

REMOTE SENSING IMAGE PROCESSING

Juelich Earth Observation Parallel Data Analysis (JEOPARDA)

GABRIELE CAVALLARO, ROCCO SEDONA, JENIA JITSEV, THOMAS NEUMANN

JUELICH SUPERCOMPUTING CENTRE (JSC)

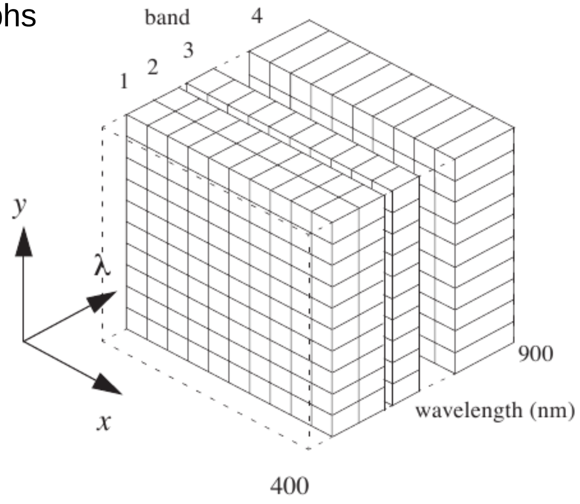
FORSCHNGZENTRUM JUELICH

JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE

HAiCU | HELMHOLTZ ARTIFICIAL INTELLIGENCE COOPERATION UNIT

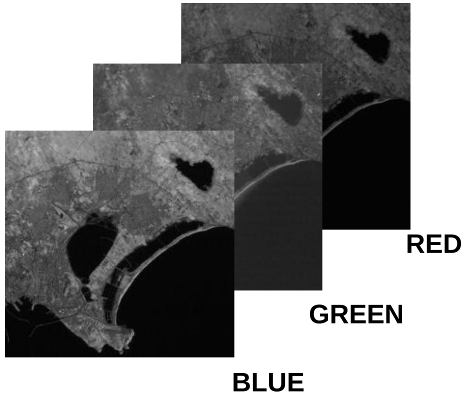
MULTISPECTRAL IMAGES

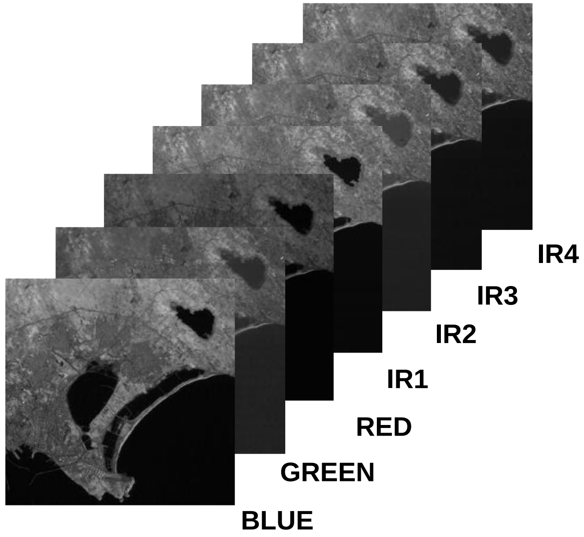
Differ significantly from photographs of objects recorded with standard hand-held cameras



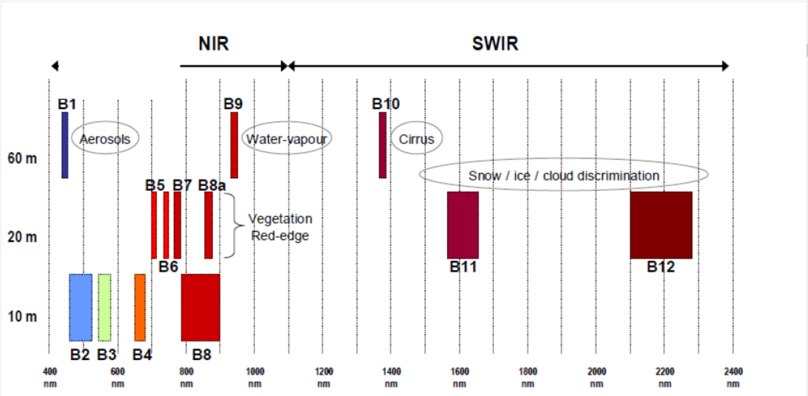
- x,y spatial coordinates
- λ spectral coordinate

