

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



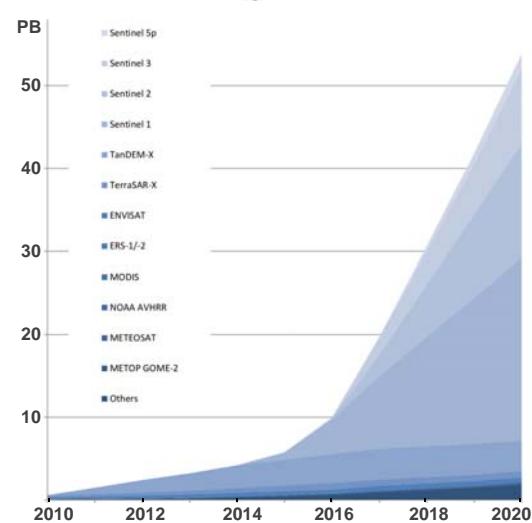
The Golden Era of Big Earth Observation Data

- 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 → Al₄EO

But:

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



Data Cubes – Decadal Time Series for Climate Research

Evolution of Arctic Sea Ice

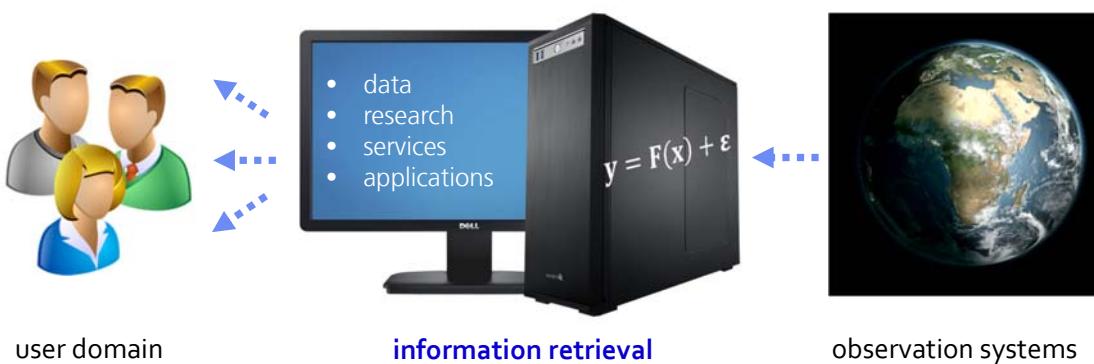


1980 1990 2000 2010

Courtesy: C. Künzer, DFD

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Why do we need data science and AI4EO?



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

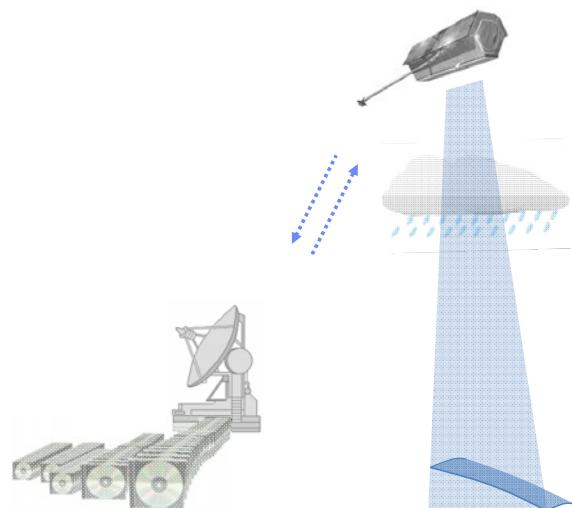


Data Science in Earth Observation

Model-Based Analytics
explorative signal processing methods

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

Data-driven Analytics
machine/deep learning methods



Geoscientific Application – Global Urban Mapping

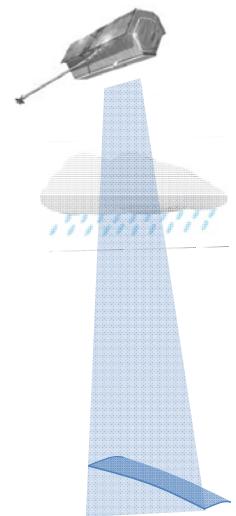


Data Science in Earth Observation

Model-Based Analytics

explorative signal processing methods

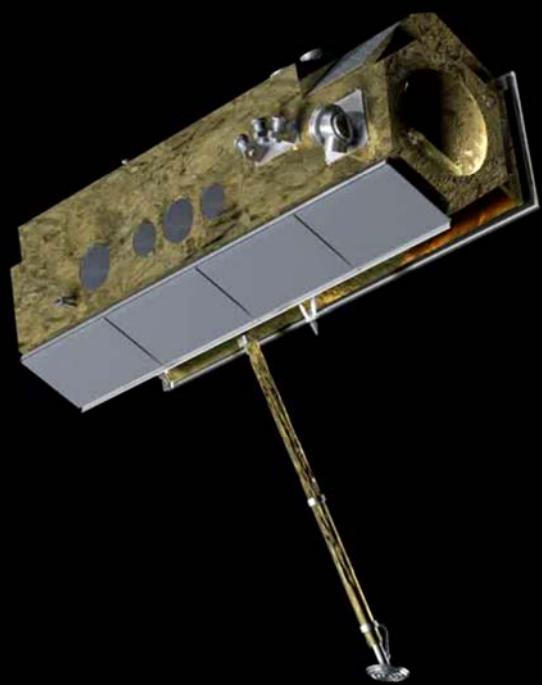
$$y = F(x) + \varepsilon$$



Data-driven Analytics

machine/deep learning methods

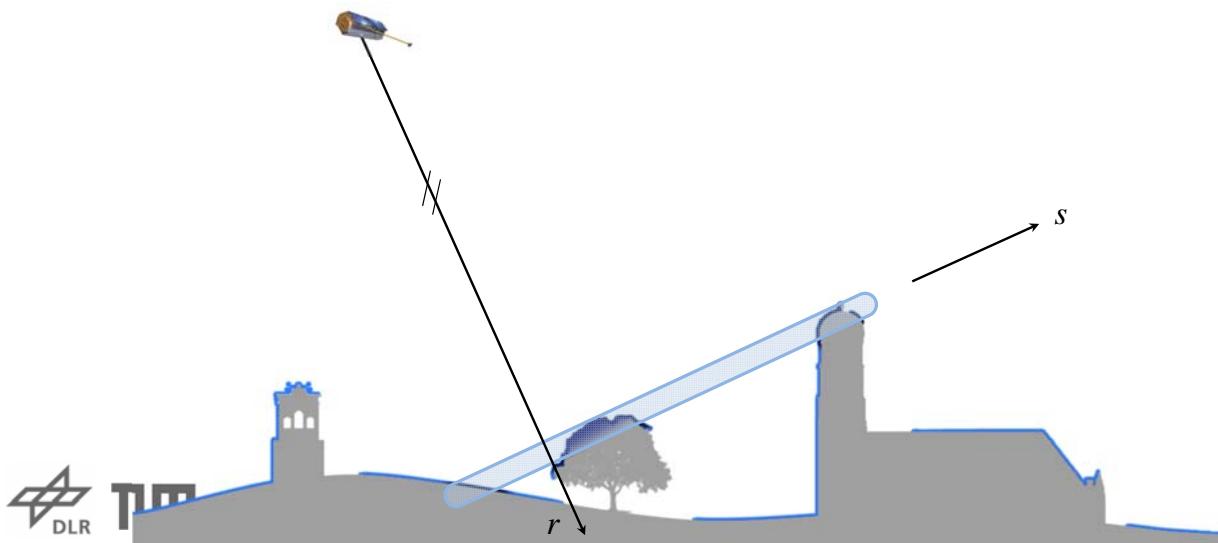
Geoscientific Application – Global Urban Mapping



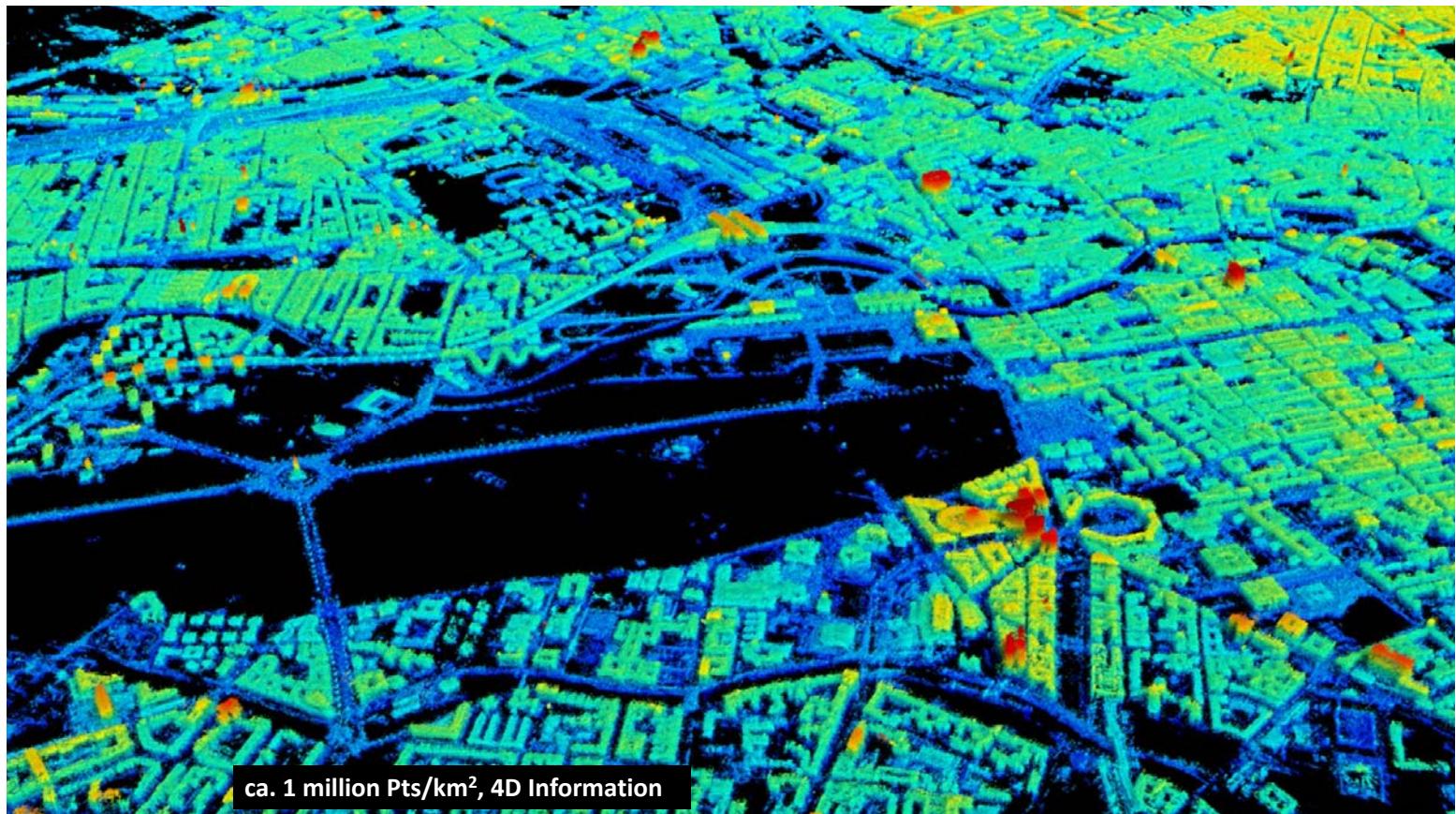
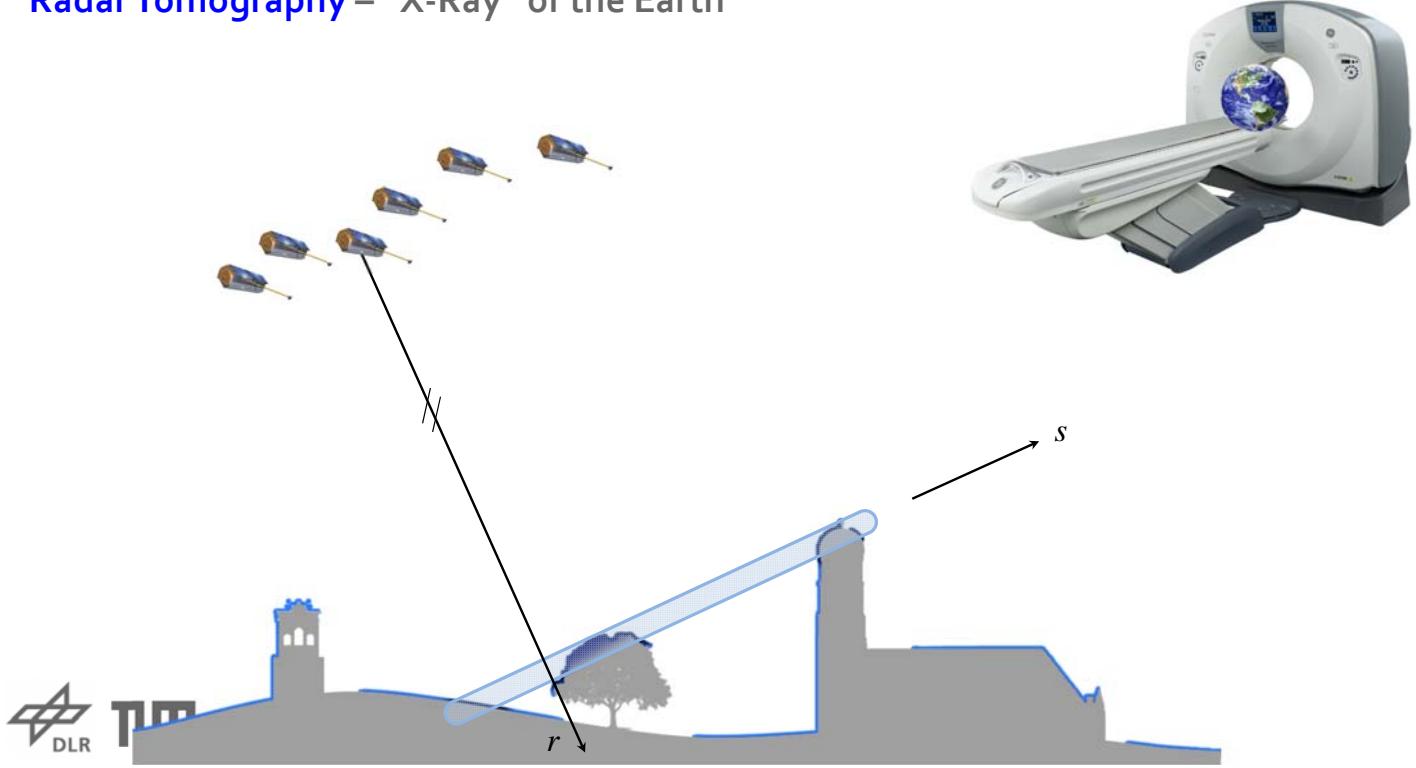


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Radar Geometry in Range-Elevation Plane



Radar Tomography – “X-Ray” of the Earth





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...

