A two-branch Deep Learning architecture for land cover classification of PAN and MS imagery

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Outline

Earth Observation Data Fusion Challenge

MultiResoLCC: Multi-Resolution Land Cover Classification

Data Description

Experimental Settings

Results & Findings

Conclusions and Future Works

Earth Observation Data Fusion Challenge

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)

Earth Observation Data Fusion Challenge

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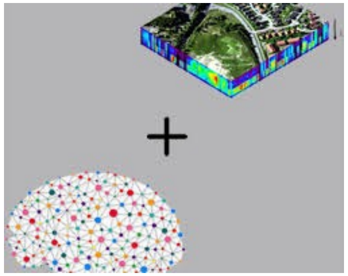
Main Challenge

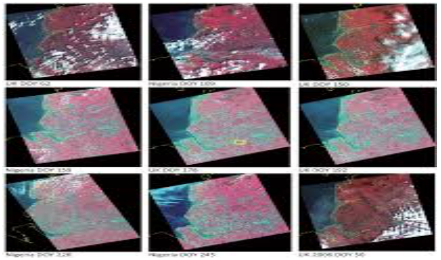
How to exploit the complementarity of Satellite information? i.e. How to leverage such heterogeneity for Land Cover?

Deep Learning
& Earth Observation Data (EOD)

Satellite imagery analytic uses **Machine Learning** techniques to:

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





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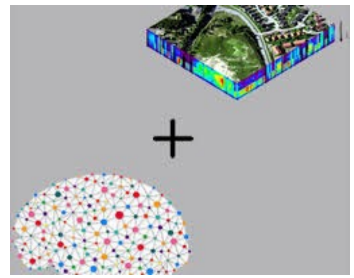
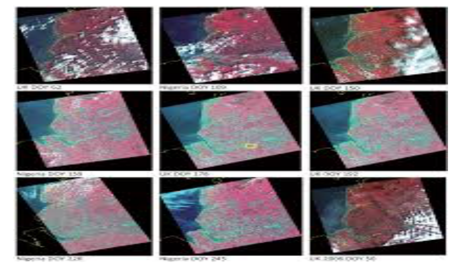
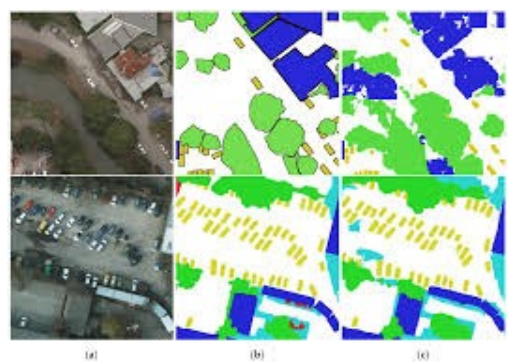
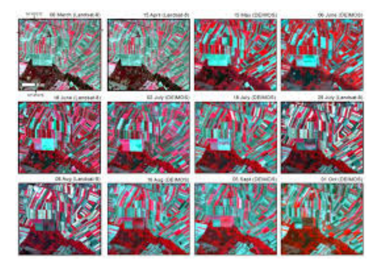


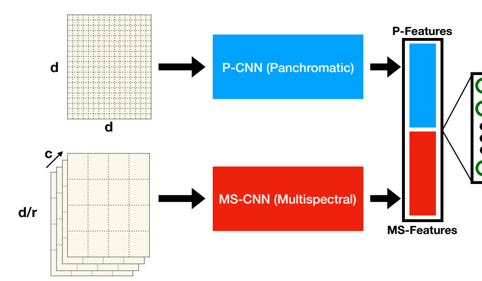


Nowadays, DL is becoming a common tool:
- Inspired by human brain
- Layers architecture

Successful results in different domains:
+ Speech Recognition
+ Image Recognition
+ Natural Language Processing







Deep Learning
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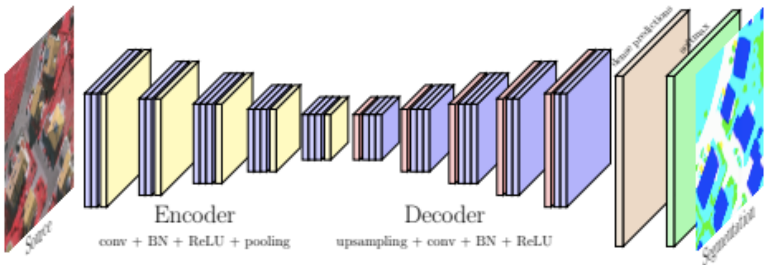

(Very High Spatial Resolution)
VHSR + DEM [Audebert17]

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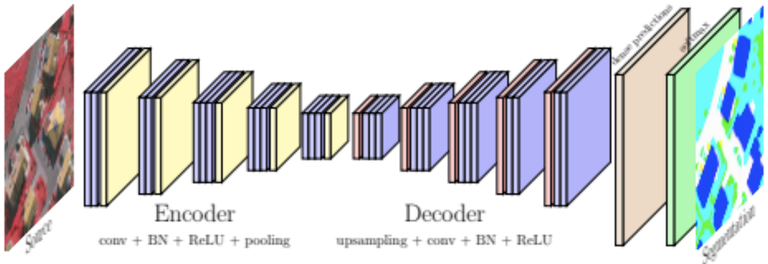

