AI4EO – Successful Stories and Open Issues

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DLR

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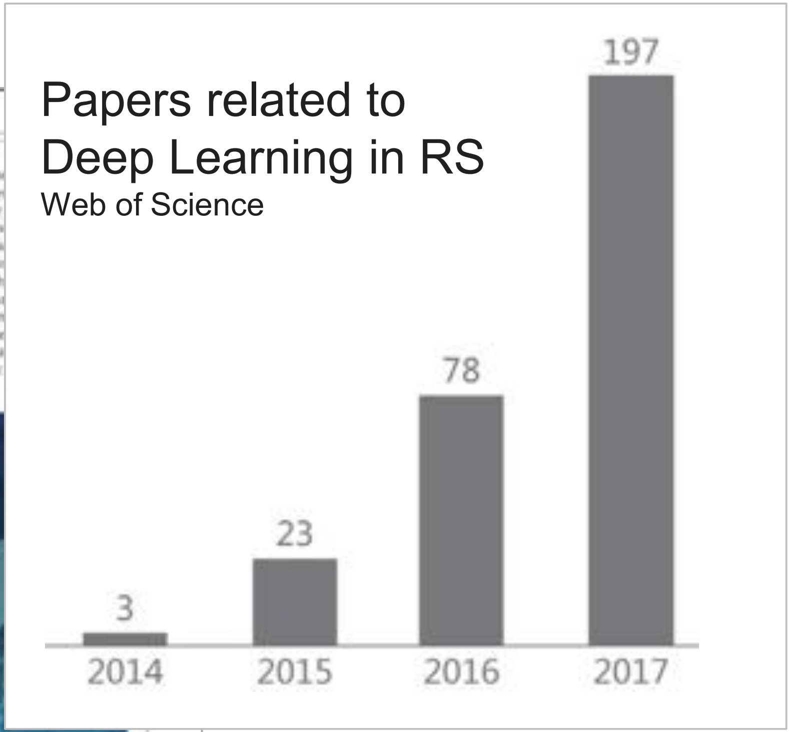
Deep Learning in Remote Sensing

A comprehensive review and list of resources

MOTIVATION



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,...

One of Our Phase 1 Successes

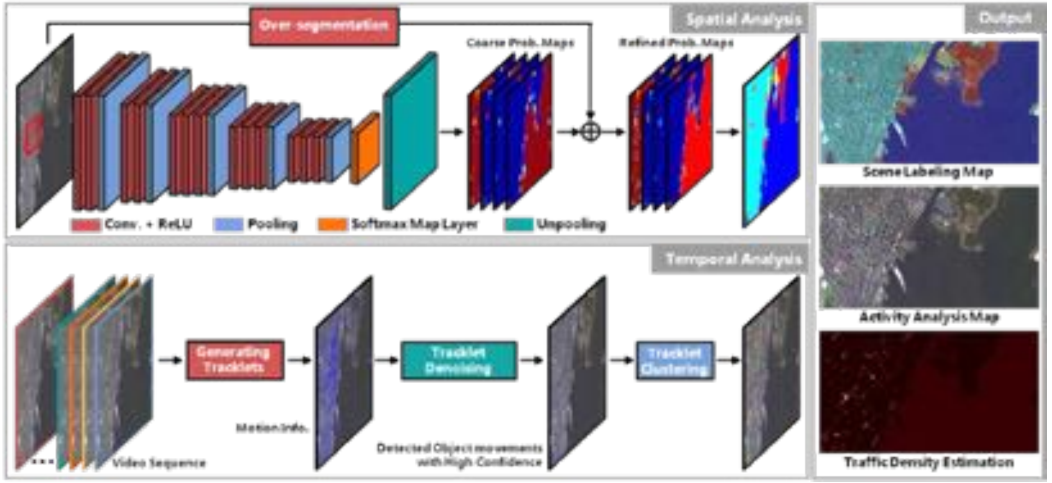
Spatiotemporal Scene Interpretation of Space Videos via Deep Neural Network and Tracklet Analysis

Winner of

Data Fusion Contest 2016

Data

Workflow



Results

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

What makes Deep Learning in Earth Observation Special?

– Classification and detection are only small fractions of EO problems

– Focus on retrieval of physical or bio-chemical variables
    – High accuracy 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

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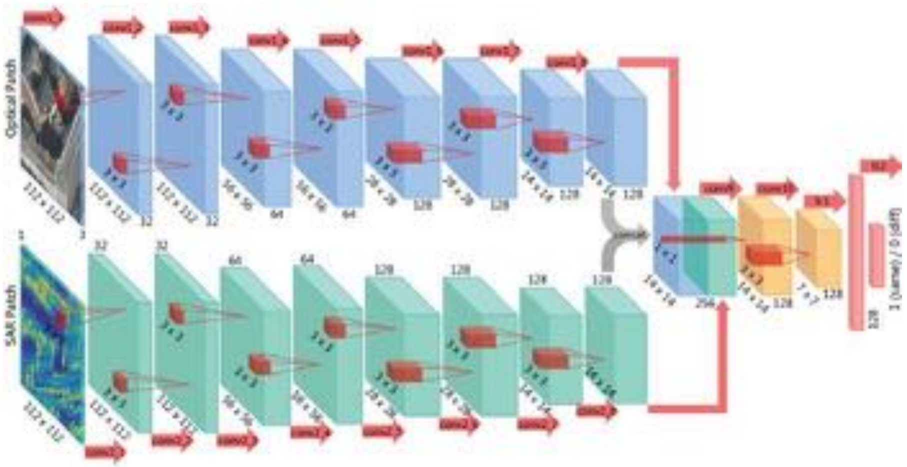
Deep Learning @ My Group

- Detection and tracking of ships, vehicles…
- Segmentation and classification of buildings, slums
- Classification of Land Use/Land Cover, Settlement Types and LCZs
- Change Detection and Time Series Analysis
- SAR/Optical Matching
- 2D/3D optical/SAR/PolSAR/LiDAR fusion
- Synthesizing optical images from SAR data and vice versa
- Sentinel-2 cloud removal
- IM2Height and IM2Building Footprint
- Fusion of EO and social media data (image and text)
- Monitoring Global Changes



