Super-Resolution: a pre-processing step for Hyperspectral Pansharpening

LONCAN Laëtitia 3ème année
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ANR HYEP
Hyperspectral Imagery for Environmental Urban Planning

gipsa-lab

Summary

I) Context

II) State of the art

III) Proposed approach: Super-resolution PAN

IV) Conclusion & perspectives

I) What is pansharpening?

Context: Preparation of the spatial Earth's observatory mission, HYPXIM

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➢Panchromatique camera: High **spatial** resolution image (1,8 m)

Panchromatique image (PAN)

- **High spatial** resolution
- **Poor spectral** resolution
- Give information on the geometry of the scene

I) What is pansharpening?

Context: Preparation of the spatial Earth's observatory mission, HYPXIM

- ➢Panchromatique camera: High **spatial** resolution image (1,8 m)
- ➢Hyperspectral sensor: High **spectral** resolution image (8 m)

Hyperspectral image (HS)

- **Low spatial** resolution
- **High spectral** resolution
- Give information on the composition of the scene

I) What is pansharpening?

Context: Preparation of the spatial Earth's observatory mission, HYPXIM

→ **Targeted application** classification of urban area (< 5 m)

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Panchromatique image (PAN) 1,8m

Hyperspectral image (HS) 8m

?

Fusion

I) What is pansharpening?

Context: Preparation of the spatial Earth's observatory mission, HYPXIM

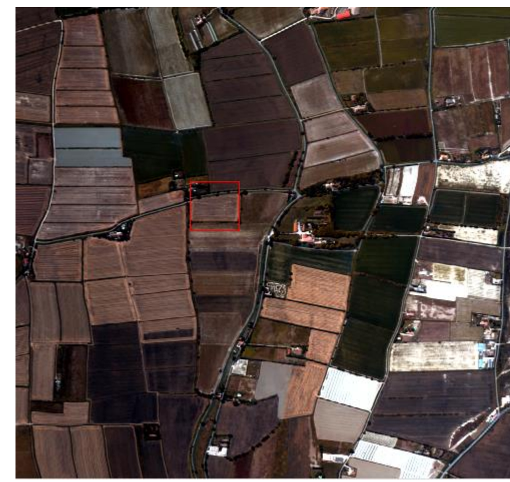
→ **Targeted application** classification of urban area (< 5 m)

Panchromatique image (PAN) 1,8m

Hyperspectral image (HS) 8m

?

Fusion



Ideal result of the fusion 1,8m

- Good spatial and spectral resolutions
- Give information on both the geometry and the nature of the scene

Summary

II) State of the art

5 main families of methods:

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5 main families of methods:

- **Component Substitution (CS)**

Method originally designed for MS + PAN fusion
→ Spatial information is well preserved
→Can create spectral distorsion

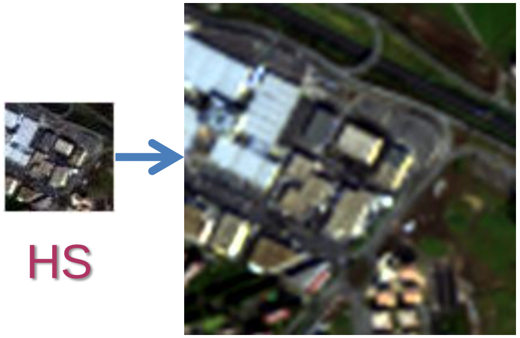
Example of methods:
-Principal Component Analysis (PCA) [Chavez1989]
-Gram Schmidt adaptive (GSA) [Laben2000]

II) Component Substitution (CS)

HS

PAN Image

II) Component Substitution (CS)

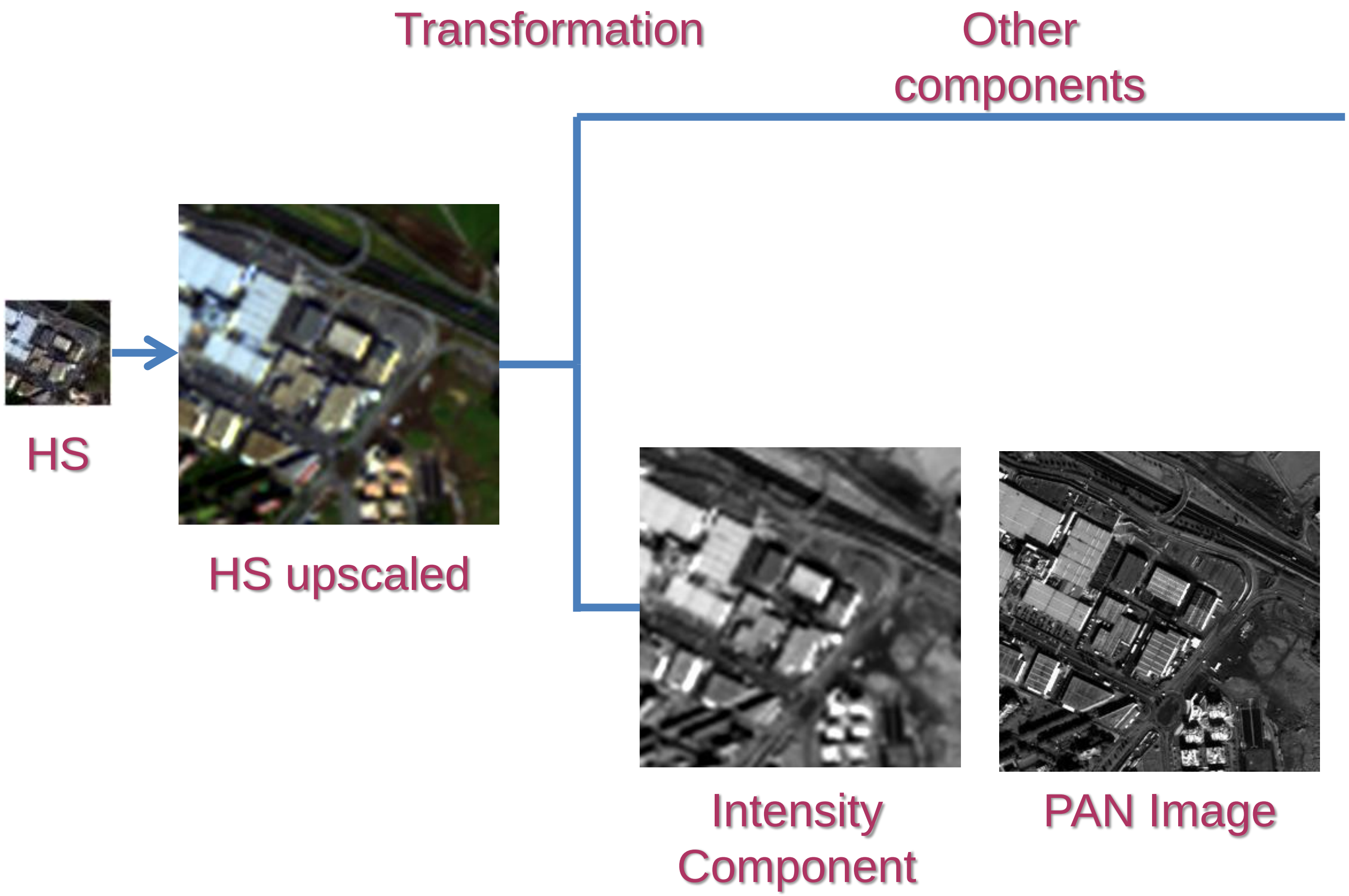


HS

HS upscaled

PAN Image

II) Component Substitution (CS)



II) Component Substitution (CS)

