# ECMWF-ESA Workshop on Machine Learning for Earth Observation and Prediction

## Remote Sensing of Floods

Ronny Hänsch


DLR

# Sustainable Development Goals (SDGs)

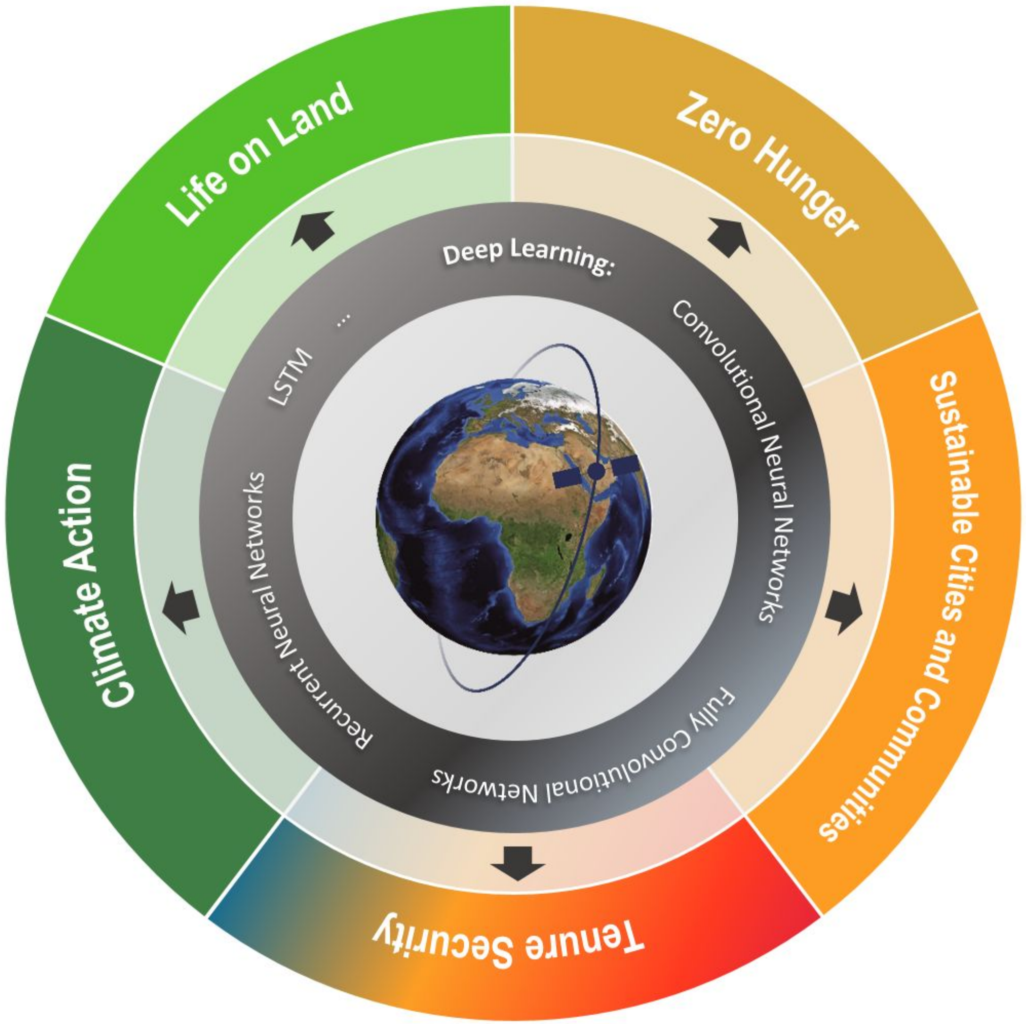
- Data-driven framework defined by the United Nations
- Set of seventeen goals representing actions to reach peace and prosperity for all people by 2030
  → Social, economic, and environmental challenges
- 169 targets and 232 indicators to measure, monitor, and report the progress

*"If you can't measure it, you can't manage it!"*

⇒ Need for objective, accurate and trustworthy information.

# SDGs and EO

- Continuous temporal information over the globe
- Data at multiple scales
- Monitors the state of natural ecosystems, natural resources, oceans, coasts, land, built infrastructure and their change over time
- Spatially and temporally consistent
- Complementary with traditional statistical methods (e.g. household surveys and administrative data)




C. Persello et al., "Deep Learning and Earth Observation to Support the Sustainable Development Goals: Current approaches, open challenges, and future opportunities," in IEEE Geoscience and Remote Sensing Magazine, vol. 10, no. 2, pp. 172-200, June 2022

# SDGs and EO

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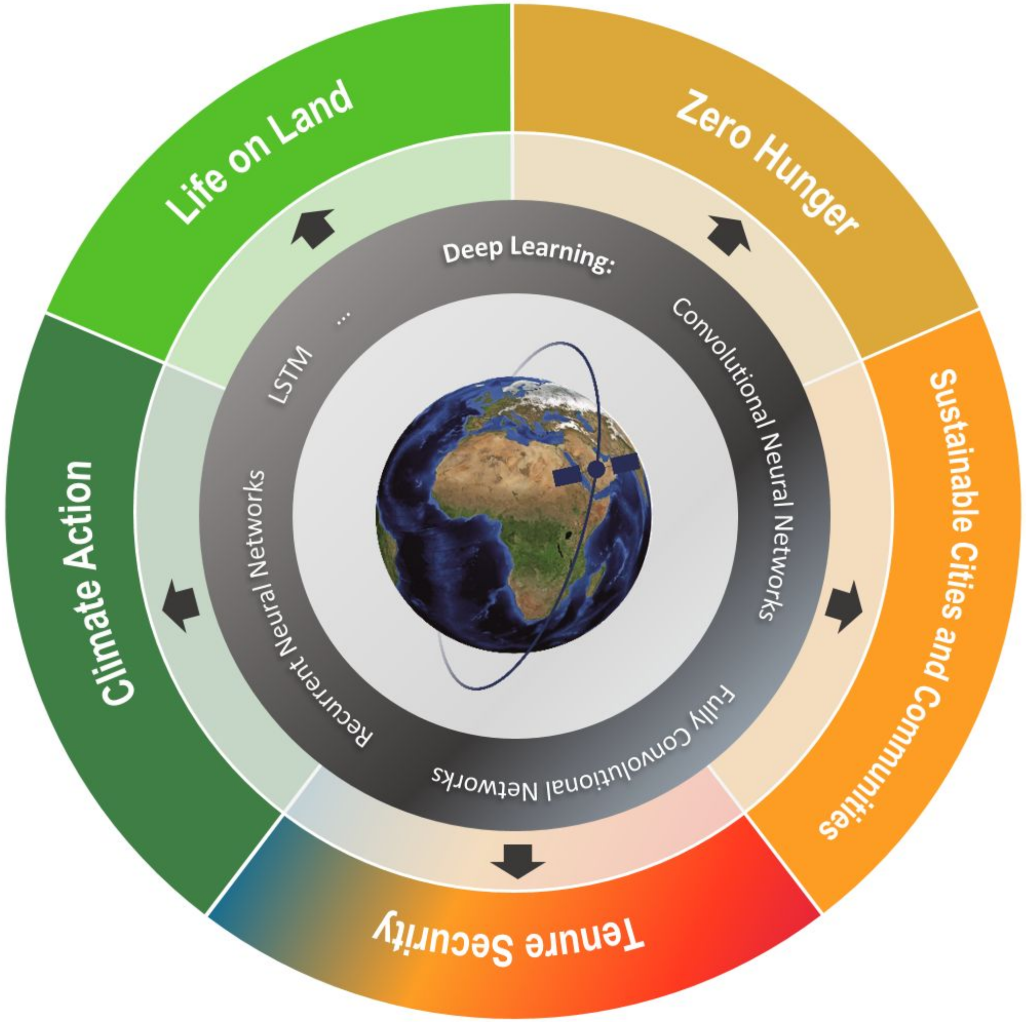
- 34 SDG indicators across 29 targets and 11 goals can be informed with EO data
- Effective comparison among different countries
- Reduce the cost of monitoring SDG targets

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# SDGs and EO

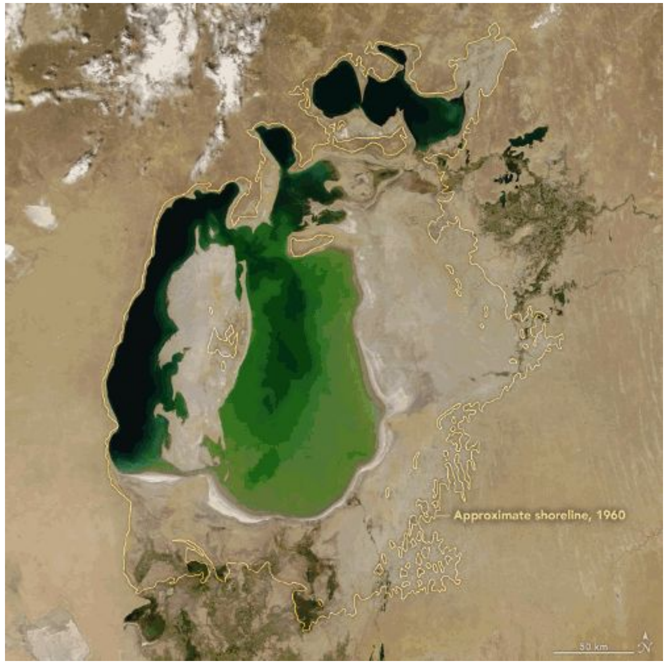
Monitoring of extreme events and quantifying their socioeconomic impacts

Urbanization
Shanghai 1984-2019

https://earthobservatory.nasa.gov/world-of-change/Shanghai


Deforestation
Amazon 2000-2012

https://earthobservatory.nasa.gov/world-of-change/Deforestation/



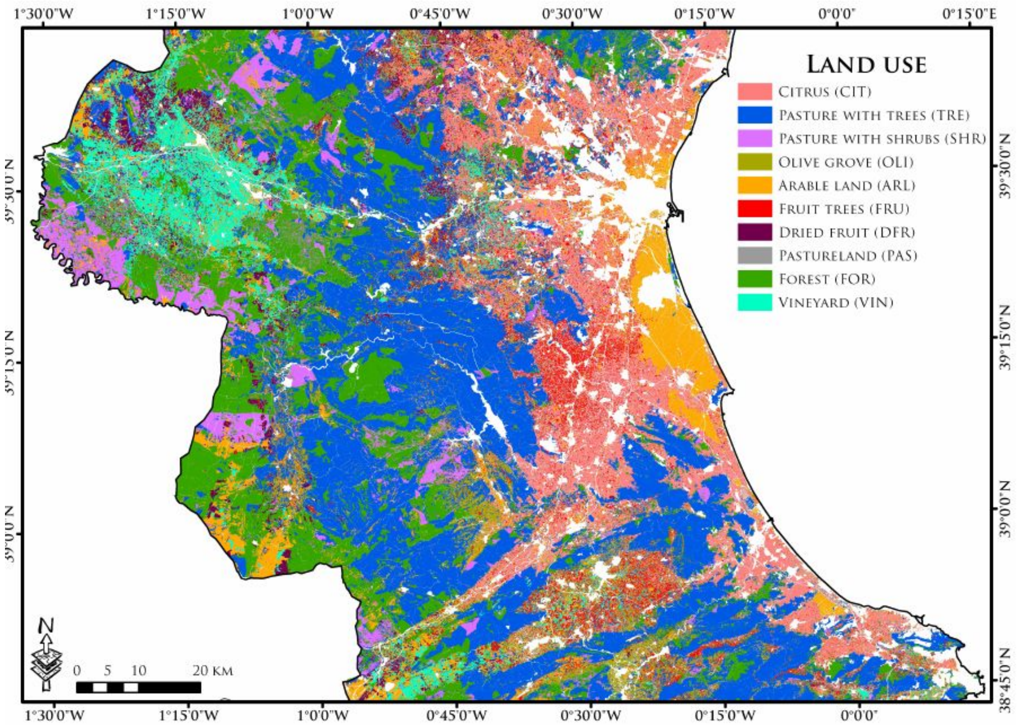

Drought
Aral Sea 2000-2018

https://earthobservatory.nasa.gov/world-of-change/AralSea/

# SDGs and EO: Zero Hunger (SDG 2)

- Rising pressure on uncultivated and existing agricultural areas due to increasing population, climate change, and changes in food consumption
- Cropland expansion and intensive use of agricultural areas connected to negative ecological impacts
  - Deforestation, biodiversity loss, degradation of water quality

→ **Monitoring agricultural land use and production**
  - Some areas extensively used as grassland, promote a certain crop mix
  - Traditional methods (self-reporting, spot checking) laborious, costly, and prone to errors



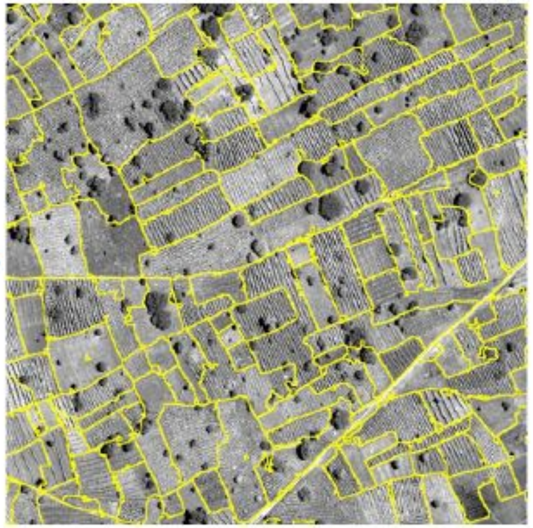

Spatio-temporal deep learning (bi-LSTM) for crop monitoring from Sentinel-2.

M. Campos-Taberner et al., "Understanding deep learning in land use classification based on sentinel-2 time series," Scientific reports, vol. 10, no. 1, pp. 1–12, 2020.