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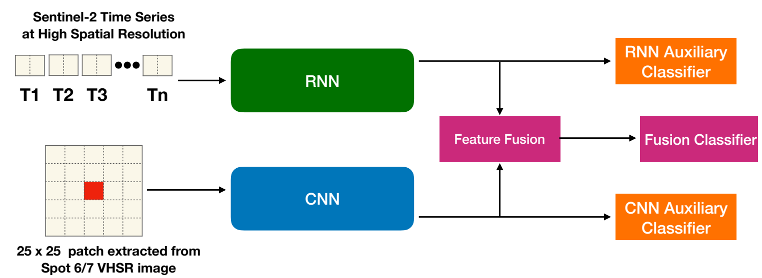

Time Series + VHSR [Benedetti18]

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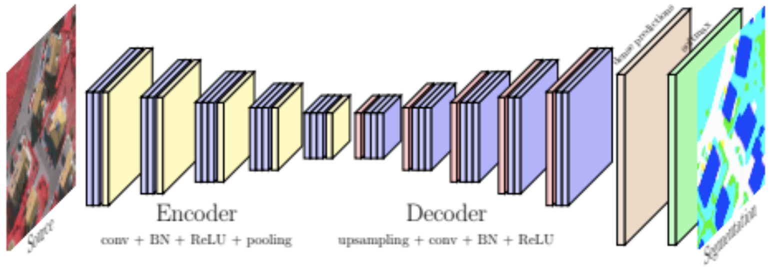

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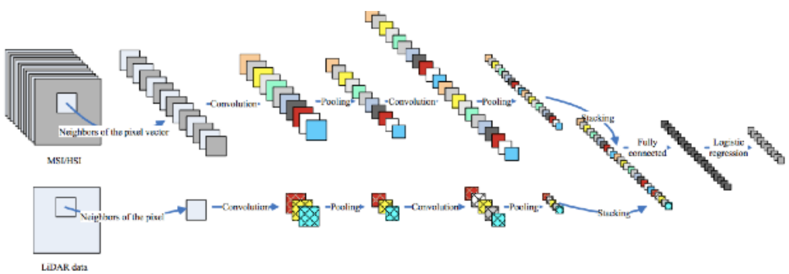
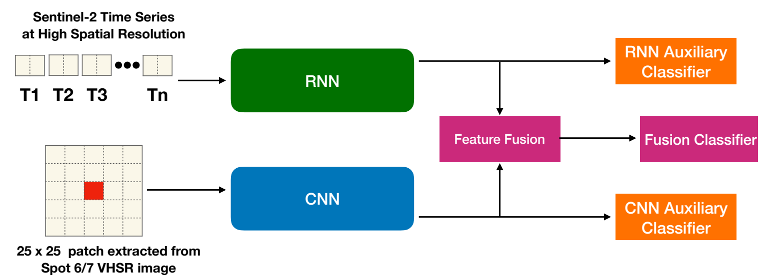


Hyperspectral + DEM [Chen17]



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

Different Data fusion scenario [Schmitt16]:

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

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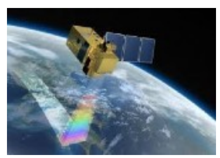

Single-Sensor Data Fusion on SPOT6:

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

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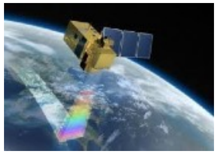

Single-Sensor Data Fusion on SPOT6:

- **Panchromatic Image (1.5m)**
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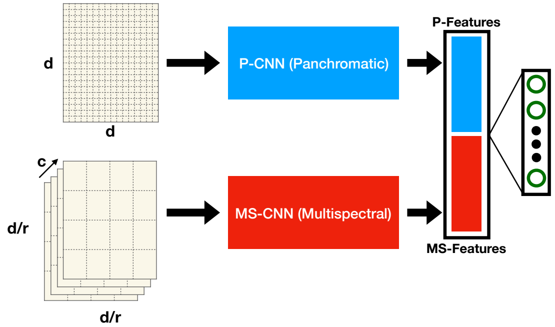
To this end, we conceive a Deep Learning approach leveraging:

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



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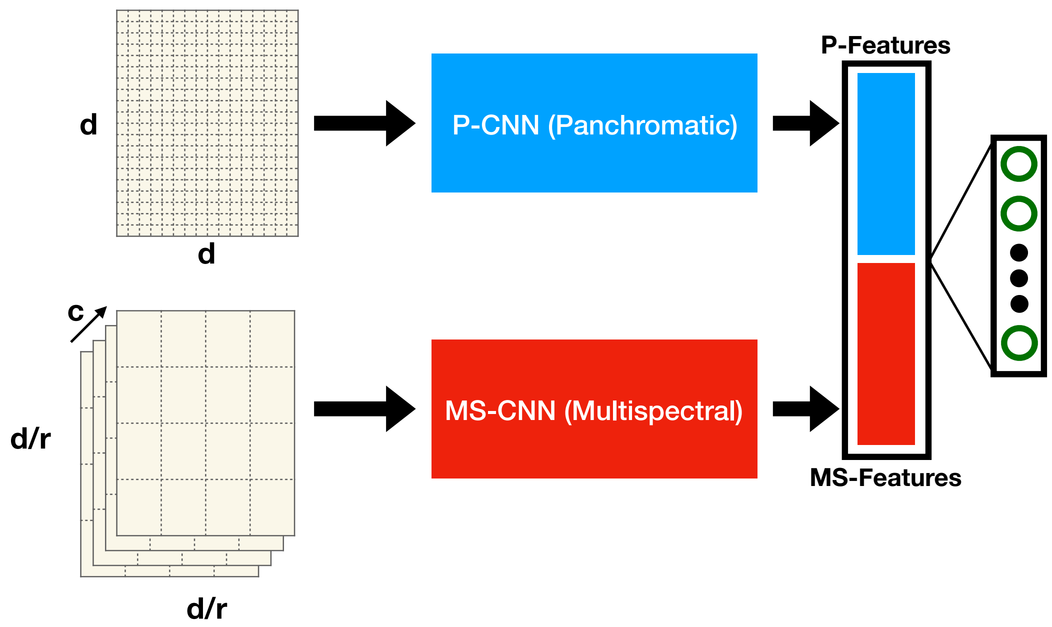
MultiResoLCC: A DL approach to fuse PAN and MS for LC mapping

MRFusion: Single-Sensor Multi-Resolution data fusion architecture



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

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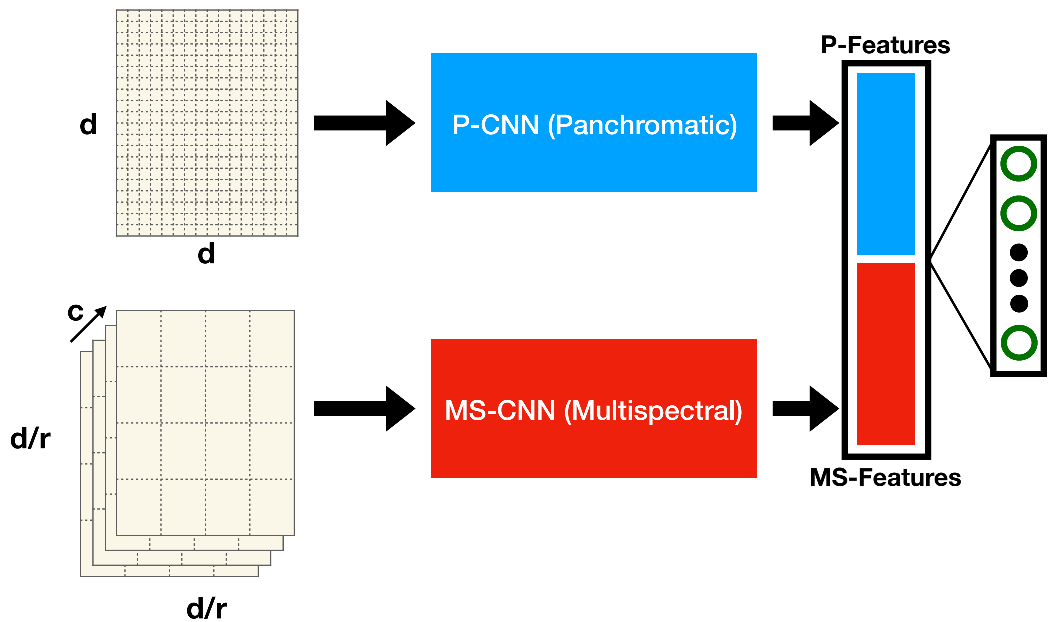
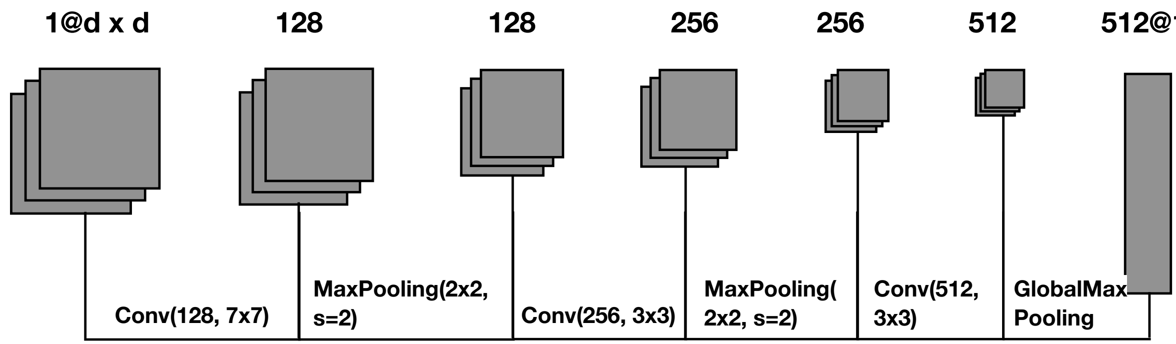


d = patch size on the PAN image
r = spatial ratio between PAN and MS (i.e. in SPOT6 is 4)
c = number of channels in the MS image

