Dear Editor and Reviewer,

Thank you very much for your careful evaluation of our manuscript entitled "Selection of onset of acceleration points and failure time prediction of landslides based on ground-based radar" (Manuscript ID: egusphere-2026-4006). We sincerely appreciate the constructive comments and suggestions, which have helped us improve the scientific clarity, methodological rigor, and presentation of the manuscript. We have carefully considered each comment and revised the manuscript accordingly. Detailed point-by-point responses are provided below.

**Comment 1:** Please state the central research hypothesis explicitly and distinguish the study's methodological contribution from the application of established techniques.

**Response:** We sincerely thank the reviewer for this valuable comment. We agree that explicitly stating the central research hypothesis and clarifying the distinction between the methodological contribution and the application of established techniques are important for improving the scientific positioning of this study. Following the reviewer's suggestion, we have revised the Introduction section to explicitly state the central research hypothesis of this study:

For ground-based radar-monitored landslides, the transition from stable creep deformation to accelerated failure is accompanied not only by temporal changes in displacement or velocity, but also by increasing spatial heterogeneity within the deformation zone. Therefore, the temporal evolution of displacement dispersion among radar pixels can provide an effective indicator for identifying the onset of acceleration and improving failure-time prediction. Based on this hypothesis, the primary methodological contribution of this study is the development of the deformation standard deviation-based onset of acceleration identification method (DSD-OOA). Unlike conventional OOA identification approaches that mainly rely on temporal variations of displacement or velocity series, the proposed method extracts spatial statistical information from the deformation field observed by ground-based radar. By characterizing the evolution of deformation heterogeneity among multiple radar pixels, DSD-OOA provides an additional perspective for identifying the transition from relatively uniform deformation to accelerated deformation.

We also clarify that the inverse velocity (INV) method is not considered the methodological contribution of this study. The INV method is an established landslide failure-time prediction approach based on creep deformation theory. In this work, INV is used as an evaluation framework to investigate whether the OOA points identified by different strategies can provide more reliable inputs for failure-time prediction. The contribution of this study lies in improving the identification of the acceleration onset point by incorporating spatial deformation characteristics available from ground-based radar observations, rather than in modifying the fundamental principles of the INV method. Accordingly, we have revised the Introduction and Discussion sections to better distinguish:

(1) the established application of the inverse velocity method for landslide failure-time prediction.

(2) the proposed methodological contribution of extracting spatial deformation heterogeneity through DSD-OOA identification.

We sincerely appreciate the reviewer's comment, which has helped us improve the clarity of the research hypothesis and the scientific contribution of this work.

**Comment 2:** Please provide a complete description of the data sources, sampling frequency, spatial coverage, observation period, missing values, quality control procedures, and inclusion criteria.

**Response:** We sincerely thank the reviewer for this important comment. We agree that the original manuscript did not provide a sufficiently complete and systematic description of the radar datasets, particularly with respect to the acquisition intervals, observation periods, spatial coverage, missing acquisitions, quality-control procedures, and case-inclusion criteria. In response to this comment, we have revised the opening paragraphs of the three case-study sections to provide the principal acquisition characteristics of each dataset. All deformation data used in this study were acquired using ground-based radar systems.

For Case 1, a total of 260 radar scenes were collected from 11:18 on 17 June 2024 to 07:48 on 18 June 2024. The average acquisition interval was approximately 4.7 min, corresponding to approximately 12.6 acquisitions per hour. The radar observations covered a range distance of 100~900 km and an azimuth sector of 0° ~300° .

For Case 2, the radar observation period extended from 00:00 on 18 April 2021 to 10:00 on 21 April 2021. The nominal acquisition interval was approximately 20 min. Owing to a small number of missing acquisitions during the monitoring period, 225 valid radar scenes were retained, corresponding to an overall average interval of approximately 22 min, or approximately 2.7 valid acquisitions per hour. The observations covered a range distance of 100 – 1000 m and an azimuth sector of 0° ~80°.

For Case 3, a total of 153 radar scenes were collected from 13:00 on 6 June 2024 to 06:00 on 7 June 2024. The acquisition interval was approximately 6.6 min, corresponding to approximately nine acquisitions per hour. The observations covered a range distance of 100 – 1400 m and an azimuth sector of 0° ~160°.

