Mapping Informal Settlements in Developing Countries Using Machine Learning

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Sustainable Development Goals + EO Data

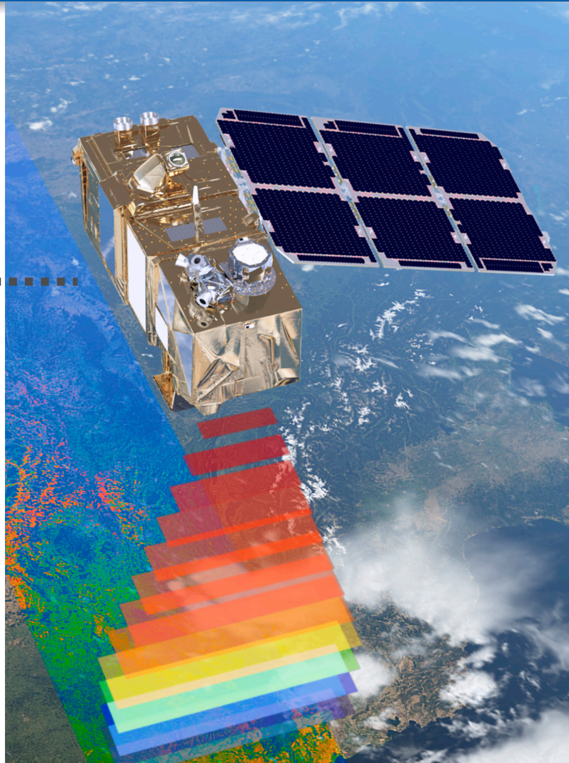
Large amount of Earth observation data

Copernicus Sentinel-2 Data available from 2015

Global challenges: Global vision for humanity

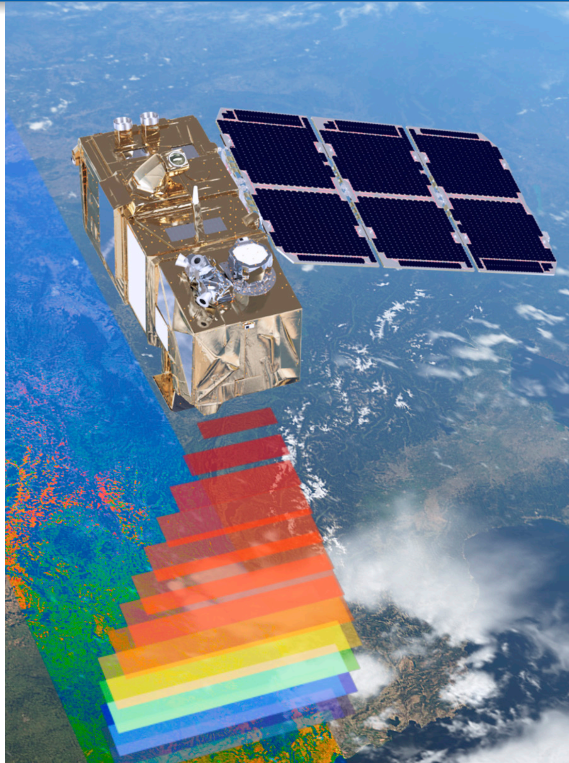
SDG: Defined by UN in 2015

esa



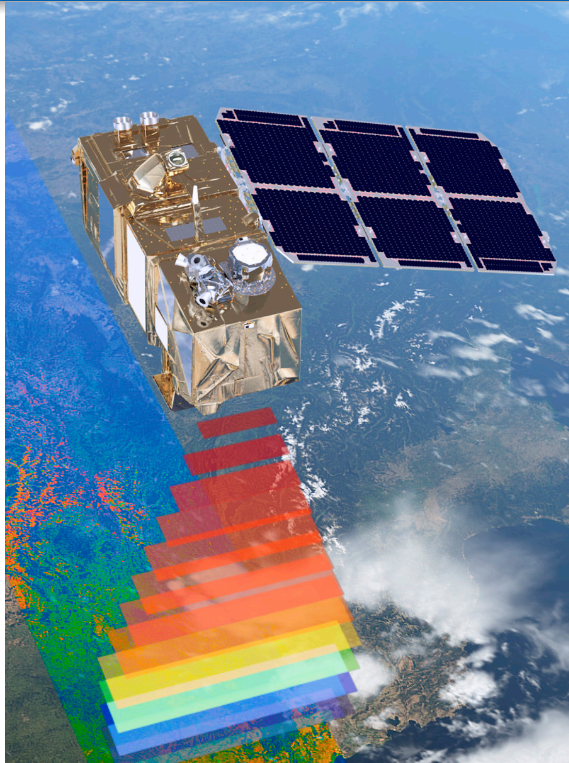
Sustainable Development Goals + EO Data

- **Half of humanity** – 3.5 billion people – lives in cities today and 5 billion people are projected to live in cities by 2030
- **95 per cent of urban expansion** in the next decades will take place in **developing world**
- **883 million people live in slums**
- **Rapid urbanization is exerting pressure** on fresh water supplies, sewage, the living environment, and public health



Sustainable Development Goals + EO Data

- Ensure **access** for all to adequate, **safe** and affordable **housing** and **basic services and upgrade slums**
- **Reduce people affected by disasters** with a focus on protecting the poor and people in vulnerable situations
- **Building sustainable** and resilient **buildings** utilizing local materials
- **Expansion monitoring** to deliver effective economic and social aid to **informal settlements**



Machine Learning-Based Detection and Mapping of Informal Settlements

With freely and openly available multi-spectral low-resolution satellite imagery


esa
Video: ESA/ATG medialab

Informal Settlement (Slums)

United Nations (UN) and OECD:

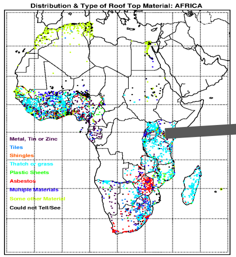
- Inhabitants have **no security of tenure** vis-à-vis the land or dwellings they inhabit
- Neighborhoods lack, or are **cut off from, basic services and city infrastructure**.
- The housing may **not comply** with **current planning**

The Problem

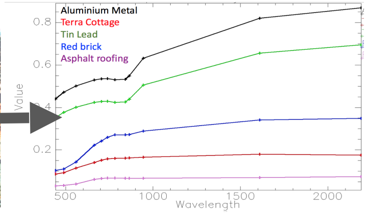
Lack of information about
the informal settlements (slums)

- The **locations** of (small) slums are often unknown
- No reliable **information** about the number of **residents**
- **Most vulnerable** in case of **natural disaster situations**

Spectral Model: Extracting materials from single-pixel spectra



Tin Lead Roof Material



Spectrum

Textural Model: Extracting context information using convolutional filter

El Geneina, Sudan

Informal

Formal

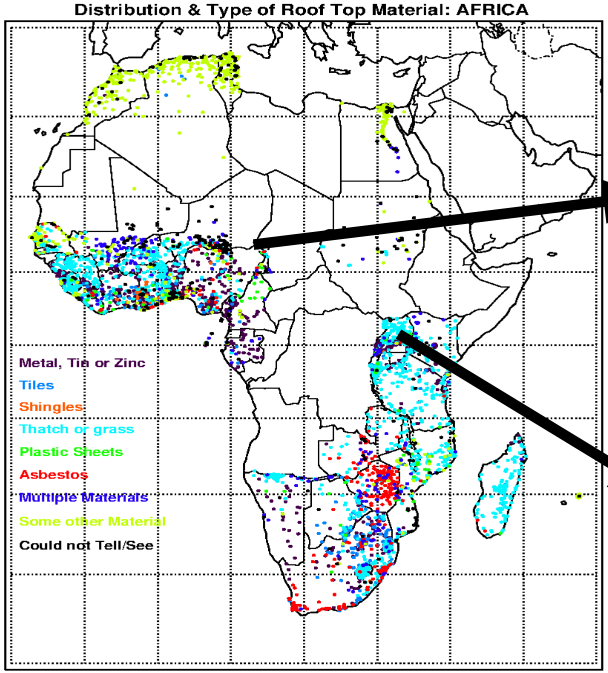
Approach

Informal Settlements can be characterized remotely by:

- Roofing materials
- Roofing size
- Building density

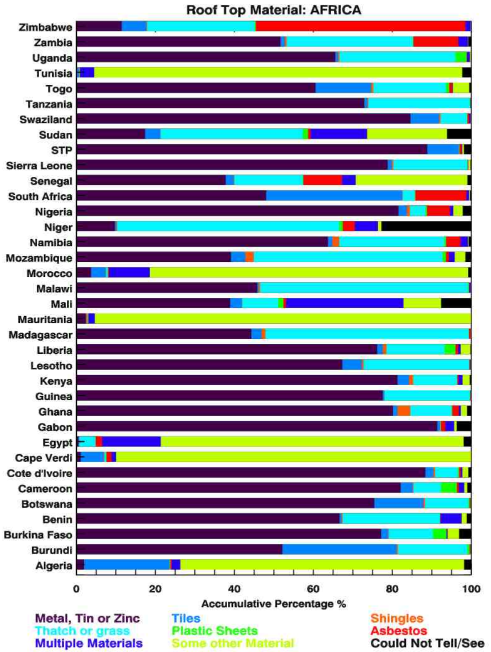
Creation of a spectral and textural model

