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Reply on RC2

Anirudh Rao et al.

Author comment on "Earthquake building damage detection based on synthetic-aperture-radar imagery and machine learning" by Anirudh Rao et al., Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2022-125-AC2, 2022

The comments made by the reviewer are well taken. We would like to emphasize that the focus of the article is more about the integration of multiple input datasets including InSAR data for building damage detection, rather than on machine learning itself.

As far as we are aware, multi-class damage classification at the building level using SAR data has not been attempted before, so we are unfortunately unable to compare our results with any existing literature, and indeed this was precisely one of the reasons we pursued this study. It was also our intention to propose an open framework and data that other earthquake engineers and risk modellers could use for rapid loss assessment.

Deep learning techniques are more suited for structured data (images, audio, text) with large sample sizes, while the datasets used in this study are tabular (each row representing one building unit) and are small or medium sized (typically of the order of 1,000–10,000 samples). While it's true that for tabular data, both decision forest based approaches and deep neural networks could be used, as the reviewer acknowledges, deep learning techniques perform better with large sample sizes, which was unfortunately not the case for this study, given the limited availability of building-level damage datasets and the limited number of labelled damaged buildings within each dataset. Grinsztajn et al. (2022) conclude that for medium sized tabular data (~10,000 samples), tree-based models outperform deep learning methods, with much less computational cost. Similarly, Xu et al. (2021) also conclude that forests perform better than deep neural nets for tabular data with small sample sizes.

The reviewer's comment about the selection of appropriate building damage categories is apt. Dell'Acqua and Gamba (2012) highlight the need to develop damage scales specific to earth observation based damage assessments, possibly tied to existing damage scales that are widely used for field surveys of building damage (such as EMS 98). Cotrufo et al. (2018) propose a building damage assessment scale tailored for optical satellite imagery and aerial imagery. However, a similar damage scale tailored for InSAR based building damage assessment is still lacking. We propose to update the manuscript to list these limitations and potential areas for future research.

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