HS

HS upscaled

Transformation

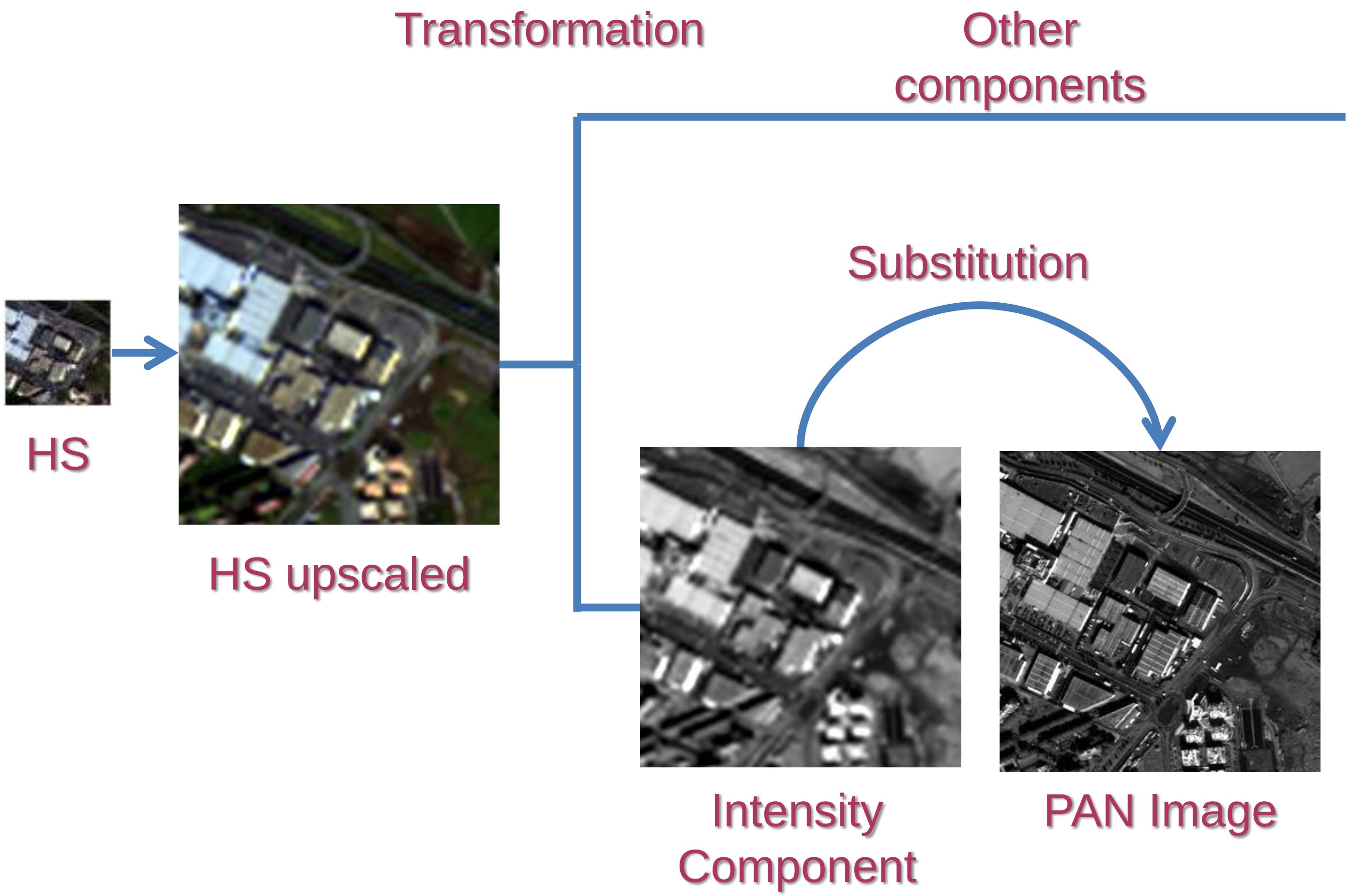
Other components

For PCA: Intensity Component = First Principal Component

Intensity Component

PAN Image

II) Component Substitution (CS)



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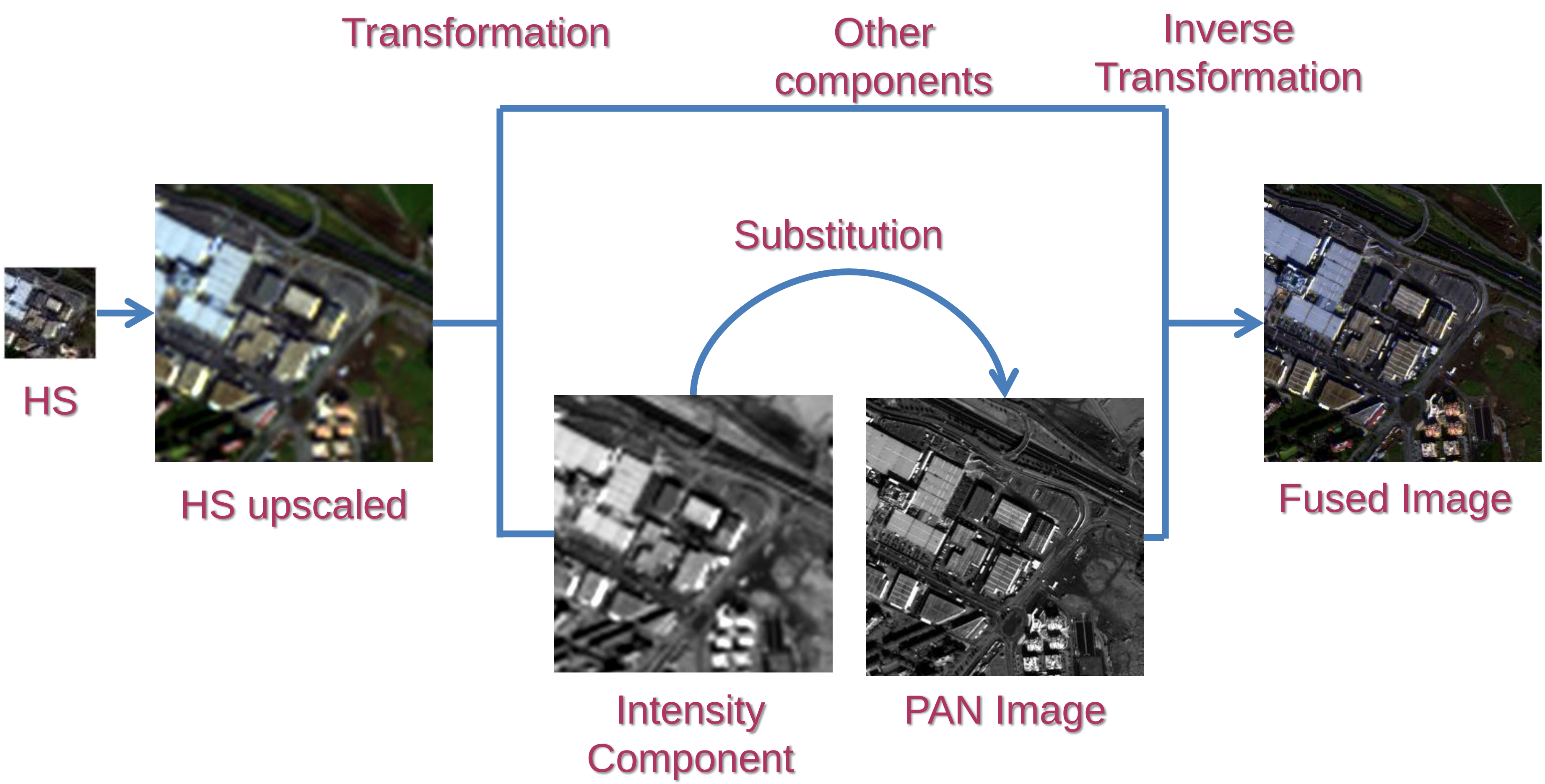


II) State of the art

5 main families of methods:

- Component Substitution (CS)
- **Multi-Resolution Analysis (MRA)**

Method originally designed for MS + PAN fusion
Similar to CS method, main difference → use spatial filter

→Spectral information is well preserved
→Can create some spatial blur

Example of methods:

-Modulation transfert function Generalized Laplacian Pyramid with High Pass Modulation (MTF-GLP-HPM) [Vivone2014] → Laplacian Pyramid

-Smoothing filter-based intensity modulation (SFIM) [Liu2000] → single linear time invariant low pass filter

II) Component Substitution (CS)

HS

HS upscaled

PAN Image

II) Component Substitution (CS)