RGB ≠ Multispectral

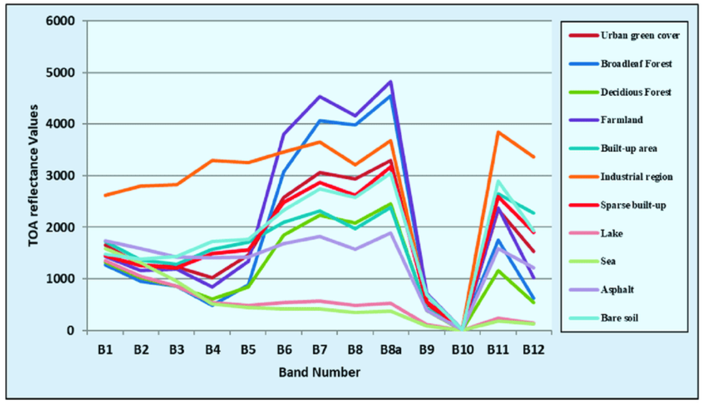




- Example: Multispectral Instrument (MSI) on-board SENTINEL-2
  - **Platform**: Twin polar-orbiting satellites, phased at 180° to each other
  - **Temporal resolution** of 5 days at the equator in cloud-free conditions



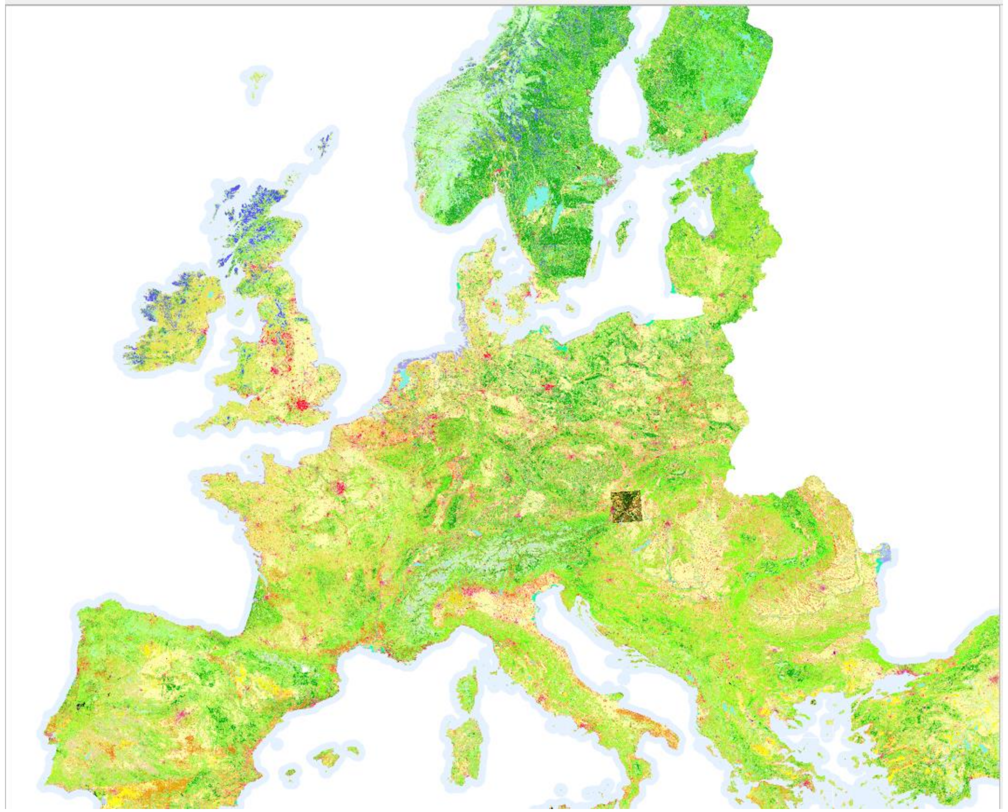
By analyzing the signature it is possible to discriminate between different materials



CORINE

Levels of the Nomenclature: hierarchical structure of 43 classes

- The production of this map was based on **visual interpretation** of **optical/near-infrared satellite images** and **ancillary data** such as aerial photograph, topographic maps, or forestry maps

