REVIEWER 2

COMMENT 2.1. This investigates the impact of changing the land cover (LC) classification within ISBA (driven by ERA5 forcing) on the SWE estimates. ESA CCI SWE is used as the reference SWE dataset. Comparisons are also made with ERA5. Replacing the old LC information with one based on the ESA CCI LC v2.0.7 improved the SWE bias when compared to ESA CCI over the full temporal and spatial domain. Although New LC improved versus CCI, ERA5 often has better performance with CCI compared to the ISBA simulation. The authors also look at the impact of change in LC on LST but are unable to attribute LST differences to the changes in SWE. The manuscript is clear and well presented however I found the analysis and the discussion to be a bit limited. I would like to see additional analysis that looks at changes in SWE according to changes in LC classification. As it stands, the analysis shows that changing the LC information alters the SWE which is an expected result but it stops short of linking the SWE changes to specific changes in LC classification. Overall, while the manuscript is well-written and clear I found it lacking in analysis to support the main research objective.

RESPONSE 2.1:

We would like to thank the reviewer for their constructive and insightful comments. In response, we have conducted further analyses that explicitly link changes in snow water equivalent (SWE) to land cover (LC) transitions. These analyses include:
(1) the spatial identification of dominant land-cover transitions;
(2) the quantification of their frequency and impact; and
(3) the attribution of SWE and RMSD changes to specific transitions. The results are presented below in the form of new figures and a summarised transition table.

COMMENT 2.2. Did all LC changes lead to SWE changes? If not, which LC changes did not result in a SWE change (i.e. SWE agnostic to those different LCs). One suggestion is to quantify the number of pixels that experienced a reclassification and to further categorize those according to type of change (i.e. % of pixels that changed from 13 to 7) and finally to examine the change in SWE according to these LC changes.

RESPONSE 2.2:

We appreciate this relevant question from the reviewer. Following this recommendation, we conducted a thorough quantification of LC changes across the domain. Specifically, we calculated the number of grid cells affected by each transition and their relative spatial coverage (percentage of grid cells), as well as the associated changes in SWE and model performance metrics (bias, RMSD and ubRMSD). Our analysis shows that LC changes are highly heterogeneous in both space and impact. The most frequent transitions (e.g. grasslands to DBF and grasslands to CNF) affect approximately 4–5% of grid cells, whereas the majority of transitions affect less than 1% of the domain individually (see Table R2.1). While not all areas experiencing an LC change lead to a significant change in SWE, some of these transitions can produce noticeable local changes in SWE despite their limited spatial extent. This is illustrated by the scatterplot in Fig. R2.1, which compares SWE values simulated with Old LC (ECOCLIMAP-II) and New LC (ECOCLIMAP-SG). The very high correlation (R = 0.996) indicates that, at the domain scale, most grid cell values remain close to the 1:1 relationship. This means that a large proportion of LC changes do not result in significant differences in SWE. This behaviour is consistent with the spatial analysis. As Fig. R2.2 shows, only a subset of the snow-relevant domain exhibits a change in dominant plant functional type (PFT), while large areas remain unchanged. Furthermore, Fig. R2.2 and Table R2.1 show that although multiple LC transitions occur, their spatial extent and frequency vary considerably. The largest impacts, however, are associated with transitions from grasslands to forested classes (DBF and CNF), as these substantially modify vegetation structure and snow–vegetation interactions. These changes affect processes such as canopy interception, sublimation and radiative exchanges, resulting in more pronounced differences in SWE. Importantly, Fig. R2.3 shows that changes in SWE are not restricted to areas where the dominant PFT changes. Significant variations can also occur where the dominant PFT remains unchanged but sub-grid vegetation fractions (PATCH) are redistributed. The quantity Σ|ΔPATCH| reflects the magnitude of these internal changes in vegetation composition. In such cases, modifications in canopy density or vegetation mixture can alter snow-related processes and induce SWE changes independently of dominant LC transitions. Overall, these results suggest that SWE does not systematically respond to all LC changes. Rather, its response depends on the type of transition and the magnitude of the associated structural changes in vegetation.