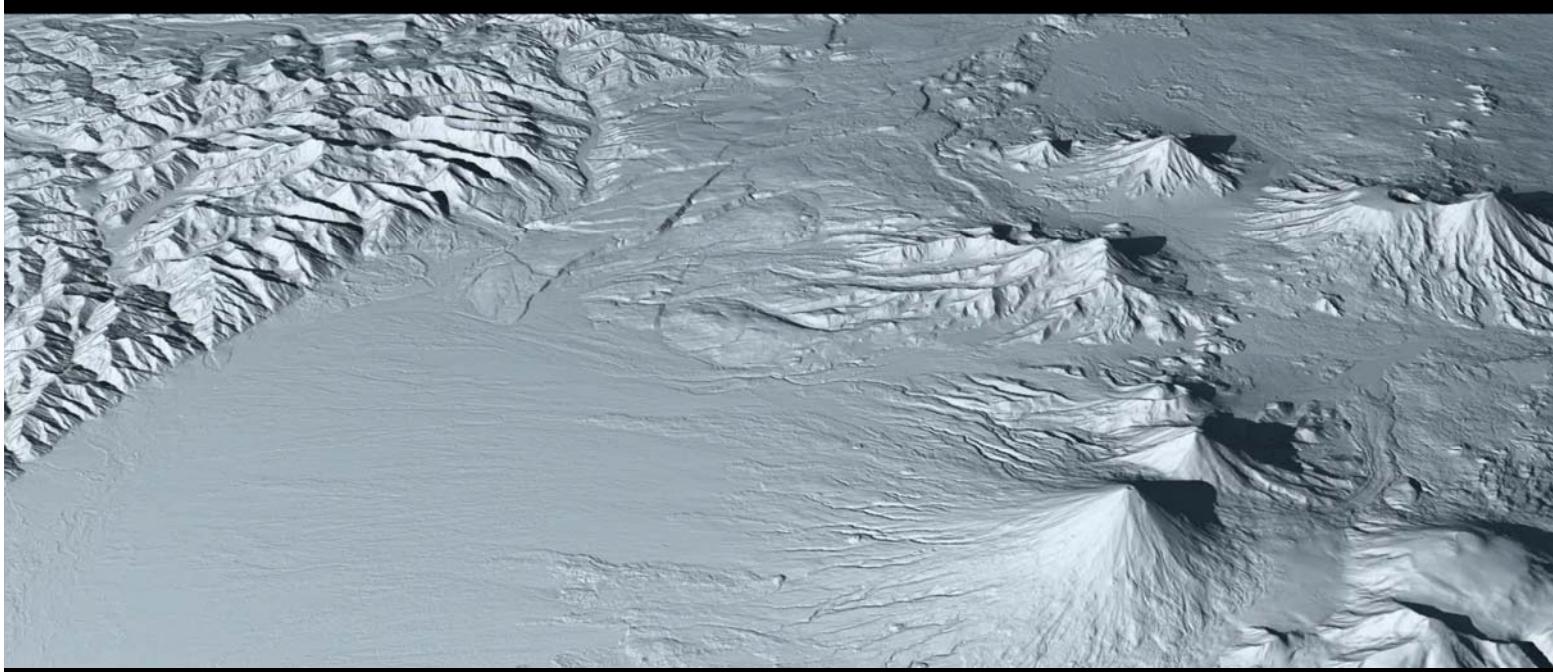




Deutsche
Fernerkundung
Technology Institute



Kamtschatka



Relative Height Error – Evolution over Time

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Remote Sensing Technology Institute

First Coverage

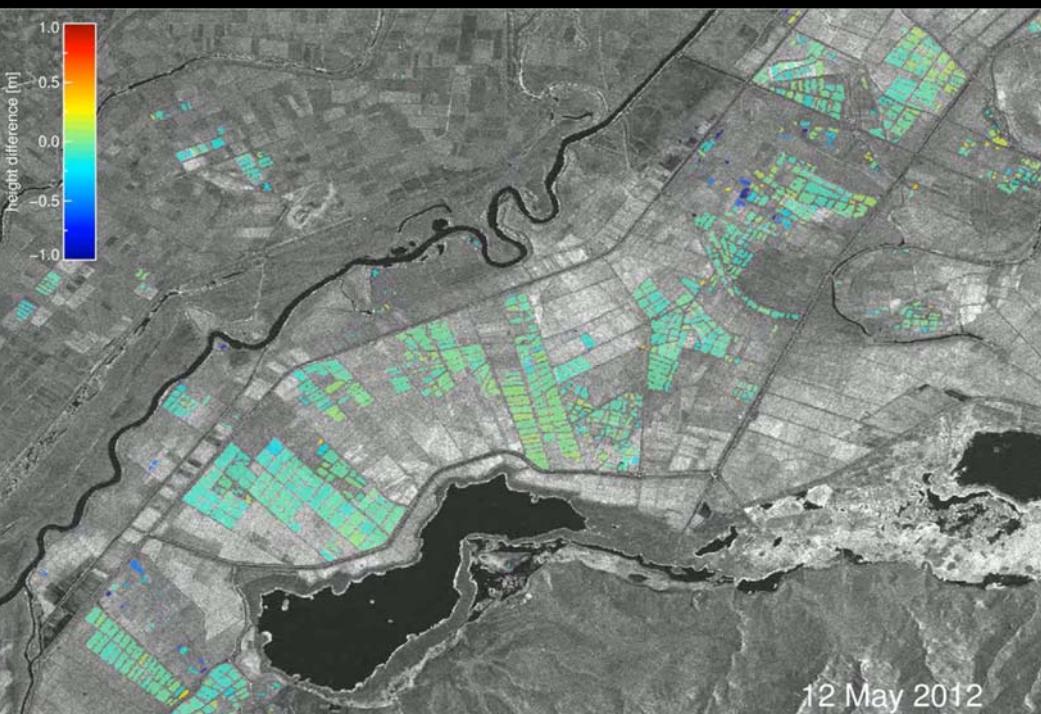
(Acquisition started: Dec 12, 2010)

Relative Height Error



2010-12-12

TanDEM-X “Watches” The Rice Growing



SRTM, 2000
30/90m

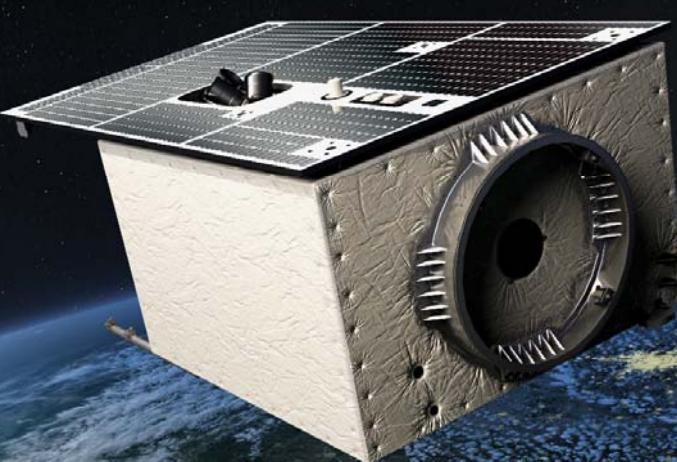
TanDEM, 2012
12m

TanDEM "HD", 2013
6m

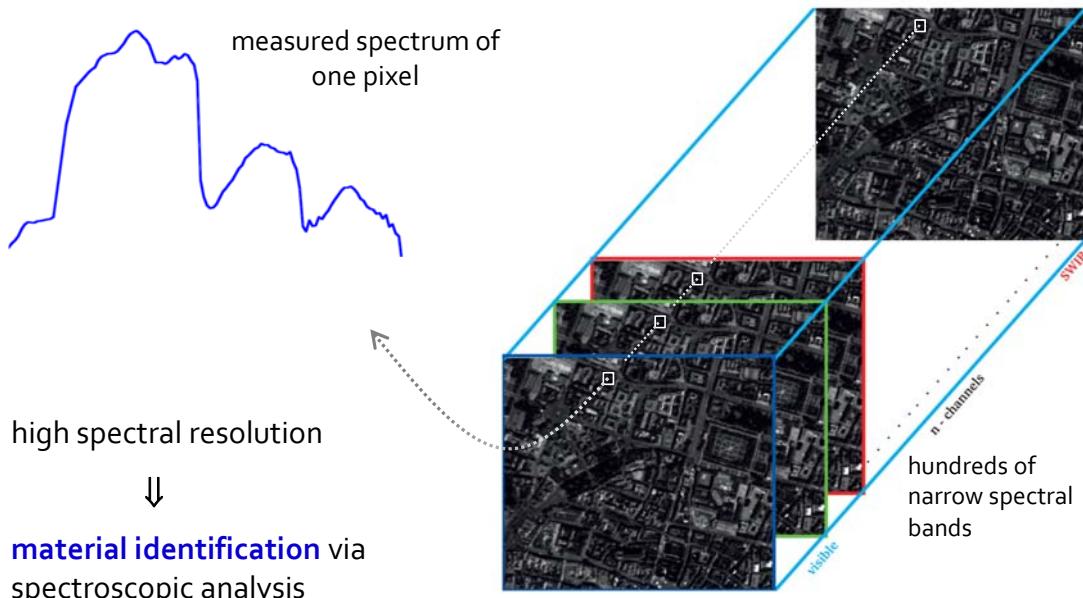
new satellite

new algorithm

Launch in 2020

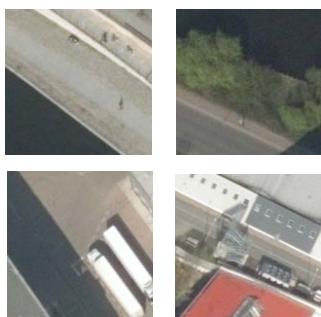


Hyperspectral Imaging – Spectral Resolution



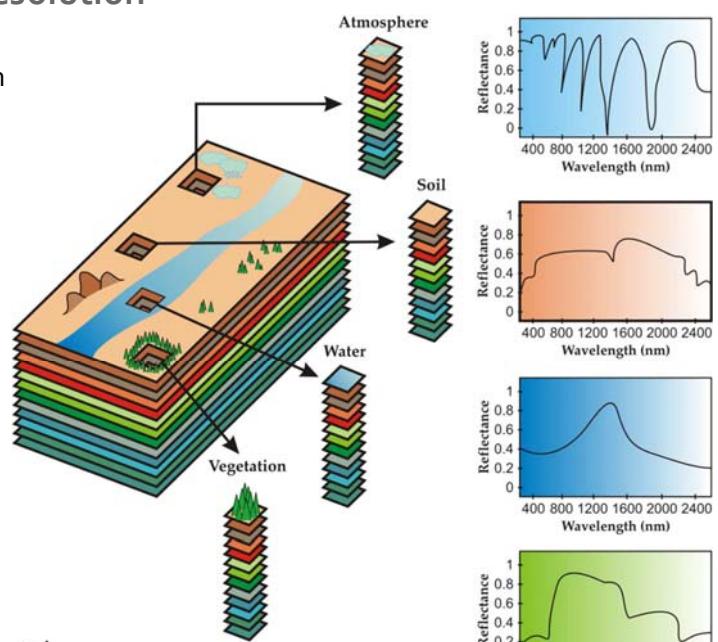
Hyperspectral Imaging – Spatial Resolution

typical spatial resolution ~ 30m



medium spatial resolution

↓
Spectral unmixing, i.e. material unmixing within the pixel, is crucial



From: Bioucas-Dias et al. 2012

Red Tile Roof



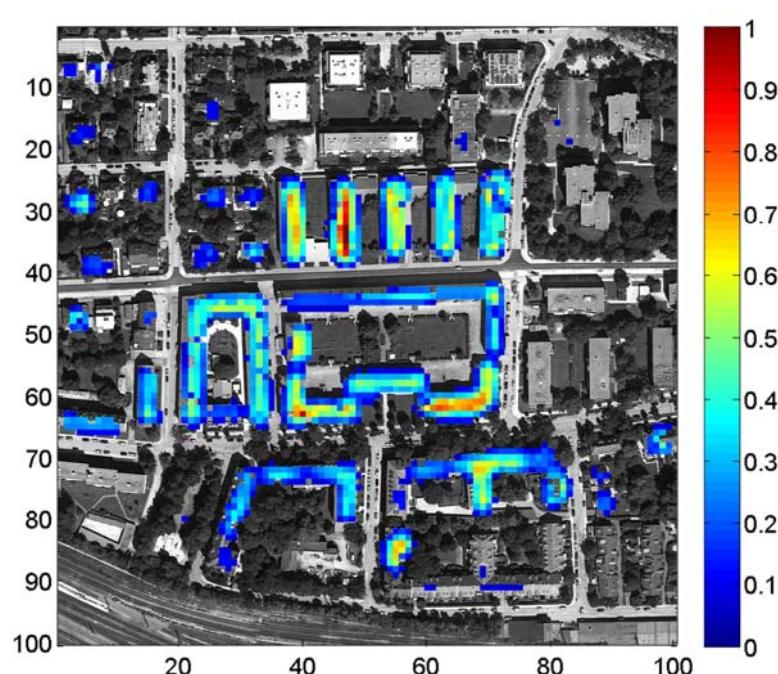
© Google Earth



HySpex



Joint Sparsity Model

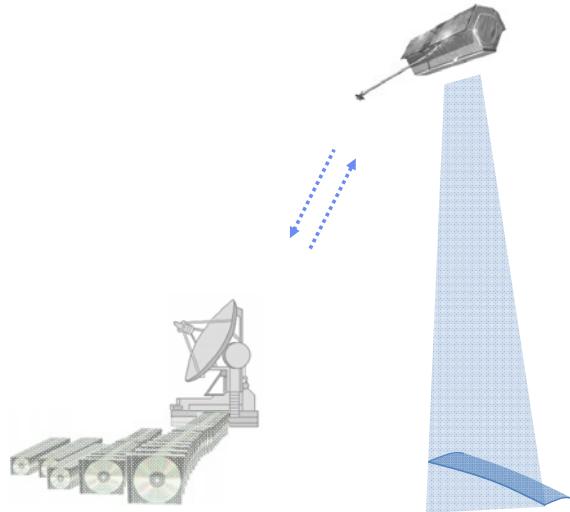


Data Science in Earth Observation

Model-Based Analytics
explorative signal processing methods

Data-driven Analytics
machine/deep learning methods

Geoscientific Application – Global Urban Mapping



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

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 popular. 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 shall we resist a black-box solution? These are controversial issues within the remote-sensing community. In this article, we analyze the state-of-the-art of 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 impact general model to tackle complex and largely unstructured 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 on domain knowledge. Deep learning has become so popular that 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

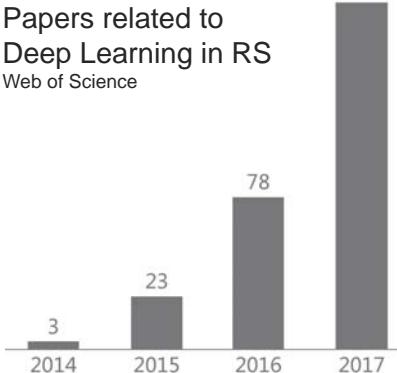
even humans in solving highly computational tasks (consider, e.g., the widely reported Go match between Google's AlphaGo and the world champion Lee Sedol). Based on such exciting success, deep learning is increasingly the model of choice in many application fields.

For instance, convolutional NNs (CNNs) have proven to be great at learning spatial feature maps from two 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]. Furthermore, an important part of the RS tasks have demonstrated significant improvements in sequential data analysis tasks involved in sequential data analysis and image captioning [9], [10] and image captioning [11].

In the wake of this success and the availability of data and computation, deep learning is also making its way into RS. Remote-sensing data present some unique challenges, because satellite images and scenes that pose difficult new scientific

Papers related to Deep Learning in RS Web of Science



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

- 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,...

