An introduction to Remote Sensing Analysis with applications on land cover mapping

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Outline

Introduction to Remote Sensing, Opportunities & Challenges

Data Fusion & Remote Sensing

Deep Learning (DL) for Remote Sensing

DL-Based Data Fusion for Land Cover Mapping:
- Combine Single-Sensor Data
- Combine Multi-Source Time Series Data

Perspectives

Introduction

Nowadays, many earth observation satellite missions exist:

- Sentinel [Senti]
- LandSat-8 [LandSat]
- SPOT 6/7[Spot]
- …

Acquired images have different:

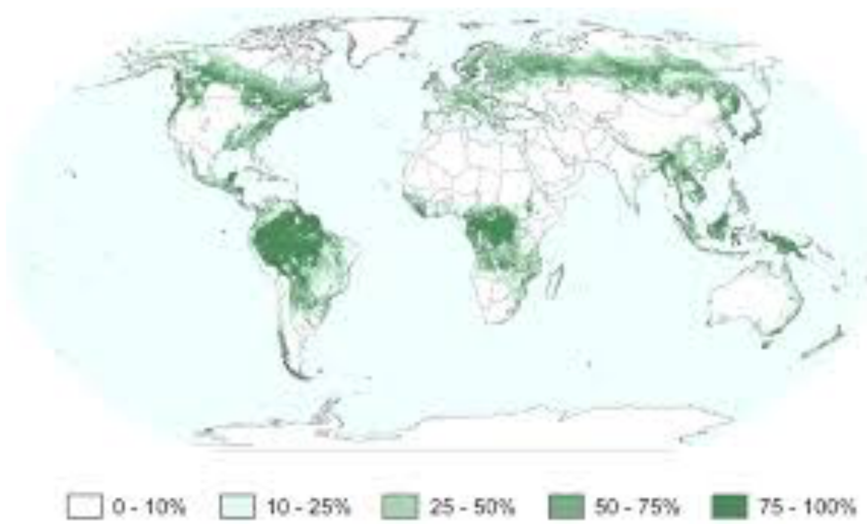
- spatial resolution (0.5 – 30 meters)
- radiometric content (spectral bands)
- temporal resolution (every 5 – 365 days)

HUGE quantity of Satellite Images Describing Earth Phenomena at different scales

Why EOD is an Opportunity

Earth Observation Data can have practical influence on different domains:

Continental Surface analysis



Precise Agriculture

Climate Changes Analysis

Biodiversity Monitoring

Why EOD is an Opportunity

Analyze, Mining and Exploit EOD data can also improve practices on:

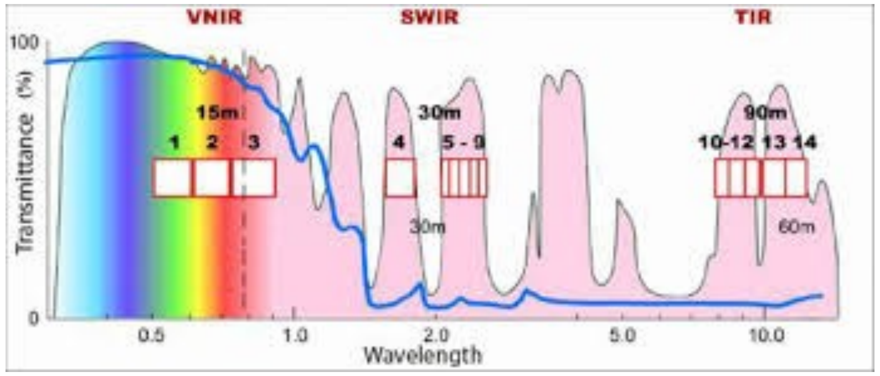
- Forestry characterization
- Lithological classification and mineral mapping
- Food Risk prevention
- Environmental monitoring
- Urban development
- Wildlife and Habitat Monitoring

This is why Satellite imagery analytics is becoming more IMPORTANT

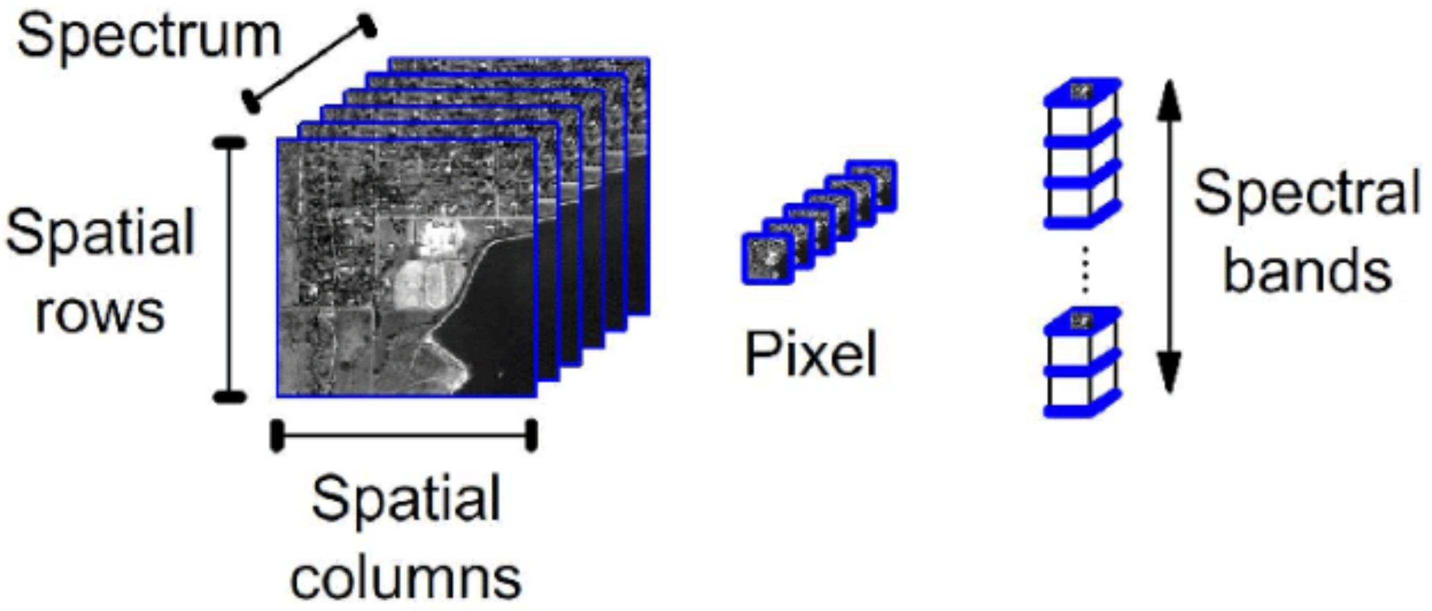
Introduction to RS

A Satellite Image:

A data cube that describes a spatial area by means of several spectral bands



Spectral Bands



Introduction to RS

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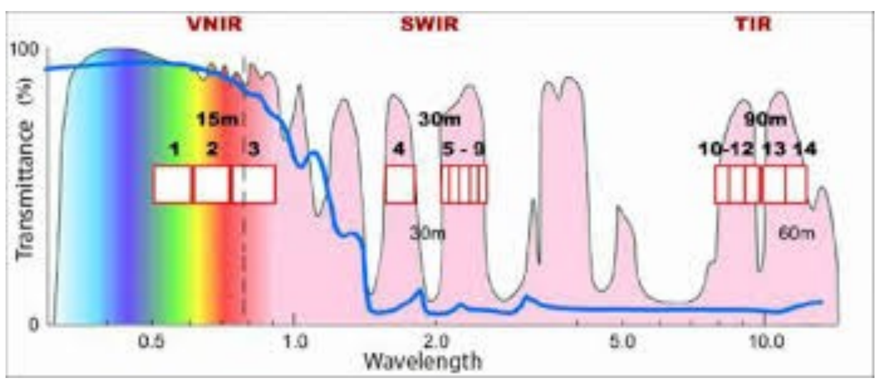
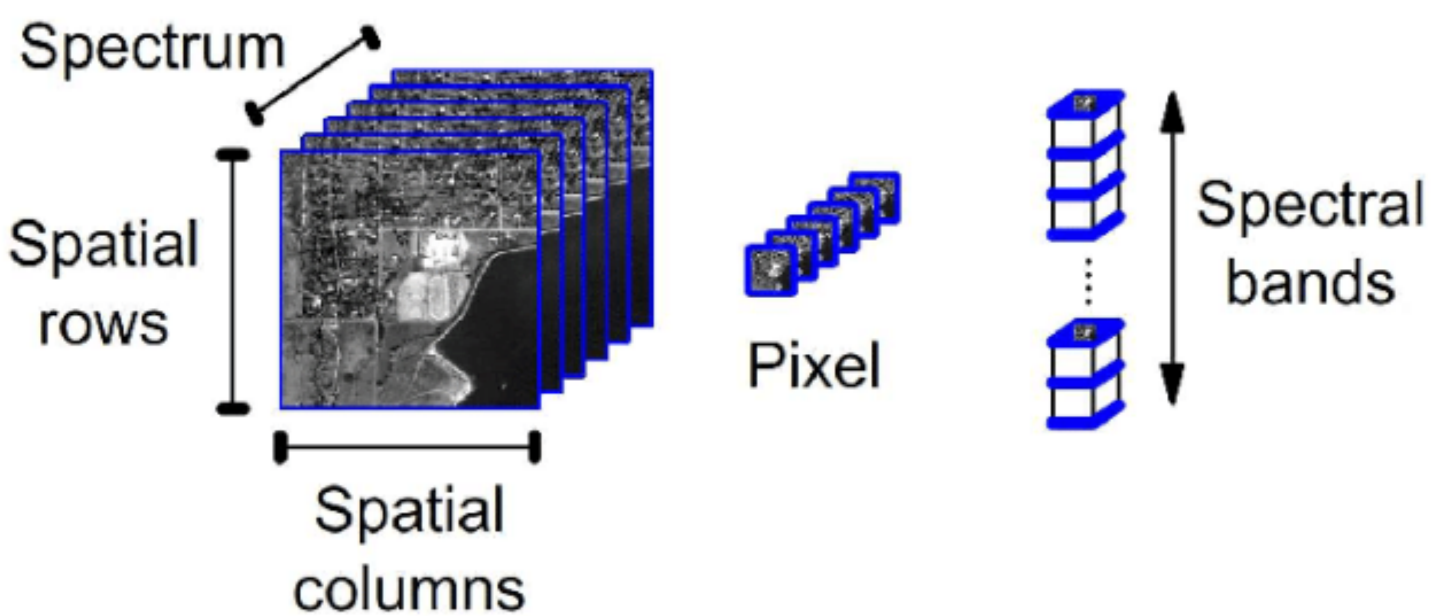


Spectral Bands



Type of information:

- **Optical** Images (Multi-Spectral / Hyperspectral)
- **Radar** Images (phase, amplitude, etc…)
- **LIDAR** (point clouds)
- Etc…

Introduction to RS

EOD allows also to collect **Very High Resolution** Images (VHR) i.e. Spot6/7 (at 1.5m), Pléiades (.5m), WorldView3 (.3m) at Low Temporal Frequency (once or twice per year)

VHSR data are useful to obtain fine resolution information to characterise spatial pattern and spatial texture

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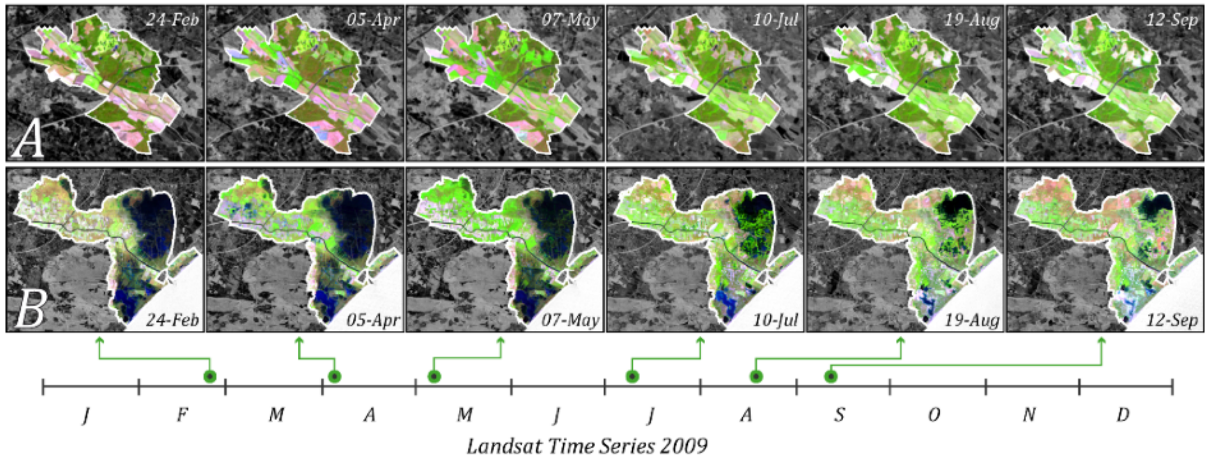
VHSR data are useful to obtain fine resolution information to characterise spatial pattern and spatial texture

EOD allows to collect **Satellite Image Time Series** (SITS) at High Spatial Resolution (Sentinel ~10m) and High Temporal Frequency (every 5/10 days)

The same geographical area is observed over



SITS data are useful to analyze spatio-temporal phenomena (trends and changes) over the time

Sentinel Missions

Sentinel Missions belong to the **Copernicus Programme**

Copernicus Programme is provided by the **ESA** (European Space Agency)

Provide Remote Sensing data at **High Spatial/Temporal Resolution** of the **Earth**

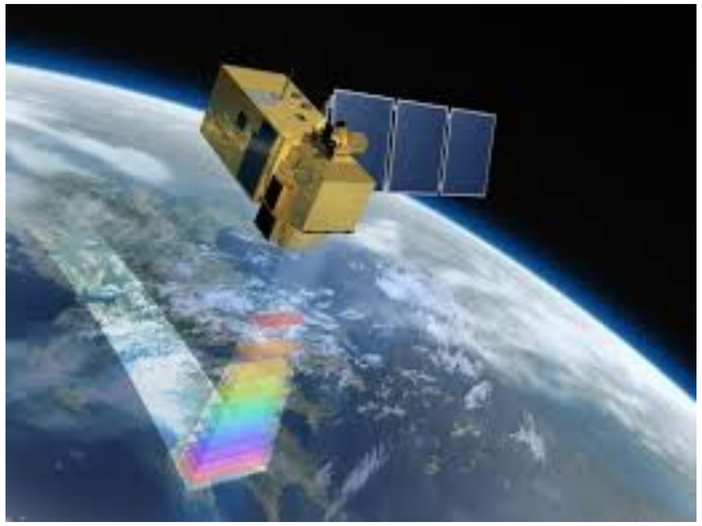
Different kind of sensors for different uses:

Sentinel 1: two satellites, operating day and night performing C-band synthetic aperture radar imaging.

Sentinel 2: two satellites placed in the same sun-synchronous orbit supplying optical information.

Sentinel 3: measure sea surface topography, sea and land surface temperature, and ocean and land surface colour.

Sentinel 4 & Sentinel 5: air quality & aerosols.

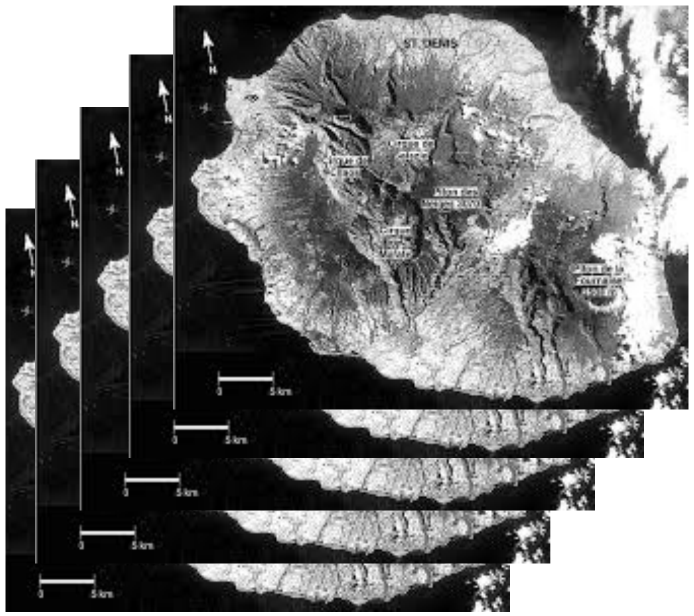


Sentinel 1

Two satellites (Sentinel 1A and Sentinel 1B) operating day and night performing C-band synthetic aperture radar imaging

Especially useful to monitor **soil and structural properties** (i.e. rugosity and humidity)

An image **every 5/6 days** more or less with information about two polarization (**VV** and **VH**).



A spatial resolution of 10m or 20m

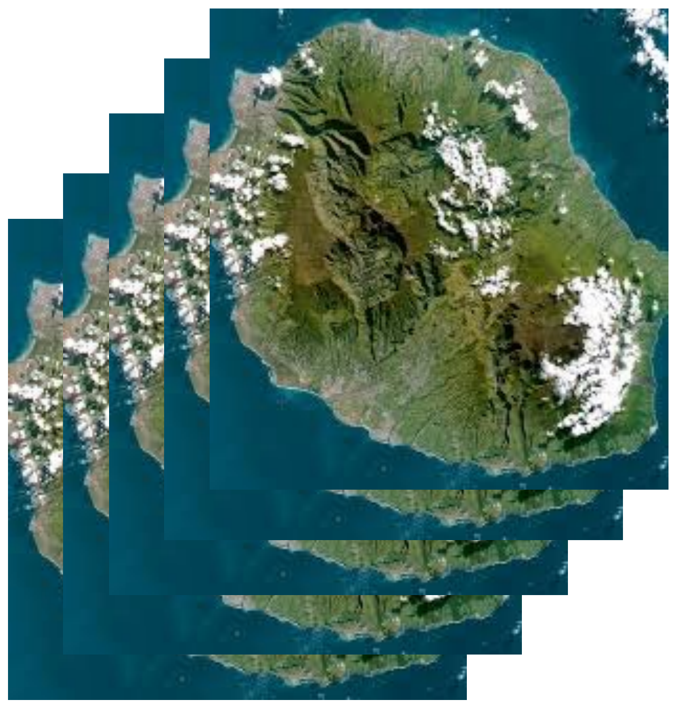
Images can be arranged to create (radar) Satellite Image Time Series

Sentinel 2

Two satellites (Sentinel 2A and Sentinel 2B) placed in the same sun-synchronous orbit supplying optical information

Especially useful to observe **surface reflectance** with **13 bands**:

- 4 bands at 10m of spatial resolution (Red, Green, Blue, NIR)
- 6 bands at 20m of spatial resolution (Vegetation Red Edge, Narrow Nir, SWIR)
- 3 bands at 60m of spatial resolution (dedicated to atmospheric correction mainly)



An image **every 5 days** more or less (from mid-2018) and an image every 10 days more or less (from December 2015).

Images can be arranged to create (optical) Satellite Image Time Series

To Sum-Up on Sentinel

Optical and Radar images available, more or less, **every 5/10 days**

Complementary source of information freely available inside and outside Europe

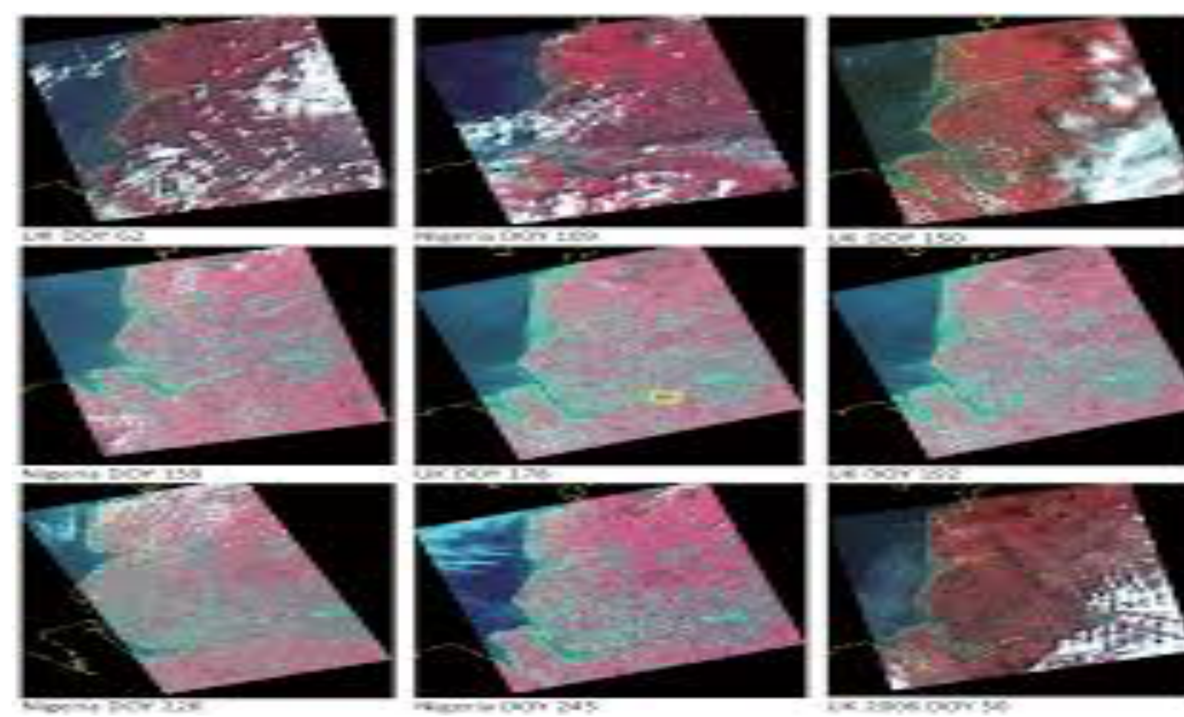
Some limitations:
- **Cloud phenomena** can affect **optical** images and reduce the temporal frequency
- **Rain or heavy humidity** phenomena can influence the **radar** signal

Huge amount of data available all around the world to monitor spatio-temporal phenomena at high spatial resolution

… but, spatial resolution of 10m is not adapted for every task

Challenges in EOD

Satellite imagery analytic is challenging
due to EOD diversity



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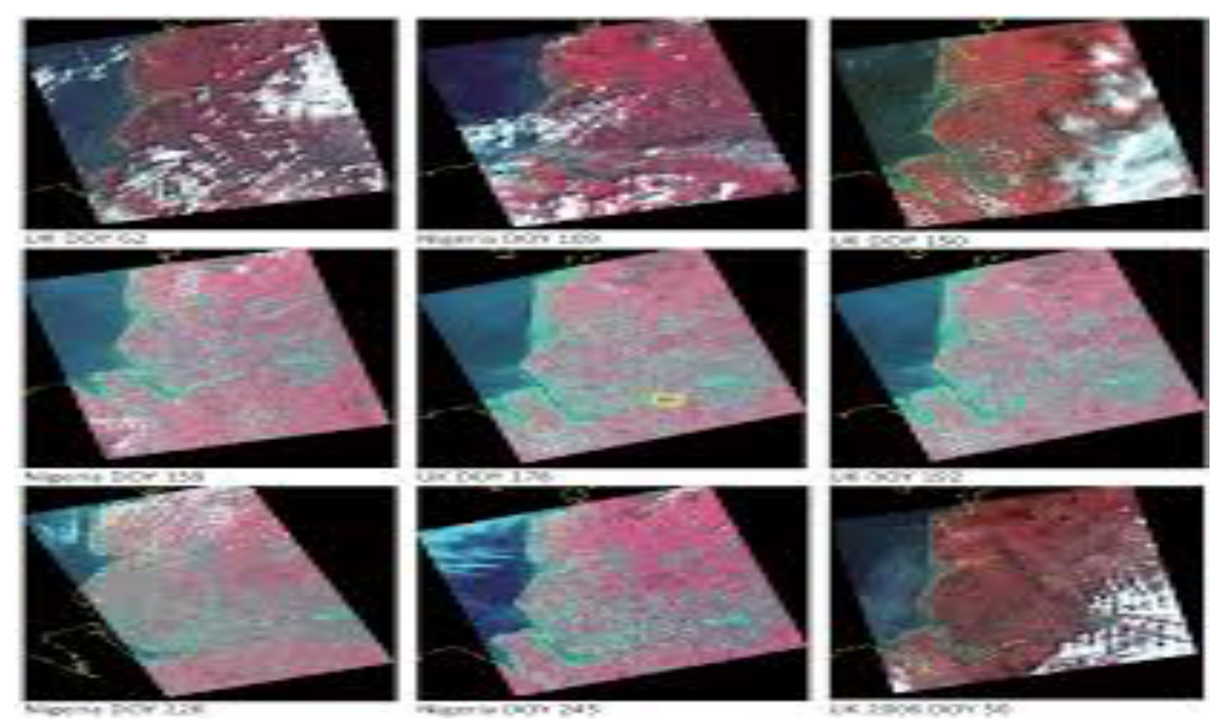