# SDGs and EO: Zero Hunger (SDG 2)

- Rising pressure on uncultivated and existing agricultural areas due to increasing population, climate change, and changes in food consumption
- Cropland expansion and intensive use of agricultural areas connected to negative ecological impacts
  - Deforestation, biodiversity loss, degradation of water quality

→ **Delineation of field boundaries:**
  - Essential for digital agricultural services (e.g. estimation of cropland areas)
  - Facilitate the extraction of land tenure boundaries for recording land rights

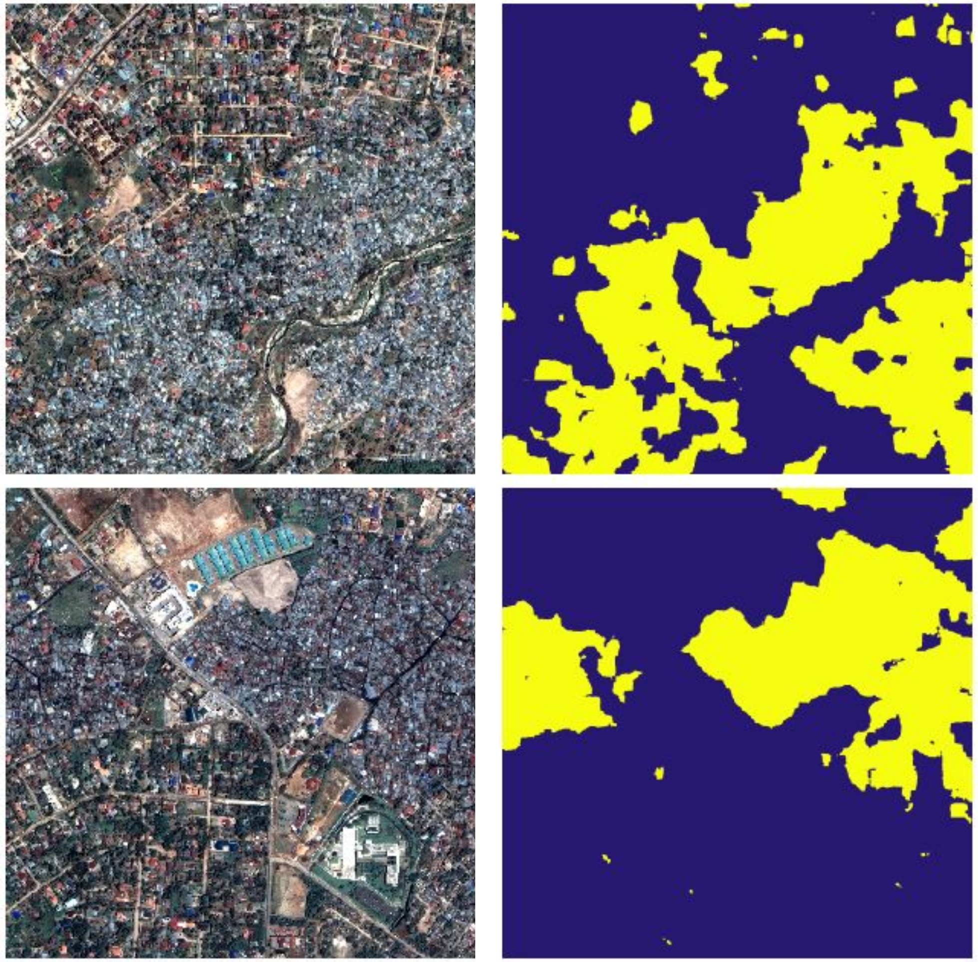


C. Persello et al., "Delineation of agricultural fields in smallholder farms from satellite images using fully convolutional networks and combinatorial grouping," Remote Sensing of Environment, vol. 231, p. 111253, 9 2019.

# SDGs and EO: Sustainable Cities (SDG 11)

- 1 billion people reside in informal settlements
  - Lacking access safe water, acceptable sanitation, and durable housing
  - Vulnerable to disasters such as floods, heat waves, droughts, landslides, storms, wildfires
- Official statistics often outdated or inaccurate

→ **Mapping slums and urban poverty:**
  - Identify informal settlements
  - Repeatable and consistent mapping over large areas
  - Support planning and monitoring of urban upgrading projects



C. Persello and A. Stein, "Deep Fully Convolutional Networks for the Detection of Informal Settlements in VHR Images," IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 12, pp. 2325–2329, 12 2017.

# SDGs and Floods


2.4.1: Adaptation to climate change, extreme weather, drought, flooding and other disasters


11.b.2: Disaster risk reduction
11.5.1: Reduced number of deaths related to disasters
11.5.3: Mitigate disaster damage to infrastructure


15.3.1: Maps of deserts and degraded land, prediction of drought and floods

# Why floods?

- Danger to human lives
- Damage to buildings and infrastructure
- Costs for cleanup and rebuilding
- Power outages
- Disrupts transportation
- Landslides and erosion of arable land
- Environmental hazards

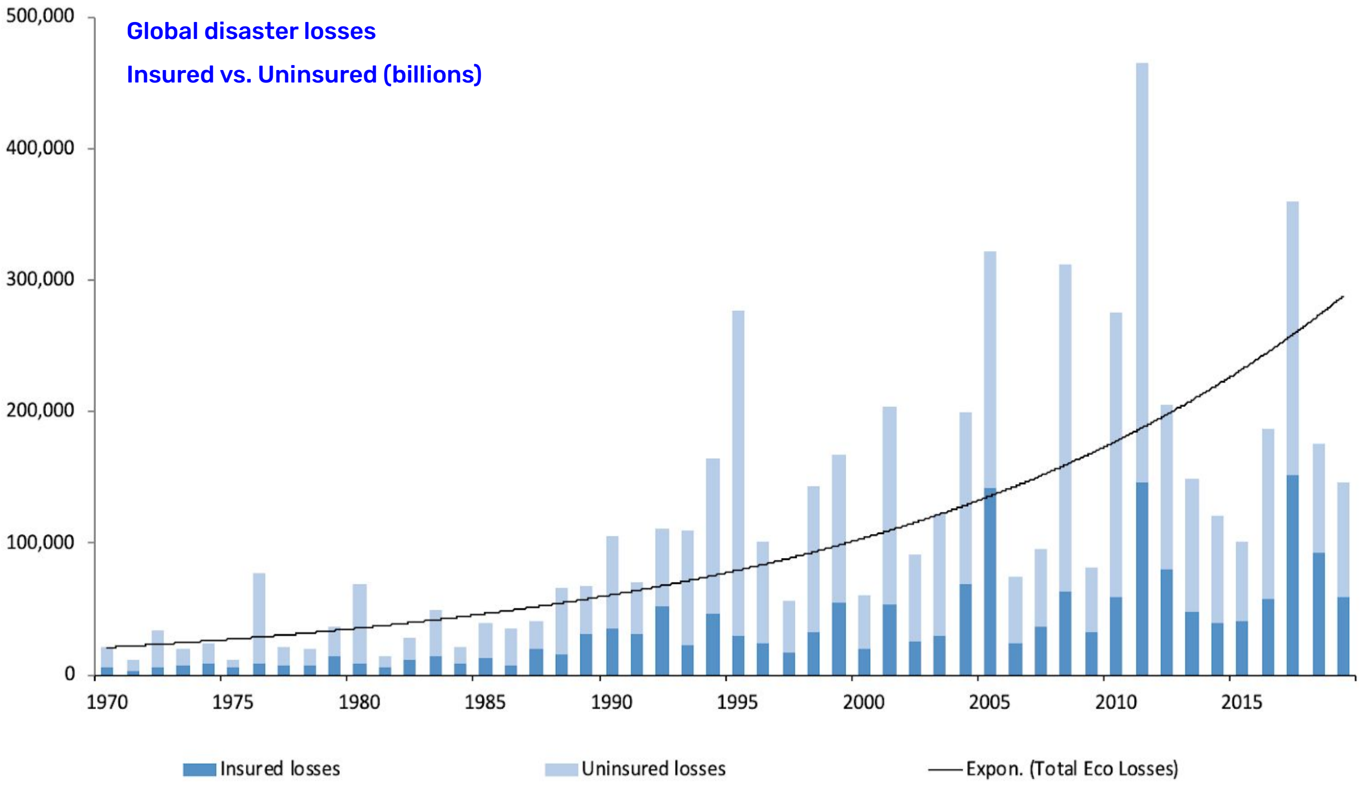
# Why floods?

- Most common disaster
- Affect more people than all other natural disasters combined.

- 223 of 432 catastrophic events in 2021 were floods[1]
- 163 of 357 annual catastrophic events on average in 2000-2020

- 2.23 million km² flooded and 255-290 million people affected in the last 15 years

- $80 billion economic loss from floods in 2021[2]




1 https://reliefweb.int/report/world/2021-disasters-numbers
2 Source: The World Bank, Swiss Re Institute
3 Figure with courtesy S.Chakrabarti, Cloud2Street (Source: SwissRe Institute)

# Why floods?

Two thirds of the world's population will be living in urban areas by 2050

- Rapid and unplanned urbanization
- Growing numbers of slum dwellers
- Inadequate infrastructure
- Housing along rivers and creeks
- Opening flood plains for building construction
- River straightening and dredging

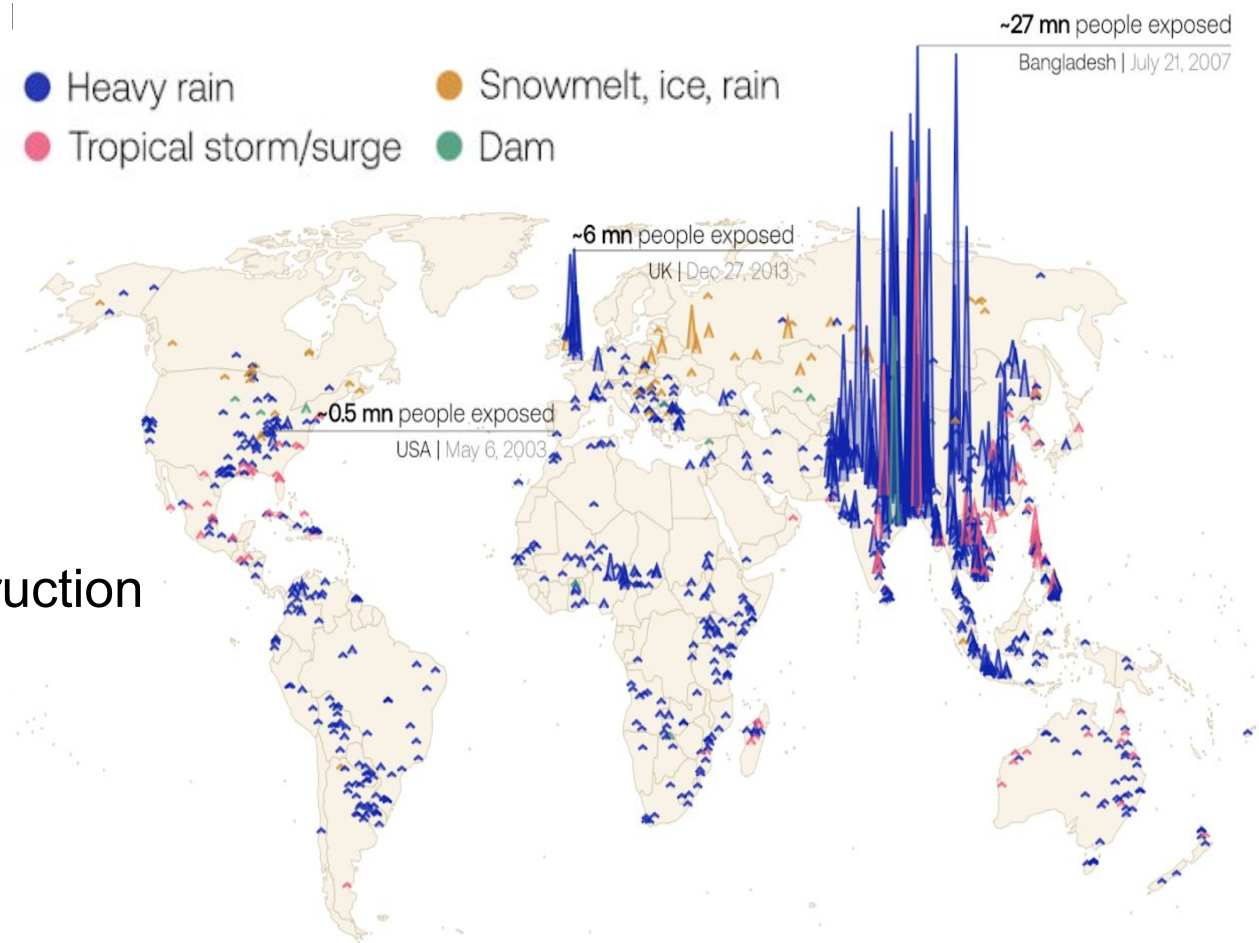



Figure with courtesy S.Chakrabarti, Cloud2Street (Source: SwissRe Institute)

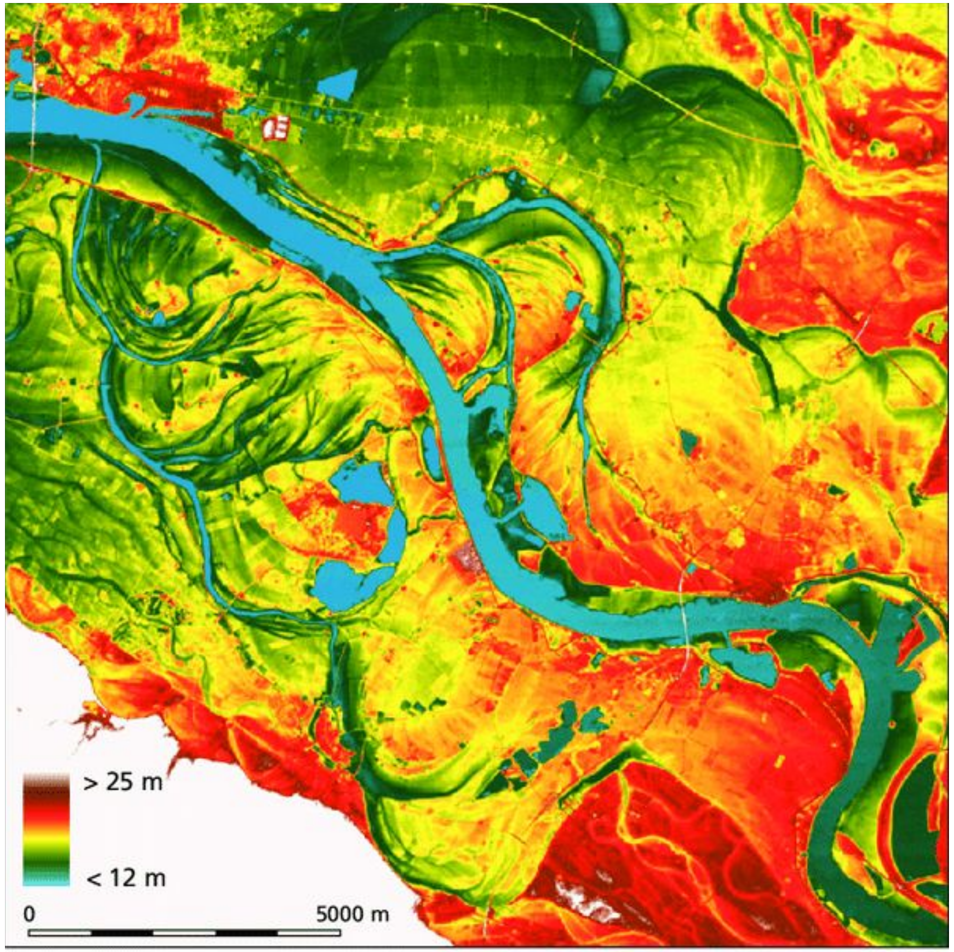
# Causes for flooding

- Strong precipitation
- Snowmelt
- Overbank flow
- Storms
- Changing sea level
- Lack of proper drainage systems
- Impervious surfaces
- Infrastructure failure (dam, pipes, etc.)