The revised manuscript also clarifies that the reported scene numbers refer to the actual radar acquisitions retained for analysis. Missing acquisition times were treated as temporal gaps rather than as valid observations, and no artificial radar scenes were introduced to replace them. The available scenes were retained in their original chronological order. At the spatial level, DSD was calculated from the radar pixels located within the delineated deformation zone, thereby excluding areas outside the monitored unstable region from the spatial-dispersion calculation. The same data-processing and OOA-identification rules were applied consistently to all three cases. In particular, each candidate breakpoint was required to have at least five consecutive DSD observations on both sides, preventing isolated measurements or short data segments from controlling the two-segment fitting result. The reported acquisition intervals also allow the temporal support associated with this minimum-observation requirement to be interpreted for each case.

These revisions provide a more transparent description of the data sources and monitoring configurations and clarify how incomplete observations and data inclusion were handled. We sincerely appreciate the reviewer’s comment, which has improved the reproducibility and clarity of the manuscript.

**Comment 3:** Please justify the selected predictors and explain how multicollinearity, data leakage, temporal dependence, and physically implausible observations were addressed.

**Response:** We sincerely thank the reviewer for this important comment. We have revised the manuscript to clarify the selection and roles of the quantities used in the analysis.

Pixel-level cumulative displacement is the direct deformation observation provided by the ground-based radar. DSD was selected because it quantifies the spatial dispersion of displacement within the deformation zone and is therefore used to identify candidate OOA points. Velocity and inverse velocity are subsequently derived from the displacement sequence and used within the established INV framework for candidate assessment and failure-time estimation. Although these quantities originate from the same radar observations, they are used sequentially rather than jointly as predictors in a multivariable model. Therefore, conventional multicollinearity and related diagnostics are not applicable to the present framework.

The temporal order and actual acquisition times of the radar observations were preserved throughout the analysis. As each new radar scene became available, the DSD sequence and candidate breakpoint were updated using only the observations available at that update time; no random splitting or temporal shuffling was performed. Because at least five post-break observations were required, the estimated OOA could only be confirmed after a short delay. Potentially implausible or transient acceleration events were addressed at the candidate-OOA level. Only breakpoints with a positive post-break DSD slope greater than the pre-break slope were retained. Candidate points not followed by sustained acceleration and an approximately linear decrease in inverse velocity were rejected as transient events, as illustrated by the first DSD-OOA candidate in Case 3.

**Comment 4:** Please replace any random train-test split with a strict chronological evaluation strategy that reflects the intended forecasting scenario.

**Response:** We sincerely thank the reviewer for this comment. We would like to clarify that the present study does not employ a trainable statistical or machine-learning model; therefore, no random train-test split was used in the original analysis.

The DSD-OOA identification and inverse-velocity prediction procedures are deterministic and are applied independently to each landslide case as a chronological radar observation sequence. The radar scenes were retained in their original temporal order. As each new radar scene became available, the DSD sequence, candidate OOA point, and inverse-velocity fit were updated using only the observations available up to that time. No random partitioning or temporal shuffling was performed. Because the breakpoint-identification procedure requires at least five observations after a candidate breakpoint, the estimated OOA time necessarily precedes its operational confirmation time. A candidate OOA was confirmed only after the required post-break observations had become available, after which failure-time estimates were progressively updated as additional radar scenes were acquired. The recorded slope-failure time was used solely for post-event performance evaluation and was not used to identify the OOA point or fit the inverse-velocity model. Therefore, replacement of a random train-test split was not required because no such split was used in this study. Nevertheless, to avoid misunderstanding, we have revised Section 2.2 to explicitly describe the chronological updating and evaluation procedure.

We appreciate the reviewer’s comment, which has helped us clarify the temporal implementation of the proposed method.

**Comment 5:** Please report all preprocessing and feature engineering operations separately for training and testing data to demonstrate that no information from the evaluation period influenced model development.

**Response:** We sincerely thank the reviewer for this comment. We would like to clarify that the present study does not involve a trainable statistical or machine-learning model and therefore does not contain separate training and testing datasets or training-dependent feature engineering. Accordingly, preprocessing operations are not estimated from a training set and subsequently transferred to a test set.

