Artificial Intelligence and Data Science in Earth Observation

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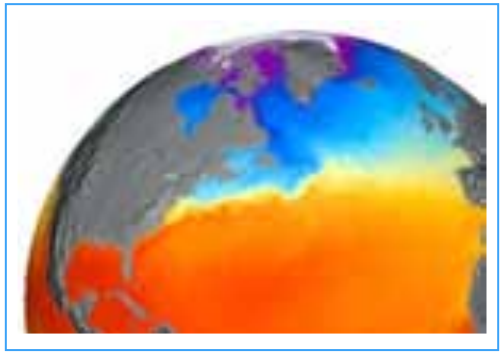
@xiaoxiang_zhu

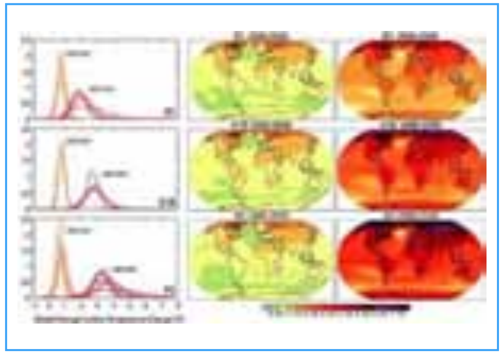
DLR TUM

DLR’s Mission in Earth Observation

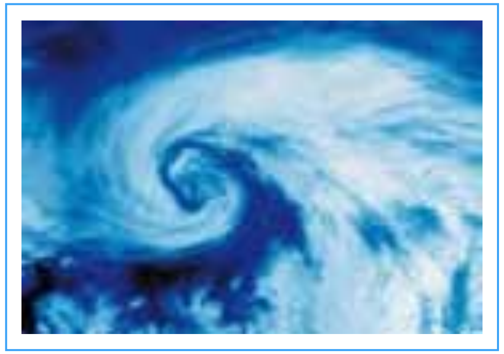
We research and develop solutions for major challenges in the following areas …



Earth System Research and Environmental Sciences



Global Change Research

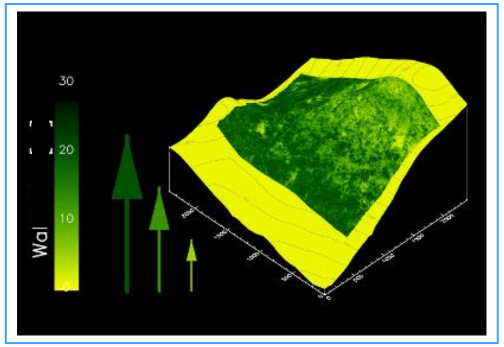


Meteorology

Sustainable Development

Security

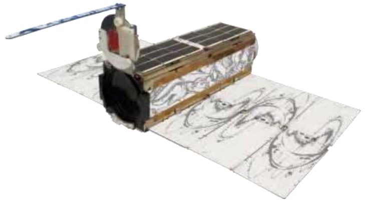
Mobility



Resource Management

City Planning

The Golden Era of Big Earth Observation Data

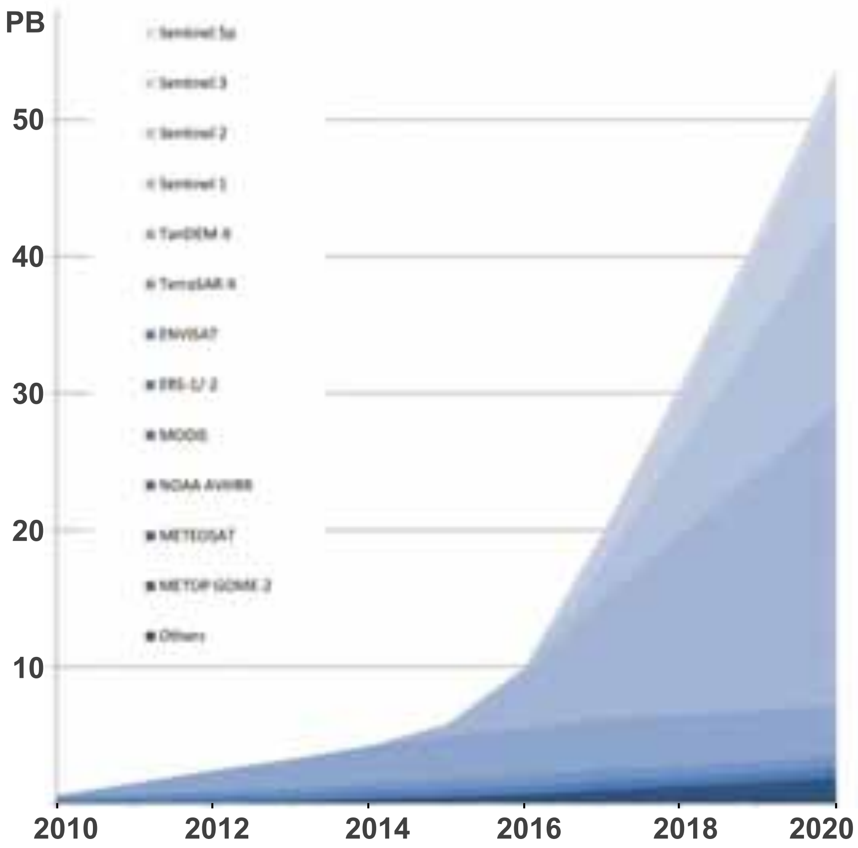


- Sentinels and future national satellites provide
  - continuous, reliable and quality controlled acquisition of big EO data
  - free and open data
  - long-term perspective
- Complementary NewSpace approaches, e.g. Planet
- Internet giants and Start-Ups (Descartes Lab, Orbital Insight,…) enter EO

Classical evaluation methods no longer sufficient → AI4EO

But:

High EO quality requirements and wide application diversity call for EO-specific AI research and innovative AI4EO methods



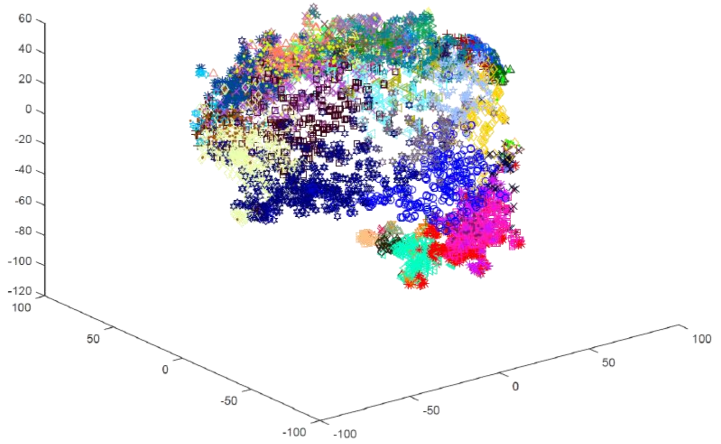
Data Science and AI in Earth Observation

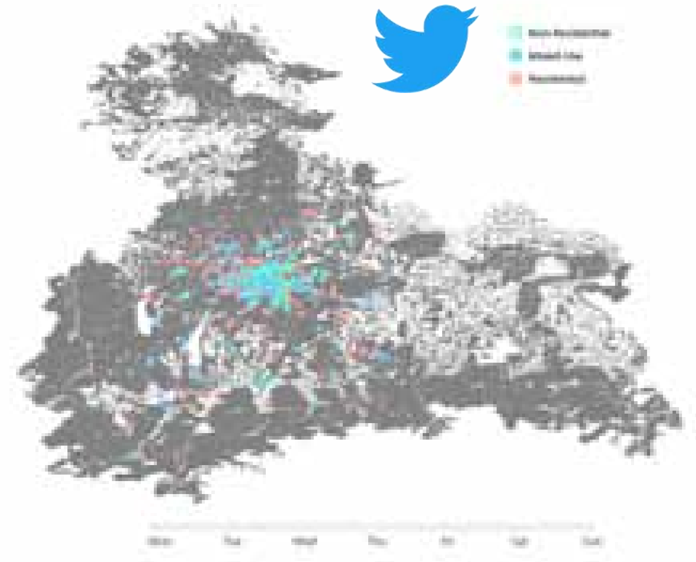
Date Fusion

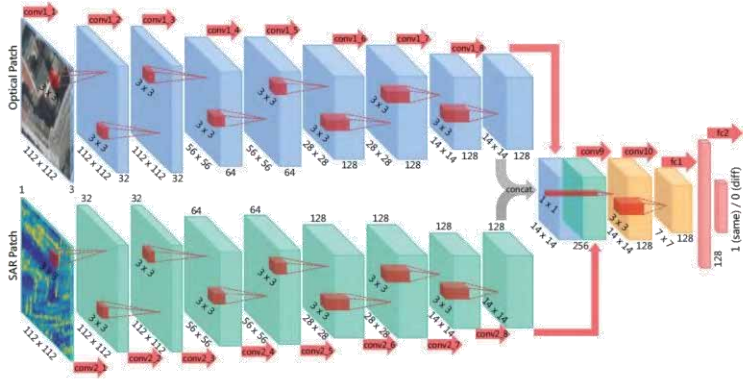
Data Mining

Machine Learning/Deep Learning

Big Data Management and HPC







Main Course – Two EO Data Science Stories

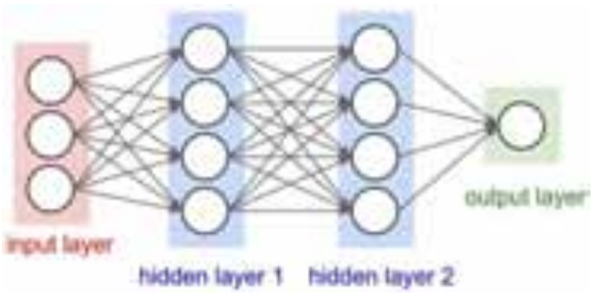
AI4EO

Deep Learning in Remote Sensing

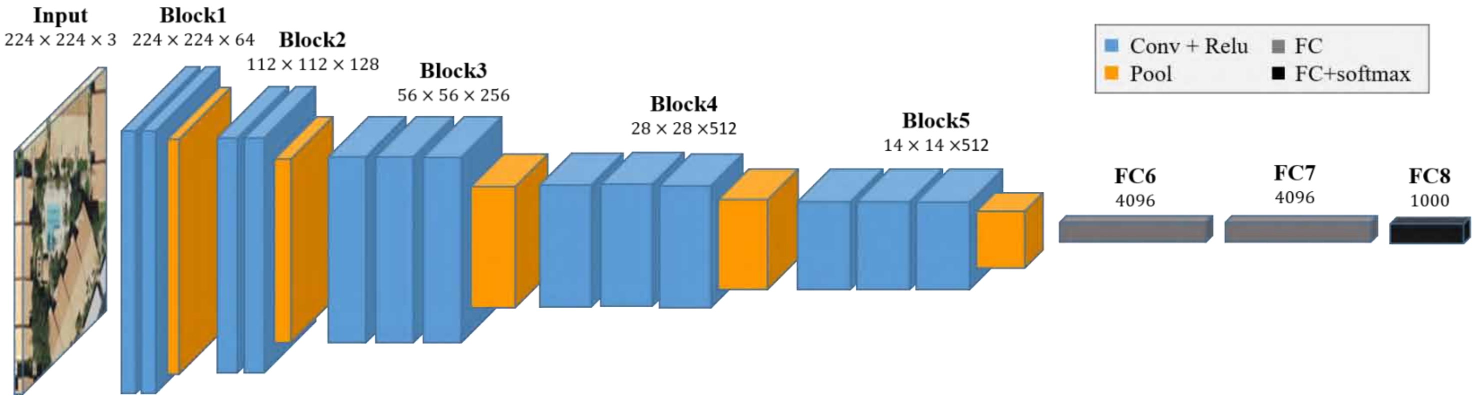
Geoscientific applications

Global Urban Mapping

Machine Learning/Deep Learning



Classical Neural Net
mid 1980s

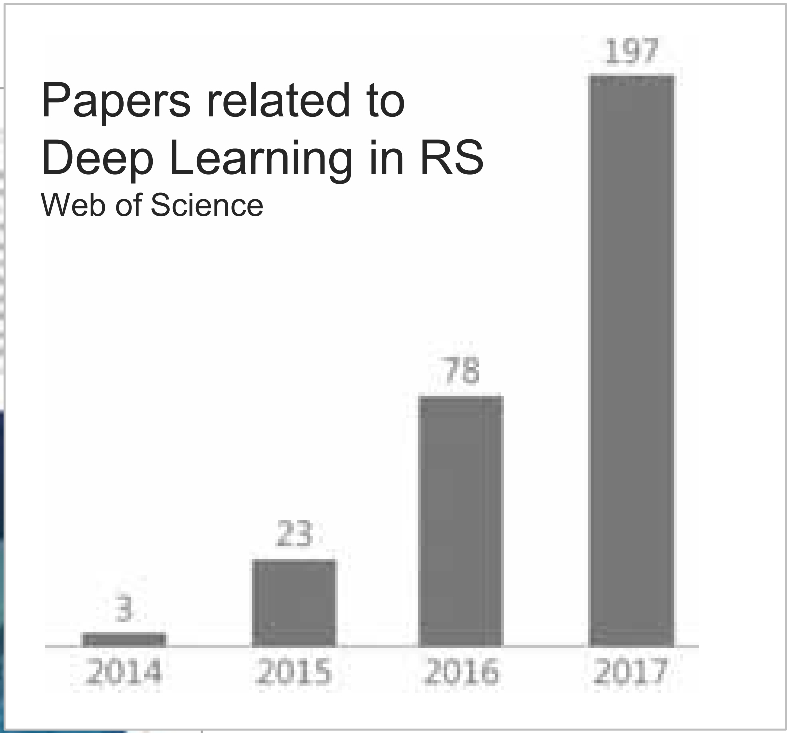


Deep Neural Net
since 2006/2012

XIAO XIANG ZHU, DEVIS TUIA, LICHAO MOU, GUI-SONG XIA, LIANGPEI ZHANG, FENG XU, AND FRIEDRICH FRAUNDORFER

Deep Learning in Remote Sensing

A comprehensive review and list of resources



IEEE Geoscience and Remote Sensing Magazine, Dec. 2017

Deep Learning in EO – Hot Topic or Hype?

- **Phase 1: Quick wins and quick papers**

  "we can also do it with DL" " e.g. 86.7 % → 89.3 %"

- **Phase 2: Understand that EO is different from internet image labelling**
  - Design new architectures for specific problems, and train from scratch

- **Phase 3: Remember your EO expert knowledge and find how to integrate it into DL**
  - "Opening the black box", "turn the black box gray"
  - Re-implant physics, Bayes and domain expertise into the learning process

One of Our Phase 1 Successes

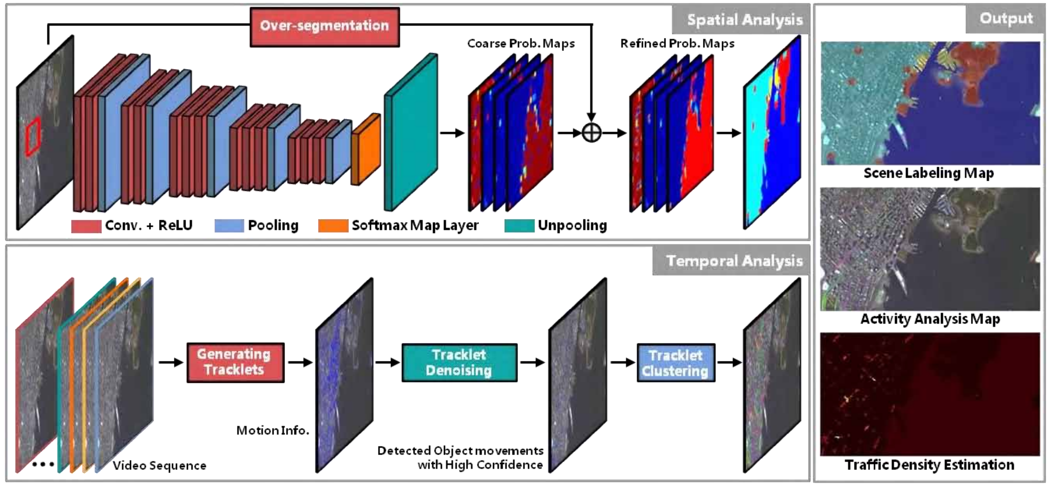
Spatiotemporal Scene Interpretation of Space Videos via Deep Neural Network and Tracklet Analysis

Winner of

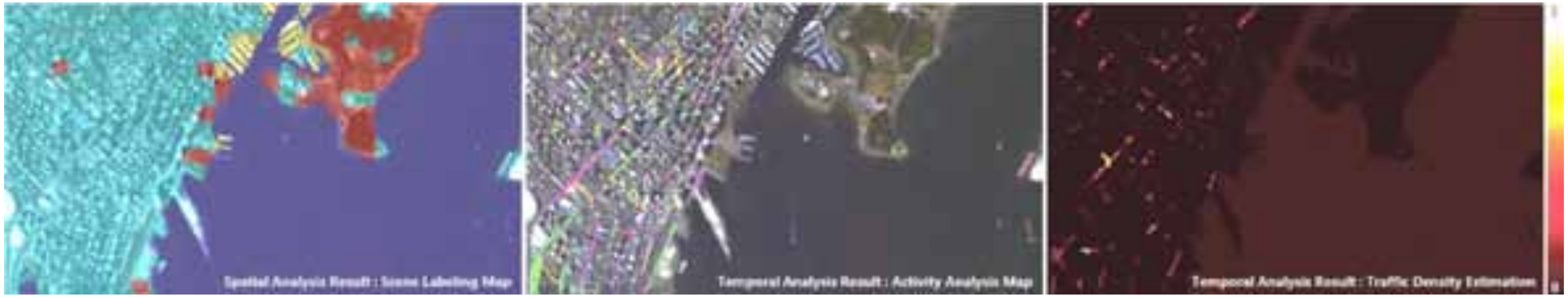
Data Fusion Contest 2016

Data

Workflow



Results



"Spatiotemporal Scene Interpretation of Space Videos via Deep Neural Network and Tracklet Analysis", L. Mou, X. Zhu

What makes Deep Learning in Earth Observation Special?