# Floods and EO: Data Needs

- Natural
  - Floodplain map: terrain, digital elevation model, drainage channels
  - River stage and inundation
  - Coastal surges and inundation
  - Weather data: Precipitation intensity, frequency, forecast
  - Flood hazard map

- Artificial
  - Storm water system design and capacity
  - Design and capacity of dams and levees
  - Exposed Soil versus built-up areas
  - Human population
  - Infrastructure (e.g., buildings, roads)

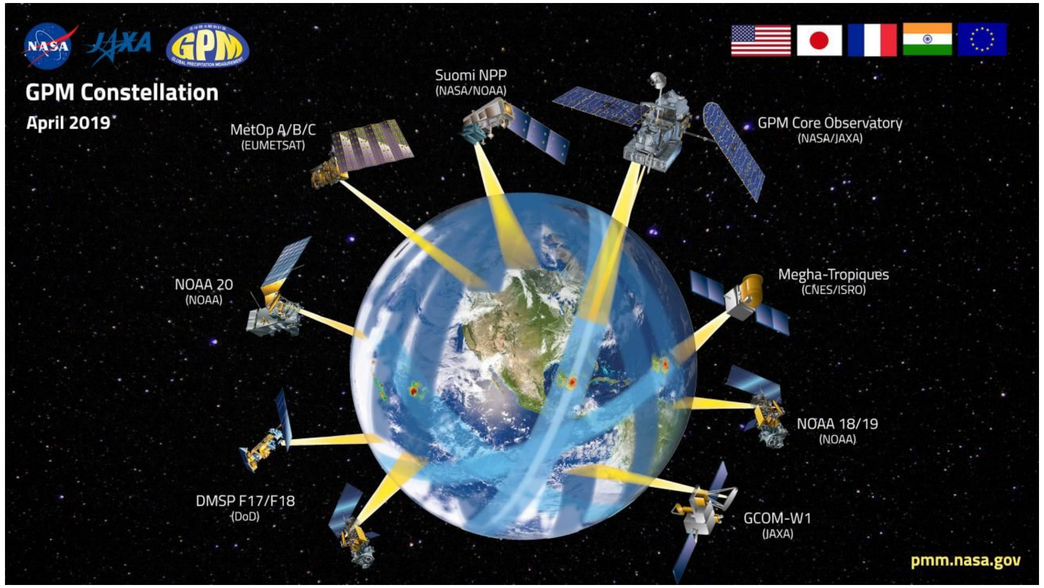



Floodplain topography of the river Rhine (based on laser altimetry, courtesy Cohen et al., 2009).

# Satellites and Sensors

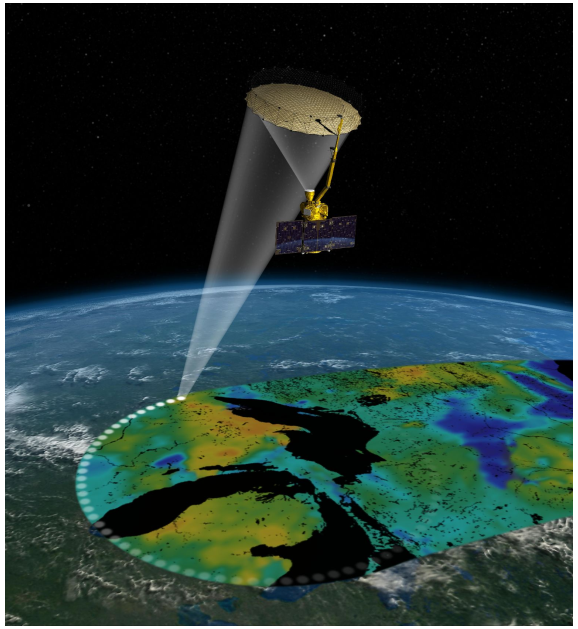
- Global Precipitation Measurement (GPM) Mission
  - Revisit time of 2-4 hrs over land (via satellite constellation)
  - Sensors: GMI (GPM Microwave Imager)
    DPR (Dual Precipitation Radar)
  - IMERG: Integrated Multi-satellitE Retrievals for GPM

http://pmm.nasa.gov/GPM/

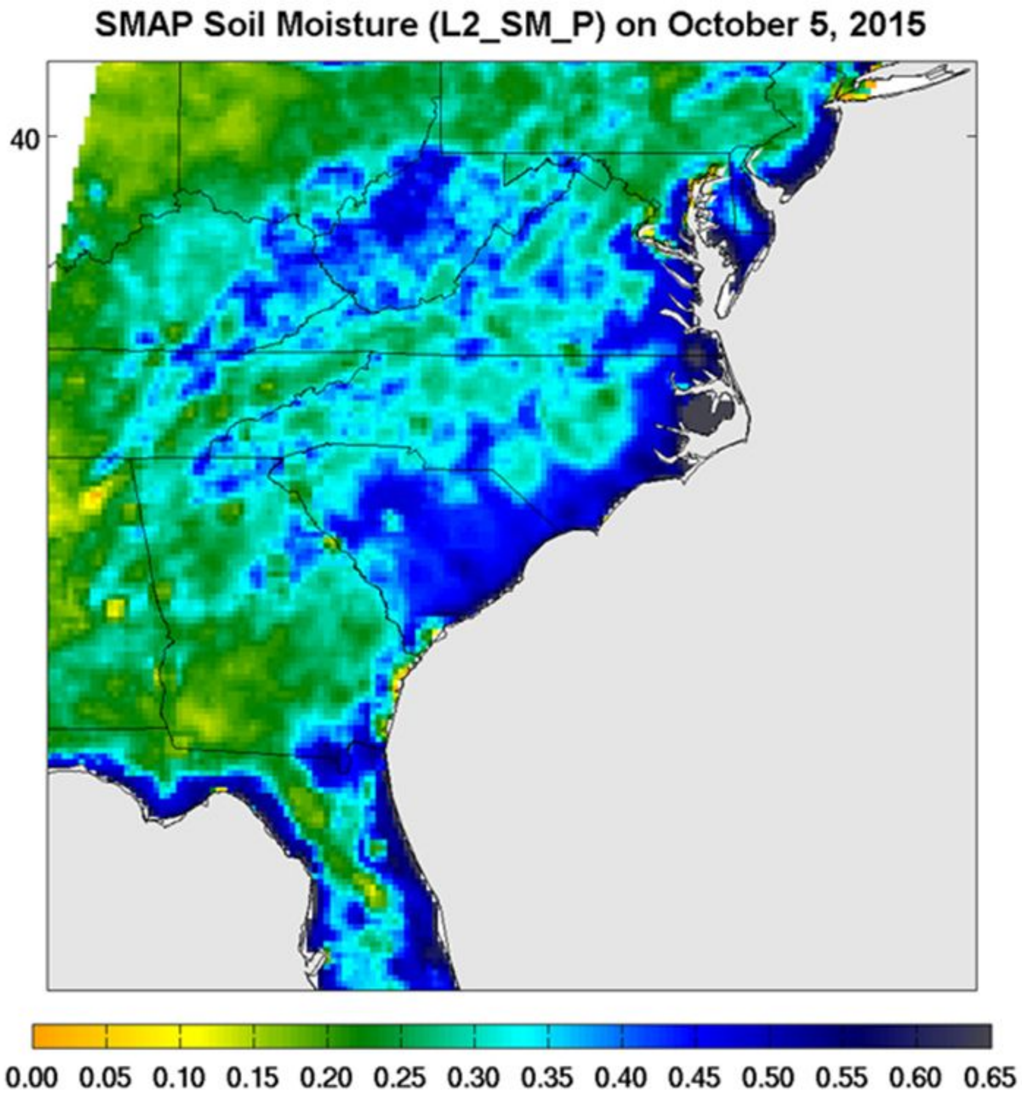


# Satellites and Sensors

- Global Precipitation Measurement (GPM) Mission
- Soil Moisture Active Passive (SMAP)
  - Global spatial coverage
  - Microwave radiometer
  - Spatial resolution: 40 km
  - Temporal resolution: 3 days



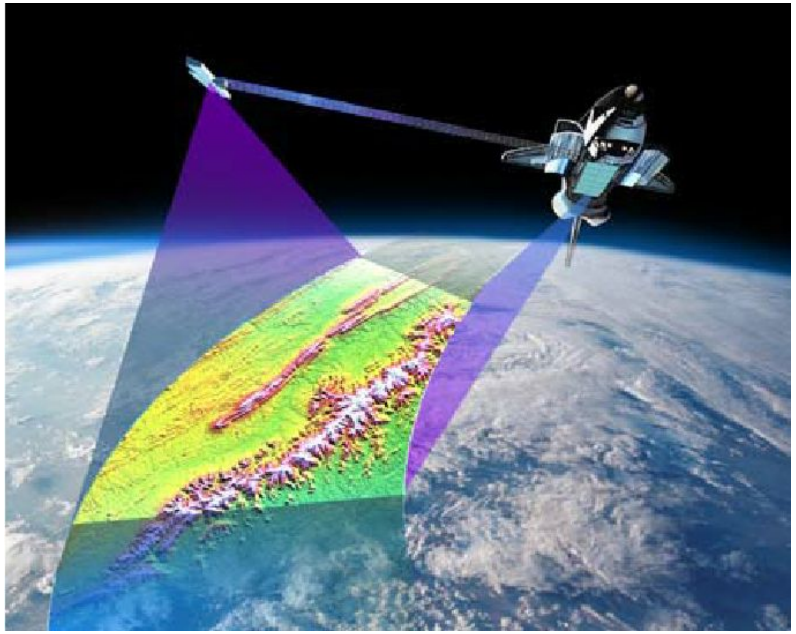
Credit: NASA/JPL-Caltech




2015 Carolina floods viewed by SMAP

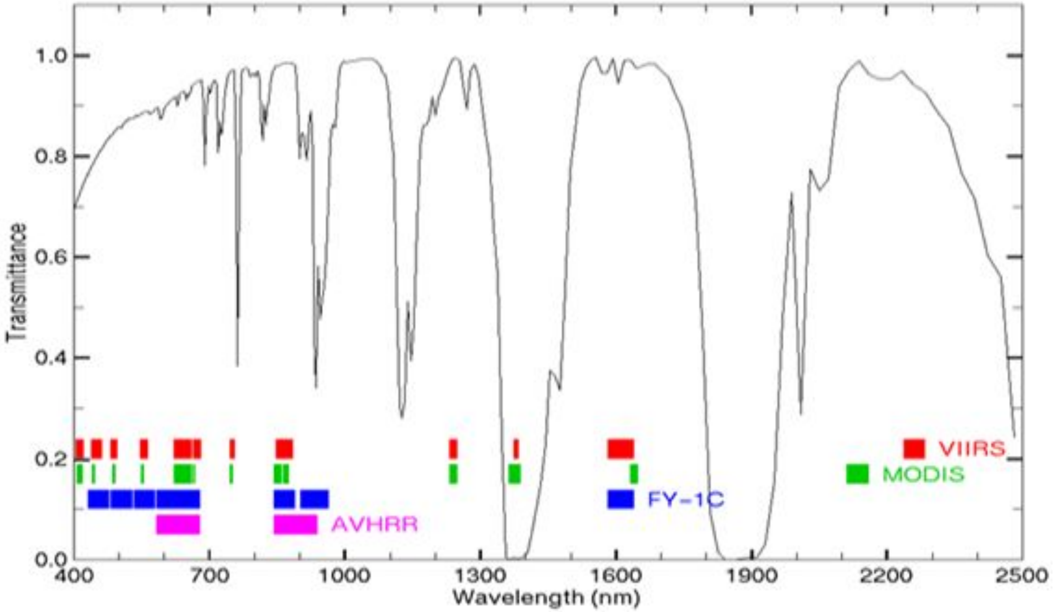
# Satellites and Sensors

- Global Precipitation Measurement (GPM) Mission
- Soil Moisture Active Passive (SMAP)
- Terrain Data From Shuttle Radar Topography Mission (SRTM)
  - On NASA Space Shuttle Endeavour
  - 176 orbits around Earth in 11 days in February 2000
  - Radar interferometry at C-band (5.6 cm)
  - Acquired digital terrain elevation data (60°N – 56°S, roughly 80% of the land mass)



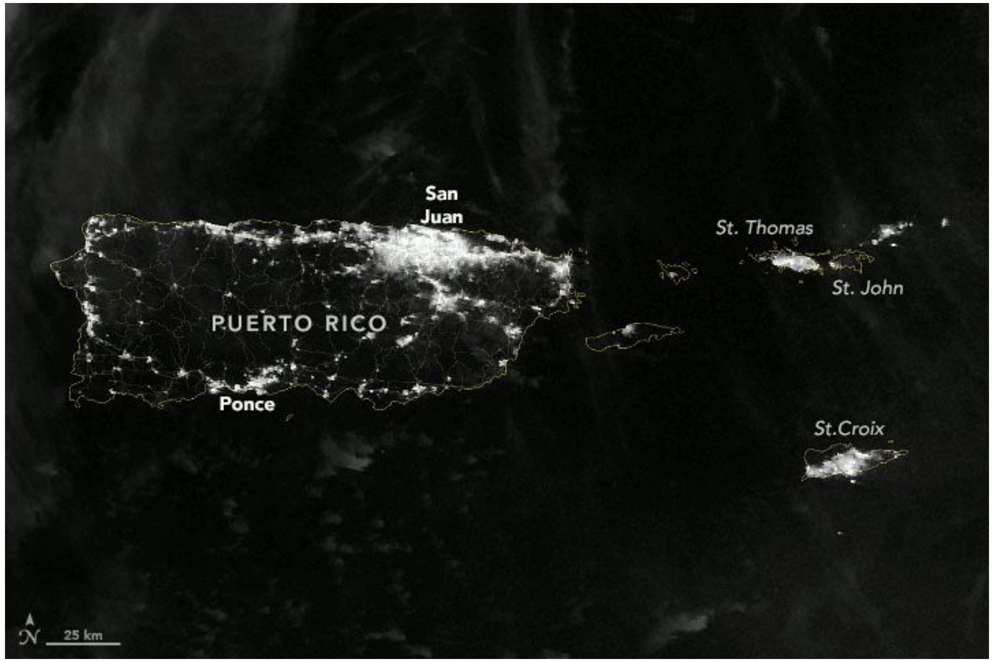
# Satellites and Sensors

- Global Precipitation Measurement (GPM) Mission
- Soil Moisture Active Passive (SMAP)
- Terrain Data From Shuttle Radar Topography Mission (SRTM)
- Terra / Aqua and MODIS Sensor
  - 1-2 observations per day
  - 36 Spectral Bands
  - Spatial resolution: 250 m, 500 m, 1 km



# Satellites and Sensors

- Global Precipitation Measurement (GPM) Mission
- Soil Moisture Active Passive (SMAP)
- Terrain Data From Shuttle Radar Topography Mission (SRTM)
- Terra / Aqua and MODIS Sensor
- Suomi National Polar Partnership (SNPP); Visible Infrared Imaging Radiometer Suite (VIIRS)
  - 1-2 observations per day
  - 22 spectral bands
  - Spatial resolution: 375 – 750 m




Power outages in Puerto Rico after Hurricane Fiona mid-September 2022
(Imagery courtesy of W. Straka, SSEC/CIMSS)

