Response to reviewers

We thank both reviewers and the community commenter for their careful and constructive engagement with our manuscript. These reviews have led to substantial improvements in our newly revised manuscript, and have also prompted additional analyses that we believe make the product and manuscript more useful and more carefully characterized. Below we respond to each comment individually. Reviewer text is shown in black text, our response follows in blue text, and proposed manuscript changes are noted with a "**Original / Revised**" table structure or with an "**Added:**" / "**Removed:**" where appropriate.

Response to reviewer #1

Overall Comments

This manuscript presents a technically ambitious and potentially valuable global dataset of snowmelt runoff onset derived from Sentinel-1 SAR observations constrained by MODIS-based snow phenology information. The study addresses an important observational gap between coarse passive microwave snowmelt products and sparse in situ measurements, and the large-scale implementation of a multi-orbit SAR processing framework represents a substantial engineering achievement. The manuscript is generally well structured, and the authors provide extensive discussion of environmental controls, validation results, and potential applications.

However, despite the strong technical contribution, the current manuscript contains several conceptual, methodological, and interpretational weaknesses that substantially limit confidence in the physical meaning and global applicability of the dataset. The most important issue is that the study implicitly treats the SAR backscatter minimum as a physically meaningful and globally transferable indicator of "runoff onset," while the manuscript itself simultaneously acknowledges that the backscatter minimum is influenced by multiple interacting processes, including liquid water content, snow surface roughness, canopy interactions, and environmental variability. In its current form, the manuscript demonstrates empirical consistency under selected conditions, but it does not yet establish that the retrieved timing represents a physically consistent runoff onset metric across different snow regimes. In addition, the validation framework is geographically limited relative to the claimed global applicability, several methodological choices appear heuristic and insufficiently justified, and the uncertainty characterization remains incomplete. Overall, the dataset has strong publication potential, but the manuscript requires clearer physical framing, more cautious interpretation, stronger sensitivity analyses, and more rigorous uncertainty quantification.

We are grateful for this very thorough review and we have revised the manuscript to be more explicit with its assumptions, interpretations, and methodological justifications.

Major Comments

1. Physical interpretation of “Runoff Onset” needs clearer framing

The central conceptual issue of the manuscript is the interpretation of the SAR backscatter minimum as “snowmelt runoff onset.” The manuscript repeatedly presents the backscatter minimum as a direct indicator of runoff initiation, yet the physical basis for this interpretation remains insufficiently demonstrated. As discussed in Sect. 5.2–5.3 and in the studies cited by the authors themselves, particularly Carletti et al. (2025), the SAR backscatter minimum is not a direct measurement of runoff generation, but rather the integrated result of multiple processes, including liquid water absorption, snowpack wetting, evolving surface roughness, vegetation interactions, and changes in scattering mechanisms. Importantly, none of these processes necessarily occur at a fixed temporal offset relative to actual meltwater outflow from the snowpack. The relationship between backscatter minima and true runoff initiation is therefore likely to vary systematically among maritime, continental, tundra, alpine, and shallow snow environments. The manuscript currently does not provide any physically based transfer function or process model capable of quantifying this variability. As a result, the study demonstrates empirical correspondence rather than physical equivalence.

We thank the reviewer for raising this central issue which has prompted us to clarify the physical interpretation of backscatter minima and runoff onset timing throughout the manuscript. We agree with the core of this comment, that the SAR backscatter minimum is indeed an integrated response to multiple processes. We also agree that the temporal offset between the backscatter minimum and true runoff initiation is not necessarily fixed and could vary across snow regimes.

To clarify, our intended claim is indeed one of *empirical correspondence*–that the SAR backscatter minima timing tracks independently observed in situ estimates of runoff onset timing, and not one of direct *physical equivalence* between the timing of the backscatter minima and the timing of meltwater outflow. For example, in the introduction we note:

“Carletti et al. (2025) provided a more rigorous physical understanding of the relationship between this characteristic backscatter minimum and runoff onset, combining high-resolution field measurements and radiative transfer modeling. They demonstrated that the decrease in backscatter to the characteristic minimum is caused by signal absorption from increasing liquid water content, while the subsequent post-minimum backscatter increase is controlled by evolving snow surface roughness during the runoff phase. Importantly, Carletti et al. (2025) emphasized that rather than directly detecting the initiation of runoff onset, the backscatter minimum is caused by the complex interplay of these factors when the snowpack is already isothermal and likely releasing water. Despite these complexities at the process scale, this relationship between backscatter minimum and runoff onset timing has been validated in diverse mountain environments against various reference measurements, including snow pillows at automated weather stations (Darychuk et al., 2023, 2025; Gagliano et al., 2023; Gao & Ma, 2024; Marin et al., 2020), soil moisture pulses at automated weather stations (Detre et al., 2025), snow pit measurements (Lund et al., 2022; Rickenbaugh et al., 2026), a C-band SAR tower-based study (Brangers et al., 2024), and streamflow observations (Gagliano et al., 2023; Lund et al., 2022; Rickenbaugh et al., 2026)."

To emphasize our claim of empirical correspondence early on, we made the following revisions.

Original	**Revised**
Abstract "We created this dataset by identifying backscatter minima indicative of runoff onset in a time series of Sentinel-1 C-band SAR images, with detection constrained by a custom MODIS-derived snow phenology dataset."	"We created this dataset by identifying backscatter minima empirically associated with runoff onset in a time series of Sentinel-1 C-band SAR images, with detection constrained by a custom MODIS-derived snow phenology dataset."
Section 1 "Carletti et al. (2025) provided a more rigorous physical understanding of the relationship between this characteristic backscatter minimum and runoff onset, combining high-resolution field measurements and radiative transfer modeling. They demonstrated that the decrease in backscatter to the characteristic minimum is caused by signal absorption from increasing liquid water content, while the subsequent post-minimum backscatter increase is controlled by evolving snow surface roughness during the runoff phase. Importantly, Carletti et al. (2025) emphasized that rather than directly detecting the initiation of runoff onset, the backscatter minimum is caused by the complex interplay of these factors when the snowpack is already isothermal and likely releasing water. Despite these complexities at the process scale, this relationship between backscatter minimum and runoff onset timing has been validated in diverse mountain environments against various reference measurements, including snow pillows at automated weather stations (Darychuk et al., 2023, 2025; Gagliano et al., 2023; Gao & Ma, 2024; Marin et al., 2020), soil moisture pulses at automated weather stations (Detre et al., 2025), snow pit measurements (Lund et al., 2022; Rickenbaugh et al., 2026), a C-band SAR tower-based study (Brangers et al., 2024), and streamflow observations (Gagliano et al., 2023; Lund et al., 2022; Rickenbaugh et al.,	"Carletti et al. (2025) established a physical basis for this relationship using high-resolution field measurements and radiative transfer modeling, showing that backscatter decreases to the characteristic minimum as rising liquid water content absorbs the C-band signal, and then recovers as snow surface roughness evolves during the runoff phase. Importantly, Carletti et al. (2025) emphasized that the backscatter minimum does not directly detect the initiation of runoff, but instead emerges from the combined effects of liquid water absorption and surface roughness once the snowpack is already isothermal and likely releasing water. Despite these complexities at the process scale, the relationship between the timing of the backscatter minimum and runoff onset has been validated in diverse mountain environments against various reference measurements, including snow pillows at automated weather stations (Darychuk et al., 2023, 2025; Gagliano et al., 2023; Gao & Ma, 2024; Marin et al., 2020), soil moisture pulses at automated weather stations (Detre et al., 2025), snow pit measurements (Lund et al., 2022; Rickenbaugh et al., 2026), a C-band SAR tower-based study (Brangers et al., 2024), and streamflow observations (Gagliano et al., 2023; Lund et al., 2022; Rickenbaugh et al., 2026; Torralbo et al., 2023). We therefore treat the timing of backscatter minimum as an empirically validated indicator of runoff onset rather than a direct measurement of meltwater outflow."

2026)."	

We also note that our controls analysis (Section 4.1, Fig. 4), is, in effect, an empirical characterization of where this correspondence is strong and where it degrades: rather than a single global offset, we report how our dataset's agreement with independent runoff onset estimates varies with the variables that most directly modulate the detectability of the backscatter minimum.

2. Global dataset but regionally limited validation

The dataset is presented as a global product, yet the evaluation is based almost entirely on snow pillow observations from the western United States. While this region provides an exceptional observational network for algorithm development and validation, it represents only a subset of global snow environments.

Snowpack properties, vegetation structure, climate regimes, melt processes, and SAR interactions vary substantially among maritime, continental, alpine, tundra, boreal, Arctic, and High Mountain Asia environments. Therefore, it remains unclear whether the empirical thresholds identified in the manuscript, including the forest cover threshold (~0.5), SWE threshold (~20 cm), and temporal resolution threshold (<14 days), are broadly transferable beyond the western United States. The manuscript currently does not provide sufficient evidence to support the global applicability of these relationships.

We thank the reviewer for their important point about the geographic scope of our evaluation. We agree that the Western U.S. represents only a subset of the global distribution of snow, and that the transferability of our empirically-derived thresholds warrants direct testing. We have addressed this concern in two complementary ways. First, we substantially expanded the geographic extent of the in situ evaluation network, and show that all of the major seasonal snow classes of the Sturm & Liston (2021) seasonal snow classification are represented. Second, we used the newly added stations as an independent, held-out test of the empirical relationships and thresholds originally derived from the Western U.S.

Expanded evaluation network

In addition to the original evaluation network, which comprised exclusively of stations in the contiguous Western U.S., we compiled additional daily snow pillow measurements from Alaska, British Columbia, Norway, and Nepal. We applied the same quality filters and runoff onset definition uniformly across the entire network, expanding our evaluation dataset from 4,763 water-year observations at 735 stations to 7,294 water-year observations at 1,116 stations. Despite a roughly 50% increase in water-year observations across new geographies, the station-level statistics are nearly identical, with a median difference of -2.0 days and MAD of 10.0 days (revised Fig. 5), compared to -1.0 and 9.0 days for the Western U.S. alone.