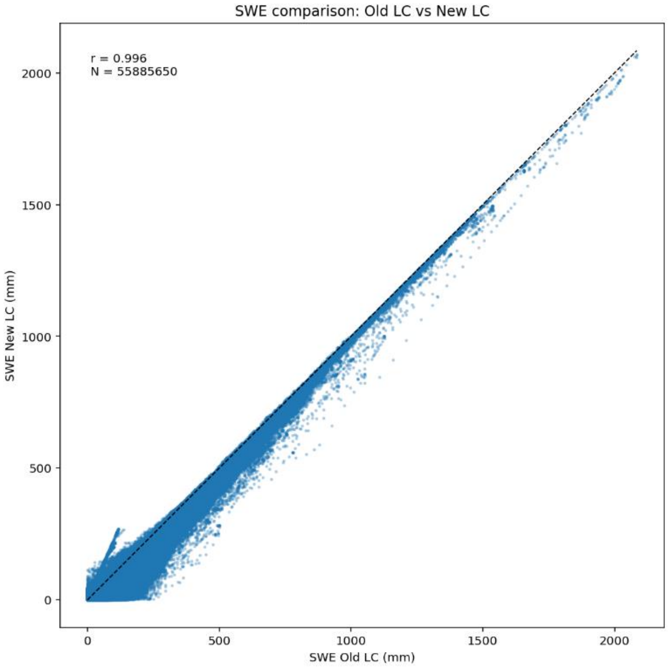

Figure R2.1. *Scatterplot of simulated SWE with New LC (ECOCLIMAP-SG) versus Old LC (ECOCLIMAP-II). SWE simulations are indicated where valid ESA CCI SWE values are available. The dashed line indicates the 1:1 relationship.*

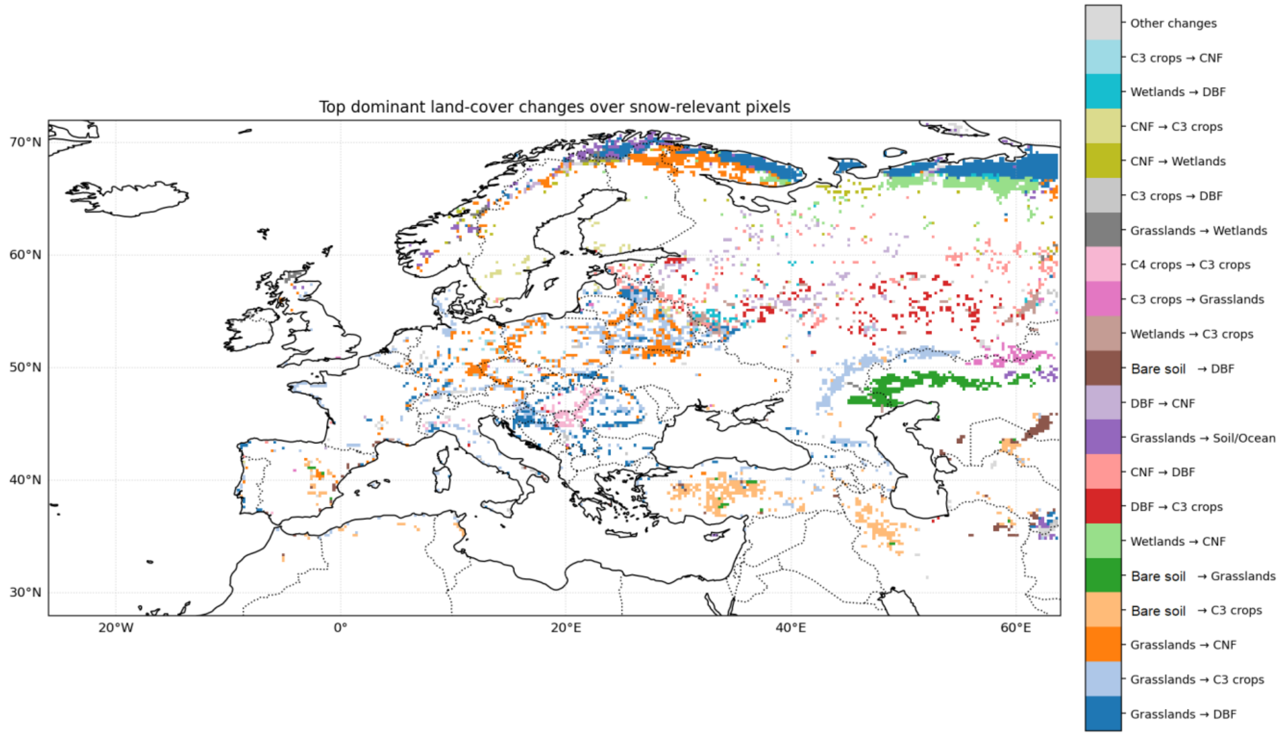

Figure R2.2. *Spatial distribution of the top 20 most frequent dominant land-cover transitions from ECOCLIMAP-II to ECOCLIMAP-SG over snow-relevant grid cells where valid ESA CCI SWE data are available. All remaining transitions are grouped as "Other changes". Only transitions involving a change in dominant PFT are shown.*

