National Aeronautics and Space Administration

Humanitarian Applications Using NASA Earth Observations

Part 1: Monitoring Urban Damage with Interferometric Synthetic Aperture Radar (InSAR)

June 14, 2022

Outline

This webinar series is scheduled around **World Refugee Day** on **June 20, 2022**, and includes four parts:

Part 1: Monitoring Urban Damage with InSAR (14 June)

Part 2: Mapping Refugee Settlement Growth and Population Change (16 June)

Part 3: Detecting Agricultural and Vegetation Changes In and Surrounding Refugee Settlements (21 June)

Part 4: Assessing Climate Hazards at Refugee Camps (23 June)

Each part is 2 hours long, including a question-and-answer session at the conclusion.

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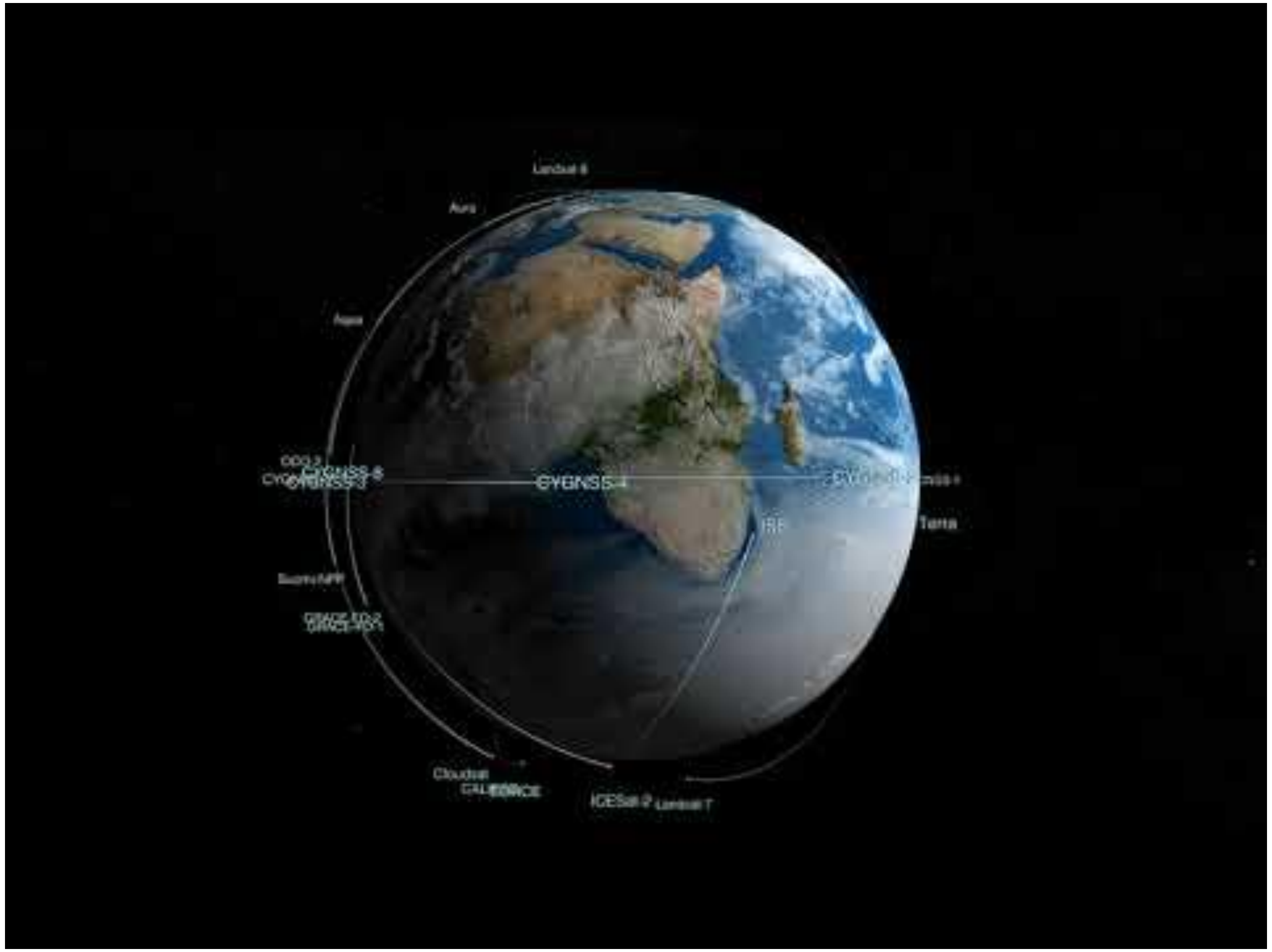
Why do we need a training on remote sensing applications in humanitarian settings? What is special about humanitarian settings?

Any remote sensing approach that is effective for mapping environmental condition or change – land cover classification, building detection, hazard assessment, etc. – outside of a humanitarian setting should still be effective (to some extent) in a humanitarian setting.

Pixels are just pixels, after all, and we can measure the normalized difference vegetation index (NDVI) just as well in a small refugee camp as in a megacity.



Why do we need a training on remote sensing applications in humanitarian settings? What is special about humanitarian settings?

Any remote sensing approach should still be effective (to some extent) in a humanitarian setting. Pixels are just pixels, after all.

However, being familiar with the specific concerns in humanitarian settings and understanding the sometimes-unique form, layout, and temporal dynamics of landscapes and reasons for change in a conflict zone or refugee settlement, for example, is important to make the best use of available remote sensing data.

This is all the more important since remote sensing offers a wealth of (a certain kind of) data about a humanitarian setting when data scarcity is usually the normal.

After participating in the training, attendees will be able to:

- Conceptualize landscape- and settlement-level monitoring in a variety of humanitarian contexts with satellite remote sensing
- Understand the benefits and limitations of different kinds of satellite imagery (i.e., optical, radar, nighttime lights, etc.) for humanitarian applications
- Recognize the value of time series analysis for monitoring acute and long-term changes in humanitarian contexts
- Integrate satellite-derived humanitarian data with other open-access geospatial products on population, building footprints, infrastructure, etc.
- Determine if satellite data are appropriate/useful for an application, and know what compromises are acceptable

* While our attention will be on humanitarian settings associated with conflict or displacement (i.e., refugee settlements), the concepts and techniques discussed should have relevance for natural hazard-related humanitarian applications as well.

Part 1: Monitoring Urban Damage with InSAR

Motivation:

- Widespread, repeat damage within cities is a hallmark of modern and increasingly urbanized warfare.
- Monitoring urban damage is important for protecting civilians, guiding humanitarian response and relief, and identifying affected infrastructure throughout a conflict.
- Multitemporal satellite remote sensing data have a unique but still developing role in mapping urban damage.

Goals:

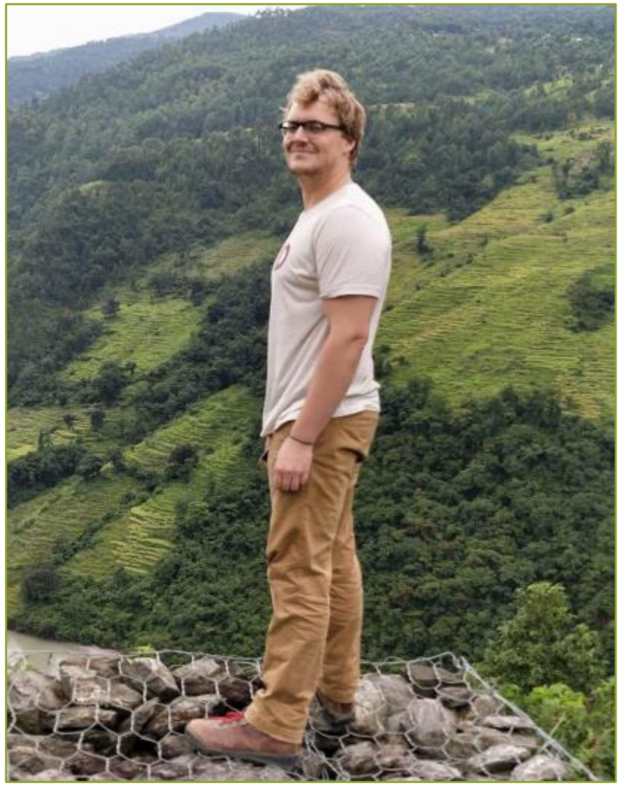
- Detect locations of urban change during armed conflict
- Leverage InSAR time series data for long-term analysis
- Understand different strengths and limitations of radar data compared to perhaps more traditional data sources from optical or nighttime lights data, for example

Meet your presenters!

Corey Scher

PhD student

City University of New York



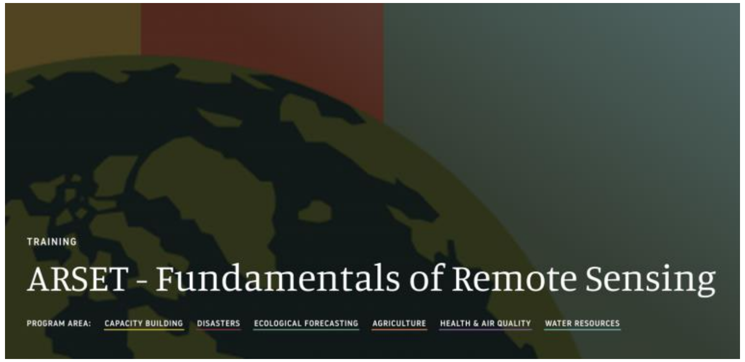
Jamon Van Den Hoek

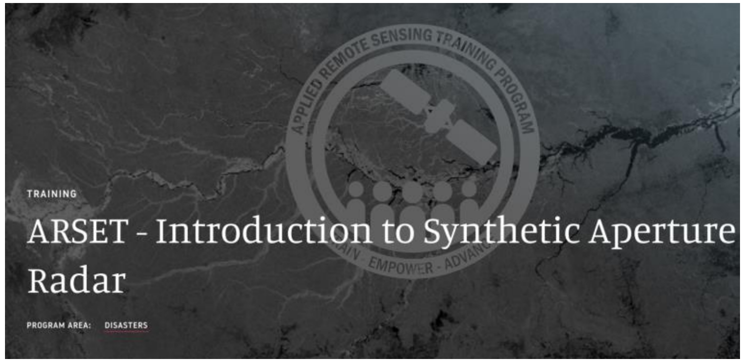
Associate Professor of Geography

Oregon State University

Prerequisites

- **Fundamentals of Remote Sensing:**
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-fundamentals-remote-sensing
- **Introduction to Synthetic Aperture Radar:**
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-introduction-synthetic-aperture-radar
- **SAR for Disasters and Hydrological Applications:**
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-sar-disasters-and-hydrological-applications





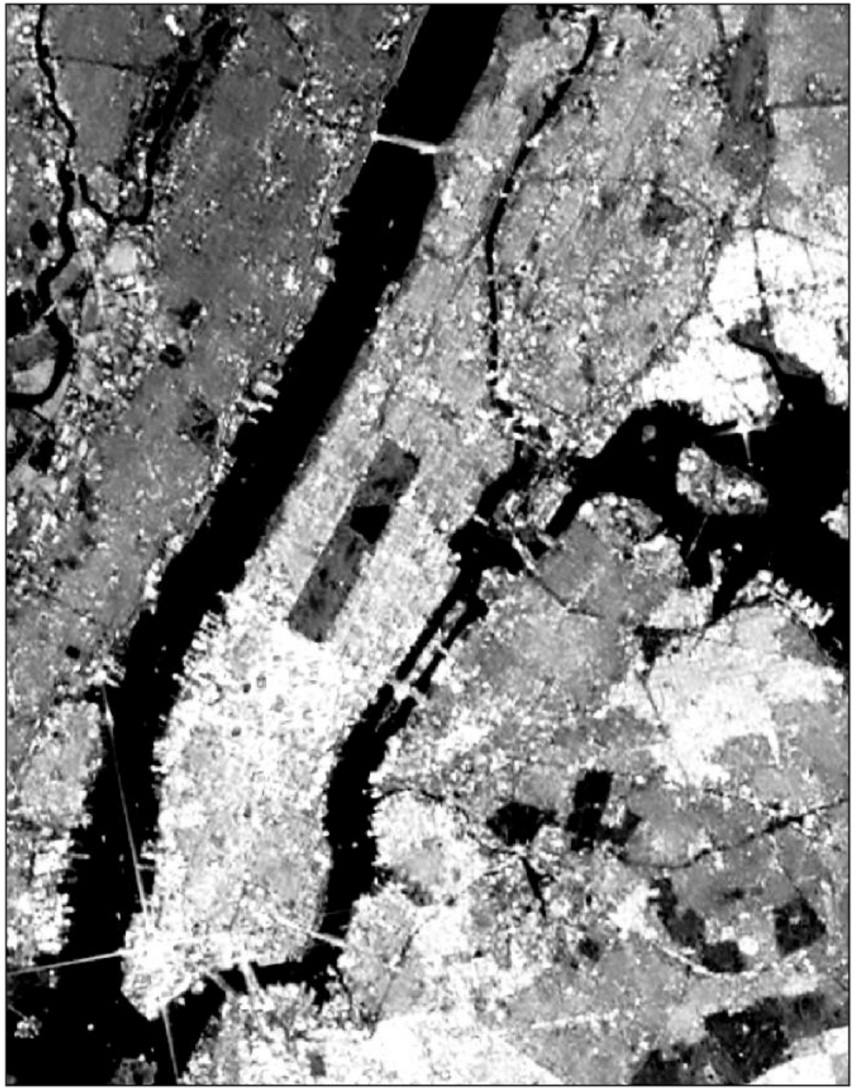
Background

Optical and Synthetic Aperture Radar (SAR) systems offer complementary views of a complicated world.

Imagery of New York City

Sentinel-2 True Color (RGB)
(April 12, 2022)

Sentinel-1 SAR Backscatter Intensity (VV)
(May 10, 2022)



Optical images tell us about the color and spectral characteristics of a surface.

Sentinel-2 True Color (RGB)
(April 12, 2022)

In turn, spectral characteristics tell us about the **chemistry** (i.e., the color) of a pixel.

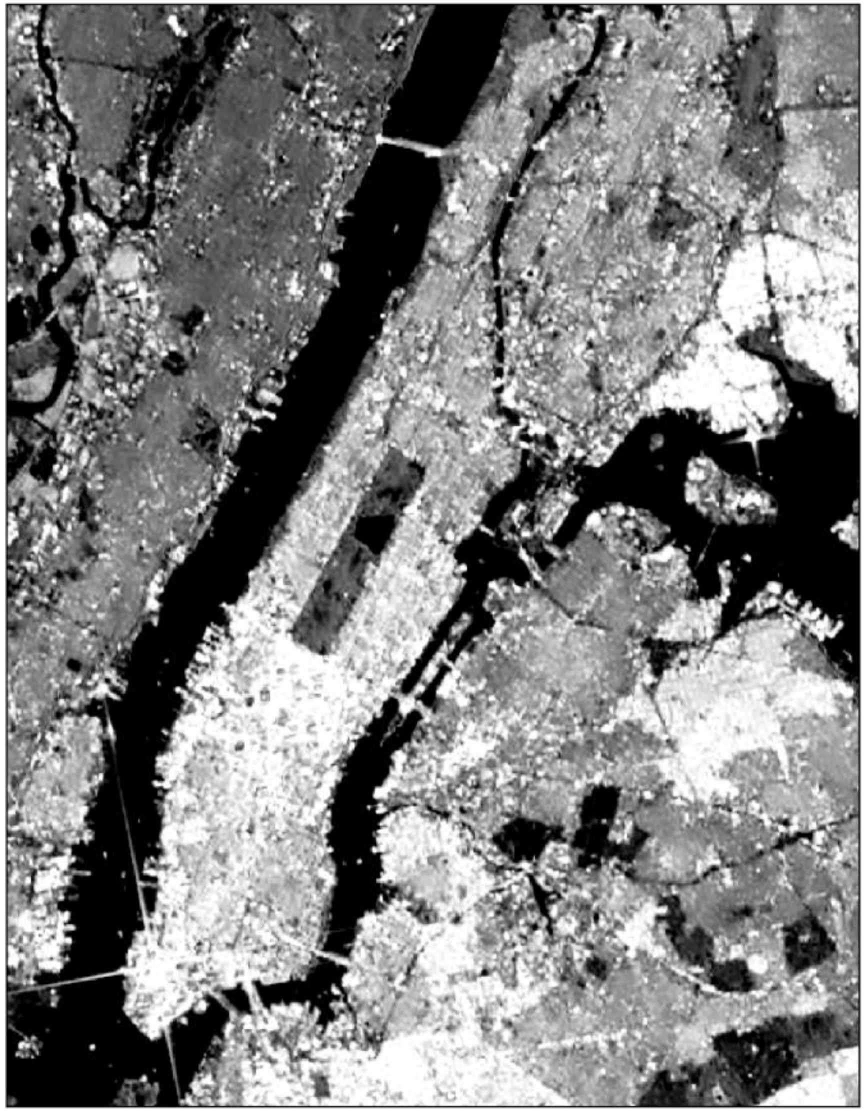
This is a reservoir in Central Park.

This is Times Square.

Radar images tell us about the structure of a region.

Synthetic Aperture Radar (SAR) is a remote sensing technique that **illuminates a region** with microwaves and records the echo of the microwave pulses that are reflected back to the satellite sensor.

