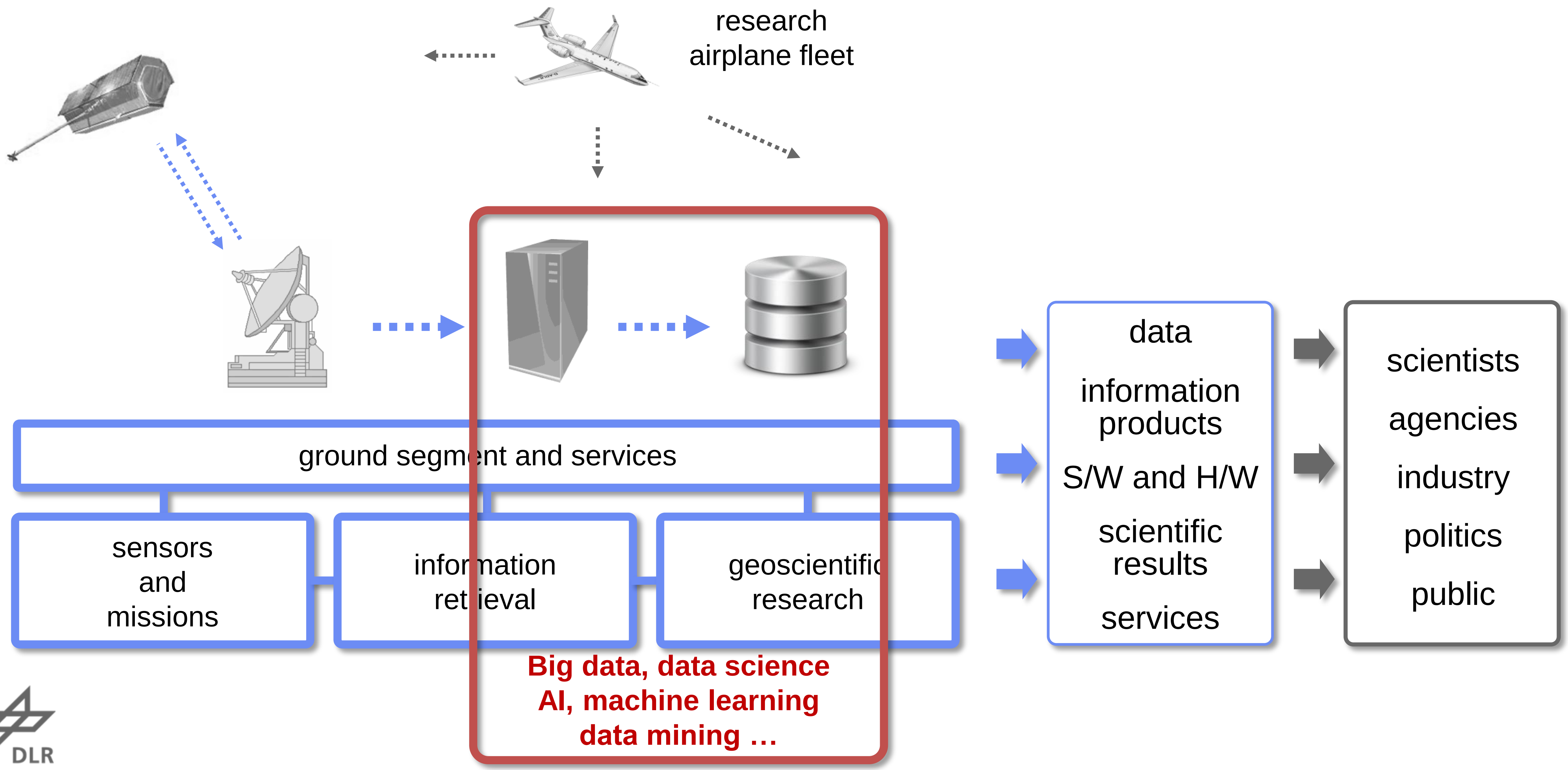
Big Data und KI-Verfahren in der Erdbeobachtung

Richard Bamler
Institut für Methodik der Fernerkundung

11. Juli 2018

DLR

DLR’s System Competence in EO



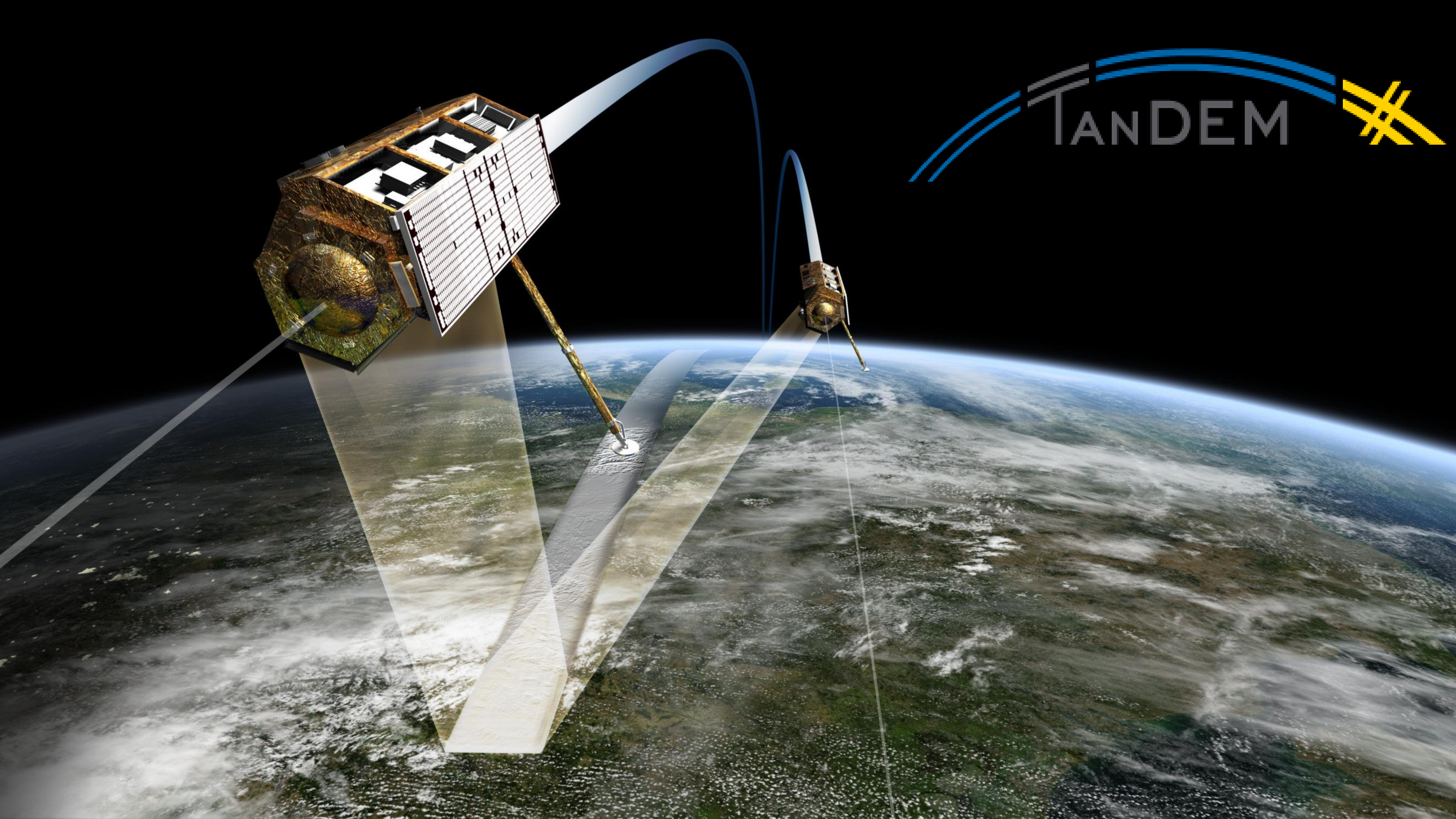
DLR

Earth Observation Center

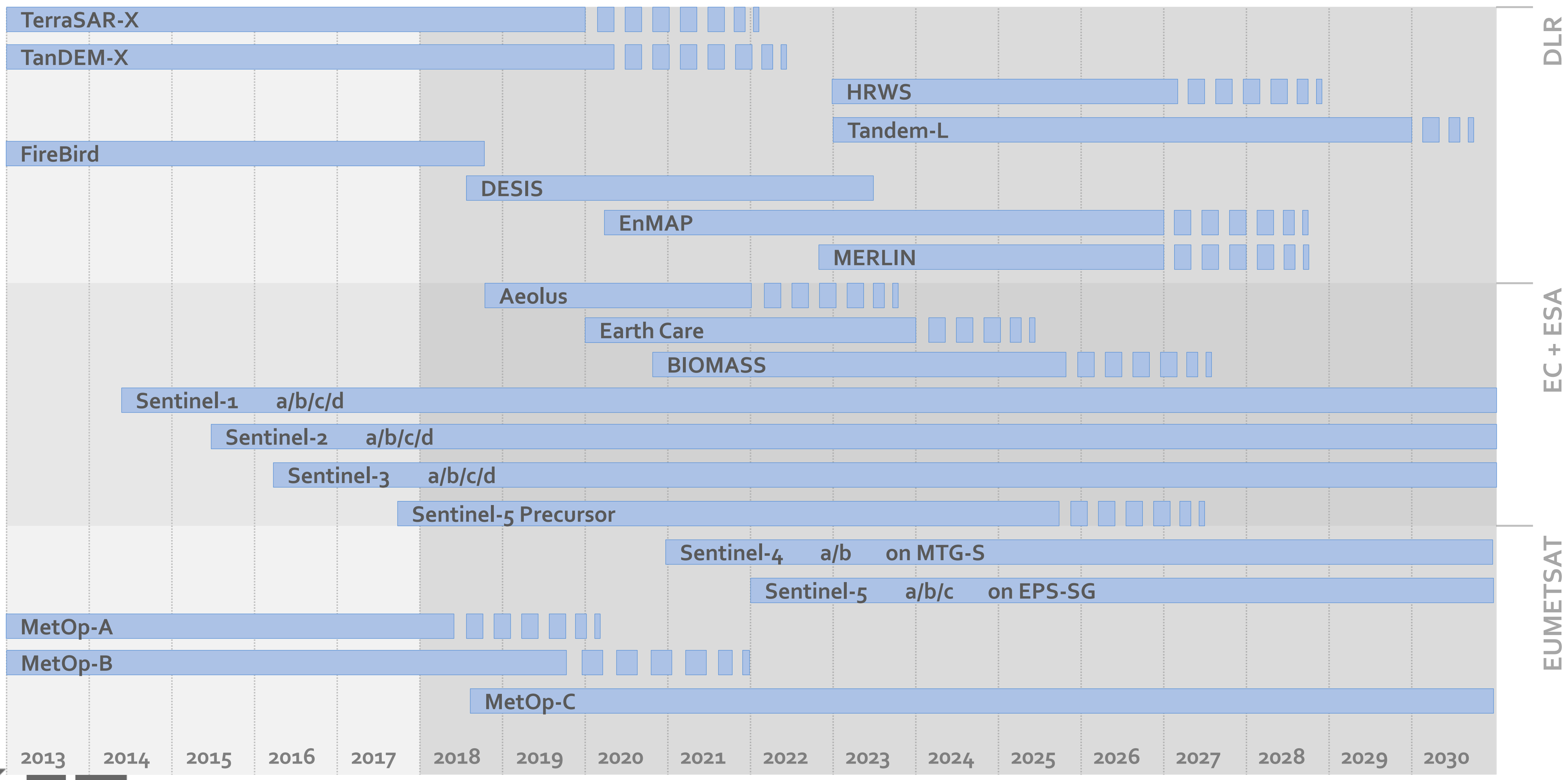
Institut für Methodik der Fernerkundung (IMF)
Direktor: Prof. Dr. Richard Bamler

Deutsches Fernerkundungsdatenzentrum (DFD)
Direktor: Prof. Dr. Stefan Dech

DLR


TanDEM

Relevant EO Missions (DLR and European)



Game Changer Copernicus-Programm

- Information und Wissen aus Erdbeobachtung unverzichtbar für alle geo-relevanten wissenschaftlichen und wirtschaftlichen Fragestellungen

