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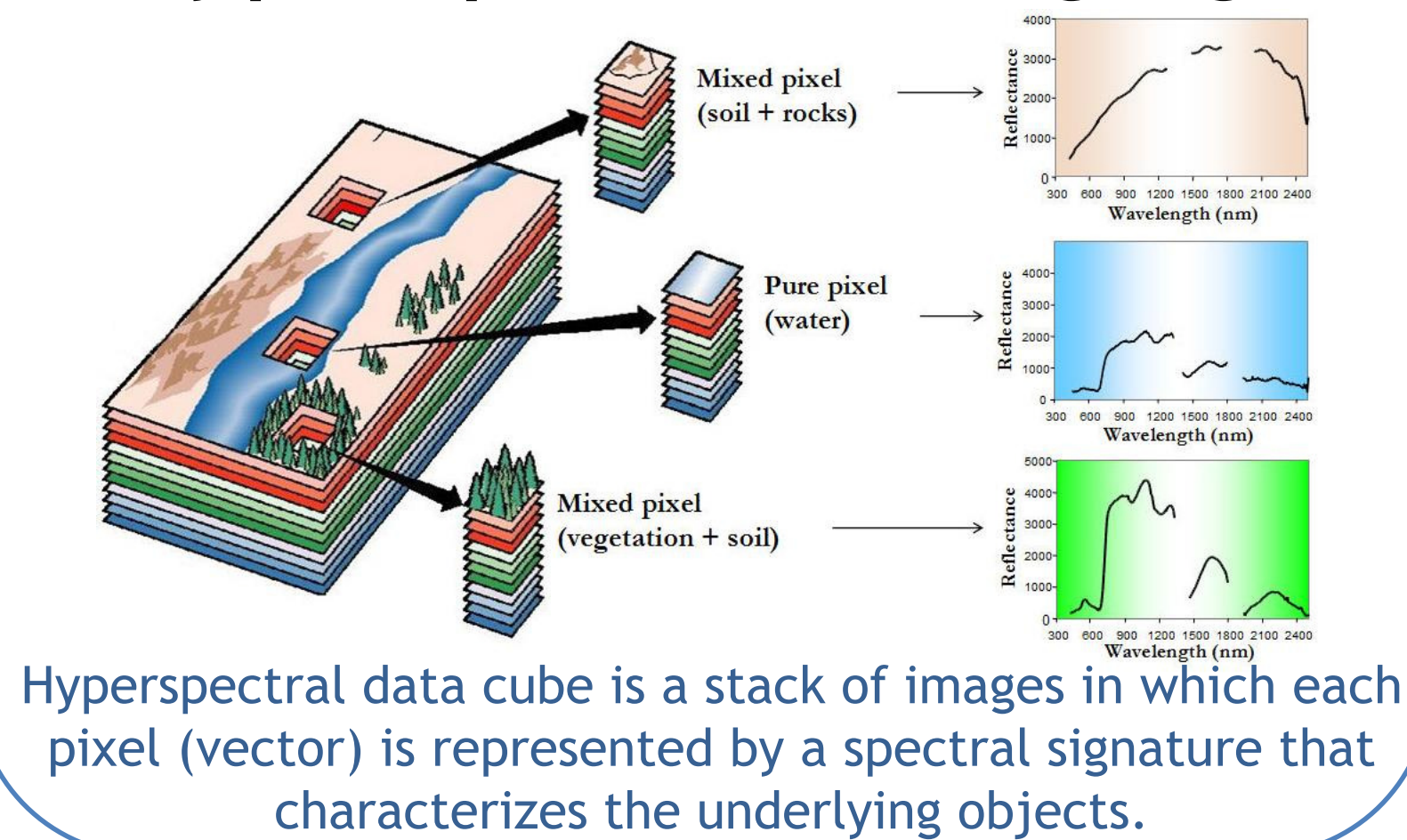
Classification for Hyperspectral Imaging

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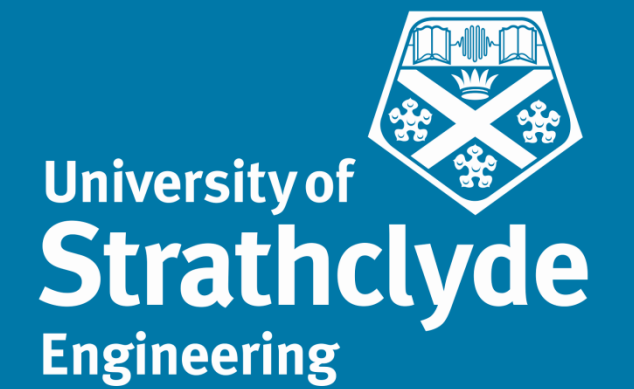
➢ One of the objectives of HSI data analysis is identification of imaged objects.