Types of Roofing Material in Africa

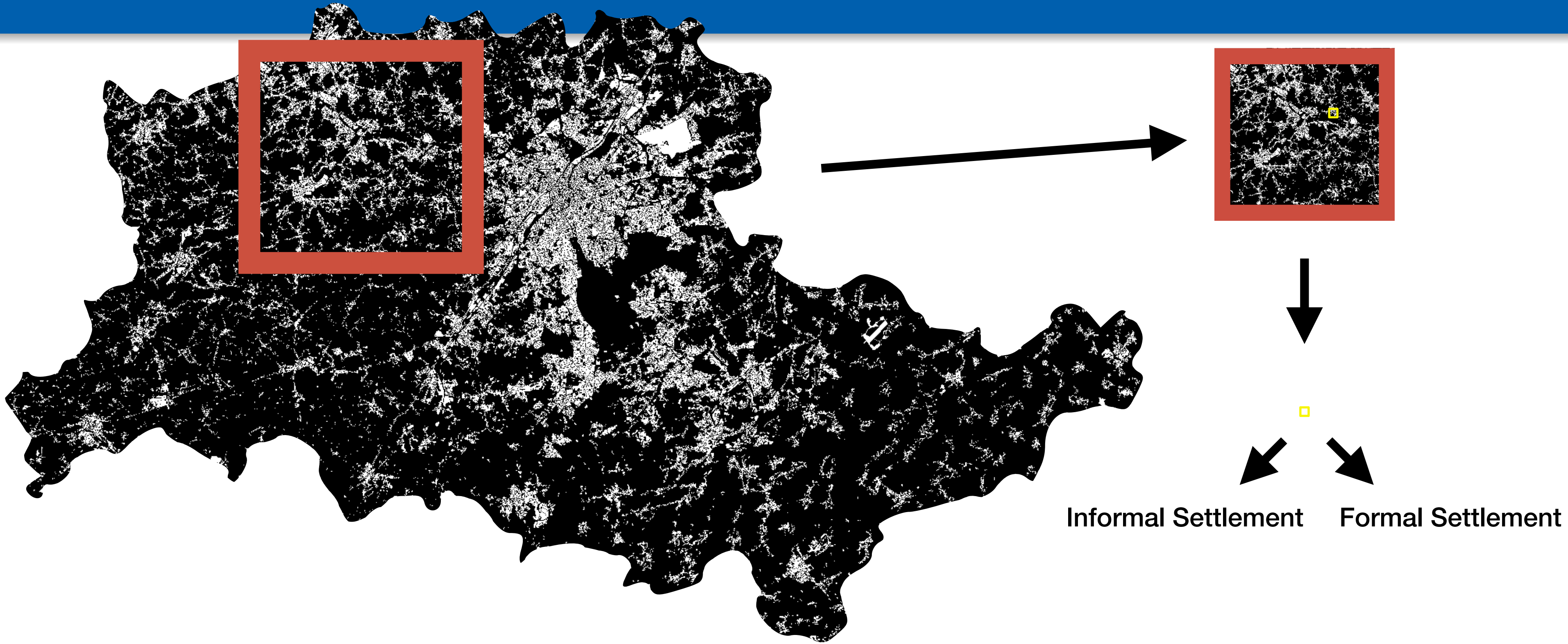


Tin roof

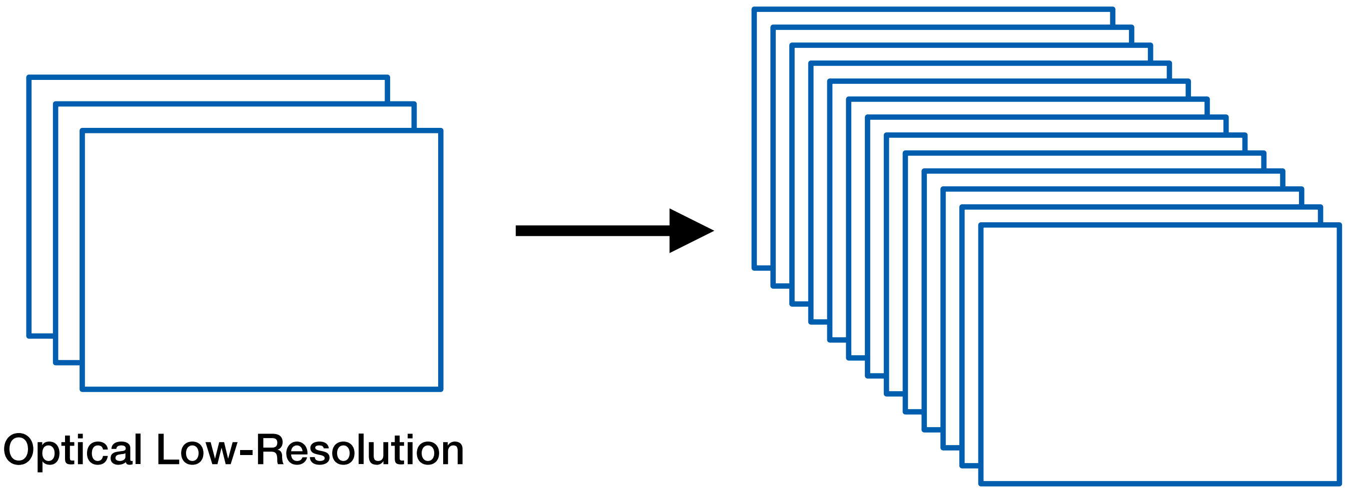
Thatch roof



Detecting and Mapping Informal Settlements



Single-Pixel Spectral Analysis



Optical Low-Resolution

Multi-Spectral Low-Resolution

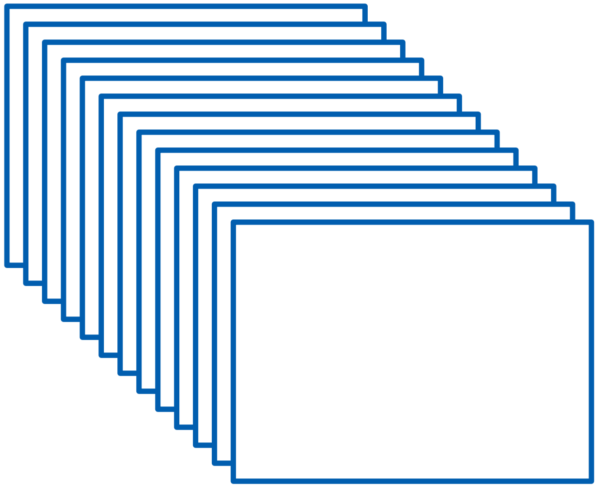
This work!

How is it possible?

Not possible with features based on the spatial resolution

Upsampling (super resolution) methods not applicable

Use of multi-spectral sensor information



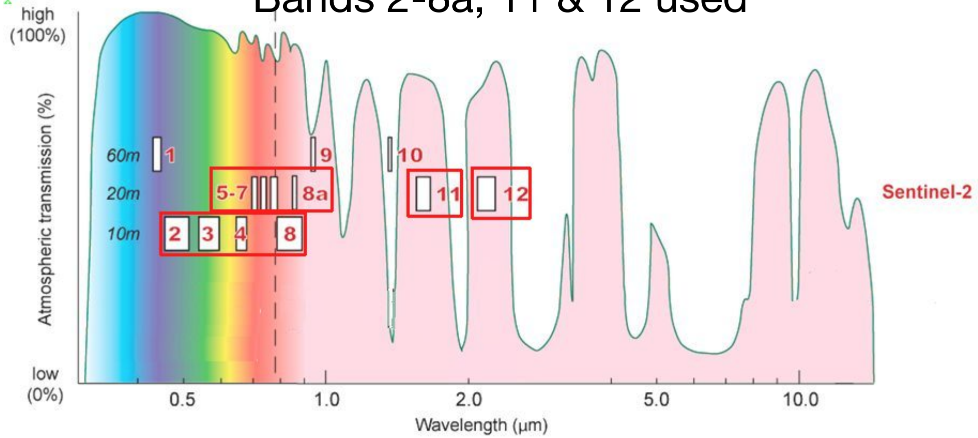
Multi-Spectral Low-Resolution

This work!

Sentinel-2 Multi-Spectral Sensing

Optical Near-Infrared Short-Wave-Infrared

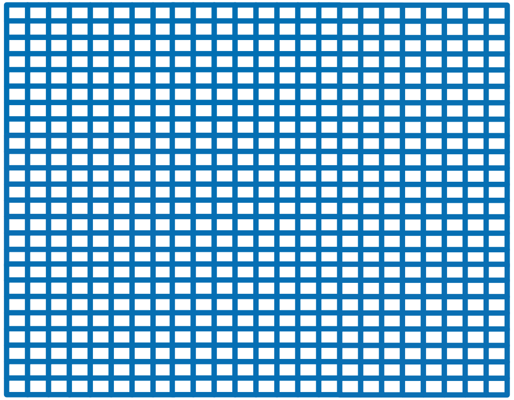
Bands 2-8a, 11 & 12 used



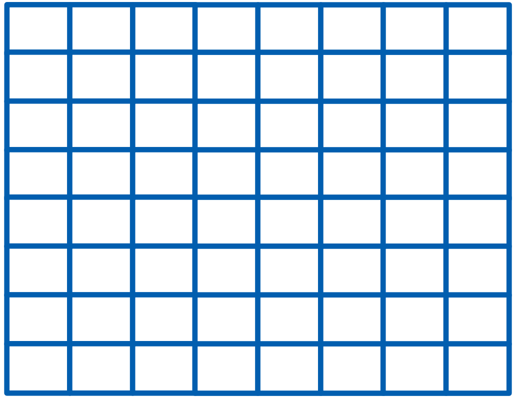
Band	Spatial resolution *in meter*	Central wavelength *in nanometer*	Band width *in nanometer*
B01 - Aerosols	60	443	20
B02 - Blue	10	490	65
B03 - Green	10	560	35
B04 - Red	10	665	30
B05 - Red Edge 1	20	705	15
B06 - Red Edge 2	20	740	15
B07 - Red Edge 3	20	783	20
B08 - NIR	10	842	115
B08A - Red Edge 4	20	865	20
B09 - Water vapor	60	945	20
B10 - Cirrus	60	1375	30
B11 - SWIR 1	20	1610	90
B12 - SWIR 2	20	2190	180

Sentinel-2 Multi-spectral bands

Single-Pixel Spectral Analysis



Very-High-Resolution

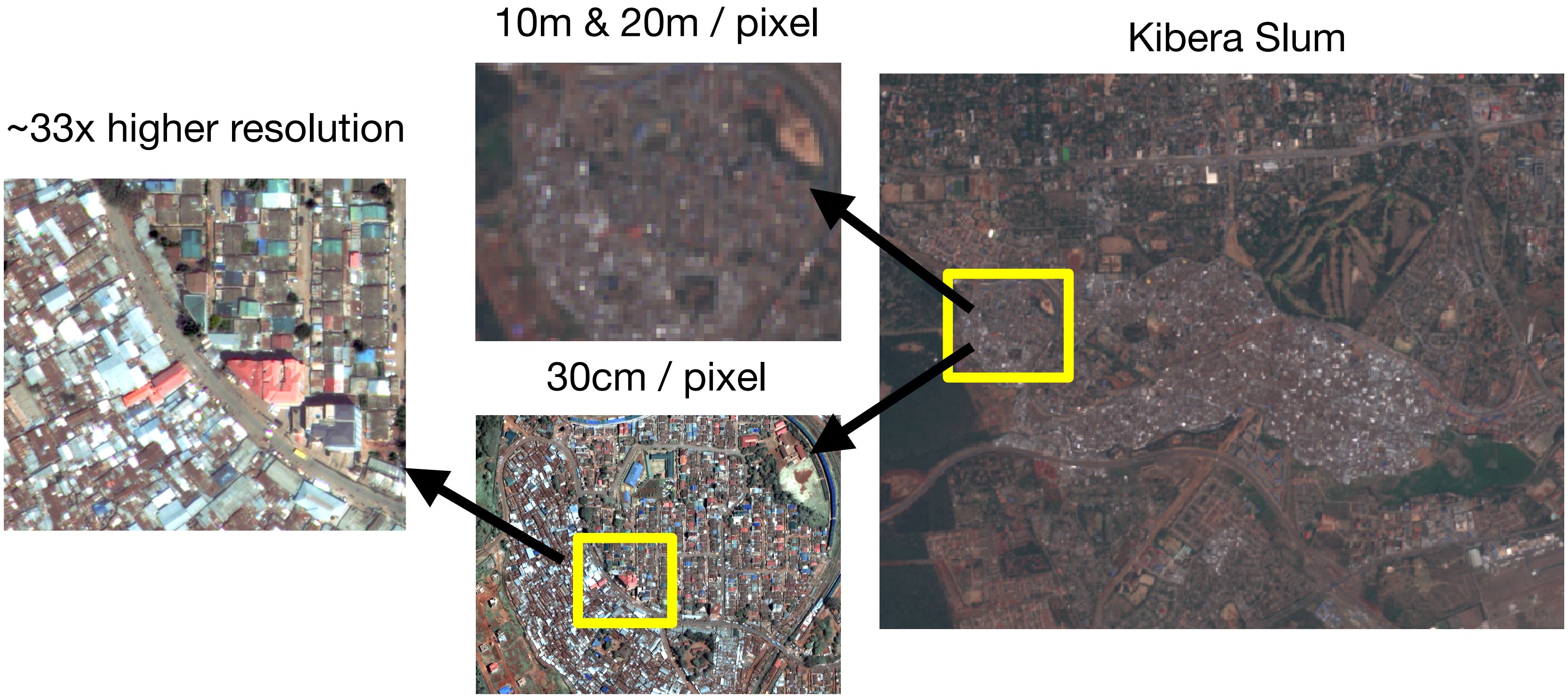


High-Resolution

Low-Resolution

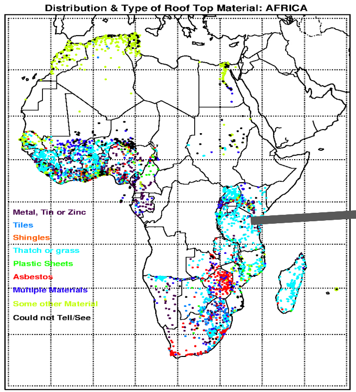
This work!

