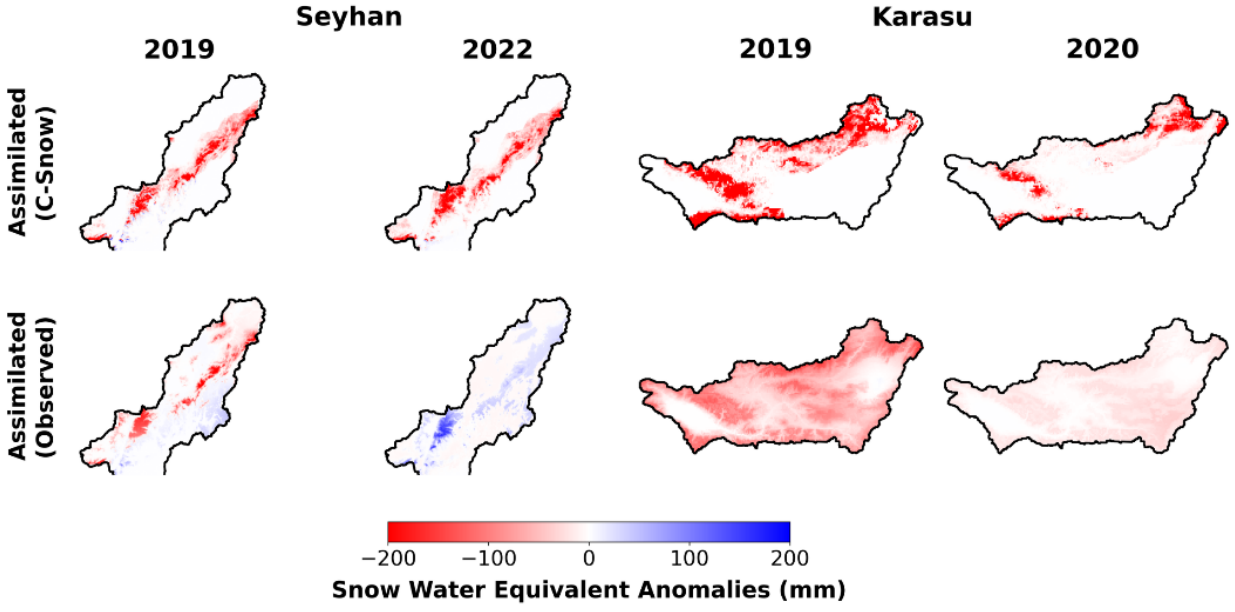


Figure 13. Anomaly maps for two different assimilation forcings a) Seyhan b) Karasu Basin.

5.5.4 Station-level performance

465 To assess the local-scale impact of the nudging framework, Kling-Gupta Efficiency (KGE) scores were cross-examined against open-loop station observations (Fig. 14). Broadly, the assimilation of multi-source data succeeds in enhancing point-scale model representativeness, though its relative efficiency is tightly bounded by the underlying physical deficiencies of the unconstrained runs (Fig. 9).

For the Seyhan Basin, local performance gains are highly consistent and widespread, with assimilation yielding a positive
470 skill elasticity across 7 out of 8 stations. The open-loop baseline profiles (Fig. 8) reveal a persistent tendency of the unconstrained gridded configurations (ERA5-L and MSWX-P) to exhibit a systematic positive mean bias error (up to +15 cm) which prematurely triggers spring ablation or misjudges peak accumulation (e.g., Develi K.K. and Yahyalı S.K.). Because these errors stem primarily from unconstrained local forcing inputs, the continuous injection of observational data

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

acts as a highly effective corrective baseline, producing substantial KGE jumps at previously poorly simulated sites (e.g., Develi K.K. rising from 0.28 to 0.61).

For the Karasu Basin, in contrast, the continental domain exhibits a highly localized and uneven response to assimilation, highlighting the inherent challenges of cell-to-point representativeness matching in rugged alpine terrain. While substantial skill gains are achieved at highly unconstrained sites like Aşkale O. (KGE rising from 0.43 to 0.81), localized performance drops are observed at Güzelyayla and Erzincan B. The open-loop dynamics explain these regressions: at Güzelyayla, the actual snowpack exhibits a prolonged, late-season persistence into May, whereas all open-loop configurations prematurely collapse to zero by early April. When the nudging framework attempts to reconcile this severe, topographically driven phase discrepancy near the melting margin, it introduces representative errors that conflict with local micro-climatic accumulation realities.

These regime-dependent performance bounds are strongly governed by the localized orographic configurations of the validation stations. In the Seyhan Basin, the meteorological stations occupy a tightly clustered, mid-altitude elevation band ranging from 1,350 m to 1,835 m. In this transitional Mediterranean zone, the snowpack is highly vulnerable to marginal temperature shifts around the freezing threshold, meaning that assimilation yields a uniform, systematic correction of premature melt phases across the entire elevation bracket.

Conversely, the Karasu Basin features extreme, high-gradient vertical topography, spanning from low-altitude valley floors like Erzincan Bölge (1,216 m) to high alpine peaks like Palandöken (2,615 m). When the regional nudging framework operates across these severe altitudinal gradients, horizontal scale-matching introduces representative errors. This is particularly evident at high-altitude persistent sites like Güzelyayla (2,080 m), where regional spatial updates smooth over the micro-climatic orographic controls that sustain late-season snowpacks, resulting in localized point-scale KGE regressions despite improving broader basin-wide magnitude trends.

