Artificial Intelligence and Deep Learning in Earth Observation

Xiaoxiang Zhu

Institut für Methodik der Fernerkundung
Remote Sensing Technology Institute

Copernicus
The European Earth Observation Programme

The Golden Era of Big Earth Observation Data

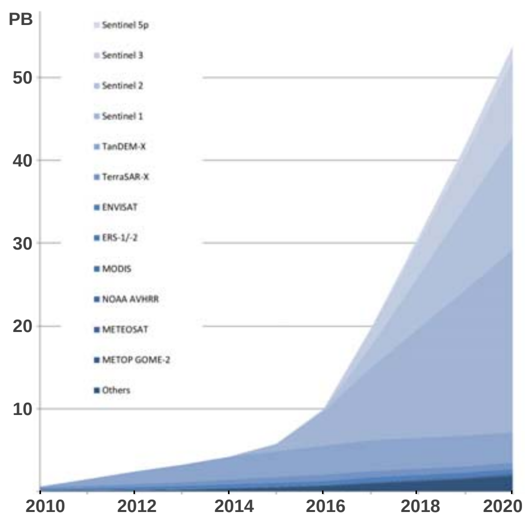
Copernicus
Europe's eyes on Earth

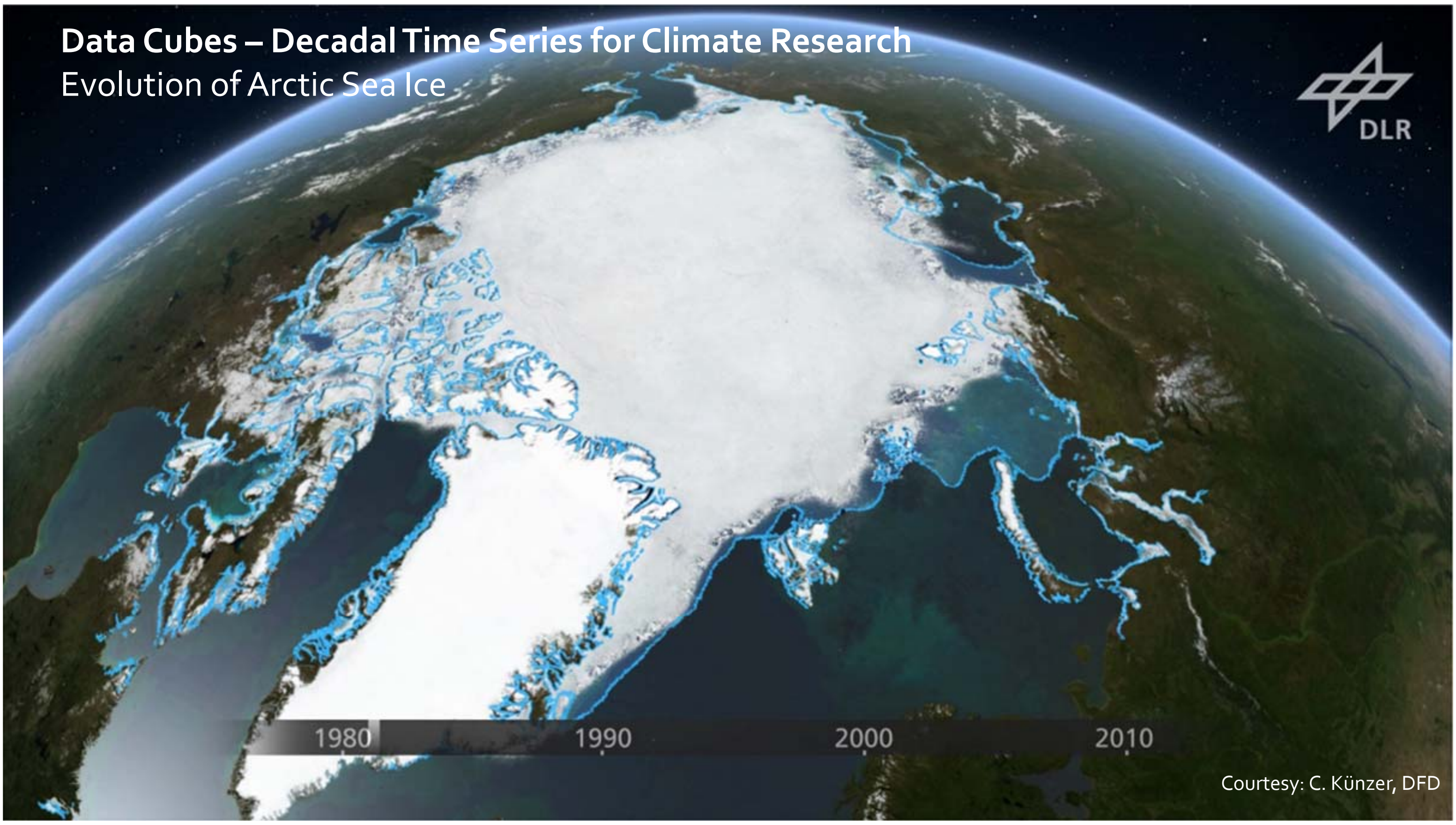
- Sentinels and future national satellites provide
  - continuous, reliable and quality controlled acquisition of big EO data
  - free and open data
  - long-term perspective
- Complementary NewSpace approaches, e.g. Planet
- Internet giants and Start-Ups (Descartes Lab, Orbital Insight,…) enter EO

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





Why do we need data science and AI4EO?

user domain | **information retrieval** | observation systems

costs	€	€ € €
development and life cycle	days ~ year	10 ~ 20 years
level of innovation	high, e.g. Moore's law	"old" technologies

AI research – Publication Statistics (Scopus Journals) 2013 – 2017

Searches in ca 50 Mio. Papers

Machine Learning
Natural Language Processing
Expert system
Computer Vision
Speech Recognition
Voice Recognition
Deep Learning
Supervised Learning
Unsupervised Learning
Machine Vision
Pattern Recognition
Artificial Neural Network
Neurocomputing
Convolutional Neural Network
Self-Organizing Map
Bayesian Belief Network
Swarm Intelligence
Multi-Agent System
Intelligent Agent
Knowledge-Based System
Reinforcement Learning
Bayesian Network
Recurrent Neural Network
Feedforward Neural Network
Support Vector Machine
Autoencoder
Genetic Programming
Naive Bayes
Cluster Analysis
Artificial Intelligence
Feature Selection
Feature Extraction

	Publication count	H5 index	Highest citation number
DLR (total)	255	18	143
- thereof IMF	98	15	143
Karlsruhe Institute of Technology	321	21	102
Deutsches Forschungszentrum für Künstliche Intelligenz	190	15	92
Fraunhofer Inst. f. Intelligent Analysis and Information Systems	44	8	118
Max Planck Institute for Intelligent Systems	116	20	308

von: M. Azzam, Koordinator Digitalisierung, DLR

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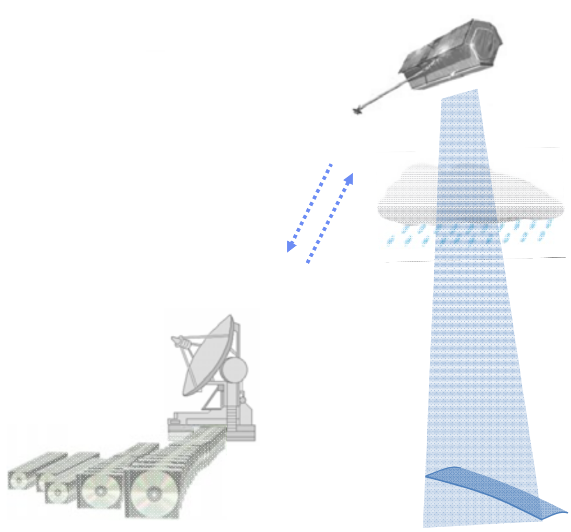
Data Science in Earth Observation

Model-Based Analytics
explorative signal processing methods

Data-driven Analytics
machine/deep learning methods

Geoscientific Application – Global Urban Mapping

$$y = F(x) + \varepsilon$$



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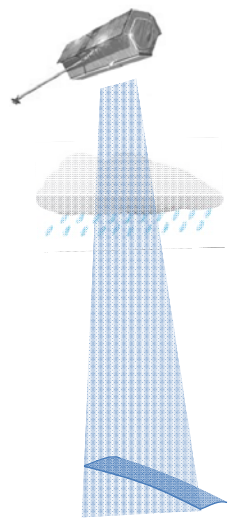

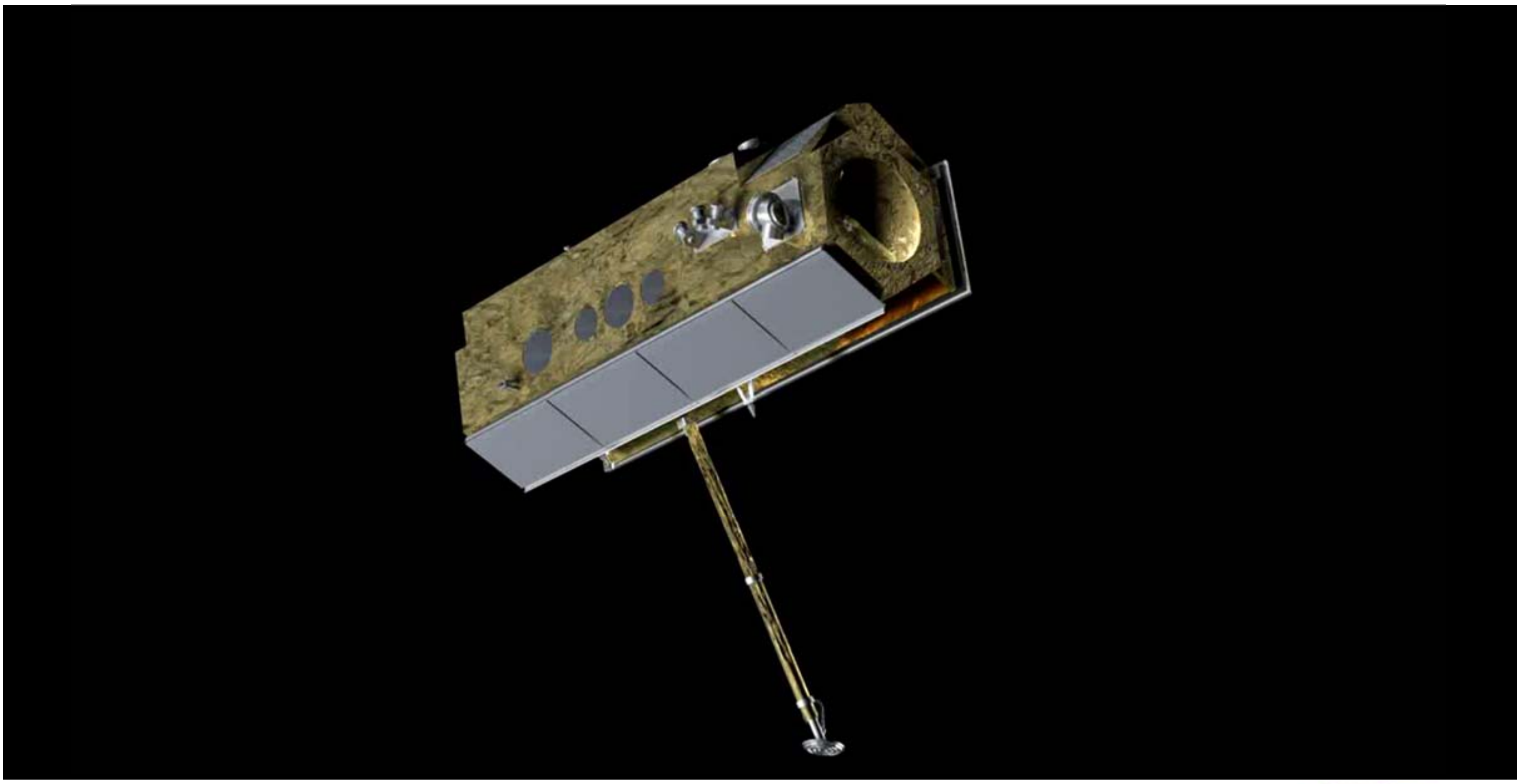

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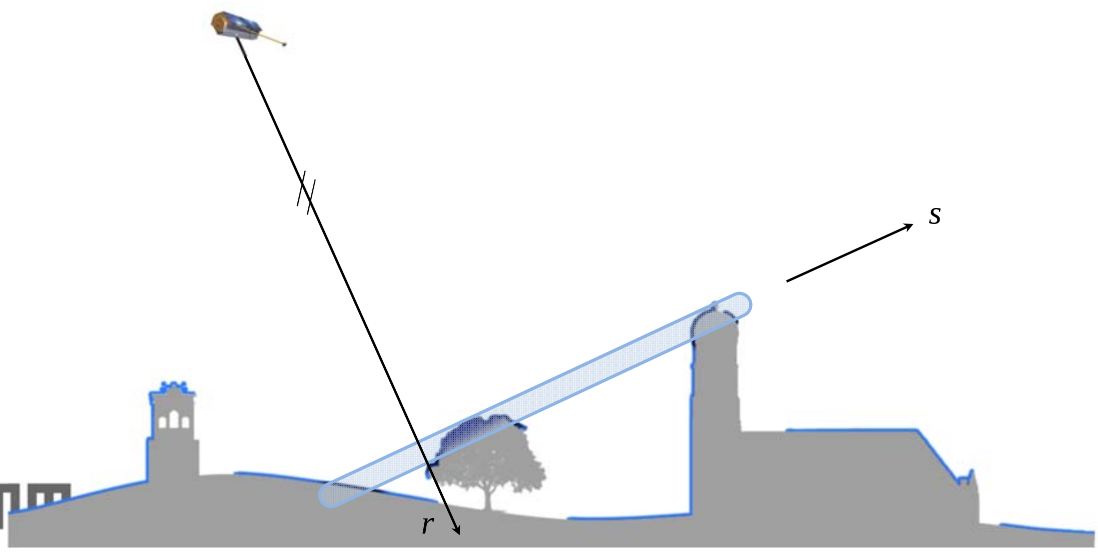
Radar Geometry in Range-Elevation Plane



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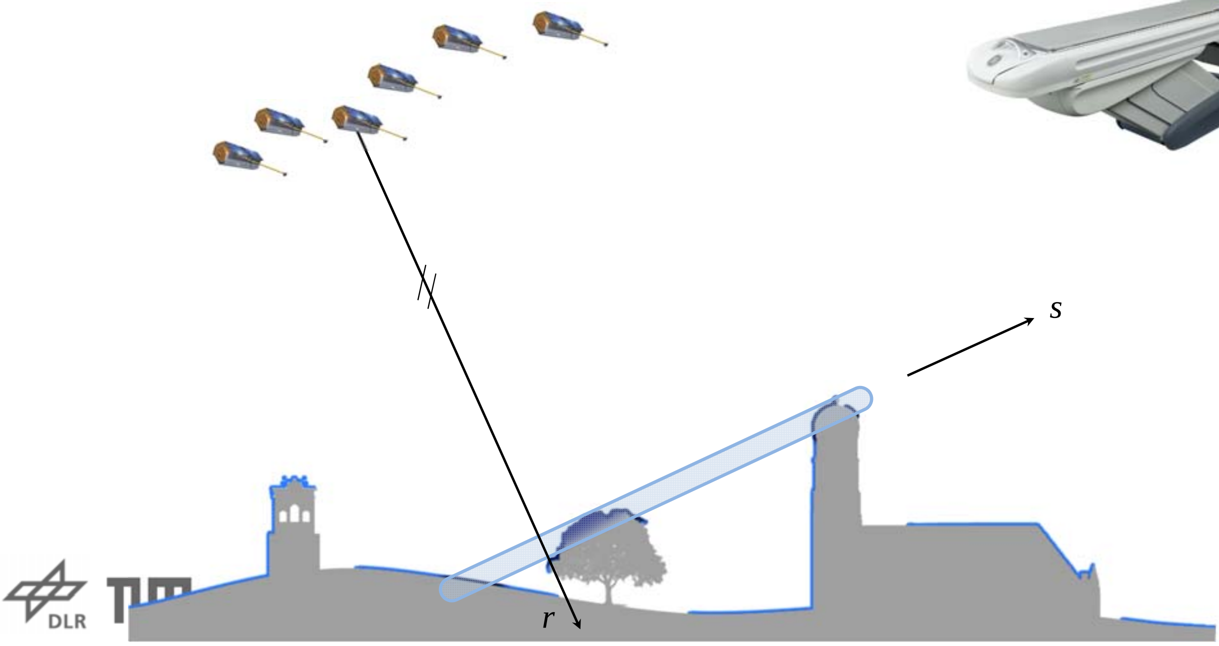
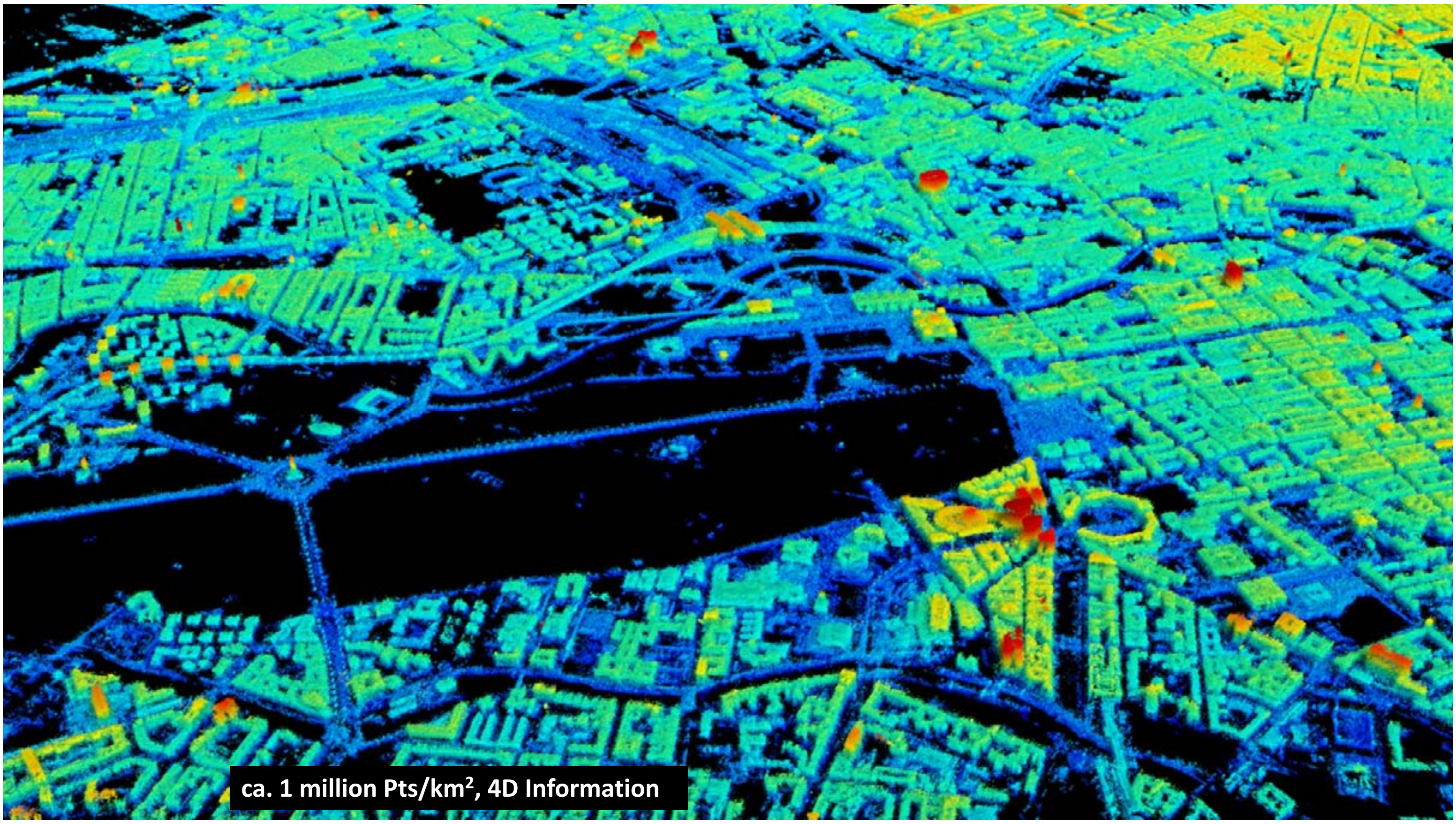
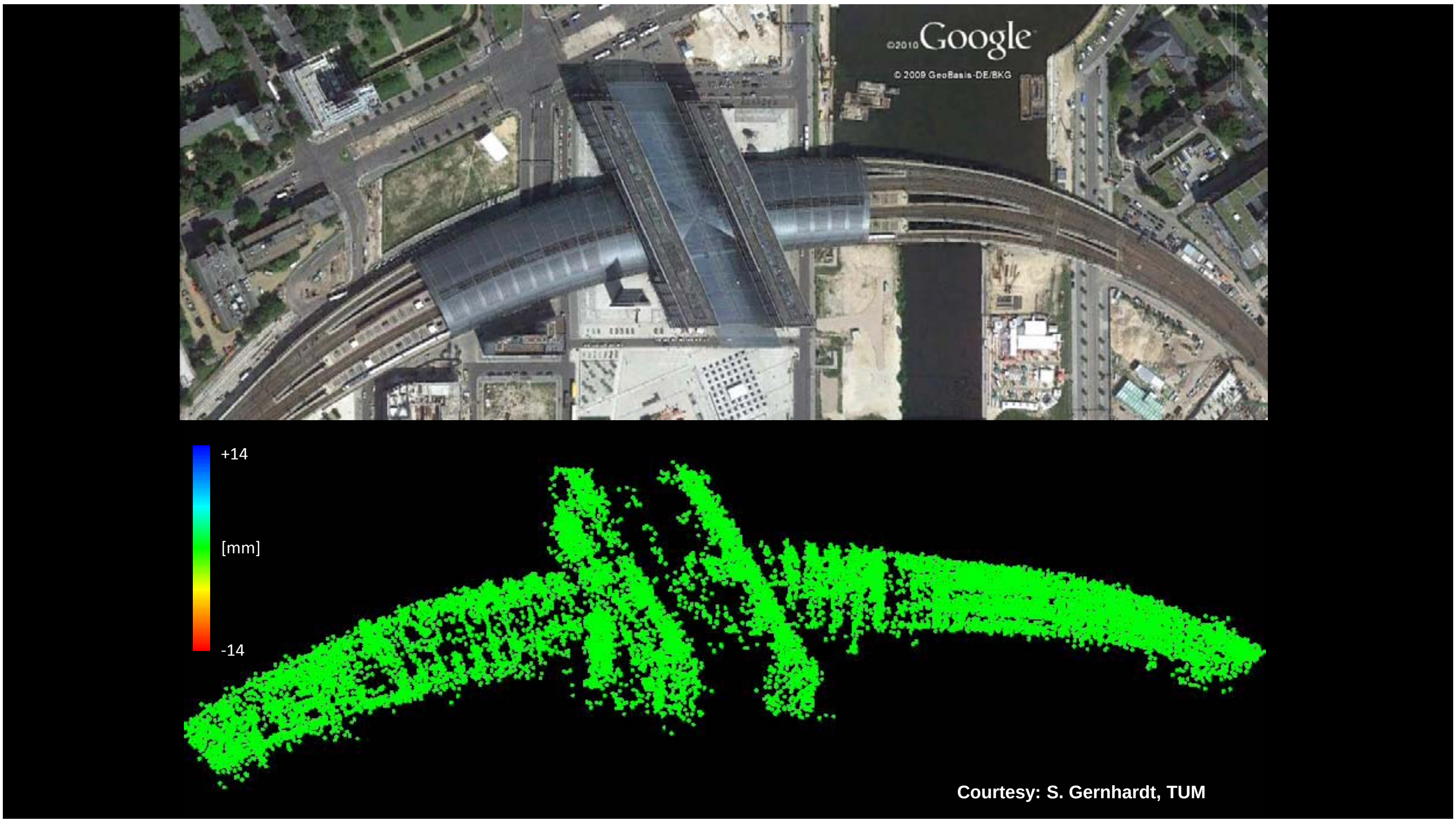
Radar Tomography – “X-Ray” of the Earth