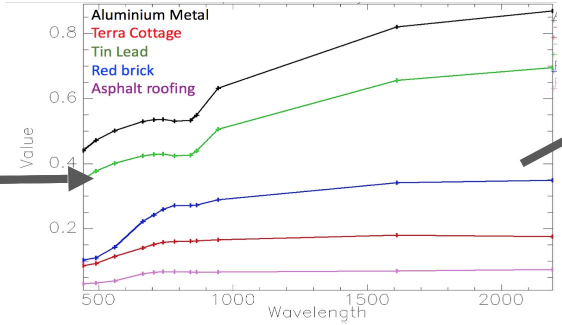
Very-High-Resolution vs. Low-Resolution

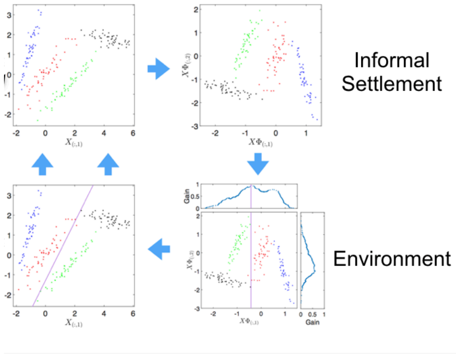


The Spectral Model

Spectral Model: Extracting materials from single-pixel spectra

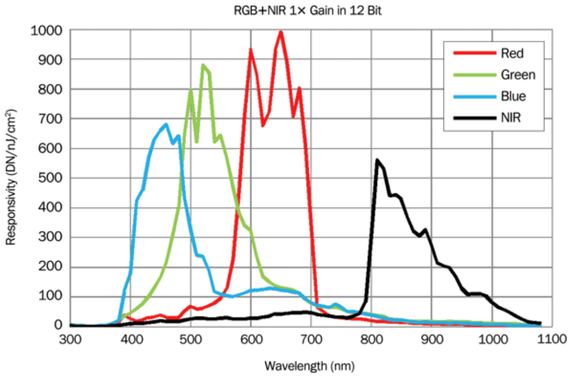


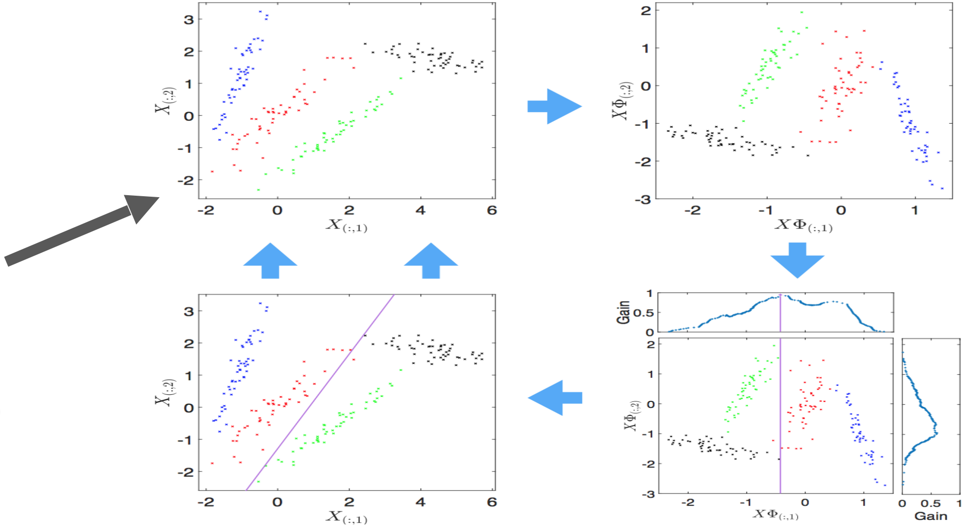




Canonical Correlation Analysis

- Use of a **Canonical Correlation Forests**





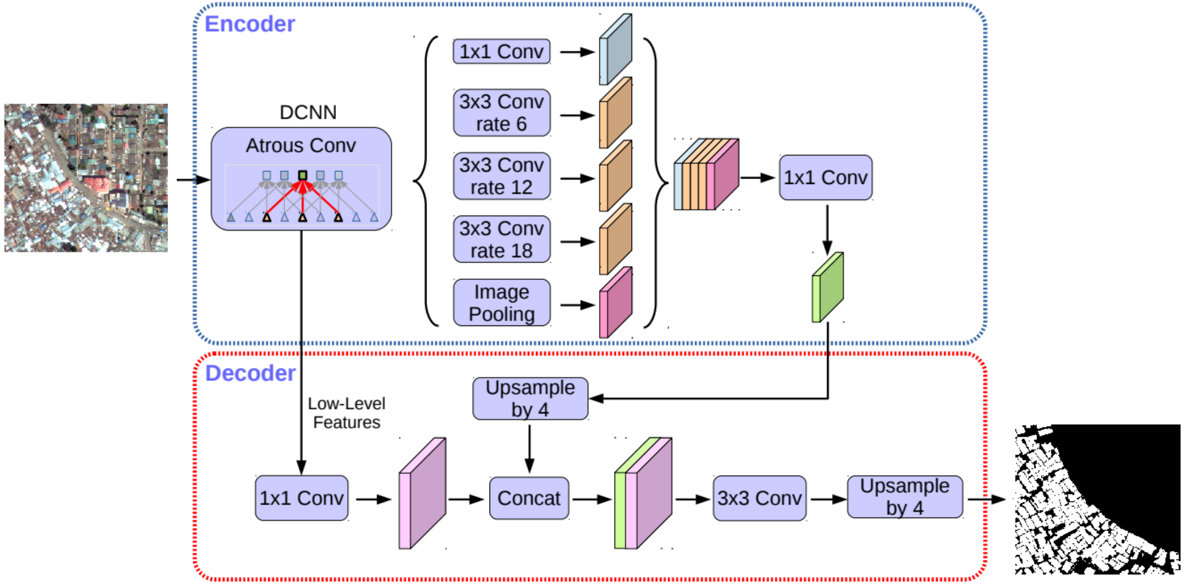
Informal Settlement

Formal / Environment

The Textural Model

Convolutional Neural Network (CNN) for spatial features

- Trained on VHR satellite images
- Multi-Resolution
- Single-Scale Evaluation
- Deeplabv3+ is pre-trained using Pascal VOC
- Trained using 8 GPUs (Batch Size 32. initial LR 0.001) $y[i] = \sum_{k} x[i + r \cdot k] w[k]$



Mapping Informal Settlements in Developing Countries using Machine Learning and Low Resolution Multi-spectral Data. Bradley Gram-Hansen*, Patrick Helber* (shared first author), Indhu Varatharajan, Faiza Azam, Alejandro Coca-Castro, Veronika Kopackova, Piotr Bilinski. AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society, 2019 *(accepted)*

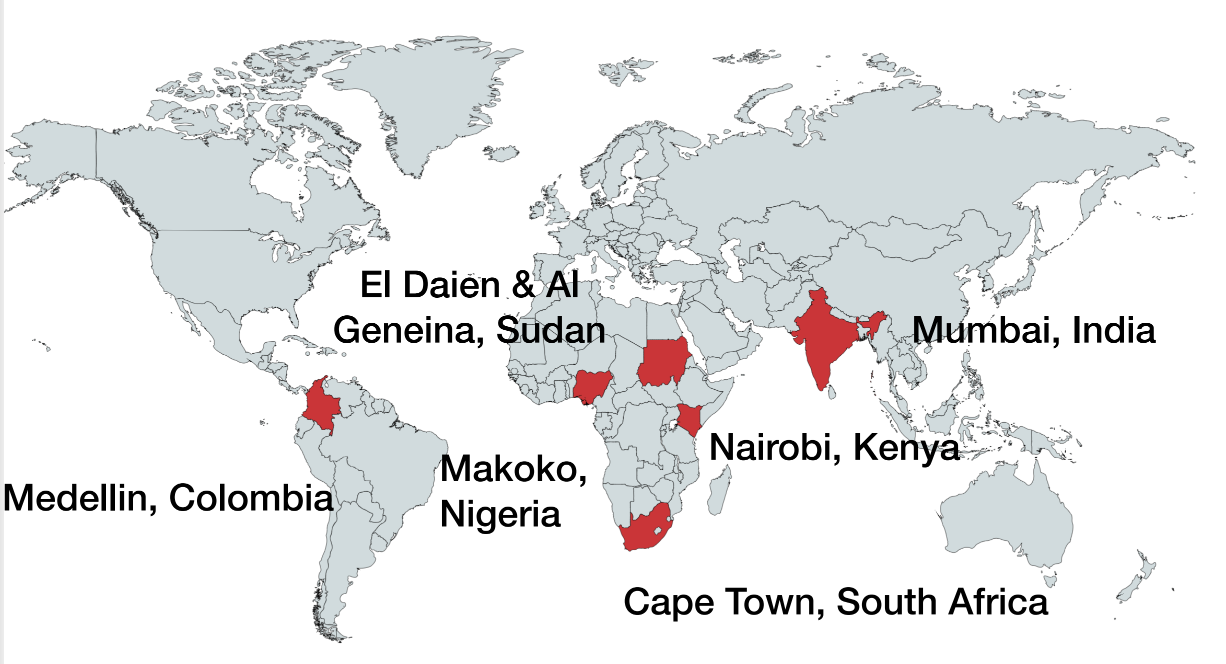
Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation, Liang-Chieh Chen et al., arXiv: 1802.02611, 2018.

Global Case Study

Provided Benchmarks

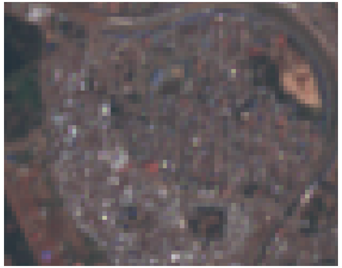
Low-Resolution Multi-Spectral Satellite Imagery

Very-High-Resolution Satellite Imagery



Quantitative Results

SpecM



TexM

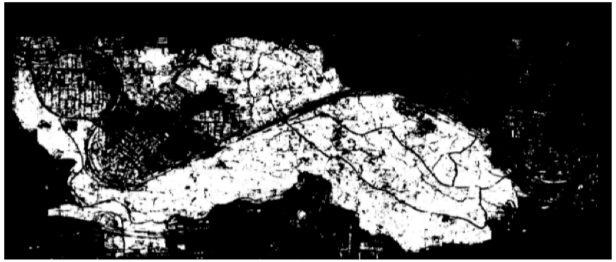
Pixel-wise Classification of Informal Settlements (SpecM) and Contextual Classification(TexM)

Continent	Region	Mean IOU		Pixel Accuracy	
Informal Settlements		**SpecM**	**TexM**	**SpecM**	**TexM**
Africa	Kenya (Northern Nairobi)	62.0 %	80.8 %	69.4 %	93.1 %
	Kenya (Kibera)	**73.3 %**	**65.5 %**	69.0 %	78.2 %
	Sudan (El Daien)	61.3 %	73.4 %	78.0 %	86.0 %
	Sudan (Al Geneina)	**35.7 %**	**76.3 %**	83.2 %	89.2 %
	Nigeria (Makoko)*	59.9 %	74.0 %	76.2 %	87.4 %
Asia	India (Mumbai)*	40 %	-	97 %	-
South America	Colombia (Medellin)*	74.0 %	83.0 %	84.2 %	95.3 %

Qualitative Results

Predictions of informal settlements (white pixels) in Kibera, Nairobi

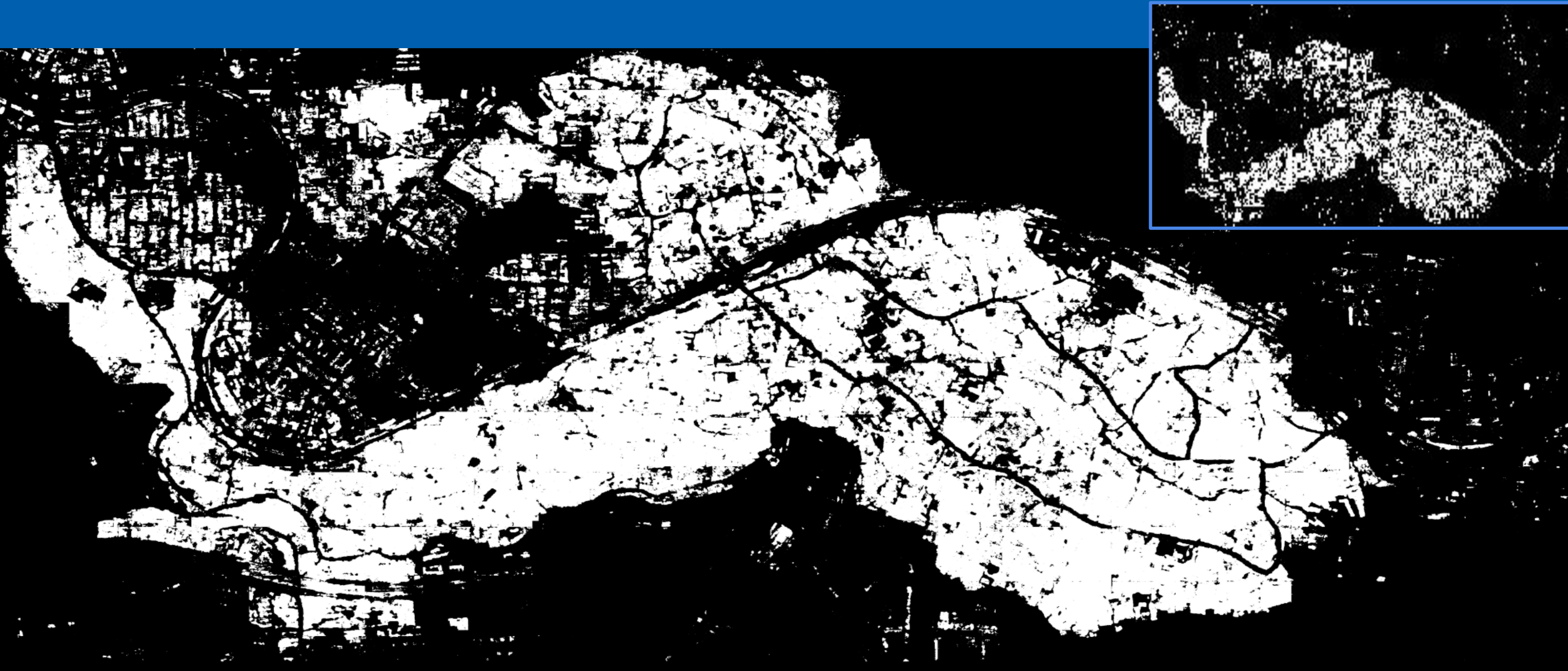
CCF prediction (LR MS)



