# DIFFERENT APPROACHES FOR THE FUSION OF HYPERSPECTRAL AND PANCHROMATIC IMAGES USING INDUSION AND NONLINEAR PCA

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ANR

# Hyperspectral Feature reduction

One of the main difficulty in processing hyperspectral images is related to their huge number of bands:

Dimensionality reduction techniques

PCA, MNF, KPCA, ICA, …

Dimensionality reduction obtained by discarding the components with the lowest information content.

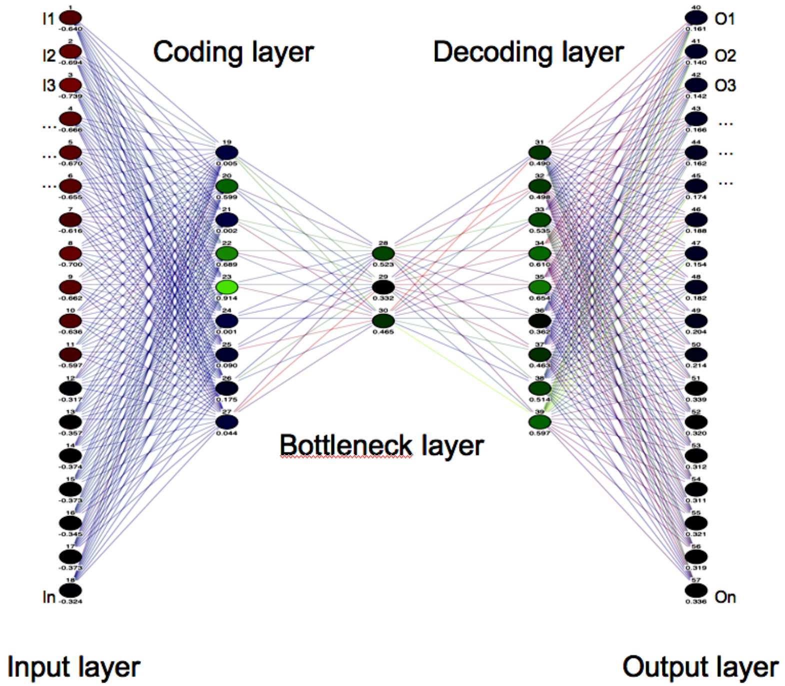
Components linearly uncorrelated, but the physical interpretation of the image can be nonlinear.

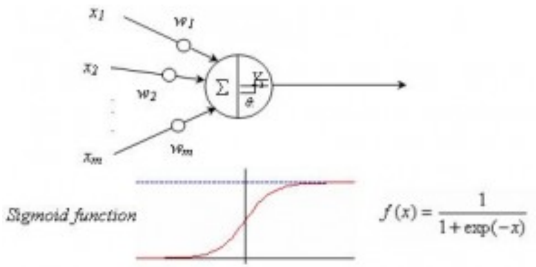
Loss of information

Need of a **lossless** dimensionality reduction technique

# Nonlinear Principal Component Analysis

Nonlinear generalization of the standard PCA, performed by Autoassociative Neural Networks (AANN)

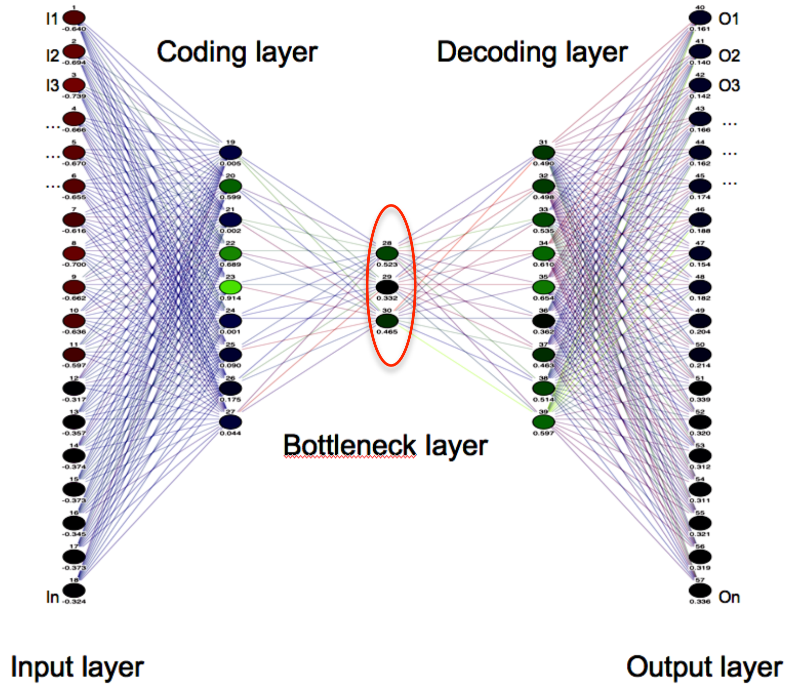



Multi-layer neural networks (NN) of a conventional type, featuring feed-forward connections and sigmoidal nodal transfer functions, trained by back-propagation or similar algorithms.

# Nonlinear Principal Component Analysis

Three hidden layers, including an internal **bottleneck layer** of smaller dimension than either input or output.

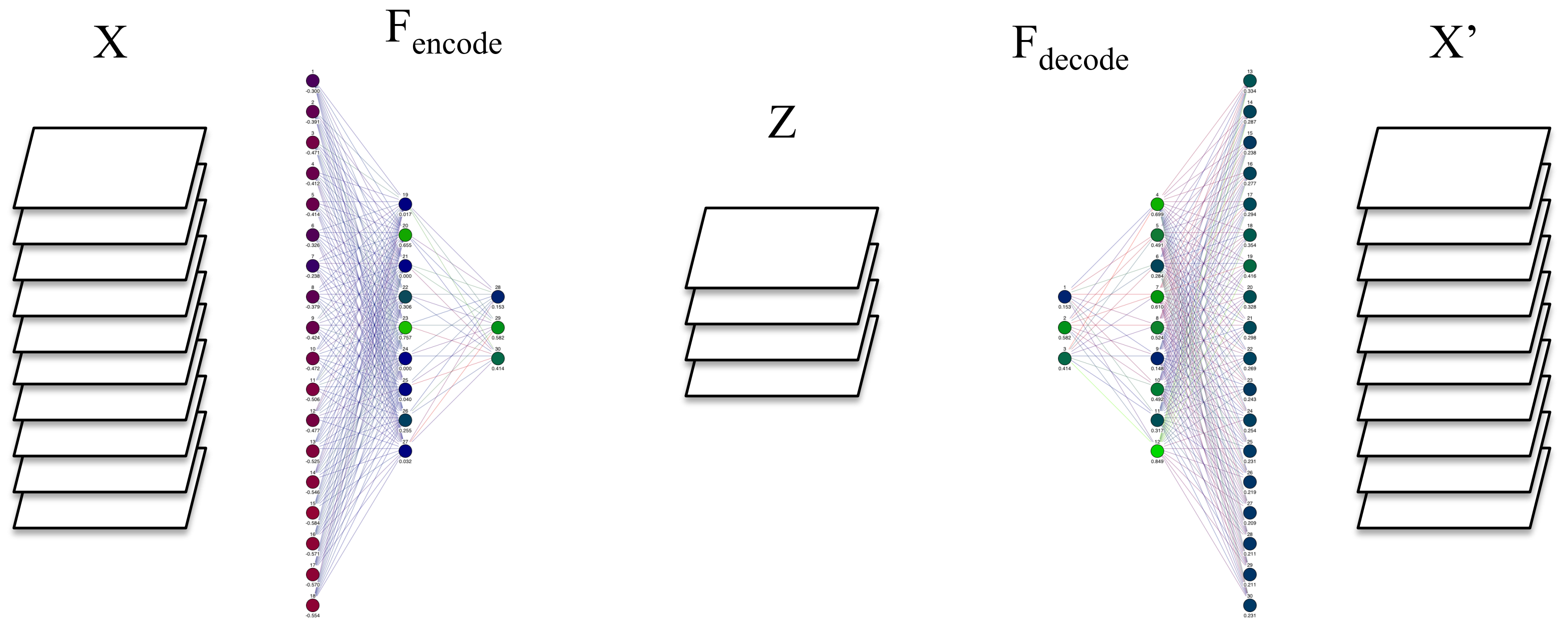



The network is trained to perform identity mapping:

**Input ≅ Output**

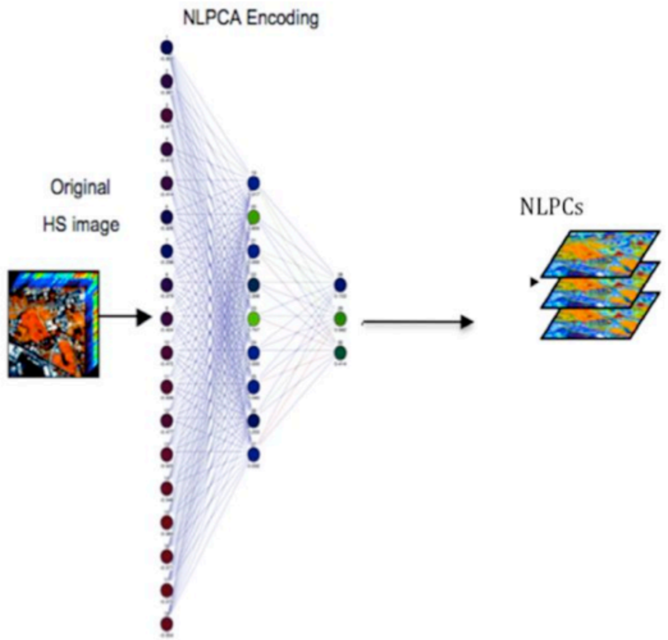
# Nonlinear Principal Component Analysis

An AANN can be divided into two parts: the first part represents the encoding or extraction function $F_{encode}$ : X ➔ Z , while the second part represents the inverse function, called decoding function $F_{decode}$ : Z ➔ X' .