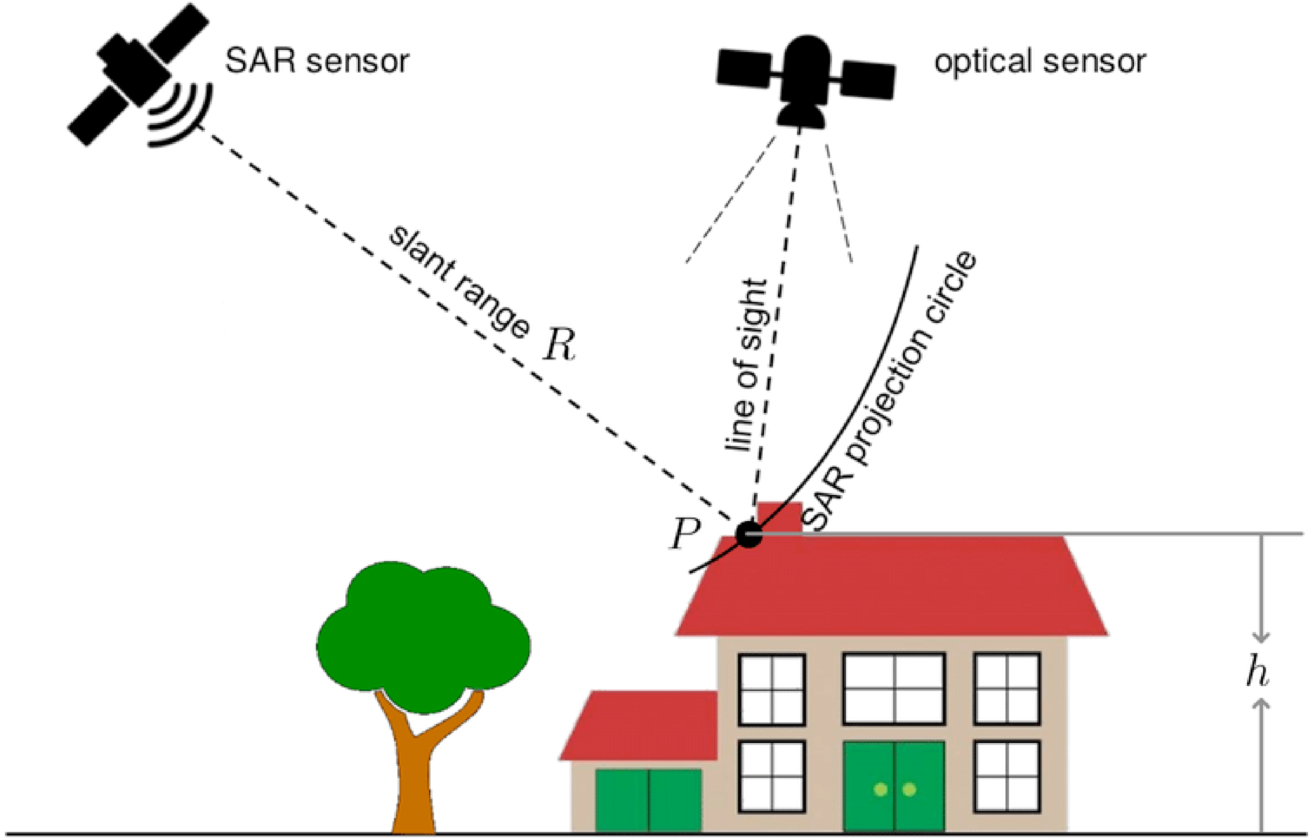
This SAR “intensity” image tells us about the **strength** of microwave reflection back to the sensor, which we refer to as scattering.



RTC product processed by ASF DAAC HyP3 2022 using GAMMA software. Contains modified Copernicus Sentinel data 2022, processed by ESA.

SAR looks at objects differently than optical sensors.

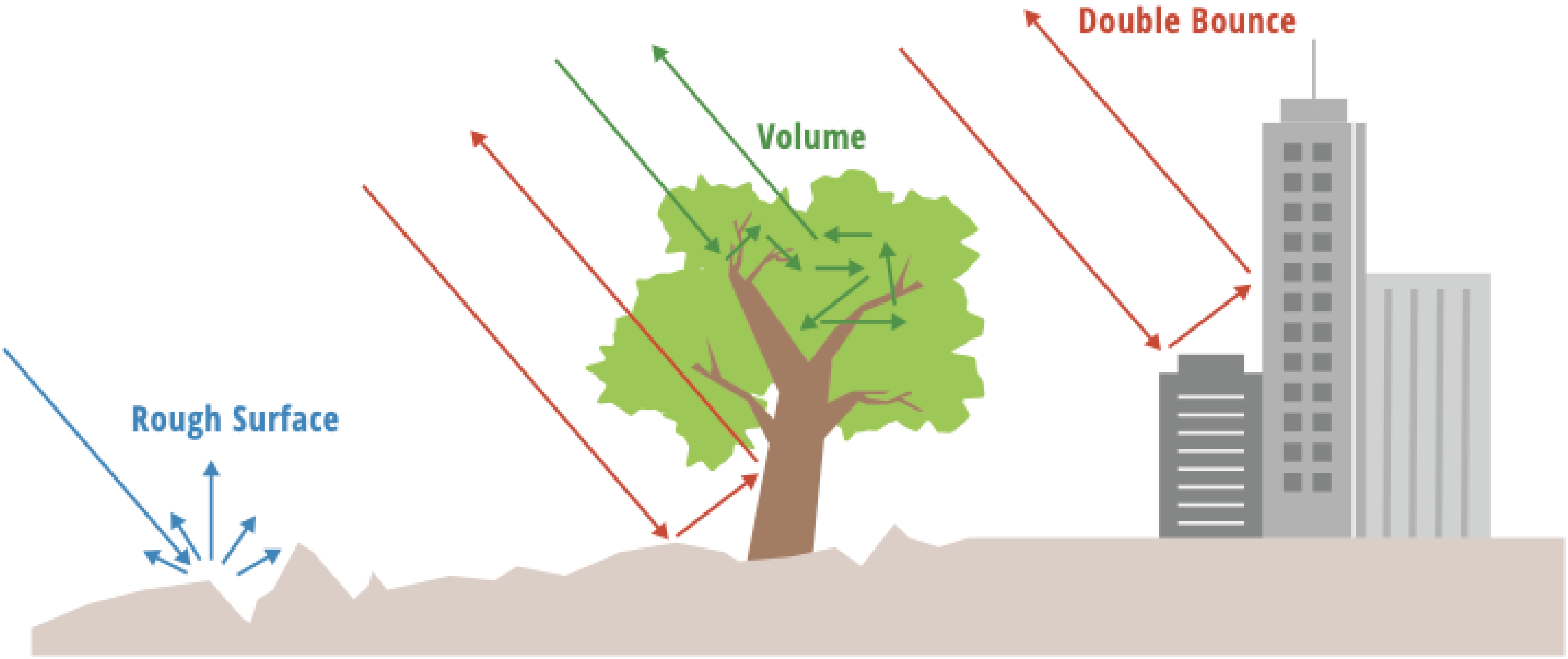
Sensors send a radar signal that **illuminates a target area** from an angle. Optical sensors passively receive reflected sunlight near or at nadir (above a target).



Source: Qui et al. (2017)

SAR images tell us about the structure of an image region.

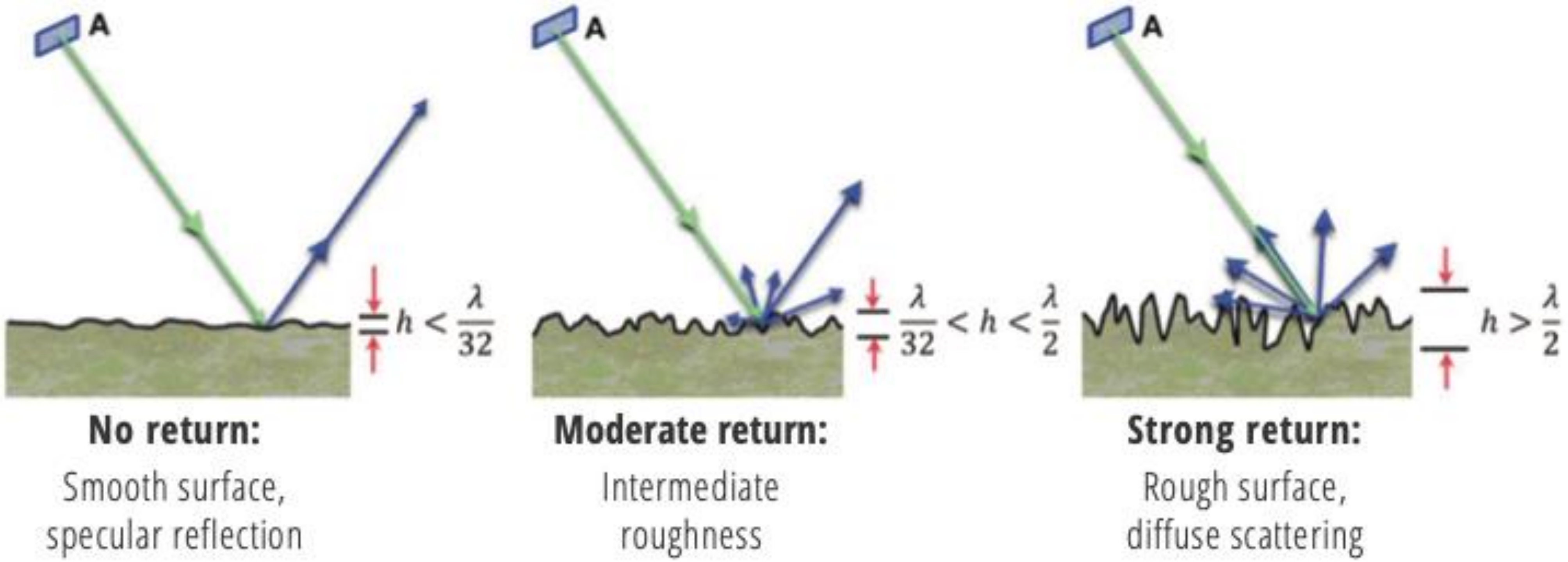
Scattering mechanisms differ based on the structure of objects. This **scattering** affects how regions appear in different types of SAR imagery.



Source: [The SAR Handbook]

The “roughness” of the surface is important.

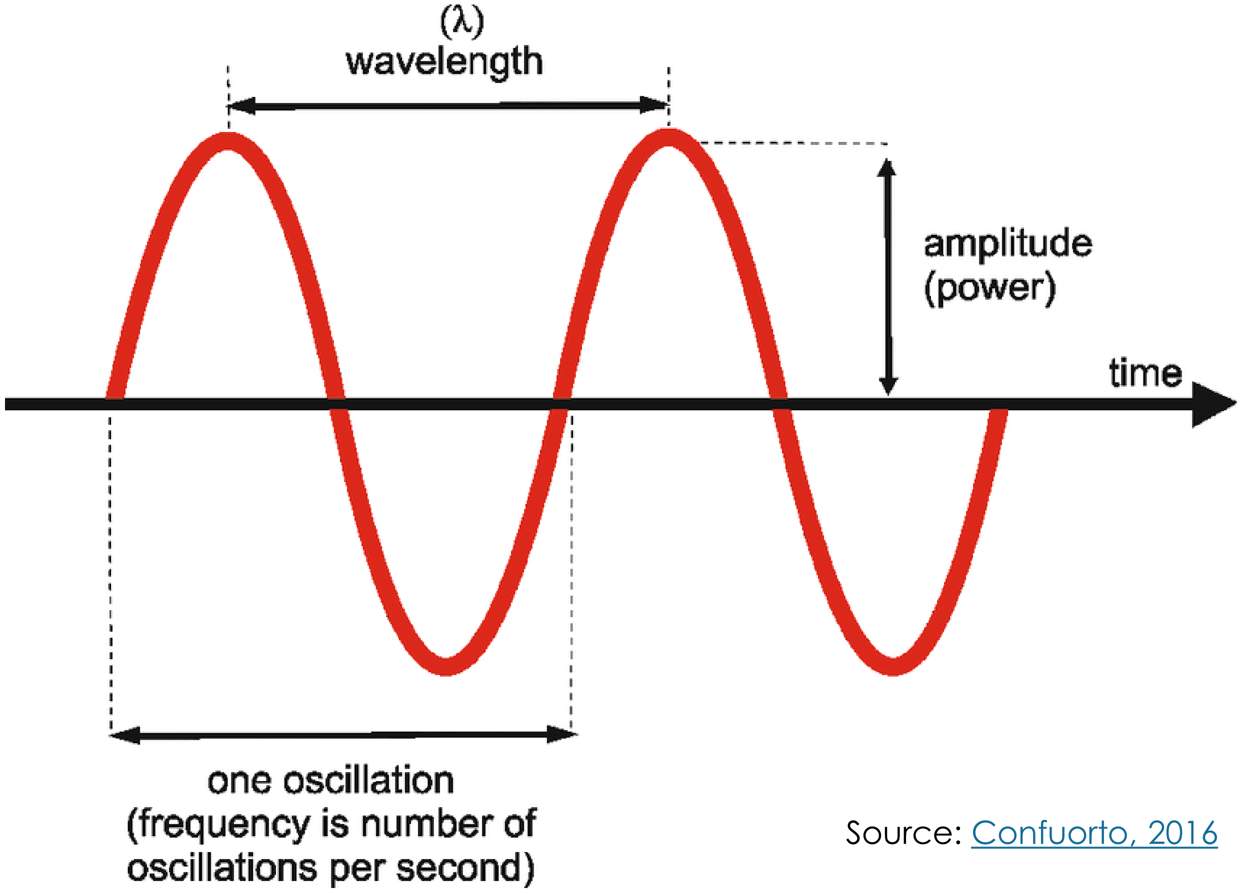
Smooth surfaces will reflect radar signals **away** from the satellite while rougher surfaces will reflect signals back **toward** the satellite. Roughness is defined relative to the outgoing **signal wavelength** (denoted by **lambda**).



Source: [The SAR Handbook]

SAR sends out a signal with a fixed frequency.

The returned echos are directly related to the outgoing signal. The wavelength of the Sentinel-1 sensor is about 5.5 cm. Both cities and freshly tilled agricultural soils would be considered **rough** for Sentinel-1.

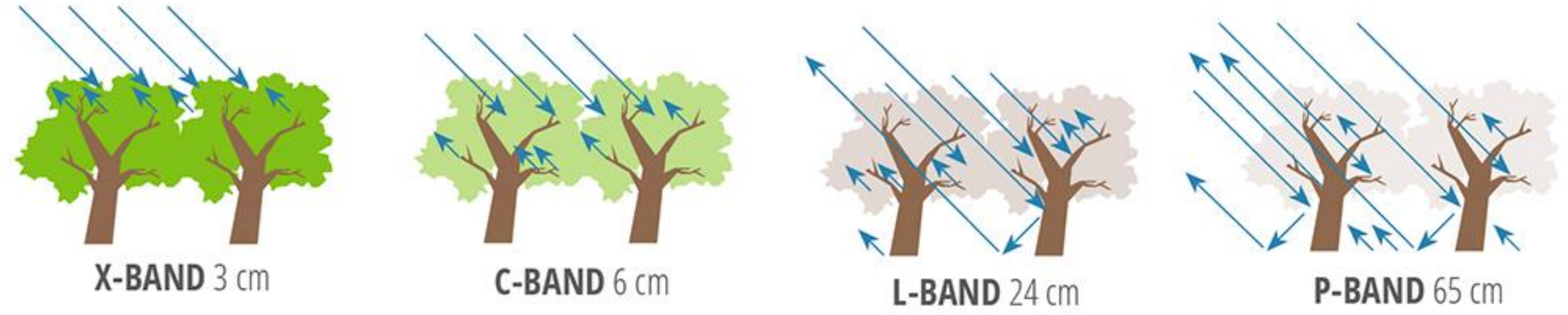


Source: Confuorto, 2016

The SAR wavelength affects scattering characteristics

Signals with a longer wavelength can penetrate deeper into forest canopies, for example, compared to shorter wavelength signals.

Note that X-band (3 cm wavelength) and C-band radar (6 cm wavelength) do not make it through the canopy because they are reflected (scattered) by the canopy's leaves and branches.



Source: The SAR Handbook

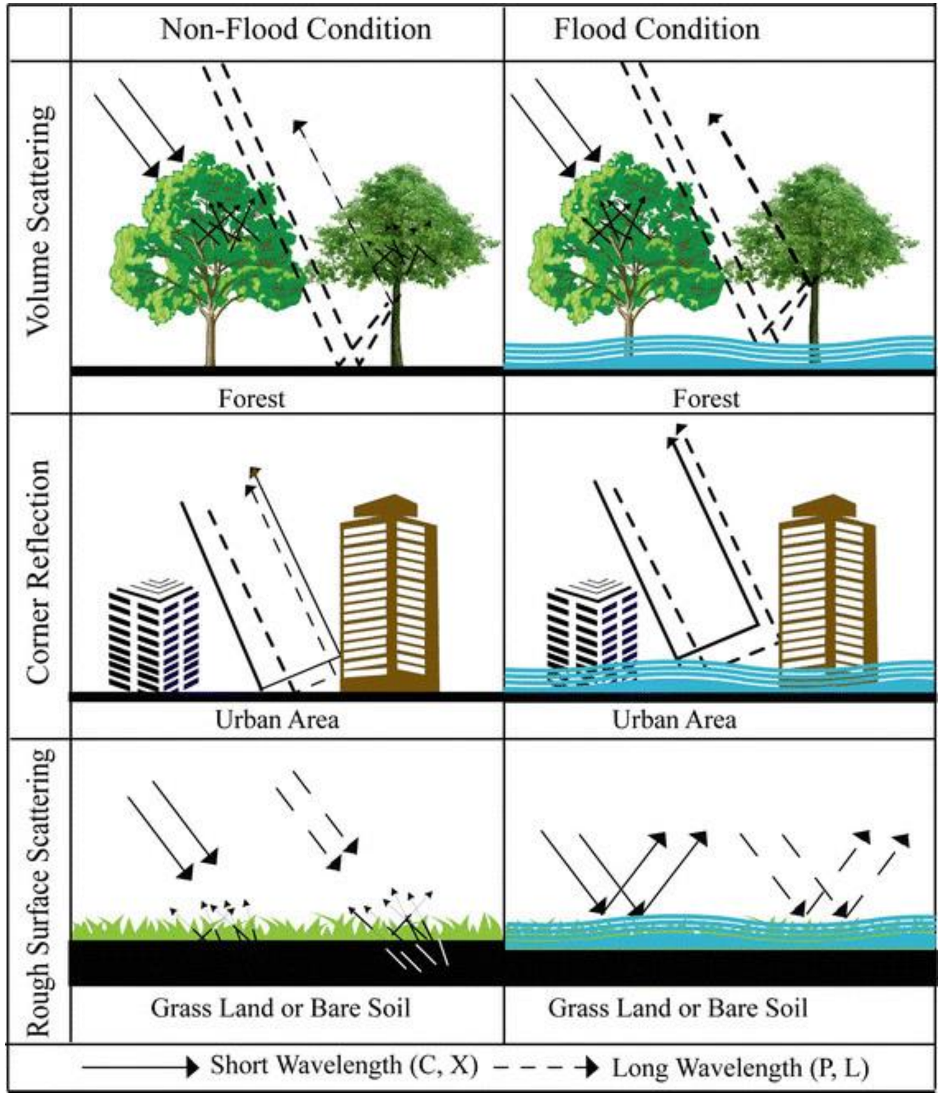
Urban areas are “strong” reflectors of radar signals while water surfaces are not.