CNN prediction (VHR RGB)

Ground Truth

Qualitative Results



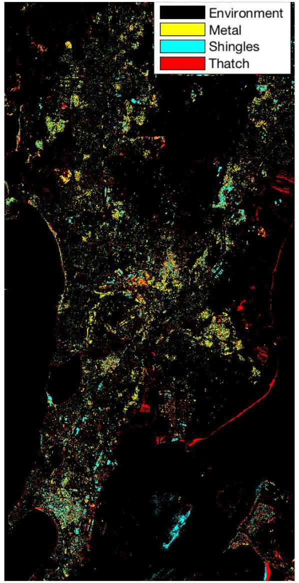
Generating Material Maps to Map Informal Settlements

Mumbai, India

Sentinel-2

Ground Truth*

Prediction



Generating Material Maps to Map Informal Settlements. Patrick Helber*, Bradley Gram-Hansen* (shared first author), Indhu Varatharajan, Faiza Azam, Alejandro Coca-Castro, Veronika Kopackova, Piotr Bilinski. NeurIPS 2018 Machine Learning for the Developing World Workshop, 2018

Open Source Solutions - Map Visualizations

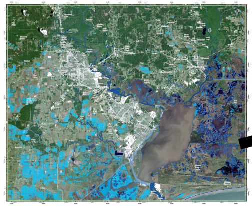
Open Source
Code + Models + Data

Pre-Disaster and Disaster Relief

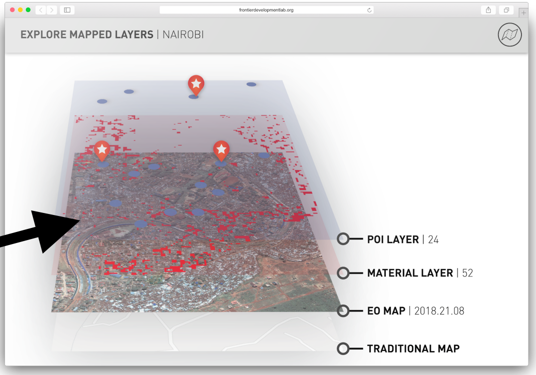
- Government

Support Well-Being

- Government, NGOs, Developing Organizations



Flooding
Event



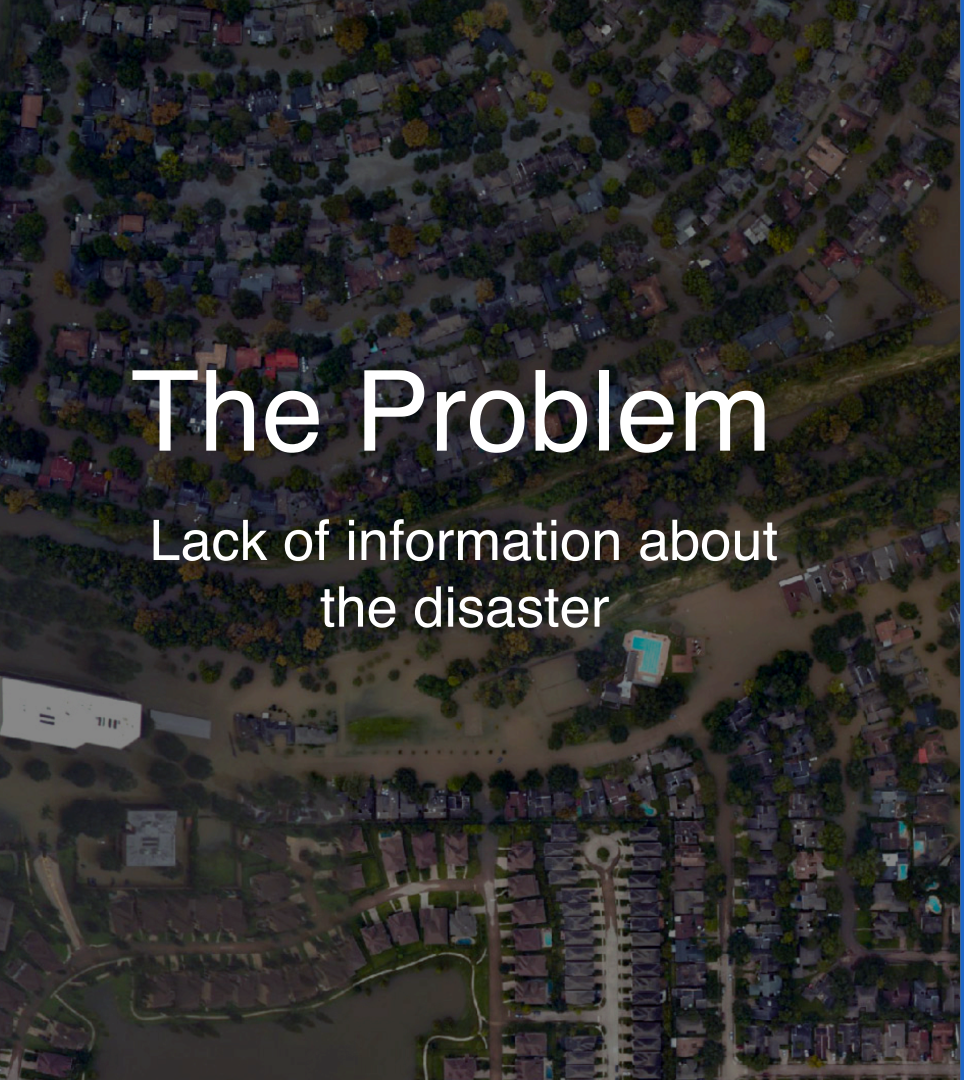
Map Visualization

https://frontierdevelopmentlab.github.io/informal-settlements/

Machine Learning-Aided Disaster Response

Identifying flood-affected buildings after disaster events
for emergency response

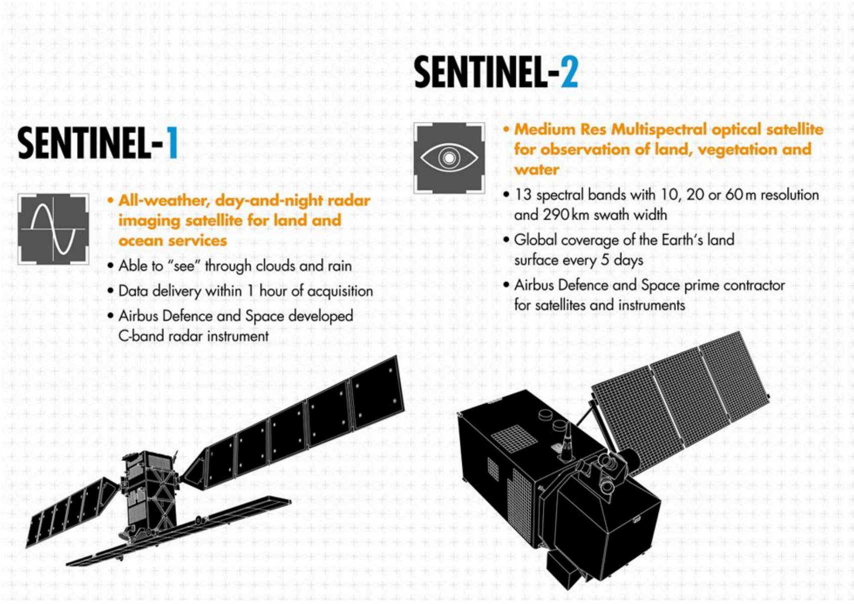
Primeviewtv, 2018



The Problem

Lack of information about the disaster

- the **location** of affected communities
- the **severity** of the event/ **level of damage**
- rapid **response time over accuracy**



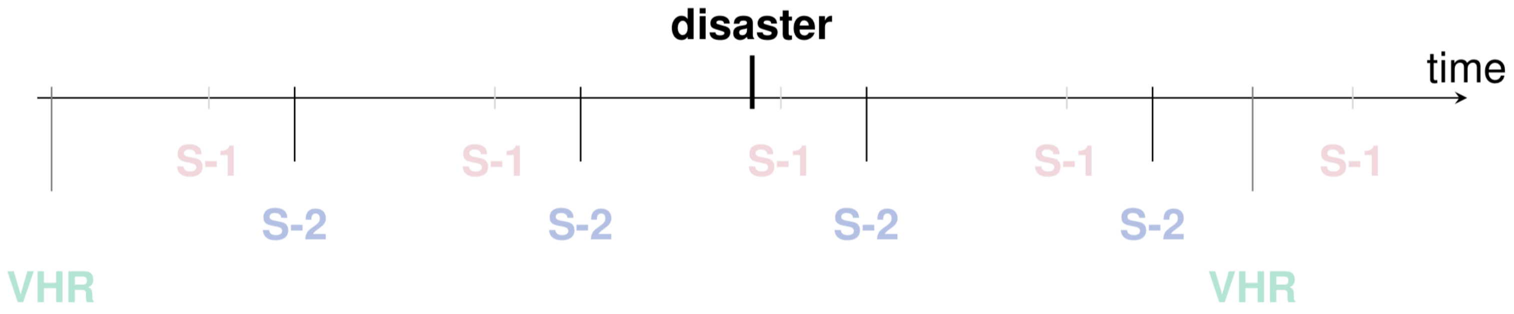
Approach

Fast **building** and **damage detection** by fusion of **multi-resolution** and **multi-temporal** satellite imagery

Input data sources:

- Radar: Sentinel 1 (public)
- Optical: Sentinel 2 (public)
- Very high resolution (commercial)

What satellite data is available?



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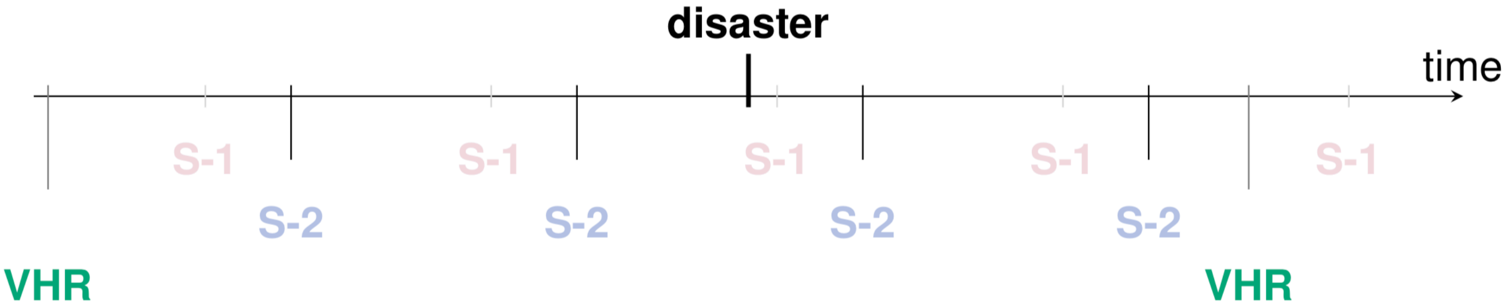

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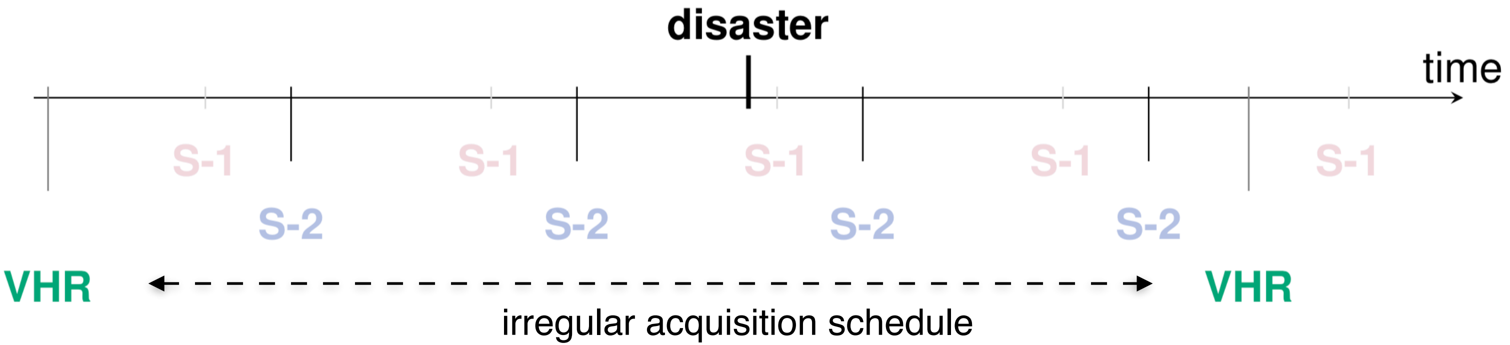