➢ One pixel vector not necessarily represent pure signature of the object. In most of the cases the spectra contain micro- or macroscopically mixed signatures of different materials which occupy the same pixel.

➢ Measured spectrum can be decomposed into linear combination of pure spectral signatures called endmembers - process this is known as **spectral unmixing**.

Hyperspectral Imaging

Mixed pixel (soil + rocks)
Pure pixel (water)
Mixed pixel (vegetation + soil)

Hyperspectral data cube is a stack of images in which each pixel (vector) is represented by a spectral signature that characterizes the underlying objects.

➢ Definition of one endmember per object do not necessarily properly represent all the pixels which contain this object on the image.

➢ **Spatial classification** could divide the image into local areas where endmember extraction would be more reliable.

PLS based spectral classification

➢ PLS – *Partial Least Squares* or *Projection to Latent Structures*

➢ Multivariate analysis technique helpful to predict set of properties based on range of measurements.

➢ Two-block PLS regression method models relationship between matrices X (predictors) and Y (responses).

➢ Method this can be used for spectral unmixing where observations of reflectance spectra are in the predictors matrix and the fractions of all the endmembers form the response matrix.
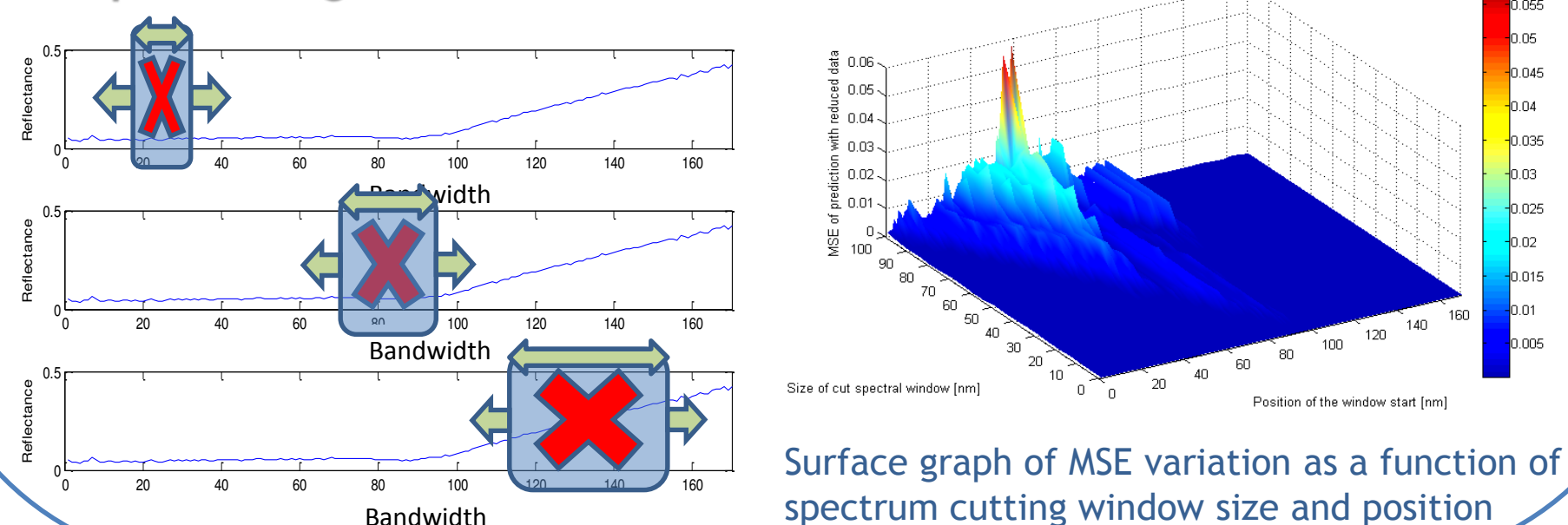