Trees scatter SAR signals throughout the **volume** of a forest.

Buildings in urban areas act as **corner reflectors** of radar signals, sending back radar echoes with high intensity.

Soils scatter signals at the **surface**, generally with lower intensity.

Calm water scatters signals **away** from the sensor.



Source: Di (2017)

Imaging radar is also sensitive to the surface dielectric.

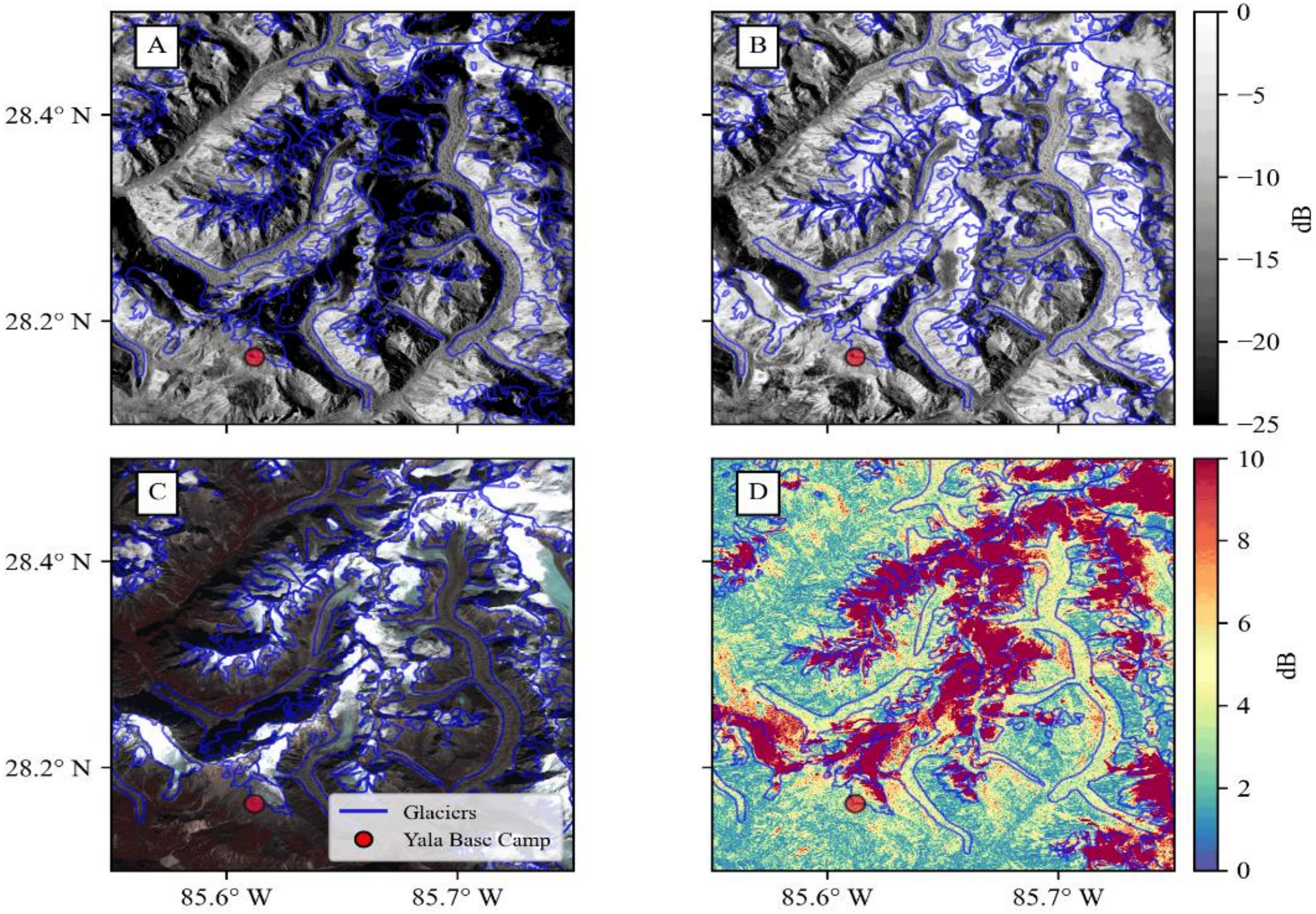
Changes in moisture content, like snowmelt, also affect radar scattering. Wet snow appears much darker than dry snow in backscatter imagery.

A: Average Sentinel-1 backscatter intensity (VH) image during a **snowmelt period**

B: Average backscatter during a **frozen period**

C: True color image from Sentinel-2

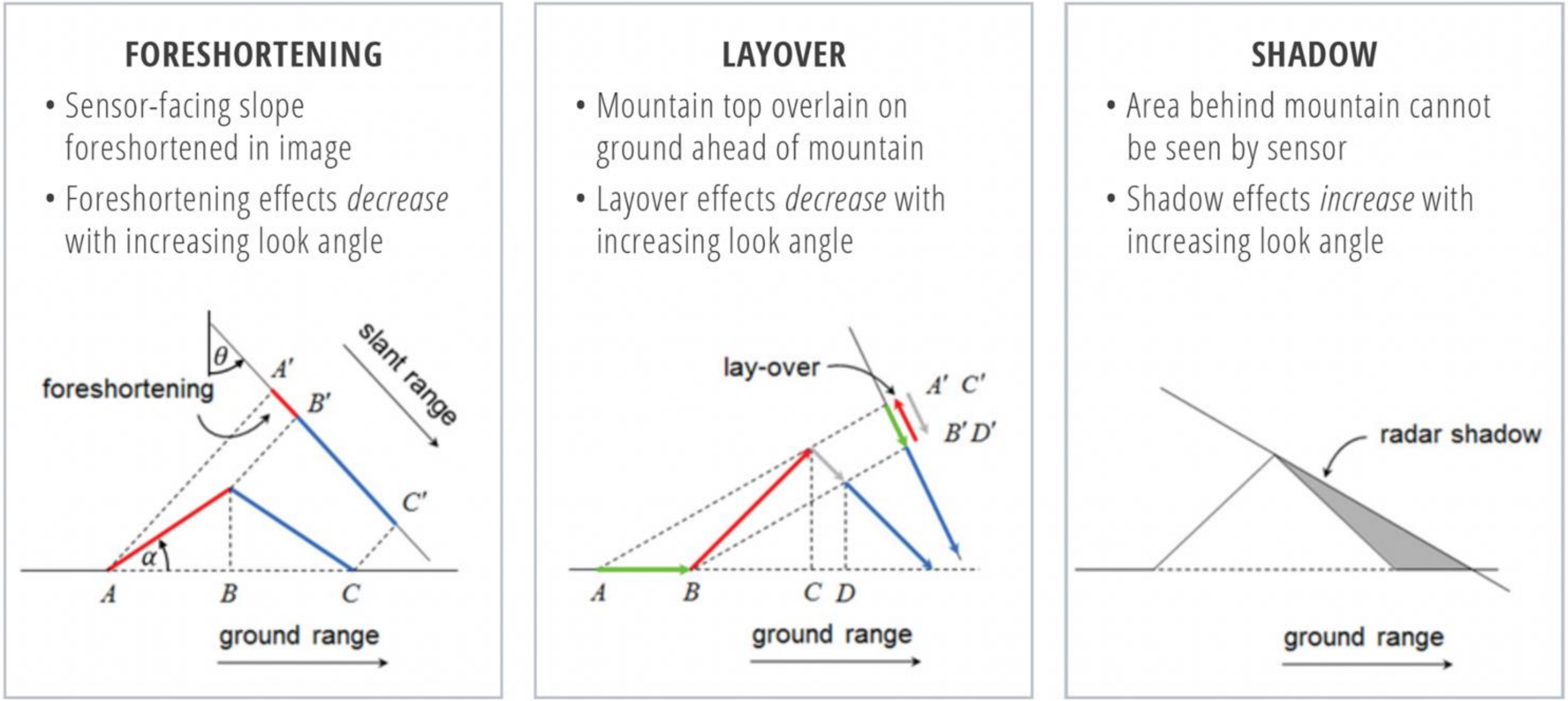
D: Difference in backscatter intensity between A and B



Source: Scher, et al. (2021)

The "side-looking" nature of SAR causes geometric distortions

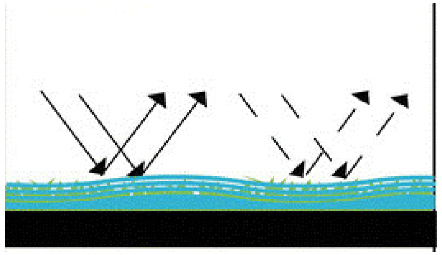
These distortions affect the **ground sampling frequency**. Uncorrected images are referred to as being in **slant range** while images corrected for look-angle are referred to as **ground range detected** imagery.



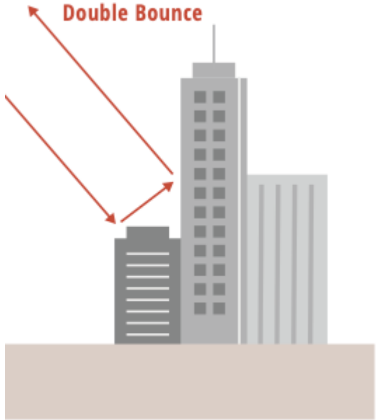
Source: The SAR Handbook

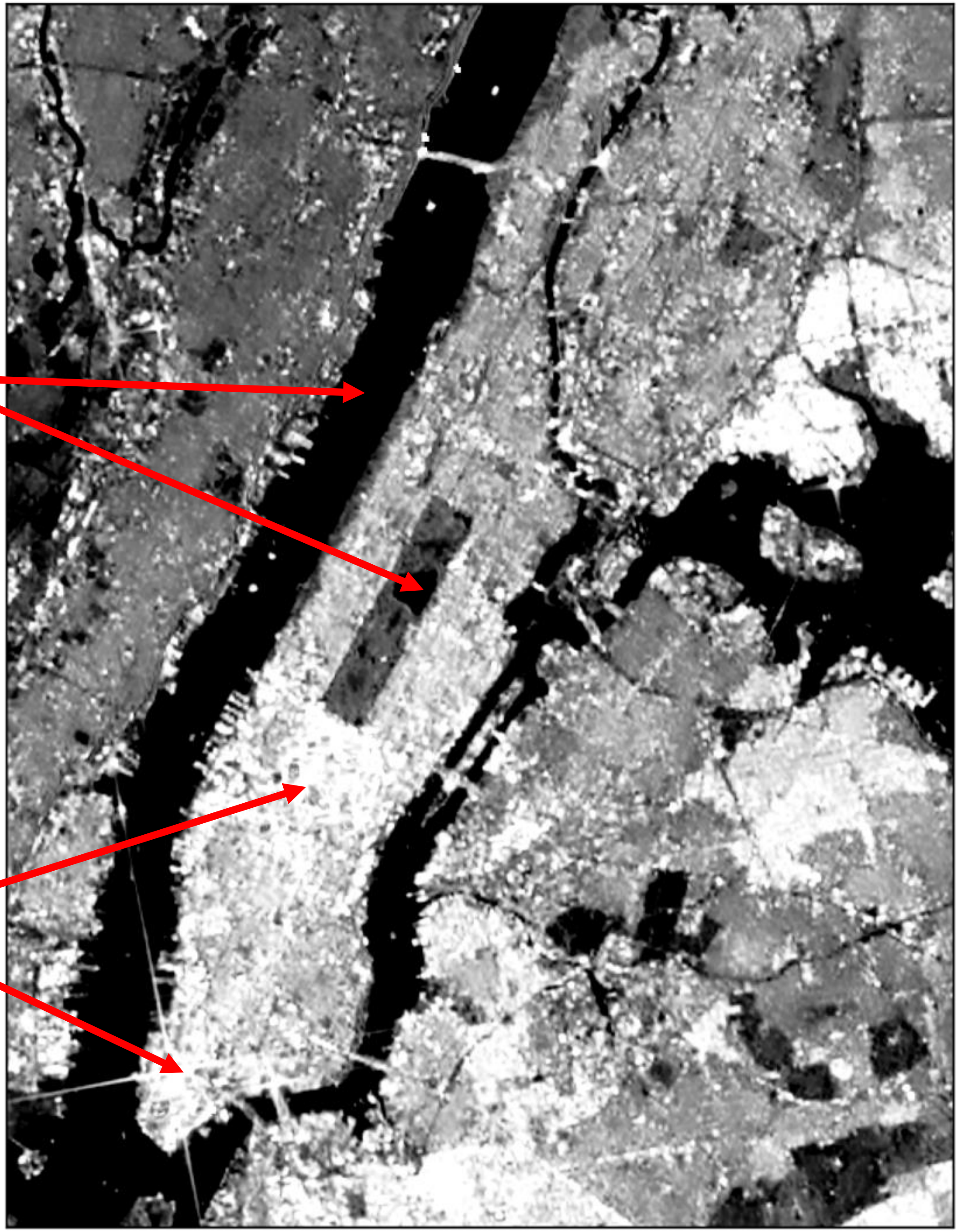
So, how should we read this image?

Water appears dark because the SAR signal is scattered **away** from the sensor.



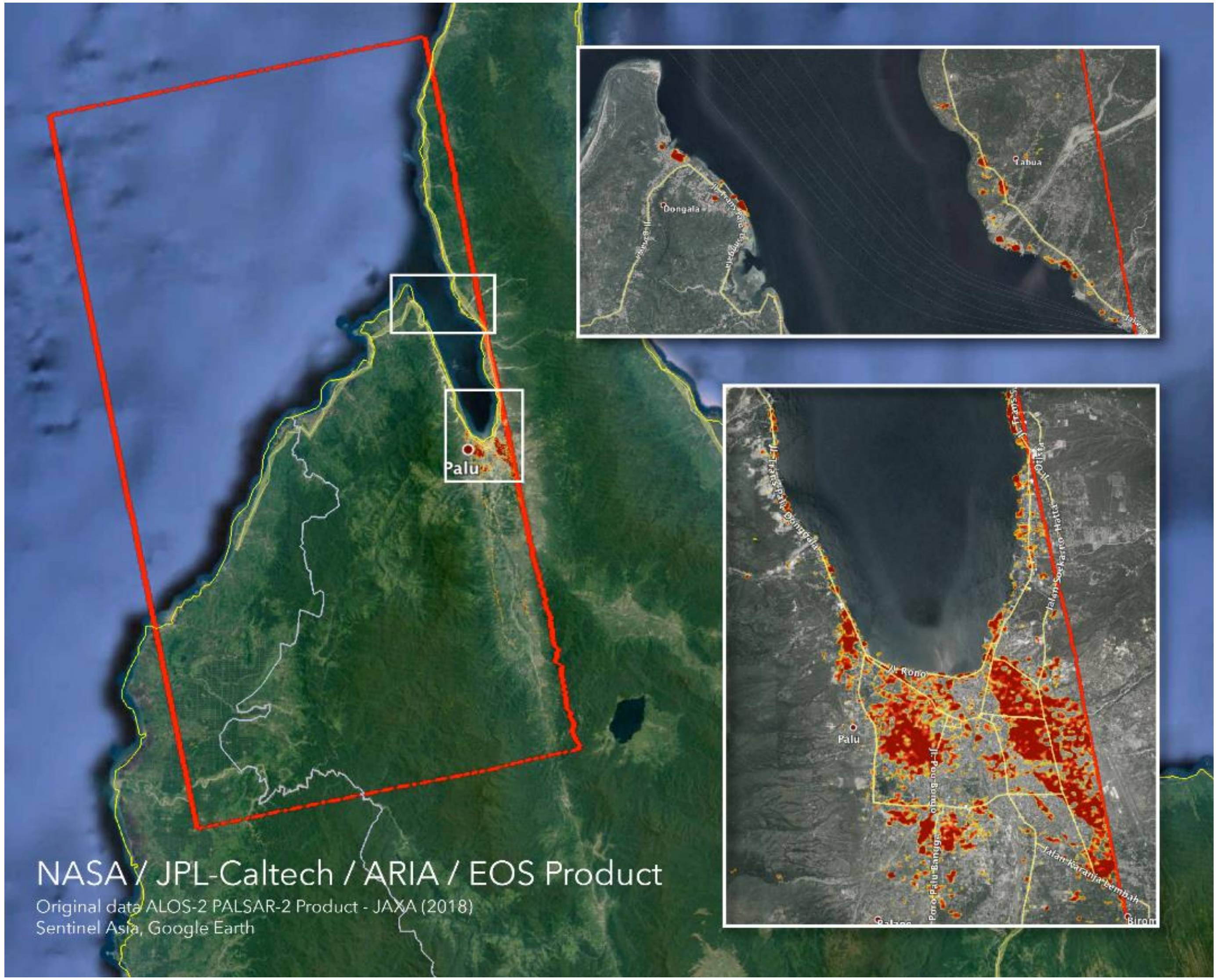
Built-up areas appear bright because buildings scatter radar signals back **toward** the satellite.