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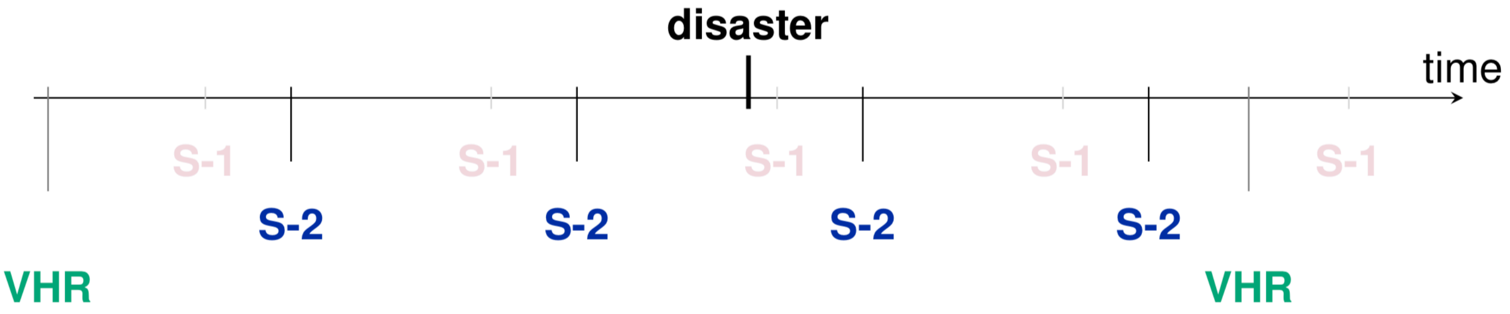


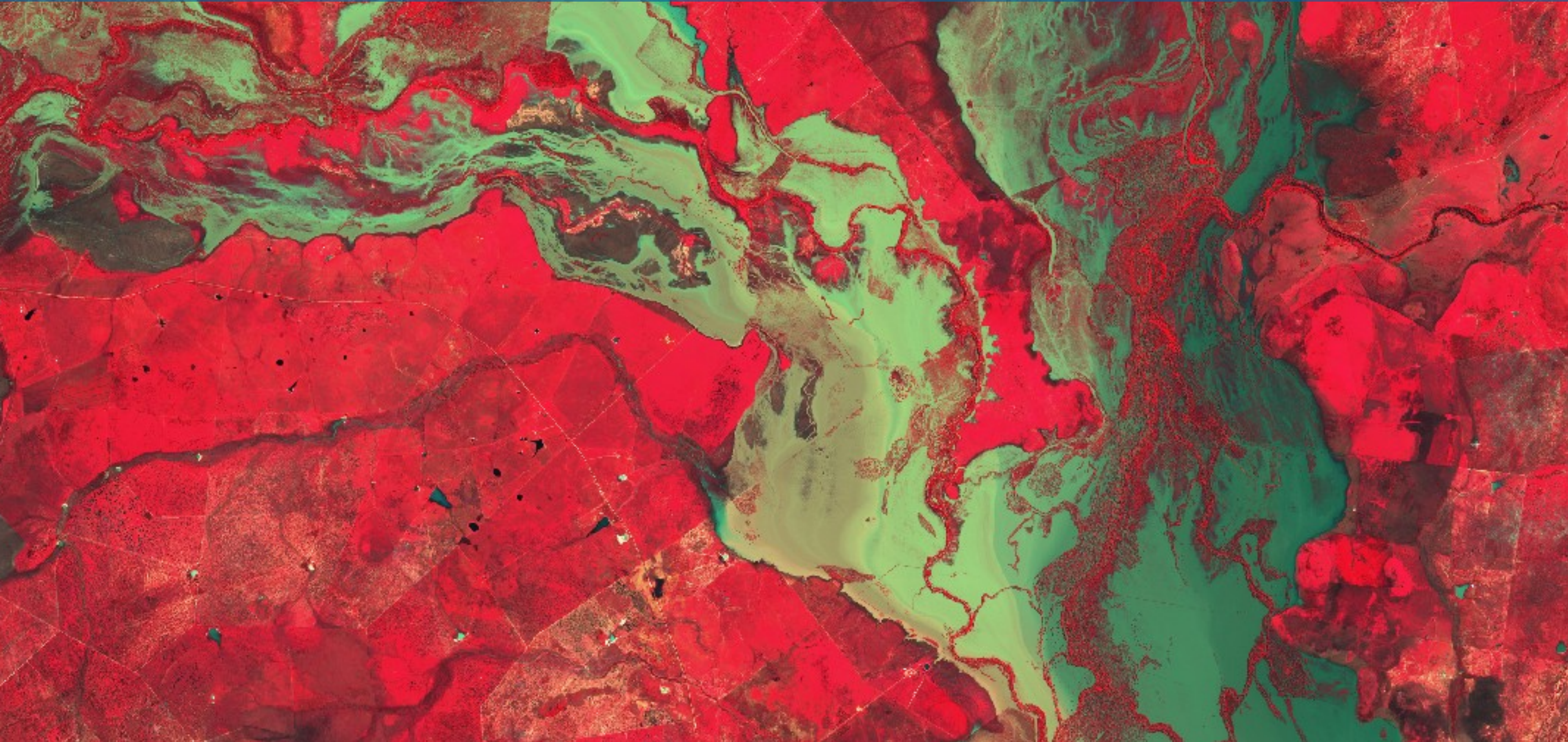

pre


during

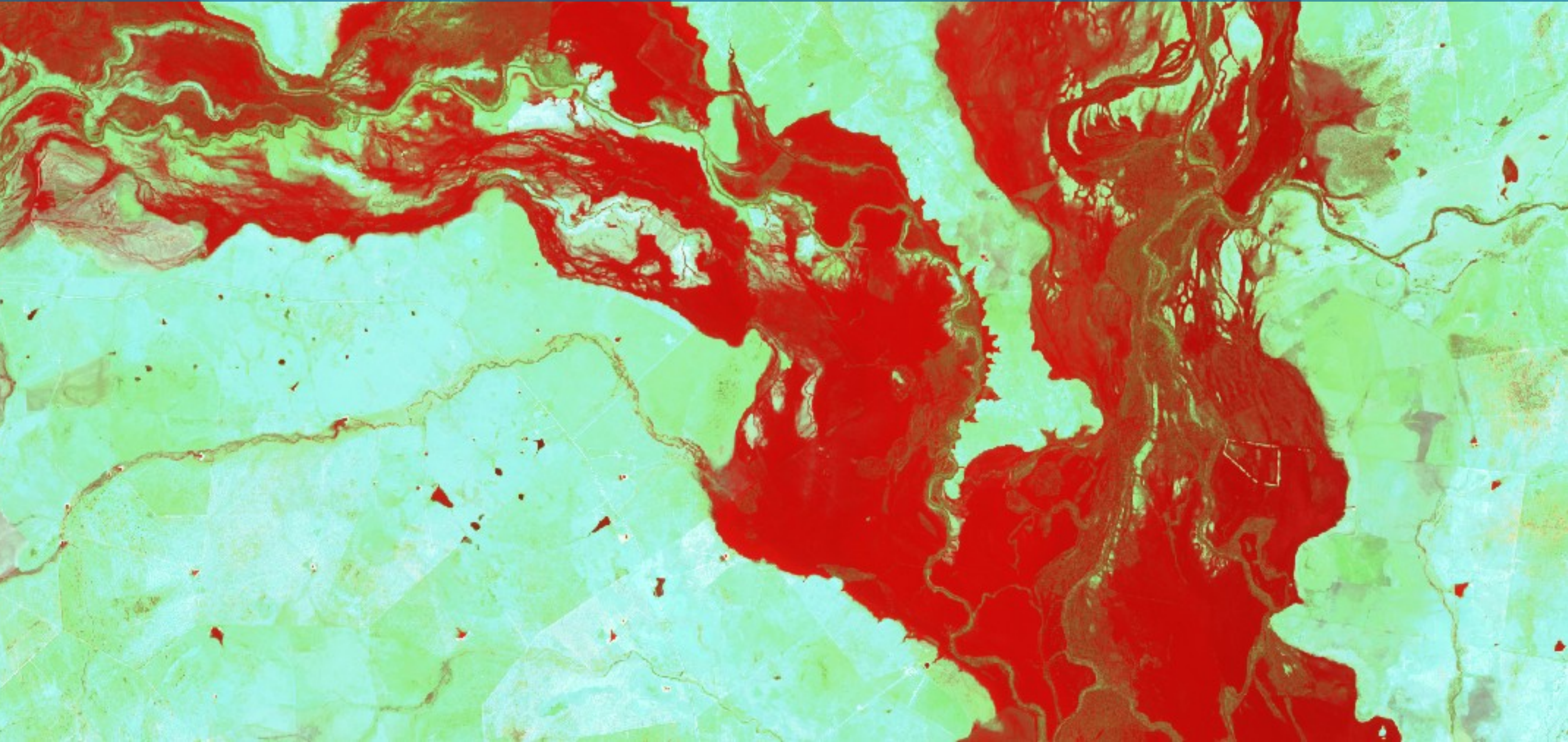

post

Optical Satellite Imagery: multispectral Information

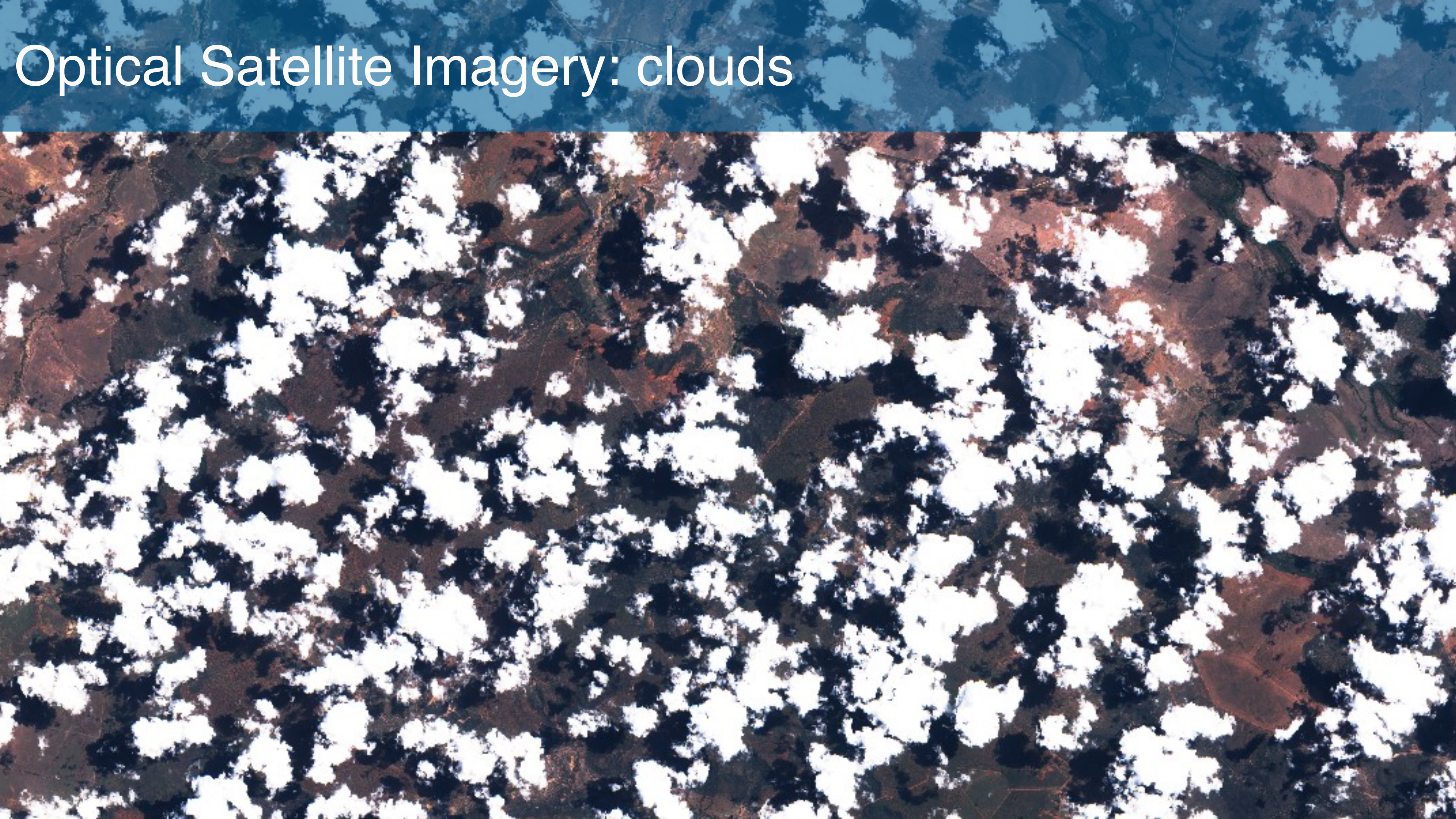
Optical Satellite Imagery: multispectral Information