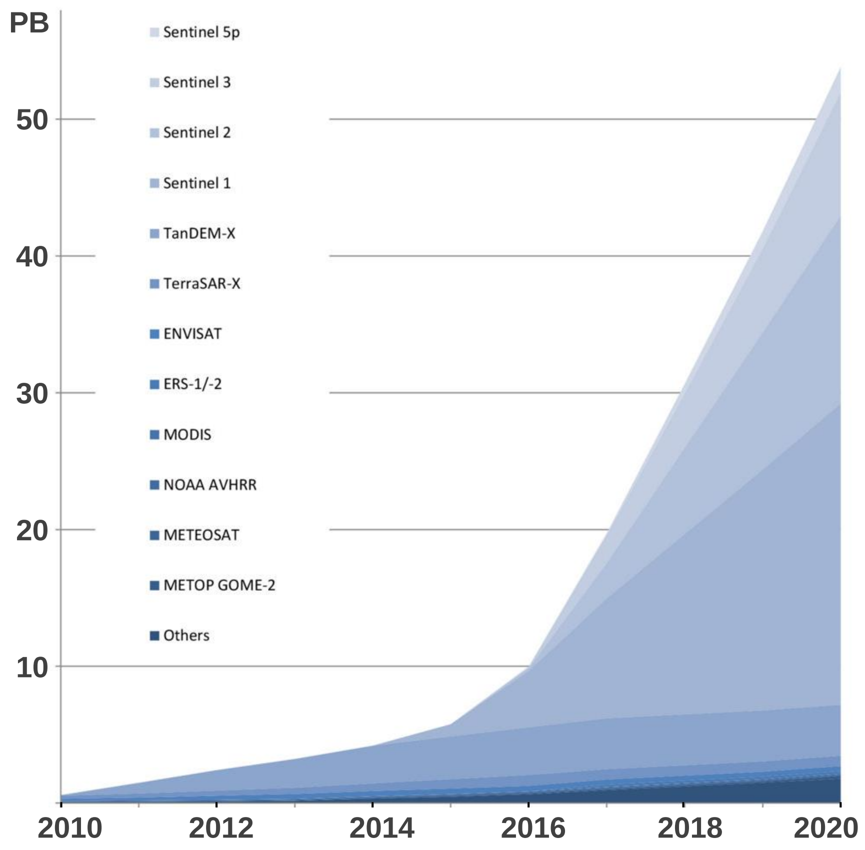
- Hohe Akzeptanz satellitenbasierter Geoinformation

- Sentinel-Satellitenflotte als nachhaltige Hochleistungs-Datenquelle
  - 15 TB/Tag
  - 2020: >50 PB im DLR Datenarchiv
  - Versorgungssicherheit bis weit über 2030
  - Daten „free and open“

- Klassische Auswerteverfahren nicht mehr ausreichend → KI

- Spezifische Qualitätsanforderungen und Anwendungsvielfalt
  → nicht nur Adaption bekannter KI-Methoden, sondern neue Forschung und innovative Entwicklungen nötig

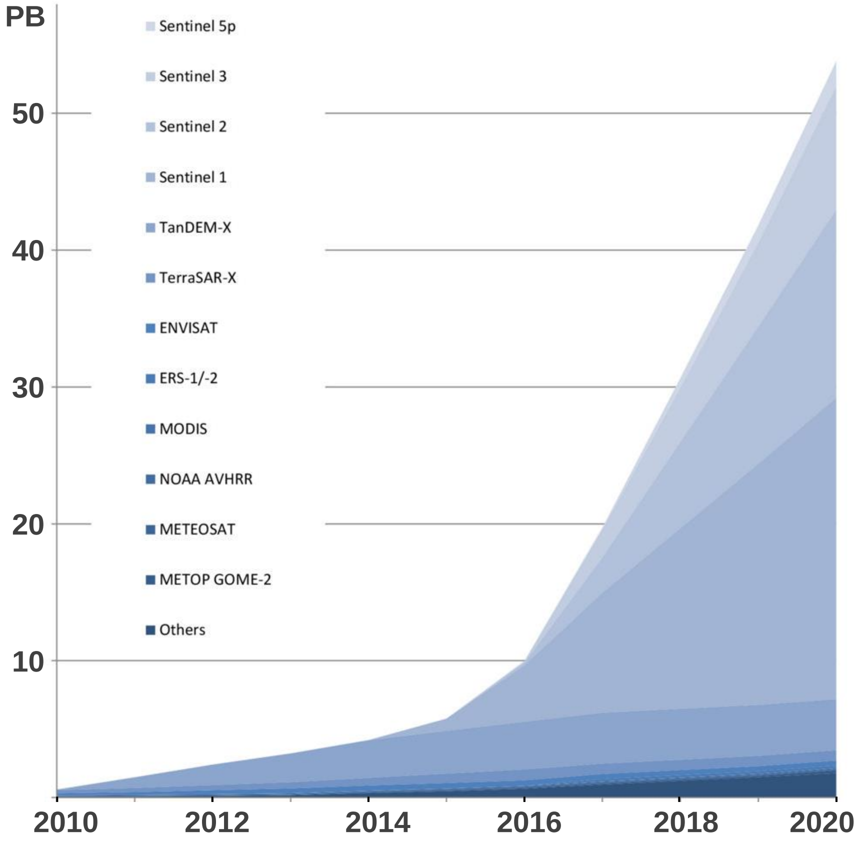
Copernicus
Europe's eyes on Earth

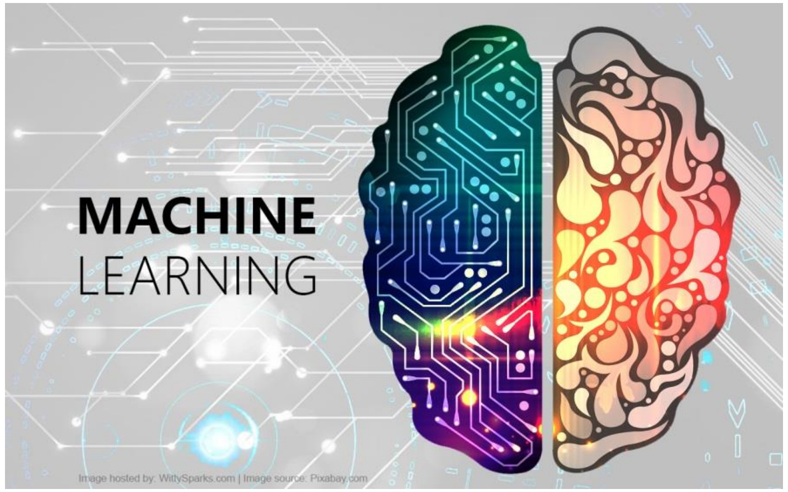


DLR

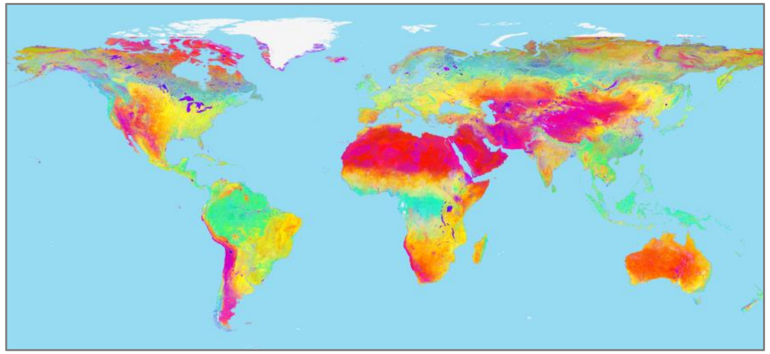
AI for Earth Observation
New Aspects and Challenges

- Massive growth of free and open satellite data
  - Increasing number of satellite missions
  - Increasing spatial and spectral resolution
- Global scale processing at high spatial resolution
- Generation of decadal time series
- Google, Amazon et al. enter EO and provide data access and computing capacity
- Machine learning has become <u>the</u> data analysis concept

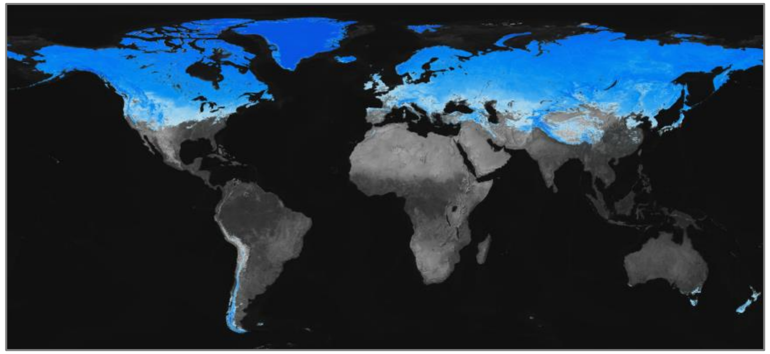




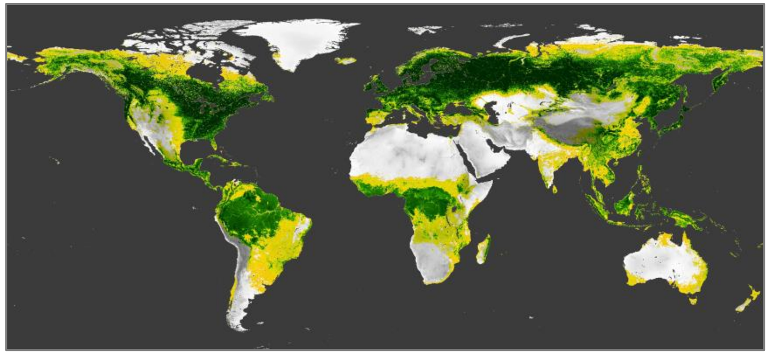
Decadal Time Series for Global Change Research
DLR-DFD



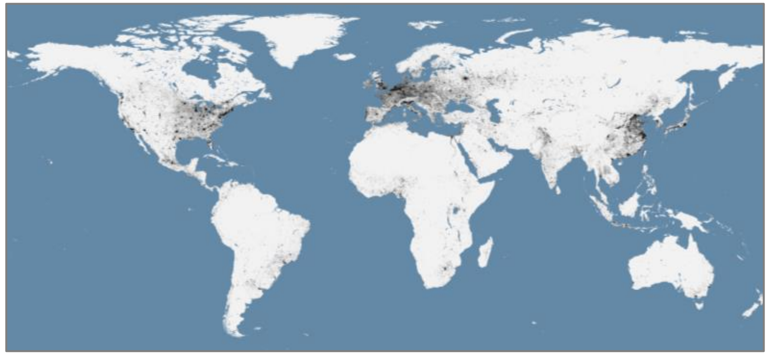
TimeScan
25 years of 30 statistics of indices