Ultimately, these combined results demonstrate that data assimilation functions as a robust error-correction mechanism across transition zones, achieving its highest efficiency where open-loop simulations suffer from uniform forcing biases. However, where models suffer from severe phase shifts or steep micro-climatic gradients, local topographic complexities can constrain the spatial propagation of point-scale corrections.

The contrasting assimilation response likely reflects fundamental differences in snow regime characteristics between the two basins. In the transient Seyhan Basin, frequent accumulation–ablation transitions increase the sensitivity of snow evolution to short-term meteorological variability, allowing sequential assimilation updates to more effectively constrain the temporal evolution of the snowpack. In contrast, the continental Karasu Basin is characterized by longer periods of persistent seasonal snow accumulation, where assimilation primarily reduces systematic biases in snow storage rather than substantially altering snowpack evolution. Similar dependence of assimilation performance on snowpack persistence, meteorological forcing uncertainty, and observation characteristics has been reported in previous snow data assimilation studies (Slater and Clark, 2006; Piazzi et al., 2018). Together, these findings suggest that assimilation strategies should be adapted to prevailing snow regime characteristics rather than applied uniformly across climatically contrasting mountain environments.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

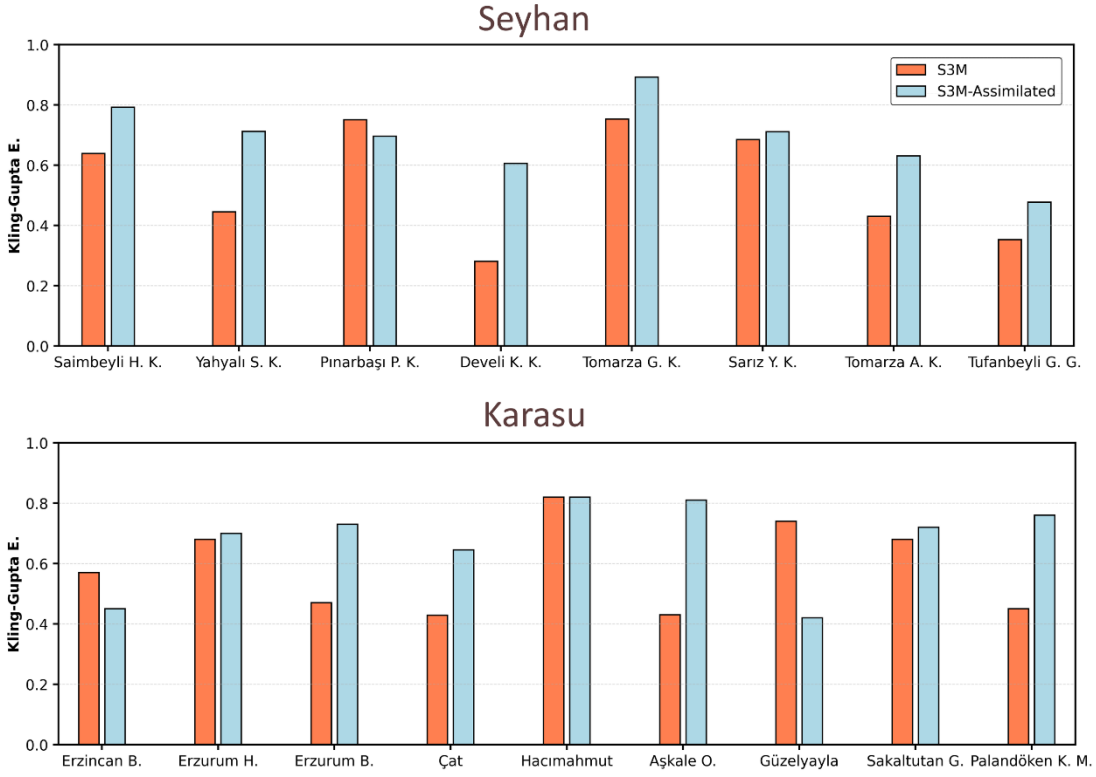


Figure 14. Station-level performance metrics (KGE) before and after assimilation for the Seyhan and Karasu Basin.

While the contrasting assimilation responses observed between Seyhan and Karasu primarily reflect differences in snow-regime characteristics and forcing uncertainty, they also depend on the accuracy of the assimilated observations. Consequently, the improvements obtained through assimilation should be interpreted as the combined outcome of model performance and observational uncertainty, rather than as a direct measure of assimilation algorithm efficiency alone. Although the multi-source evaluation adopted in this study reduces dependence on any single observational dataset, further work incorporating explicit observation-error characterization or probabilistic assimilation frameworks would provide a more comprehensive assessment of uncertainty propagation.