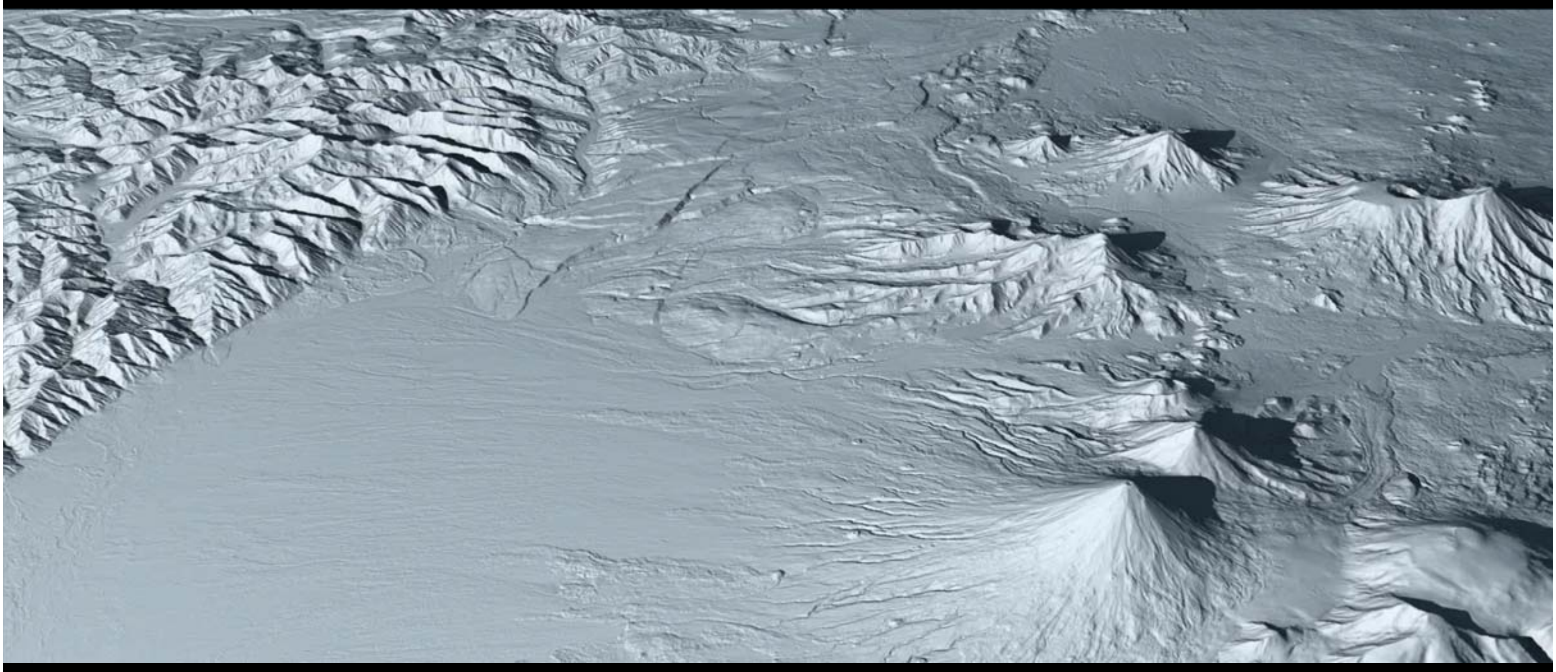


Courtesy: S. Gernhardt, TUM

Applications

- Underground construction monitoring
- Railway monitoring
- High voltage poles monitoring
- Dam monitoring
- Urban infrastructure monitoring, city planning
- Natural disasters (e.g. Volcano, earthquake)
- And many more…

Kamtschatka



Relative Height Error – Evolution over Time

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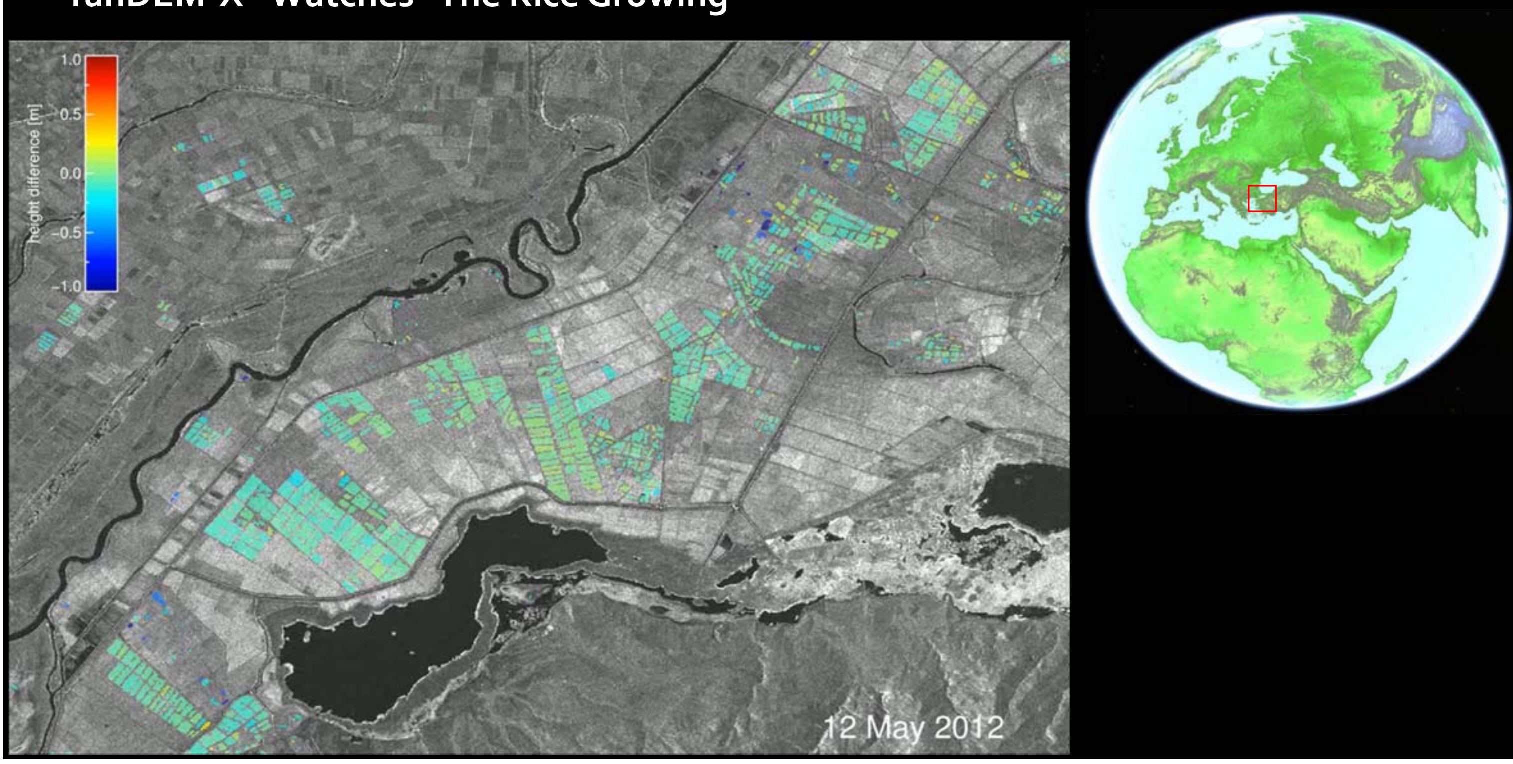
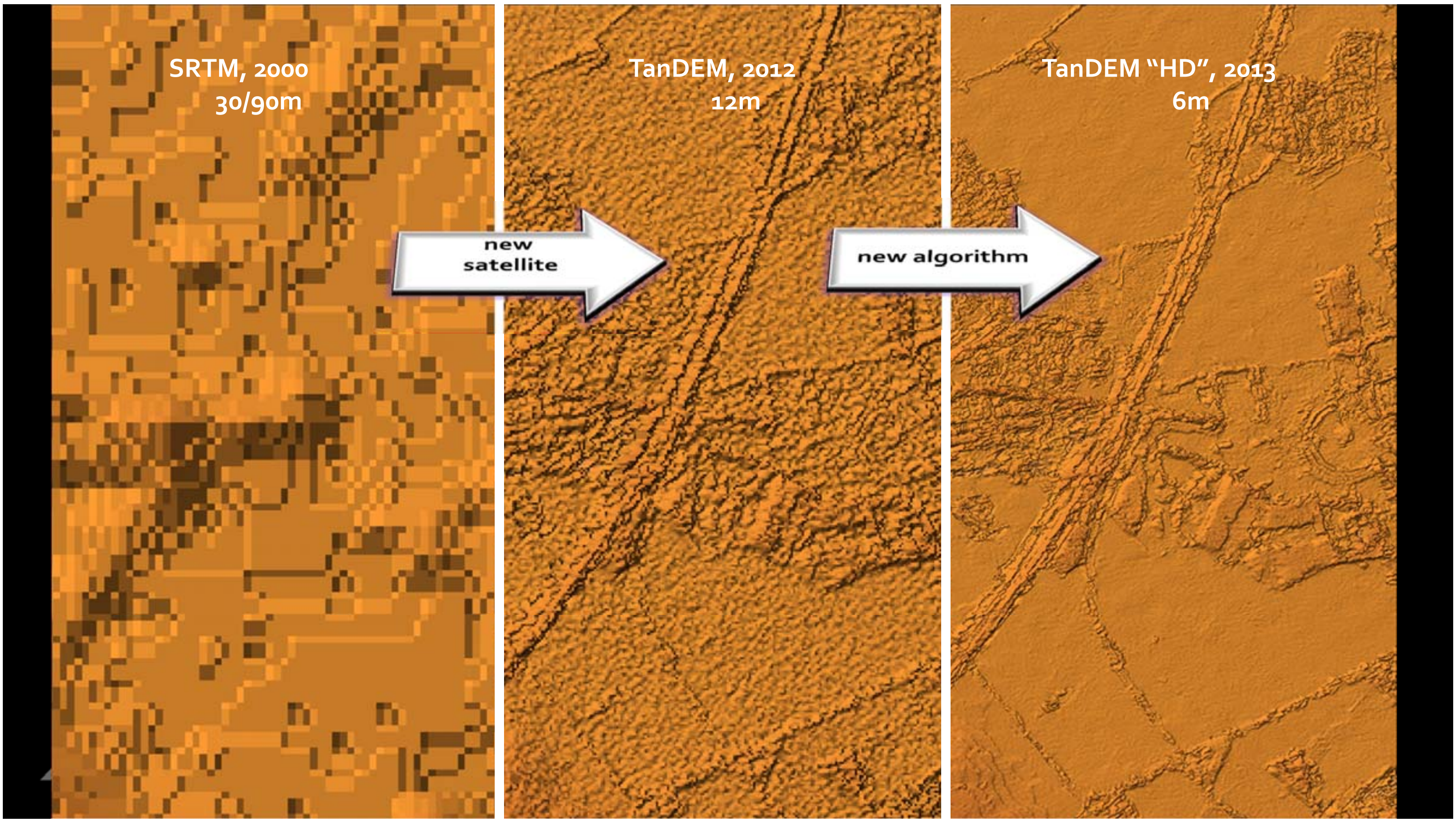
TanDEM-X "Watches" The Rice Growing

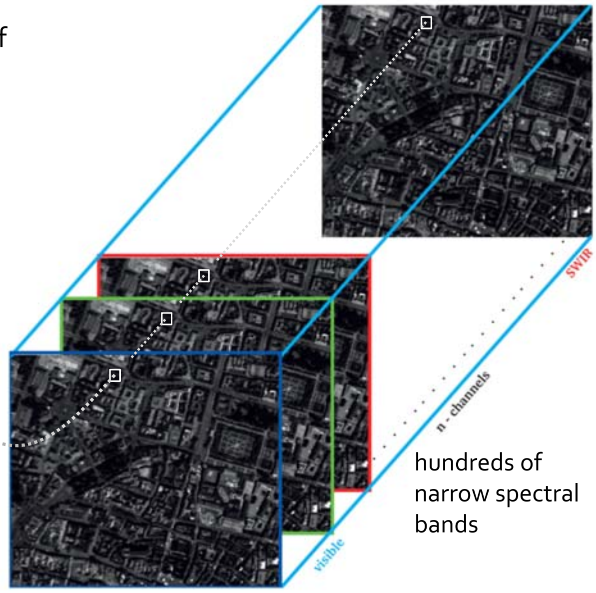



SRTM, 2000
30/90m
new
satellite
TanDEM, 2012
12m
new algorithm
TanDEM "HD", 2013
6m


Launch in 2020

Hyperspectral Imaging – Spectral Resolution

measured spectrum of
one pixel



hundreds of narrow spectral bands

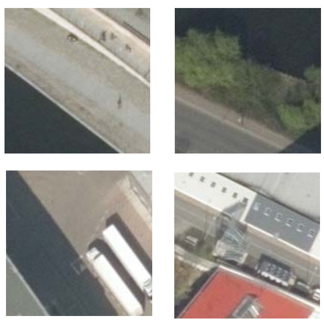
high spectral resolution

⇓

material identification via spectroscopic analysis

Hyperspectral Imaging – Spatial Resolution

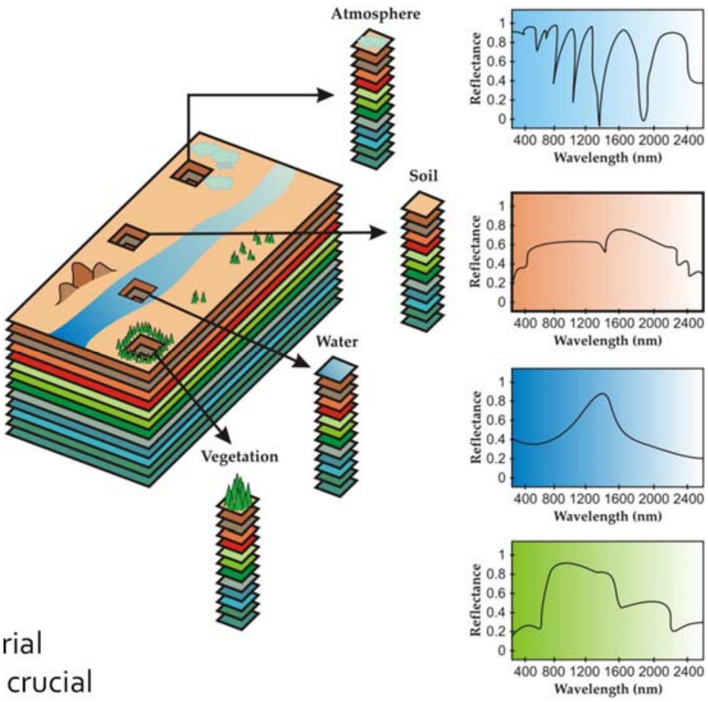
typical spatial resolution ~ 30m



medium spatial resolution

⇓

Spetral unmixing, i.e. material unmixing within the pixel, is crucial



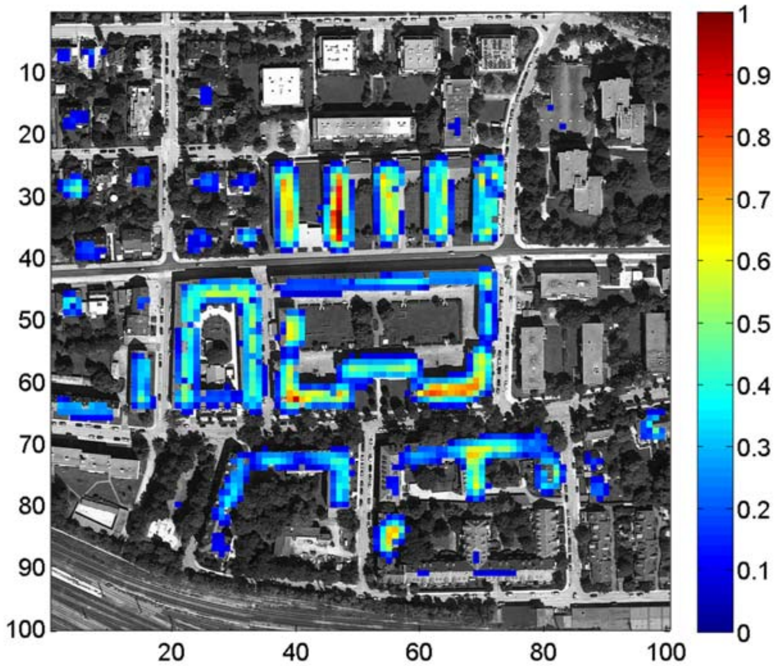
From: Bioucas-Dias et al. 2012

Red Tile Roof

© Google Earth

HySpex

Joint Sparsity Model



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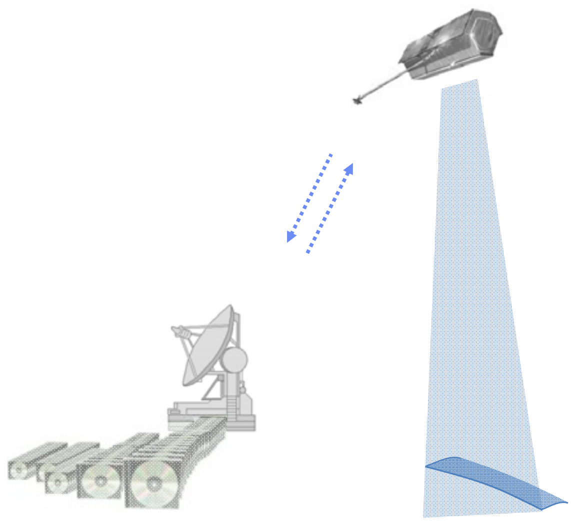


DLR TUM

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

Central to the looming paradigm shift toward data-intensive science, machine-learning techniques are becoming increasingly important. In particular, deep learning has proven to be both a major breakthrough and an extremely powerful tool in many fields. Shall we embrace deep learning as the key to everything? Or should we resist a black-box solution? These are controversial issues within the remote-sensing community. In this article, we analyze the challenges of using deep learning for remote-sensing data analysis, review recent advances, and provide resources we hope will make deep learning in remote sensing seem ridiculously simple. More importantly, we encourage remote-sensing scientists to bring their expertise into deep learning and use it as an implicit general model to tackle unprecedented, large-scale, influential challenges, such as climate change and urbanization.