# Nonlinear Principal Component Analysis

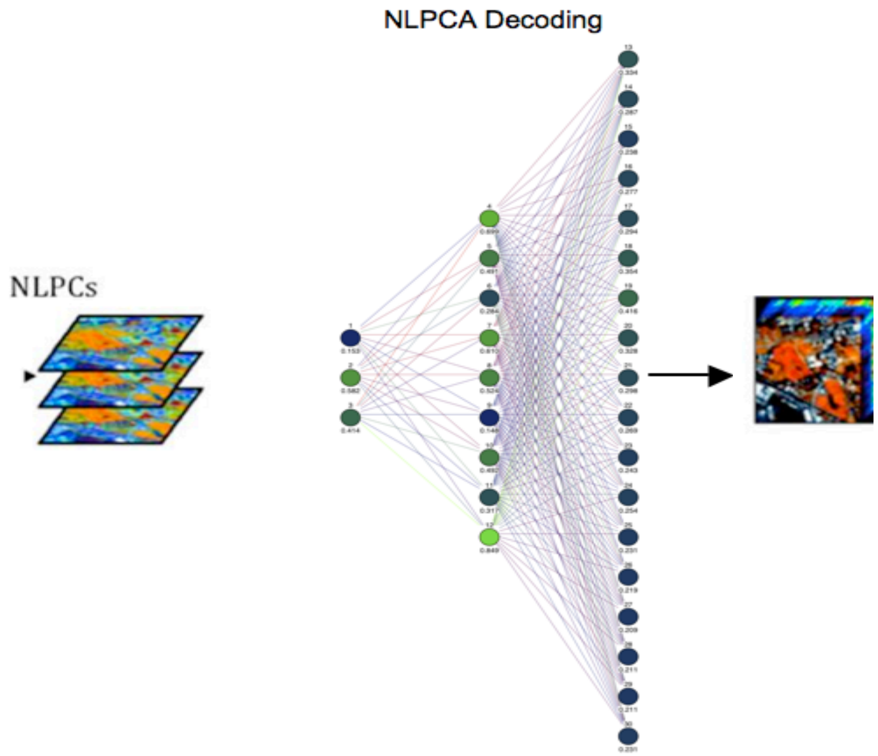
Since there are fewer units in the bottleneck layer than the output, the bottleneck nodes must represent or encode the information obtained from the inputs for the subsequent layers to reconstruct the input.




The Nonlinear Principal Components (NLPCs) can be extracted from the bottleneck nodes, after the training of the AANN.

# Nonlinear Principal Component Analysis

Using the decoding function it is possible to reconstruct the original spectral space from the previously extracted NLPCs.



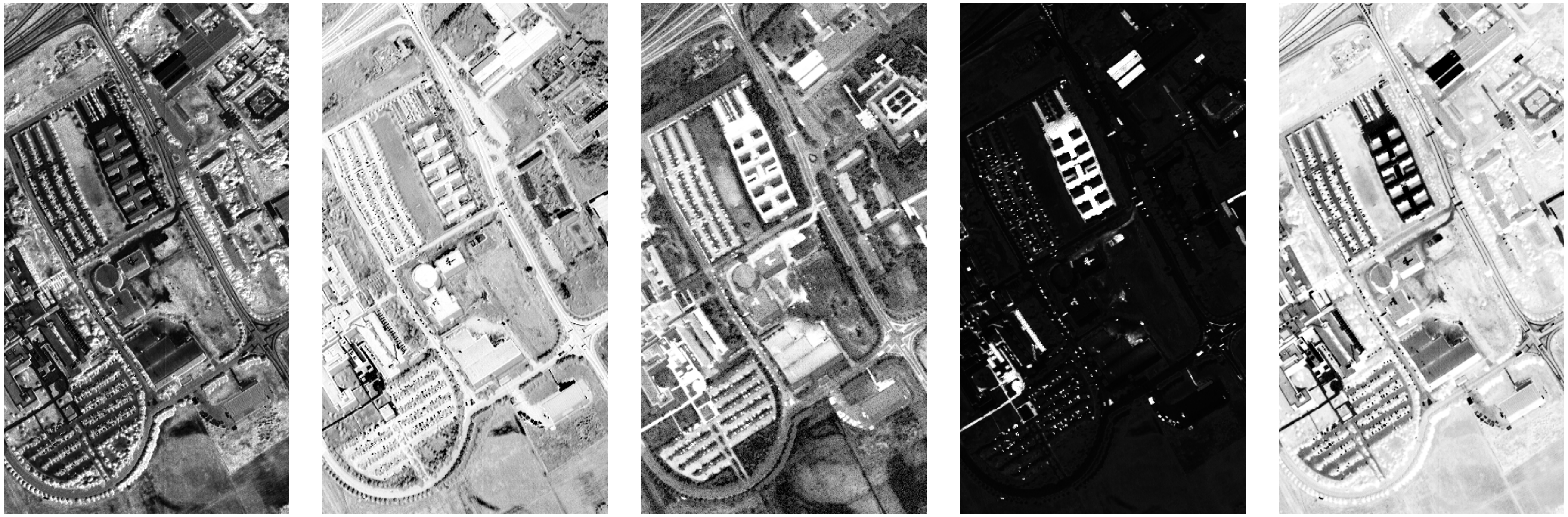
# Nonlinear Principal Component Analysis

Many advantages:

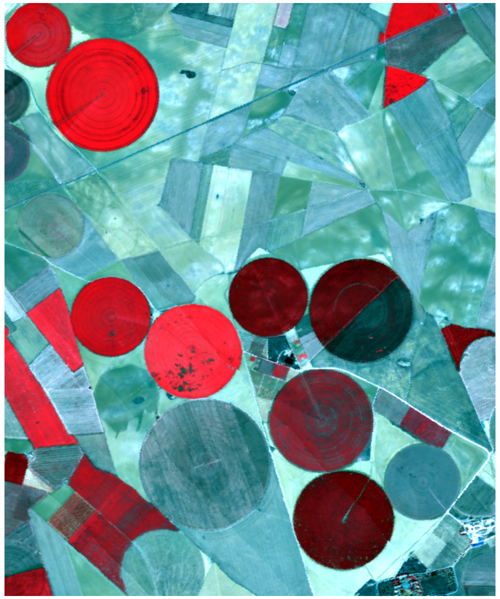
•Identify both linear and nonlinear correlations between bands

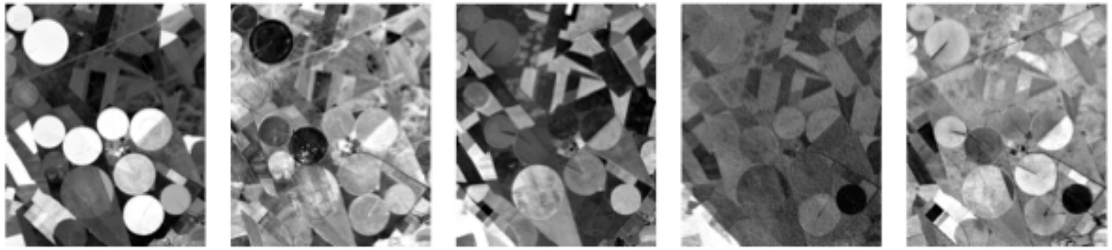
•Does not require discarding of components

•Robust to noise and errors introduced by the sensor (i.e.: smile effect)



# Linear Principal Component Analysis





PCA:

99% cumulative variance = 5 components

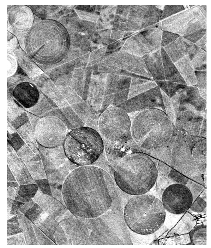
HyMap

Airborne
126 bands
0.45-2.5 µm
6 mt spatial resolution

Relevant information discarded!

