REMOTE SENSING IMAGE PROCESSING

Juelich Earth Observation Parallel Data Analysis (JEOPARDA)

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OUTLINE

- Remote Sensing Background
  - Multispectral Images
  - Classification of Land Cover Classes

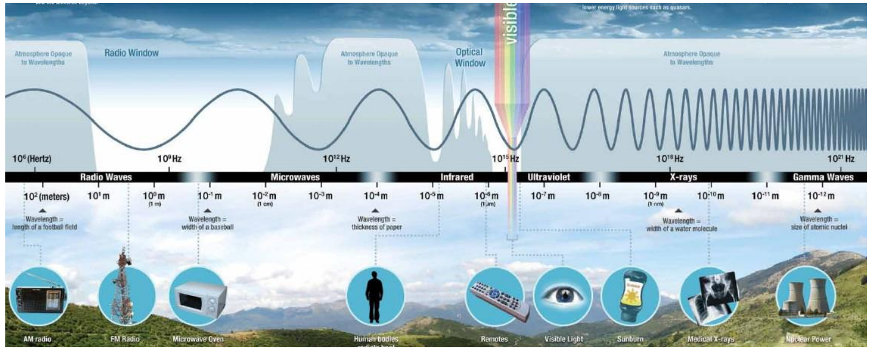
- Deep Learning in Remote Sensing

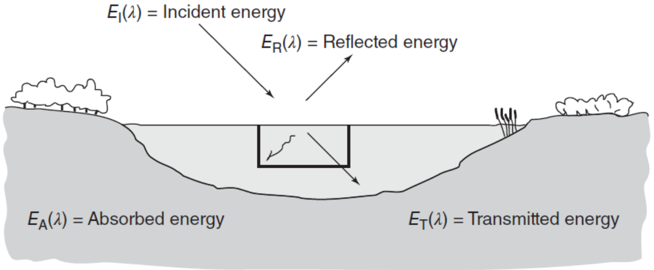
- Our applications:
  1. Multi land-cover class patch-based classification
  2. Multispectral Superesolution

REMOTE SENSING

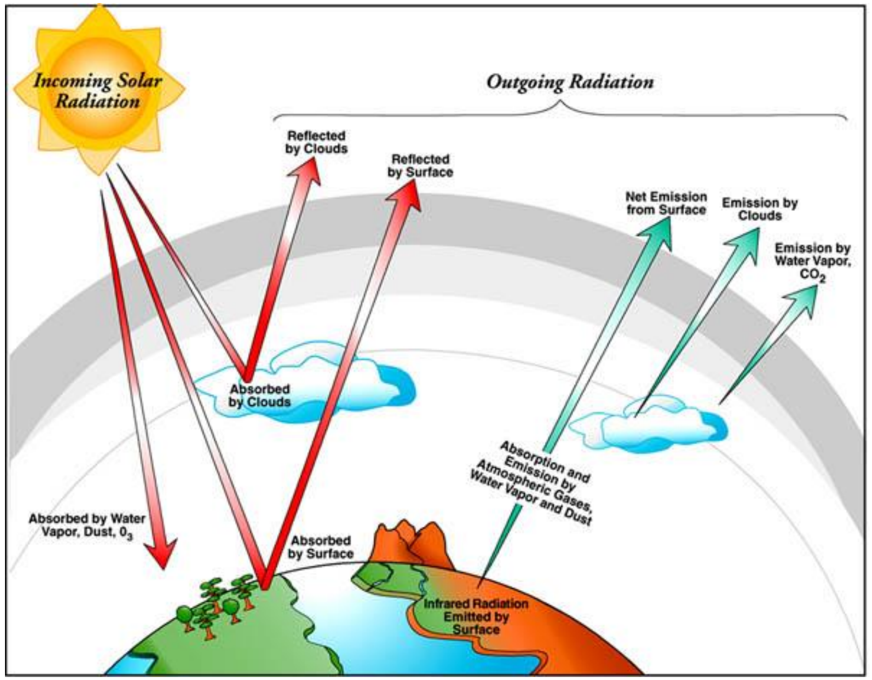
[1] Satellite (1960)

- **Remote** (without physical contact) **Sensing** (measurement of information)
- The term remote sensing was first used in the United States in the 1950s by Ms. Evelyn Pruitt of the U.S. Office of Naval Research
- Measurement of **radiation** of **different wavelengths** **reflected** or **emitted** from distant **objects** or **materials**





[2] K. Tempfli et al.