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

CNNs for Spatial Information

PAN-CNN



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

CNNs for Spatial Information

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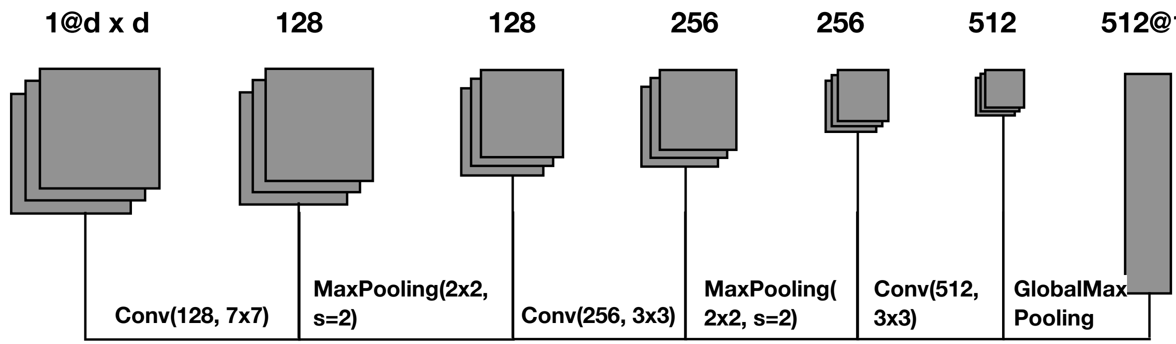

Relu

Batch Norm.

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

CNNs for Spatial Information

Relu

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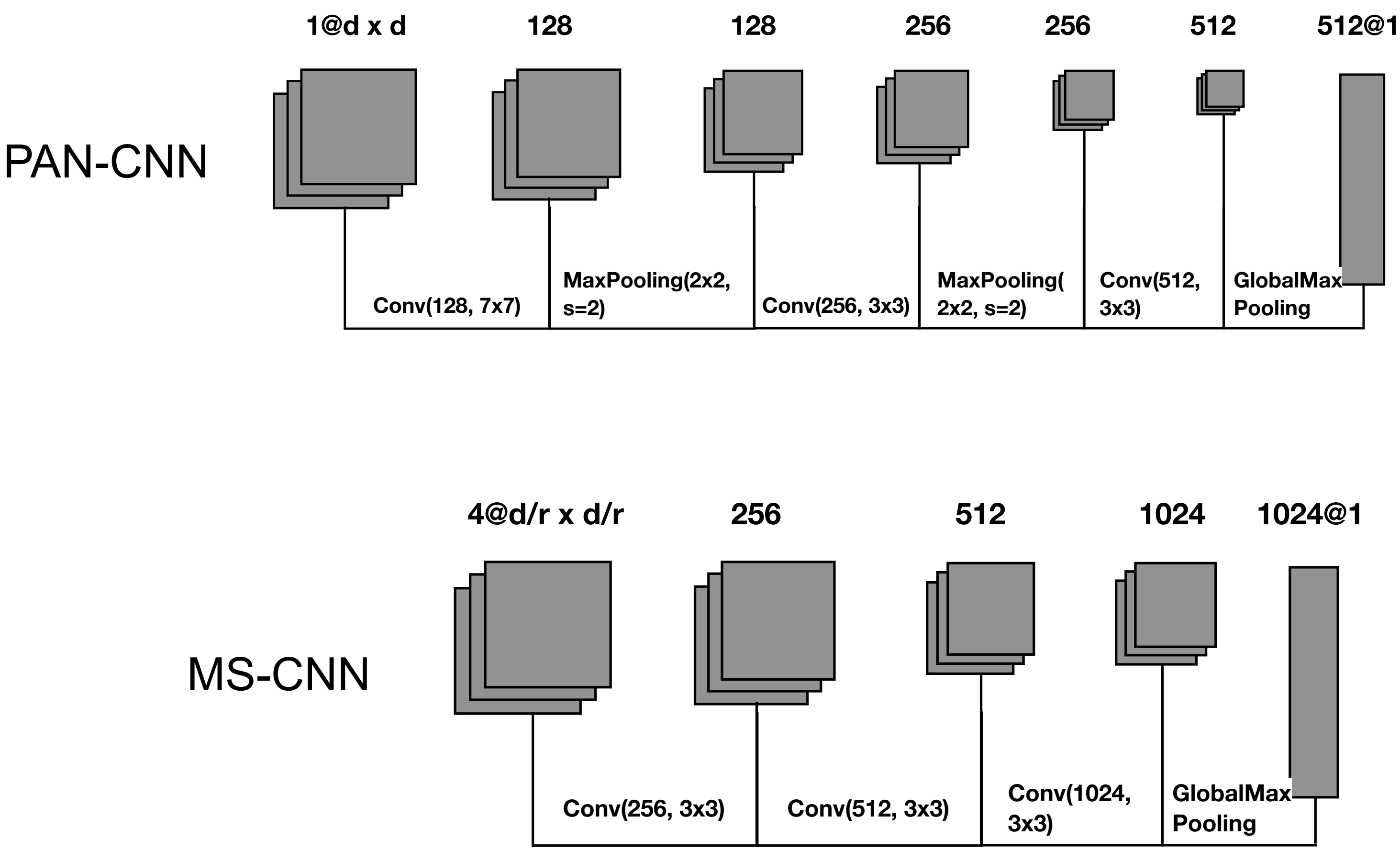