HS

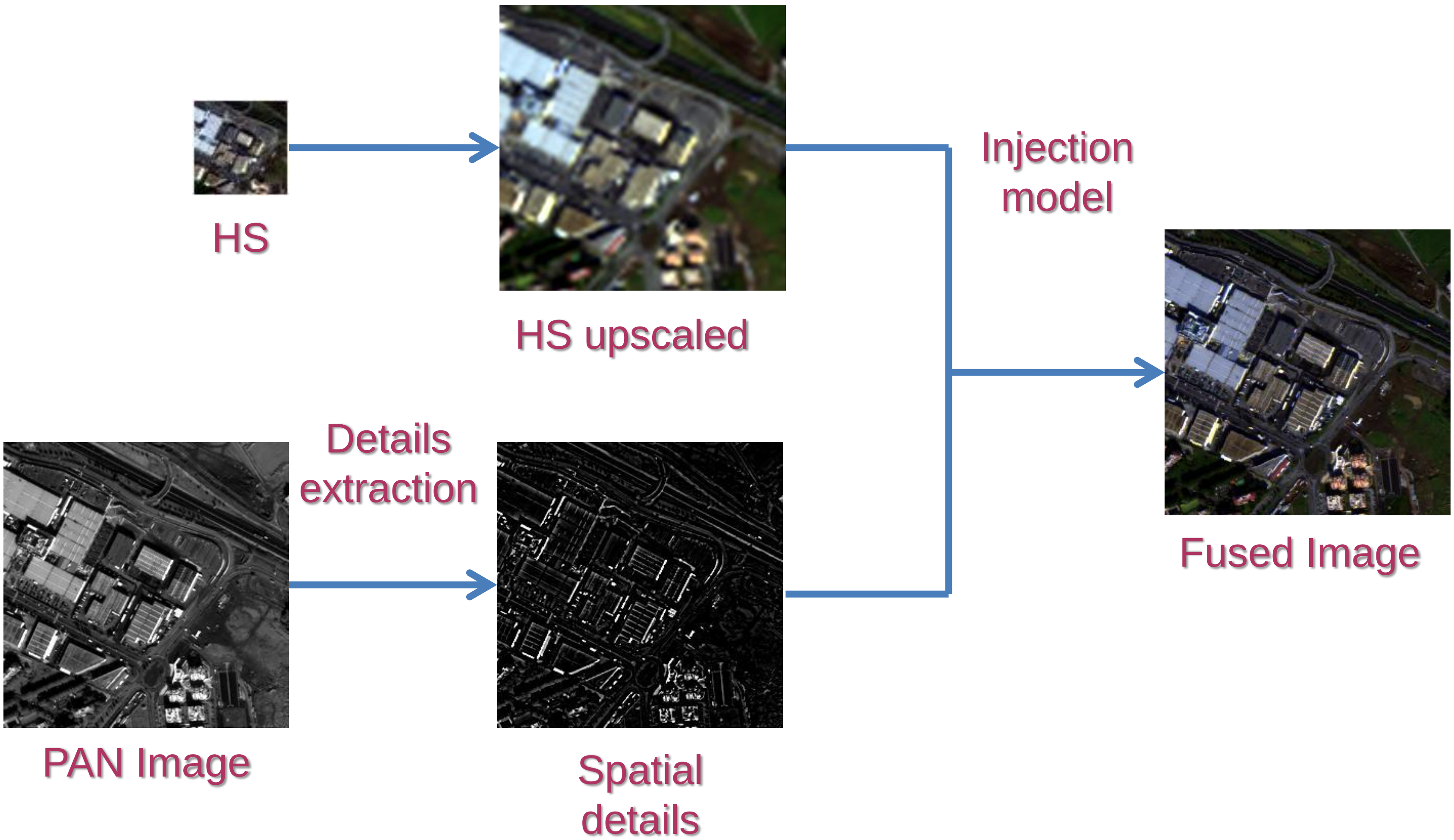
HS upscaled

Details extraction

PAN Image

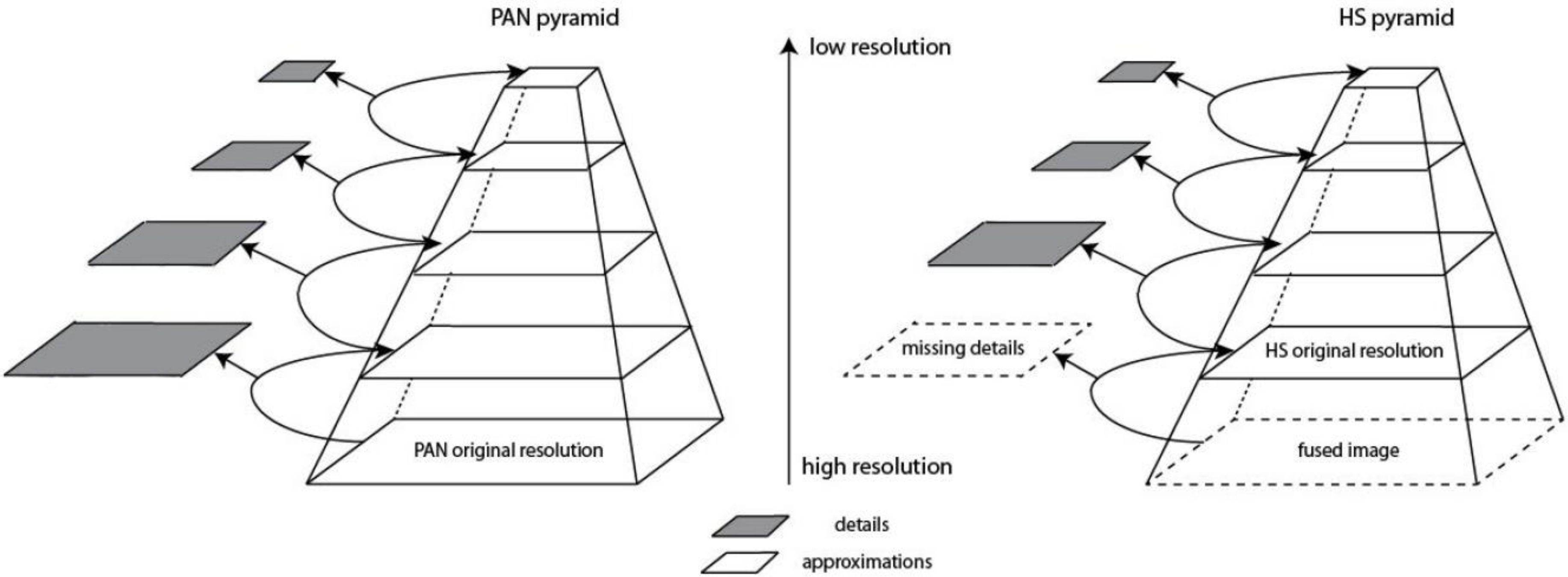
Spatial details

II) Component Substitution (CS)



II) MultiResolution Analysis (MRA)

Details extraction and injection model using Laplacian Pyramid method



II) State of the art

5 main families of methods:

- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- **Hybrid**

Combine elements from differents families

Example: Guided Filter PCA (GFPCA) [LiaoSubmitted]

II) State of the art

5 main families of methods:

- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- Hybrid
- **Matrix Factorization**

Originally designed for MS + HS
Use unmixing to write MS and HS image as a product of two matrices : abundance and endmembers

Example: Coupled Non-negative Matrix Factorization (CNMF) [Yokoya2012]

II) State of the art

5 main families of methods:

- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- Hybrid
- Matrix Factorization
- **Bayesian Method**

Originally designed for MS + HS
Use bayesian method to modelise the fusion process
Sensor characteristic is needed

Methods: [Wei2015] [Simoes2015]

II) State of the art

5 main families of methods:

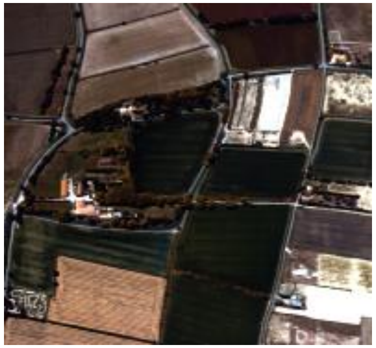
- Component Substitution (CS)
- Multi-Resolution Analysis (MRA)
- Hybrid
- Matrix Factorization
- Bayesian Method

A review paper has been written on this topic:

Review paper on Hyperspectral Pansharpening:
L. Loncan, L. B. Almeida, J. M. Bioucas-Dias, X. Briottet, J. Chanussot, N. Dobigeon, S. Fabre,W. Liao, G. A. Licciardi,M. Simoes, J-Y. Tourneret,M. A. Veganzones, G. Vivone, Q. Wei, and N. Yokoya, "**Hyperspectral pansharpening: A review**, to appear in IEEE Geoscience and Remote Sensing Magazine