5 Limitations of the study

While this study demonstrates the reliable performance of the distributed S3M model across different climatic regimes, several inherent limitations regarding the data infrastructure and sensor characteristics should be noted. First, the spatial scarcity of high-altitude meteorological and snow observation stations in rugged mountain terrains limits our ability to fully capture sharp, topographically driven variability in temperature, precipitation amounts, and precipitation phase (rain/snow separation). Although in situ observations provide the most reliable reference for model evaluation, measurement uncertainties associated with sensor accuracy, wind-induced snow redistribution, and local microclimatic variability remain

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

unavoidable, particularly in complex mountain terrain. Second, satellite-derived snow products introduce distinct sensor-specific uncertainties; for instance, while the MODIS Cloud Gap Filled (CGF) product successfully minimizes data gaps, prolonged overcast periods still pose inherent challenges for optical sensors in tracking real snow cover transitions. On the other hand, the new-generation, radar-based Sentinel-1 C-SNOW product used in our data assimilation framework offers a crucial advantage by completely bypassing cloud cover; however, long-term validation across diverse climate zones remains limited, and its regional accuracy can fluctuate due to the complex interaction of radar backscatter with topography, canopy cover, and changing physical properties of the snowpack itself. Finally, although reanalysis datasets provide spatially consistent forcing across wide areas, they are fundamentally atmospheric model and data assimilation outputs rather than direct observations; their relatively coarse grid resolutions cannot fully replicate fine-scale orographic precipitation, sharp temperature lapse rates, and microclimates typical of steep alpine topography. Acknowledging these limitations does not diminish the operational value of our findings; rather, it highlights the need for increasingly integrated multi-source observation and data assimilation frameworks for mountain hydrology.

5 Conclusion

This study presented a comprehensive evaluation of the spatially distributed S3M snow model across two climatically contrasting basins in Türkiye the Mediterranean-transition Seyhan Basin and the continental Karasu Basin using a multi-source framework including meteorological, reanalysis, satellite, and ground-based observations. By comparing alternative forcing datasets and implementing a station-based assimilation scheme, the study assessed forcing sensitivity, spatial snow detection skill, interannual variability, and basin-dependent model behavior over a 22-year period.

Results indicate that meteorological forcing uncertainty strongly influences simulated snow magnitude. MSWX-P generally provided improved representation of temperature and precipitation, leading to SWE and HS estimates closer to ground observations, whereas ERA5-L tended to produce higher snow magnitudes, particularly in the Karasu Basin. In contrast, seasonal timing and spatial snow detection showed comparatively lower sensitivity to forcing choice, indicating a decoupling between snow extent and snow magnitude. Our findings therefore reinforce the growing consensus that improvements in forcing quality may yield greater gains than further refinement of snow model structure alone.

Clear basin-scale contrasts were observed. The Karasu Basin exhibited deeper and more persistent snowpack characteristic of a continental regime, while the Seyhan Basin showed more fragmented and variable snow conditions. These differences were reflected in both spatial detection metrics and magnitude-based evaluations, as well as in interannual anomaly patterns, which suggest increasing occurrence of below-average snow conditions after approximately 2013. In addition, the analysis revealed that snow magnitude and persistence do not always co-vary, particularly in the Mediterranean-continental transition basin, highlighting the importance of considering both metrics jointly when evaluating snow regime dynamics.

Assimilation experiments further highlighted strongly regime-dependent model behavior across different observation scales. In the continental Karasu Basin, the framework is highly effective at driving large-scale, spatially coherent mass adjustments

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

that mitigate systematic regional overestimation biases, particularly during high-snow years. Conversely, in the transient Seyhan Basin, the impact of assimilation manifests as localized, topographically guided adjustments that are highly successful at stabilizing local simulations and correcting critical premature melt phases across local stations. These results suggest that while assimilation impact is more visually evident as large spatial blocks under deep and persistent snow conditions, its capacity to correct crucial timing errors provides a vital performance upgrade in transient snow environments.

Beyond the specific basins analyzed, the results indicate that snow regime characteristics act as a first-order control on both model sensitivity to forcing and the nature of data assimilation success. This highlights the need for regime-aware modeling strategies; approaches must balance the correction of bulk water volume margins in persistent continental snowpacks with the optimization of temporal phase thresholds in highly dynamic Mediterranean-transition environments.

The observed decoupling between snow magnitude and persistence has important hydrological implications, as it may lead to shifts in runoff timing and increased uncertainty in seasonal water availability, particularly in basins where snow cover is intermittent and sensitive to temperature fluctuations. From an operational perspective, the findings suggest that data assimilation is an essential tool across both regimes: it acts as a robust regional mass-balancer in continental domains to correct broad accumulation biases, and serves as an indispensable local tracking stabilizer in transient regimes where unconstrained simulations are acutely vulnerable to marginal forcing deficiencies.

Building on these findings, future research should focus on probabilistic data assimilation frameworks that explicitly represent both observation and model uncertainty, together with improved characterization of observation errors and the integration of next-generation high-resolution snow products. Such developments would further strengthen uncertainty assessment and operational snow monitoring in complex mountain environments.

To our knowledge, this represents the first long-term distributed snow modeling assessments in Türkiye integrating reanalysis, satellite, and ground-based data within a unified framework. Beyond its regional application, this study contributes to the broader literature by (i) quantifying forcing sensitivity in distributed snow modeling across contrasting climatic regimes, (ii) demonstrating the relative robustness of snow detection compared to snow magnitude simulations, and (iii) highlighting the regime-dependent effectiveness of station-based assimilation. The findings emphasize the importance of high-quality forcing data and multi-source evaluation for reliable snow modeling in data-scarce mountainous environments.

