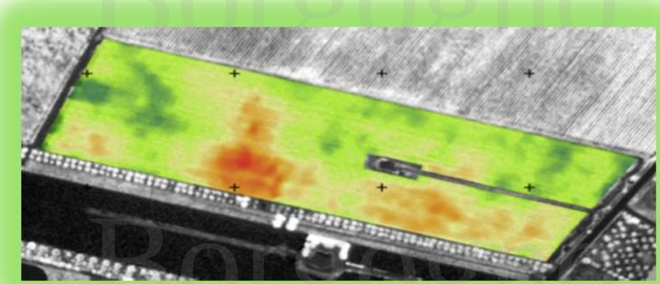
IMAGE CLASSIFICATION



REMOTE SENSING AND AGRICULTURE
CLASSIFICATION or ZONATION ?

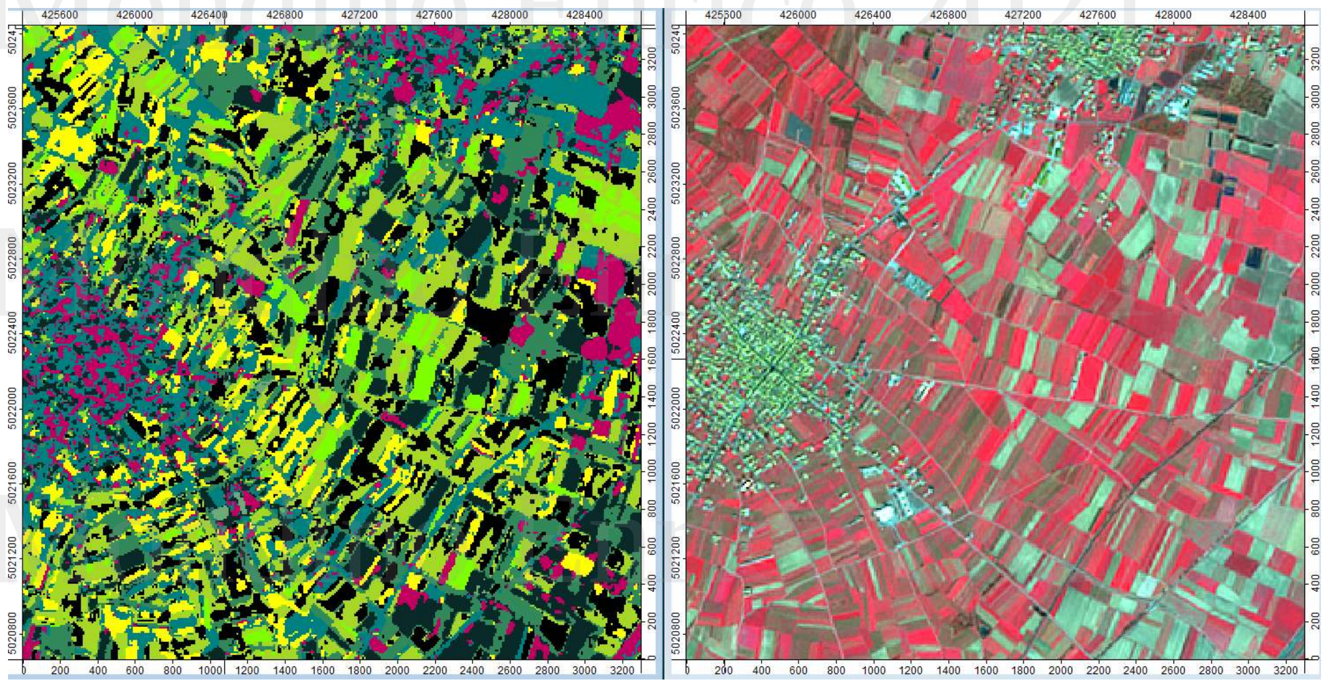
GOAL:
Group of pixels having similar properties have to be recognized and mapped. Classification result depends on algorithm and class discriminants.

Class discriminants are those features that makes possible to interpret pixel meaning, i.e to assign it to a group

WHAT CLASSIFYING (IN AGRICULTURE)?

1. Soil classification/zonation

2. Crop classification/zonation



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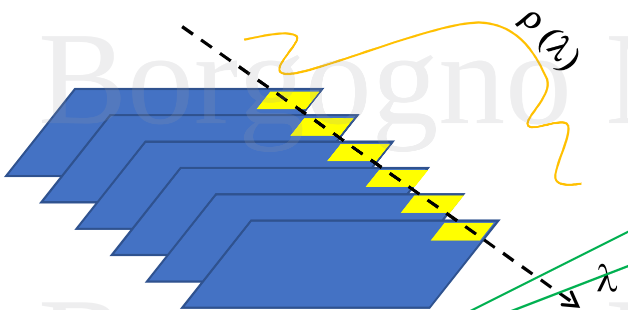
REMOTE SENSING AND AGRICULTURE
CLASSIFICATION or ZONATION ?