Figure A5 (newly added to the appendix, shown below) displays the expanded evaluation network in the context of the global seasonal snow classification of Sturm & Liston (2021), along with the number of pixel samples each class contributes to the pixel-wise analysis of Sect. 4.1 (Fig. 4). Sampling is not proportional to global class area: the Montane Forest class are overrepresented, while Tundra and Prairie classes are underrepresented. Every class is sampled, and even the most underrepresented classes contribute sample sizes in the hundreds of thousands of pixels. Since each class represents a major, physically distinct snow regime, the evaluation network captures a broad range of global snow conditions.

Newly added Figure A5 and accompanying caption:

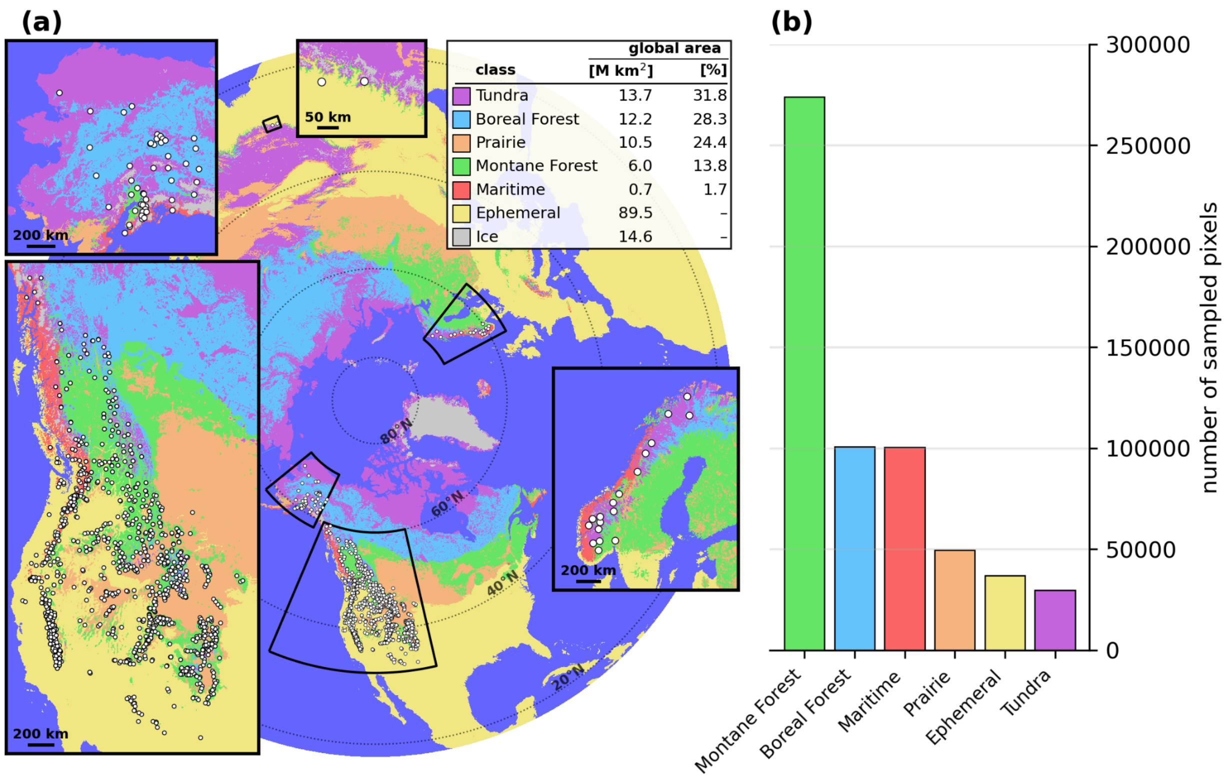

Figure A5. Evaluation network representativeness. **(a)** Locations of the evaluation stations overlaid on the global seasonal snow classification of Sturm & Liston (2021). **(b)** Number of 80 m sampled pixels within 1000 m radius of evaluation stations used in our pixel-wise analysis (Sect. 4.1, Fig. 4) by seasonal snow class.

Independent test of threshold transferability

The expanded network enables a direct test of the reviewer's central question. The empirical relationships and quality thresholds reported in Sect. 4.1 (forest cover fraction < 0.5, water year maximum SWE > 20 cm, temporal resolution < 14 days) were originally derived from stations in the contiguous Western U.S. The newly added stations therefore constitute an independent test set, drawn from regions geographically distinct from the original evaluation set.

We repeated the full pixel-wise controls analysis of Sect. 4.1, and though we propose a revised manuscript Fig. 4 based on that analysis in the revisions below, here we perform the analysis separately for just the original stations (Fig. R1) and for just the newly added stations (Fig. R2). Despite a lower sample count for the newly introduced stations, all three empirical relationships emerge: agreement declines sharply below ~20 cm of SWE, degrades with forest cover fraction greater than 0.5, and improves with finer temporal resolution when evaluated at fixed forest cover fraction and SWE. That the same relationships and approximate thresholds arise, without any tuning, and in geographies and snow regimes not used in their derivation, directly supports the transferability of our dataset and empirical thresholds beyond the Western U.S.

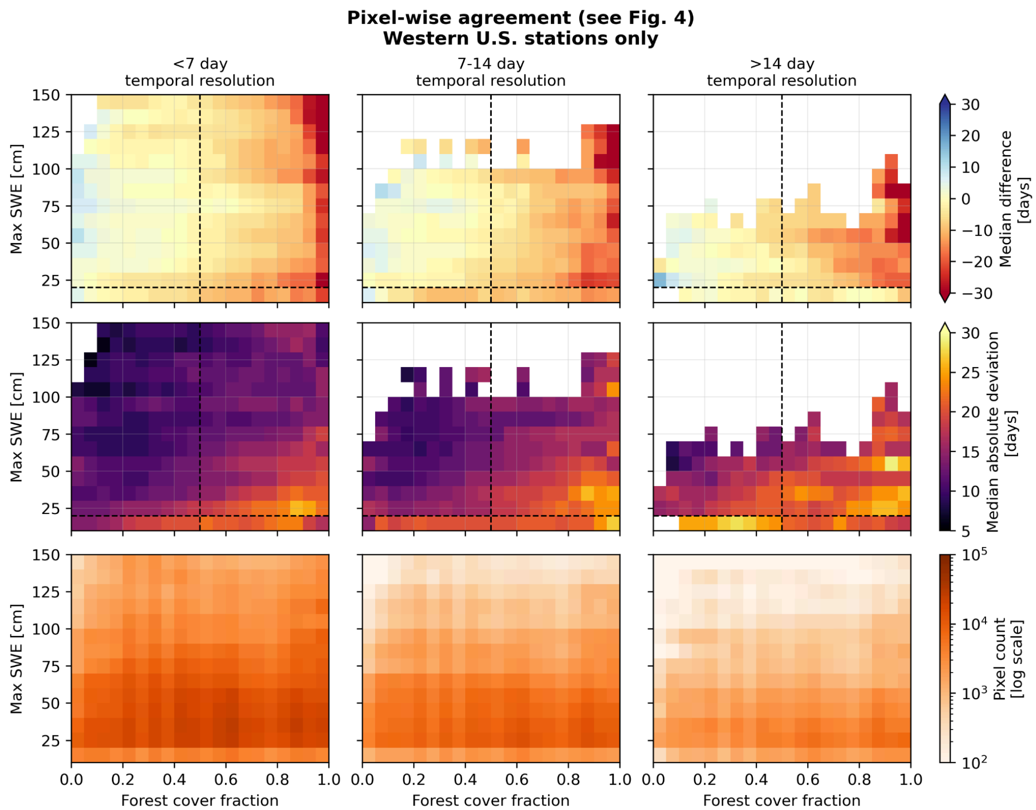

Figure R1. Pixel-wise agreement between our runoff onset estimates and snow pillow estimates (as in manuscript Fig. 4), computed using only contiguous Western U.S. stations (the stations from which the quality thresholds were originally derived).

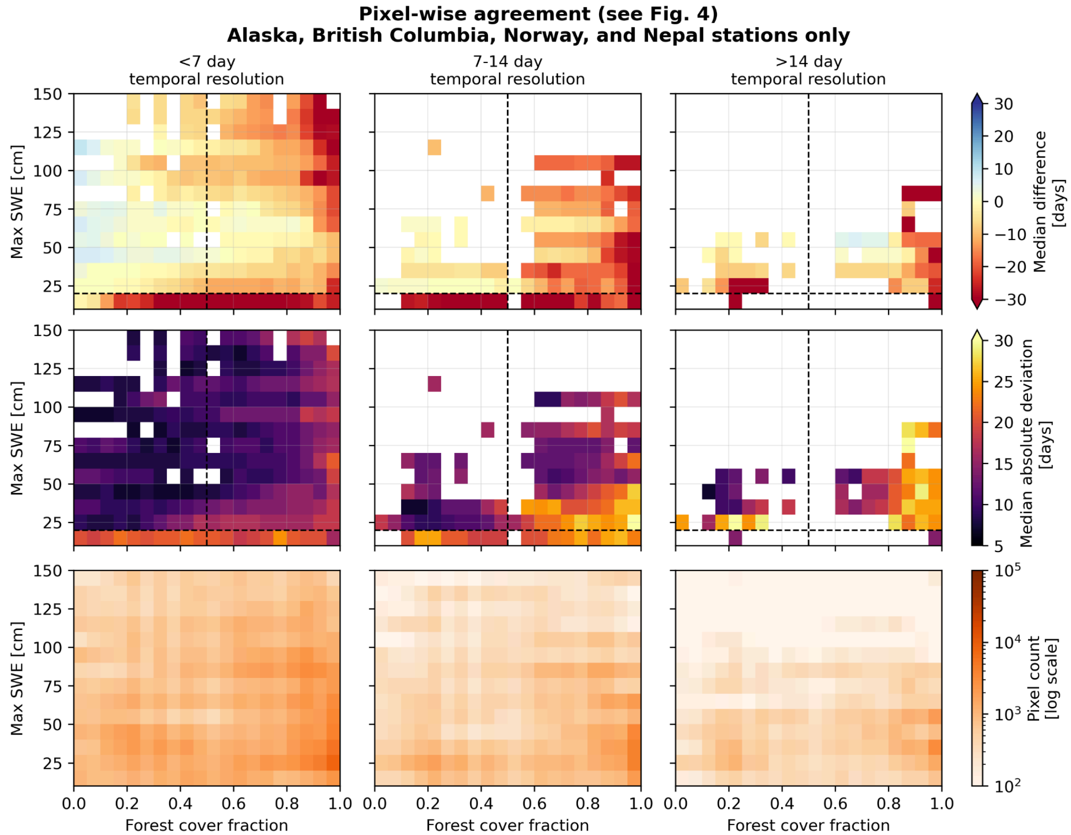

Figure R2. As Fig. R1, but computed using only the independent Alaska, British Columbia, Norway, and Nepal stations. Because fewer pixel samples fall in each bin, more bins are empty. Even so, roughly the same forest cover fraction, SWE, and temporal resolution relationships emerge.