II) Dataset and evaluation

PAN



Reference

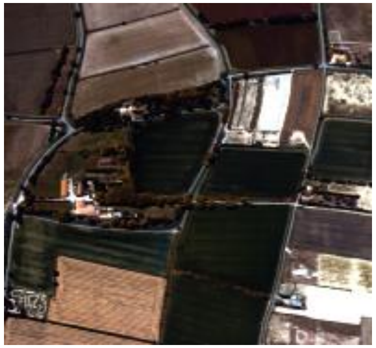
HS upscaled

Dataset information

- Rural area from Camargue (France)
- Source data: Airbone HS data acquired with Hymap
- Simulated dataset
- Spatial resolution: PAN: 2 m, HS: 8 m (ratio 4)

II) Dataset and evaluation

PAN



Reference

HS upscaled

Criteria for the evaluation of the results: Wald's protocole + Visual spatial analysis + Visual spectral analysis

- Spatial → CC: cross correlation (ideal value 1)
- Spectral → SAM: spectral Angle Mapper (ideal value 0)
- Global → RMSE: root mean squared error & ERGAS*: Dimensionless Global Error (ideal value 0)

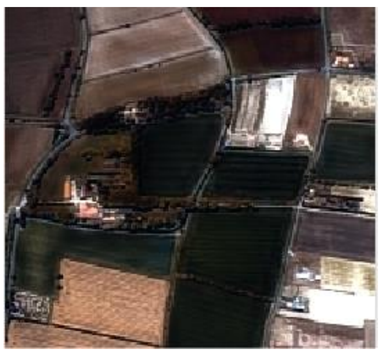
*« Erreur relative globale adimensionnelle de synthèse »

II) Results: Visual analysis (0,4 – 0,8 µm domain)


PAN


Reference


HS upscaled


SFIM


MTF-GLP-HPM

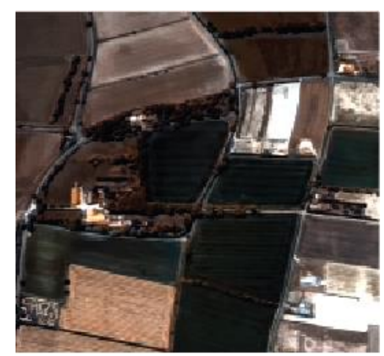

GSA


PCA


GFPCA


CNMF


Bayesian sparse


HySure

II) Results: Visual analysis (0,4 – 0,8 µm domain)

