

AI4EO – Successful Stories and Open Issues

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Wissen für Morgen



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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 domain segmentation [5], [6]. Further (RNNs), an important branch of the have demonstrated significant achievements in sequential data analysis tasks involved in image captioning [9], [10] and image captioning [11].

In the wake of this success and the availability of data and computational power, deep learning is finally taking off in remote-sensing data processing. Remote-sensing data present some learning, because satellite image analysis poses difficult new scientific



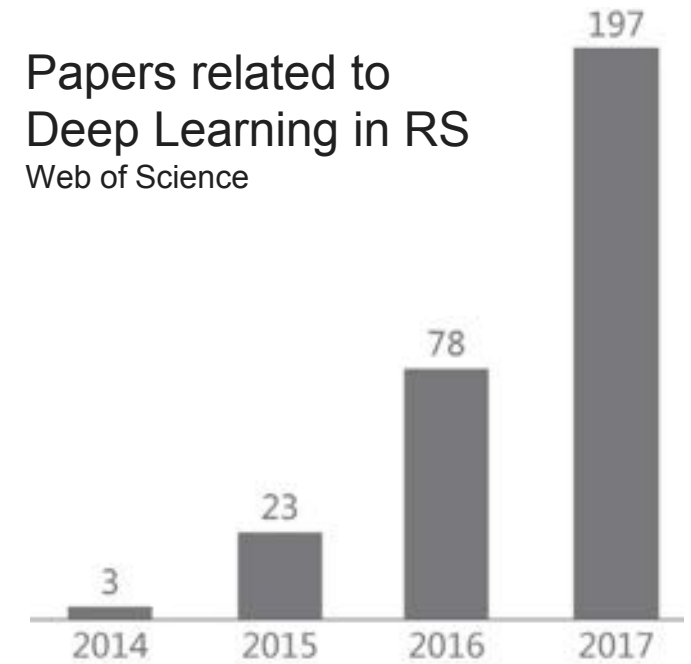
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Date of publication: 27 December 2017

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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,...

One of Our Phase 1 Successes

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

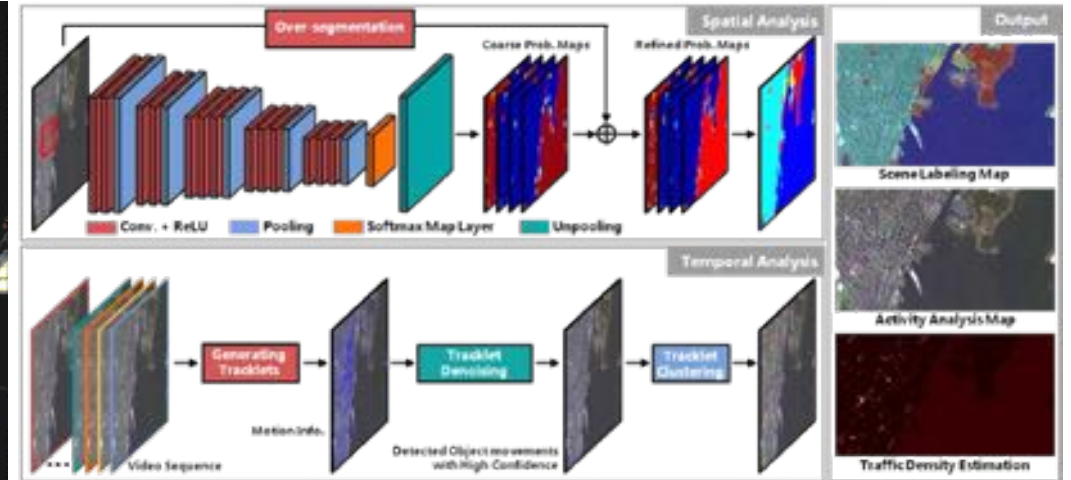


Data Fusion
Contest 2016

Data



Workflow



Results



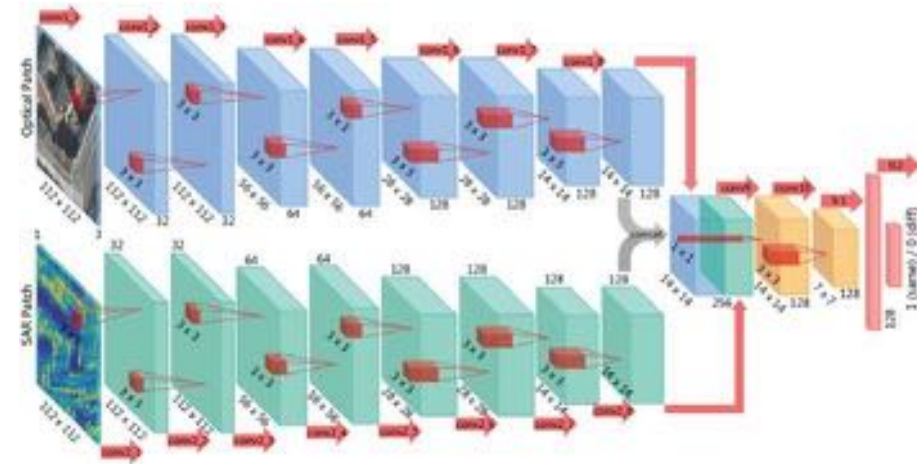
“Spatiotemporal Scene Interpretation of Space Videos via Deep Neural Network and Tracklet Analysis”, L. Mou, X. Zhu

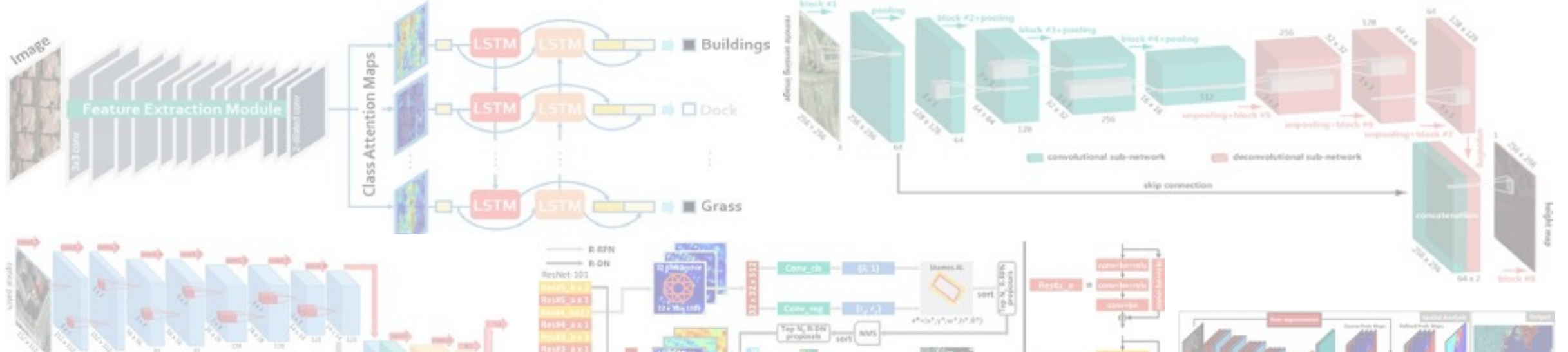
What makes Deep Learning in Earth Observation Special?