 We are here



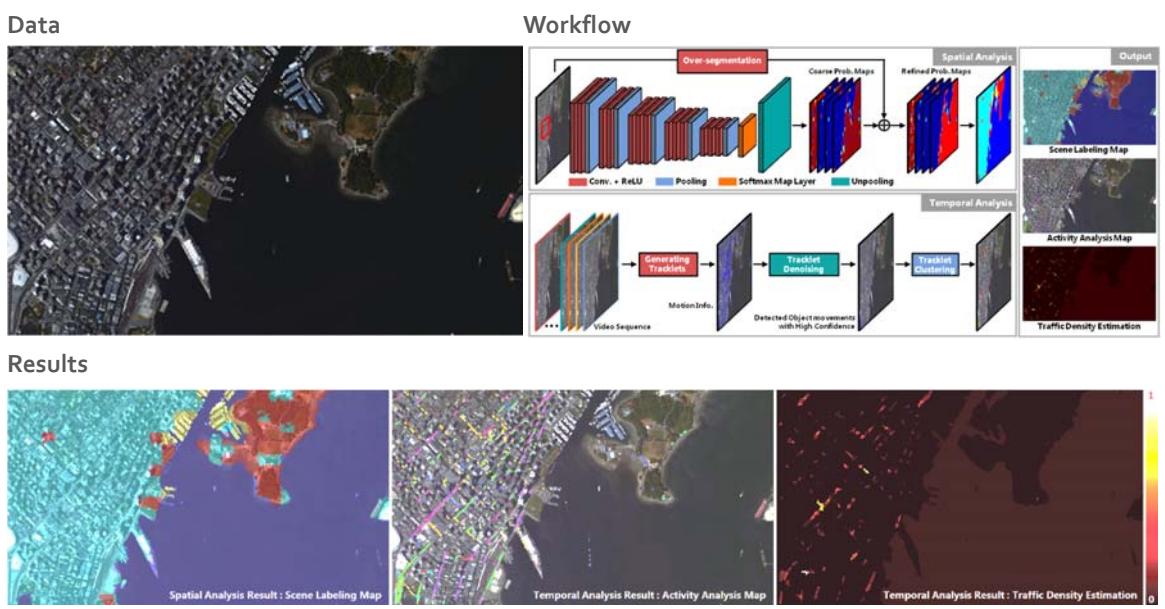
One of Our Phase 1 Successes

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

Winner of



Data Fusion
Contest 2016



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



Hot Topic or Hype?

IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, VOL. 55, NO. 7, JULY 2017

3639

Deep Recurrent Neural Networks for Hyperspectral Image Classification

Lichao Mou, Student Member, IEEE, Pedram Ghamisi, Member, IEEE, and Xiao Xiang Zhu, Senior Member, IEEE

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Deep Recurrent Neural Networks for Hyperspectral Image Classification

!?

3 | Lichao Mou | Pedram Ghamisi | Xiao Xiang Zhu

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IEEE Transactions on Geoscience and Remote Sensing

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Deep Recurrent Neural Networks for Hyperspectral Image Classification
Lichao Mou ; Pedram Ghamisi ; Xiao Xiang Zhu
Publication Year: 2017, Page(s):3639 - 3655
Cited by: Papers (25) | Patents (1)
DOI | PDF | Abstract | HTML

Deep Feature Extraction and Classification of Hyperspectral Images Based on Convolutional Neural Networks
Yushu Chen ; Hanlu Jiang ; Chunyang Li ; Xuping Jia ; Pedram Ghamisi
Publication Year: 2016, Page(s):6232 - 6251
Cited by: Papers (140)
DOI | PDF | Abstract | HTML

Convolutional Neural Networks for Large-Scale Remote-Sensing Image Classification
Emmanuel Maggiore ; Yuliya Tarabalka ; Guillaume Charpiat ; Pierre Alliez
Publication Year: 2017, Page(s):645 - 657
Cited by: Papers (66)
DOI | PDF | Abstract | HTML

When Deep Learning Meets Metric Learning: Remote Sensing Image Scene Classification via Learning Discriminative CNNs
Gong Cheng ; Ceyuan Yang ; Xiwen Yao ; Lei Guo ; Junwei Han
Publication Year: 2018, Page(s):2811 - 2821
Cited by: Papers (4)
DOI | PDF | Abstract | HTML

Accurate Object Localization in Remote Sensing Images Based on Convolutional Neural Networks
Yang Long ; Yiping Gong ; Zhiqiang Xiao ; Qing Liu
Publication Year: 2017, Page(s):2486 - 2498
Cited by: Papers (16)
DOI | PDF | Abstract | HTML

Is This Still Healthy?

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

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Popular Documents (January 2018)

Includes the top 50 most frequently accessed documents for this publication according to the usage statistics for the month of January 2018.

Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data
Natalia Kusničová ; Mlyna Lávrenčík ; Štefan Skutánek ; Andrej Šimola
Publication Year: 2017, Page(s):771 - 782
Cited by: Papers (2)
DOI | PDF | Abstract | HTML

Vehicle Detection in Satellite Images by Hybrid Deep Convolutional Neural Networks
Xueyan Chen ; Shengli Kang ; Chenglin Liu ; Chun-Hong Pan
Publication Year: 2014, Page(s):1797 - 1801
Cited by: Papers (88)
DOI | PDF | Abstract | HTML

Deep Learning Feature Selection for Remote Sensing Scene Classification
Qin Zou ; Lihai Ni ; Tong Zhang ; Qian Wang
Publication Year: 2017, Page(s):2321 - 2326
Cited by: Papers (27)
DOI | PDF | Abstract | HTML

Hyperspectral Image Classification With Gabor Filtering and Convolutional Neural Network
Liang Tang ; Lin Zhu ; Peilin Ghamisi ; Xuejing Jia ; Guoyu Li ; Xian Sun
Publication Year: 2017, Page(s):2350 - 2359
Cited by: Papers (11)
DOI | PDF | Abstract | HTML

Generative Adversarial Networks for Change Detection in Multispectral Imagery
Meiqiu Gong ; Xuting Liu ; Juhua Zheng ; Zhefei Li
Publication Year: 2017, Page(s):2310 - 2314
Cited by: Papers (10)
DOI | PDF | Abstract | HTML

MARTA-GAN: Unsupervised Representation Learning for Remote Sensing Image Classification
Deyu Li ; Kun Fu ; Yang Wang ; Guoqiang Xu ; Xian Sun
Publication Year: 2017, Page(s):2084 - 2096
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Object Detection Using Convolutional Neural Networks in a Coarse-to-Fine Manner
Xiaonan Li ; Shengyu Wang ; Mingming Fan
Publication Year: 2017, Page(s):2037 - 2041
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Classification of Hyperspectral Imagery Using a New Fully Convolutional Neural Network
Jiajia Yu ; Ji Zhou ; Mingming Fan ; Qian Guo ; Bobo Xie ; Jing Hu
Publication Year: 2016, Page(s):282 - 296
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Remote Sensing Image Registration Using Convolutional Neural Network Features
Kunhai Zou ; Guoping Xu ; Kun Fu ; Xian Sun ; Hui Sun
Publication Year: 2016, Page(s):232 - 236
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Hypercubes-Based Selection Based on Deep Convolutional Neural Network and Distance Measure
Ying Zhou ; Dan Huo ; Huihua Xing ; Xuechen Yu
Publication Year: 2017, Page(s):2365 - 2368
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

An Unsupervised Convolutional Feature Fusion Network for Feature Reconstruction of Hyperspectral Imagery
Ying Yu ; Zhipeng Gong ; Cheng Wang ; Peng Dong
Publication Year: 2016, Page(s):23 - 27
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Aircraft Type Recognition Based on Segmentation With Deep Convolutional Neural Networks
Jiwei Zou ; Guoping Xu ; Kun Fu ; Xian Sun ; Hui Sun
Publication Year: 2016, Page(s):282 - 285
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Atmospheric Correction of Hyperspectral Imagery Using a Deep Convolutional Neural Network
Yuning Yu ; Furu Liu
Publication Year: 2016, Page(s):287 - 291
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Deep Learning Each: Classification Using Inception-Resnet Networks
Dmitry Marinov ; Mike Celio ; Thomas Erhart ; Uwe Döll
Publication Year: 2016, Page(s):105 - 109
Cited by: Papers (33)
DOI | PDF | Abstract | HTML

Land Surface Temperature Retrieval Methods From Landsat-8 Thermal Remote Sensing
Juan C. Jiménez ; Daniel R. Fernández ; Ana Sóbredo ; Daniel González
Publication Year: 1993, Page(s):1840 - 1843
Cited by: Papers (10)
DOI | PDF | Abstract | HTML

Deep Fusion of Remote Sensing Data for Accurate Classification
Yiwei Chen ; Chunyang Li ; Pedram Ghamisi ; Xuping Jia ; Yufeng Guo
Publication Year: 2017, Page(s):1253 - 1257
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Remote Sensing Image Scene Classification Using Bag of Convolutional Features
Gong Cheng ; Zhenyu Yang ; Xian Sun ; Xian Sun ; Xian Sun
Publication Year: 2017, Page(s):1735 - 1739
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Change Detection Based on Deep Features and Low Rank
Bin Huo ; Yuhong Wang ; Lingjie Guo
Publication Year: 2017, Page(s):2419 - 2423
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Vision Satellite Image Super Resolution via Convolutional Neural Networks
Yiwei Lin ; Liguo Zhou ; Shu Wang ; Zhongyuan Wang
Publication Year: 2017, Page(s):2399 - 2405
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Polarimetric SAR Image Classification Using Deep Convolutional Neural Networks
Yu Zhou ; Haipeng Wang ; Feng Xu ; Ya-Qiu Jin
Publication Year: 2016, Page(s):1935 - 1939
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Deep Neural Network Initialization Method for Micro-Doppler Classification With Low Training Sample Support
Mehmet Saygılıaylıoğlu ; Sevgi Zelalay Gözütük
Publication Year: 2017, Page(s):2442 - 2460
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Training Deep Convolutional Neural Networks for Land-Cover Classification of High-Resolution Imagery
Grant J. Scott ; Matthew R. Englund ; William A. Sterns ; Richard M. Moore
Publication Year: 2017, Page(s):549 - 553
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

A Self-Improving Convolutional Neural Network for the Classification of Hyperspectral Data
Pedram Ghamisi ; Yihui Chen ; Xiao Xiang Zhu
Publication Year: 2017, Page(s):1537 - 1547
Cited by: Papers (7)
DOI | PDF | Abstract | HTML

Hyperspectral Imagery Denoising by Deep Learning With Tractable Nonlinearity Function
Wenying Xie ; Yunming Li
Publication Year: 2017, Page(s):1963 - 1967
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Atmospheric Correction of Hyperspectral Imagery Using a Deep Convolutional Neural Network
M. Tadevosyan ; J. R. Parker ; M. J. N. Lewis ; G. J. Gao
Publication Year: 2016, Page(s):320 - 324
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Modified Self-Attention Layer for Hyperspectral Imagery Classification Using Convolutional Neural Networks
Byung-Kwan Kim ; Hyun-Sang Kang ; Seung-Cuk Park
Publication Year: 2017, Page(s):43 - 42
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

Modified Self-Attention Layer for Dimensionality Reduction of Hyperspectral Images
Yang-Jun Deng ; Xiang-Yang Guo ; Li-Ping Pan ; Li-Yang Shao ; Qian-Jiang Tang
Publication Year: 2016, Page(s):277 - 281
Cited by: Papers (1)
DOI | PDF | Abstract | HTML

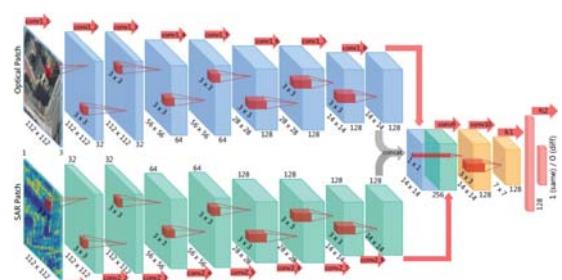
What makes Deep Learning in Earth Observation Special?

- 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 ($x-y-z-t-\lambda$), complex-valued and multi-modal :
 - SAR
 - Lidar
 - multi-/super-/hyperspectral
 - GIS, OSM, citizen science, social media,...
- Often: lack of sufficient training data

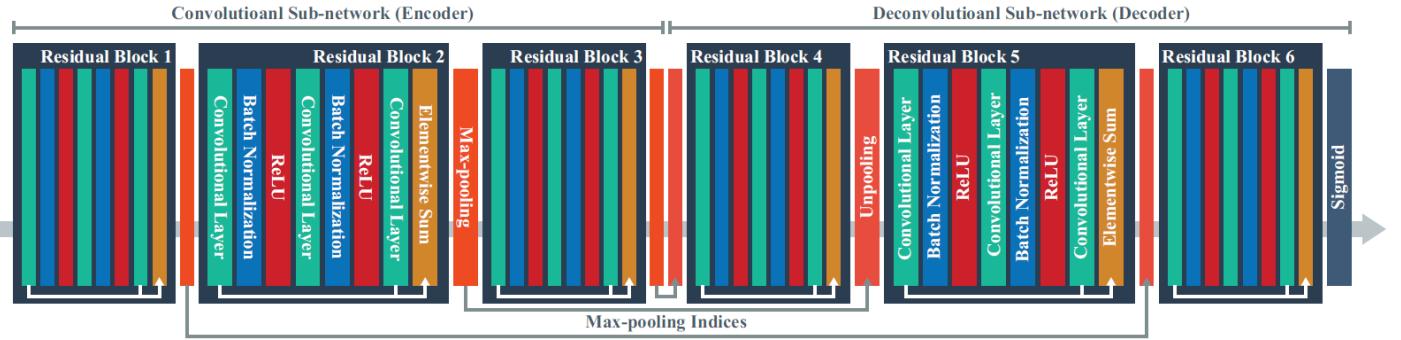


Deep Learning@IMF

- 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



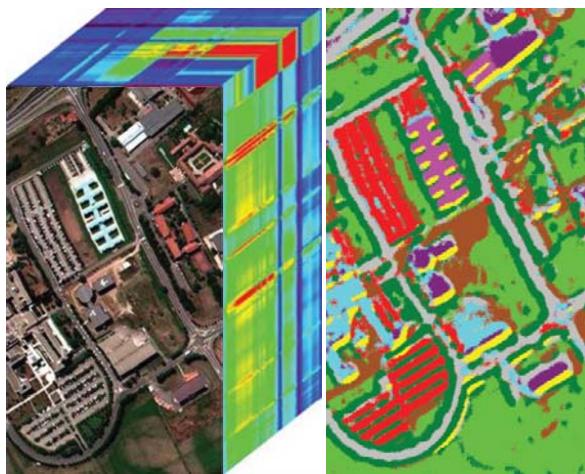
L. Mou, P. Ghamisi, and X. X. Zhu, "Unsupervised spectral–spatial feature learning via deep residual conv–deconv network for hyperspectral image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 1, pp. 391–406, 2018.



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

Results

Application I: Classification



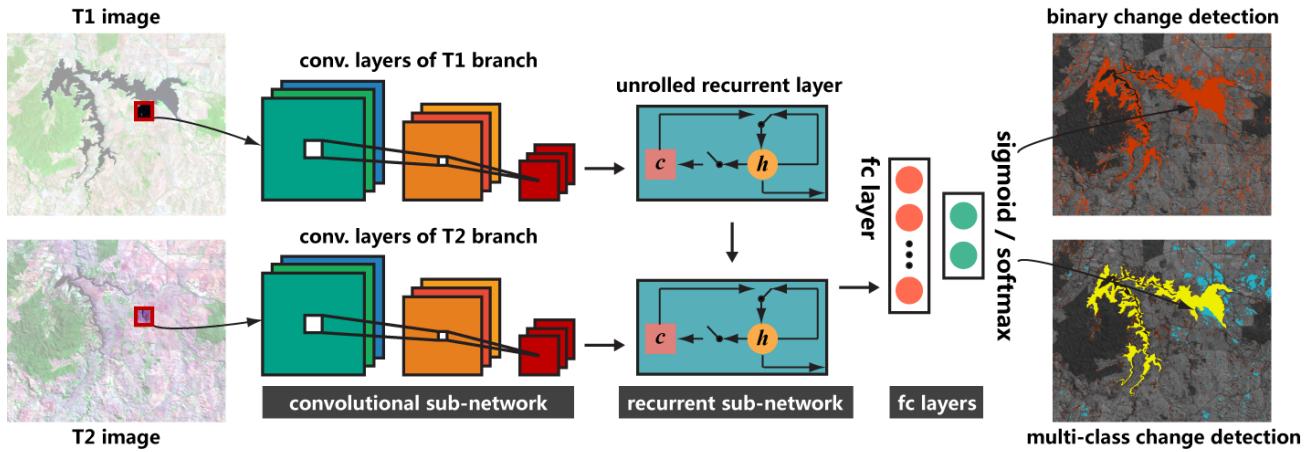
Application II: "Free" Object Localization



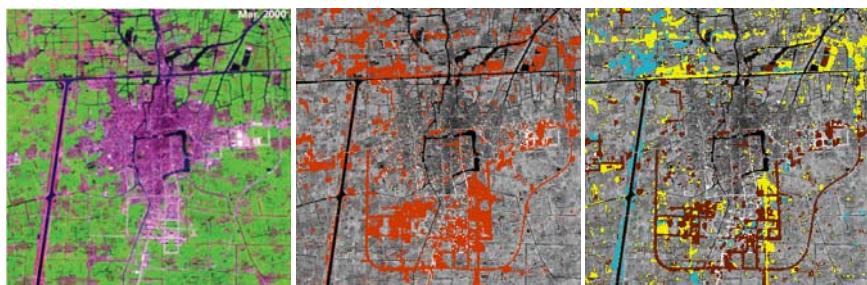
We found some neurons in our network own good description power for semantic visual patterns in the object level. For example, the neurons #52 and #03 can be used to precisely capture **metal sheets** (left) and **vegetative covers** (right).