- Classification and detection are only small fractions of EO problems
- Focus on retrieval of physical or bio-chemical variables
  High accuracy , traceability and reproducibility of results, Quality measures
- Decadal expert domain knowledge available
- Well-controlled data acquisition (radiometric, geometry, spectrometric, statistical, SNR,...)
- Data can be 5-dimensional (x-y-z-t-λ), complex-valued and multi-modal :
  SAR, Lidar, multi-/super-/hyperspectral, GIS, OSM, citizen science, social media,...
- Often: lack of sufficient training data

DLR

Deep Learning@EOC

– Detection, segmentation and classification of buildings, ships, vehicles, persons…

– Classification of Land Use/Land Cover, Settlement Types and LCZs

– Change Detection and Time Series Analysis

– SAR/Optical Matching

– 2D/3D optical/SAR/PolSAR/LiDAR fusion

– Synthesizing optical images from SAR data and vice versa

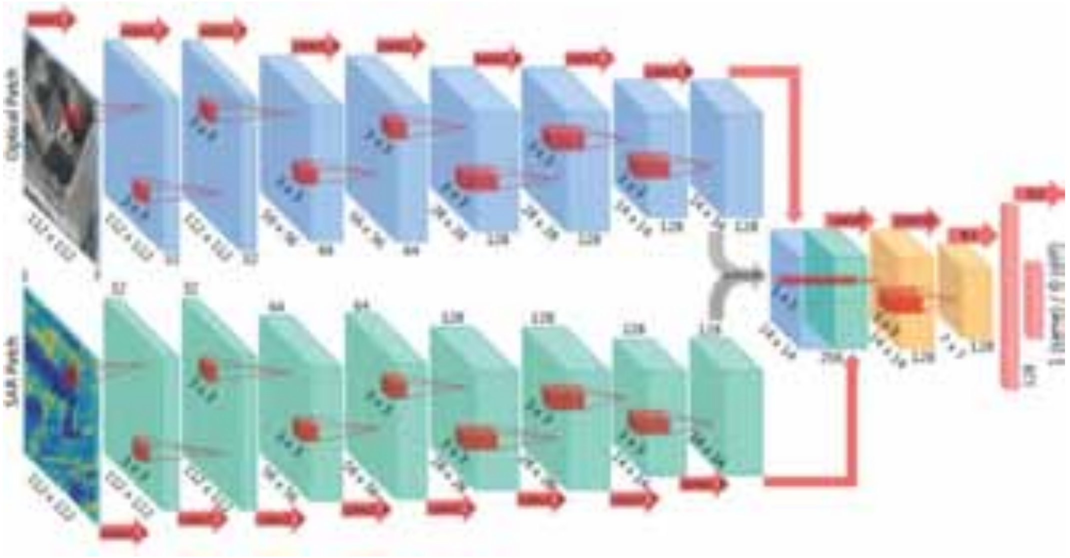
– Sentinel-2 cloud removal

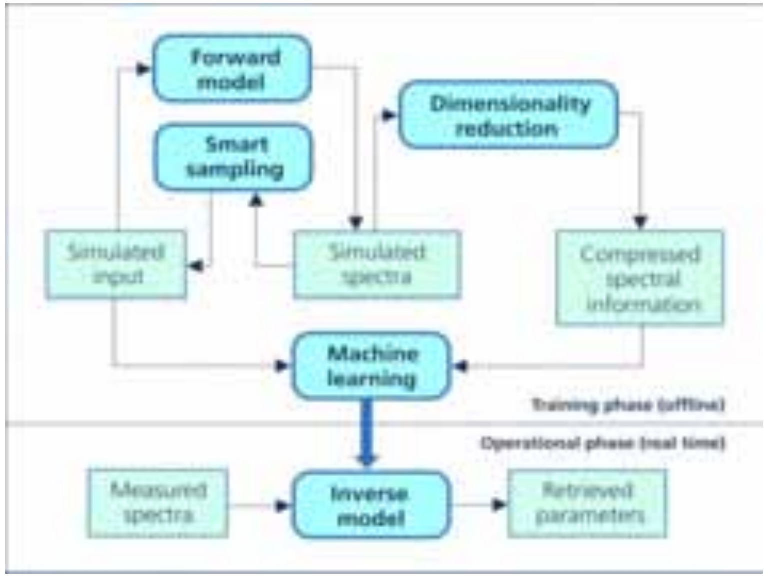
– IM2Height and IM2Building Footprint

– Fusion of EO and social media data (image and text)

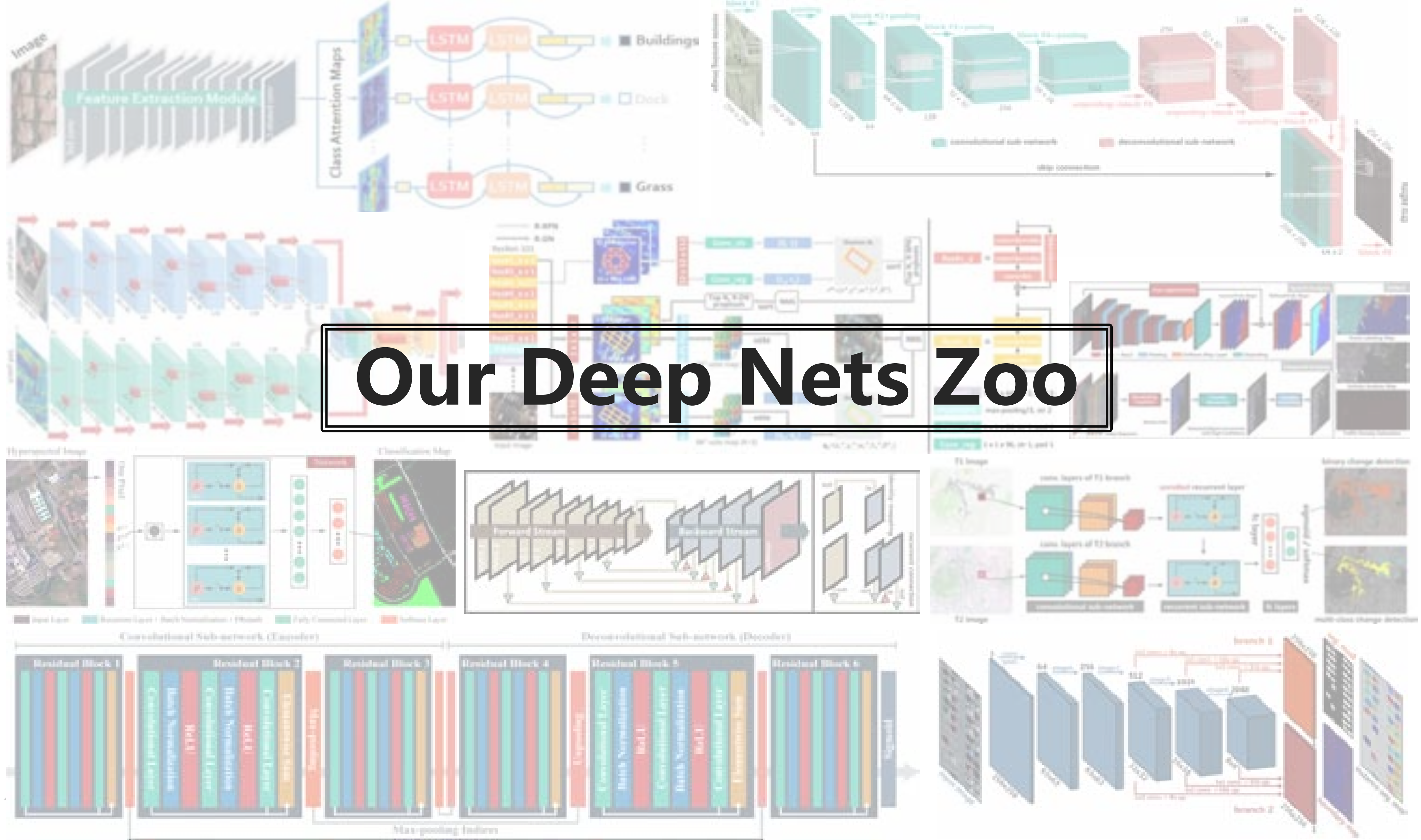
– Solving non-linear inverse problems in atmospheric sensing

– Merging multi-decadal satellite data for climate studies



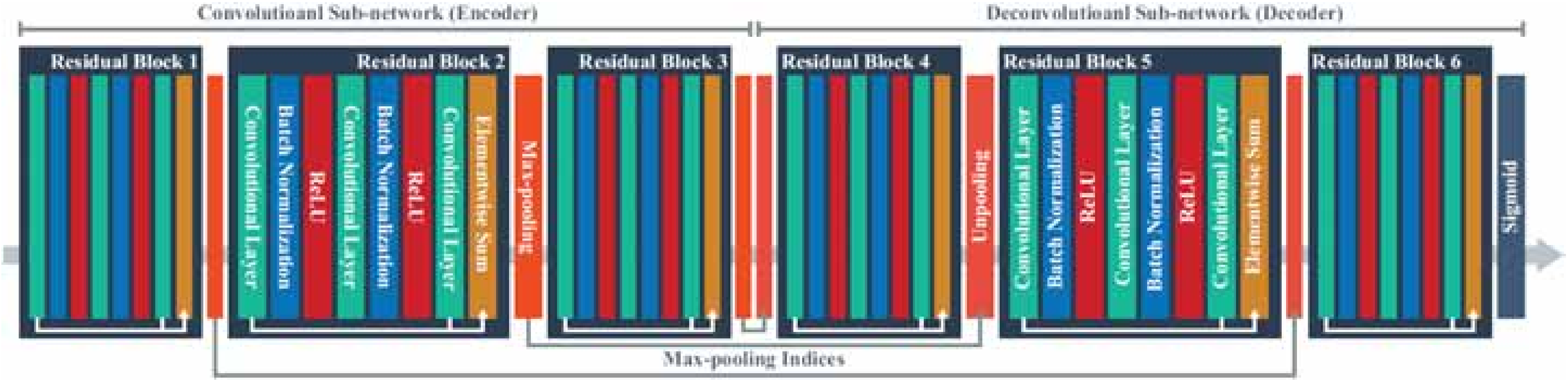


Our Deep Nets Zoo



Hyperspectral Image Analysis

Unsupervised Spectral-Spatial Feature Learning via Deep Residual Conv-Deconv Net

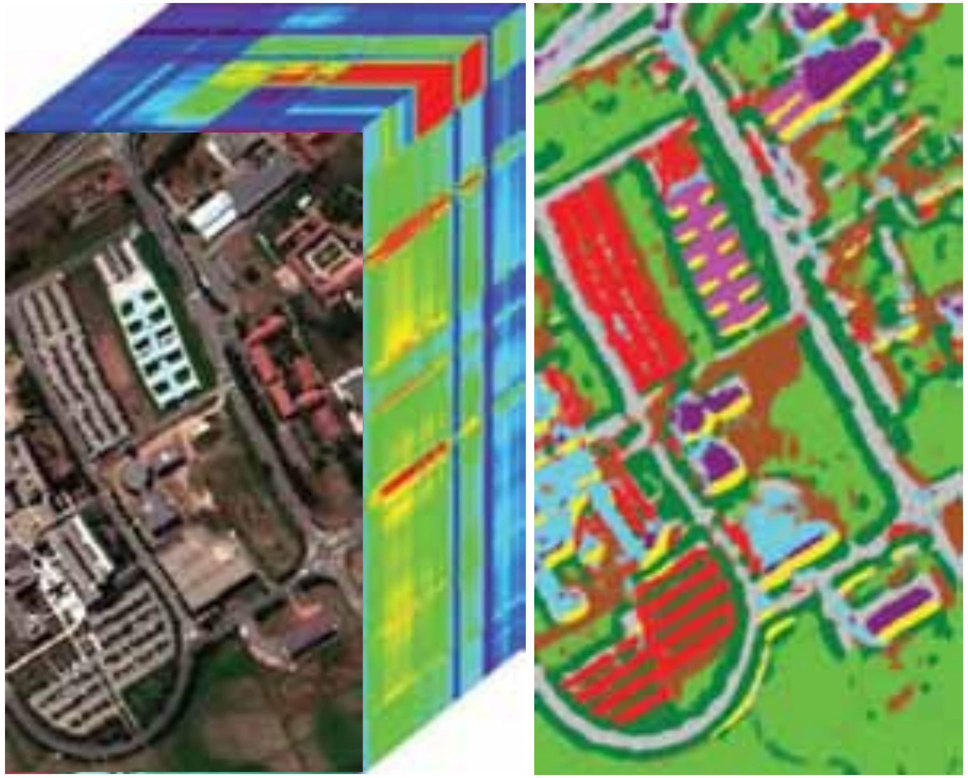


Mou, Ghamisi, and Zhu, *IEEE TGRS* 56 (1), pp. 391-406, 2018.

DLR

Unsupervised Spectral-Spatial Feature Learning via Deep Residual Conv-Deconv Net

Application I: Classification



University of Pavia, Italy

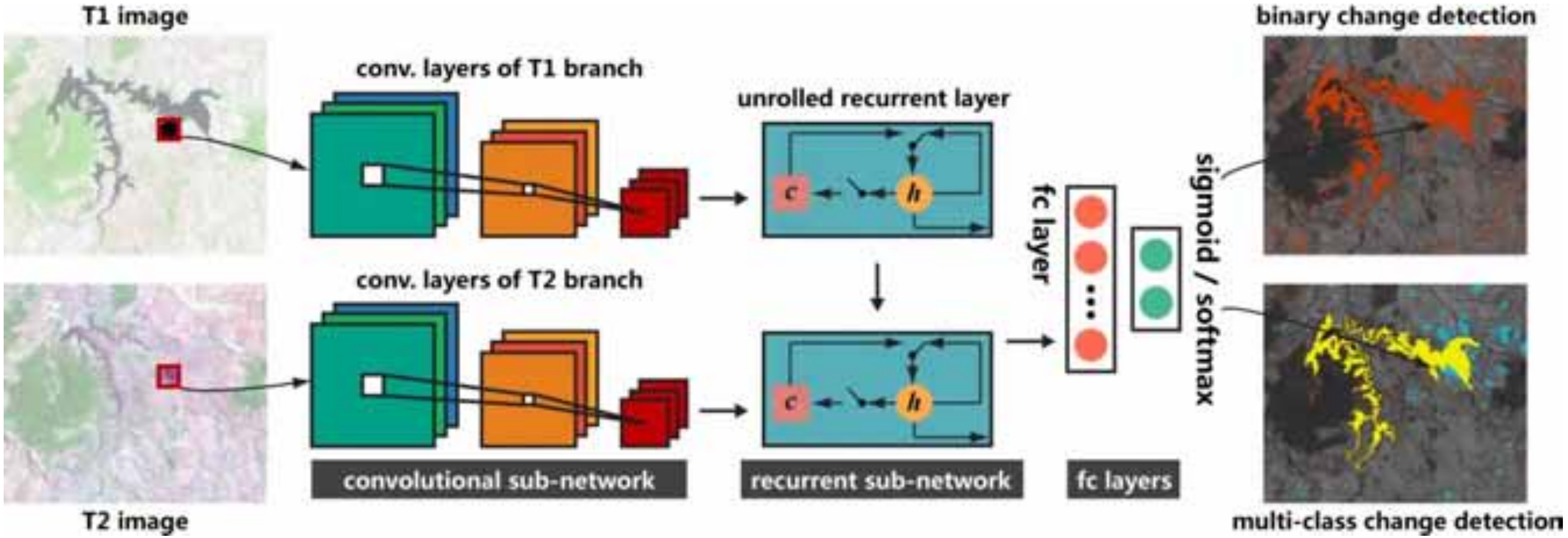
Application II: "Free" Object Localization

- We found some neurons in our network own good description power for semantic visual patterns in the object level. For example, the neurons **#52** and **#03** can be used to precisely capture **metal sheets** (left) and **vegetative covers** (right).

Mou, Ghamisi, and Zhu, *IEEE TGRS* 56 (1), pp. 391-406, 2018.