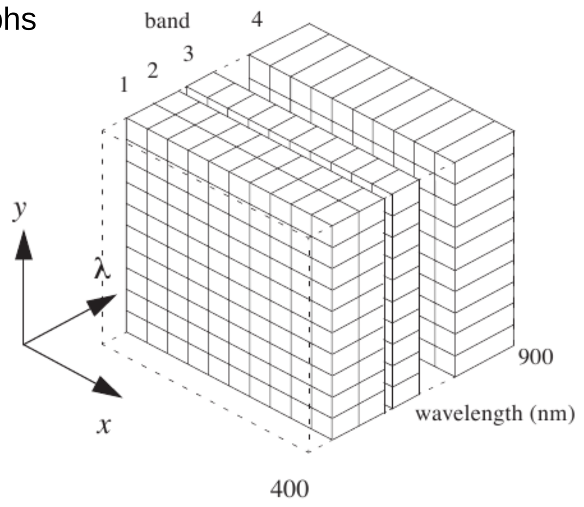


[3] The Earth-Atmosphere Energy Balance

- They may be **categorized** by **class**/type, substance, and spatial distribution

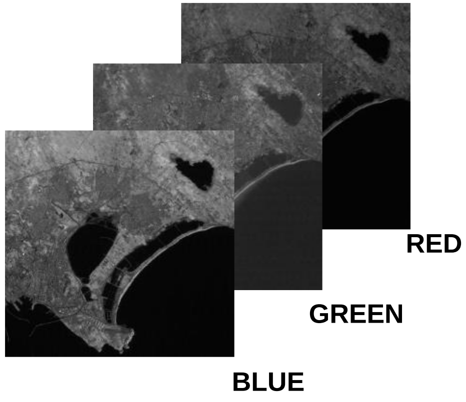
MULTISPECTRAL IMAGES

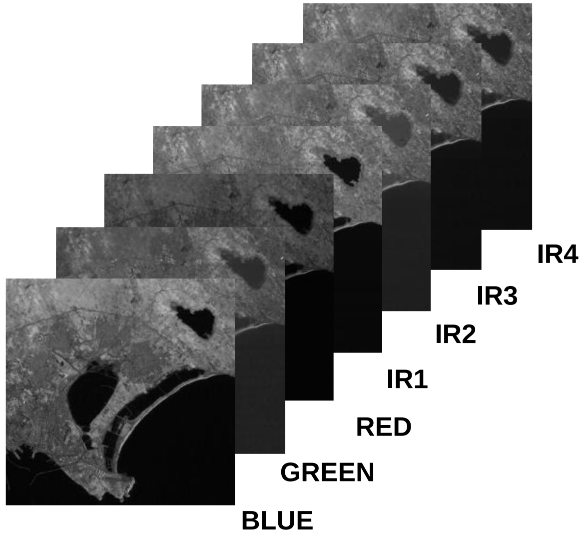
Differ significantly from photographs of objects recorded with standard hand-held cameras



