



Remote Sensing Laboratory
Dept. of Information Engineering and Computer Science
University of Trento
Via Sommarive, 9, I-38123 Povo, Trento, Italy










Tecniche di ultima generazione per l'analisi automatica di immagini iperspettrali satellitari

Lorenzo Bruzzone
Claudia Paris

E-mails. lorenzo.bruzzone@unitn.it
claudia.paris@unitn.it
Web page. rslab.disi.unitn.it

Outline

-  Introduction
-  System Architecture of HSI Image Processing
-  Feature Extraction for HSI images
-  Feature Selection for HSI images
-  Classification/Regression of HSI images
-  Fusion of HSI images and RS data
-  Conclusion

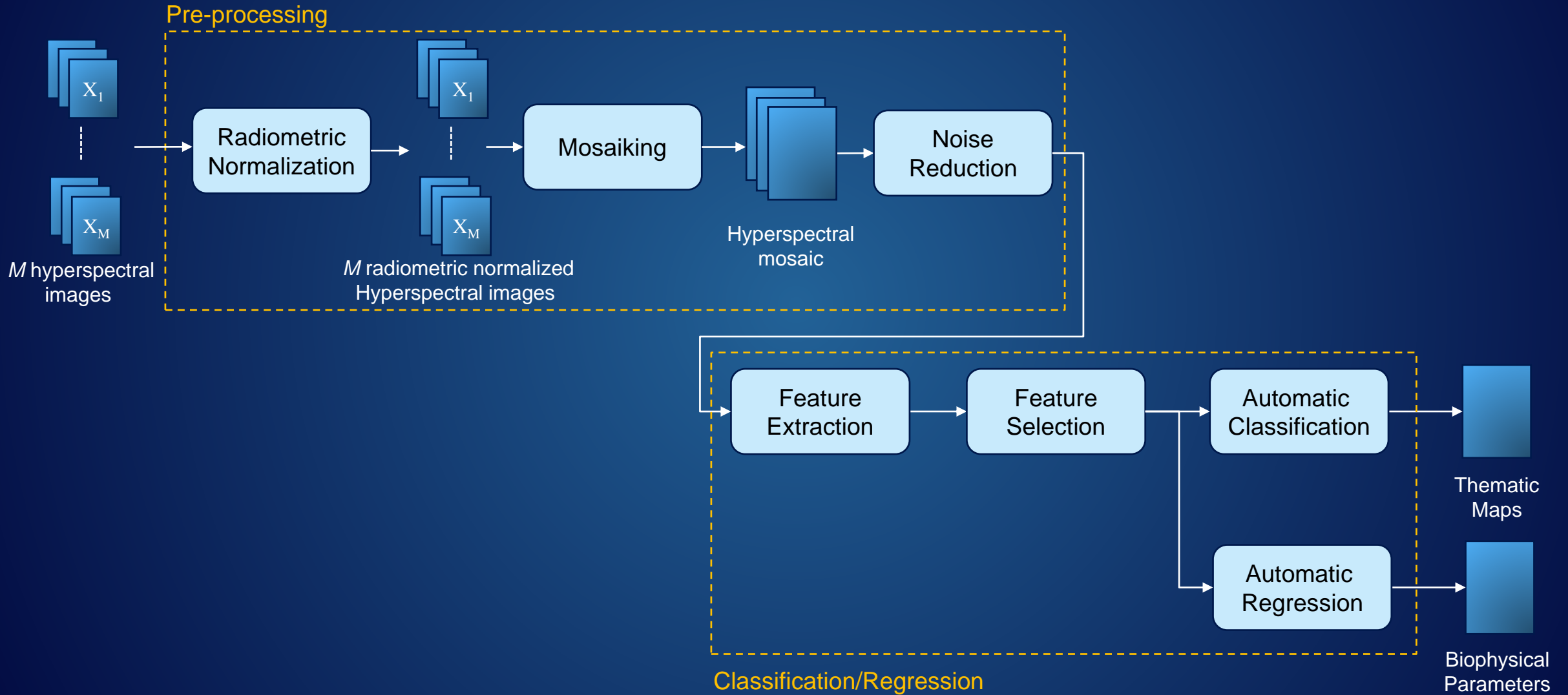
Introduction

- Improvements in spectral resolution of hyperspectral images (HSIs) requires advances in signal processing and exploitation algorithms, opening the doors to new application domains.
- HSI images are typically characterized by:
 - high dimensionality of the pixels;
 - high spectral redundancy;
 - heterogeneities at subpixel level;
 - impact of atmospheric and geometric distortions;
 - spatial variability of the spectral signature;
 - nonlinear feature relations.
- All of these factors, together with **few labeled samples** typically available, make HSI image processing a complex problem. Moreover, high computational time is required for the analysis of large images (**Big Data challenge**).