MultiResoLCC: A DL approach to fuse PAN and MS for LC mapping

Ent-To-End Process from scratch

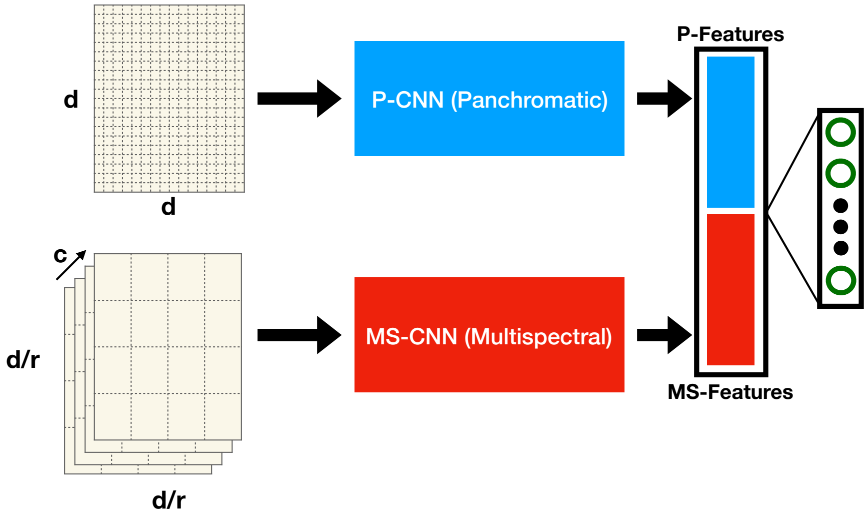
One CNN Module dedicated for each source **(PAN** and **MS)**

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)

Patch-Based solution is preferred to manage very sparse labeled Data



Data Description

Reunion Island Dataset:
- Spot6 image
- 13 Land Cover Classes
- PAN Image 44374 x 39422
- MS Image 11094 x 9856
- GT: around 464K pixels over 1749M pixels

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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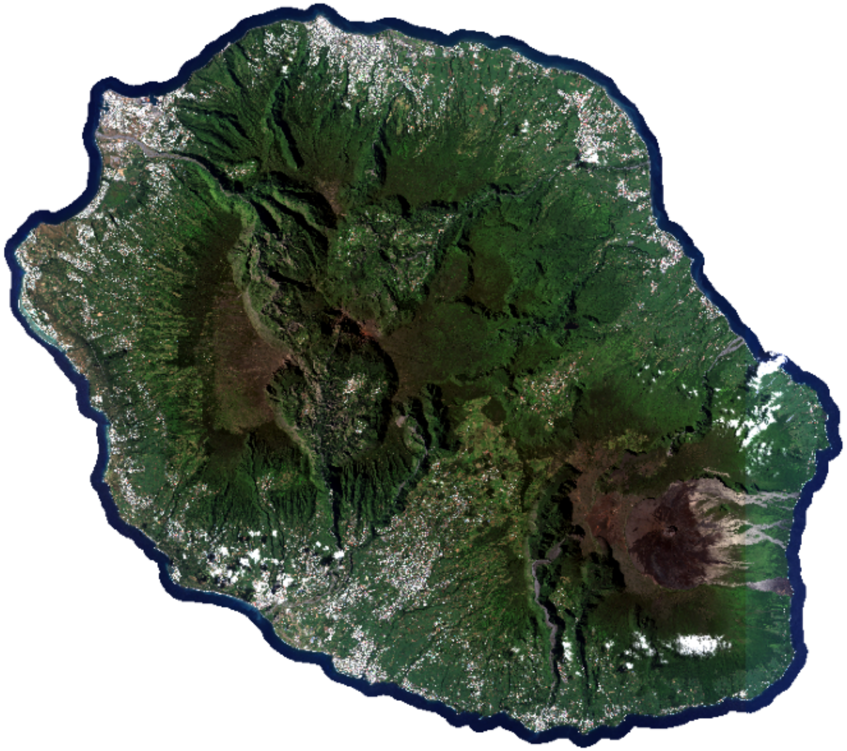
13	*Shadows*	38	11400