Evaluation gaps do remain, notably in High Mountain Asia, the tropical Andes, and northern Asia. Accordingly, we retain the caution in Sect. 5.4 that the empirical bias and spread relationships in Fig. 4 provide practical quality guidance but should not be extrapolated as formal uncertainty estimates, especially in snow regimes that are not represented in the evaluation network.

We have made the following changes throughout the manuscript to reflect the expanded evaluation.

Original	**Revised**
Abstract “We validated our dataset using in situ snow pillow estimates of runoff onset from 735 automated weather stations in the Western United States, finding a median timing difference of -1.0 days and a median absolute deviation of 9.0 days.”	“We evaluated our dataset using in situ snow pillow estimates of runoff onset from 1,116 automated weather stations across the Western United States, British Columbia, Norway, and Nepal, finding a median timing difference of -2.0 days and a median absolute deviation of 10.0 days.”
Section 2.1.3 “For in situ estimation of snowmelt runoff onset, we accessed snow pillow measurements in the Western U.S. from both the SNOTEL network (Fleming et al., 2023; USDA Natural Resources Conservation Service, 2022) and the network operated by the California Cooperative Snow Surveys program, available through the California Data Exchange Center (California Department of Water Resources, 2025). To improve SNOTEL site geolocation accuracy, we used updated coordinates for 455 SNOTEL site locations (Detre et al., 2025). Though the snow pillow data are available with an hourly interval, we used daily values because they are quality-controlled and reduce measurement noise (Fleming et al., 2023).”	“For in situ estimation of snowmelt runoff onset, we compiled daily snow pillow measurements from four networks: the SNOTEL network in the Western U.S. (Fleming et al., 2023; USDA Natural Resources Conservation Service, 2022), the California Cooperative Snow Surveys program network (California Department of Water Resources, 2025), the British Columbia Snow Survey network (BC Ministry of Environment, 2024), and the Norwegian Water Resources and Energy Directorate network (Stranden & Saloranta, 2021), which includes a few affiliate stations in the Nepalese Himalaya. Though the snow pillow data are often available with an hourly interval, we used daily values because they are quality-controlled and reduce measurement noise (Fleming et al., 2023).”
Section 2.3 “We employed a two-stage evaluation approach, comparing our snowmelt runoff onset estimates against independent runoff onset estimates from a distributed network of in situ snow water equivalent (SWE) measurements acquired by snow pillows at 946 automated weather stations across the Western U.S.”	“We employed a two-stage evaluation approach, comparing our snowmelt runoff onset estimates against independent runoff onset estimates from a distributed network of in situ snow water equivalent (SWE) measurements acquired by snow pillows at 1,210 automated weather stations across the Western U.S. (including Alaska), British Columbia, Norway, and Nepal.”

Section 2.3 "Further, we excluded water years with less than 10 cm SWE, less than 60 days of continuous snow cover, or data gaps exceeding 10 days, resulting in a total of 7,916 water years of snow pillow time series across 946 stations."	"Further, we excluded water years with less than 10 cm SWE, less than 60 days of continuous snow cover, or data gaps exceeding 10 days, resulting in a total of 9,570 water-year observations of snow pillow time series across 1,210 stations."
Section 2.3 "This resulted in a total of 4,763 water years with valid runoff onset estimates across 735 stations."	"This resulted in a total of 7,294 water-year observations with valid runoff onset estimates, spanning 1,116 of the 1,210 stations (stations were excluded only when no water years passed the filters)."
Section 4.2 "The evaluation of runoff onset estimates from our annual products and the in situ snow pillow sensors revealed generally good agreement with notable temporal and spatial patterns across the Western U.S. (Fig. 5). Across all water years, the bias, represented by the median residual (our product minus snow pillow), was -1.0 days and the spread, represented by the median absolute deviation of residuals, was 9.0 days. In other words, 50% of the runoff onset residuals were within 9 days, which is similar to the dataset temporal resolution for Western North America (Fig. 2c)."	"After applying the quality filters identified in Sect. 4.1, the evaluation of runoff onset estimates from our annual products and the in situ snow pillow sensors revealed generally good agreement with notable temporal and spatial patterns across the evaluation network (Fig. 5). Across all water years, the bias, represented by the median residual (our product minus snow pillow), was -2.0 days and the spread, represented by the median absolute deviation of residuals, was 10.0 days. In other words, 50% of the runoff onset residuals were within 10 days of the median, which is similar to the dataset temporal resolution for Western North America, where the majority of our evaluation network resides (Fig. 2c)."
Section 5.3 "Our comprehensive evaluation using 735 automated weather stations across the Western U.S. demonstrates strong agreement between runoff onset estimates from our annual products and in situ snow pillows. The overall evaluation metrics – a median difference of -1.0 days and a median absolute deviation of 9.0 days (50% of residuals fall within 9.0 days) – indicate minimal systematic bias and a spread that approaches the temporal resolution of the original Sentinel-1 observations."	"Our evaluation using 1,116 automated weather stations across the Western U.S., British Columbia, Norway, and Nepal demonstrates strong agreement between runoff onset estimates from our annual products and in situ snow pillows, with an overall median difference of -2.0 days and a median absolute deviation of 10.0 days–minimal systematic bias and a spread that approaches the temporal resolution of the original Sentinel-1 observations."
Section 5.3 "However, statistical aggregation over the 4,763 water years across 735 stations ensures that these local effects do not	"However, statistical aggregation over the 7,294 water-year observations across 1,116 stations ensures that these local effects do not compromise the overall conclusions of the

compromise the overall conclusions of the evaluation."	evaluation."
Conclusion "A comprehensive evaluation of our dataset using 735 automated weather stations in the Western U.S. over a 10-year period confirmed the reliability of our methodology, with a median difference of -1.0 days and a median absolute deviation of 9.0 days compared to in situ snow pillow measurements."	"A comprehensive evaluation of our dataset using 1,116 automated weather stations across the Western U.S., British Columbia, Norway, and Nepal over a 10-year period confirmed the reliability of our methodology, with a median difference of -2.0 days and a median absolute deviation of 10.0 days compared to in situ snow pillow measurements."

Added to Section 5.3:

"This evaluation network samples all major classes of the global seasonal snow classification of Sturm & Liston (2021), though sampling density is highest in the Montane Forest class and lowest in the Tundra and Prairie snow classes (Fig. A5)."

Revised Figure 4 and accompanying caption:

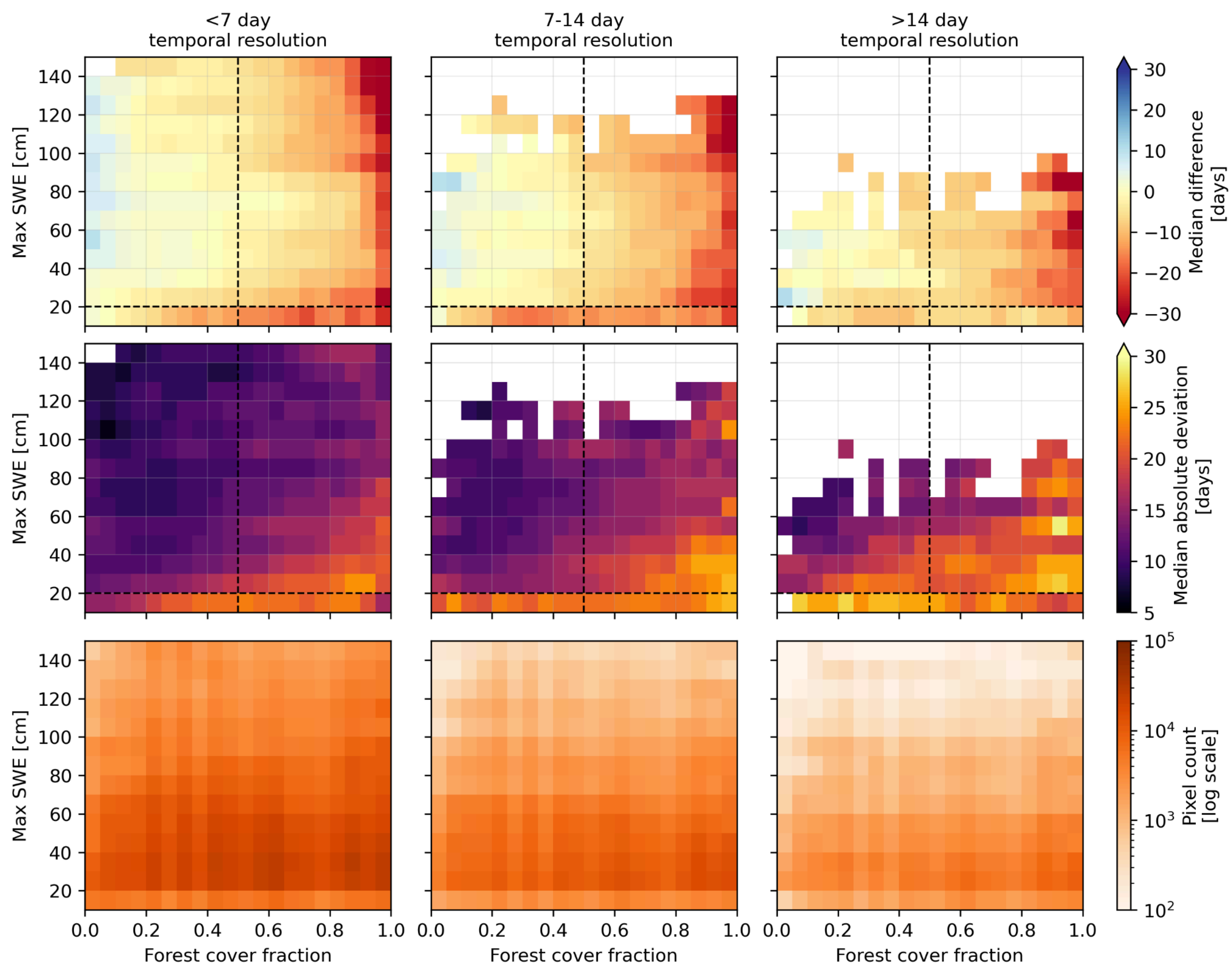

Figure 4. Agreement between our runoff onset estimates and snow pillow runoff onset estimates as a function of forest cover fraction, SWE, and temporal resolution. Top row shows the median of residuals (our product minus snow pillow, used to assess bias), middle row shows median absolute deviation of residuals (used to assess spread), and bottom row shows pixel counts per bin. Metrics are binned for different combinations of forest cover fraction (x-axis), water year maximum SWE (y-axis), and temporal resolution (columns: <7 days, 7-14 days, >14 days). Note increase in the median and median absolute deviation values for forest cover fraction values above 0.5 (vertical dashed lines), water year maximum SWE values less than 20 cm (horizontal dashed lines), and temporal resolution coarser than 14 days (third column).