[RTC product processed by ASF DAAC HyP3 2022 using GAMMA software]. Contains modified Copernicus Sentinel data 2022, processed by ESA.

Radar satellites have commonly been used to map natural hazard-related damage.



Red areas are "damage proxies" from the Palu, Indonesia earthquake in September 2018. This is called a **damage proxy map.**

Source: NASA ARIA

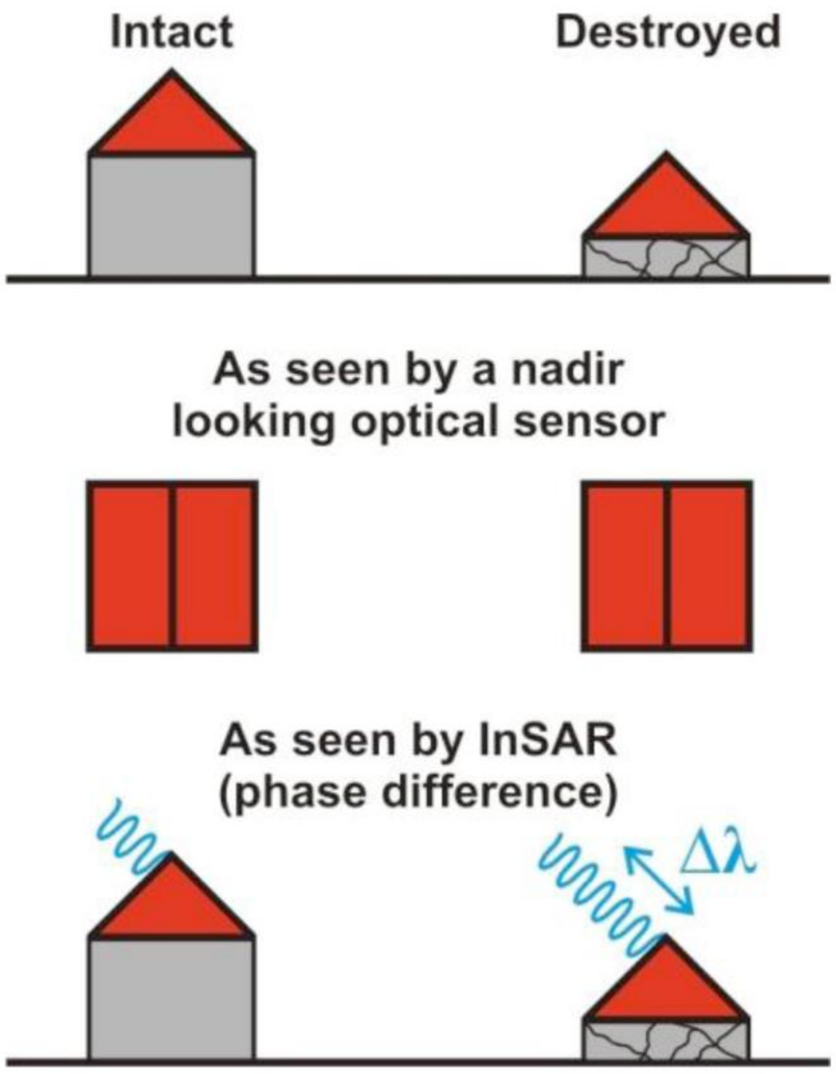
How can radar be used to map damage?

SAR's structural sensitivity enables damage mapping.

Partial building collapse changes the position of the **scatterer** in an image region.

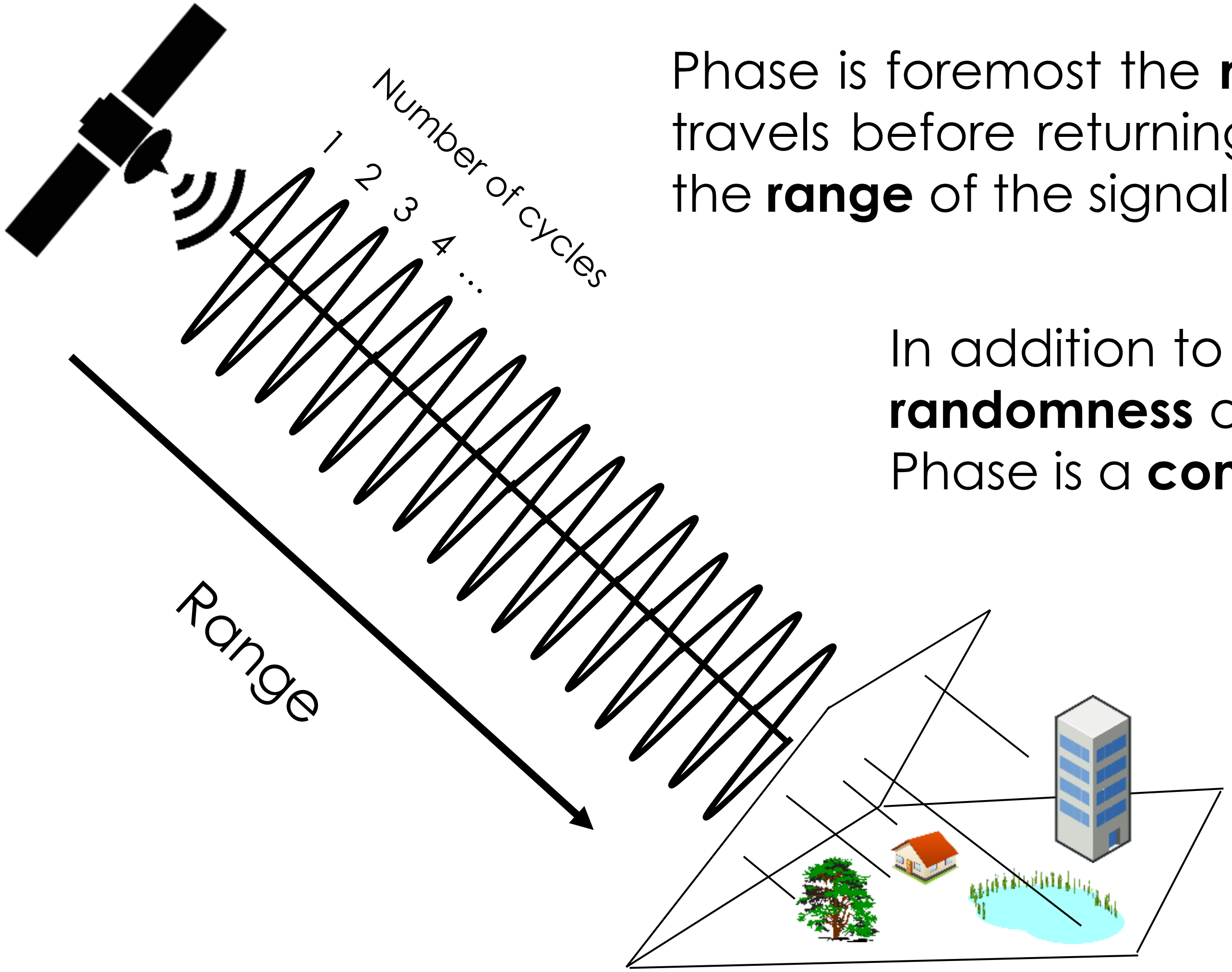
But directly from above (i.e., nadir), an optical sensor wouldn't detect this change.

Detection of changes to the structure is possible by using **phase information** from the SAR image.



Source: Plank (2014)

Phase measures "the range and the complexity" of a region[1].



Phase is foremost the **number of wave cycles** a SAR signal travels before returning to the sensor. This is a measure of the **range** of the signal.

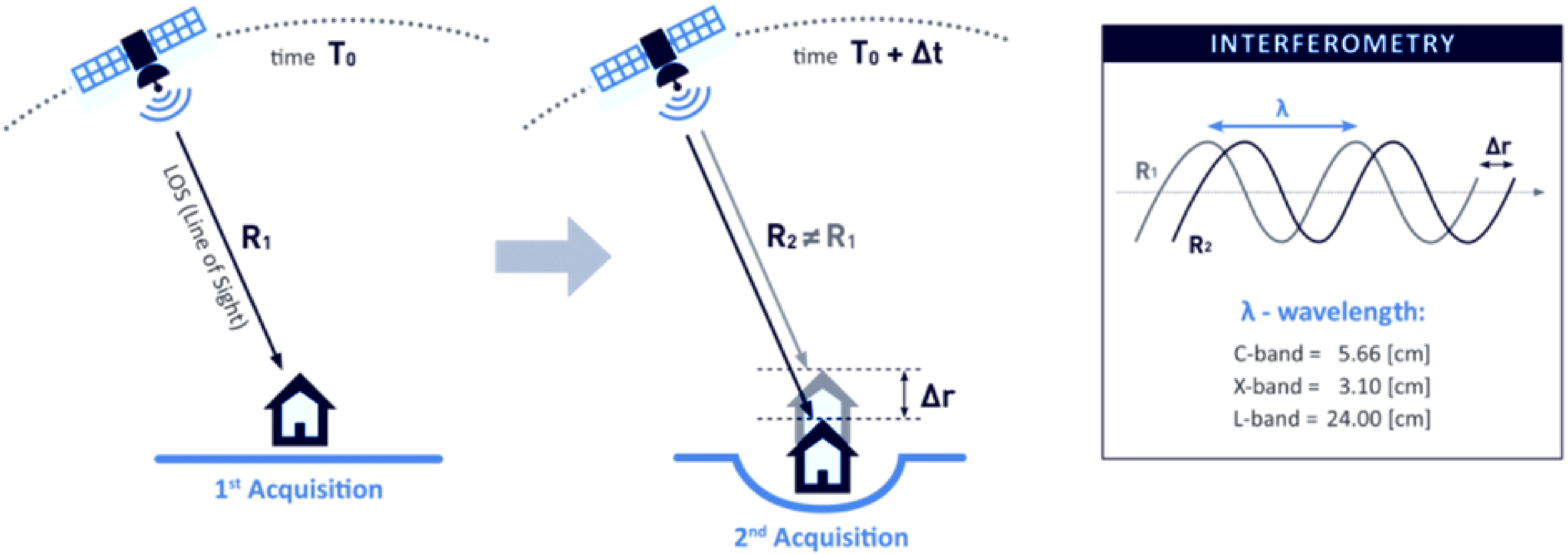
In addition to the **range**, SAR phase measures the **randomness** of path lengths in an imaging region. Phase is a **complex signal.**

Differencing two SAR phases (InSAR) can help us understand the **randomness of an image region** by accounting for the range component between acquisitions.

1. Slide closely adapted from Principles and Theory of Radar Interferometry (Rosen, 2008)

Interferometry measures the difference in two SAR phases.

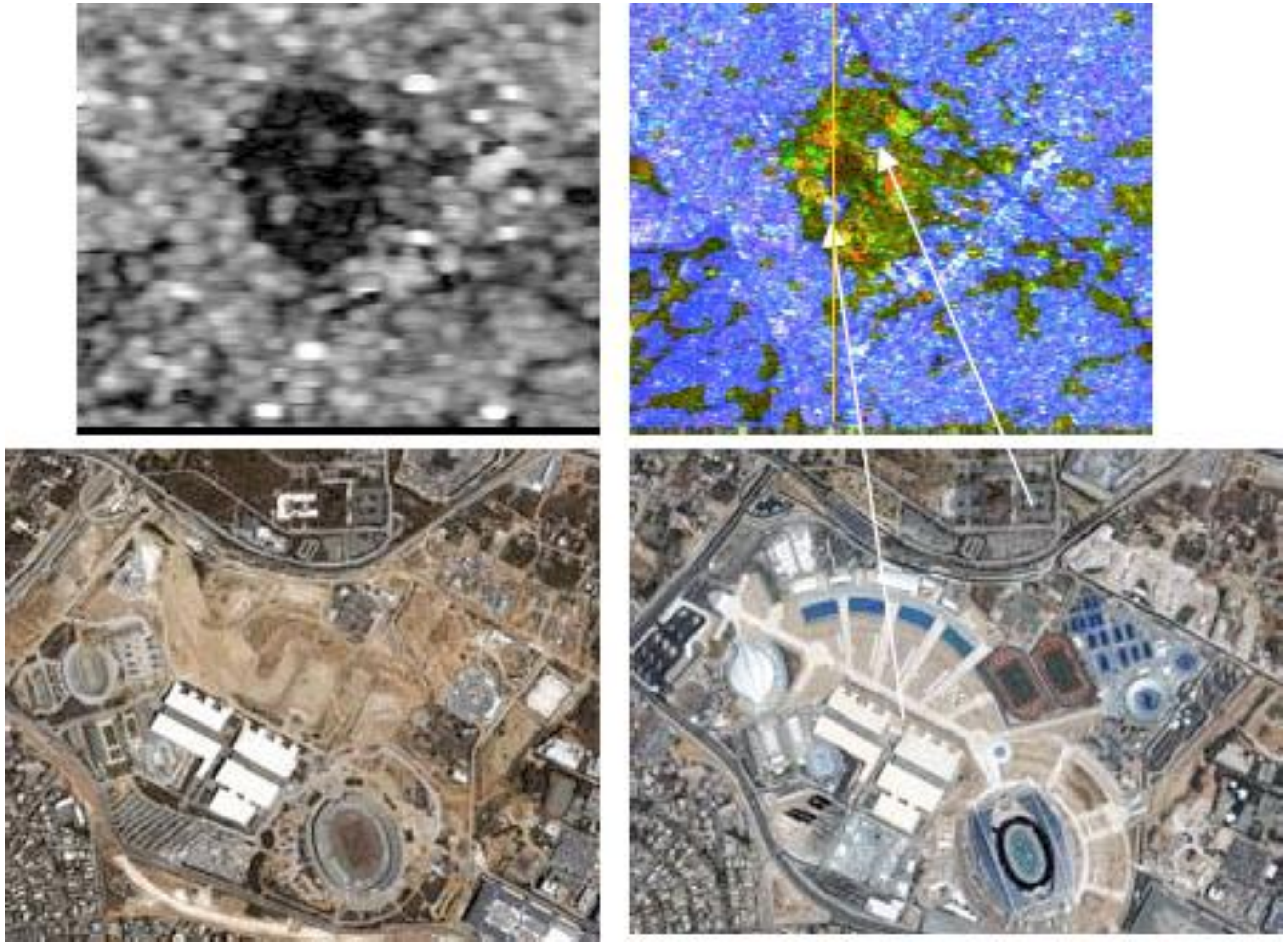
Interferometric SAR (InSAR) is the difference in complex phase between two SAR acquisitions. It is used to map topography and **changes** in structure, like ground motion from an earthquake.



Source: [TRE ALTAMIRA]

InSAR can also be sensitive to construction of buildings like this stadium.

Coherence Image Temporal Coherence Composite

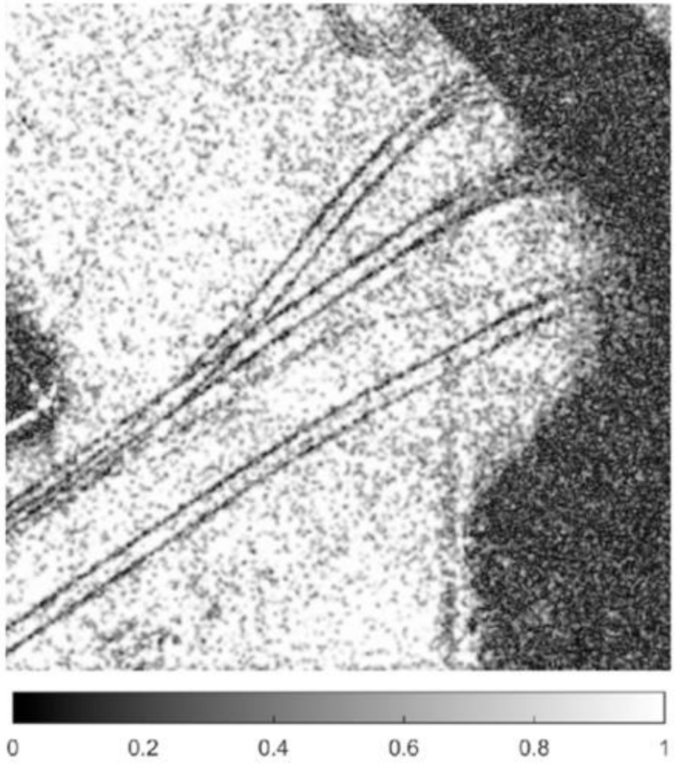


Source: [Wright et al. (2006)]

InSAR is used in intelligence applications.

InSAR data can be used to map things like vehicle tracks through vegetated fields because of the difference in texture that results.

