Turkey Building Damage Assessment

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Overview

After the earthquake in Turkey on February 6th, our team began to utilize artificial intelligence (AI) methods and high-resolution satellite imagery to assess the extent of damage to buildings in the affected region. Specifically, we partnered with Turkey's Ministry of Interior Disaster and Emergency Management Presidency (AFAD) to deliver building level damage estimates over four cities in southeast Turkey using satellite imagery from the first 3 days of the disaster. We estimate 3,849 buildings were damaged/destroyed across the four cities. We found the city of Marash* to be the most heavily affected, with 7.44% of buildings in the city sustaining some level of damage visible from satellite imagery.

* Also known as Kahramanmaraş

Our results can be downloaded in GeoPackage format from the following URLs:

Turkoglu results, February 9th, Planet Labs

Nurdagi results, February 9th, Maxar Technologies

Marash results, February 9th, Planet Labs

Islahiye results, February 7th, Maxar Technologies

Methodology

We use satellite imagery from two commercial providers, Planet Labs and Maxar Technologies, which offer images at spatial resolutions of 50cm and 30cm, respectively. We model the problem of identifying damaged buildings from satellite imagery as a semantic segmentation problem. More specifically, we use convolutional neural networks (CNNs) to estimate whether each pixel in an input satellite image is either: part of a damaged building, part of an undamaged building, or part of the background (i.e., anything not belonging to the first two classes). We pre-train a CNN on the xBD dataset [1] which provides fine-grained building damage polygons across different types of disasters. We then fine-tune a CNN for each area of interest (AOI) with labels collected using our open-source "satellite-imagery-labeling-tool" [2]. This tool allows a user to quickly annotate satellite imagery with examples of the three classes (see Figure 1 for an example of this interface) and integrate their annotations into a machine learning model training workflow.

After fine-tuning a model for each AOI, we run the model across all the satellite imagery available for that AOI during the time of interest and summarize the model's output over the Microsoft Building footprint dataset [3]

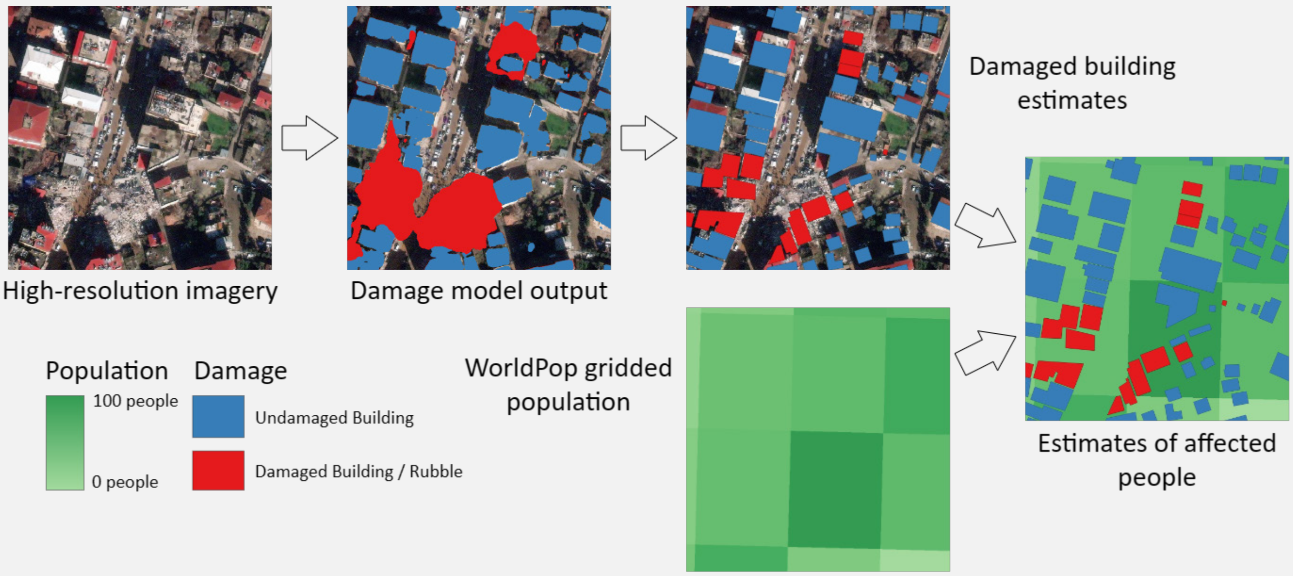
Figure 1: Screenshot of the Satellite Imagery Labeling Tool deployment for the city of Marash.
https://github.com/microsoft/satellite-imagery-labeling-tool