Heterogeneity:
- **Spatial** (Different resolutions)
- **Temporal** (time steps not always constant)
- **Acquisition Sensor** (Optical Images, Radar Images, DEM, LiDAR, etc..)
- **Very High Spatial vs High Temporal Resolution** (VHR & SITS)

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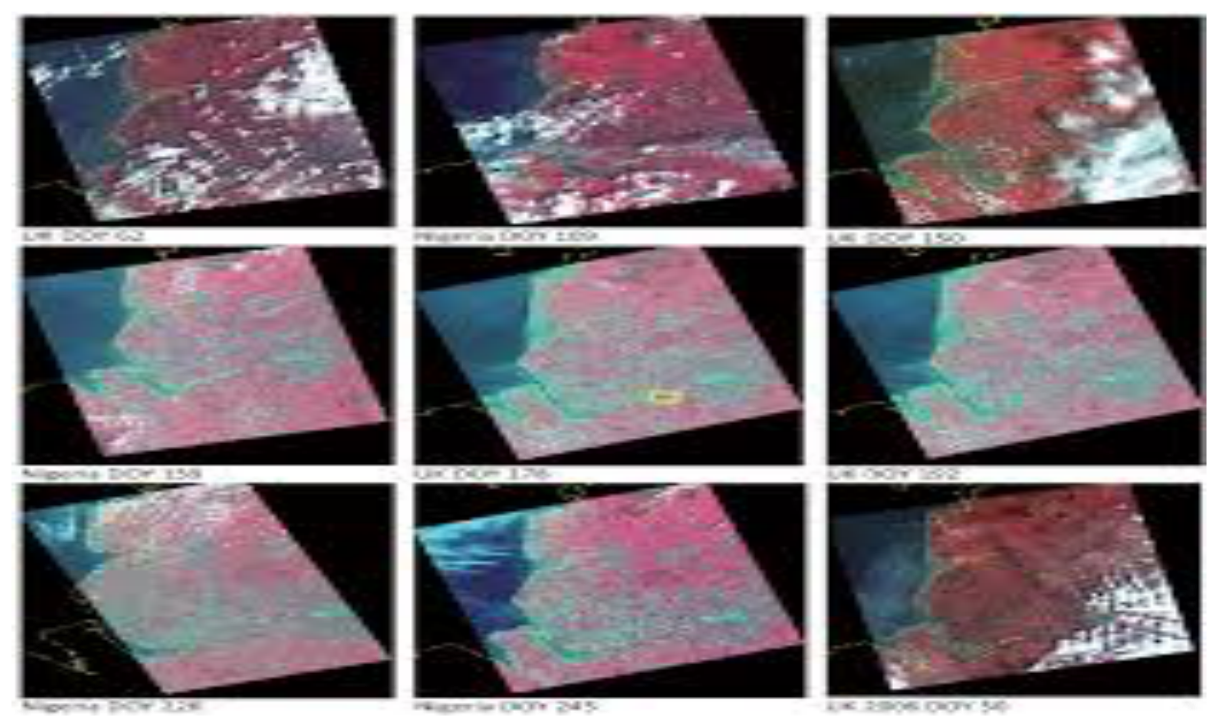
…and **Ground Truth** (or annotation) to build predictive models.



Heterogeneity & Data Fusion

Due to the huge amount of different sensors, today available,
Data Fusion is a very **important and hot topic** in Remote Sensing Community

[Schmitt16] M. Schmitt and X. X. Zhu, "Data Fusion and Remote Sensing: An ever-growing relationship". IEEE Geoscience and Remote Sensing Magazine 4(4): 6--23, 2016

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Data Fusion process (for Remote Sensing Data) [Schmitt16] :

- **MATCHING AND COREGISTRATION** (i.e. align together sources via coordinate transformations and unit adjustments)

- **FUSION BY ESTIMATION** (the step in which data are really fused together):
  - Combine multiple images covering the same area to **reduce uncertainty**
  - Combine together multiple images with **complementary** spatio/spectral **information**
  - Combine images with **shared information**: i.e. combine multiple VHR images for 3-D reconstruction

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Heterogeneity & Data Fusion

Fusion can happen at different levels

[Schmitt16]

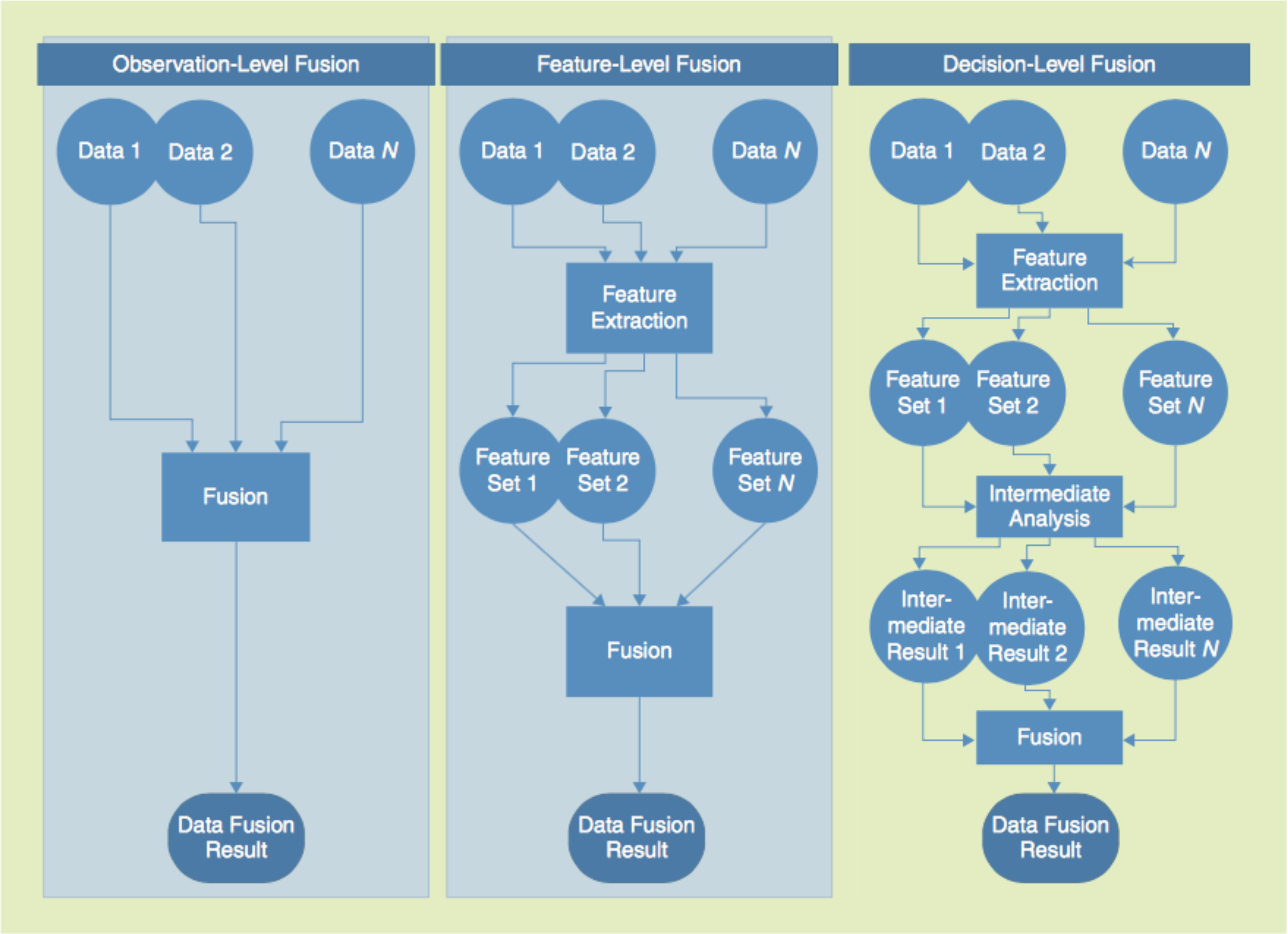

FIGURE 3. The three types of data fusion are compared side by side: observation level, feature level, and decision level.

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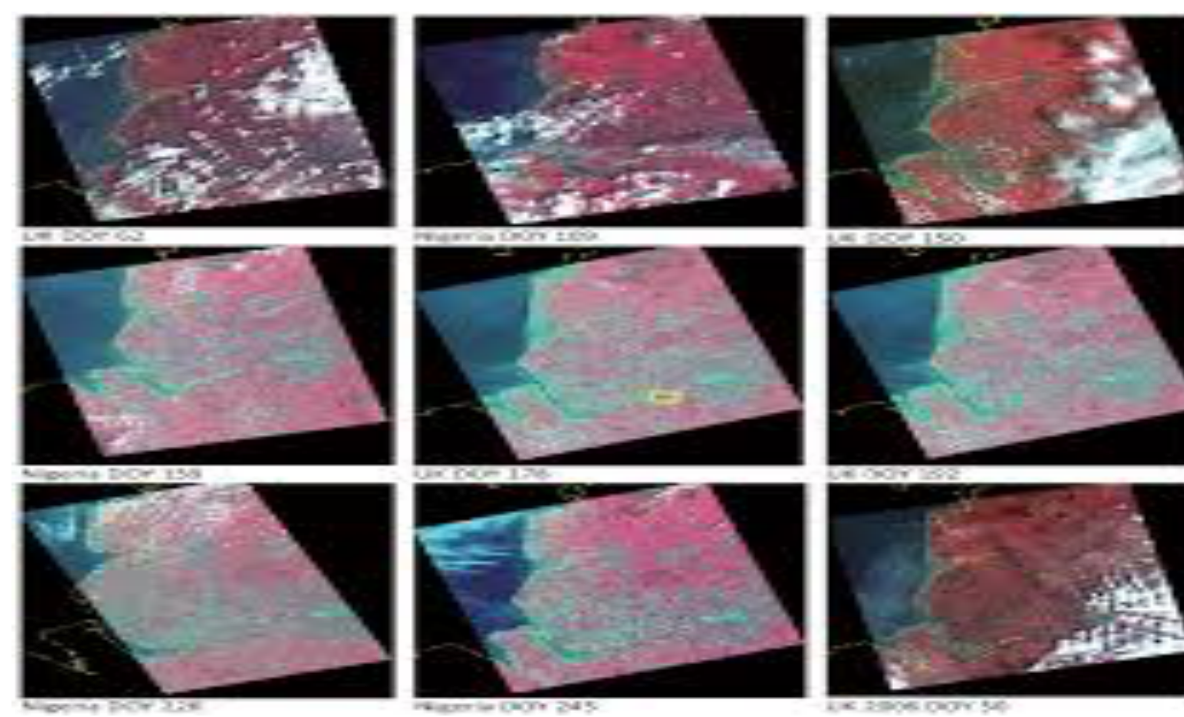

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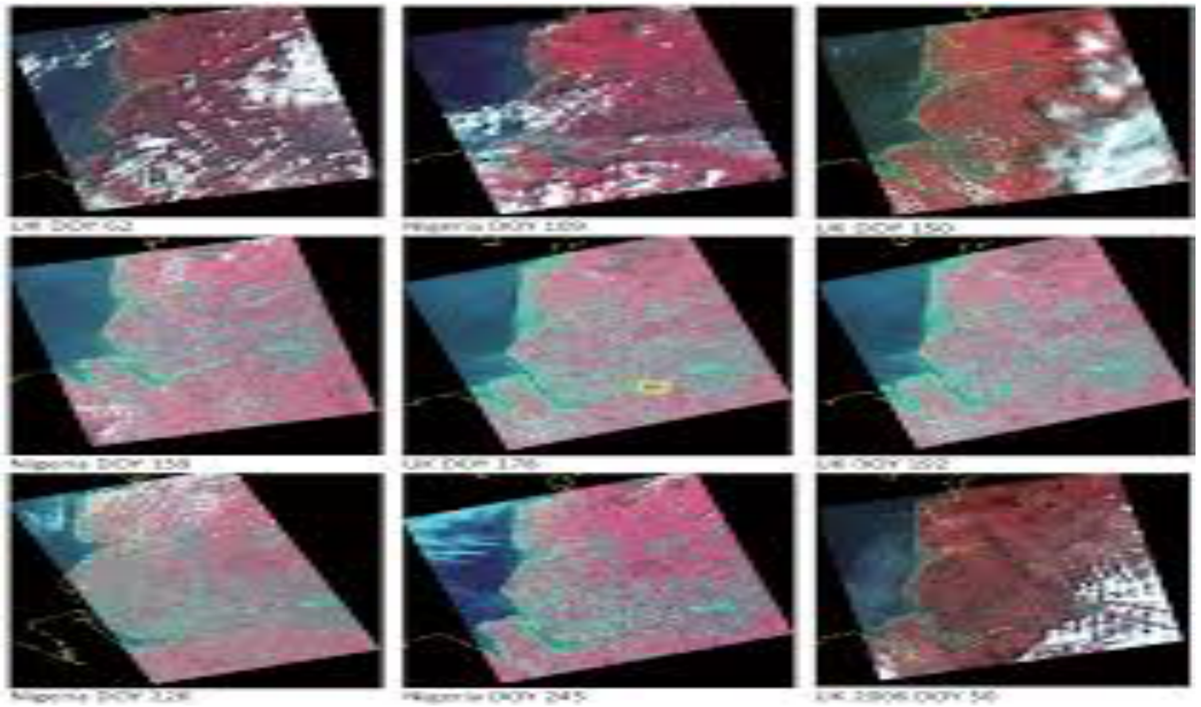

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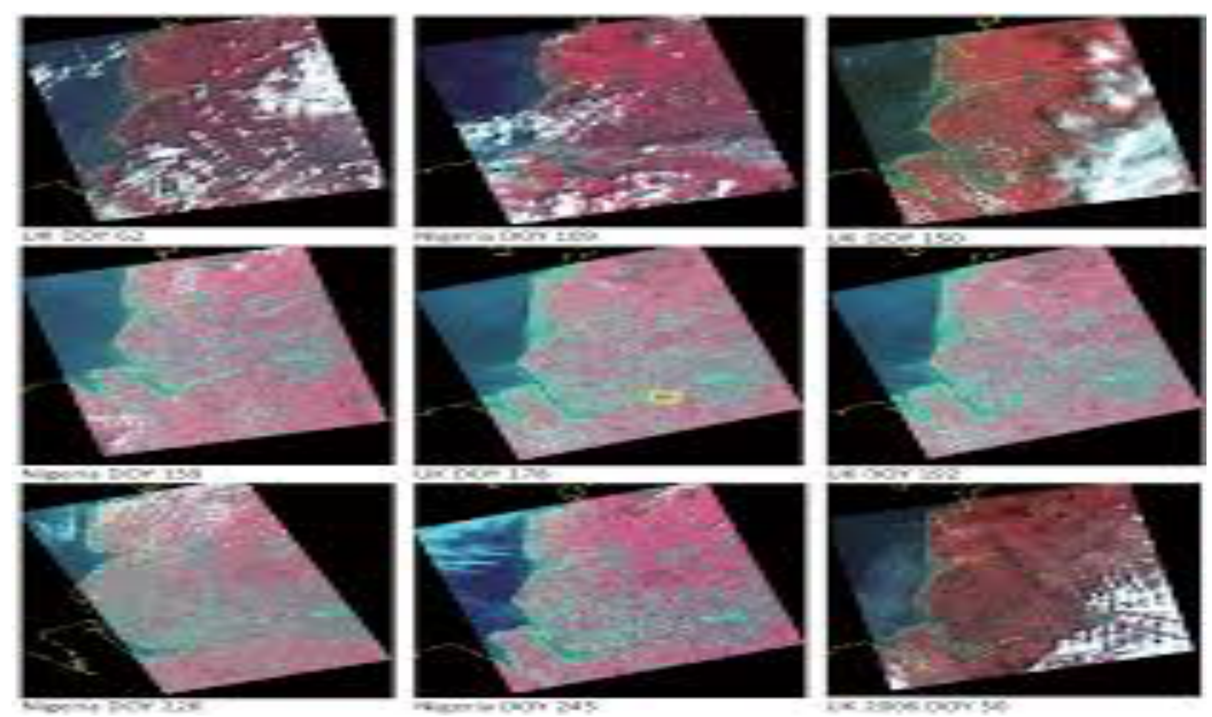

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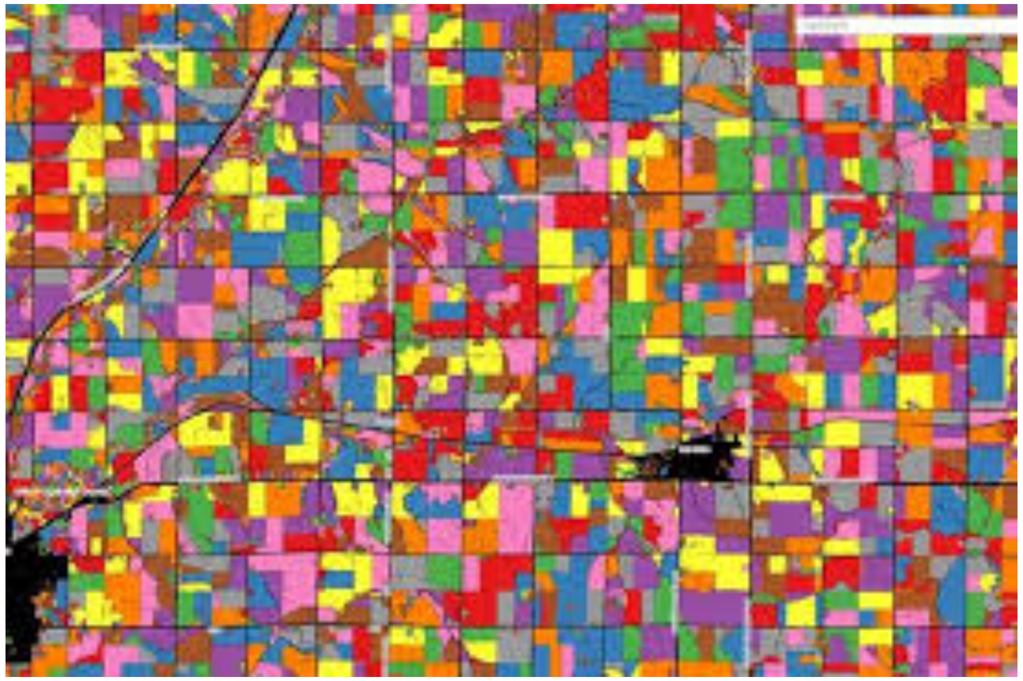
Current Trends in RS

Nowadays, Machine Learning techniques are a standard tool in Remote Sensing analytics [Holloway18]:

- Deal with huge amount of data
- Automatically build predictive methods
- Group together similar areas
- Detect Objects of Interest



[Holloway18] J. Holloway, K. Mengersen: Statistical Machine Learning Methods and Remote Sensing for Sustainable Development Goals: A Review. Remote Sensing 10(9): 1365 (2018)

[LeCun15] Y. LeCun, Y. Bengio and G. Hinton. “Deep Learning” In Nature 52(8): 436-444 (2015).

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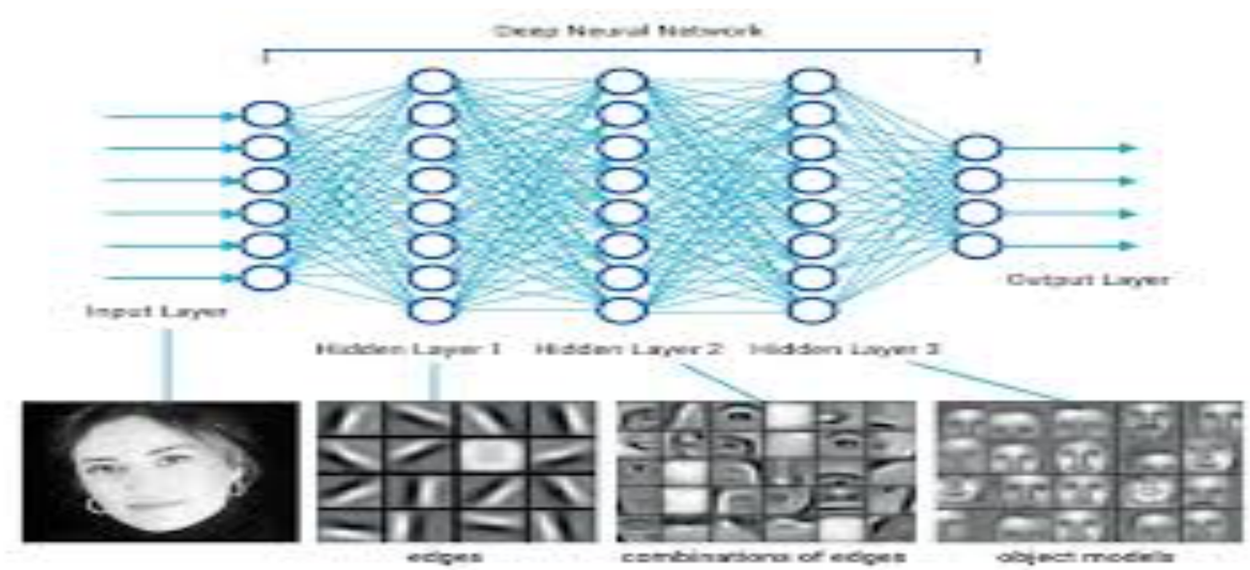
Recent Trends ‘**Deep Learning Methods’** [LeCun15] **:**

- Inspired by human brain
- Layers architecture
- Applications in different domains:
  + Speech Recognition
  + Image Recognition
  + Natural Language Processing



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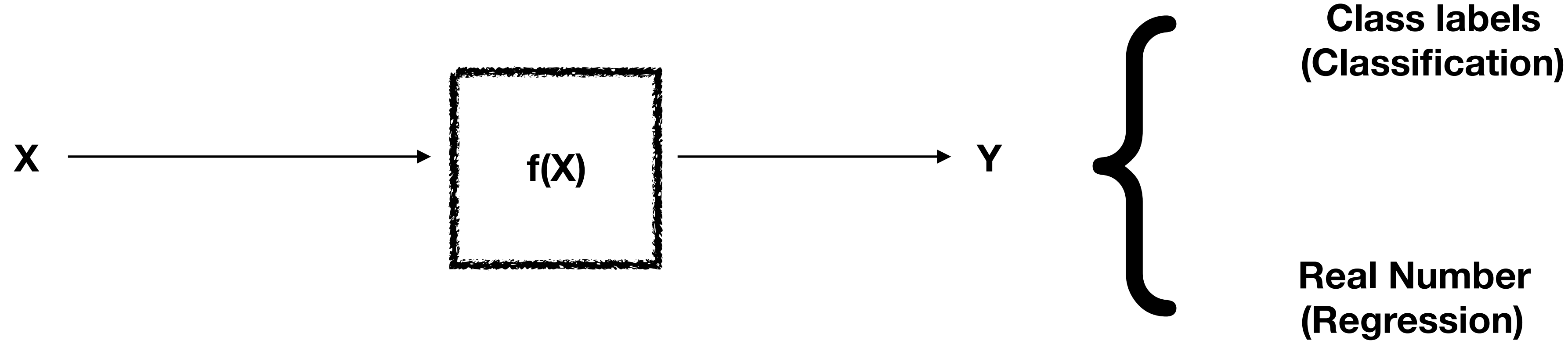
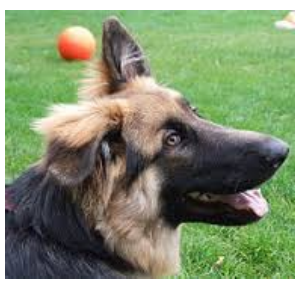
Machine Learning