MOTIVATION

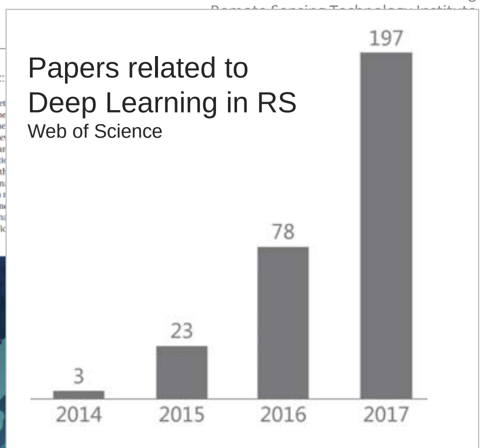
Deep learning is the fastest-growing trend in big data analysis and was deemed one of the ten breakthrough technologies of 2013 [1]. It is characterized by neural networks (NNs) involving usually more than two hidden layers (for this reason, they are called *deep*). Like shallow NNs, deep NNs exploit feature representations learned exclusively from data, instead of handcrafting features that are designed based mainly on domain-specific knowledge. Deep learning research has been extensively pushed by Internet companies, such as Google, Baidu, Microsoft, and Facebook, for several image analysis tasks, including image indexing, segmentation, and object detection.

Based on recent advances, deep learning is proving to be a very successful set of tools, sometimes able to surpass even humans in solving highly computational tasks (consider, e.g., the widely reported Go match between Google's AlphaGo artificial intelligence program and the world Go champion Lee Sedol). Based on such exciting successes, deep learning is increasingly the model of choice in many application fields.

For instance, convolutional NNs (CNNs) have proven to be good at extracting mid- and high-level abstract features from raw images by interleaving convolutional and pooling layers (i.e., by spatially shrinking the feature maps layer by layer). Recent studies indicate that the feature representations learned by CNNs are highly effective in large-scale image recognition [2]–[4], object det mantic segmentation [7], [8]. Furthe (RNNs), an important branch of the have demonstrated significant achie tasks involved in sequential data ar recognition [9], [10] and image captio

In the wake of this success and th availability of data and computationa deep learning is finally taking off in r Remote-sensing data present some n learning, because satellite image ana sues that pose difficult new scientific

Digital Object Identifier 10.1109/MGRS.2017.2762307
Date of publication: 27 December 2017



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Deep Learning in EO – Hot Topic or Hype?

- **Phase 1: Quick wins and quick papers**
  - Use known architectures and pre-trained networks to solve problems in EO that have been solved before ("we can also do it with DL")
  - Show that/whether DL gives better results than existing ML methods, e.g. 86.7 % → 89.3 %
- **Phase 2: Understand that EO is different from internet image labelling**
  - Design new architectures for specific problems
  - Extend DL to non-conventional data and problems, e.g. interferometric SAR, social network data, quantitative estimation of geophysical variables,…
- **Phase 3: Remember your EO expert knowledge and find how to integrate it into DL** ◀ We are here
  - Re-implant physics, Bayes and domain expertise into the learning process
  - Understand what DL really does with the data ("opening the black box"), use information and estimation theory, break the end-to-end-learning dogma,…

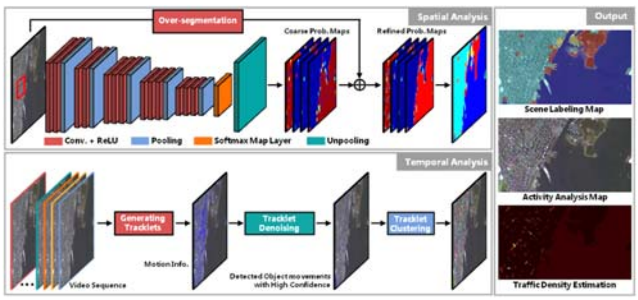
One of Our Phase 1 Successes

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

Winner of IEEE GRSS **Data Fusion Contest 2016**

Data

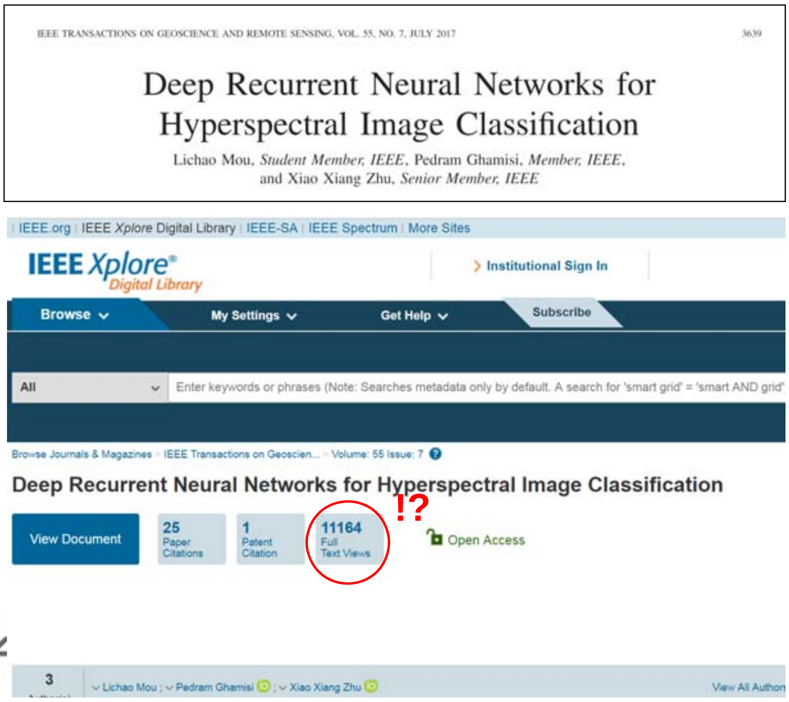
Workflow



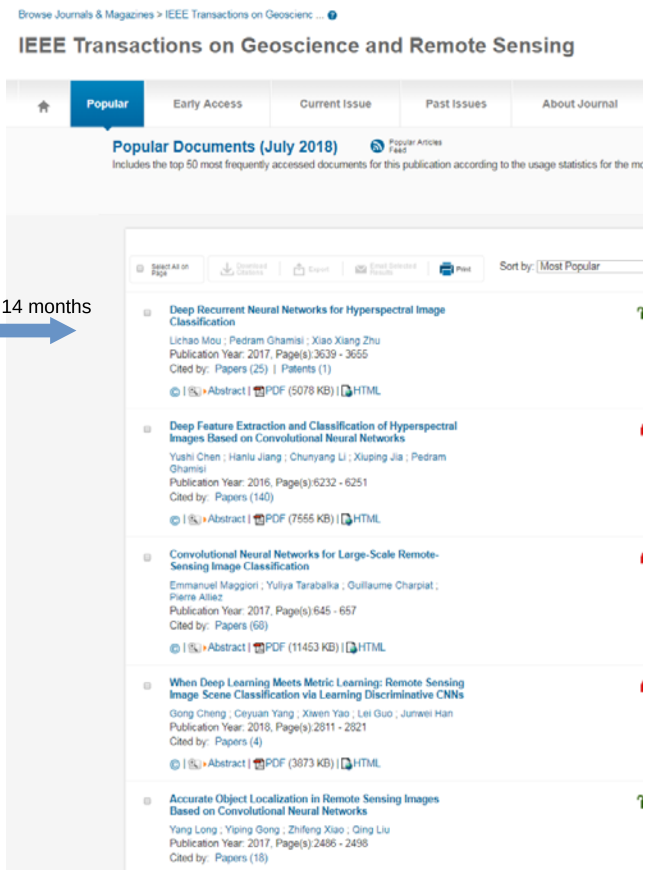
Results

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

Hot Topic or Hype?

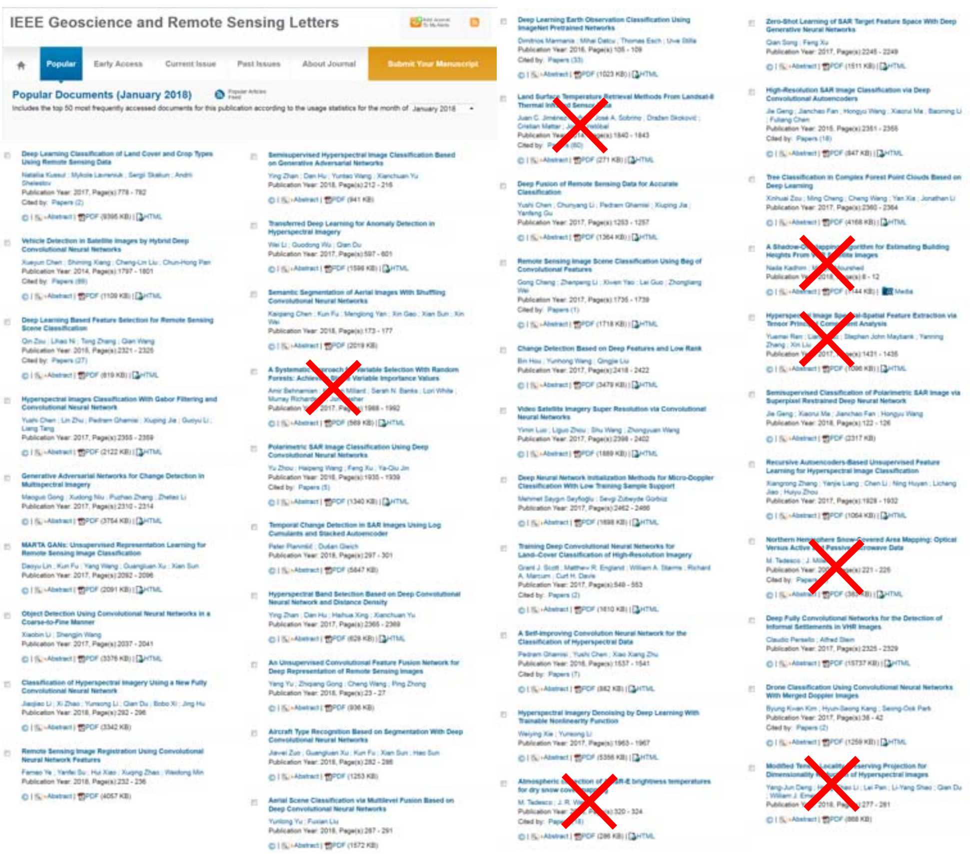


since 14 months



Is This Still Healthy?

Only 7 out of 41 most popular/ downloaded papers are not about deep learning

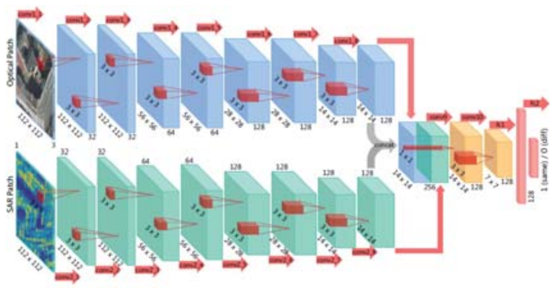


What makes Deep Learning in Earth Observation Special?

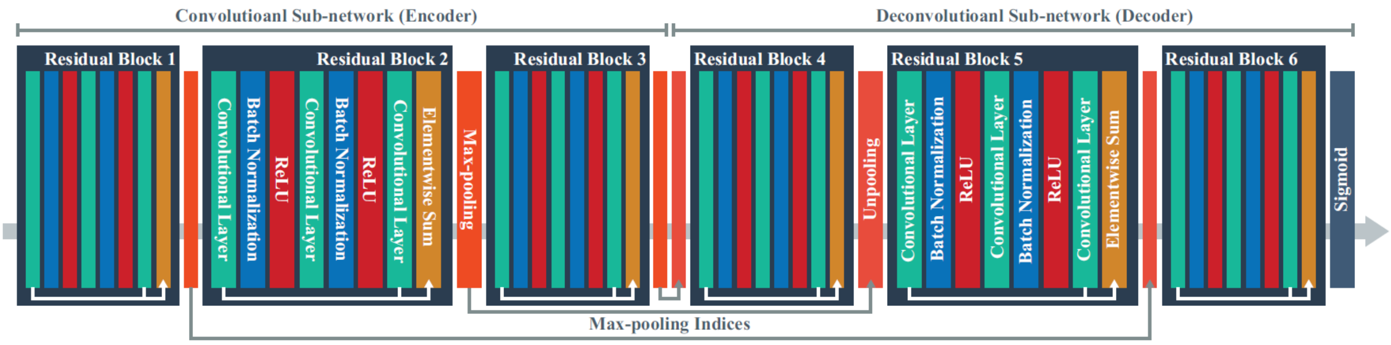
- Classification and detection are only small fractions of EO problems
- Focus on retrieval of physical or bio-chemical variables
  - High accuracy requirements (data generation is expensive)
  - Traceability and reproducibility of results
  - Quality measures (error bars, outlier flags,...) indispensable
- 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

Deep Learning@IMF

- 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 and 3D SAR/Optics/Lidar fusion
- Synthesizing optical images from SAR data and vice versa
- DSM to DTM conversion
- IM2Height and IM2Building Footprint
- Fusion of EO and social media data (image and text)
- Solution of nonlinear inverse problems of atmospheric remote sensing
- Generation of long atmosphere time series for climate research



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

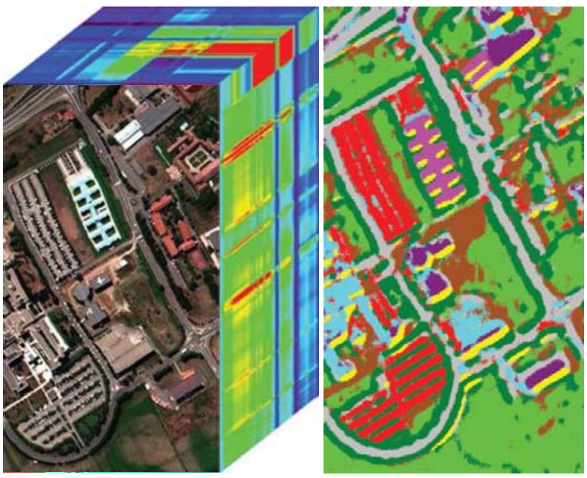


L. Mou, P. Ghamisi, and X. X. Zhu, "Unsupervised spectral–spatial feature learning via deep residual conv–deconv network for hyperspectral image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 1, pp. 391-406, 2018.

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

Results

Application I: Classification



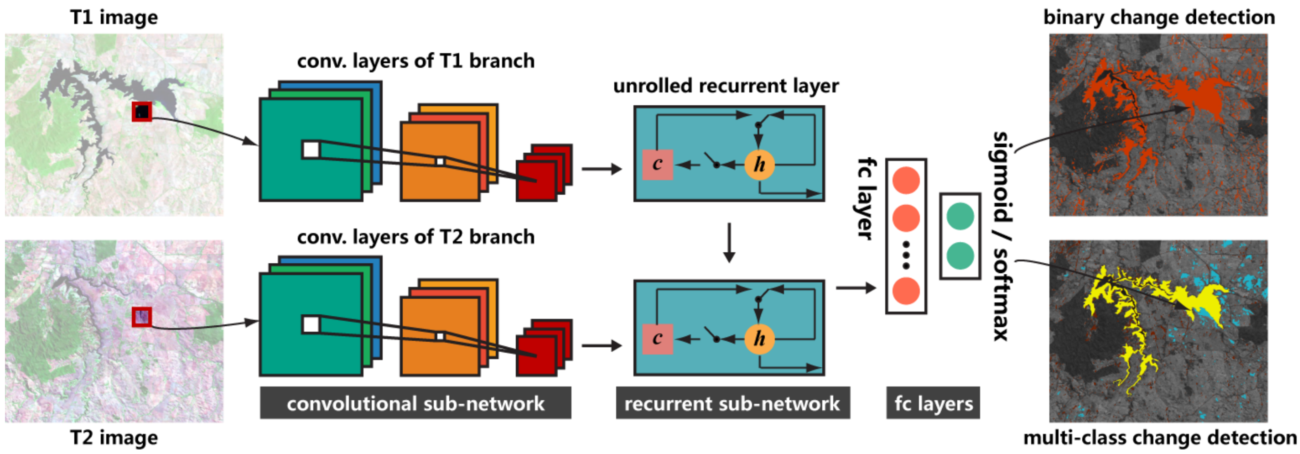
University of Pavia, Italy

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).

L. Mou, P. Ghamisi, and X. X. Zhu, "Unsupervised spectral–spatial feature learning via deep residual conv–deconv network for hyperspectral image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 1, pp. 391-406, 2018.