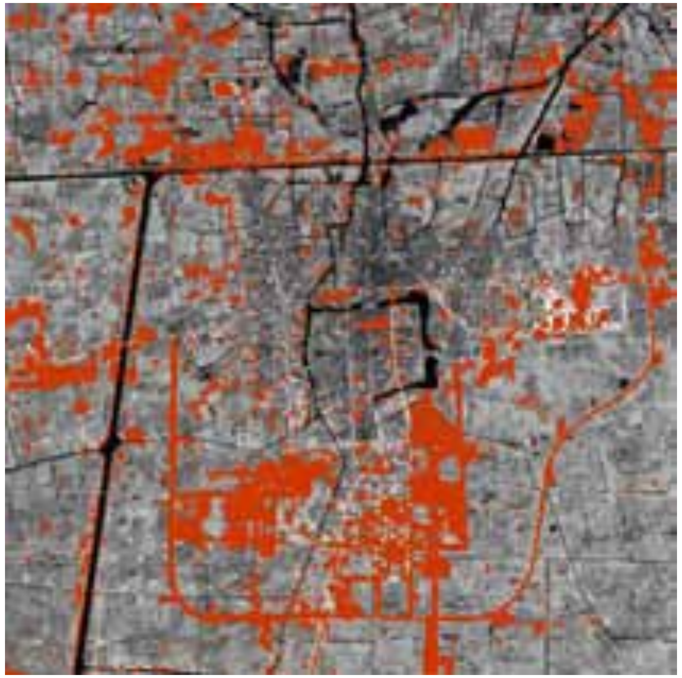
Time Series Data Analysis

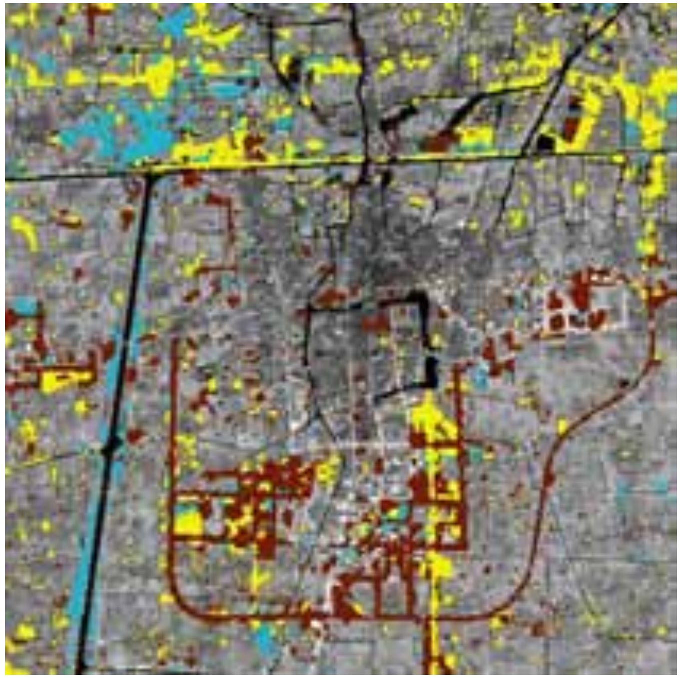
Recurrent Convolutional Neural Network for Change Detection



Mou , Bruzzone, Zhu, IEEE TGRS 57 (2), pp. 924-935, 2019

Recurrent Convolutional Neural Network for Change Detection



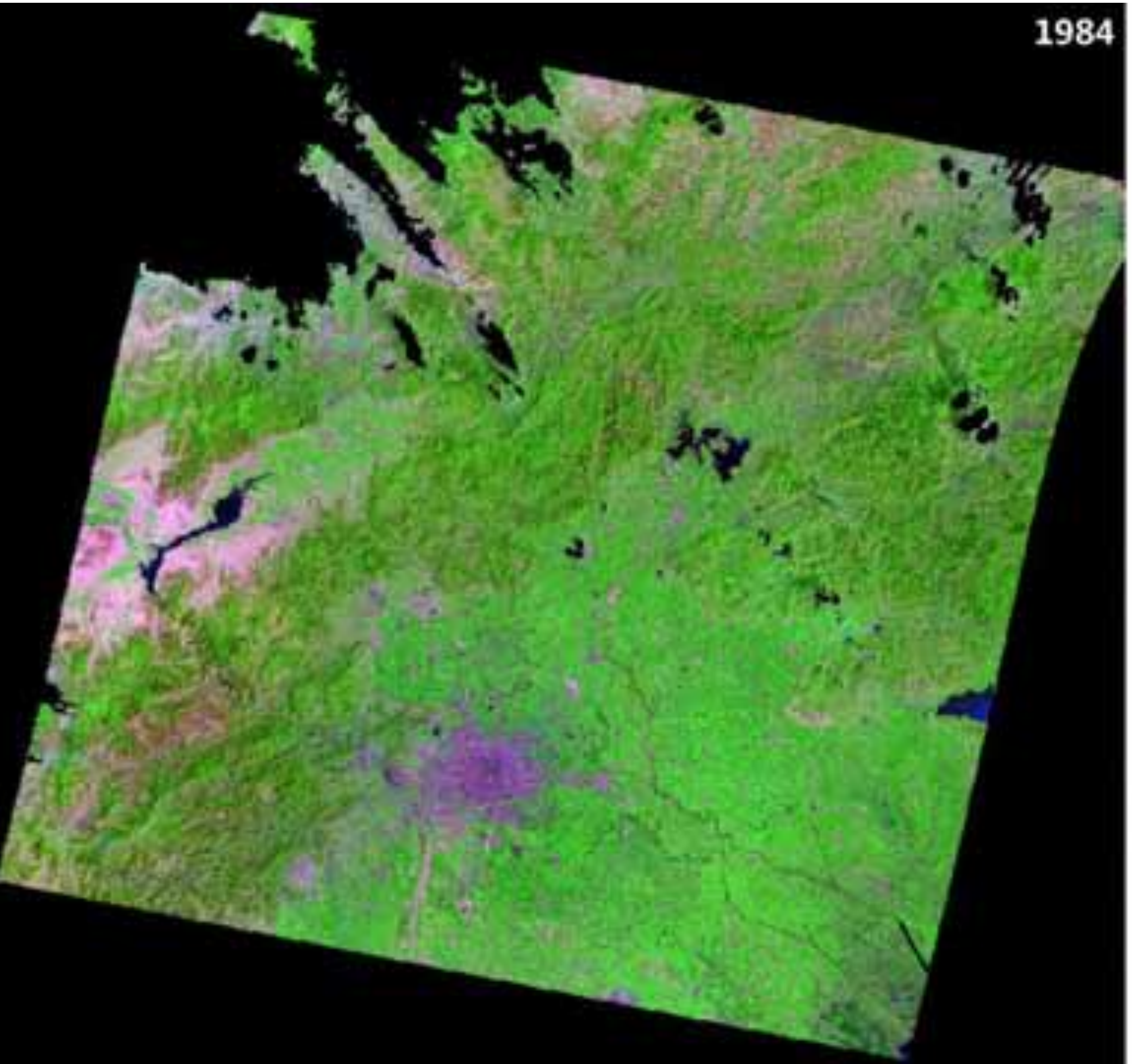


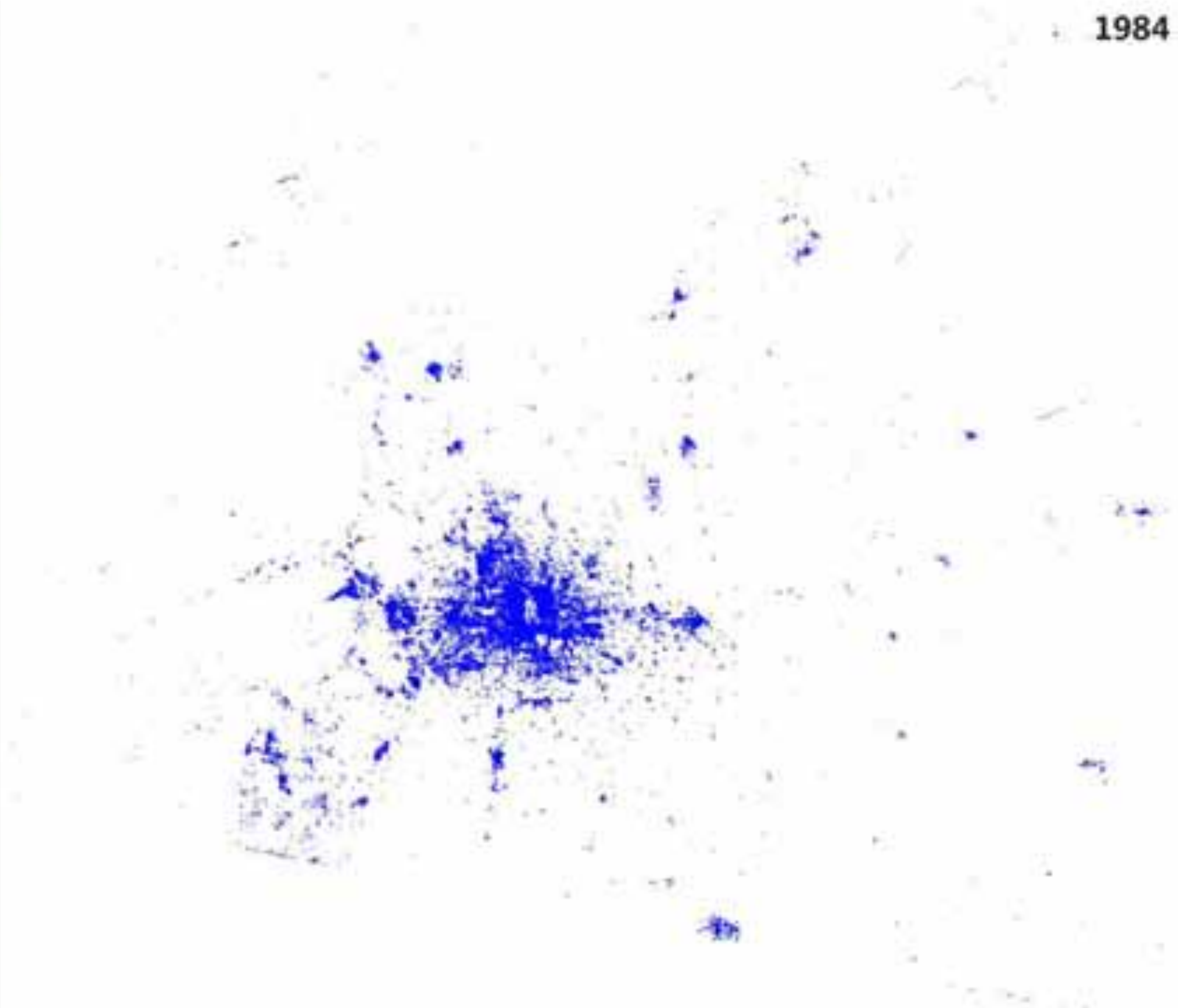
Location: Taizhou City, China

*Legend: **Changed areas** (in binary change detection); **city expansion**; **soil change**; **water change***

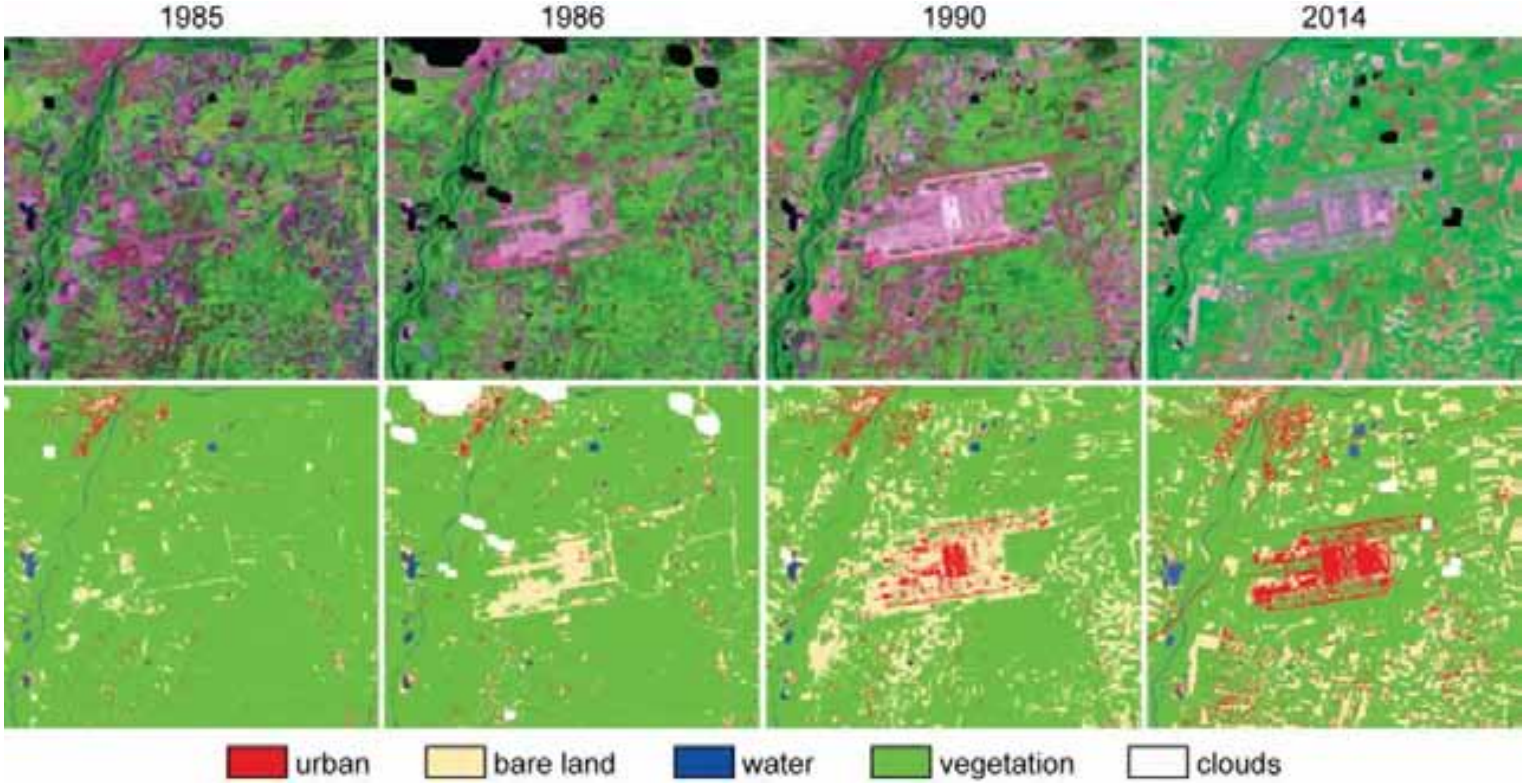
Mou , Bruzzone, Zhu, IEEE TGRS 57 (2), pp. 924-935, 2019

Example – Urban Growth of Beijing (1984 - 2016)





Munich Airport



Global Applications with Sentinels

Global Cloud Cover – 67%

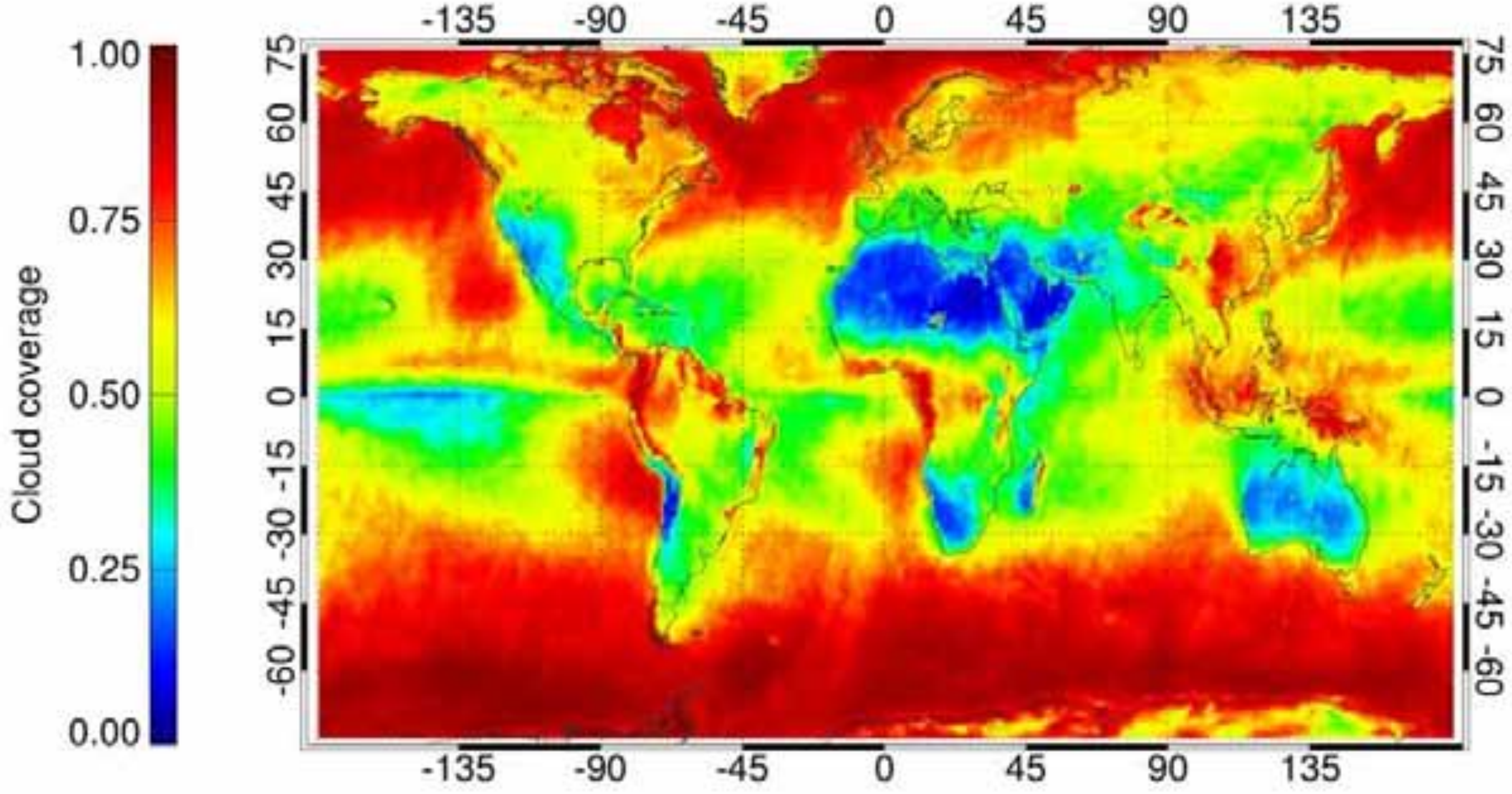
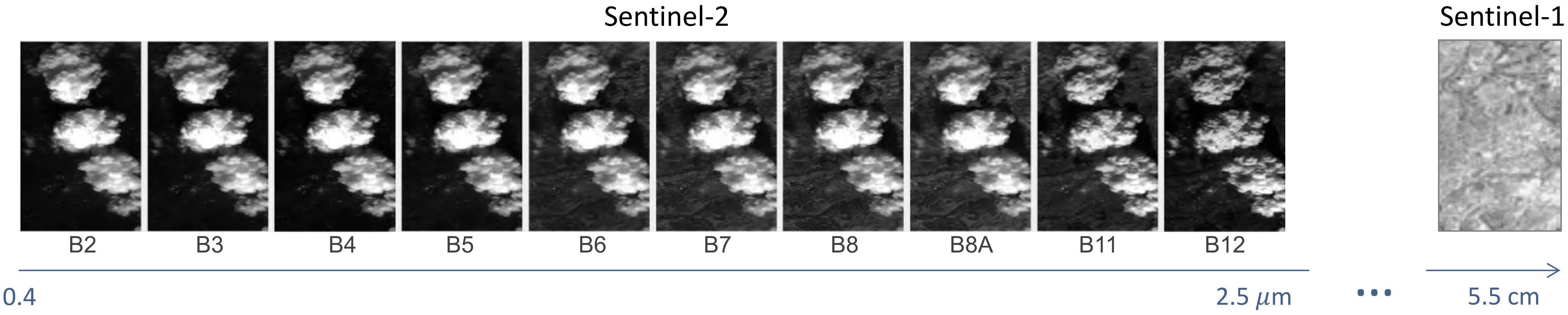