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

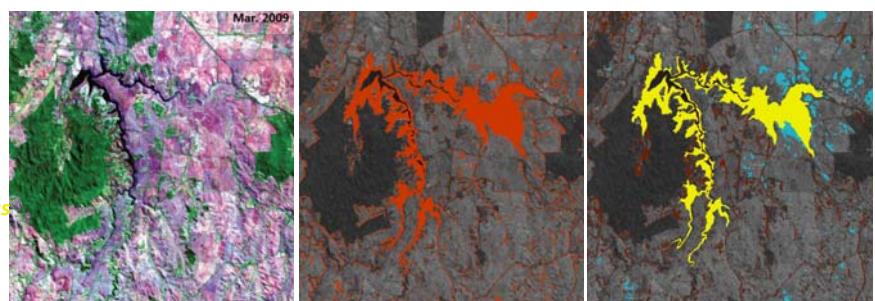


Recurrent Convolutional Neural Network for Change Detection in Bi-temporal Images

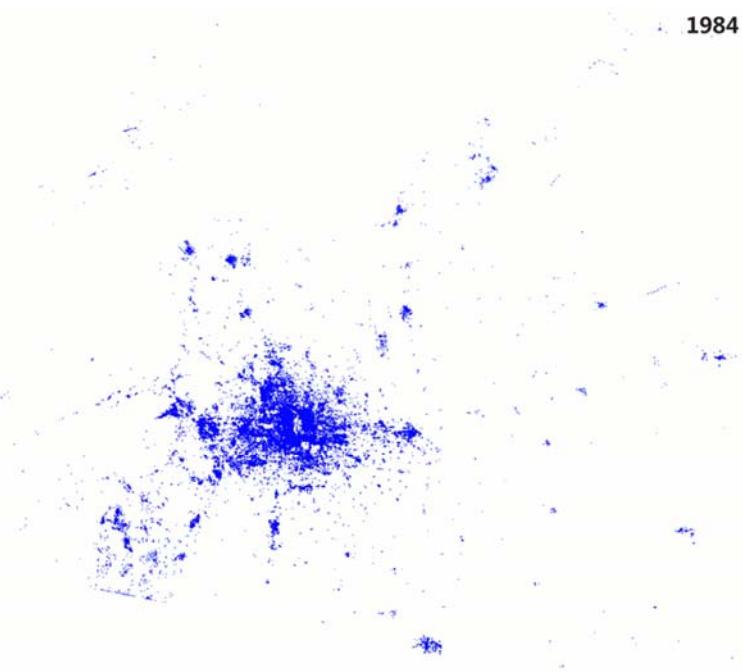
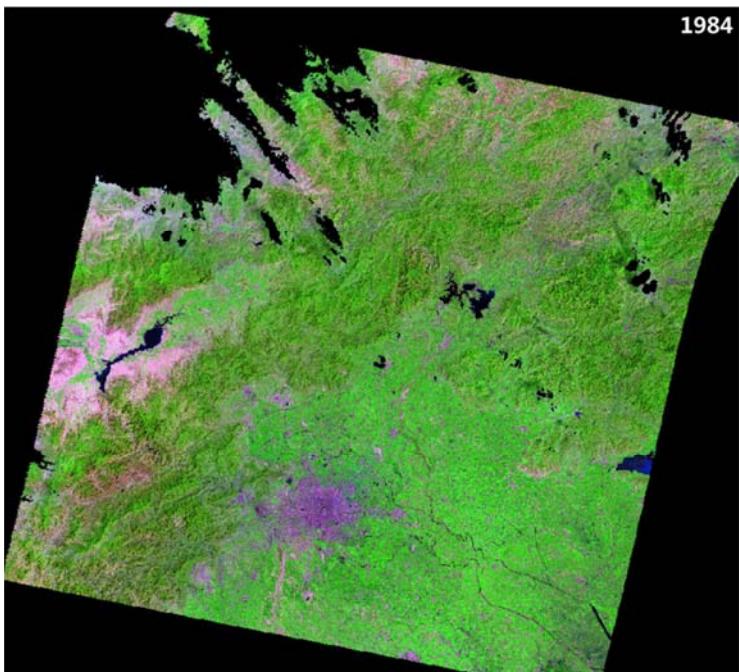


- Location: Taizhou City, China
- Time: Mar. 2000 and Feb. 2003
- Data Source: Landsat ETM+
- Legend:
 - Changed areas (in binary change detection);
 - city expansion; soil change; water change

- 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)



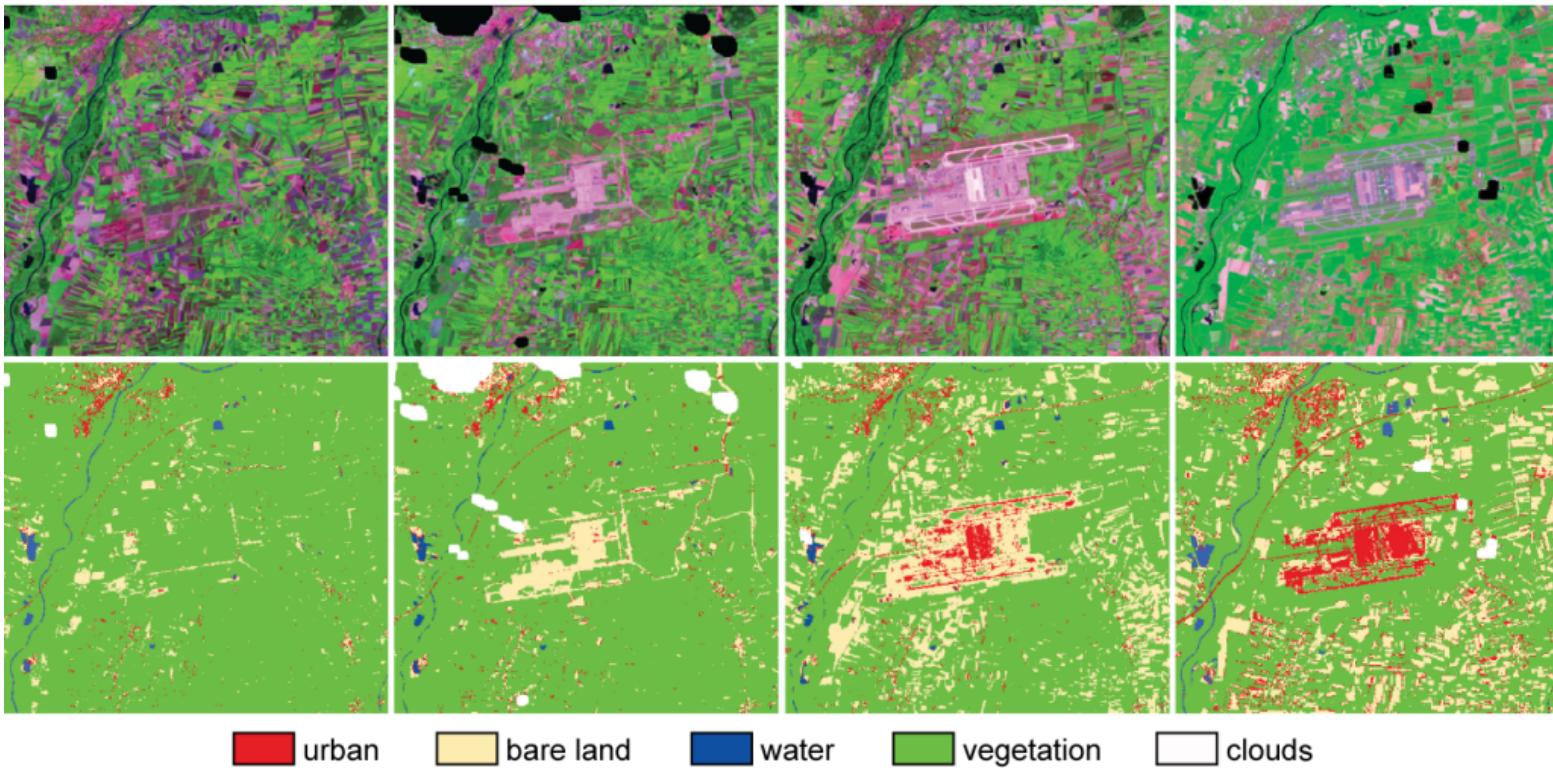
Munich Airport

1985

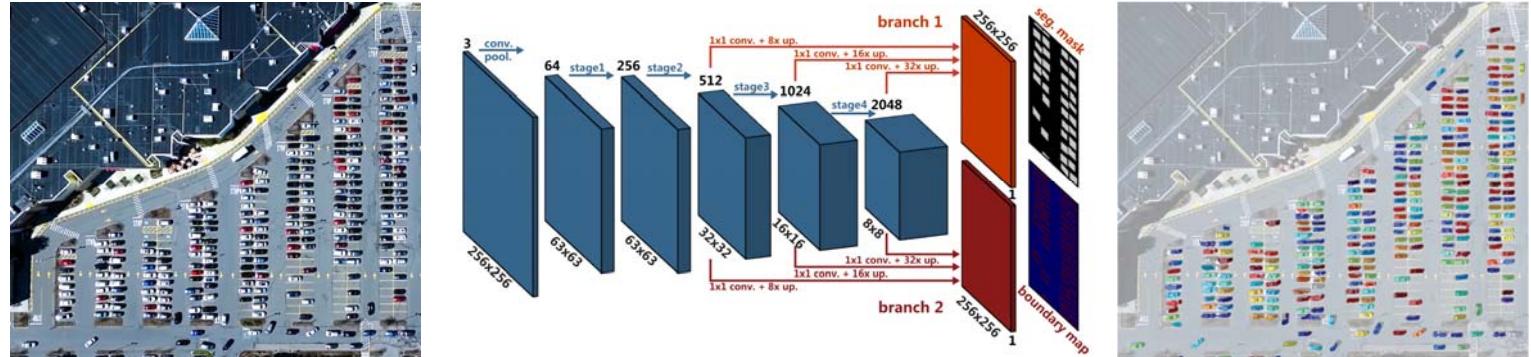
1986

1990

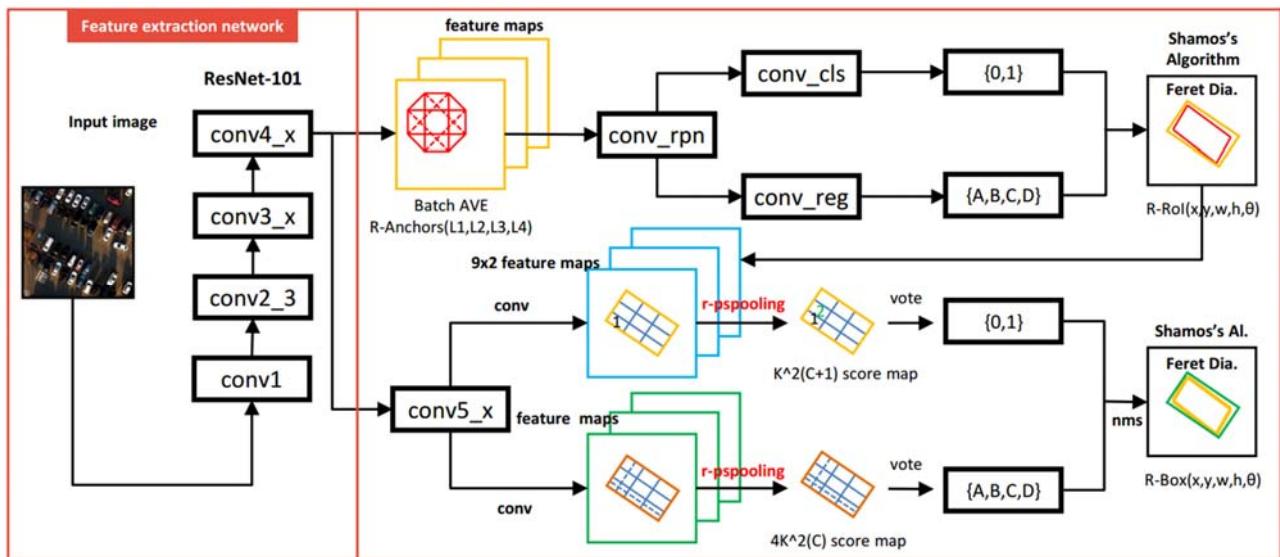
2014



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



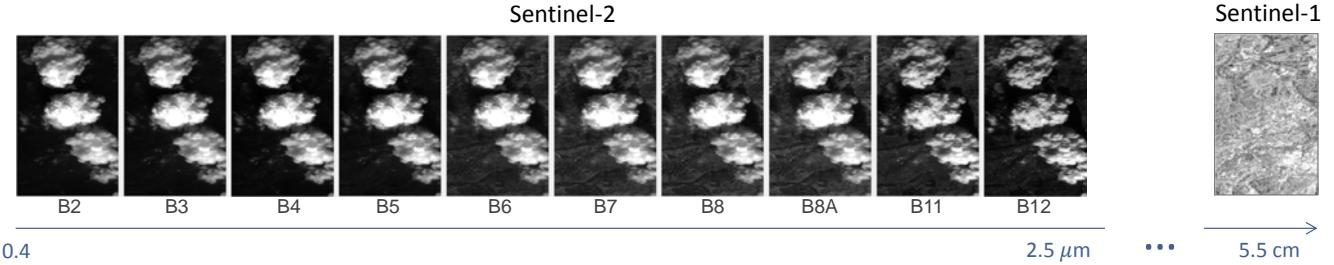
The architecture of the proposed network, which is capable of generating rotatable anchors for predicting rotatable object proposals and final detections.