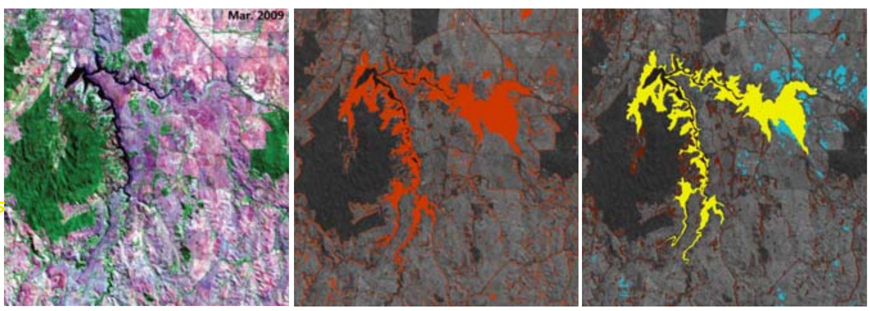
Recurrent Convolutional Neural Network for Change Detection in Bi-temporal Images



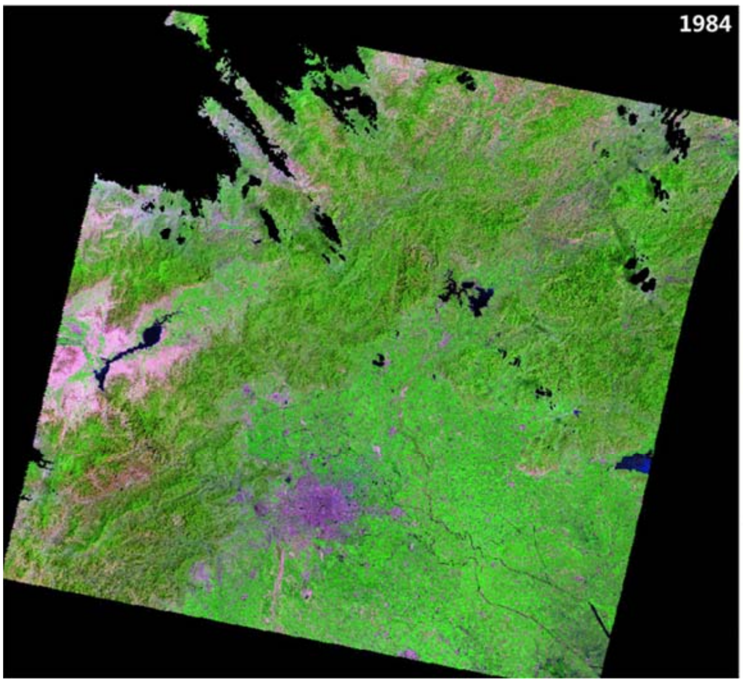
Recurrent Convolutional Neural Network for Change Detection in Bi-temporal Images

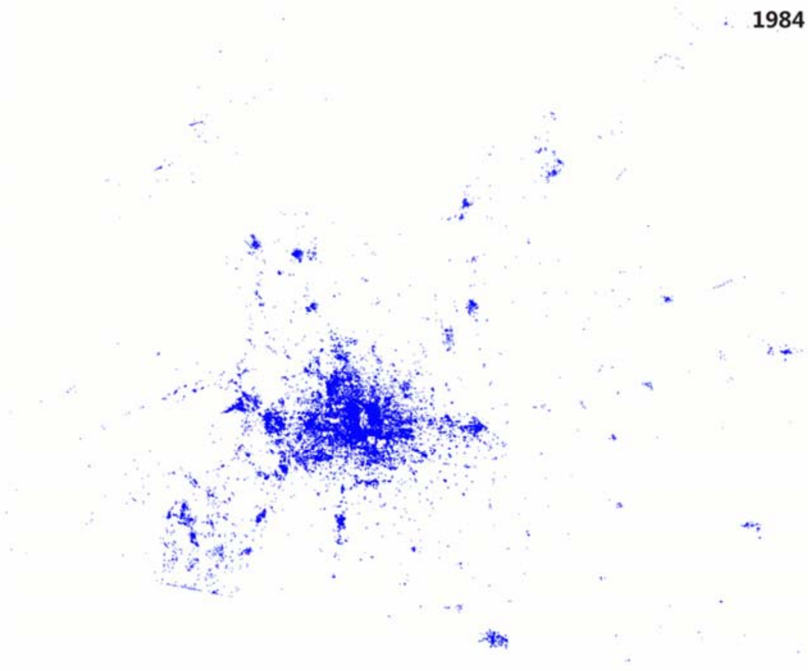
- *Location: Taizhou City, China*
- *Time: Mar. 2000 and Feb. 2003*
- *Data Source: Landsat ETM+*
- *Legend:*
  ***Changed areas** (in binary change detection);*
  city expansion**; **soil change**; **water change

- *Location: Lake Eppalock, Australia*
- *Time: Feb. 1991 and Mar. 2009*
- *Data Source: Landsat ETM+*
- *Legend:*
- ***Changed areas** (in binary change detection);*
- ***city expansion**; **soil change**; **water loss***

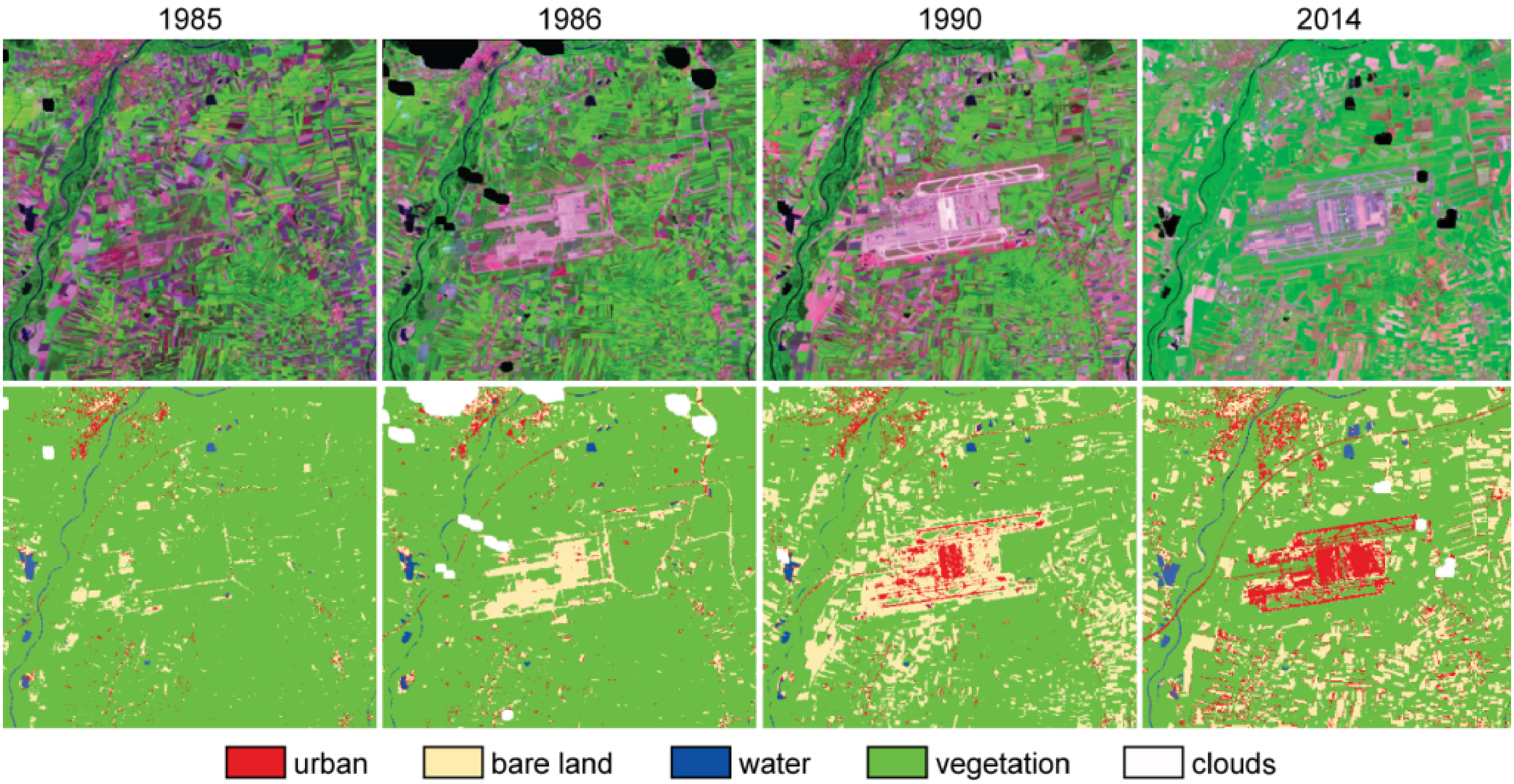


Example – Urban Growth of Beijing (1984 - 2016)

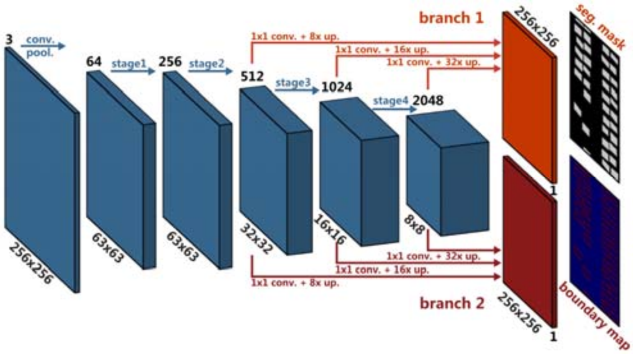




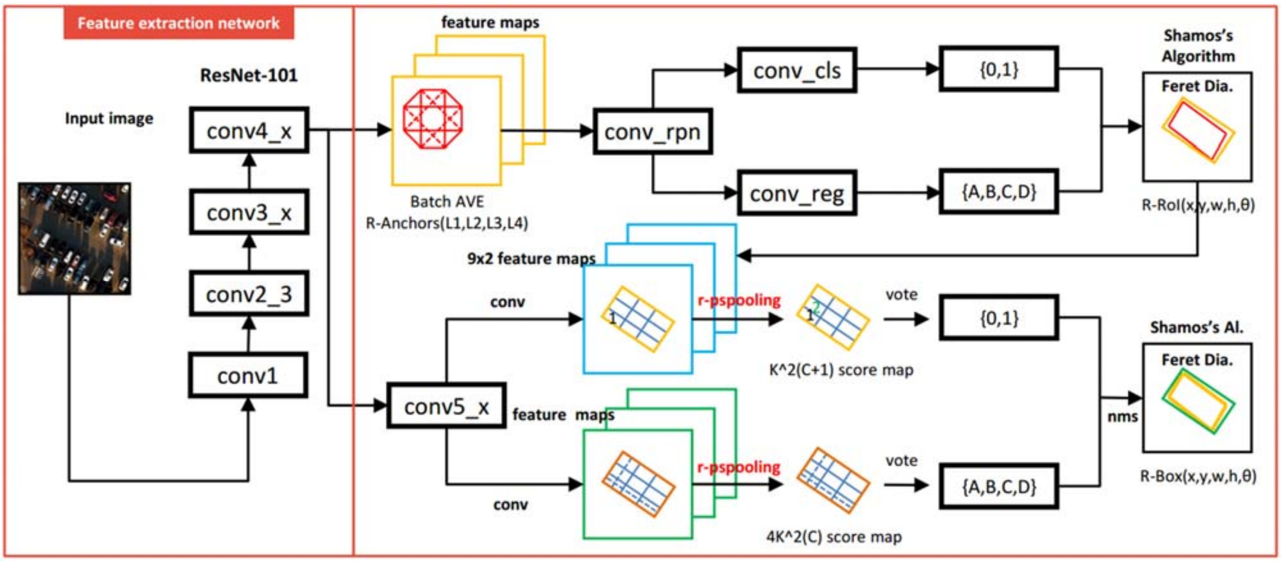
Munich Airport



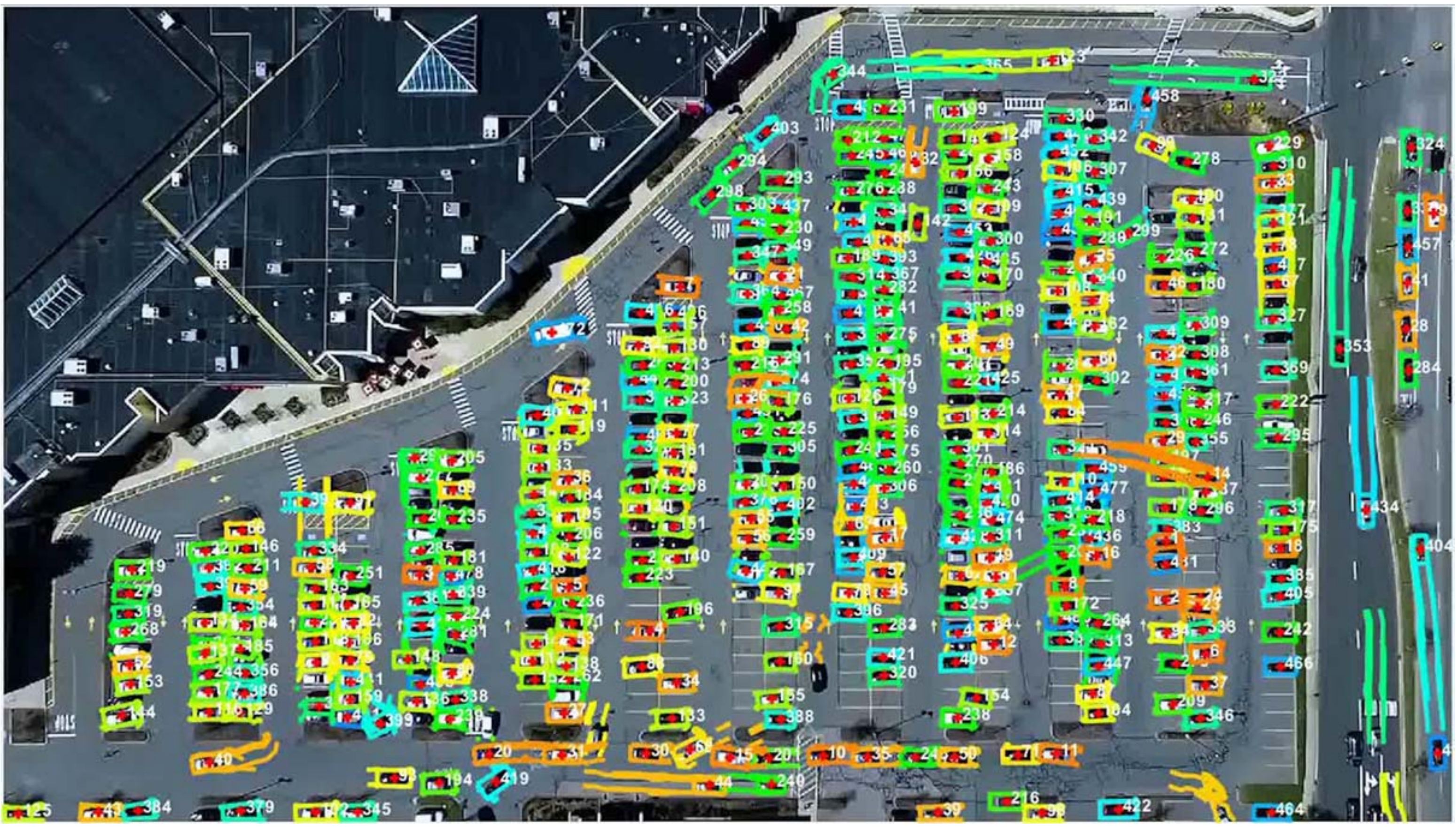
Multi-task CNNs for Car Instance Segmentation



R3-Net: A Rotatable Region-Based Residual Network for Multi-Oriented Vehicle Detection in Aerial Image and Video



The architecture of the proposed network, which is capable of generating rotatable anchors for predicting rotatable object proposals and final detections.



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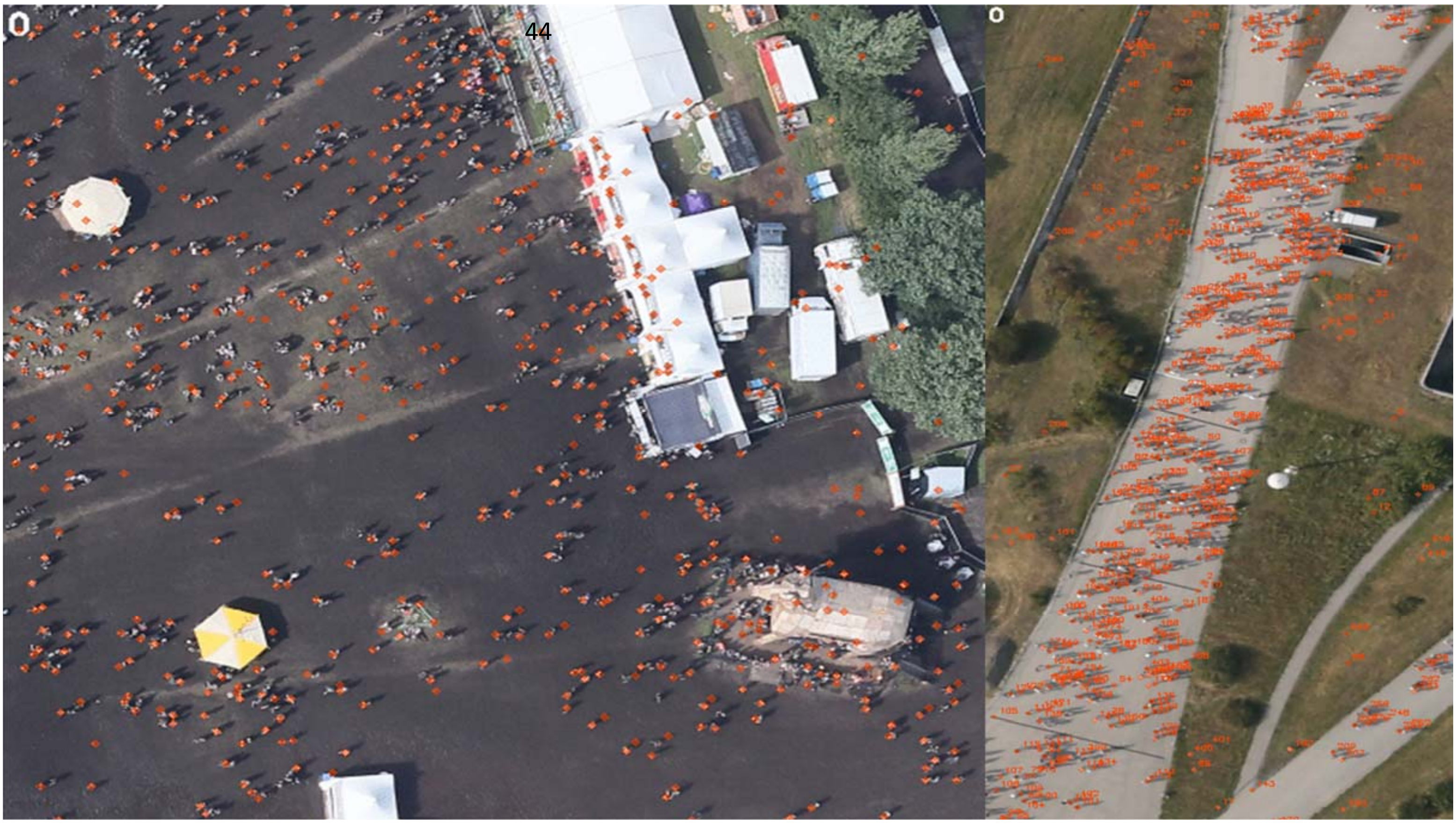
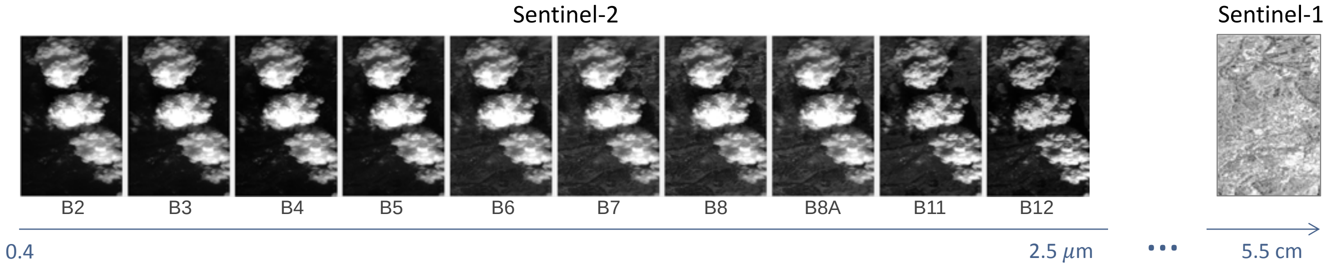


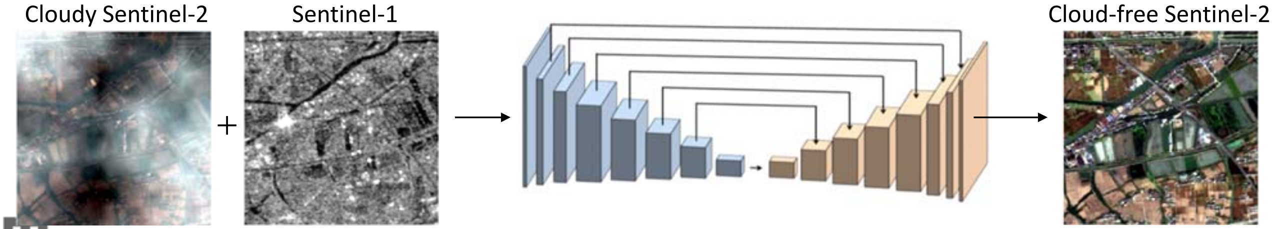
cGAN-based Enhancement of Optical Remote Sensing Data

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



cGAN-based Enhancement of Optical Remote Sensing Data

Removing clouds from Sentinel-2 data using cloud-free radar data

Data:

– 25,000 pairs of (cloud-free) Sentinel-2 / Sentinel-1 co-registered image pairs

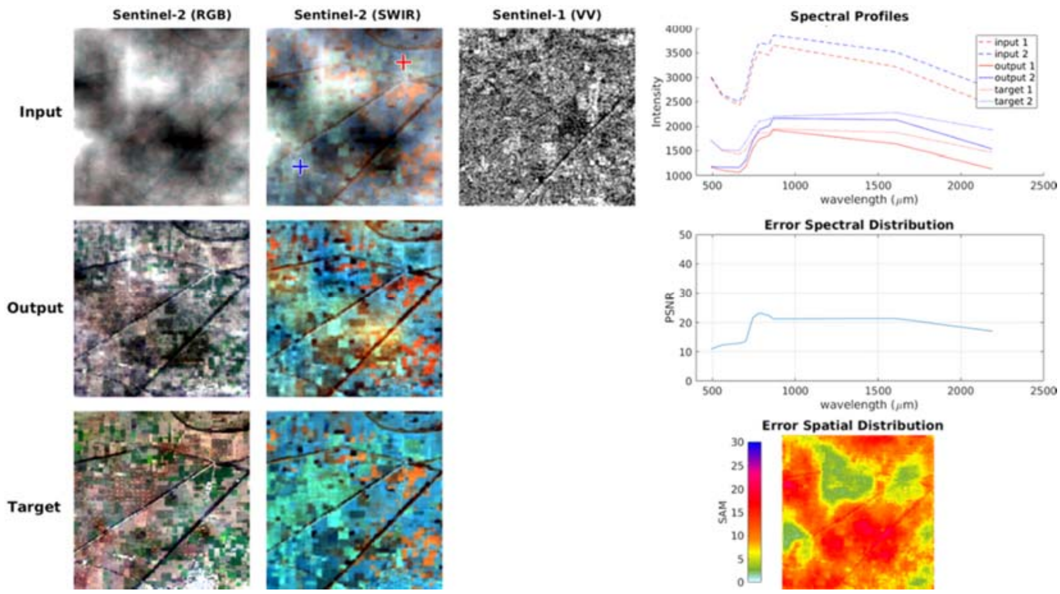
– Simulate cirrus clouds using Perlin noise

First Qualitative Results

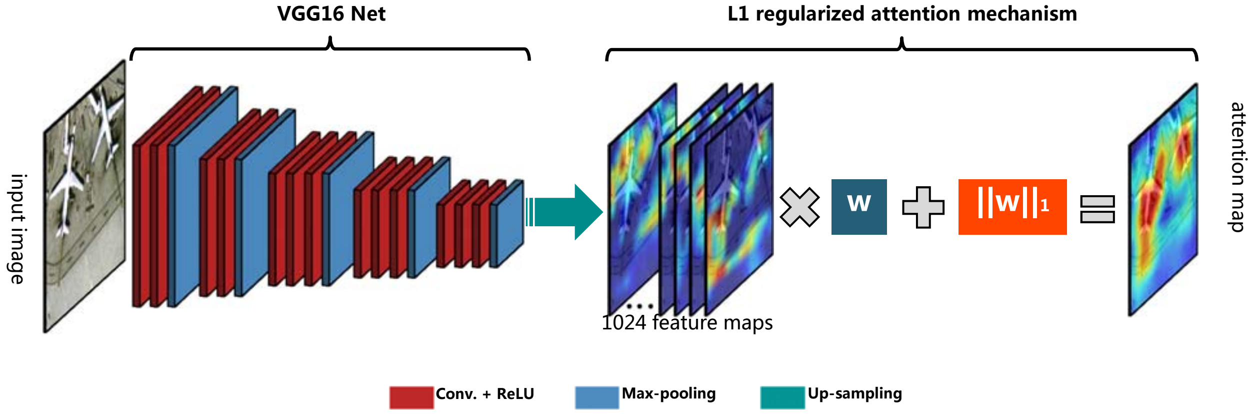
– Clouds successfully removed from validation data set, but artifacts visible

Next step

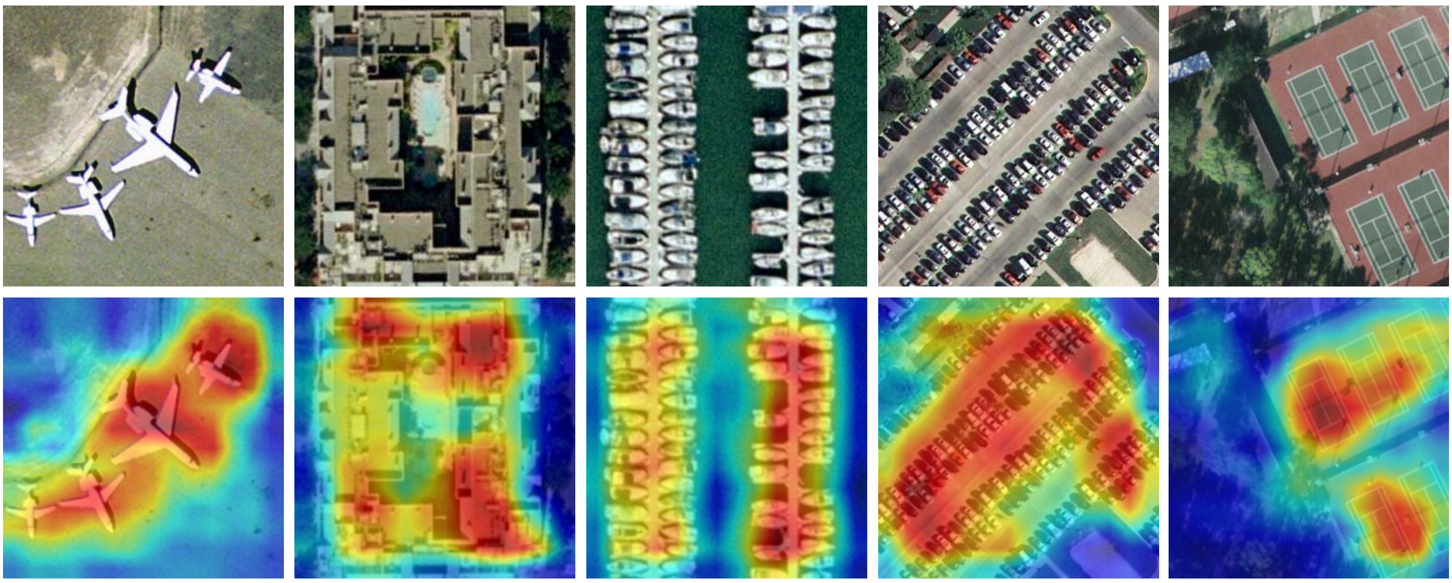
– Train network with real, thick clouds and tune hyper-parameters



How Does CNN Recognize Different Objects?



Deep Convolutional Neural Networks with Attention Mechanism for Aerial Scene Classification



airport buildings harbor parking lot tennis court

Recurrently Exploring Class-wise Attention in A Hybrid Convolutional and Bidirectional LSTM Network for Multi-label Aerial Image Classification

Scene label: Free way

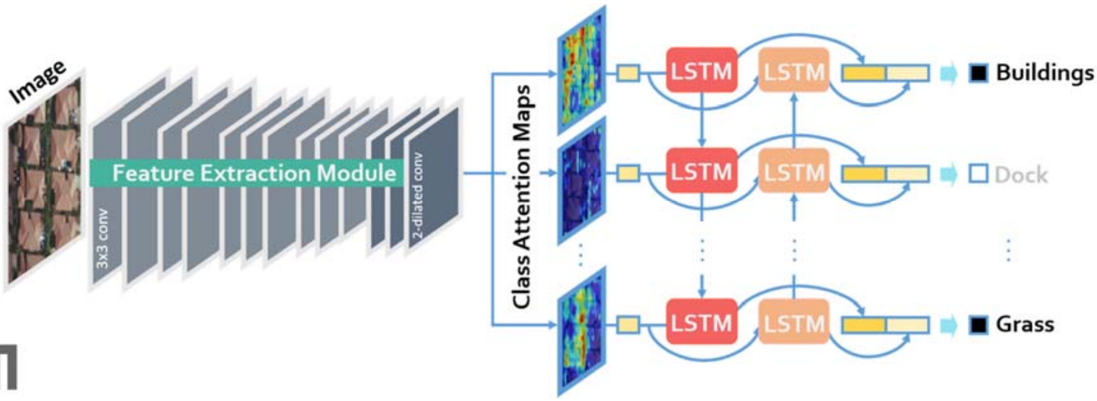
Multi-object labels: *bare soil, car, grass, pavement, and tree*

Scene label: Parking lot

Multi-object labels: *car and pavement*

Scene label: Free way

Multi-object labels: *bare soil, car, grass, pavement, and tree*



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Recurrently Exploring Class-wise Attention in A Hybrid Convolutional and Bidirectional LSTM Network for Multi-label Aerial Image Classification

Example Predictions on UCM and DFC15 Multi-label Dataset

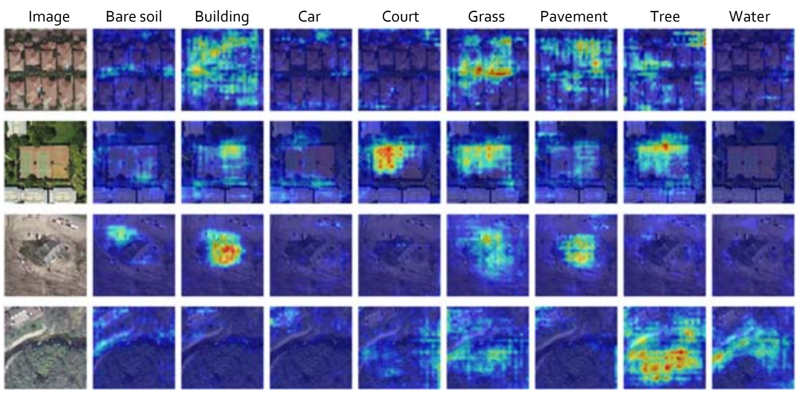
Images in UCM Multi-label Dataset					
Ground Truths	dock, ship, and water	bare soil, building, car, pavement, and tree	building, court, pavement, grass, and tree	grass, sand, mobile-home, and tree	car, grass, and pavement
Predictions	dock, ship, and water	bare soil, building, car, pavement, and tree	building, court, pavement, grass, and tree	car, grass, sand, mobile-home, and tree	car, grass, pavement, and tree
Images in DFC15 Multi-label Dataset					
Ground Truths	impervious, water, and building	impervious, vegetation, and building	impervious, vegetation, building, clutter, and car	water, vegetation, tree	impervious, building, car
Predictions	impervious, water, and building	impervious, vegetation, and building	impervious, vegetation, building, clutter, and car	impervious, water, tree, vegetation, building	impervious, vegetation, building, clutter, and car

Red predictions indicate false positives, while blue predictions are false negatives.

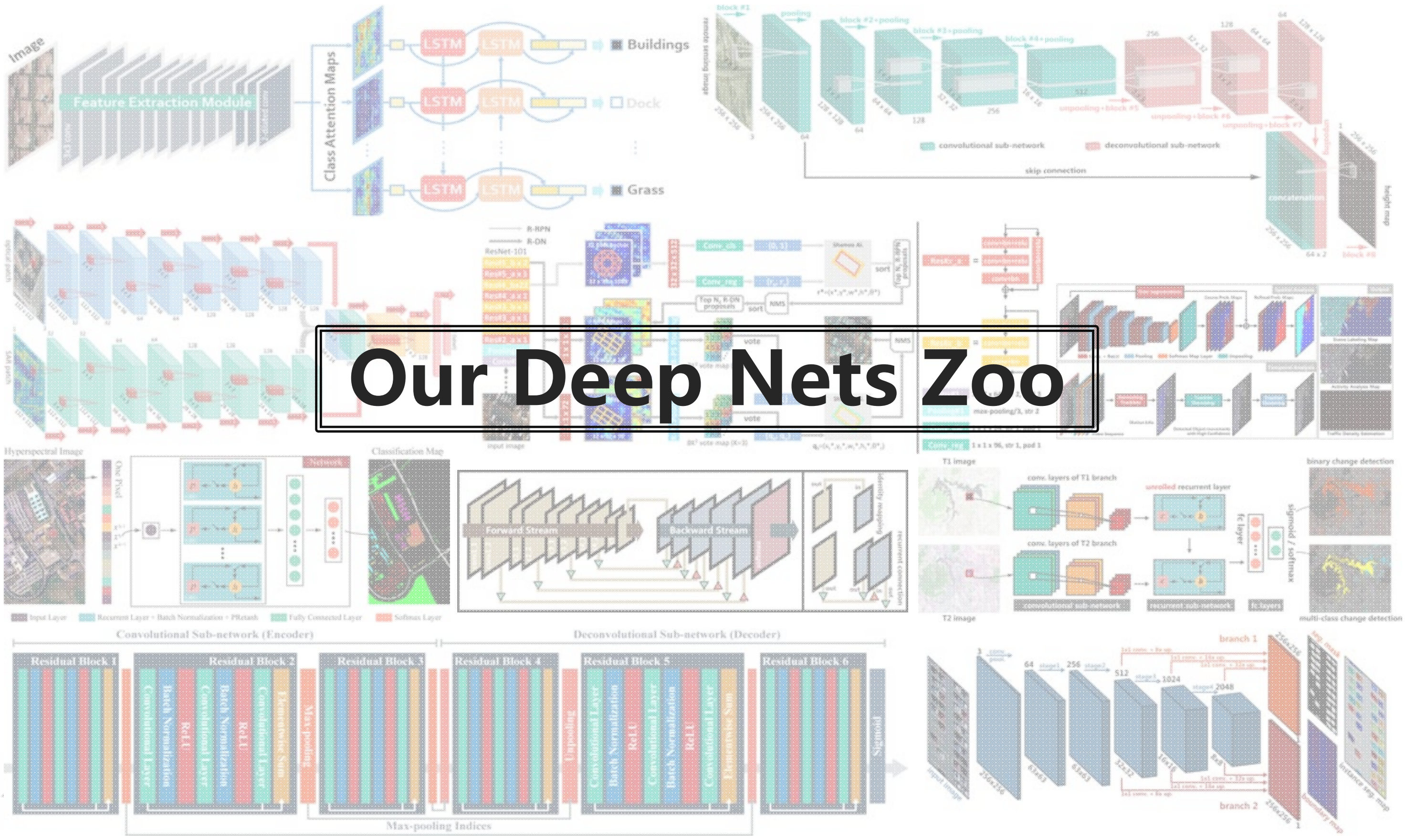
Mean F_2 on UCM and DFC15 Multi-label Dataset

Model Name	mean F_2 (U)	mean F_2 (A)
GoogLeNet	0.8082	0.7371
CA-GoogLeNet-LSTM	0.8423	0.7505
CA-GoogLeNet-BiLSTM	**0.8528**	**0.7656**

Visualization of Class Attention Maps



Our Deep Nets Zoo



Open Issues

– **novel applications**, other than classification and detection related tasks
– **transferability** of deep nets
– **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…

Institut für Datenwissenschaften

Center for Advanced Intelligence Project

NVIDIA

lrz

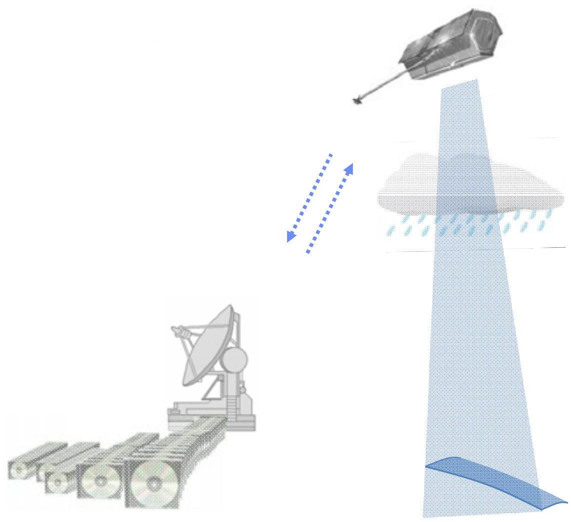
Data Science in Earth Observation

Model-Based Analytics
explorative signal processing methods

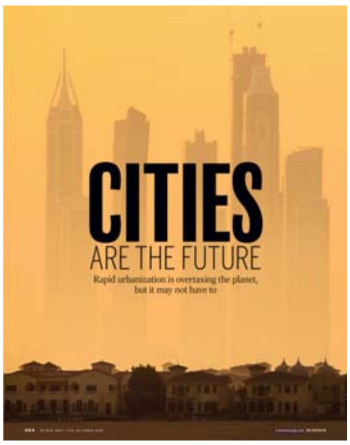
Data-driven Analytics
machine/deep learning methods

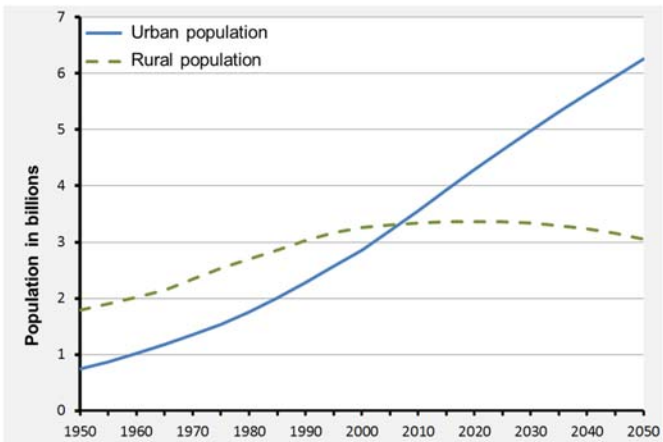
Geoscientific Application – Global Urban Mapping

$y = F(x) + \varepsilon$



Special Issue – Science Magazine, May 2016, on Our Urban Planet





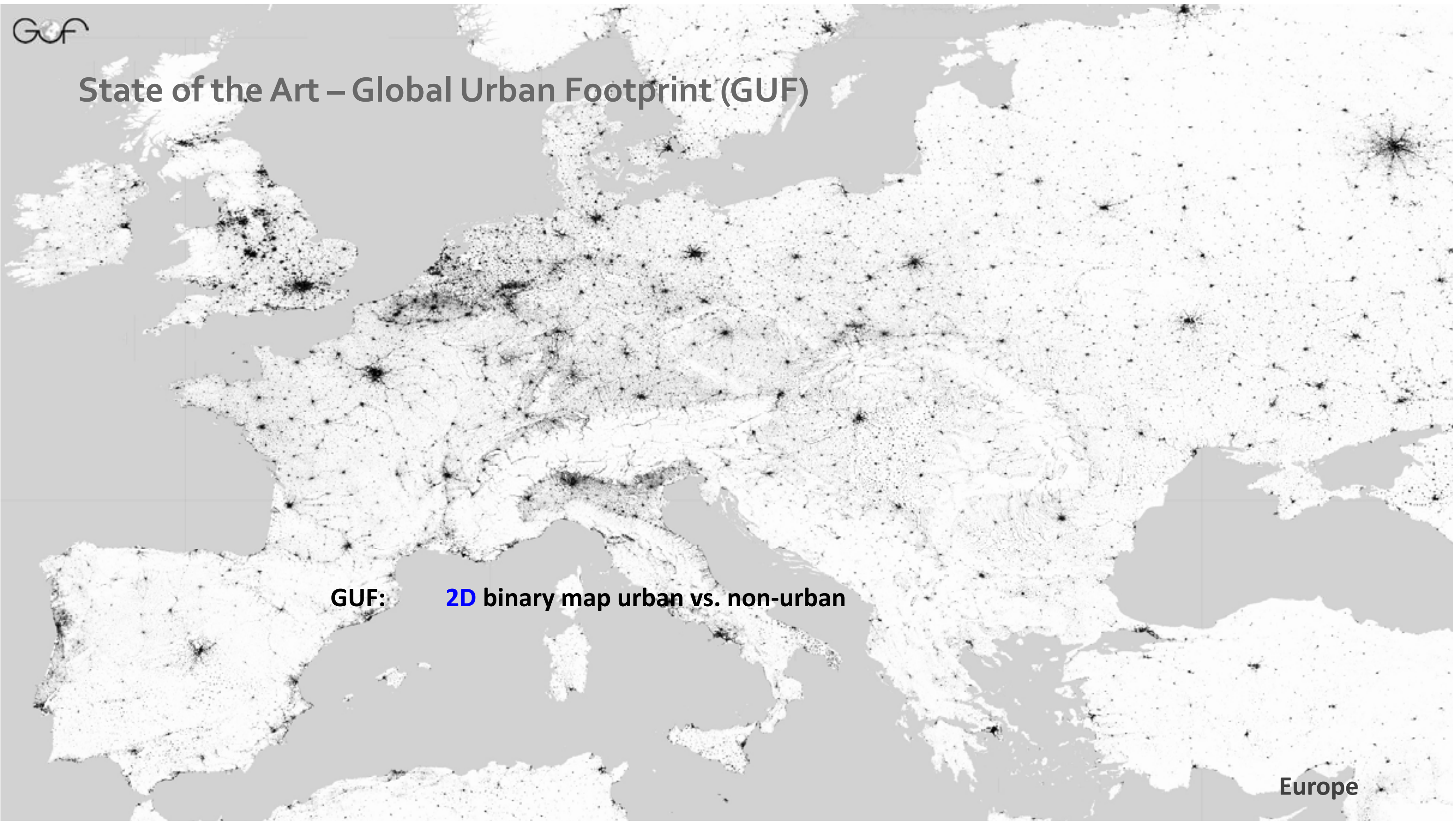
Uncontrolled Growth in Mumbai Slums Leads to Massive Fires and Floods