SnowPack
18 years of daily snow cover

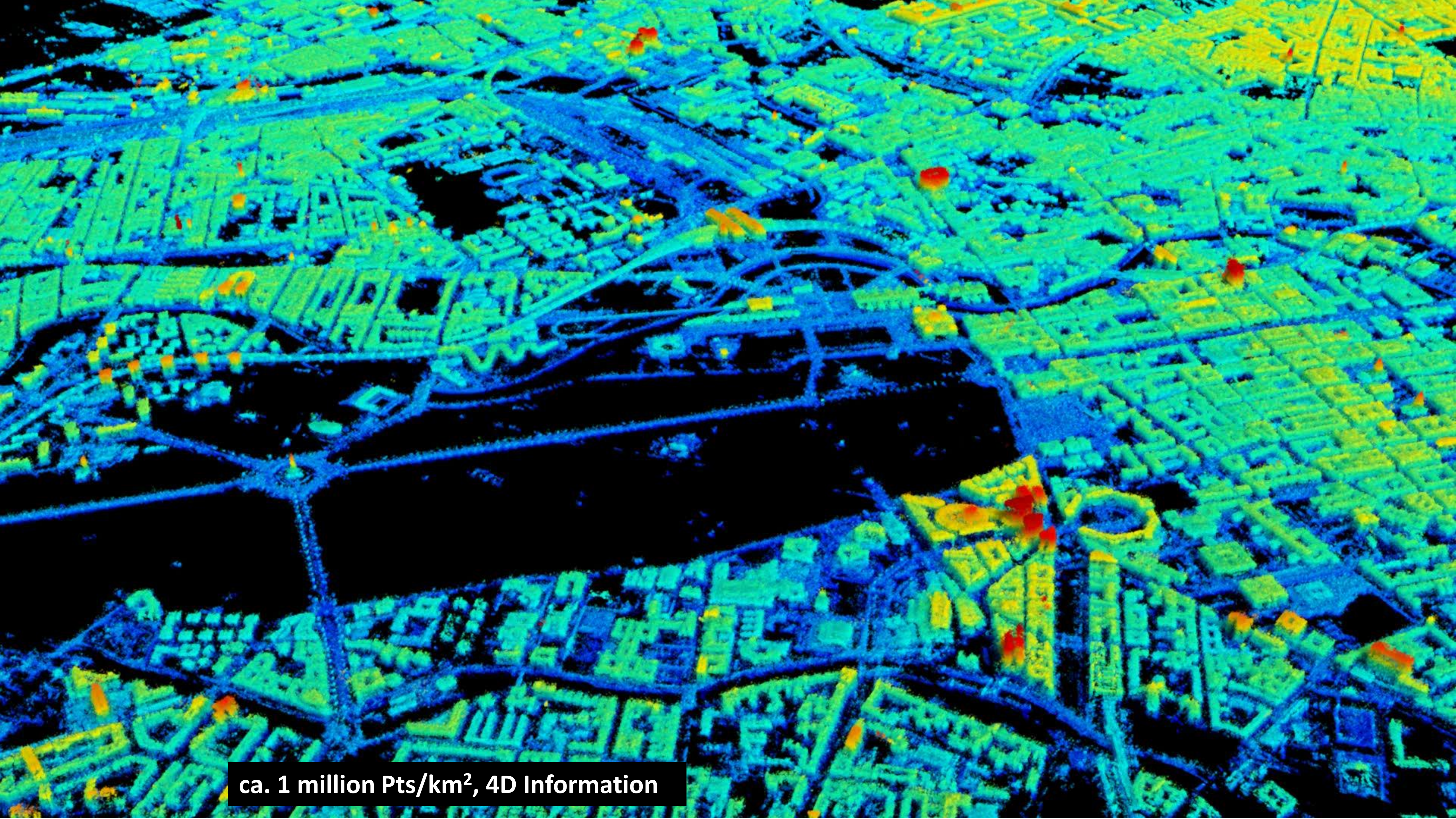


Net Primary Productivity
14 years



Global Urban Footprint
30 years

WaterPack
16 years of daily inland water cover

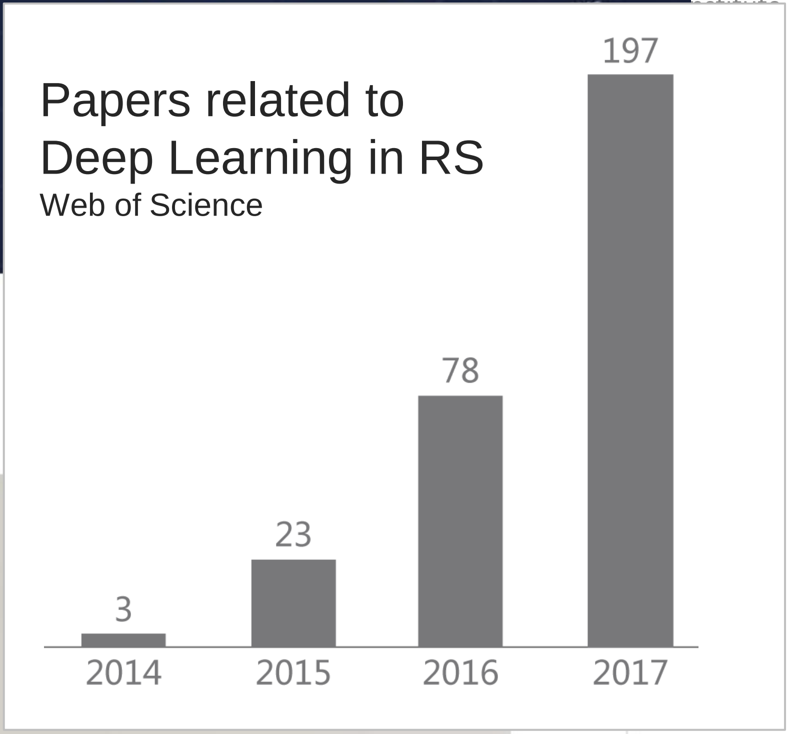

ca. 1 million Pts/km², 4D Information

Home Who We Are Activities Existential Risk Get Involved Contact

undung

future of life INSTITUTE

News: AI Biotech Nuclear Climate Partner Orgs



DeepMind's AlphaGo Zero Becomes Go Champion Without Human Input

October 18, 2017 / by Jessica Cussins

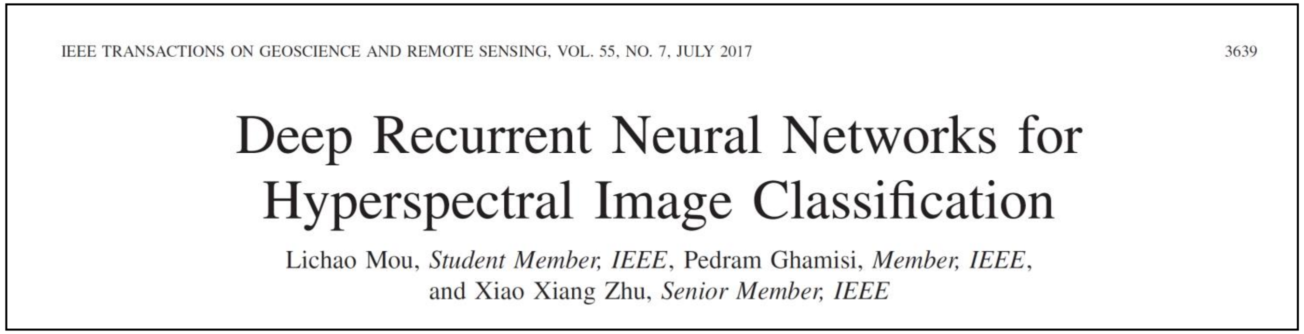
DLR

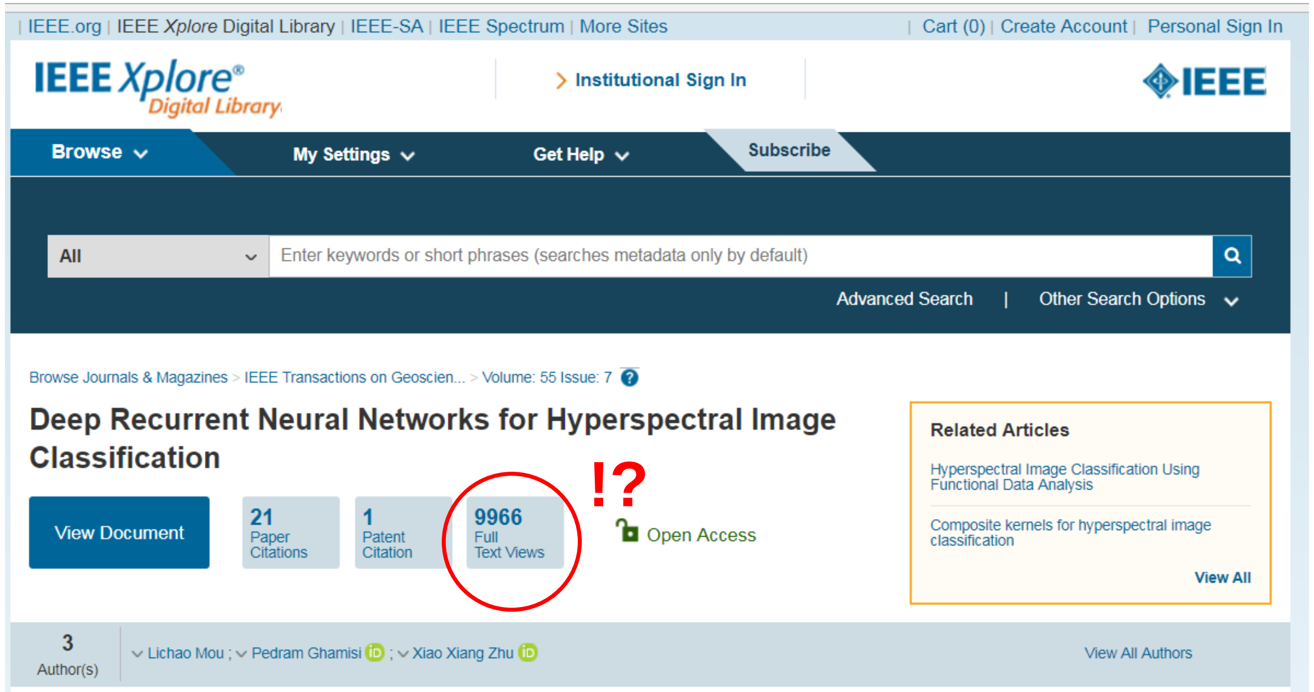
Deep Learning in EO – Hot Topic or Hype?

- **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

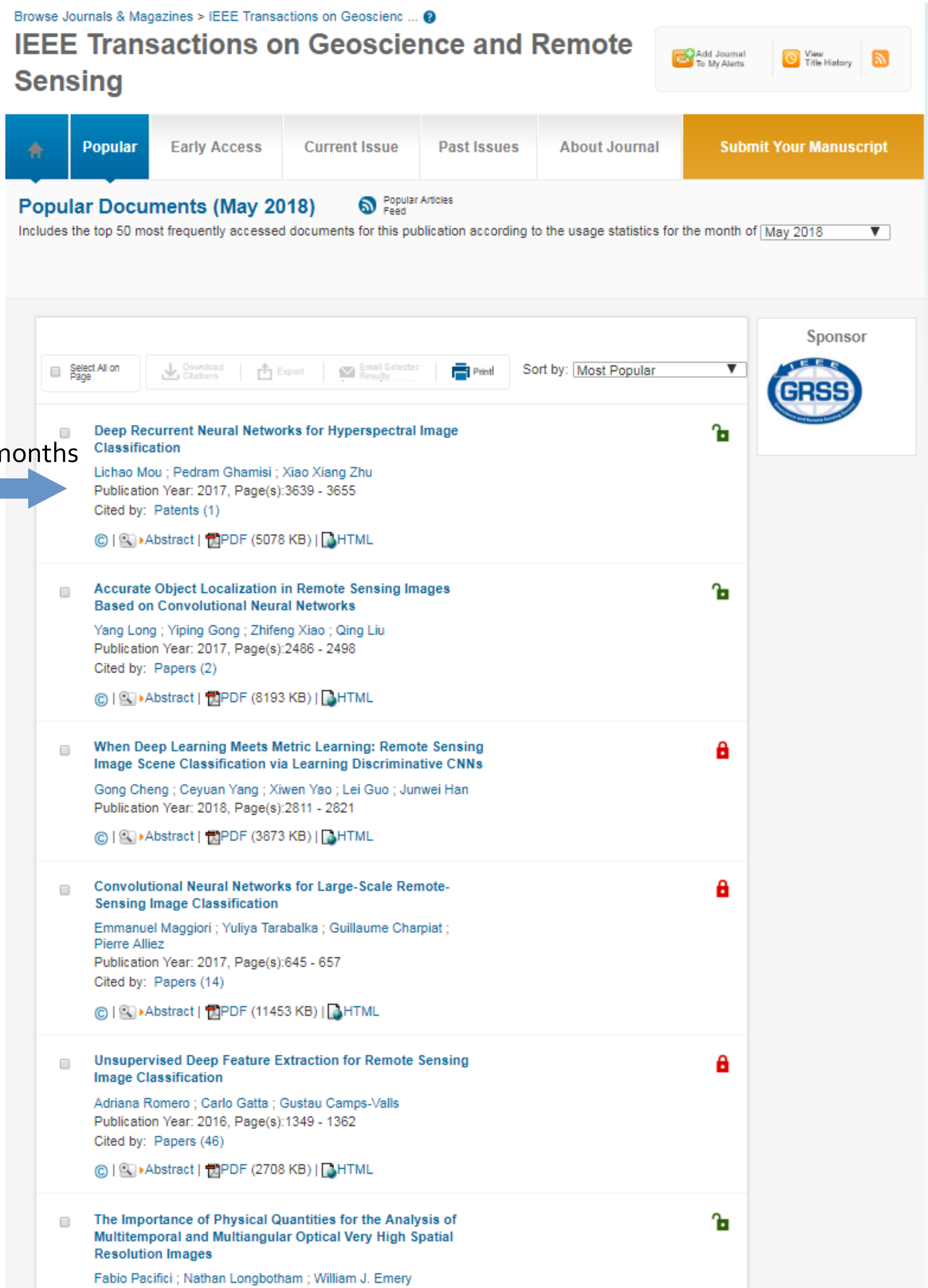
  We are here
  - Re-implant physics, Bayes and domain expertise into the learning process
  - Understand what DL really does with the data: "opening the black box", information theory, estimation theory, breaking the end-to-end-learning dogma,…

Hype or Frenzy?





since 12 months



IEEE Geoscience and Remote Sensing Magazine, Dec. 2017

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 detection [5], [6], and semantic segmentation [7], [8]. Furthermore, recurrent NNs (RNNs), an important branch of the deep learning family, have demonstrated significant achievement on a variety of tasks involved in sequential data analysis, such as action recognition [9], [10] and image captioning [11].

In the wake of this success and thanks to the increased availability of data and computational resources, the use of deep learning is finally taking off in remote sensing as well. Remote-sensing data present some new challenges for deep learning, because satellite image analysis raises unique issues that pose difficult new scientific questions.