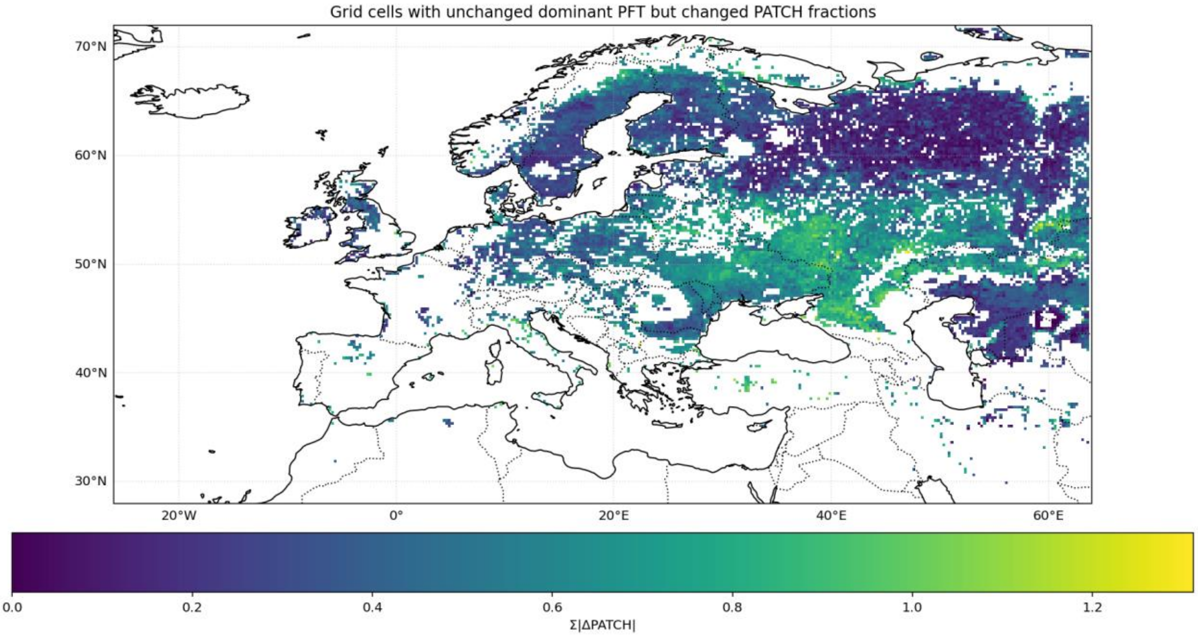

Figure R2.3*. Spatial distribution of grid cells with unchanged dominant PFT but modified sub-grid vegetation fractions (PATCH). The colour scale represents the sum of absolute changes in PFT fractions (Σ|ΔPATCH|). Values may exceed 1 due to the use of absolute differences across multiple PFT fractions.*

Table R2.1. Summary of the top 20 dominant land-cover transitions ranked by SWE RMSD changes. For each transition (Old LC to New LC), the domain-wide number and percentage of affected grid cells are reported, alongside the associated area-weighted reductions in SWE mean bias, RMSD and ubRMSD, in regions where snow is observed. Changes larger than 4 % are in bold. The remaining transitions are reported as "Other changes".

Transition	N° grid cells	% grid cells	Total contribution to Δbias (%)	Total contribution to ΔRMSD (%)	Total contribution to ΔubRMSD (%)
Grasslands -> DBF	932	4.8	**54.2**	**43.5**	**36.3**
Grasslands -> CNF	676	3.5	**10.3**	**11.8**	**12.0**
Grasslands -> C3 crops	822	4.2	**4.5**	**9.2**	**12.9**
Wetlands -> CNF	266	1.4	**6.8**	**6.5**	**6.6**
Grasslands -> Bare soil	188	1.0	3.8	**5.9**	**5.4**
Bare soil -> C3 crops	403	2.1	2.0	3.7	**5.3**
Grasslands -> Wetlands	86	0.4	2.3	3.5	3.4
CNF -> Wetlands	86	0.4	1.7	2.5	2.6
Bare soil -> Grasslands	278	1.4	1.0	1.6	2.0
C3 crops -> Grasslands	96	0.5	0.9	1.6	1.9
DBF -> C3 crops	237	1.2	1.3	1.5	1.6
Wetlands -> DBF	66	0.3	2.3	1.1	1.2
Wetlands -> C3 crops	109	0.6	0.4	1.0	1.3
DBF -> CNF	174	0.9	1.4	1.0	0.9
CNF -> C3 crops	75	0.4	0.5	0.6	0.7
Bare soil -> DBF	116	0.6	0.5	0.3	0.5
C3 crops -> DBF	86	0.4	0.6	0.3	0.4
C4 crops -> C3 crops	88	0.5	0.0	0.1	0.1
C3 crops -> CNF	34	0.2	0.1	0.1	0.1
CNF -> DBF	228	1.2	0.8	-0.6	-0.8
Other changes	147	2.8	**4.8**	**4.9**	**5.6**
Total	5193	28.8	100	100	100