# Satellites and Sensors

- Global Precipitation Measurement (GPM) Mission
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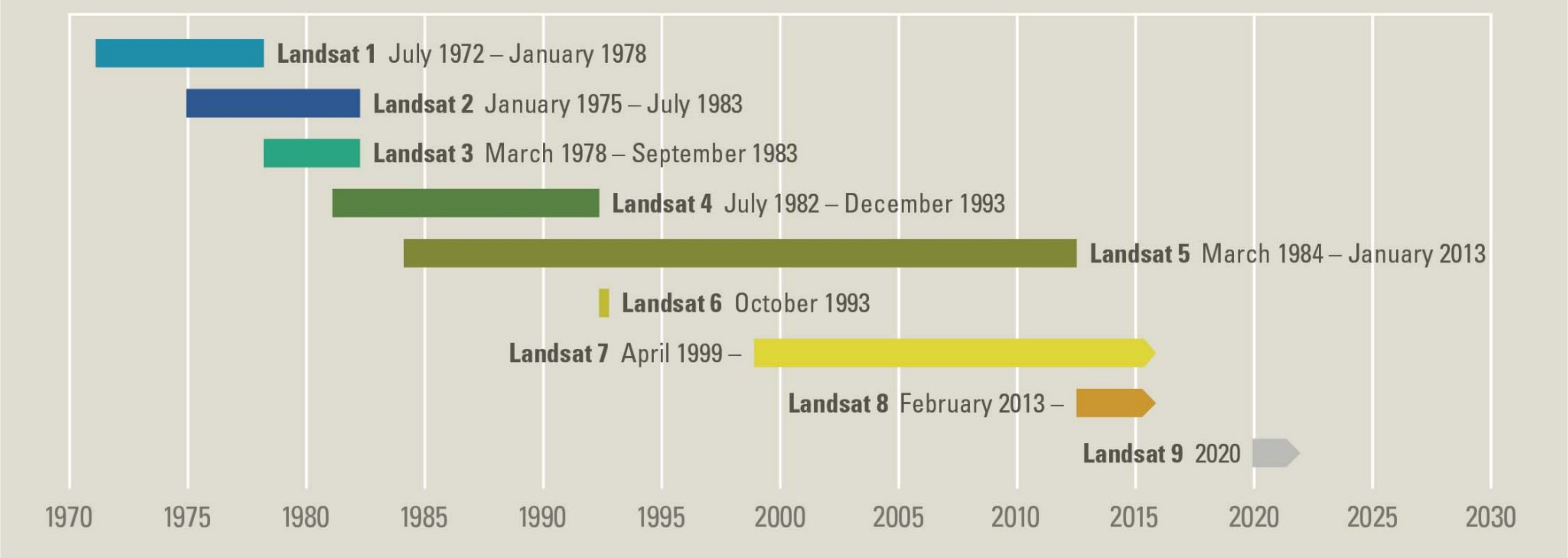
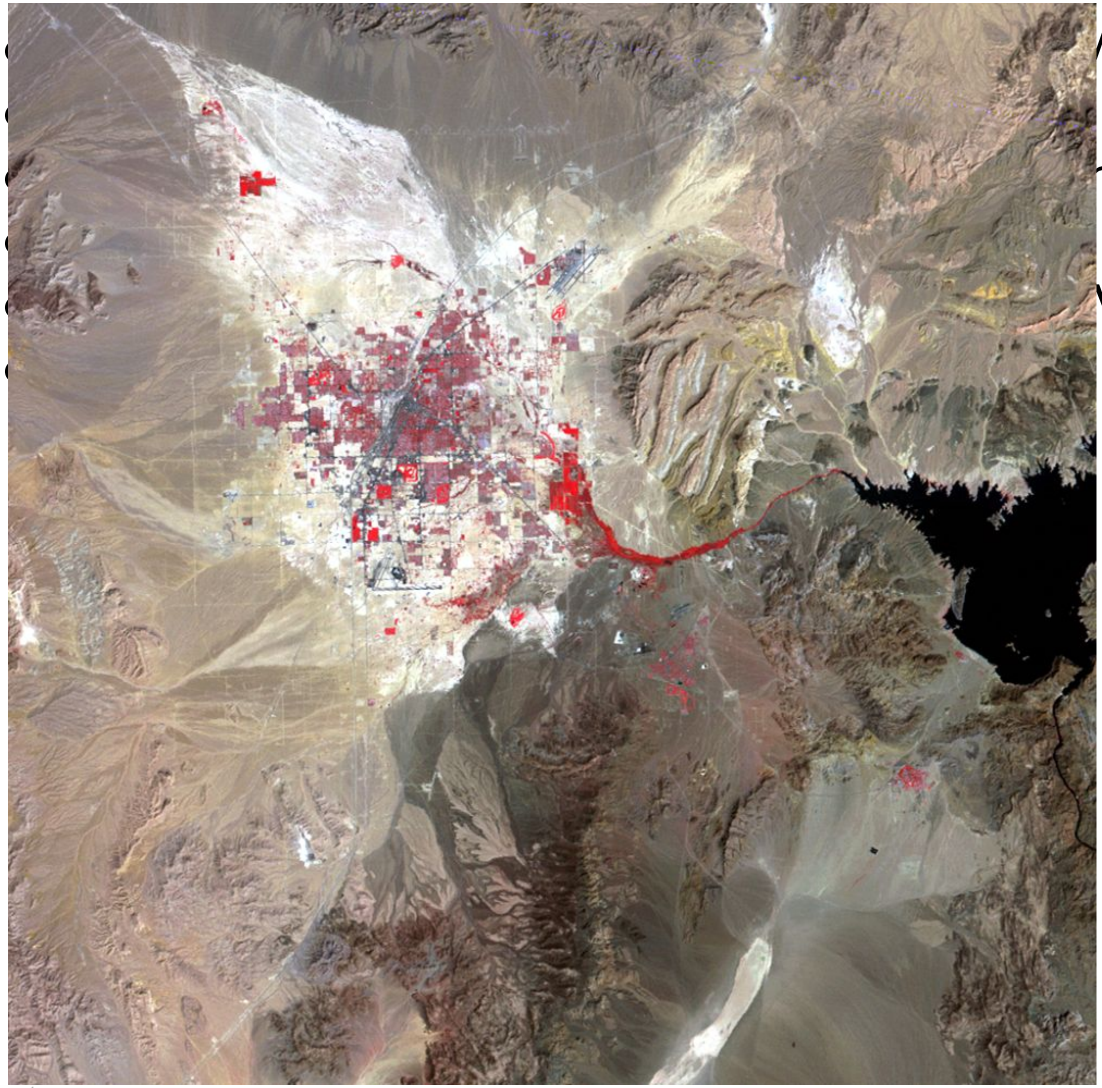
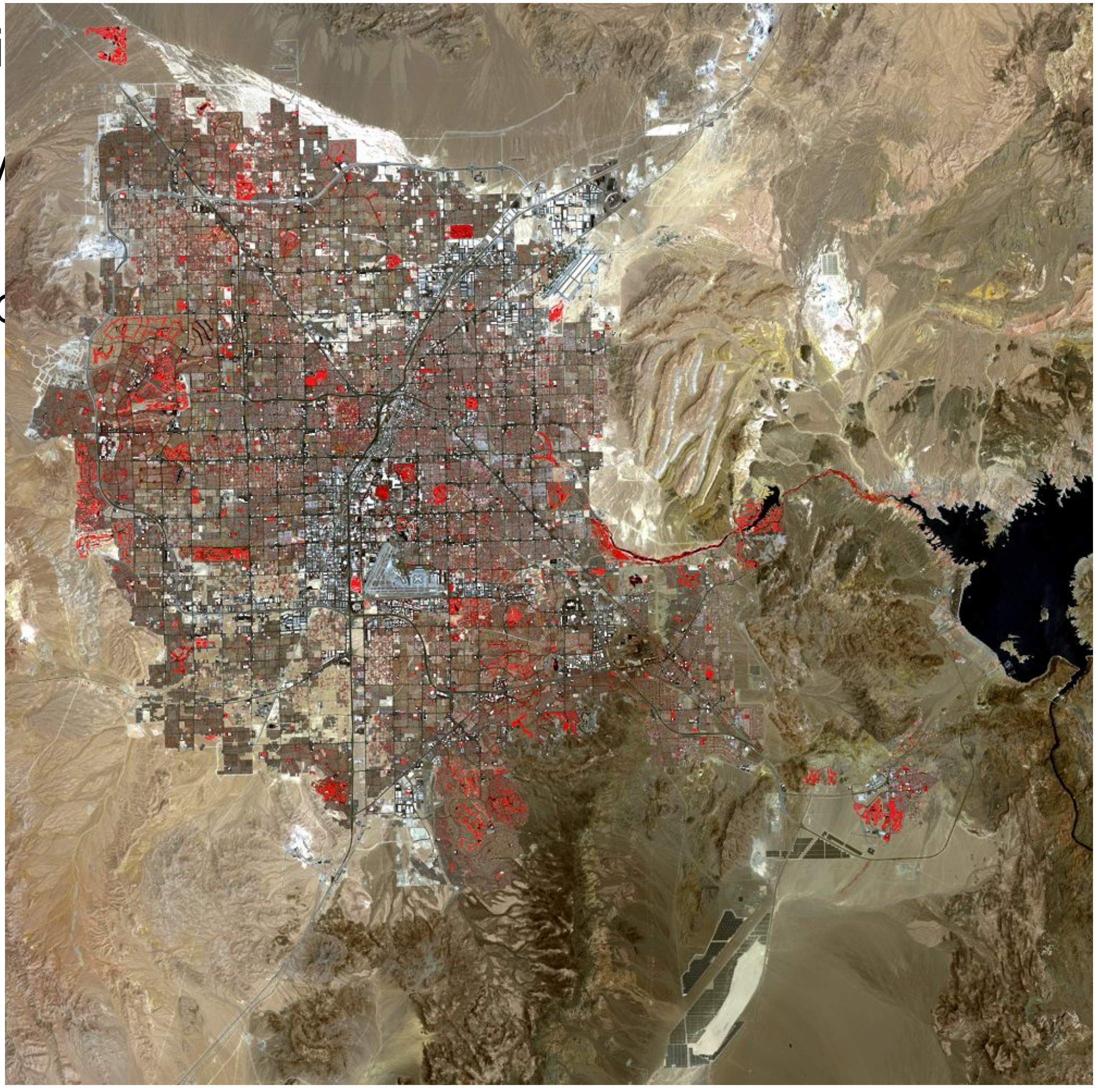
- Terrain Data From Shuttle Radar Topography Mission (SRTM)
- Terra / Aqua and MODIS Sensor
- Suomi National Polar Partnership (SNPP); Visible Infrared Imaging Radiometer Suite (VIIRS)
- Landsat 1-9




The Earth Resources Technology Satellite (ERTS, later renamed Landsat 1) launched aboard a Delta 900 from Vandenberg Air Force Base on July 23, 1972.
***Credits: NASA photography courtesy Landsat science team***

# Satellites and Sensors





***Credits: Data Available from the U.S. Geological Survey***

# Satellites and Sensors

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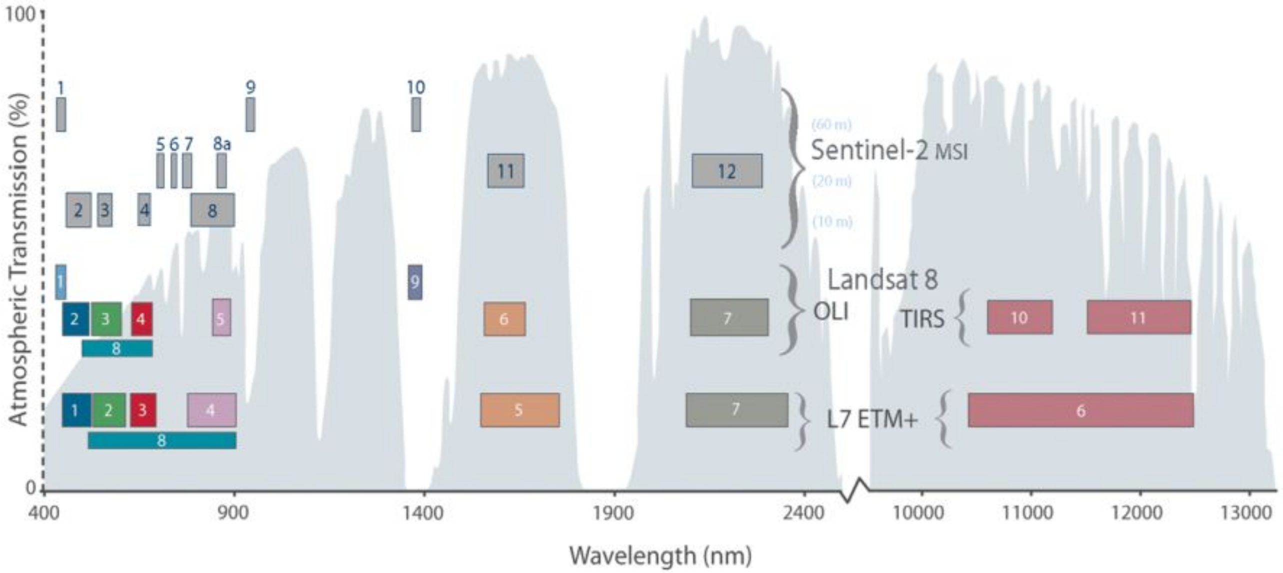
- Terra / Aqua and MODIS Sensor
- Suomi National Polar Partnership (SNPP); Visible Infrared Imaging Radiometer Suite (VIIRS)
- Landsat 1-9
  - ETM+ onboard Landsat-7
    - Spatial resolution: 15m, 30m, 60m
    - 16-day revisit time
    - 8 spectral bands
  - OLI onboard Landsat-8
    - Spatial resolution: 15m, 30m
    - 16-day revisit time
    - 9 spectral bands



# Satellites and Sensors

One of the first flood events captured from space (by Landsat 1 aka ERTS-1):
→ Mississippi floods
→ March / May 1973

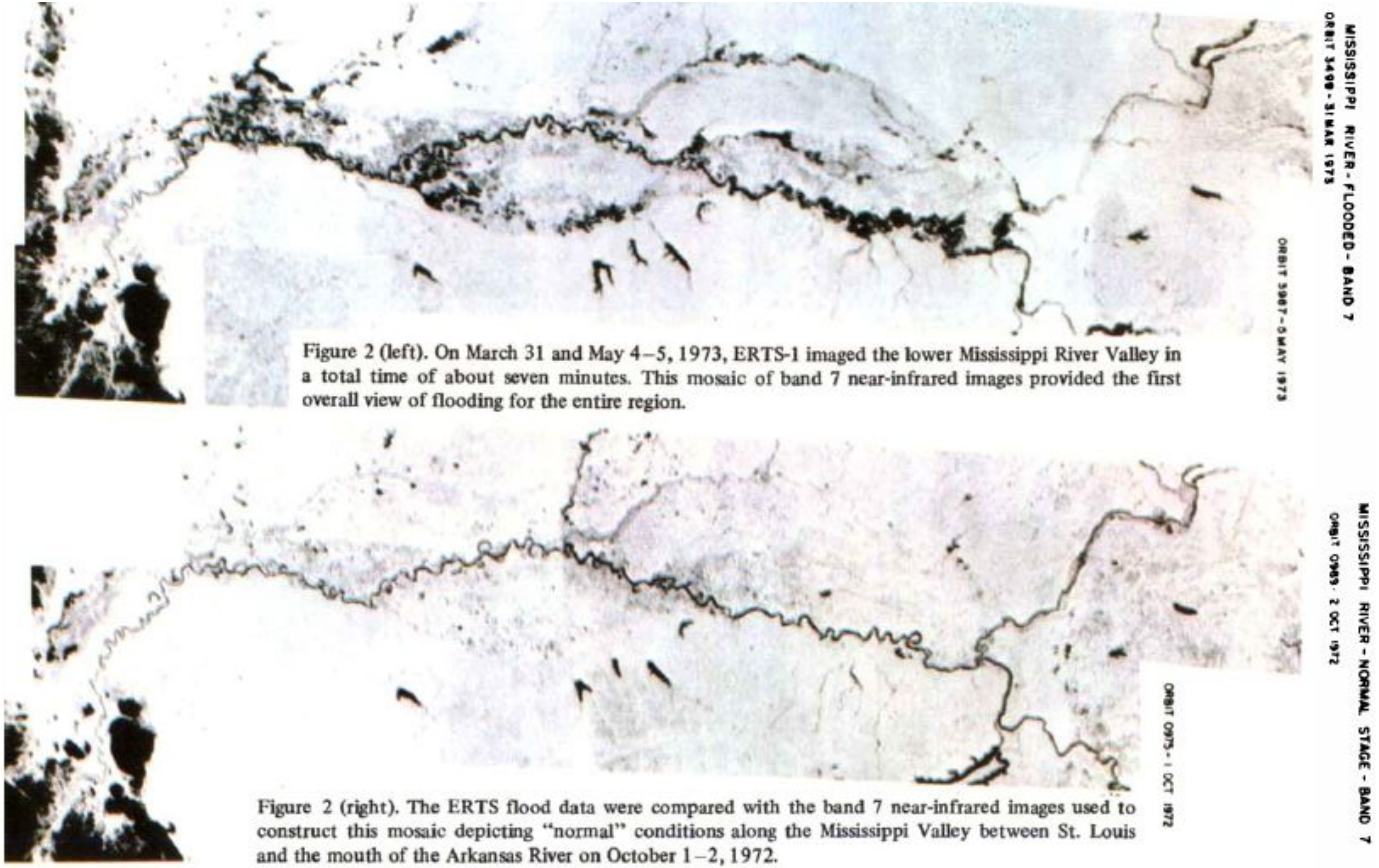



Figure 2 (left). On March 31 and May 4–5, 1973, ERTS-1 imaged the lower Mississippi River Valley in a total time of about seven minutes. This mosaic of band 7 near-infrared images provided the first overall view of flooding for the entire region.