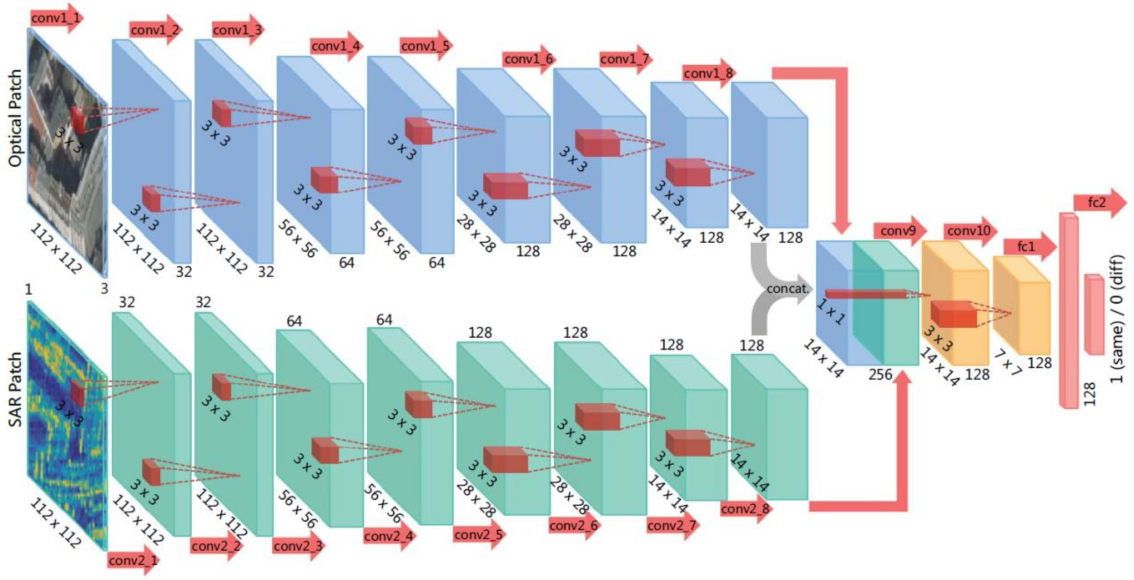
BRAIN IMAGE WITH MAP—IMAGE LICENSED BY INGRAM PUBLISHING, ELECTRONIC CIRCUIT BOARD—©ISTOCKPHOTO.COM/HENRIK5000

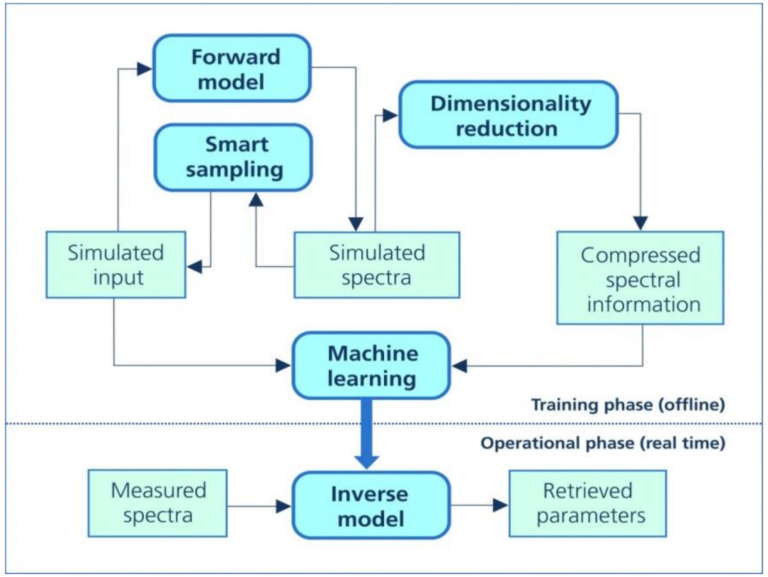
Digital Object Identifier 10.1109/MGRS.2017.2762307
Date of publication: 27 December 2017

AI4EO@IMF – Machine Learning Examples

Focus on Deep Neural Networks

- Ship/vehicles/pederstrian detection and classification
- Land use/land cover/settlement type classification
- Change detection
- Improved optical/SAR coregistration
- 2D and 3D optical/SAR fusion
- Synthesizing optical from SAR data and vice versa
- DSM-to-DTM conversion
- Image-to-height conversion
- 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

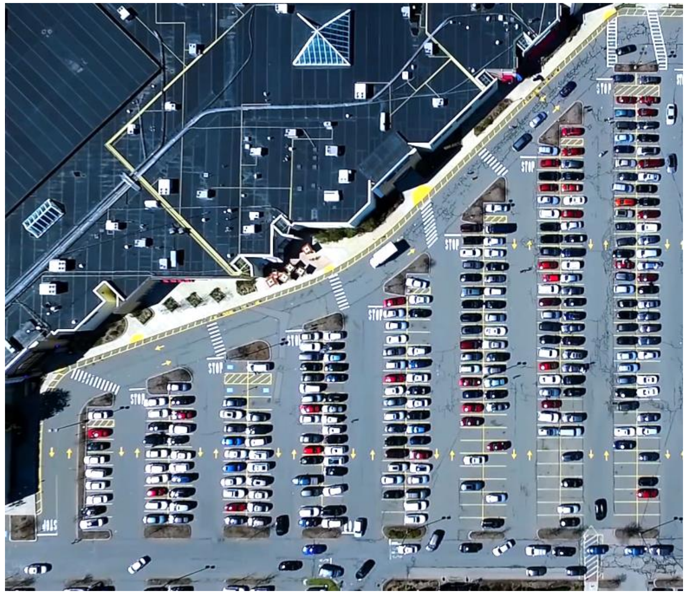


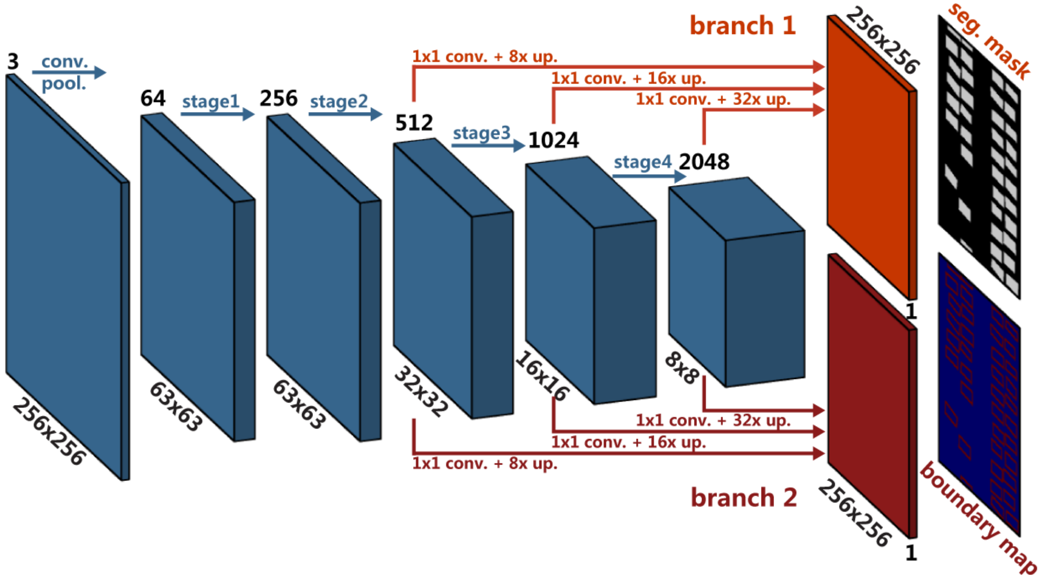


Deep Learning for Detection of Ships, Vehicles etc.

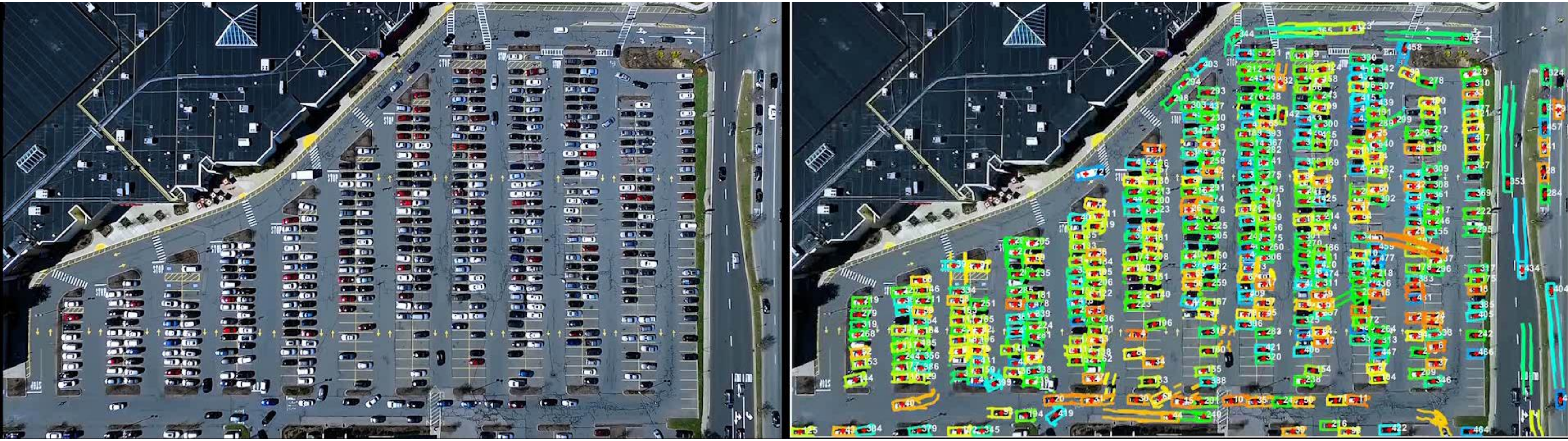

San Francisco
MovingShip 0.999
MovingShip 1.000
MovingShip 0.997
StaticShip 0.999
StaticShip 0.998

Deep Learning zur Fahrzeugdetektion



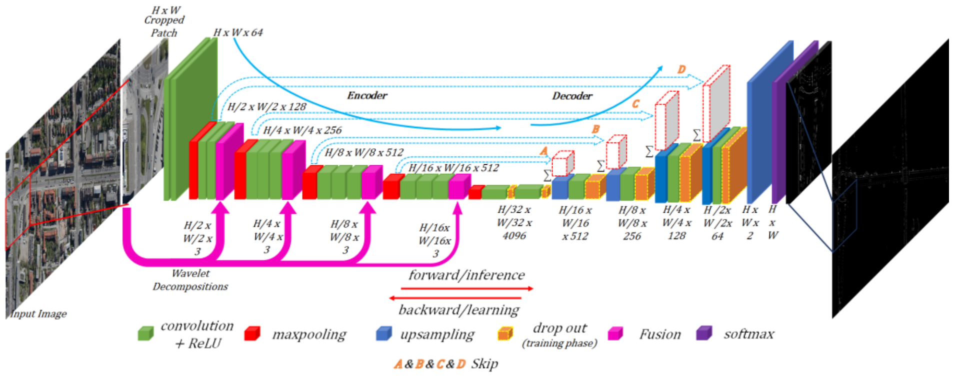


Deep Learning zur Fahrzeugdetektion und -verfolgung

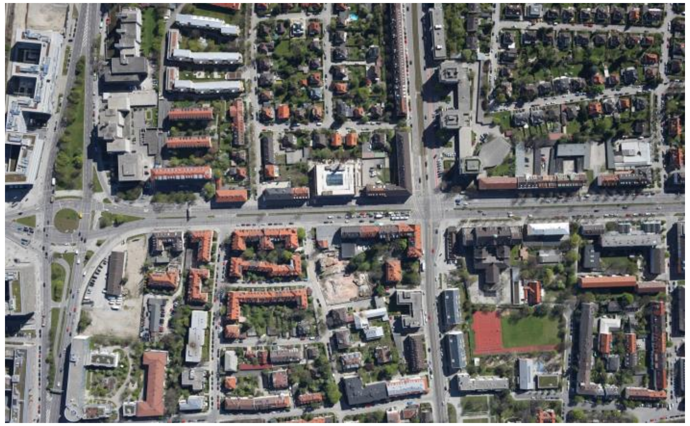


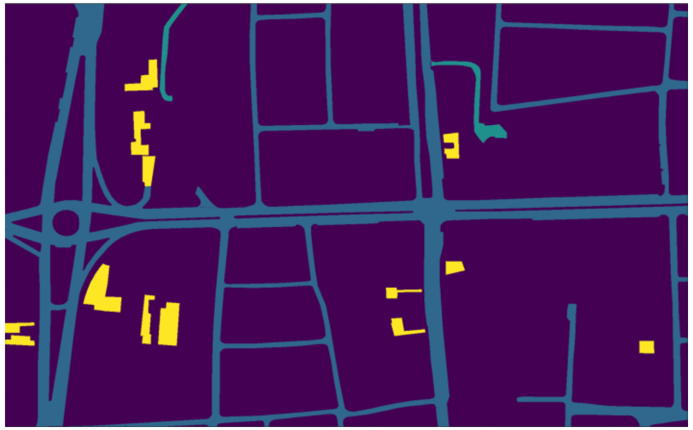
Mapping to Support Autonomous Driving

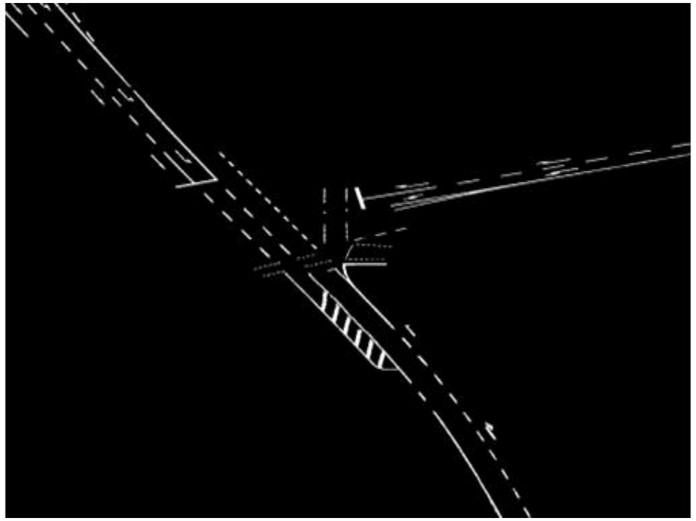
Aerial LaneNet: Wavelet-Enhanced Cost-sensitive Symmetric CNN



Street and parking place segmentation







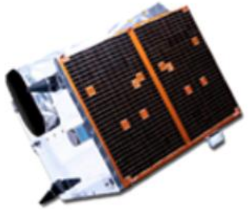
Lane marking segmentation

Seyed Majid Azimi, Peter Fischer, Marco Körner, and Peter Reinartz, Aerial LaneNet: Lane Marking Semantic Segmentation in Aerial Imagery using Wavelet-Enhanced Cost-sensitive Symmetric Fully Convolutional Neural Networks, IEEE TGRS, in review.

