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Deep learning-based object detection on LiDAR-derived hillshade images: Insights into grain size distribution and longitudinal sorting of debris flows

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Response to Referees

We thank the reviewer for taking the time to review our manuscript and for the constructive feedback. We provide our point-by-point responses below.

1. *Please more explicitly describe the algorithms and parameters used for coordinate transformation, wobble correction, and artifact removal to ensure reproducibility.*

   Thank you for pointing out that this was not clear enough. We transformed the point-clouds into a coordinate system where the y-axis is parallel to the channel and the z-axis is vertical (cf. Spielmann & Aaron, 2024). Sensor wobble due to wind was corrected via a rigid iterative closest point (ICP) transformation, aligning successive scans by minimizing point-to-point distances (in stable areas outside the channel bed). This was only done for station CDG. Artifacts such as raindrop-induced holes were mitigated by filtering isolated returns and either locally interpolating or omitting the areas completely. We will expand the Methods section to list these steps and parameters explicitly.

2. *Authors should briefly explain why these six specific models (YOLO variants, RT-DETR, etc.) were chosen over others, especially given their similar performance.*

   We selected models to represent both one-stage (YOLO series, RetinaNet) and two-stage (Faster R-CNN) detectors, plus a recent Transformer-based detector (RT-DETR). Together, these cover the main approaches of modern object detection (e.g., Chen et al., 2024; Zhao et al., 2024; Zou et al., 2023). Within YOLO, we compared three recent generations (v5, v8, v11) to assess whether architectural improvements affect debris-flow feature detection. For example, small objects are generally harder to detect, and sensitivity can differ across architectures. Including multiple architectures helps ensure our results are not biased by a single detection paradigm. We will better highlight in the introduction that these are the most widely used object detection models and represent different architectural classes of models.

3. *Could you discuss why BoT-SORT was ultimately preferred over SORT in more detail, especially regarding high-velocity object handling?*

   Thank you for pointing out that this was not clear. SORT failed for many high-velocity objects (>5 m s^{-1}), which are common in debris flows. BoT-SORT addresses this by (i) expanding the Kalman-filter state for improved localization and (ii) compensating for global motion (Aharon et al., 2022). In practice, this yielded more stable track IDs and longer trajectories for fast-moving boulders. We will clarify this in the discussion of our results and add a figure showing a SORT and BoT-SORT example to the Supporting Information.

4. *Add confidence intervals or p-values to velocity and size comparisons to strengthen quantitative claims.*

   Thank you for this suggestion. We agree that confidence interval estimates will strengthen our quantitative claims. In the revision, we will report confidence intervals and provide a discussion of uncertainty, similar to the comment given to Referee 1. Furthermore, we will include a comparison of velocities and object sizes derived from manually labeled tracks and detector-based tracks to clarify the uncertainty estimation.

5. *How is the loss of 3D information in hillshade projection? And its effect on vertical velocity underestimation?*

   Thank you for bringing up this point. We report 2D velocities and ignore the vertical component. The channel inclination on the fan is low (3-4°), so the vertical component of velocity is relatively minor. Fig. 6 supports this assumption, as the PIV velocities are in fact 3D and match well with the 2D object velocities. We will mention this limitation and reasoning in the discussion, and also that 3D velocities could be obtained by projecting the vectors to the 3D point cloud.

References:

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