Machine Learning

X → f(X) → Y

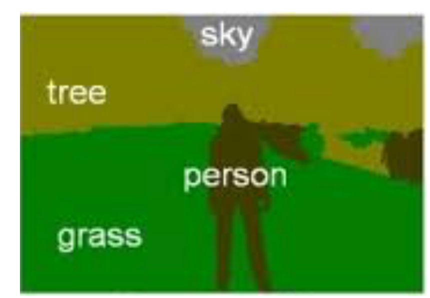
Y:
- **Class labels (Classification)**
- **Real Number (Regression)**



Object Recognition →

{Dog, Cat, Sheep, Bear, Lion, …}

Semantic Segmentation →



Sentiment Classification →

Deep Learning
Learning representation

Traditional Machine Learning systems leverage **feature engineering** to represent the data:
- Text Analysis: Bag of Words
- Image Analysis: Hog (Histogram of Oriented gradient), SIFT (Scale Invariant Feature Transform)

→ **Hand-Crafted Features** → **Simple Trainable Classifier (SVM, RF, NB, ...)**

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Deep Learning approaches **learn internal representations (new features)** without necessity of hand-crafted features

Trainable Feature Extractor → **Trainable Classifier**

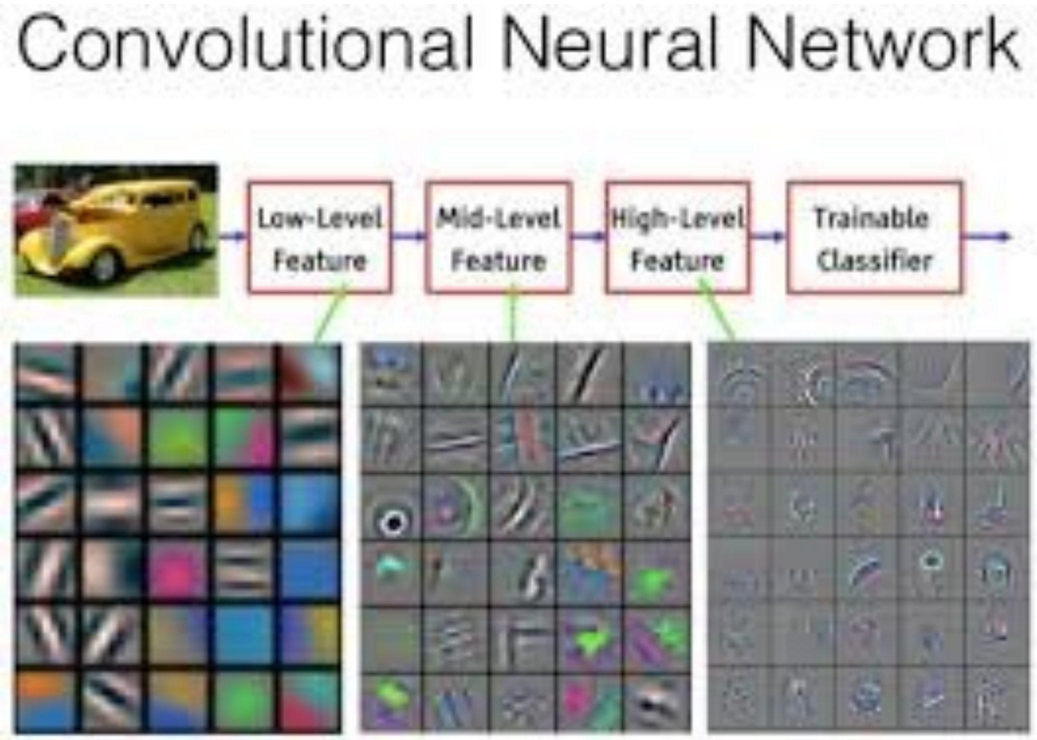
Deep Learning Model

Deep Learning
Learning representation

Deep Learning allows to:

Learn different level of features from low-level to high-level in a kind of hierarchical organisation

Can share the low-level representation for many different tasks



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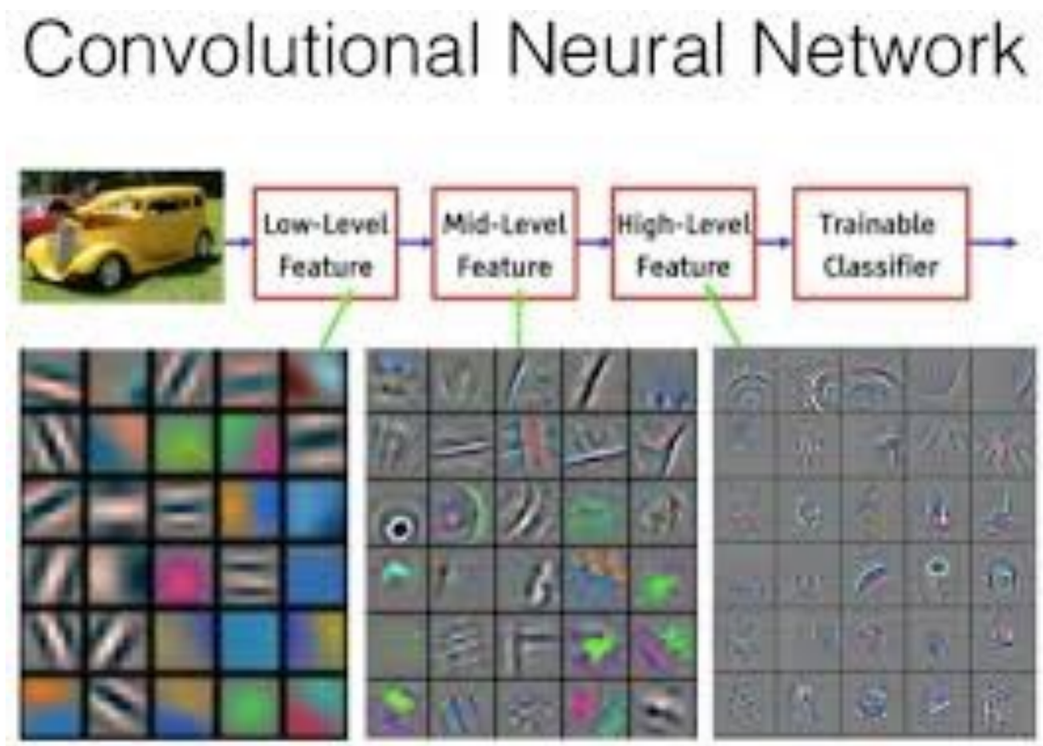


Deep Learning, nowadays, is used in many domains:

Computer Vision (Object Detection and Segmentation, Image SuperResolution, Image Classification)

Natural Language Processing (NLP) and Speech

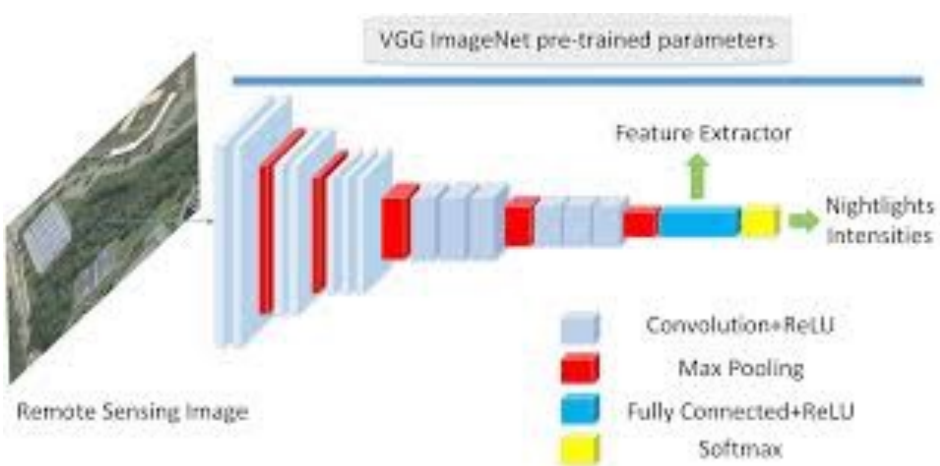
Robotics and AI

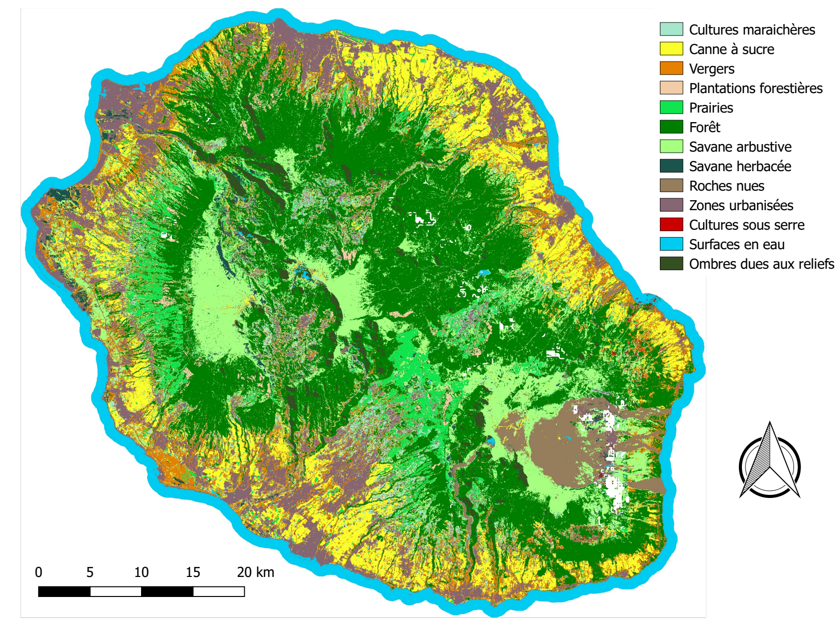
Music and arts!

TERRITOIRE ENVIRONNEMENT TÉLÉDÉTECTION INFORMATION SPATIALE

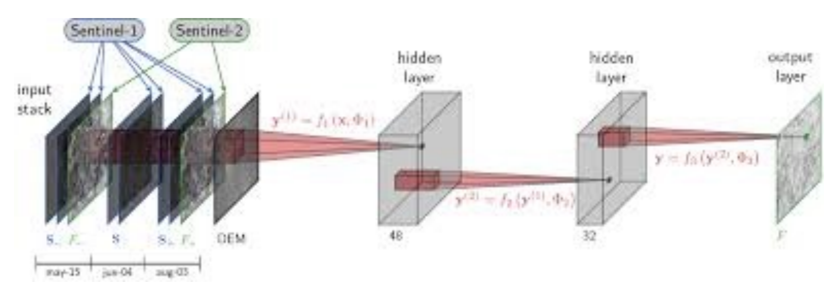
Deep Learning & Earth Observation (EO) Data

Scene Classification



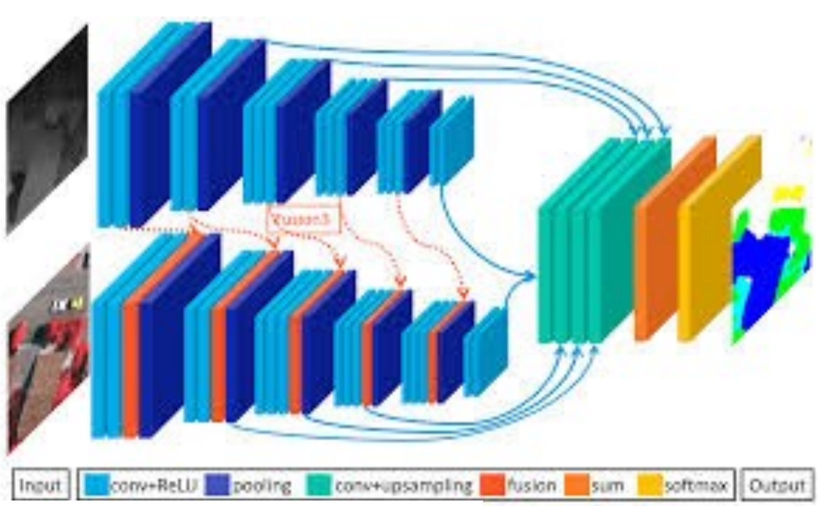


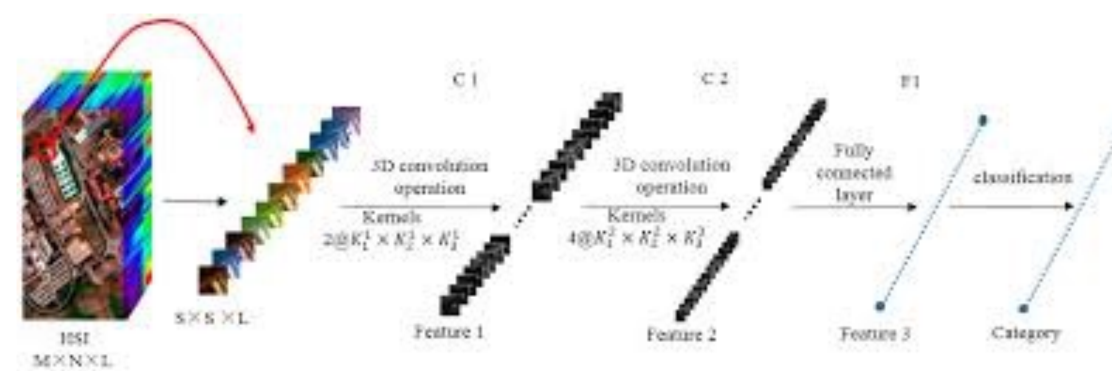
Satellite Image Time Series Analysis



Land Cover Mapping

Remote Sensing Data Fusion





Hyperspectral Classification and Retrieval

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Deep Learning & Earth Observation (EO) Data

Three popular Deep Learning base blocks in Remote Sensing are:

- Convolutional Neural Network (**CNNs**)
- Recurrent Neural Networks (**RNNs**)
- Convolutional Recurrent Neural Networks (**ConvRNNs**)

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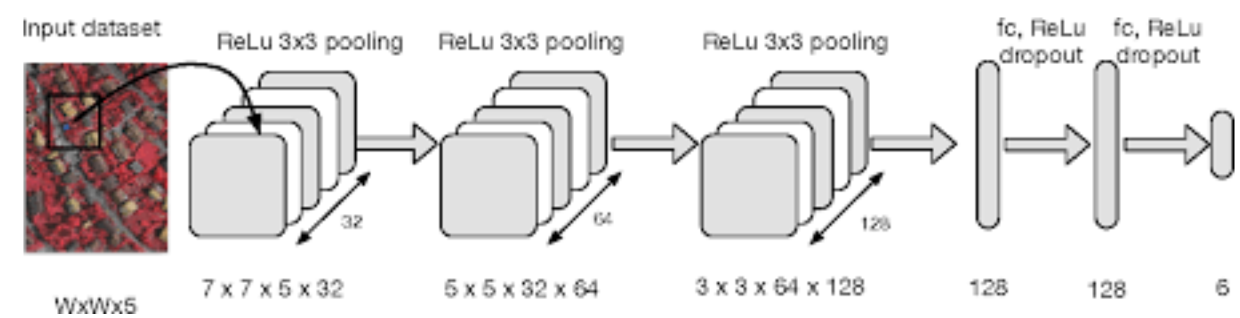
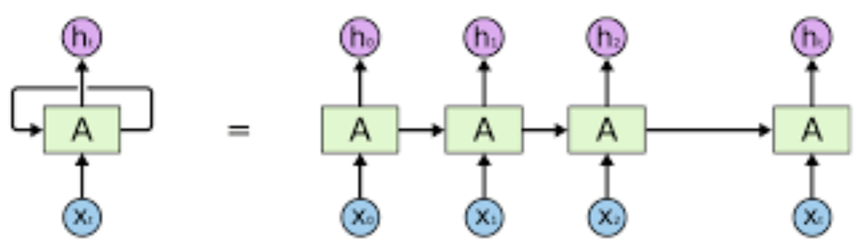
CNNs



Well suited neural networks to model (mainly) spatial-autocorrelation via Convolution

RNNs



Well suited neural networks to model temporal correlation via recurrent operations

CNNs

CNNs are a special type of neural network whose hidden units are only connected to local receptive field.

The number of parameters needed by CNNs is much smaller than a Fully Connected counterpart.

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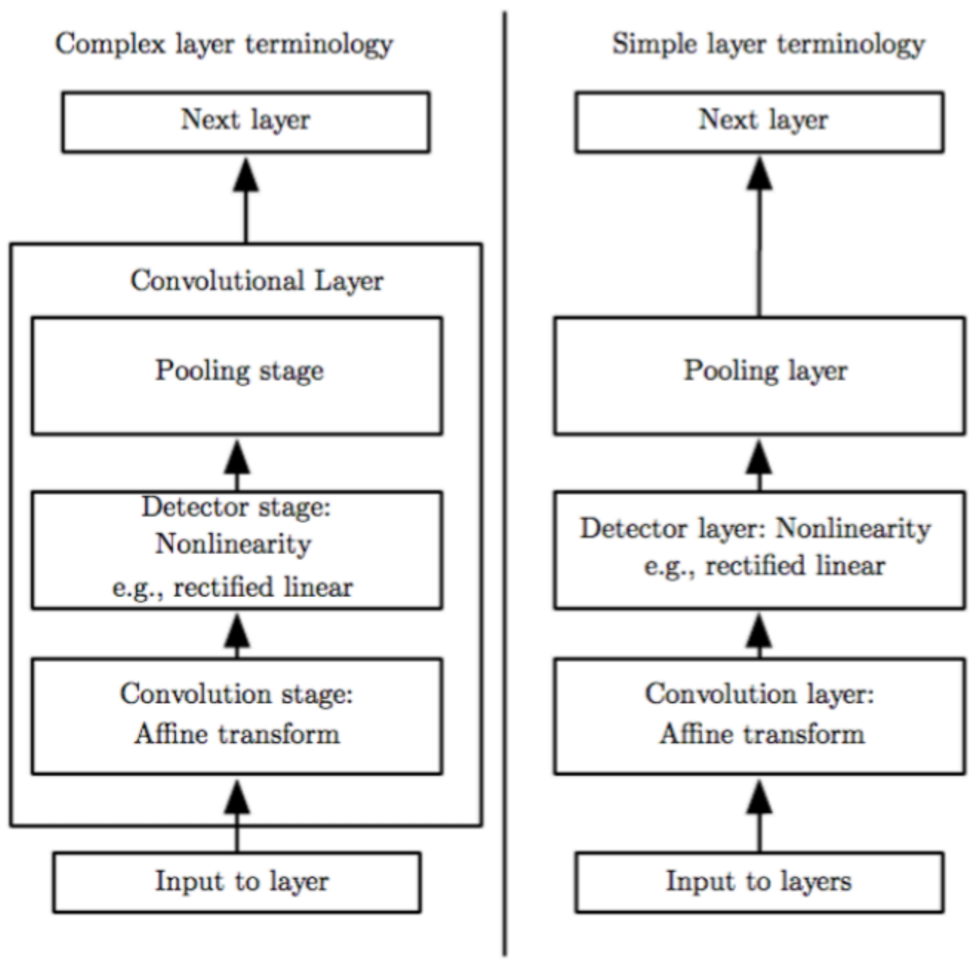


CNN has three main stages:

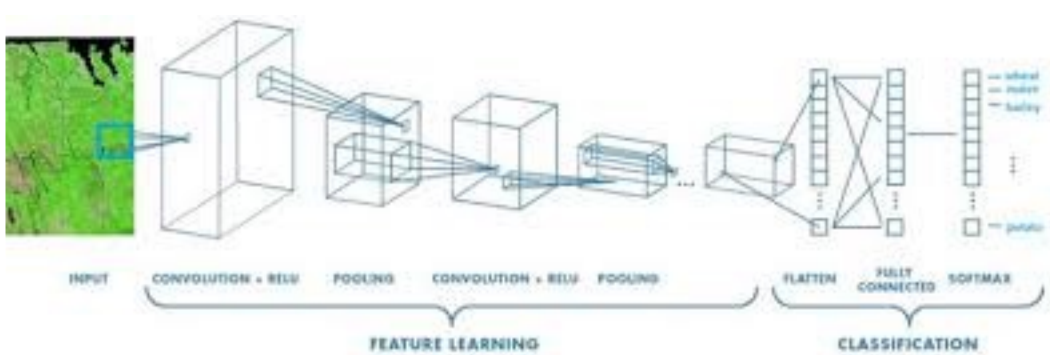
1) Convolution Stage
2) Non-linearity Stage
3) Pooling Stage

Commonly, a normalisation stage is added between 1) and 2)

Deep Learning & Earth Observation (EO) Data

CNN can be employed to perform:
- Image Classification
- Semantic Segmentation

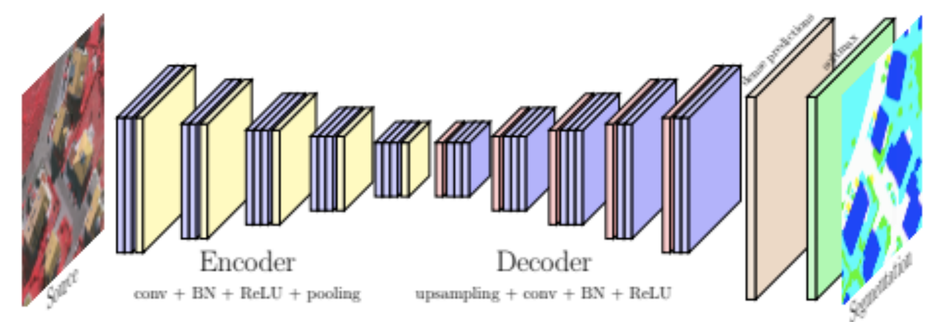
Image Classification



The input is an image and the output is a label for the whole image

In Remote Sensing, the image classification is also employed to perform patch-based classification

Semantic Segmentation



The input is an image, the output is an image with a label for each input pixel

The common architecture for Semantic Segmentation is called AutoEncoder

RNNs

RNNs are a special type of neural network **characterised by recurrent connections**.
The output of the network **at time t** is exploited by the network itself **at time t+1**

Nowadays, two different RNNs model are mainly employed:

- **LSTM** (Long-Short Term Memory)
- **GRU** (Gated Recurrent Unit)

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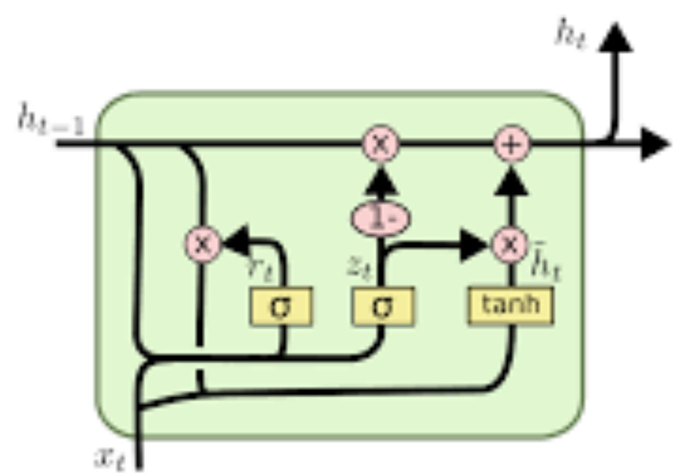
Such kind of network are heavily exploited in Natural Language Processing and Speech Recognition or other kind of 1-D signal