Overall, the results indicate that S3M provides a robust and adaptable framework for distributed snow simulation, with potential for operational implementation in snow-fed basins. As climate variability intensifies, integrating regime-aware modeling strategies will be critical for ensuring robust snow monitoring and water resource management in climatically heterogeneous and data-scarce mountain regions.

Code and data availability

The S3M (Spatial Snow Multidata Mapping) model used in this study is openly available through its GitHub repository and is described by Avanzi et al. (2021). All publicly available datasets used in this study, including ERA5-Land, CERRA-Land,

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

MSWX-Past, MODIS Cloud Gap Filled, IMS, SE-D SEVIRI, SWE-E and C-SNOW, are available from their respective providers and are fully referenced in the manuscript. The in situ meteorological and snow observations used for model forcing and evaluation were provided by the respective Turkish national institutions for research purposes and cannot be redistributed by the authors. Requests for access to these observations should be directed to the respective data providers.

Author contributions

AŞ and AAŞ conceived the study, formulated the research objectives, and and provided scientific supervision. MS, FA, and AŞ developed and refined the methodology and modelling framework. MS performed the simulations, software implementation, and model validation under the supervision of AAŞ, FA, and AŞ. AAŞ, MS, and AŞ curated the data and processed the satellite products. MS, AAŞ, and AŞ carried out the formal analysis and visualization. FA and SG contributed software tools, computational resources, and technical expertise. AŞ and MS prepared the original draft. All authors contributed to the interpretation of the results, critically revised the manuscript, and approved the final version.

Competing interests

At least one of the (co-)authors is a member of the editorial board of The Cryosphere.

Acknowledgements

This work is dedicated to the loving memory of Prof. Dr. A.Ünal ŞORMAN, a revered mentor and pioneer of snow hydrology in Türkiye, whose lifetime of dedication and visionary guidance profoundly shaped this field of research and inspired this study.

The authors sincerely thank the Turkish State Meteorological Service (TSMS) and the General Directorate of State Hydraulic Works (DSI) for providing the in situ meteorological and snow observations used in this study. We also gratefully acknowledge the international scientific teams and agencies that develop, maintain, and freely provide the reanalysis and satellite datasets used in this study. The authors further acknowledge the EUMETSAT H SAF project for fostering international scientific collaboration. Partial support from Eskişehir Technical University (Project No. 25LÖT021), which facilitated the research visit that strengthened the scientific collaboration underpinning this study, is also gratefully acknowledged.

References

Akyurek, Z., Kuter, S., Karaman, Ç. H., and Akpınar, B.: Understanding the Snow Cover Climatology over Turkey from ERA5-Land Reanalysis Data and MODIS Snow Cover Frequency Product, Geosciences, 13, 311, https://doi.org/10.3390/geosciences13100311, 2023.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Alexopoulos, K., Willis, I. C., Pritchard, H. D., Kyros, G., Kotroni, V., and Lagouvardos, K.: Greek mountain snow cover halved in past four decades due to regional warming, The Cryosphere, 20, 2209–2236, https://doi.org/10.5194/tc-20-2209-2026, 2026.

Anderson, E. A.: Snow accumulation and ablation model–SNOW-17, US National Weather Service, Silver Spring, MD, 61, 2006.

Andreadis, K. M. and Lettenmaier, D. P.: Assimilating remotely sensed snow observations into a macroscale hydrology model, Advances in Water Resources, 29, 872–886, https://doi.org/10.1016/j.advwatres.2005.08.004, 2006.

Avanzi, F., De Michele, C., Morin, S., Carmagnola, C. M., Ghezzi, A., and Lejeune, Y.: Model complexity and data requirements in snow hydrology: seeking a balance in practical applications, Hydrological Processes, 30, 2106–2118, https://doi.org/10.1002/hyp.10782, 2016.

Avanzi, F., Ercolani, G., Gabellani, S., Cremonese, E., Pogliotti, P., Filippa, G., Morra di Cella, U., Ratto, S., Stevenin, H., Cauduro, M., and Juglair, S.: Learning about precipitation lapse rates from snow course data improves water balance modeling, Hydrology and Earth System Sciences, 25, 2109–2131, https://doi.org/10.5194/hess-25-2109-2021, 2021.

Avanzi, F., Gabellani, S., Delogu, F., Silvestro, F., Cremonese, E., Morra di Cella, U., Ratto, S., and Stevenin, H.: Snow Multidata Mapping and Modeling (S3M) 5.1: a distributed cryospheric model with dry and wet snow, data assimilation, glacier mass balance, and debris-driven melt, Geoscientific Model Development, 15, 4853–4879, https://doi.org/10.5194/gmd-15-4853-2022, 2022.

Barnett, T. P., Adam, J. C., and Lettenmaier, D. P.: Potential impacts of a warming climate on water availability in snow-dominated regions, Nature, 438, 303–309, https://doi.org/10.1038/nature04141, 2005.