Figure 2 (right). The ERTS flood data were compared with the band 7 near-infrared images used to construct this mosaic depicting "normal" conditions along the Mississippi Valley between St. Louis and the mouth of the Arkansas River on October 1–2, 1972.

Deutsch, M. and Ruggles, F. (1974), "Optical data processing and projected applications of the ERTS-1 imagery covering the 1973 Mississippi river valley floods", JAWRA Journal of the American Water Resources Association, 10: 1023-1039

DLR

# Satellites and Sensors

- Global Precipitation Measurement (GPM) Mission
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- Terrain Data From Shuttle Radar Topography Mission
- Terra / Aqua and MODIS Sensor
- Suomi National Polar Partnership (SNPP); Visible Infra
- Landsat 1-9
- Other optical satellites (e.g WorldView)

MAXAR

**EVENTS FROM 2022**

| EVENT | DATE |
|---|---|
| Hurricane Fiona | Sept. 19, 2022 |
| Sudan Flooding | Aug. 22, 2022 |
| The Gambia Flooding | Aug. 09, 2022 |
| Kentucky Flooding | July 29, 2022 |
| Pakistan Flooding | July 26, 2022 |
| Bangladesh Flooding | June 22, 2022 |
| Afghanistan Earthquake | June 21, 2022 |
| Yellowstone Flooding | June 15, 2022 |
| South Africa Flooding | April 13, 2022 |
| Tropical Storm Megi | April 10, 2022 |
| Brazil Flooding | April 06, 2022 |
| Louisiana Tornadoes | March 23, 2022 |

https://www.maxar.com/open-data

# Satellites and Sensors

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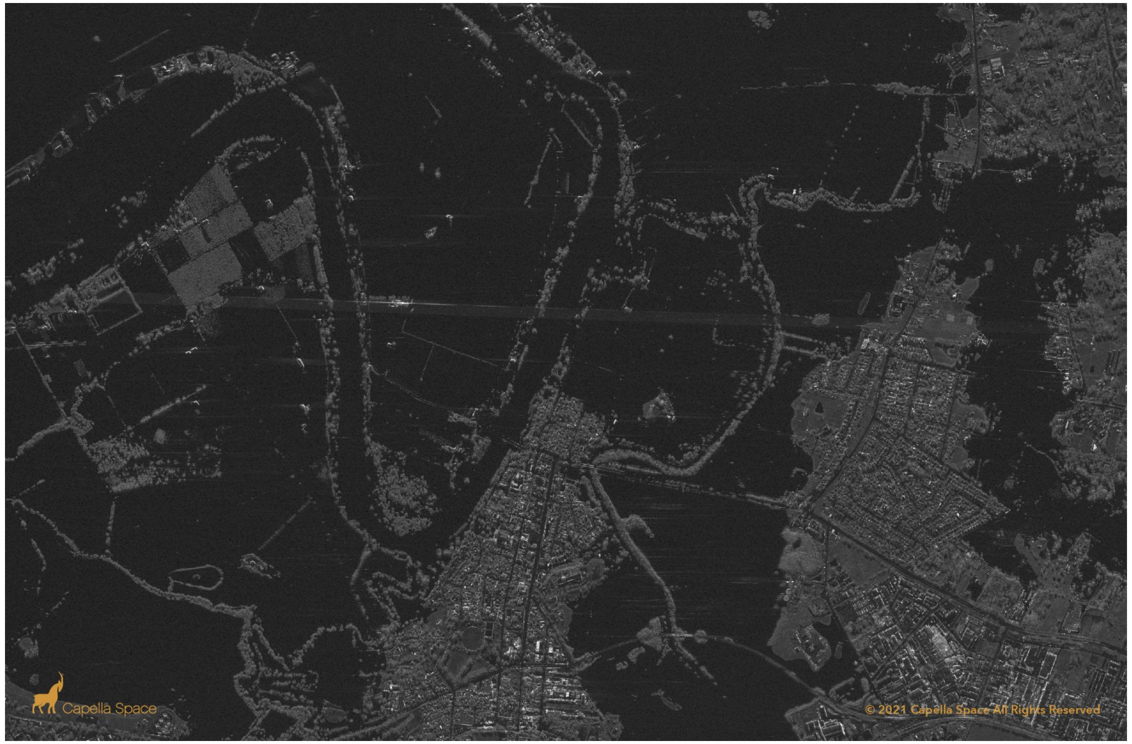
- Terra / Aqua and MODIS Sensor
- Suomi National Polar Partnership (SNPP); Visible Infrared Imaging Radiometer Suite (VIIRS)
- Landsat 1-9
- Other optical satellites
- SAR (Sentinel 1, TSX/TDX, RadarSAT, Cosmo-SkyMed, Capella Space, Iceye, …)
  - Daylight independent
  - Penetrate clouds
  - Sensitive for surface roughness and permittivity (moisture)




2021 New South Wales Floods, Australia, https://www.capellaspace.com/gallery/

# Data Challenges

- Low spatial resolution of remote sensing data for
  - Precipitation: ~10 km
  - Weather forecast: ~35 km x 50 km
  - Runoff and streamflow: ~12 km

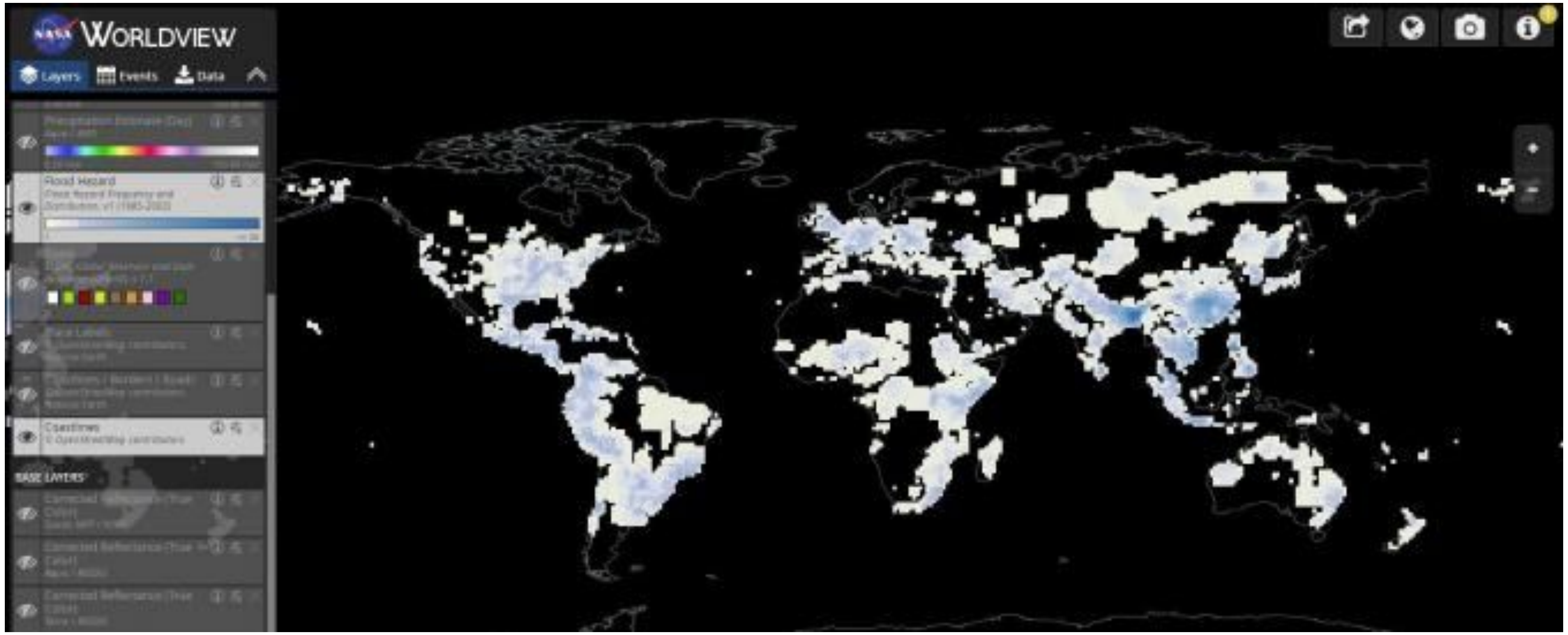
- Medium spatial resolution of surface inundation
  - MODIS: 250 m
  - Landsat: 30 m; But: 185 km swath and 16 days temporal resolution
  - Sentinel-1 SAR: 5 m; But temporal resolution of multiple days

- Optical data often contaminated with clouds

- SRTM Terrain data available globally but has 30m resolution
- LIDAR data (~5 to 10 m) has no global coverage

# Services

- MODIS NRT Global Flood Mapping and NASA Worldview
  - Based on MODIS reflectance at 250 m resolution
  - Provides near real-time flood mapping since Jan 2013
  - https://floodmap.modaps.eosdis.nasa.gov/; https://worldview.earthdata.nasa.gov/

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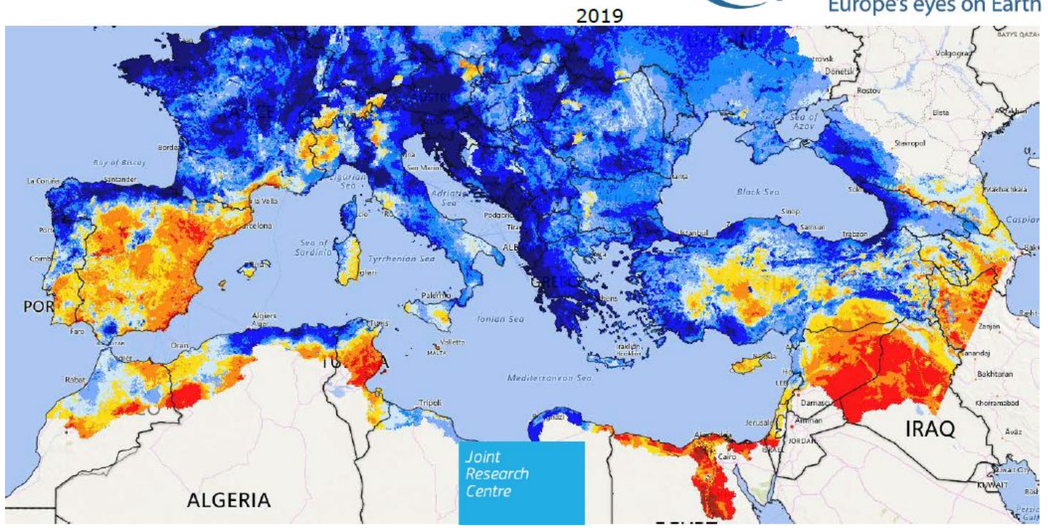
# Services

- MODIS NRT Global Flood Mapping and NASA Worldview
- Dartmouth Flood Observatory (DFO River Watch)
- HYDrologic Remote Sensing Analysis for Floods (HYDRAFloods)
- European Flood Awareness Systems (EFAS)
  - Part of Copernicus Emergency Management Service (CEMS)
  - Operational pan-European flood forecasting and monitoring
  - Based on weather predictions and radar-based precipitation monitoring

Copernicus Europe's eyes on Earth

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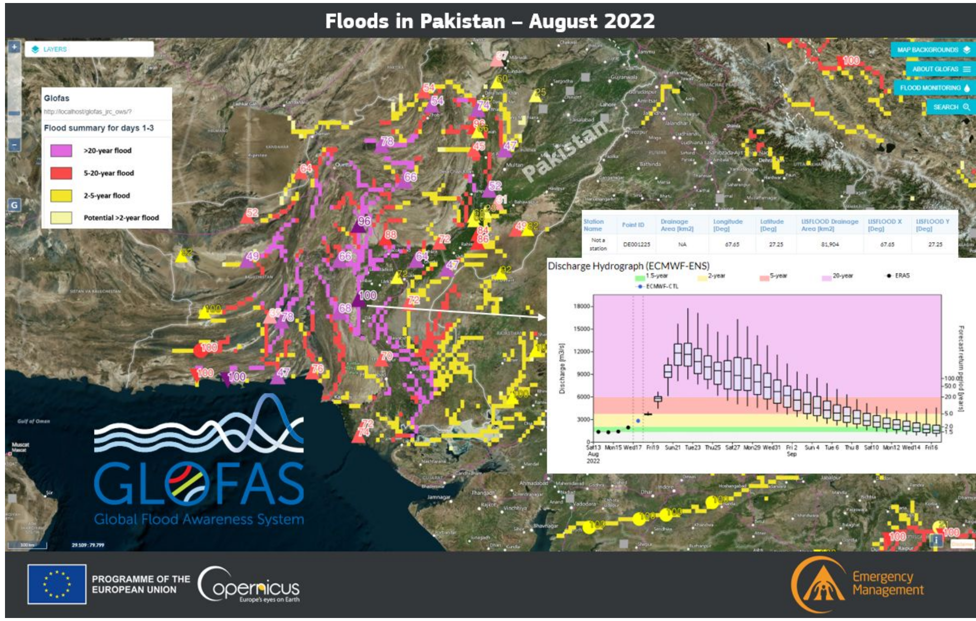
# Services

- MODIS NRT Global Flood Mapping and NASA Worldview
- Dartmouth Flood Observatory (DFO River Watch)
- HYDrologic Remote Sensing Analysis for Floods (HYDRAFloods)
- European Flood Awareness Systems (EFAS)
- Global Flood Awareness System (GloFAS)
    - Operational global hydrological forecasting and monitoring
    - Acquisition of satellite images can be pre-tasked