Gard Dataset:
- Spot6 image
- 8 Land Cover Classes
- Pan image 24110 x 33740
- MS image 6028 x 8435
- GT: around 400K pixels over 813M pixels

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 Morph. Features extracted from pan sharpened image
- **CNN** approach applied on Pansharpened image
- **DMIL** [Liu18] recent DL method to combine PAN and MS for land cover mapping
- **Random Forest** applied on features extracted by the DL approaches

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*
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
MultiResoLCC	**79.65** ± 0.87	**79.56** ± 0.91	**0.7764** ± 0.0096
$RF(PATCH)$	72.22 ± 1.31	71.53 ± 1.4	0.6943 ± 0.0144
$RF(MRSSF)$	76.24 ± 0.71	75.97 ± 0.66	0.7387 ± 0.0077
$RF(CNN_{PS})$	75.77 ± 1.14	75.56 ± 1.19	0.7334 ± 0.0125
$RF(DMIL)$	71.98 ± 0.46	71.94 ± 0.47	0.6918 ± 0.0051
$RF(MultiResoLCC)$	**79.67** ± 0.82	**79.52** ± 0.86	**0.7763** ± 0.0090

Reunion Island Results

	Accuracy	*F-Measure*	*Kappa*
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
MultiResoLCC	**70.48** ± 0.55	**70.19** ± 0.67	**0.6627** ± 0.0063
RF(PATCH)	69.93 ± 0.76	69.55 ± 0.77	0.6564 ± 0.0087
$RF(MRSSF)$	68.30 ± 0.33	68.18 ± 00.51	0.6377 ± 0.0038
RF(CNN_{PS})	68.04 ± 0.82	67.72 ± 0.84	0.6348 ± 0.0093
RF(DMIL)	64.79 ± 0.73	64.43 ± 0.82	0.5976 ± 0.0084
RF(MultiResoLCC)	**71.98** ± 0.58	**71.73** ± 0.54	**0.6797** ± 0.0066