CLASSIFICATION :
detection and mapping of specific classes of LAND COVER based on an a-priori knowledge about classes to be recognized (SUPERVISED CLASSIFICATION)

ZONATION :
detection and mapping of AREAS showing SIMILAR (SPECTRAL) properties. It aim at grouping pixels in CLUSTERS not having an a-priori known meaning. CLUSTER meaning has to be interpreted after zonation. This type of analysis is also called UNSUPERVISED CLASSIFICATION.

IMAGE CLUSTERING
UNSUPERVISED CLASSIFICATION

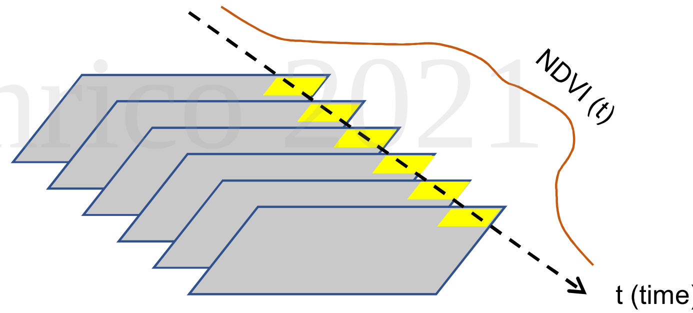
Class discriminants can rely on **SPECTRAL SIGNATURE, SPECTRAL INDICES** and **SPECTRAL INDEX TIME PROFILE** of pixels