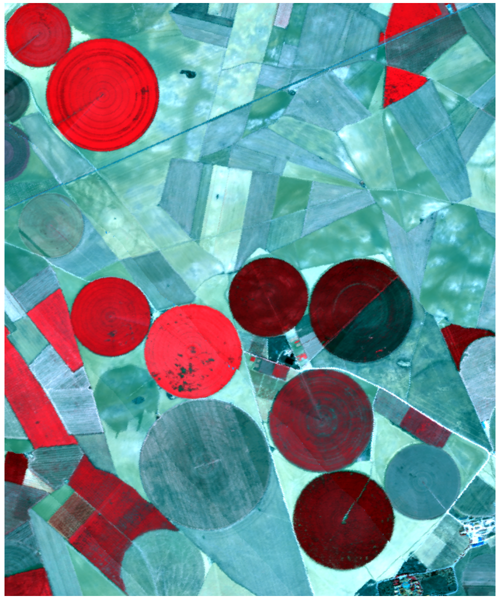
PC9

PC19



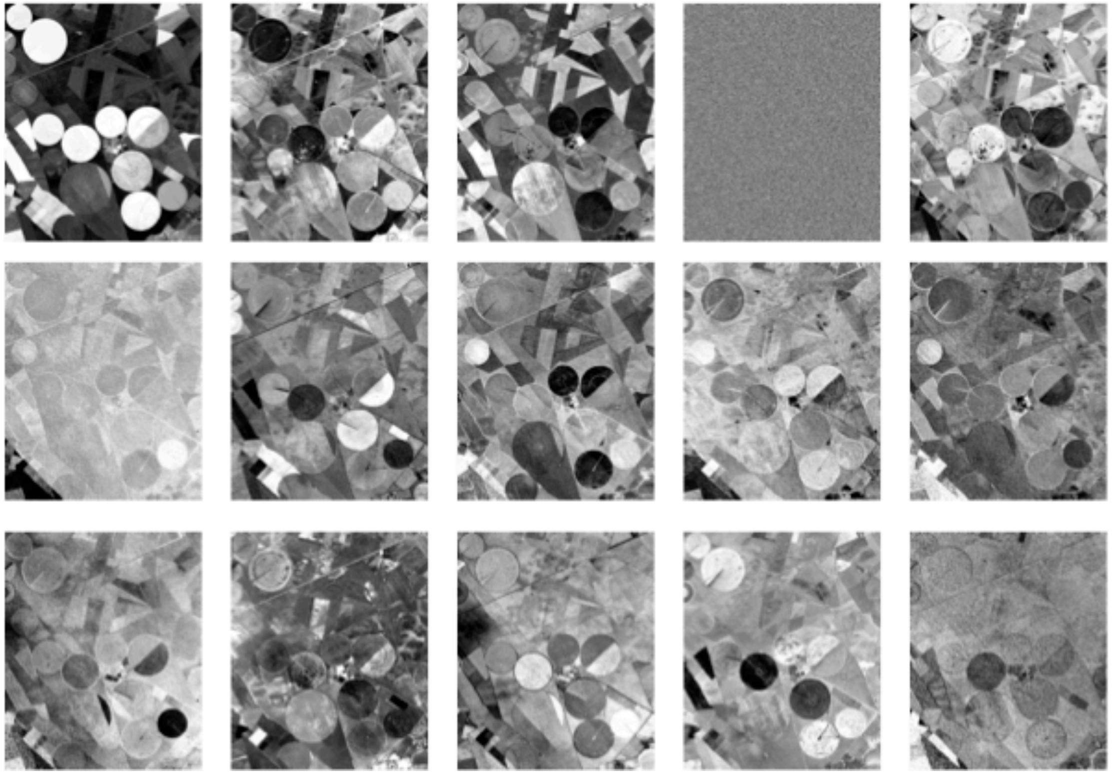
PC28

# Kernel Principal Component Analysis



HyMap

Airborne
126 bands
0.45-2.5 μm
6 mt spatial resolution

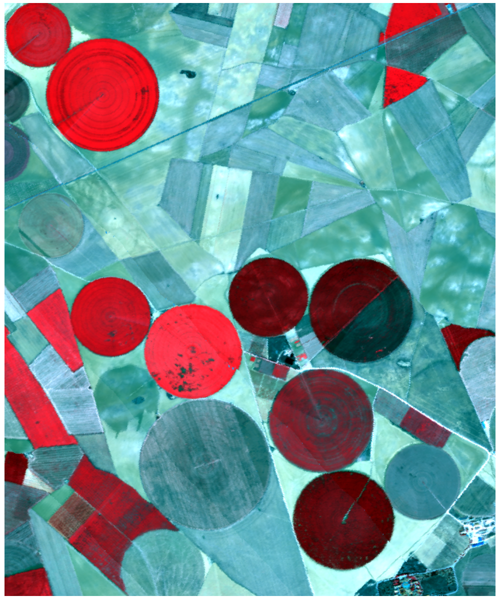


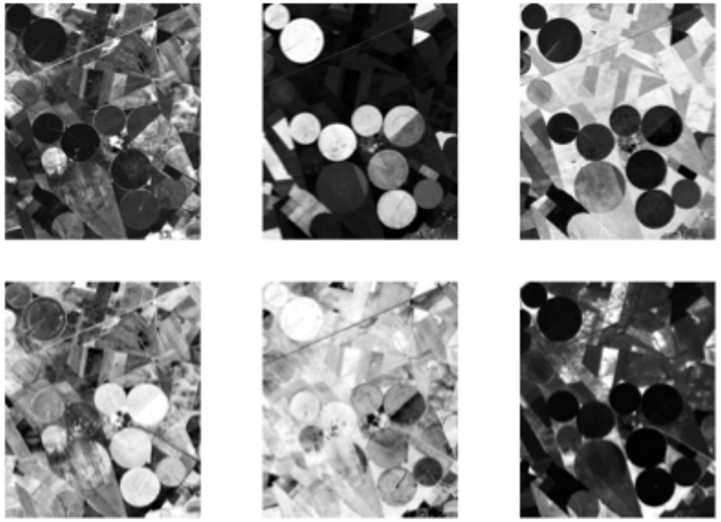
KPCA:

99% cumulative variance = 15 components!

Noisy components

# Nonlinear Principal Component Analysis





HyMap

Airborne
126 bands
0.45-2.5 μm
6 mt spatial resolution

NLPCA:

6 components

MSE=0.001

Almost whole information content contained in the NLPCs

# Image fusion - pansharpening

Pansharpening, or image fusion, is the process of improving the spatial quality of a low spatial resolution image (HS or MS) by fusing it with a high resolution PAN image preserving the original spectral information.

This requires addition of pertinent spatial details to each band of the image.

- Due to the high number of bands the pansharpening of HS images results in increased computational load and complexity.

- It is also important that the reduction method allows a reconstruction of the original spectral information content.

# Image fusion - pansharpening

In literature the fusion process can be subdivided into two steps:

- The low resolution image is scaled up to the same size as the PAN image;
- High-frequency content of the PAN image is added using a certain criteria to the HS image to achieve the fusion.

There criteria, can generally be divided into:

- **component substitution** methods;
- **multi-resolution analysis** based methods.

# Image fusion – sobstitution methods

**Substitution methods:**

- Intensity-hue-saturation (IHS)
- Principal Component Analysis (PCA)

The fusion is achieved by substituting the Intensity component or the first PC with the PAN image, whose histogram has previously been matched with that of PC. In this way the spatial information present in the histogram matched PAN image is combined with the spectral information of each HS band.

Advantages:
High spatial quality

Disadvanteages:
Strong spectral distortions

# Image fusion – multi-resolution methods

**<u>multi-resolution methods:</u>**

- Discrete wavelet transform
- Laplacian pyramid algorithms
- Induction based algorithms

In multi-resolution type methods the high-frequency information is extracted from a PAN image and then injected into an expanded low resolution image.

Advantages:
Spectrally consistent

Disadvantages:
Not as sharp as component substitution methods

# Image fusion - pansharpening

Both substitution and filtering approaches are considered adequate when applied to multispectral (MS) and PAN images, but have many drawbacks when the low-resolution image is a hyperspectral image.

Desired requirements:

- PAN and HS images should cover the same spectral range
- PAN and HS should be acquired under the same observation conditions

Pansharpening applies to each bands of the HS image → NLPCA

# Image fusion - Induction

The Induction technique, considers enlargement (up-scaling) as the inverse problem of reduction (down-scaling). This yields the condition that an enlarged image should, when reduced, give the initial image back. This condition is called the *reduction constraint.*

$$I^{1/a} * R \downarrow a = I.$$

$$\Omega_I = \{X \mid [X * R] \downarrow a = I\}.$$

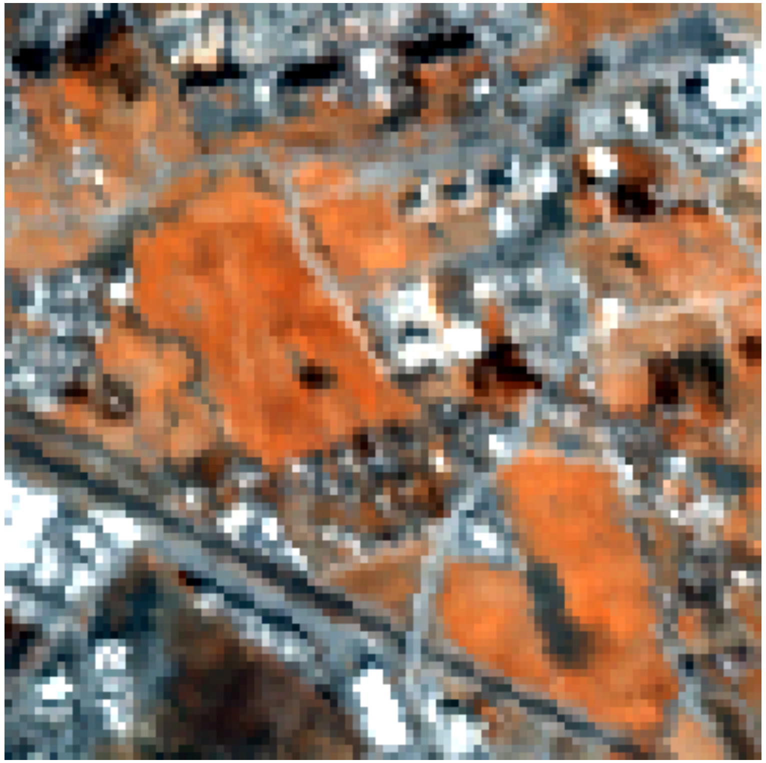
$I$=original image
$R$: reduction filter
$A$: enlarging filter
$a$: reduction ratio
$\Omega_I$= Induced set that satisfies the reduction constraint

Induction simply consists in projecting an upscaled image $J$, not adhering to the induction constraint onto the induced set $\Omega_I$ so to obtain an induced image $K$ belonging to the induced set.

