#essd-2024-451 - Author's response

Reviewer 1

General Comment — The authors have thoughtfully addressed most of my primary concerns. From my perspective, the manuscript will be suitable for publication after the below two minor, but important, comments are addressed.

Reply: Thank you for recognizing the value of our contribution.

Reviewer Comment 1.1 — Follow-up on Comment 1.4: I appreciate the authors' response focused on the SCF/snow depth comparisons; however, it seems lacking. First, does this explanation (that relies on derivation of SCF/snow depth relationships) suggest that the model used in this study does not explicitly calculate SCF? If that is the case, how are SCF biases (e.g., in Figure 9) calculated?
If the model does directly derive SCF, then the scheme used to calculate SCF in the simulations should be reported. Is the snow cover area shown in these plots from the model output; if so then there is clearly an SCF scheme used by the model, and that should be noted in the paper. These figures show distinct regimes for snow depth/SCF relationships for both shallow and deep snowpacks, likely from diIerences in SCF/snow depth relationships during accumulation vs. ablation periods, which is often parameterized in models based on snow density (e.g., Niu and Yang, 2007).

Niu, G.-Y., Yang, Z.-L., 2007. An observation-based formulation of snow cover fraction and its evaluation over large North American river basins. J. Geophys. Res. 112, D21101. https://doi.org/10.1029/2007JD008674

Reply: We thank the reviewer for the opportunity to clarify how SCF is handled in Crocus-ERA5 and how to interpret the SCF–snow-depth relationships shown.
In the Crocus-ERA5 product, the model is run in an "open-field" configuration (Brun et al., 2013): snow–vegetation interactions are disabled and forests are not represented. In this setting, the snow-covered fraction (SCF) is not parameterized at sub-grid scale; instead, it is diagnosed in a simple, quasi-binary manner from snow water equivalent (SWE):

$$SCF = min(1, \frac{W_{sn}}{W_{lim}})$$

where W_{sn} is the snow mass (kg m^{-2}) and W_{lim} set to 1 kg m^{-2}. Hence, as soon as a thin snowpack is present, SCF rapidly approaches 1. We adopt this choice since the previous Crocus-ERAI product of Brun et al. (2013) for the reasons set out below.

(i) Our aim is to resolve intrinsic snowpack properties (stratigraphy, metamorphism, albedo, thermal properties, etc.), which would be diluted by a surface-averaged mixture including snow-free areas; a quasi-binary SCF avoids that dilution. This logic is also consistent with satellite products such as IMS, whose SCF is binary at its grid resolution (1/4/24 km: 1 if snow is present, 0 otherwise).

(ii) Consequently, comparisons with IMS are like-for-like: our SCF diagnostic targets presence/absence of snow at the grid scale, as IMS does.

(iii) Finally, following Brun et al. (2013) in the Crocus-ERAI replay, the "open-field" setup facilitates comparison with local in-situ observations in open terrain and provides a more direct physical meaning, avoiding uncertainties from snow–vegetation interactions that are not represented in our framework.

There was therefore an error in the previous version of the manuscript, on page 6 (lines 174-178). The text has now been corrected and improved (lines 168-183). The main changes are as follows:

"Because these interactions are complex and remain challenging to simulate accurately, Crocus-ERA5 adopts a simplified "open-field" configuration, simulating the snowpack over an idealised grassland cover with climatological physiography (e.g., no interannual variability in leaf area index). In this configuration, the SCF is computed directly from the simulated SWE rather than from a vegetation, depth, or density dependent sub-grid scheme. Crocus-ERA5 applies a ramp-to-one diagnostic: SCF increases linearly with snow mass up to a small threshold (1 kg m^{-2} of SWE) and saturates at 1 beyond it. This design centers the evaluation on intrinsic snowpack properties and ensures consistency with both the binary IMS product at its grid resolution and local open-field in-situ observations. For consistency, the IMS product was processed to obtain a comparable continuous SCF. Daily categorical values (water, land, ice, and snow) were averaged over time, producing intermediate values that reflect the frequency of snow occurrence within each grid cell. These mean values were linearly rescaled to express SCF as a continuous percentage. Despite their distinct formulations - physical for Crocus-ERA5 and statistical for IMS - both approaches provide consistent measures of snow cover extent suitable for climatological comparison. The snow cover fraction (SCF) was derived consistently from both model and observational datasets, each according to its native definition. These mean values were linearly rescaled to express SCF as a continuous percentage. Despite these conceptual differences, both estimates provide compatible measures of snow cover extent suitable for climatological comparison."