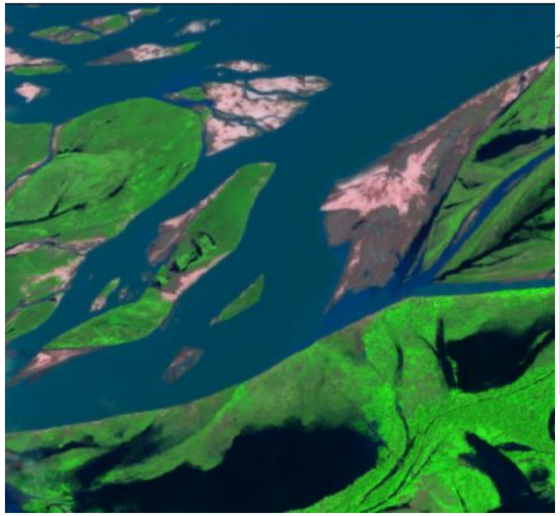
# Services

- Global Flood Monitoring
  - Operational, near real-time service
  - Continuous, global, automated satellite-based monitoring
  - All incoming Sentinel-1 images are analysed by 3 flood detection algorithms
  - Provides
    - Observed flood extent
    - Observed water extent
    - Reference water mask
    - Exclusion mask
    - Uncertainty values
    - Affected population
    - Affected land cover

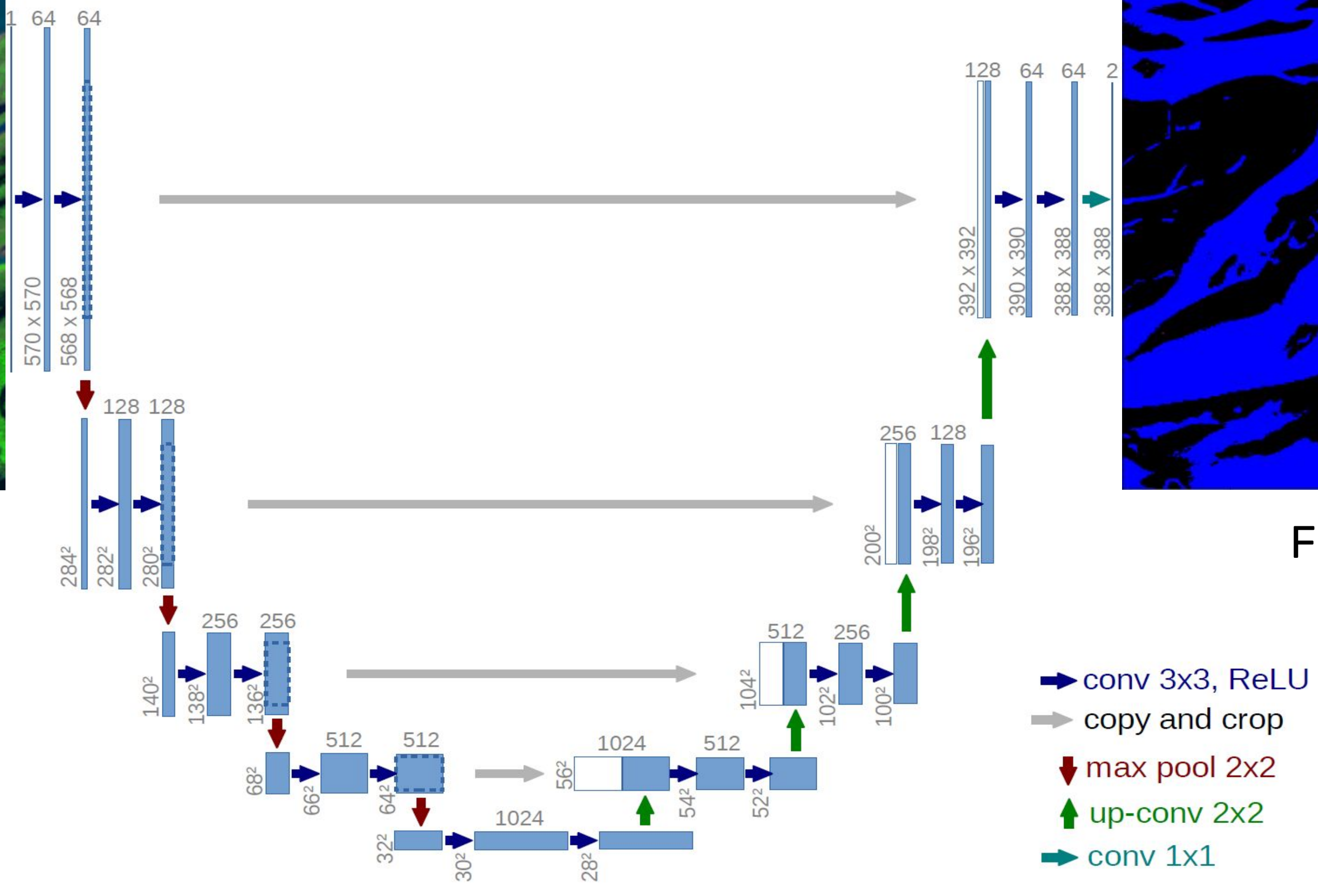
# Services (Industry): Cloud to Street

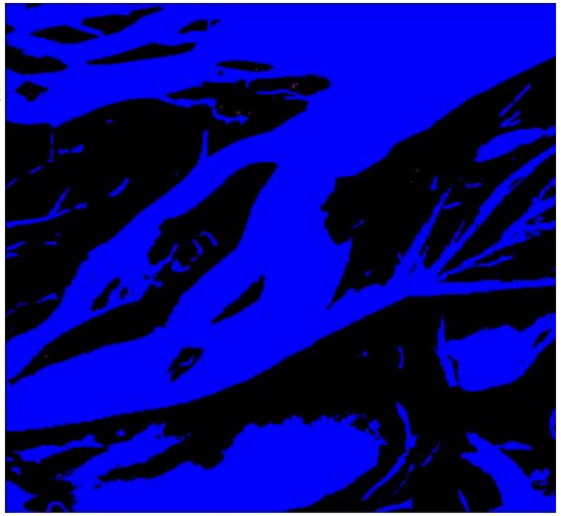
https://www.cloudtostreet.ai/

Cloud to Street



Satellite Image



Flood Map

Figure courtesy S.Chakrabarti, Cloud2Street

# Services (Industry): Cloud to Street

https://www.cloudtostreet.ai/

Cloud to Street

| Sensor | Weighted global Intersection over Union (IOU) Score* | |
|---|---|---|
| | Cloud to Street | Baseline |
| MODIS | **0.470** | 0.093[4] |
| Sentinel-1 | **0.823** | 0.291[3] |
| Landsat | **0.839** | 0.590[2] |
| Sentinel-2 | **0.872** | 0.712[1] |

*Excludes Permanent Water

1Du, Yun, et al. "Water bodies' mapping from Sentinel-2 imagery with modified normalized difference water index at 10-m spatial resolution produced by sharpening the SWIR band." Remote Sensing 8.4 (2016): 354.
2Fisher, Adrian, Neil Flood, and Tim Danaher. "Comparing Landsat water index methods for automated water classification in eastern Australia." Remote Sensing of Environment 175 (2016): 167-182.
3Nobuyuki Otsu. A threshold selection method from gray level histograms. Automatica, 11(285-296):23–27, 1975.
4Nigro, Joseph, et al. "NASA/DFO MODIS near real-time (NRT) global flood mapping product evaluation of flood and permanent water detection." Evaluation, Greenbelt, MD 27 (2014).

Figure courtesy S.Chakrabarti, Cloud2Street

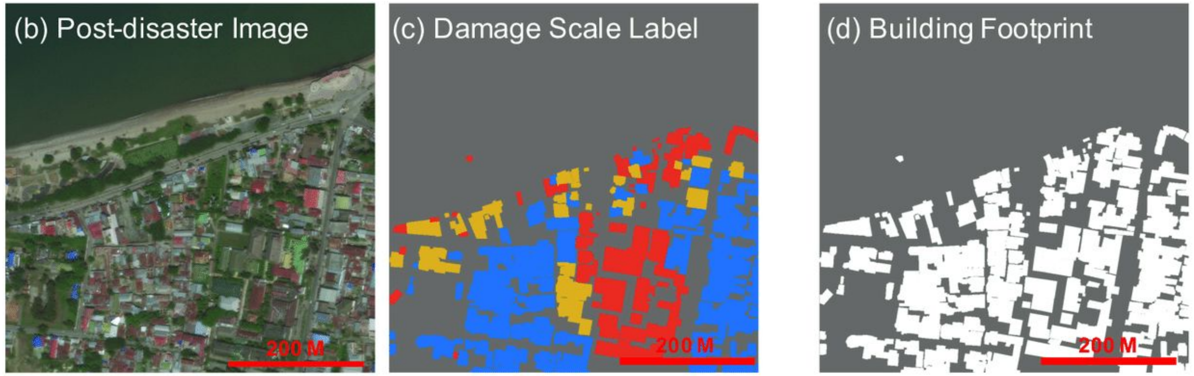
# Datasets


## FloodNet

- More than 2k optical images acquired by an UAS
- After Hurricane Harvey
- 20% are annotated.
- Contains also buildings and road annotations
- https://grss-ieee.org/earthvision2021/challenge.html

## xBD Dataset

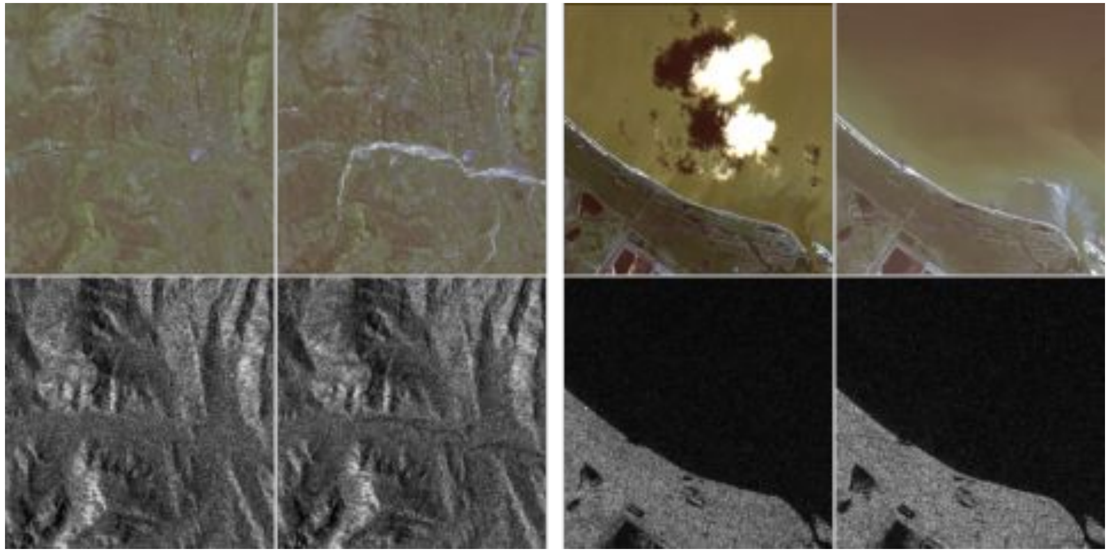
- Images of natural disasters
- Focus on building damage assessment
- Optical satellite imagery
- Flood data from Midwestern US and Nepal
- ~57k buildings of which ~20% are damaged



# Datasets

## Sen12-FLOOD

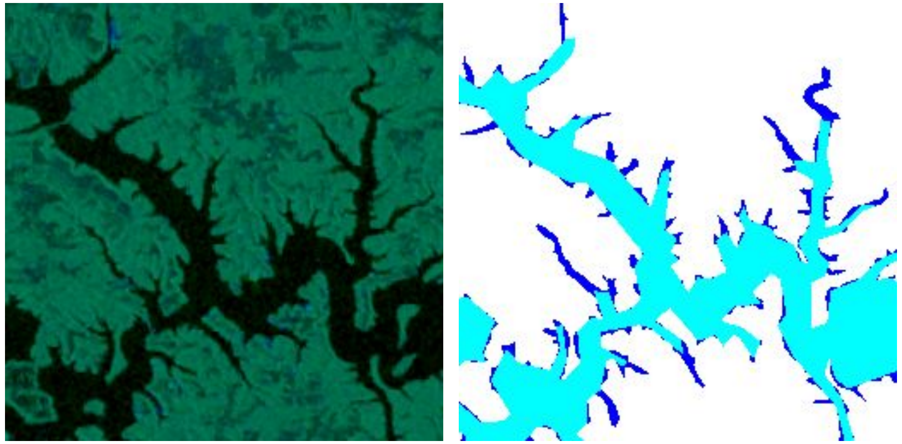
- Sentinel 1&2 images
- 412 time series (~9 optical, ~14 SAR images)
- Flood event in ~45\% of the cases
- Flood label only on image level



## Flood Extent Detection

- More than 30k Sentinel 1 image patches (256 x 256)
- https://nasa-impact.github.io/etci2021/

Interagency Implementation and Advanced Concepts Team



# Datasets: SpaceNet

- Founded by In-Q-Tel Labs' CosmiQ Works and Maxar Technologies in August 2016
- Partners: Maxar, IEEE GRSS, AWS, Topcoder, and Oak Ridge National Laboratory
- Web: www.spacenet.ai Twitter: @Spacenet_AI
- AWS: registry.opendata.aws/spacenet

# Public SpaceNet Data

**~67,000**

Square km of high-resolution imagery

**>11M**

Building footprints

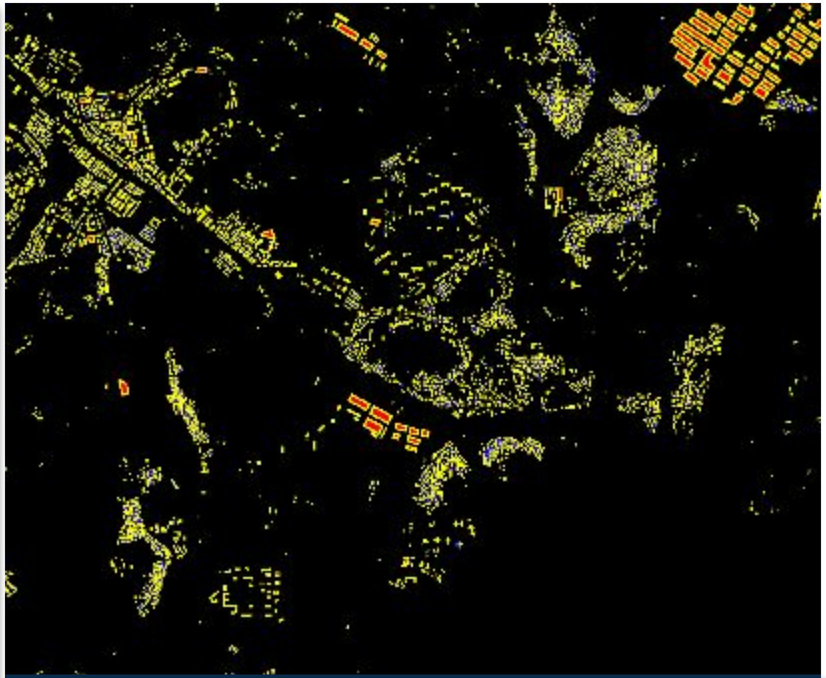
**~20,000**

km of road labels

# SpaceNet

**Buildings (High-Res)**

900,000+ Footprints for 8 Geographic Areas



**Buildings (Med-Res)**

10M+ Footprints for 100+ Geographic Areas

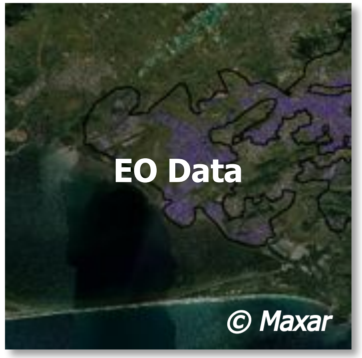
**Roads (High-Res)**

~20,000km of Roads for 9 Geographic Areas

Foundational mapping serves as a strong proxy for a variety of geospatial challenges.