Revised Figure 5 and accompanying caption:

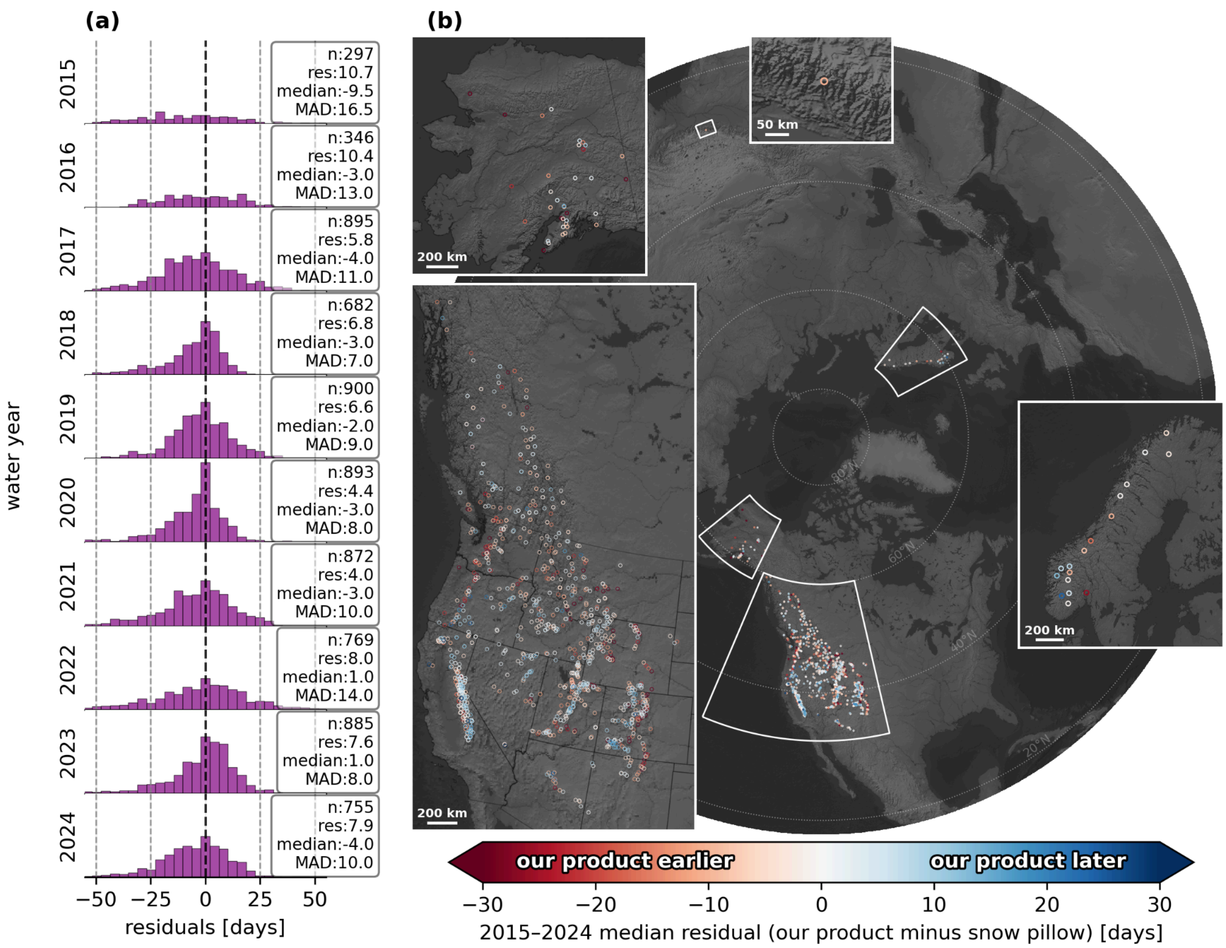

Figure 5. Evaluation of runoff onset estimates from our annual products and 1,116 automated weather station snow pillow observations for the 10-year period spanning 2015 to 2024. **(a)** Distribution of residuals (our product minus snow pillow) for each water year. Text annotations show residual statistics: number of stations (n), average temporal resolution of our annual runoff

onset products across evaluated stations (res), median of the residuals (median), and median absolute deviation (MAD) of the residuals. **(b)** Median of 2015-2024 residuals (our product minus snow pillow) for each station. At each station, positive values (blue) indicate that the runoff onset estimate from our products usually occurs after the snow pillow estimate, and negative values (red) indicate the runoff onset estimate from our products usually occurs before the snow pillow estimate.

3. Strong dependence on MODIS snow phenology constraints

The retrieval framework relies heavily on the MODIS MOD10A2 snow product to define the temporal search window for runoff onset detection. However, the implications of uncertainties in the MODIS-derived snow phenology information are not sufficiently assessed.

Because the runoff onset retrieval is constrained by MODIS-derived snow presence and disappearance dates, any biases or uncertainties in the snow phenology product may directly propagate into the final runoff onset estimates. While the manuscript briefly acknowledges inherited MODIS limitations, it does not quantify the sensitivity of the retrieval results to uncertainties in the MODIS constraints. As a result, the robustness of the retrieval framework to uncertainties in the underlying snow phenology information remains unclear.

A related issue concerns the spatial consistency between the 500 m MODIS product and the 80 m Sentinel-1 retrieval. The manuscript provides limited discussion of how the substantial difference in spatial resolution is reconciled. Potential effects of cross-scale inconsistencies may become important in heterogeneous terrain, patchy snow environments, forest edges, and complex mountain regions where sub-pixel variability is large.

We thank the reviewer for highlighting uncertainties related to the MODIS product. We have revised Sects. 2.2.1 and 2.2.2 to make clear the role of MOD10A2 data as a temporal constraint and add information about the related uncertainty it can introduce. We also clarify how we reconcile the spatial scale difference between MODIS and Sentinel-1.

Added to Section 2.2.1:

“Because of the 8-day compositing of the underlying MOD10A2 8-day maximum snow extent product, the final reported snow appearance dates and snow disappearance dates could potentially be biased up to 7 days early or late, respectively (Hall & Riggs, 2021). This inherent limitation effectively widens rather than clips the temporal window used in the search for Sentinel-1 backscatter minima.”

Added to Section 2.2.2:

“This search window approach is consistent with the findings of Darychuk et al. (2025), which showed that constraining backscatter minima detection with MODIS-derived snow presence data reduced Sentinel-1 snowmelt runoff onset estimation errors by more than 50% relative to unconstrained approaches.”

Original	**Revised**
Section 2.2.2	“We extended the temporal search window 16

"The 16-day extension of the temporal search window accounted for the spatial scale difference between MODIS (500 m) and Sentinel-1 (80 m) data, as residual patches of snow cover may have persisted within the coarser MODIS pixel, even when the MODIS products indicated snow disappearance (Crumley et al., 2020; Pflug et al., 2024)."	days beyond the MODIS snow disappearance date to reconcile the spatial scale difference between MODIS (500 m) and Sentinel-1 (80 m) data, as residual patches of snow cover within the coarser MODIS pixel may persist for weeks beyond the apparent snow disappearance date from MODIS, especially in regions with heterogeneous topography and vegetation (Boudreau, 2025; Crumley et al., 2020; Pflug et al., 2024)."

4. Several methodological parameters appear heuristic and insufficiently justified

Several key methodological parameters appear to be selected empirically, yet their robustness is not systematically evaluated. Examples include the 56-day continuous snow criterion, the 16-day search-window extension, the 30-day orbit-gap threshold, and the 95% SWE runoff definition used in the validation framework. Although these choices may be operationally reasonable, the manuscript provides limited evidence demonstrating their applicability across different snow regimes and environmental conditions.

We thank the reviewer for this comment and have added clearer justifications for the key methodological choices.

We now explain that the 56-day continuous snow cover criterion follows the established MOD10A2-based seasonal snow threshold used by Wrzesien et al. (2019) and approximates the conventional 60-day seasonal snow definition at the 8-day MODIS compositing interval.

Original	**Revised**
Section 2.2.2 "Specifically, we analyzed pixels with at least 56 days of continuous snow presence, approximating the 60-day threshold from Sturm et al. (1995) with the 8-day temporal resolution of our phenology product."	"Specifically, we analyzed pixels with at least 56 days of continuous snow presence, a criterion that, following Wrzesien et al. (2019) for MOD10A2 data, approximates the 60-day threshold between ephemeral and seasonal snow (Petersky & Harpold, 2018; Sturm et al., 1995) based on the 8-day temporal resolution of our phenology product."

We now clarify that the 16-day extension of the temporal search window is intended to accommodate residual sub-pixel snow persistence after MODIS snow disappearance. **Please see the revised text in our response to Reviewer #1, Major Comment #3.**

We now describe the 30-day orbit gap filter as a practical safeguard to avoid relative orbits with sampling gaps for two or more consecutive missed acquisitions. We acknowledge that the precise value of 30 days is somewhat arbitrary, but the choice is effectively discrete rather than continuous: because gaps occur at multiples of the repeat cycle, the relevant values for a 12-day repeat orbit are ~24 days (one missed acquisition) and ~36 days (two missed acquisitions, so any threshold in between tolerates a single miss while excluding longer gaps that risk missing the backscatter minimum entirely (Torralbo et al., 2023). Comparable criteria to ensure adequate temporal sampling have been applied in previous SAR snowmelt studies (e.g., Torralbo et al., 2023; Gao and Ma, 2024).