Global Building Footprint Generation Using Planet Data

multi-scale resolution and update everyday for entire Earth surface

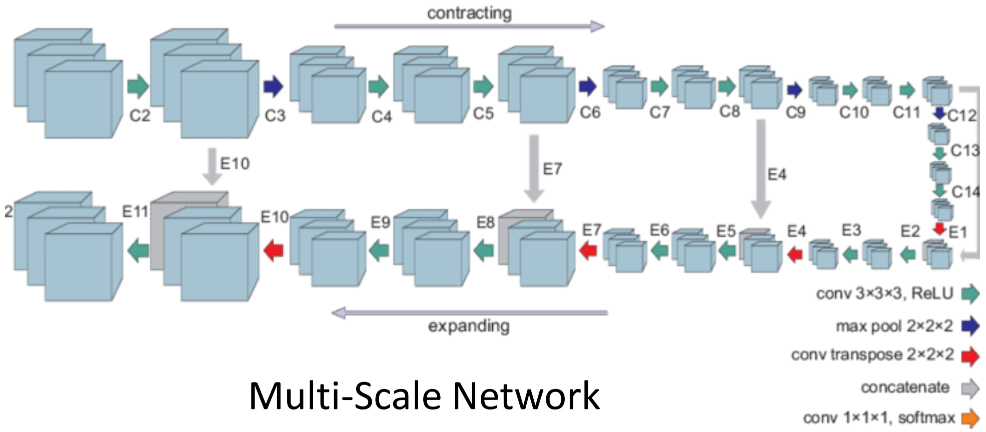
PlanetScope
- 3 m
- RGB NIR
- 175+



RapidEye
- 5 m
- RGB RE NIR
- 13

SkySat
- 0.8 m
- RGB NIR
- 5

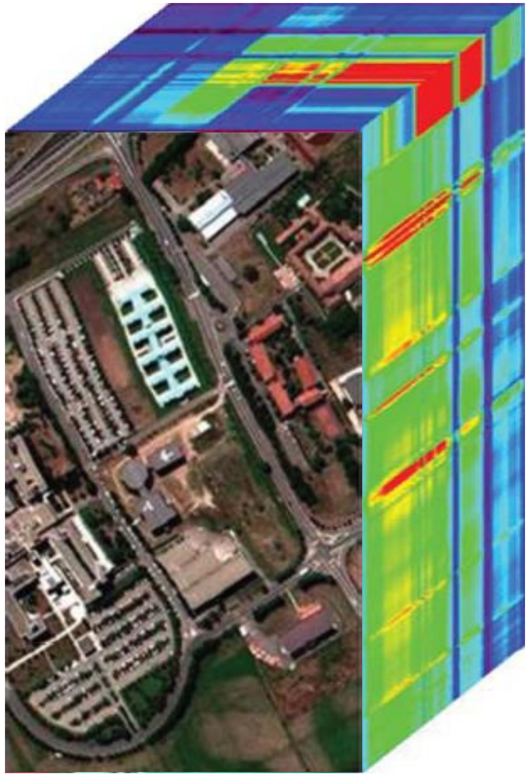
global high-resolution building footprint using multi-scale neural network



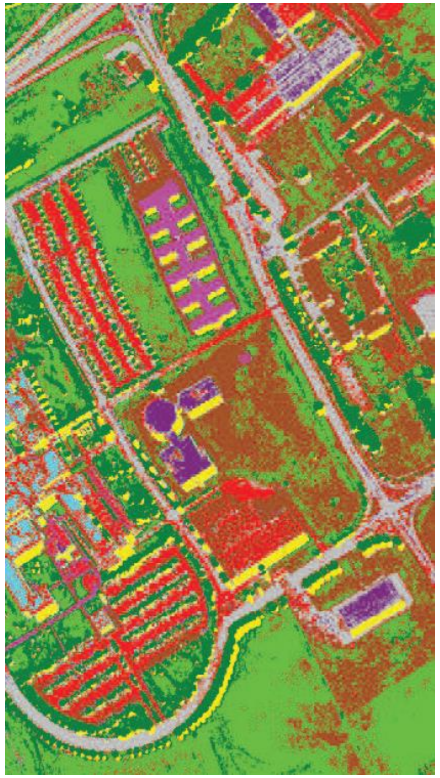
Multi-Scale Network

Deep Learning Hyperspectral Classification

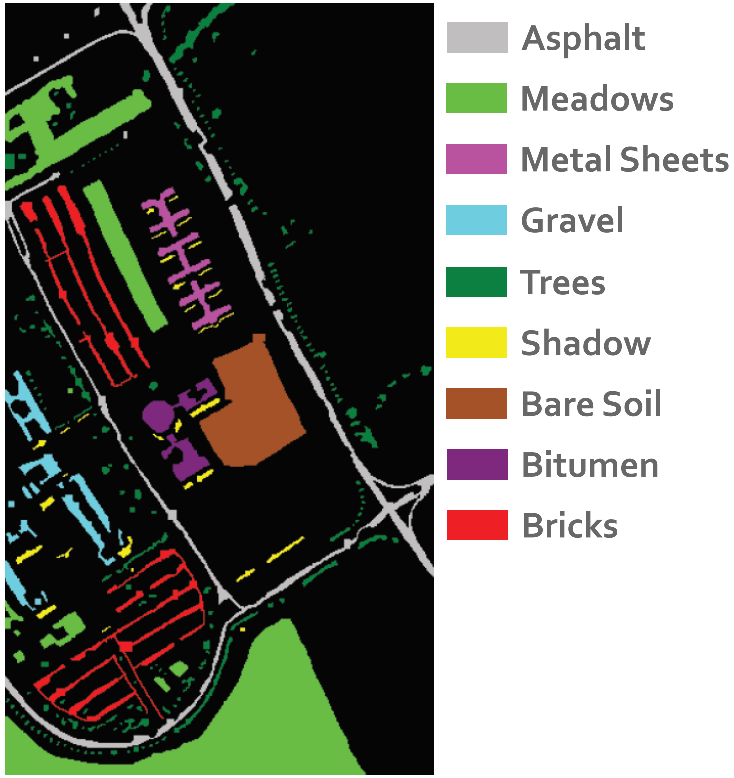
Recurrent Neural Networks for Hyperspectral Image Classification



University of Pavia, Italy



Our Classification Map

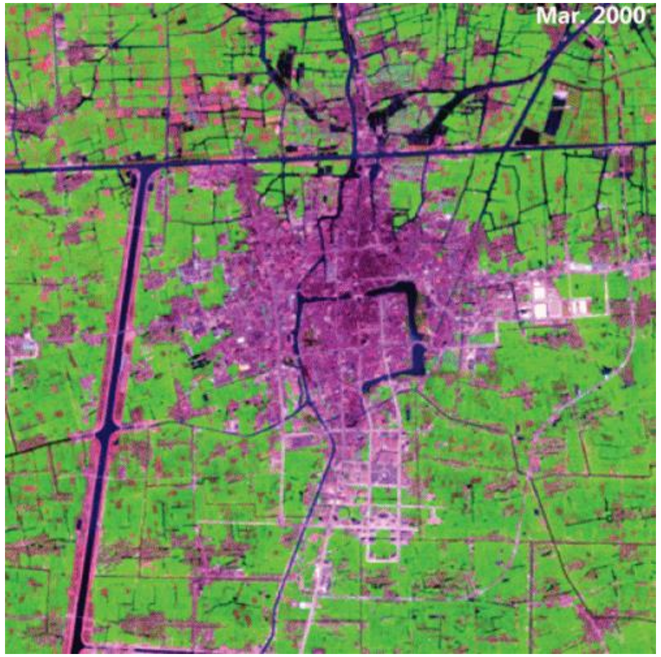


Ground Truth

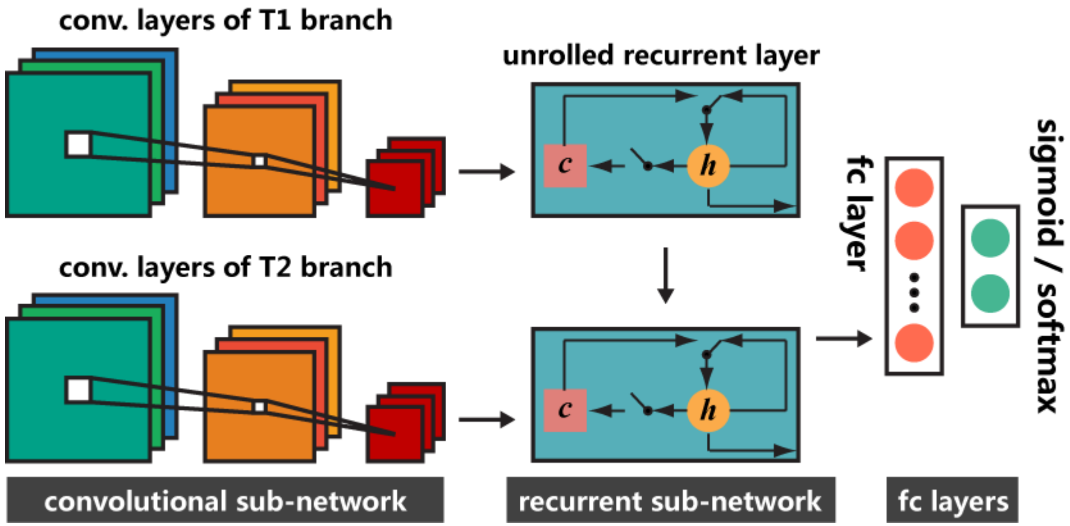
	RF-200	SVM-RBF	CNN	RNN-LSTM	RNN-GRU-tanh	RNN-GRU-PRetanh
OA	71.37	78.82	79.27	75.92	77.70	**84.99**

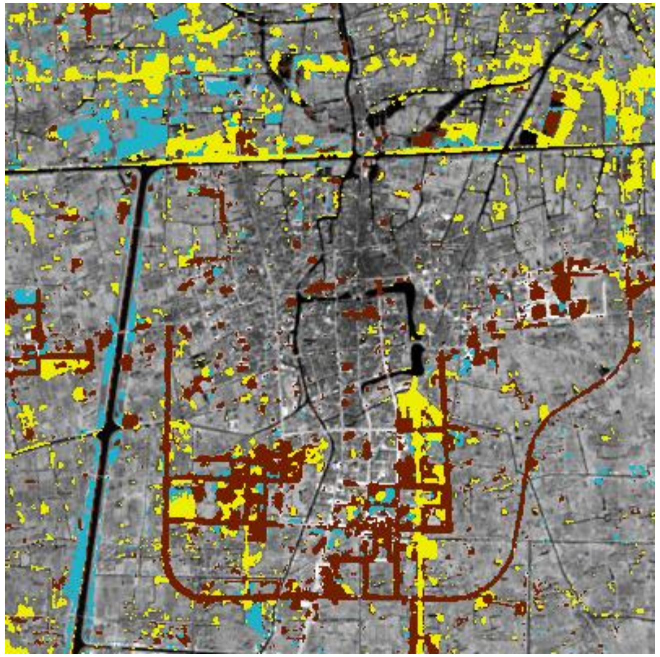
L. Mou, P. Ghamisi, and X. X. Zhu, “Deep recurrent neural networks for hyperspectral image classification,” *IEEE TGRS*, 2017.

Neuronale Netze zur semantischen Änderungsdetektion in Satellitenbildern



Mar 2000 – Feb 2003





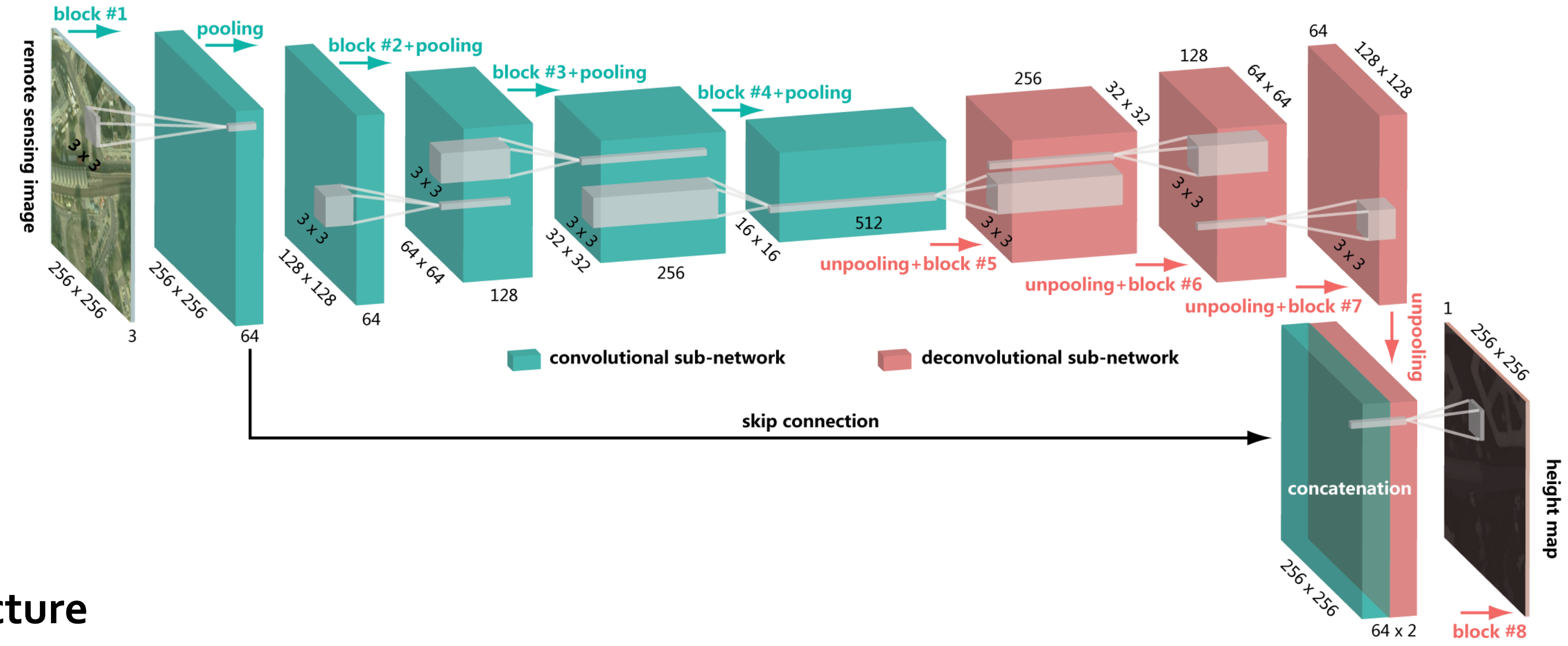
city expansion
soil change
water change

Non-conventional Applications

IM2HEIGHT

Motivation

Height (e.g., DSM) is very important for many remote sensing tasks. But, often, such information is available. A system estimating a physically plausible height map from a single image would be valuable.