Gard Results

Comparison Results

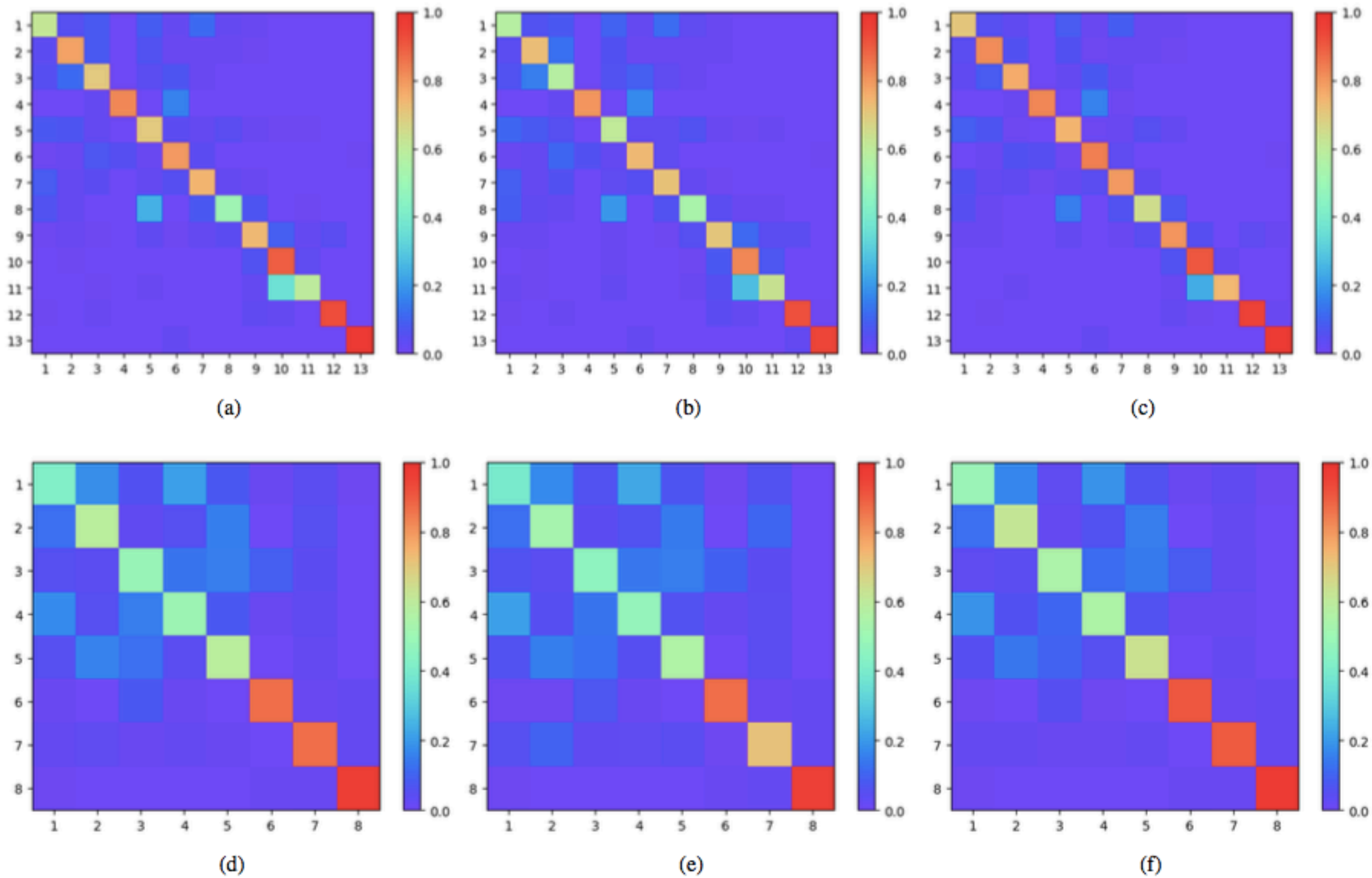


Figure 6: Confusion matrices of the Deep Learning approaches on the *Reunion Island* dataset (CNN_{PS} (a), $DMIL$ (b) and $MRFusion$ (c)) and on the *Gard* dataset (CNN_{PS} (d), $DMIL$ (e) and $MRFusion$ (f)).

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Map Details on some particular extracts