$$P_i = \begin{bmatrix} \rho_1 \\ \rho_2 \\ \dots \\ \rho_m \end{bmatrix}$$

$$P_i = \begin{bmatrix} NDVI \\ NDRE \\ \dots \\ NDWI \end{bmatrix}$$

SPECTRAL SIGNATURE or different
SPECTRAL INDICES at a SINGLE DATE

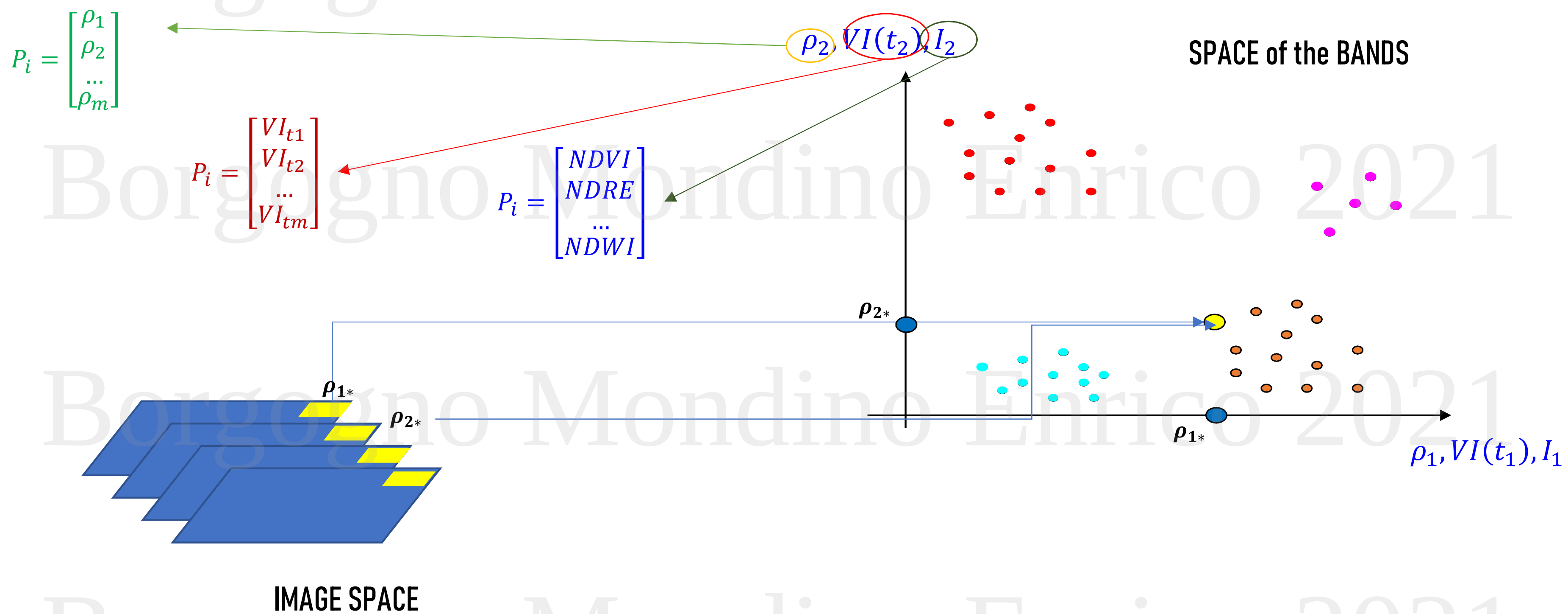


SPECTRAL INDEX (e.g. NDVI) TIME PROFILE

$$P_i = \begin{bmatrix} VI_{t1} \\ VI_{t2} \\ \dots \\ VI_{tm} \end{bmatrix}$$

CLASSIFICATION ALGORITHMS assume that a PIXEL to be classified is a multi-variate statistical variable having as many dimensions as the number of bands (spectrally or time-based). The generic pixel (*Pi*) can be therefore described as an array.

IMAGE CLUSTERING
UNSUPERVISED CLASSIFICATION

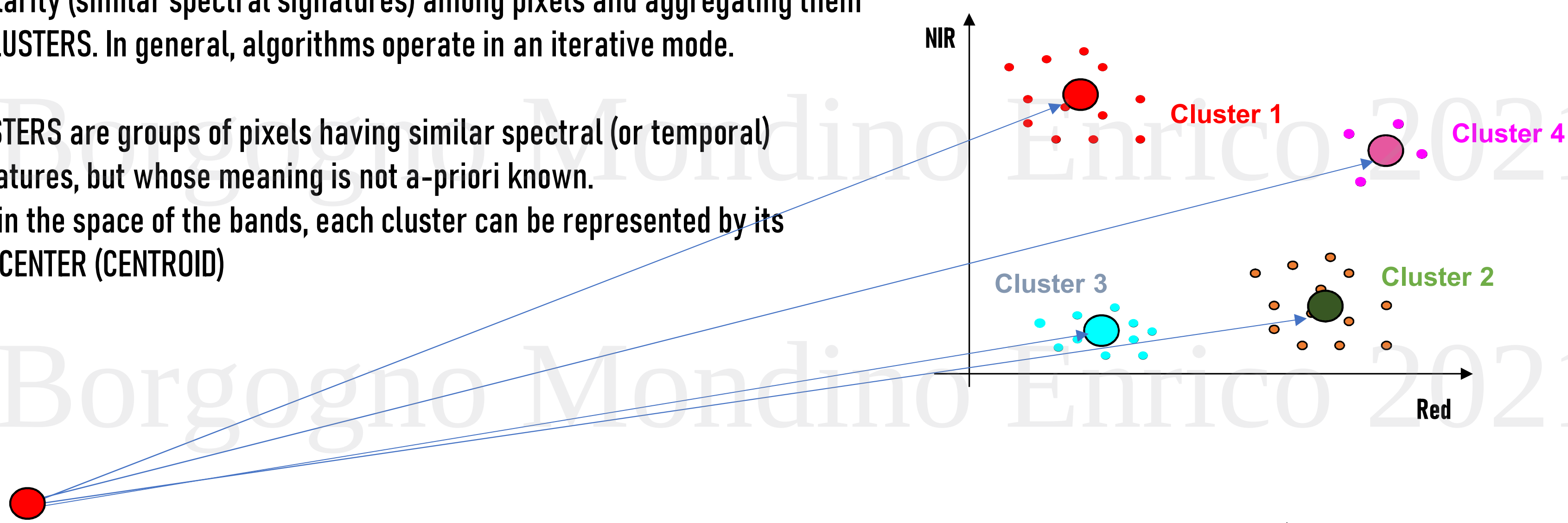


A pixel can be interpreted like **a point** in a Cartesian representation (SPACE of BANDS) having as many dimensions (axes) as the number of bands/indice/dates of the image to be classified.

IMAGE CLUSTERING
UNSUPERVISED CLASSIFICATION

An unsupervised classification is in charge of recognizing spectral similarity (similar spectral signatures) among pixels and aggregating them in CLUSTERS. In general, algorithms operate in an iterative mode.