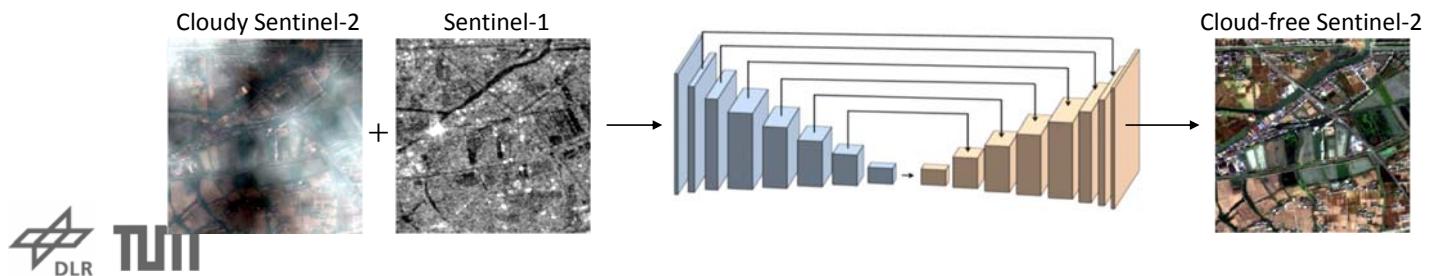
cGAN-based Enhancement of Optical Remote Sensing Data

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:

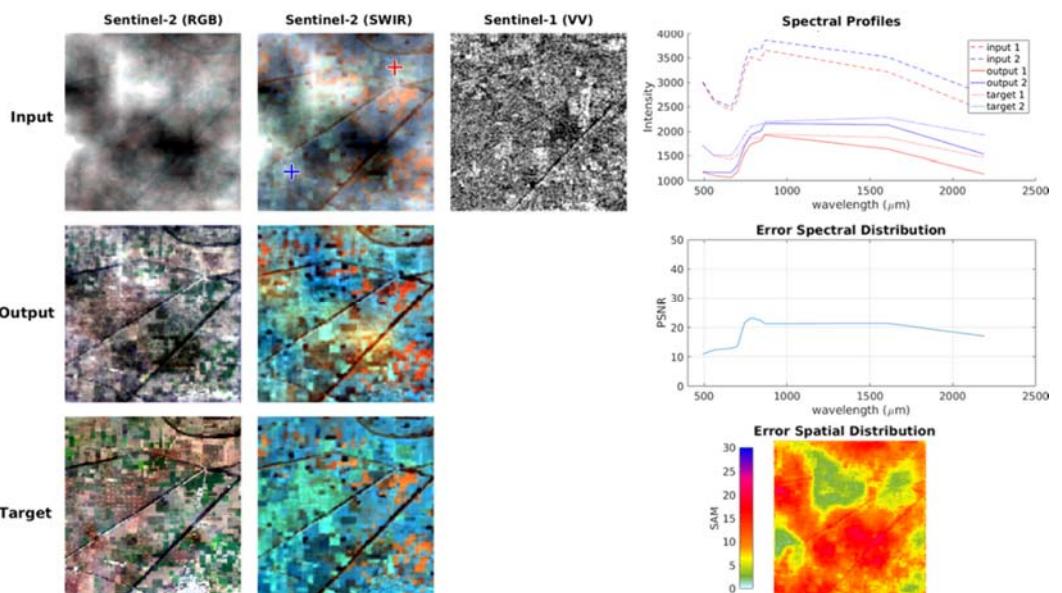
- 25,000 pairs of (cloud-free) Sentinel-2 / Sentinel-1 co-registered image pairs
- Simulate cirrus clouds using Perlin noise

First Qualitative Results

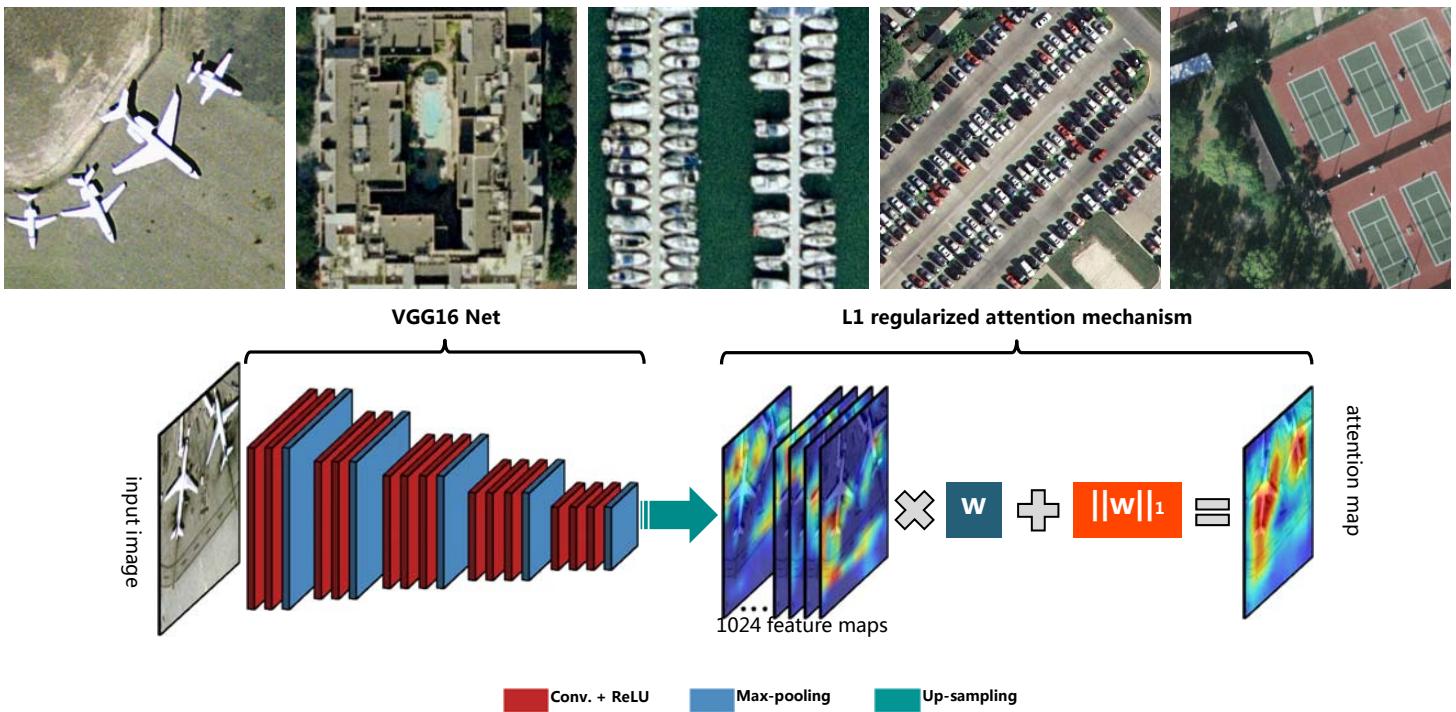
- Clouds successfully removed from validation data set, but artifacts visible

Next step

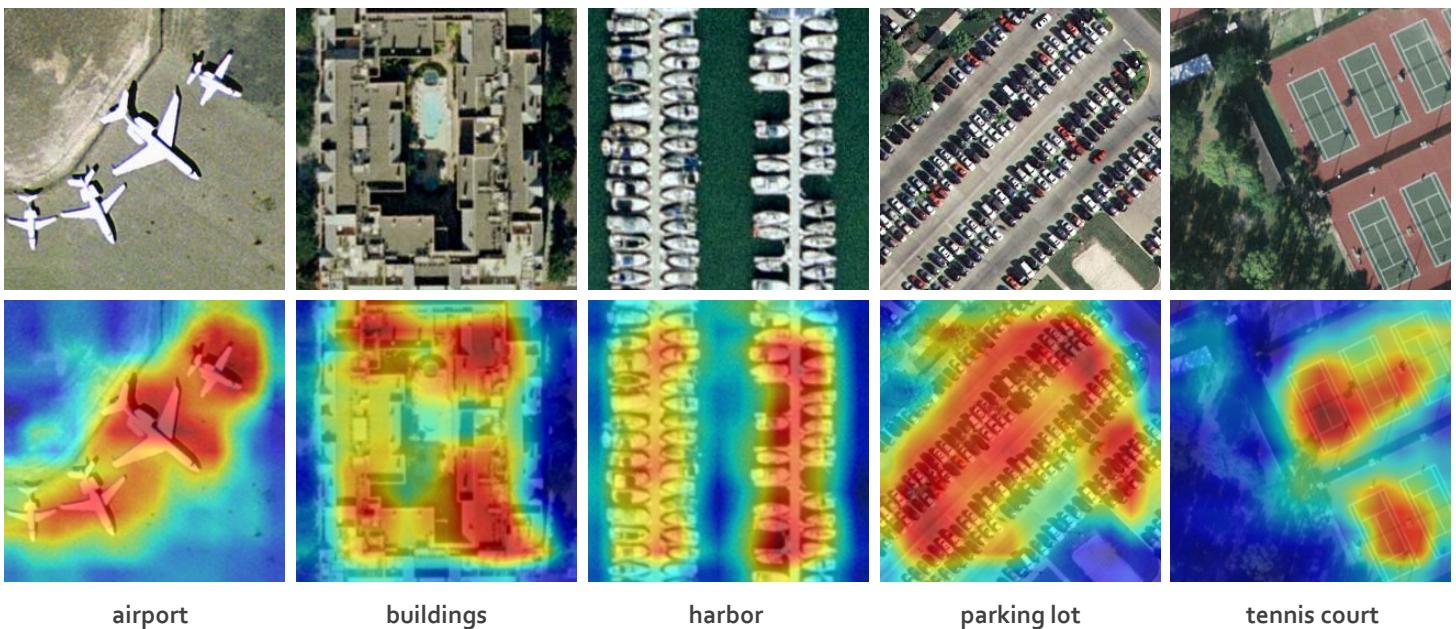
- Train network with real, thick clouds and tune hyperparameters



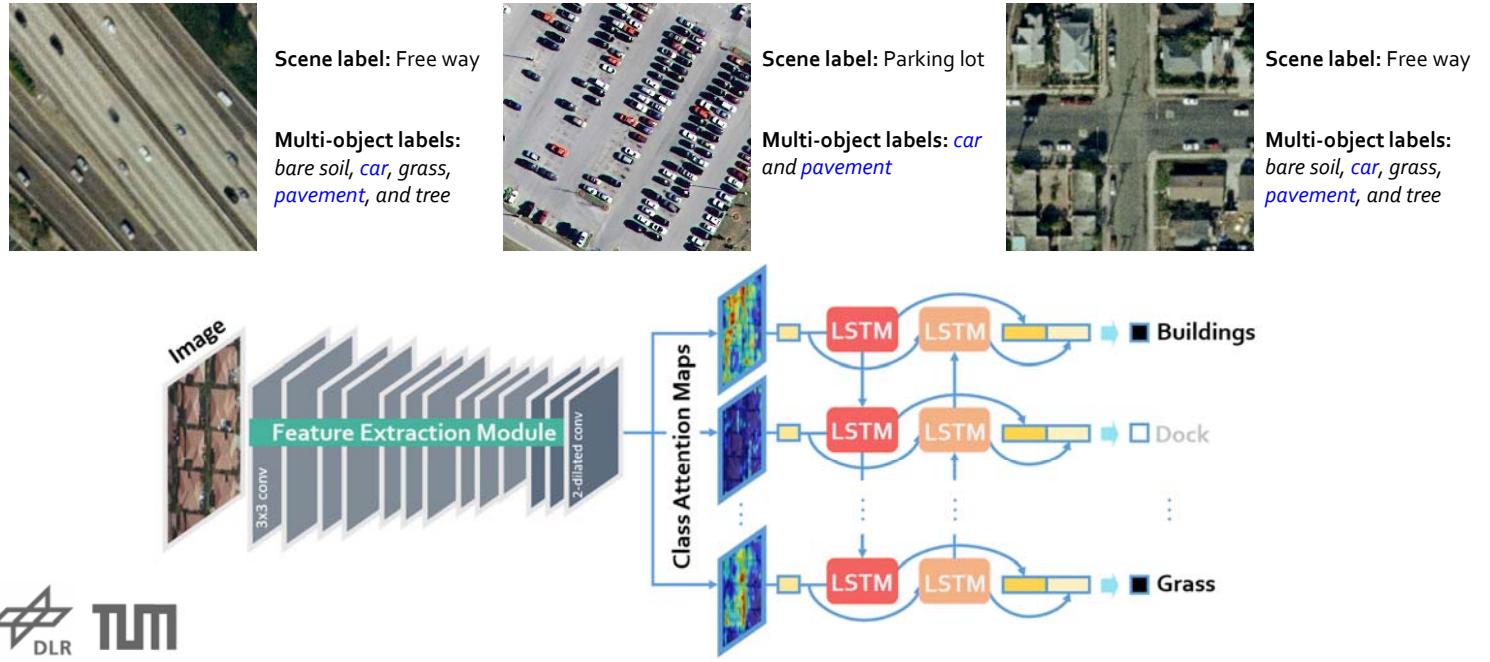
How Does CNN Recognize Different Objects?



Deep Convolutional Neural Networks with Attention Mechanism for Aerial Scene Classification



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



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

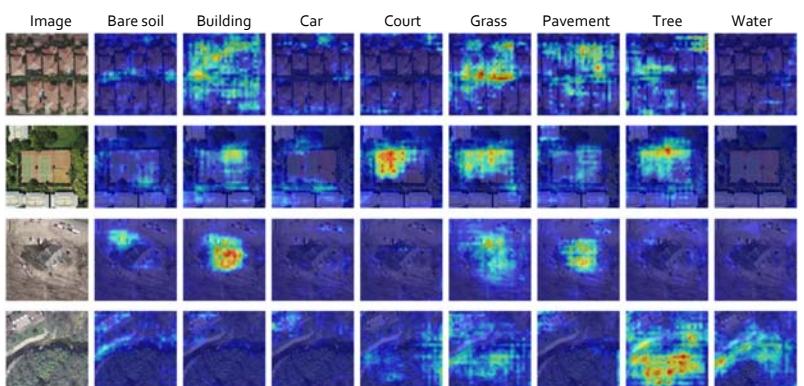
Images in UCM Multi-label Dataset					
Ground Truths	dock, ship, and water	bare soil, building, car, pavement, and tree	building, court, pavement, grass, and tree	grass, sand, mobile-home, and tree	car, grass, and pavement
Predictions	dock, ship, and water	bare soil, building, car, pavement, and tree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

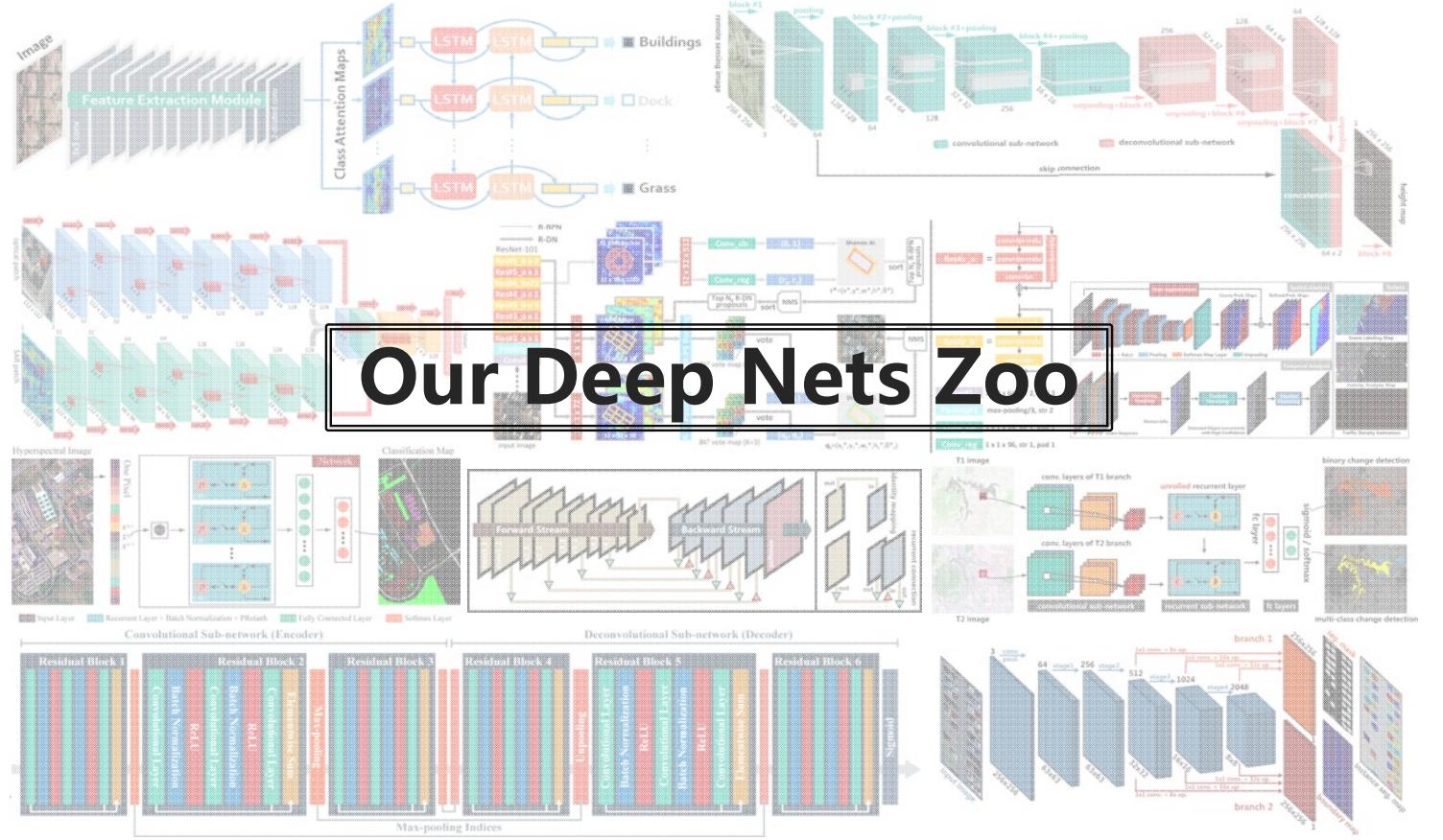
Red predictions indicate false positives, while blue predictions are false negatives.