- 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

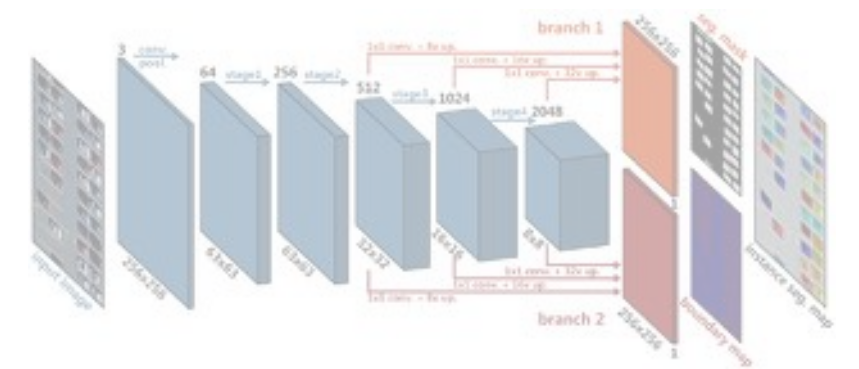
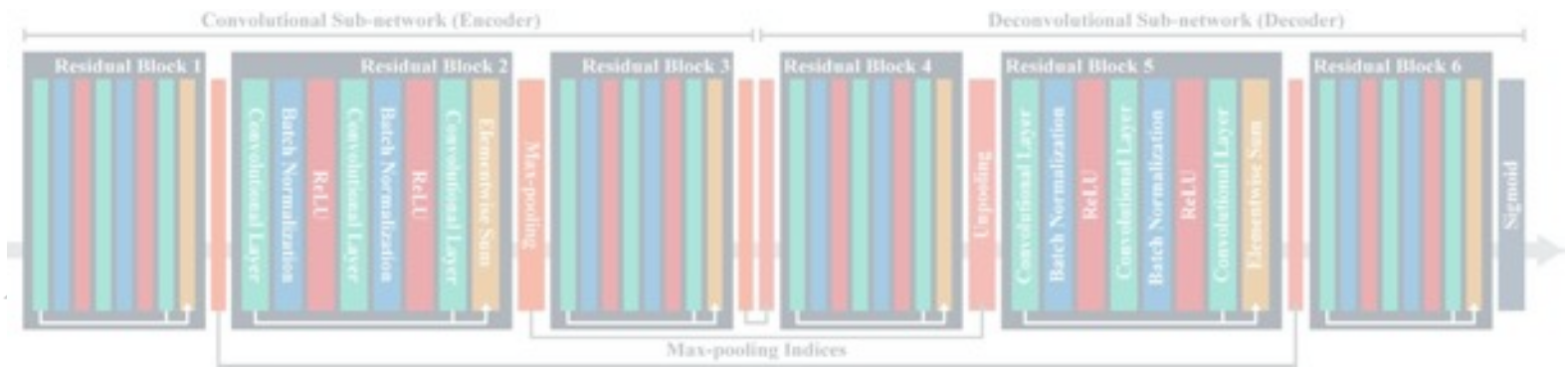
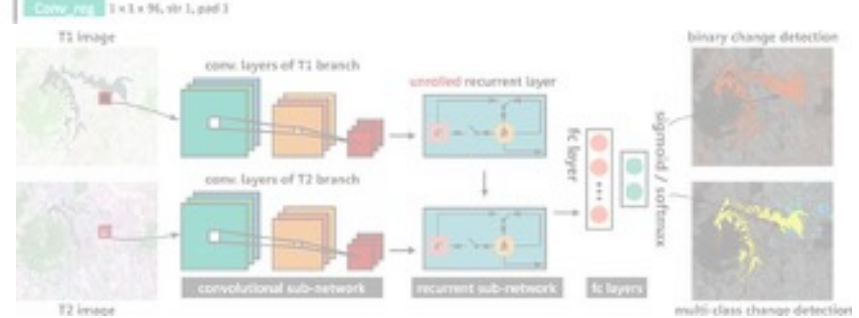
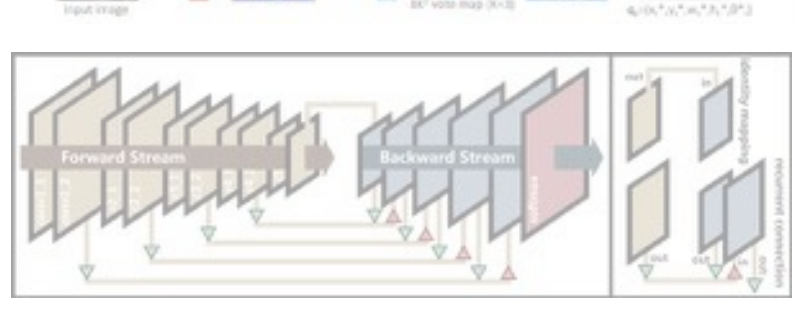
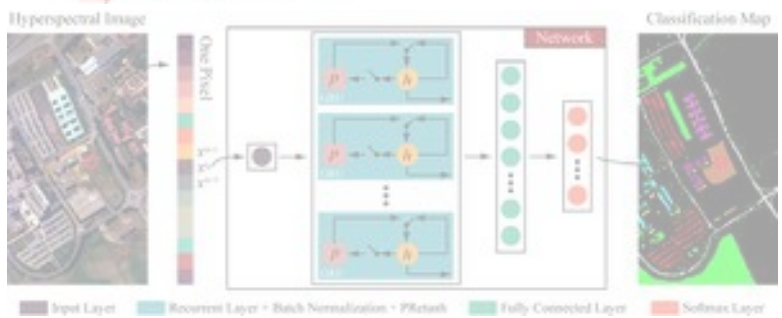
Deep Learning @ My Group

- 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/PoISAR/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