Coherence Image

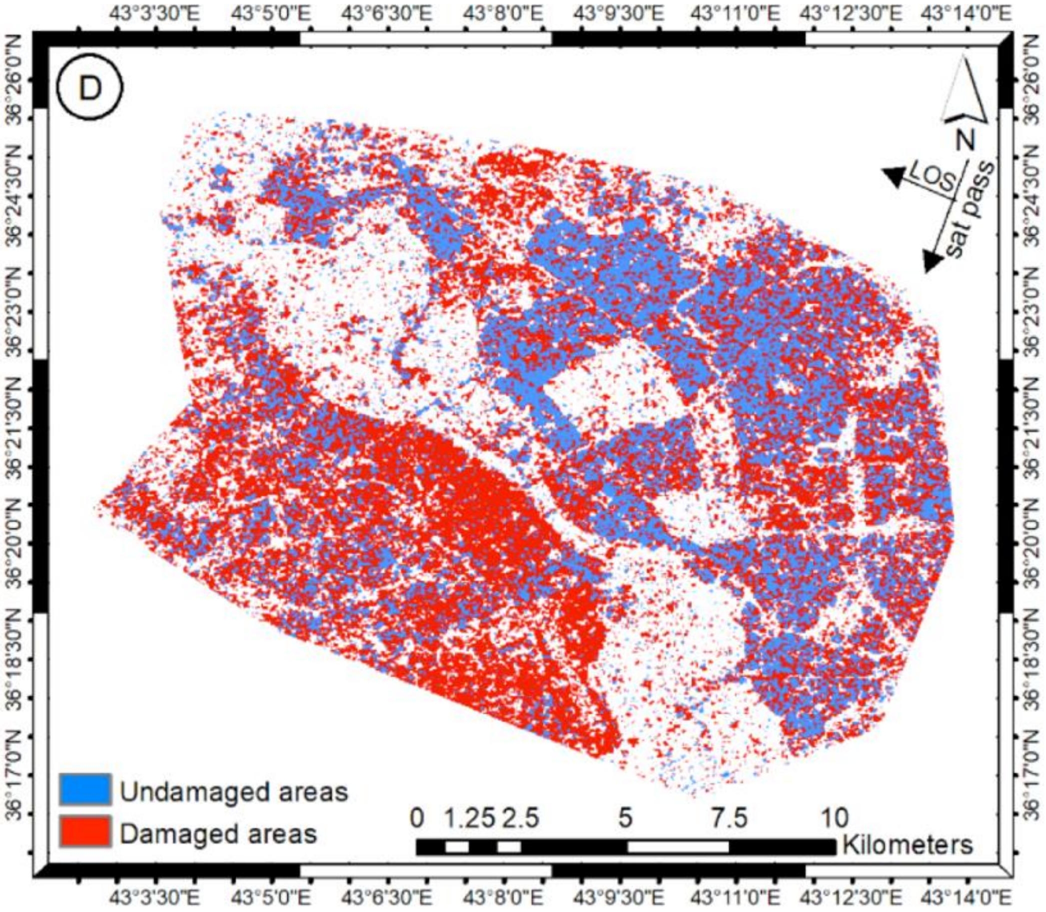


Thresholded Image

Vehicle Tracks

Source: [Hammer et al. (2021)]

InSAR can also be used to map building damage and destruction due to conflict.

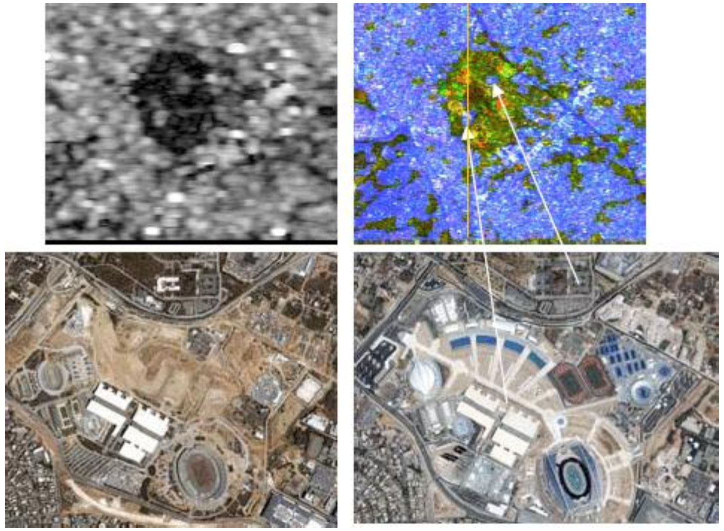


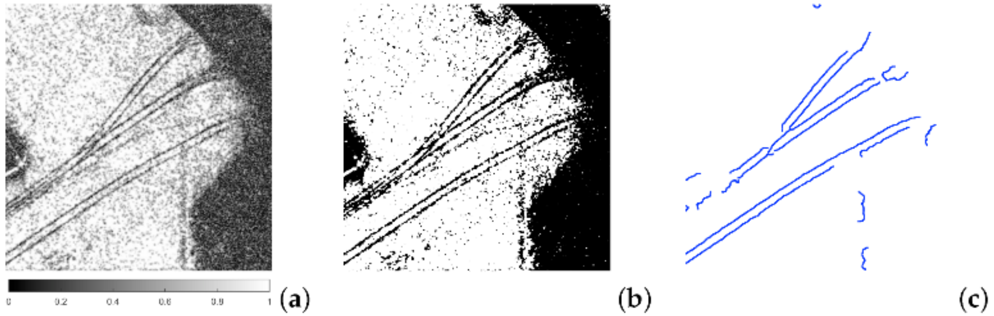
Damage proxy maps over Mosul, Iraq for the time period 2014–2017.

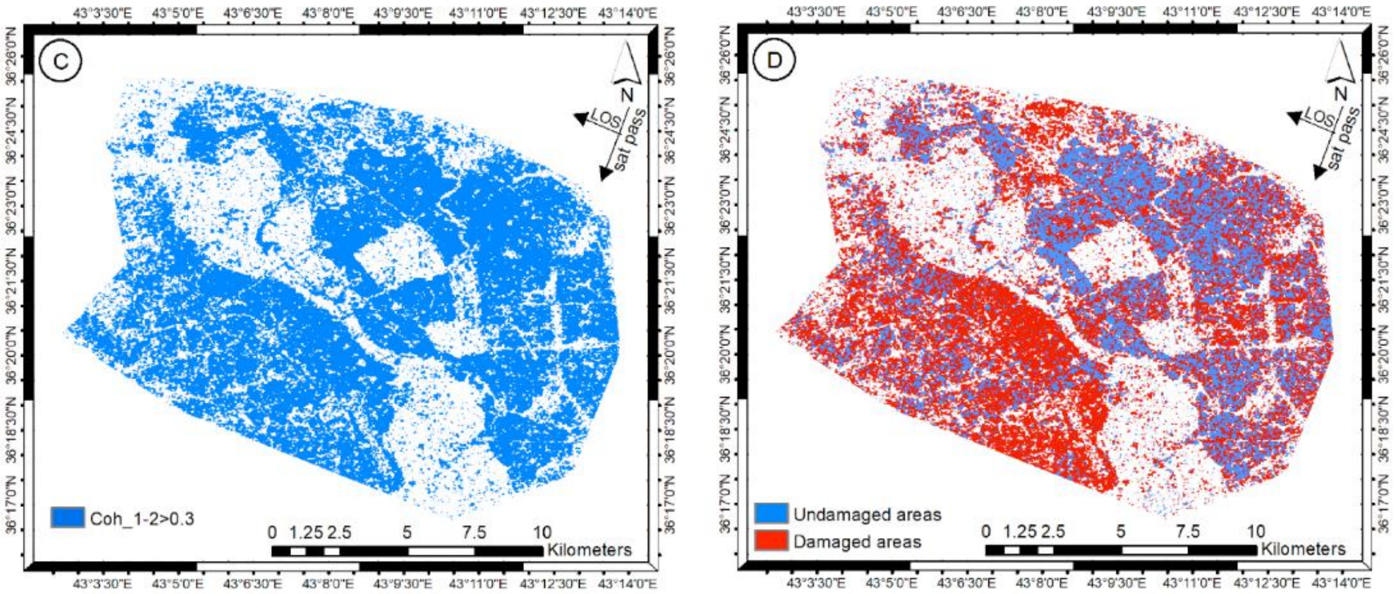
Source: [Boloorani, et al. (2021)]

All of these examples use InSAR coherence to detect change.

Coherence is an estimate of the **scattering stability** of an image region.



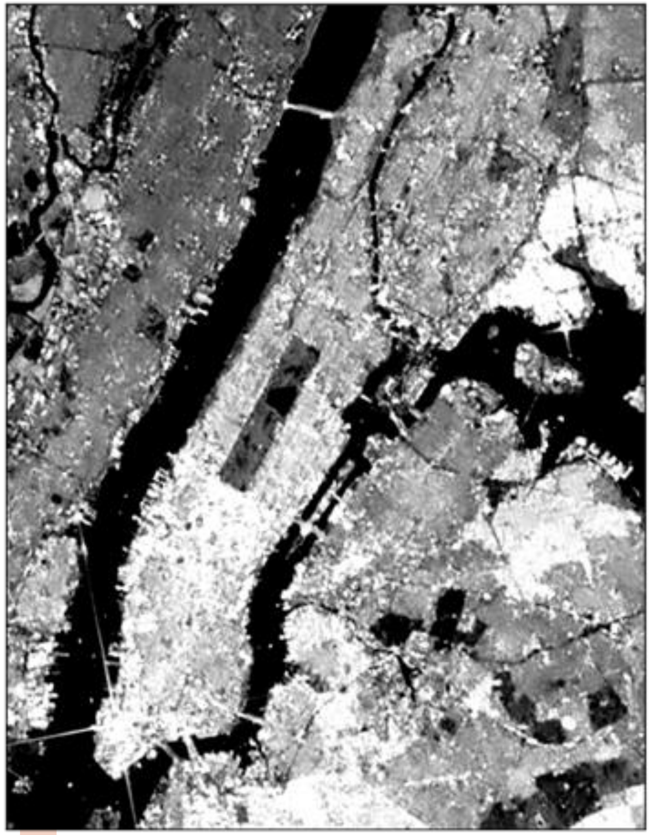




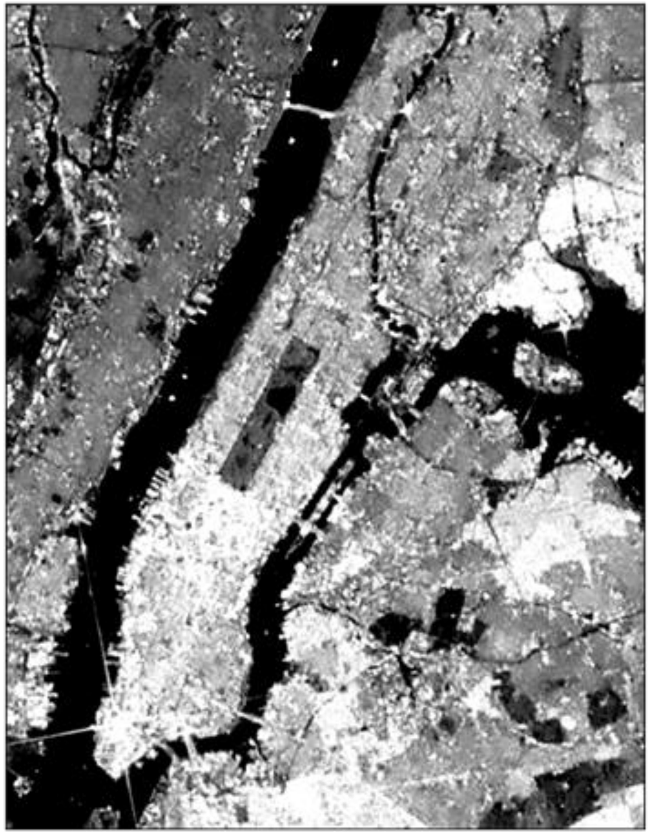
Coherence estimates the correlation between two phases

Coherence is the **complex correlation** between two phase signals and estimates the **randomness** of a region. **Coherence** is measured from 0 (incoherent, completely random) to 1 (perfectly coherent, stable structures).

NYC May 10 (VV)



NYC May 22 (VV)



InSAR Coherence

Coherence is equally sensitive to different types of changes.

Coherence is often denoted by γ and is made up of various components. The components of coherence **multiply**, so any source of decorrelation can result in low coherence.

Knowledge of the local characteristics is necessary to **properly conceptualize and interpret** InSAR coherence.

Accounting for γ_t , for example, is important as coherence generally decreases with increasing temporal baseline.

$\gamma = \gamma_v \gamma_g \gamma_t \gamma_c$

where

γ_v is volumetric (trees)

γ_g is geometric (steep slopes)

γ_t is temporal (gradual changes)

γ_c is sudden changes

Source: ARSET [Introduction to Interferometric SAR]

For proxy damage mapping from conflict, we want γ_c.

Proxy damage mapping means minimizing decorrelation related to processes that are not likely associated to sudden structural damage occurring during a conflict period.

We can try to mitigate other types of decorrelation by:

1. Masking out areas of low coherence in **pre-event** scenes
2. Minimizing difference in $\boldsymbol{\gamma}_t$ by choosing InSAR pairs with similar temporal baseline
3. Minimize $\boldsymbol{\gamma}_g$ using small perpendicular baseline InSAR pairs

$\gamma = \gamma_v \gamma_g \gamma_t \gamma_c$

where

γ_v is volumetric (trees)

γ_g is geometric (steep slopes)

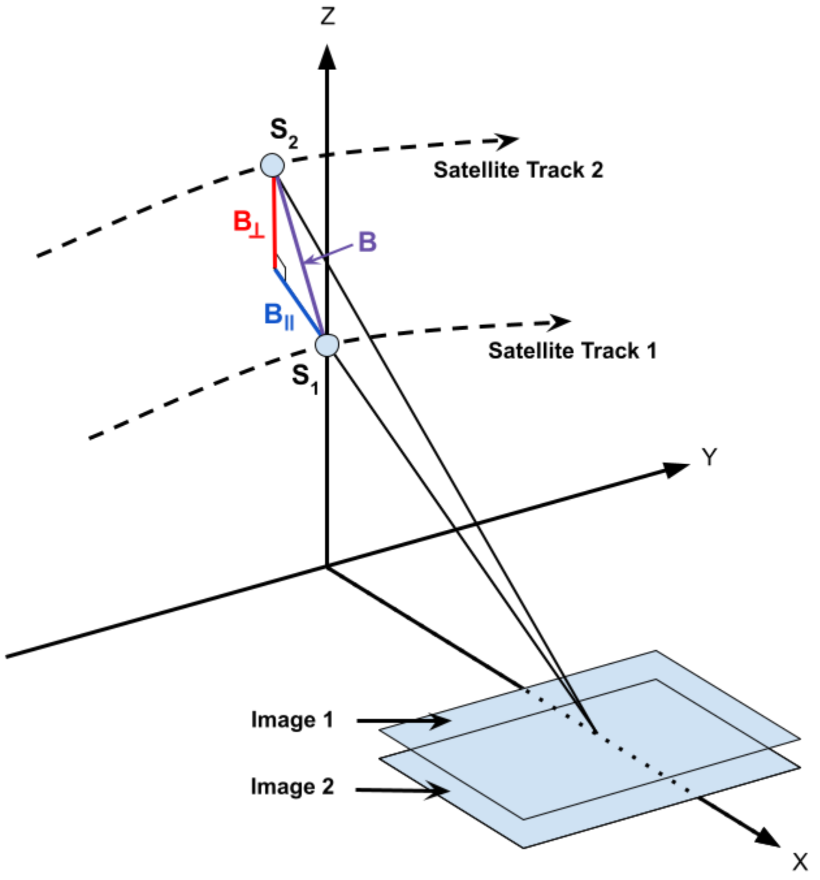
γ_t is temporal (gradual changes)

γ_c is sudden changes

Source: ARSET Introduction to Interferometric SAR

Geometric distortions affect coherence.

Perpendicular baseline ($B_\perp$) is the perpendicular component of the difference between "two vantage points from which images used as an InSAR pair are acquired." (ASF) For InSAR damage mapping, we want $B_\perp$ to be **small.**



Sentinel-1 InSAR Product Guide. Source: ASF

We want to map coherent areas that decorrelate with conflict.

This means that we want to look for **coherent image regions** that show reduced coherence during a conflict event.

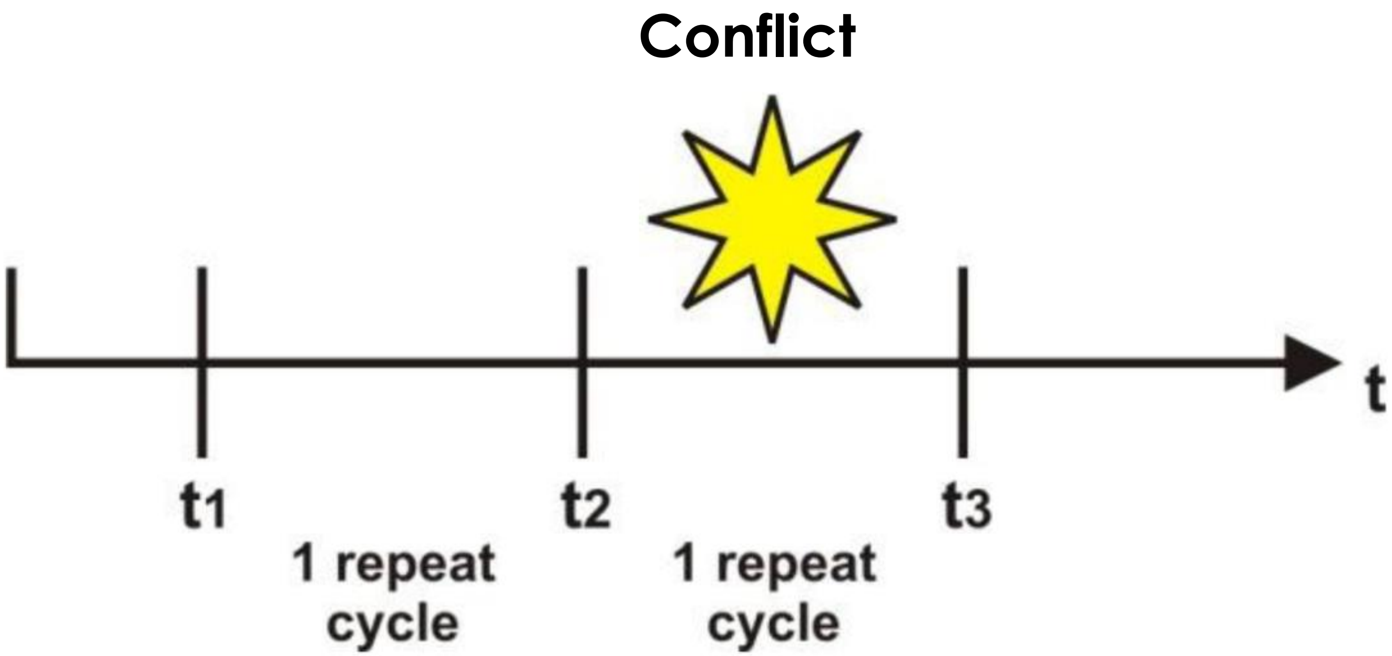
Source: History.com

We expect coherence to decrease after a conflict event.