$$y = B_1 \times \alpha_1 + B_2 \times \alpha_2 + B_3 \times \alpha_3 + B_4 \times \alpha_4 + noise$$
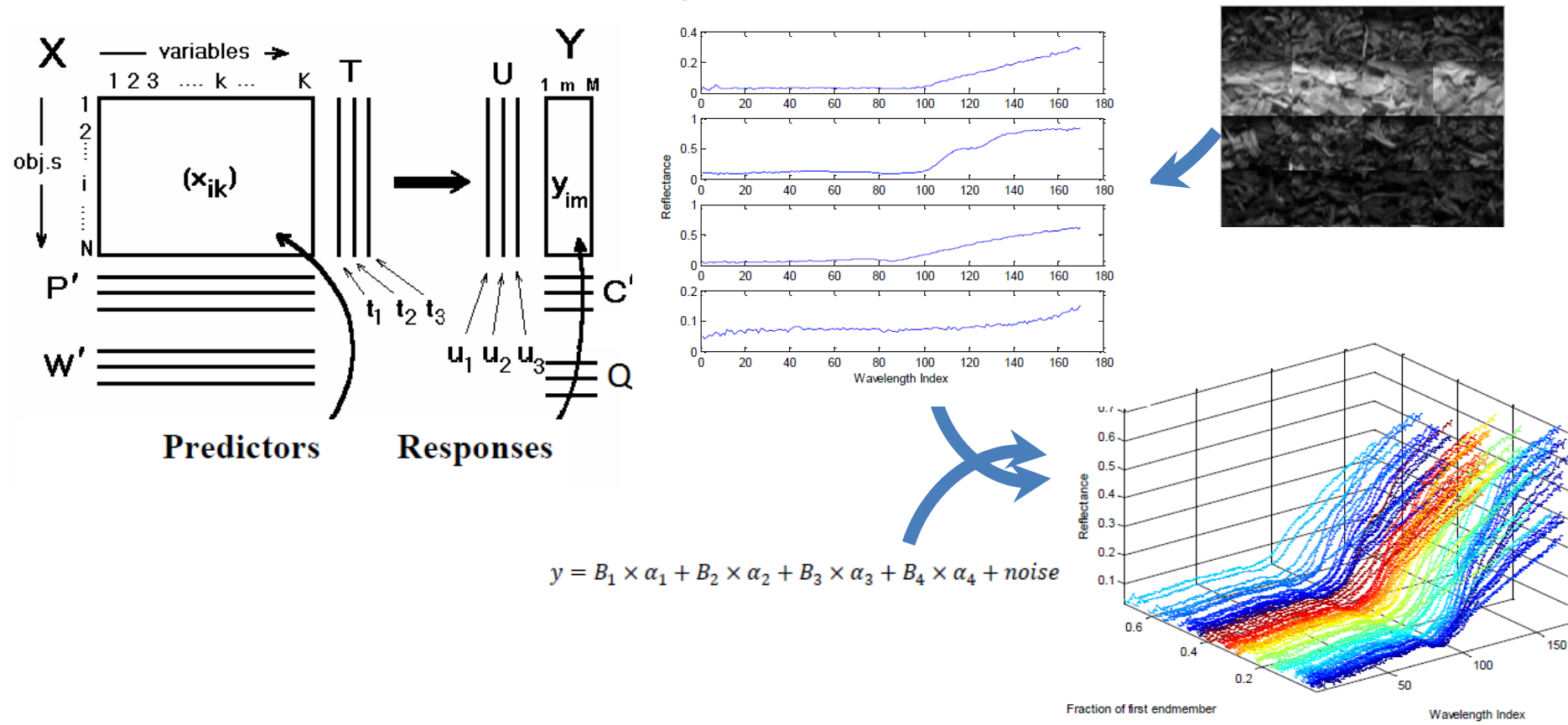
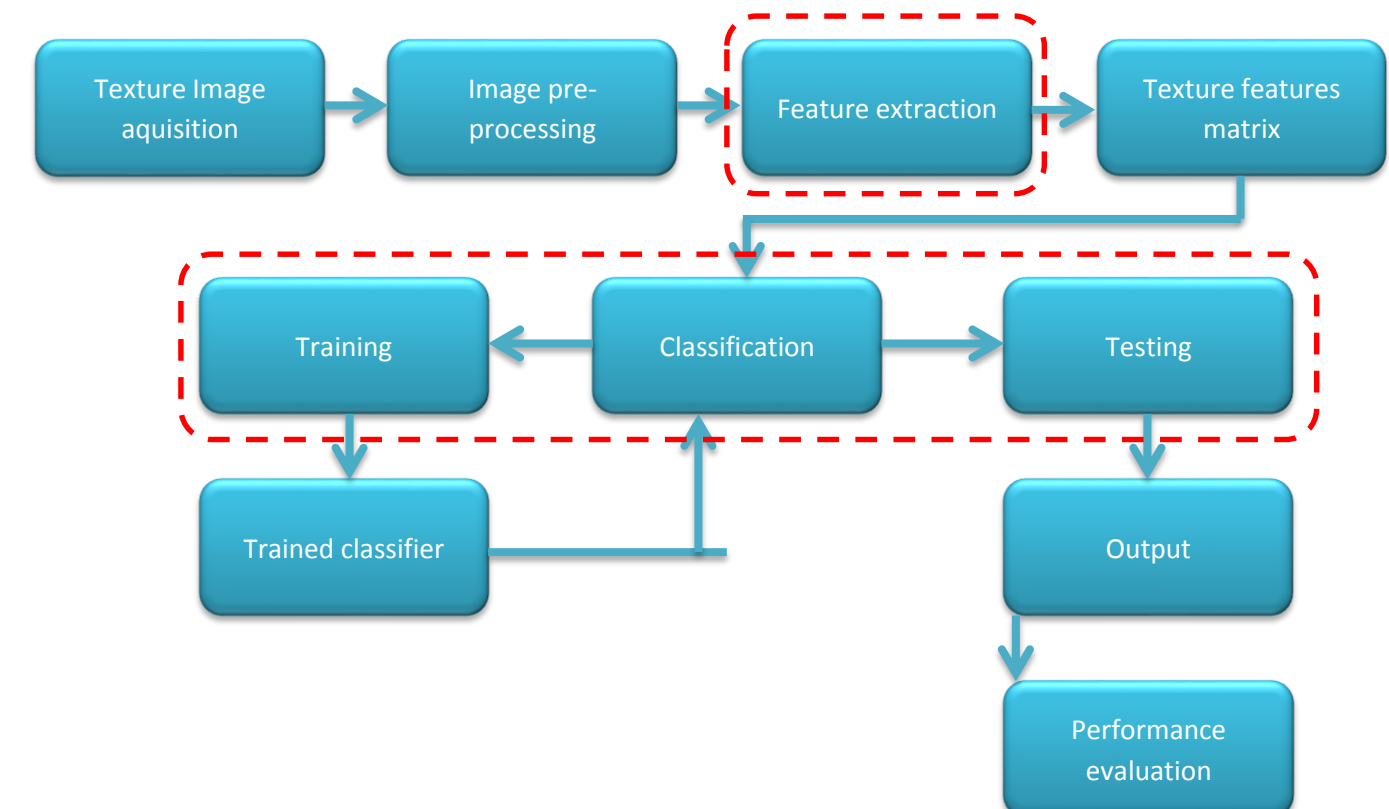Scatter plot of fitted vs. observed response value per each variable; a) g=2, b) g=4
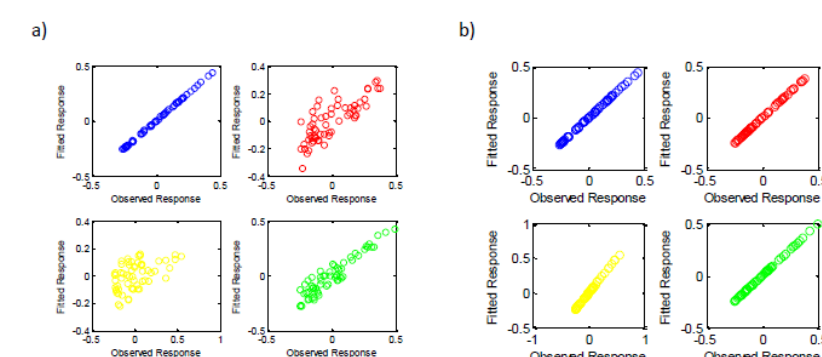
➢ Reflectance spectra contain a lot of data, but not all of the data points carry significant information