# SpaceNet

**SpaceNet 1**
**11/2016 – 1/2017**

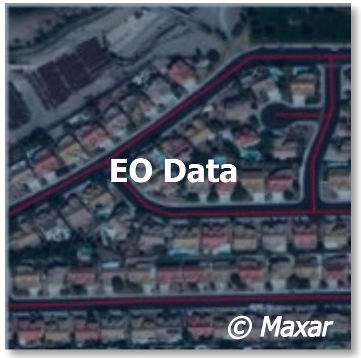



**Building Footprint Detection**

**SpaceNet 2**
**6/2017 – 8/2017**

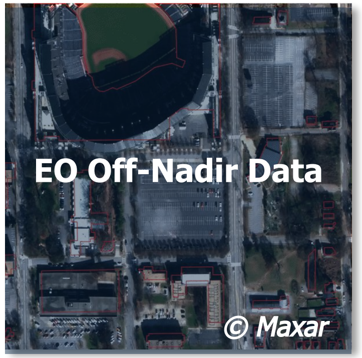

**Building Footprint Detection**

**SpaceNet 3**
**11/2017 – 2/2018**




**Road Extraction & Routing**

**SpaceNet 4**
**10/2018 – 1/2019**

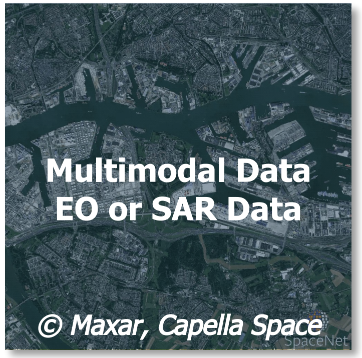



**Building Footprint Detection**

**SpaceNet 5**
**9/2019 – 10/2019**


**Road Extraction, Routing & Times**

**SpaceNet 6**
**3/2020 – 5/2020**




**Building Footprint Detection**

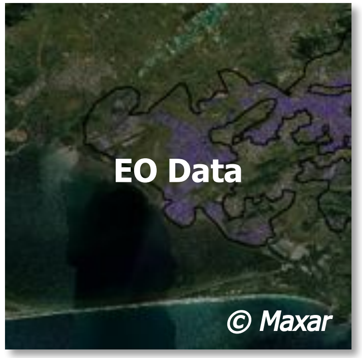
**SpaceNet 7**
**8/2020 – 10/2020**


**Building Footprint Detection & Tracking**

DLR

# SpaceNet 8 – Motivation

**SpaceNet 1**
**11/2016 – 1/2017**




Building Footprint Detection

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Building Footprint Detection

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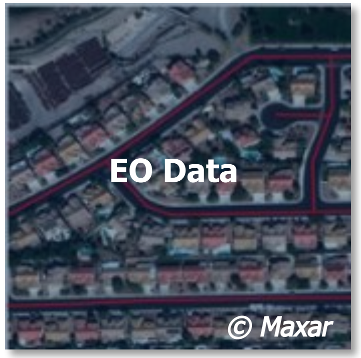


Road Extraction & Routing

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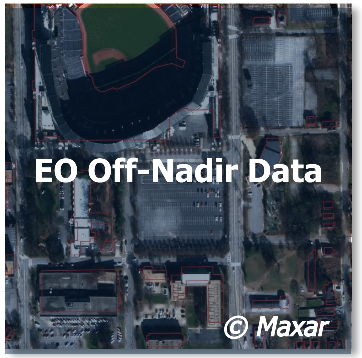
**10/2018 – 1/2019**

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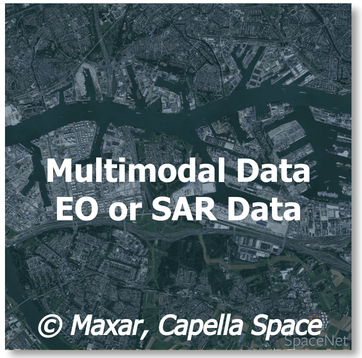



Building Footprint Detection

**SpaceNet 7**
**8/2020 – 10/2020**


Building Footprint Detection & Tracking

## Build upon previous challenges …

## … but go beyond pure foundation mapping

# SpaceNet 8 – Task

- Detect the impact of floods on buildings and roads
  - Accurately map pre-event infrastructure and identify post-event flood attributes
  - New dataset released for three AOIs
  - Featured in the CVPR 2022 EarthVision Workshop

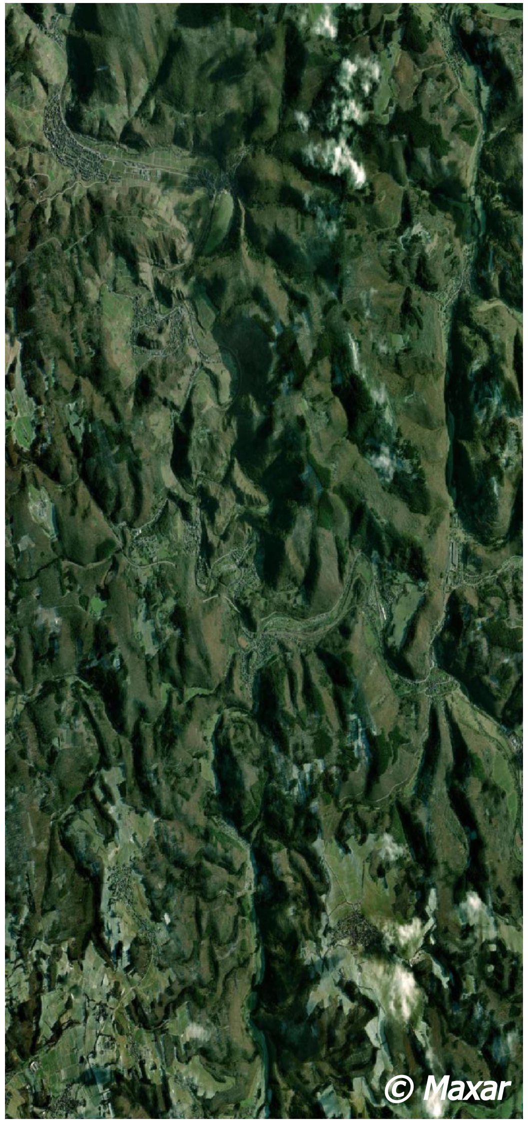
- Challenge hosted on Topcoder
  - $50,000 in total prizes
  - Awards to top 5 overall teams
  - Plus, top undergrad & grad academic teams

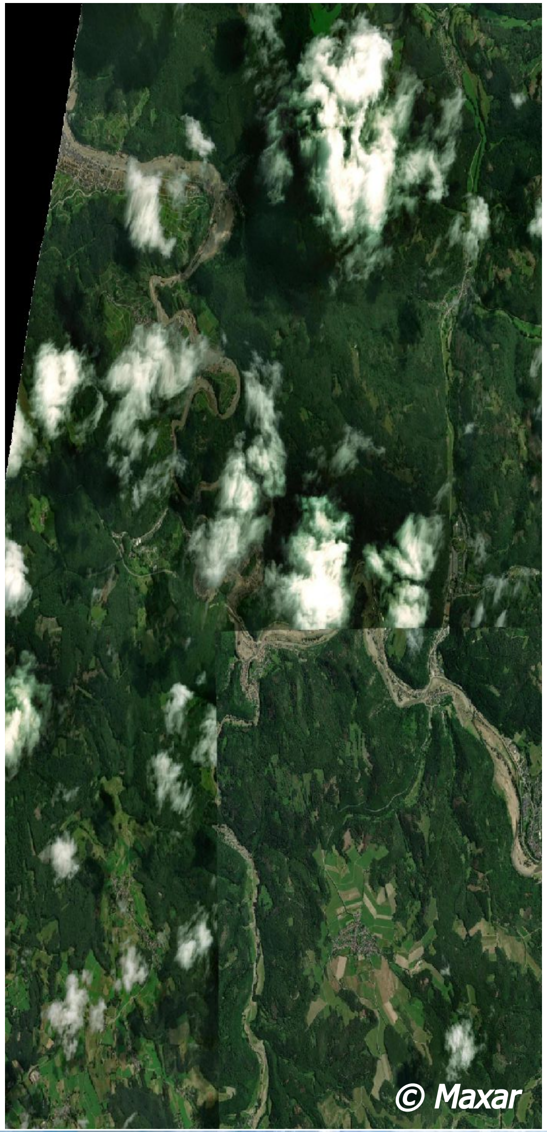

*Germany AOI*
*GeoEye-1 | July 18, 2021*

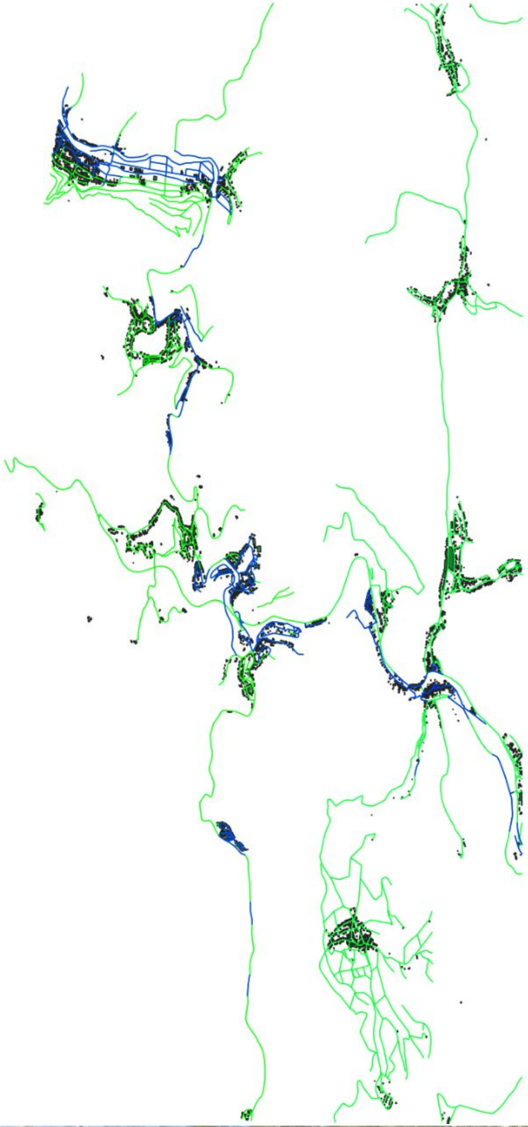
# SpaceNet 8 – Louisiana AOI



# SpaceNet 8 – Germany AOI



# SpaceNet 8 – Challenges: High Level of Detail

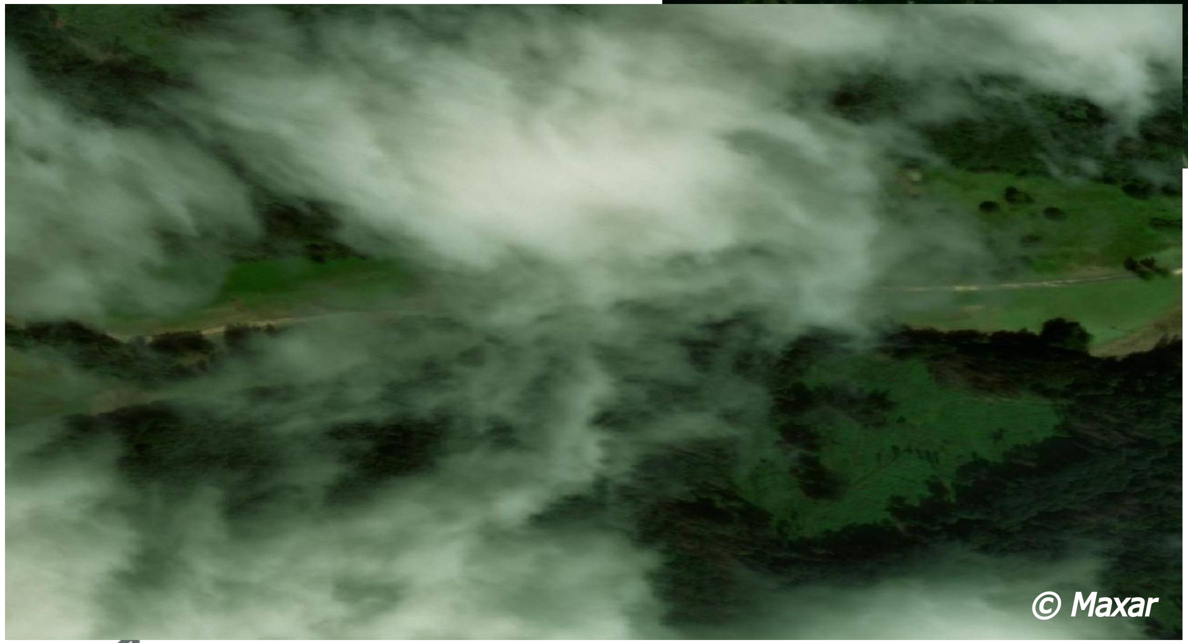
# SpaceNet 8 – Challenges: Significant Content Change

# SpaceNet 8 – Challenges: Significant Content Change

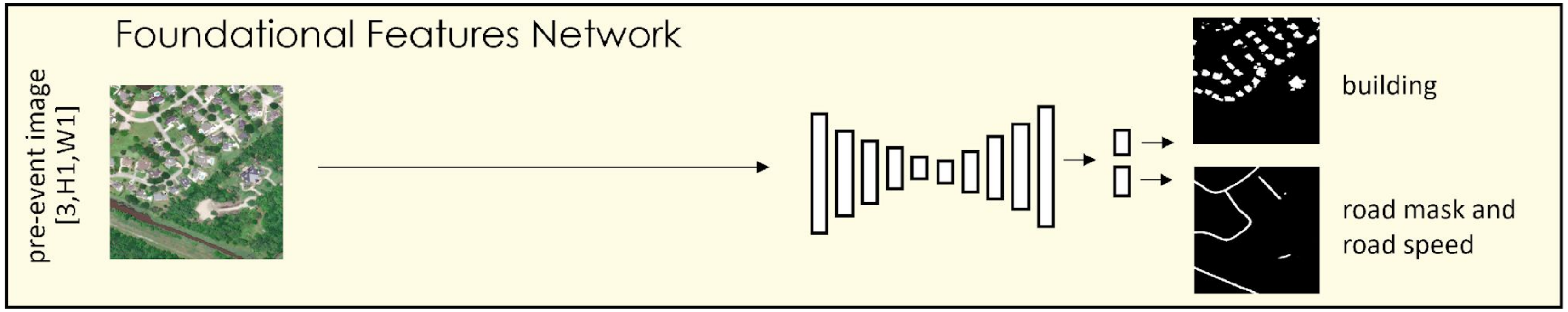
# SpaceNet 8 – Challenges: Significant Appearance Change