Original	**Revised**
Section 2.2.2 “To ensure adequate temporal sampling, we did not consider relative orbits that had any gap exceeding 30 days between consecutive acquisitions within the snow-covered period.”	“We excluded relative orbits with any temporal gap exceeding 30 days (i.e., two or more missed acquisitions for a 12- day repeat orbit) within the snow-covered period to reduce the risk of missing the backscatter minimum (Torralbo et al., 2023).”

We define snow pillow runoff onset as the day SWE drops below 95% of the water year maximum. This operational choice builds on established work linking the onset of the runoff phase to the departure from maximum snow pillow SWE (Darychuk et al., 2023, 2025; Dingman, 2015; Fassnacht et al., 2014; Gao & Ma, 2024; Marin et al., 2020), while the 5% tolerance separates sustained ablation from minor fluctuations near peak SWE, similar in spirit to the near-peak 97% margin of Darychuk et al. (2025). We now add a clearer justification for the use of this definition.

Original	**Revised**
Section 2.3 “We chose this timing instead of directly selecting the timing of maximum SWE in order to account for SWE decreases due to wind redistribution and/or sublimation, as well as to mitigate scenarios where maximum SWE occurs early in a season and persists but doesn’t melt significantly until later in the season (Dingman, 2015; Fassnacht et al., 2014).”	“This timing builds on established work linking runoff onset to the departure from maximum snow pillow SWE (Darychuk et al., 2023, 2025; Dingman, 2015; Fassnacht et al., 2014; Gao & Ma, 2024; Marin et al., 2020), while also including a 5% tolerance to account for SWE decreases due to wind redistribution and/or sublimation, as well as to mitigate issues in scenarios where maximum SWE occurs early in a season, but significant melt does not occur until later in the season (Darychuk et al., 2025).”

The justification for the selection of the 80 m spatial resolution is also not fully convincing. The manuscript links the chosen resolution to previously reported variance-stabilization scales, yet the logical connection between variance minimization and retrieval optimality is not clearly established. A minimum variance scale does not necessarily correspond to the most physically meaningful or information-rich scale for snowmelt detection. Furthermore, no sensitivity analysis is presented to evaluate how retrieval performance changes with spatial resolution.

We revised the justification for the 80 m Sentinel-1 processing resolution to avoid implying that the variance-minimizing scale from Manickam and Barros (2020) is itself the unique optimum for snowmelt retrieval. The new wording frames 80 m as a pragmatic processing scale that is finer than the variance-minimizing scale (preserves melt-related spatial structure without excessive mixing), reduces speckle, and importantly remains computationally feasible.

Original	**Revised**
Section 2.1.1 "Though the RTC images are available at 10-meter resolution, we leveraged the pre-computed 80-meter overview embedded in the Cloud-Optimized GeoTIFF files in order to balance computation costs, accuracy, and spatial resolution. This resolution selection aligns with Manickam and Barros (2020), who found through area-variance scaling analysis that SAR backscatter measurements of snow exhibit minimum variance at characteristic spatial scales (~100-1000 m depending on terrain and forest cover), suggesting that our 80 m resolution captures wet snow spatial variability while remaining computationally efficient."	"Although the RTC products are available at 10-meter resolution, we used the pre-computed 80-meter overview embedded in the Cloud-Optimized GeoTIFF files in order to balance computation costs, accuracy, and spatial resolution. The area-variance analysis of Manickam and Barros (2020) showed that the spatial variance of snow backscatter is minimized at characteristic scales of ~100-250 m over barren terrain and grassland, and increasing to >1 km in forested and cropland areas. An 80 m pixel is smaller than these characteristic spatial scales, ensuring that our products resolve melt-related spatial structure without mixing spatially distinct snowmelt behavior that coarser pixel sizes would miss. Further, aggregation to a coarser pixel size reduces radar speckle, stabilizing the backscatter values for more accurate time series analysis (Darychuk et al., 2025; Lievens et al., 2022)."

In addition, the statistical robustness of the 10-year composite products requires further consideration. In some regions, particularly northern Asia, the composite products are derived from only a small number of valid years. The manuscript does not quantify the uncertainty associated with such limited temporal sampling, making it difficult to determine whether observed spatial patterns reflect meaningful climatic variability or sampling effects.

We agree that composites built from fewer valid years (e.g. parts of northern Asia) are less robust, and we now note this in the manuscript.

Original	**Revised**
Section 3.3 "In addition to the 10-year median temporal resolution (Fig. 2c), it is important to consider the spatial variability in the total number of years with valid observations (Fig. A4).	"In addition to the 10-year median temporal resolution (Fig. 2c), it is important to consider the spatial variability in the total number of years with valid observations (Fig. A4). Despite coarser temporal resolution,

Despite coarser temporal resolution, northwest North America has 10 years of valid runoff onset observations, which is similar to northern Europe, while large swaths of northern Asia only have 3-4 years of valid observations.”	northwest North America has 10 years of valid runoff onset observations, which is similar to northern Europe, while large swaths of northern Asia only have 3-4 years of valid observations. In these regions with fewer years of valid observations, the 10-year composite products are less robust.”

5. Uncertainty characterization and quality information are insufficient

As a global Earth system dataset, uncertainty characterization represents a critical component of the product description. However, the current manuscript provides limited information regarding retrieval uncertainty.

The dataset includes annual runoff onset estimates, temporal resolution information, and composite statistics, but it does not provide a direct characterization of retrieval uncertainty. In particular, the reported median absolute deviation primarily reflects variability among years rather than uncertainty associated with the retrieval itself. Consequently, users may have difficulty distinguishing between genuine environmental variability and methodological uncertainty.

We agree that the manuscript should emphasize that the 10-year median absolute deviation composite represents interannual variability and not uncertainty. We have clarified further in Section 3.2.3.

Original	**Revised**
Section 3.2.3 “The “runoff_onset_median” variable stores the 10-year median runoff onset composite integer DOWY values (Fig. 2a, Fig. 3), while the “runoff_onset_mad” variable contains the 10-year median absolute deviation composite values in decimal days, with a precision of 0.1 days (Fig. 2b). The “temporal_resolution_median” variable stores the 10-year local median temporal resolution composite values in decimal days, with a precision of 0.1 days (Fig. 2c). These 2-dimensional (latitude, longitude) products are useful for understanding typical runoff onset timing, interannual variability of runoff onset timing, and the typical local temporal resolution of the dataset, respectively. As described in Sect. 2.2.4, these composite	“The “runoff_onset_median” variable stores the 10-year median runoff onset composite values as integer DOWY, useful for understanding typical runoff onset timing (Fig. 2a, Fig. 3). The “runoff_onset_mad” variable stores the 10-year median absolute deviation composite values as decimal days (rounded to the nearest 0.1 days), providing a measure of interannual variability in runoff onset timing (Fig. 2b). More specifically, this composite quantifies the dispersion of valid annual runoff onset timing estimates at each pixel and should not be considered a proxy for retrieval uncertainty. The “temporal_resolution_median” variable stores the 10-year local median temporal resolution composite values as decimal days (rounded to the nearest 0.1 days), summarizing typical local observation frequency during the study period (Fig. 2c). These 2-dimensional (latitude, longitude) composite products are only calculated at pixels that have 3 or more

products are only calculated at pixels that have 3 or more water years of valid data.”	water years of valid data, as described in Sect. 2.2.4.”

The manuscript also identifies several factors that strongly influence retrieval performance, including forest cover fraction, SWE, temporal resolution, and observation availability. However, these relationships are not translated into a quantitative assessment of spatially varying data quality. As a result, the reliability of the product remains difficult to evaluate in regions where environmental conditions differ substantially from those represented in the validation dataset

We agree with the reviewer about the value of uncertainty characterization. We do not include a per-pixel retrieval uncertainty product, as a globally complete uncertainty product would require globally consistent datasets for several predictors, particularly local SWE at the time of runoff onset. These quantities are not currently available globally at spatial resolutions comparable with our dataset.

However, we do provide an empirical characterization of retrieval quality through the pixel-wise residual analysis in Fig. 4 and Sects. 4.1 and 5.2. In this analysis, the binned median residuals quantify the expected bias of runoff onset estimates, while the binned median absolute deviations quantify the expected spread of estimates across combinations of forest cover fraction, SWE, and temporal resolution. Users could combine the temporal resolution product from our dataset, the forest cover fraction dataset we used, and, where available, independent SWE estimates to approximate the expected bias and spread for their specific study area using the empirical relationships in Fig. 4. We now make this interpretation clearer in Sect. 5.4 where we frame these relationships as practical quality guidance, and we additionally emphasize that these relationships should be interpreted cautiously in snow regimes that are not well represented by the evaluation network.

Original	**Revised**
Section 5.4 “Users should consider the local temporal resolution when interpreting runoff onset dates for a given water year (see Fig. A3). In practice, these thresholds are best interpreted as approximate guidelines, as the underlying relationships are complex, and conditions just outside the recommended ranges may still yield useful estimates.“	“These thresholds are best interpreted as approximate guidelines, as the underlying relationships are complex, and conditions just outside the recommended ranges may still yield useful estimates. To estimate expected retrieval quality for a given study area, users with independent SWE measurements can use local forest cover fraction together with the annual temporal resolution product to identify the expected bias and spread from the relationships shown in Fig. 4. These relationships provide practical quality guidance but should not be interpreted as formal per-pixel uncertainty estimates,

	particularly in snow regimes that are not well represented by the evaluation network.”

We recognize this as an important direction for future dataset versions, and would welcome suggestions for estimating per-pixel uncertainty reliably at the global scale using publicly available measurements.

6. Interpretation of temporal resolution effects may be confounded by environmental heterogeneity

The manuscript concludes that finer temporal resolution improves agreement between SAR-derived runoff onset estimates and snow pillow observations. While such a relationship is plausible, the current analysis does not clearly isolate temporal resolution from other environmental factors.

Temporal resolution is not randomly distributed across the study domain. Regions with finer revisit frequency often differ systematically from regions with coarser revisit intervals in terms of snow climate, vegetation structure, topography, and snowpack characteristics. Therefore, part of the observed relationship between temporal resolution and retrieval performance may reflect environmental differences rather than temporal sampling effects alone.