$$K = J - [J * R] \downarrow a] \uparrow a * A + [I] \uparrow a * A.$$

$$K = PAN - [[PAN * R] \downarrow a] \uparrow a * A + [I] \uparrow a * A.$$

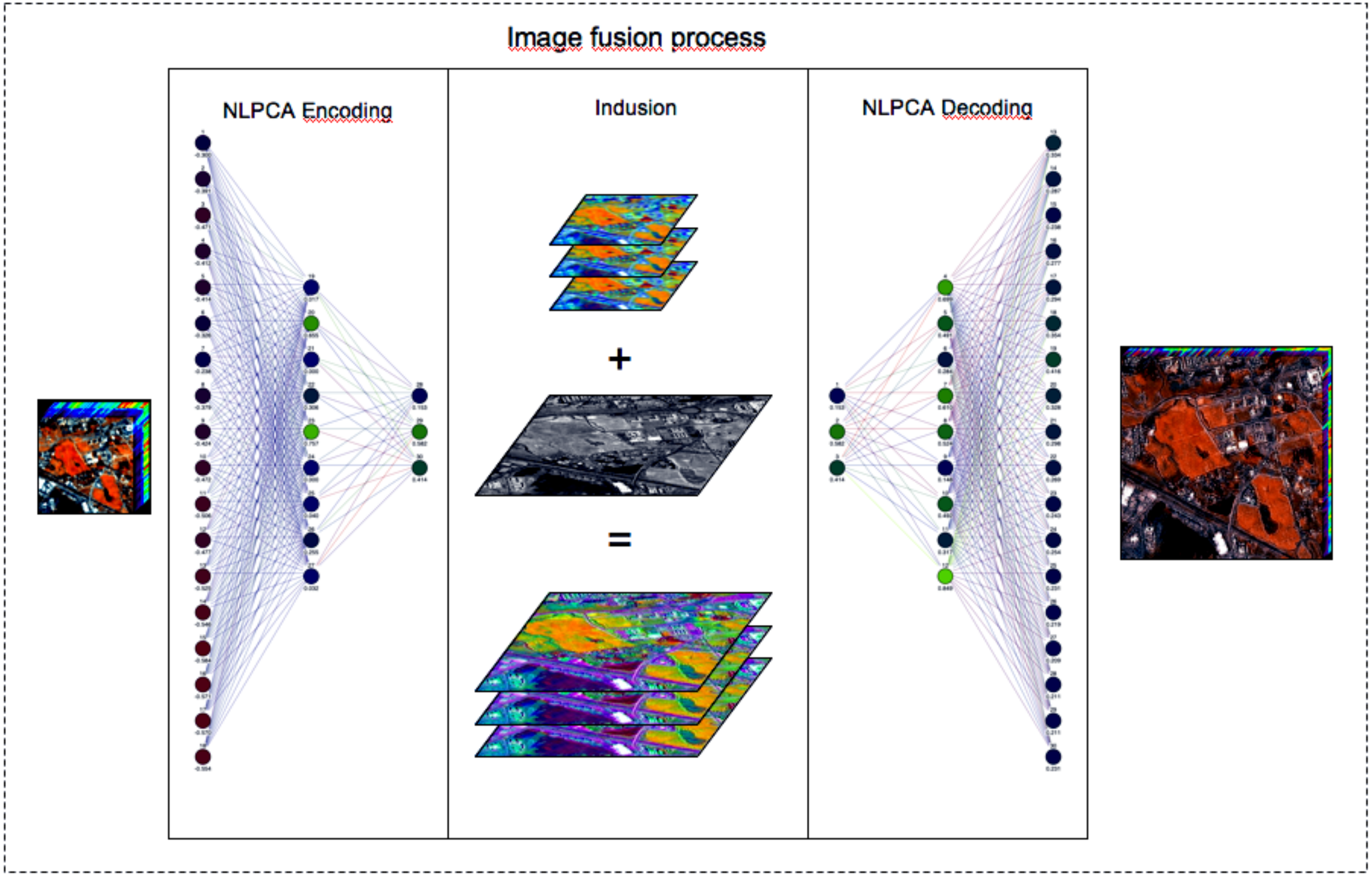
# Image fusion – CHRIS Proba



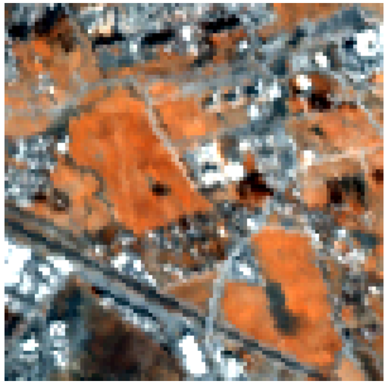
Quickbird PAN
5 m
405 nm-1053nm

CHRIS mode-3
20 m
(438 nm - 1035 nm)

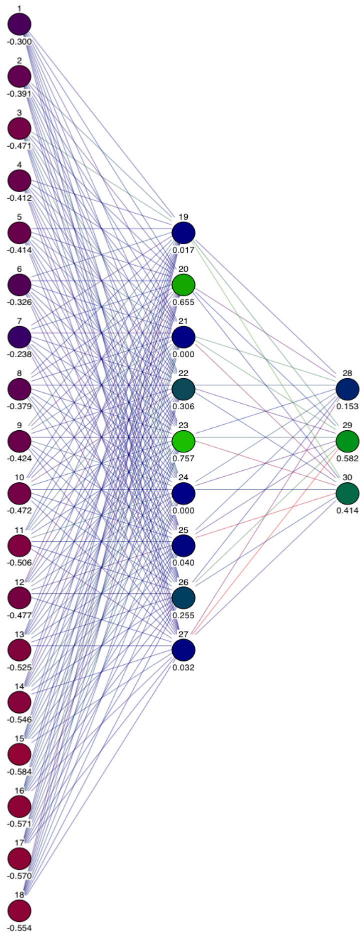
# Processing chain

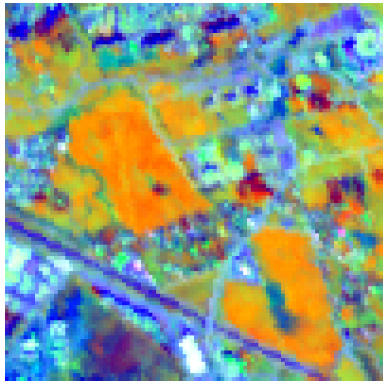


# Image fusion – CHRIS dimensionality reduction



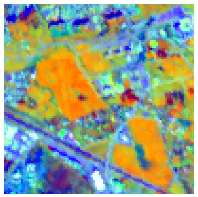
*18 bands*
*20 mt spatial resolution*



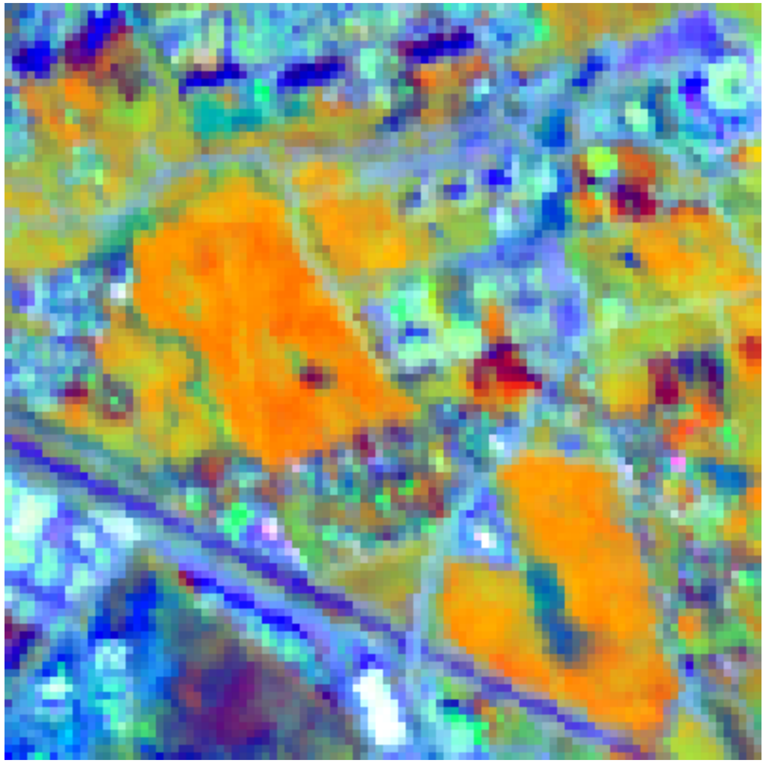



*3 NLPCs*

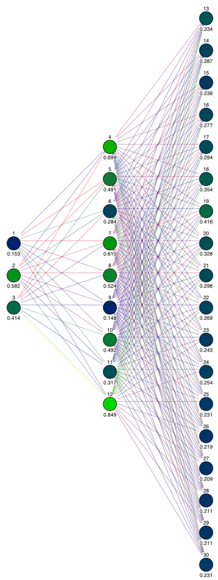
# Image fusion – NLPCs Indusion

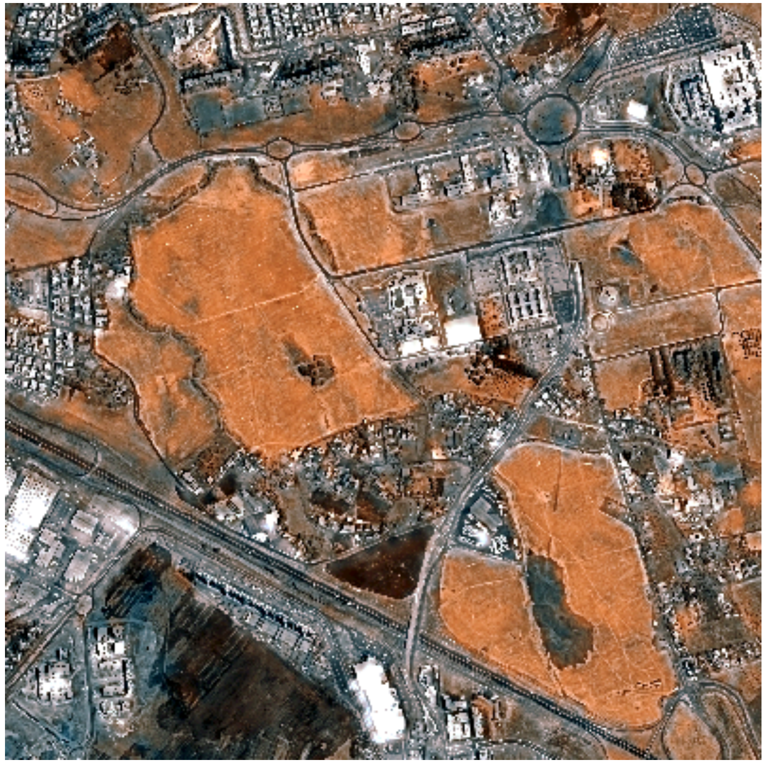


# Image fusion – NLPCs Indusion



# Image fusion – CHRIS Proba fusion





# Image fusion – Quality indexes

*ERGAS*

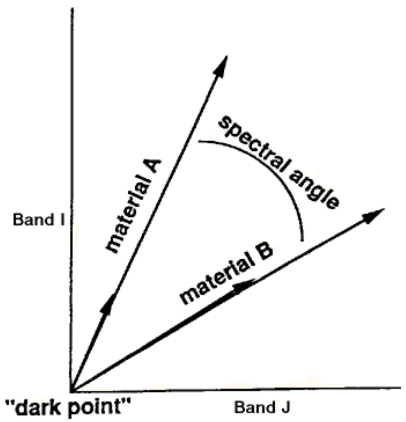
$$\mathrm{ERGAS} \triangleq 100\frac{h}{l}\sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{\mathrm{RMSE}(k)}{\mu(k)}\right)^2}$$