CLUSTERS are groups of pixels having similar spectral (or temporal) signatures, but whose meaning is not a-priori known.
Within the space of the bands, each cluster can be represented by its BARICENTER (CENTROID)



CLUSTER meaning, i.e. cover class, can be deduced after clustering by exploring spectral statistics of clusters (e.g average spectrum an band standard deviation)
The most used algorithms are:

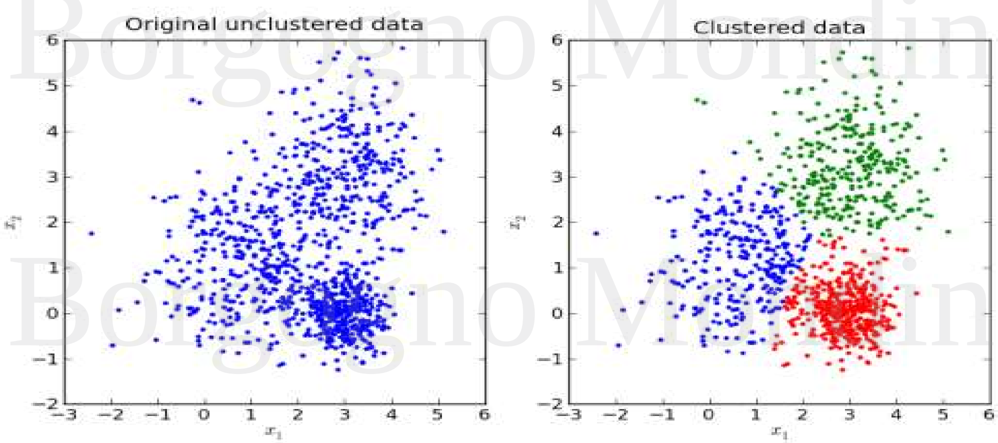
1) K-MEANS
2) 2) ISO-DATA

Unsupervised Classification
K-MEANS

It is basically an optimization algorithm to find ‘k’ clusters in the given set of data points. Initially, it randomly assigns k-cluster centers and then on the basis of some distance metric (for example, euclidean distance) it aims to minimize within cluster sum of squared distance of the data points from the cluster center. There are two steps in k-means clustering algorithm:

a) **Assignment step** – Each data point is assigned to the cluster whose centre is nearest to it.
b) **Update step** – New means (centroids) are calculated from the data points assigned to the new clusters.

(https://appliedmachinelearning.wordpress.com/2017/03/08/image-compression-using-k-means-clustering/)



K-means clustering with K=3

Unsupervised Classification
ISO-DATA

The ISODATA algorithm has some further refinements (JENSEN, 1996): some checks are performed after each iteration to test geometry of groups.

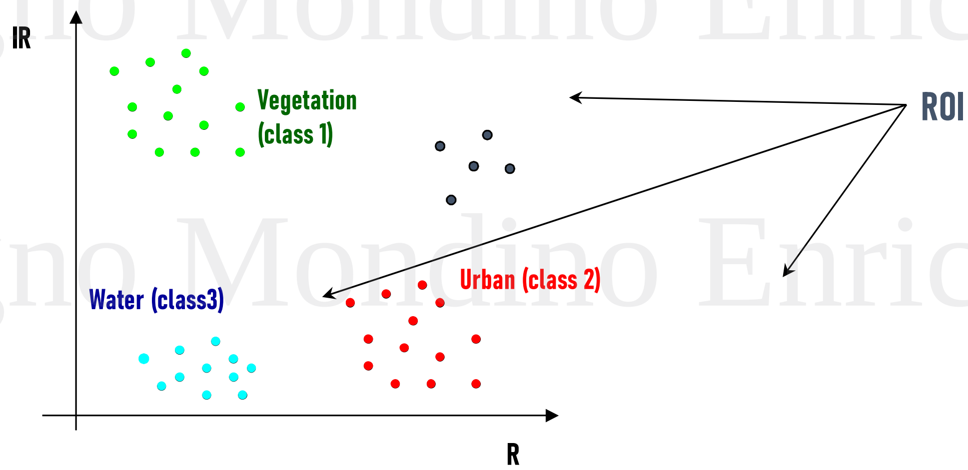
MERGING: different clusters are merged if either the number of members (pixels) in a cluster is less than a certain threshold (KILLING), or if the centers of two clusters are closer than a certain threshold (distance in band space).

SPLITTING: Clusters are split into two different clusters if the cluster standard deviation exceeds a predefined value and the number of members (pixels) is twice the threshold for the minimum number of members.