Urban Growth Happens Mostly in Developing Areas

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

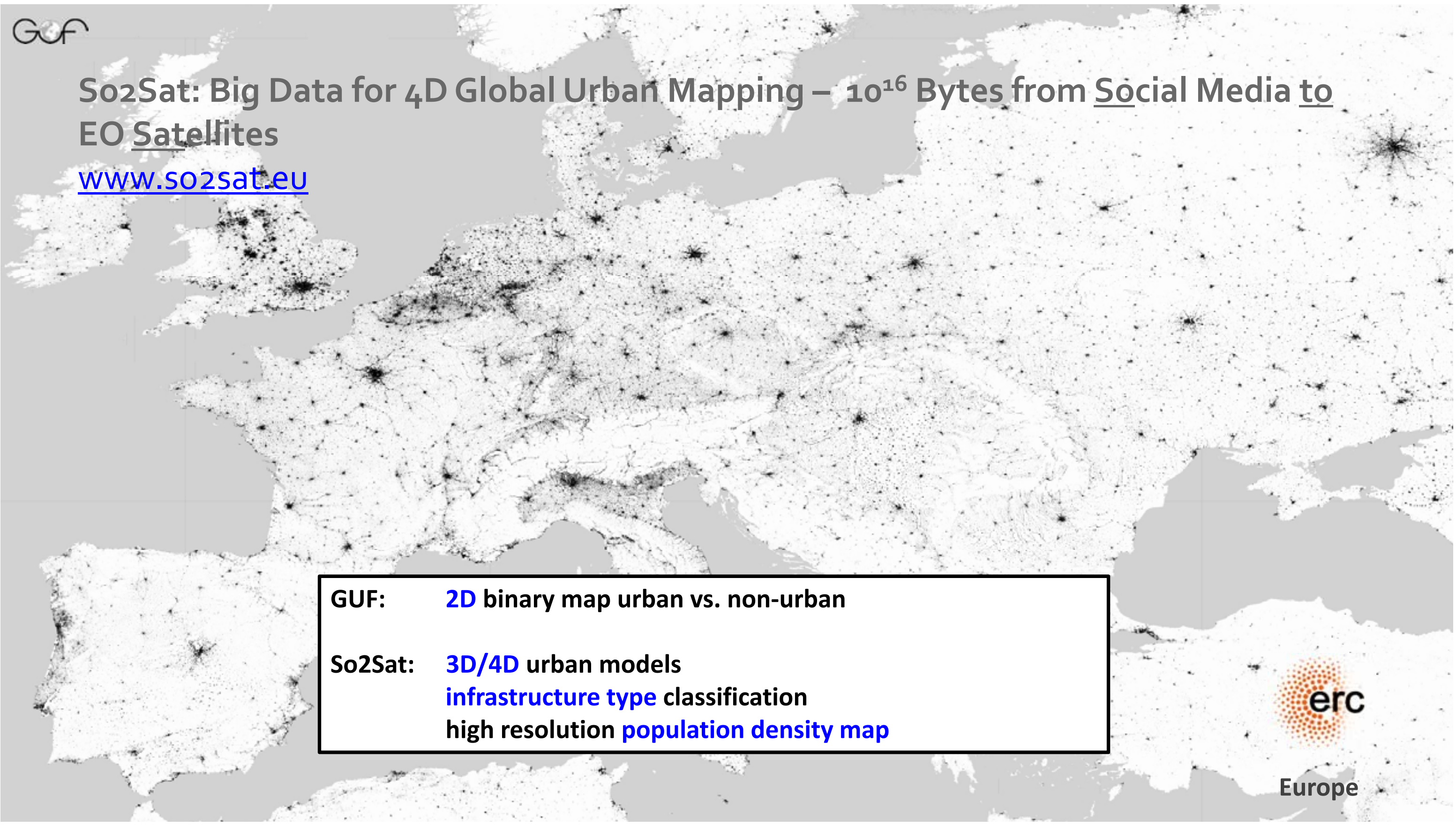
3D Models Missing for Most of the Cities

State of the Art – Global Urban Footprint (GUF)

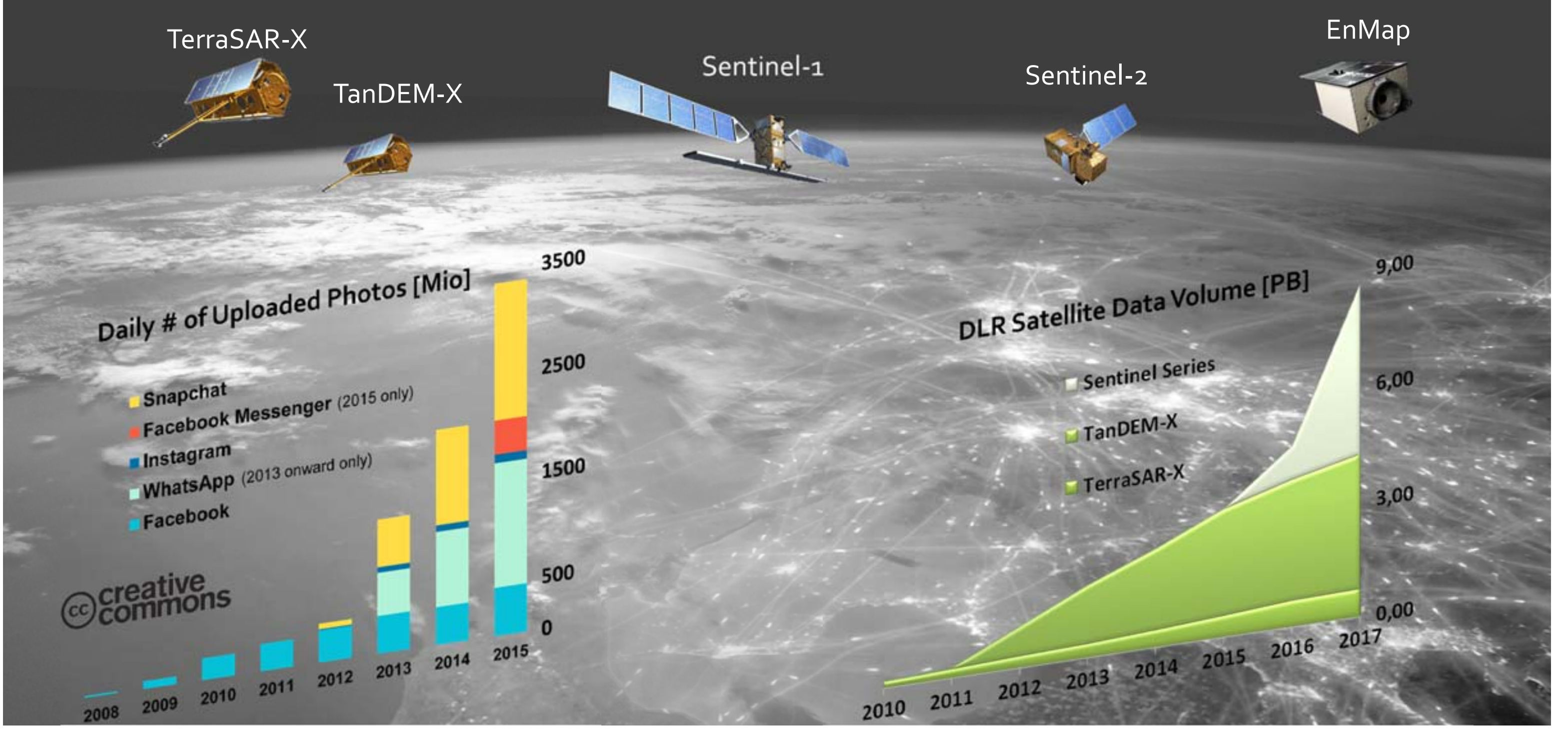


So2Sat: Big Data for 4D Global Urban Mapping – 10^{16} Bytes from Social Media to EO Satellites

www.so2sat.eu



10 Peta Bytes from Social Media to EO Satellites



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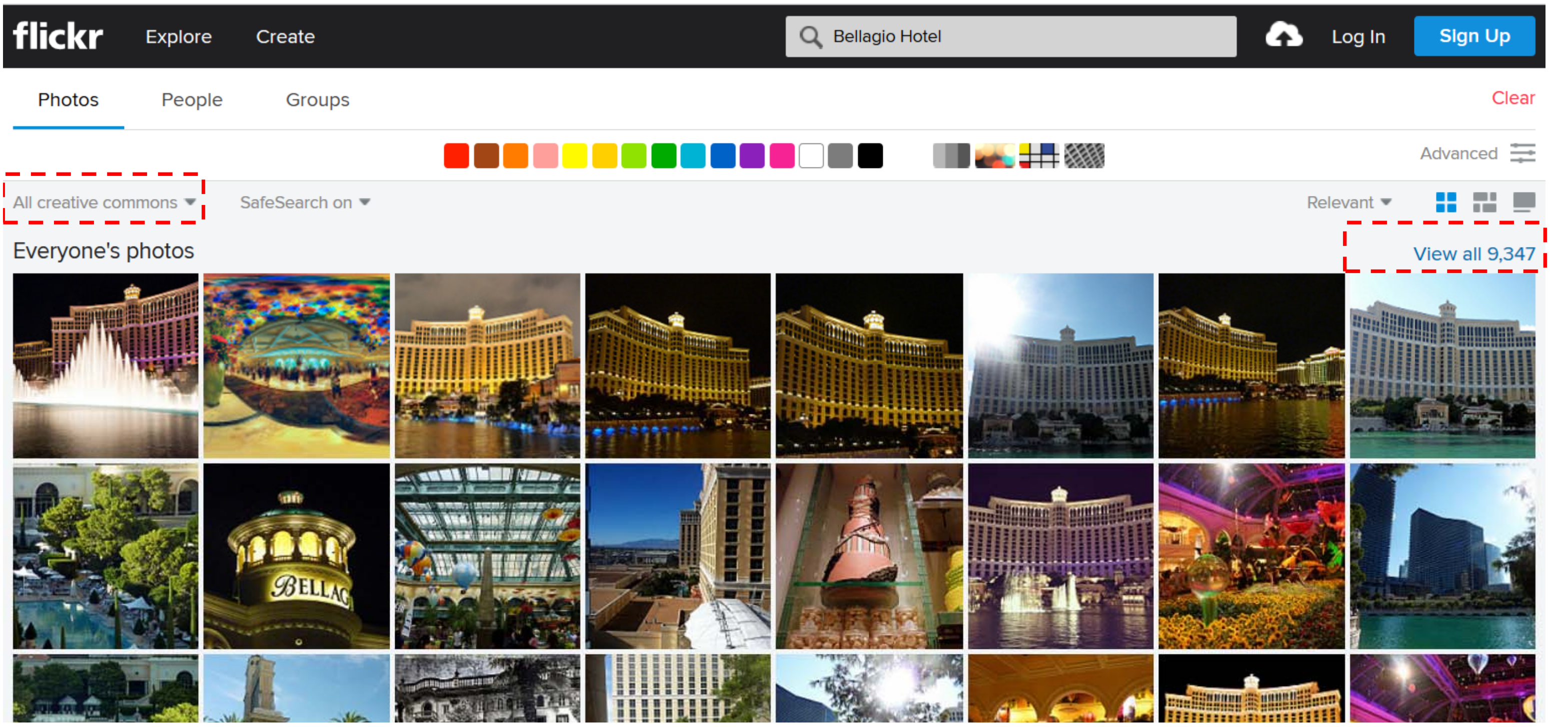
Social Media Images – Abundance of Hotspots



So2Sat in a Nutshell

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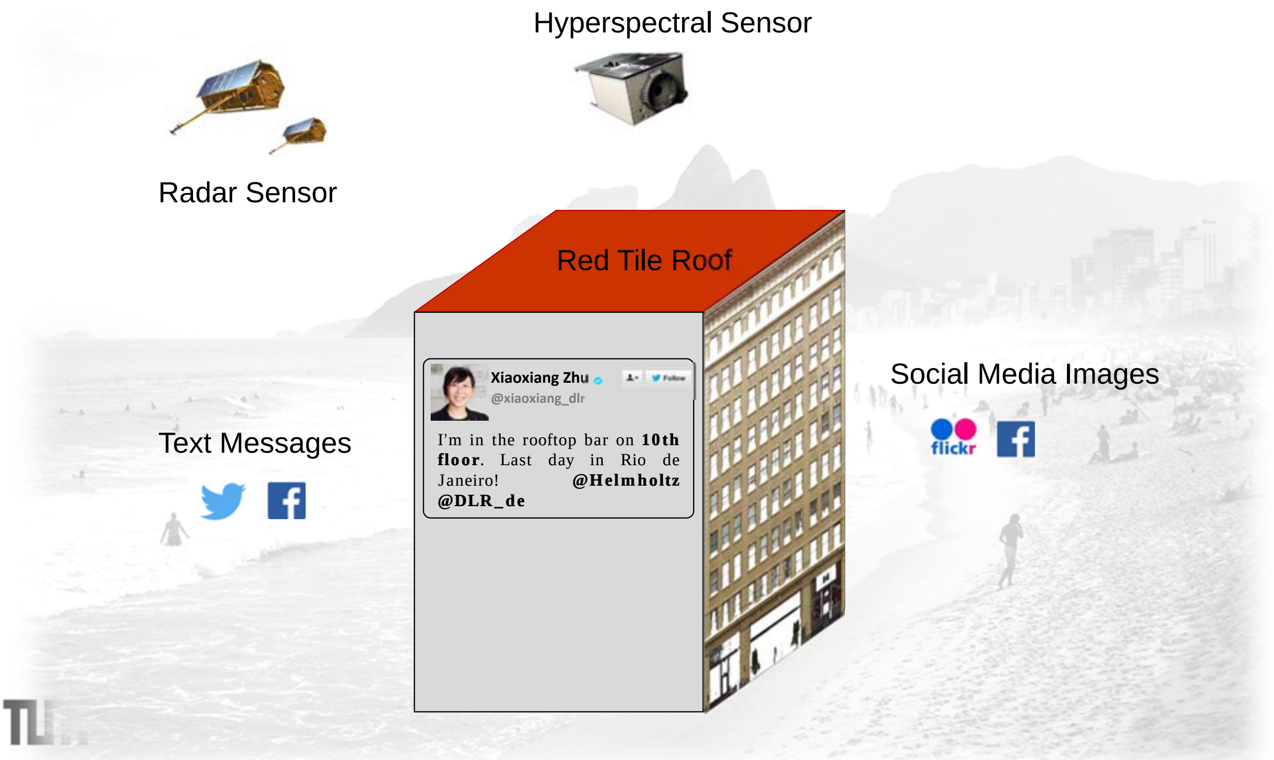
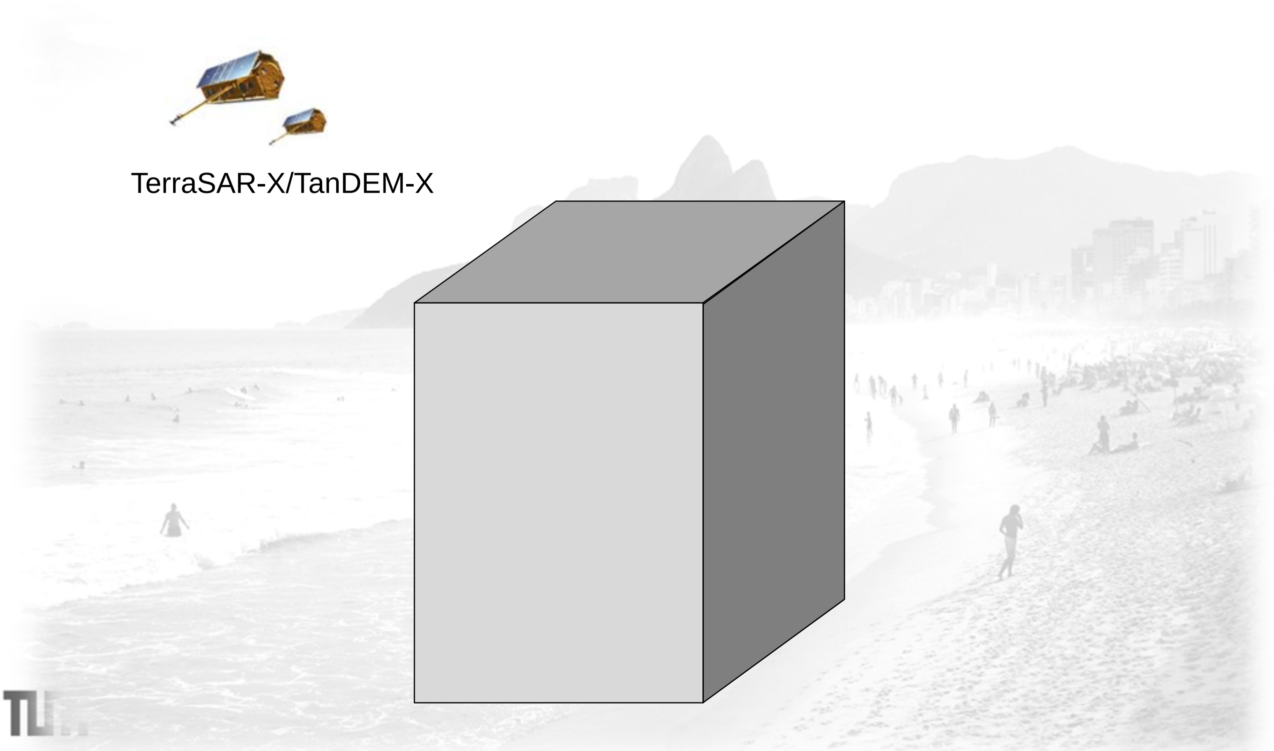
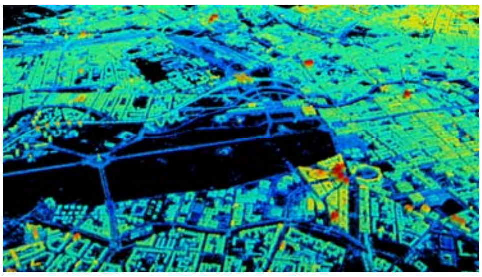


Global 3D/4D Urban Mapping



Challenges

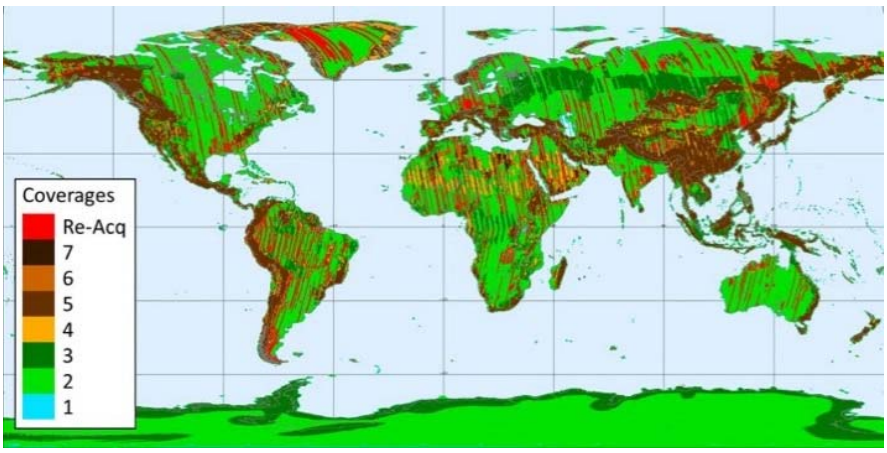


High quality tomographic reconstruction requires **20 – 100 high resolution** acquisitions → **not globally available**

TanDEM-X has global coverage, but ...