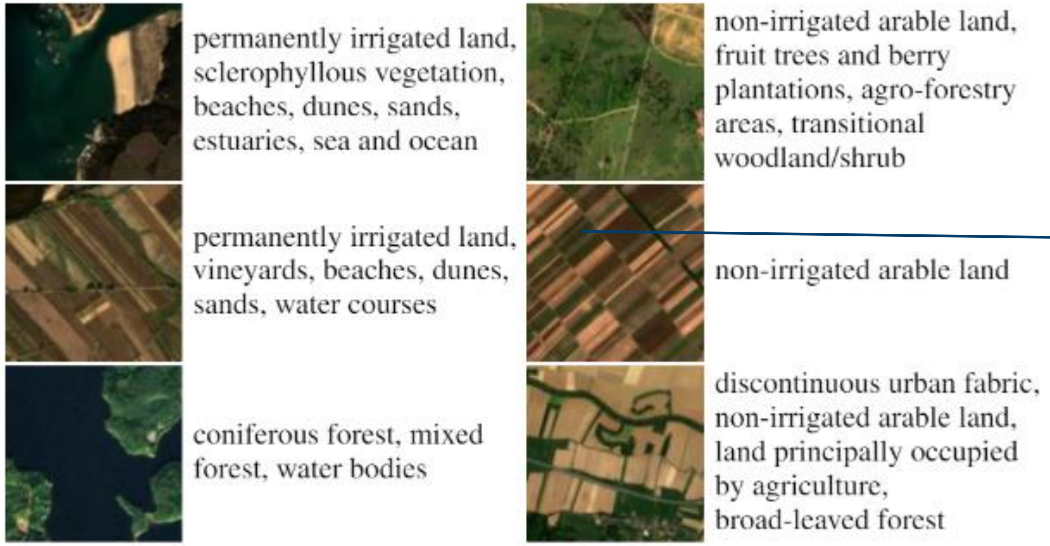


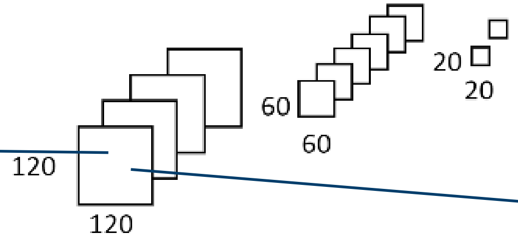
Level 1	Level 2	Level 3
1. Artificial surfaces	1.1. Urban fabric	1.1.1. Continuous urban fabric
		1.1.2. Discontinuous urban fabric
	1.2. Industrial, commercial and transport units	1.2.1. Industrial or commercial units
		1.2.2. Road and rail networks and associated land
		1.2.3. Port areas
		1.2.4. Airports
	1.3. Mine, dump and construction sites	1.3.1. Mineral extraction sites
		1.3.2. Dump sites
		1.3.3. Construction sites
	1.4. Artificial non-agricultural vegetated areas	1.4.1. Green urban areas
		1.4.2. Sport and leisure facilities
2. Agricultural areas	2.1. Arable land	2.1.1. Non-irrigated arable land
		2.1.2. Permanently irrigated land
		2.1.3. Rice fields
	2.2. Permanent crops	2.2.1. Vineyards
		2.2.2. Fruit trees and berry plantations
		2.2.3. Olive groves
	2.3. Pastures	2.3.1. Pastures
	2.4. Heterogeneous agricultural areas	2.4.1. Annual crops associated with permanent crops
		2.4.2. Complex cultivation patterns
		2.4.3. Land principally occupied by agriculture, with significant areas of natural vegetation
		2.4.4. Agro-forestry areas
3. Forests and semi-natural areas	3.1. Forests	3.1.1. Broad-leaved forest
		3.1.2. Coniferous forest
		3.1.3. Mixed forest
	3.2. Shrub and/or herbaceous vegetation associations	3.2.1. Natural grassland
		3.2.2. Moors and heathland
		3.2.3. Sclerophyllous vegetation
		3.2.4. Transitional woodland shrub
	3.3. Open spaces with little or no vegetation	3.3.1. Beaches, dunes, and sand plains
		3.3.2. Bare rock
		3.3.3. Sparsely vegetated areas
		3.3.4. Burnt areas
		3.3.5. Glaciers and perpetual snow
4. Wetlands	4.1. Inland wetlands	4.1.1. Inland marshes
		4.1.2. Peatbogs
	4.2. Coastal wetlands	4.2.1. Salt marshes
		4.2.2. Salines
		4.2.3. Intertidal flats
5. Water bodies	5.1. Inland waters	5.1.1. Water courses
		5.1.2. Water bodies
	5.2. Marine waters	5.2.1. Coastal lagoons
		5.2.2. Estuaries
		5.2.3. Sea and ocean