The ISODATA algorithm is similar to the *K-MEANS* algorithm with the distinct difference that the ISODATA algorithm allows for different number of clusters (user has to define a minimum and maximum value for the expected number of clusters), while the k-means assumes that the number of clusters is known a priori.

(http://www.wu.ece.ufl.edu/books/EE/communications/UnsupervisedClassification.html)

SUPERVISED CLASSIFICATION



In a supervised classification the operator, according to ground data (or through image interpretation), defines some target spectral signatures (one for each desired land cover class).

Target spectral signatures are derived from the statistics of groups of pixels selected from the image (training areas). These groups of target pixels are called ROI (Regions of Interest) or AOI (Areas of Interest).

Supervised classifiers (algorithms) use ROIs as reference spectra to compare the generic pixel spectrum with. The highest similarity determines pixel assignation to the correspondent class.

Spectral similarity can be measured through different criteria. Different the criterion, different the classifier.

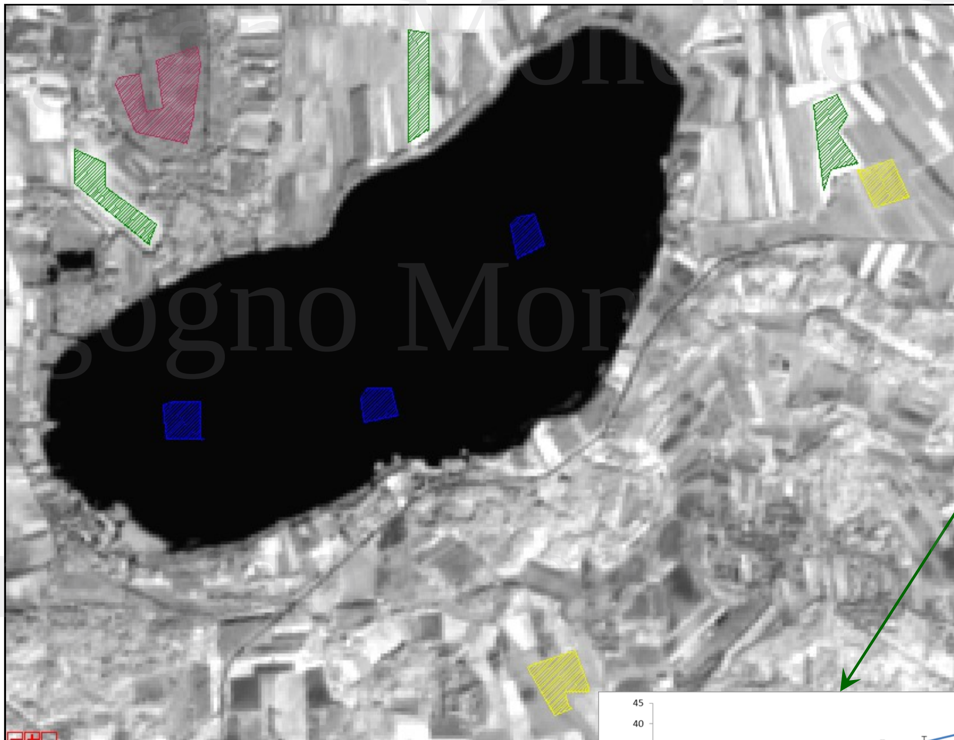
Supervised Classification

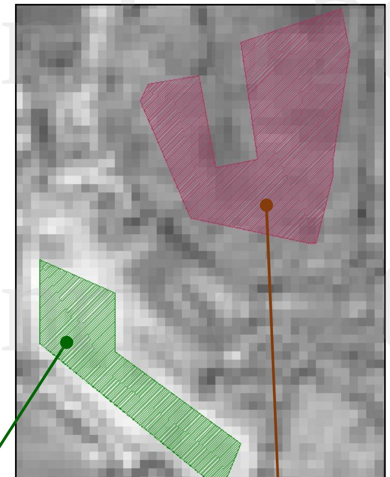
In a supervised classification user “supervises” the process. User supplies reference spectra to be associated with investigated classes. This is done by selecting representative sample sites of known cover type called Training Sites or Areas/Region of Interest (**ROI**, *Region of Interest*). The classification algorithm uses the spectral signatures from these training areas to classify the whole image. Ideally the classes should not overlap or should only minimally overlap with other classes.