COMMENT 2.3. Which types of classification change experience the largest change in SWE? Were certain LC changes responsible for most of the change in MB?

RESPONSE 2.3:

The impact of LC change on SWE is strongly transition-dependent. A small number of transitions dominate the overall signal, exhibiting both a relatively large spatial extent and a strong local effect on SWE (see Table R2.1). The largest SWE changes are associated with transitions from grasslands to forest types, particularly the transitions from grasslands to DBF and CNF. As shown in Table R2.1, these transitions produce the strongest area-weighted reduction in SWE RMSD in regions where snow is observed (43.5% and 11.8%, respectively), and are also associated with substantial improvements in mean bias (54.2% and 10.3%, respectively), and ubRMSD (36.3% and 12%, respectively). Transitions from grasslands to C3 crops, wetlands to CNF, grasslands to bare soil and bare soil to C3 crops also make a significant contribution to the area-weighted reduction in SWE ubRMSD, at 12.9%, 6.6%, 5.4% and 5.3% respectively. These transitions are widespread across the landscape (see Fig. R2.2) and occur in regions where increased vegetation density and canopy effects significantly modify snow accumulation and melt processes. Notably, the sign of ΔBias (New LC − Old LC) is predominantly negative for these dominant transitions, indicating a systematic reduction in positive bias when using the New LC configuration. This suggests that the

New LC configuration generally improves the representation of SWE magnitude in the affected regions compared to the Old LC configuration. Conversely, many other transitions exhibit only minor contributions, either because they affect a limited number of grid cells, or because their local impact on SWE is weak. These transitions can therefore be considered as having a negligible influence on the domain-scale bias. Overall, these results demonstrate that change in MB is largely controlled by a small number of meaningful vegetation transitions rather than being uniformly distributed across all LC changes.

COMMENT 2.4. From a qualitative perspective it appears that moving from bare soil (3) to deciduous broadleaf (9) had an impact on SWE. This should be discussed further.

RESPONSE 2.4:

We agree with the reviewer that this transition should be discussed in more detail. Transitions from bare soil to deciduous broadleaf forest (DBF) are present in the domain (see Fig. R2.2) and are associated with local changes in SWE that can be detected (see Table R2.1). These transitions are physically meaningful as they correspond to substantial modifications to surface properties, notably the introduction of vegetation where none was previously dominant. From a process-based perspective, the transition from bare soil to DBF affects several key mechanisms that control snow accumulation and ablation. Notably, the presence of a forest canopy results in the interception of snowfall, enhanced sublimation from the canopy and modifications to the surface energy balance through changes in albedo, longwave radiation and turbulent fluxes. These processes can lead to a reduction in snow accumulation on the ground and/or changes in melt dynamics, thereby impacting SWE. However, despite these clear local effects, these transitions only have a limited impact on the domain-wide SWE signal. As shown in Table R2.1, transitions involving bare soil (e.g. bare soil to DBF) account for only a small proportion of grid cells, contributing modestly to the total change in both RMSD and mean bias compared to more widespread transitions, such as grasslands to DBF or CNF. This suggests that, although bare soil to forest transitions can have a significant local impact on SWE, they do not dominate the large-scale response. Instead, overall SWE changes are primarily driven by extensive vegetation shifts that affect a larger portion of the snow-relevant domain. In the revised manuscript, we will clarify this point by explicitly discussing the physical mechanisms associated with these transitions, and by contextualising their impact with respect to the dominant LC changes.

COMMENT 2.5. I am curious why areas that did not appear to have a change in LC (e.g. Sweden) seem to have more SWE in the ISBA run with the New LC compared to the Old LC. This should be examined.