Instead of:

"Crocus-ERA5 addresses this by simulating snowpack evolution in detail, including the snow cover fraction (SCF), and by distinguishing snow-covered from snow-free areas (e.g., vegetation or bare soil) within each grid cell (Brun et al., 2013). This separation limits unrealistic vegetation–snow interactions and improves the simulation of snowmelt and rain infiltration."

Consequently, SCF biases calculation (e.g., in Figure 9) are computed as the difference between the model-diagnosed SCF and the IMS-derived SCF at the grid scale. Theses biases mainly stem from: **(i)** ERA5 forcing uncertainties (precipitation amount/phase, temperature), **(ii)** timing of melt in Crocus (too early or too late), and **(iii)** representativeness differences between our quasi-binary SCF and the binary IMS product.

On the dual-regime structure (SCF–snow depth), the observed two-regime pattern for shallow vs. deep snow does not arise from an active sub-grid SCF scheme in our configuration. It reflects the quasi-binary nature of our SCF diagnostic combined with the temporal evolution of SWE through accumulation and ablation. This is consistent with hysteresis-like behaviors reported in the literature (e.g., Niu and Yang, 2007), even though we do not parameterize SCF as a function of snow density or vegetation here.

Reviewer Comment 1.2 — Follow-up on Comment 1.7: Although large scale temperature and precipitation forcing may govern interannual variability of SWE anomalies for a given area, land cover characteristics, such as land cover type, can drive large spatial heterogeneity. For example, the same meteorological conditions that occur in a forest could result in substantially different snowpack dynamics relative to a nearby grassy meadow. This limitation is important to address.

Reply: We thank the reviewer for the clarification. We would like to emphasize a point about scale: the original Comment 1.7 addressed interannual variability (i.e., year-to-year anomalies), whereas the follow-up comment focuses on spatial heterogeneity driven by land cover. These are related but distinct issues.

Our initial statement remains valid in the stated context: for non-assimilative products forced by the same reanalysis, the interannual SWE anomaly signal is primarily controlled by large-scale forcing (temperature and precipitation). The lack of an explicit snow–forest scheme mainly affects mean levels (SWE/HS biases) rather than the temporal coherence of anomalies and trends at large scales. Conversely, at local scales, we agree that land-cover type (forest vs. grassland) produces strong spatial contrasts in snow processes (interception, shading, wind, sublimation, etc.) that our "open-field" setup does not represent—this is indeed a limitation that we state explicitly.

We also note that land-cover changes (e.g., logging, conversion to cropland) can indeed affect interannual variability at the time they occur. However, with constant land cover, spatial heterogeneity should not be conflated with interannual variability: the former concerns differences across sites, the latter evolution over time under the same forcing.

We will revise the end of the conclusion of the manuscript to:

(i) make this temporal vs. spatial distinction explicit;

(ii) bound the scope of our conclusions (robust for large-scale anomalies over open terrain); and

(iii) clearly state that local forest–meadow contrasts are not reproduced in our configuration and that averages over heavily forested areas may be biased.

We will add the following paragraph (last version, line 554):

"In this context, it is important to clearly delineate the limitations of the Crocus-ERA5 product, particularly those arising from the lack of explicit snow–forest interactions. Building on the comparison above, we emphasize the distinction between temporal and spatial aspects of performance. Our conclusions primarily concern interannual anomalies driven by large-scale temperature and precipitation forcing in an open-field configuration (non-forested, grass-dominated surfaces), for which Crocus-ERA5 reproduces year-to-year variability robustly across most regions. By contrast, local spatial contrasts associated with land cover, such as differences between forest and meadow, are not represented in our setup (canopy interception, shading, wind sheltering, and enhanced sublimation are absent). Consequently, forest-meadow differences are not reproduced, and absolute values of SWE and snow depth over heavily forested areas may be biased. These limitations should be considered when interpreting spatial patterns, while our findings on large-scale anomalies over open terrain remain robust. Notably, Mudryk et al. (2025) recently showed that Crocus-ERA5 ranks among the most effective product for reproducing SWE in the Northern Hemisphere, at least in plain areas."