PAN

Reference

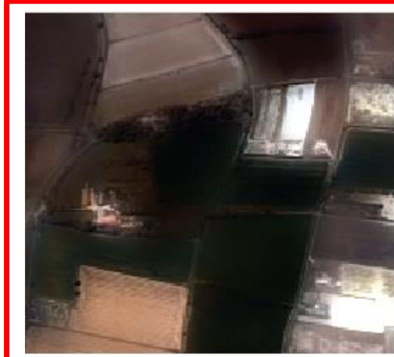
HS upscaled

SFIM

MTF-GLP-HPM

GSA

PCA



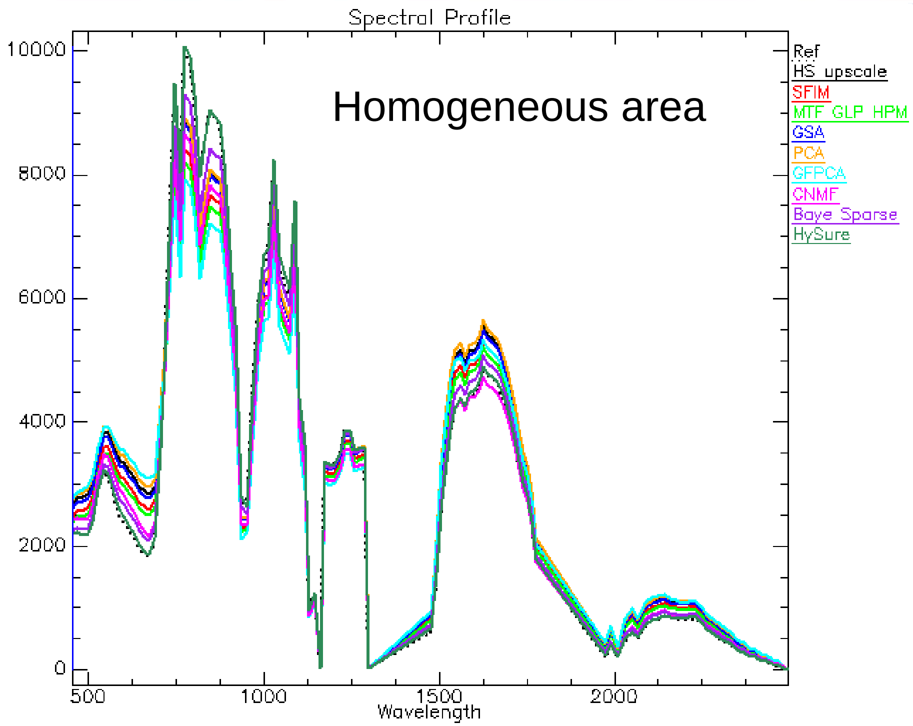
GFPCA

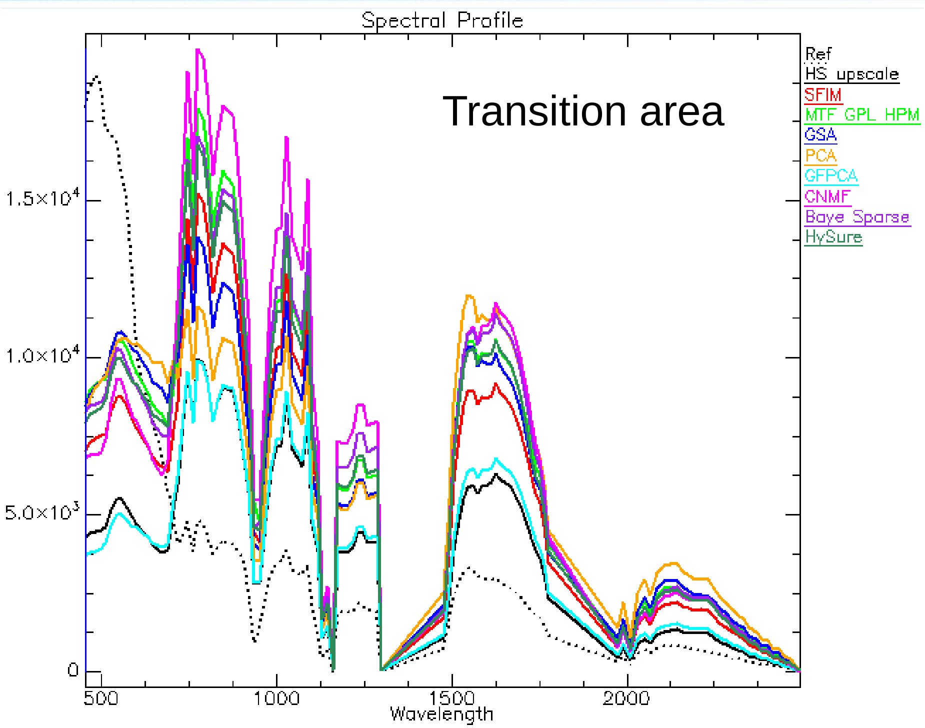
CNMF

Bayesian sparse

HySure

II) Results: Visual spectral analysis





Good performance on homogenous area but some problem with transition area

→ Case of mixed pixels is generally ignored

Summary

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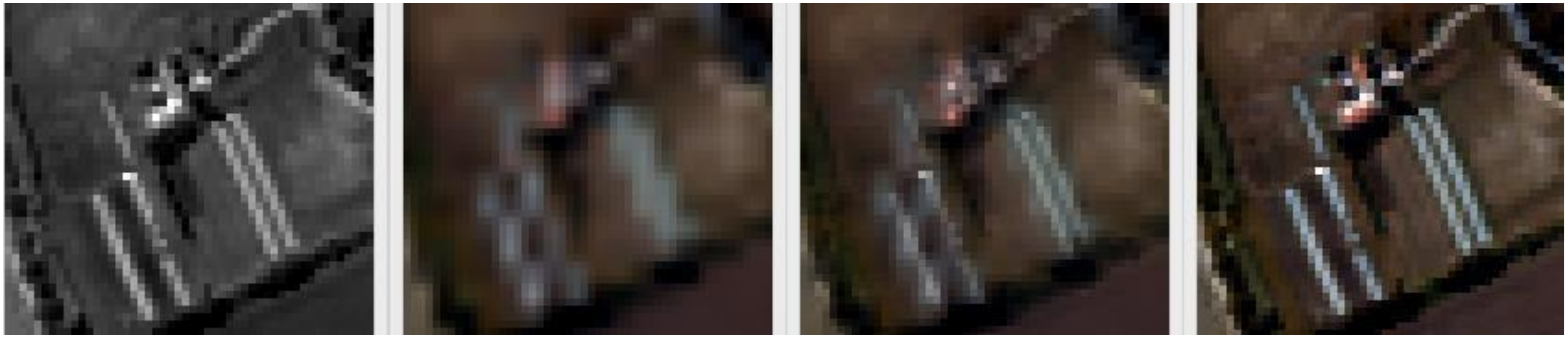
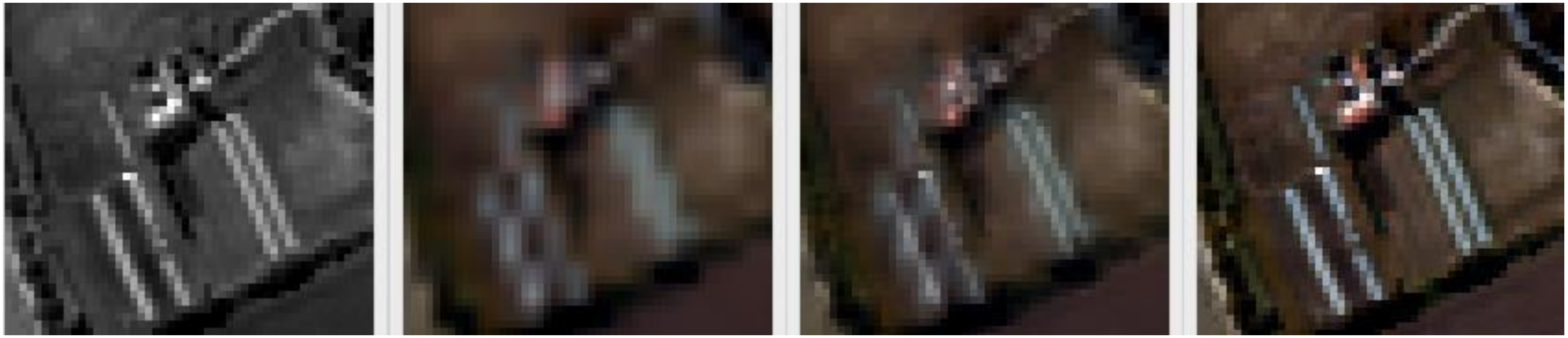
III) Problematic: Case of the mixed pixels



PAN HS fusion result Reference

Currently, most of the methods do not modify the spectral information of HS
→ Mixed pixels will stay mixed, which creates halo around small objects

III) Problematic: Case of the mixed pixels



PAN HS fusion result Reference

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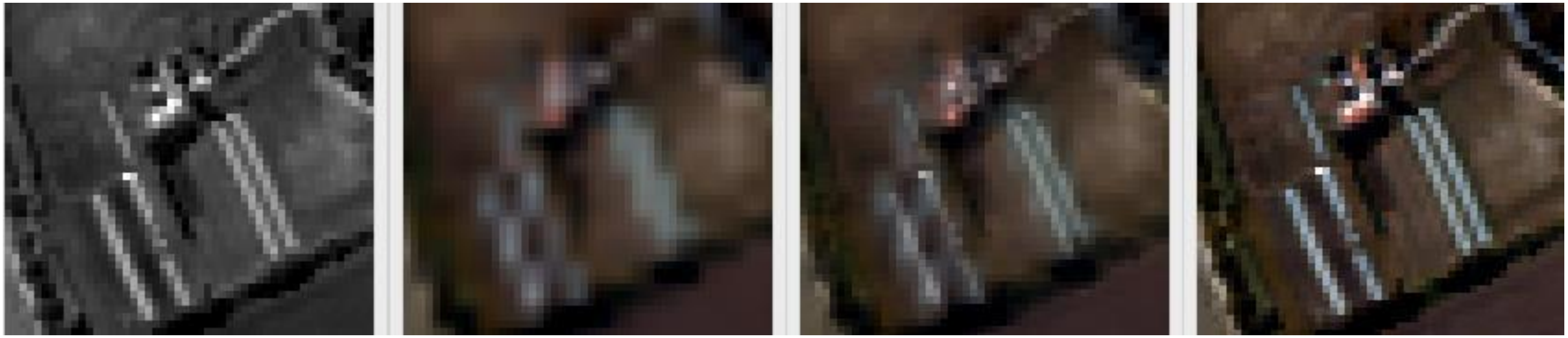
Solution:
→ Adding a pre-proceeing step to unmix these pixels

III) Problematic: Case of the mixed pixels



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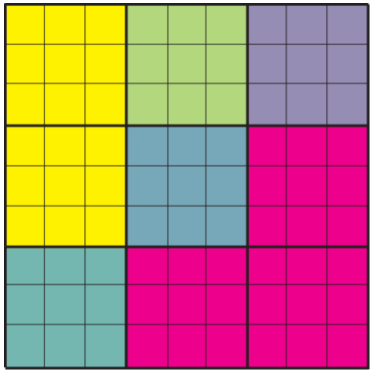

Original HS image

III) Problematic: Case of the mixed pixels


PAN


HS


fusion result


Reference

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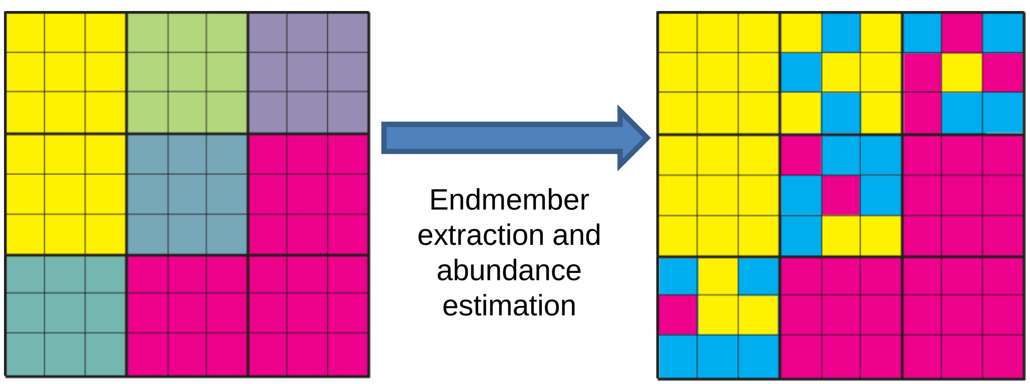
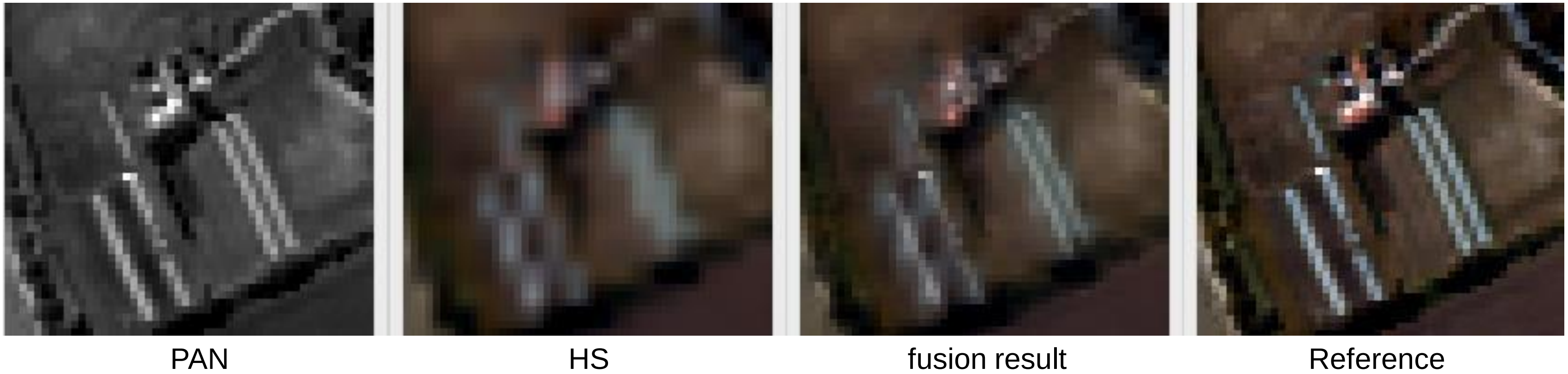