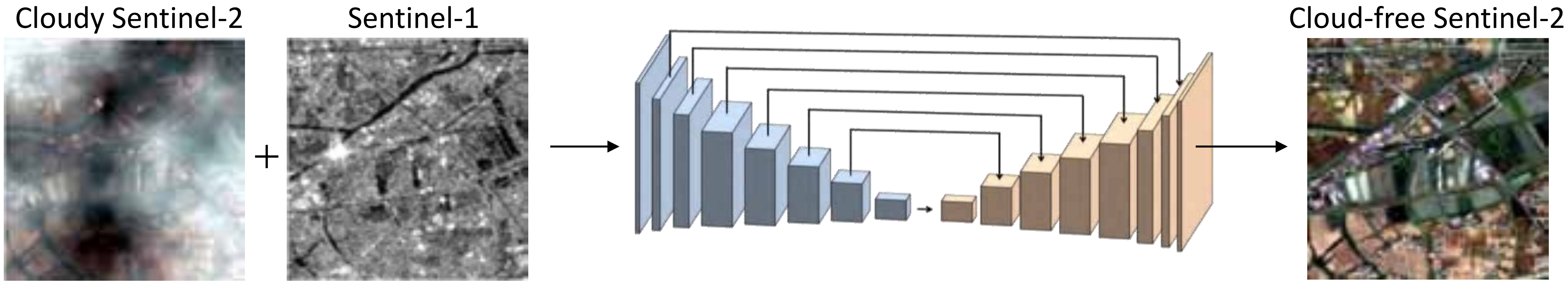
Image: ESA/Cloud-CCI

cGAN for Removing Clouds from Sentinel-2 Data using Cloud-free Radar Data

Motivation: Optical sensors cannot penetrate clouds, but microwaves do.



Objective: Train generative adversarial network to produce cloud-free optical imagery

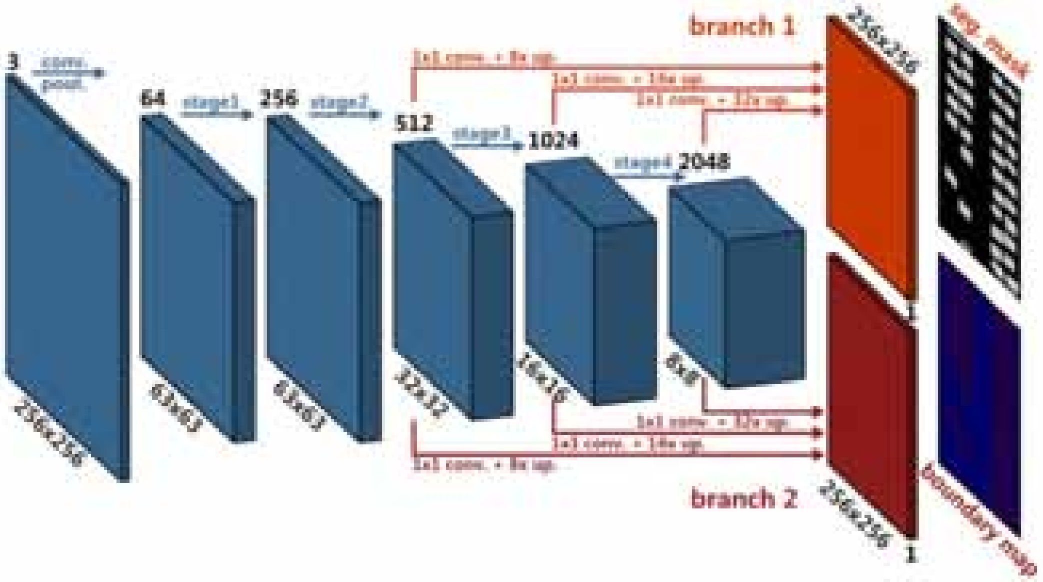


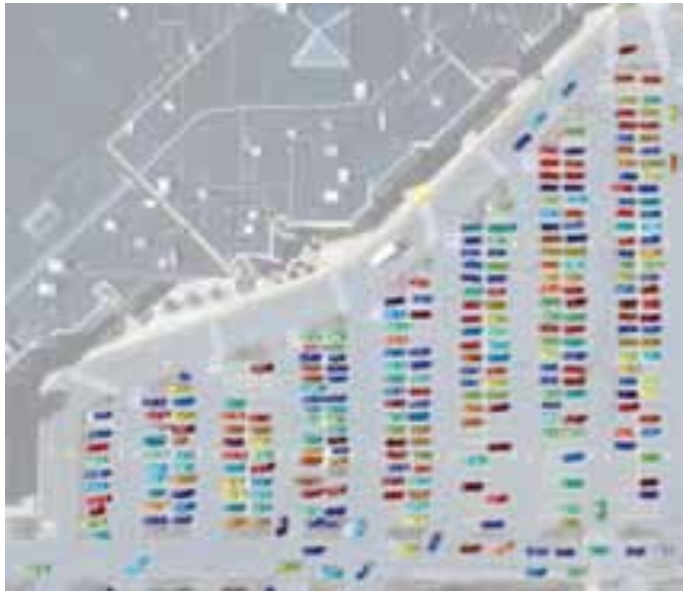
Grohnfeldt, Schmitt, **Zhu** (2018), Proceeding of the ISPRS TC II Symposium 2018, Riva del Garda, Italy.

High Resolution Remote Sensing Imagery Analysis

Shi , Li, Zhu, IEEE GRSL, in press, 2019

Multi-task CNNs for Car Instance Segmentation





Mou & Zhu, IEEE TGRS 56(11), pp. 6699-6711, 2018.

Li et al., IEEE TGRS, in press, 2019

Open Issues

– **novel applications**, other than classification and detection related tasks
– **transferability** of deep nets
– **automated deep topology learning**
– **very limited annotated data** in remote sensing
– how to **benchmark** the fast growing deep-learning algorithms in remote sensing?
– how to combine **physics-based modeling and deep neural network**?
– and many more…

MuDS Munich School for Data Science @ Helmholtz, TUM & LMU

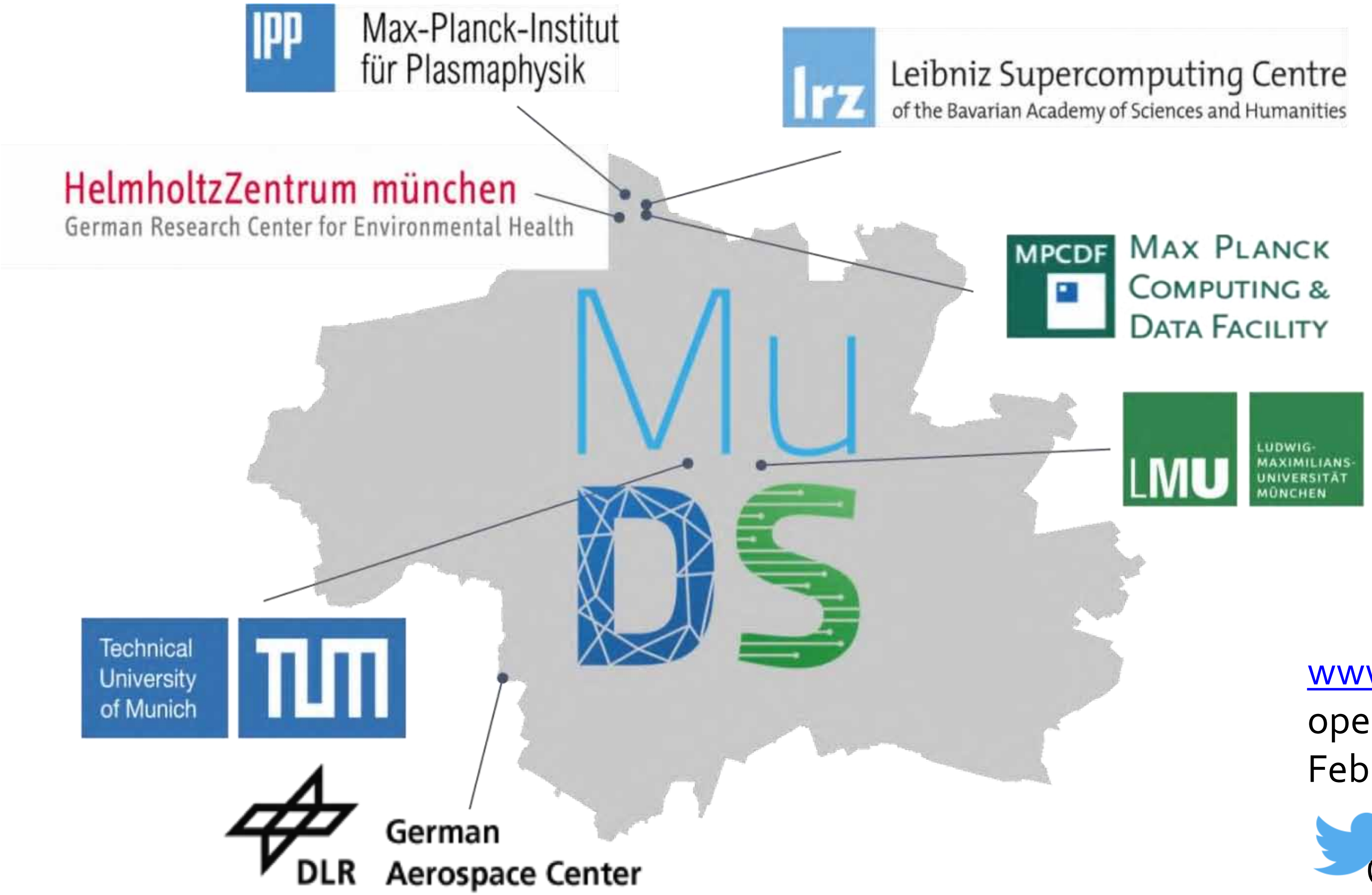
Technische Universität München

DLR Institut für Datenwissenschaften

Munich School for Data Science @ Helmholtz, TUM & LMU (MuDS)

Speakers: Fabian Theis (HMGU), Frank Jenko (IPP), Xiaoxiang Zhu (DLR)

Scale: 12M€, 38 Doctoral candidates



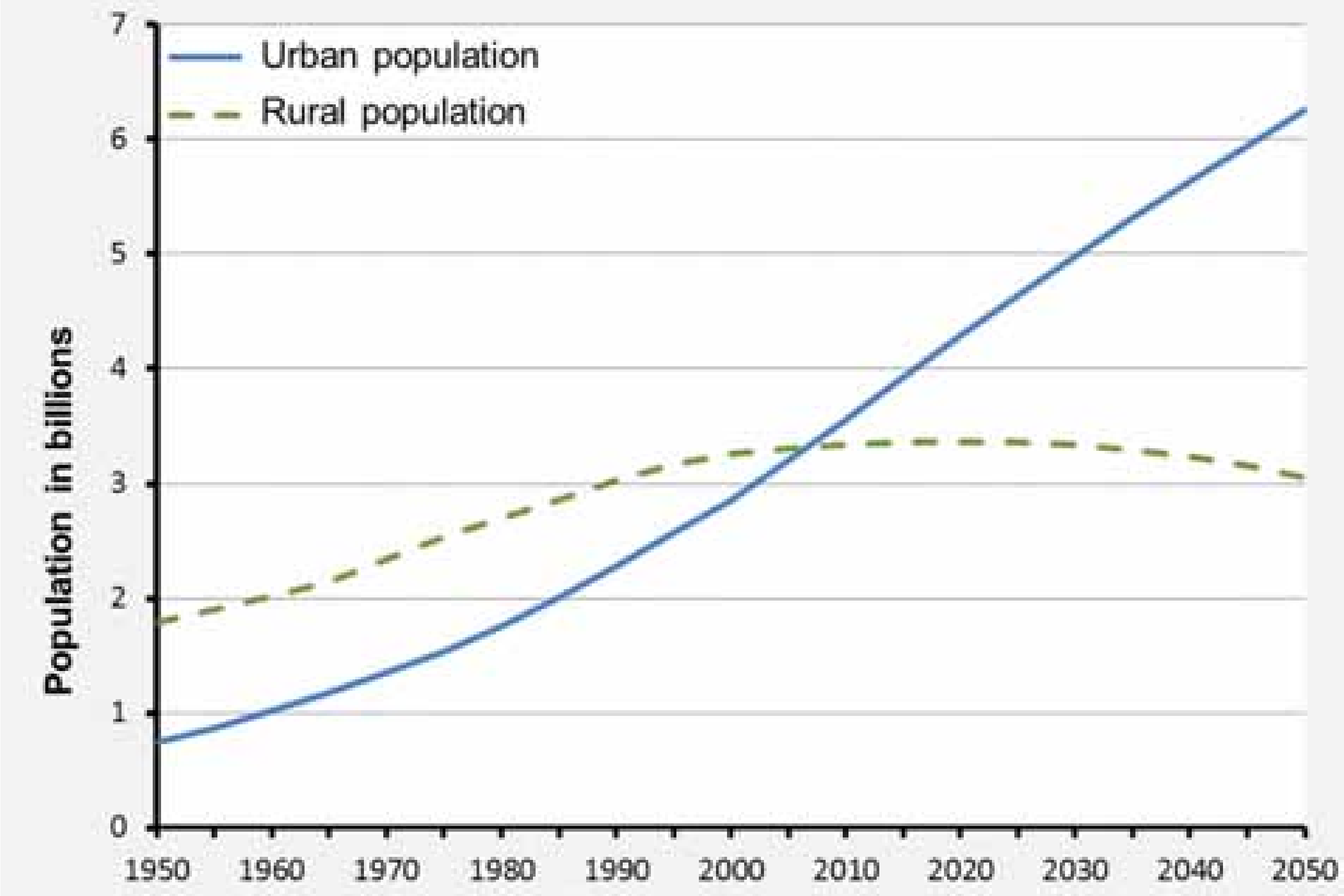
www.mu-ds.de

open for application by Feb 28th 2019

@MunichDS

Global Urban Mapping

Urban Planet



[UN, 2014]