Bartelt, P. and Lehning, M.: A physical SNOWPACK model for the Swiss avalanche warning: Part I: numerical model, Cold Regions Science and Technology, 35, 123–145, https://doi.org/10.1016/S0165-232X(02)00074-5, 2002.

Beck, H. E., Dijk, A. I. J. M. van, Larraondo, P. R., McVicar, T. R., Pan, M., Dutra, E., and Miralles, D. G.: MSWX: Global 3-Hourly 0.1° Bias-Corrected Meteorological Data Including Near-Real-Time Updates and Forecast Ensembles, https://doi.org/10.1175/BAMS-D-21-0145.1, 2022.

Beniston, M., Farinotti, D., Stoffel, M., Andreassen, L. M., Coppola, E., Eckert, N., Fantini, A., Giacona, F., Hauck, C., Huss, M., Huwald, H., Lehning, M., López-Moreno, J.-I., Magnusson, J., Marty, C., Morán-Tejéda, E., Morin, S., Naaim, M., Provenzale, A., Rabatel, A., Six, D., Stötter, J., Strasser, U., Terzago, S., and Vincent, C.: The European mountain cryosphere: a review of its current state, trends, and future challenges, The Cryosphere, 12, 759–794, https://doi.org/10.5194/tc-12-759-2018, 2018.

Clark, M. P., Slater, A. G., Barrett, A. P., Hay, L. E., McCabe, G. J., Rajagopalan, B., and Leavesley, G. H.: Assimilation of snow covered area information into hydrologic and land-surface models, Advances in Water Resources, 29, 1209–1221, https://doi.org/10.1016/j.advwatres.2005.10.001, 2006.

De Lannoy, G. J. M., Reichle, R. H., Arsenault, K. R., Houser, P. R., Kumar, S., Verhoest, N. E. C., and Pauwels, V. R. N.: Multiscale assimilation of Advanced Microwave Scanning Radiometer–EOS snow water equivalent and Moderate

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Resolution Imaging Spectroradiometer snow cover fraction observations in northern Colorado, Water Resources Research, 48, https://doi.org/10.1029/2011WR010588, 2012.

Deschamps-Berger, C., Cluzet, B., Dumont, M., Lafaysse, M., Berthier, E., Fanise, P., and Gascoin, S.: Improving the Spatial Distribution of Snow Cover Simulations by Assimilation of Satellite Stereoscopic Imagery, Water Resources Research, 58, e2021WR030271, https://doi.org/10.1029/2021WR030271, 2022.

Dozier, J.: Mountain hydrology, snow color, and the fourth paradigm, Eos, Transactions American Geophysical Union, 92, 373–374, https://doi.org/10.1029/2011EO430001, 2011.

Essery, R., Martin, E., Douville, H., Fernández, A., and Brun, E.: A comparison of four snow models using observations from an alpine site, Climate Dynamics, 15, 583–593, https://doi.org/10.1007/s003820050302, 1999.

Finger, D., Vis, M., Huss, M., and Seibert, J.: The value of multiple data set calibration versus model complexity for improving the performance of hydrological models in mountain catchments, Water Resources Research, 51, 1939–1958, https://doi.org/10.1002/2014WR015712, 2015.

Frei, A., Tedesco, M., Lee, S., Foster, J., Hall, D. K., Kelly, R., and Robinson, D. A.: A review of global satellite-derived snow products, Advances in Space Research, 50, 1007–1029, https://doi.org/10.1016/j.asr.2011.12.021, 2012.

Gan, Y., Zhang, Y., Liu, Y., Kongoli, C., and Grassotti, C.: Assimilation of blended in situ-satellite snow water equivalent into the National Water Model for improving hydrologic simulation in two US river basins, Science of The Total Environment, 838, 156567, https://doi.org/10.1016/j.scitotenv.2022.156567, 2022.

Girotto, M., Formetta, G., Azimi, S., Bachand, C., Cowherd, M., De Lannoy, G., Lievens, H., Modanesi, S., Raleigh, M. S., Rigon, R., and Massari, C.: Identifying snowfall elevation patterns by assimilating satellite-based snow depth retrievals, Science of The Total Environment, 906, 167312, https://doi.org/10.1016/j.scitotenv.2023.167312, 2024.

Günther, D., Marke, T., Essery, R., and Strasser, U.: Uncertainties in Snowpack Simulations—Assessing the Impact of Model Structure, Parameter Choice, and Forcing Data Error on Point-Scale Energy Balance Snow Model Performance, Water Resources Research, 55, 2779–2800, https://doi.org/10.1029/2018WR023403, 2019.

Hall, D. K. and Riggs, G. A.: MODIS/Terra Snow Cover Daily L3 Global 500m SIN Grid, Version 61, https://doi.org/10.5067/MODIS/MOD10A1.061, 2021.

Hall, D. K., Riggs, G. A., DiGirolamo, N. E., and Román, M. O.: Evaluation of MODIS and VIIRS cloud-gap-filled snow-cover products for production of an Earth science data record, Hydrology and Earth System Sciences, 23, 5227–5241, https://doi.org/10.5194/hess-23-5227-2019, 2019.

Hao, D., Bisht, G., Rittger, K., Stillinger, T., Bair, E., Gu, Y., and Leung, L. R.: Evaluation of E3SM land model snow simulations over the western United States, The Cryosphere, 17, 673–697, https://doi.org/10.5194/tc-17-673-2023, 2023.