- x,y spatial coordinates
- λ spectral coordinate

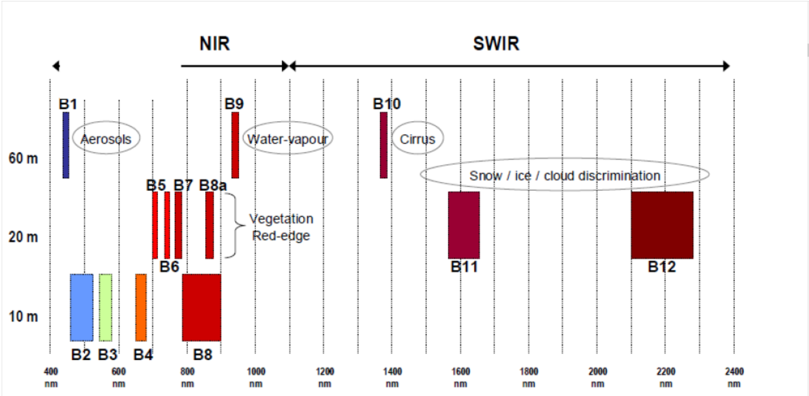
RGB $\neq$ Multispectral





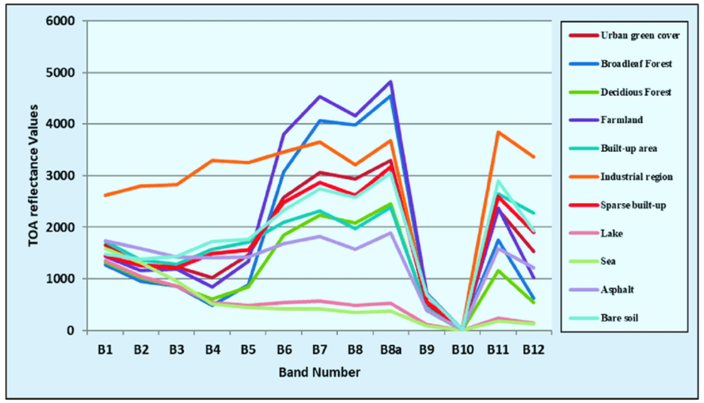
- Example: Multispectral Instrument (MSI) on-board SENTINEL-2
  - **Platform**: Twin polar-orbiting satellites, phased at 180° to each other
  - **Temporal resolution** of 5 days at the equator in cloud-free conditions

~23 TB data stored per day



[4] Earth Observation Mission Sentinel 2

By analyzing the signature it is possible to discriminate between different materials

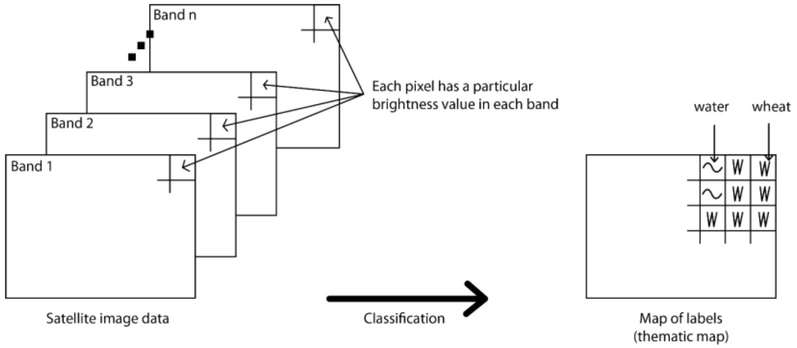


[5] P. Ettehadi et al.

CLASSIFICATION TASKS

Output variable takes a class label

- **Pixel-wise** classification



- **Patch-based** classification (with **single** or **multiple** land-cover class labels)

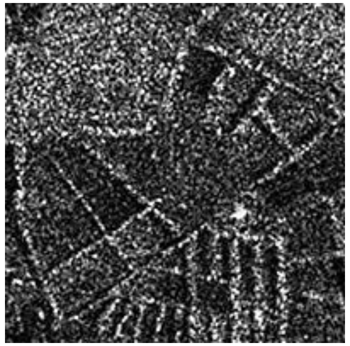
[6] P. Helber et al.

[7] G. Sumbul et el.

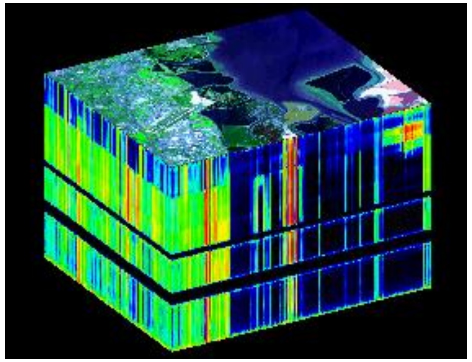
DEEP LEARNING

Has brought in revolutionary achievements in classification of remote sensing images

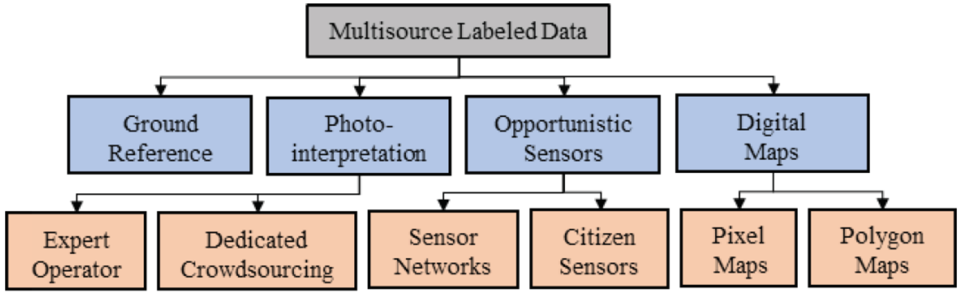
- However, in remote sensing there are **limited annotated training datasets**
- **Multimodal data**: geometries and content are completely different
  - From optical (multi- and hyperspectral), Lidar, and Synthetic Aperture Radar (SAR) sensors
- **High temporal resolutions data**
  - Shift from individual image analysis to time-series processing
- **Big remote sensing data**: high spatial and more spectral dimensionality
  - Traditional DL systems operate on relatively small grayscale or RGB imagery



