Pixel-Wise T-Test

A New Algorithm for Persistent Building Damage Detection in Synthetic Aperture Radar Imagery

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Summary

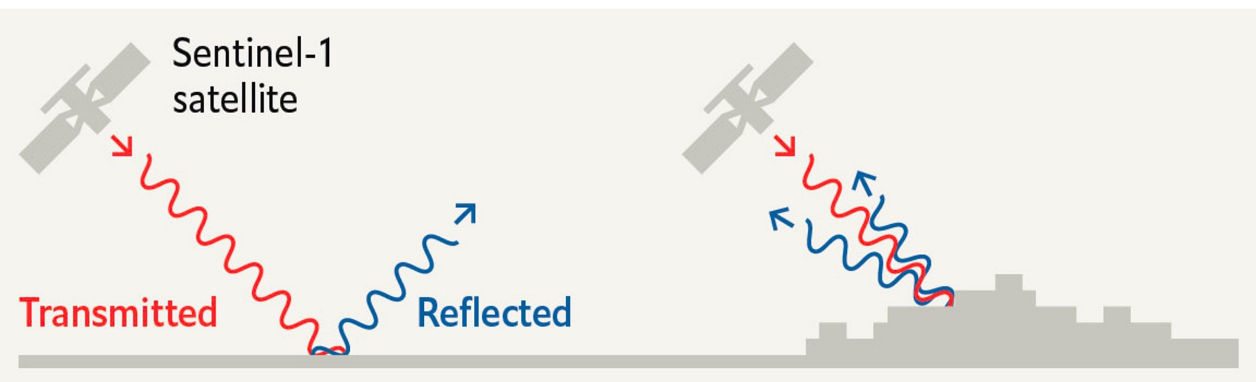
This paper proposes a novel method for the generation of building-level damage estimates using a Pixel-Wise T-test (PWTT) applied to Synthetic Aperture Radar imagery. Despite being lightweight and only using open access data, the algorithm produces results with accuracy statistics rivalling State of the Art methods that use deep learning and expensive high-resolution imagery. The algorithm is deployed on a cloud computing platform, enabling the generation of near-real time damage maps that allow humanitarian practitioners to immediately get the count of damaged buildings in a user-specific area of interest.

Problem

Satellite imagery is used extensively to detect damaged buildings. The highest levels of accuracy are generally achieved using Deep Learning and Very High Resolution optical satellite imagery. However, such approaches are both financially and computationally expensive, optical imagery is not consistently available due to cloud cover, and neural networks require retraining to be accurate in different geographies.

Solution

Sentinel-1 SAR imagery is free, has a high revisit rate, and can penetrate clouds. Static structures are thus highly consistent in multitemporal imagery. A destructive event results in a change in backscatter amplitude, but relatively low variance in pixel values in both the pre- and post- shock periods for damaged buildings. A standard T-test can be used to calculate the ratio of the change in amplitude to general pixel variance, detecting collapsed buildings.



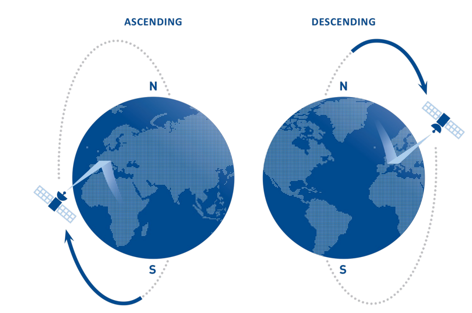
Pixel-Wise T-Test

Building damage estimates are generated by pre-processing the SAR imagery, computing the test statistic for each pixel, and calculating the mean value of this raster within building footprints.

Pre-Processing

1. Sentinel-1 imagery is disaggregated by orbital trajectory (ω) to ensure consistency in the look angle.
2. Scenes are then separated by polarization; VV is more sensitive to linearly oriented structures such as buildings tend to preserve the coherence of the polarimetric signal, while VH is more sensitive to randomly oriented structures.
3. Scenes are split into pre- and post- shock samples using a cutoff date (e.g. the onset of war, or date of an earthquake).