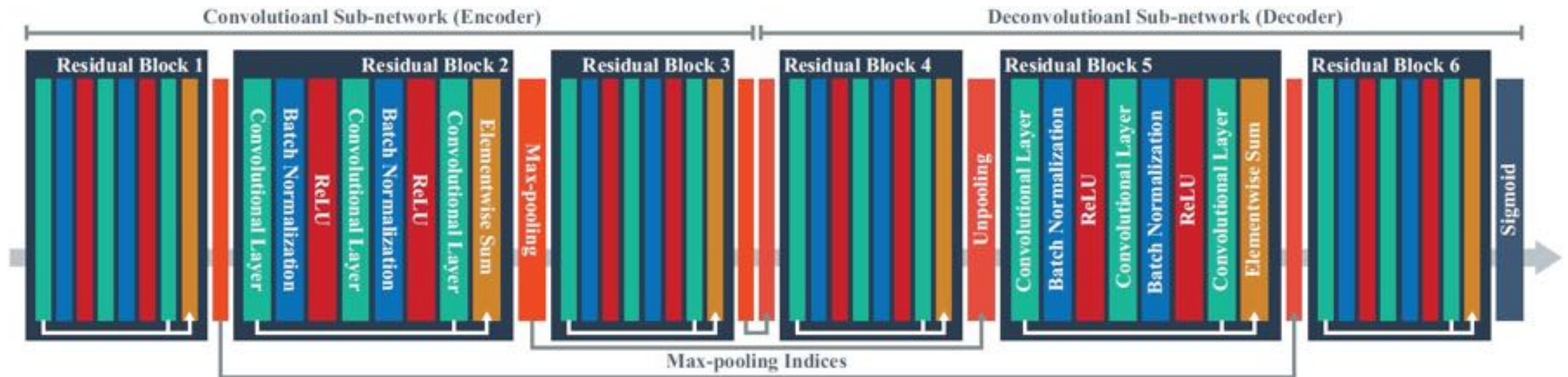


Our Deep Nets Zoo



Hyperspectral Image Analysis

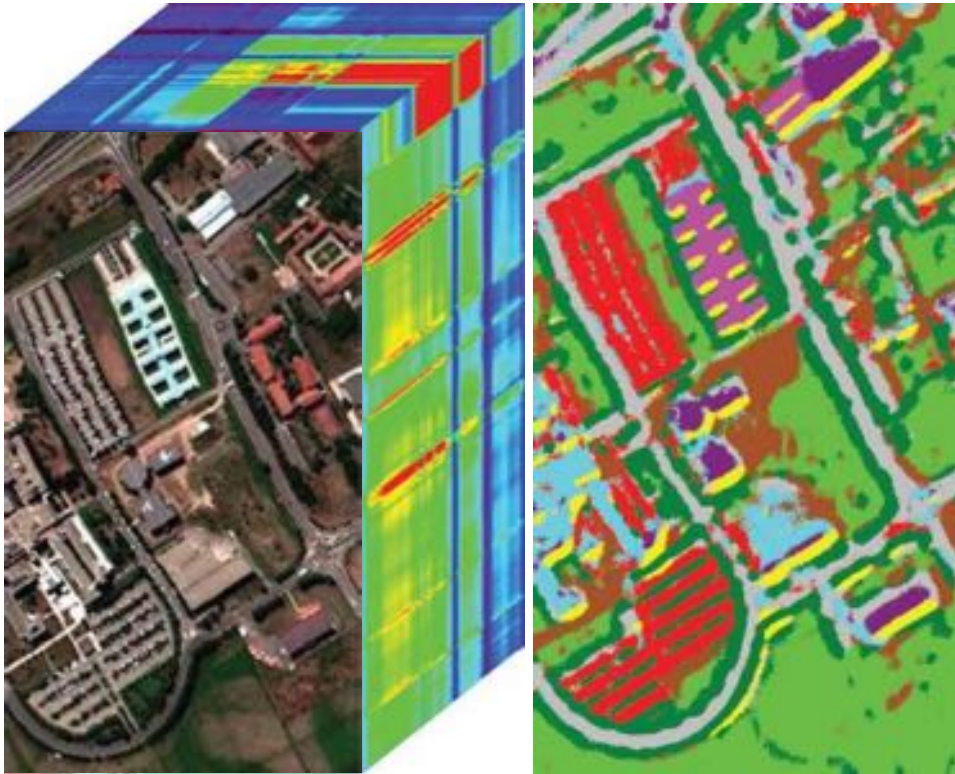
Unsupervised Spectral-Spatial Feature Learning via Deep Residual Conv-Deconv Net



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.

