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Reply on RC1

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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-AC1, 2022

We would like to thank the reviewer for highly constructive comments on the article. The suggestions are highly appreciated. Our responses to the comments are provided below.

Reply to Comment 1

In previous events where earthquake DPMs were generated by the ARIA team, such as the 2015 Gorkha earthquake in Nepal and the 2016 Central Italy earthquakes, the DPMs were found to have good correlation with the actual damage mapped in field surveys [Yun et al. (2015), Sextos et al. (2018)]. However, landslides and rockfall can also lead to surface-level changes, and so can changes in vegetation and other phenomena such as building construction. Thus, while attempting to detect building damage, care needs to be exercised to limit the focus of the DPMs to locations where buildings are known to exist. The time-span between the acquisition of the pre-event and post-event images can also have a considerable impact on the potential false positives. The closer the 'before' and 'after' bracket the event, the fewer the false positives that are likely to be observed.

It is also certainly possible to have seismic building damage without observing significant change in the ground surface level. Damage to internal walls or columns that may have severely compromised the structural integrity of the building without causing externally visible damage or collapse may not be detectable through remote sensing. Storey drifts of 2% for braced steel structures or concrete shear wall structures may be technically classified as 'collapsed' (eg. FEMA 356), but such drift levels might be smaller than the level detectable with the 1–3 m spatial resolution offered by the current generation of SAR sensors. Dong and Shan (2013) provide a good review of previous studies that investigated the relationship between building appearance in remote sensing data and building damage grades. In general, they concluded that the higher damage states like complete collapse are more detectable through remote sensing data, but lower damage states are more challenging to detect. With the advent of commercial SAR satellite constellations like Capella Space and ICEYE, sub-meter SAR imagery is becoming available, and some of these deficiencies should be addressable.

In recognition of these limitations in the SAR and EO datasets, in our study we have also proposed to incorporate other variables (such as building attributes or the expected macroseismic intensity at the location of the building) to mitigate these issues. We propose to update this section of the manuscript to clarify these limitations, and how we propose to address them.

Reply to Comment 2

In a preliminary phase, we compared different algorithms that permit multiclass classification, including support vector machines, k-nearest neighbours, Naive Bayes, and Random Forest. Since the problem of damage classification typically involves highly imbalanced datasets, where the buildings in "no damage" state dominate the buildings in all other damage states, often by multiple orders of magnitude, all of the above classifier algorithms tended to overlearn the label with the higher number of training examples (i.e., "no damage"). The Random Forest algorithm was eventually selected for the study as it allows for the assignment of weights to the training examples. The training examples in each damage class were then weighted in inverse proportion to the class frequencies observed in the input data, in order to better handle the class imbalance in the input damage datasets. The Histogram-Based Gradient Boosting classifier was preferred in the cases where categorical features were present amongst the selected building attributes, in addition to purely numerical features. This was because the Histogram-Based Gradient Boosting classifier provides native categorical support, which helps avoid one-hot encoding to transform categorical features as numeric arrays. We propose to include this explanation in the revised version of the manuscript.

Reply to Comment 3

There is certainly a tradeoff between using more samples for training the algorithm versus reserving sufficient samples for the test set. Using a higher fraction of the available data for training can result in overfitting. Previous empirical studies have demonstrated that using 70-80% of the data for training and reserving 20-30% of the data for testing yields optimal results in terms of improving the accuracy of the model while minimizing the tendancy for overfitting [see Gholamy et al. (2018) for instance]. The decision to choose a 70%/30% split for the training and testing set (say, over an 80%/20% split) was ultimately driven by the paucity of 'collapse' labels in the damage datasets, particularly for the 2017 Puebla event where reserving only 20% of the dataset for testing would leave very few 'collapse' labels in the test set to evaluate the accuracy of the fitted model. We propose to add this explanation in this section, with references that justify this approach.

Reply to Comment 4

Lines 211-213: The paucity of building damage data that can be used for training is one of the main challenges affecting machine learning models for damage prediction. Different countries use different methodologies and different damage scales to assess building damage following earthquakes. While the definition of the lower damage grades might differ considerably between different scales, collapse is often consistently defined. Thus, if the focus is restricted to identifying collapsed buildings from non-collapsed buildings, a wider set of events from the region can be used train the model, given that the training labels in this case coming from different events will be consistently defined. We propose to include this information in the revised version of the manuscript, with some examples of damage scales.

Lines 325-329: The location/region-specific concerns expressed by the reviewer are well appreciated. One of the eventual promises of the framework described in this paper is to be able to predict damage using InSAR data even for locations that aren't present in the training data. Ideally, region-specific damage detection models could be developed that take into consideration input features that are region-specific. Alternatively, region-specific or location-specific characteristics could be encoded as additional input features to a global remote-sensing based damage detection model. For instance, one of the inputs in the proposed methodology is the ground shaking intensity map (ShakeMap) generated by the US Geological Survey, which does take into consideration local site conditions, albeit through a proxy measure (Vs30). The tectonic setting is also taken into account implicitly in the derivation of the ShakeMap, as the choice of the ground motion model used to predict the ground shaking intensities in the affected area depends on the tectonic region type. If information about building construction types is available, this can be encoded as a categorical input feature, as was done for the 2015 Gorkha and 2017 Puebla examples in this study. Other researchers such as Moya et al. (2018) have also attempted to incorporate fragility functions into a machine learning framework. The concerns raised by the reviewer are also valid for the current state-of-practice in earthquake risk assessment, where ground motion models or empirical fragility / vulnerability models that have been derived for a particular region where sufficient data are available, are routinely employed for damage / loss assessment in other regions (ideally sharing similar characteristics) where not enough data are available. We propose to describe this limitation and potential source of bias in the concluding remarks.

Reply to Comment 5

Lines 320-323: This statement is meant to depict how the proposed framework would work in a real-time post-event damage assessment environment. Within the scope of the current study, we unfortunately did not come across building-level damage data from multiple events within the same country or geographic region that could be used to train a ML model for the region using data from previous events prior to a disaster and test the ML model after the subsequent earthquake event. The phrasing of the sentence could be improved to better convey the intention, potentially to: "*The training of the machine learning models would have been undertaken prior to the disaster event, and the trained model can then be deployed for damage detection following an earthquake as soon as the pre-event building inventory, ShakeMap, and DPM become available*"

Reply to Comment 6

The folder containing the data and code related to the Puerto Rico earthquake has been added to the repository.

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