Urban Growth Happens Mostly in Developing Areas

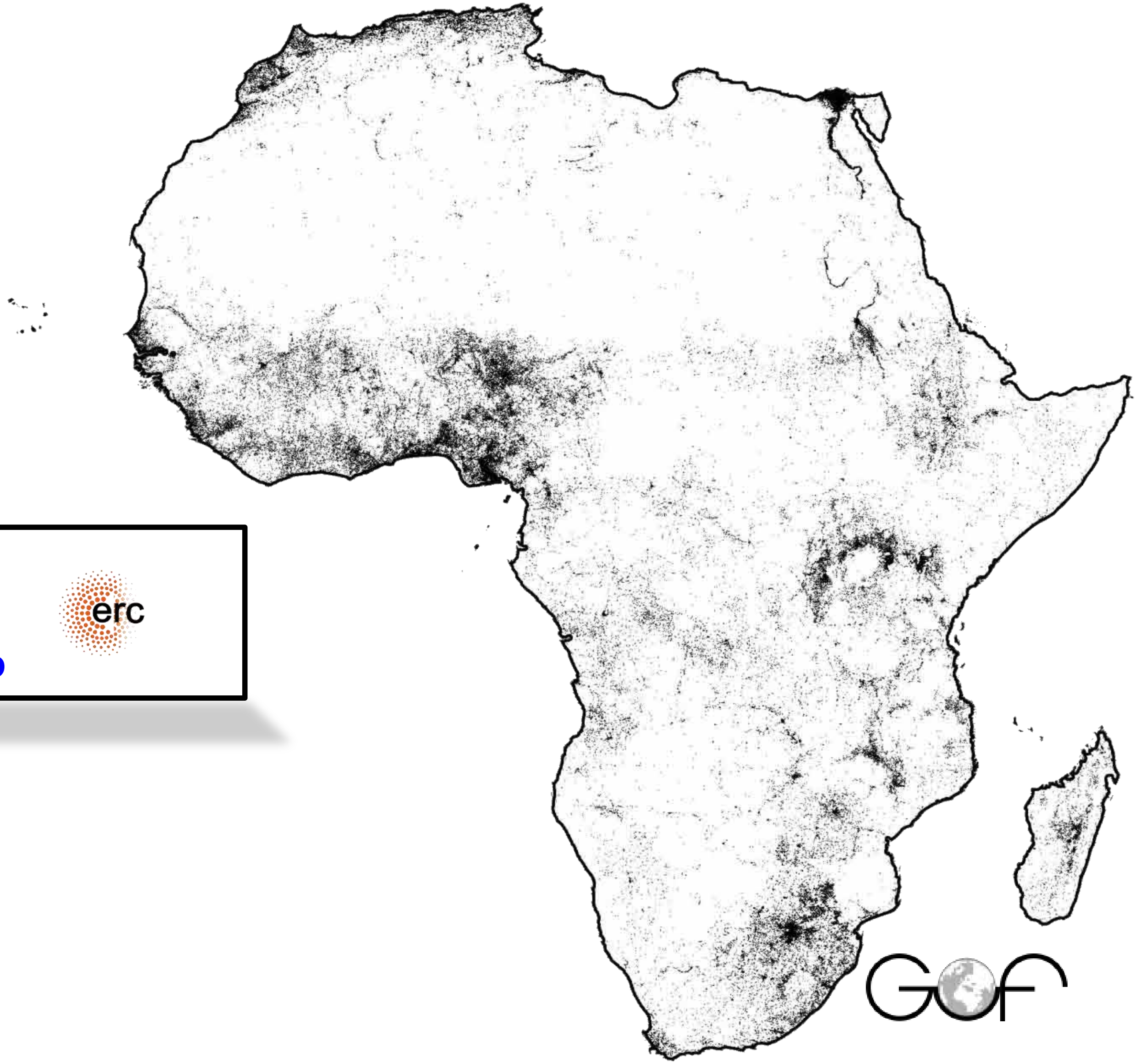

hindustantimes

Faulty wiring behind 69% of 50,000 fires in Mumbai in past decade, data reveals

Data: United Nations World Urbanization Prospects 2014. Minimum city population threshold: 300k.
Cartography: D. A. Smith, CASA UCL

So2Sat: Understanding Global Urbanization from Space to Social Networks

www.so2sat.eu



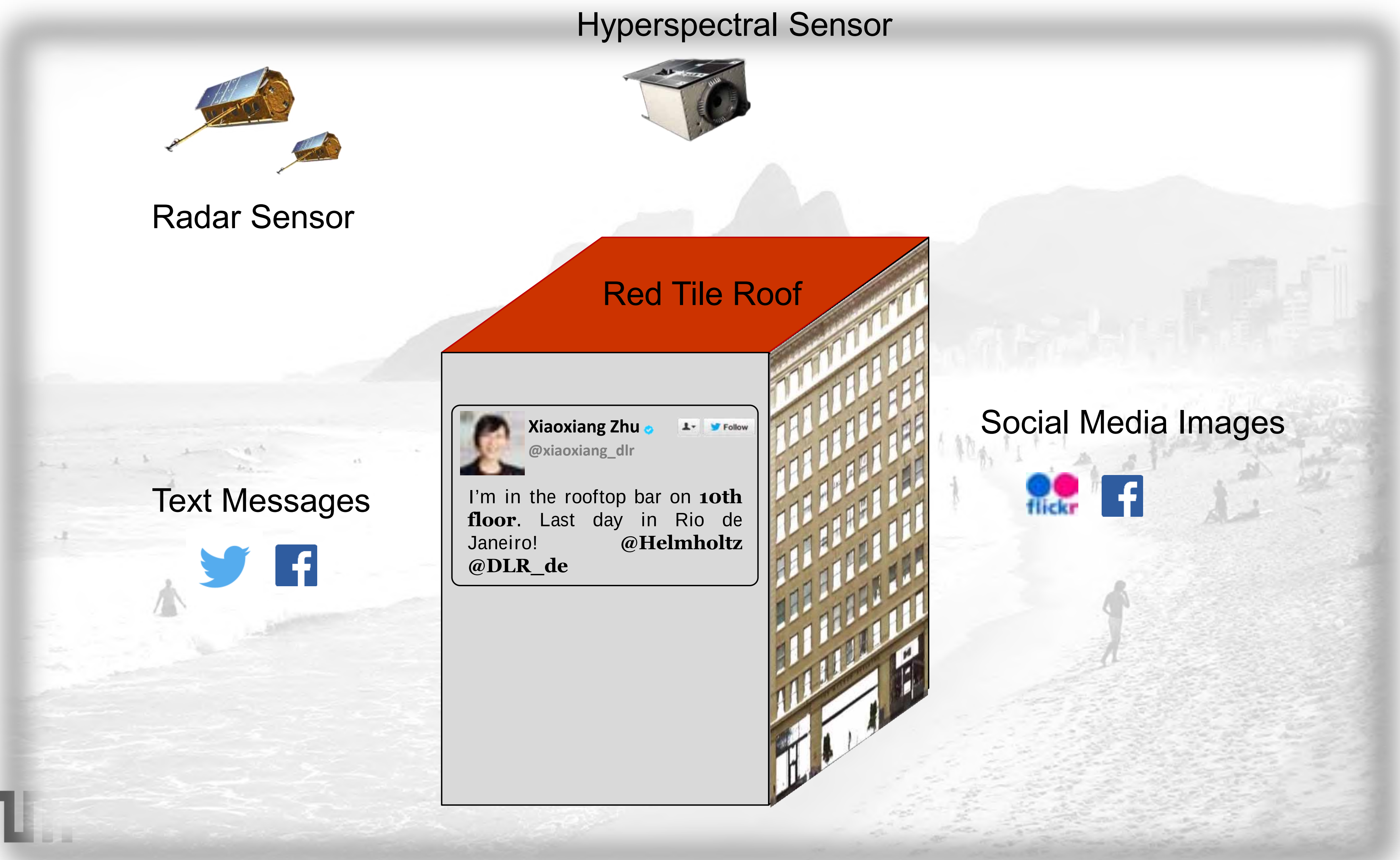
So2Sat: 3D/4D urban models
infrastructure type classification
high resolution population density map