Because these factors are not explicitly disentangled, the current evidence is insufficient to establish a causal relationship between revisit frequency and retrieval accuracy.

We agree that temporal resolution is not randomly distributed and that disentangling it from other environmental factors is important.

However, we disagree with the reviewer that our analysis cannot isolate this effect. The pixel-wise analysis in Fig. 4 examines temporal resolution alongside forest cover fraction and SWE. When interpreting this figure, a reader can select a fixed forest cover fraction and SWE bin, and then consider temporal resolution (<7 day, 7-14 day, >14 day), which isolates the improvement from finer temporal resolution.

To emphasize that temporal resolution is evaluated while holding forest cover fraction and SWE constant to mitigate confounding / spatial autocorrelation, we make the following text change.

Original	**Revised**
Section 4.1 “Increased temporal resolution shows moderate but consistent effects, with both the bias and spread decreasing with improving temporal resolution. This effect is most pronounced between forest cover fraction of 0.4 and 0.7, with spread improving from 21 days for pixels with >14 day temporal resolution, to 14 days for pixels with 7-14 day temporal resolution. This relationship holds	“Increased temporal resolution, evaluated at fixed values of forest cover fraction and SWE, shows moderate but consistent effects, with both the bias and spread decreasing with improving temporal resolution. This effect is most pronounced between forest cover fraction of 0.4 and 0.7, with spread improving from 20-25 days for pixels with >14 day temporal resolution, to 10-15 days for pixels with 7-14 day temporal resolution. This

for forest cover fraction below 0.4, albeit weaker in strength.”	relationship holds for forest cover fraction below 0.4, albeit weaker in strength.”

We also acknowledge that part of the benefit of finer temporal resolution operates through the associated increase in available relative orbits and viewing geometries, which we discuss as a methodological rather than environmental effect in Section 5.2.

7. Coverage statistics and evaluation strategy may lead to overly optimistic interpretations

The presentation of spatial coverage may lead readers to overestimate the effective completeness of the dataset. The reported coverage percentages are calculated relative to “observable seasonal snow extent,” which already excludes regions lacking Sentinel-1 IW coverage, including portions of Greenland, Arctic islands, and Antarctica. Because these exclusions occur within the denominator itself, the reported coverage values may appear substantially closer to complete global coverage than is actually the case.

On coverage, we understand the reviewer’s concern that computing percentages relative to “Observable seasonal snow extent” could make our dataset’s “true global” coverage appear more complete than it is. These exclusions were already explicitly acknowledged in Section 3.3:

“Sentinel-1 acquires data over Antarctica and much of the Arctic in Extra Wide mode, so our dataset does not include ~1.6 million km^2 of seasonal snow over the ice-free areas of Greenland, the Canadian Arctic Archipelago, and the Russian Arctic Islands (Liston & Sturm, 2021).”

Despite this, we agree that a more pragmatic coverage statistic should include this uncapturable snow cover extent in the denominator. Therefore, we’ve changed “Observable seasonal snow extent” to “Global seasonal snow extent”, which now includes seasonal snow over ice-free areas of Antarctica, Greenland, the Canadian Arctic Archipelago, and the Russian Arctic Islands, areas that Sentinel-1 Interferometric Wide mode doesn’t capture. We’ve also recalculated the % coverage values accordingly.

Original	**Revised**
Section 3.3 “The spatial coverage of our global snowmelt runoff onset dataset is constrained by the availability of Sentinel-1 Interferometric Wide mode data. Sentinel-1 acquires data over Antarctica and much of the Arctic in Extra Wide mode, so our dataset does not include ~1.6 million km^2 of seasonal snow over the ice-free areas of Greenland, the Canadian Arctic Archipelago, and the Russian Arctic	“The spatial coverage of our global snowmelt runoff onset dataset is constrained by the availability of Sentinel-1 Interferometric Wide mode data. Sentinel-1 acquires data over Antarctica and much of the Arctic in Extra Wide mode, so our dataset does not include ~1.6 million km^2 of seasonal snow over the ice-free areas of Antarctica, Greenland, the Canadian Arctic Archipelago, and the Russian Arctic Islands (Brooks et al., 2019;

Islands (Liston & Sturm, 2021)."	Liston & Sturm, 2021)."

Revised Table 1 and accompanying caption:

Table 1. Global snowmelt runoff onset dataset spatial coverage, global seasonal snow extent, percent coverage of global seasonal snow extent, and average temporal resolution for each water year and the 10-year composites. Spatial coverage represents the total area with valid runoff onset estimates. Global seasonal snow extent is the annual seasonal snow extent from the MODIS-derived snow phenology dataset, including regions without Sentinel-1 Interferometric Wide mode coverage (i.e., ice-free areas of Antarctica, Greenland, the Canadian Arctic Archipelago, and Russian Arctic Islands). See Fig. A3 for annual maps of coverage and temporal resolution.

Water year	**Spatial coverage [km^2]**	**Global seasonal snow extent [km^2]**	**Coverage [%]**	**Average temporal resolution [days]**
2015	9,779,036	37,059,659	26.4%	16.5
2016	8,690,212	37,425,507	23.2%	16.1
2017	35,539,625	39,355,177	90.3%	9.5
2018	31,639,543	37,560,297	84.2%	9.7
2019	31,818,050	38,180,790	83.3%	9.1
2020	32,028,753	37,655,625	85.1%	9.6
2021	32,430,436	37,667,025	86.1%	8.6
2022	16,006,632	37,980,576	42.1%	8.9
2023	17,542,407	38,298,028	45.8%	8.5
2024	15,702,889	37,706,870	41.6%	10.6
10-year composites	36,761,636	40,863,365	90.0%	9.5

A related concern involves the evaluation strategy. Several empirical filtering criteria are applied prior to reporting station-level agreement statistics, including restrictions based on forest cover fraction, SWE, and temporal resolution. While such filtering may be useful for identifying favorable retrieval conditions, it also removes many of the most challenging environments before performance metrics are reported. Consequently, it remains difficult to determine how the product performs across the full range of environmental conditions represented within the dataset.

On the evaluation strategy, it’s important to note that we do not filter the data and then report performance only on the favorable subset. The pixel-wise analysis in Section 4.1 (Fig. 4) characterizes agreement across the full, unfiltered range of forest cover fraction, SWE, and temporal resolution. This includes all combinations of the most challenging conditions, where we report corresponding bias and spread up to 30 days. The empirical quality filters were derived from this full-range characterization to identify the conditions where the dataset performs optimally, as outlined in the usage guidance (Section 5.4).

Accordingly, we have clarified in Section 4.1 that the pixel-wise analysis characterizes agreement across the full range of residuals, and in Section 4.2 that the station-level statistics presented in Fig. 5 describe performance under the recommended-use conditions, not across all conditions.

Original	**Revised**
Section 4.1 “The pixel-wise analysis reveals that forest cover fraction, SWE, and temporal resolution systematically affect the bias (median) and spread (median absolute deviation) of residuals between runoff onset estimates from our annual products and the in situ snow pillow sensors (Fig. 4).”	“The pixel-wise analysis reveals that forest cover fraction, SWE, and temporal resolution systematically affect the bias (median) and spread (median absolute deviation) between runoff onset estimates from our annual products and the in situ snow pillow sensors computed using the full, unfiltered set of residuals across the complete range of each variable (Fig. 4).”
Section 4.2 “The evaluation of runoff onset estimates from our annual products and the in situ snow pillow sensors revealed generally good agreement with notable temporal and spatial patterns across the Western U.S. (Fig. 5).”	“After applying the quality filters identified in Sect. 4.1, the evaluation of runoff onset estimates from our annual products and the in situ snow pillow sensors revealed generally good agreement with notable temporal and spatial patterns across the evaluation network (Fig. 5).”

Minor Comments

1. Line 97-98 contains multiple hyphenated “-ed” adjectives that are grammatically acceptable but stylistically awkward. The sentence could be improved by rephrasing to “available as radiometrically terrain-corrected, cloudoptimized GeoTIFFs” or similar wording.

We have rephrased. **Please see revised text in our response to Reviewer #1, Minor Comment #3.**

2. The rationale linking the variance analysis of Manickam and Barros (2020) to the selection of 80 m resolution in Lines 103-106 should be revised. The current interpretation incorrectly implies that the minimum variance scale identifies the optimal scale for capturing variability.

We agree and have made modifications accordingly. **Please see the revised text in our response to Reviewer #1, Major Comment #4.**

3. In Sect. 2.1, the manuscript should provide direct URLs or DOIs for all primary input datasets, particularly the MODIS snow products and Sentinel-1 RTC products, to improve reproducibility and accessibility.

We note that Microsoft Planetary Computer does not currently provide DOIs for their datasets, so we instead reference the URLs of the current dataset landing pages. The citations for the SNOTEL network, California Cooperative Snow Surveys program network, and Copernicus forest cover fraction product each already link to their respective datasets.

Original	**Revised**
Section 2.1.1 "We utilized the entire archive of Sentinel-1 C-band SAR data in Interferometric Wide mode, available as radiometrically terrain-corrected (RTC) Cloud-Optimized GeoTIFF files hosted on Microsoft Planetary Computer (Microsoft Open Source et al., 2022)."	"We used the entire archive of Sentinel-1 C-band SAR Interferometric Wide mode data, available as radiometrically terrain-corrected (RTC) products hosted on Microsoft Planetary Computer as a collection of Cloud-Optimized GeoTIFF files (Microsoft Open Source et al., 2022; Microsoft Planetary Computer, 2022b)."
Section 2.1.2 "We used the 500-meter resolution MODIS MOD10A2 8-day maximum snow extent product (Hall & Riggs, 2021) hosted on Microsoft Planetary Computer (Microsoft Open Source et al., 2022) to prepare a custom snow phenology dataset."	"We used the 500-meter resolution MODIS MOD10A2 8-day maximum snow extent product (Hall & Riggs, 2021) hosted on Microsoft Planetary Computer (Microsoft Open Source et al., 2022; Microsoft Planetary Computer, 2022a) to prepare a custom snow phenology dataset."