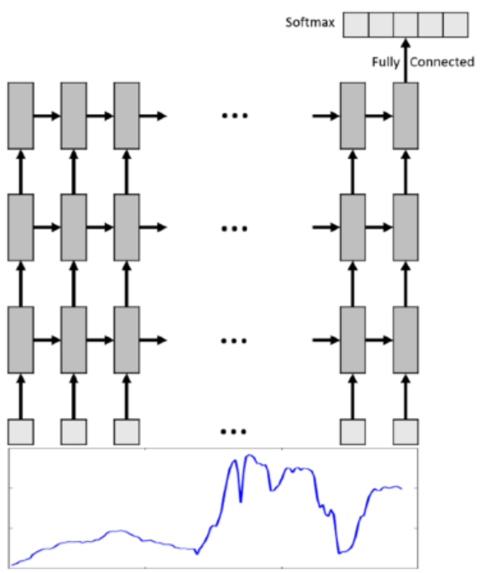


$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$
$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$
$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Deep Learning & Earth Observation (EO) Data

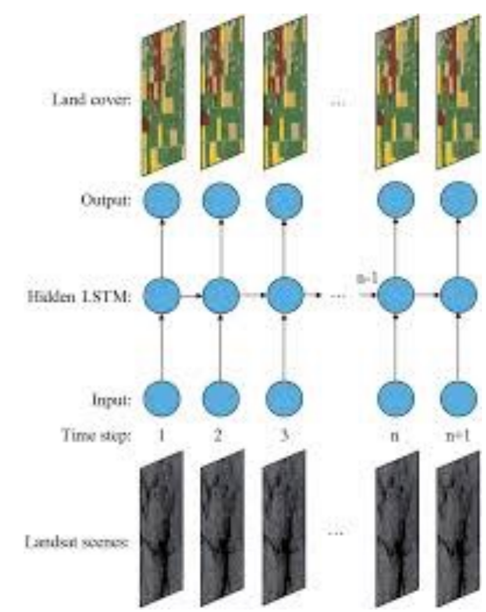
RNN can be employed to perform:
- Signal Classification
- Time Series Analysis

Time Series Classification



The input is a multidimensional Time Series and the output is the classification label

Per-Time classification



The input is a multidimensional Time Series and the output is a label per timestamps

Deep Learning & Earth Observation (EO) Data

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- Signal Classification
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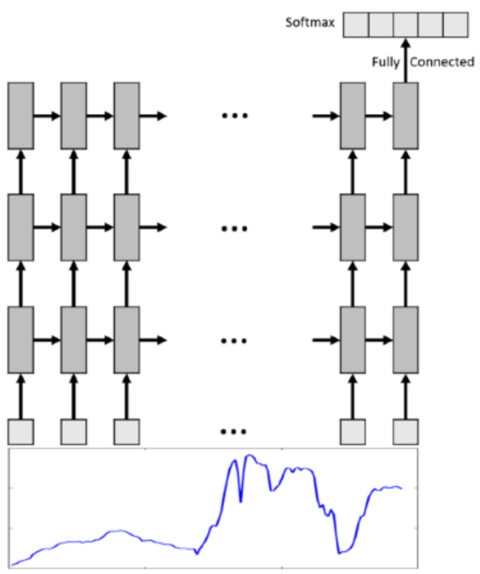
Time Series Classification



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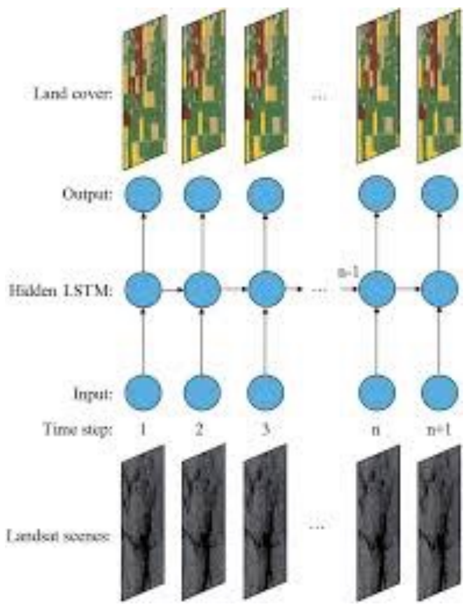

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In Remote Sensing, RNN models are especially employed for **Satellite Image Time Series** or **Hyperspectral** data

ConvRNN

ConvRNNs are neural network models that combine Convolutional and Recurrent Neural Network together to manage spatio-temporal information characterised by spatial as well as temporal correlations.

The ConvRNN Unit is a recurrent unit that integrates convolutional filters.

The output of the network **at time t** is exploited by the network itself **at time t+1**

[Shi15] X. Shi, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, W.-c. Woo: Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. NIPS 2015: 802-810

Deep Learning & Earth Observation (EO) Data

ConvRNN

ConvRNNs are neural network models that combine Convolutional and Recurrent Neural Network together to manage spatio-temporal information characterised by spatial as well as temporal correlations.

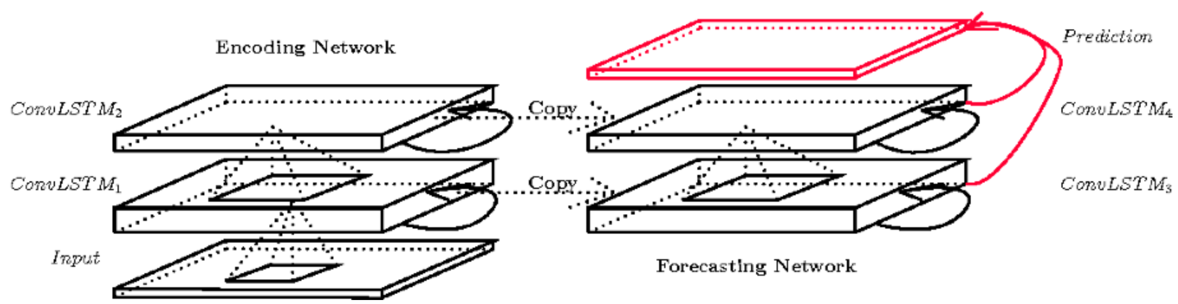
The ConvRNN Unit is a recurrent unit that integrates convolutional filters.

The output of the network **at time t** is exploited by the network itself **at time t+1**

ConvRNN can be derived considering both:

- **LSTM** (Long-Short Term Memory)
- **GRU** (Gated Recurrent Unit)

In which the inner kernel is replaced by convolutional filters



[Shi15]

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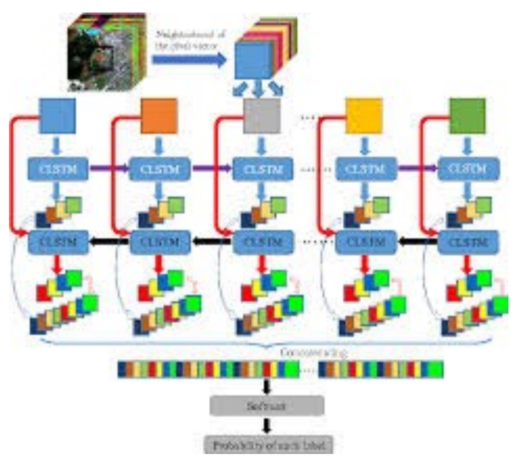
Deep Learning & Earth Observation (EO) Data

ConvRNN

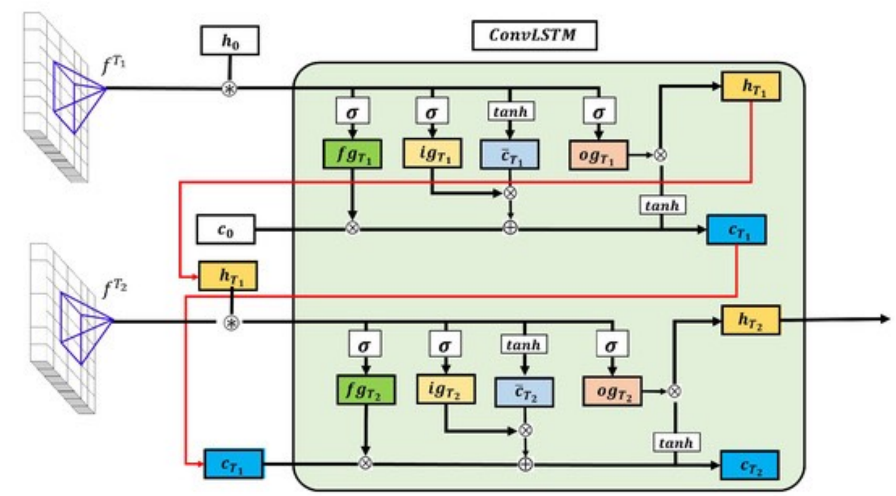
ConvRNN can be employed to perform:
- Semantic Segmentation for Time Series
- Spatio-Spectral Analysis
- Change Detection

Semantic Segmentation for Time Series



The input is a Time Series of images and the output is the classification label for each pixel

Spatio-Spectral Analysis



The input is an hyper spectral signal with spatial context and the output is a label

Deep Learning & Earth Observation (EO) Data

ConvRNN

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- Spatio-Spectral Analysis
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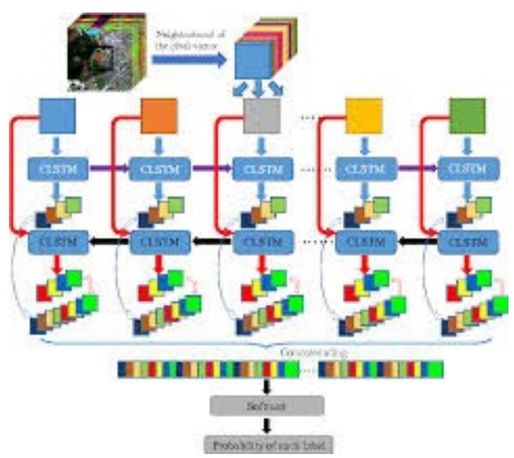
Semantic Segmentation for Time Series



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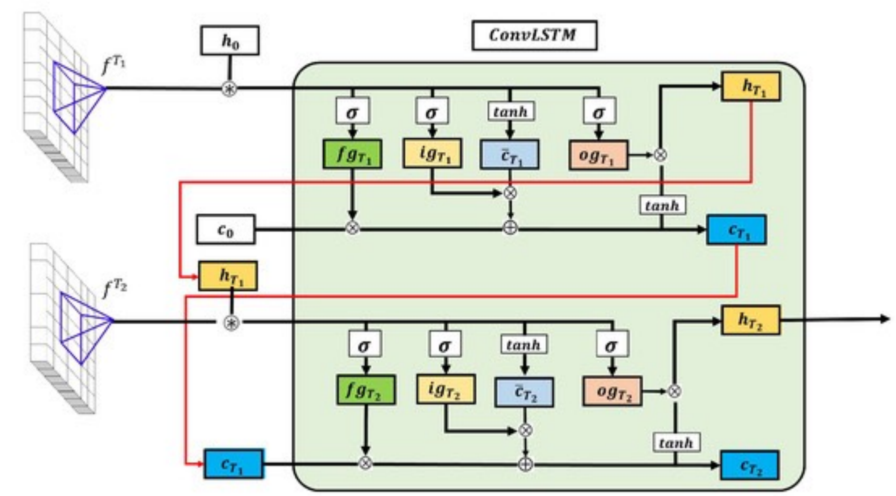
Spatio-Spectral Analysis



The input is an hyper spectral signal with spatial context and the output is a label

In Remote Sensing, ConvRNN models are especially employed for **Satellite Image Time Series** or **Hyperspectral** data

Sparsely vs Densely Annotated Data

In classical Computer Vision we have (mainly) two scenarios:

- A **label** associated to **each image** (image classification)
- A **label** associated to **each pixel** (semantic segmentation)

Sparsely vs Densely Annotated Data

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On the other hand, in Remote Sensing we have (mainly) two scenarios:
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- A **label** associated to **a (small) sets of segments/objects** in a geographical area

Deep Learning & Earth Observation (EO) Data

Sparsely vs Densely Annotated Data

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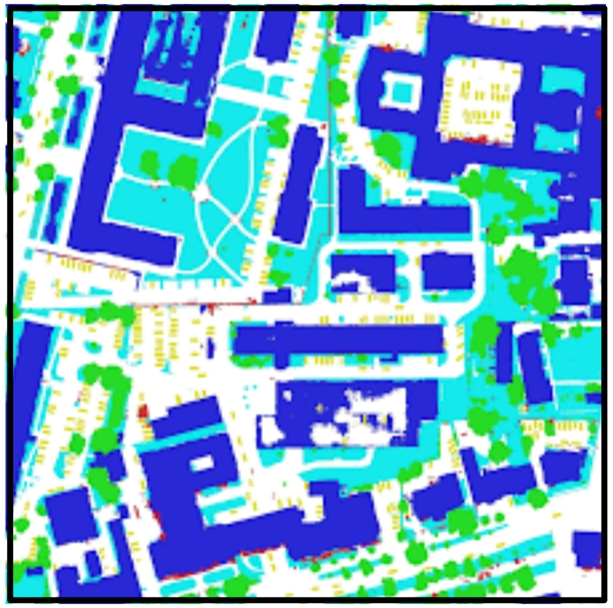
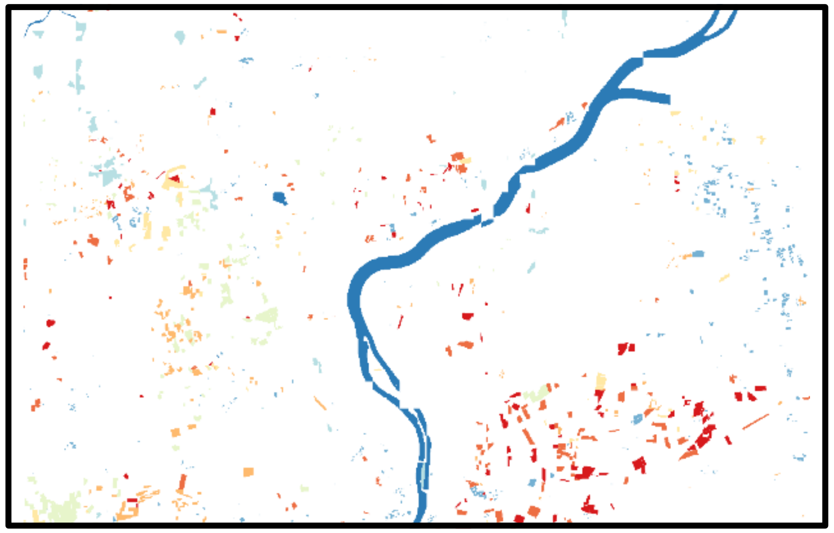


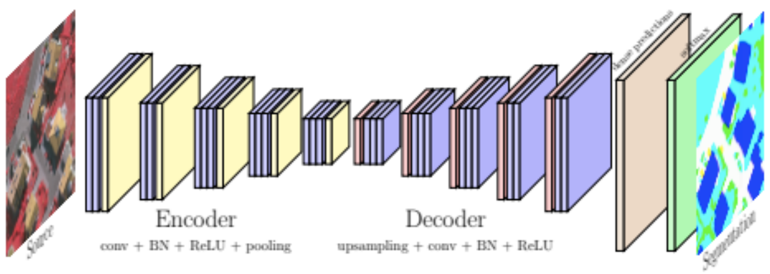
Densely Annotated



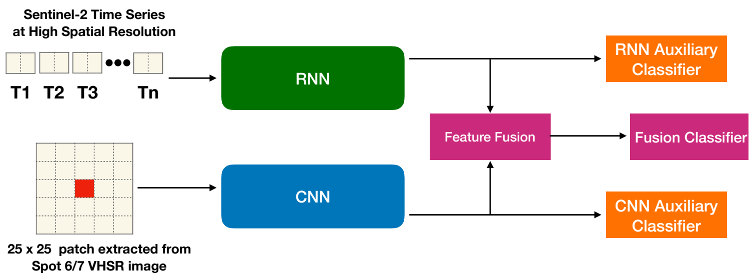
Sparsely Annotated

The white pixels are:
- A specific class -> Densely Annotated
- No knowledge about the class -> Sparsely Annotated

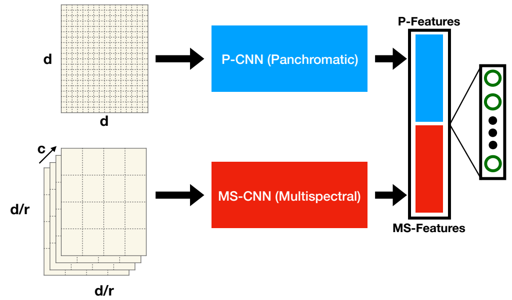
Deep Learning & EO Data Fusion



(Very High Spatial Resolution)
VHSR + DEM [Audebert17]



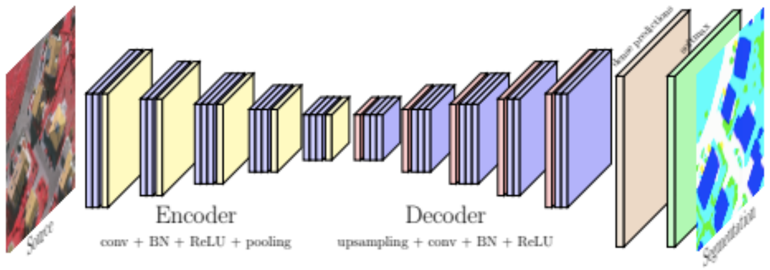
Time Series + VHSR [Benedetti18]



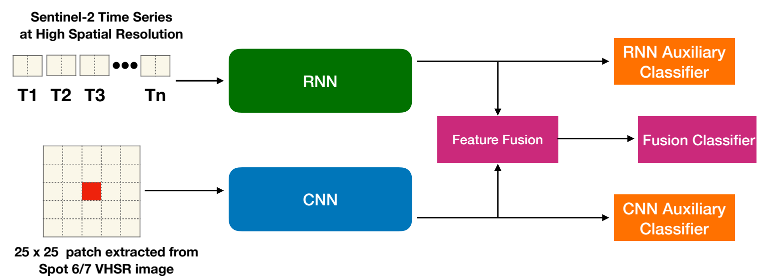
Pan + MS information from VHSR
[Gaetano18]

[Chen17] Y. Chen, C. Li, P. Ghamisi, X. Jia, Y. Gu: Deep Fusion of Remote Sensing Data for Accurate Classification. IEEE GRSL 14(8): 1253-1257 (2017)
[Audebert17] N. Audebert, B. Le Saux, S. Lefèvre: Beyond RGB: Very High Resolution Urban Remote Sensing With Multimodal Deep Networks. ISPRS J. of Photogrammetry and Rem. Sens. 140, 20-32 (2018)
[Benedetti18] P. Benedetti, D. Ienco, R. Gaetano, K. Ose, R. G. Pensa, S. Dupuy: M3Fusion: A Deep Learning Architecture for Multi-{Scale/Modal/Temporal} satellite data fusion. IEEE JSTARS (2018)
[Gaetano18] R. Gaetano, D. Ienco, K. Ose, C. Cresson: MRFusion: A Deep Learning architecture to fuse PAN and MS imagery for land cover mapping CoRR abs/ (2018)
[Ienco19] D. Ienco, R. Gaetano, R. Interdonato, K. Ose and D. Ho Tong Minh: Combining Sentinel-1 and Sentinel-2 time series via RNN for object-based Land Cover Classification. IGARSS (2019).
[Cresson19] R. Cresson, D. Ienco, R. Gaetano, K. Ose and D. Ho Tong Minh: Optical images gap filling with deep convolutional autoencoder. IGARSS (2019).

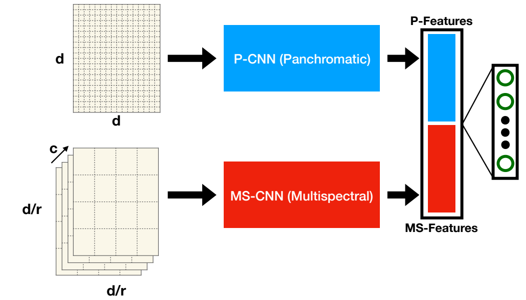
Deep Learning & EO Data Fusion



(Very High Spatial Resolution) VHSR + DEM [Audebert17]



Time Series + VHSR [Benedetti18]



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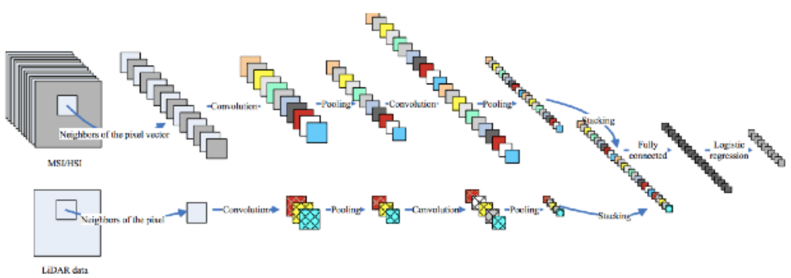
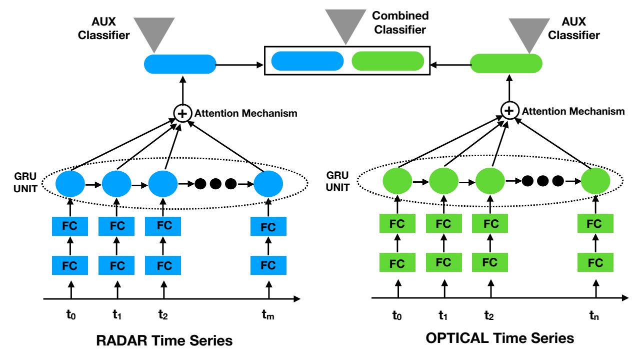
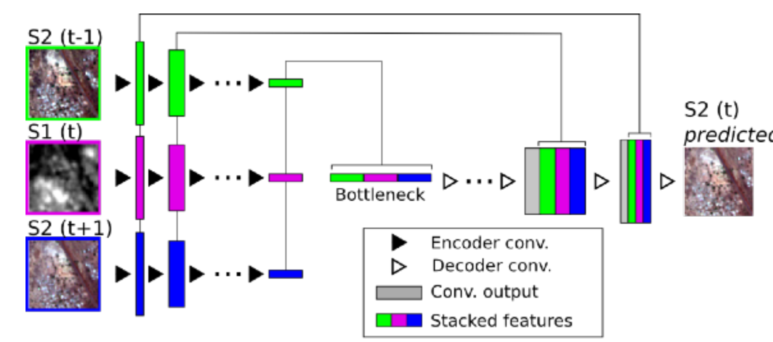


Hyperspectral + DEM [Chen17]



Sentinel1 & Sentinel2 Satellite Image Time Series Classification [Ienco19]



Sentinel1 & Sentinel2 Satellite Image Time Series Restoration [Cresson19]

[Chen17] Y. Chen, C. Li, P. Ghamisi, X. Jia, Y. Gu: Deep Fusion of Remote Sensing Data for Accurate Classification. IEEE GRSL 14(8): 1253-1257 (2017)
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DL & EO Data Fusion: Applications Examples