Network Architecture

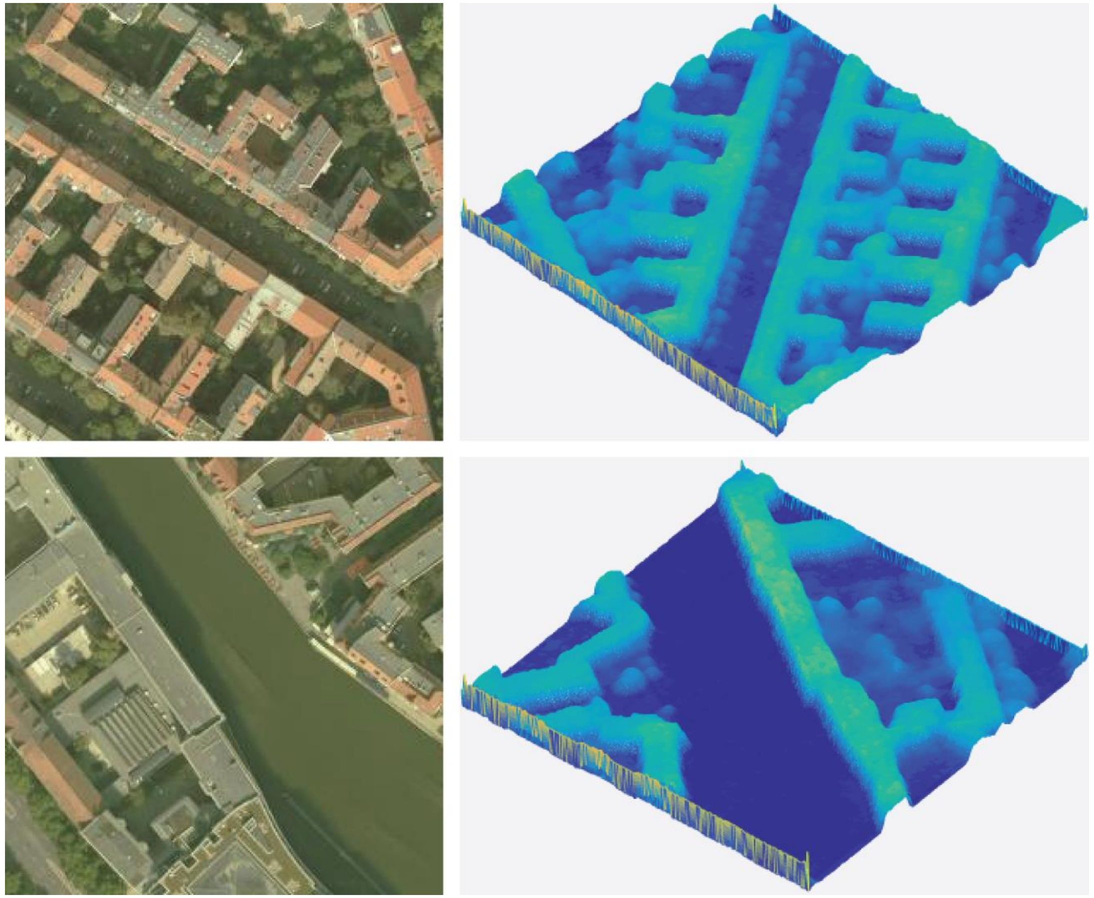
We learn an end-to-end trainable fully residual conv-deconv network with a skip connection that allows to shuttle low-level visual information, e.g., object boundaries and edges, directly across the network.

L. Mou and X. X. Zhu, "IM2HEIGHT: Height estimation from single monocular imagery via fully residual convolutional-deconvolutional network," *IEEE TGARS*, submitted.

IM2HEIGHT

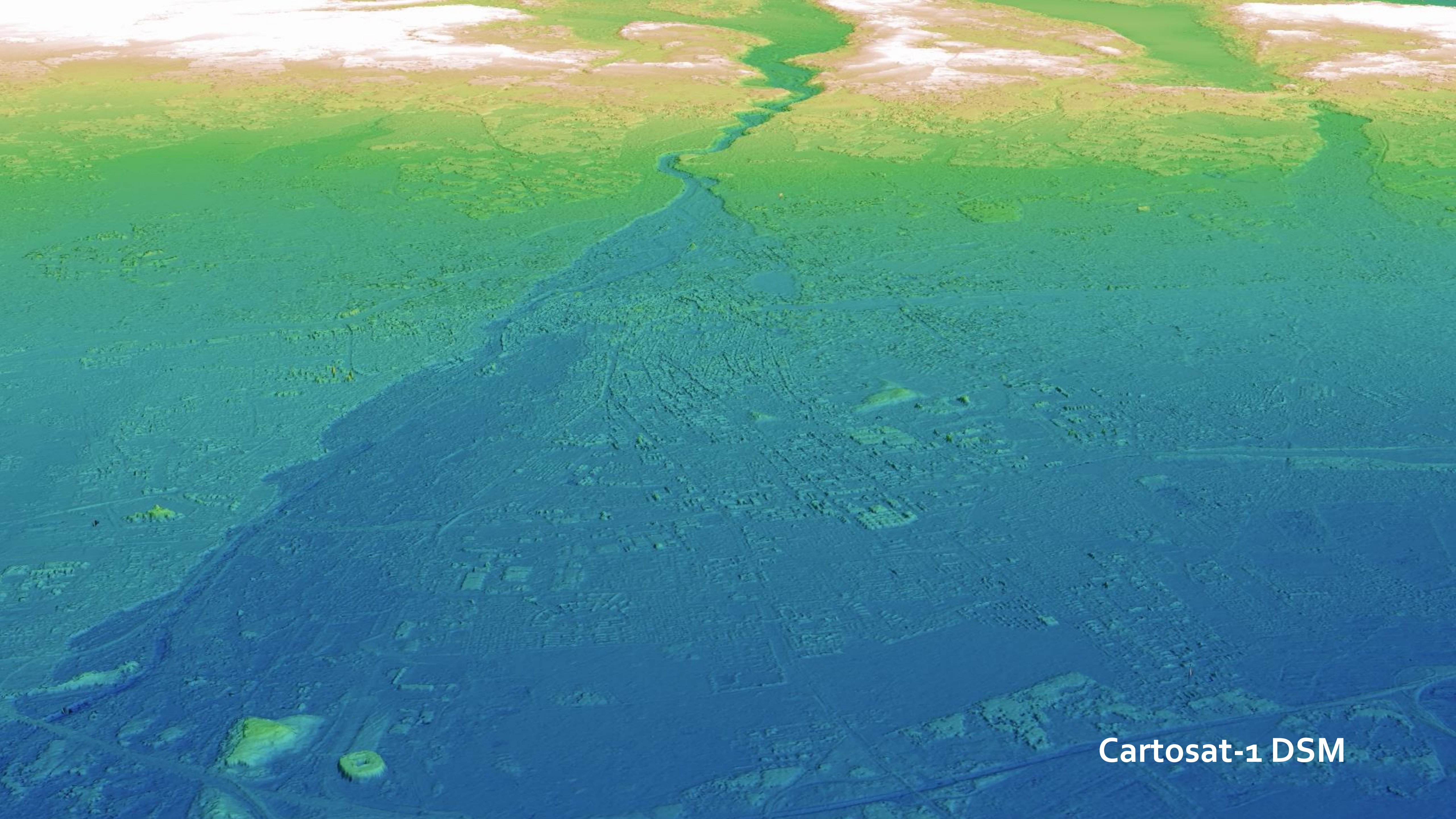
Applications

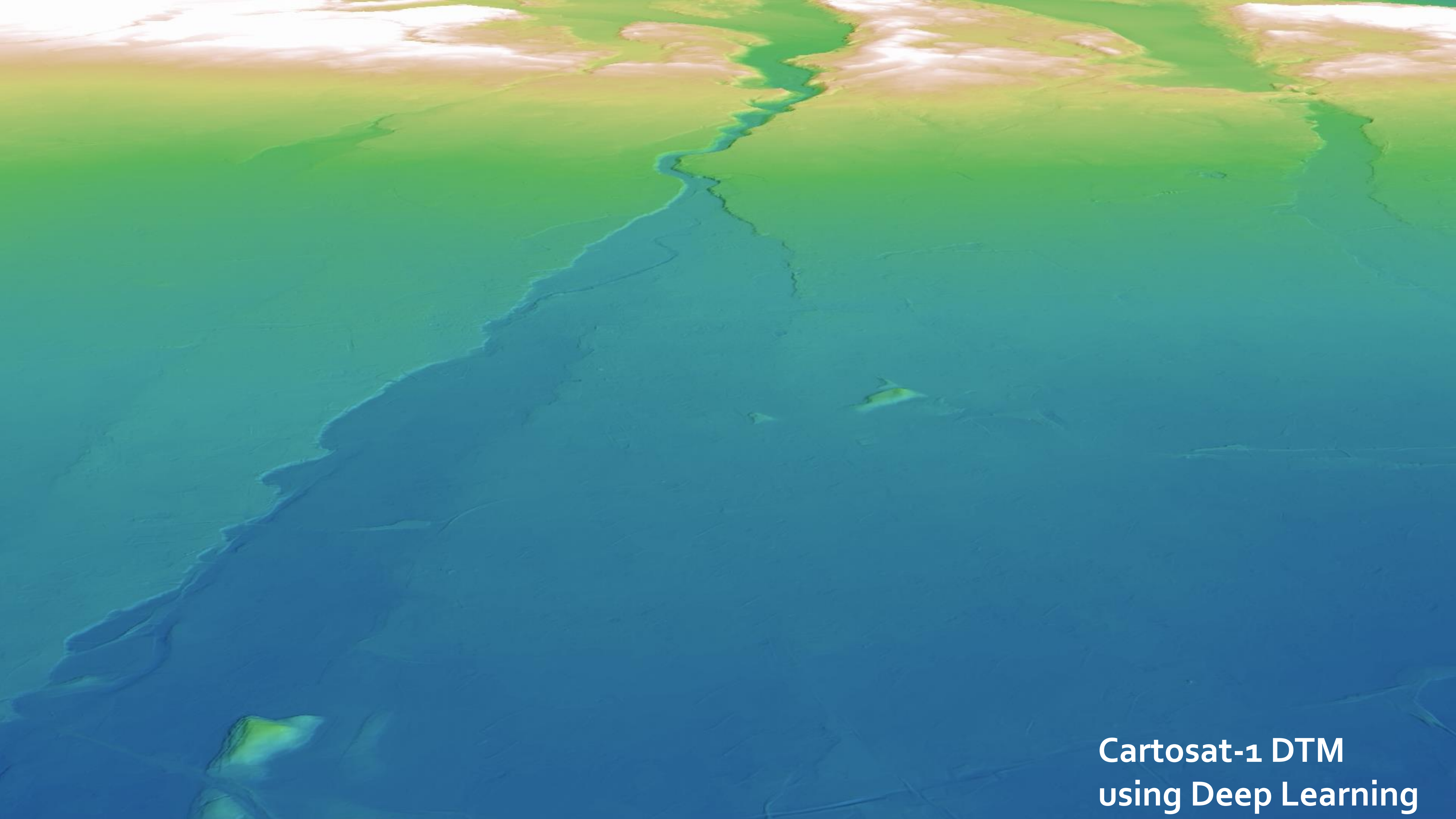
Genaration of 3D View from A Monocular Image