*UIQI*

$$Q4 = \frac{|\sigma_{z1z2}|}{\sigma_{z1}\cdot\sigma_{z2}}\cdot\frac{2\sigma_{z1}\cdot\sigma_{z2}}{\sigma_{z1}^2+\sigma_{z2}^2}\cdot\frac{2\cdot|\overline{z}_1|\cdot|\overline{z}_2|}{|\overline{z}_1|^2+|\overline{z}_2|^2}$$

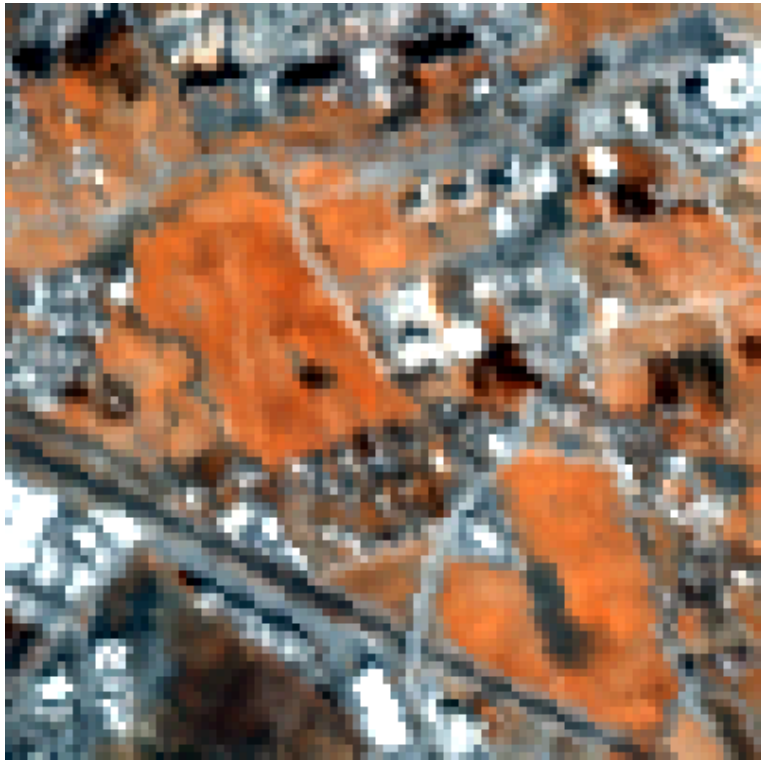
| Index | Ideal value |
|---|---|
| ERGAS | 0 |
| UIQI | 1 |
| SAM | 0 |

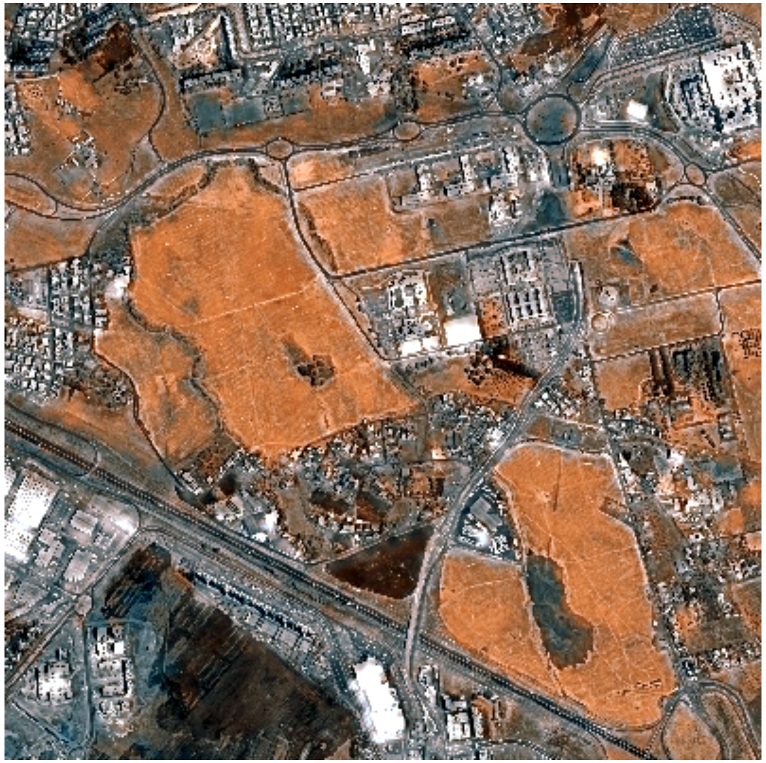
*SAM*




SAM is useful for measuring the spectral quality of the enhanced image, while ERGAS and UIQI measure both spectral and spatial quality.

# Image fusion – CHRIS Proba

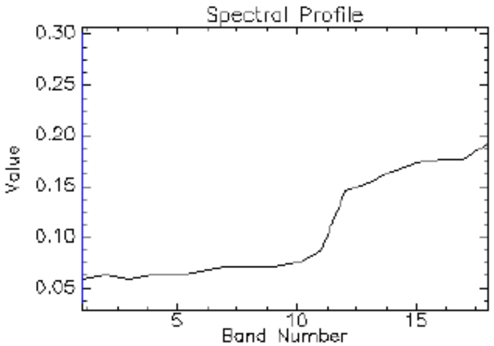




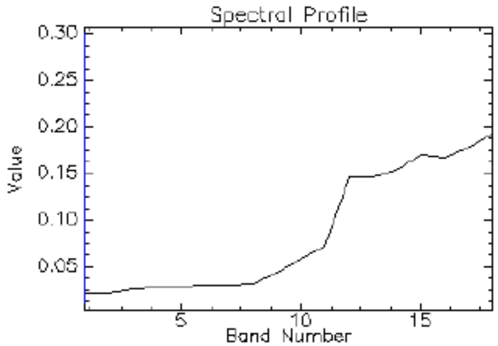
| | UIQI | ERGAS | SAM |
|---|---|---|---|
| Reference | 1 | 0 | 0 |
| NLPCA | 0.9945 | 0.7953 | 0.8317 |
| INDUSION | 0.9627 | 1.6798 | 2.3751 |
| Complete image | 0.9229 | 2.6797 | 2.7413 |
| Pasture | 0.9373 | 2.2180 | 2.1511 |
| Industrial | 0.9313 | 2.2978 | 2.3871 |
| Dense Urban fabric | 0.8616 | 4.1971 | 3.9812 |

# Image fusion – CHRIS Proba

Original | Enhanced

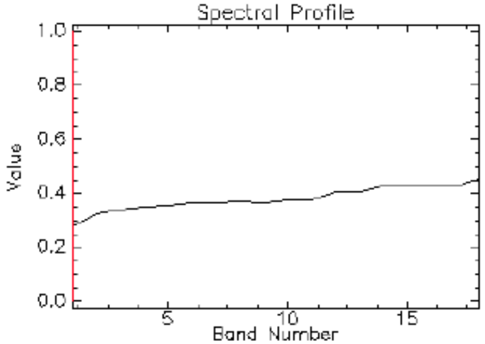



a.

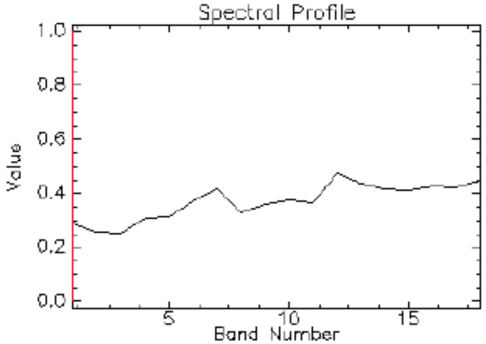



b.

Vegetation

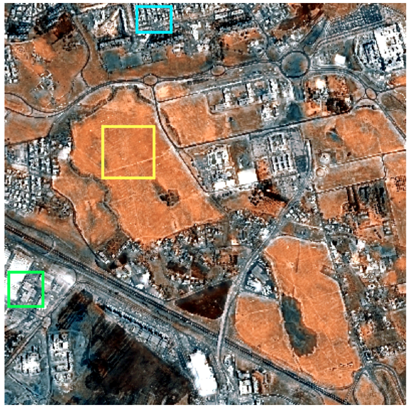


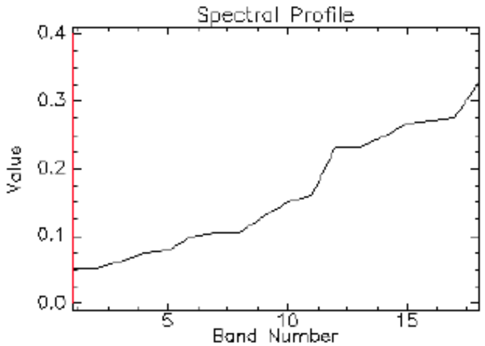

c.