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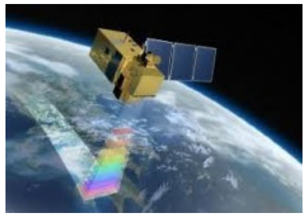
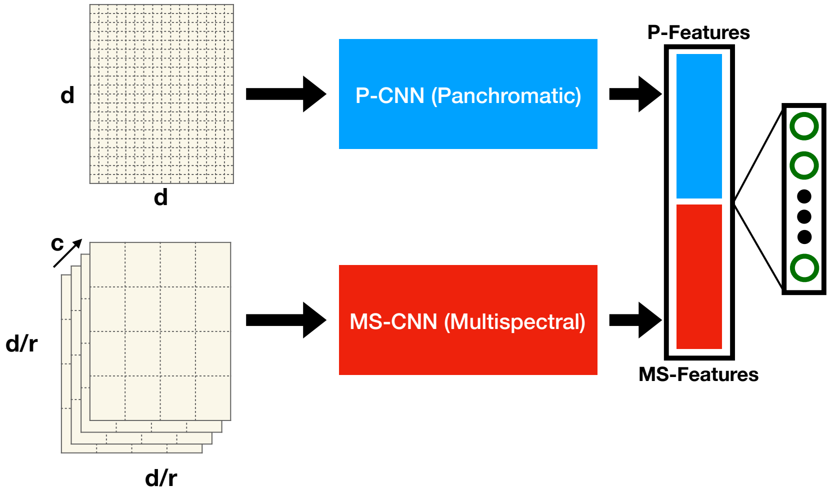
MRFusion: A DL approach to fuse PAN and MS for LC mapping



Single-Sensor Data Fusion on SPOT6:
- **Panchromatic Image (1.5m)**
- **Multi-Spectral Image (6m)**



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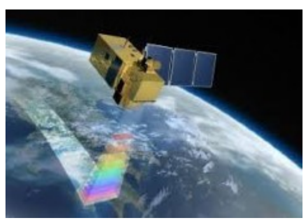

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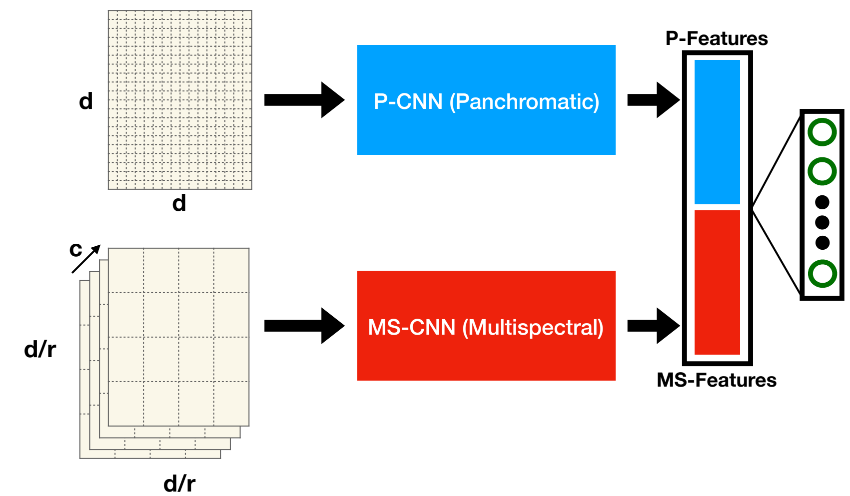
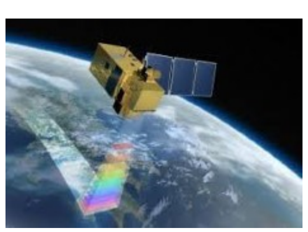
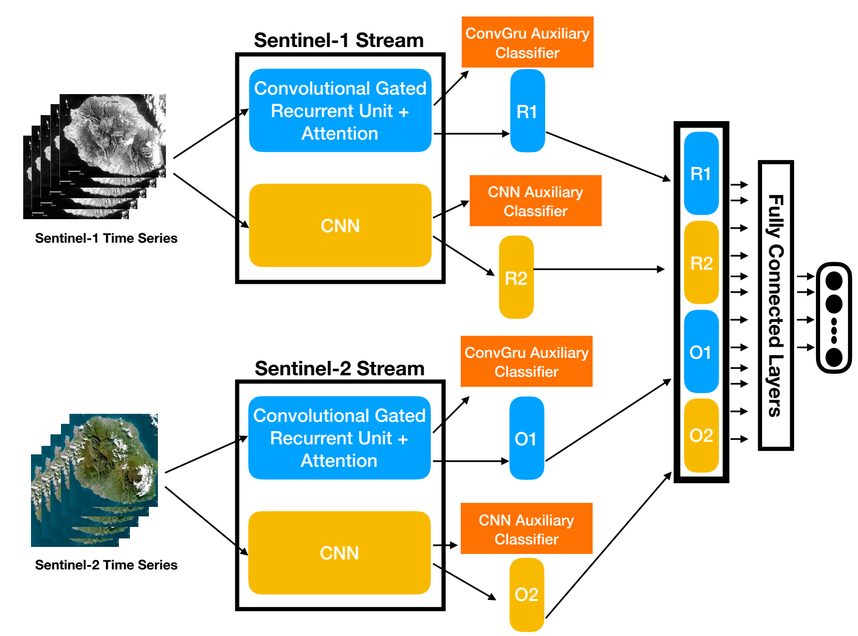


TWINNS: fuse Radar/Optical Time Series for LC Mapping via DL



Multi-Sensor Multi-Temporal Data Fusion
- **Sentinel 1 Time Series Images (10m)**
- **Sentinel 2 Time Series Images (10m)**



MRFusion: A DL approach to fuse PAN and MS for LC mapping [Gaetano18]

[Gaetano18] R. Gaetano, D. Ienco, K. Ose, R. Cresson: "A Two-Branch CNN Architecture for Land Cover Classification of PAN and MS Imagery". Remote Sensing 10(11): 1746 (2018)

Different Data fusion scenario [Schmitt16]:

- **Single-Sensor Data Fusion**
- Multiple-Sensor Data Fusion
- Temporal Data Fusion
- **Machine Learning-Based Data Fusion**
- And so on….

[Schmitt16] M. Schmitt and X. X. Zhu, "Data Fusion and Remote Sensing: An ever-growing relationship". IEEE Geoscience and Remote Sensing Magazine 4(4): 6--23, 2016

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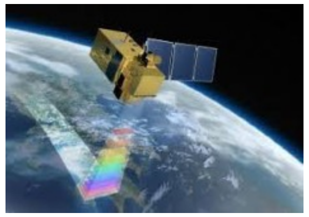

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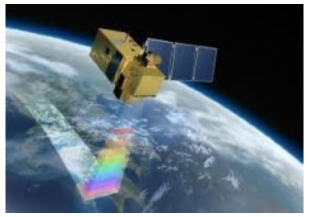
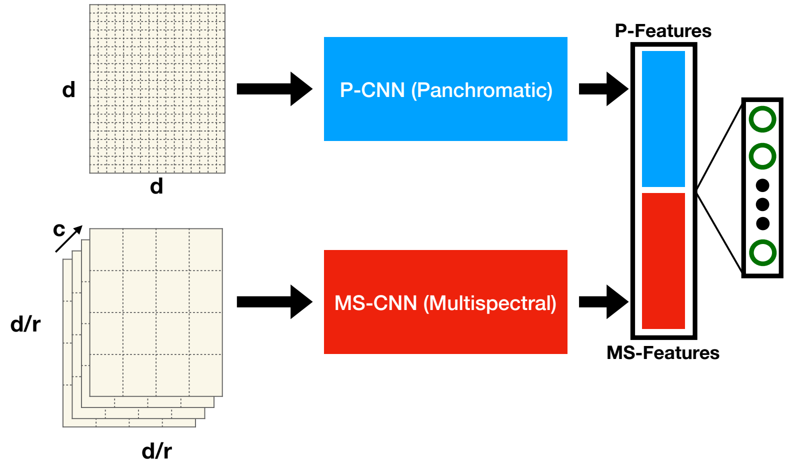


Single-Sensor Data Fusion on SPOT6:

- **Panchromatic Image (1.5m)**
- **Multi-Spectral Image (6m)**

To this end, we conceive a Deep Learning approach leveraging:

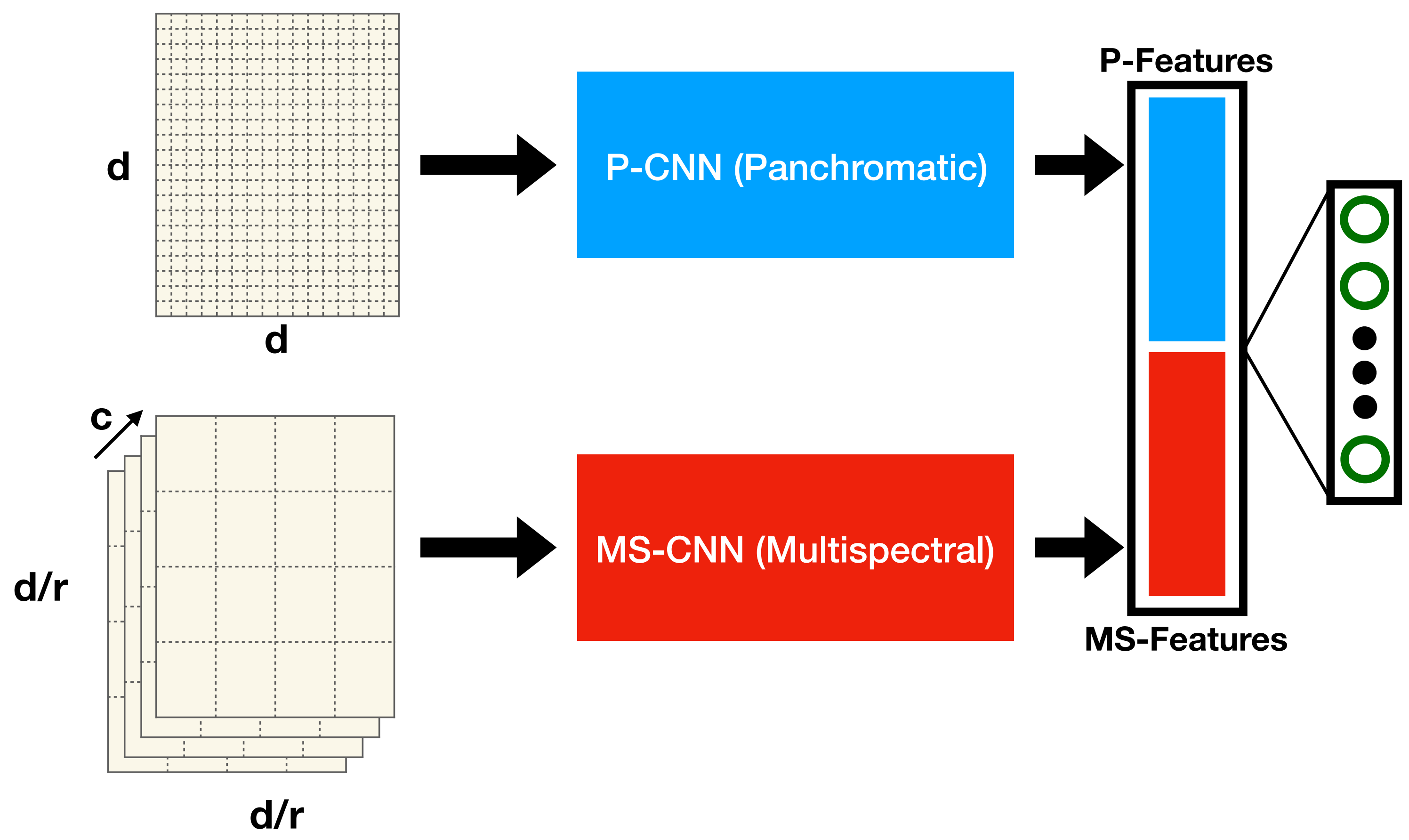
- Convolutional Neural Network (PAN)
- Convolutional Neural Network (MS)



[Schmitt16] M. Schmitt and X. X. Zhu, "Data Fusion and Remote Sensing: An ever-growing relationship". IEEE Geoscience and Remote Sensing Magazine 4(4): 6--23, 2016

MRFusion: A DL approach to fuse PAN and MS for LC mapping

MRFusion: Single-Sensor Multi-Resolution data fusion architecture



MRFusion: A DL approach to fuse PAN and MS for LC mapping

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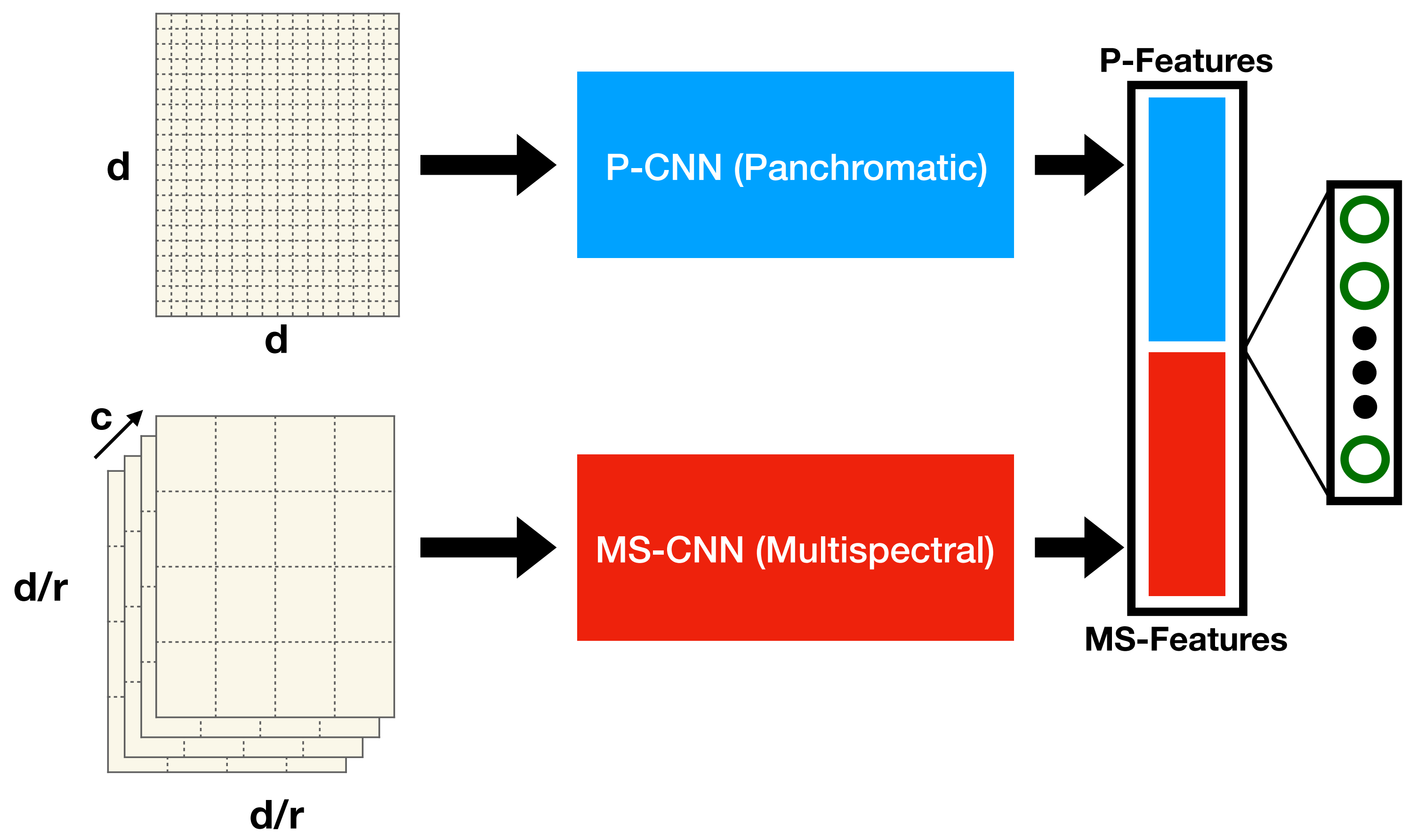
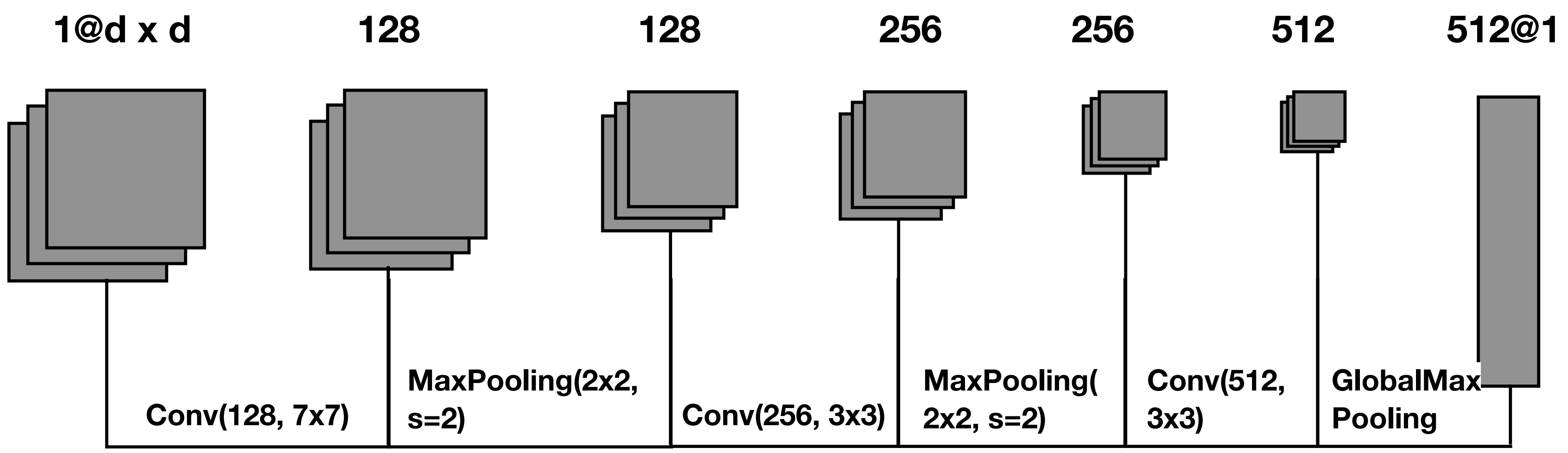


d = patch size on the PAN image
r = spatial ratio between PAN and MS (i.e. in SPOT6 is 4)
c = number of channels in the MS image

MRFusion: A DL approach to fuse PAN and MS for LC mapping

CNNs for Spatial Information

PAN-CNN



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CNNs for Spatial Information

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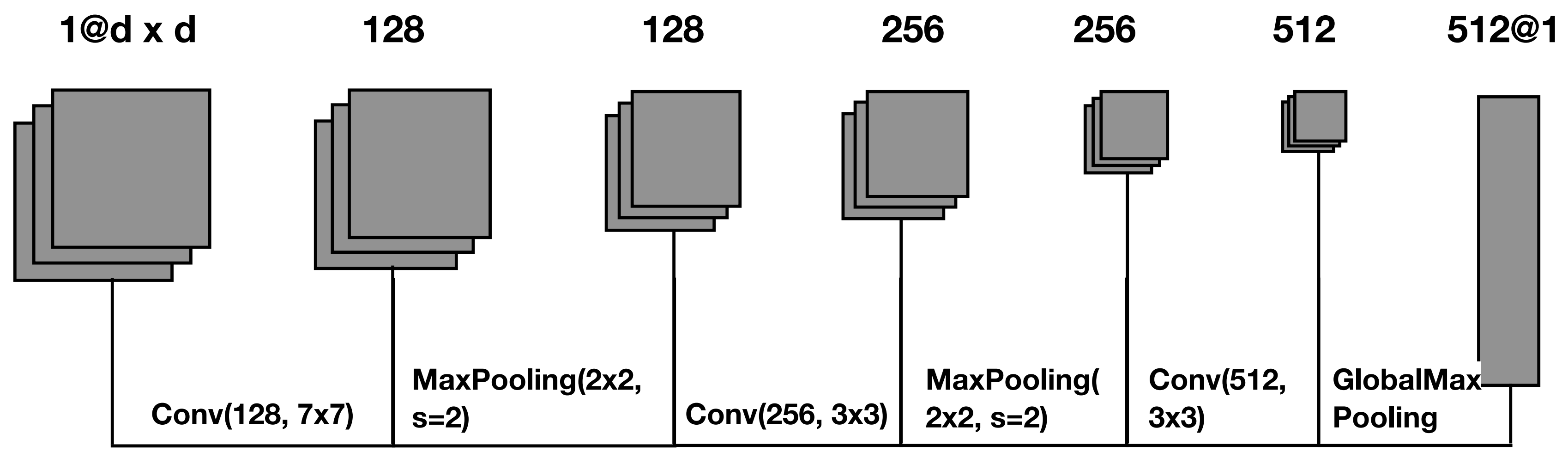


Relu

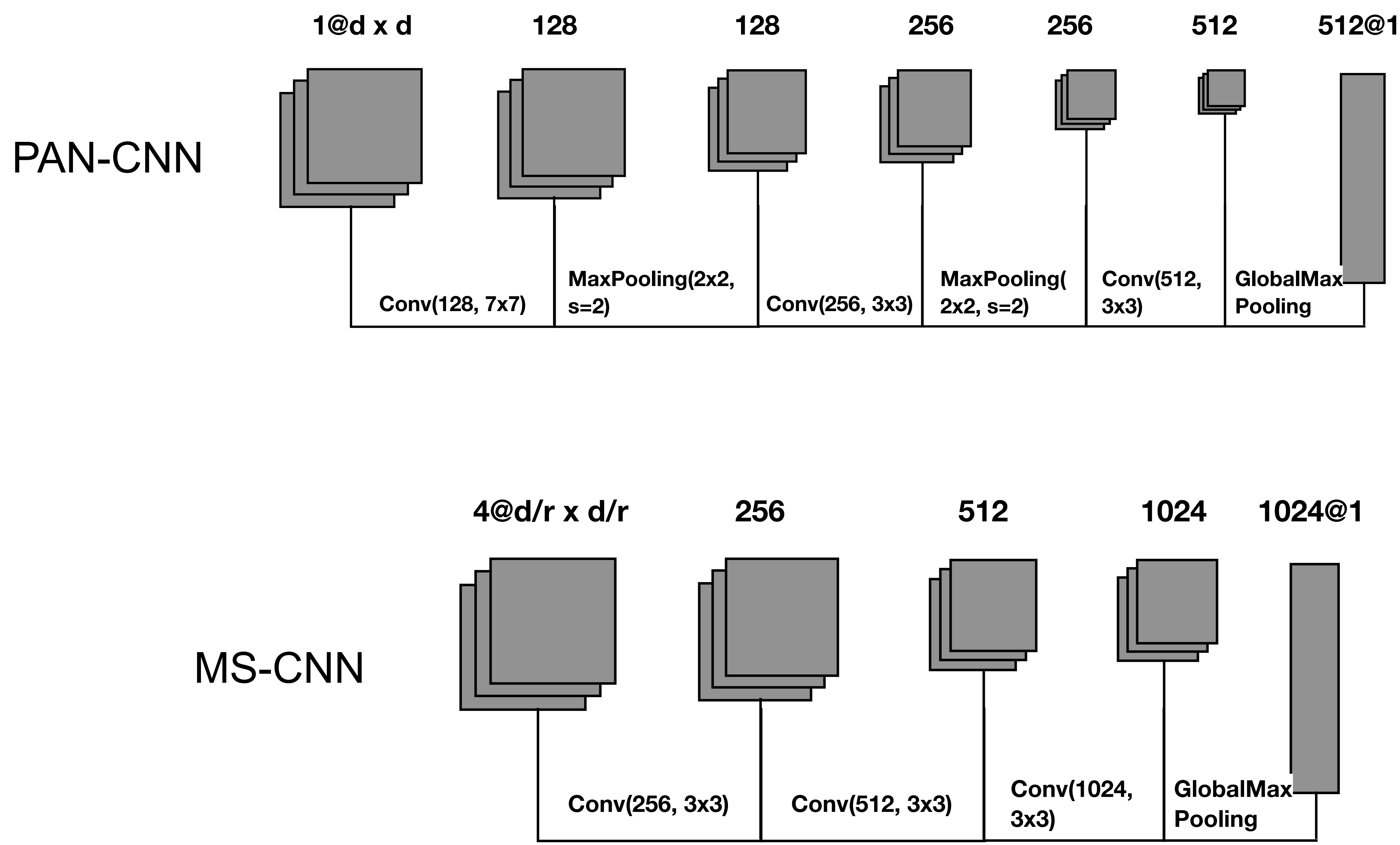
Batch Norm.