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

Application I: Classification



University of Pavia, Italy

Application II: "Free" Object Localization

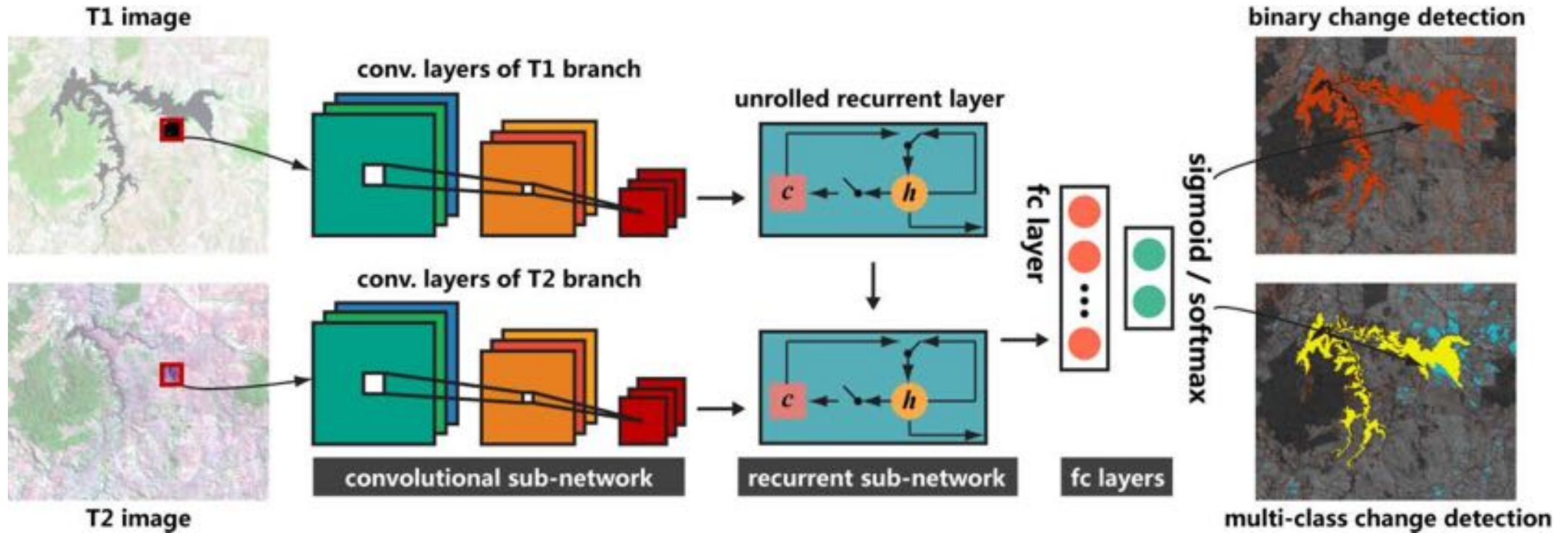


- We found some neurons in our network own good description power for semantic visual patterns in the object level. For example, the neurons **#52** and **#03** can be used to precisely capture **metal sheets** (left) and **vegetative covers** (right).

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.

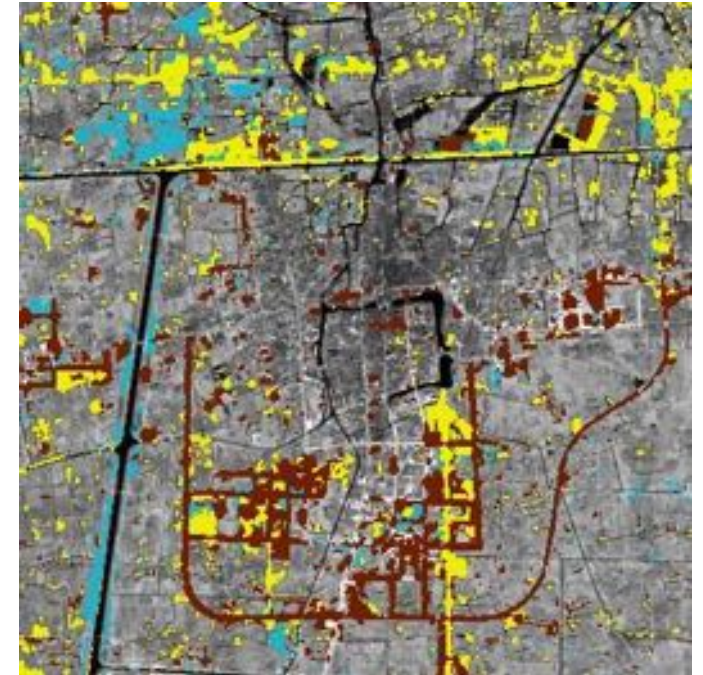
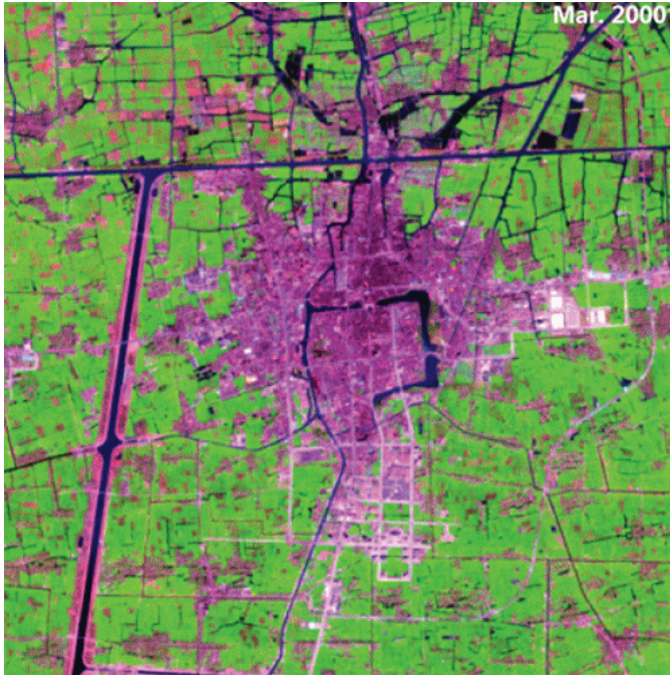
Time Series Data Analysis