erc

DLR TUM

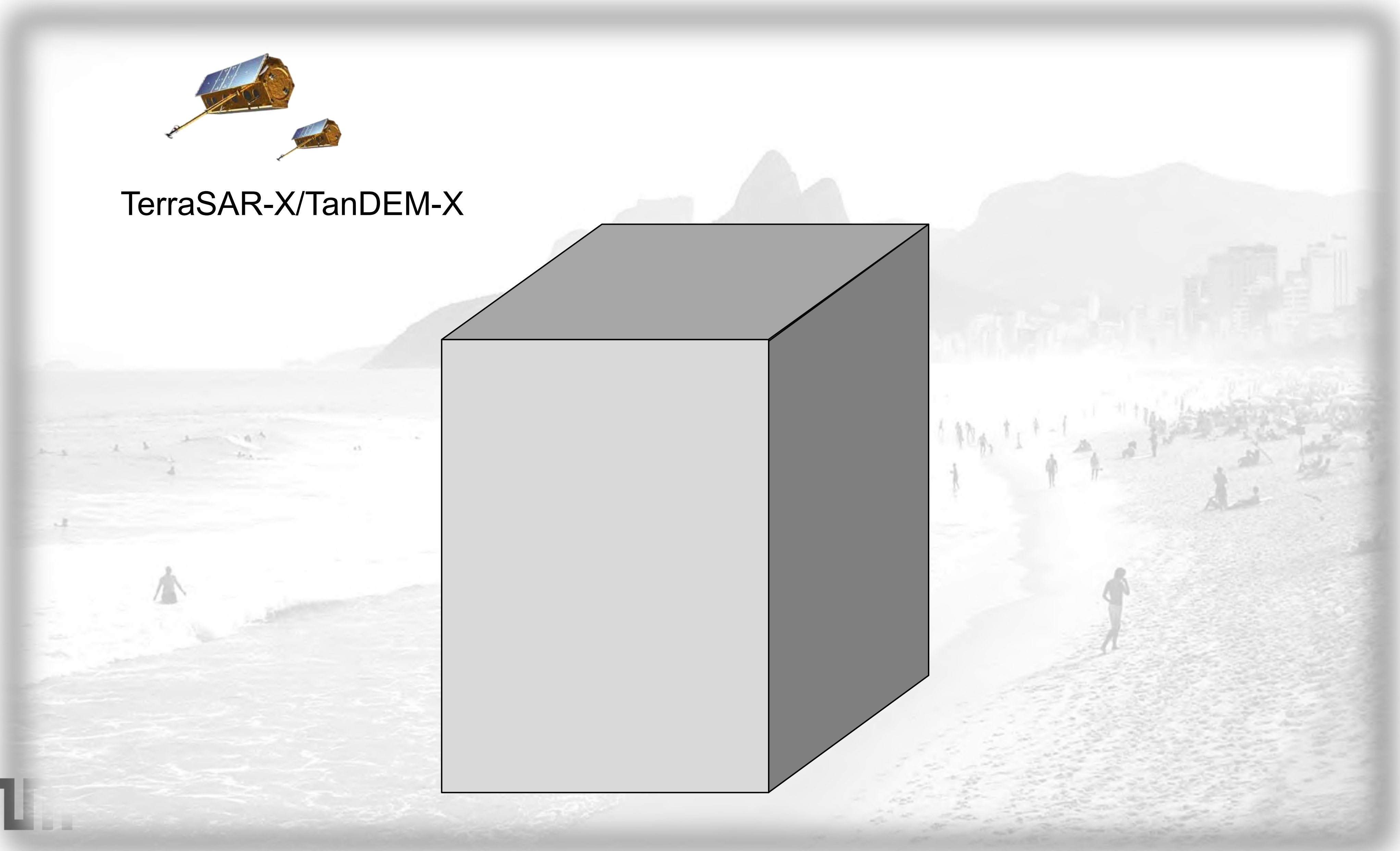
GOF

So2Sat in a Nutshell

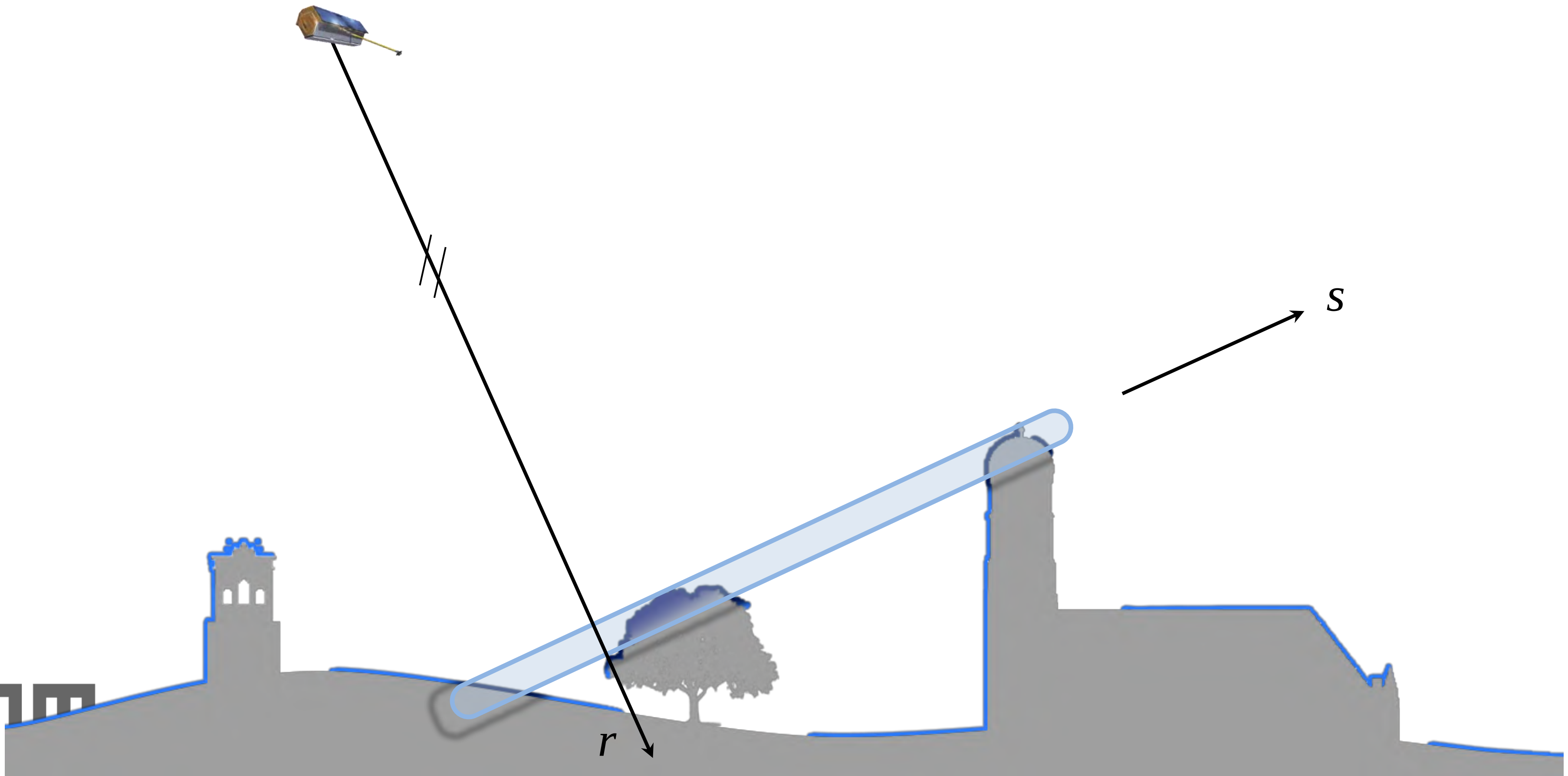



10 Petabytes = half of the archive at DFD

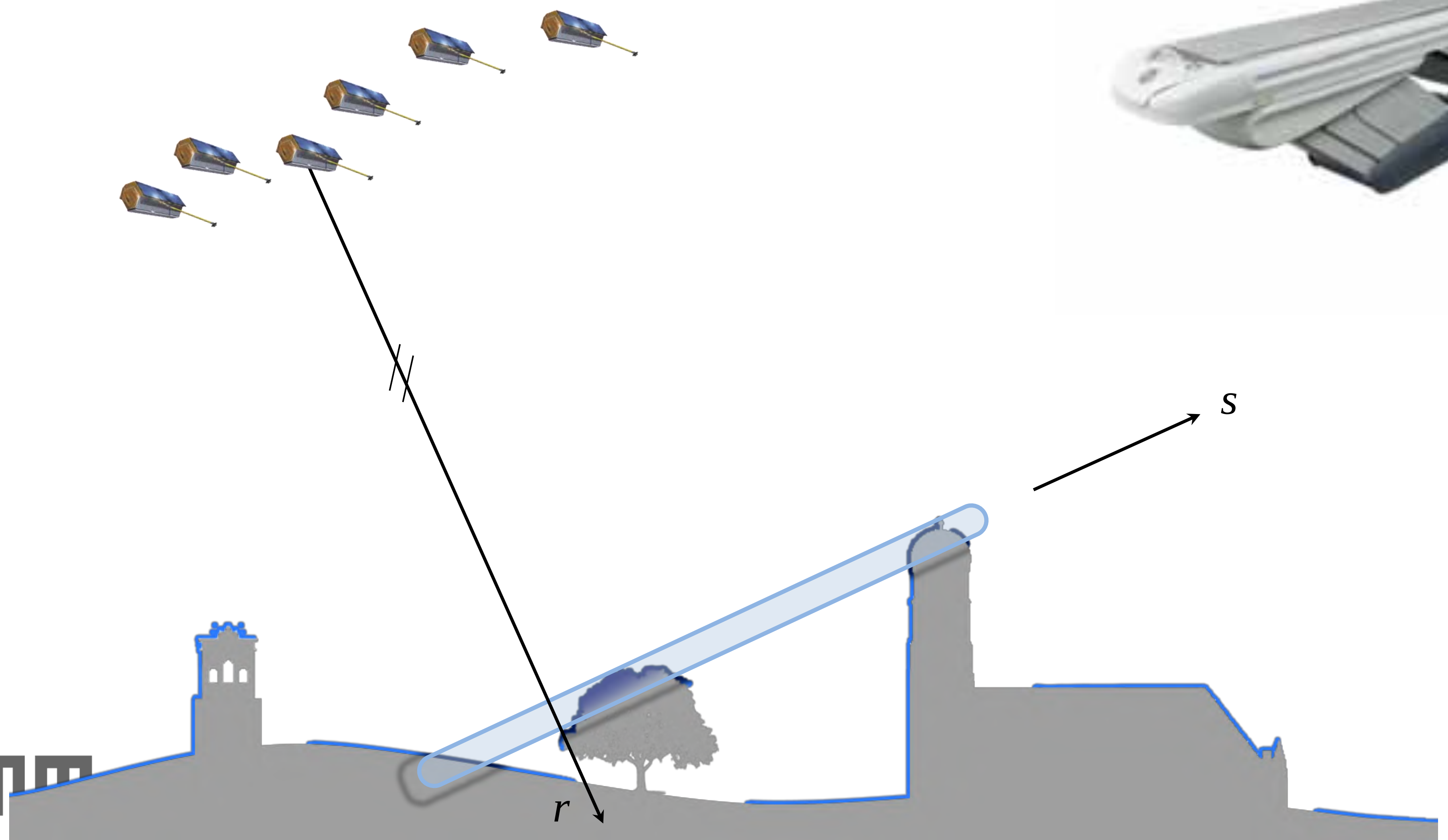
Global 3D/4D Urban Mapping



Radar Geometry in Range-Elevation Plane



Radar Tomography – "X-Ray" of the Earth



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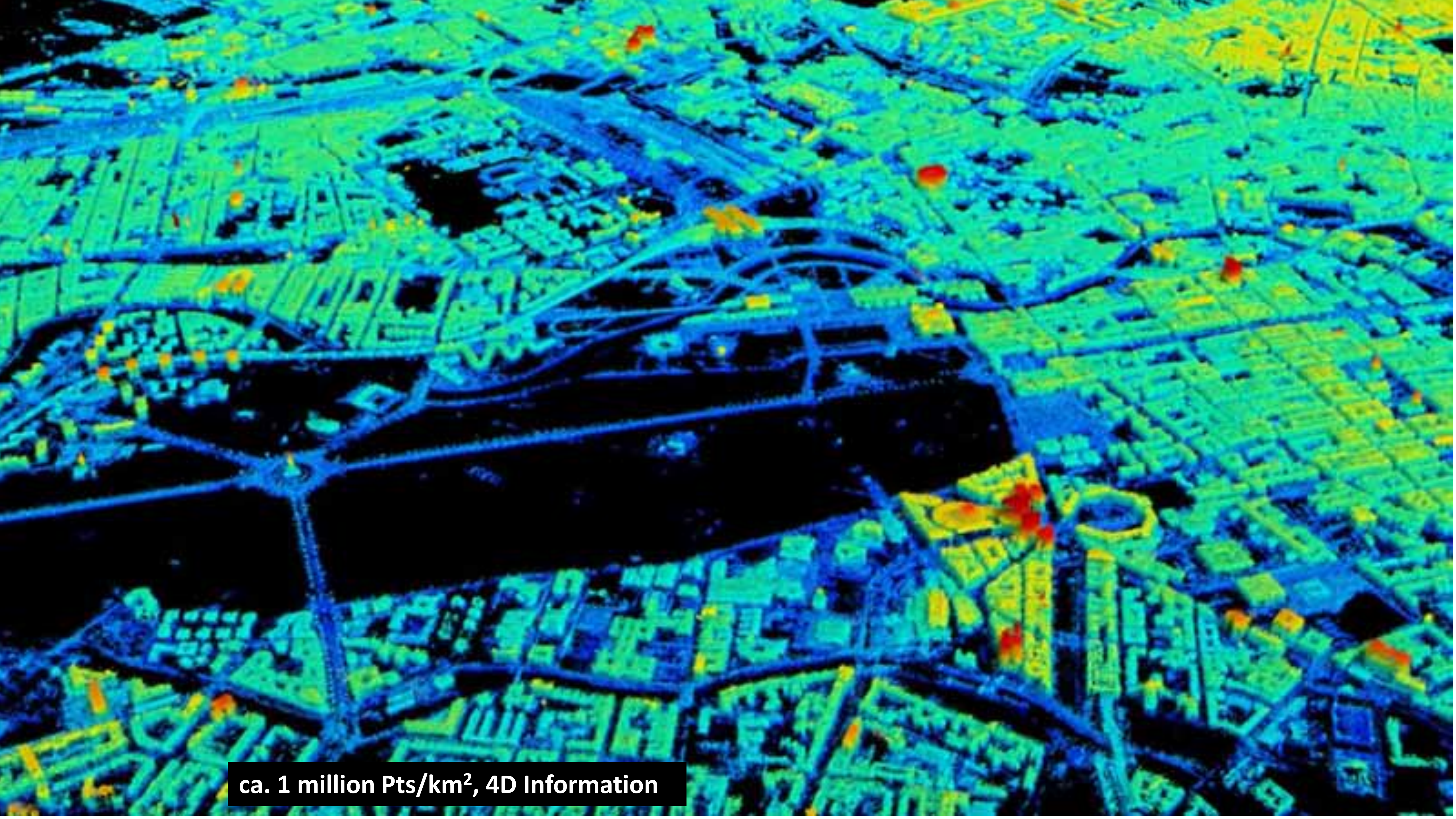
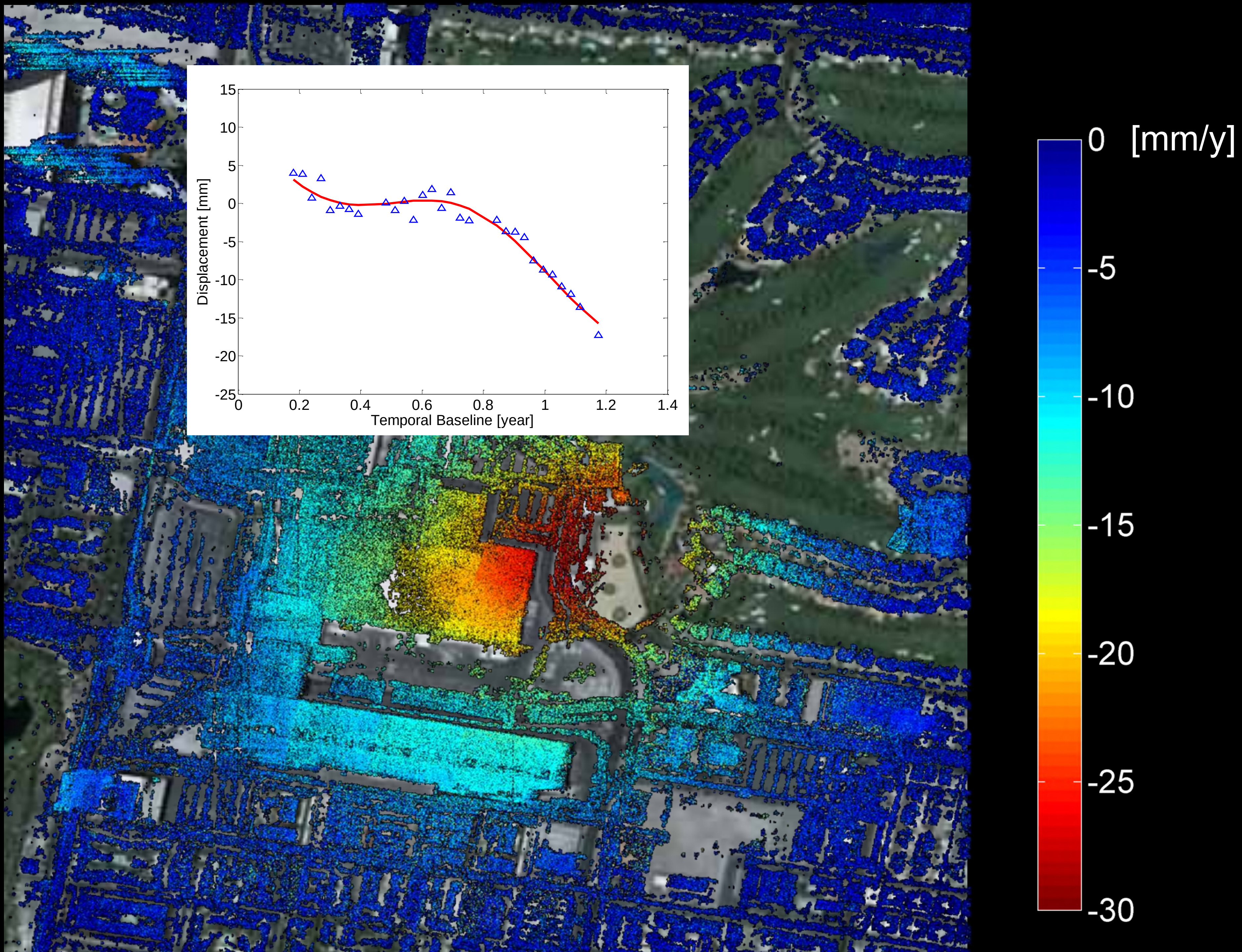
Why HPC?

4D City@ LRZ

Calculation for **every single pixel =** solving optimization problem with **a matrix dimension of ca. $10^2 \times 10^6$**

since 2012, 26mio CPU hours granted


ca. 1 million Pts/km², 4D Information



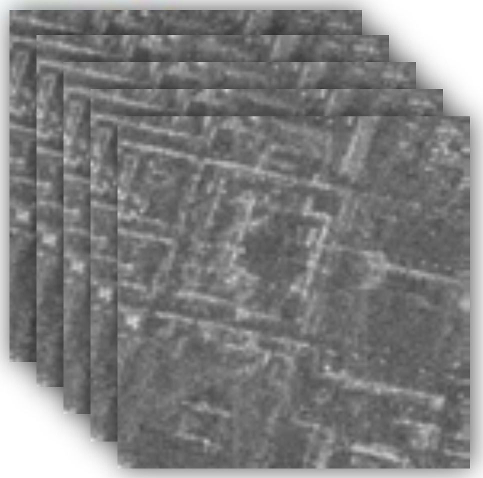
Displacement [mm]
Temporal Baseline [year]
15
10
5
0
-5
-10
-15
-20
-25
0
0.2
0.4
0.6
0.8
1
1.2
1.4
0 [mm/y]
-5
-10
-15
-20
-25
-30

global?

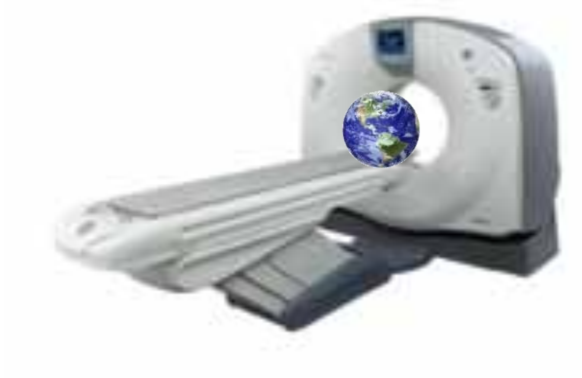
TanDEM-X for Global Coverage, But…

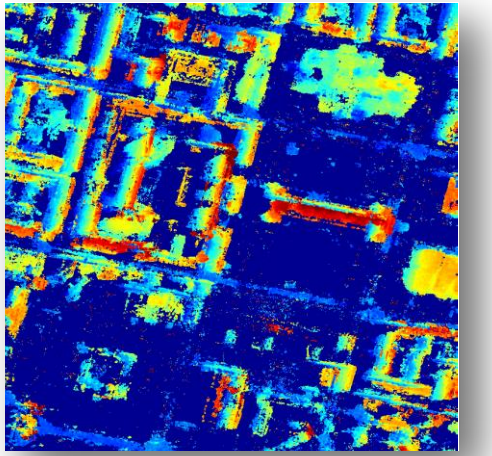
medium resolution , small number of images

Signal Processing Algorithms



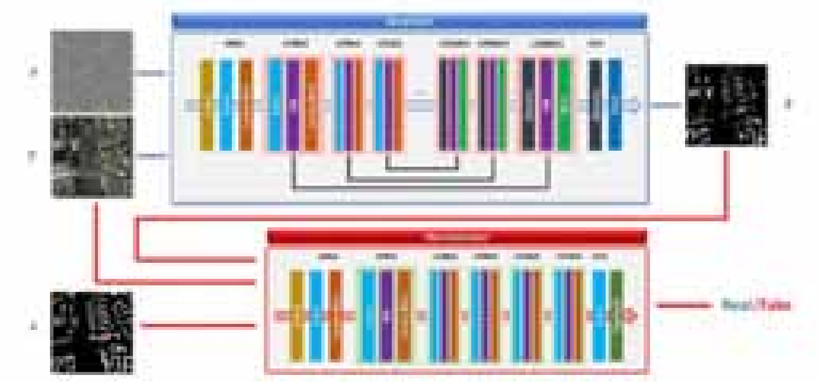
X-Ray of the Earth

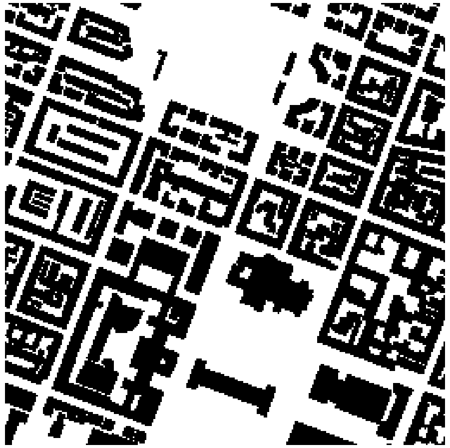




Building heights

Deep Learning Algorithms

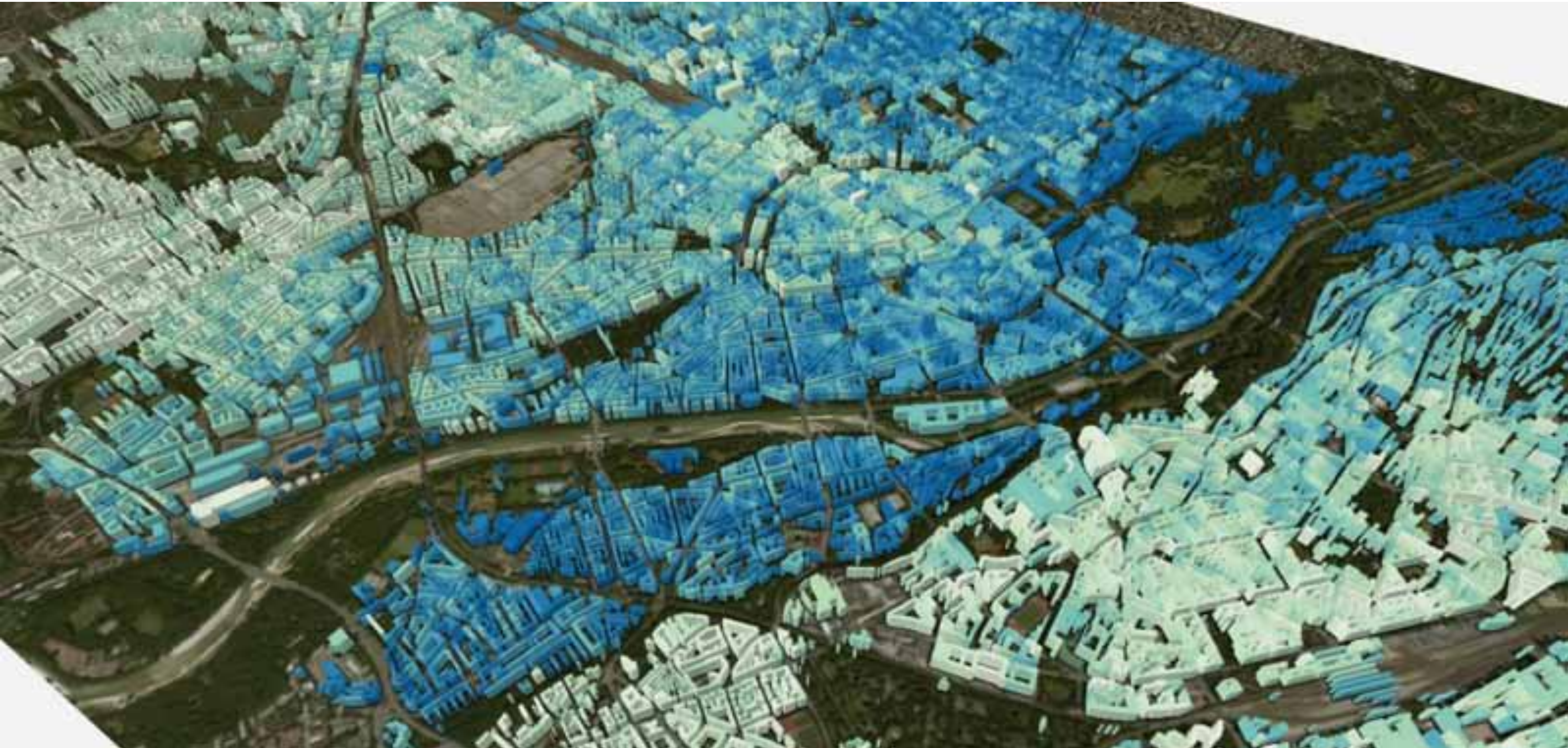




Building shapes

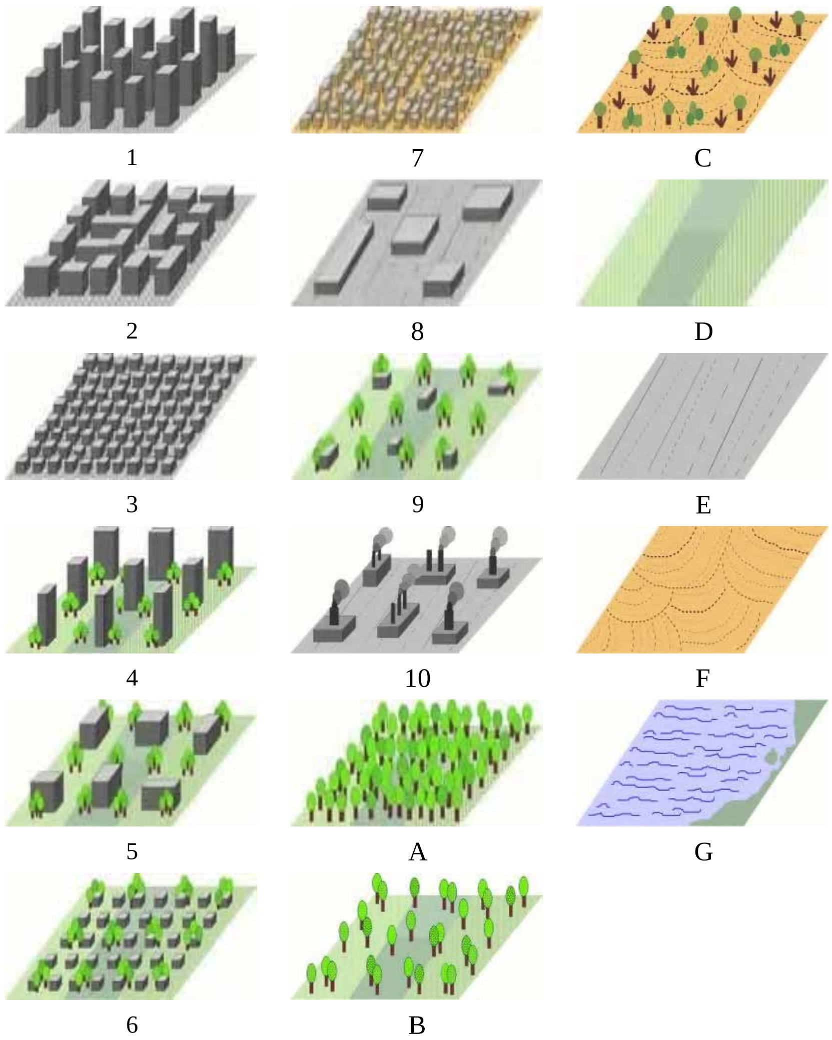
First Impression of the Global 3D Urban Models