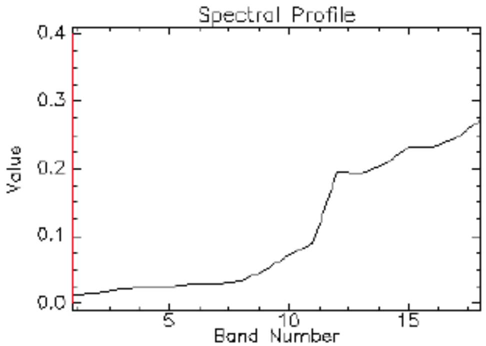

d.

Industrial





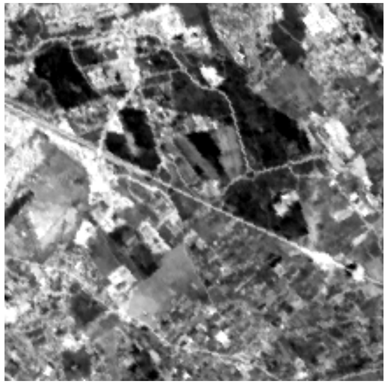

e.



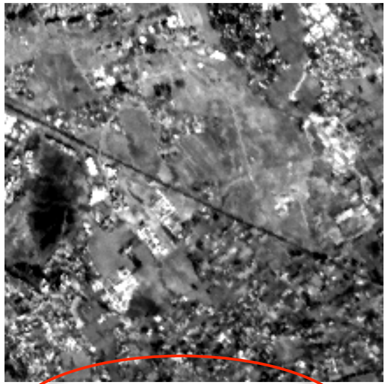

f.

Buildings

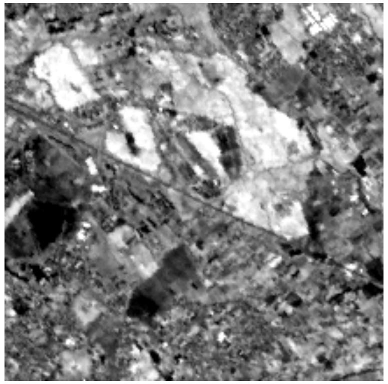
# Image fusion – CHRIS sobstitution/Hybrid



*NLPC 1*



*NLPC 2*

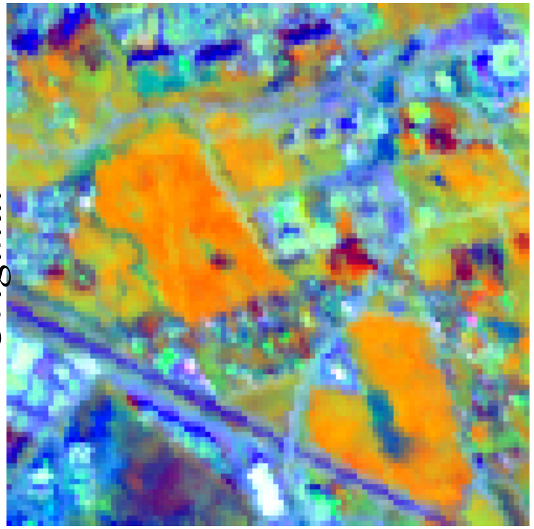


*NLPC 3*

*PAN image*

# Image fusion – CHRIS Proba

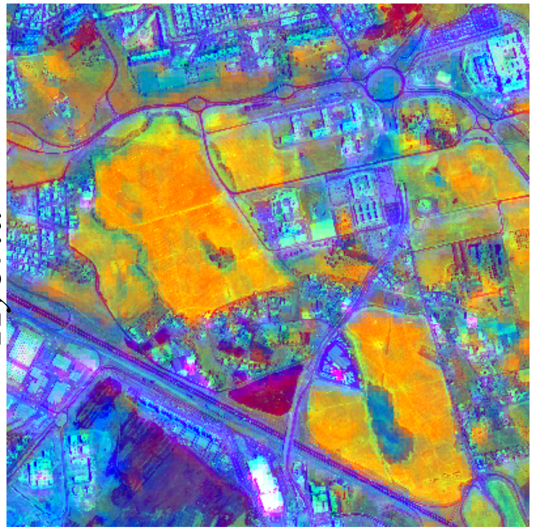
*Original*



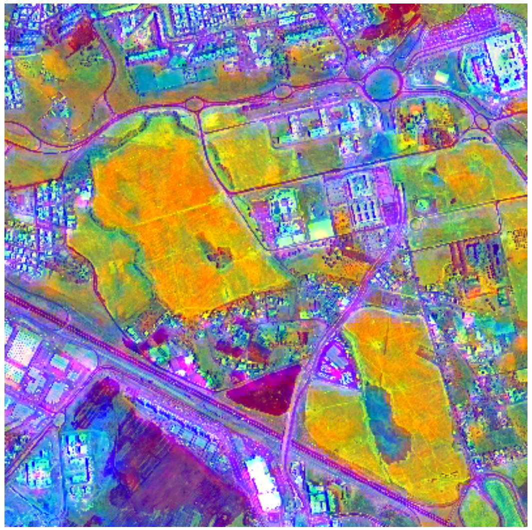
*Substitution*

| | UIQI | ERGAS | SAM |
|---|---|---|---|
| Reference | 1 | 0 | 0 |
| Indusion | 0.9627 | 1.6798 | 2.3751 |
| Substitution | 0.9609 | 0.9285 | 2.8153 |
| Mixed | 0.9737 | 1.3586 | 2.1131 |