Original HS image

III) Problematic: Case of the mixed pixels



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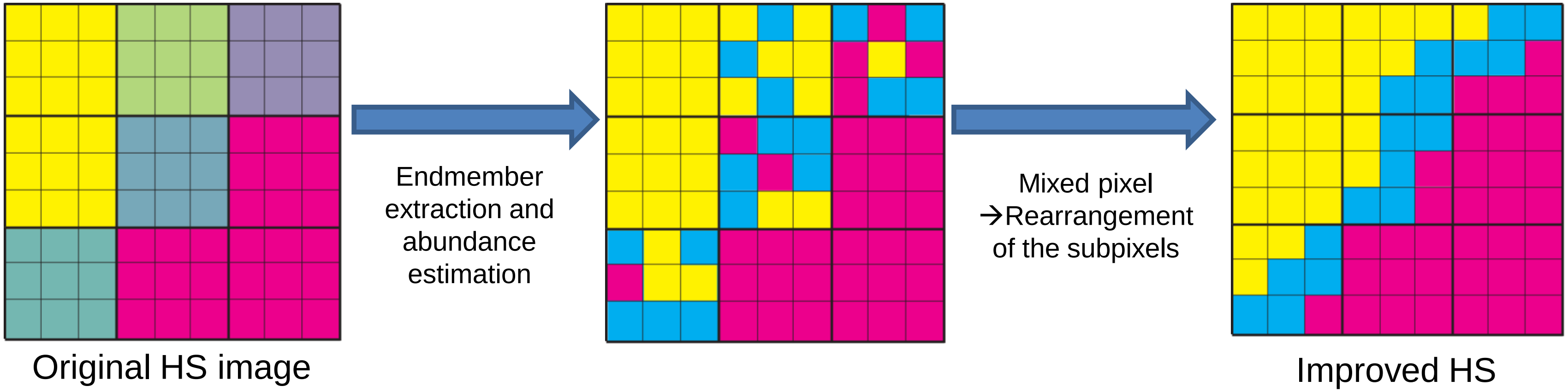
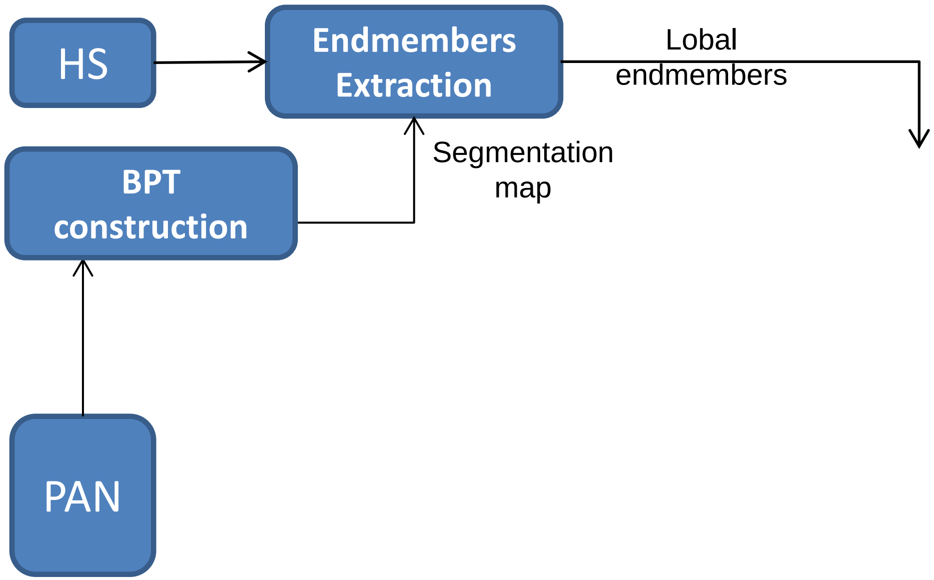