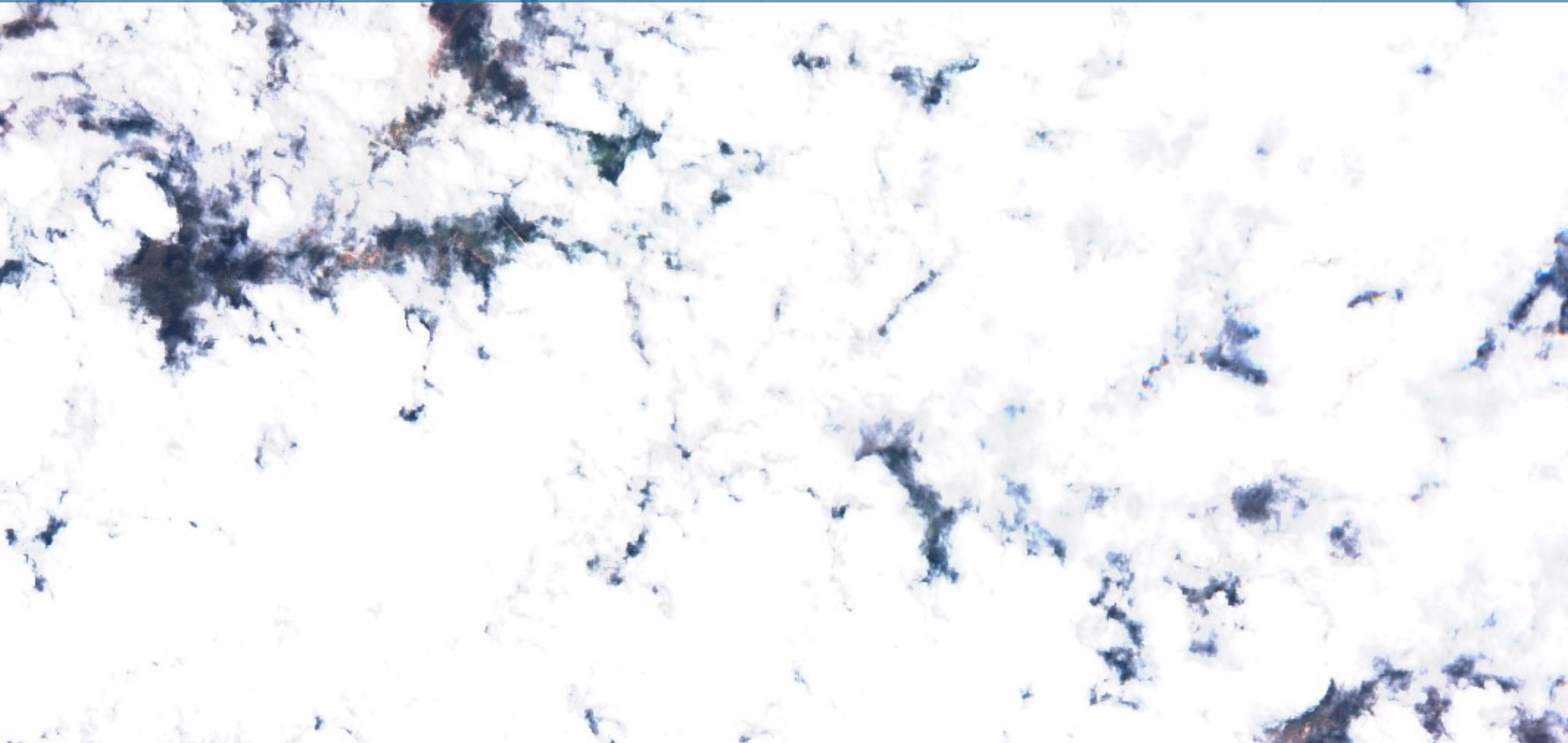
Optical Satellite Imagery: multispectral Information



Optical Satellite Imagery: clouds



Optical Satellite Imagery: clouds everywhere



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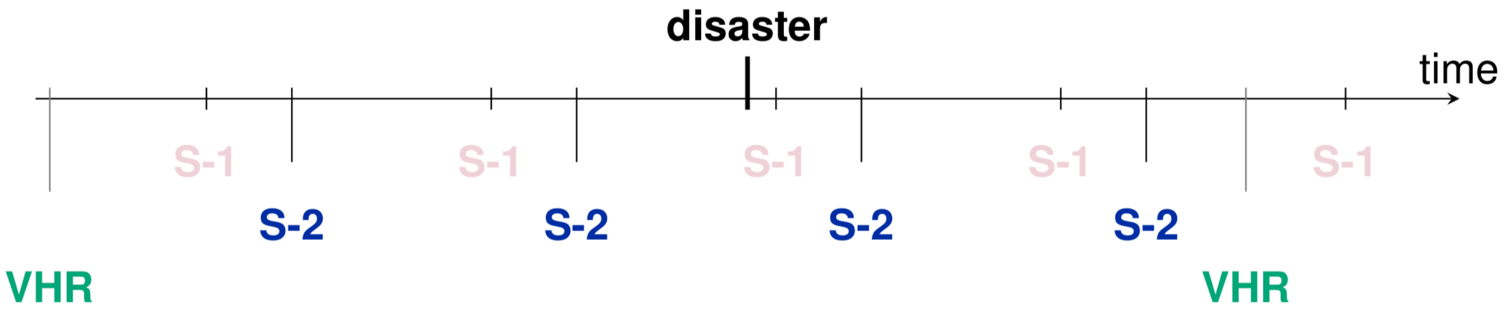

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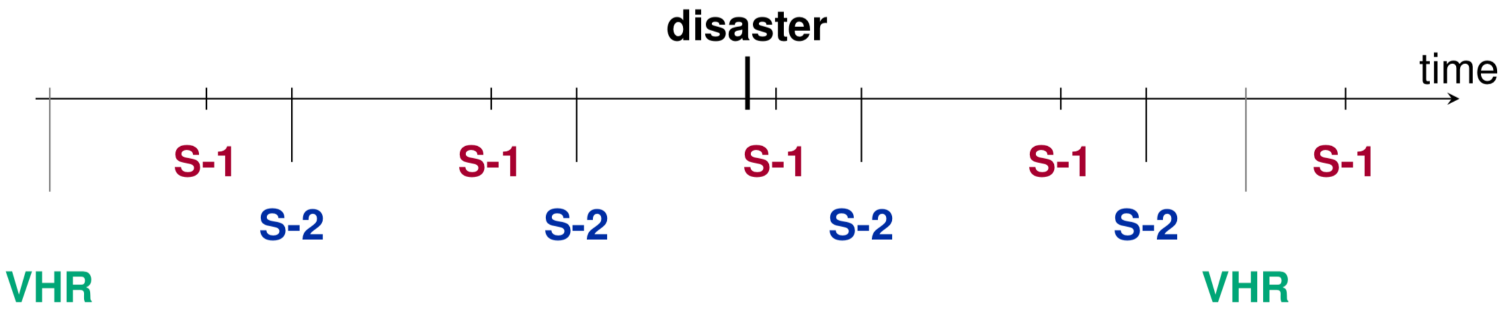

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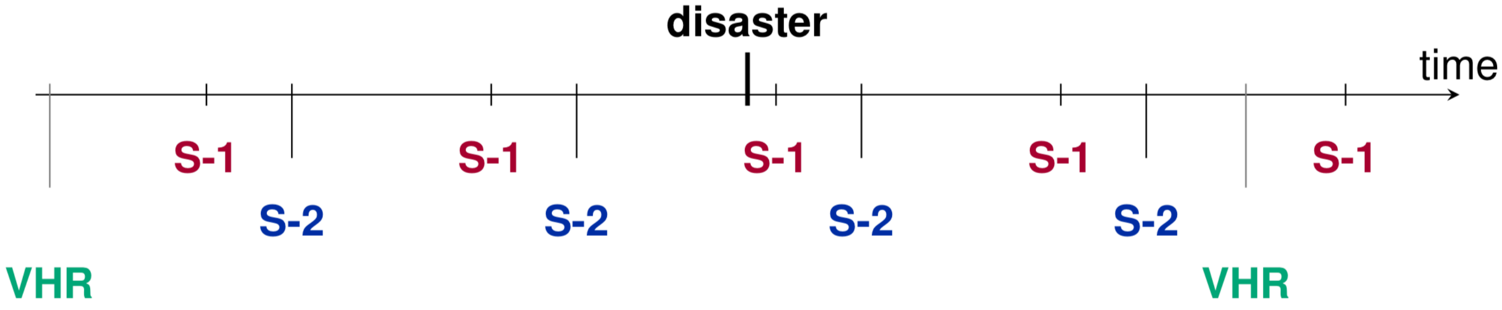
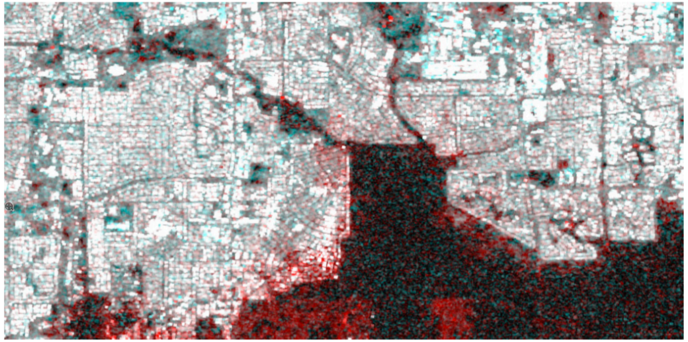


coherence pre

high correlation values

coherence post

correlation decreases



coherence RGB pre & post

Challenge: different spatial resolutions

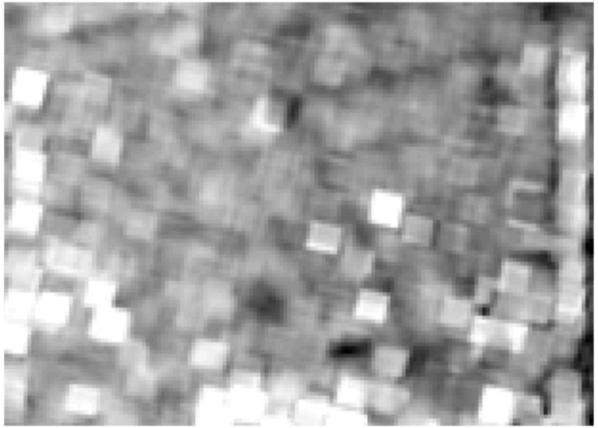
0.5m post-disaster

very high resolution

10m post-disaster

optical

10m post-disaster



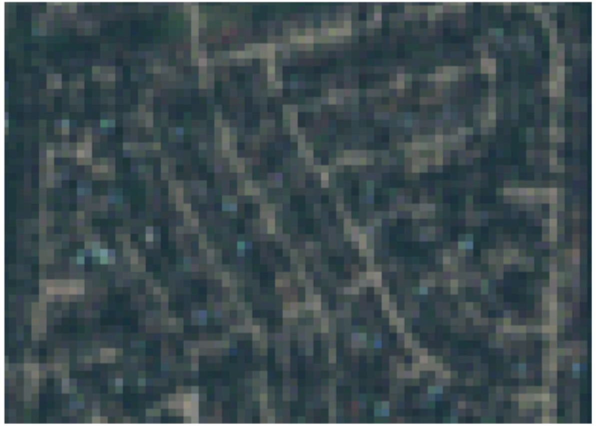
radar

Advantage: spatiotemporal information

0.5m post-disaster

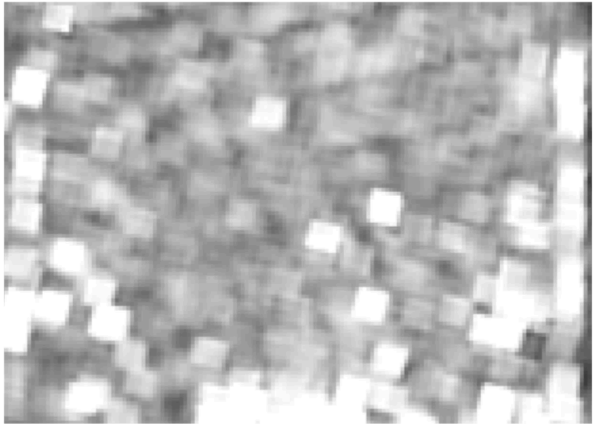
very high resolution

10m pre-disaster



optical

10m pre-disaster



radar

Flooded-Affected Buildings

Hurricane Events (2017)