# SpaceNet 8 – Challenges: Significant Appearance Change

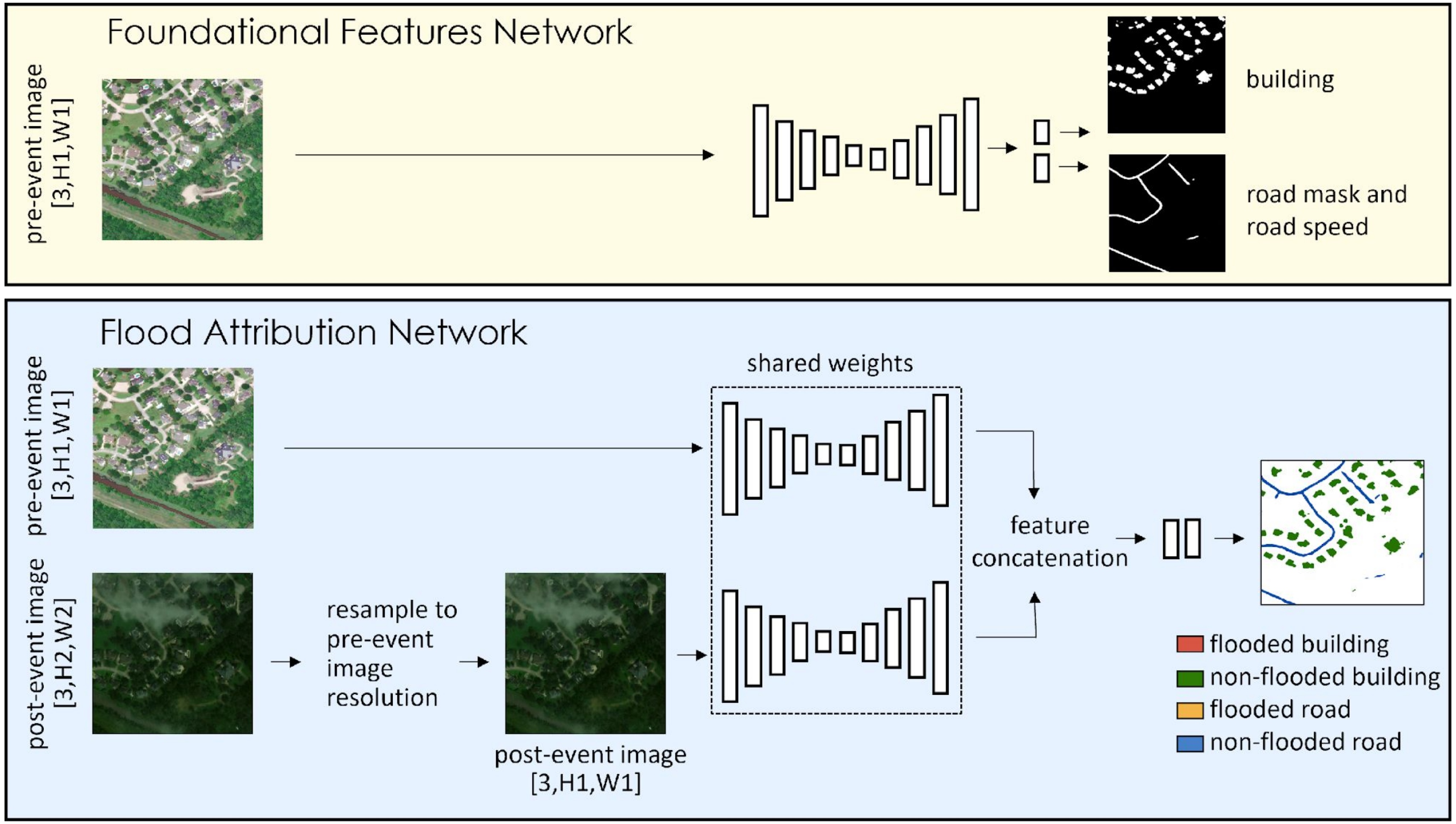
# SpaceNet 8 – Challenges: Cloud Cover

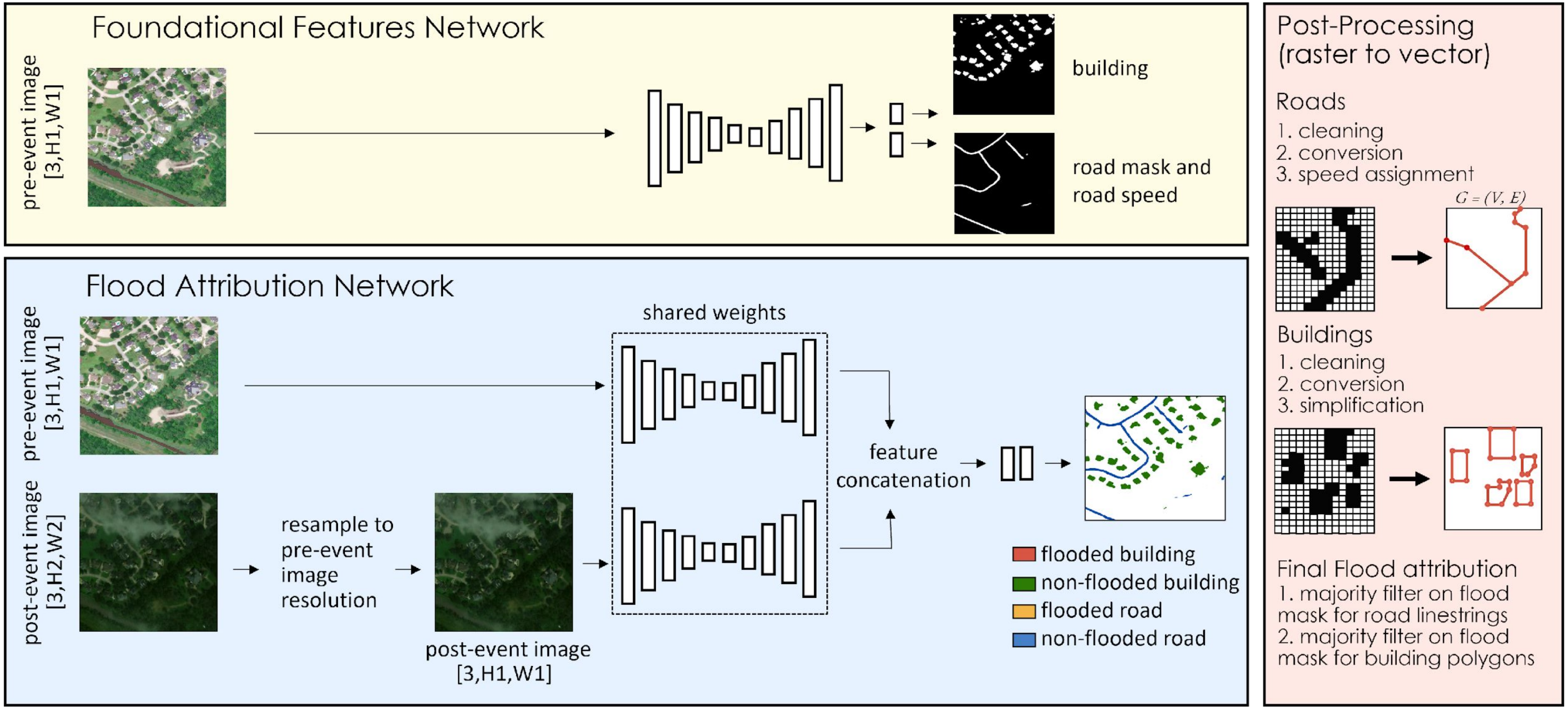

# SpaceNet 8 – Baseline Algorithm



# SpaceNet 8 – Baseline Algorithm

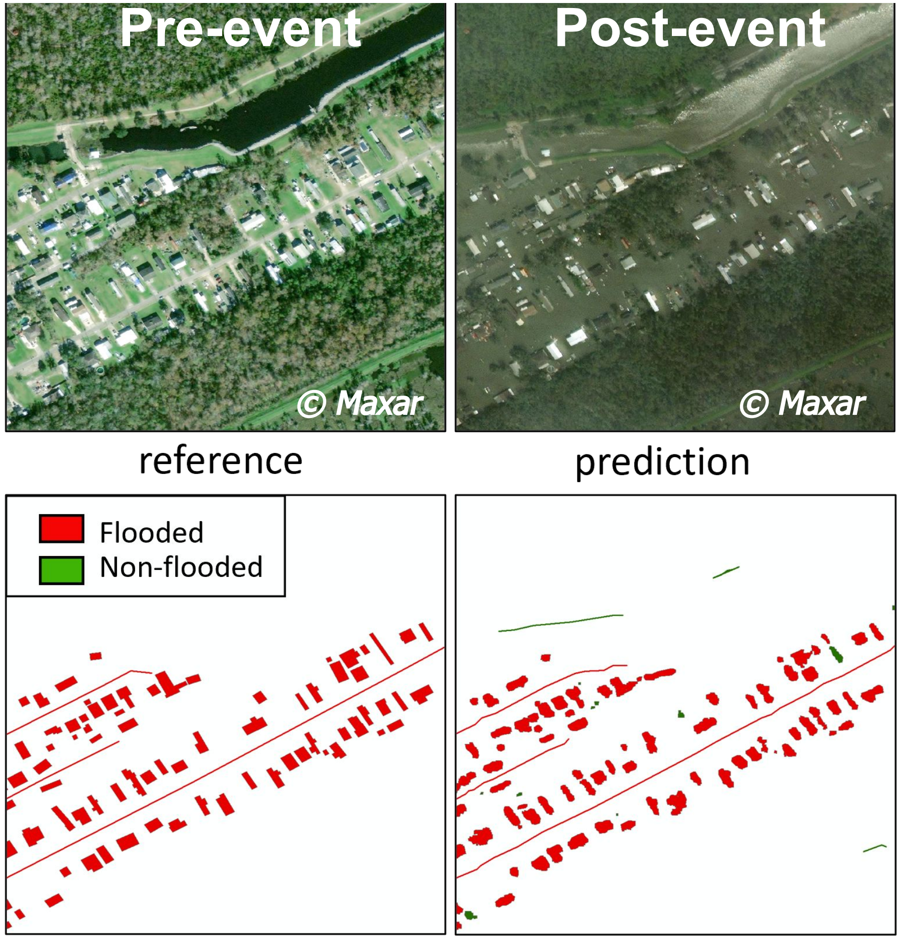


# SpaceNet 8 – Baseline Algorithm



# SpaceNet 8 – Evaluation

- Scoring is designed to be relevant for real-world applications
- Metrics:
  - Intersection over Union (IoU) for building footprints
  - Average Path Length Similarity (APLS) for roads
- Submitted solutions are assigned a single score composed of building damage and road networks



# SpaceNet 8 – Results

- Run from July 12 to Aug 23 (292 registrations)

| Place | Competitor | Score out of 100 |
|---|---|---|
| 1st | Ohhan777 | 66.998 |
| 2nd | Number13 | 66.242 |
| 3rd | SIAnalytics | 65.852 |
| 4th | Zaburo | 65.520 |
| 5th | Motokimura | 64.828 |
| Baseline | N/A | 44.341 |

- Dominating factors were
  - data augmentation,
  - pre-training (incl. previous SN data),
  - neural network ensembles,
  - and U-Nets.

# Summary

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- Cause loss of life, destruction of infrastructure, damage to buildings, environmental hazards
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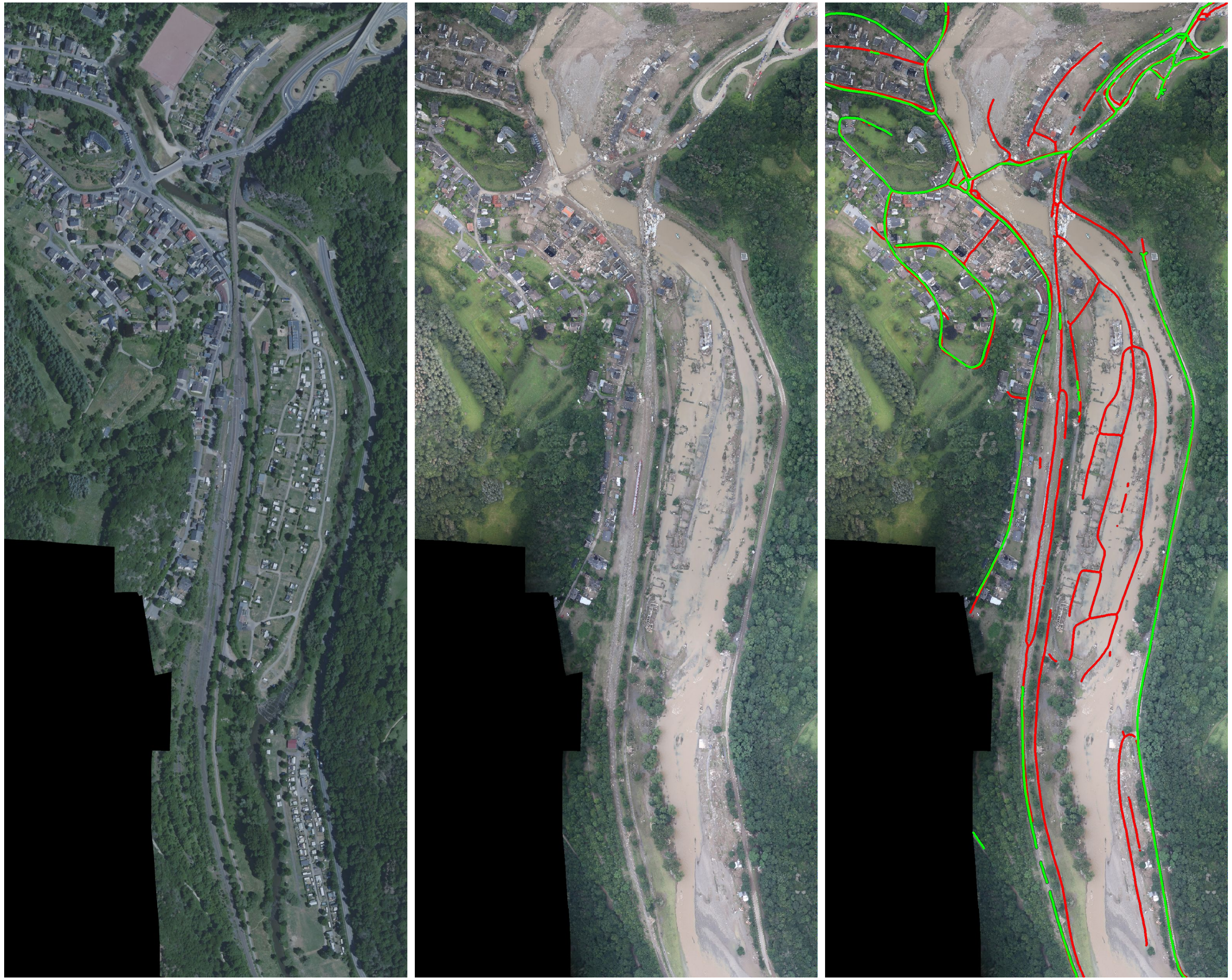
- Automatic analysis of RS imagery has not yet reached its potential
  - Fast (includes domain adaptation and cross-modal learning)
  - Reliable and accurate
  - Trustable and interpretable

# Questions?



Ahr valley, Germany – 2021 – Flooding – Road segmentation
Credits: ZKI, DLR