or building footprints from OpenStreetMap. For each building footprint in the AOI, we compute the percentage of the building's footprint that is predicted to be "part of a damaged building" by the CNN model (see Figure 2 for an illustration of the workflow). Downstream analysis, e.g. by GIS experts at AFAD, can threshold this percentage damaged value to quickly identify totally destroyed buildings versus buildings with minor damage. A weakness of this methodology is that rubble that has been identified as "damage", but that falls outside of a building footprint is not able to be attributed to any nearby building, potentially leading to an underestimate of the number of damaged buildings. Another weakness is that the building footprints in the Microsoft Building footprint dataset are derived from Bing basemap imagery that is potentially outdated for the different AOIs, therefore recently constructed buildings will possibly be missing in the analysis.

Finally, we attempt to compute the number of people that are directly affected in the damaged buildings using WorldPop's unconstrained 2020 gridded population estimates [4]. This data source consists of a grid of 100 x 100 meter cells that cover the entirety of Turkey, where each cell contains an estimate of the number of people living in that area. We count the population of a grid cell as "affected" if there is a damaged building within the cell and sum the affected population at a city level.

Our overall workflow is summarized in Figure 2.

Figure 2: Building damage assessment and affected population estimate workflow.



Results

Our analysis covers four cities in southeast Turkey:

- Marash (population 610,000)
- Turkoglu (population 82,483)
- Nurdagi (population 31,202)
- Islahiye (population 52,622)

with satellite imagery ranging from Feb 7th (the day after the earthquake) to Feb 9th, 2023.

Our results (Table 1) show that there are a total of 3,849 damaged buildings – ranging from partially damaged to destroyed -- and 160,411 impacted people over these cities. The city of Marash is the most heavily affected out of the four cities, both proportionally (by fraction of buildings affected) and in magnitude (total number of buildings). Marash is a major population center in the region, and centrally located between the two major earthquakes (45 kilometers from the first magnitude 7.8 earthquake and 55 kilometers from following magnitude 7.5 earthquake).

The following subsections summarize the results per city.

Figure 3: Four cities included in the study.

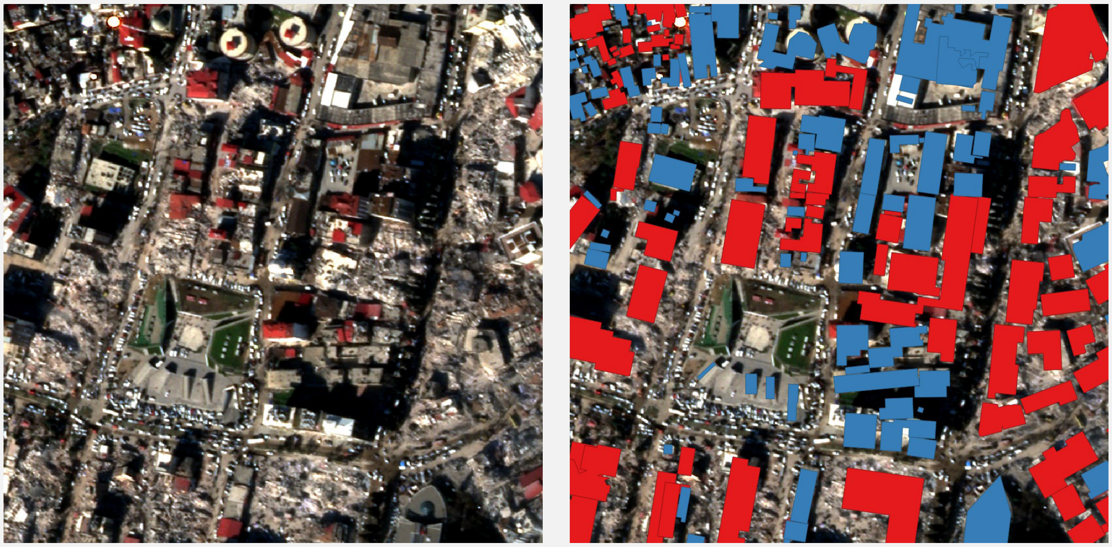
Table 1: Results over the four study areas in Turkey.