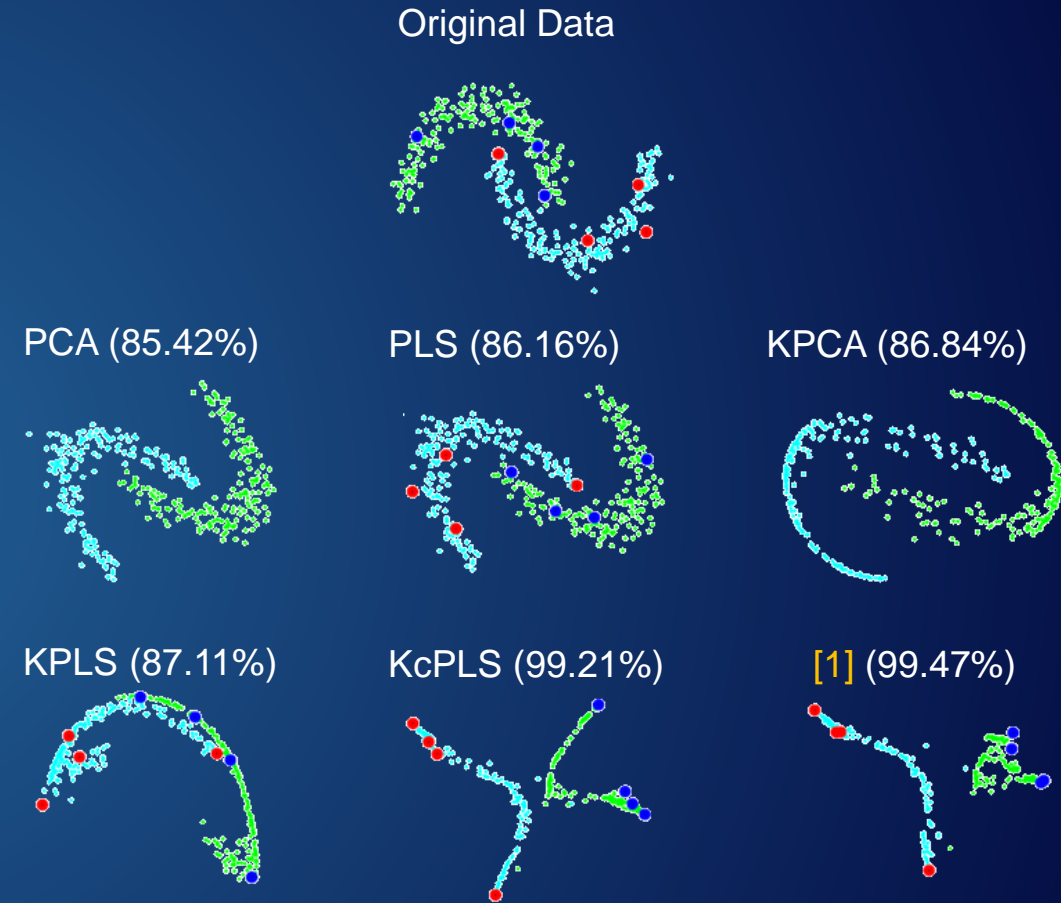
Picture from <http://www.evolved-analytics.com/?q=technology/courses/featuresselection>

System Architecture of HSI Image Processing



Feature Extraction for HSI images

- The **high dimensionality** of HSI images, as well as the high redundancy among spectral bands, can compromise the classification/estimation results.
- Feature extraction methods allow the identification of the **most discriminative variables** for data classification, regression, clustering, ranking, compression, or data visualization.
- In many situations, **nonlinear feature extraction** is necessary to obtain an acceptable performance. This is a very complex problem when **few labeled data** points are available.



Projections extracted by different feature extraction methods.
The OA obtained on the test set is provided.

[1] Izquierdo-Verdiguier, E., Gomez-Chova, L., Bruzzone, L., & Camps-Valls, G. . "Semisupervised kernel feature extraction for remote sensing image analysis." *IEEE transactions on geoscience and remote sensing* 52.9 (2014). 5567-5578.