accuracy better than **2m**

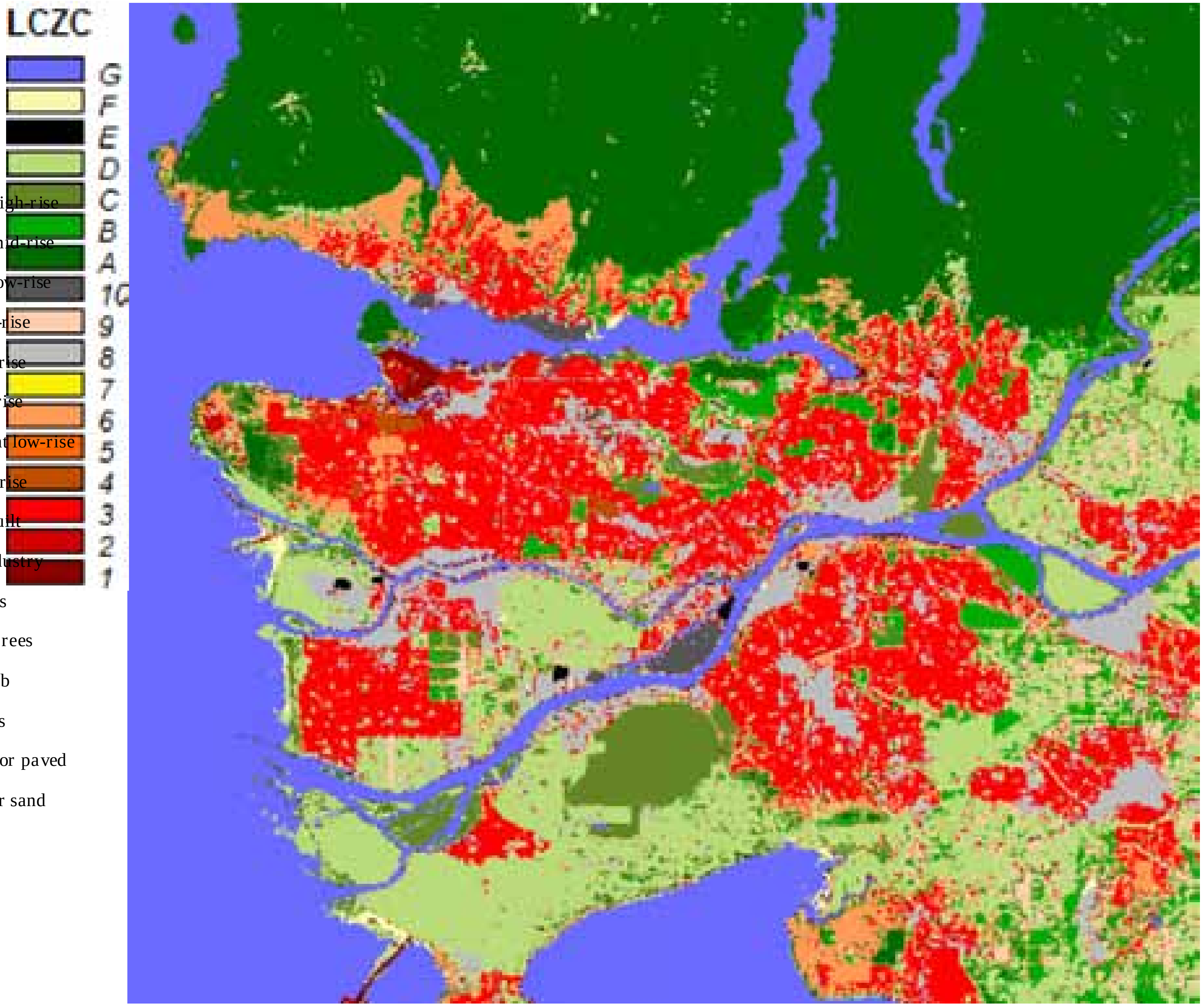


settlement type? → morphological structure first

Global Local Climate Zones Classification
will be global soon



1: Compact high-rise
2: Compact mid-rise
3: Compact low-rise
4: Open high-rise
5: Open mid-rise
6: Open low-rise
7: Lightweight low-rise
8: Large low-rise
9: Sparsely built
10: Heavy industry
A: Dense trees
B: Scattered trees
C: Bush, scrub
D: Low plants
E: Bare rock or paved
F: Bare soil or sand
G: Water



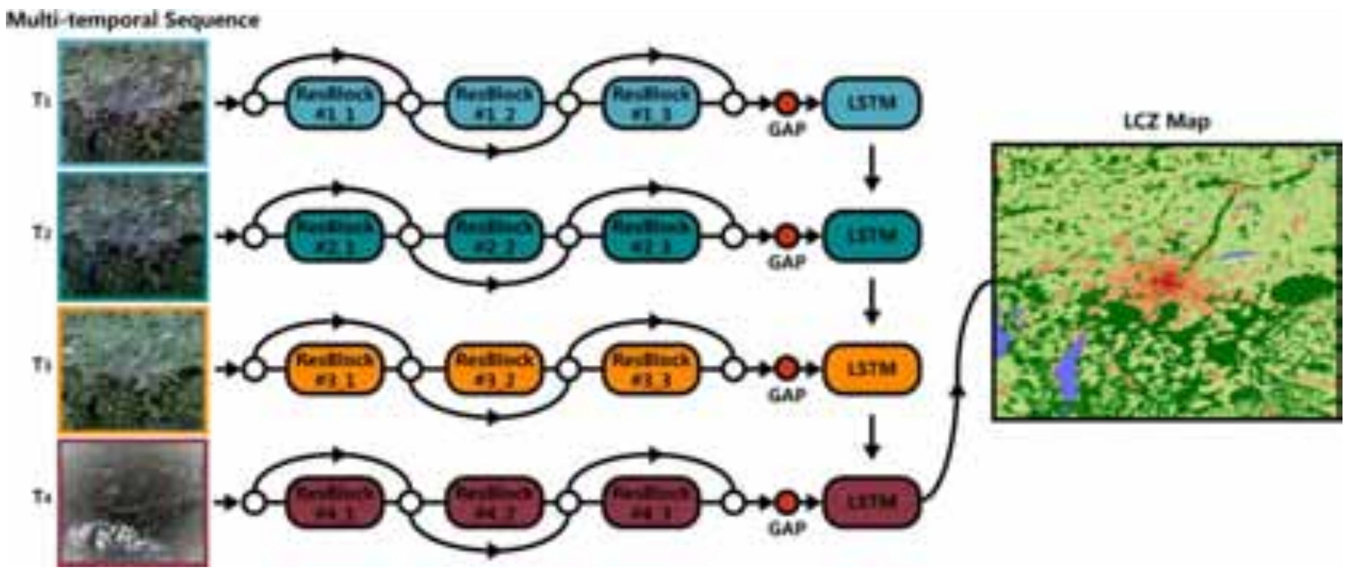
So2Sat LCZ42 Benchmark Dataset

– Hand labelled 42 cities covering 10 culture zones

– Data:
  – Sentinel-1
  – Sentinel-2, seasonal

– 10 votes for each label

Labeling effort: 15 person × 1 Month/person



CANADA
UNITED STATES
Pacific Ocean
Atlantic Ocean
BRAZIL
RUSSIA
CHINA
Indian Ocean
AUSTRALIA

DLR/StepStone/AliCloud Tianchi Contest 2018 Germany

Contestants

200k data talents in 91 countries and regions

Task

Solution

TIANCHI
Data Scientists

Demand

Product

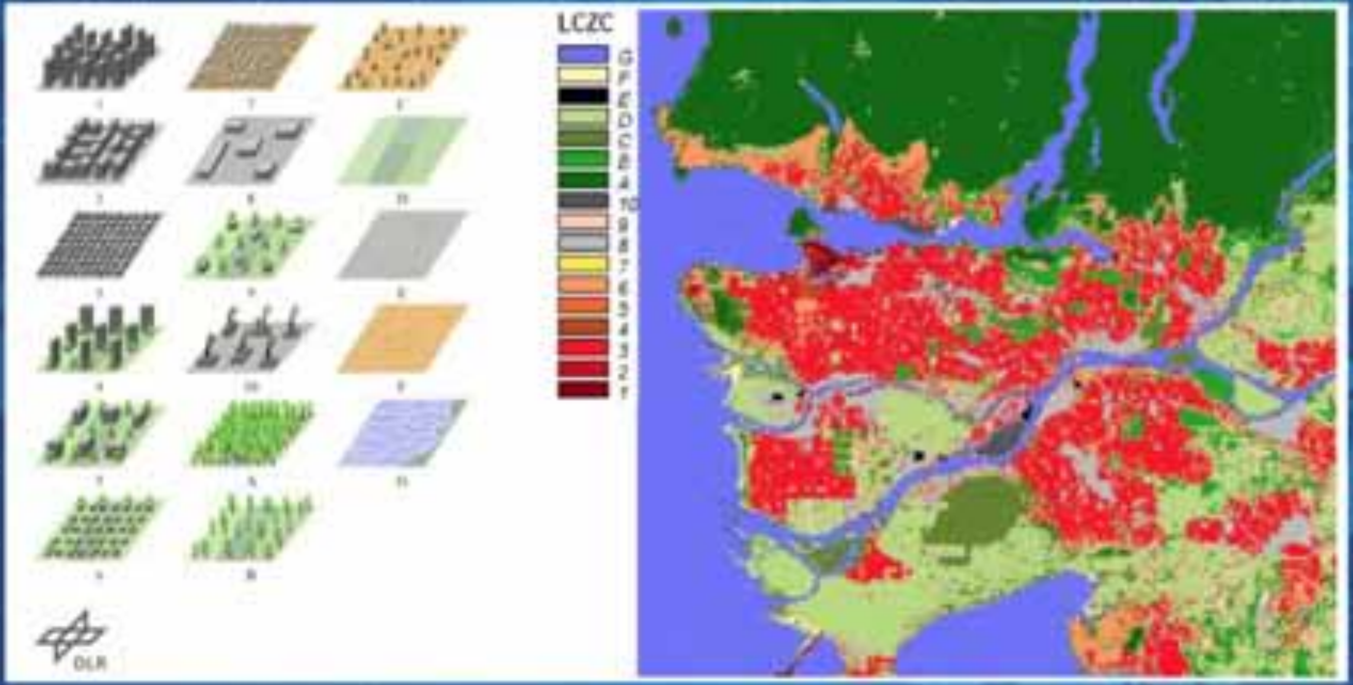
Customers

StepStone

DLR

Challenge

- Consolidate the data obtained from different satellite sensors
- Classify the image patches into 17 classes (local climate zones)



LCZ applications

- Quantifying Urban Heat Island magnitude
- Classifying weather stations
- Mapping urban terrain
- Assessing social inequalities

tweeting for social good?

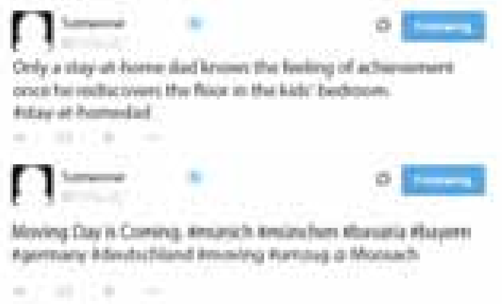
Building Settlement Type Classification

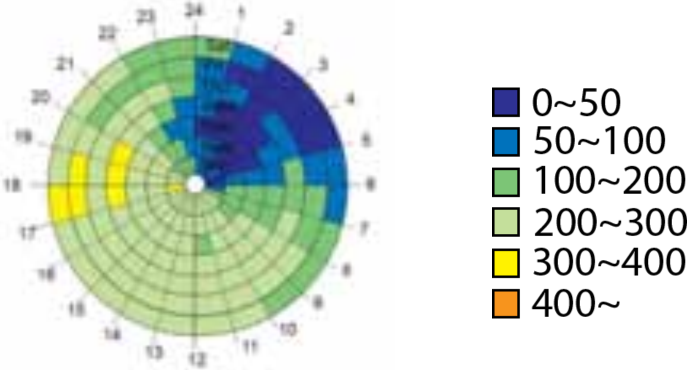
– by the Fusion of Remote Sensing and Social Media Text Messages

Text Messages

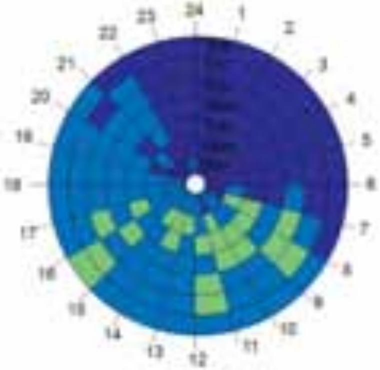
Tweets for Building Functions Identification

