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Image Classification Extensions

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Extensions

- **Segmentation**
  - Used here as a preprocessing step for classification
  - Related to classification -> Segmentation using multiple spectral channels similar to multispectral classification.

- **Object-based classification** (versus pixel-based treated in a previous lecture)

- **Spectral unmixing**

- **Fuzzy classification** (treated in a later lecture)

Object-based Classification

Aim is object-based, in reality method is segment-based

(an object, e.g. building roof, can have many segments !!)

Aims

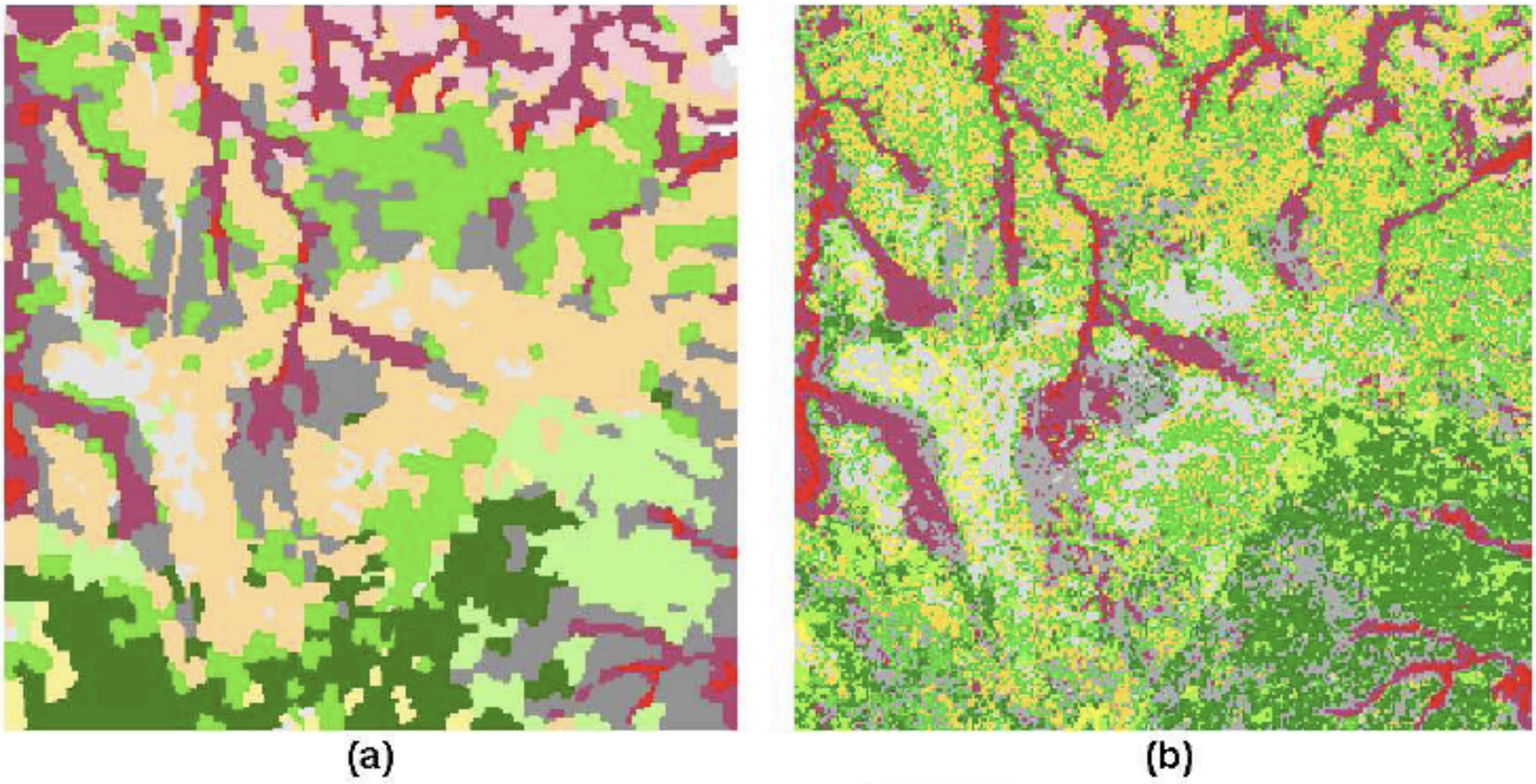
- avoid salt and pepper noise of pixel-based classification, especially when classes are spatially heterogeneous (class regions are small and mixed)
- get more meaningful, object-related results

Method

- perform segmentation
- classify segments
- in both segmentation and classification, properties other than spectral information can be used

Rarely implemented in software packages (one example is eCognition, http://www.ecognition.com/)

Object-based Classification



Object-based (left) versus pixel-based (right) classification.