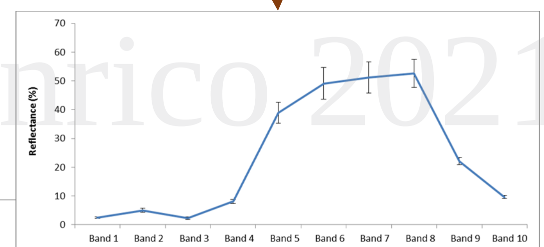
Training sites are areas that are known to be representative of a particular land cover type. The computer determines the spectral signature of the pixels within each training area, and uses this information to define the mean and variance of classes. Preferably the location of the training sites should be based on field collected data or high resolution reference imagery.

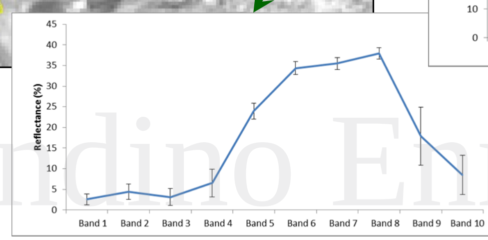
It is important to choose ROIs that cover the full range of variability within each class to accurately classify the rest of the image. If ROIs are not representative of the range of variability found within a particular land cover type, classification may result significantly less accurate. Multiple and spatially distributed small ROIs are preferable and have to be selected for each class. The more time and effort spent in collecting and selecting ROIs the better the classification results.

Supervised Classification (ROIs)









Reference spectra from ROIs

Supervised Classification (ROIs)

ROI can be obtained from:

- Ground surveys, aimed at locating properly sized areas representing the cover type one expects to classify (recognize)
- Auxiliary available data from existing maps
- Photo interpretation of RGB composite from the multispectral (or multitemporal) image one is going to classify, possibly supporting interpretation with high resolution satellite images from public services (e.g. Google Earth or WMS).

In general, we can say that what remote sensing can do is providing a classification of LAND COVER. It cannot refer about LAND USE that, differently, depends on the utilization a certain cover can be related to (e.g. a grass field can be a PASTURE and a Football area)

Whatever the source of the ROI, they have to be preventively assessed testing their

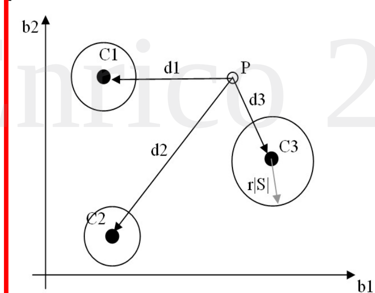
- REPRESENTATIVENESS (size)
- SIGNIFICANCE (level of class spreading around its average value)

This can be achieved with reference to ordinary GIS tools (ZONAL STATISTICS) that permits to derive statistics about pixel values falling within a vector polygon (ROI)

Supervised Classification
Minimum Distance

Euclidean distance in the band space is computed between the generic pixel P and centroids (whose position is computed as the average spectrum of the correspondent ROI). ROIs standard deviation can be used to decide if the winning distance (closest centroid) is short enough to ensure an adequate degree of spectral similarity bewteen pixel and ROI spectra.

$$P = \begin{vmatrix} DN_1 \\ DN_2 \\ \ldots \\ DN_n \end{vmatrix} \qquad C_i = media(ROI) = \begin{vmatrix} \overline{X}_1 \\ \overline{X}_2 \\ \ldots \\ \overline{X}_n \end{vmatrix} \qquad S = \mathrm{stdev(ROI)} = \begin{vmatrix} \sigma_1 \\ \sigma_2 \\ \ldots \\ \sigma_n \end{vmatrix}$$



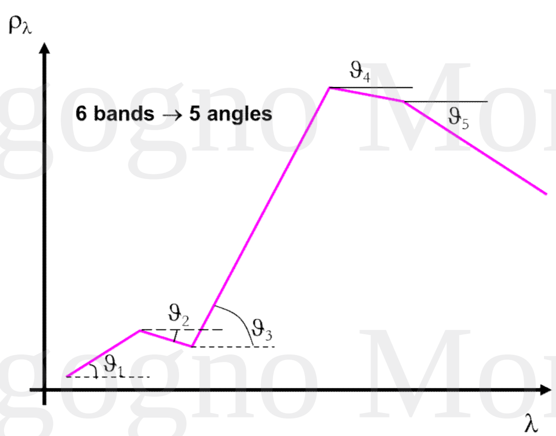
$$di = \sqrt{\sum_{i=1}^{N} (DN_i - \overline{X}_i)^2}$$