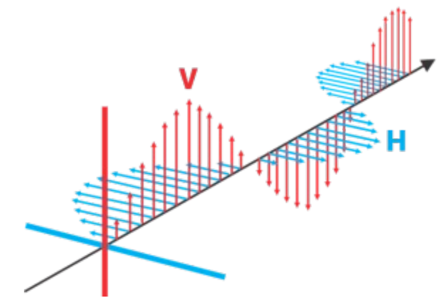
1



Orbit

$$\omega = \begin{cases} Ascending \\ Descending \end{cases}$$

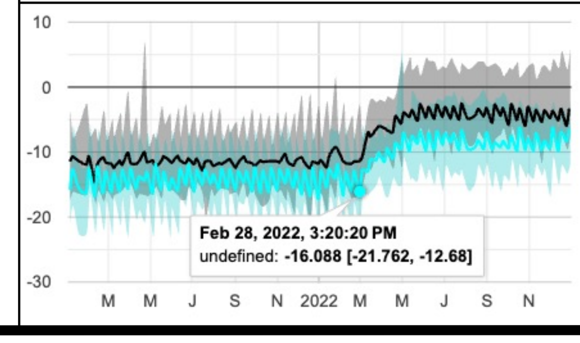
2



Polarization

$$\pi = \begin{cases} Vertical\ Vertical \\ Vertical\ Horizontal \end{cases}$$

3



Time Period

$$\tau = \begin{cases} 0, Pre\ shock \\ 1, Post\ shock \end{cases}$$

Calculating the Test Statistic

4

$$\mu_{\omega,\pi,\tau} = \frac{1}{n}\sum_{i=1}^{n} x_{i,\omega,\pi,\tau}$$

5

$$\sigma_{\omega,\pi,\tau} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{i,\omega,\pi,\tau}-\mu_{\omega,\pi,\tau})}$$

6

$$t_{\omega,\pi} = \frac{\mu_{\omega,\pi,0} - \mu_{\omega,\pi,1}}{\sqrt{\frac{\sigma^2_{\omega,\pi,0}}{n_{\omega,\pi,0}} + \frac{\sigma^2_{\omega,\pi,1}}{n_{\omega,\pi,1}}}}$$