MRFusion: A DL approach to fuse PAN and MS for LC mapping

CNNs for Spatial Information

Relu

Batch Norm.



MRFusion: A DL approach to fuse PAN and MS for LC mapping

Ent-To-End Process from scratch

One CNN Module dedicated for each source **(PAN** and **MS)**

Multi-Scale and Multi-Source data fusion automatically managed by the architecture

This architecture avoids the use of Pansharpening or Interpolation preprocessing

The classification is performed at finer resolution (1.5m)

Data Description

Reunion Island Dataset:
- Spot6 image
- 13 Land Cover Classes
- PAN Image 44374 x 39422
- MS Image 11094 x 9856

Class	Label	# Objects	# Pixels
1	*Crop Cultivations*	168	50061
2	*Sugar cane*	167	50100
3	*Orchards*	167	50092
4	*Forest plantations*	67	20100
5	*Meadow*	167	50100
6	*Forest*	167	50100
7	*Shrubby savannah*	173	50263
8	*Herbaceous savannah*	78	23302
9	*Bare rocks*	107	31587
10	*Urban areas*	125	36046
11	*Greenhouse crops*	49	14387
12	*Water Surfaces*	96	2711
13	*Shadows*	38	11400

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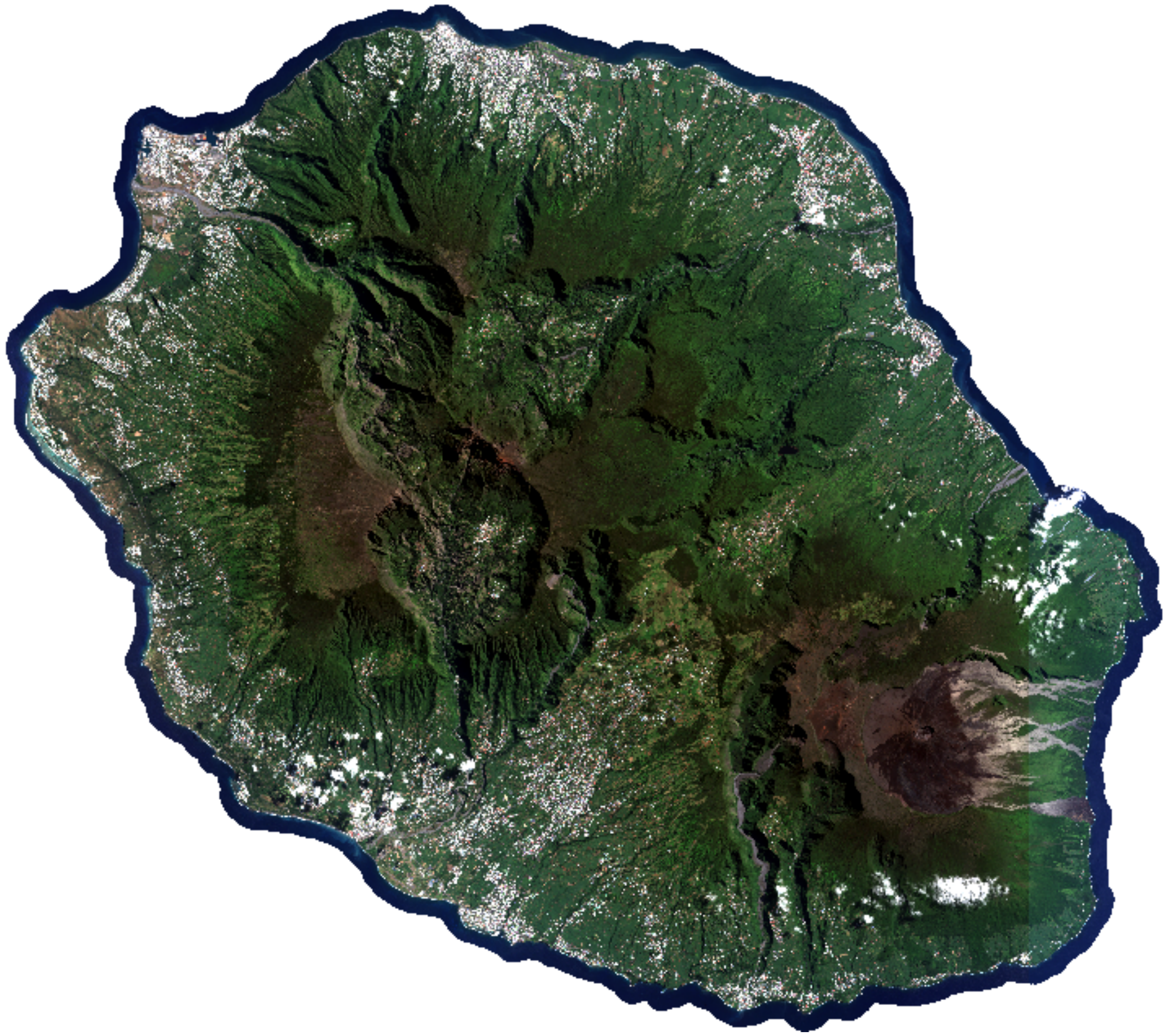
11	*Greenhouse crops*	49	14387
12	*Water Surfaces*	96	2711
13	*Shadows*	38	11400

Gard Dataset:
- Spot6 image
- 8 Land Cover Classes
- Pan image 24110 x 33740
- MS image 6028 x 8435

Class	Label	# Objects	# Pixels
1	*Cereal Crops*	167	50100
2	*Other Crops*	167	50098
3	*Tree Crops*	167	50027
4	*Meadows*	167	49997
5	*Vineyard*	167	50100
6	*Forest*	172	50273
7	*Urban areas*	222	50275
8	*Water Surfaces*	167	50100

Data Description



Reunion Island Site
Indian Ocean
East of Madagascar

Gard Site
South of France
East of Montpellier

Experimental Settings

Data splits:

30% of objects used as Train data and 70% of objects used as TEST

Results are averaged over 10 random splits 30%/70%

Competitors:

- **Random Forest** applied on the pixel or patch information
- **CNN** approach applied on Pansharpened image
- **DMIL**[Liu18] a deep learning method recently introduced to combine PAN and MS for land cover mapping

Deep Learning approaches are fed by patches:

- 32 x 32 patch size for the PAN information
- 8 x 8 patch size for the MS information

Evaluation Measures (On Test Data):

Accuracy (Global Accuracy)

F-Measure (it helps to take into account unbalance class distribution)

Kappa Measure

[Liu18] X. Liu, L. Jiao, J. Zhao, J. Zhao, D. Zhang, R. Liu, S. Yang, X. Tang: Deep Multiple Instance Learning-Based Spatial-Spectral Classification for PAN and MS Imagery. IEEE Trans. Geoscience and Remote Sensing 56(1): 461-473 (2018)

Comparison Results

	Accuracy	*F-Measure*	*Kappa*
RF(PIXEL)	24.87 ± 0.2	23.66 ± 0.2	0.1719 ± 0.0024
$RF(PATCH)$	72.22 ± 1.31	71.53 ± 1.4	0.6943 ± 0.0144
CNN_{PS}	74.49 ± 1.20	74.25 ± 1.24	0.7195 ± 0.0131
DMIL	69.40 ± 1.11	69.34 ± 1.12	0.6637 ± 0.0121
MRFusion	$\mathbf{79.65} \pm 0.87$	$\mathbf{79.56} \pm 0.91$	$\mathbf{0.7764} \pm 0.0096$

Reunion Island Results

	Accuracy	*F-Measure*	*Kappa*
RF(PIXEL)	25.91 ± 0.16	25.52 ± 0.11	0.1532 ± 0.18
RF(PATCH)	69.93 ± 0.76	69.55 ± 0.77	0.6564 ± 0.87
CNN_{PS}	66.14 ± 0.78	65.80 ± 0.77	0.6131 ± 0.0089
$DMIL$	61.96 ± 1.00	61.76 ± 1.01	0.5652 ± 0.0115
MRFusion	$\mathbf{70.48} \pm 0.55$	$\mathbf{70.19} \pm 0.67$	$\mathbf{0.6627} \pm 0.0063$

Gard Results

Comparison Results

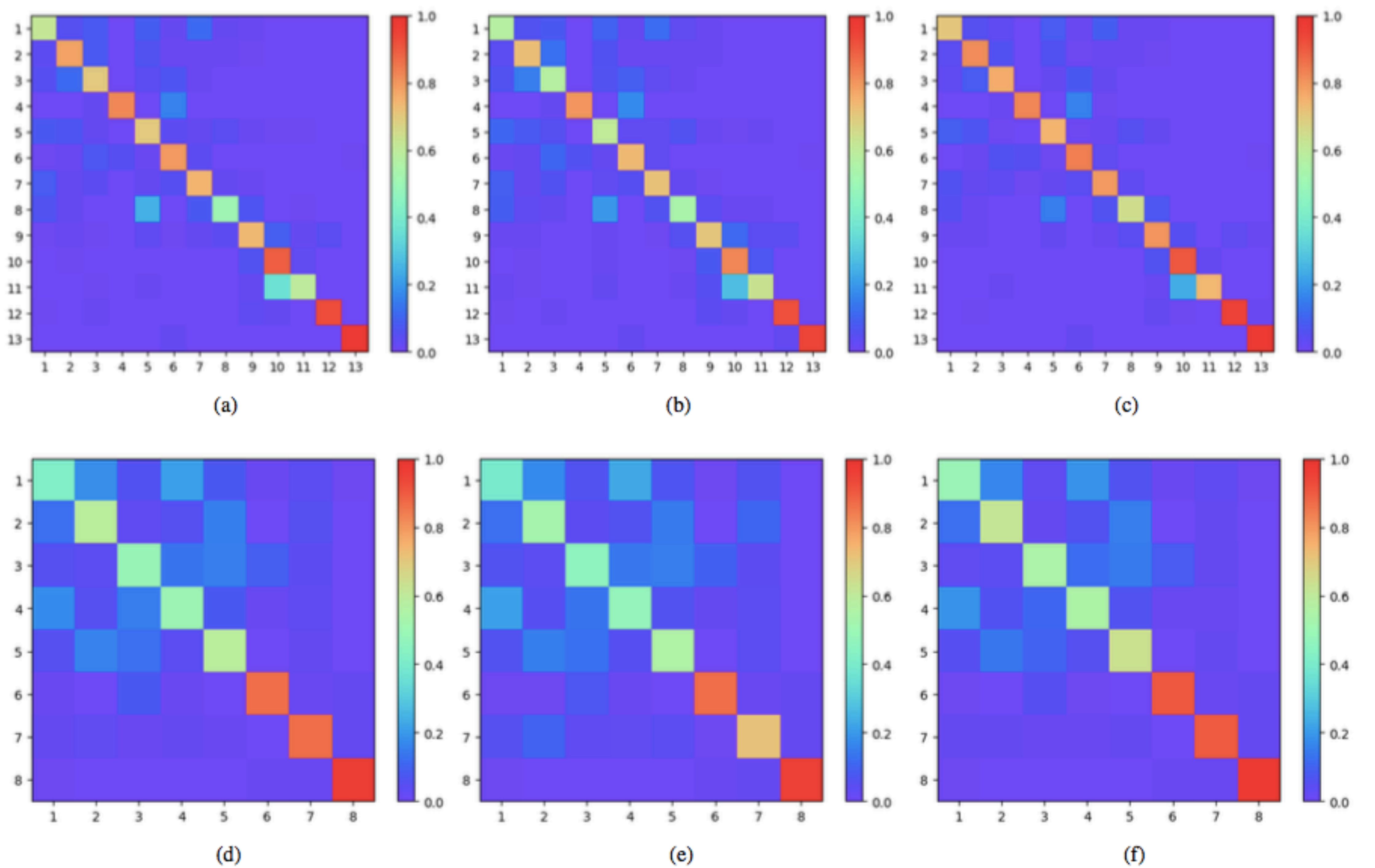


Figure 6: Confusion matrices of the Deep Learning approaches on the *Reunion Island* dataset (CNN_{PS} (a), $DMIL$ (b) and $MRFusion$ (c)) and on the *Gard* dataset (CNN_{PS} (d), $DMIL$ (e) and $MRFusion$ (f)).

Map Details on some particular extracts

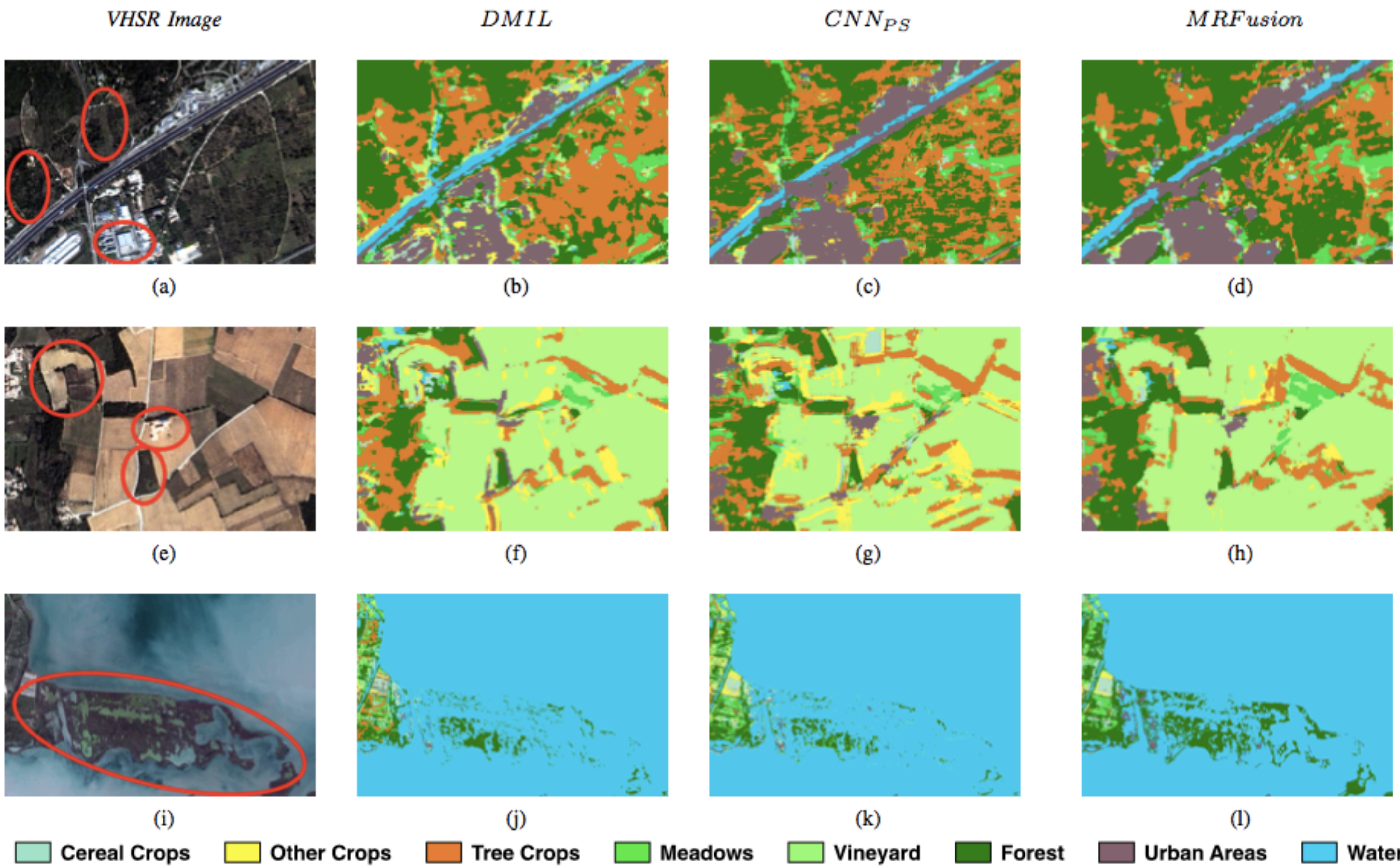


Table VIII: table caption GARD

Map Details on some particular extracts

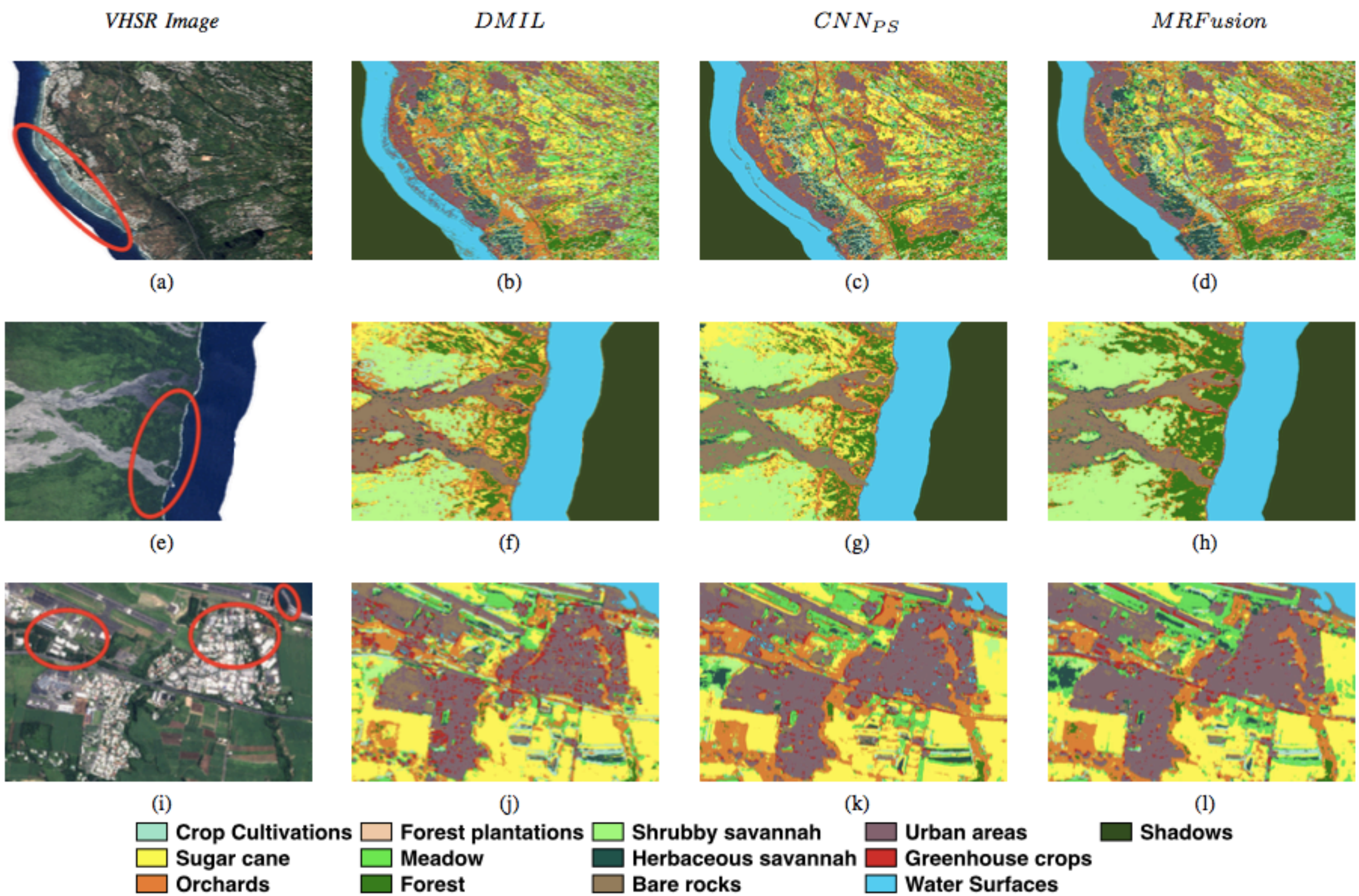


Table IX: table caption REUNION

TWINNS: fuse Radar/Optical Time Series for LC Mapping via DL

Different Data fusion scenario [Schmitt16]:

- Single-Sensor Data Fusion
- **Multiple-Sensor Data Fusion**
- **Temporal Data Fusion**
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- And so on….

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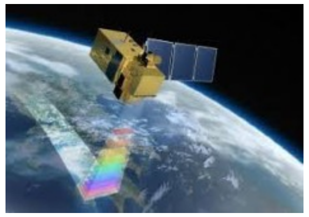
- And so on….



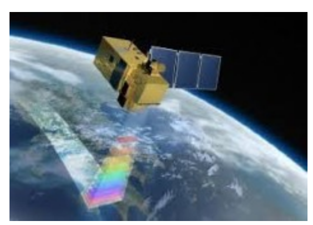
Multiple-Sensor Data Fusion on S1/S2:

- **Sentinel 1 Time Series (10m)**
- **Sentinel 2 Time Series (10m)**

[Schmitt16] M. Schmitt and X. X. Zhu, "Data Fusion and Remote Sensing: An ever-growing relationship". IEEE Geoscience and Remote Sensing Magazine 4(4): 6--23, 2016

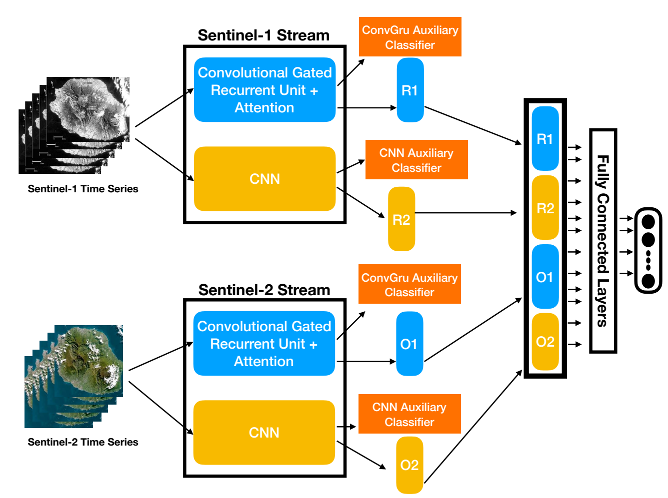
TWINNS: fuse Radar/Optical Time Series for LC Mapping via DL

Different Data fusion scenario [Schmitt16]:
- Single-Sensor Data Fusion
- **Multiple-Sensor Data Fusion**
- **Temporal Data Fusion**
- **Machine Learning-Based Data Fusion**
- And so on….