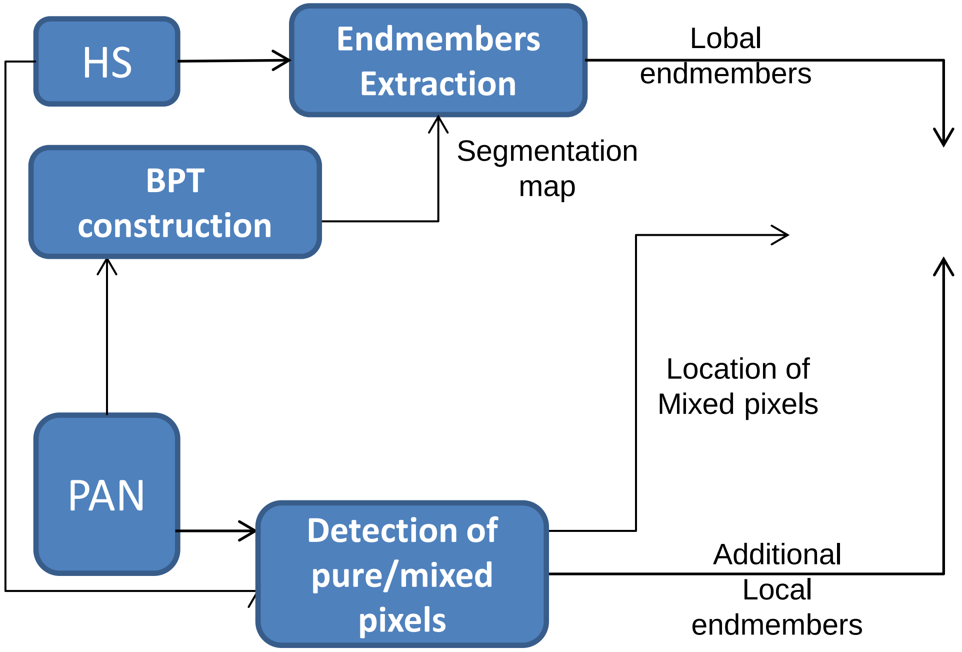
III) Step 1: Endmembers Extraction



Local endmember → to take into account spectral variability

Endmembers extraction step done by using VCA

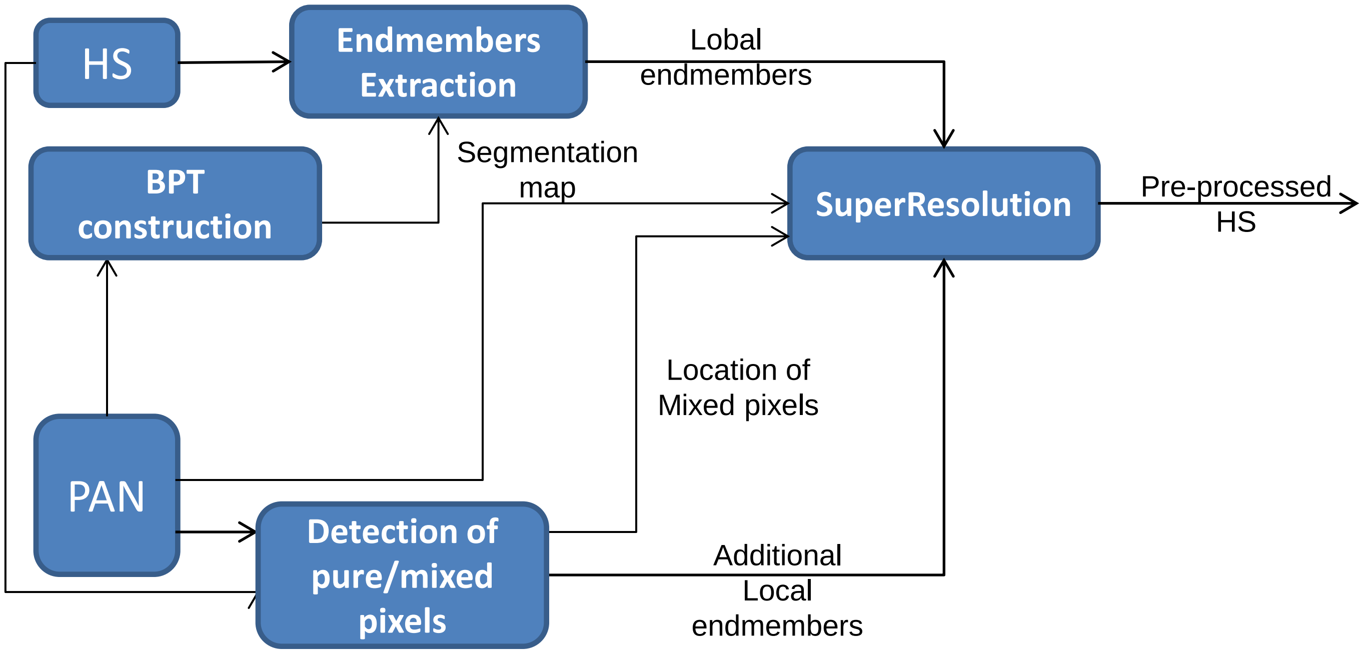
III) Step 2: detection of pure/mixed pixels



Hypothesis: Homogeneous area in PAN → pure HS pixel

Local endmember → Pure pixels close to mixed pixels

III) Step 3: Unmixing of mixed pixels

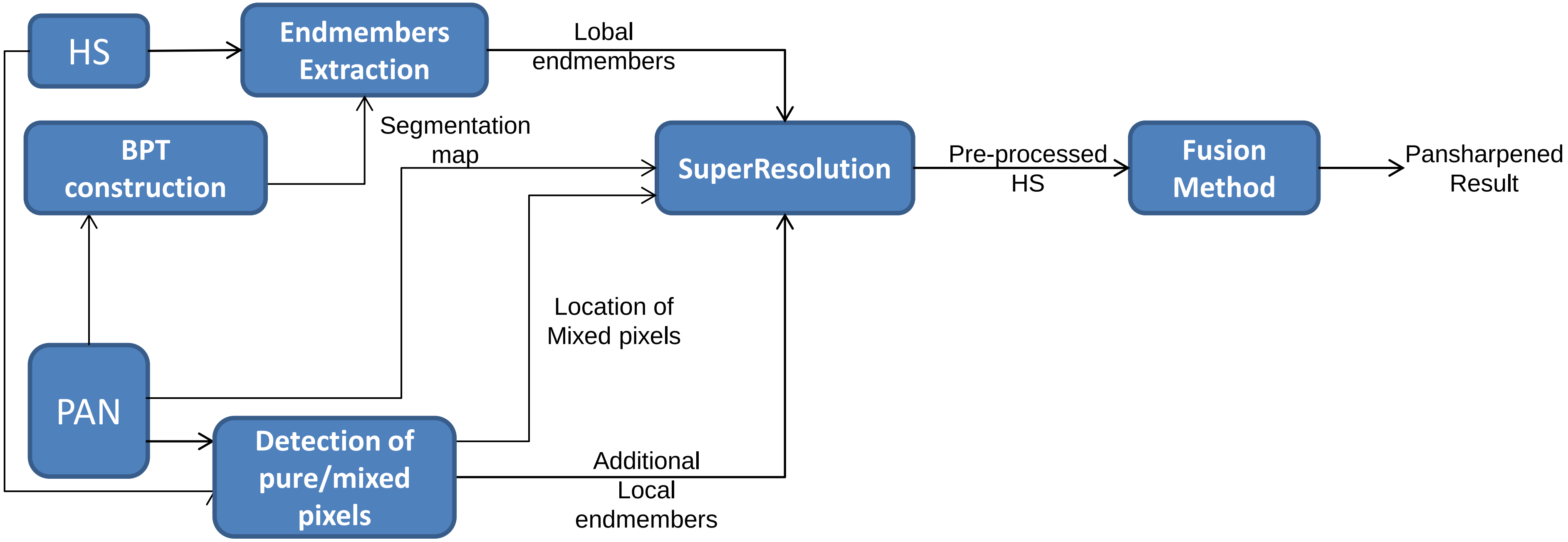


Principle:

Each candidate endmember -> converted in PAN domain

Spatially arrange the converted endmembers to mimic PAN information with respect to the abundance information

III) Step 4: Addition of spatial information

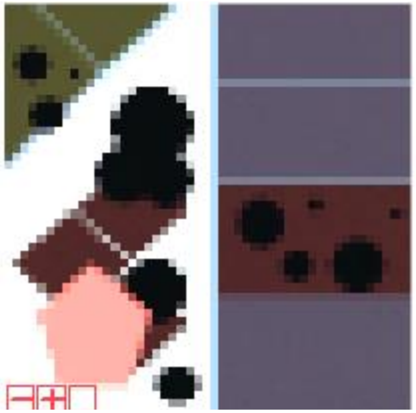


Simple method based on a gain to add spatial information without modifying spectral information

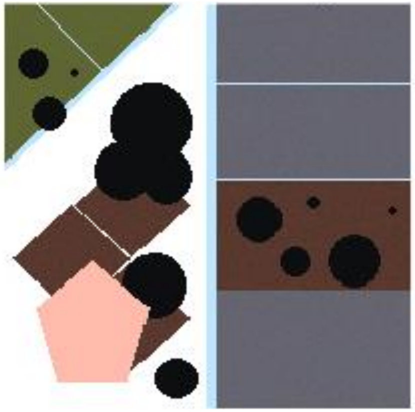
III) Evaluation of the super-resolution step on a synthetic image

(a) PAN image

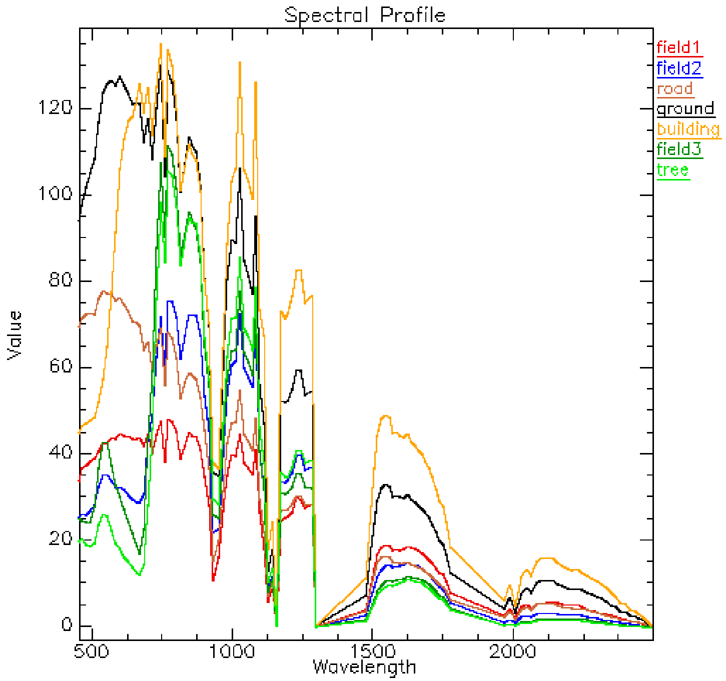
(b) Reference image



(c) Enlarged HS



(d) Super-resolution PAN



Endmembers used for the synthetic image

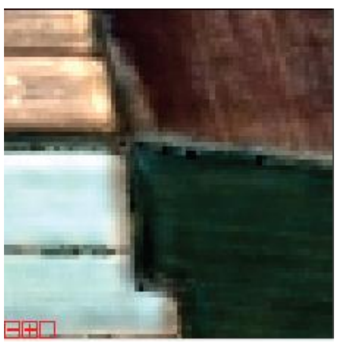
method	Rate of reconstruction error
Super-resolution PAN	0,0001%

III) Evaluation of the full method on real dataset (extract)