Deep Learning in Remote Sensing

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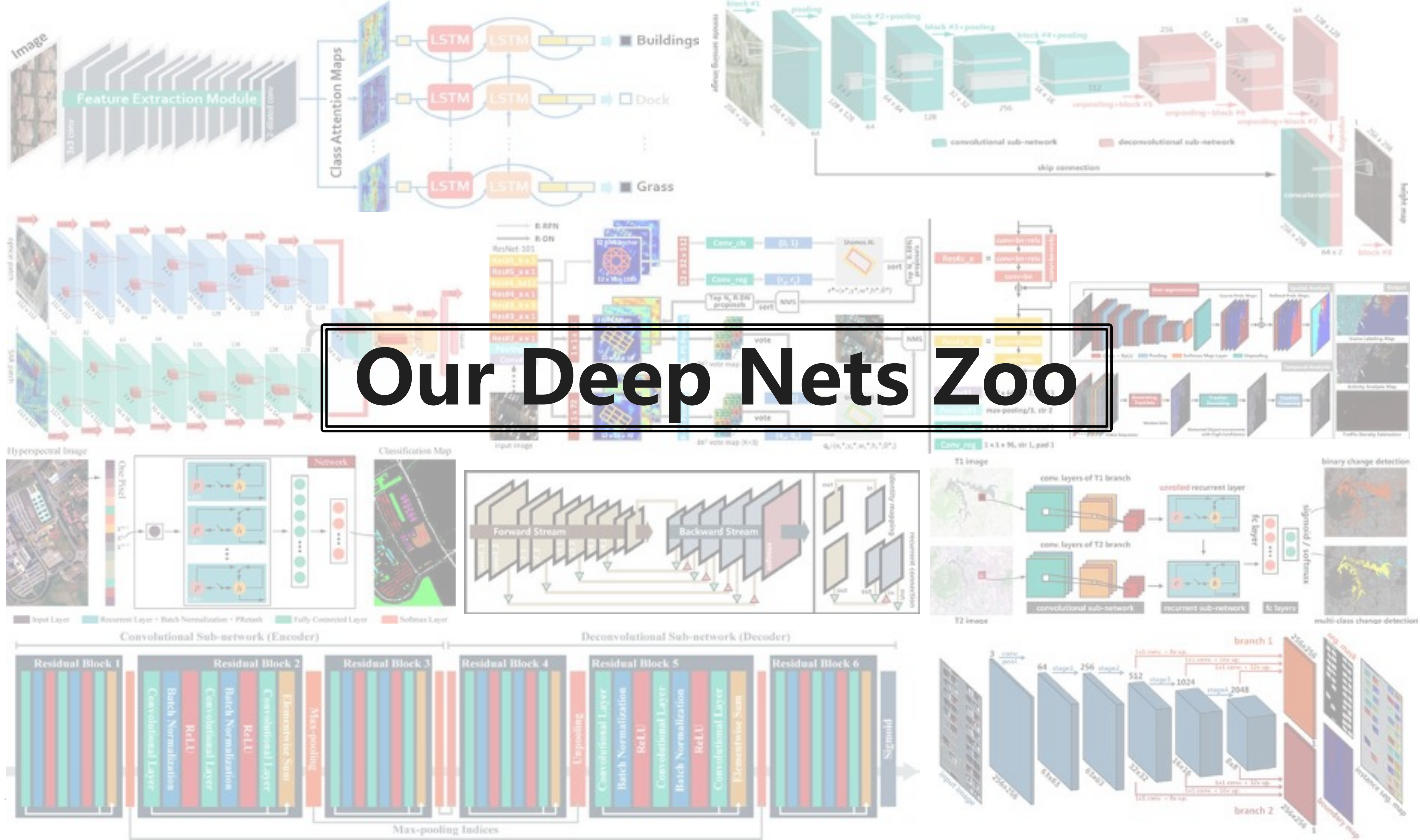
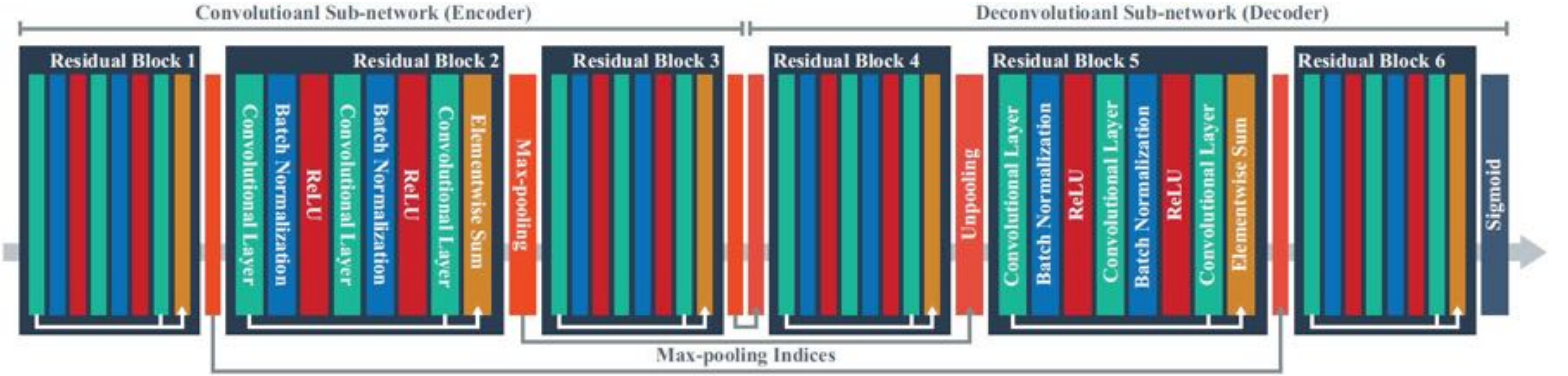
Our Deep Nets Zoo



Hyperspectral Image Analysis

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.

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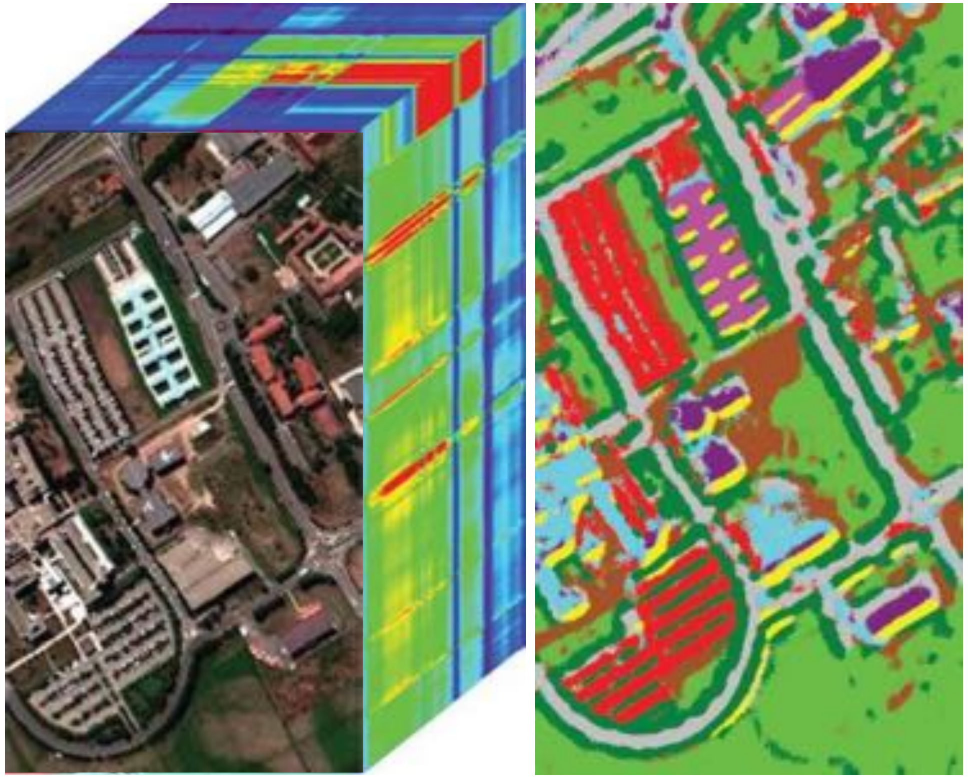
Unsupervised Spectral-Spatial Feature Learning via Deep Residual Conv-Deconv Net