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

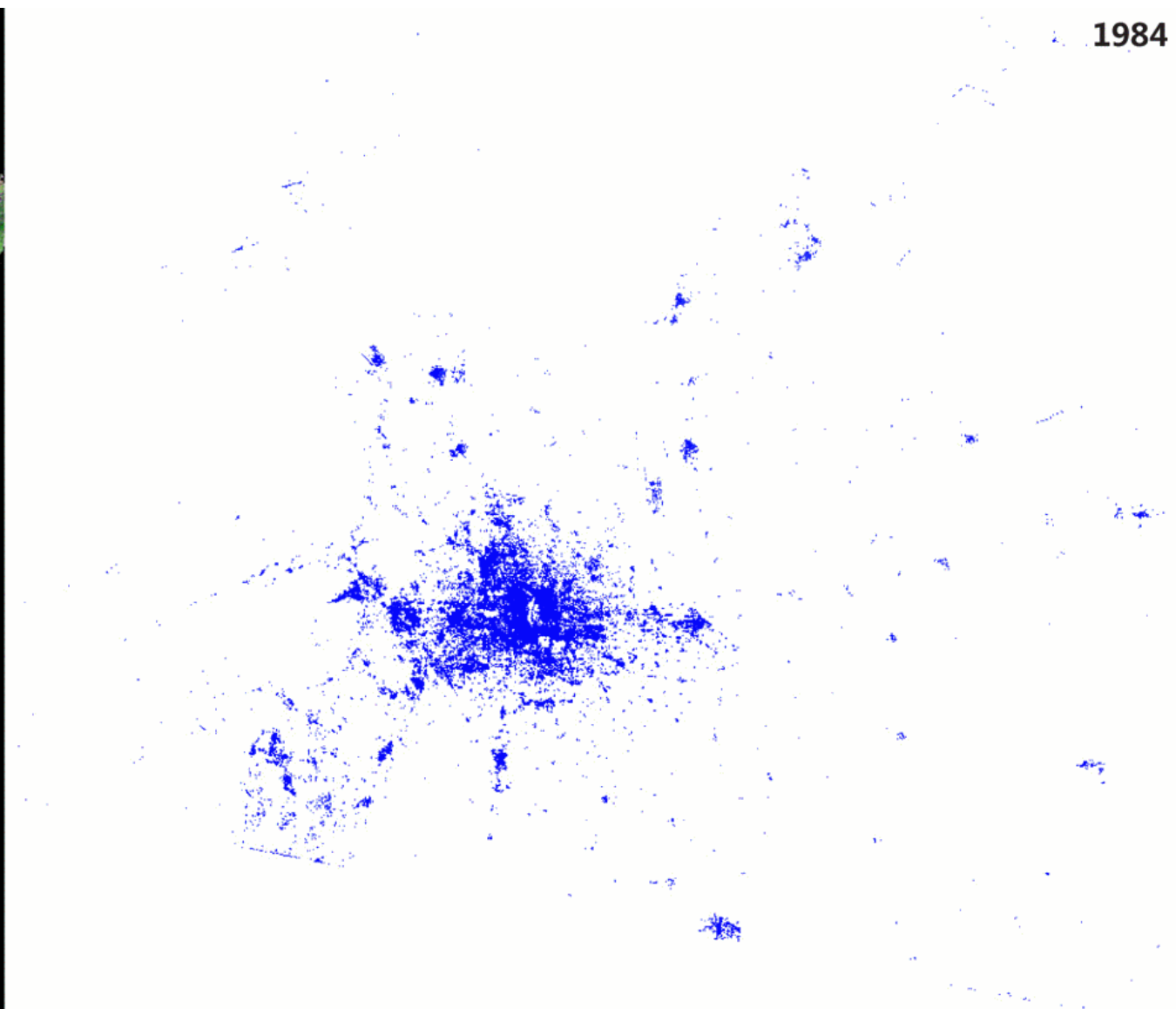
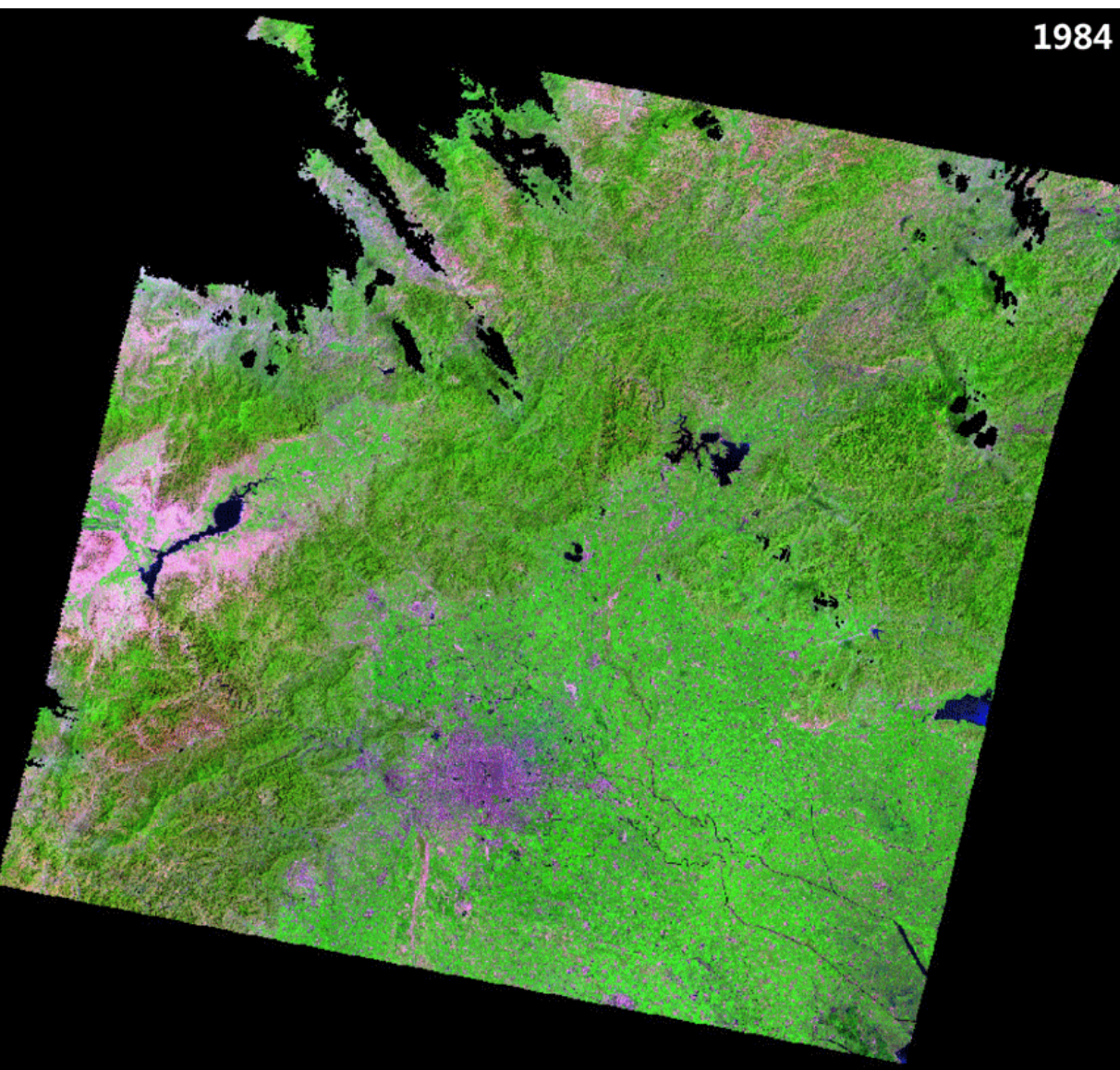