In mapping proxies for conflict damage, our main assumption is that damage causes deviations in the scattering profiles of features in a city, and this disrupts the temporal stability of the image.

To capture this decrease in coherence, we need to assemble one "**reference**" and one "**event**" coherence image.

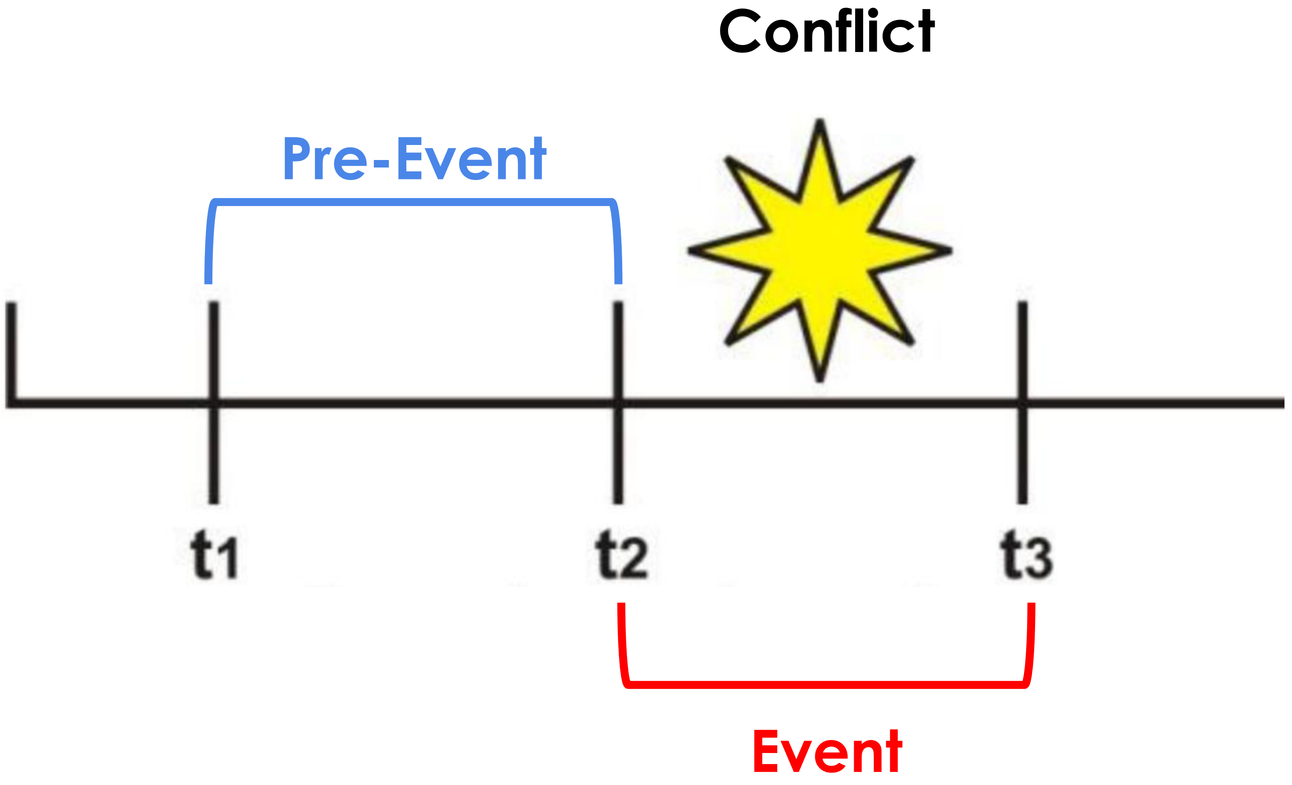
This requires three SAR images to make two InSAR pairs: one pair for the **pre-event period (e.g., t_1 and t_2)** and one pair for the **event period (t_2 and t_3)**.



Adapted from Planck (2014)

We select a pre-conflict image based on the conflict chronology

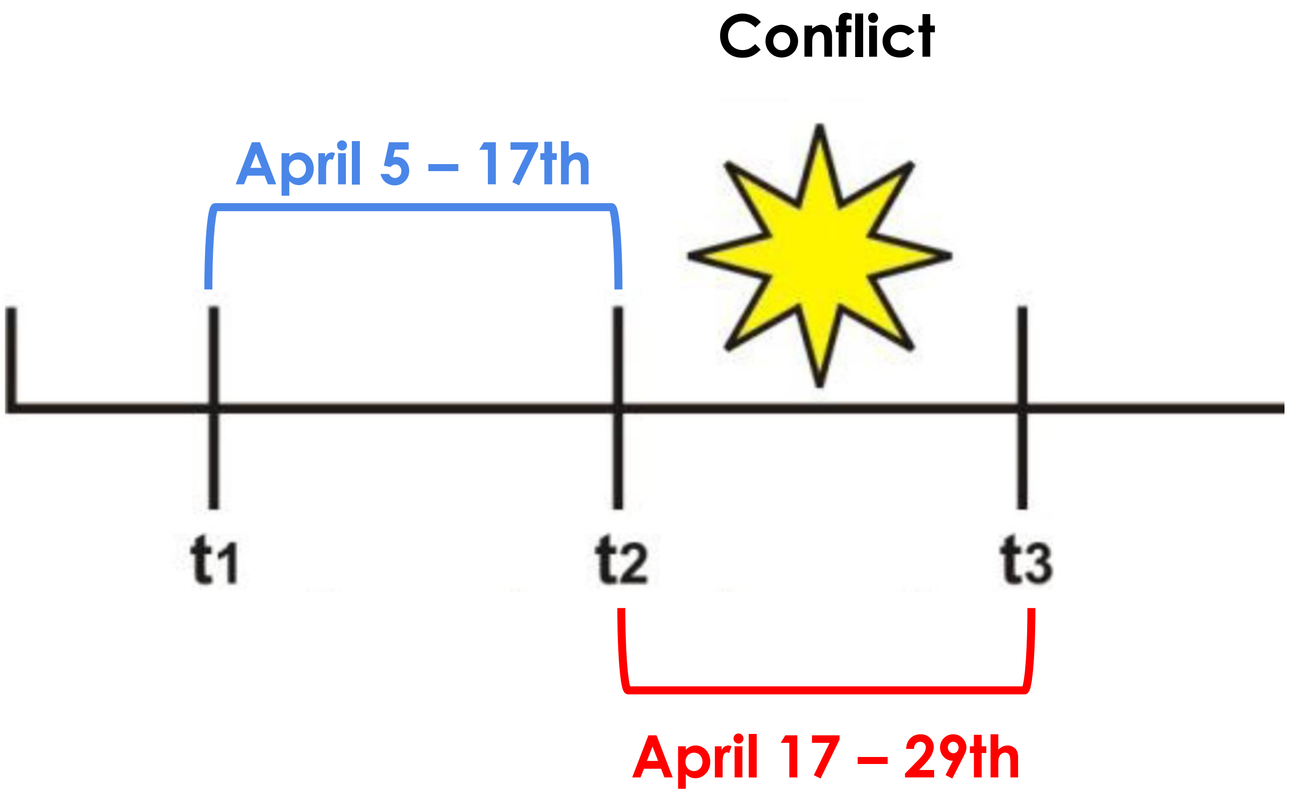
We want to use a reference scene from **before** the conflict period of study. An image acquired at time $\mathbf{t_2}$ will be a common reference for the **pre-event** and the **event** InSAR coherence images that we generate from images acquired at $\mathbf{t_1}$ and $\mathbf{t_3}$.



Adapted from [Planck (2014)]

Illustrative Example: Twelve Days in Aleppo, Syria in April 2016

Our **pre-event** period will be **April 5 – 17th** and the **event** period will be **April 17 – 29th**. This way our comparison has a **common reference** image on April 17th, 2016.



Adapted from Planck (2014)

Case Study Analysis: Aleppo, Syria

Source: Euronews

Our approach

Overview of tutorial

1. Register for SAR processing resources at Alaska Satellite Facility
2. Search for a reference image
3. Select our InSAR pairs using the baseline tool
4. Submit tasks to process the interferograms
5. Download processed data
6. Load **pre-event** and **event** coherence images to analytical environment
7. Calculate percent change in coherence
8. Mask out areas of low coherence in the **pre-event** image
9. Visualize and interpret the results

Logins/platforms needed

1. Alaska Satellite Facility (ASF) Vertex
2. Analytical GIS environment (e.g., QGIS, Python, R, etc.)

Calculate the difference in coherence

Raster band math on **“…_cor.tif” files** for the pre-event and event datasets

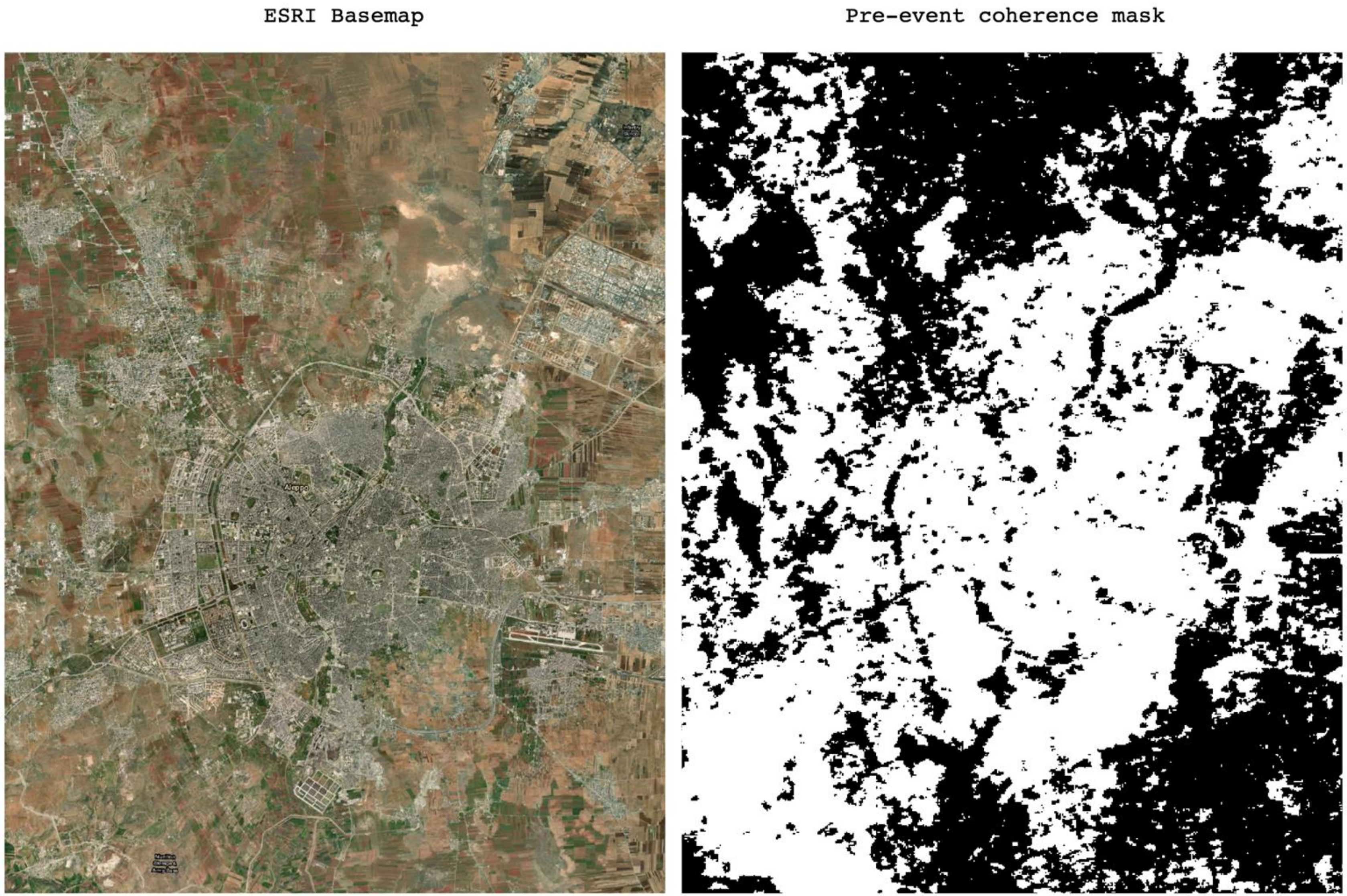
$$\Delta\gamma = \frac{\gamma_{event} - \gamma_{pre-event}}{\gamma_{pre-event}}$$

$\boldsymbol{\Delta\gamma}$ is the **change** in coherence between the pre-event and event coherence images.

Now we need to mask out areas of low pre-event coherence.

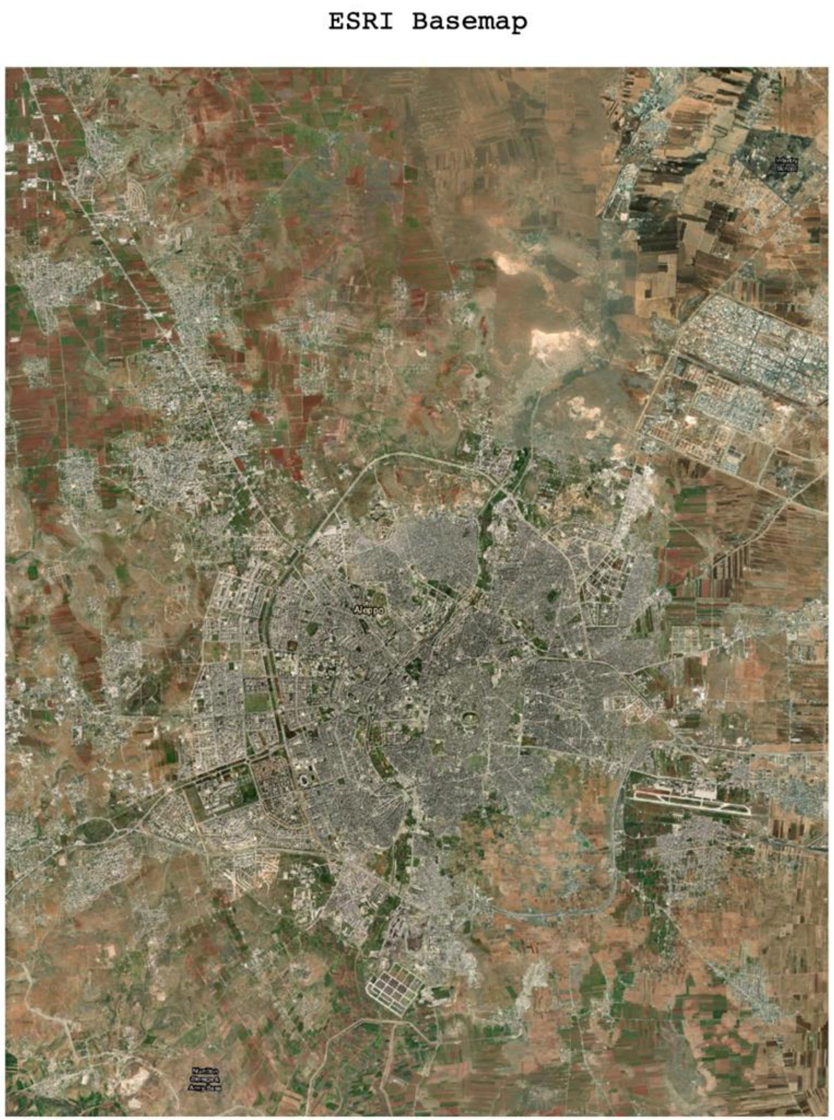
A strict threshold for pre-event coherence is important to deal with potential noise. We make a mask using a **fixed threshold of 0.9**.

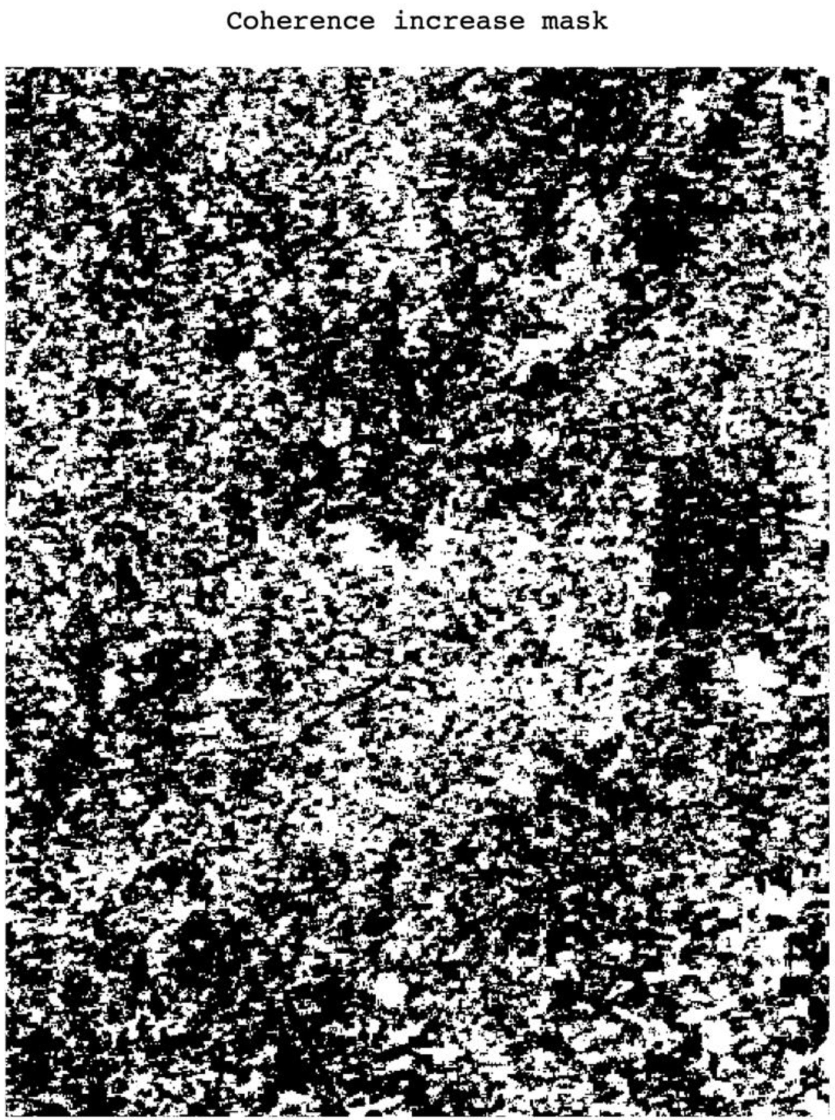
Notice how much of the image region had a pre-event coherence of >0.9.