Application I: Classification



University of Pavia, Italy

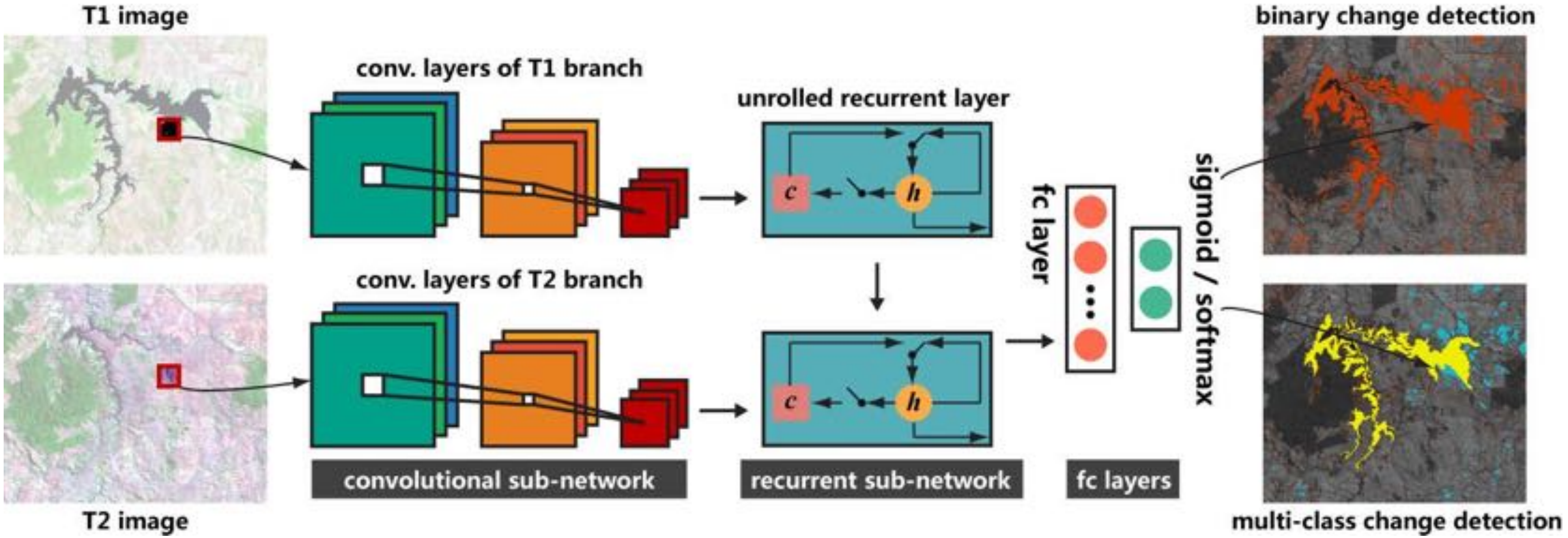
Application II: "Free" Object Localization

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

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.

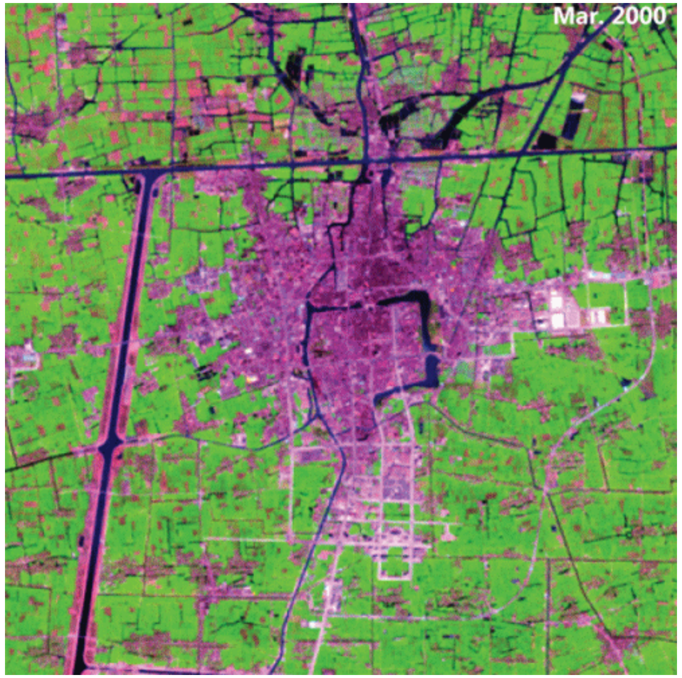
Time Series Data Analysis

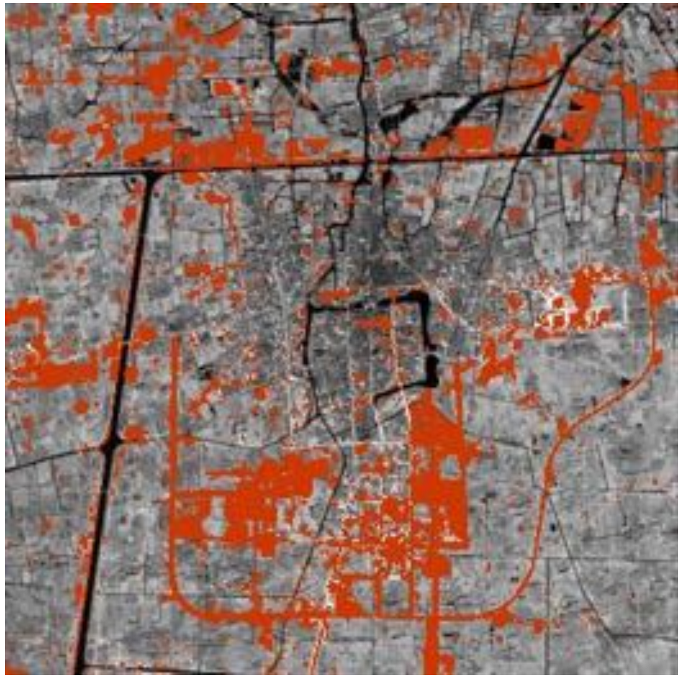
Recurrent Convolutional Neural Network for Change Detection