Location: Taizhou City, China

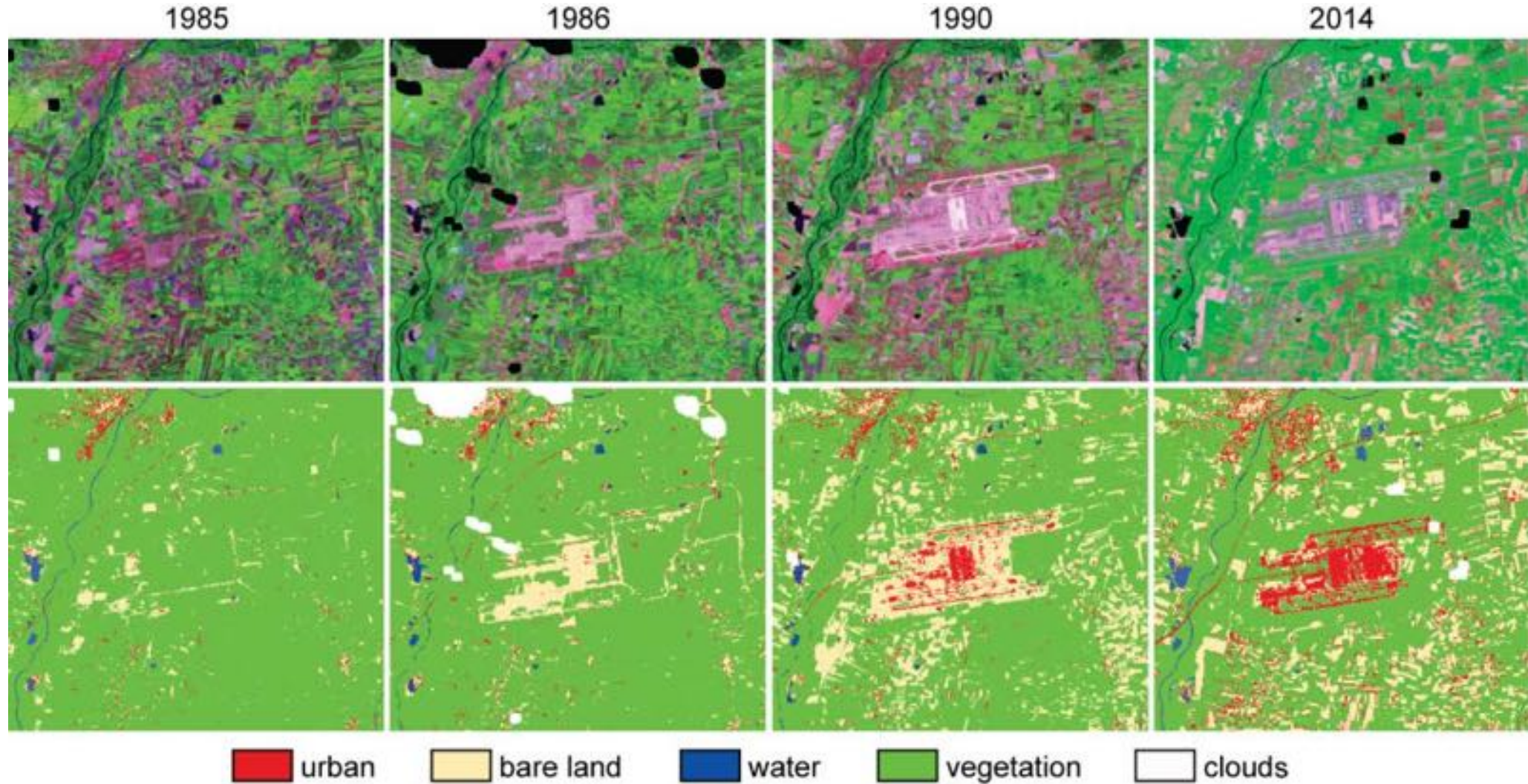
*Legend: **Changed areas** (in binary change detection); **city expansion**; **soil change**; **water change***

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.

Example – Urban Growth of Beijing (1984 - 2016)



Munich Airport

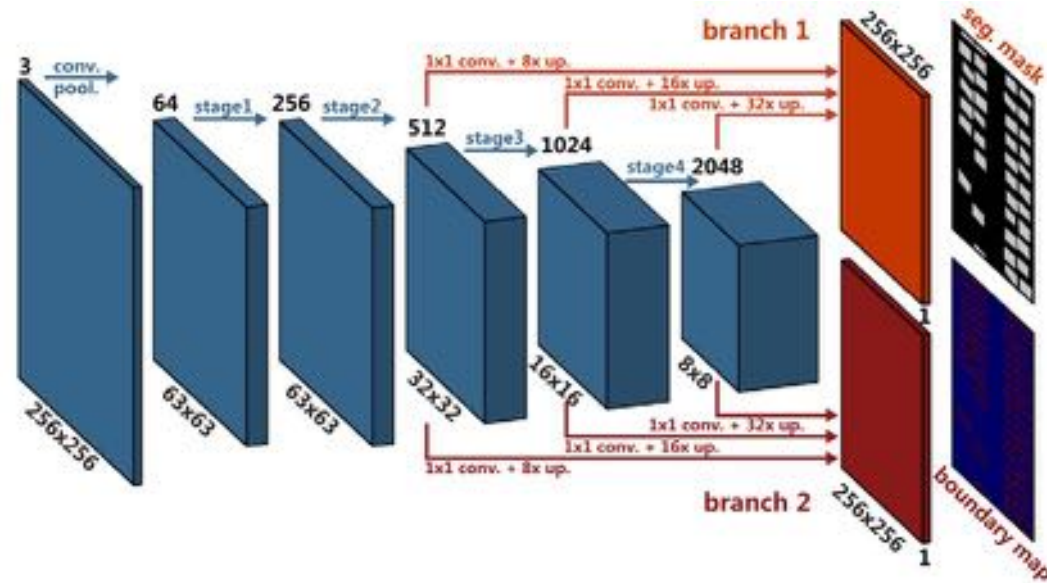


Mou L., Bruzzone L., Zhu X., 2018. Learning Spectral-Spatial-Temporal Features via a Recurrent Convolutional Neural Network for Change Detection in Multispectral Imagery, IEEE Transactions on Geoscience and Remote Sensing, in press.

High Resolution Remote Sensing Imagery Analysis



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.