Spectral region removal

Surface graph of MSE variation as a function of spectrum cutting window size and position

SVM based spatial classification

Basic architecture of spatial image classification

Texture Image aquisition → Image pre-processing → Feature extraction → Texture features matrix

Training ← Classification → Testing

Trained classifier

Output

Performance evaluation

➢ One could consider various approaches for image classification. In this example spatial classification was done based on textures present on the image.

➢ Since texture is a spatial property that characterises groups of pixels, their features are computed locally over selected area of the image

➢ Two feature extraction techniques implemented in the experiment
  ➢ Statistical
  ➢ Signal processing

➢ The SVM classifies data by finding the best hyperplane that separates all data points of one class from those of the other class.

4 different classes – training data	Test images	Ground truth

Block size [pixel]	Correct classification rate [%]	Execution time [seconds]	Visualisation of results	Ground truth	Fixed settings
8x8	90.27	42.15			Wavelet function: bior1.3
16x16	95.34	9.44			Size of training set: 100%
32x32	93.50	3.04			Features: selected coefficients of 1 and 2 level DWT
64x64	89.43	1.38			

Amount of classes	Correct classification rate [%]	Execution time [seconds]	Visualisation of results	Ground truth	Fixed settings
2 classes	95.34	9.44			Block size 16x16 pixel
3 classes	82.03	15.07			Wavelet function: bior1.3 Size of training set: 100%
4 classes	81.55	24.39			Features: selected coefficients of 1 and 2 level DWT

Nowadays Hyperspectral Imaging is being transformed from sparse research tool into a commodity product available to a broad user community

Signal processing tools can change this sophisticated way of capturing images into a source of specific and meaningful information

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