Feature Selection for HSI images

- The high dimensionality of the feature space with respect to the typical small amount of labeled training samples represents one of the main challenge of the automatic processing of HSI images.
- Feature selection methods select a subset of original features more informative for the desired application. In this context, we developed feature selection methods to:
 - select the **most informative spectral channels** for image classification [2];
 - select the most significant filter parameters to **extract spatial information** from the scene [3];
 - detect the set of features that minimize the distributions distance between different HSI images for **domain adaptation** [4].

[2] Yang, C., Liu, S., Bruzzone, L., Guan, R., & Du, P. "A feature-metric-based affinity propagation technique for feature selection in hyperspectral image classification." *IEEE Geoscience and Remote Sensing Letters* 10.5 (2013). 1152-1156.

[3] Pedergnana, M., Marpu, P. R., Dalla Mura, M., Benediktsson, J. A., & Bruzzone, L. "A novel technique for optimal feature selection in attribute profiles based on genetic algorithms." *IEEE Transactions on Geoscience and Remote Sensing* 51.6 (2013). 3514-3528.

[4] C. Persello, and L. Bruzzone. "Kernel-based domain-invariant feature selection in hyperspectral images for transfer learning." *IEEE Transactions on Geoscience and Remote Sensing* 54.5 (2016). 2615-2626.

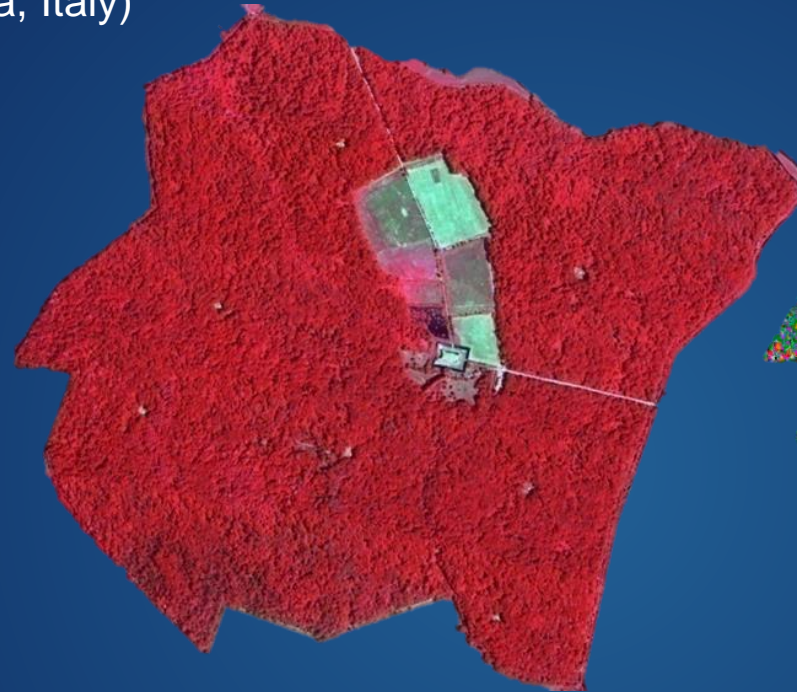
Example – Feature Selection for Classification

Study Area: Bosco Fontana (Mantova, Italy)

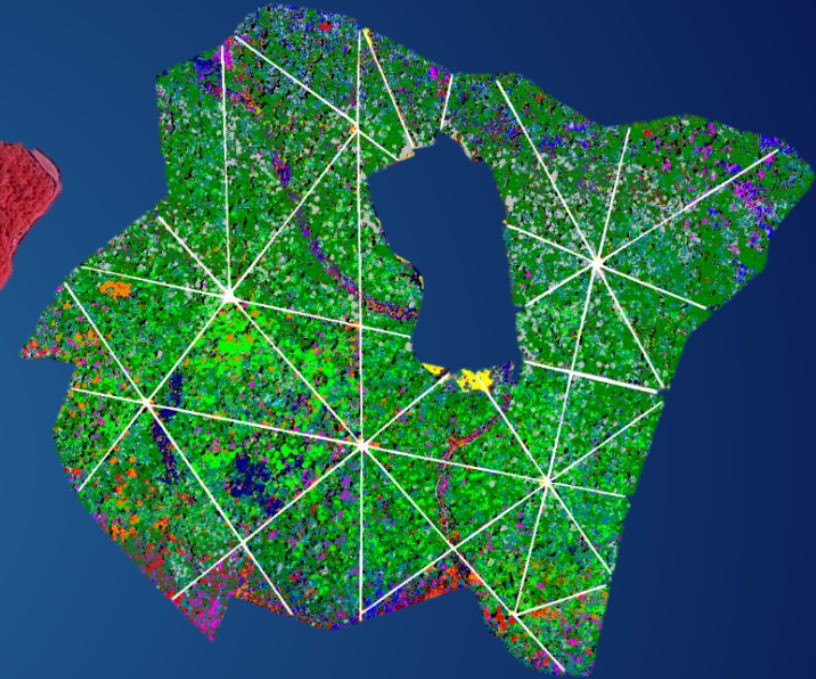
- ✓ Extension: 233 ha;
- ✓ 23 forest species.