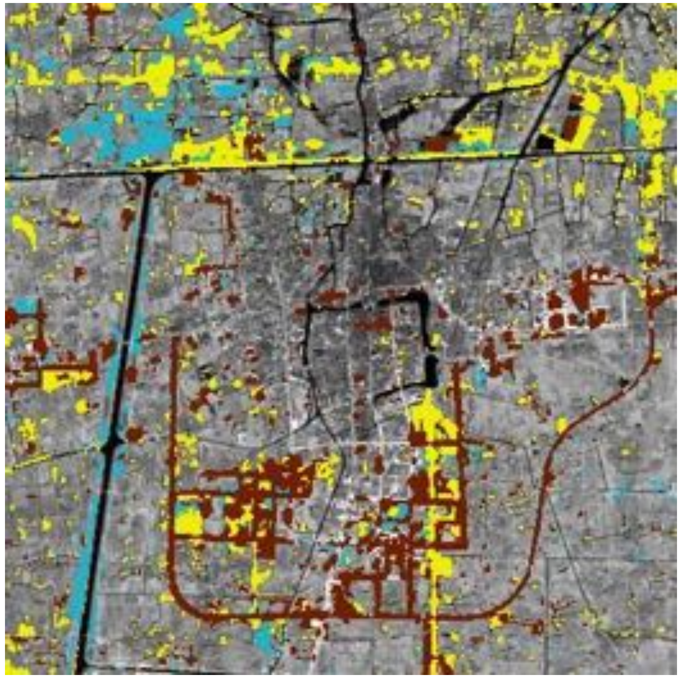


Mou L., Bruzzone L., Zhu X., 2018. Learning Spectral-Spatial-Temporal Features via a Recurrent Convolutional Neural Network for Change Detection in Multispectral Imagery, IEEE Transactions on Geoscience and Remote Sensing, in press.

Recurrent Convolutional Neural Network for Change Detection







Location: Taizhou City, China

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

Mou L., Bruzzone L., Zhu X., 2018. Learning Spectral-Spatial-Temporal Features via a Recurrent Convolutional Neural Network for Change Detection in Multispectral Imagery, IEEE Transactions on Geoscience and Remote Sensing, in press.