SAR images: noisy data



Optical data: From four to hundreds of channels



[L. Bruzzone, Multisource Labeled Data: An Opportunity for Training Deep Learning Networks, IGARSS 2019]

AVAILABLE REMOTE SENSING ANNOTATED DATASETS

RGB and Multispectral

Datasets	Image type	Image per class	Scene classes	Annotation type	Total images	Spatial resolution (m)	Image sizes	Year
UC Merced	Aerial RGB	100	21	Single/Multi label	2100	0.3	256x256	2010
WHU-RS19	Aerial RGB	~50	19	Single label	1005	up to 0.5	600x600	2012
RSSCN7	Aerial RGB	400	7	Single label	2800	--	400x400	2015
SAT-6	Aerial MS	--	6	Single label	405000	1	28x28	2015
SIRI-WHU	Aerial RGB	200	12	Single label	2400	2	200x200	2016
RSC11	Aerial RGB	~100	11	Single label	1323	0.2	512x512	2016
Brazilian Coffee	Satellite MS	1438	2	Single label	2876	--	64x64	2016
RESISC45	Aerial RGB	700	45	Single label	31500	~30 to 0.2	256x256	2016
AID	Aerial RGB	~300	30	Single label	10000	0.6	600x600	2016
EuroSAT	Satellite MS	~2500	10	Single label	27000	10	64x64	2017
RSI-CB128	Aerial RGB	~800	45	Single label	36000	0.3 to 3	128x128	2017
RSI-CB256	Aerial RGB	~690	35	Single label	24000	0.3 to 3	256x256	2017
PatternNet	Aerial RGB	~800	38	Single label	30400	0.062~4.693	256X256	2017
BigEarthNet	Satellite MS	328 to 217119	43	Multi label	590326	10,20,60	120x120 60x60 20x20	2018

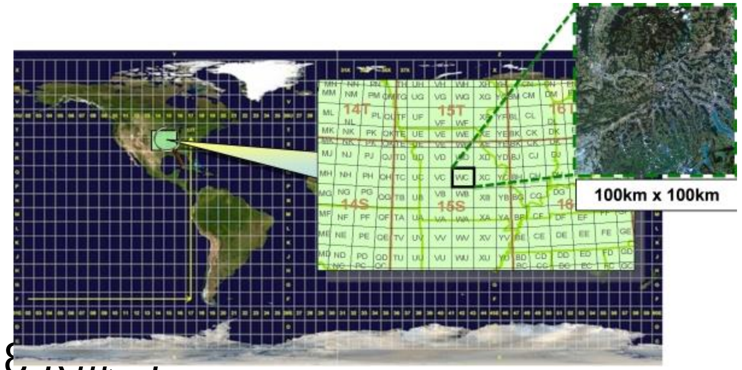
- Despite recent advances in EO benchmark data creation, large gap with the computer vision datasets
  - E.g., ImageNet dataset: **14197122 labeled images (with 21841 classes)**
- Key limiting factor for the development of operational deep network classifiers