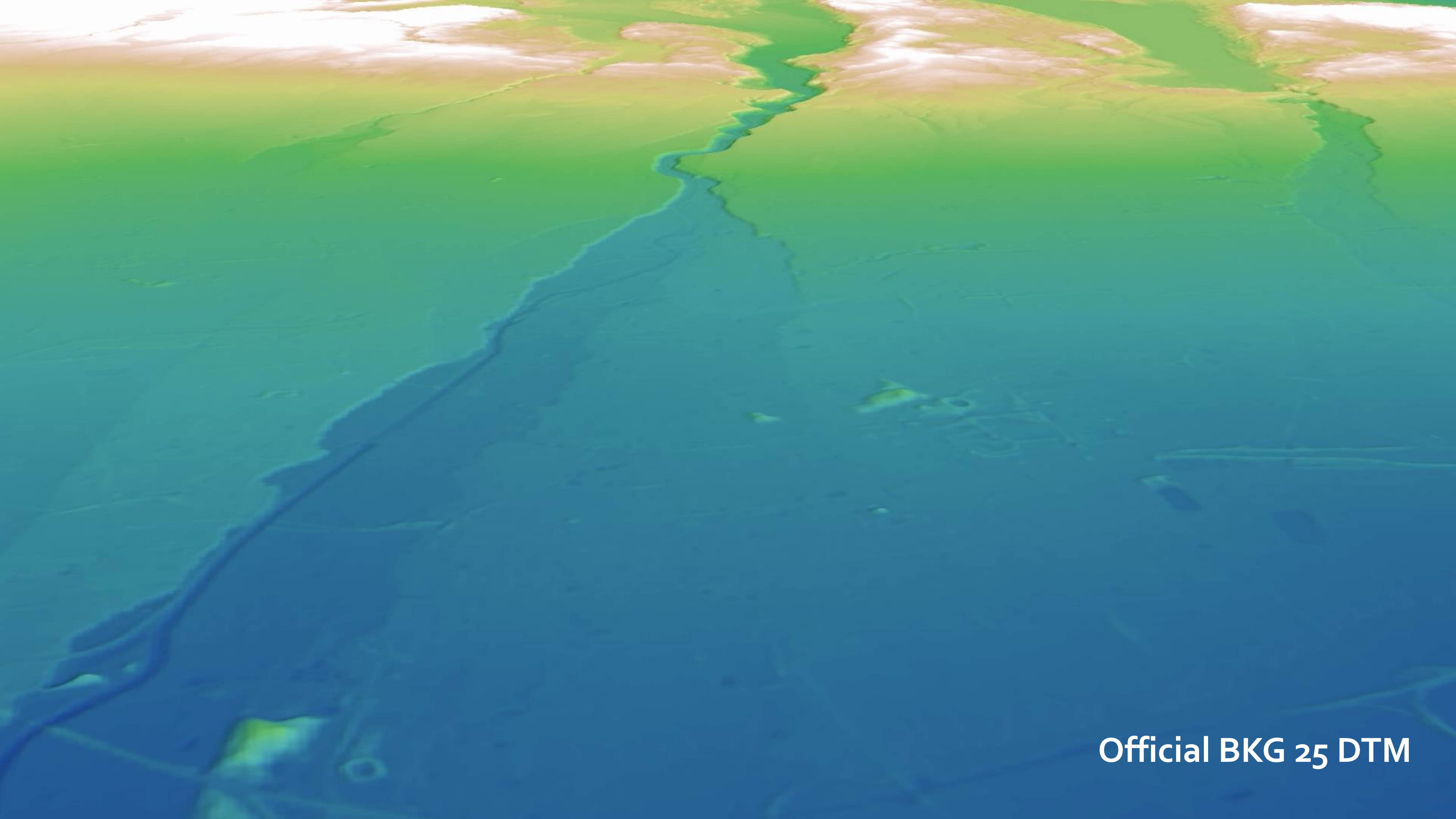


Building Instance Segmentation Using Predicted Height

L. Mou and X. X. Zhu, "IM2HEIGHT: Height estimation from single monocular imagery via fully residual convolutional-deconvolutional network," *IEEE TGARS*, submitted.


Cartosat-1 DSM

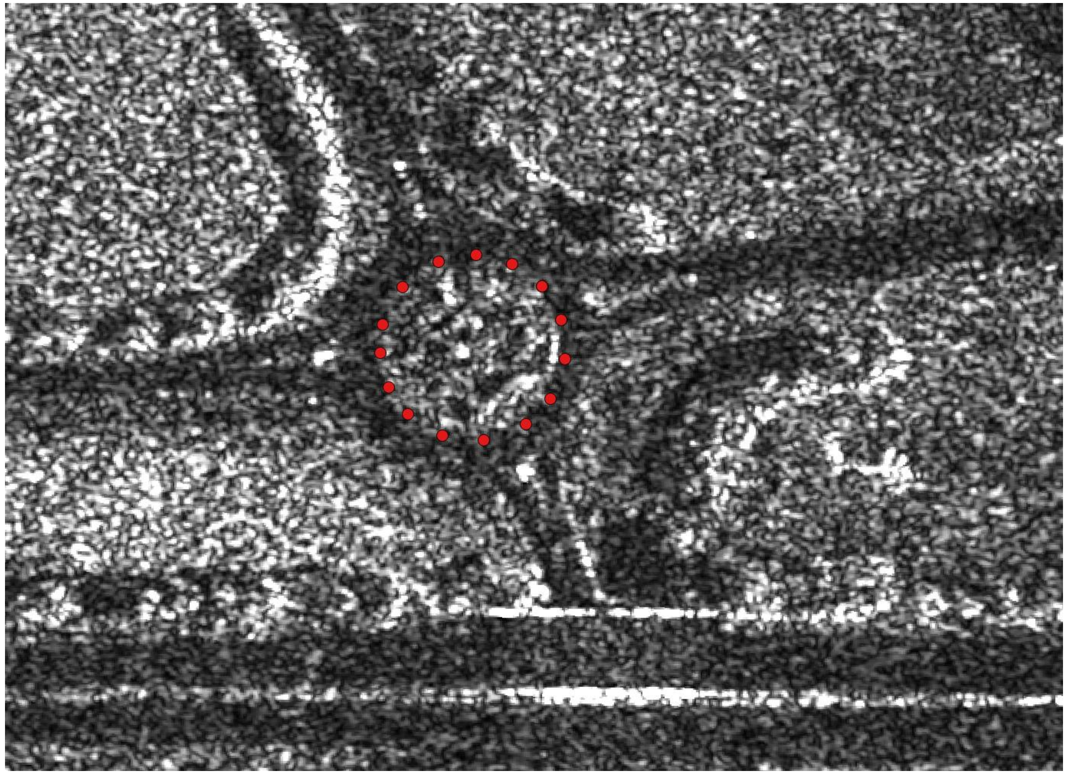

Cartosat-1 DTM
using Deep Learning


Official BKG 25 DTM

Deep Learning/Fusion for Multimodal Data Analysis

Improvement of Absolute Geometric Accuracy of Optical Images by Using High Resolution SAR Images as Reference

SAR: TerraSAR-X (accuracy decimeter)



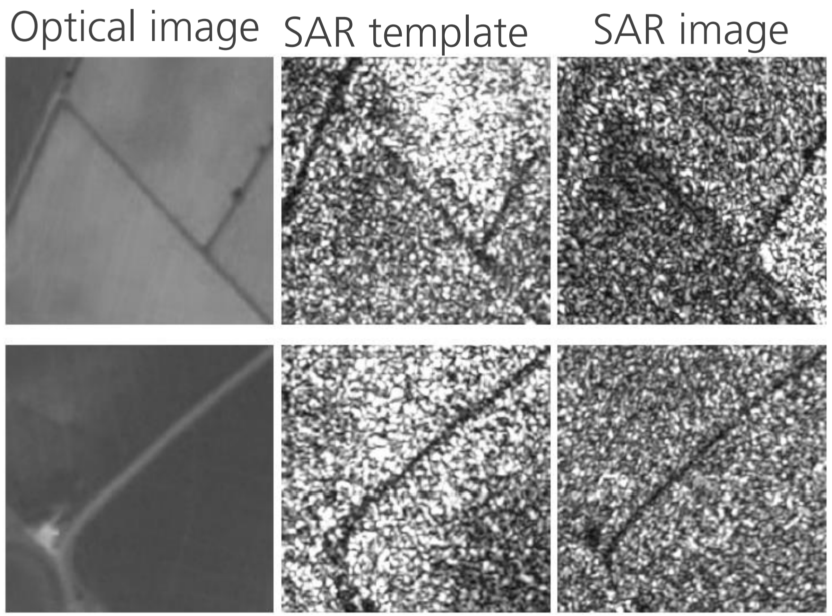
OPTICAL: PRISM (accuracy several meters)

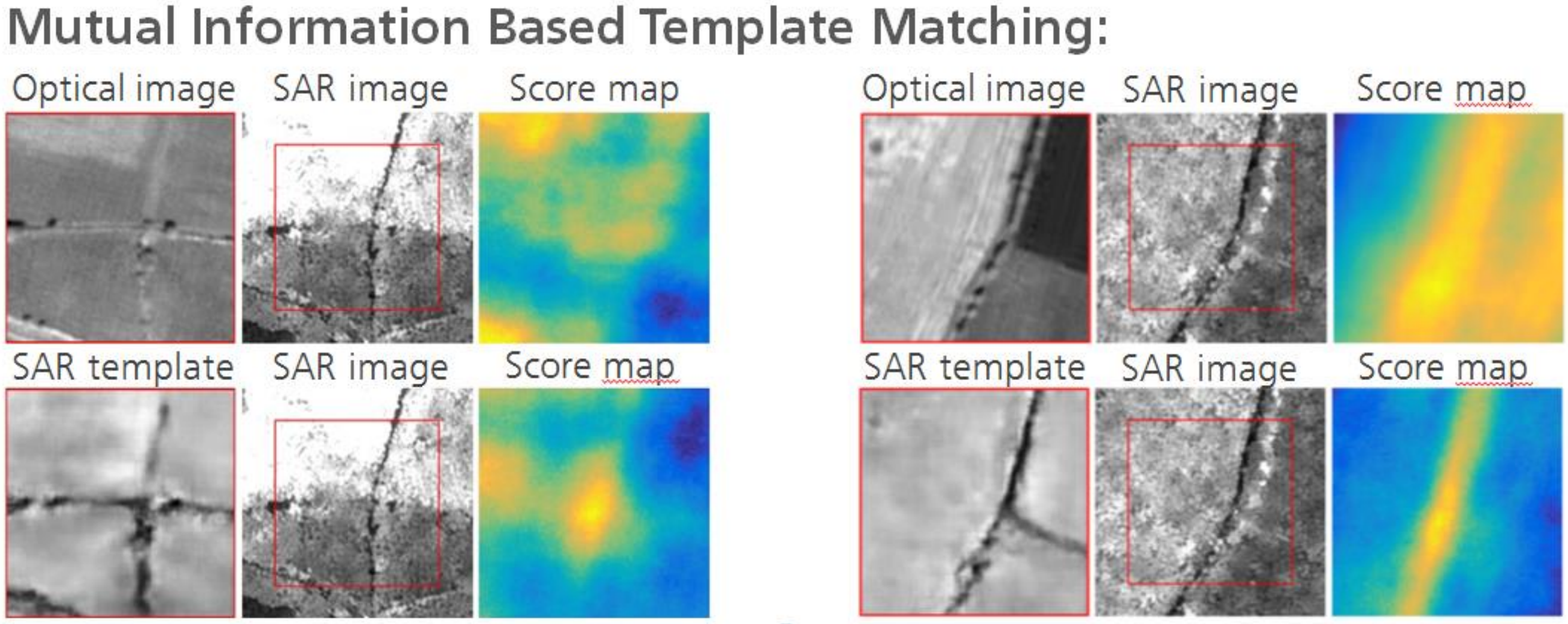
Task: find some, but good identical points