Helfrich, S. R., McNamara, D., Ramsay, B. H., Baldwin, T., and Kasheta, T.: Enhancements to, and forthcoming developments in the Interactive Multisensor Snow and Ice Mapping System (IMS), Hydrological Processes, 21, 1576–1586, https://doi.org/10.1002/hyp.6720, 2007.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Helmert, J., Şensoy Şorman, A., Alvarado Montero, R., De Michele, C., De Rosnay, P., Dumont, M., Finger, D. C., Lange, M., Picard, G., Potopová, V., Pullen, S., Vikhamar-Schuler, D., and Arslan, A. N.: Review of Snow Data Assimilation Methods for Hydrological, Land Surface, Meteorological and Climate Models: Results from a COST HarmoSnow Survey, Geosciences, 8, 489, https://doi.org/10.3390/geosciences8120489, 2018.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, Quarterly Journal of the Royal Meteorological Society, 146, 1999–2049, https://doi.org/10.1002/qj.3803, 2020.

Hou, J., Huang, C., Chen, W., and Zhang, Y.: Improving Snow Estimates Through Assimilation of MODIS Fractional Snow Cover Data Using Machine Learning Algorithms and the Common Land Model, Water Resources Research, 57, e2020WR029010, https://doi.org/10.1029/2020WR029010, 2021.

Largeron, C., Dumont, M., Morin, S., Boone, A., Lafaysse, M., Metref, S., Cosme, E., Jonas, T., Winstral, A., and Margulis, S. A.: Toward Snow Cover Estimation in Mountainous Areas Using Modern Data Assimilation Methods: A Review, Front. Earth Sci., 8, https://doi.org/10.3389/feart.2020.00325, 2020.

Legg, S.: IPCC, 2021: Climate Change 2021 - the Physical Science basis, Interaction, 49, 44–45, https://doi.org/10.3316/informit.315096509383738, 2021.

Lehning, M., Bartelt, P., Brown, B., Fierz, C., and Satyawali, P.: A physical SNOWPACK model for the Swiss avalanche warning: Part II. Snow microstructure, Cold Regions Science and Technology, 35, 147–167, https://doi.org/10.1016/S0165-232X(02)00073-3, 2002.

Lehning, M., Völksch, I., Gustafsson, D., Nguyen, T. A., Stähli, M., and Zappa, M.: ALPINE3D: a detailed model of mountain surface processes and its application to snow hydrology, Hydrological Processes, 20, 2111–2128, https://doi.org/10.1002/hyp.6204, 2006.

Leisenring, M. and Moradkhani, H.: Snow water equivalent prediction using Bayesian data assimilation methods, Stoch Environ Res Risk Assess, 25, 253–270, https://doi.org/10.1007/s00477-010-0445-5, 2011.

Lemmetyinen, J., Pulliainen, J., Rees, A., Kontu, A., Qiu, Y., and Derksen, C.: Multiple-Layer Adaptation of HUT Snow Emission Model: Comparison With Experimental Data, IEEE Transactions on Geoscience and Remote Sensing, 48, 2781–2794, https://doi.org/10.1109/TGRS.2010.2041357, 2010.

Levin, S. B., Briggs, M. A., Foks, S. S., Goodling, P. J., Raffensperger, J. P., Rosenberry, D. O., Scholl, M. A., Tiedeman, C. R., and Webb, R. M.: Uncertainties in measuring and estimating water-budget components: Current state of the science, WIREs Water, 10, e1646, https://doi.org/10.1002/wat2.1646, 2023.

Li, S., Liu, M., Adam, J. C., Pi, H., Su, F., Li, D., Liu, Z., and Yao, Z.: Contribution of Snow-Melt Water to the Streamflow over the Three-River Headwater Region, China, Remote Sensing, 13, 1585, https://doi.org/10.3390/rs13081585, 2021.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Lievens, H., Demuzere, M., Marshall, H.-P., Reichle, R. H., Brucker, L., Brangers, I., de Rosnay, P., Dumont, M., Girotto, M., Immerzeel, W. W., Jonas, T., Kim, E. J., Koch, I., Marty, C., Saloranta, T., Schöber, J., and De Lannoy, G. J. M.: Snow depth variability in the Northern Hemisphere mountains observed from space, Nat Commun, 10, 4629, https://doi.org/10.1038/s41467-019-12566-y, 2019.

Liu, Y., Peters-Lidard, C. D., Kumar, S., Foster, J. L., Shaw, M., Tian, Y., and Fall, G. M.: Assimilating satellite-based snow depth and snow cover products for improving snow predictions in Alaska, Advances in Water Resources, 54, 208–227, https://doi.org/10.1016/j.advwatres.2013.02.005, 2013.

Magnusson, J., Wever, N., Essery, R., Helbig, N., Winstral, A., and Jonas, T.: Evaluating snow models with varying process representations for hydrological applications, Water Resources Research, 51, 2707–2723, https://doi.org/10.1002/2014WR016498, 2015.