– only moderate resolution

– number of coverages limited



A Data Science Approach

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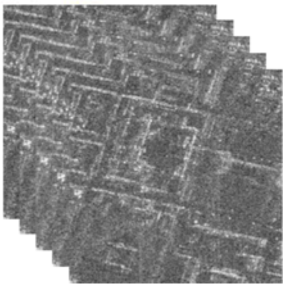
erc

Model-based Algorithms

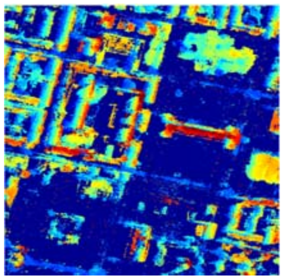
TanDEM



Stack Non-Local Filtering
$\mathcal{N}(\mathbf{g}) = f(\boldsymbol{\theta})$

Spectral Estimation
$\hat{\boldsymbol{\gamma}} = \operatorname{argmin}\|\mathbf{R}\boldsymbol{\gamma} - \mathcal{N}(\mathbf{g})\|_2^2 + \lambda\|\boldsymbol{\gamma}\|_1$

Model Selection
$\hat{K} = \operatorname{argmin}\{-2\ln p(\mathbf{g}|\boldsymbol{\theta}(K)) + 2C(K)\}$

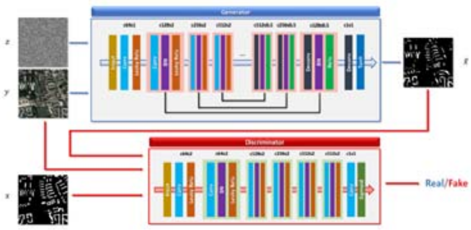


Building heights

Data-driven Algorithms

planet

DLR TUM



Building shapes

First Impression of the Global 3D Urban Models

accuracy better than **2m**

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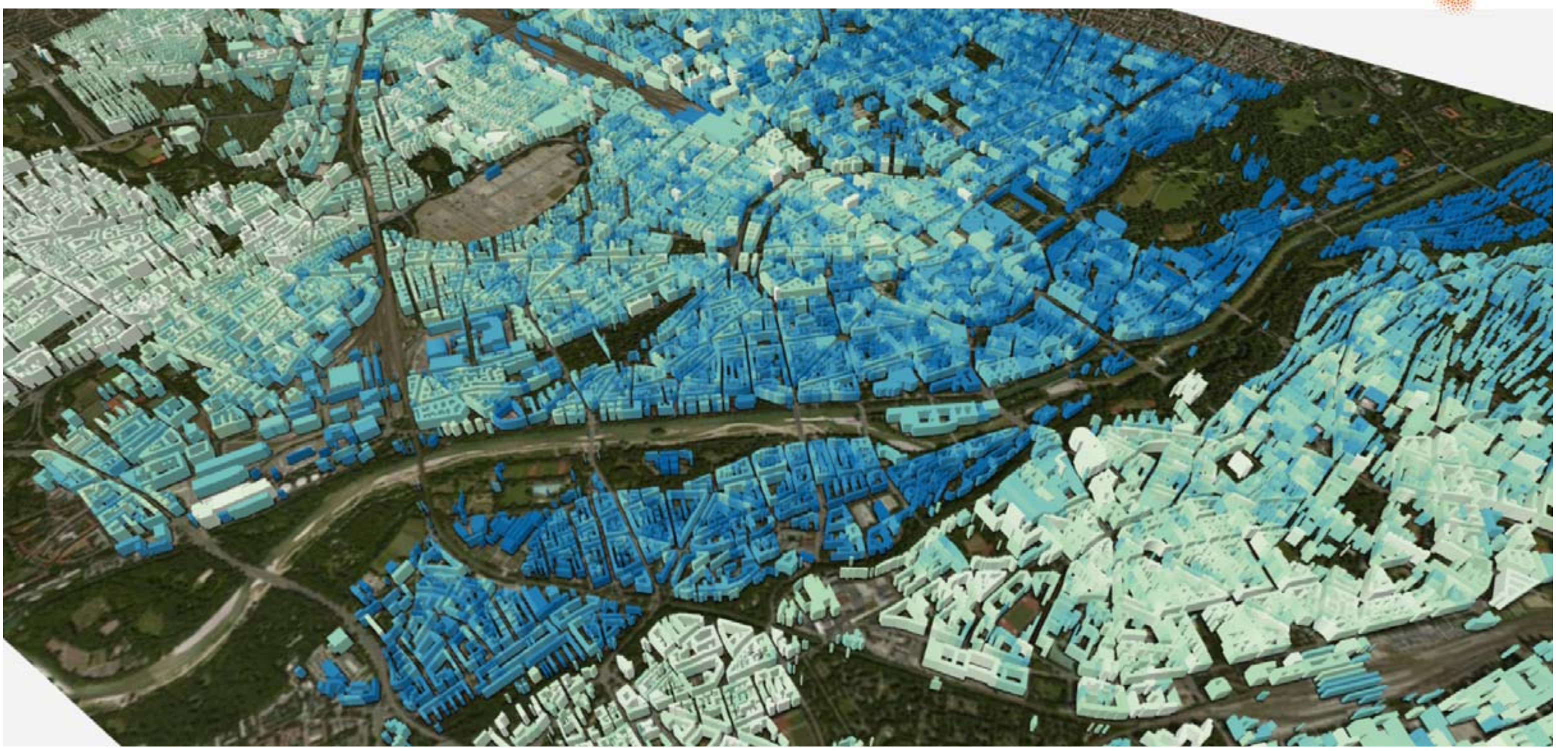

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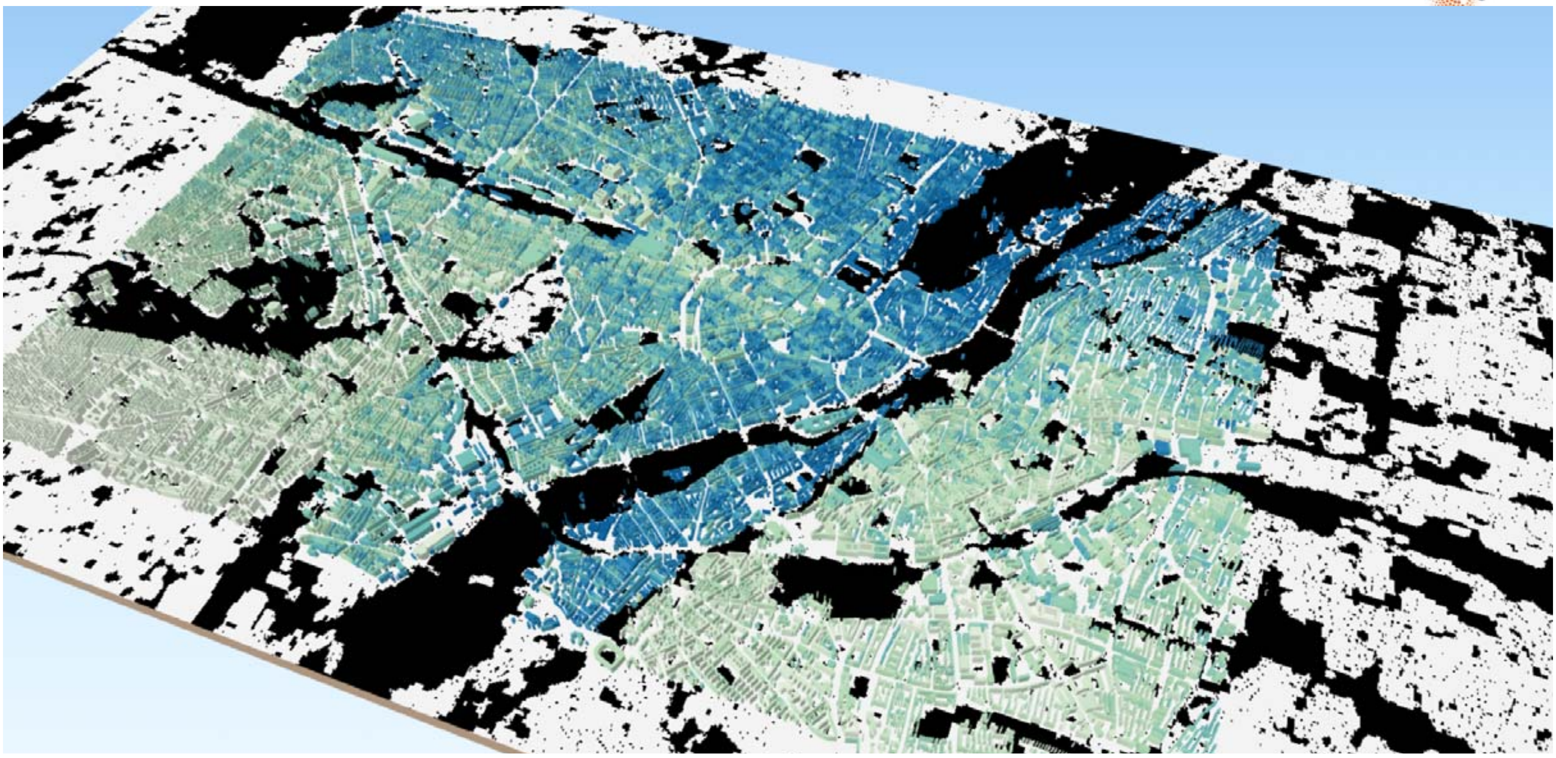
We Go Global in 2021!



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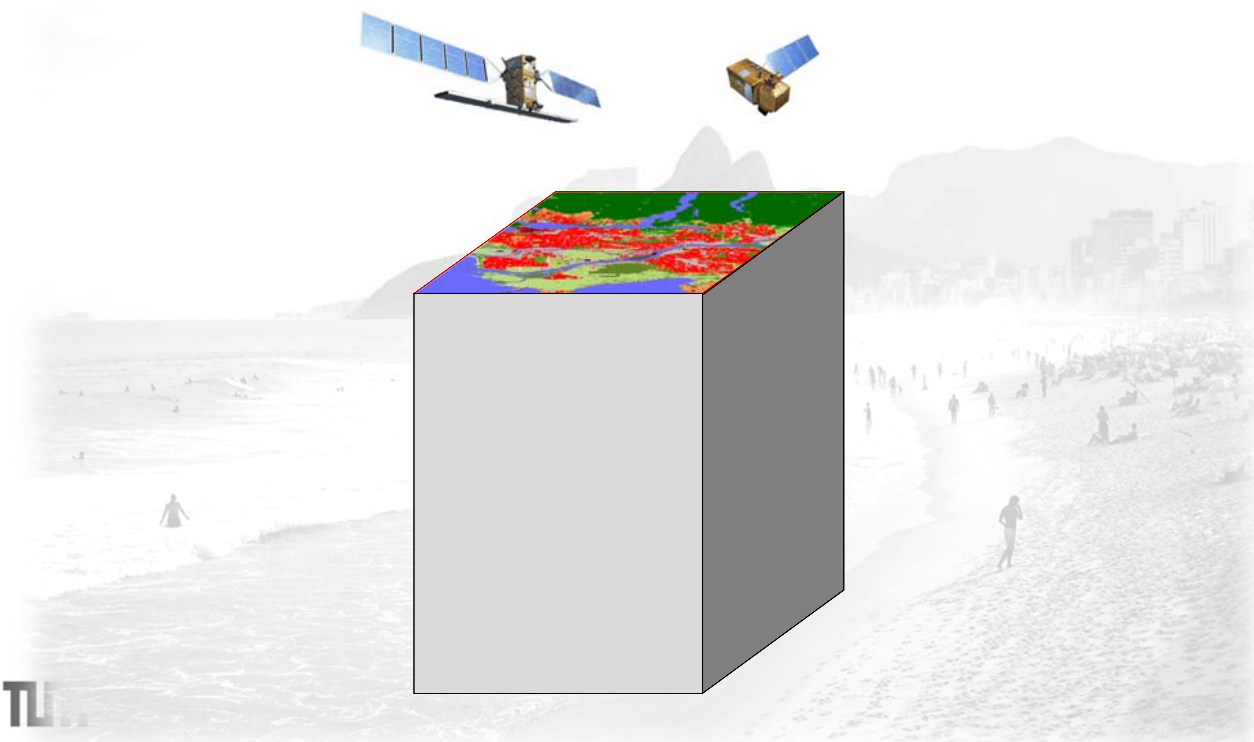
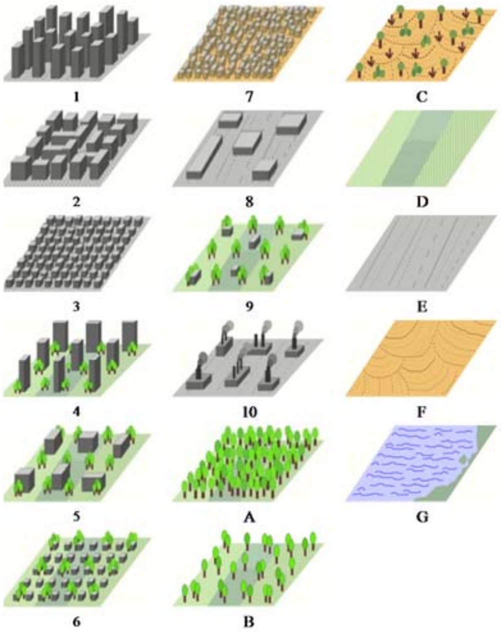
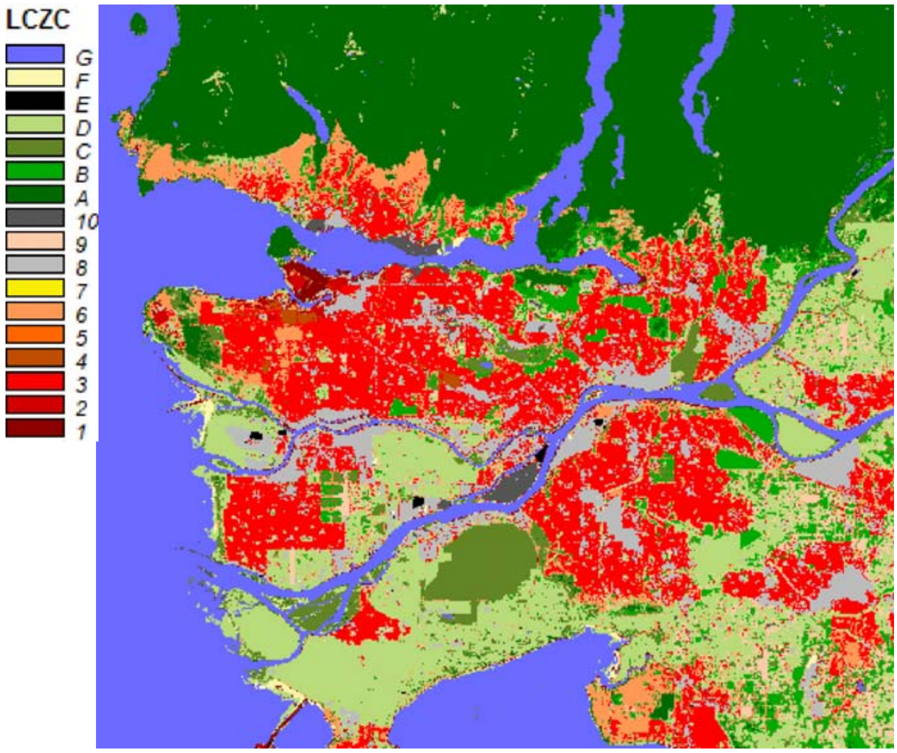
Global Local Climate Zones Classification



Global Local Climate Zones Classification
will be global soon

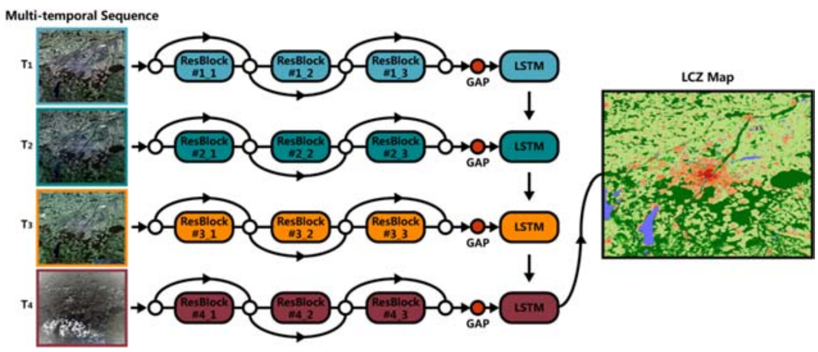




So2Sat LCZ42 Benchmark Dataset

- Hand labelled 42 cities covering 10 culture zones
- Data:
  - Sentinel-1
  - Sentinel-2, seasonal