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





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Open Issues

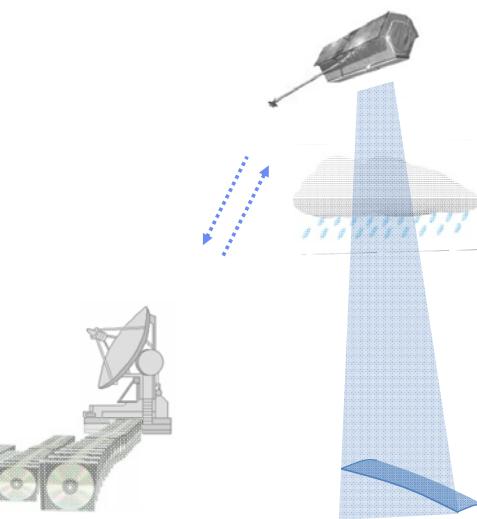
- **novel applications**, other than classification and detection related tasks
- **transferability** of deep nets
- **very limited annotated data** in remote sensing
- how to **benchmark** the fast growing deep-learning algorithms in remote sensing?
- how to combine **physics-based modeling and deep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

Data Science in Earth Observation

Model-Based Analytics
explorative signal processing methods

Data-driven Analytics
machine/deep learning methods

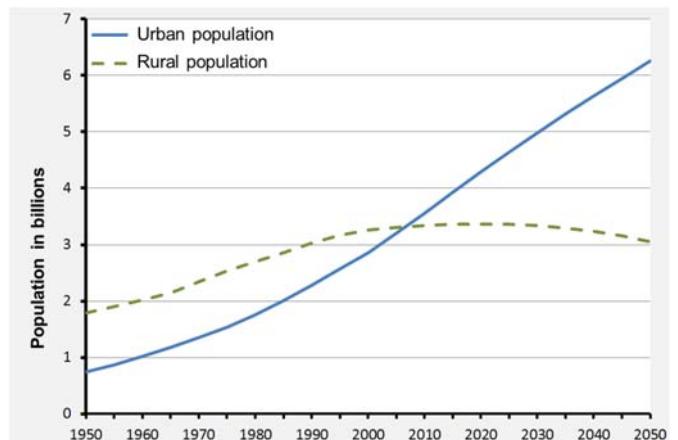
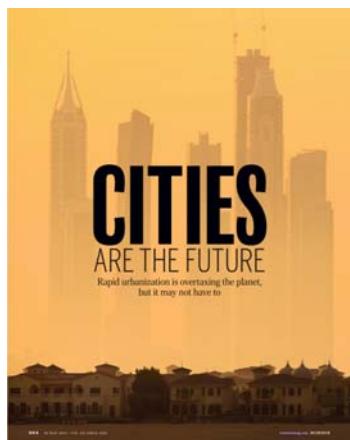
$$y = F(x) + \varepsilon$$



Geoscientific Application – Global Urban Mapping



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



Uncontrolled Growth in Mumbai Slums Leads to Massive Fires and Floods

Mumbai will likely flood again – and nobody's doing much about it

The 2005 flood that devastated Mumbai could just be the beginning, as more rain, more visitors and more people make the city even more vulnerable to disaster. So why won't anyone act?

• Hotter summers are coming to Mumbai, and it won't be pretty

Business as usual ... a high-street vegetable stall in a flooded Mumbai street. Photograph: Arun Datta/Reuters

Shanti Ravindran in Mumbai
Thursday 27 November 2014 05.05 GMT

Any discussion of floods in Mumbai begins with a ritual invocation of one fateful date: 26 July 2005. On this day, the megacity received 944mm of rainfall - the average amount for the entire season, and a 100-year high. This, combined with high tides, set off a devastating flood in the city, much of which is built on low-lying land reclaimed in the 19th century. In the catastrophe that ensued, almost the entire communications network and public transportation

Most popular in US

- Kentucky and Oregon primary results track the vote, county by county
- James Deen taken on MMA, saying open face 'unfair' government scrutiny
- I worked on Facebook's trending team - the most toxic work experience of my life
- West and Russia on course for war, says ex-Nato deputy commander
- The first 50 lashes a Saudi activist gets in the kingdom's brutal antisodomy laws

Fire destroys around 1,000 slum homes in Mumbai, 2 killed

Fahim Shahid, Hindustan Times, Mumbai | Updated: Dec 08, 2015 01:16 IST

top news

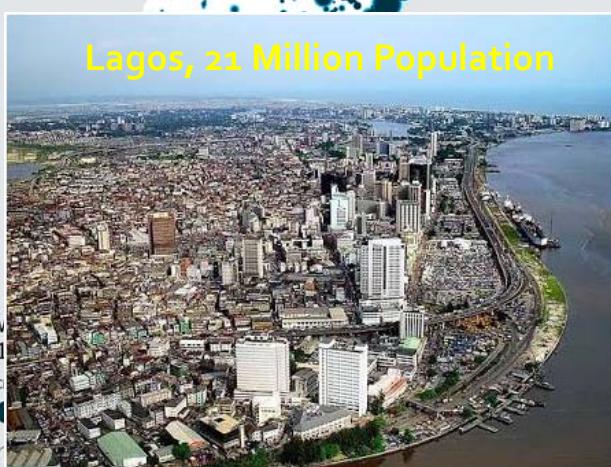
- First Chibok girl; Boko Haram foul pregnant: Relat
- Delhi sizzles at 4 weather dept ca people
- Congress calls R 'power hungry' a blasts Gandhi

most popular

- Nurses go to coq defamation case Kapil's 'vulgar' s
- Aishwarya Rai B purple lips at Cai Twitter feuds...



Urban Growth Happens Mostly in Developing Areas



V
1
C

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



State of the Art – Global Urban Footprint (GUF)

GUF: **2D binary map urban vs. non-urban**

Europe

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

www.so2sat.eu

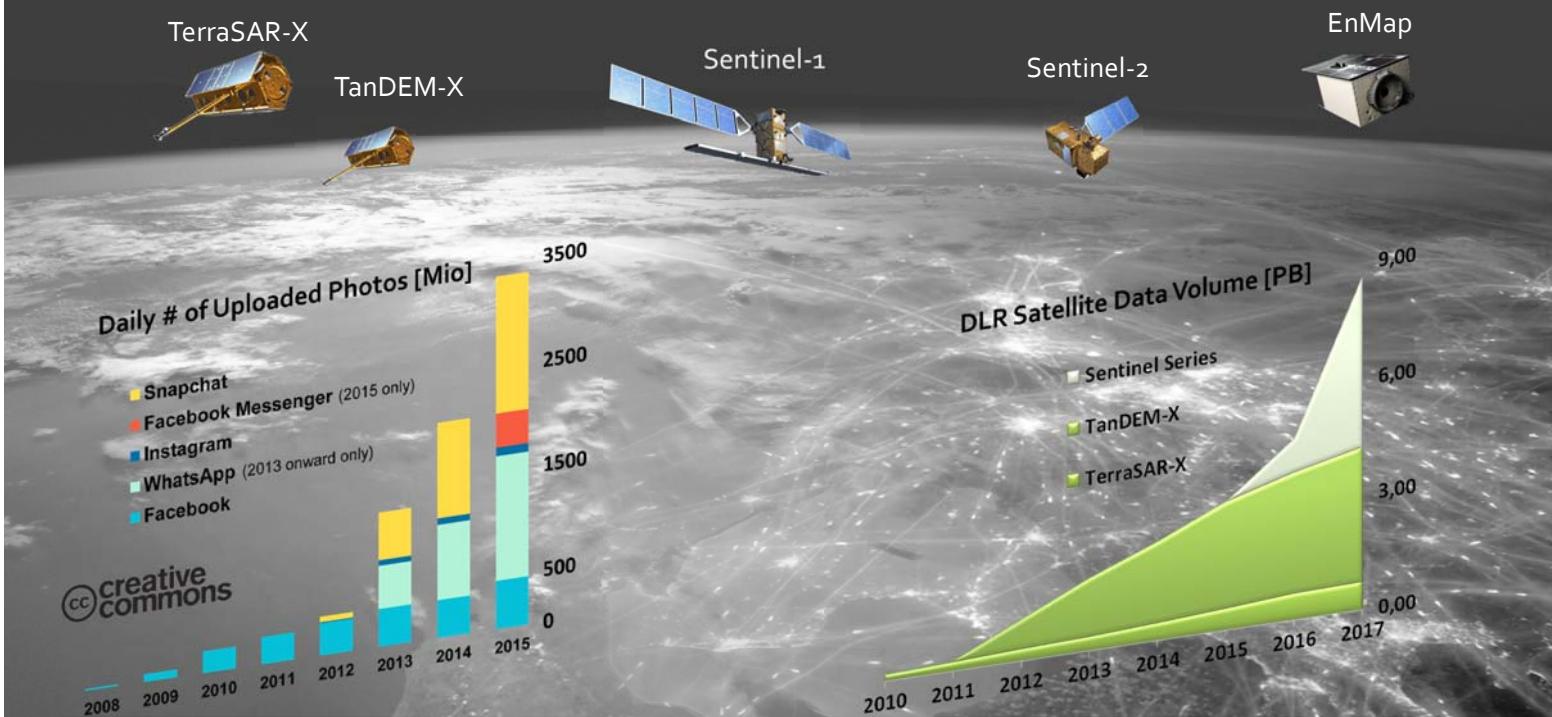
GUF: **2D binary map urban vs. non-urban**

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

erc

Europe

10 Peta Bytes from Social Media to EO Satellites



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Social Media Images – Abundance of Hotspots

The screenshot shows a Flickr search results page for "Bellagio Hotel".

Header: flickr Explore Create Search: Bellagio Hotel Log In Sign Up

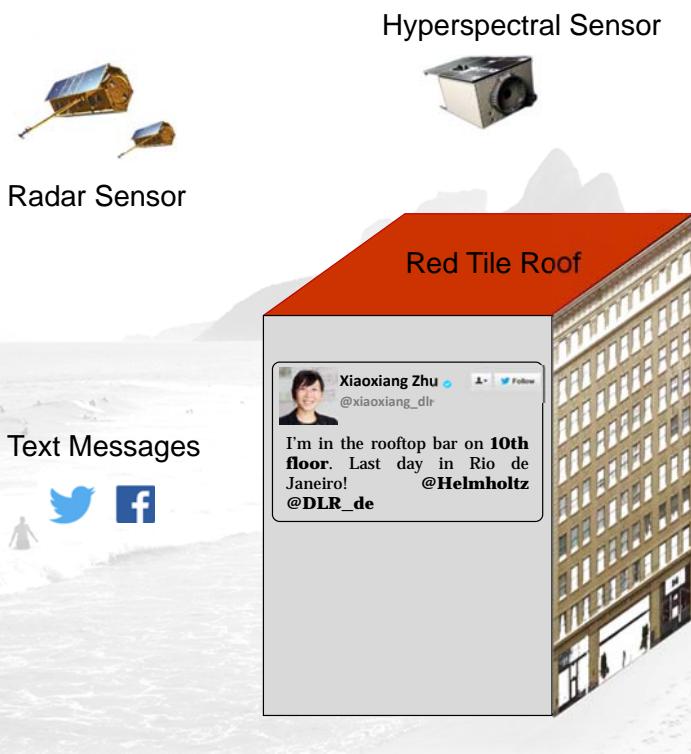
Filter: Photos People Groups Advanced Clear

Search filters: All creative commons SafeSearch on Relevant View all 9,347

Results: Everyone's photos (grid of images showing various views of the Bellagio Hotel and its fountains).

So2Sat in a Nutshell

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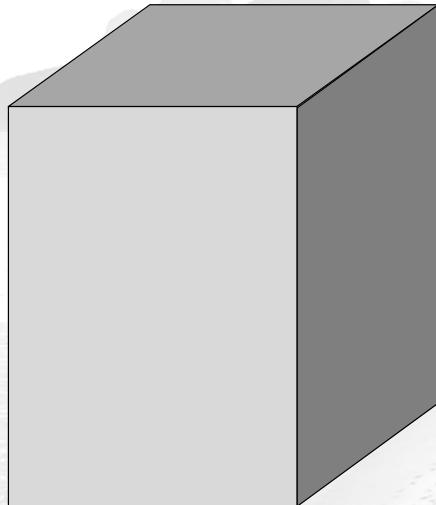
10 Petabytes = half of the German remote sensing data archive

Global 3D/4D Urban Mapping

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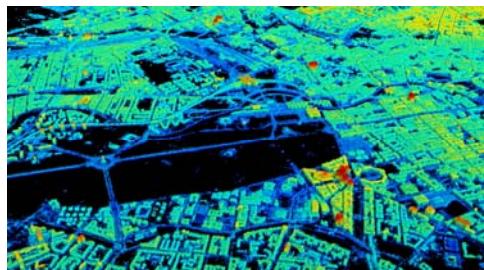
TerraSAR-X/TanDEM-X



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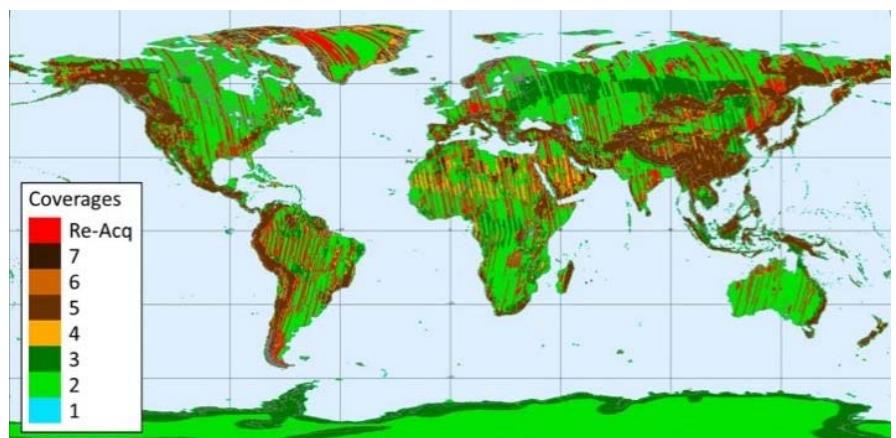
Challenges