APPLICATIONS

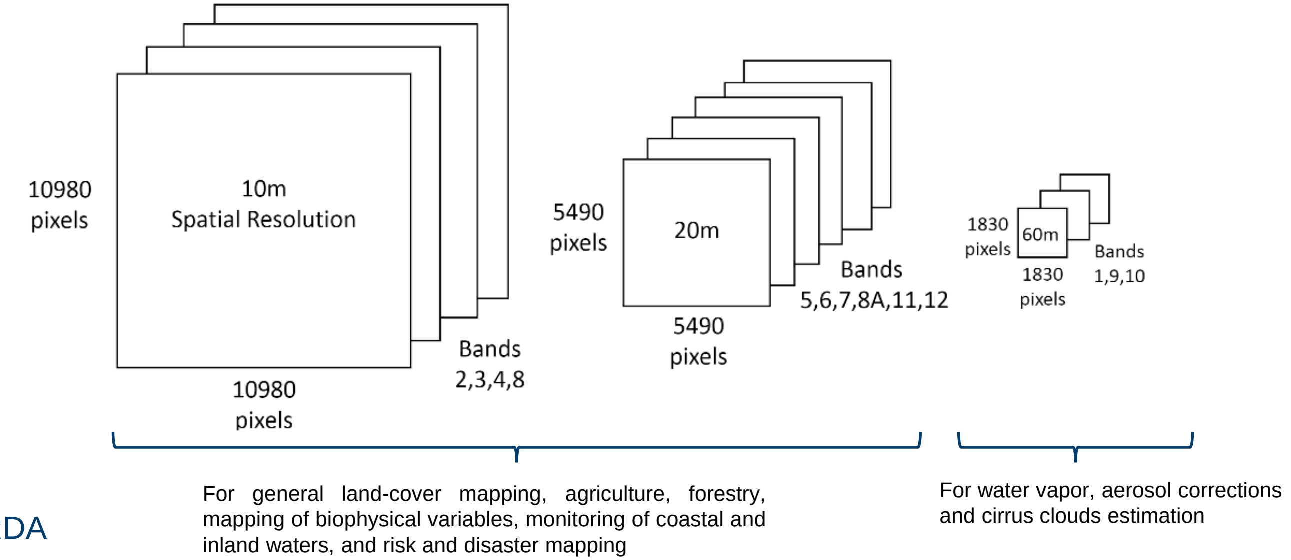
For the Hackathon

1. **Multi land-cover class patch-based classification**
2. **Multispectral Superesolution**

- Both applications are based on **Sentinel -2 Multispectral Images**
  - Sentinel-2 tile gridding is based on the NATO Military Grid Reference System
  - Each **tile** covers an area of $100 \times 100\ Km^2$ (excluding overlapping edges of 9.8 Km^2)
  - Each tile includes **13 bands with different spatial resolutions**



[9] Sentinel-2 products

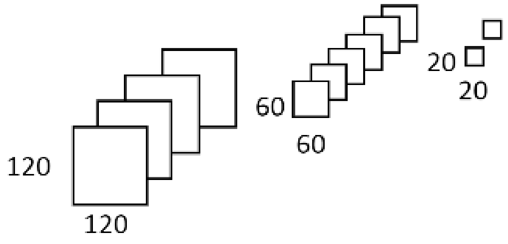


Spatial Resolution (m)	Band Number	S2A Central Wavelength (nm)	S2A Bandwidth (nm)	S2B Central Wavelength (nm)	S2B Bandwidth (nm)
10	2	496.6	98	492.1	98
	3	560.0	45	559	46
	4	664.5	38	665	39
	8	835.1	145	833	133
20	5	703.9	19	703.8	20
	6	740.2	18	739.1	18
	7	782.5	28	779.7	28
	8a	864.8	33	864	32
	11	1613.7	143	1610.4	141
	12	2202.4	242	2185.7	238
60	1	443.9	27	442.3	45
	9	945.0	26	943.2	27
	10	1373.5	75	1376.9	76

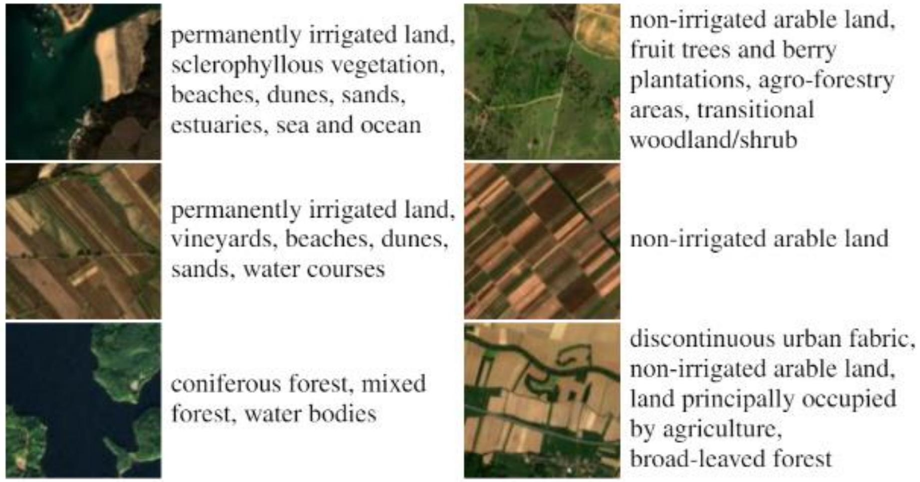
MULTI LAND-COVER CLASS PATCH-BASED CLASSIFICATION