The analysis is based directly on chronologically acquired ground-based radar observations. Pixel-level cumulative displacement is obtained from the radar deformation measurements, DSD is calculated at each acquisition time from the spatial distribution of displacement values within the deformation zone, and velocity and inverse velocity are subsequently derived for OOA assessment and failure-time estimation. These operations are deterministic transformations of the radar observations rather than learned features or parameters. As clarified in response to Comment 4, each landslide case is treated as an independent chronological observation sequence. As new radar observations become available, the DSD sequence and subsequent inverse-velocity analysis are updated using the observations available at that stage. No random partitioning, normalization based on evaluation data, parameter learning, or data-driven feature selection is involved. Missing radar acquisitions are retained as temporal gaps rather than artificially treated as valid observations.

To avoid possible misunderstanding, we have revised Section 2.2 to explicitly describe the sequential roles of the radar-derived quantities and the chronological processing procedure. We appreciate the reviewer's comment, which has helped us clarify that the preprocessing and feature-engineering concerns associated with trainable data-driven models are not directly applicable to the present deterministic framework.

**Comment 6:** Please compare the proposed approach with strong statistical and machine learning baselines using identical input data, forecast horizons, and evaluation periods.

**Response:** We sincerely thank the reviewer for this valuable suggestion. We agree that comparisons with strong statistical and machine-learning baselines are important when evaluating a general forecasting model. However, we would like to clarify that the objective of the present study is more specific: rather than developing a general data-driven forecasting model, we investigate how the identification of the onset of acceleration (OOA) from ground-based radar observations affects subsequent failure-time prediction within the inverse velocity (INV) framework.

Many existing statistical change-point detection and machine-learning forecasting approaches operate primarily on one-dimensional displacement or velocity time series. In contrast, ground-based radar provides spatially continuous deformation observations over an entire landslide area. The proposed DSD-OOA method was specifically developed to exploit this characteristic by quantifying the evolving spatial dispersion of pixel-level displacement values. Therefore, DSD-OOA should be interpreted as a spatial-statistical OOA identification approach rather than as an alternative general-purpose machine-learning forecasting model. For the comparative evaluation, we intentionally kept the downstream failure-time prediction framework unchanged and varied only the OOA identification strategy. Specifically, DSD-OOA and the established MA-OOA method were applied to the same radar observations, and the OOA points identified by both approaches were subsequently used in the same modified INV model. Thus, the comparison isolates the effect of OOA identification while avoiding confounding differences in prediction models, input representations, or model-training procedures.

We selected MA-OOA because it is a representative and widely applied OOA identification approach specifically developed for inverse-velocity-based landslide failure prediction. Accordingly, the purpose of the comparison is not to claim that DSD-OOA universally outperforms statistical or machine-learning forecasting methods, but to test whether incorporating spatial deformation heterogeneity provides a more suitable OOA input than a conventional temporal velocity-based criterion under an otherwise identical INV prediction framework. We also note that the present INV-based analysis does not involve model training, train-test partitioning, or predefined forecast horizons. Failure-time estimates are progressively updated as additional radar observations become available after OOA identification. A direct comparison with machine-learning forecasting models would therefore require the definition of a different prediction task, including training and testing datasets, input windows, prediction horizons, feature representations, and model-specific optimization procedures. Such a comparison would not isolate the methodological question addressed in this study and is beyond the present scope.

Following the reviewer's suggestion, we have revised the manuscript to clarify the scope of the comparative evaluation. We now explicitly state that the comparison is intended to evaluate alternative OOA identification strategies under the same radar observations and INV prediction framework, rather than to establish a general benchmark against all statistical and machine-learning landslide forecasting methods.

**Comment 7:** Please include a rigorous ablation study quantifying the contribution of each major input variable, architectural component, preprocessing step, and optimization strategy.

**Response:** We sincerely thank the reviewer for this suggestion. We agree that ablation studies are important for trainable multicomponent models, particularly for quantifying the contributions of different input variables, architectural components, preprocessing operations, and optimization strategies.