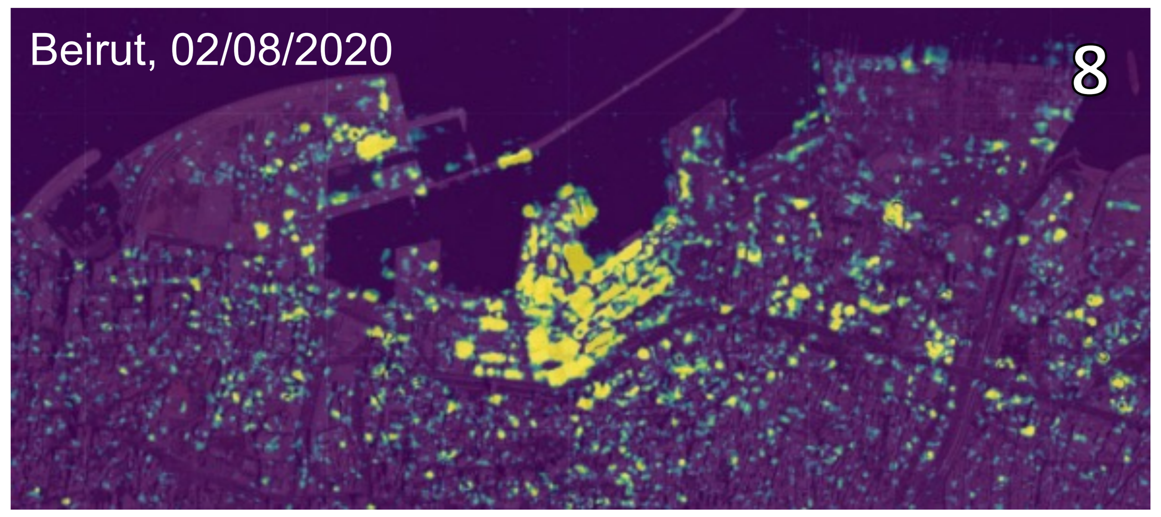
7

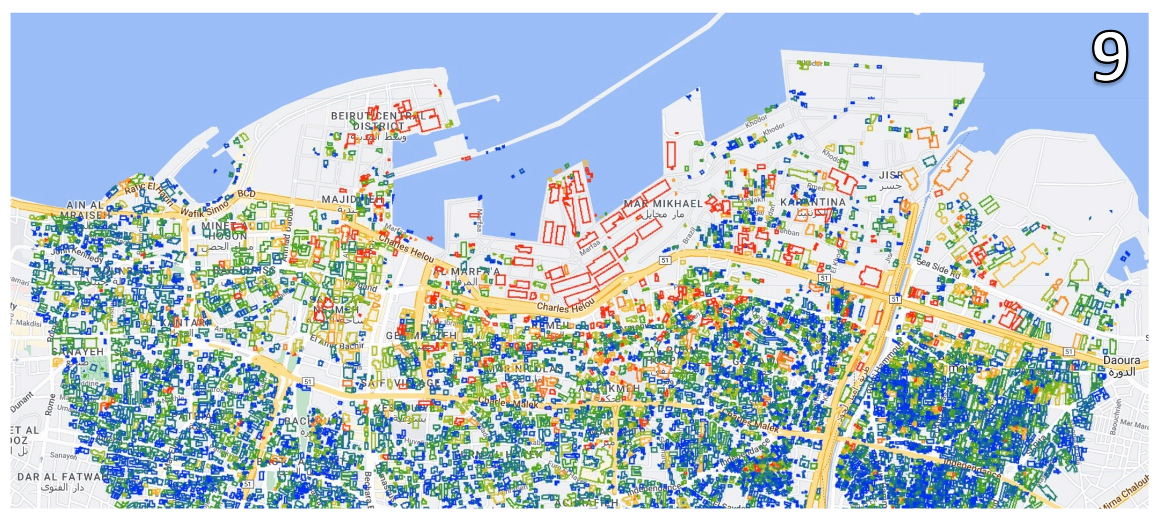
$$\Delta = \frac{1}{4}\sum_{t\in\omega,\pi}|t|$$

4. The mean μ for each pixel x in scene i with a given orbital pass ω, polarization π, and time period τ.
5. The corresponding pixel's standard deviation σ.
6. A standard T-test is computed for each unique combination of orbital trajectory (ascending/descending) and polarization (VV/VH). There are thus four T-values per pixel
7. The final test statistic is the average of the absolute T-values; A cutoff value of the test statistic is chosen based on the degrees of freedom and conventional statistical significance thresholds.

Building-Level Prediction

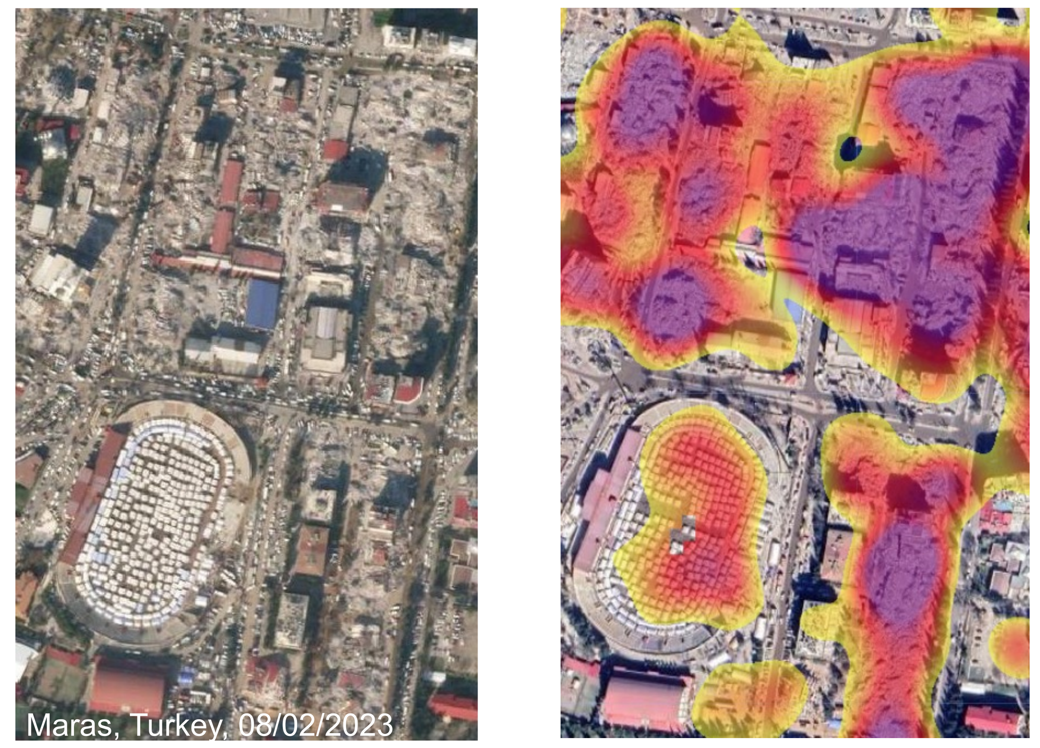
8. The result is a damage probability raster, in which each pixel value reflects the average of four T-values. On the right, the PWTT algorithm is applied to Beirut following the explosion in August 2020.
9. Building-level inference is carried out using Microsoft Buildings, an open-access global building footprint dataset. The mean pixel value of the damage probability raster is calculated within each building footprint, and added as a feature.