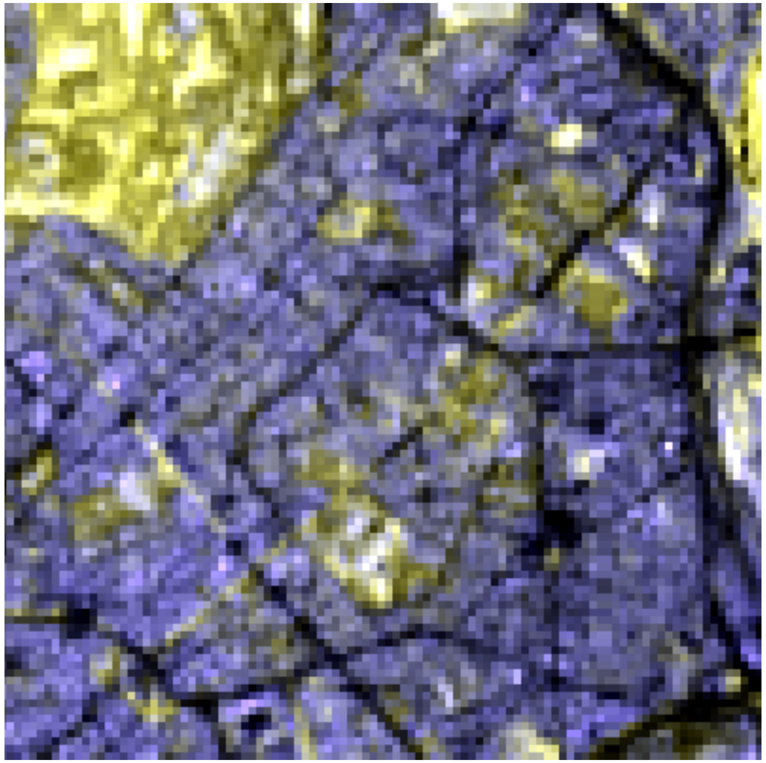
*Hybrid*



*Indusion*



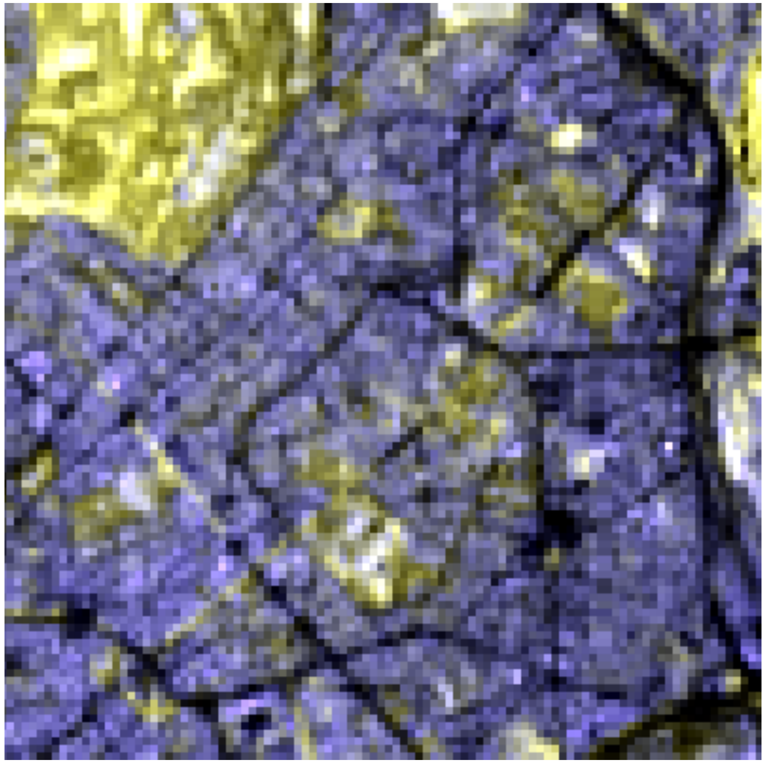
# Image fusion – Hyperion + Quickbird

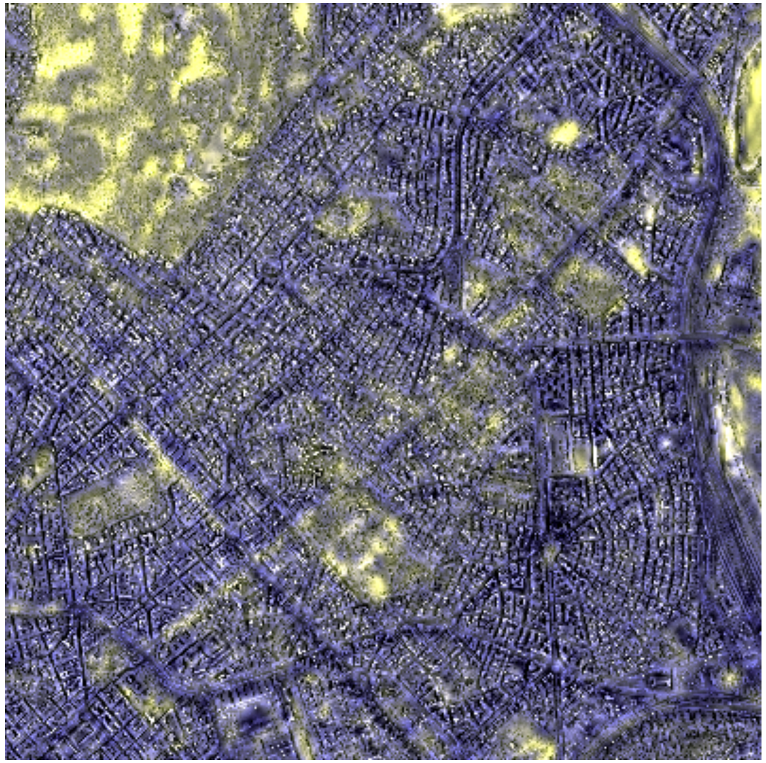


*Hyperion*
*220 (168) Bands*
*400 nm – 2500 nm*
*30 mt Spatial resolution*

*QuickBird PAN*
*405 nm-1053nm*
*7.5 mt Spatial resolution*

# Image fusion – Hyperion + Quickbird

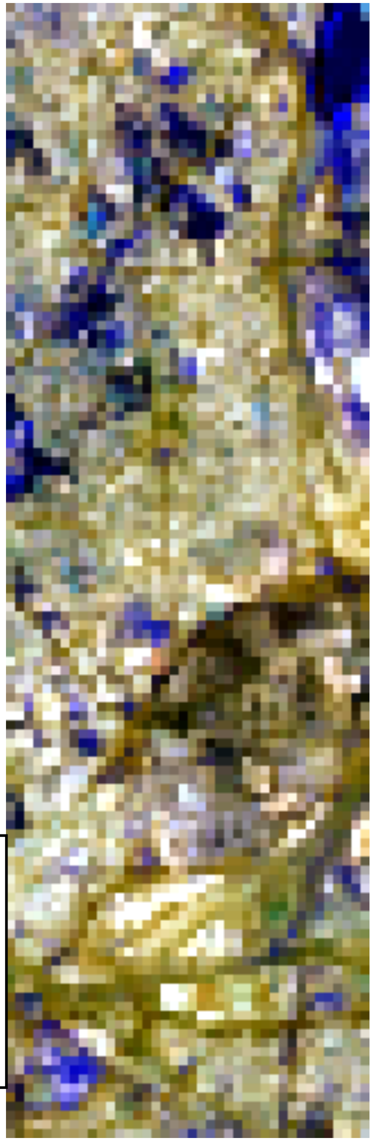




Strong spectral distortions introduced by the different acquisition angles and also different spectral coverage .

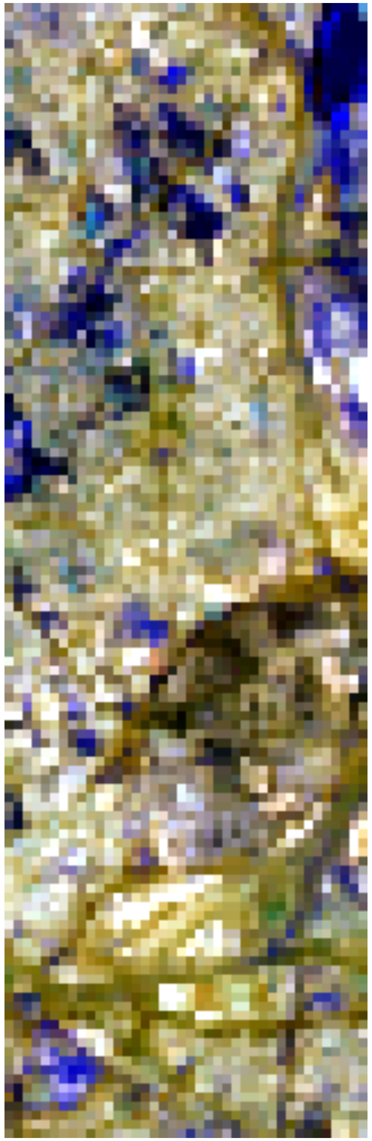
# Image fusion – Hyperion + ALI

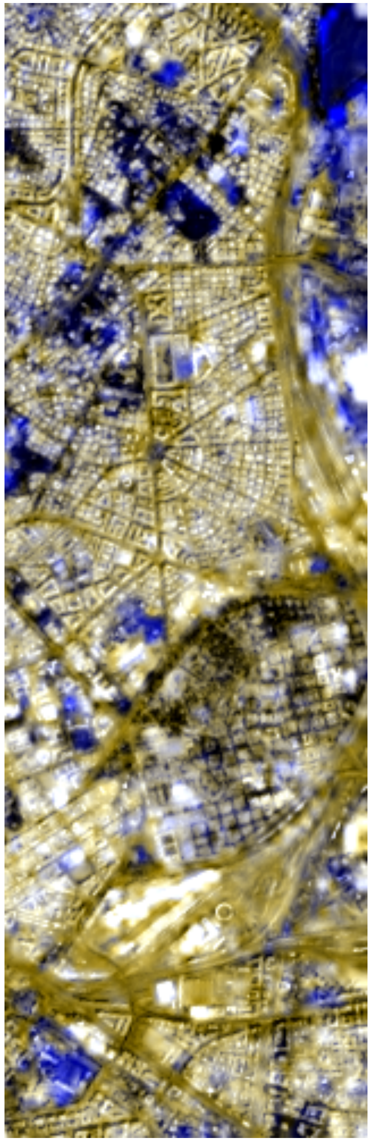
*ALI PAN*
*10 mt Spatial resolution*
*480 nm – 690 nm*



*Hyperion*
*220 (168) Bands*
*40 mt Spatial resolution*
*400 nm – 2500 nm*

# Image fusion – Hyperion + ALI

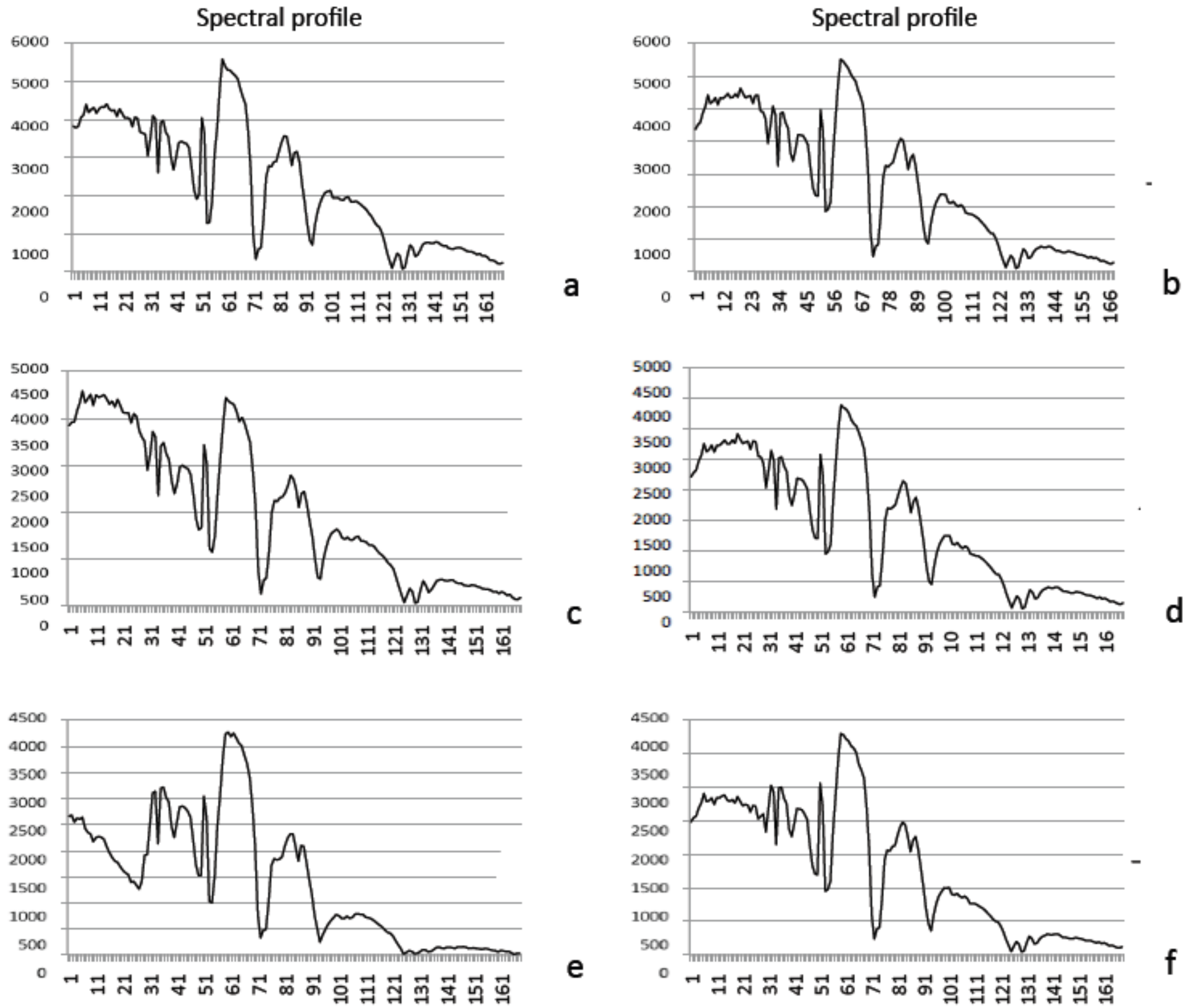




| | UIQI | ERGAS | SAM |
|---|---|---|---|
| Reference | 1 | 0 | 0 |
| NLPCA | 0.9759 | 3.0622 | 1.3400 |
| INDUSION | 0.9627 | 1.6798 | 2.3751 |
| Hyperion + QuickBird | 0.7941 | 4.7472 | 6.3233 |
| Hyperion + ALI-PAN | 0.9001 | 3.6562 | 1.4861 |