MULTI LAND-COVER CLASS PATCH-BASED CLASSIFICATION

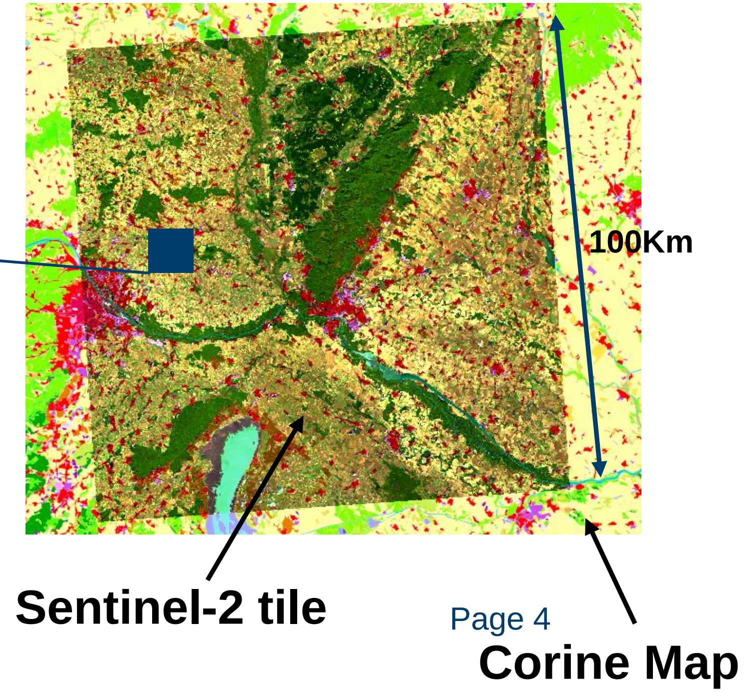
Dataset: Sentinel-2 Data Patches and Annotated with CORINE Land Covers

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



CHALLENGES

- **Unbalanced** classes

- Some **land cover classes** are difficult to distinguish
  - Need of higher spatial and temporal resolution
  - E.g., Burnt areas, olive groves

- Some **land use classes** cannot be discriminated only with spectral information
  - Discontinuous urban fabric, sport and leisure facilities

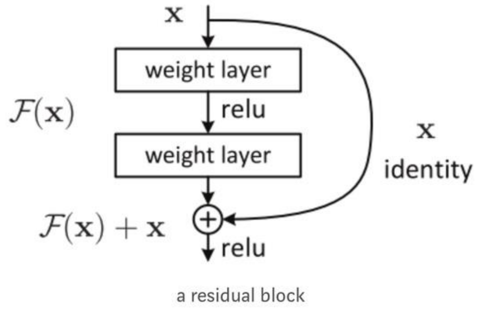
Land-Cover Classes	Number of Images
Mixed forest	217, 119
Coniferous forest	211, 703
Non-irrigated arable land	196, 695
Transitional woodland/shrub	173, 506
Broad-leaved forest	150, 944
Land principally occupied by agriculture, with significant areas of natural vegetation	147, 095
Complex cultivation 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

43 classes
Imbalanced dataset

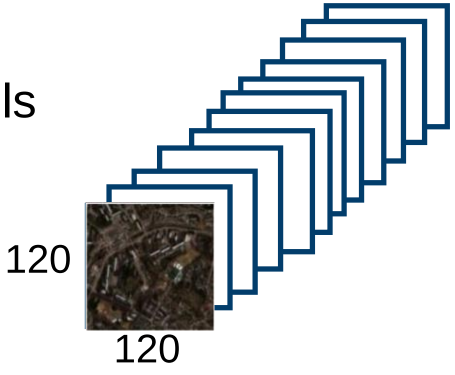
PRELIMINARY RESULTS

Before the Hackathon

- Deep learning classifier: **ResNet50**
  - Use skip connections to overcome the issue of the vanishing gradient