Multiple-Sensor Data Fusion on S1/S2:
- **Sentinel 1 Time Series (10m)**
- **Sentinel 2 Time Series (10m)**

To this end, we conceive a Deep Learning approach leveraging:
- Convolutional Neural Network - **CNNs**
- Conv Recurrent Neural Networks - **convRNNs**



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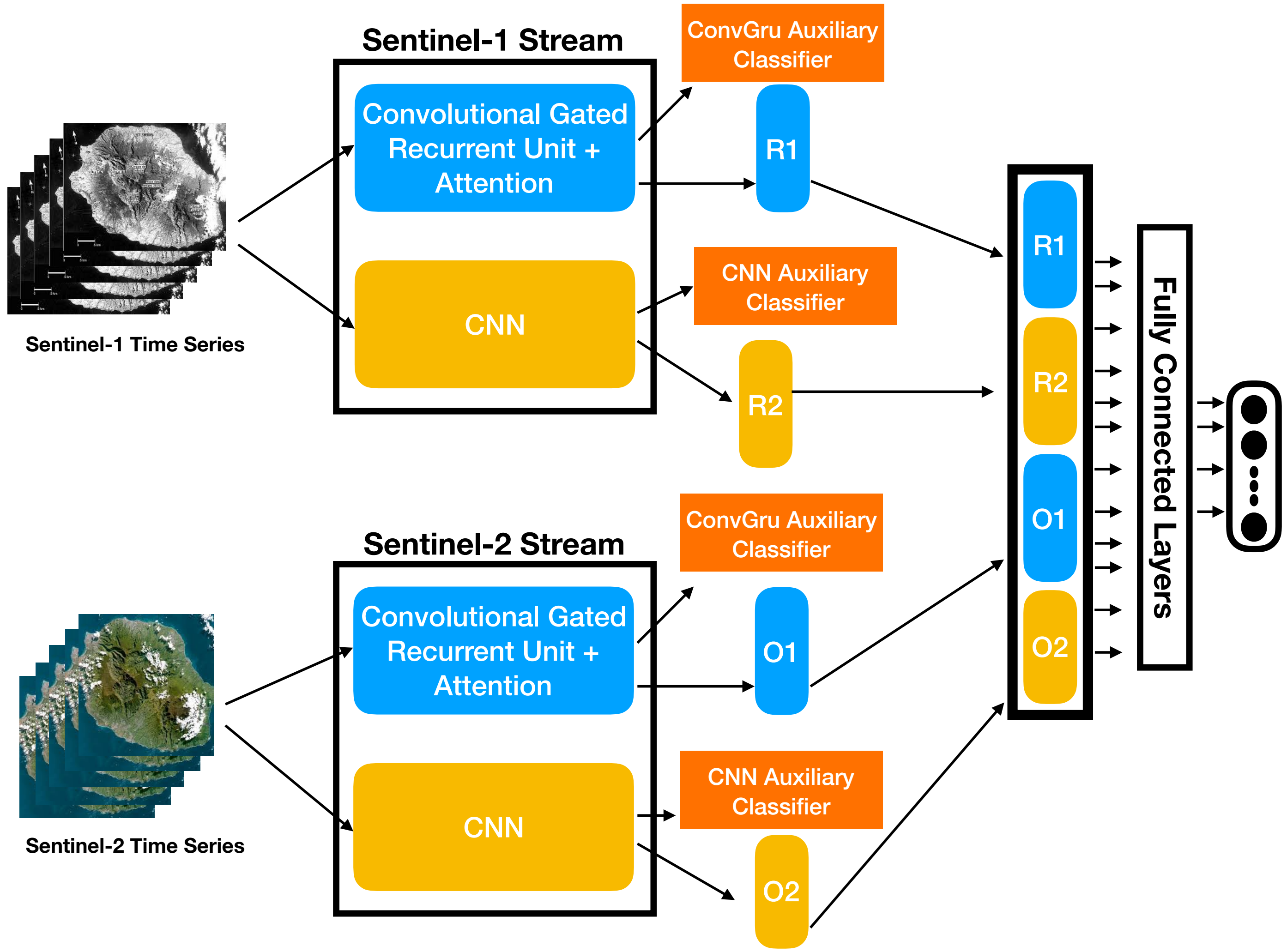
TWINNS: fuse Radar/Optical Time Series for LC Mapping via DL

MRFusion: TWIn Neural Networks for Sentinel data

Ent-To-End Process (from scratch)

Multi-Sensor/ Temporal architecture



Exploit both CNN and convRNN to process the same information to introduce diversity in the data representation

More detail on the (conv)RNN branch

GRU with Attention - Temporal Component

More detail on the (conv)RNN branch

GRU with Attention - Temporal Component

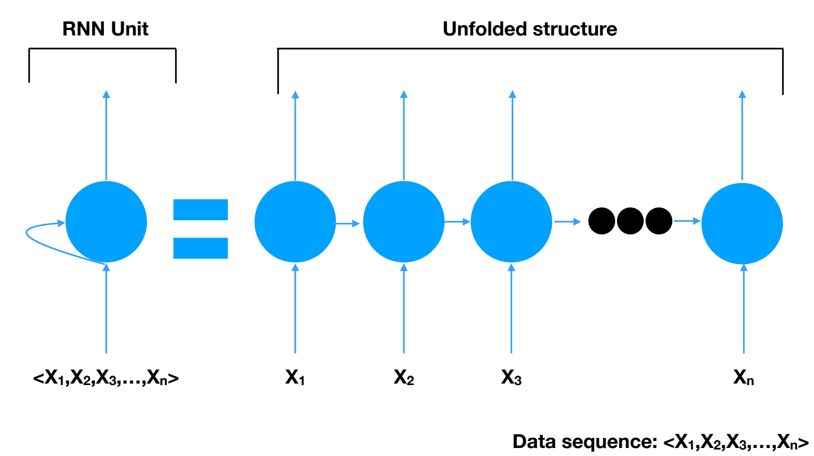
$$z_t = \sigma(W_{zx}x_t + W_{zh}h_{t-1} + b_z)$$

$$r_t = \sigma(W_{rx}x_t + W_{rh}h_{t-1} + b_r)$$

$$h_t = z_t \odot h_{t-1} + \\ (1 - z_t) \odot \tanh(W_{hx}x_t + W_{hr}(r_t \odot h_{t-1}) + b_h)$$

We use DropOut to alleviate overfitting

Gated Recurrent Unit:
- Lighter architecture than LSTM
- Recurrent Unit with gates
- Widely employed in NLP



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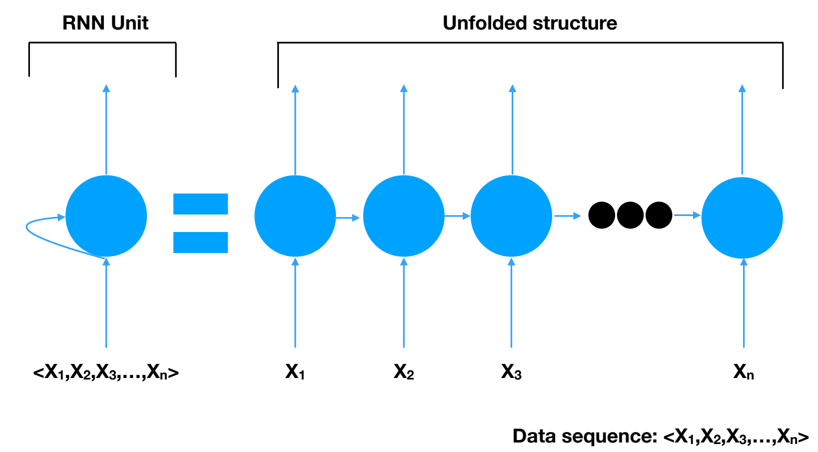

Attention Mechanism
Combine the information extracted at each timestamps together

$$v_a = tanh(H \cdot W_a + b_a)$$
$$\lambda = SoftMax(v_a \cdot u_a)$$
$$rnn_{feat} = \sum_{i=1}^{N} \lambda_i \cdot h_{t_i}$$

M3F: Spatio-Temporal Data Fusion via Deep Learning

convRNN Module dedicated to manage **Temporal Correlations**

CNN Module dedicated to manage **Spatial Correlation between different timestamps**

Multi-Sensor and Multi-Temporal data fusion automatically managed by the architecture

Dedicated approach to **fuse** together **Multi-Temporal** information by **Deep Learning**

[Hou17] S. Hou, X. Liu, Z. Wang: DualNet: Learn Complementary Features for Image Recognition. ICCV 2017: 502-510

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Auxiliary Classifiers adapted from [Hou17], the goal is to boost the discrimination power of each set fo features independently

In our context, sources are naturally complementary w.r.t the work proposed in [Hou17]

$$L_{total} = L_{fus}([cnn^{S1}_{feat}, rnn^{S1}_{feat}, cnn^{S2}_{feat}, rnn^{S2}_{feat}]) + \alpha * \sum_{s \in \{S1,S2\}} \sum_{p \in \{rnn,cnn\}} L_{s,p}(p^{s}_{feat})$$

[Hou17] S. Hou, X. Liu, Z. Wang: DualNet: Learn Complementary Features for Image Recognition. ICCV 2017: 502-510

Data Description

Reunion Island Dataset:
- 24 Sentinel-1 images (2 bands)
- 34 Sentinel-2 images (10 bands + 6 indices)
- Spatial Extent: 6656 x 5913 pixels
- 13 Land Cover Classes (322748 pixels / 2656 objs)

Class	Label	**# Objects**	**# Pixels**
1	*Crop Cultivations*	168	50061
2	*Sugar cane*	167	50100
3	*Orchards*	167	50092
4	*Forest plantations*	67	20100
5	*Meadow*	167	50100
6	*Forest*	167	50100
7	*Shrubby savannah*	173	50263
8	*Herbaceous savannah*	78	23302
9	*Bare rocks*	107	31587
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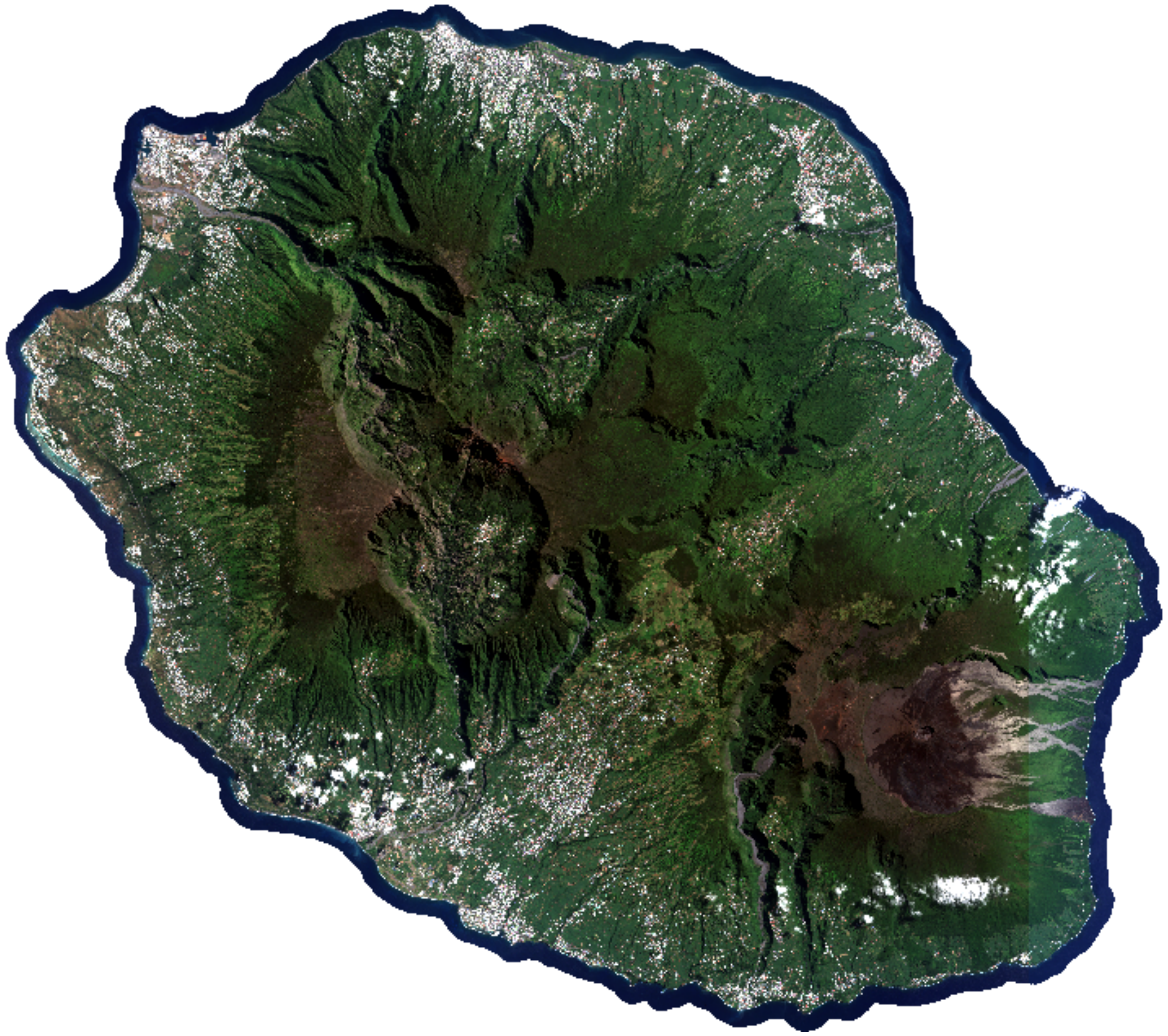
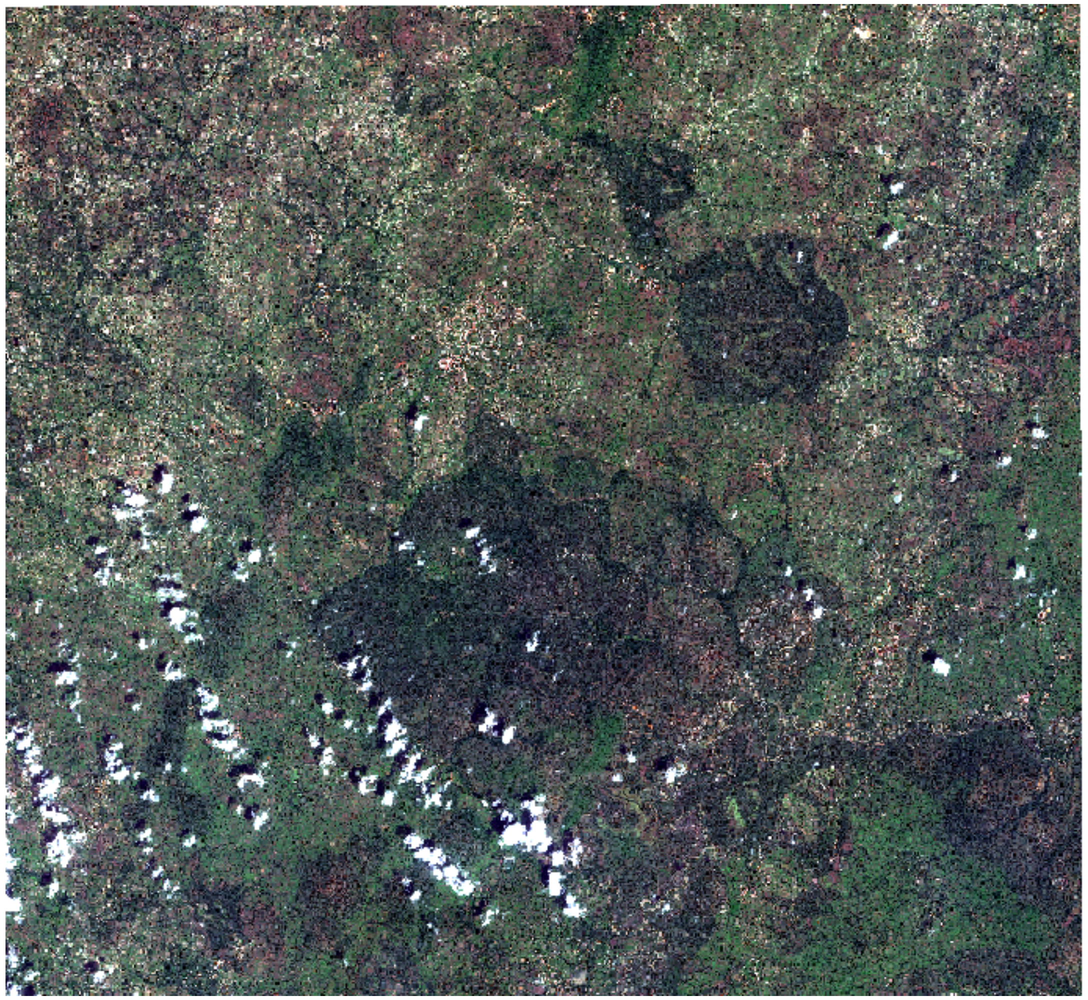
Koumbia Dataset:
- 29 Sentinel-1 images (2 bands)
- 23 Sentinel-2 images (10 bands + 6 indices)
- Spatial Extent: 5253 x 4797 pixels
- 7 Land Cover Classes (90123 pixels / 1137 objs)

Class	Label	# Polygons	# Pixels
0	*Annual Cropland*	671	31 075
1	*Fallows*	57	1 808
2	*Natural Forest*	64	15 843
3	*Savannah*	87	25 156
4	*Grassland*	142	12 883
5	*Rocks*	29	852
6	*Built up*	71	1 096
7	*Water*	16	1 410





Reunion Island Site
Indian Ocean
East of Madagascar

Koumbia Site
Province of Tuy
Burkina Faso

Experimental Settings

Data splits (Training / Validation / Test)**:**

Reunion Island Dataset: 30% / 20% / 50% (at object level) repeated 10 times
Koumbia Dataset: 50% / 30% / 20% (at object level) repeated 10 times
We consider patches of size 5x5

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Ablation Study:

- A version of TWINNS for each source (**TWINNS(S1)** and **TWINNS(S2)**)
- A version of TWINNS without Auxiliary Classifiers (**TWINNS$_{_NoAux}$**)
- A version of TWINNS with only the CNN branches (FullCNN)
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Competitors:

- Multiple **Random Forests competitors:**
  - **RF(S1,S2)**
  - **RF_{LF}(S1,S2)**
- **A two branch Convolutional LSTM (2ConvLSTM)**
- A RF competitor **fed with the representation** learnt by TWINNS - RF(TWINNS)

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Evaluation Measures (On Test Data):
Accuracy (Global Accuracy)
F-Measure (it helps to take into account unbalance class distribution)
Kappa Measure

Experimental Evaluation

Ablation Study

Reunion Island

	F-Measure	*Kappa*	*Accuracy*
TWINNS(S1)	73.22 ± 1.23	0.6926 ± 0.0144	73.89 ± 1.24
TWINNS(S2)	84.29 ± 1.19	0.8159 ± 0.0143	84.26 ± 1.26
FullCNN	87.69 ± 0.85	0.8560 ± 0.0107	87.71 ± 0.92
FullRNN	88.23 ± 1.43	0.8620 ± 0.0169	88.22 ± 1.45
TWINNS_{NoAux}	83.92 ± 1.05	0.8109 ± 0.0117	83.84 ± 0.97
TWINNS	**89.87** ± 0.65	**0.8814** ± 0.0080	**89.88** ± 0.69

Koumbia

	F-Measure	*Kappa*	*Accuracy*
TWINNS(S1)	80.93 ± 2.18	0.7530 ± 0.0283	81.84 ± 2.13
TWINNS(S2)	81.47 ± 4.12	0.7563 ± 0.0556	81.99 ± 4.30
FullCNN	**86.81** ± 2.38	**0.8303** ± 0.0303	**87.51** ± 2.29
FullRNN	85.90 ± 2.72	0.8186 ± 0.0363	86.65 ± 2.75
TWINNS_{NoAux}	81.87 ± 4.43	0.7631 ± 0.0599	82.49 ± 4.61
TWINNS	86.65 ± 2.50	0.8298 ± 0.0322	87.50 ± 2.44

Experimental Evaluation

Competitors

Reunion Island

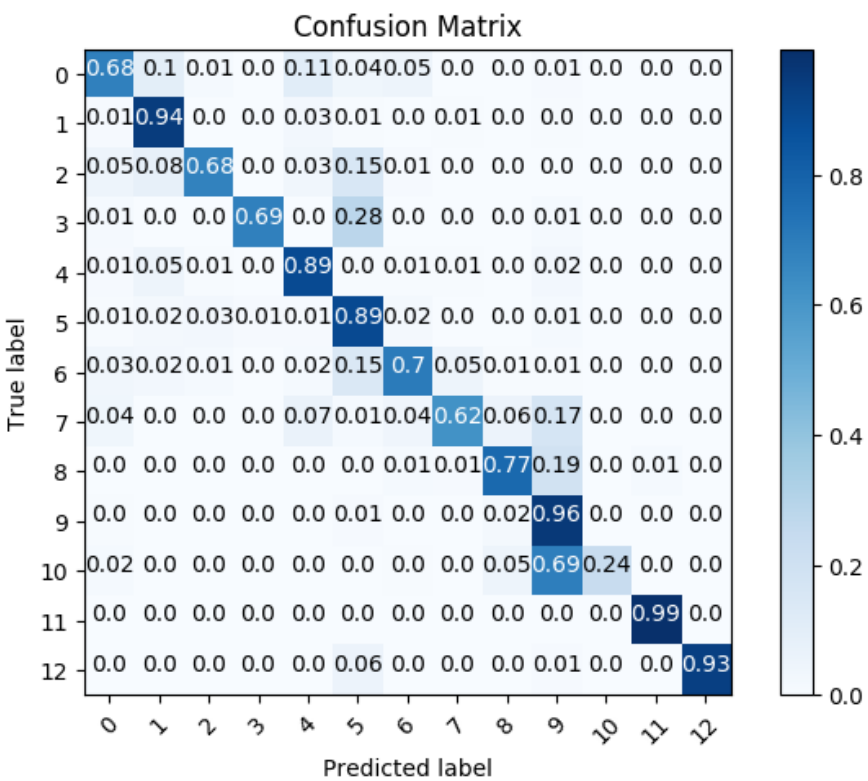
	F-Measure	*Kappa*	*Accuracy*
$RF(S1, S2)$	86.10 ± 0.58	0.8402 ± 0.0065	86.42 ± 0.54
$RF_{LF}(S1, S2)$	87.73 ± 0.58	0.8611 ± 0.0069	88.27 ± 0.59
$2ConvLSTM$	83.21 ± 0.90	0.8031 ± 0.0103	83.17 ± 0.90
TWINNS	89.87 ± 0.65	0.8814 ± 0.0080	89.88 ± 0.69
$RF(TWINNS)$	**90.07** ± 1.04	**0.8840** ± 0.0124	**90.10** ± 1.07

Koumbia

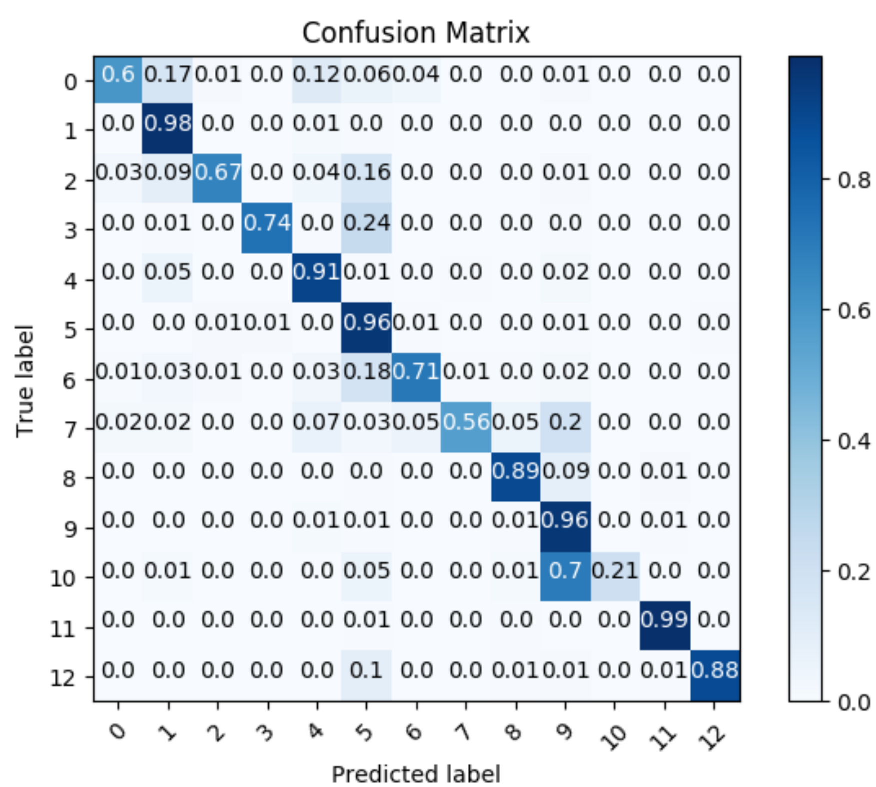
	F-Measure	*Kappa*	*Accuracy*
$RF(S1, S2)$	79.79 ± 5.30	0.7424 ± 0.0694	81.25 ± 5.16
$RF_{LF}(S1, S2)$	84.78 ± 2.36	0.8079 ± 0.0315	86.00 ± 2.35
$2ConvLSTM$	85.73 ± 2.24	0.8165 ± 0.0276	86.48 ± 2.08
TWINNS	**86.65** ± 2.50	**0.8298** ± 0.0322	**87.50** ± 2.44
$RF(TWINNS)$	85.79 ± 2.62	0.8172 ± 0.0351	86.54 ± 2.68