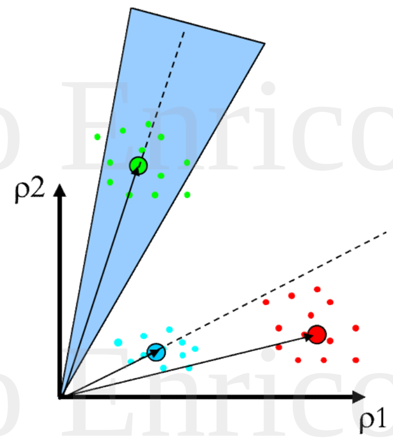
$$|S| = \sqrt{\sum_{i=1}^{n} (\sigma_i)^2}$$

In figure: the winning centroid (closest to the pixel P to be assigned) is C3. The MD algorithm, if required by user, takes care about the goodness of pixel assignation, testing if the winning distance is consistent with a declared threshold. Threshold is, in general, set using an integer multiplier of the class standard deviation, *r|S|*, where S is the module of the vector «class standard deviation» (stdev(ROI)). S is used to define a circular area around the centroid repreesnting the maximu admittable distance to assign the pixel to the winning class. If the distance is higher than S, the P pixel will be labelled as «Unclussified», therefore not assigned to any class.

Supervised Classification
Spectral Angle Mapper (SAM)

Spectral Angle Mapper (SAM) is a physically-based spectral classification that uses an *n*-D angle to match pixels to reference spectra. The algorithm determines the spectral similarity between two spectra by calculating the angle between the spectra in the band space. This technique, when used on calibrated reflectance data, is relatively insensitive to illumination and albedo effects. Reference spectra used by SAM can come from ASCII files or spectral libraries, or you can extract them directly from an image (as ROI average spectra). SAM compares the angle between the reference spectrum and each pixel vector in *n*-D space. Smaller angles represent closer matches to the reference spectrum. Pixels further away than the specified maximum angle threshold in radians are not classified. SAM classification assumes reflectance data. However, if you use radiance data, the error is generally not significant because the origin is still near zero (*ENVI 4.8 Guide*).





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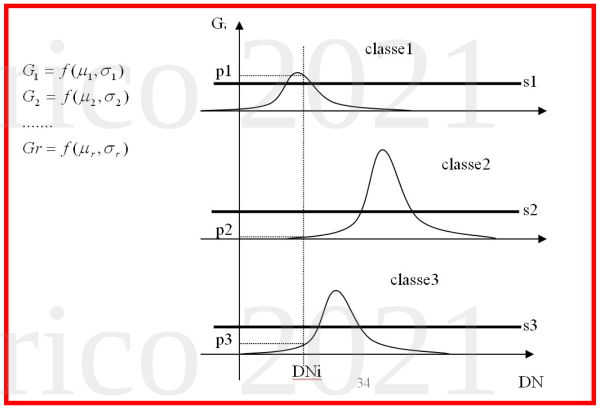
Supervised Classification
Maximum Likelihood

Classification is performed based on statstical criteria. Roi pixels are a-priori considered to be normally (Gaussian) distributed. A Gaussian multi-variate PDF (*Probability Density Function*) is computed using Mean and Standard Deviation of each ROI.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Mono-variate Gaussian PDF

A different PDF (G_i in figure) is defined for each ROI. The generic pixel P is assigned to the class having the highest probability of extraction. In figure a mono-dimensional (only one band is taken into account) example. Three classes are considered, whose correspondent PDF are obtained from ROIs. p1, p2, p3 are the probabilities that P belongs to each classe. Winning class is the one with the highest probability (p1). A probability threshold (a value ranging between 0 and 1) can be set to decide if the winning probability is high enough. If not, the pixel is labelled as «Unclassified».



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Supervised Classification
Accuracy Assesment

For a SUPERVISED CLASSIFICATION an ACCURACY ASSESSMENT is always required, to measure classification uncertainties. Assessment can be operated at two levels:

- one is devoted to evaluate classification performance in respect of the selected ROIs. Good performances means that training sites are well representing correspondent classes. In other words, a goog level of generalization is reached. Stats are computed comparing labeling of ROIs pixels after classification with the expected one (Water is water? Wheat is wheat? Etc.)

- one is devoted to evaluate if classification results are really consistent, and how much, with ground truth. Since ROIs were used to train classification algorithm, classification performances evaluation based on ROI pixel analysis is not enough to admit that classification is proper. This information can only come from ground surveys in areas different from those included in ROIs. Operationally speaking this can be obtained surveying more ROIs splitting them in a TRAINING SET (ROIs used to train algorithm) and TEST SET (ROIs used to test classification results).

In both the situations, the tool to be applied is the **ERROR** or **CONFUSION MATRIX** (CM).