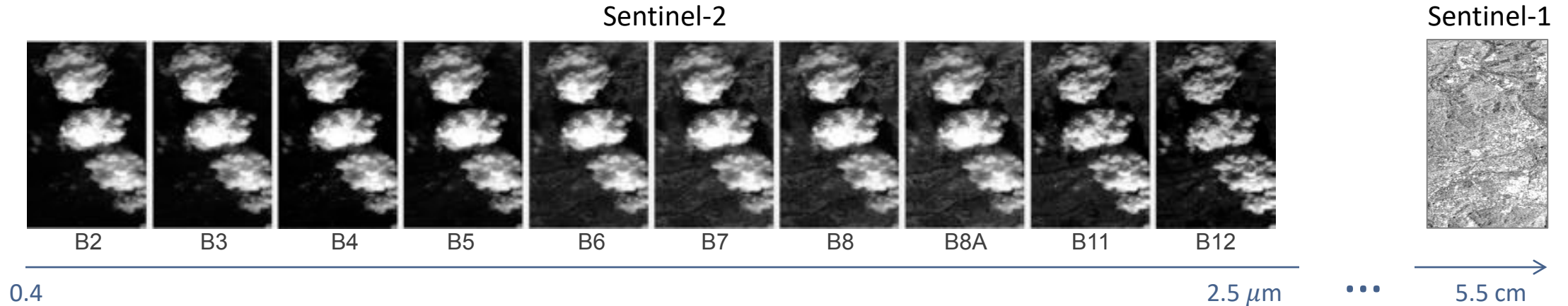


Global Applications with Sentinels

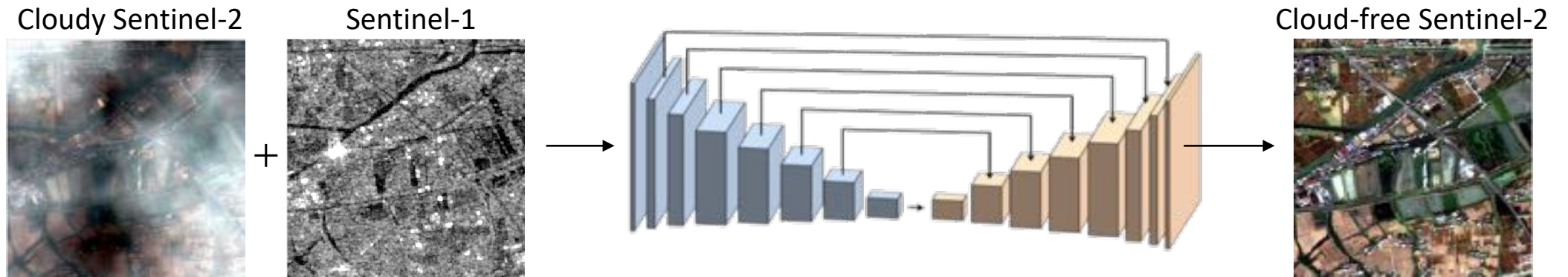
cGAN-based Enhancement of Optical Remote Sensing Data

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

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



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



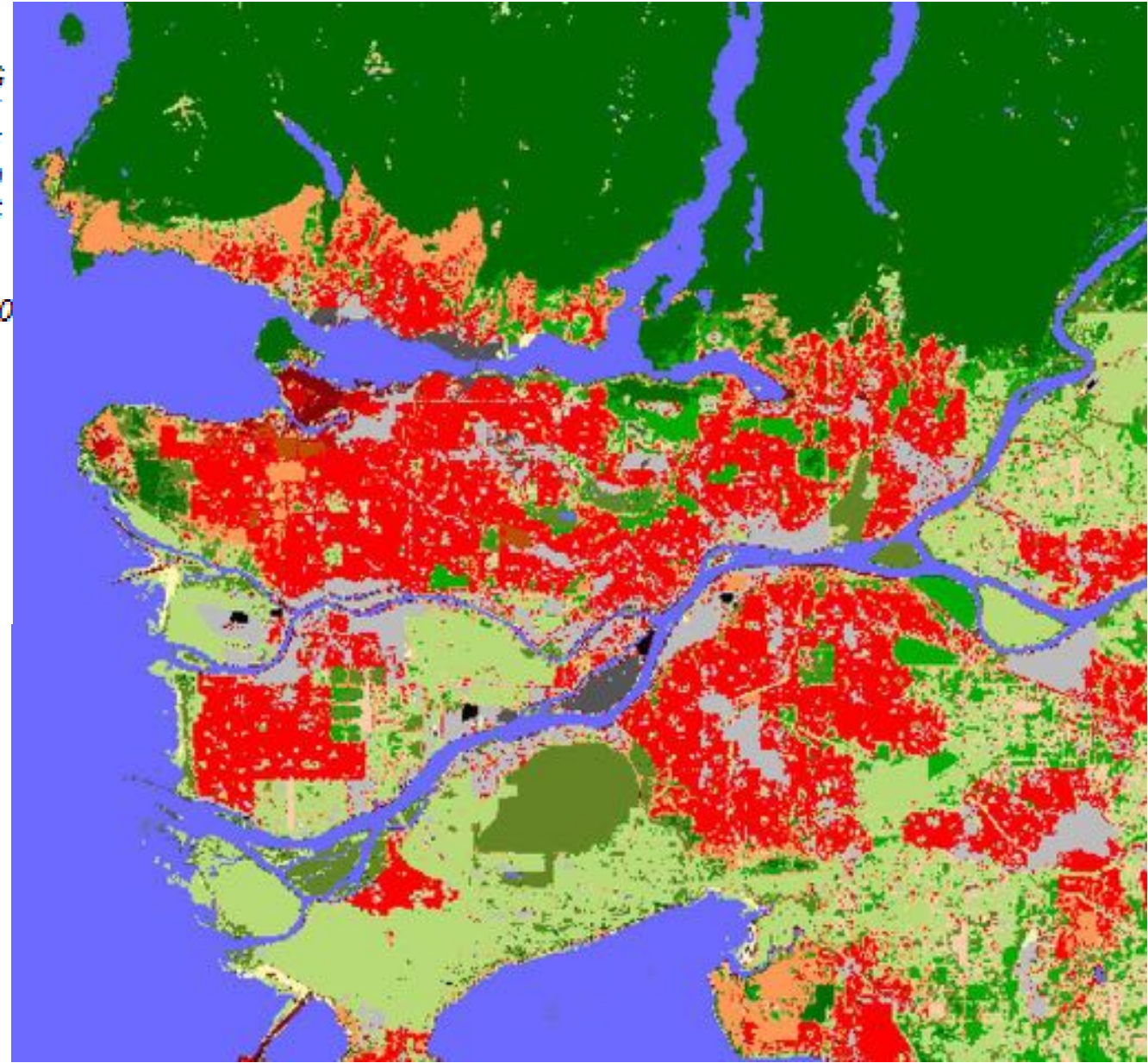
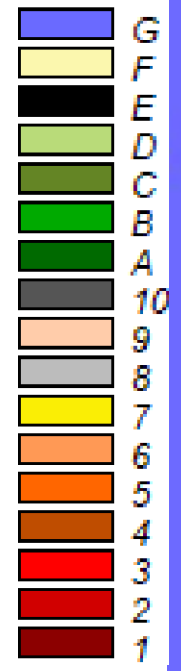
Grohnfeldt C., Schmitt M., Zhu X. (2018): A Conditional Generative Adversarial Network to Fuse SAR and Multispectral Optical Data for Cloud Removal from Sentinel-2 Images, Proceeding of the ISPRS Technical Commission II Symposium 2018, Riva del Garda, Italy.