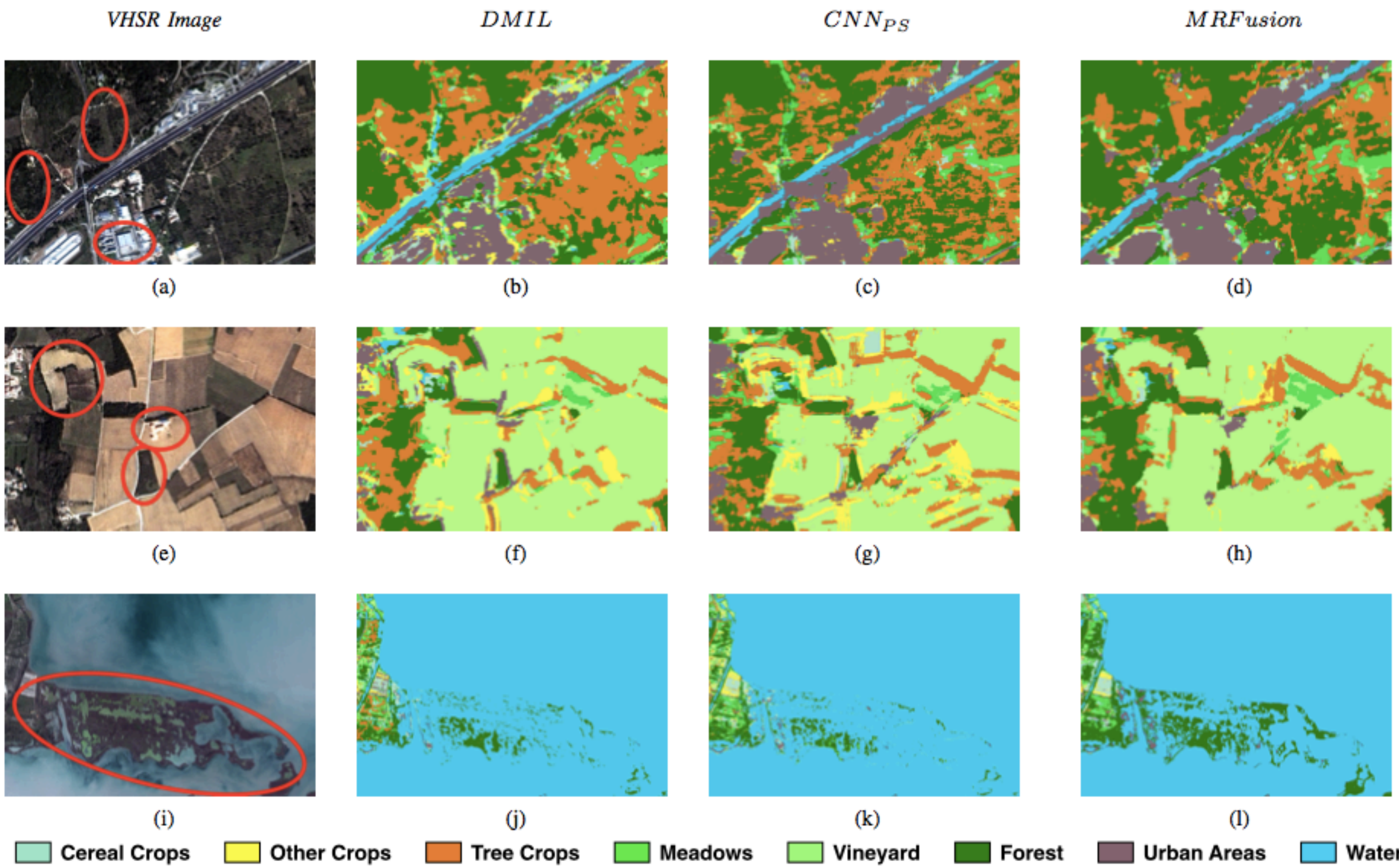

Table VIII: table caption GARD

Map Details on some particular extracts

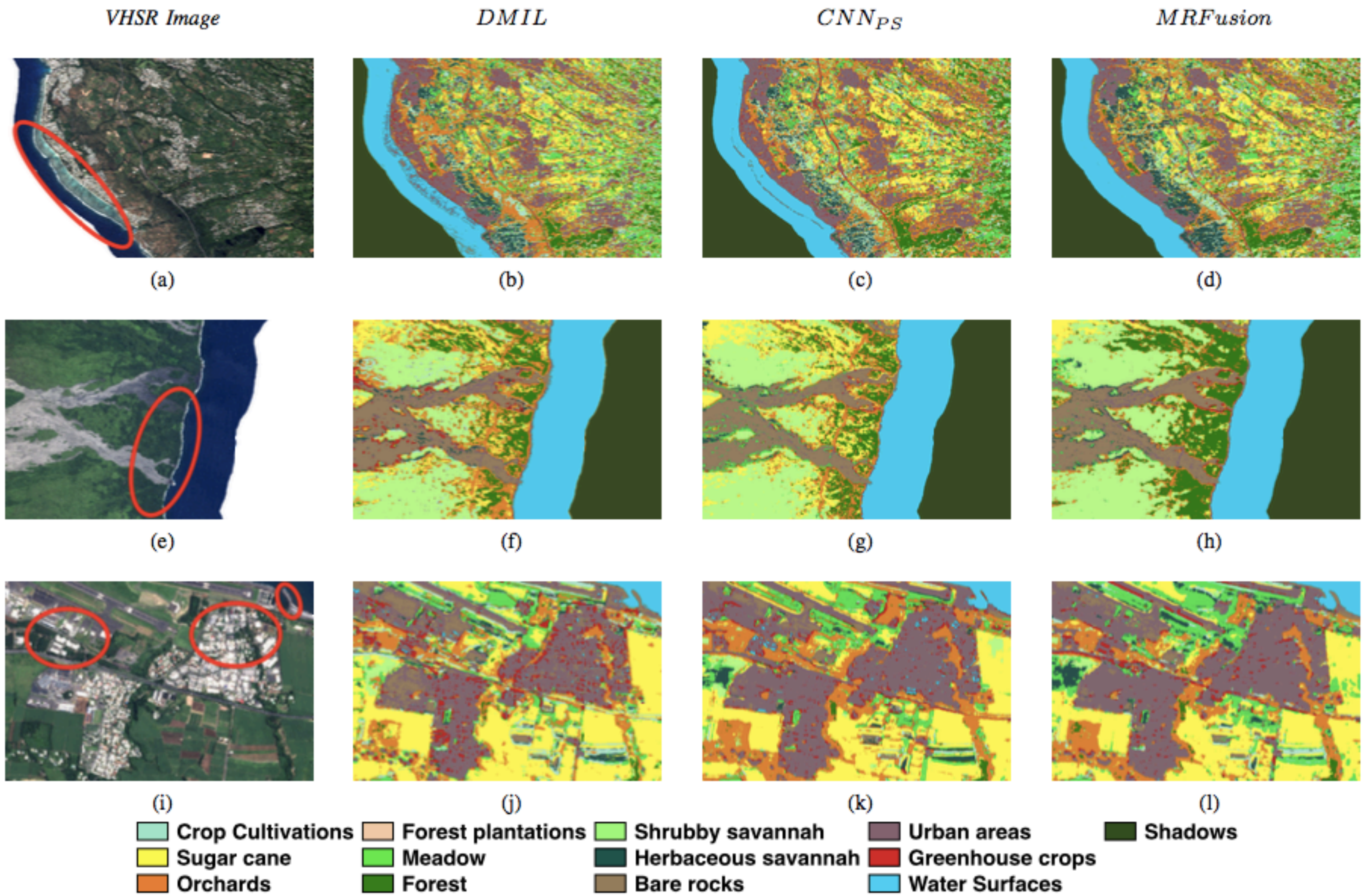

Table IX: table caption REUNION

Conclusion and Future Works

A deep architecture to merge PAN and MS image avoiding useless preprocessing (i.e. pansharpening)

The approach is especially conceived to deal with sparsely annotated data

Performance results underline the effectiveness of the proposed approach

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Future Works

Introduce external information (i.e. VGI information from OSM)

In depth study on the features extracted by our approach to evaluate the importance of each data source

The MDL4EO
(Machine and Deep Learning for Earth Observation)
team @UMR TETIS





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Remi Cresson, IRSTEA, Research Engineer - High Performance Computing & Signal processing

Kenji Osé, IRSTEA, Research Engineer - Geomatics and Remote Sensing

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Thank you for your Attention

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Questions

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