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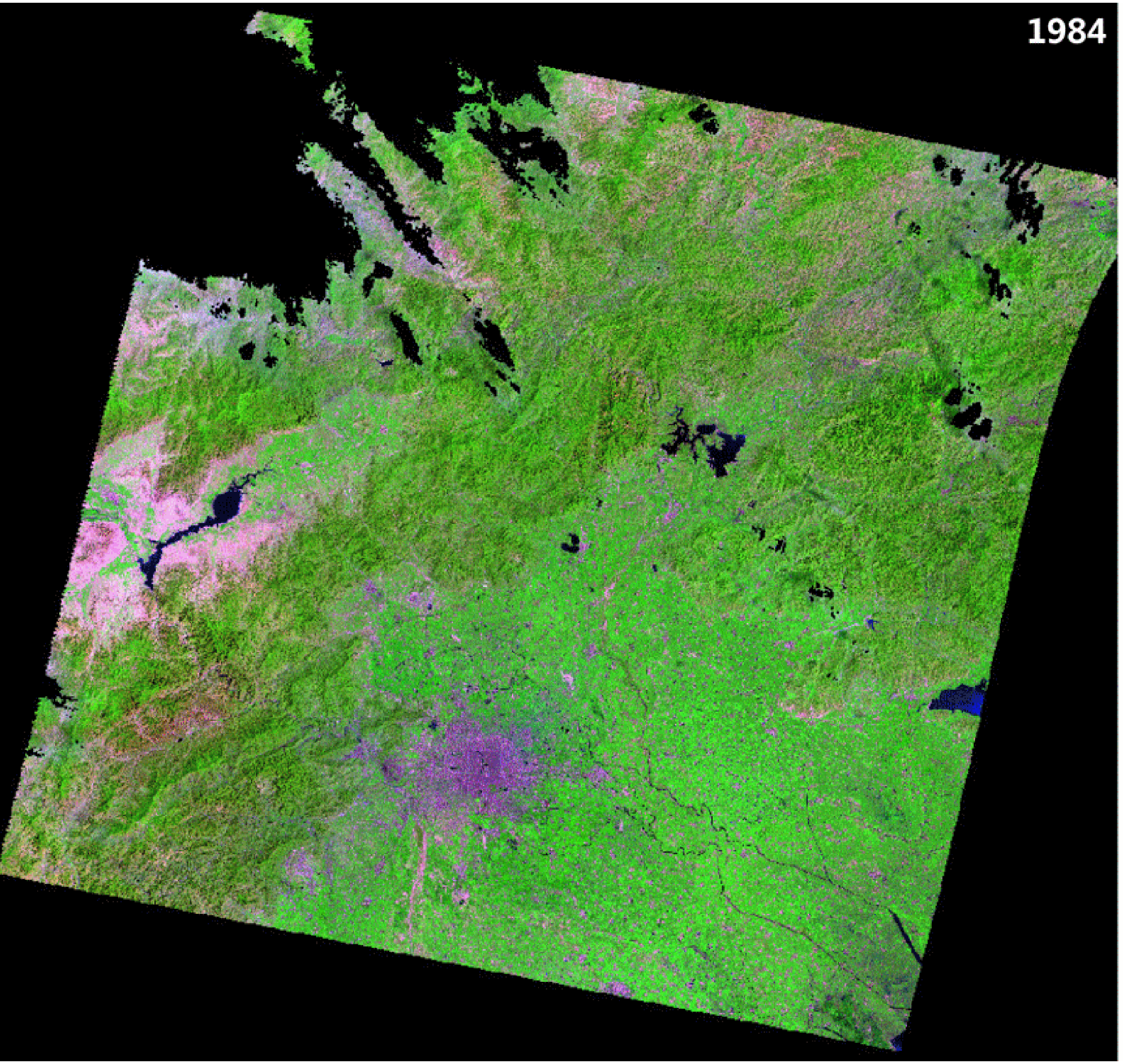
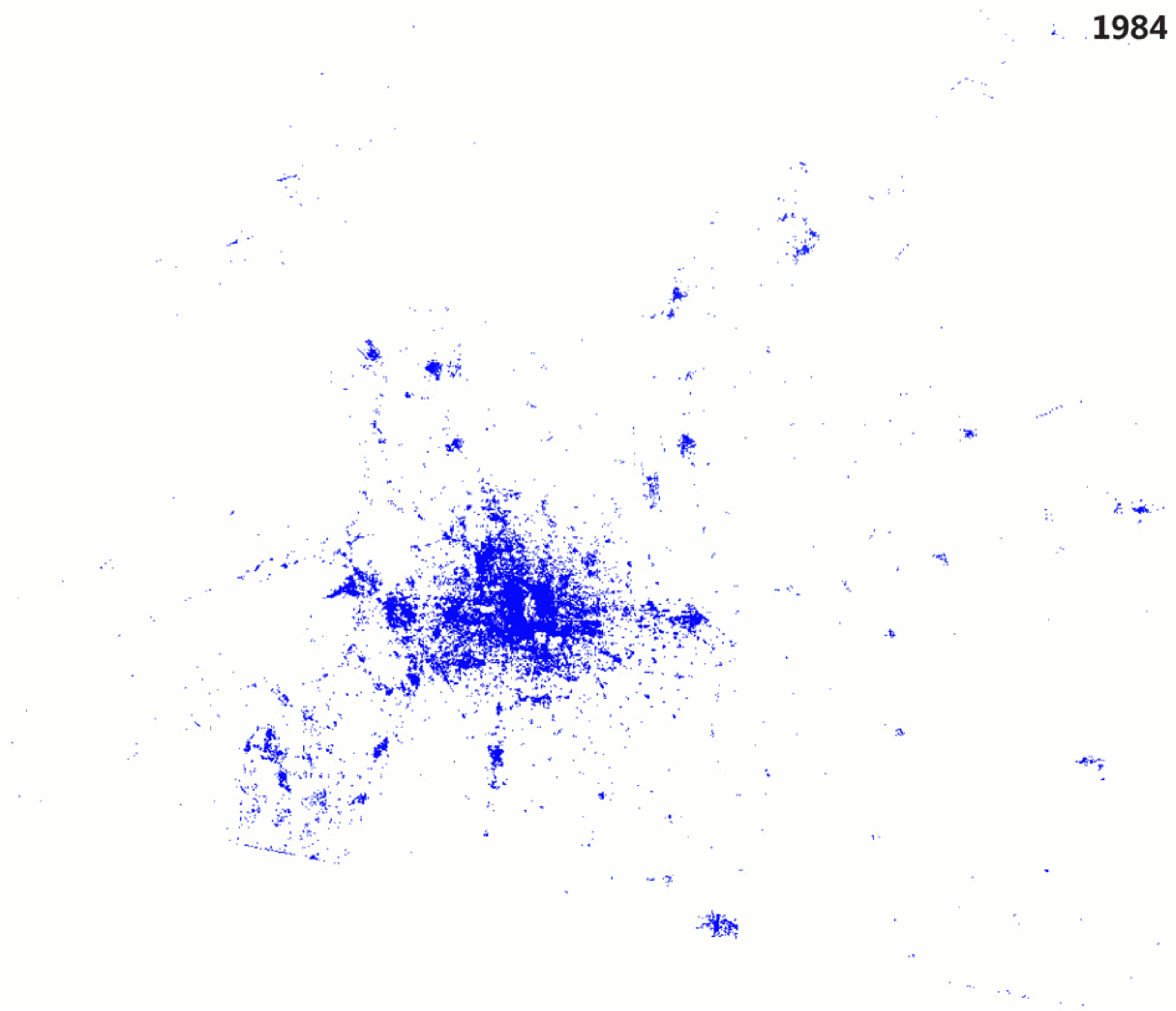
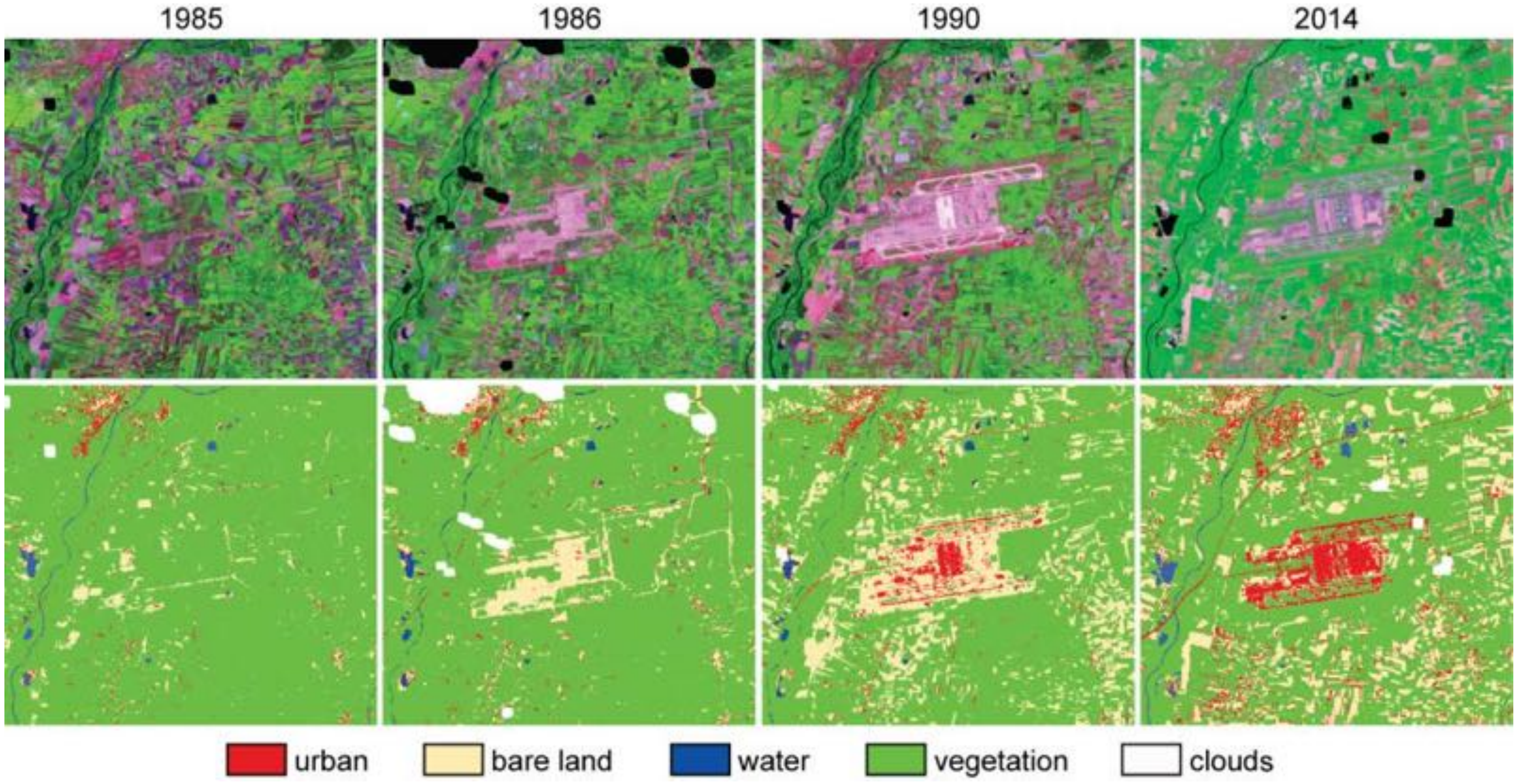
Example – Urban Growth of Beijing (1984 - 2016)