We acknowledge that the original manuscript did not sufficiently distinguish the proposed deterministic sequential framework from a trainable data-driven model, which may have led to this concern. We have therefore revised the relevant descriptions to clarify the methodological structure and avoid possible misunderstanding. The proposed DSD-OOA-INV approach is not a machine-learning or deep-learning architecture and therefore does not contain trainable network components, optimization strategies, or multiple learned input features that can be removed individually in a conventional ablation study. Instead, the method follows a deterministic sequential procedure: pixel-level displacement is directly obtained from ground-based radar observations, DSD is calculated to characterize the spatial dispersion of deformation and identify candidate OOA points, and the established INV framework is subsequently used for candidate assessment and failure-time estimation.

The comparative experiment in this study was specifically designed to isolate the contribution of the proposed OOA identification strategy. DSD-OOA and MA-OOA were applied to the same radar observations and subsequently evaluated using the same modified INV prediction framework. Thus, the observational data and downstream prediction method were held constant, while only the OOA identification strategy was changed. This controlled comparison directly evaluates whether incorporating the spatial dispersion information represented by DSD improves the suitability of the identified OOA point for subsequent INV prediction. Across the three investigated cases, the OOA points identified by DSD-OOA produced inverse-velocity sequences with stronger linearity and resulted in lower failure-time prediction errors than those obtained using MA-OOA. The RMSE values of DSD-OOA-INV were 0.726, 0.417, and 0.545 for Cases 1-3, respectively, compared with 1.568, 1.100, and 0.843 for MA-OOA-INV; the corresponding $R^2$ values were also consistently higher for DSD-OOA-INV.

Therefore, a conventional ablation study involving architectural modules, optimization strategies, or learned feature components is not directly applicable to the present framework. To avoid overinterpretation, we have revised the Methods section to more clearly describe the sequential structure of the proposed approach and the controlled nature of the DSD-OOA versus MA-OOA comparison.

We sincerely appreciate the reviewer's comment, which has helped us improve the clarity of the methodological description and the interpretation of the comparative analysis.

**Comment 8:** Please report uncertainty estimates and prediction intervals rather than relying exclusively on point predictions, particularly where the results are intended to support environmental or policy decisions.

**Response:** We sincerely thank the reviewer for this important comment. We agree that uncertainty quantification is valuable for landslide failure-time prediction, particularly when prediction results are used to support early warning and risk-management decisions.

We would like to clarify that the present study evaluates failure-time prediction in a sequential manner. As shown in Figures 9, 13, and 18, the predicted remaining lifetime is continuously updated as new radar observations become available, allowing the temporal evolution, stability, and convergence of the prediction to be directly examined. In addition, RMSE and $R^2$ are used to quantify the overall prediction error and goodness of fit across the updating sequence. However, we acknowledge that these metrics characterize overall prediction performance rather than the uncertainty associated with an individual failure-time estimate. The current deterministic DSD-OOA-INV framework does not explicitly produce probabilistic prediction intervals for each updated prediction time. To avoid overstating the capability of the present method, we have clarified this limitation in the revised Discussion section. Future work will extend the current framework toward probabilistic failure-time prediction, in which uncertainty associated with OOA identification, inverse-velocity fitting, and radar observations can be propagated to provide confidence or credible intervals for the estimated failure time.

**Comment 9:** Please supplement aggregate performance metrics with seasonal, extreme event, location-specific, and horizon-specific analyses, including confidence intervals or statistical significance tests.

**Response:** We sincerely thank the reviewer for this valuable comment. We agree that stratified evaluation and statistical uncertainty analysis are important for assessing the generalizability of forecasting methods when sufficiently large and diverse datasets are available.

We would like to clarify that the present study adopts an event-based evaluation rather than a long-term multi-season forecasting design. The three datasets correspond to three independent pre-failure monitoring events, and each case is analyzed separately to preserve its site-specific deformation characteristics. Accordingly, the manuscript already reports case-specific prediction trajectories and quantitative performance metrics for each landslide rather than relying solely on aggregate performance measures. Seasonal stratification is not supported by the present data structure because each dataset covers a relatively short pre-failure monitoring period rather than continuous observations spanning multiple seasons. Similarly, all three datasets correspond to documented slope-failure events, and therefore a conventional comparison between normal and extreme events cannot be meaningfully constructed from the available cases. We also clarify that the INV framework does not generate predictions at predefined forecast horizons. Instead, the estimated remaining time to failure is continuously updated as new radar observations become available. Therefore, the prediction trajectories presented in Figures 9, 13, and 18 characterize the evolution, stability, and convergence of failure-time estimates throughout the pre-failure stage rather than performance at fixed forecast horizons.