Let’s also mask for areas that increased in coherence.

Regions that increased in coherence during our event period (where $\Delta\gamma >= 0$) **are not relevant** to the signal we are trying to retrieve.





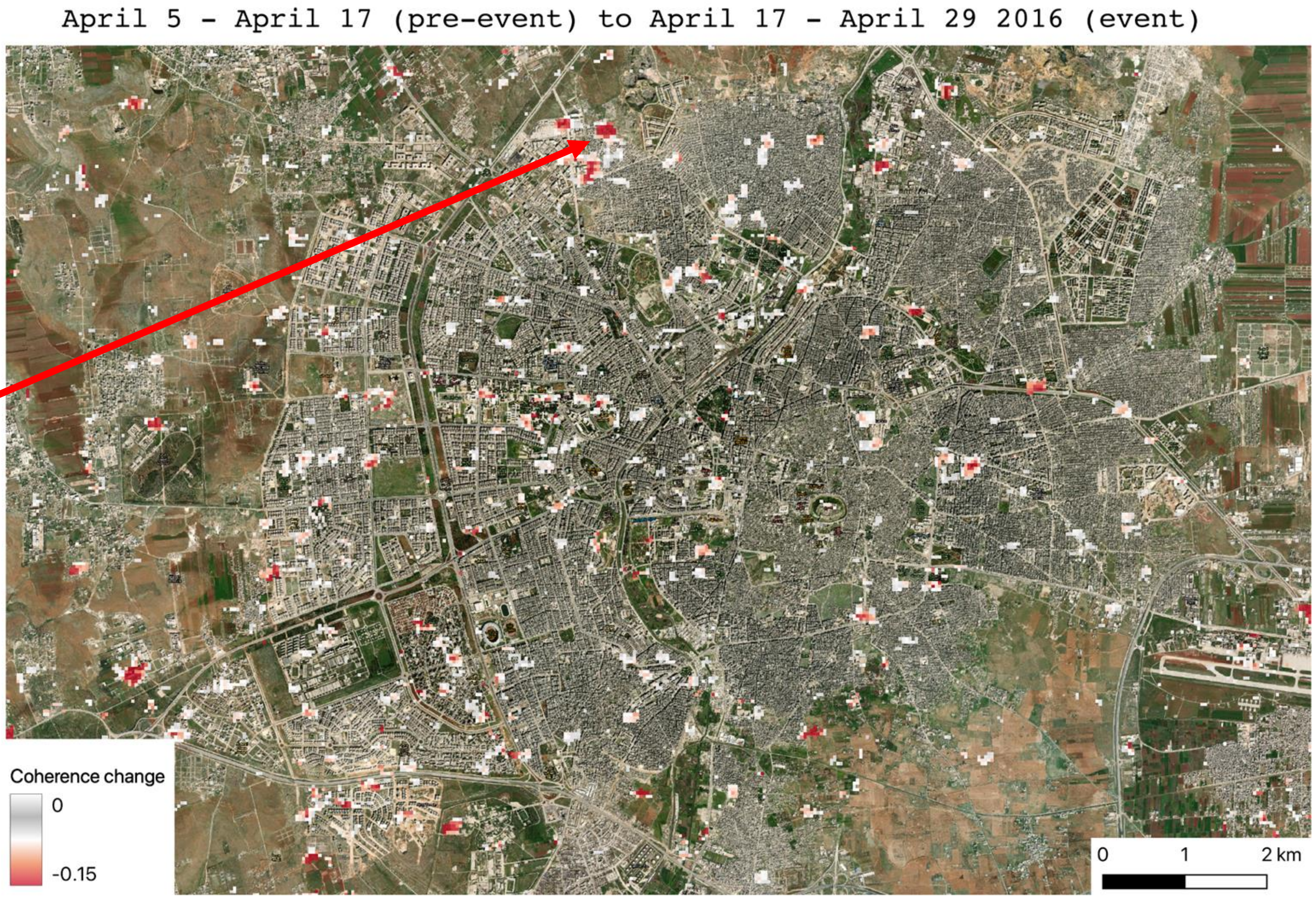
Damage proxies overlaid onto an ESRI basemap in QGIS

April 5 - April 17 (pre-event) to April 17 - April 29 2016 (event)

Damage proxies overlaid onto an ESRI basemap in QGIS

Red areas illustrate a **>15% decrease** in coherence during the "event" period.

Let's focus on one of these red areas and compare to Google Earth Pro historical imagery

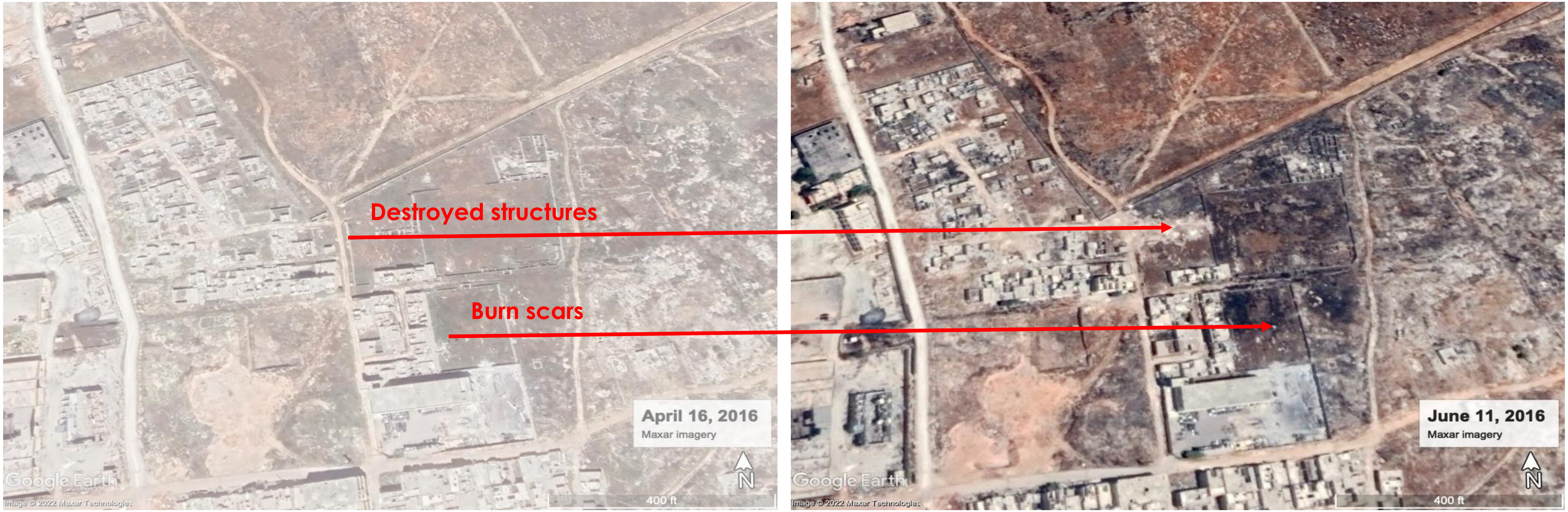


Compare that area to Google Earth Pro historical imagery

A Maxar image on Google Earth was acquired **just before** our pre-event period ended. In a June 11 Maxar image also on Google Earth **destruction is visible.**

Compare that area to Google Earth Pro historical imagery

A Maxar image on Google Earth was acquired **just before** our pre-event period ended. In a June 11 Maxar image also on Google Earth **destruction is visible.**



Coherence anomalies can guide optical image analysis.

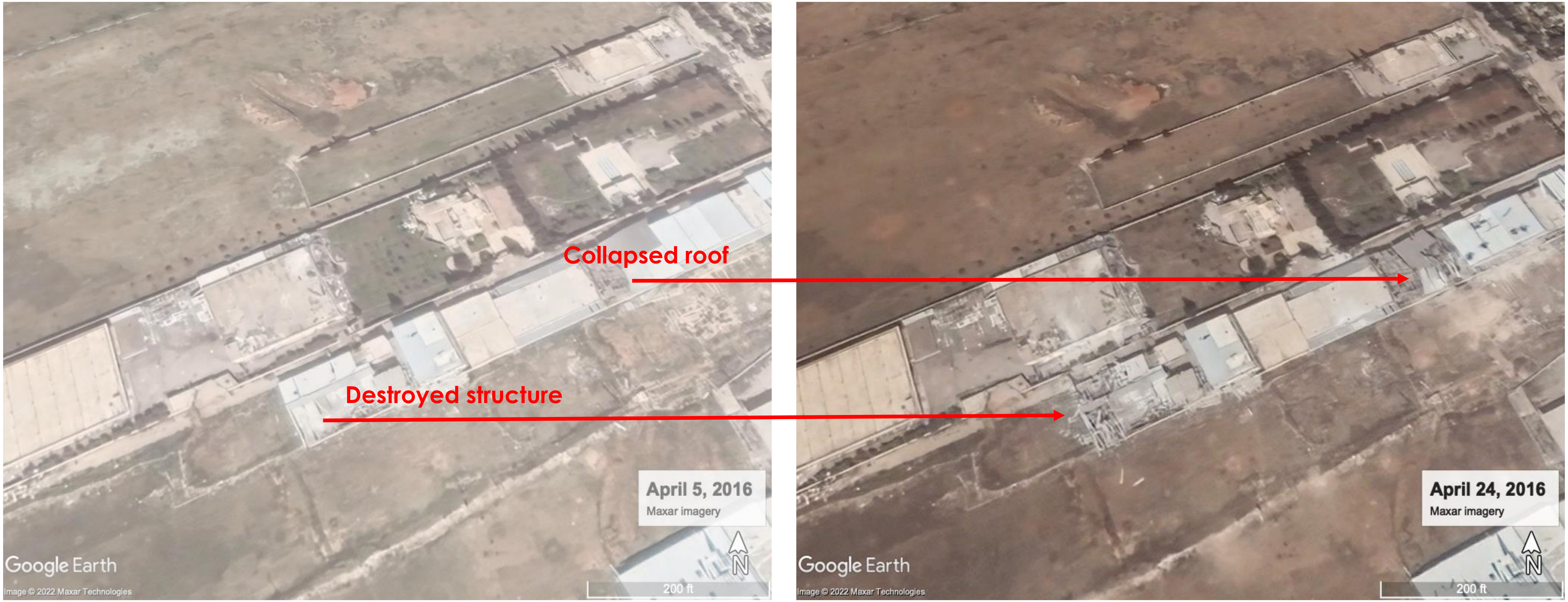
Let's look at another area on the western edge of our image region.

Zoom in on this patch of coherence loss and compare to optical images in Google Earth

April 5 – April 17 (pre-event) to April 17 – April 29 2016 (event)

Damage to these structures appears to have occurred between April 5 – 24.

Damage to these structures appears to have occurred between April 5 – 24.



There was an attack on a school and hospital in this time.

An MSF hospital was bombed on **April 28, 2016**

© BBC5

Figure 28: Map indicates Al Quds hospital's location in East Aleppo.

© ASSS6

Figure 29: Satellite imagery of Al Quds hospital on 25 April 2016 indicated by the red box.

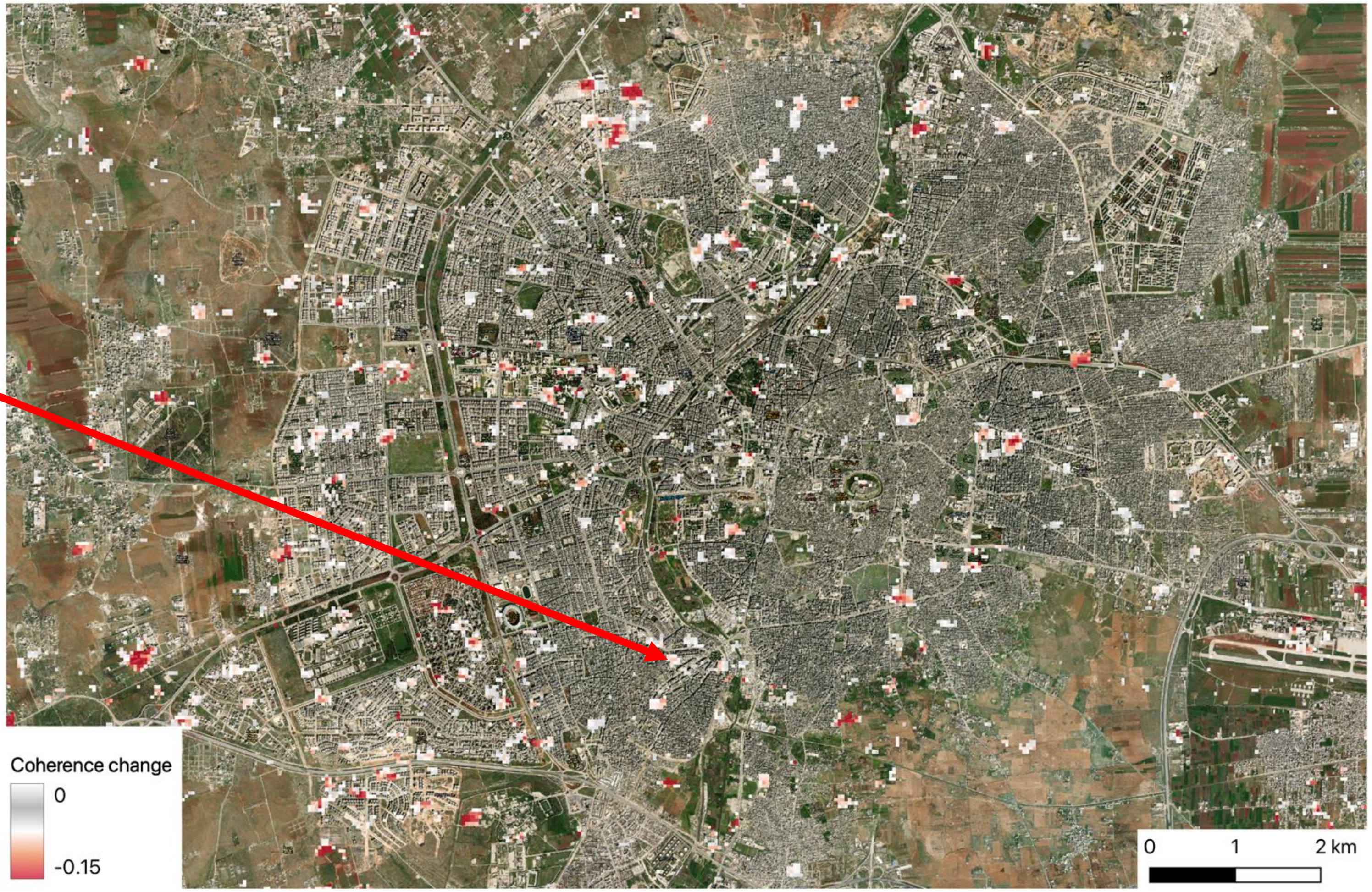
Source: MSF

That area appears as a small (<10%) coherence anomaly

The hospital that was struck was small and did not completely collapse.

Here is where it appears on our map

April 5 – April 17 (pre-event) to April 17 – April 29 2016 (event)



We can only see a small change in coherence there.

The hospital that was struck was small and did not completely collapse.

© Association Press[1]

Figure 1: Al Quds hospital post-attack.