Damage Detection & Estimation

Ground truth, towards two objectives

building footprints

Open Street Map

damaged sites

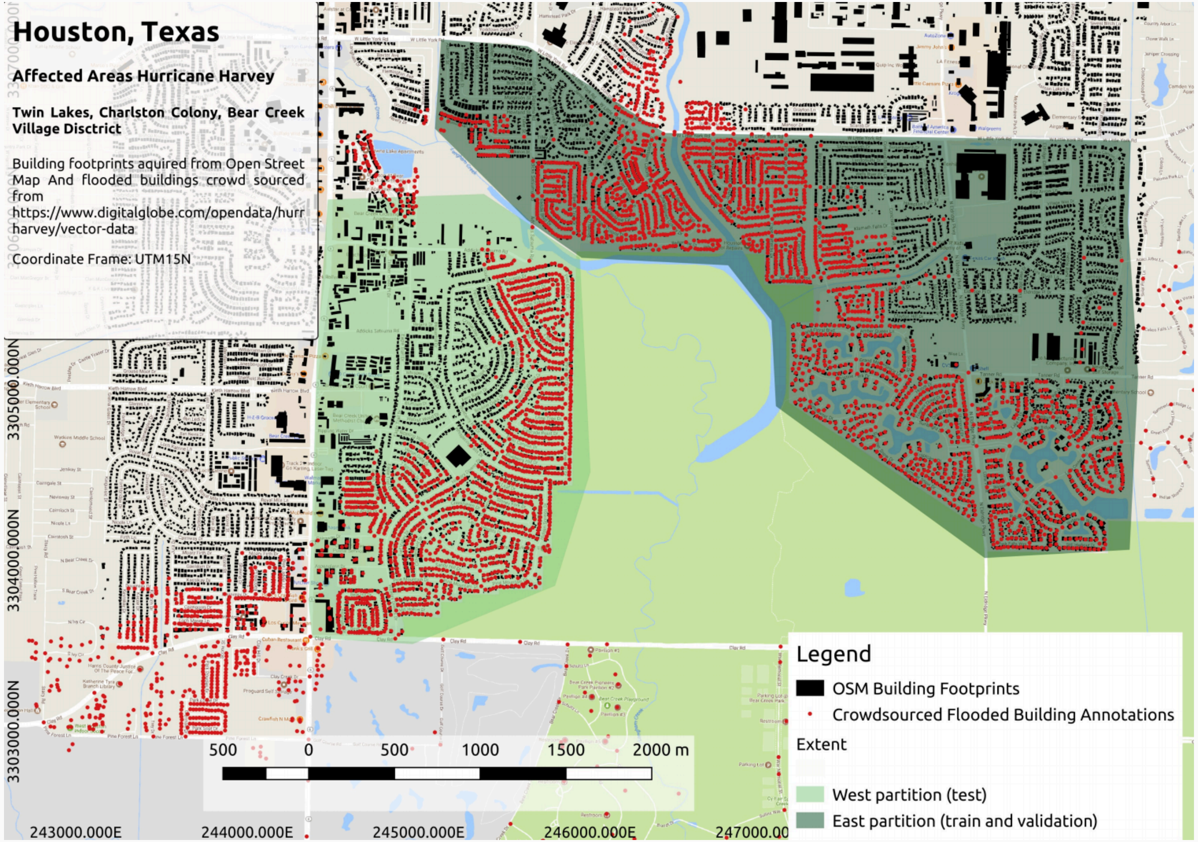
UNOSAT

Dataset

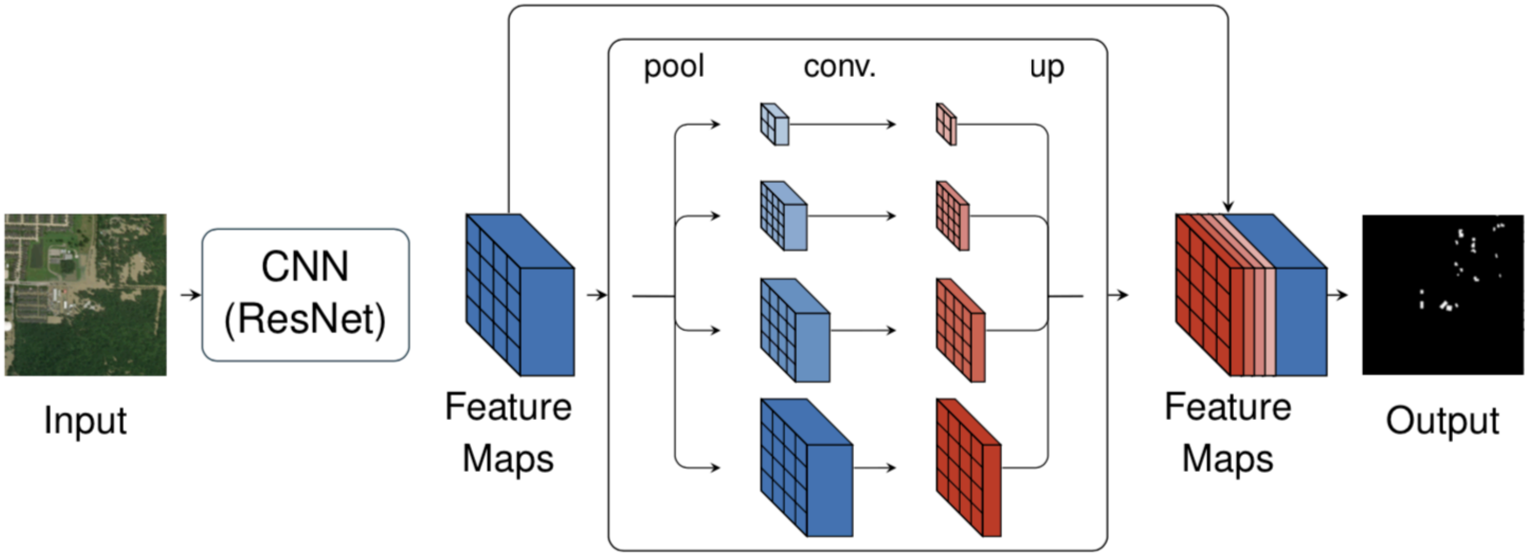
- Preprocessed imagery
- Crowdsourced labels
- Two Partitions

Metrics

- Intersection over Union
- Pixel Accuracy



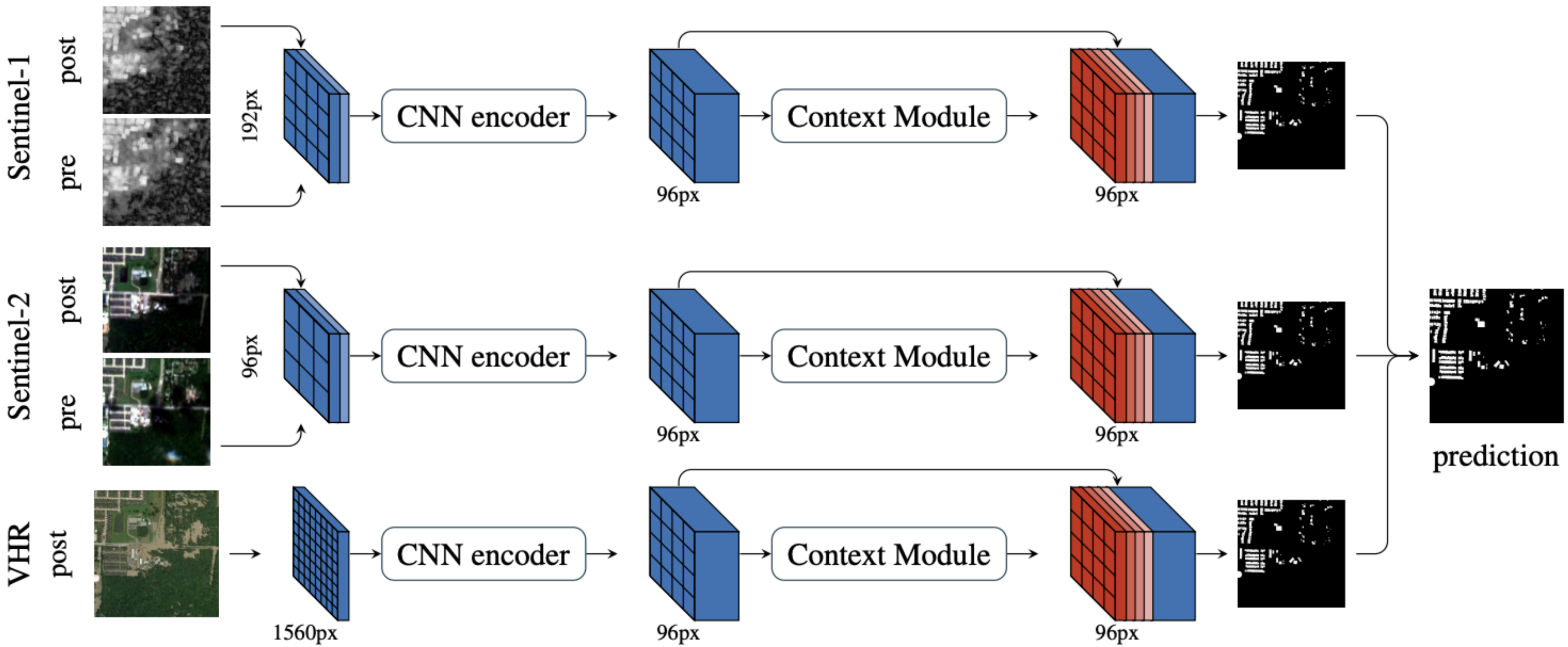
Semantic Segmentation with Context Aggregation



Pyramid Scene Parsing (PSP)[1]

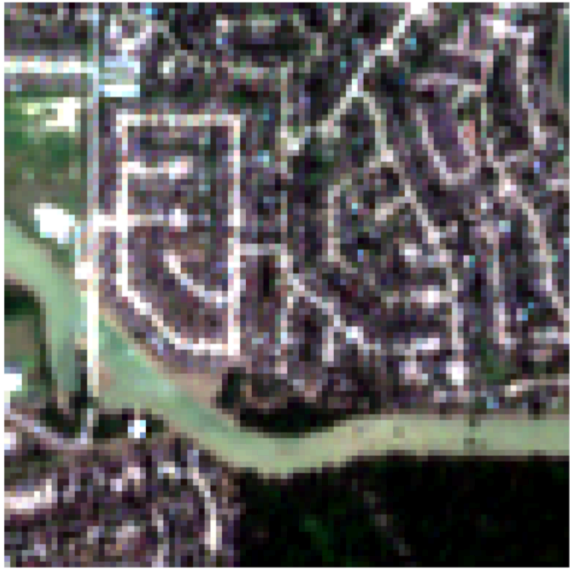
[1] Hengshuang Zhao et al. “Pyramid scene parsing network”. In: IEEE Conf. on Computer Vision and Pattern Recognition (CVPR). 2017

