NHESS comments

Rew1

This manuscript presents a practical procedure for using free data of Sentinel-2 and Google Earth Engine to create an inventory of shallow landslides. The procedure was applied to two landslide areas and the results were compared with the manual landslides. Overall, the methodology is well presented and the data analysis is performed in detail. The methodology shows the potential to create inventories of landslides that are fundamental to landslide research. I have some minor comments for the authors to consider:

We thank the reviewer for her/his positive comments and the very useful revision and constructive suggestions. We reply here to the minor comments suggested by the reviewer. Meanwhile, we are working on an improved manuscript and figures version. We will upload the revised when the revision process is completed with other reviewers reports.

(1) Figs. 1 and 2 included the rock formation of the studied sites. What is the role of geological information in the creation of landslide inventories?

R: Thank you for the observation. The geological information is not used in the creation of landslide inventories (PL and ML), however, they are essential ancillary information added to the database for statistical analysis of the landslide density distribution or future studies on landslide susceptibility. In addition, the geological setting is important to understand the context in which the events occurred.

(2) Line 190, Eq.1, could the authors elaborate how the eq. 1 is applied to determine the NDVI value of the studied area? What is the 'pixel' size (the calculation area) for each of single NDVI?

R: The equation 1 (the NDVI calculation) is made using the rasters of a single band of Sentinel-2 (Red-band 4, NIR-band 8) and calculated with the raster calculator of QGIS. The NDVIvar is a simple difference of pre-post event NDVI also calculated with the QGIS raster calculator tool. The same equation can be used on Google Earth Engine or any other software that manages raster data. The pixel size corresponds to the spatial resolution of the bands used (10 m for red and NIR bands of Sentinel-2) consequently, the NDVI raster also has 10 m of pixel size. In the new version of the manuscript, we add a more detailed explanation of this point

(3) The authors should detail how a polygon of PLs is formed?

R3: The rasters of NDV_{Ivar} and slope are converted in a Boolean raster (0-1) using the thresholds in a rater calculator of QGIS (e.g. B = NDVIvar<-0.16 and slope>15). In the obtained boolean raster, the values 1 correspond to the potential landslides (PL). Then on QGIS, we converted the values 1 of raster into vectors (polygon). Then, the median slope (always with QGIS) is calculated for each PL polygon and filtered with a certain threshold. The polygons are also smoothed to obtain a shape more geomorphological based. As the creation of PL from raster could be made with several GIS software, describing the detailed procedure used with QGIS on the manuscript could be too specific.

(4) Reference to Eq. 2 and Eq. 3 should be provided. The definitions of Eq. 2 and Eq. 3 seem to be different from other studies.

R4: We used these equations specifically for this study, there are no specific references available. However, similar equations can be found in several works on landslide detection (Catani et al., 2021, Prakash et al., 2021, Volpe et al., 2022, Meena et al., 2022), and we add them to the manuscript. In this work, we considered complex intersection cases. In addition to the simple true positive, false negative, and false positive cases used in other studies, we have the partial intersection. It was necessary to take into account also the partial intersection because of the different spatial resolutions of the images: PL are based on Sentinel-2 images (10 m spatial resolution). At the same time, ML are mapped on high-resolution images with 0.5 m of spatial resolution. In many cases, PL and ML polygons shapes did not fully match because they were based on two different images.

(5) Figs. 4 and 8 C, could the authors remove the PL data to clearly show the color map of NDVI?

R5: Thank you for the helpful suggestion. In the revised version, we improved these figures.

(6) Fig. 13, there is no 'C' in the caption. Also, comment on how C is created. From A and B, it seems that the kernel density points/locations are slightly different.

R6: Thank you for the comment, the caption has some errors referring to the sub-figures. In the new version of the manuscript, we will provide to add the description of 'C' in the caption. Yes, the kernel points' density and distribution are different because they are derived from PL and ML datasets, respectively. Figures C (Gavi area) and F (Tanarello area) show the scatter plots of PL (x-axis) and ML (y-axis) median density calculated over regular grids (1x1 km for 'C', and 2.5x2.5 km for 'F') on QGIS. From these data, we also calculated the coefficient of correlation.

(7) The methodology still needs to be improved to capture the landslide inventory accurately. Could the authors comment on the limitations and the area for improvement?

R7: Thank you for the comments. The main limitation is the spatial resolution of the satellite: basically, the landslides smaller than satellite spatial resolution largely underestimated. Using commercial satellites with high spatial resolution would improve the number and the shape accuracy of landslides detected, which implies a higher cost of mapping. Other improvements can be related to the filters used to select the PL on slope and NDVI index. Also, as you suggest in the following comment, the use of machine learning could be an improvement

(8) Instead of having operators change the mapping parameters and visually compare the ML and PL, are there any qualitative ways (e.g. machine learning, optimization methods...)to get the most appropriate parameters to have the highest degree of match between ML and PL?

R8: Thank you for the observation. The use of machine learning or multivariate analysis would undoubtedly be an improvement for the detection of shallow landslides. However, machine learning development that identifies landslides needs a dedicated investigation and training on a considerable amount of data. The methodology presented in this was focused on a fast and user-friendly approach that allows not skilled people in remote

sensing or coding to create a map of potential landslides. The proposed methodology could be an interesting topic for future study, in this sense, we also published the dataset of PL and ML (https://zenodo.org/record/6617194) to encourage the community to improve our methodology.