Dataset: Sentinel-2 Data Patches and Annotated with CORINE Land Covers

Datasets	Image type	Image per class	Scene classes	Annotation type	Total images	Spatial resolution (m)	Image sizes	Year	Ref.
BigEarthNet	Satellite MS	328 to 217119	43	Multi label	590,326	10 20 60	120x120 60x60 20x20	2018	

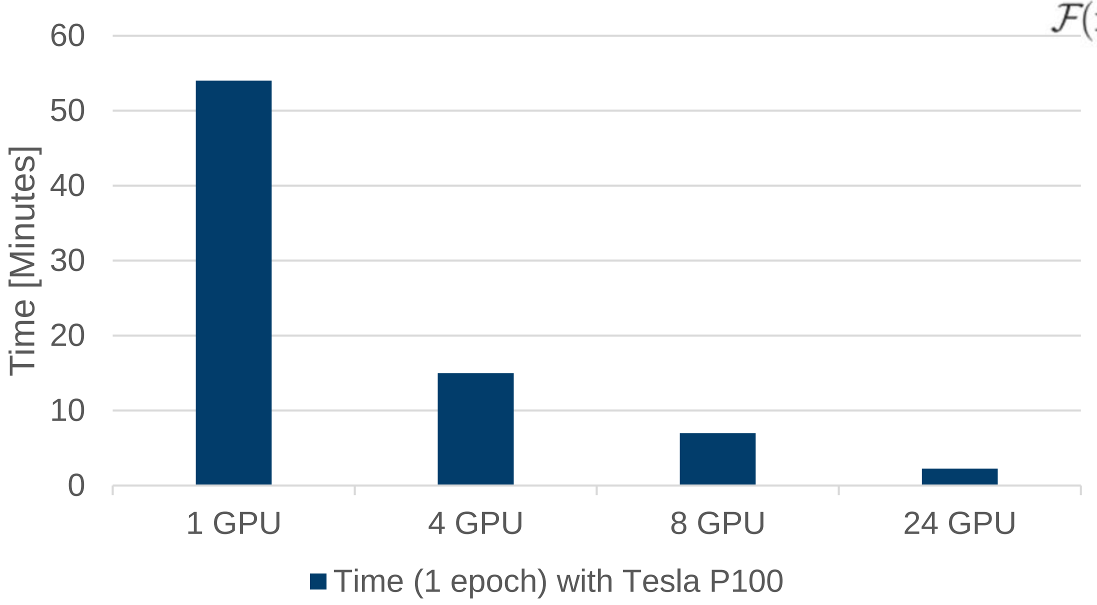


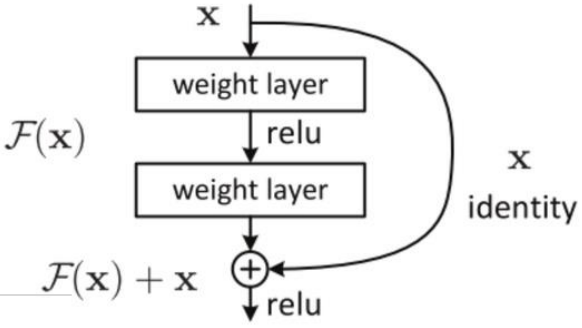
Patch and its dimension



PRELIMINARY EXPERIMENTAL SETUP

- The selected deep learning classifier is **ResNet50**
  - Use skip connections to overcome the issue of the vanishing gradient
- Distributed training framework with **Horovod**
  - Data parallelization with **MPI**





a residual block

[10] H. Kaiming et al.

Land-Cover Classes	Number of Images
Mixed forest	217, 119
Coniferous forest	211, 703
Non-irrigated arable land	196, 695
Transitional woodland/shrub	173, 506
Broad-leaved forest	150, 944
Land principally occupied by agriculture, with significant areas of natural vegetation	147, 095
Complex cultivation patterns	107, 786
Pastures	103, 554
Water bodies	83, 811
Sea and ocean	81, 612
Discontinuous urban fabric	69, 872
Agro-forestry areas	30, 674
Peatbogs	23, 207
Permanently irrigated land	13589
Industrial or commercial units	12895
Natural grassland	12, 835
Olive groves	12, 538
Sclerophyllous vegetation	11, 241
Continuous urban fabric	10, 784
Water courses	10, 572
Vineyards	9, 567
Annual crops associated with permanent crops	7, 022
Inland marshes	6, 236
Moors and heathland	5, 890
Sport and leisure facilities	5, 353
Fruit trees and berry plantations	4, 754
Mineral extraction sites	4, 618
Rice fields	3, 793
Road and rail networks and associated land	3, 384
Bare rock	3, 277
Green urban areas	1, 786
Beaches, dunes, sands	1, 578
Sparsely vegetated areas	1, 563
Salt marshes	1, 562
Coastal lagoons	1, 498
Construction sites	1, 174
Estuaries	1, 086
Intertidal flats	1, 003
Airports	979
Dump sites	959
Port areas	509
Salines	424
Burnt areas	328