residential

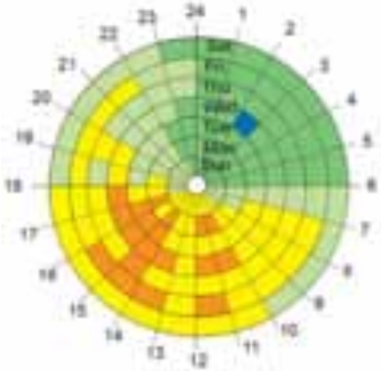




non-residential



mixed used



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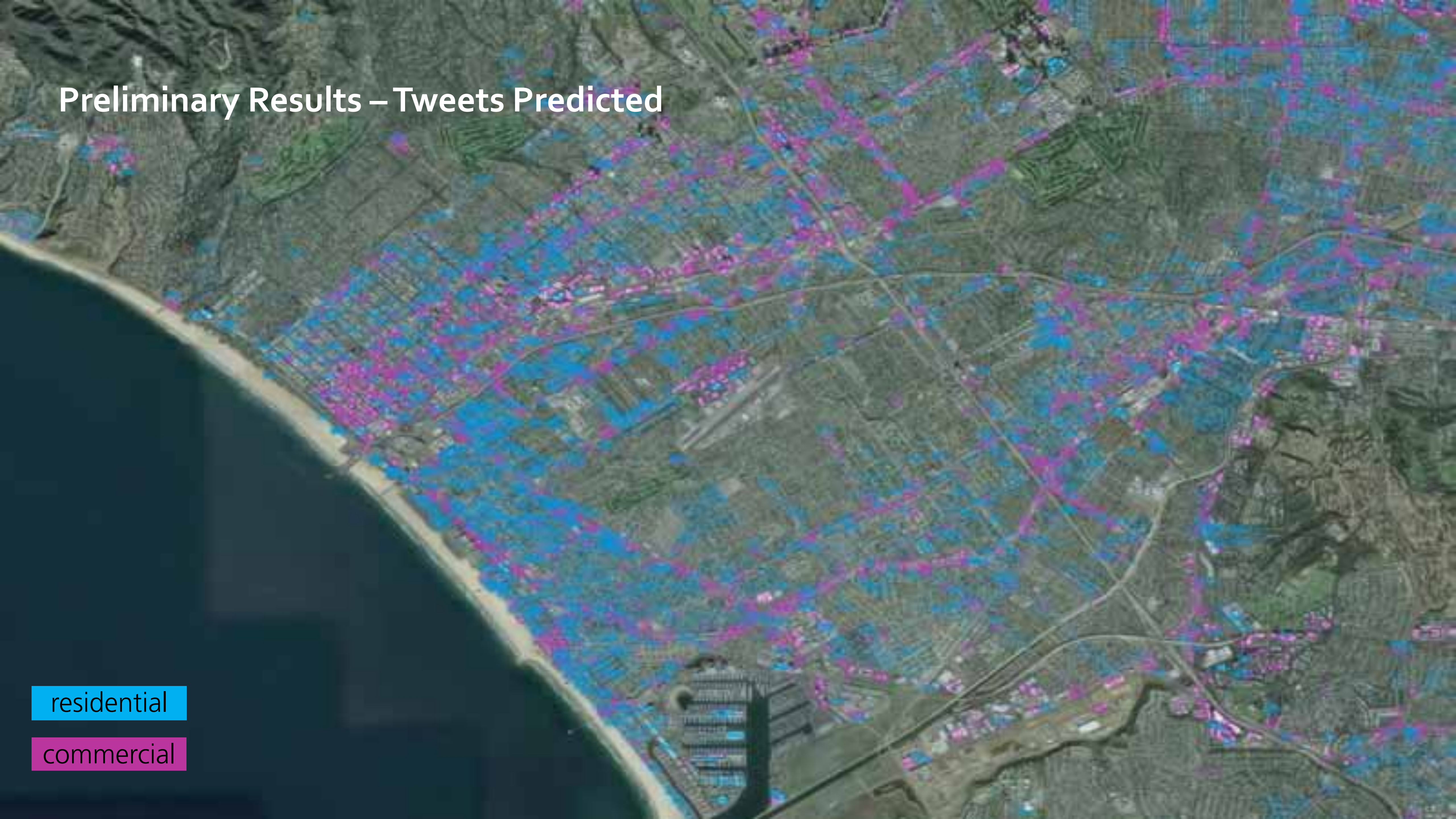
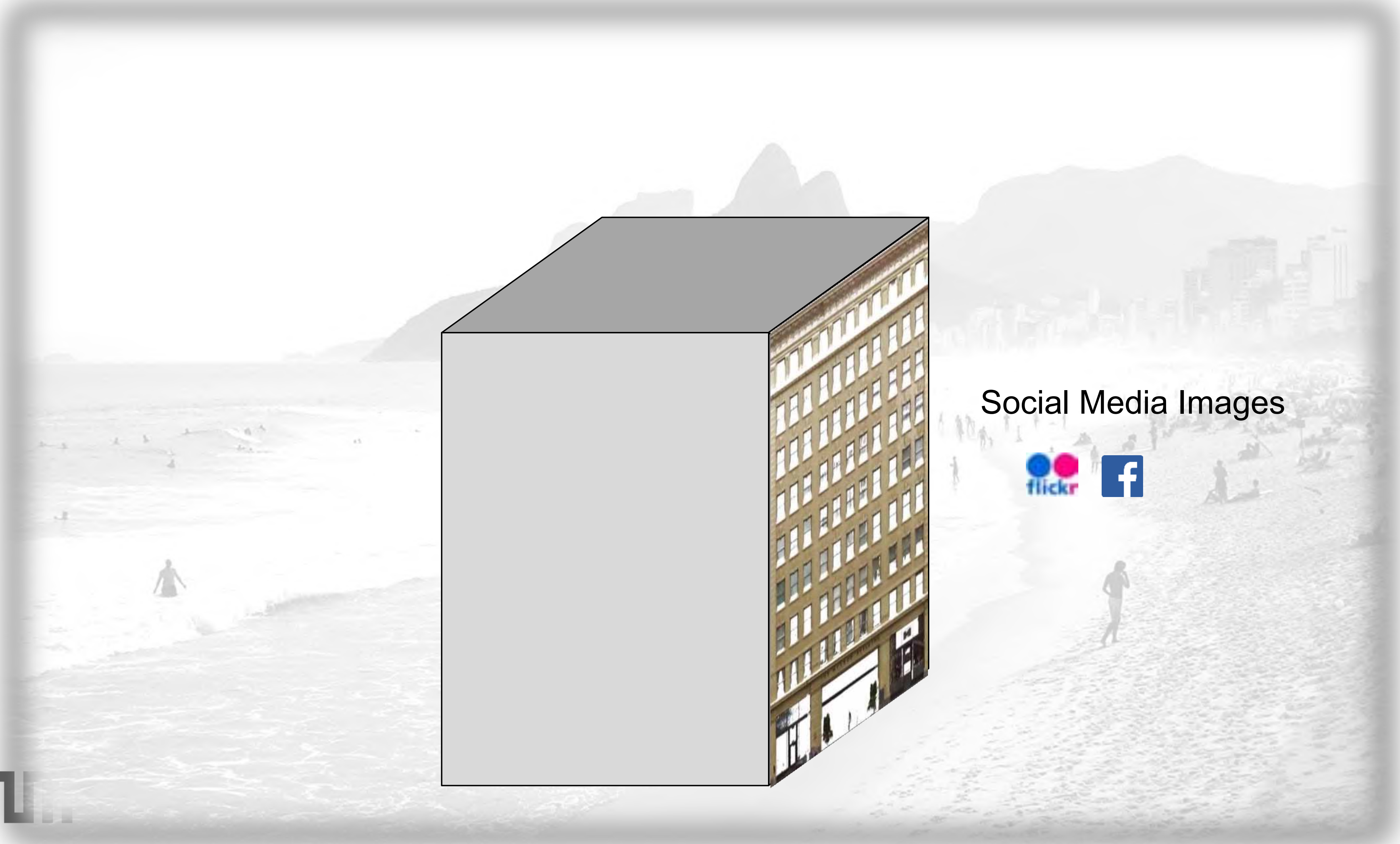
Preliminary Results – OSM Ground Truth

Preliminary Results – Tweets Predicted



Building Settlement Type Classification

– by the Fusion of Remote Sensing and Social Media Images



Building Instance Classification from Street View Data by CNN

- apartment
- church
- garage
- house
- industrial
- office building
- retail
- roof

Munich

Kang et al. , ISPRS J. Photogramm. Remote Sens. 56(6), 3062-3077, 2018

Flickr Random Search

flickr

– Queries Flickr API with random bounding boxes

– Up to 100,000 geotagged photos/day per bot

– Ca. 17.1 Mio geotagged Images

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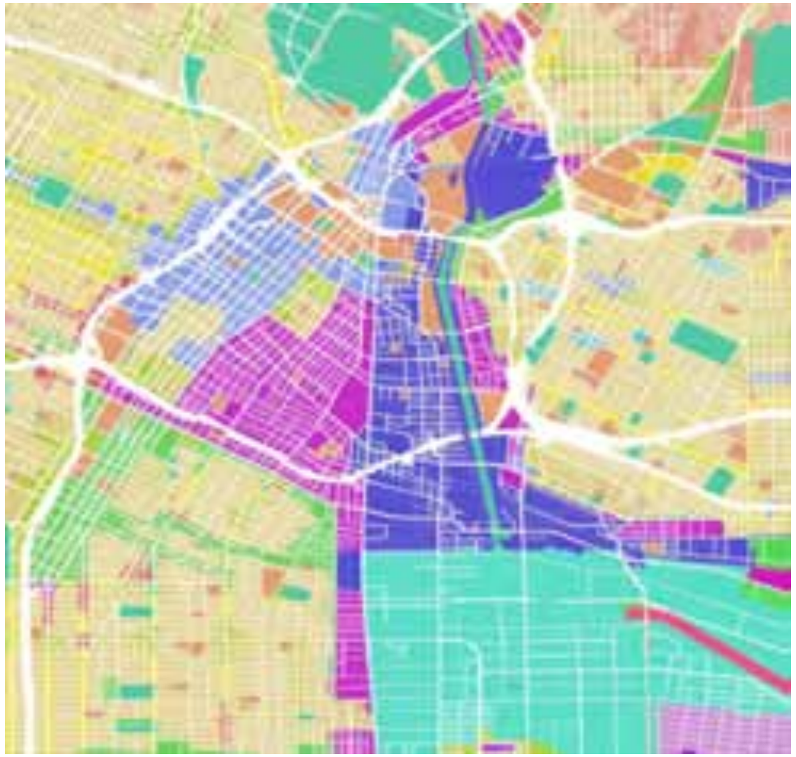
Predict Settlement Types Using Social Media Images

Extract **geospatial knowledge** from social media images for **building instance classification**



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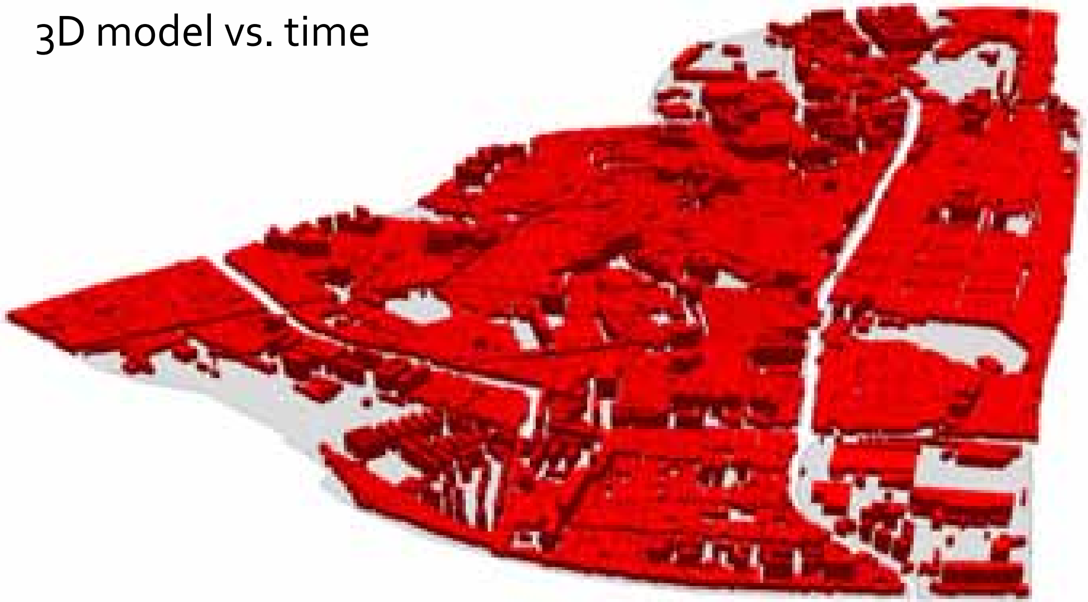
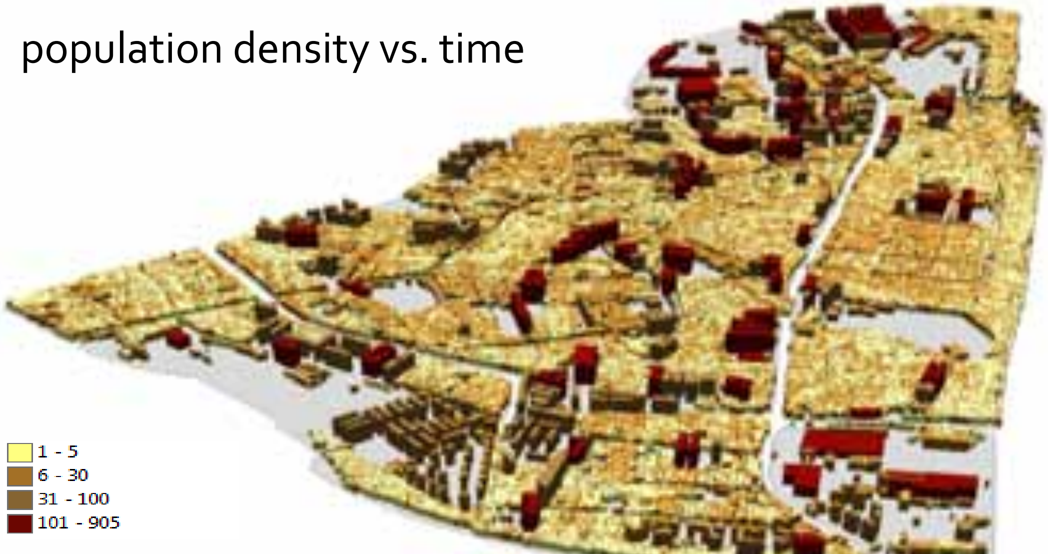
Our Vision in 2022

A first and unique global and consistent 3D/4D spatial data set on the urban morphology

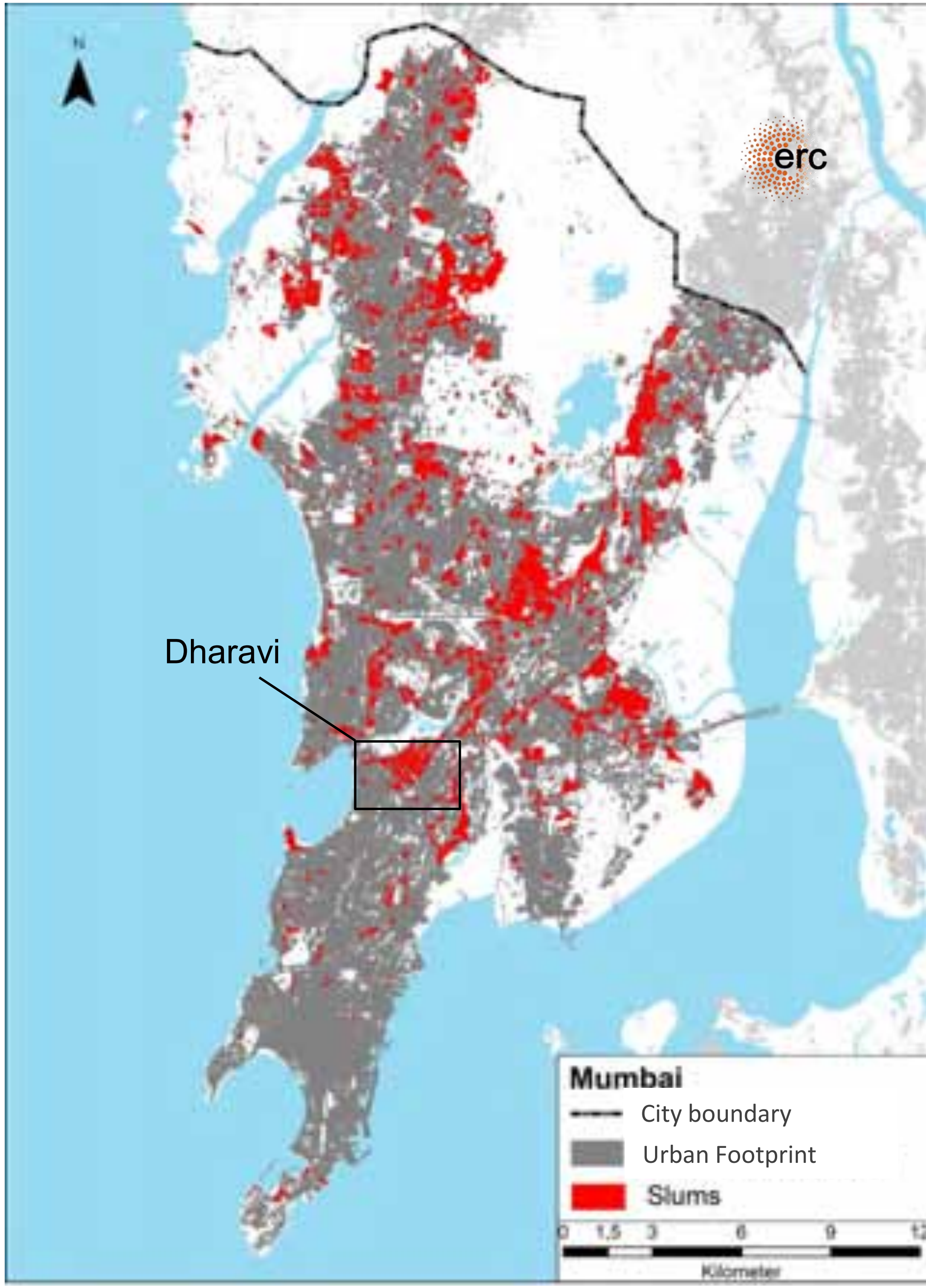
3D model vs. time



population density vs. time

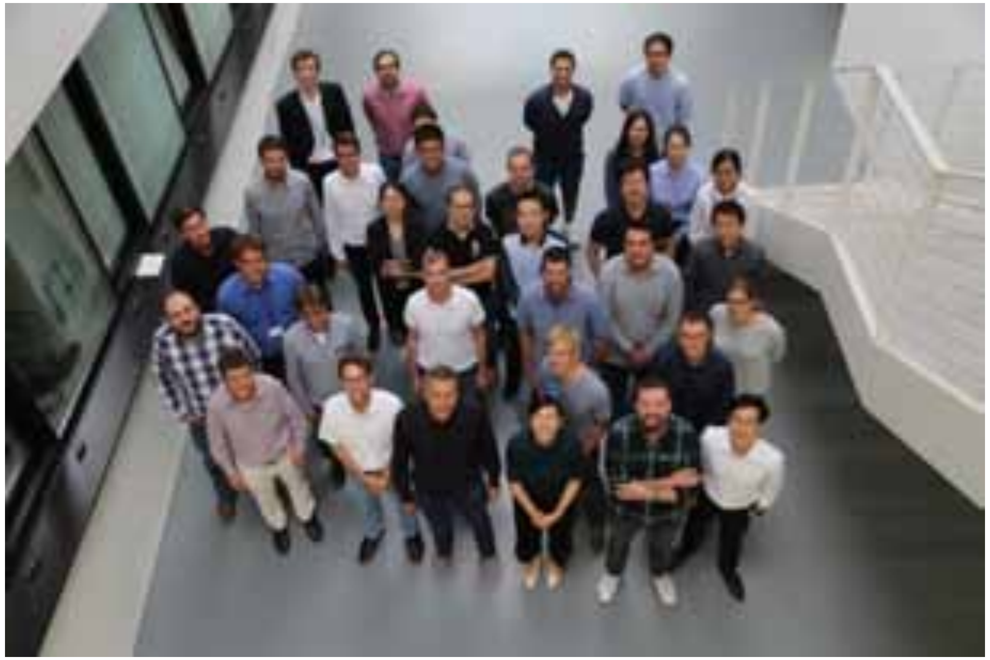


Courtesy: H. Taubenböck, DFD



The So2Sat Data will be Open

- **better understanding** and **boosting research** on the global change process of urbanization
- unique data set for stakeholders such as the **United Nations**
- a helping hand to address **poverty**



So2Sat @ LRZ
Demand: > 100 mio CPU hours; >10 PB Storage

DLR/Alibaba AI4EO Challenge

Global urban mapping So2Sat

AI4EO research @DLR&TUM

Join us for AI4EO:

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