Deep Learning-based Damage Mapping with InSAR Coherence Time Series

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Satellite remote sensing is playing an increasing role in rapid mapping of damage after natural disasters. In particular, synthetic aperture radar (SAR) can image the Earth's surface and map damage in all weather conditions, day and night. However, current SAR damage mapping methods struggle to separate damage from other changes in the Earth's surface. In this study, we propose to map damage using the full time history of SAR observations of an impacted region from a single satellite constellation in order to detect anomalous variations in the Earth's surface properties due to a natural disaster. We quantify Earth surface change using time series of sequential interferometric SAR coherence, then use a recurrent neural network (RNN) as a probabilistic anomaly detector on these coherence time series. The RNN is first trained on pre-event coherence time series, and then forecasts a probability distribution of the coherence between pre- and post-event SAR images. The difference between the forecast and observed co-event coherence provides a measure of the confidence in the identification of damage. The method allows the user to choose a damage detection threshold that is customized for each location, based on the local temporal behavior before the event. We apply this method to calculate estimates of damage for three earthquakes using multi-year time series of Sentinel-1 SAR acquisitions. Our approach shows good agreement with measured damage and quantitative improvement compared to using pre- to co-event coherence loss as a damage proxy.