Mou L., Bruzzone L., Zhu X., 2018. Learning Spectral-Spatial-Temporal Features via a Recurrent Convolutional Neural Network for Change Detection in Multispectral Imagery, IEEE Transactions on Geoscience and Remote Sensing, in press.

Munich Airport

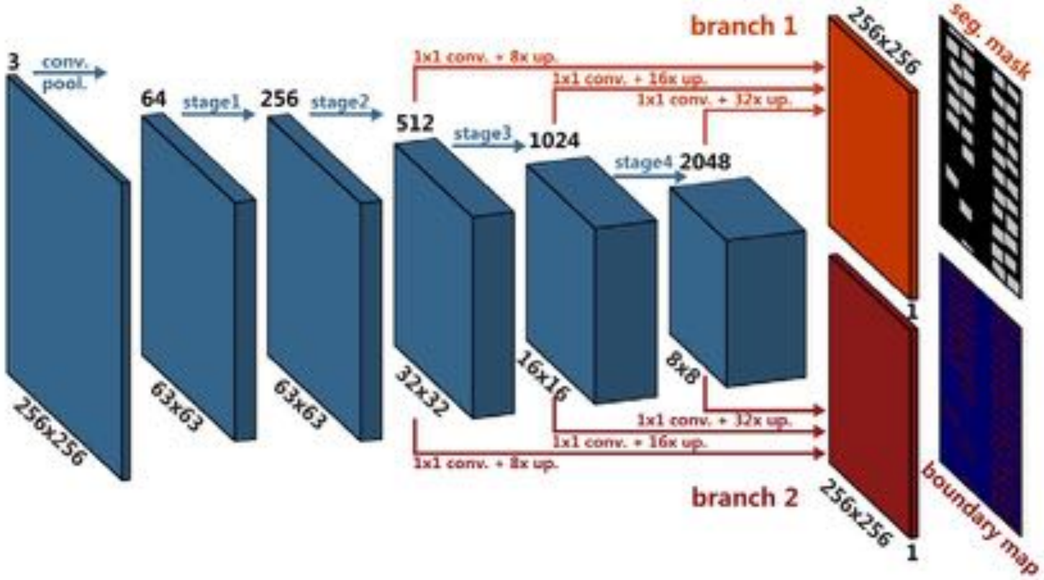


Mou L., Bruzzone L., Zhu X., 2018. Learning Spectral-Spatial-Temporal Features via a Recurrent Convolutional Neural Network for Change Detection in Multispectral Imagery, IEEE Transactions on Geoscience and Remote Sensing, in press.

High Resolution Remote Sensing Imagery Analysis

Shi Y., Li Q., Zhu X., 2018. Building Footprint Generation using Improved Generative Adversarial Networks, IEEE Geoscience and Remote Sensing Letters, in press.

Multi-task CNNs for Car Instance Segmentation



Mou L., Zhu X., 2018. Vehicle Instance Segmentation from Aerial Image and Video Using a Multi-Task Learning Residual Fully Convolutional Network, IEEE Transactions on Geoscience and Remote Sensing, in press.

Li Q., Mou L., Xu Q., Zhang Y., **Zhu X.** (2018): R3-Net: A Deep Network for Multi-oriented Vehicle Detection in Aerial Images and Videos, IEEE GRS

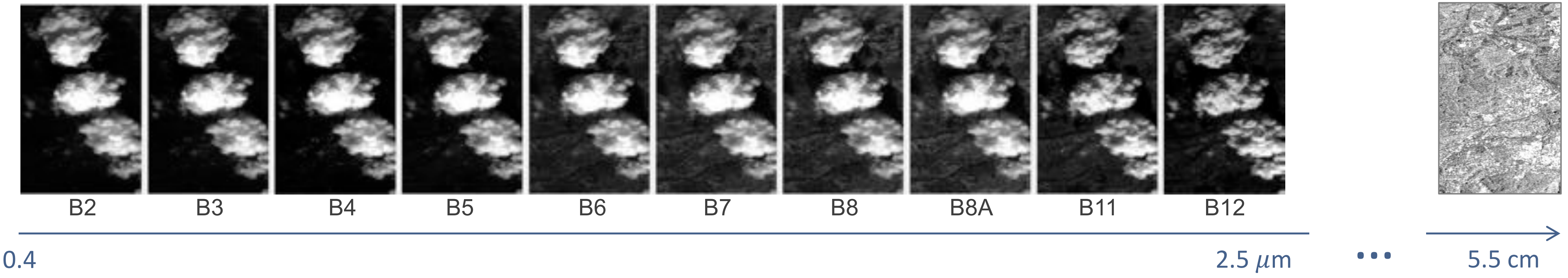
Global Applications with Sentinels

cGAN-based Enhancement of Optical Remote Sensing Data

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

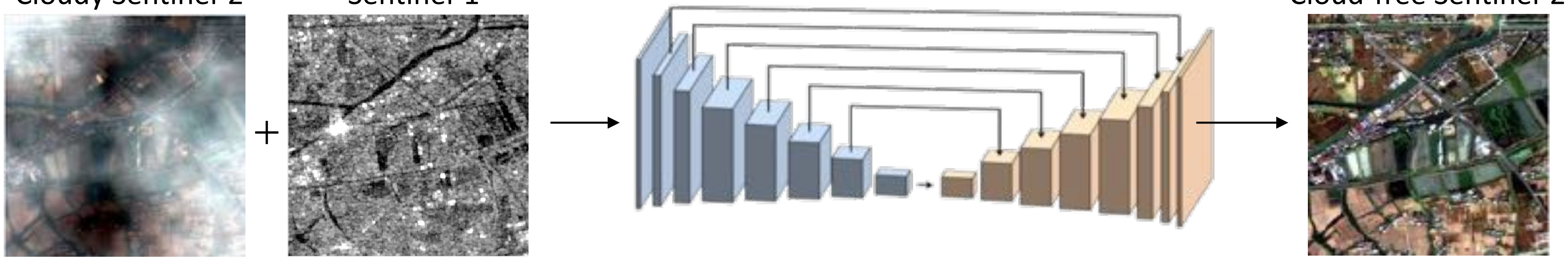
Motivation: Optical sensors cannot penetrate clouds, but microwaves do.