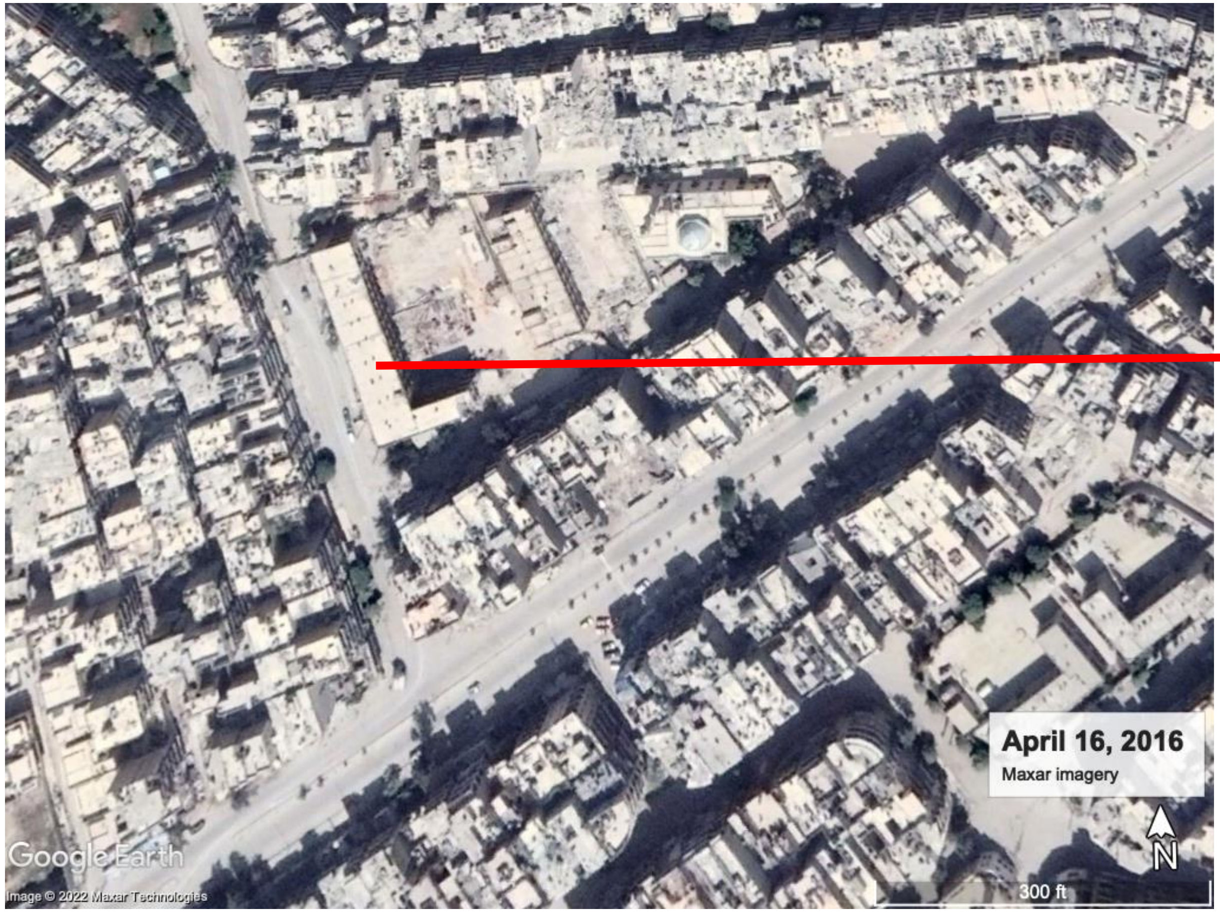
© Reuters[2]

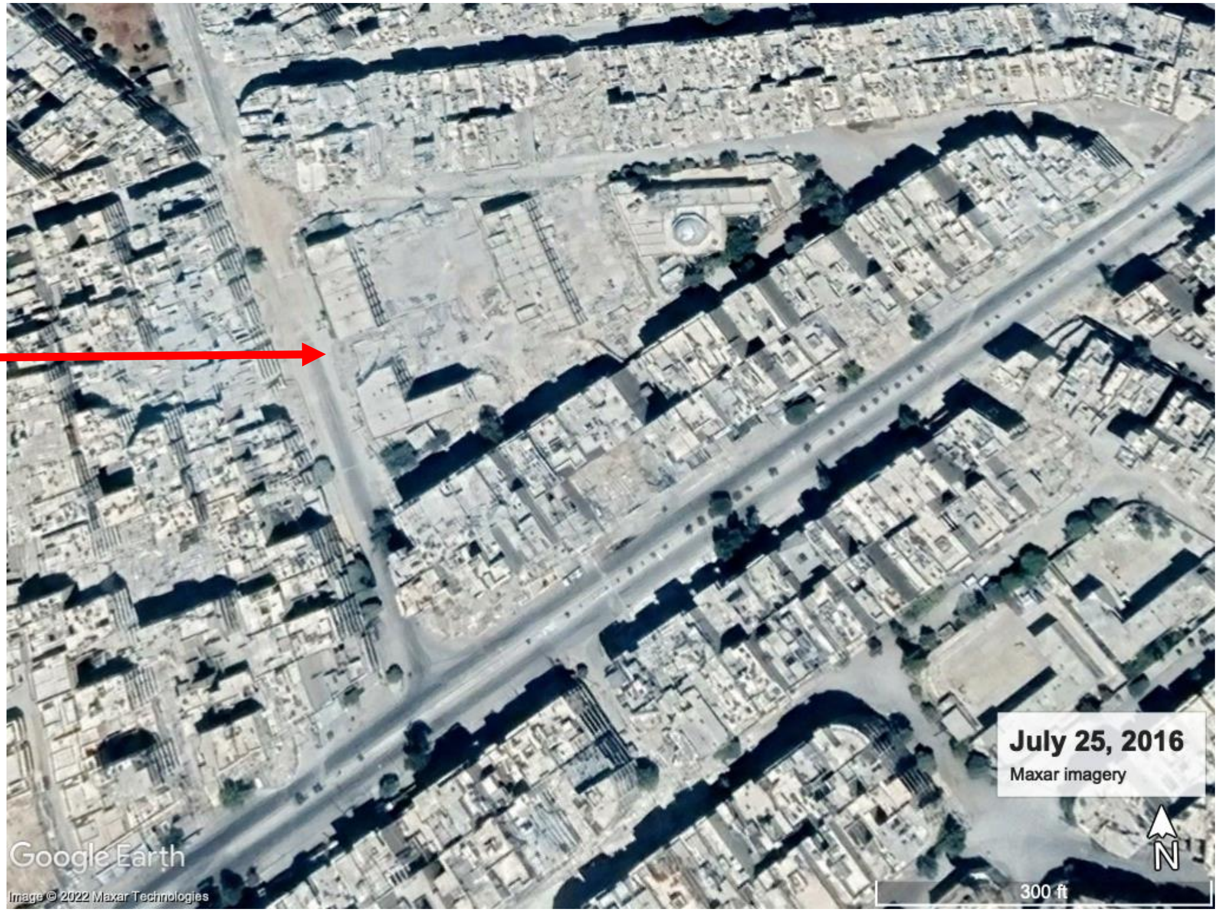
Figure 2: Al Quds hospital post-attack.

Source: [MSF]

A school across the street was struck and partially collapsed.

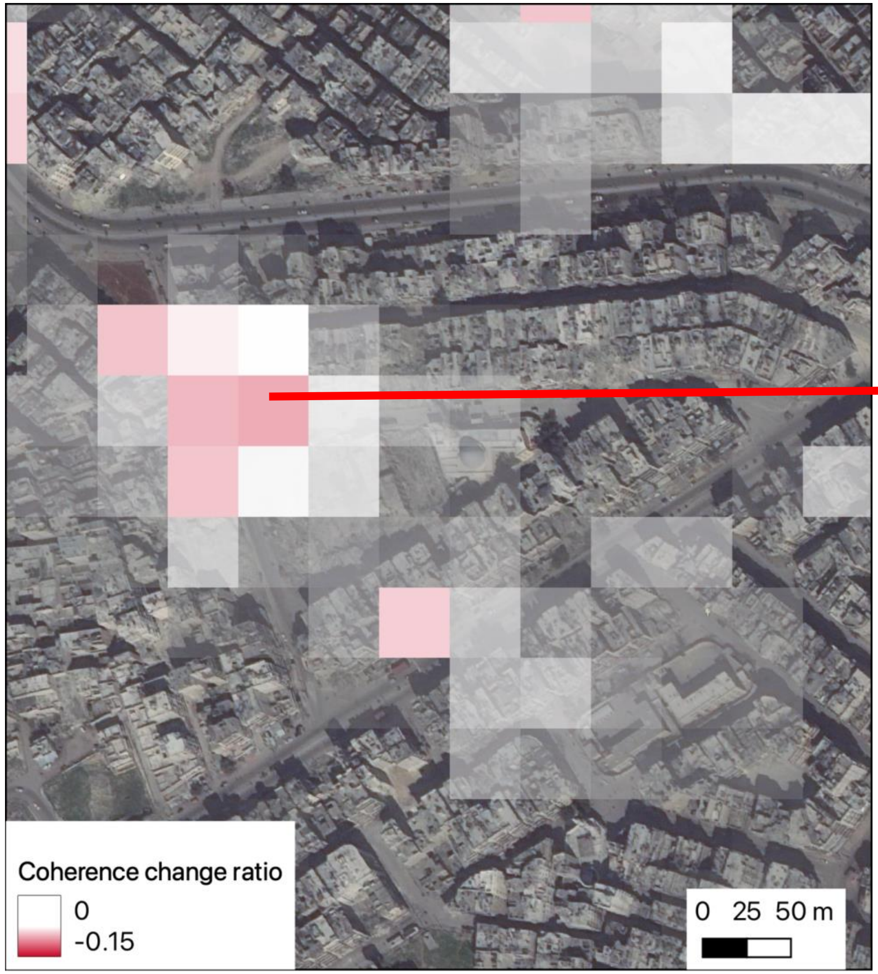
This is where the coherence decrease is the **greatest.**

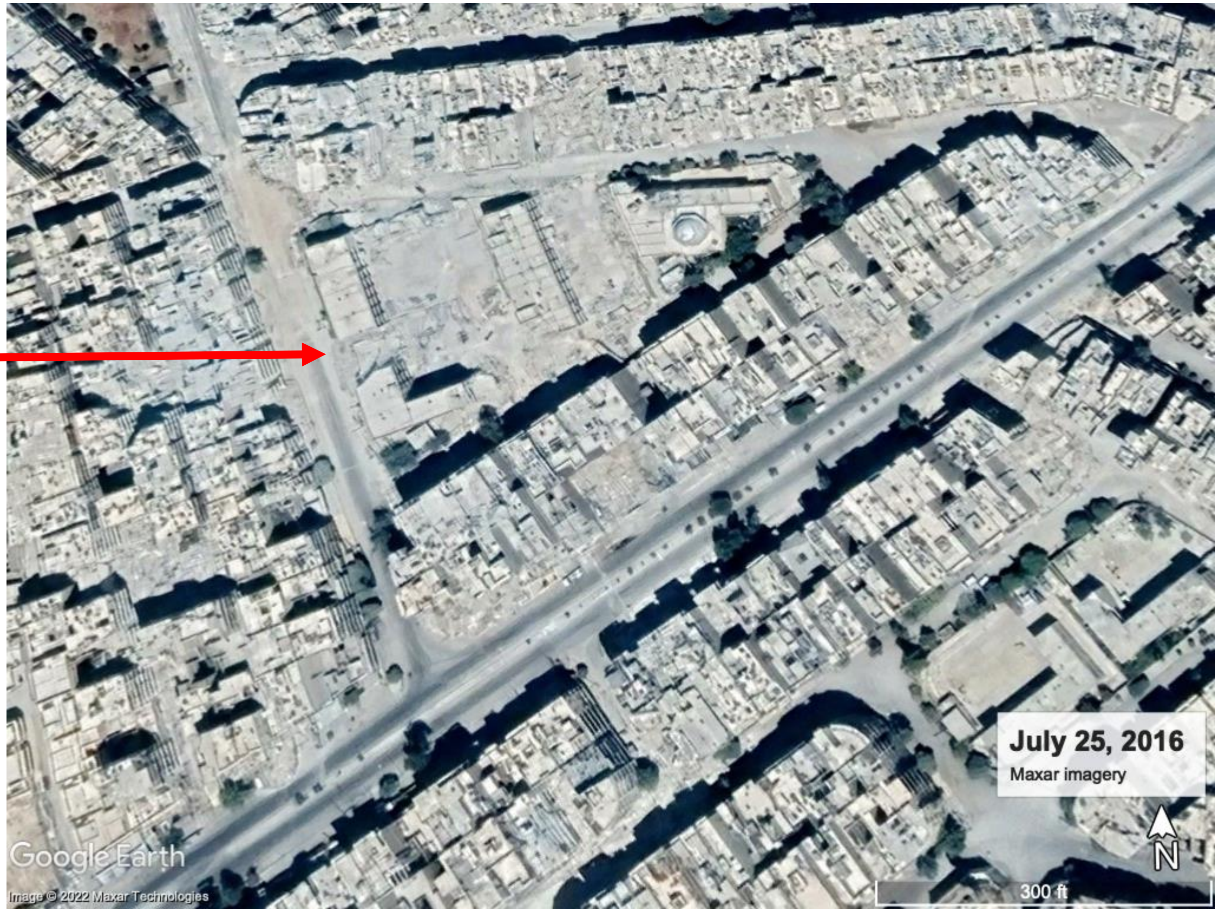




The school across the street partially collapsed.

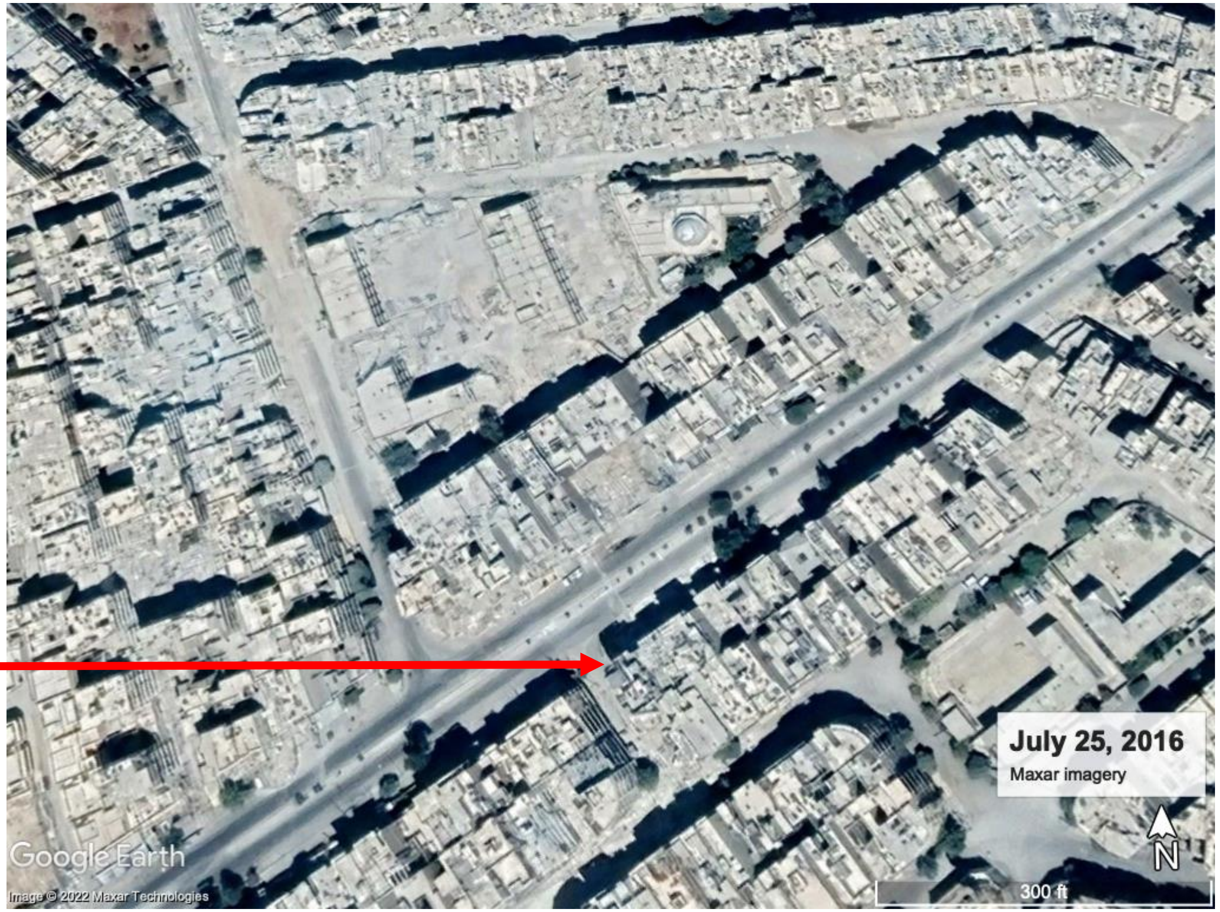
This is where the coherence decrease is the **greatest.**





There is only a small coherence decrease by Al Quds Hospital.

The hospital only covers **a portion of a pixel.** We don't detect a large change.



Suggestions for Using InSAR to Monitor Urban Damage

1. Start from the **basics**. Review the freely-available materials on Introduction to SAR and introduction to InSAR. Look at other tutorials on InSAR applications (i.e., ARSET training on landslide observations).
2. Build your **conceptual understanding** of coherence and how different dynamics at the surface can lead to low coherence.
   a. Dielectric changes (e.g., rain, snowmelt)
   b. Structural change (e.g., tilling of agricultural fields, construction)
3. Identify key dates or large-scale conflict damage events to detect. Have a **clear idea** of what you are looking for.
4. Take advantage of new cloud InSAR processing tools like ASF Vertex. These drastically lower the barrier to entry for working with InSAR data.
5. **Scrutinize** output datasets with any and all available data for comparison.

We also have an example in a Python Jupyter Notebook.

The exact same tutorial is available in Python using the ASF Vertex HyP3 SDK here.

InSAR Coherent Change Detection over Aleppo, Syria (April 17-29, 2016)

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Introduction

In this training we will walk through an example of bi-temporal coherent change detection over Aleppo, Syria to map proxies for urban damage that occurred as a result of air bombardments over a two week period in April 2016. We will be using the Alaska Satellite Facility's Vertex tool to generate two synthetic aperture radar interferogram (InSAR) datasets to look for anomalous decreases in InSAR measurements of coherence that occurred following a series of airstrike bombardments. This workflow can be completed either using the ASF Hyp3 Python SDK, as we will demonstrate in this notebook, or by generating InSAR coherence images manually using the ASF Vertex user interface and raster band math in a geographic information system interface, such as QGIS.

[42]:
```
import os
import folium
#import rioxarray
import shapely.wkt
import pandas as pd
import xarray as xr
import geopandas as gpd
import asf_search as asf
from hyp3_sdk import HyP3
import shapely.geometry as shp
import matplotlib.pyplot as plt
```

Questions?

- Please enter your questions in the Q&A box. We will answer them in the order they were received.
- We will post the Q&A to the training website following the conclusion of the webinar.

Credit: US DoS

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- Training Webpage:
  - https://appliedsciences.nasa.gov/join-mission/training/english/arset-humanitarian-applications-using-nasa-earth-observations

Citations

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Thank you and please join us for Part 2 of the training:

Mapping Refugee Settlement Growth and Population Change