4. The manuscript should more clearly explain whether the MOD10A2 8-day maximum snow extent product is appropriate for identifying snow phenology metrics such as onset and disappearance timing, given the compositing nature of the product.

The maximum-extent compositing of the MOD10A2 8-day maximum snow extent product reduces the influence of clouds on snow presence detection, especially during the spring melt season when daily products are least reliable for most locations. Beyond this benefit, we now explicitly comment on the bias introduced by the compositing nature of the product and how it widens our search window rather than clipping it. We do not require sub-8 day precision in the MODIS dates because the MODIS snow phenology dataset bounds when and where to search for runoff onset, but the runoff onset value is determined by the Sentinel-1 backscatter minimum.

Please see the revised text in our response to Reviewer #1, Major Comment #3.

5. The spatial matching strategy between 500 m MODIS data and 80 m Sentinel-1 observations should be described in greater detail, including any resampling, masking, or aggregation procedures.

We agree that we should explicitly describe the resampling procedures and have now included this in Section 2.2.1. **Please see the added text in our response to Reviewer #2, Comment "Figure 1".**

6. Figure 1 is visually cluttered and somewhat redundant. The illustration of the 56-day snow duration criterion is also difficult to interpret and may not accurately communicate the intended logic of the filtering process.

We have simplified Figure 1 as well as the corresponding caption.

Revised Figure 1 and corresponding caption:

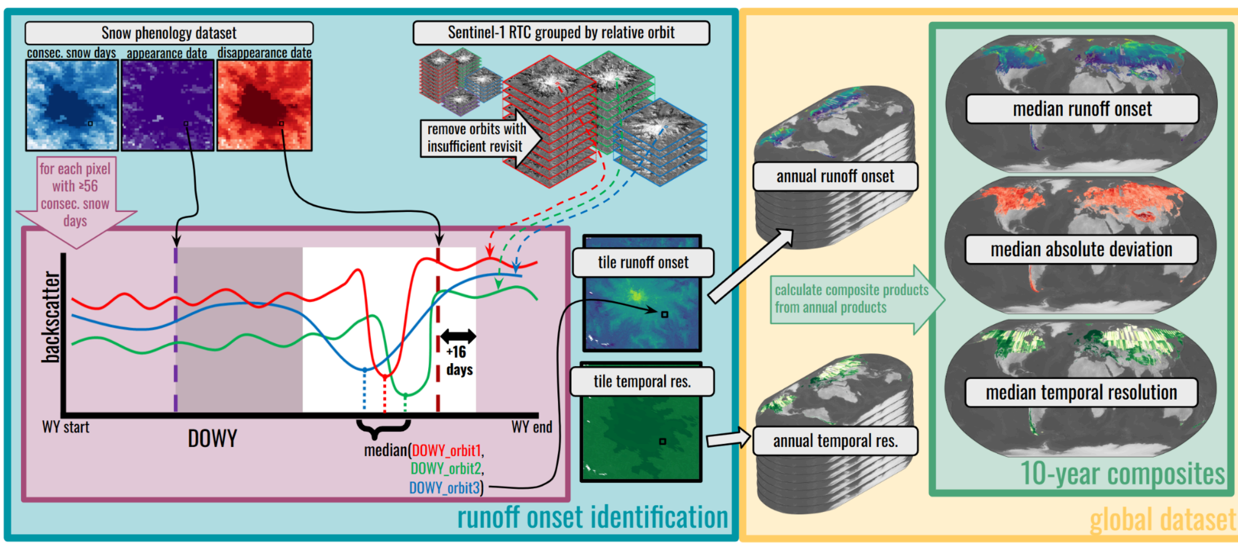

Figure 1. Graphical representation of the workflow used to create the global snowmelt runoff onset dataset. To calculate runoff onset for a single water year, Sentinel-1 data are first grouped by relative orbit and filtered to ensure sufficient revisit interval. For every pixel with ≥ 56 consecutive snow days in the snow phenology dataset, the backscatter minimum within the temporal search window (spanning from the midpoint of the snow-covered period through 16 days after the snow disappearance date, illustrated as a white background) is identified across multiple relative orbits and the median date becomes the runoff onset estimate. The resulting products for the tile are mosaicked to create global annual products, and global composite products are created from the stack of annual products.

6. Lines 177-178 mention the removal of “border noise artifacts,” but the specific filtering approach is not described. A brief explanation should be added for reproducibility.

Agreed. We’ve clarified that the thresholding of unrealistic backscatter values also removes the border noise artifacts.

Original	**Revised**
Section 2.2.2 “Our preprocessing workflow included quality filtering to remove unrealistically low backscatter values (VV backscatter < -30 dB) and border noise artifacts (Ali et al., 2018), followed by temporal filtering using our snow phenology dataset to restrict analysis to the appropriate temporal detection window for each pixel and water year.”	“Our preprocessing workflow removed all VV backscatter values below -30 dB. This single threshold removes both physically unrealistic backscatter values and residual Sentinel-1 border noise artifacts, the latter of which appear along scene edges as anomalously low-intensity values introduced during product generation (Ali et al., 2018).”

7. Line 181 should briefly define “Sentinel-1 relative orbit” for readers outside the SAR community.

We agree. We note that the term first appears earlier in the introduction, so we add an explanatory parenthetical there. Section 2.2.2 retains the expanded description of relative orbit.

Original	**Revised**
Section 1 “In previous work, we developed such an approach by integrating all available Sentinel-1 relative orbits, demonstrating enhanced temporal resolution and improved runoff onset estimate agreement with snow pillow reference measurements across 10 stratovolcanoes in the Pacific Northwest of the United States (Gagliano et al., 2023).”	“In Gagliano et al. (2023), we developed such an approach by integrating all available Sentinel-1 relative orbits (the distinct, regularly repeating ground tracks from which Sentinel-1 images a given location, each with a fixed viewing geometry and acquisition time). We demonstrated that this approach provides enhanced temporal resolution and improved runoff onset estimate agreement with snow pillow reference measurements across 10 stratovolcanoes in the Pacific Northwest of the United States (Gagliano et al., 2023).”

8. Lines 185-186 introduce the 30-day orbit-gap filtering criterion, but the manuscript does not quantify how many relative orbits were removed by this requirement. This information would help readers assess the practical impact of the filtering.

We thank the reviewer for the suggestion, but we purposely omit a count of excluded orbits because the Sentinel-1 observation plan (which determines where gaps larger than 30 days between consecutive acquisitions occur for individual relative orbits) varies substantially by geographic location and time, so any aggregate value would be difficult to interpret and likely misleading. Instead, the practical impact of this filter is reflected in the reported spatial coverage and local temporal resolution products (e.g., Figure A3) which directly capture the sampling consequences of the retained orbit set.

9. The temporal resolution metric defined in Lines 200-202 is not equivalent to a true revisit interval and more closely represents an effective local sampling interval. The manuscript should clarify this distinction.

We agree and have clarified the distinction.

Original	**Revised**
Section 2.2.2 "We also estimated the annual average temporal resolution for all pixels with runoff onset timing estimates, calculated by dividing the length of the valid observation window in days by the number of Sentinel-1 observations contained within that period."	"We also estimated the annual average temporal resolution for all pixels with runoff onset timing estimates, calculated by dividing the length of the valid observation window in days by the number of Sentinel-1 observations contained within that period. This metric represents the effective local sampling interval across all combined relative orbits rather than the revisit interval of any single relative orbit, and is therefore typically finer than the 6- or 12-day exact repeat of an individual relative orbit."

10. The manuscript states that 4,453 tiles containing both seasonal snow and Sentinel-1 RTC data were processed, but it does not indicate how many tiles contained seasonal snow without corresponding RTC coverage. This information would help clarify the true spatial limitations of the dataset.

We thank the reviewer for the suggestion. The purpose of mentioning the number of tiles was to give the reader a sense of processing scale when combined with the compute metrics also found in Section 2.2.3. Tiles vary widely in the amount of seasonal snow they contain, so reporting a raw number of tiles would be misleading. However, we agree with the underlying goal of clarifying the true spatial limits of the dataset, and we believe this is now directly served by the area-based coverage statistics in Table 1, which we have revised in response to major comment #7. Coverage in Table 1 is now expressed relative to global seasonal snow extent (rather than "observable seasonal snow extent", which excluded regions lacking Sentinel-1 IW coverage), so the reported percentages now convey, in physically meaningful units, the fraction of all seasonal snow captured by our dataset.

11. The expressions “7,916 water years of snow pillow time series” (Line 245) and “4,763 water years” (Line 268) are awkward and technically imprecise. Terms such as “station-years” or “water-year observations” would be more appropriate.

We agree. We’ve switched all instances to “water-year observations”. **Please see the updated text (with revised station counts) in our response to Reviewer #1, Major Comment #2.**

12. Lines 283-284 contain somewhat repetitive wording regarding annual and composite products and could likely be simplified.

We have simplified the wording.

Original	**Revised**
Section 3.1 “The temporal dimension spans 10 water years (2015-2024), resulting in a complete dataset structure with dimensions (water_year: 10, latitude: 195970, longitude: 499998) for annual products, and (latitude: 195970, longitude: 499998) for the 10-year composite products.”	“All products share spatial dimensions (latitude: 195970, longitude: 499998), but only the annual products add a leading water_year dimension spanning the 10 water years from 2015 to 2024.”

13. In Line 346, the phrase “of residuals” appears unnecessary and may be redundant.

We agree that the wording is unwieldy and have rephrased the sentence. **Please see the revised text in our response to Reviewer #1, Major Comment #7.**

14. The Discussion section is substantially longer than typical for a dataset-oriented paper. Sections 5.2 and 5.3 in particular contain considerable overlap between detailed interpretation of controls and evaluation discussion, making the narrative somewhat repetitive. Condensing these sections would improve readability and strengthen the overall focus of the manuscript.

We agree that Sections 5.2 and 5.3 contained overlap, especially between the controls interpretation and evaluation discussion. We have condensed both sections accordingly, trimming their collective length from 2,001 words to 1,680 words.

15. The term “unprecedented” appears repeatedly throughout the manuscript (e.g., unprecedented spatial detail, unprecedented coverage, unprecedented characterization). While the dataset clearly represents a significant advance, repeated use of superlative language may overstate the contribution. Consider using more neutral and precise descriptions where appropriate.