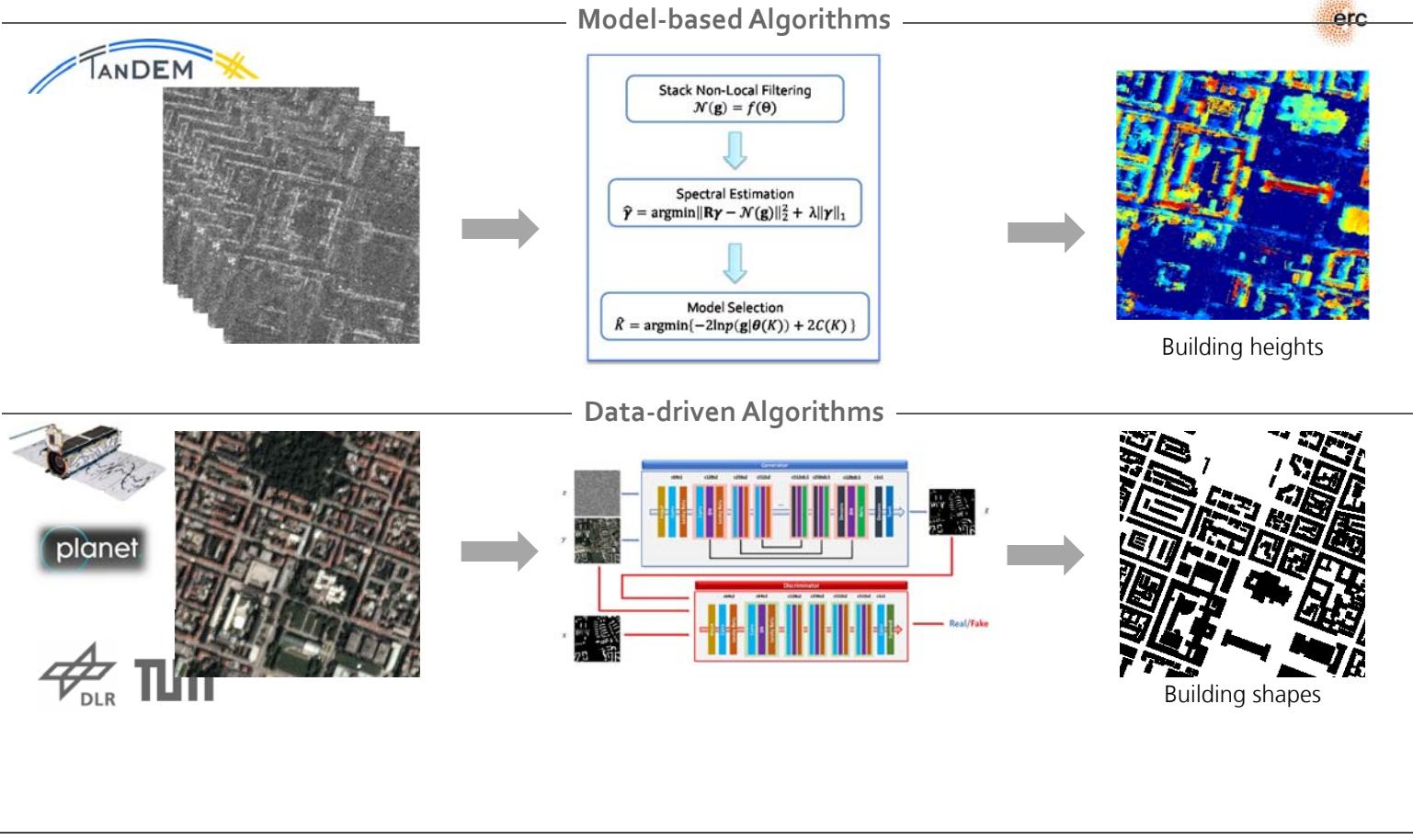
High quality tomographic reconstruction requires **20 – 100 high resolution** acquisitions → **not globally available**

TanDEM-X has global coverage, but ...

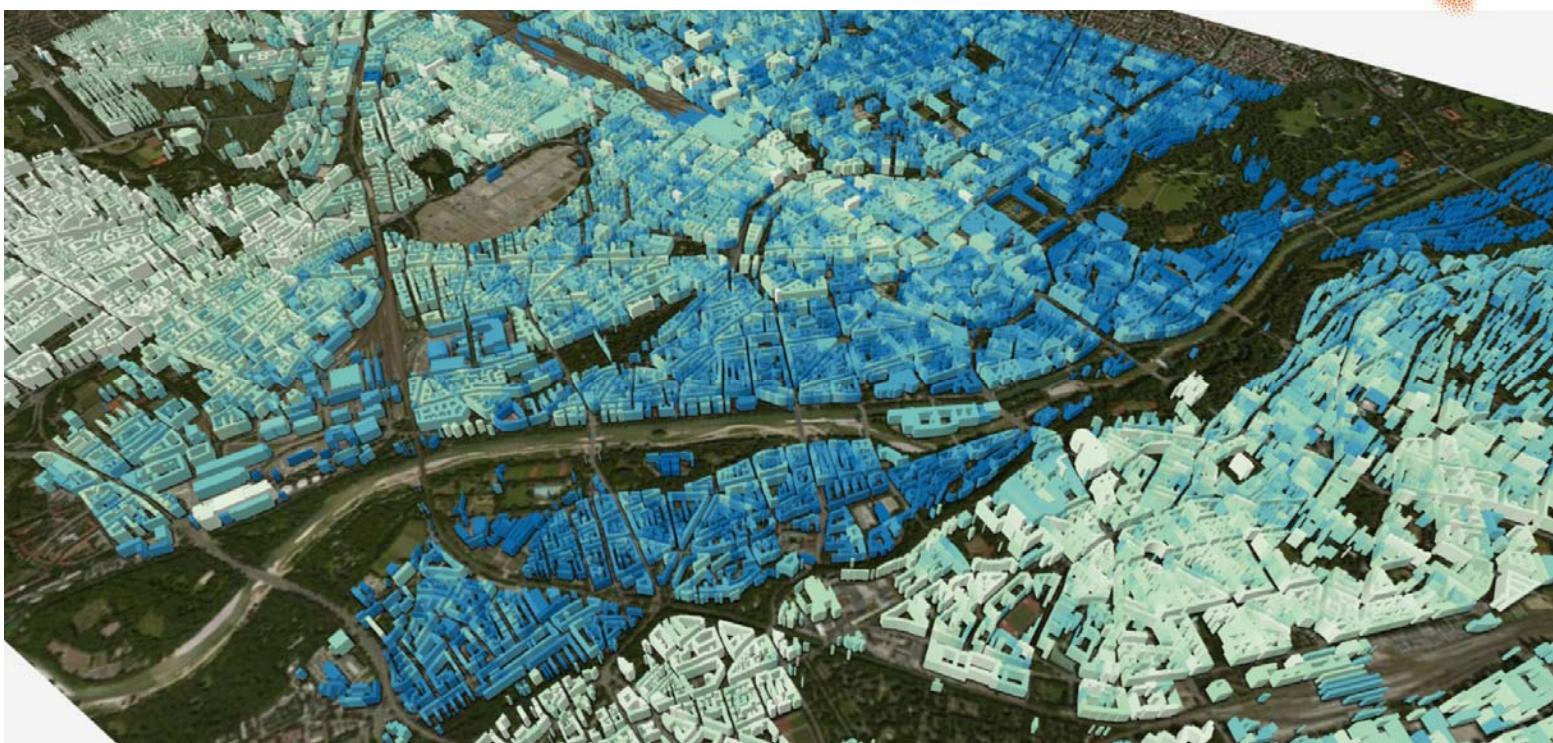
- only moderate resolution
- number of coverages limited



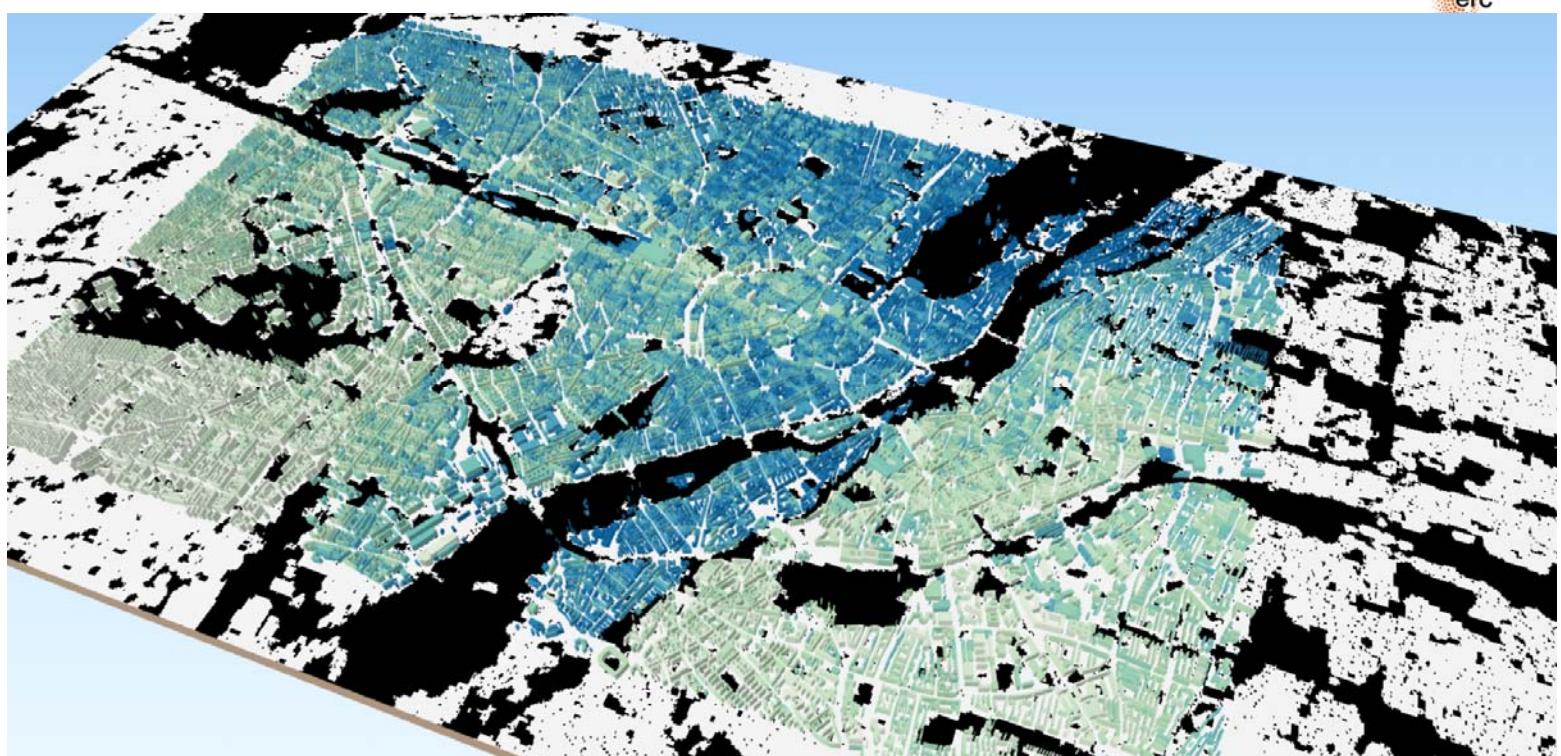
A Data Science Approach



First Impression of the Global 3D Urban Models
accuracy better than 2m



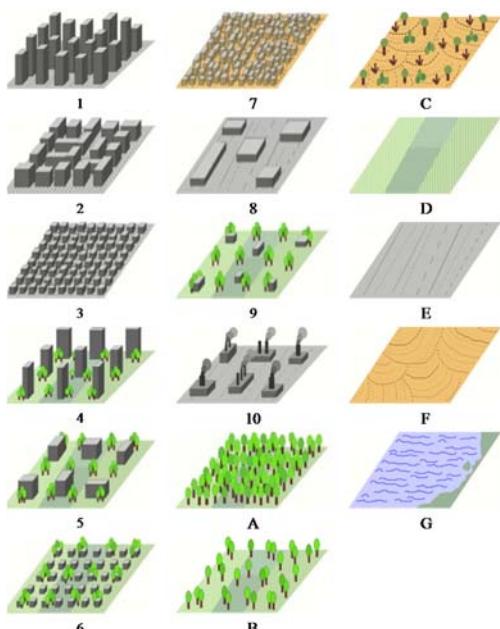
We Go Global in 2021!



Global Local Climate Zones Classification

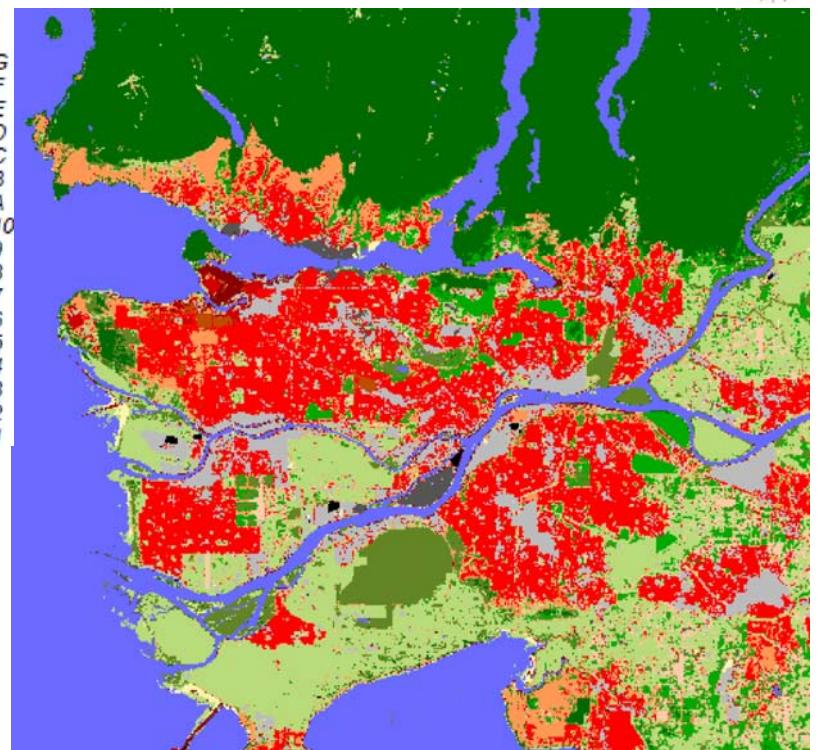
Global Local Climate Zones Classification

will be global soon



LCZC

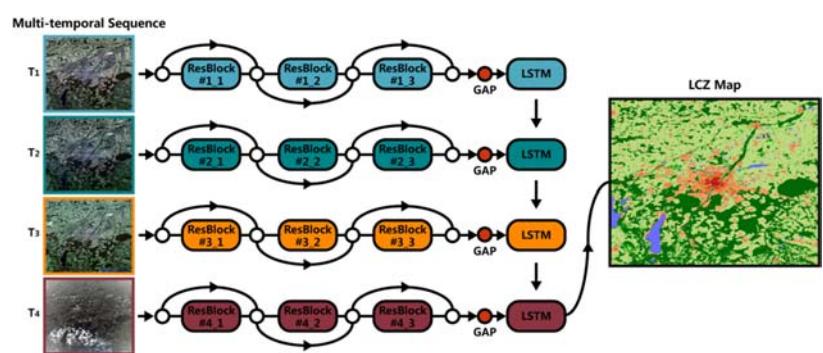
G
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1