[7] G. Sumbul et el.

43 classes
Imbalanced dataset

JURON HPC System (NVIDIA Tesla P100 GPU) - JSC

F1 score average 0.69

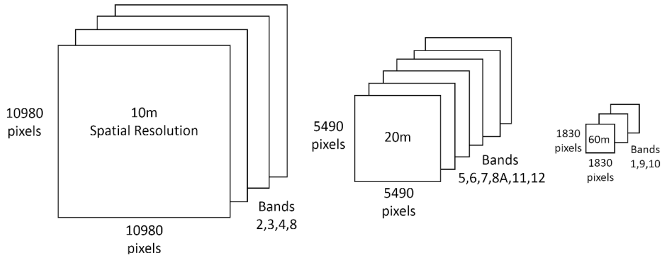
OBJECTIVES AND CHALLENGES

- **Objectives**
  - Investigating the use of different **CNN approaches**
  - Understand the contribution of **multispectral channels** (when compared with RGB)
  - Do **super-resolved Sentinel-2 tiles** achieve better classification accuracy?
  - Improve the **speed-up** of the learning step
  -
- Challenges
  - **Unbalanced** annotations
  - Some classes are very difficult to distinguish
    - E.g., Burnt areas, **land use classes**
  - Extension to multimodal datasets
    - Include co-registered Sentinel-1 patches (RADAR)

MULTISPECTRAL SUPERESOLUTION

Dataset: Sentinel 2 Tiles

- Learning a globally applicable deep neural network for the fusion of Sentinel 2 Images

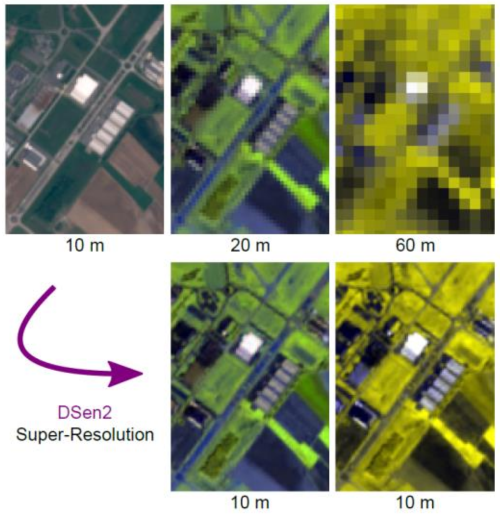


Band	B1	B2	B3	B4	B5	B6	B7	B8	B8a	B9	B10	B11	B12
Center wavelength [nm]	443	490	560	665	705	740	783	842	865	945	1380	1610	2190
Bandwidth [nm]	20	65	35	30	15	15	20	115	20	20	30	90	180
Spatial Resolution [m]	60	10	10	10	20	20	20	10	20	60	60	20	20

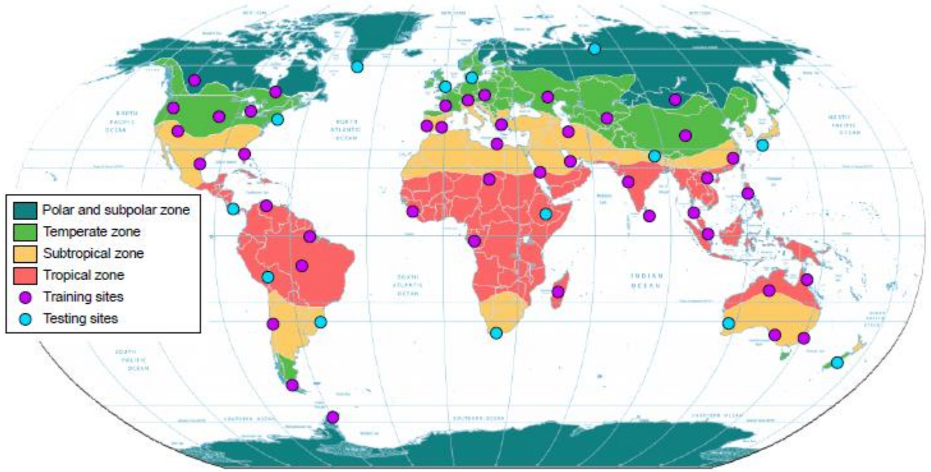
- For a single **multispectral sensor**
  - Apply super-resolution (i.e., **fuse its bands**)
  - All the acquired images cover the **same scene**