HSI data:

- ✓ Six partially overlapping images;
- ✓ Acquisition date: 28th June 2006;
- ✓ Sensor: AISA Eagle;
- ✓ Spectral Channels: 126;
- ✓ Spectral Range: 400-990 nm;
- ✓ Spectral Resolution: 4.6 nm;
- ✓ Spatial Resolution: 1 m;
- ✓ Flight Height: 750 m.



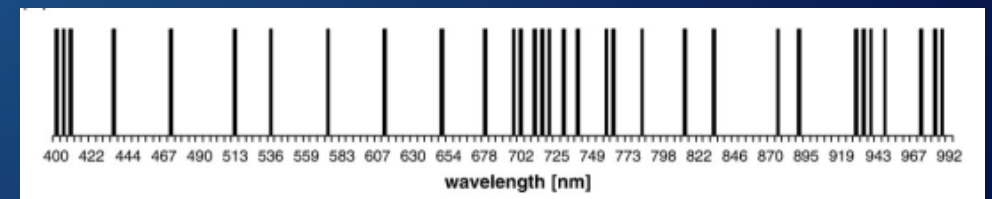
False Color HSI image



Thematic Map

■	Acer campestre
■	Alnus glutinose
■	Acer negundo
■	Corylus avellana
■	Carpinus betulus
■	Snags
■	Fraxinus an.
■	Junglas nigra
■	Junglas regia
■	Morus
■	Shadows
■	Populus ca.
■	Populus hybrid
■	Platanus
■	Prunus avium
■	Grass
■	Quercus rubra
■	Quercus cerris
■	Quercus robur
■	Robinia
■	Rubus
■	Tilia
■	Ulmus minor

Kappa Accuracy: 87.90%



[5] Dalponte, M., Bruzzone, L., Vescovo, L., & Gianelle, D. "The role of spectral resolution and classifier complexity in the analysis of hyperspectral images of forest areas." *Remote Sensing of Environment* 113.11 (2009): 2345-2355.

Example – Feature Selection for Classification

True Color HSI image



Reference Method



Overall Accuracy 93.85%
Time 57 s

[3]



Overall Accuracy 96.96%
Time 18 s

	Trees
	Gravel
	Meadows
	Asphalt
	Metal sheets
	bricks
	Bitumen
	Shadows
	Bare Soil

[3] Pedernana, M., Marpu, P. R., Dalla Mura, M., Benediktsson, J. A., & Bruzzone, L. "A novel technique for optimal feature selection in attribute profiles based on genetic algorithms." IEEE Transactions on Geoscience and Remote Sensing 51.6 (2013). 3514-3528.

Example – Classification over the Venice Lagoon

Study Area: Venice Lagoon (Venice, Italy)

✓ Six classes;

HSI data:

- ✓ Sensor: ROSIS;
- ✓ Spectral Channels: 115;
- ✓ Spectral Range: 400-990 nm;
- ✓ Spatial Resolution: 1 m;

- Spartina Maritima
- Liboneum Narbonese
- Juncus Maritimus
- Sarcocornia Fruticosa
- Bare Soil
- Water

Overall Accuracy: 89.37%



Thematic Map



False Color HSI image

[6] Bovolo, Francesca, Lorenzo Bruzzone, and Lorenzo Carlin. "A novel technique for subpixel image classification based on support vector machine." IEEE Transactions on Image Processing 19.11 (2010): 2983-2999.