Magnusson, J., Winstral, A., Stordal, A. S., Essery, R., and Jonas, T.: Improving physically based snow simulations by assimilating snow depths using the particle filter, Water Resources Research, 53, 1125–1143, https://doi.org/10.1002/2016WR019092, 2017.

Margulis, S. A., Girotto, M., Cortés, G., and Durand, M.: A Particle Batch Smoother Approach to Snow Water Equivalent Estimation, Journal of Hydrometeorology, 16, 1752–1772, https://doi.org/10.1175/JHM-D-14-0177.1, 2015.

Martinec, J., Rango, A., Roberts, R., and Baumgartner, M. F.: Snowmelt runoff model (SRM) user's manual, University of Berne, Department of Geography Berne, 1998.

McMillan, H. K., Westerberg, I. K., and Krueger, T.: Hydrological data uncertainty and its implications, WIREs Water, 5, e1319, https://doi.org/10.1002/wat2.1319, 2018.

Micheletty, P., Perrot, D., Day, G., and Rittger, K.: Assimilation of Ground and Satellite Snow Observations in a Distributed Hydrologic Model for Water Supply Forecasting, JAWRA Journal of the American Water Resources Association, 58, 1030–1048, https://doi.org/10.1111/1752-1688.12975, 2022.

Morin, S., Horton, S., Techel, F., Bavay, M., Coléou, C., Fierz, C., Gobiet, A., Hagenmuller, P., Lafaysse, M., Ližar, M., Mitterer, C., Monti, F., Müller, K., Olefs, M., Snook, J. S., van Herwijnen, A., and Vionnet, V.: Application of physical snowpack models in support of operational avalanche hazard forecasting: A status report on current implementations and prospects for the future, Cold Regions Science and Technology, 170, 102910, https://doi.org/10.1016/j.coldregions.2019.102910, 2020.

Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., and Thépaut, J.-N.: ERA5-Land: a state-of-the-art global reanalysis dataset for land applications, Earth System Science Data, 13, 4349–4383, https://doi.org/10.5194/essd-13-4349-2021, 2021.

Musselman, K. N., Lehner, F., Ikeda, K., Clark, M. P., Prein, A. F., Liu, C., Barlage, M., and Rasmussen, R.: Projected increases and shifts in rain-on-snow flood risk over western North America, Nature Clim Change, 8, 808–812, https://doi.org/10.1038/s41558-018-0236-4, 2018.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Pedersen, C. A. and Winther, J.-G.: Intercomparison and validation of snow albedo parameterization schemes in climate models, Climate Dynamics, 25, 351–362, https://doi.org/10.1007/s00382-005-0037-0, 2005.

Piazzi, G., Thirel, G., Campo, L., and Gabellani, S.: A particle filter scheme for multivariate data assimilation into a point-scale snowpack model in an Alpine environment, The Cryosphere, 12, 2287–2306, https://doi.org/10.5194/tc-12-2287-2018, 2018.

Pulliainen, J., Luojus, K., Derksen, C., Mudryk, L., Lemmetyinen, J., Salminen, M., Ikonen, J., Takala, M., Cohen, J., Smolander, T., and Norberg, J.: Patterns and trends of Northern Hemisphere snow mass from 1980 to 2018, Nature, 581, 294–298, https://doi.org/10.1038/s41586-020-2258-0, 2020.

Raleigh, M. S. and Lundquist, J. D.: Comparing and combining SWE estimates from the SNOW-17 model using PRISM and SWE reconstruction, Water Resources Research, 48, https://doi.org/10.1029/2011WR010542, 2012.

Raleigh, M. S., Lundquist, J. D., and Clark, M. P.: Exploring the impact of forcing error characteristics on physically based snow simulations within a global sensitivity analysis framework, Hydrology and Earth System Sciences, 19, 3153–3179, https://doi.org/10.5194/hess-19-3153-2015, 2015.

Ramsay, B. H.: The interactive multisensor snow and ice mapping system, Hydrological Processes, 12, 1537–1546, https://doi.org/10.1002/(SICI)1099-1085(199808/09)12:10/11%253C1537::AID-HYP679%253E3.0.CO;2-A, 1998.

Rutter, N., Essery, R., Pomeroy, J., Altimir, N., Andreadis, K., Baker, I., Barr, A., Bartlett, P., Boone, A., Deng, H., Douville, H., Dutra, E., Elder, K., Ellis, C., Feng, X., Gelfan, A., Goodbody, A., Gusev, Y., Gustafsson, D., Hellström, R., Hirabayashi, Y., Hirota, T., Jonas, T., Koren, V., Kuragina, A., Lettenmaier, D., Li, W.-P., Luce, C., Martin, E., Nasonova, O., Pumpanen, J., Pyles, R. D., Samuelsson, P., Sandells, M., Schädler, G., Shmakin, A., Smirnova, T. G., Stähli, M., Stöckli, R., Strasser, U., Su, H., Suzuki, K., Takata, K., Tanaka, K., Thompson, E., Vesala, T., Viterbo, P., Wiltshire, A., Xia, K., Xue, Y., and Yamazaki, T.: Evaluation of forest snow processes models (SnowMIP2), Journal of Geophysical Research: Atmospheres, 114, https://doi.org/10.1029/2008JD011063, 2009.