Labeling effort: 15 person × 1 Month/person



DLR/StepStone/AliCloud Tianchi Contest 2018 Germany

Contestants

200k data talents in 91 countries and regions

Task ← TIANCHI Data Scientists ← Demand

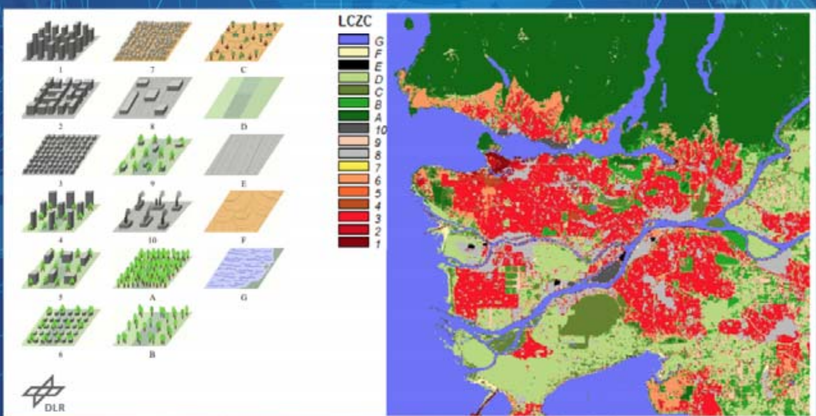
Solution → → Product

Customers

StepStone DLR

Challenge

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

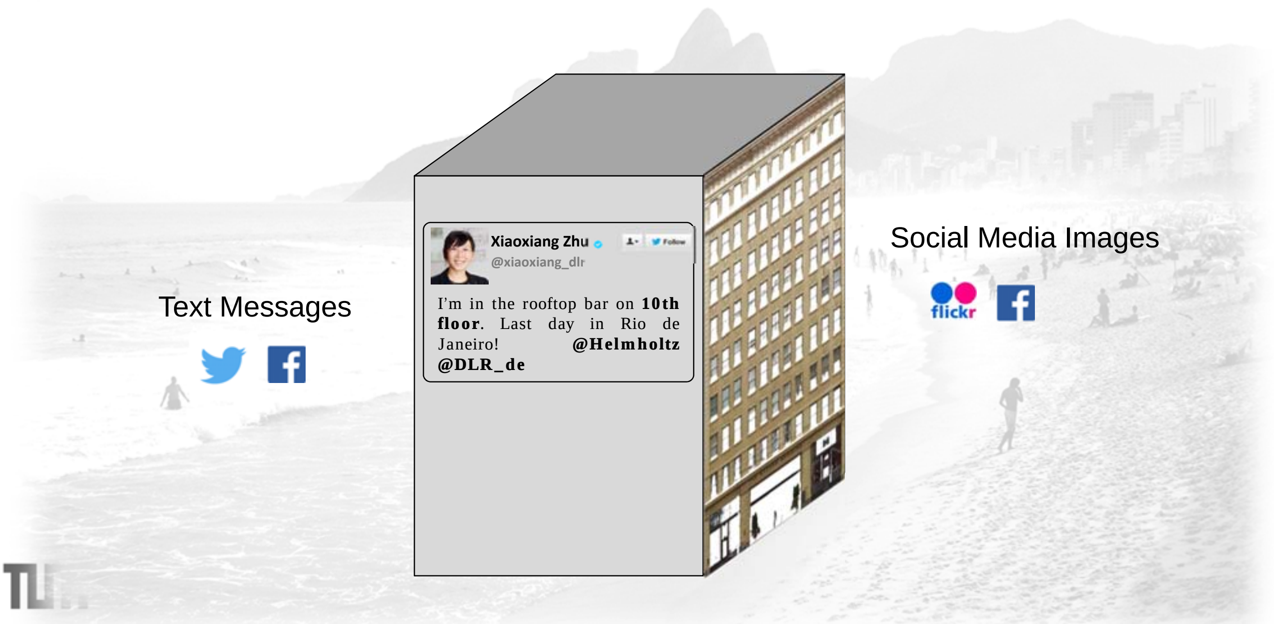


LCZ applications

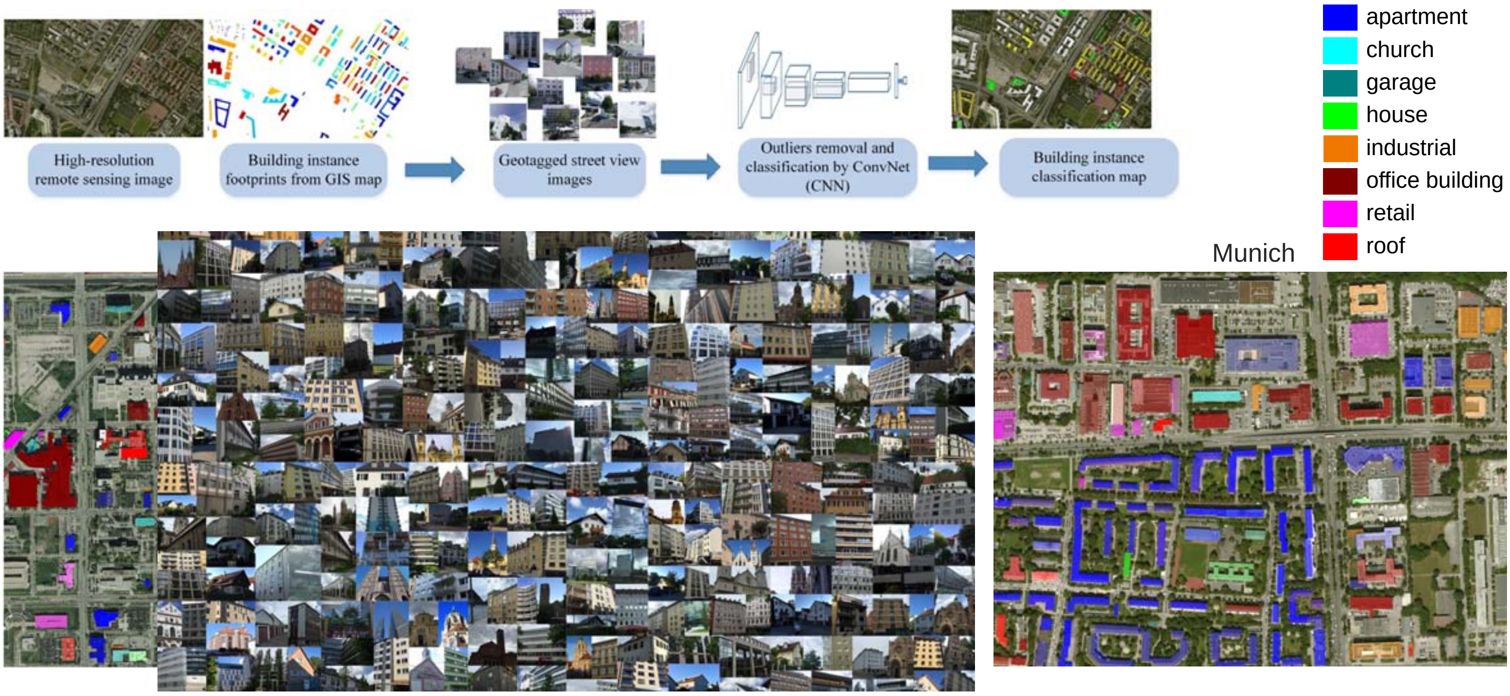
- Quantifying Urban Heat Island magnitude
- Classifying weather stations
- Mapping urban terrain
- Assessing social inequalities

Building Settlement Type Classification

– by the Fusion of Remote Sensing and Social Media Data



Building Instance Classification from Street View Data by CNN



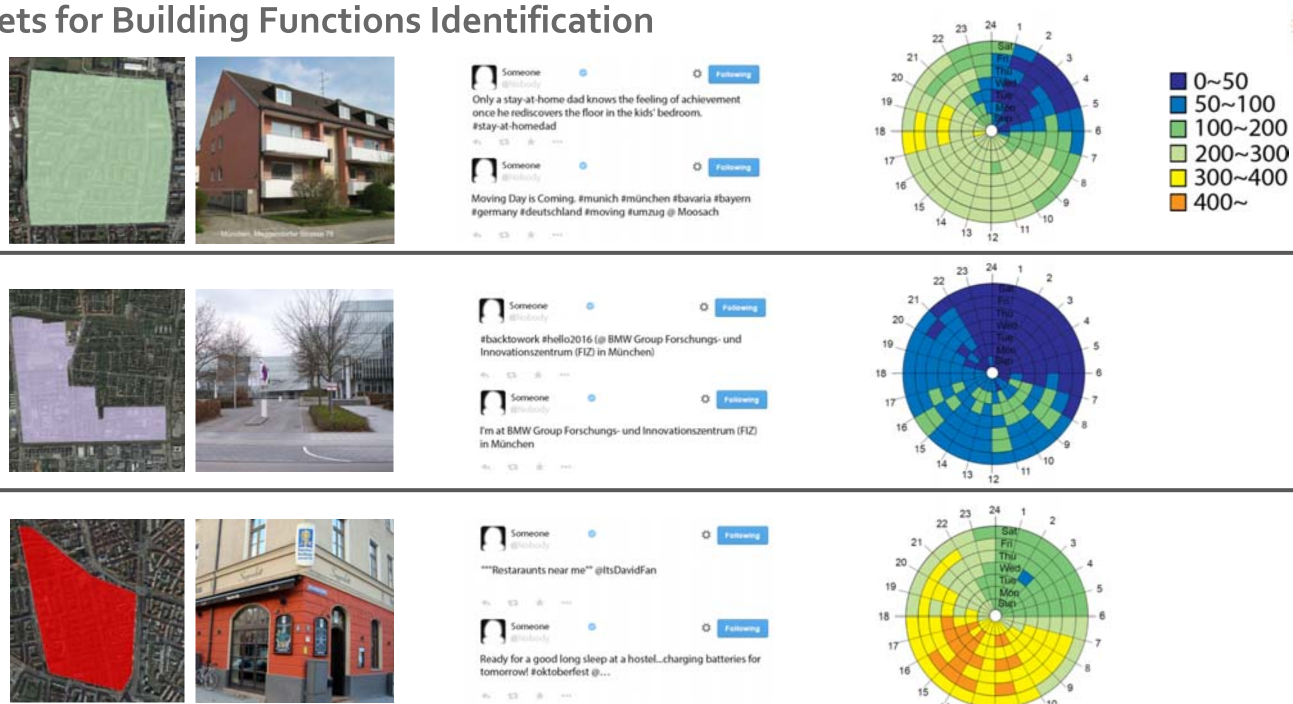
Tweets for Building Functions Identification

Tweets for Building Functions Identification

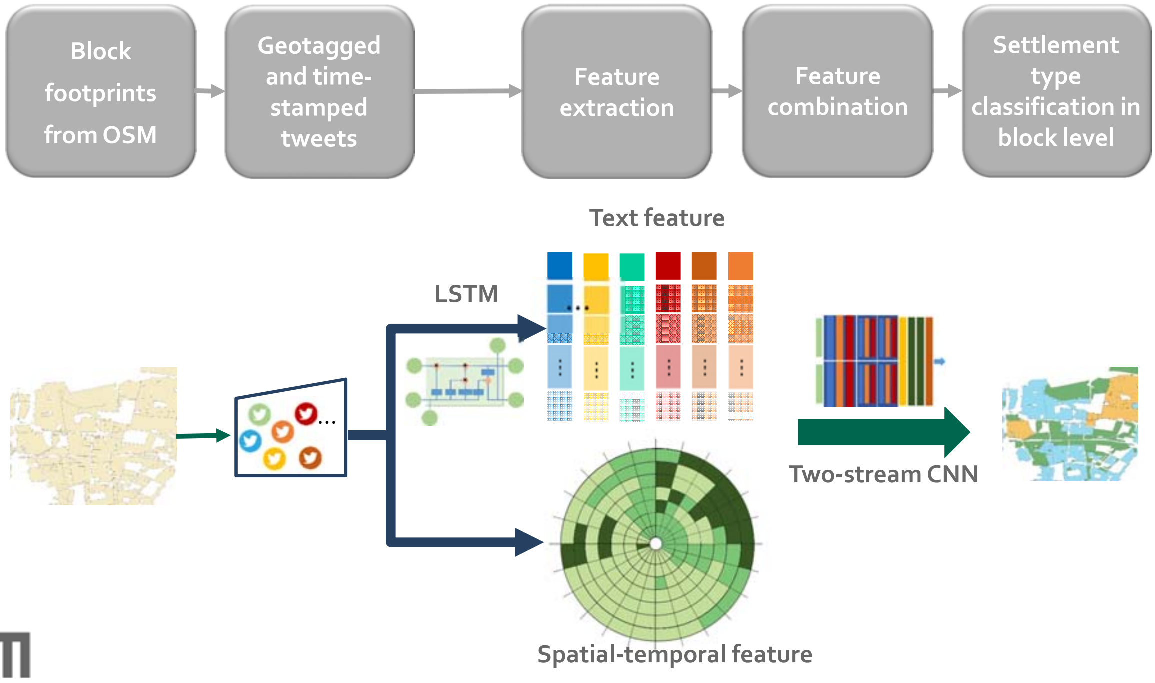
residential

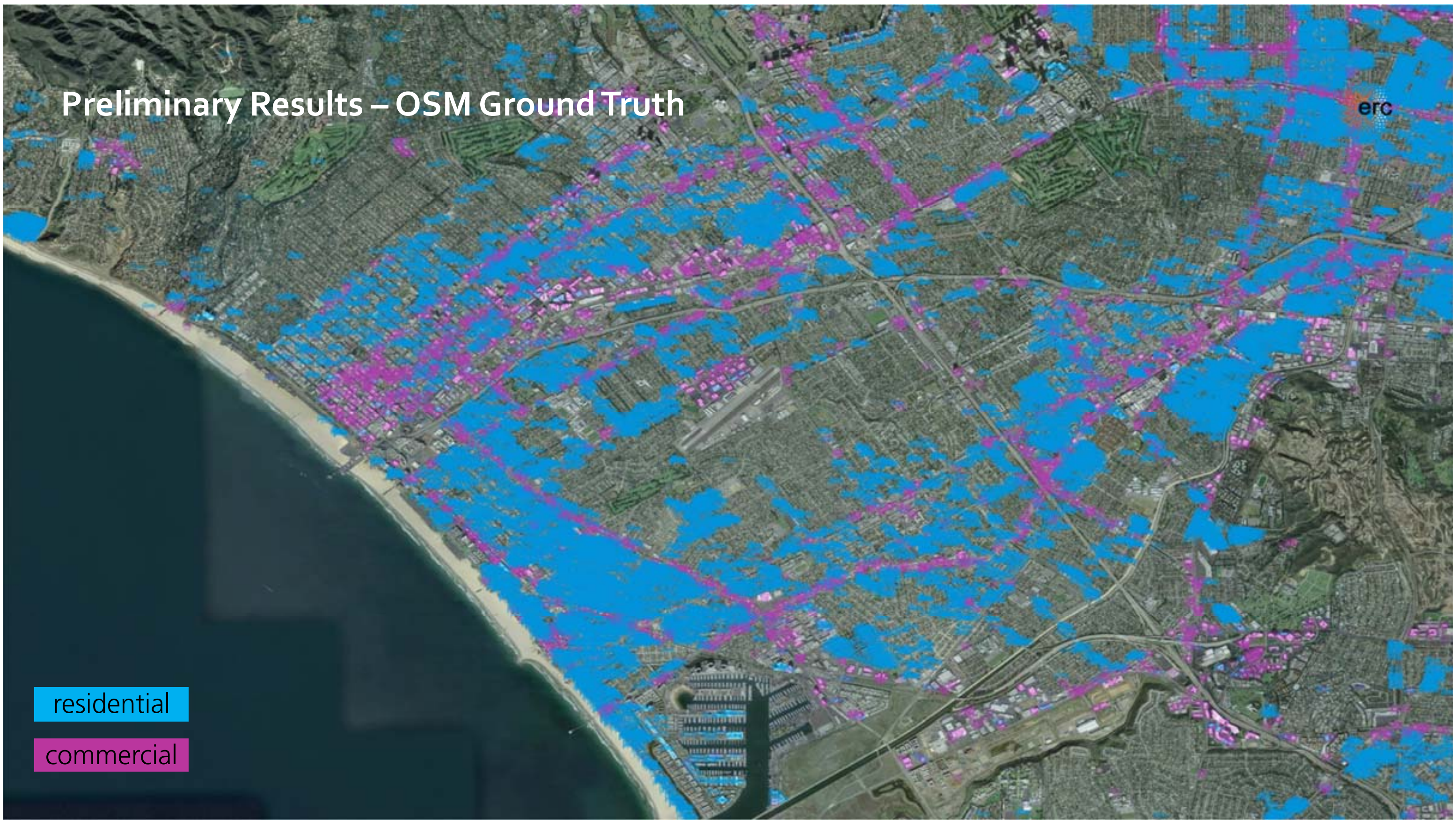
non-residential

mixed used

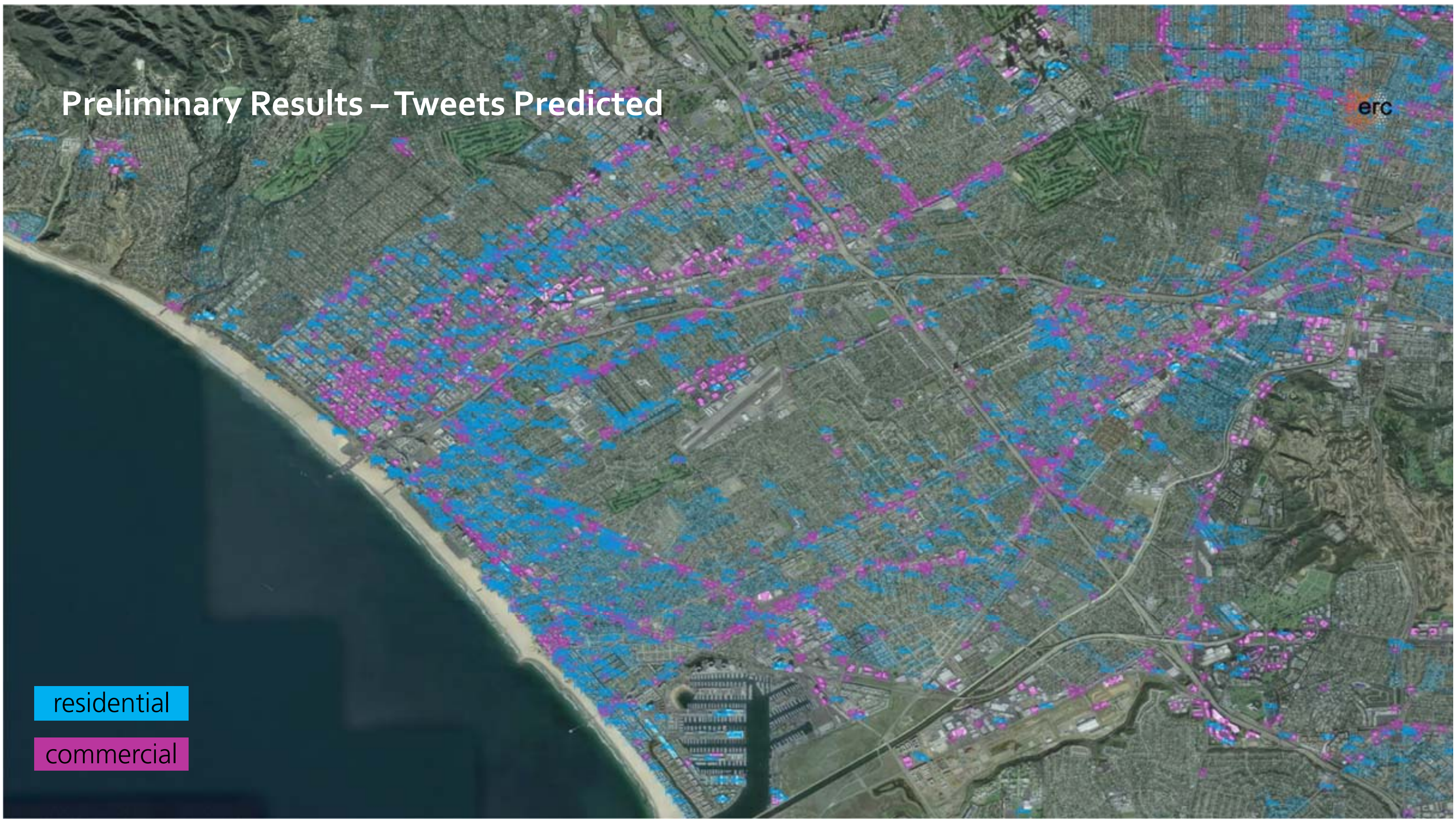


Tweets for Building Functions Identification





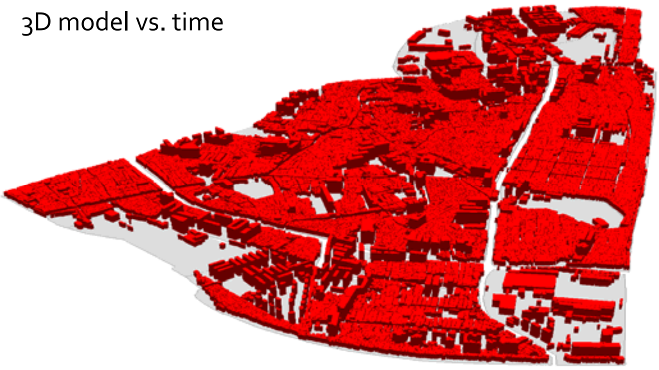
Preliminary Results – Tweets Predicted



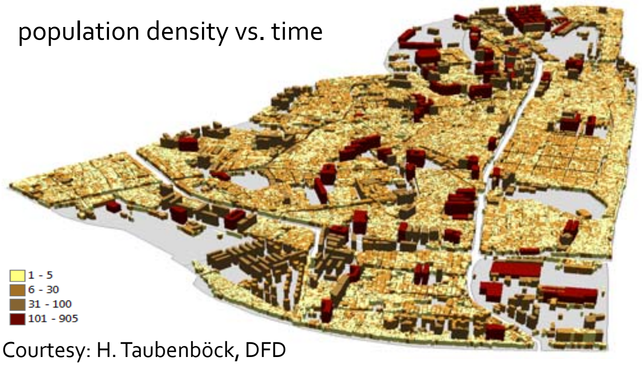
My Vision in 2022

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

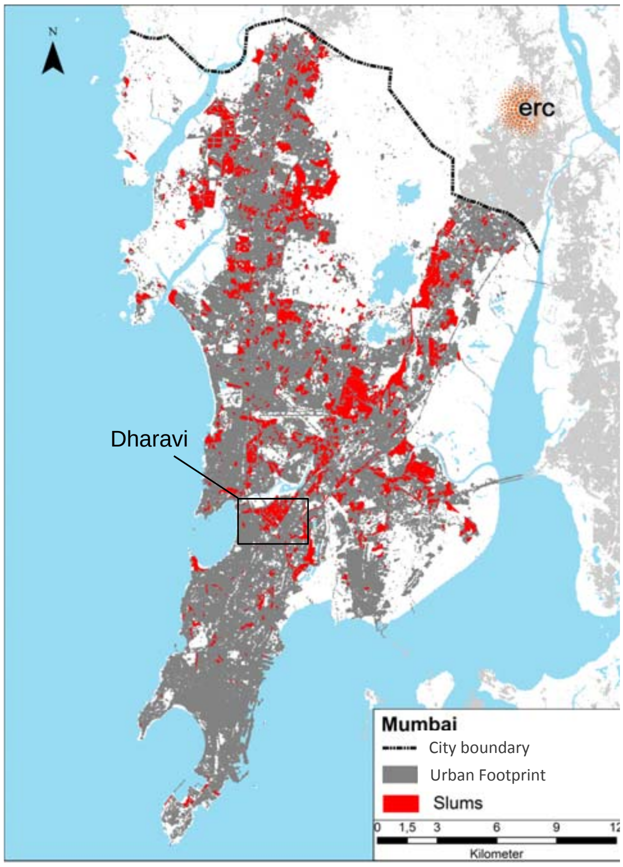
3D model vs. time



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**
- **transparent** global population assessment
- a helping hand to address **poverty**