Regarding statistical significance, only three independent failure events are available in the present study. We therefore consider formal significance testing across cases insufficiently supported and potentially prone to overinterpretation.

Instead, we report the results separately for each case and have revised the Discussion to explicitly acknowledge that, although consistent improvements of DSD-OOA-INV over MA-OOA-INV are observed across the three cases, broader statistical generalization requires validation using a larger number of independent failure events.

Following the reviewer's suggestion, we have revised Section 4.1 to clarify the event-based and case-specific nature of the evaluation, the sequential rather than fixed-horizon characteristics of INV prediction, and the limitations of statistical generalization based on the current number of independent events. We sincerely appreciate the reviewer's comment, which has helped us better define the scope and interpretation of the present evaluation.

**Comment 10:** Please improve the discussion by connecting model behavior with established physical or environmental mechanisms, clearly acknowledging limitations, reproducibility constraints, and the conditions under which the conclusions may not generalize.

**Response:** We sincerely thank the reviewer for this important comment. We agree that the behavior of the proposed method should be interpreted in relation to the underlying landslide deformation process and that its limitations, applicability boundaries, and reproducibility should be clearly stated.

In the revised manuscript, we have substantially expanded Section 4.2 to strengthen the physical interpretation of the DSD-OOA method. The proposed DSD indicator characterizes the spatial dispersion of pixel-level displacement within the radar-monitored deformation zone. During relatively stable creep deformation, different portions of the deformation zone tend to evolve at similar rates, resulting in relatively limited spatial dispersion. As the slope enters accelerated deformation, progressive deformation localization, differential movement among different parts of the slope, and expansion of the active deformation area may lead to increasing spatial heterogeneity, which is reflected by the increase in DSD. Therefore, the DSD-OOA method interprets the evolution of spatial deformation heterogeneity as an indicator of the transition toward accelerated deformation, rather than relying solely on the temporal velocity change of an individual monitoring point.

We have also explicitly clarified the applicability boundaries and limitations of the proposed method. The current results primarily support its application to ground-based-radar-monitored slopes where the transition to acceleration is accompanied by a persistent and detectable increase in spatial deformation heterogeneity. Its sensitivity may be reduced when deformation remains nearly spatially uniform, when acceleration is confined to only a small number of pixels, or when short-lived disturbances increase DSD without developing into sustained acceleration. We have therefore avoided generalizing the conclusions beyond the deformation characteristics represented by the investigated cases. The revised Discussion further considers the complexity of landslide deformation. In particular, Case 3 demonstrates that a temporary increase in DSD and velocity does not necessarily indicate imminent failure. Candidate OOA points are therefore further assessed according to the subsequent inverse-velocity behavior, allowing transient deformation events to be distinguished from sustained acceleration. We also acknowledge that step-like or episodic deformation may involve multiple acceleration transitions and that a single deterministic OOA point may not fully characterize such complex deformation processes. Accordingly, probabilistic OOA identification is identified as an important direction for future research.

Regarding reproducibility, the revised manuscript now provides more explicit descriptions of the radar data characteristics, acquisition intervals, observation periods, spatial coverage, DSD calculation, breakpoint-search rules, and candidate-assessment criteria. These additions improve the transparency and reproducibility of the proposed procedure. In particular, the same breakpoint-search and candidate-selection rules are applied consistently across the three investigated cases. Finally, we explicitly acknowledge that the present evidence is based on three open-pit slope-failure cases. Although consistent improvements are observed across these cases, broader generalization requires further validation using a larger number of independent events with different landslide types, deformation behaviors, triggering conditions, and monitoring environments.

We sincerely appreciate the reviewer's comment, which has helped us strengthen the physical interpretation, methodological transparency, and scope of the conclusions presented in the manuscript.

Once again, thank you very much for your comments and suggestions.