- Adapted to input patches of 12 channels
  - Superesolved at 10m resolution



- The patch sizes of ImageNet (240×240px) typically depict a single isolated object
  - A **120×120px** patch of BigEarthNet dataset **can cover** the area of a **whole town**

- Average F1 score: **0.69**

LITERATURE

Shallow CNN
With 3 layers

Methods	Recall	F_1 Score
Pre-trained CNN on ImageNet*	43.5 %	0.45
RGB Bands in Standard CNN	56.8 %	0.57
All Bands in Standard CNN	62.0 %	0.61
All Bands in Three Branch CNN	**71.5 %**	**0.67**

Earth Observation Φ-Week, ESRIN (Frascati), 10/09/2019
BigEarthNet: A New Large-Scale Sentinel-2 Benchmark Archive to Drive Deep Learning Studies for Earth Observation
G. Sumbul, M. Charfuelan, B. Demir and V. Markl

CLASSIFICATION RESULTS

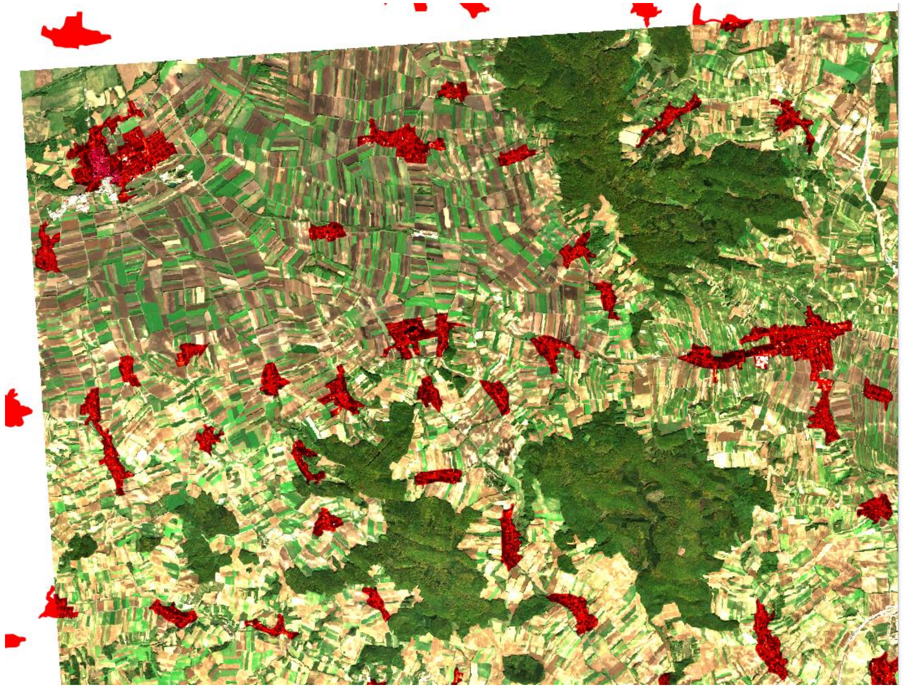
- Shallow CNN (with 20 epochs)
  - F1-score: 0.69

- ResNet50 (with 20 epochs)
  - F1-score: 0.72
  - 2 nodes (8 V100 GPUs) : $1min$ per epoch

- ResNet18 (50 epochs, mixup, 1cycle learning, heavy data aug) Taurus 1 node 2 gpu
  - F1-score 0.76
  - Only on 10% of dataset. Might not generalize

CLASSIFICATION CNN TO SEGMENTATION CNN

- Convert to fully convolutional net to get mask output



DATA CHECKING, REGULARIZATION AND DATA AUGMENTATION

Checked the dataset

- Found and corrected an error during shuffling of the dataset
- TO DO: find a more efficient way of loading the data

Implemented learning rate decay using a callback

Regularization

- We have added a Dropout before the last FC layer
- L2 regularization in the Conv2D layers

Data augmentation

- Data augmentation using a simple method: rotation by 90° and flipping
- Mix up technique: new_image = $t * \text{image1} + (1-t) * \text{image2}$