Supervised Classification
Accuracy Assesment

	ROI1	ROI2	ROI3	Total
UNCLASSIFIED	nc_1	nc_2	nc_3	$m=\Sigma nc_i$
CLASS 1	a_{11}	a_{12}	a_{13}	$m1=\Sigma a_{1i}$
CLASS 2	a_{21}	a_{22}	a_{23}	$m2=\Sigma a_{2i}$
CLASS 3	a_{31}	a_{32}	a_{33}	$m3=\Sigma a_{3i}$
Total	$n1=\Sigma a_{i1}$	$n2=\Sigma a_{i2}$	$n3=\Sigma a_{i3}$	Ntot

CM is built by counting, for each class, the number of ROIs pixels *correctly* or *wrongly* classified. A ROI member is **correctly** classified if classifier places it into the correct (expected) class (the one ROI is intended for). A ROI member is **wrongly** classified if classifier places it into the wrong class (other than the expected one). Columns in general represent the EXPECTED labelling (ROI dependent) , ROWS the assigned one (CLASSIFICATION dependent)

Accuracy parameters computed from the CONFUSION MATRIX

$$(A)\ OverallAccuracy = \frac{\sum_{i=1}^{3} a_{ii}}{Ntot}$$

$$(B)\ ClassAccuracy = \frac{a_{ii}}{n_i}$$

$$(C)\ ClassCommission = \frac{\sum_{j=1, j\neq i}^{3} a_{ij}}{m_i}$$

$$(D)\ ClassOmission = \frac{\sum_{j=1, j\neq i}^{3} a_{ji} + nc_i}{n_i}$$

A) % of ROI pixels correctly classified (include pixels of all the ROIs)

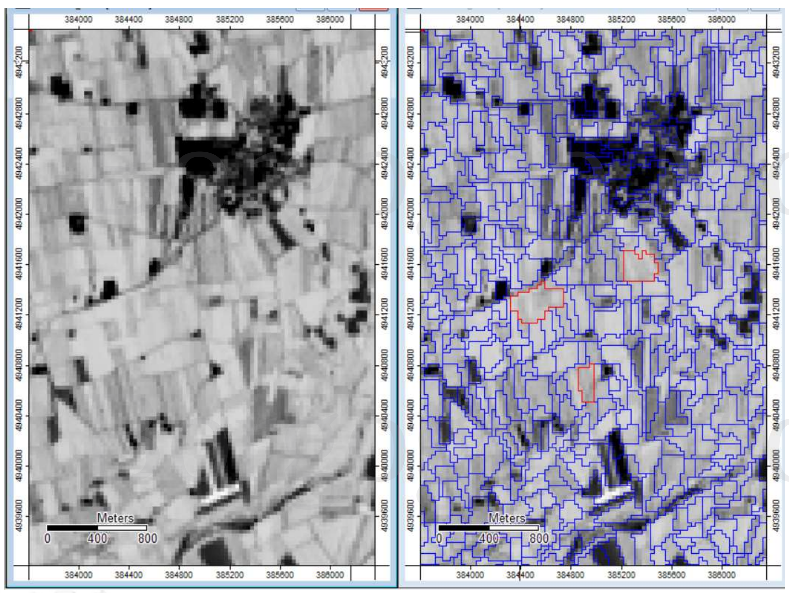
B) % of pixels of the generic *i*-class **correctly** classified

C) % of pixels of other classes **wrongly** assigned to the generic *i*-class.

D) % of pixels of the generic *i*-class that were assigned to other classes (include «unclassified»)

Object-based Classification

Object-based (or object oriented) classification involves categorization of pixels based on the spatial relationship with the surrounding pixels Object based classification methods were developed relatively recently compared to traditional pixel based classification techniques. While pixel based classification is based solely on the information in each pixel, object-based classification is based on information from a set of similar pixels called objects or image objects. Image objects are groups of pixels that are similar to one another based on the spectral properties (i.e., color), size, shape, and texture, as well as context from a neighborhood surrounding the pixels. This type of classification attempts to mimic the type of analysis done by humans during visual interpretation.



Segmentation

Image segmentation is a key component to object-based classification. Segmentation is a process by which pixels in an image are grouped into segments, or objects, that share a homogeneous spectral similarity. There are a variety of different parameters that are used in segmentation.

Object-based Classification

After an image has been segmented, objects are classified based on features and criteria set by the user. Here are some common criteria used to classify objects:

Color: mean or standard deviation of each band, mean brightness, band ratios

Size: area, length to width ratio, relative border length

Shape: roundness, asymmetry, rectangular fit

Texture: smoothness, local homogeneity

Class Level: relation to neighbors, relation to other objects