- The fusion must, as best as possible
  - **Preserve the salient information** in each source image
  - **Not introduce spectral/spatial distortion** into the fused image

- This processing step can **serve a large pool of operations**
  - Post-processing, e.g., segmentation, feature extraction, land-cover classification, objects identification, etc.



[11] C. Lanaras et al.



- Sentinel 2A and 2B data (2016-2017)
- Different continents, climate zones, land-cover
- **45 Tiles for training (~35Gb of raw data)**

- End-to-end-mapping from raw S2 imagery to super-resolved bands
  - Purely from the statistics over a large amount of image data

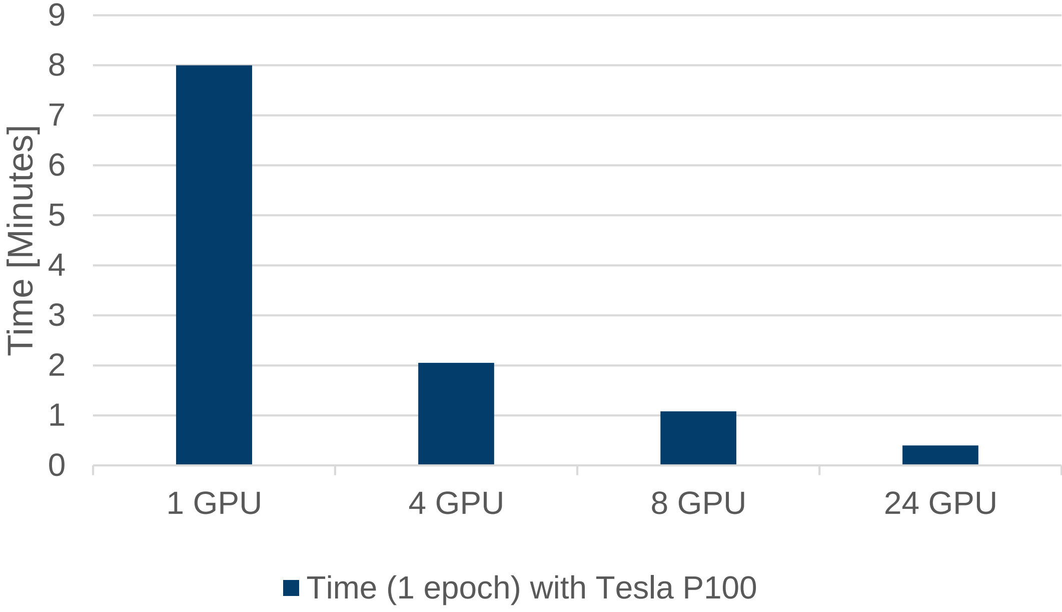
PRELIMINARY EXPERIMENTAL SETUP

- Based on **Generative Adversarial Networks (GANs)**

- Distributed training framework with **Horovod**
  - Data parallelization with **MPI**

Method/ Metric (optimal value)	RMSE (0)	SRE	ERGAS (0)	SAM (0)
GAN	38.8	34.3	1.12	0.85
DSen2	35.8	35.9	1.06	0.77

[11] C. Lanaras et al.



JUWELS HPC System (NVIDIA Tesla V100 GPU) - JSC

OBJECTIVES AND CHALLENGES

- **Improve** the **accuracy** of all superesolved bands and **preserve** their **spectral/spatial** characteristics
- Improve the **speed-up** of the learning step
- Verify if the **interpolation** for the training set preparation introduces a **solution** as an input to the network

- Sentinel-2 images contain pixels with **very high reflectance**
  - Due to the high dynamic range these reach **extreme values** without saturating

- The patch sizes of ImageNet (240×240px) typically depict a single isolated object
  - A **244×244px** cut-out of a **Sentinel-2** image **may cover** the area of a **whole town**

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