Artificial Template Generation for Image Matching

Conditional Adversarial Network

Artificial Templates



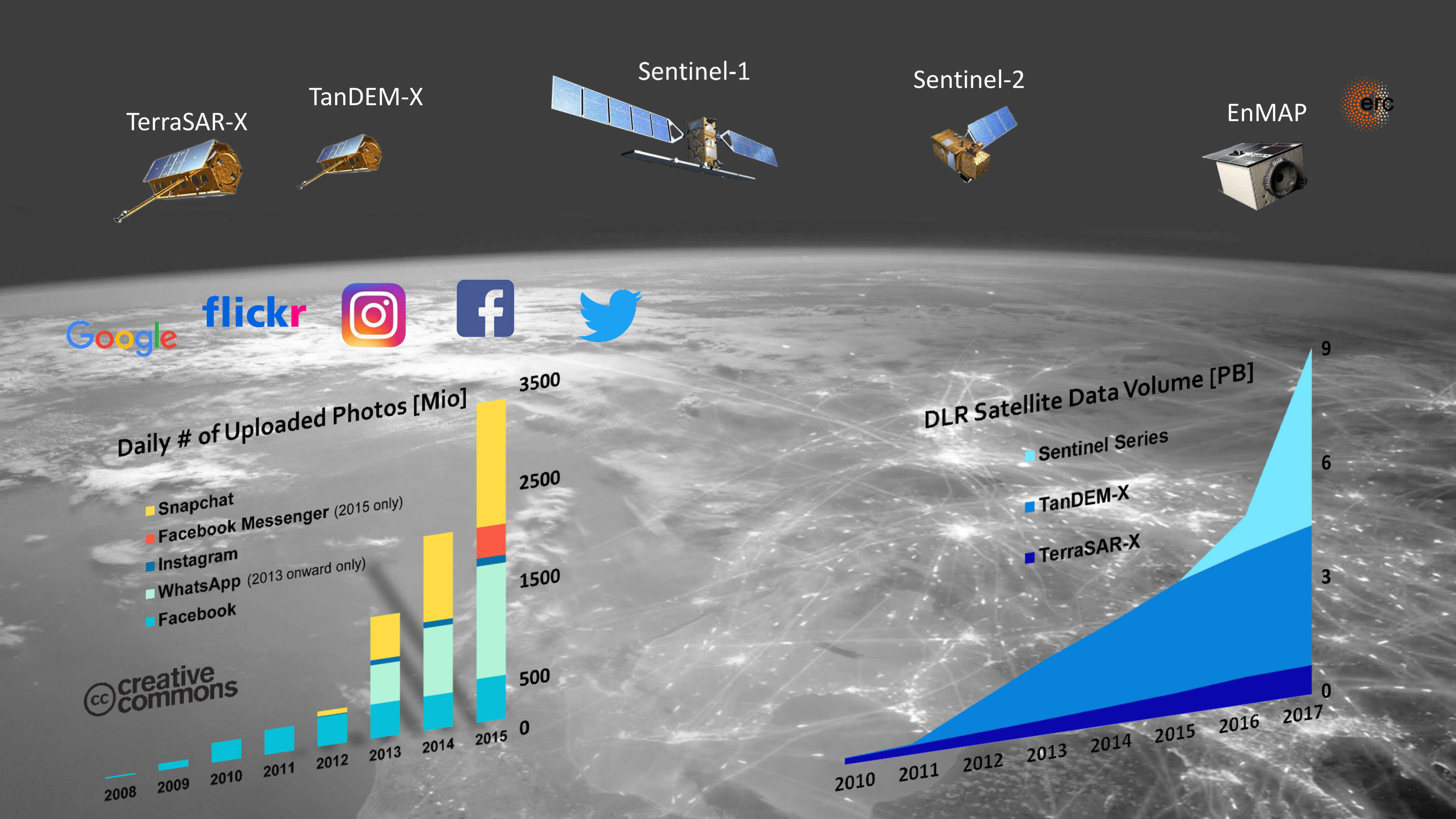


Merkle, Nina Marie und Auer, Stefan und Müller, Rupert und Reinartz, Peter (2018) Exploring the Potential of Conditional Adversarial Networks for Optical and SAR Image Matching. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. IEEE Xplore. ISSN 1939-1404

Merkle, Nina und Fischer, Peter und Auer, Stefan und Müller, Rupert (2017) On the Possibility of Conditional Adversarial Networks for Multi-Sensor Image Matching. In: Proceedings of IGARSS 2017, Seiten 1-4. IGARSS 2017, 23.-28. Jul. 2017, Fort Worth, Texas, USA.

Institut für Methodik der Fernerkundung
Remote Sensing Technology Institute

Deep Learning for Social Media Data Analysis


TerraSAR-X
TanDEM-X
Sentinel-1
Sentinel-2
EnMAP
erc
Google
flickr
Daily # of Uploaded Photos [Mio]
Snapchat
Facebook Messenger (2015 only)
Instagram
WhatsApp (2013 onward only)
Facebook
3500
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1500
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2015
creative commons
DLR Satellite Data Volume [PB]
Sentinel Series
TanDEM-X
TerraSAR-X
9
6
3
0
2010
2011
2012
2013
2014
2015
2016
2017

Building Instance Classification from Street View Data by CNN

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

Munich

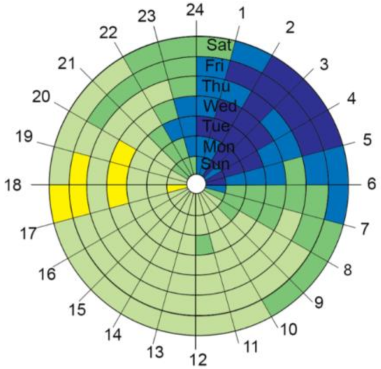
Kang et al., ISPRS JPRS, 2018

Tweets for Building Land-use Identification

residential

Someone @Nobody Following
Only a stay-at-home dad knows the feeling of achievement once he rediscovers the floor in the kids' bedroom. #stay-at-homedad

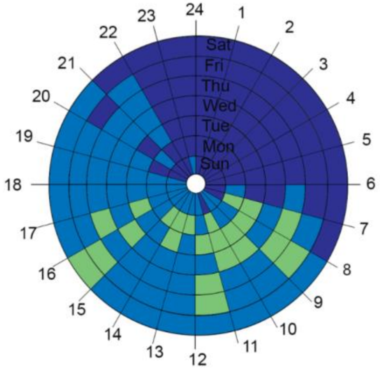
Someone @Nobody Following
Moving Day is Coming. #munich #münchen #bavaria #bayern #germany #deutschland #moving #umzug @ Moosach



non-residential

Someone @Nobody Following
#backtowork #hello2016 (@ BMW Group Forschungs- und Innovationszentrum (FIZ) in München)

Someone @Nobody Following
I'm at BMW Group Forschungs- und Innovationszentrum (FIZ) in München

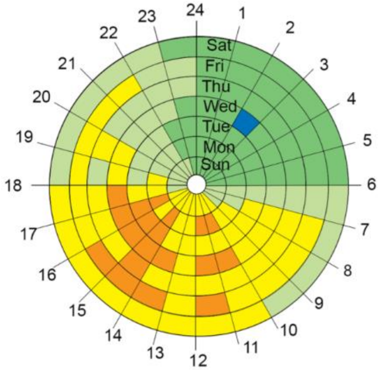


0~50
50~100
100~200
200~300
300~400
400~

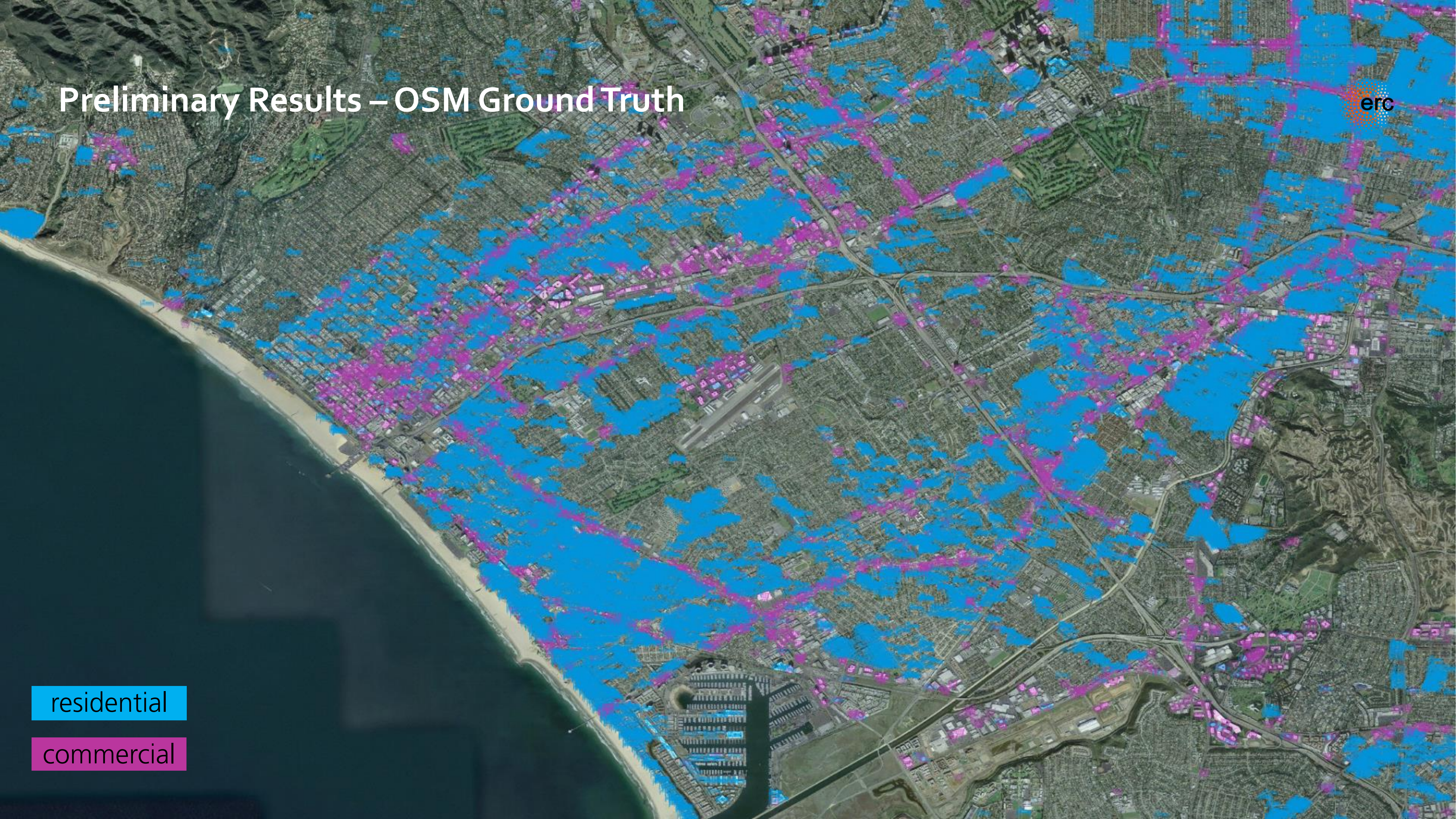
ixed used

Someone @Nobody Following
"""Restaraunts near me"" @ItsDavidFan

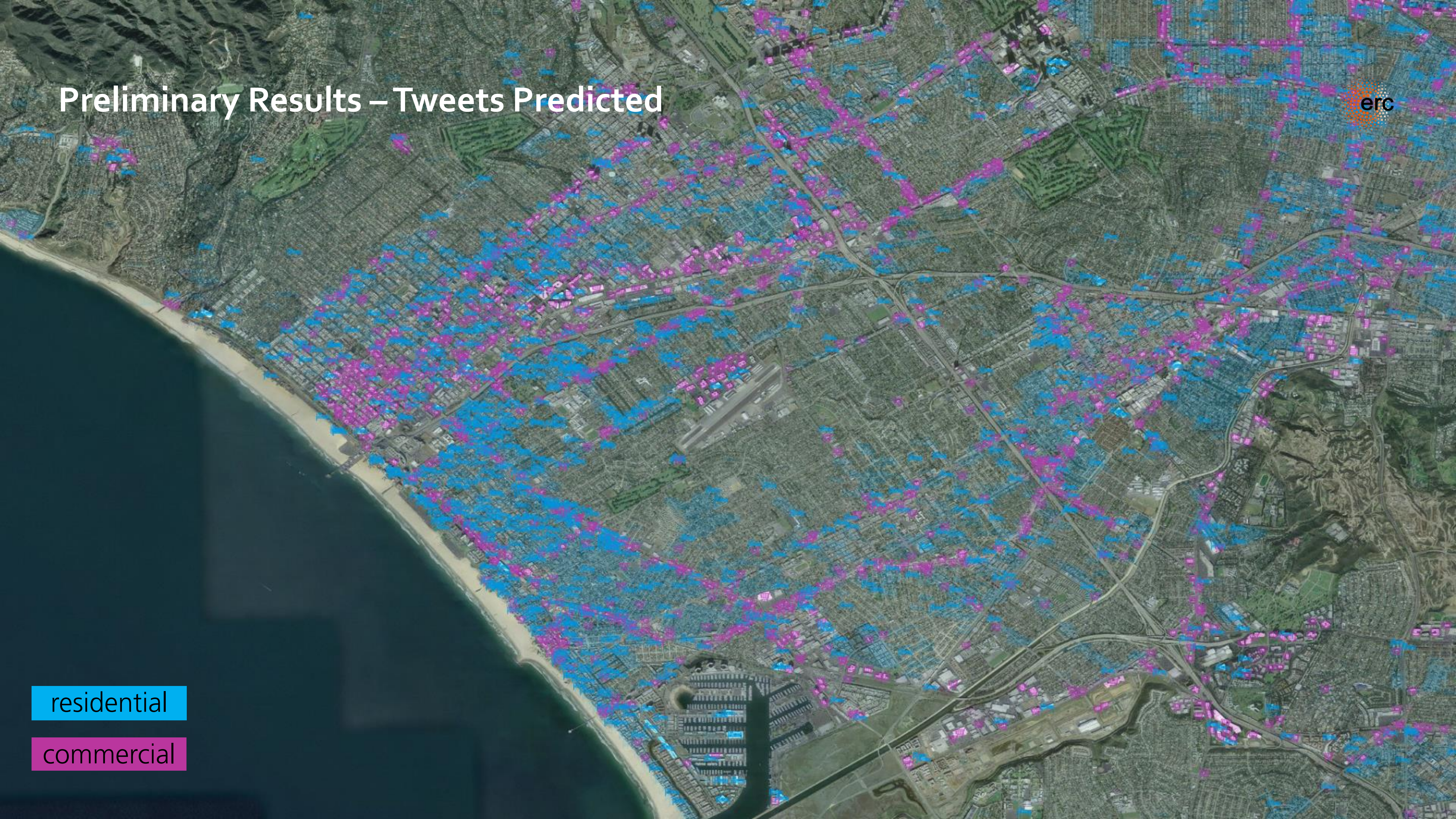
Someone @Nobody Following
Ready for a good long sleep at a hostel...charging batteries for tomorrow! #oktoberfest @…



Preliminary Results – OSM Ground Truth



Preliminary Results – Tweets Predicted



What makes Deep Learning in Earth Observation Special?
Open Research Questions

- 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

We Need More AI4EO

Graffiti, Munich
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