Sentinel-2 Sentinel-1



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

Cloudy Sentinel-2 Sentinel-1 Cloud-free Sentinel-2



Grohnfeldt C., Schmitt M., **Zhu X.** (2018): A Conditional Generative Adversarial Network to Fuse SAR and Multispectral Optical Data for Cloud Removal from Sentinel-2 Images, Proceeding of the ISPRS Technical Commission II Symposium 2018, Riva del Garda, Italy.

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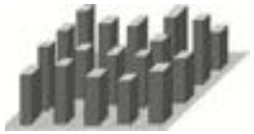
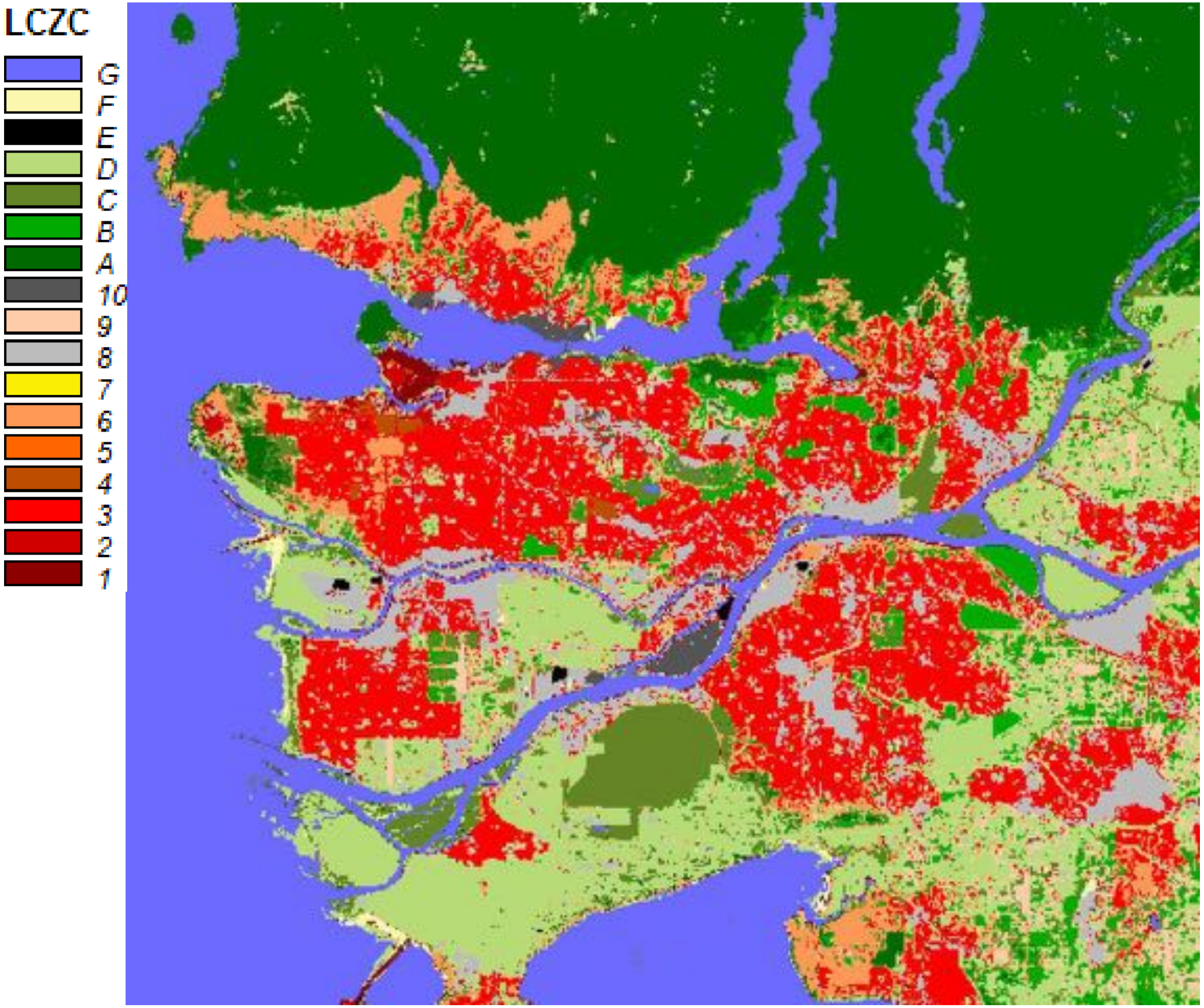
Global Local Climate Zones Classification



1	7	C
2	8	D
3	9	E
4	10	F
5	A	G
6	B	



Overview – Data Sets

So2Sat LCZ42: A Benchmark Dataset for Global Local Climate Zones Classification

- 400K of matched image patches from different sensors, including radar (Sentinel-1) and multispectral sensor (Sentinel-2)
- Area selections across the globe, covering 10 culture zones and 42 cities
- Labels voted by 10 independent experts
- A very challenging data fusion and classification task with 17 classes