Global Local Climate Zones Classification



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

LCZC



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

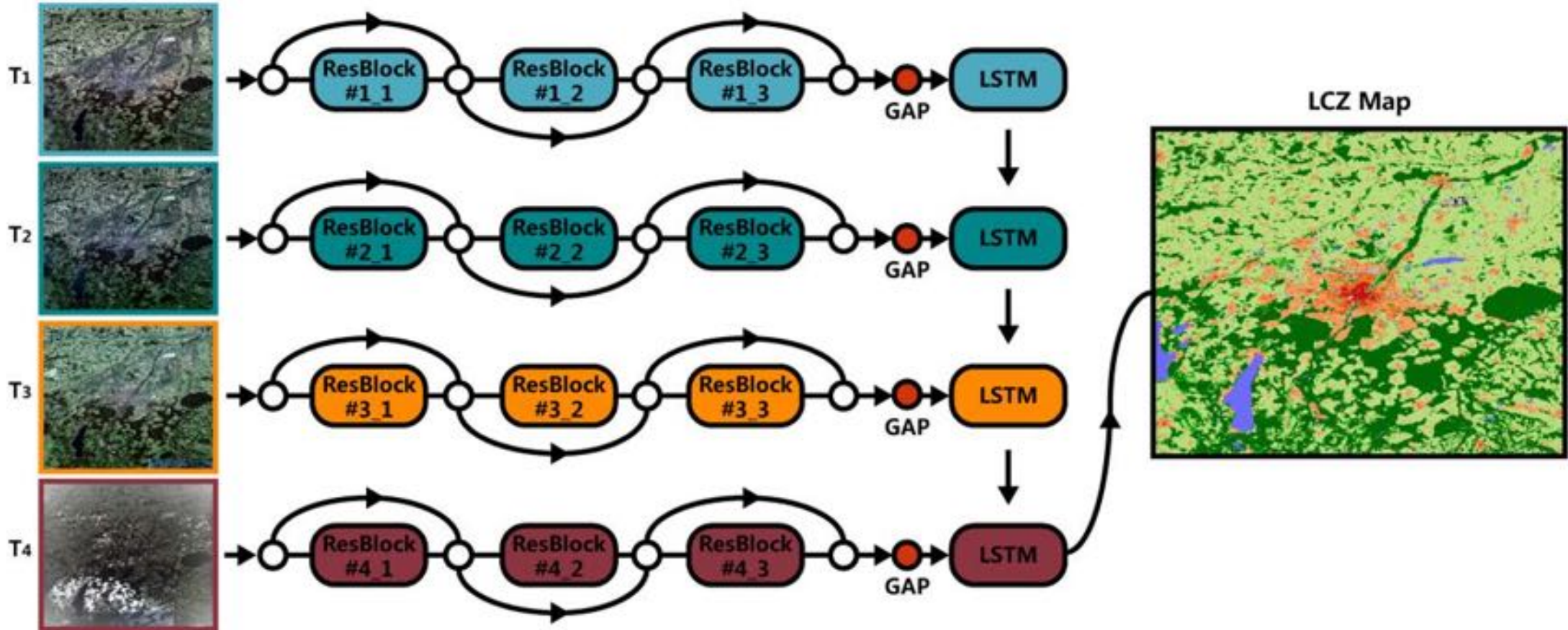
For global processing (Data gravity problem):

- 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

Multi-temporal Sequence



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.

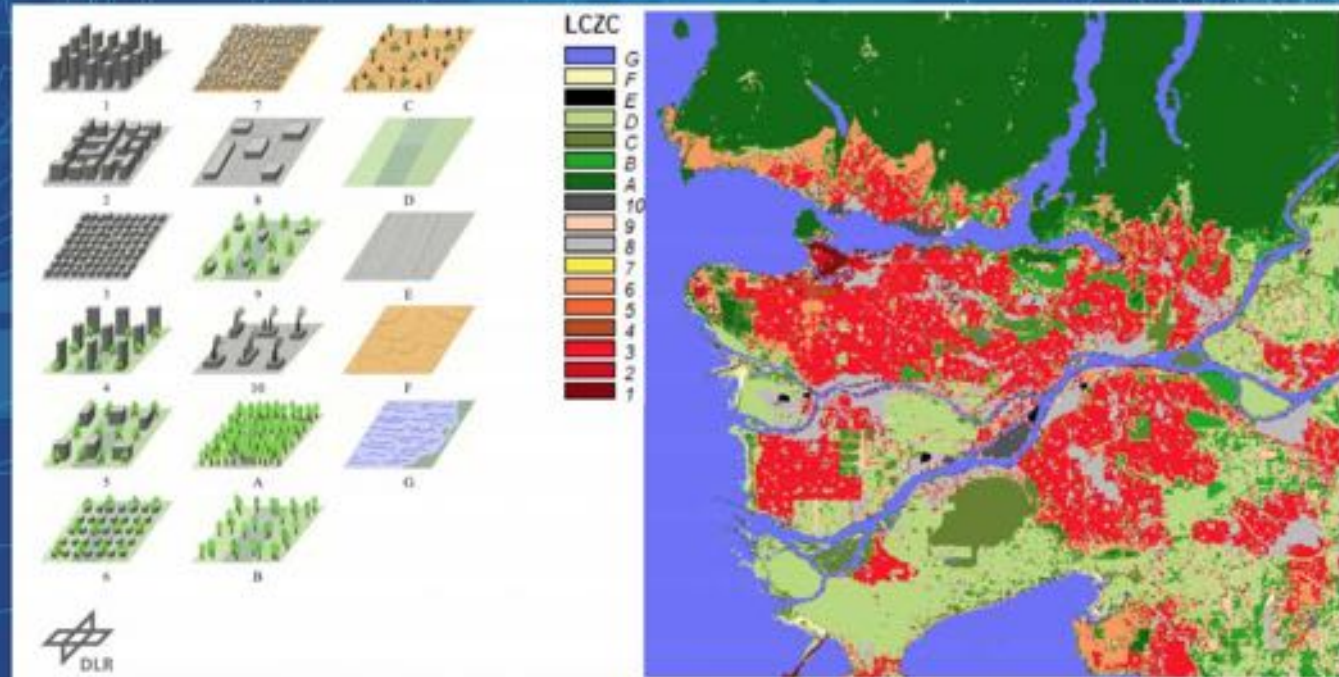


DLR/StepStone/Alibaba Tianchi Contest 2018 Germany



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



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...



DLR/Alibaba AI4EO Challenge



Global urban mapping So2Sat



AI4EO research @DLR&TUM



Join us for AI4EO:

Contact: xiaoxiang.zhu@dlr.de



@xiaoxiang_zhu

Wednesday, @Phi-Lab
Women in Science@Phiweek

🕒 10:45 - 11:00

Data Science in Earth Observation - (ID: 416)

Presenting: Zhu, Xiaoxiang