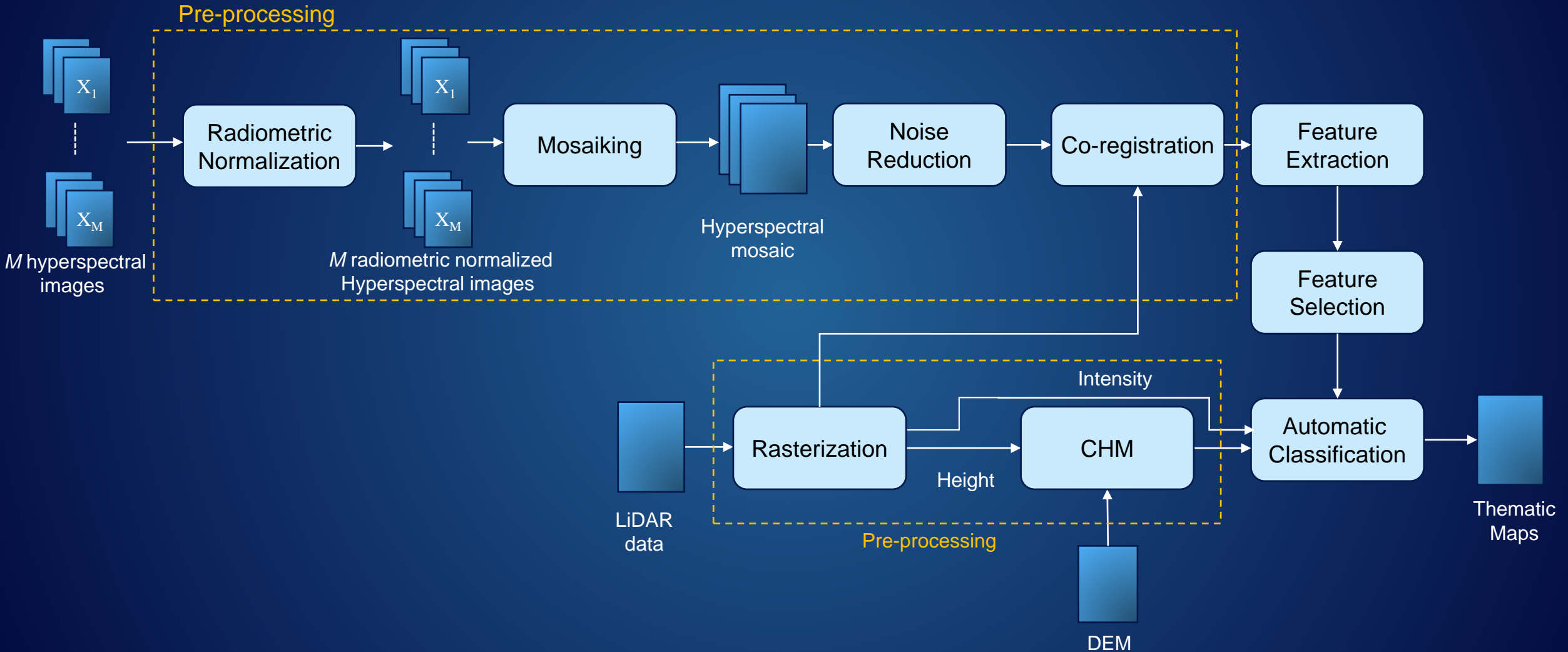
Regression for Biophysical Variable Estimation

- The estimation of biophysical parameters is of special relevance in order to understand better the environment dynamics at local and global scales.
- To accurately estimate the biophysical parameters, sophisticated methods are needed to capture the relationships between remote sensing measurements and the investigated parameters.
- In this framework, we developed advanced regression methods in order to:
 - define specific cost functions that can handle the **different types of noise [7]**;
 - address regression problems with **small size initial training data [8]**.

[7] Camps-Valls, G., Bruzzone, L., Rojo-Álvarez, J. L., & Melgani, F. (2006). Robust support vector regression for biophysical variable estimation from remotely sensed images. *IEEE Geoscience and Remote Sensing Letters*, 3(3), 339-343.

[8] Demir, Begüm, and Lorenzo Bruzzone. "A multiple criteria active learning method for support vector regression." *Pattern recognition* 47.7 (2014): 2558-2567.

Fusion of HSI images and other RS data





Development of an automatic
system based on hyperspectral
and LiDAR data for forest
monitoring and management.

Conclusion

- An overview of some of the methods and applications for the automatic analysis of the HSI images developed by the Rslab team (University of Trento) has been presented.
- The presented system architecture for HSI image processing is based on:
 - Feature Extraction for HSI images;
 - Feature Selection for HSI images;
 - Classification of HSI images;
 - Regression of Biophysical Parameters with HSI images.
- An example of integration of HSI images with other RS data has been presented.
- The proposed system architecture can be applied in different application domains and is promising for PRISMA HSI images processing.



Thank you for the attention!