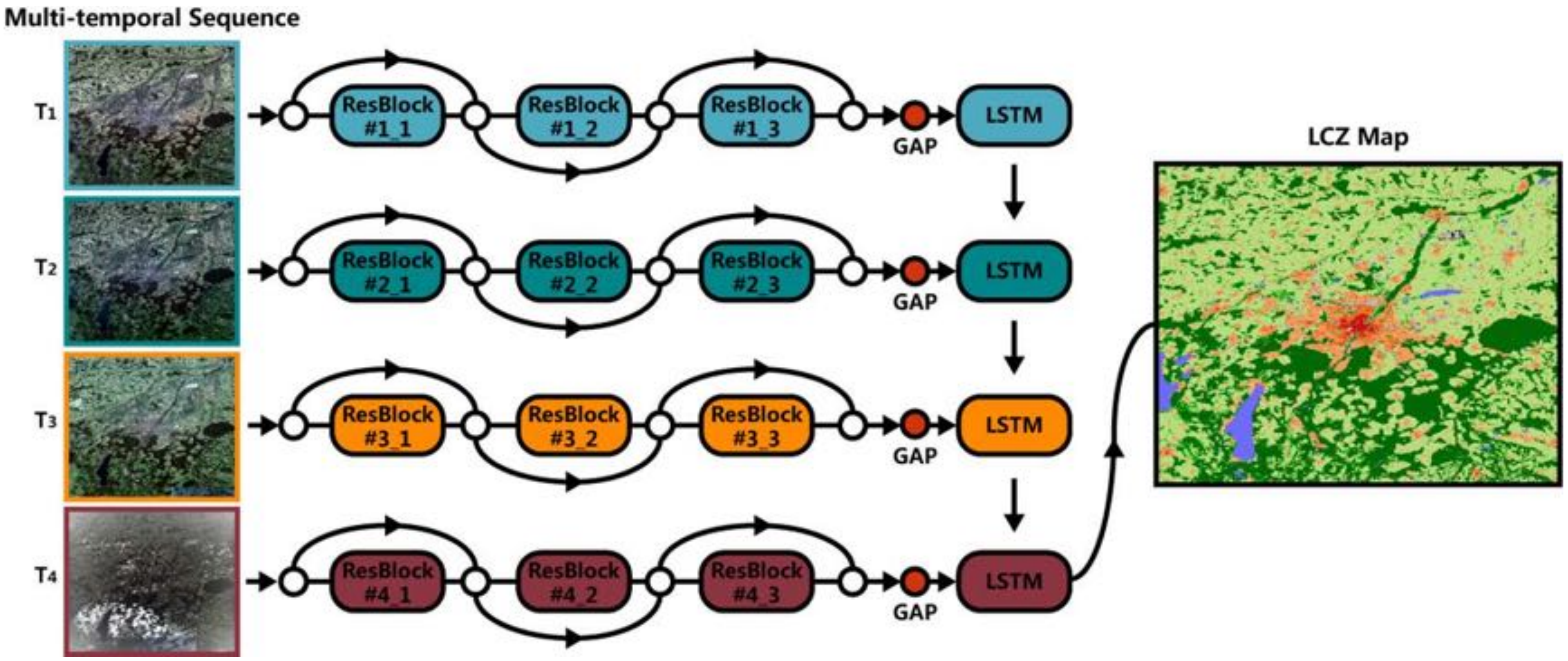
Labeling effort: 15 person × 1 Month/person

For global processing (Data gravity problem):

- One year global data of Sentinel-1 and Sentinel-2 → 4PB of satellite data

Zhu et al., So2Sat LCZ42: A Benchmark Dataset for Global Local Climate Zones Classification, CVPR 2019, in preparation

Example Architecture for Seasonal Sentinel-2 data



Qiu C., Mou L., Schmitt M., **Zhu X.** (2018): Recurrent Residual Network for Local Climate Zone Classification with Multi-Seasonal Sentinel-2 Images, Remote Sensing of Environment, submitted.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CANADA
UNITED STATES
RUSSIA
CHINA
BRAZIL
AUSTRALIA
Atlantic Ocean
Pacific Ocean
Indian Ocean

DLR/StepStone/AliCloud Tianchi Contest 2018 Germany

Contestants

200k data talents in 91 countries and regions

Task

Solution

TIANCHI
Data Scientists

Demand

Product

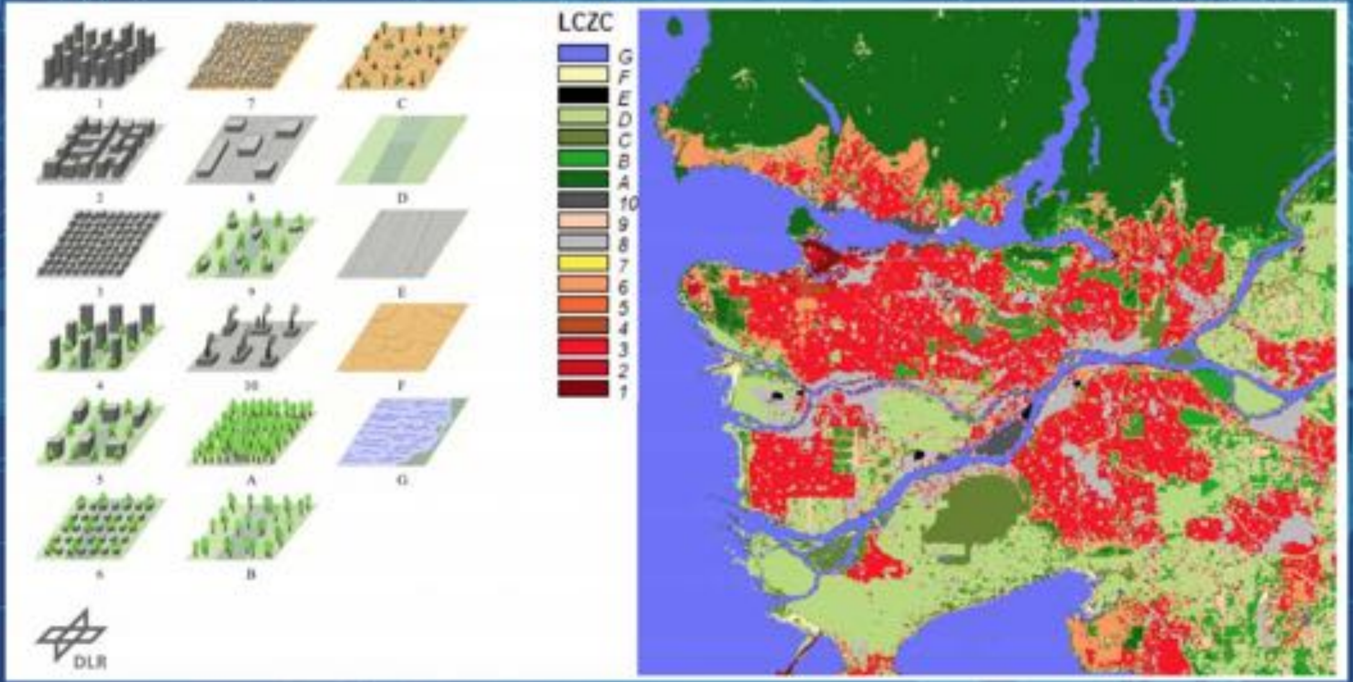
Customers

StepStone

DLR

Challenge

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



LCZ applications

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

Citizen Science

Building Instance Classification from Street View Data by CNN

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

Munich

Kang J., Körner M., Wang Y., Taubenböck H., and Zhu X., 2018. Building instance classification using street view images, ISPRS J. Photogramm. Remote Sens.,

Open Issues

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

Institut für Datenwissenschaften

Center for Advanced Intelligence Project

DLR/Alibaba AI4EO Challenge

Global urban mapping So2Sat

AI4EO research @DLR&TUM

Join us for AI4EO:

Contact: xiaoxiang.zhu@dlr.de

@xiaoxiang_zhu

Wednesday, @Φ-Lab
Women in Science@Phiweek

10:45 - 11:00
Data Science in Earth Observation · *(ID: 416)*
Presenting: Zhu, Xiaoxiang

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