Saloranta, T. M.: Operational snow mapping with simplified data assimilation using the seNorge snow model, Journal of Hydrology, 538, 314–325, https://doi.org/10.1016/j.jhydrol.2016.03.061, 2016.

Schimanke, S., Isaksson, L., Edvinsson, L., Ridal, M., Berggren, L., Hopsch, S., El-Said, A., Glinton, M., Bazile, E., Moigne, P. L., Verrelle, A., Dahlgren, P., and Randriamampianina, R.: Copernicus European regional reanalysis, Copernicus Meetings, https://doi.org/10.5194/ems2021-389, 2021.

Schlögl, S., Marty, C., Bavay, M., and Lehning, M.: Sensitivity of Alpine3D modeled snow cover to modifications in DEM resolution, station coverage and meteorological input quantities, Environmental Modelling & Software, 83, 387–396, https://doi.org/10.1016/j.envsoft.2016.02.017, 2016.

Silvestro, F., Gabellani, S., Delogu, F., Rudari, R., and Boni, G.: Exploiting remote sensing land surface temperature in distributed hydrological modelling: the example of the Continuum model, Hydrology and Earth System Sciences, 17, 39–62, https://doi.org/10.5194/hess-17-39-2013, 2013.

https://doi.org/10.5194/egusphere-2026-4921
Preprint. Discussion started: 16 November 2026
© Author(s) 2026. CC BY 4.0 License.

Slater, A. G. and Clark, M. P.: Snow Data Assimilation via an Ensemble Kalman Filter, https://doi.org/10.1175/JHM505.1, 2006.

Soci, C., Bazile ,Eric, Besson ,François, and and Landelius, T.: High-resolution precipitation re-analysis system for climatological purposes, Tellus A: Dynamic Meteorology and Oceanography, 68, 29879, https://doi.org/10.3402/tellusa.v68.29879, 2016.

Şorman, A. A., Şensoy, A., Tekeli, A. E., Şorman, A. Ü., and Akyürek, Z.: Modelling and forecasting snowmelt runoff process using the HBV model in the eastern part of Turkey, Hydrological Processes, 23, 1031–1040, https://doi.org/10.1002/hyp.7204, 2009.

Şorman, A. A., Uysal, G., and Şensoy, A.: Probabilistic Snow Cover and Ensemble Streamflow Estimations in the Upper Euphrates Basin, Journal of Hydrology and Hydromechanics, 67, 82–92, https://doi.org/10.2478/johh-2018-0025, 2018.

Sorman, A. U. and Beser, O.: Determination of snow water equivalent over the eastern part of Turkey using passive microwave data, Hydrological Processes, 27, 1945–1958, https://doi.org/10.1002/hyp.9267, 2013.

Sospedra-Alfonso, R. and Merryfield, W. J.: Influences of Temperature and Precipitation on Historical and Future Snowpack Variability over the Northern Hemisphere in the Second Generation Canadian Earth System Model, https://doi.org/10.1175/JCLI-D-16-0612.1, 2017.

Stewart, I. T.: Changes in snowpack and snowmelt runoff for key mountain regions, Hydrological Processes, 23, 78–94, https://doi.org/10.1002/hyp.7128, 2009.

Sun, H., and Margulis, A. S.: Assessing the impact of meteorological forcing and its uncertainty on snow modeling and reanalysis. The Cryosphere, 20(8), 3345–3367. https://doi.org/10.5194/tc-20-3345-2026, 2026.

Terzago, S., Andreoli, V., Arduini, G., Balsamo, G., Campo, L., Cassardo, C., Cremonese, E., Dolia, D., Gabellani, S., von Hardenberg, J., Morra di Cella, U., Palazzi, E., Piazzi, G., Pogliotti, P., and Provenzale, A.: Sensitivity of snow models to the accuracy of meteorological forcings in mountain environments, Hydrology and Earth System Sciences, 24, 4061–4090, https://doi.org/10.5194/hess-24-4061-2020, 2020.

Vernay, M., Lafaysse, M., Mérindol, L., Giraud, G., and Morin, S.: Ensemble forecasting of snowpack conditions and avalanche hazard, Cold Regions Science and Technology, 120, 251–262, https://doi.org/10.1016/j.coldregions.2015.04.010, 2015.

Verrelle, A., Glinton, M., Bazile, E., Le Moigne, P., Randriamampianina, R., Ridal, M., Berggren, L., Undén, P., Schimanke, S., Mladek, R., and Soci, C.: CERRA-Land sub-daily regional reanalysis data for Europe from 1984 to present, Copernicus Climate Change Service (C3S) Climate Data Store (CDS), https://doi.org/10.24381/cds.a7f3cd0b, 2022.

Wang, X., Xie, Z., Jia, B., Wang, L., Mutiibwa, D., and Lettenmaier, D. P.: Sensitivity of snow simulations to different atmospheric forcing data sets over the Northern Hemisphere. Journal of Geophysical Research: Atmospheres, 125(16), e2019JD032001. https://doi.org/10.1029/2019JD032001, 2020.

Zanotti, F., Endrizzi, S., Bertoldi, G., and Rigon, R.: The GEOTOP snow module, Hydrological Processes, 18, 3667–3679, https://doi.org/10.1002/hyp.5794, 2004.