So2Sat LCZ42 Benchmark Dataset

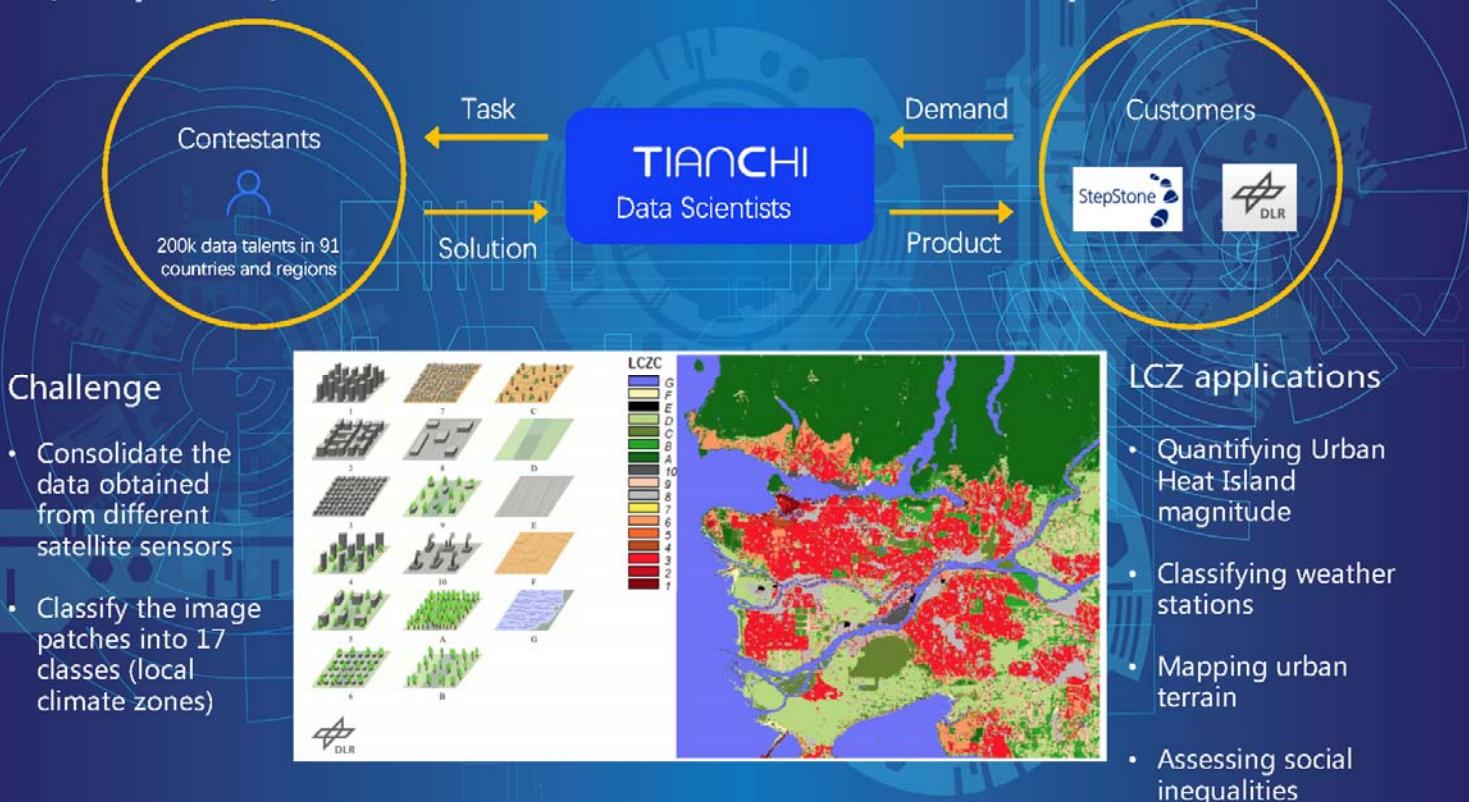
- Hand labelled 42 cities covering 10 culture zones
- Data:
 - Sentinel-1
 - Sentinel-2, seasonal

Labeling effort: 15 person × 1 Month/person





DLR/StepStone/AliCloud TIANCHI Contest 2018 Germany



Building Settlement Type Classification

– by the Fusion of Remote Sensing and Social Media Data

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Text Messages

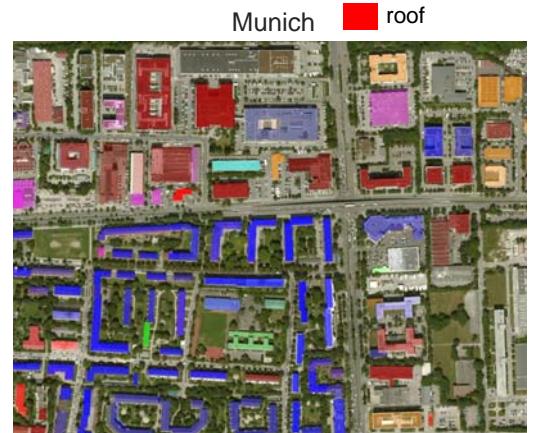
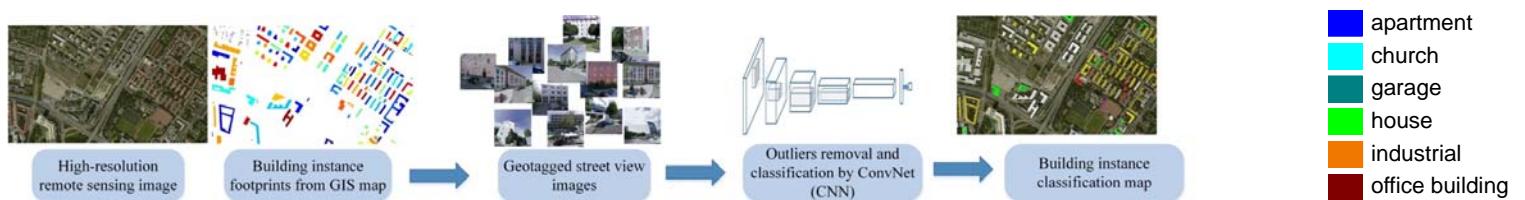


Social Media Images



Building Instance Classification from Street View Data by CNN

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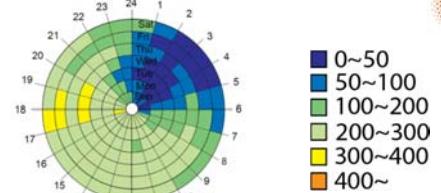


Tweets for Building Functions Identification

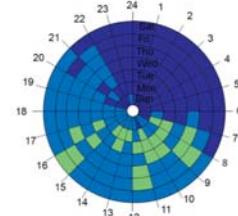


Tweets for Building Functions Identification

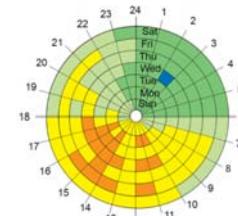
residential



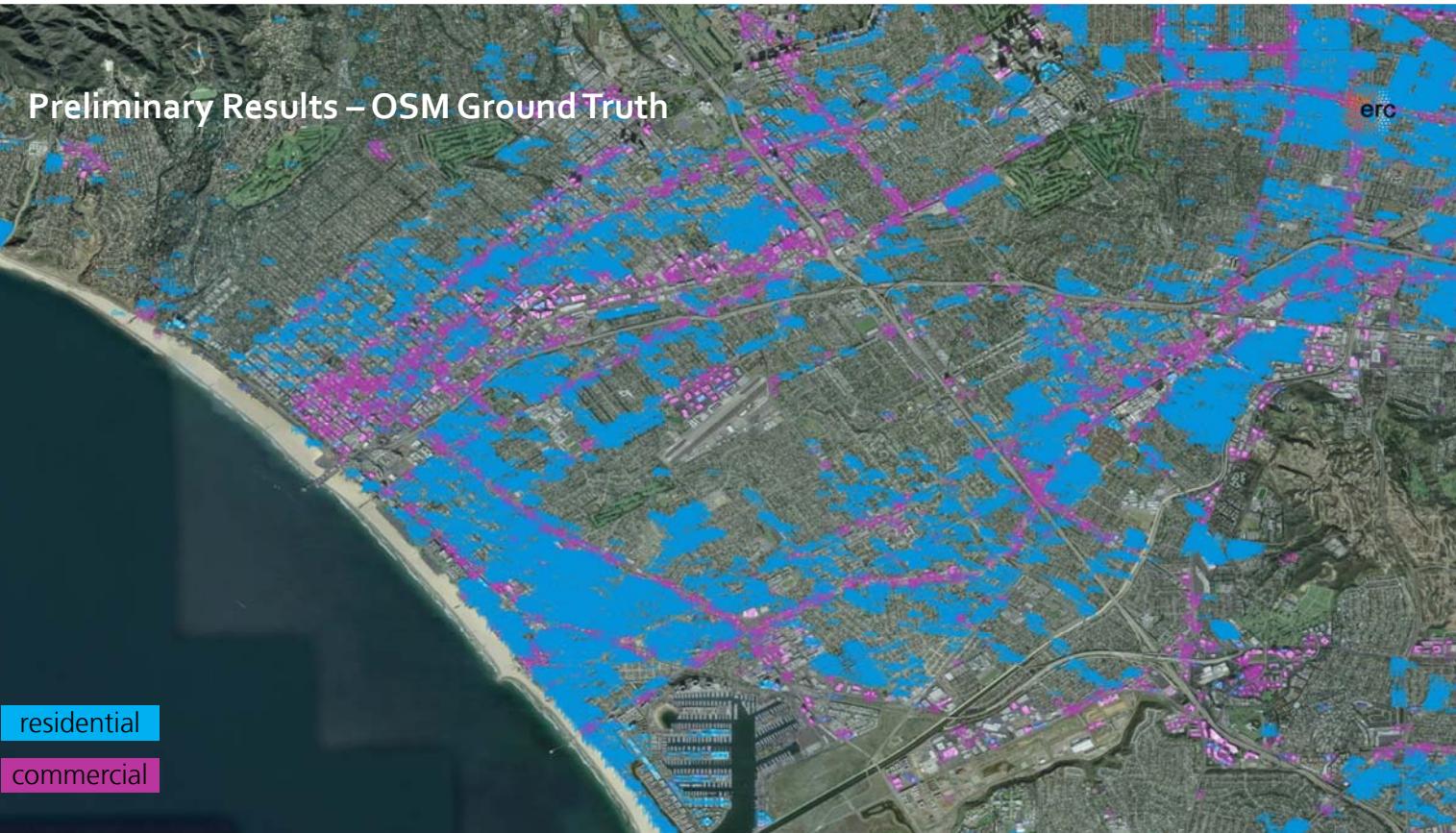
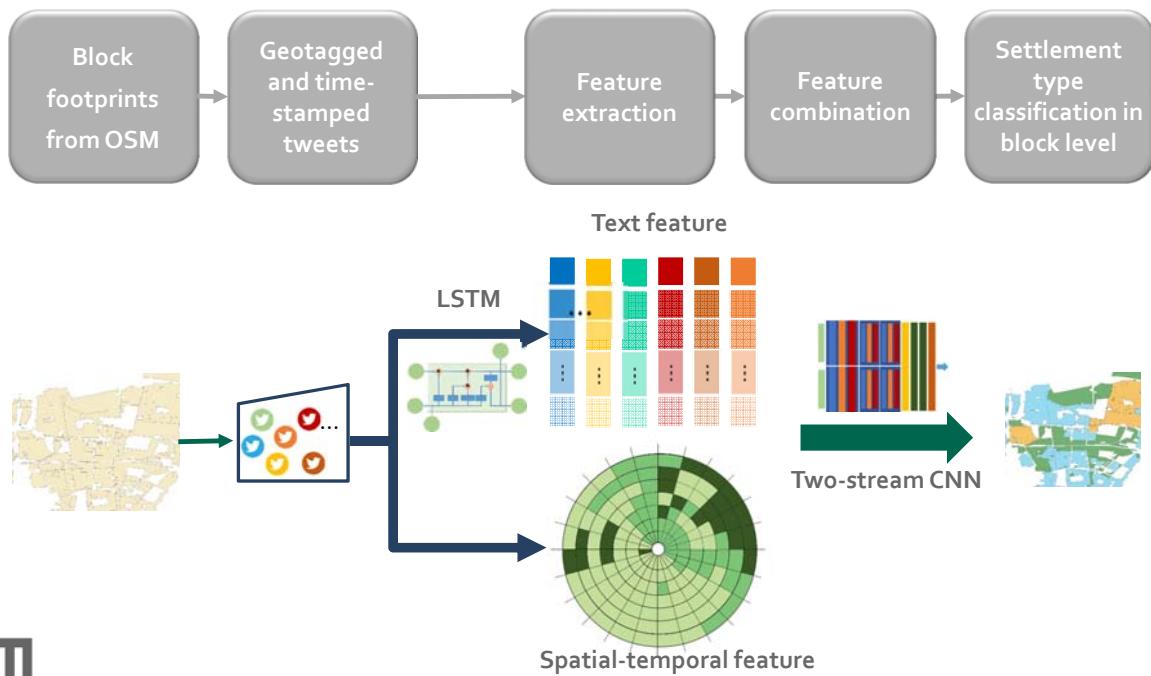
non-residential



mixed used



Tweets for Building Functions Identification



Preliminary Results – Tweets Predicted

residential
commercial

erc

My Vision in 2022

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

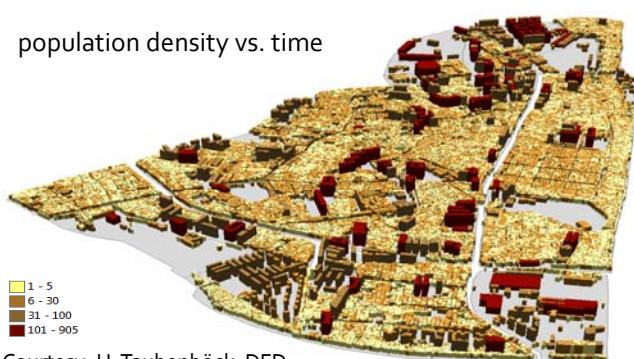
Google earth

Imagery Date: 12/14/2015 Lat: 30.844200° Lon: 14.657271° eye alt 1950.03 km

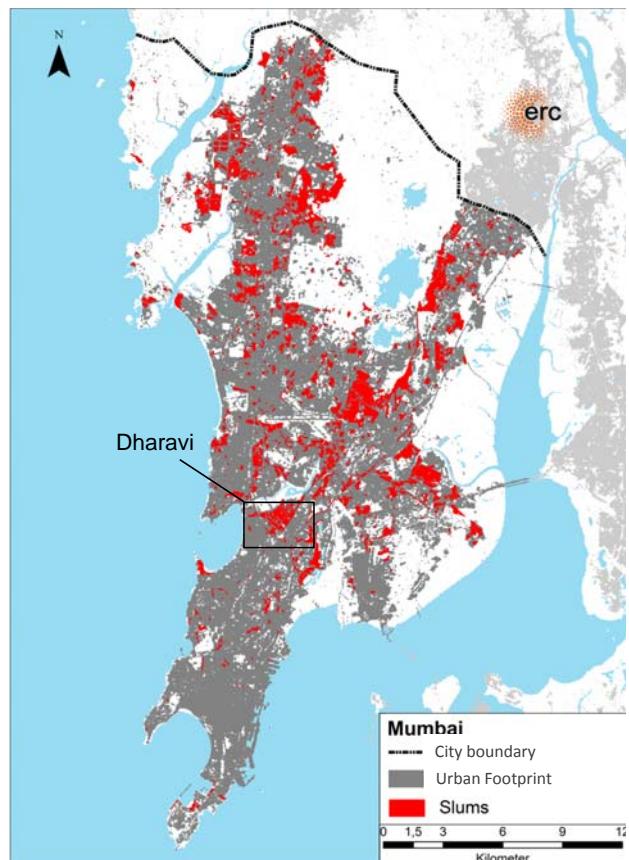
3D model vs. time



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](#)

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