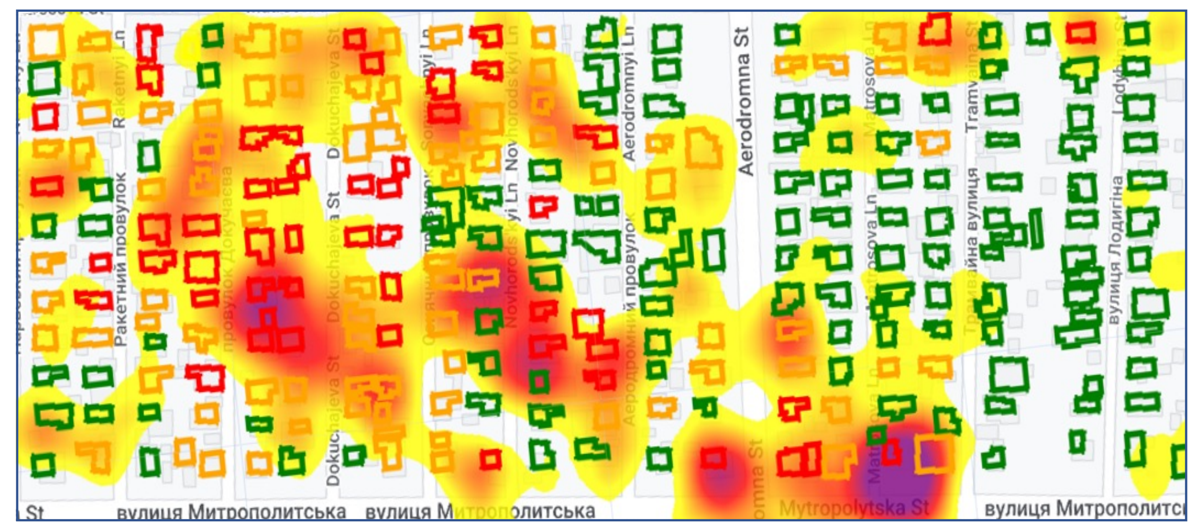
Results

The PWTT produces consistent and accurate damage probability estimates across a range of different geographies and disaster types. Visual validation has been carried out in Turkey following recent earthquakes:

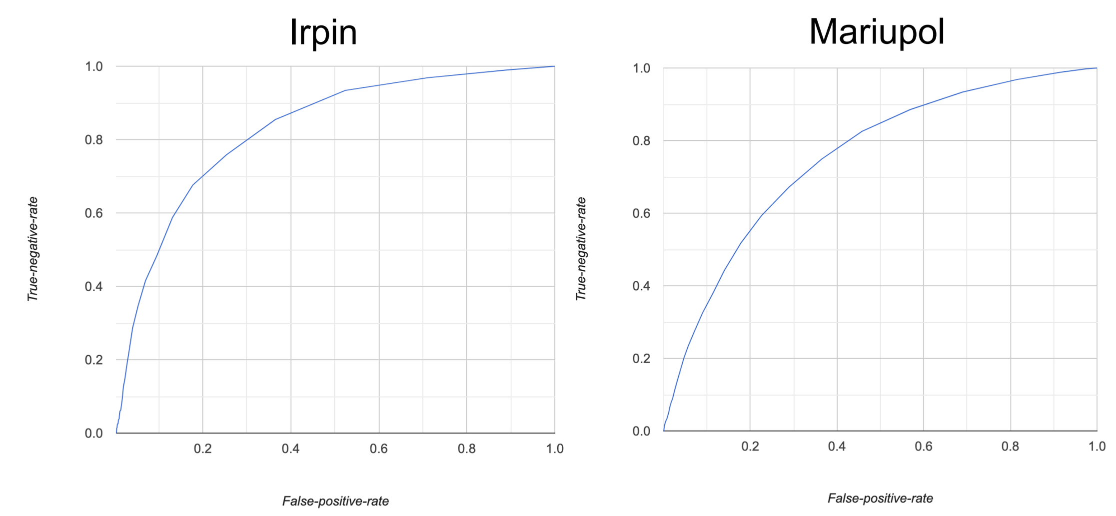


Ukraine

To assess the accuracy of this workflow, the PWTT was applied to Ukraine and damage predictions were compared with manually annotated building damage labels from UNOSAT:



The cities of Mariupol and Irpin suffered some of the most extensive damage from the war. Both endured heavy shelling in the first month of the conflict. The PWTT algorithm is run on both cities using a cutoff date of March 1st, 2022, yielding two datasets of building footprints with associated damage probability values. Receiver-Operator Curves for Irpin and Mariupol yield an **area under the curve of 0.82 and 0.75**, respectively:



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