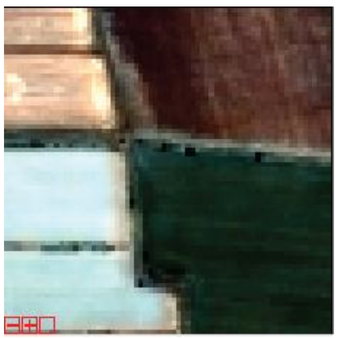
Presentation of the real dataset

(a) PAN image (b) Ref image (c) HS enlarged image

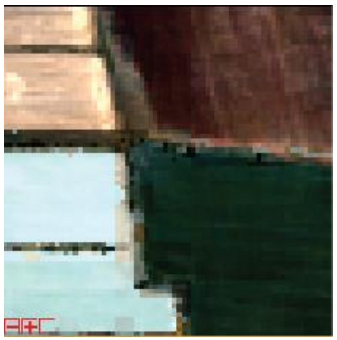
Results of the fusion



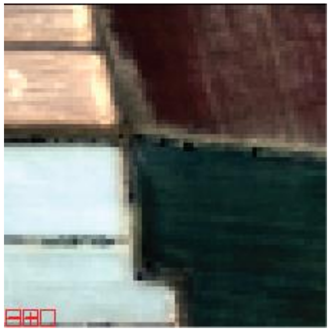
MTF-GLP-HPM



GSA



Super-resolution



CNMF

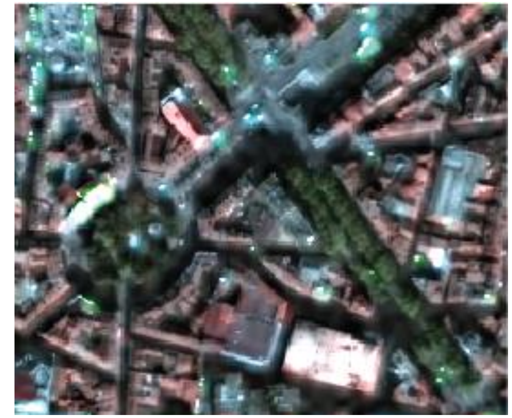
Bayesian sparse

method	CC	SAM	RMSE	ERGAS
Super-Res	**0,95**	**2,65**	3,53	**3,21**
GSA	0,93	3,51	4,12	4,07
MTF GLP HPM	0,91	3,71	4,53	4,57
CNMF	0,95	3,30	**3,42**	3,48
Bayesian Sparse	0,89	3,88	4,85	5,41

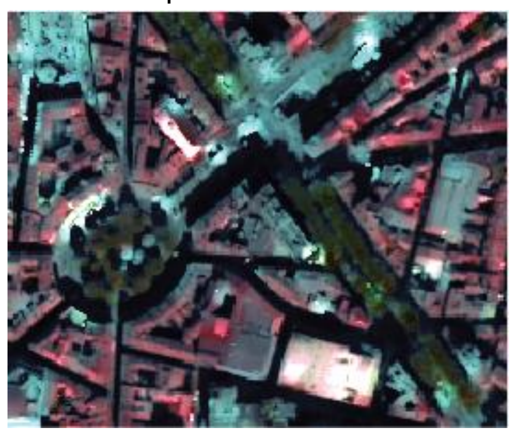
III) Evaluation of the full method on real dataset ->Toulouse (urban)


reference


Super-resolution


GSA


MTF-GLP-HPM

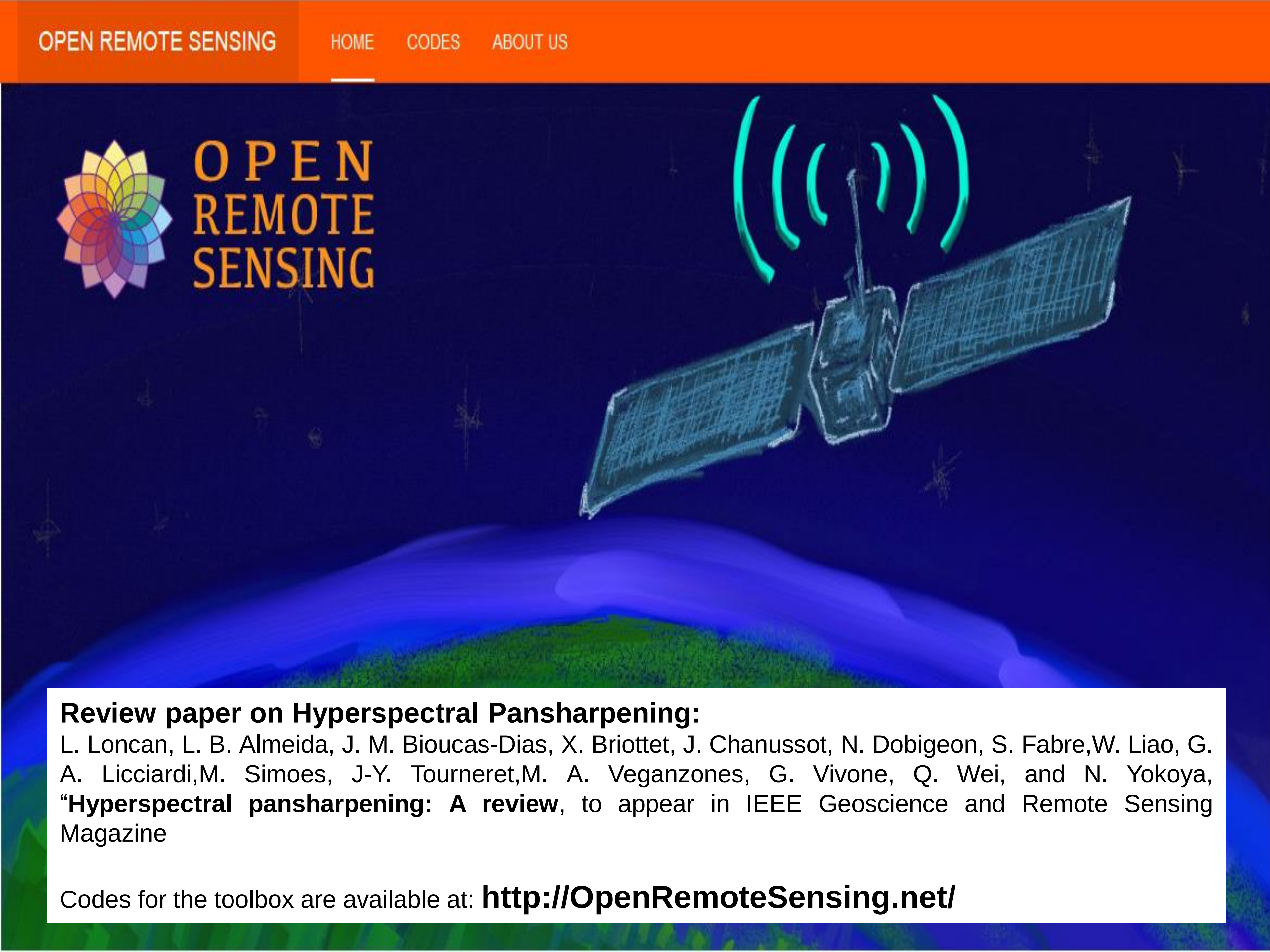

CNMF


Bayesian sparse

Conclusion & perspectives

- Most of the methods from the State of the Art have the same limitation
  → Transition area (mixed pixels)
- To address this issue some preliminary work has been presented
  → Preliminary unmixing step to improve result at subpixel level in transition area

- More tests need to be done to evaluate this approach:
  → Test on different landscape (particularly urban area: ANR HYEP)
  → Test with different ratio



Review paper on Hyperspectral Pansharpening:

L. Loncan, L. B. Almeida, J. M. Bioucas-Dias, X. Briottet, J. Chanussot, N. Dobigeon, S. Fabre,W. Liao, G. A. Licciardi,M. Simoes, J-Y. Tourneret,M. A. Veganzones, G. Vivone, Q. Wei, and N. Yokoya, “**Hyperspectral pansharpening: A review**, to appear in IEEE Geoscience and Remote Sensing Magazine

Codes for the toolbox are available at: **http://OpenRemoteSensing.net/**

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[WeiToAppear] Q.Wei et al, “Fast multi-band image fusion based on solving a Sylvester equation”, to appear, IEE Trans. Image Process.