Experimental Evaluation

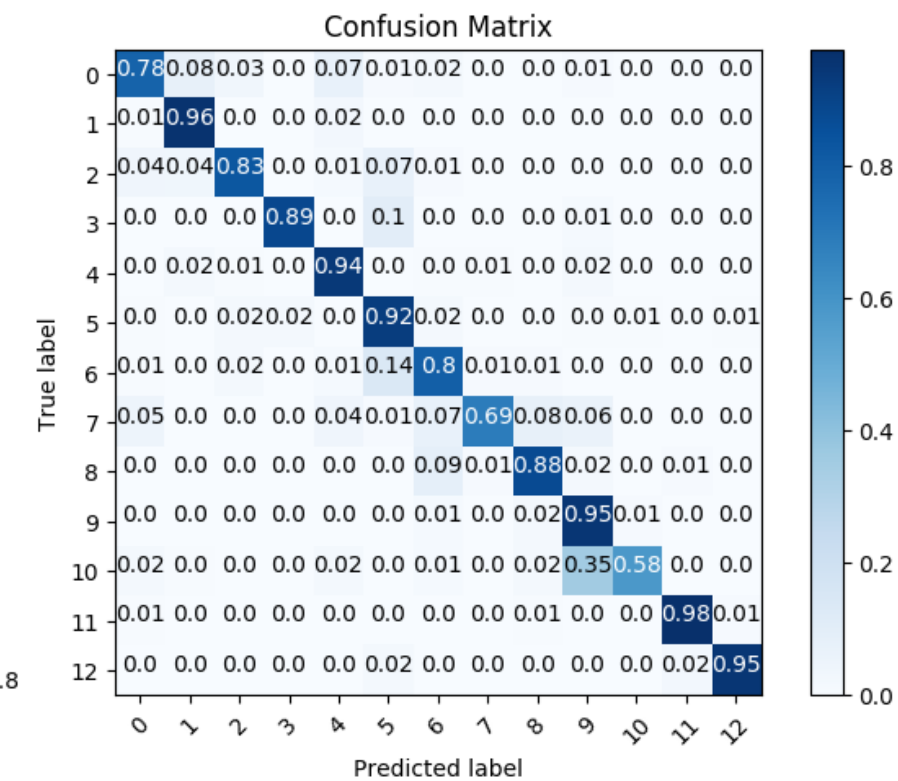
Reunion Island



RF

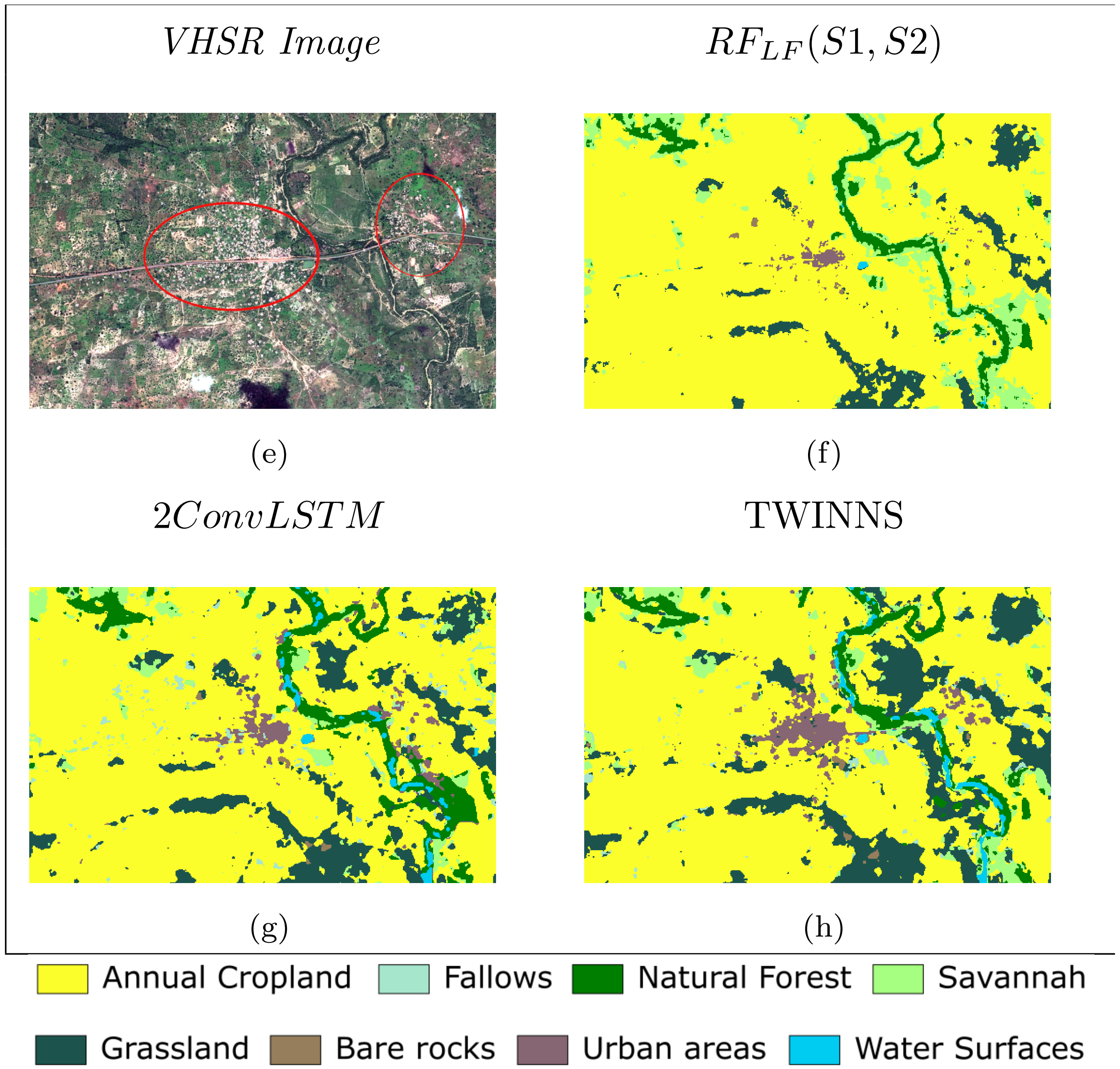


RF_{LF}



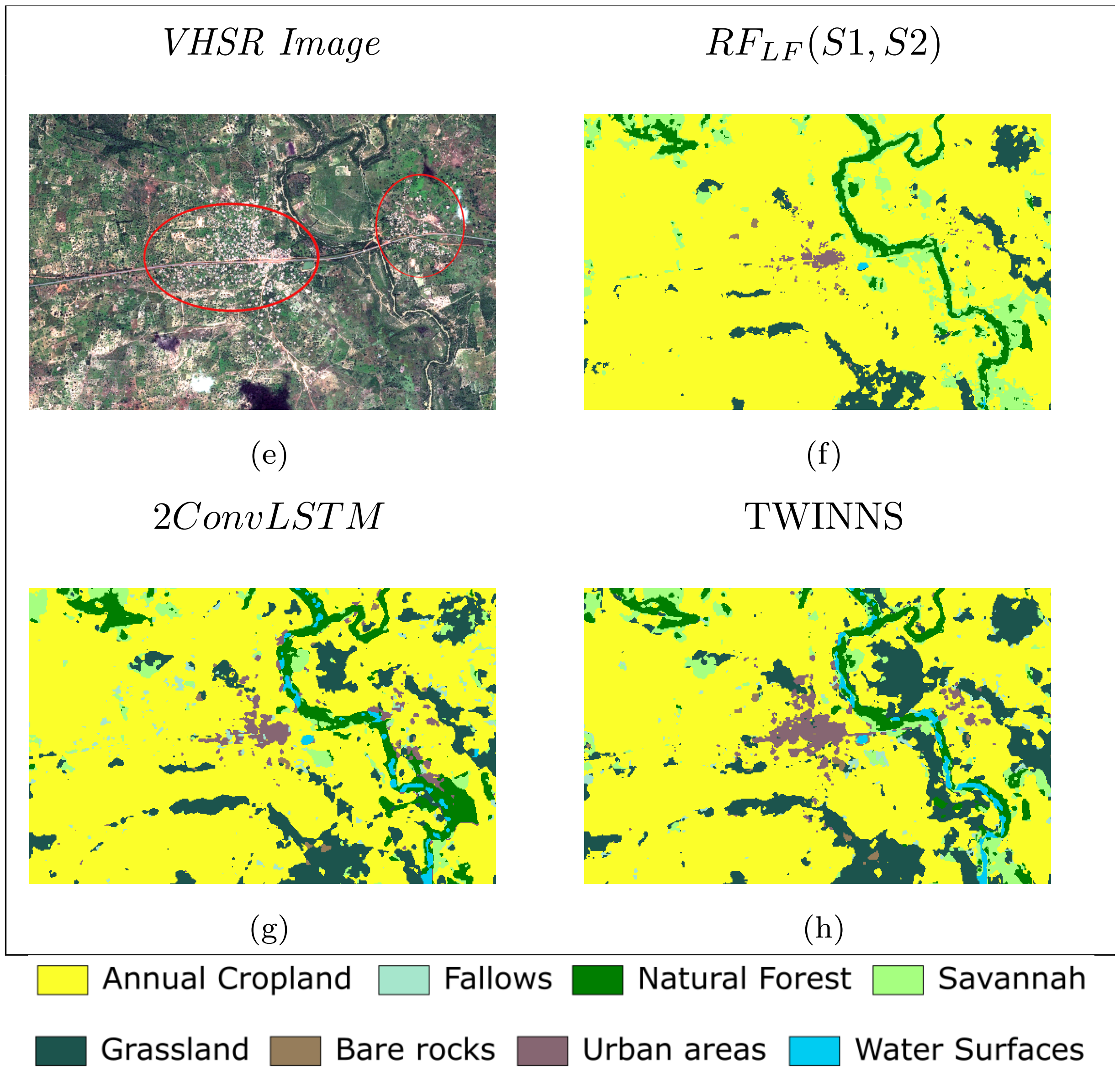
RF(TWINNS)

Map Details on some particular extracts

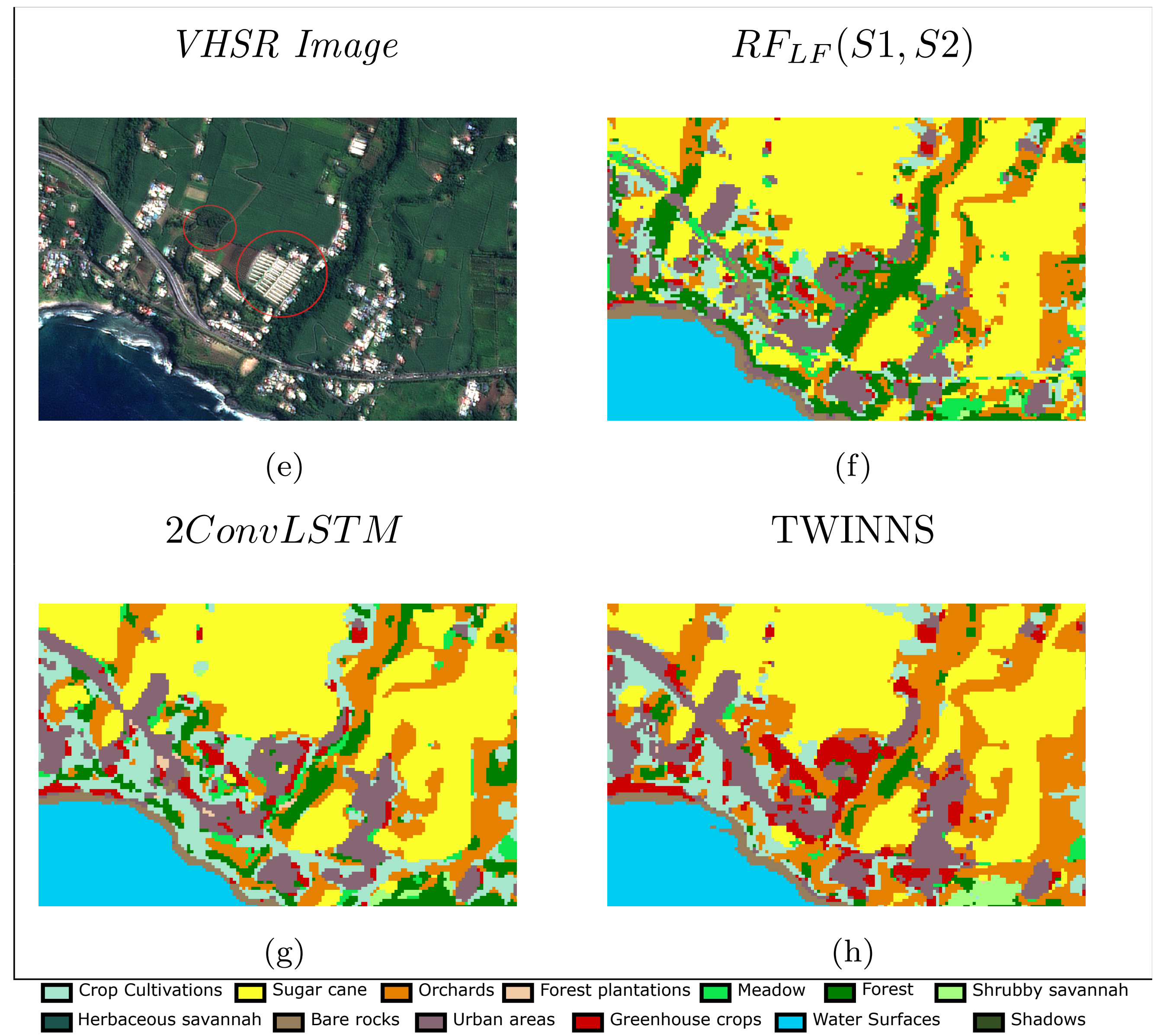


Koumbia

Map Details on some particular extracts



Koumbia



Reunion Island

To Wrap Up

Deep Learning seems a promising tool for task-driven multi source data fusion.

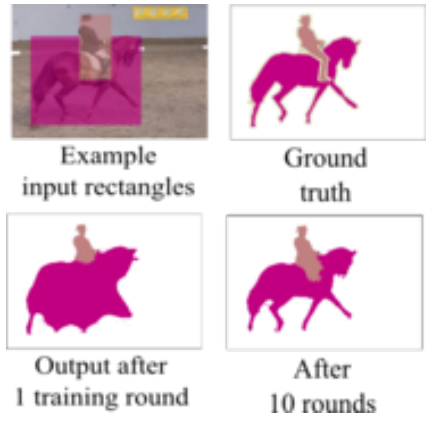
Two Deep Learning examples for data fusion considering land cover mapping:

- **MRFusion:** fuse together information from the same sensor, PAN and MS images from SPOT6 image

- **TWINNS:** fuse together Satellite Image Sentinel-1 and Sentinel-2 time series (Multi-Sensor/Temporal) for land cover classification

Combine different basic blocks (RNN, CNN, convRNN, Attention, etc…) to manage different data sources to provide decision-level data fusion frameworks.

Current Trend



Different Research directions:

- Generative Adversarial network
- Spatio - Spectral - Temporal Domain Adaptation
- Hierarchical relationships to regularise the classification (**fine-grained classification**)
- Explore more the **semi-supervised** setting (reduce the human effort)
- Explore more **weakly-supervised** settings (the model is learned with weak supervision w.r.t. the task to solve)
- Integrate alternative sources of information: **cross-modal** (i.e. text or VGI=Volunteer Geographic Information)
- Data Fusion among different remote sensors (multi-scale, multi-temporal, etc..)

Generative Adversarial Network

The framework involves:
- A **generative network** (G) that tries to simulate real examples
- A **discriminator network** (D) that tries to recognise real vs fake examples

Mainly employed to sample examples from a data distribution

In the remote sensing field, **GANs can be exploited to generate new examples** to enrich the training data

An interesting variant are **cGANs (Conditional GANs)** that constraint the generation process with a kind of supervision (for instance the label to predict).

Spatio - Spectro - Temporal Domain Adaptation

In a (unsupervised) domain adaptation (DA) setting:
- A source domain (S) has labelled examples
- A target domain (T) has no labelled examples

The goal is to transfer the model from S -> T leveraging the labelled examples in S

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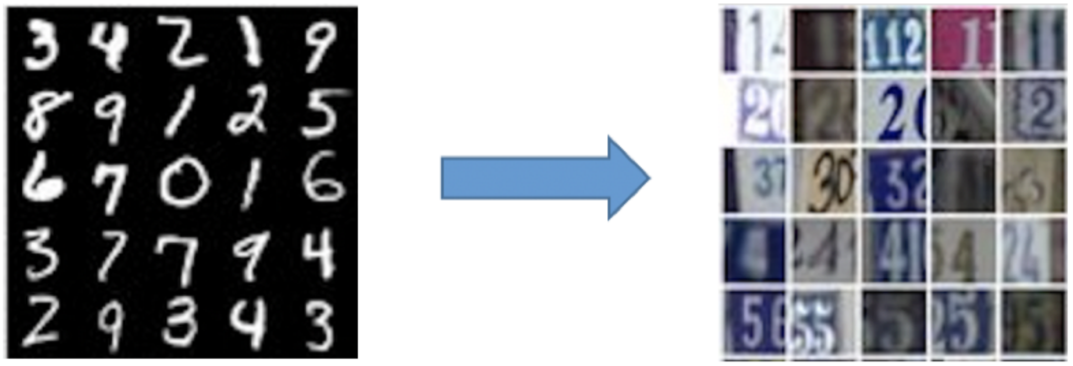
The goal is to transfer the model from S -> T leveraging the labelled examples in S

In Remote Sensing field the source/target domains can be:
- Different sensors: Spot/Pléiades, Spot/Sentinel, Landsat/Sentinel (**Spectral DA**)
- Different geographical areas (**Spatial DA**)
- Information (Images or Time Series) acquired at different time (**Temporal DA**)
- …



Source: MNIST

Target: SVHN

Hierarchical Relationships Fine-Grained Classification

In many real problems, the **label space** (classes) can be organised in a **taxonomy or hierarchy.**

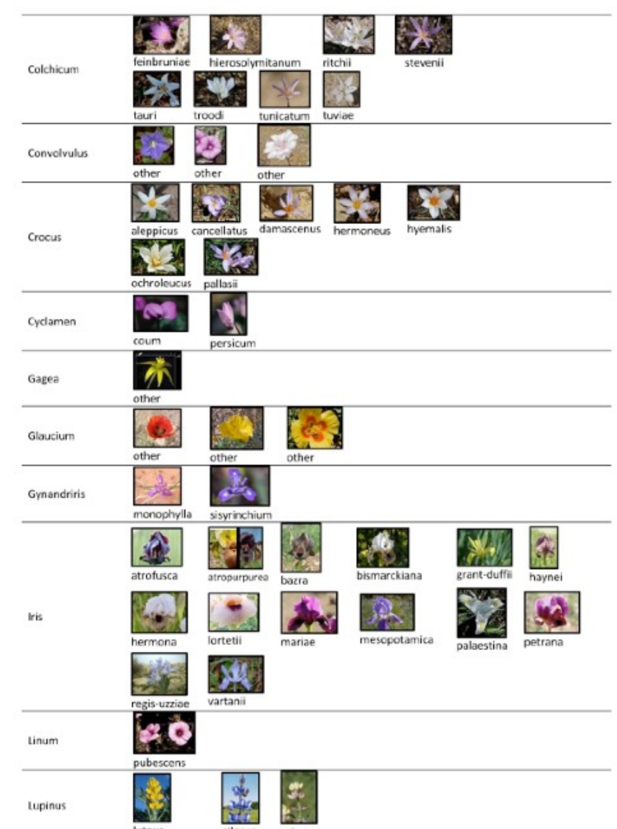
When such relationships exist in the label space, they **can be exploited to regularise the classification process.**

In Remote Sensing (especially in Land Use / Land Cover scenario), classes can be naturally arranged in taxonomies.

Such kind of scenario is called: **Fine-Grained Classification**

(a) Hierarchy among dogs

(b) Hierarchy among aircraft



Conclusion and Directions

Deep Learning seems a **promising tool for task-driven multi source data fusion** in Remote Sensing.

Most of the literature in Remote Sensing & Deep Learning exploits (almost) directly results from Computer Vision but… Remote Sensing has some peculiarity (multi-scale, multi-sensors, multi-temporal, sparsely annotated data, etc…) -> **Necessity for ad-hoc architectures.**

In operational cases, when predictive analysis need to be deployed, **some sensors can be damaged or unavailable**. How to develop methods capable to work on **misaligned (between training and test) information sources** is mandatory in Remote Sensing.

Many efforts were done in creating and developing **physical-based models and now?** Data-Driven models seem overpass previous work but…**How to combine physical-based and (DL) data-driven models** in Remote Sensing is a promising direction. **Data Assimilation can be an answer.**

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(Machine and Deep Learning for Earth Observation)
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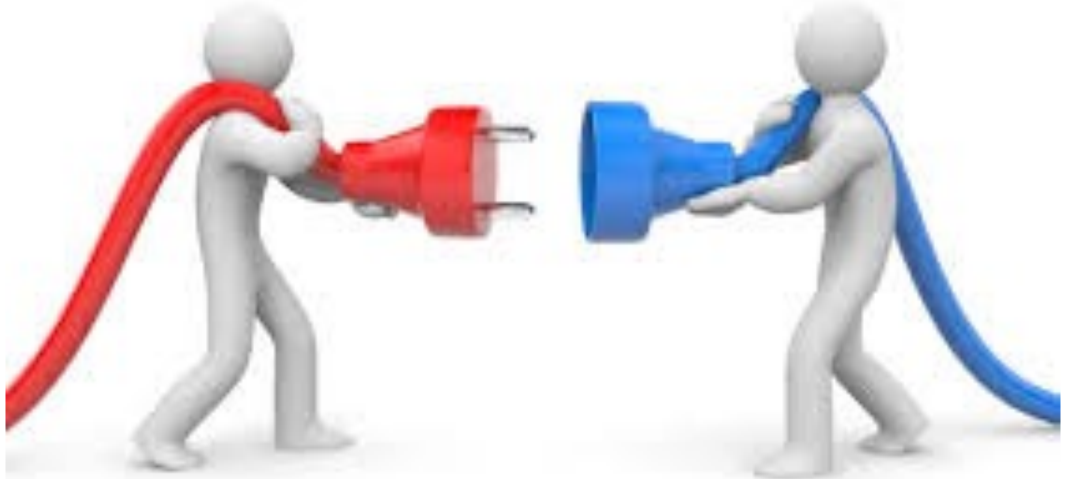
Thank you
for your Attention



Thank you for your Attention

Questions