# Image fusion – Hyperion + ALI

Original | Enhanced

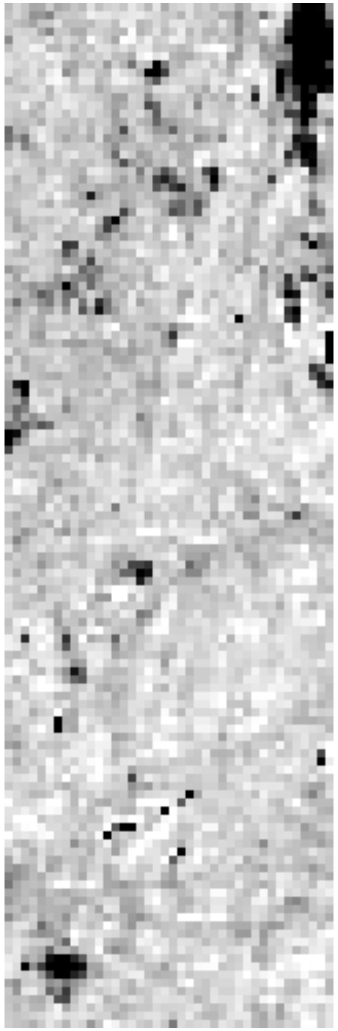



Buildings

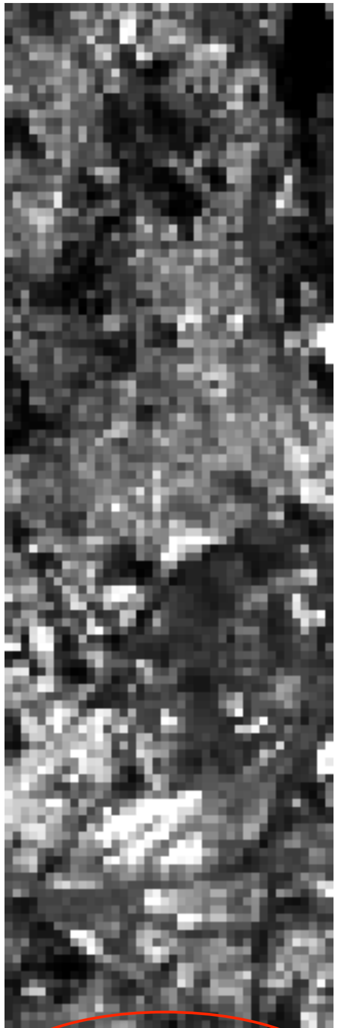
Industrial

Vegetation

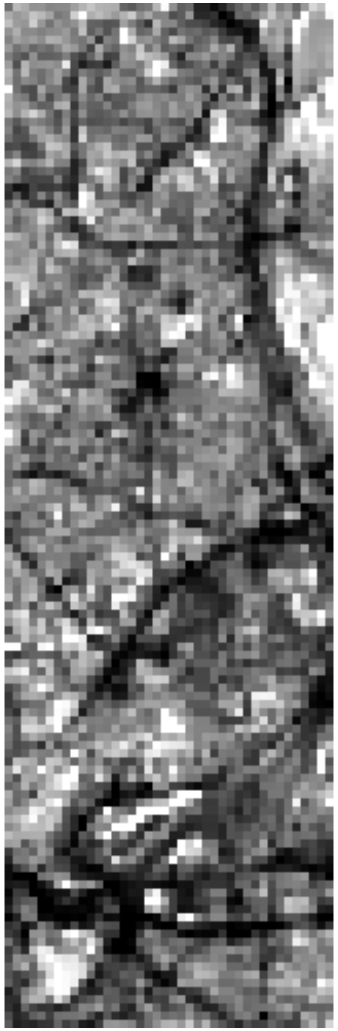
# Image fusion – Hyperion + ALI



*NLPC 1*



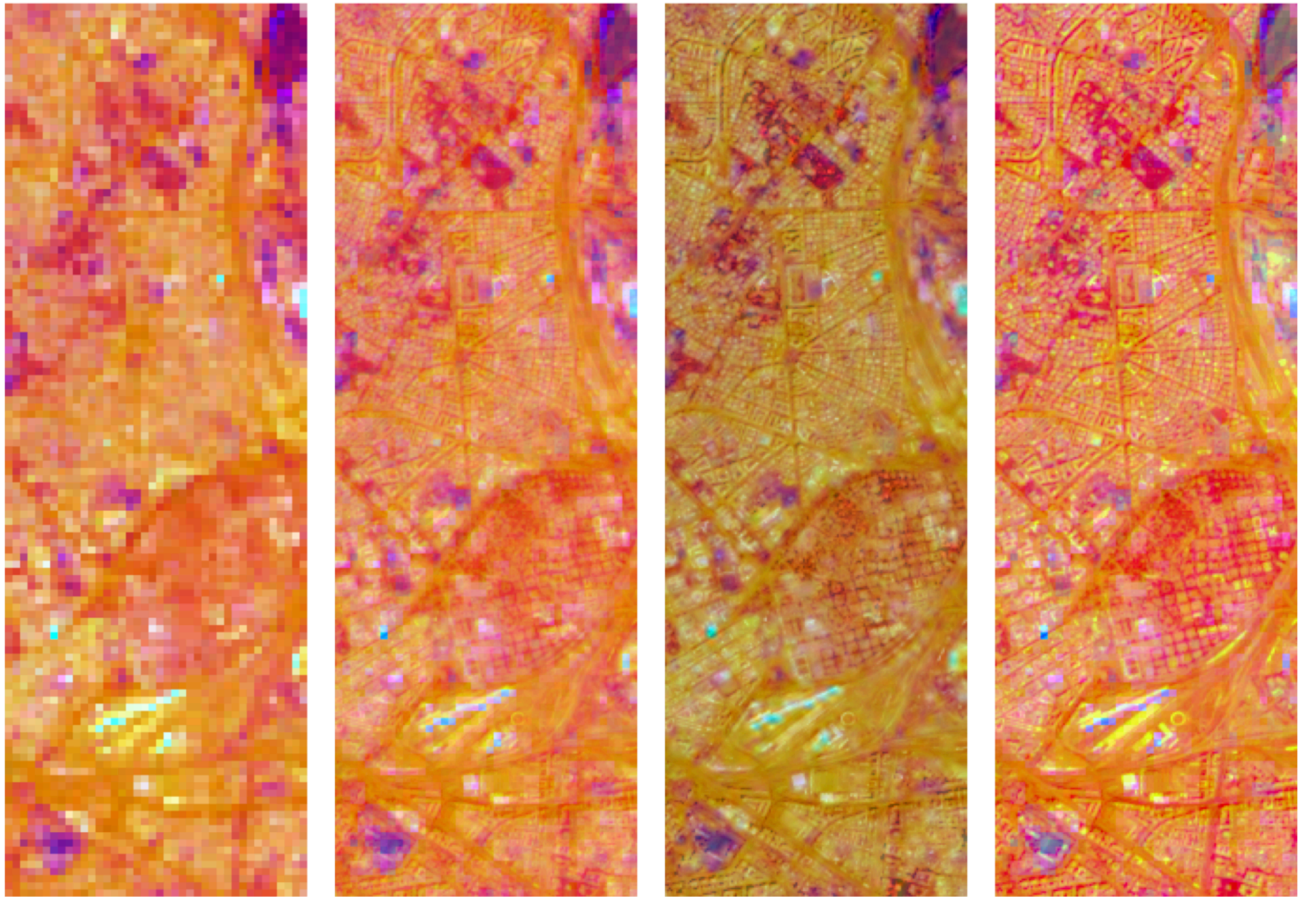
*NLPC 2*



*NLPC 3*

*PAN image*

# Image fusion – Hyperion + ALI



*Original* *Hybrid* *Indusion* *Subst.*

| | UIQI | ERGAS | SAM |
|---|---|---|---|
| Reference | 1 | 0 | 0 |
| Indusion | 0.9001 | 3.6562 | 1.4861 |
| Substitution | 0.9246 | 3.5062 | 1.3903 |
| Mixed | 0.9330 | 3.4475 | 1.0294 |

# Conclusions and perspectives

- novel approach combining dimensionality reduction and a pansharpening techniques for spatial quality improvement of hyperspectral images

- Preservation of the spectral quality of the original HS image.

- Dimensionality reduction of hyperspectral images performed by the nonlinear generalization of standard principal component analysis.

- Fusion performed by the Indusion approach

- Good results has been obtained by applying the Indusion approach directly to all the NLPCs

- Better results obtained by applying the Indusion only to one NLPC instead of the entire set of features.

# Conclusions and perspectives

proposed method applied to real data

→ many sources of spectral distortion are introduced:

- error in the registration phase
- differences in terms of angles of view, dates of acquisition and spectral coverages
- negative contributions introduced by objects that are spatially detected by the PAN image but not in the HS image where their spectral signature results to be mixed with the signatures of the surrounding objects.

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Use of spectral unmixing techniques to detect those objects