RESPONSE 2.5:

In Sweden and Finland, it appears that the dominant PFT remained largely unchanged. In contrast, significant changes occurred in the other PFTs, as illustrated in Fig. R2.3.

COMMENT 2.6. Figure 3 and associated text: How did you address the absence of SWE estimates from CCI when producing Figure 3? Were the areas masked in CCI also removed from ISBA and ERA5?

RESPONSE 2.6:

Yes, this aspect was explicitly accounted for in our analysis. All of the comparisons presented in Fig. 3 of the main manuscript were performed using a consistent spatial mask derived from the ESA CCI SWE product. More specifically, we constructed a validity mask based on the presence of satellite data, retaining only grid cells for which at least one valid CCI SWE value was available over the study period. This mask was then systematically applied to all datasets, including the ISBA simulations (Old LC and New LC configurations) and ERA5. Consequently, the time series depicted in Fig. 3 of the main manuscript are computed over a shared subset of grid cells where the ESA CCI SWE product exists, thereby ensuring spatial consistency across all datasets. This avoids artificial biases that could arise from including model-only regions (i.e. areas without satellite coverage), particularly in regions with sparse or intermittent ESA CCI SWE data. In the revised manuscript, we will clarify this point by explicitly stating that all model and reanalysis datasets are masked according to the availability of ESA CCI SWE data prior to computing spatial averages and statistics.

COMMENT 2.7. L308-310: Limit is closer to 200mm than 100mm, although SWE exceeding 200mm is common in the CCI SWE product (see Fig. 4.10 [March] in Barella et al. 2024 and also Luojus et al. 2021). See Figure 4.15 in for spatial map of local biases.

RESPONSE 2.7:

We thank the reviewer for this important remark and for highlighting the occurrence of high SWE values in the ESA CCI product. As Luojus et al. (2021) discuss, the passive microwave signal used in SWE retrievals progressively saturates for deep snowpacks, corresponding to SWE values greater than 150 mm, which typically occur for snow depths of more than ~1 m. Under these conditions, the sensitivity of the signal to additional snow mass decreases, resulting in a systematic underestimation of SWE and increased uncertainty in the satellite product. To better assess this issue in our study, we analysed the distribution of SWE values in the ESA CCI dataset over the evaluation domain (see the histogram in Fig. R2.4). This analysis shows that the vast majority of SWE values are below 150 mm, with only a small fraction exceeding this threshold (approximately 3% of the total valid points in this case). Therefore, although high SWE values (>150–200 mm) do occur, they represent only a small part of the dataset and do not dominate the overall statistics. Since the passive microwave signal used in SWE retrievals saturates, the actual proportion of SWE values above 150 mm is higher. This threshold should not be interpreted as a strict upper limit, but rather as an approximate range beyond which the reliability of satellite-derived SWE decreases. We will revise the manuscript accordingly to clarify this.

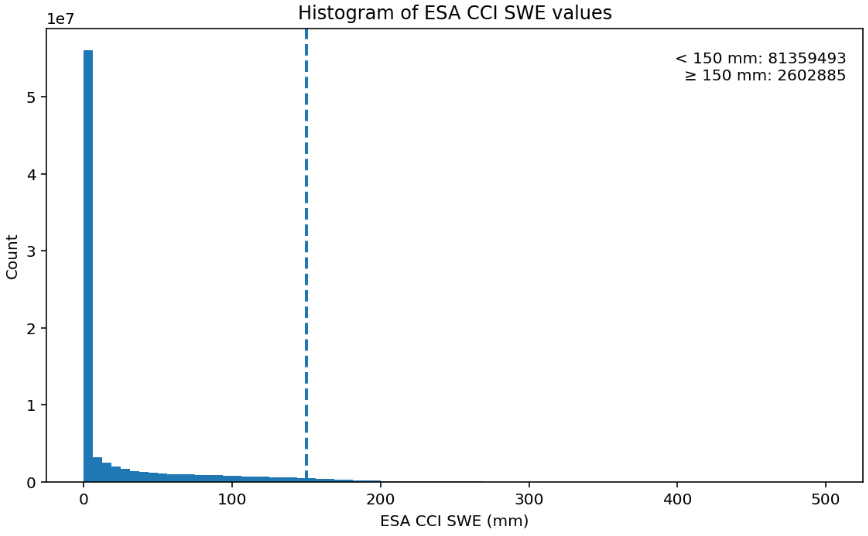

Figure R2.4. *Statistical distribution of SWE values in the ESA CCI dataset over the evaluation domain.*