Multimodal Fusion with Multi³-Net



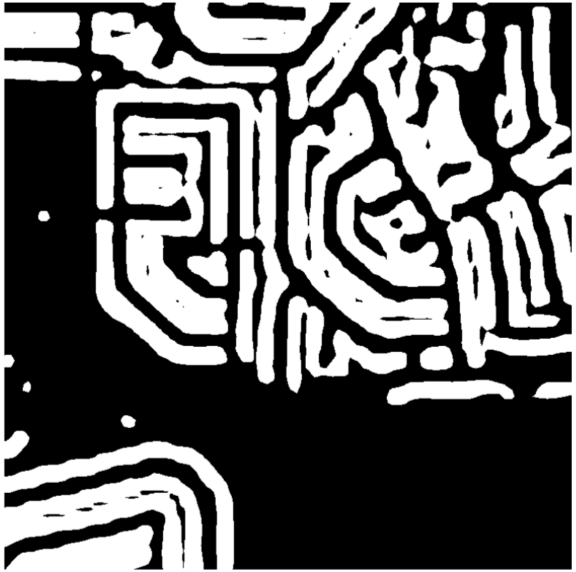
Segmentation of buildings with Sentinel-2

RGB input

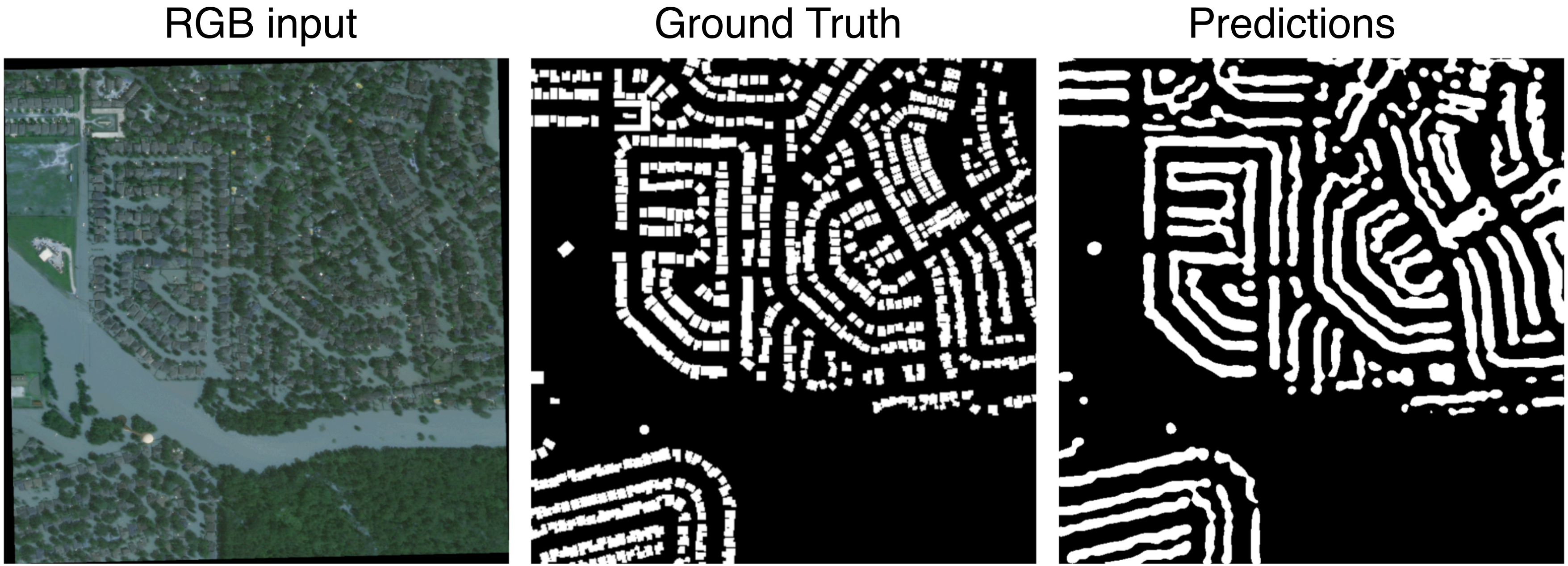


Ground Truth

Predictions



Segmentation of buildings with VHR imagery

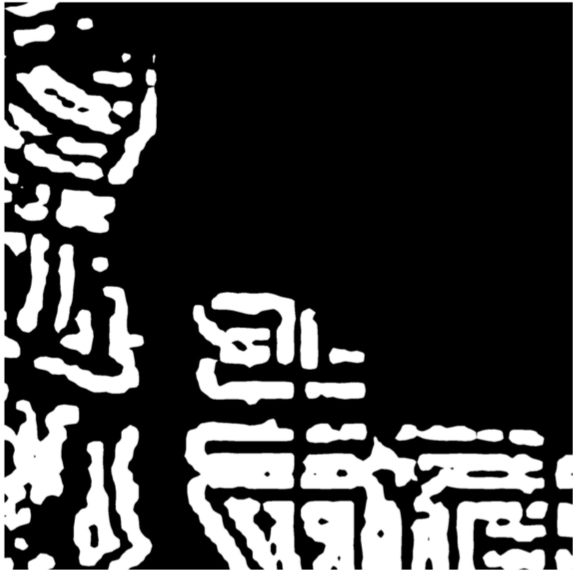


Segmentation of flood-affected buildings

RGB input

Ground Truth

Predictions



Better segmentation with fusion

VHR

VHR + S1 + S2

Ground Truth

Damage Prediction - Qualitative Results

Data	mIoU	bIoU	Acc
S1	50.2%	17.1%	88.7%
S2	52.6%	12.7%	87.4%
VHR	74.2%	56.0%	93.1%
S1 + S2	59.7%	34.1%	86.4%
S1 + S2 + VHR	75.3%	57.5%	93.7%

larger is better: mean Intersection over Union (mIoU), building Intersection over Union (bIoU), accuracy (acc)

Data

- first available (globally)
- later available (selected areas)

Findings:

- VHR > radar, optical
- radar+optical > radar, optical
- radar+optical+VHR > VHR

Damage Prediction - Qualitative Results

Data	mIoU	bIoU	Acc
S1	50.2%	17.1%	88.7%
S2	52.6%	12.7%	87.4%
VHR	74.2%	56.0%	93.1%
S1 + S2	59.7%	34.1%	86.4%
S1 + S2 + VHR	75.3%	57.5%	93.7%

larger is better: mean Intersection over Union (mIoU), building Intersection over Union (bIoU), accuracy (acc)

Data

- first available (globally)
- later available (selected areas)

Findings:

- VHR > radar, optical
- radar+optical > radar, optical
- radar+optical+VHR > VHR

Damage Prediction - Qualitative Results

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Collapsed Buildings in Ecuador

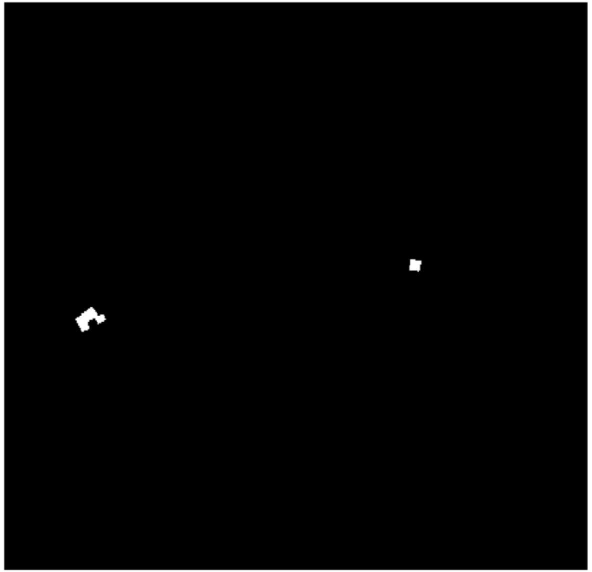
Earthquake (2016)

Damage Detection & Estimation

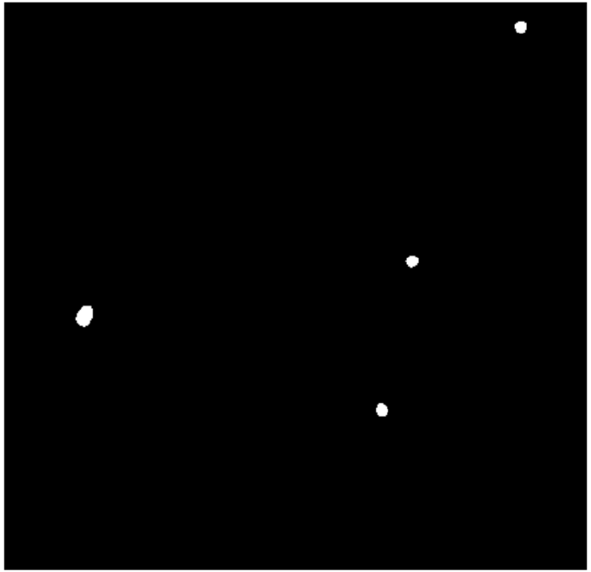
Extraction of Collapsed Buildings

RGB input

Ground Truth



Predictions



Extraction of Collapsed Buildings

final prediction overlay

Extraction of Collapsed Buildings

final prediction overlay

Publications, Data and Source Code

NIPS 2018 Conference *December 2nd - 8th in Montreal, Canada*

- **Spatiotemporal Workshop**
- **AI for Social Good**

AAAI 2019 Conference *January 27th - Feb. 1st in Hawaii, USA*

- *Multi^{3}Net: Segmenting Flooded Buildings via Fusion of Multiresolution, Multisensor, and Multitemporal Satellite Imagery*

More infos, code and data at **GitHub**

- `https://github.com/FrontierDevelopmentLab/multi3net`

Multimedia-Satellite Benchmark at MediaEval

Satellite Image Analysis + Social Media

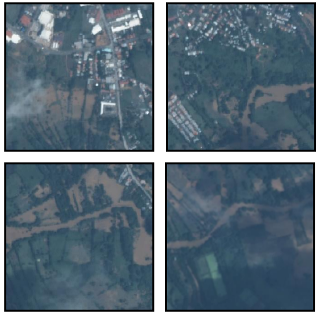
Multimedia Satellite Task at MediaEval

MMSat 2017

Detection of Flooding Events from Social Media

Based on YFCC100m

Segmentation of Flooded Areas

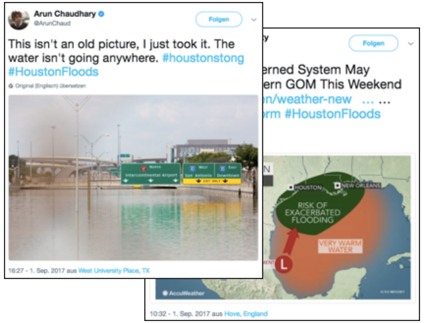


MMSat 2018

Classification of **Road possibility from Social Media**

Based on images in Tweets, newspapers

(Flooded) Road Segmentation from VHR- Imagery



Multimedia Satellite Task at MediaEval

Two subtasks: Satellite Image & Social Media Analysis

15 Teams registered in 2017 from all over the world with more than **60 submissions**

18 Teams registered in 2018 from all over the world with more than **50 submissions**

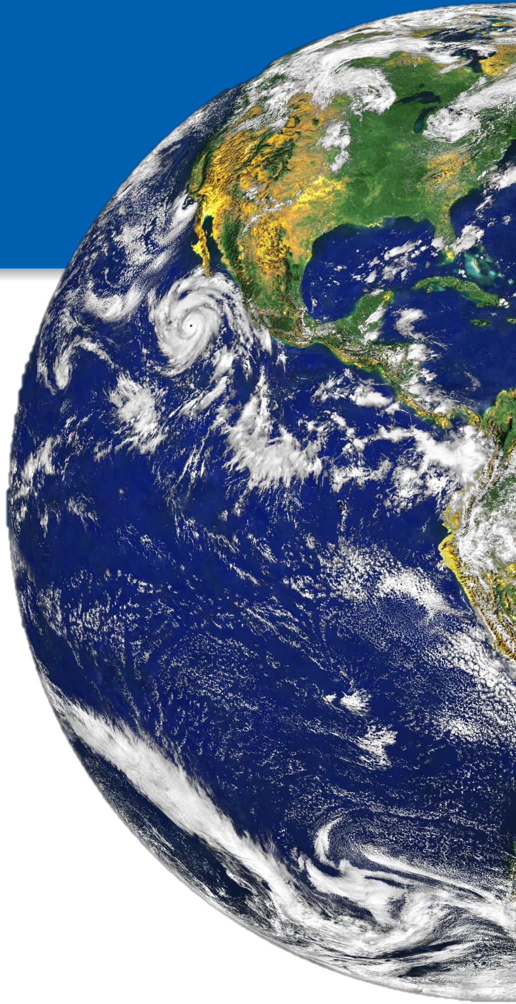
Multimedia-Satellite Benchmark at MediaEval

Satellite Image Analysis + Social Media

Contact: Benjamin.Bischke@dfki.de

Website: http://www.multimediaeval.org/mediaeval2019

Thanks!



Questions?