We agree on “unprecedented” overusage and have removed and revised two instances accordingly. We now retain only one instance of “unprecedented”, notably in the abstract where we feel its usage is most appropriate.

Removed from Section 1:
“This dataset provides unprecedented global coverage of snowmelt timing at high spatial resolution, offering valuable information for hydrological modeling, water resource management, and ecological research.”

Original	**Revised**
Section 5.1 “This global high-resolution snowmelt runoff onset dataset represents a significant advancement in snow hydrology monitoring, providing unprecedented spatial detail and temporal coverage across Earth’s seasonal snow-covered regions.”	“This global high-resolution snowmelt runoff onset dataset represents a significant advancement in snow hydrology monitoring, providing finer spatial detail and broader geographic coverage than existing snowmelt datasets.”

Response to reviewer #2

Gagliano et al. provide the global snowmelt onset timing dataset for the 10-year period spanning 2015-2024. which is first of its kind. The authors created the dataset by using time series of Sentinel-1 C-band SAR images, with detection constrained by a custom MODIS-derived snow phenology dataset. The generated dataset is validated using in situ snow pillow estimates of runoff onset from 735 automated weather stations in the Western United States. I am highly impressed by the depth and quality of discussion and explanation provided in this study. Overall, the manuscript provides a thorough and well-structured analysis supported by excellent figures and datasets. However, authors can include some of the minor comments.

We thank the reviewer for the encouraging assessment and for the constructive comments that we address below.

The introduction is nicely written and provides a good background, but it is somewhat lengthy and could be shortened to improve readability and focus.

We agree there is room to streamline the introduction for readability and focus and have made revisions accordingly.

Removed from Section 1:

“This dataset provides unprecedented global coverage of snowmelt timing at high spatial resolution, offering valuable information for hydrological modeling, water resource management, and ecological research.”

Original	**Revised**
Section 1 “Beyond its hydrological significance, snowmelt timing also serves as a key indicator of regional climate change, potentially manifesting before other environmental indicators (Dudley et al., 2017). As a process, snowmelt timing is highly sensitive to temperature and precipitation variations, and shifts in the spatial distribution of snowmelt over time provide tangible evidence of changing climate conditions. In recent decades, climate change has driven spatially heterogeneous trends in the timing and spatial distribution of global snow accumulation and snowmelt that vary in direction (earlier vs. later) and magnitude across climatic and geographic settings (Ismail et al., 2023; Royer et al., 2021; Yang et al., 2022). These changes have far-reaching consequences for water security, agricultural productivity, and ecosystem health in snow-dominated regions and beyond (Qin et al., 2022).”	“Beyond its hydrological significance, snowmelt timing also serves as a key indicator of regional climate change, potentially manifesting before other environmental indicators (Dudley et al., 2017). Because snowmelt timing is highly sensitive to temperature and precipitation variability, shifts in the spatial distribution of snowmelt over time provide tangible evidence of changing climate conditions, with heterogeneous trends observed across climatic and geographic settings worldwide (Ismail et al., 2023; Royer et al., 2021; Yang et al., 2022). These changes have far-reaching consequences for water security, agricultural productivity, and ecosystem health in snow-dominated regions and beyond (Qin et al., 2022).”
Section 1 “Traditional methods for monitoring snowmelt, such as in situ measurements from snow courses and snow pillows (Cowherd et al., 2024; Lundquist et al., 2004), provide valuable point data but require labor-intensive collection that precludes the spatial coverage necessary for regional and global analysis.”	“Traditional snowmelt monitoring methods, such as snow courses and snow pillows (Cowherd et al., 2024; Lundquist et al., 2004), provide valuable point observations but are labor-intensive and too sparse for regional and global analysis.”

Line 95-100: The criteria for selection of just VV scenes for this study are just based on literature or have the authors also explored the applicability of VV and VH images?

Though we investigated the potential of using both VV and VH in our previous work (Gagliano et al., 2023), we did not perform a new VV/VH comparison for this global product for two reasons. First, the expected benefit of adding VH appeared limited: generally, VV-only estimates of runoff onset are more accurate than VH-only estimates (Darychuk et al., 2023, 2025; Rickenbaugh et al., 2026). For the only study that demonstrated improvement by combining VV and VH, the gain in accuracy was small and not statistically significant (Darychuk et al., 2025). Second, including VH would have approximately doubled the Sentinel-1 data volume and processing cost for an already computationally intensive global workflow involving more than 100 TB of Sentinel-1 data, so we selected VV only, as supported by the recent literature.

Original	**Revised**
Section 2.1.1 "For each water year from 2015 to 2024, we selected all available VV-polarized scenes, which have demonstrated superior performance for snowmelt runoff onset identification when compared to VH polarization (Darychuk et al., 2023)."	"For each water year from 2015 to 2024, we selected all available VV-polarized scenes. We used VV polarization based on recent studies showing that VV-only estimates of runoff onset are more accurate than VH-only estimates (Darychuk et al., 2023, 2025; Rickenbaugh et al., 2026), and that improvements from combining VV and VH are not statistically significant (Darychuk et al., 2025)."

Figure 1: The resolution of Sentinel-1 SAR time series, MODIS snow cover and forest cover fraction are different. How authors have merged these in the overall methodology to generate the outputs is not very clear in the manuscript. It would be more helpful for readers to have the information.

This is a great point and we have now added the relevant information to Sections 2.2.1 and 2.3.

Added to Section 2.2.1:
"These snow phenology variables were computed on the native 500 m MODIS sinusoidal grid and bilinearly resampled to match the 80 m global processing grid. We chose bilinear resampling because the snow phenology variables – continuous snow cover (days) and snow appearance and disappearance dates (DOWY) – are continuous quantities where averaging is meaningful."

Original	**Revised**
Section 2.3 "We then binned all pixel-wise residuals across all stations and water years by each pixel's respective forest cover fraction, water year maximum SWE (maximum SWE recorded at the respective snow pillow for that water year), and temporal resolution (the pixel-wise temporal resolution for that water year as recorded in the annual temporal resolution product)."	"We then binned all pixel-wise residuals across all stations and water years by each pixel's respective forest cover fraction (bilinearly resampled from the native 100 m grid to the 80 m grid of our runoff onset product), water year maximum SWE (maximum SWE recorded at the respective snow pillow for that water year), and temporal resolution (the pixel-wise temporal resolution for that water year as recorded in the annual

	temporal resolution product)."

Line 225: "To aid in the interpretation of the annual snowmelt runoff onset products, we created three additional composite products for pixels with at least three years of valid annual data." This statement is not clear. Most of the statements in the entire manuscript are written like this. I would prefer "We created three additional composite products for pixels with at least three years of valid annual data to aid the interpretation of the annual snowmelt runoff onset products."

We agree that this wording is awkward and have accepted the reviewer's suggestion. Further, we've searched the manuscript for other instances of purpose-first clauses and have revised the most awkwardly-worded instances.

Original	**Revised**
Section 2.2.4 "To aid in the interpretation of the annual snowmelt runoff onset products, we created three additional composite products for pixels with at least three years of valid annual data."	"We created three additional composite products for pixels with at least three years of valid annual data to aid the interpretation of the annual snowmelt runoff onset products."
Section 2.2.4 "To estimate interannual variability, we created a 10-year snowmelt runoff onset median absolute deviation composite product."	"We then created a 10-year snowmelt runoff onset median absolute deviation composite product to estimate interannual variability."
Section 2.3 "To characterize the runoff onset estimate agreement for each water year across all stations, we quantified the bias and spread of the timing differences by computing the median and the median absolute deviation of the residuals."	"We quantified the bias and spread of the timing differences for each water year across all stations by computing the median and the median absolute deviation of the residuals."
Section 2.2.3 "To ensure computational feasibility, data integrity, and reproducibility, we implemented an open-source, cloud-based processing architecture."	"We implemented an open-source, cloud-based processing architecture to ensure computational feasibility, data integrity, and reproducibility."

Response to community comment #1

The authors provide an interesting and important contribution through the development of a global snowmelt runoff onset dataset from Sentinel-1 observations. Readers may also be interested in Darychuk et al. (2025), which explored the use of MODIS observations to improve Sentinel-1 snowmelt onset estimates in British Columbia. In this study, optical timing constraints reduced snowmelt onset estimation errors by more than 50% in some years relative to unconstrained approaches, providing additional evidence for the utility of optical observations in SAR-based snowmelt timing workflows.

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We thank Dr. Darychuk for pointing out this highly relevant study that we missed during earlier manuscript preparation. Though we weren't aware of it while developing our methodology, Darychuk et al. (2025) provides independent, quantitative support for one of the core design choices in our workflow – using MODIS optical observations to constrain the backscatter minima search window. We've added a sentence acknowledging this prior contribution, and have added additional references to Darychuk et al. (2025) where appropriate.

Added to Section 2.2.2:
"This search window approach is consistent with the findings of Darychuk et al. (2025), which showed that constraining backscatter minima detection with MODIS-derived snow presence data reduced Sentinel-1 snowmelt runoff onset estimation errors by more than 50% relative to unconstrained approaches."

Additional references:

Please see revised text (Introduction) in our response to Reviewer #1, Major Comment #1.

Please see revised text (Section 2.1.1) in our response to Reviewer #1, Major Comment #4.

Please see revised text (Section 2.1.1) in our response to Reviewer #2, Comment "Line 95-100:".

Original	**Revised**
Section 2.2.2 "We processed each Sentinel-1 relative orbit independently to account for systematic backscatter differences between viewing geometries caused by varying incidence angle and azimuth orientation (Gagliano et	"We processed each Sentinel-1 relative orbit independently to account for systematic backscatter differences between viewing geometries caused by varying incidence

al., 2023)."	angle and azimuth orientation (Darychuk et al., 2025; Gagliano et al., 2023)."
Section 5.3 "Conversely, diurnal melt-freeze cycles, rain-on-snow events, and isolated warm periods may temporarily increase liquid water content and alter snow surface roughness before continuous runoff begins, potentially leading to our product indicating earlier runoff onset than the snow pillows (Carletti et al., 2025)."	"Conversely, diurnal melt-freeze cycles, rain-on-snow events, and isolated warm periods may temporarily increase liquid water content and alter snow surface roughness before continuous runoff begins, potentially leading to earlier estimates from our product (Carletti et al., 2025; Darychuk et al., 2025)."

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