Region (Image date)	Number of buildings	Number of damaged buildings	% buildings damaged	Estimated people impacted
Marash (2/9)	40,375	3,005	7.44%	148,388
Turkoglu (2/9)	3,816	185	4.85%	6,202
Nurdagi (2/9)	4,537	331	7.30%	2,163
Islahiye (2/7)	13,215	328	2.48%	3,658

Marash

We found 3,005 damaged buildings in Marash, representing 7.44% of the total number of buildings in the city. The damage to these buildings has impacted a significant portion of the population, with 148,388 people, or 24.33% of the total population of 610,000, being affected by the disaster. The most significantly damaged area of the city is around the Culture Park in the city center, seen in Figure 4.

Figure 4: Extensive damage around the Culture Park area of Marash. Planet Labs PBC, February 9th.



Turkoglu

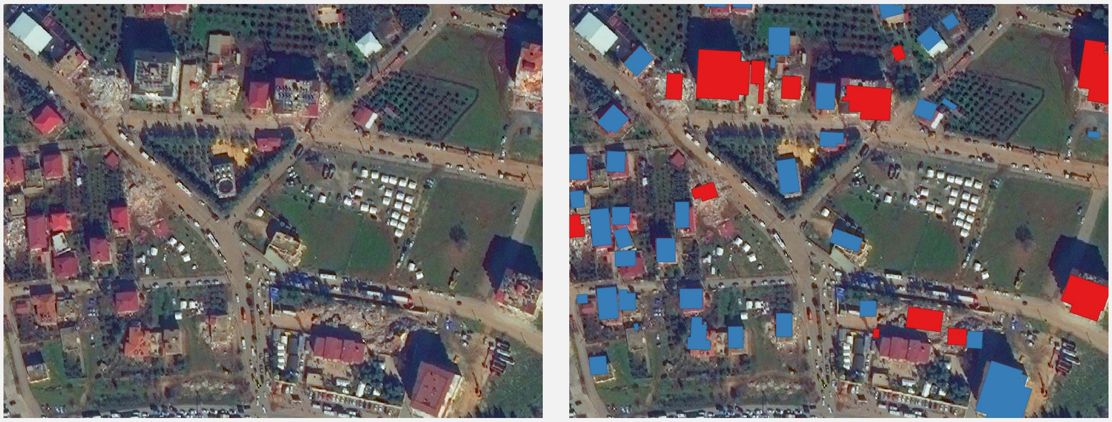
We found that damage in the city of Turkoglu was distributed throughout the city with fewer large clusters of damage (as compared to the other AOIs). In total, 4.85% of the buildings in the city were damaged, affecting an estimated 6,202 people. Figure 5 shows an example of two destroyed buildings along one of the major streets through the city.

Figure 5: Several destroyed apartment buildings in Turkoglu. Planet Labs PBC, Feb 9th.

Nurdagi

Nurdagi was the closest city to the epicenter of the first earthquake out of the four locations we analyzed. We found significant damage throughout the city, with 7.3% of buildings damaged to some extent. This affected fewer total people than in the other study areas considering Nurdagi's relatively small population. Figure 6 shows damage to the city center area and a large group of tents that were set up in the response efforts.

Figure 6:. Extensive damage in Nurdagi. Maxar Technologies, Feb 9th.



Islahiye

We found 13,215 damaged buildings in Islahiye, representing 2.48% of the total number of buildings. By the percentage of damaged buildings Islahiye was the least affected out of the four study areas, however we observed that the damaged buildings were clustered in more densely populated areas. For example, Figure 7 shows a group of nine apartment buildings that were all destroyed. Even though similar numbers of buildings were destroyed between Islahiye and Nurdagi, we estimate over one thousand more people were affected in Islahiye.

Figure 7: A set of nine destroyed 5-story apartment buildings in downtown Islahiye. Maxar Technologies, Feb 7th.

Figure 8. Pre-disaster Google Street View imagery from Islahiye of the destroyed apartments shown in Figure 7.

References

[1] "xBD: A Dataset for Assessing Building Damage from Satellite Imagery." **https://arxiv.org/abs/1911.09296**

[2] Microsoft Corp. "Spatial imagery labelling toolkit." **https://github.com/microsoft/satellite-imagery-labeling-tool.**

[3] Microsoft Corp. "Global ML Building Footprints." **https://github.com/microsoft/GlobalMLBuildingFootprints**

[4] WorldPop "The spatial distribution of population in 2020, Turkey." **https://hub.worldpop.org/geodata/summary?id=6443**

Acknowledgments

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