Object-based Classification (eCognition)

Segmentation depends on 3 factors:

- Scale (depends on classes/pixel heterogeneity, multiple scales used)
- Color (balance between color and shape homogeneity)
- Form (balance between border smoothness and compactness)

After scale selection, shape, smoothness and compactness weights are selected.

Results visually inspected. Multiple iterations usually needed.

Classification

- Class rules are established using different criteria, e.g. spectral, shape, location, context
- Training areas can be used
- Fuzzy classification with subsequent hardening is possible

Requires fine tuning of parameters and rules and multiple trials.

Often better than pixel-based but not always. It also depends on quality of pixel-based classification, use of spectral unmixing or not, postprocessing etc.

Multi-Scale Segmentation (eCognition)

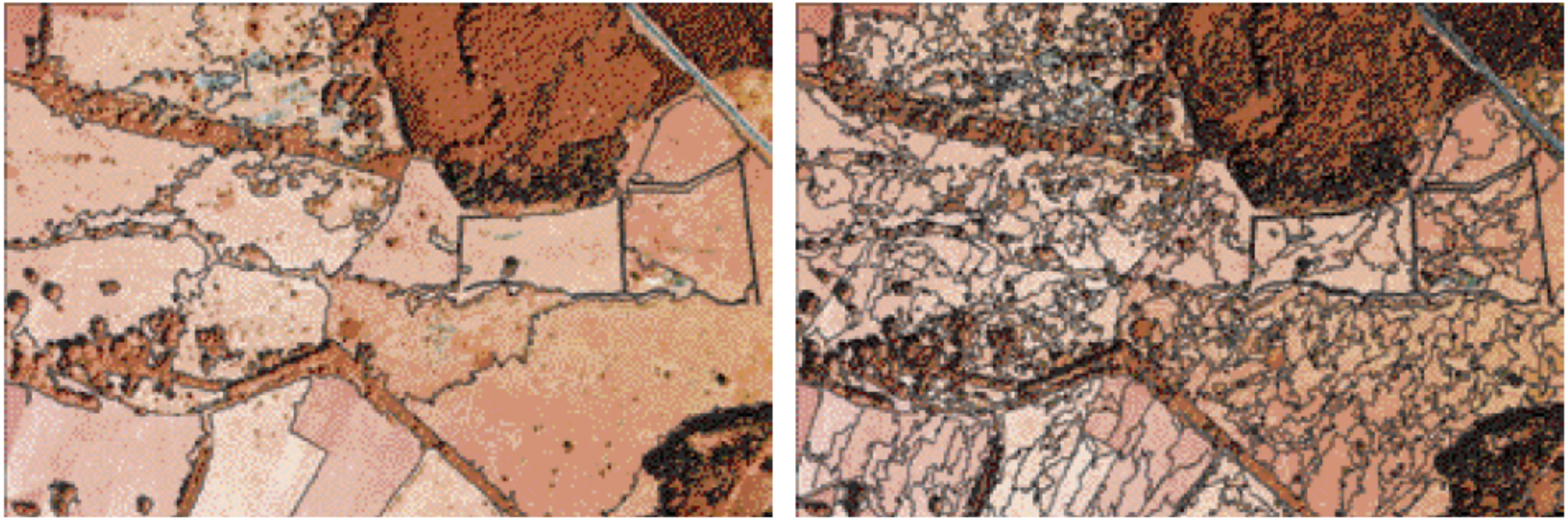


Fig. 2: Multi-scale image segmentation illustrated at only two levels of segmentation, a very coarse one aiming at pastures and enclosures and a very fine one aiming at groups of shrubs.

Spectral Unmixing

- One pixel on the ground covers more than one class
- Problem increases with
  - higher number of target classes
  - increasing ground pixel size
  - fragmented classes covering many small areas
  - at boundaries of classes

Aim of spectral unmixing

- determine which distinct spectra/classes (called endmembers) are represented in each pixel and their proportion (call fractional abundances)

Usual assumptions

- Abundance of each endmember greater equal 0
- Sum of abundances = 1

Determination of endmembers and abundances can be 2 different problems

Spectral Unmixing

Models of spectral unmixing

A. Linear Model

- most often used
- when the the endmembers cover clearly separated, large enough areas (like the squares of a checkerboard)

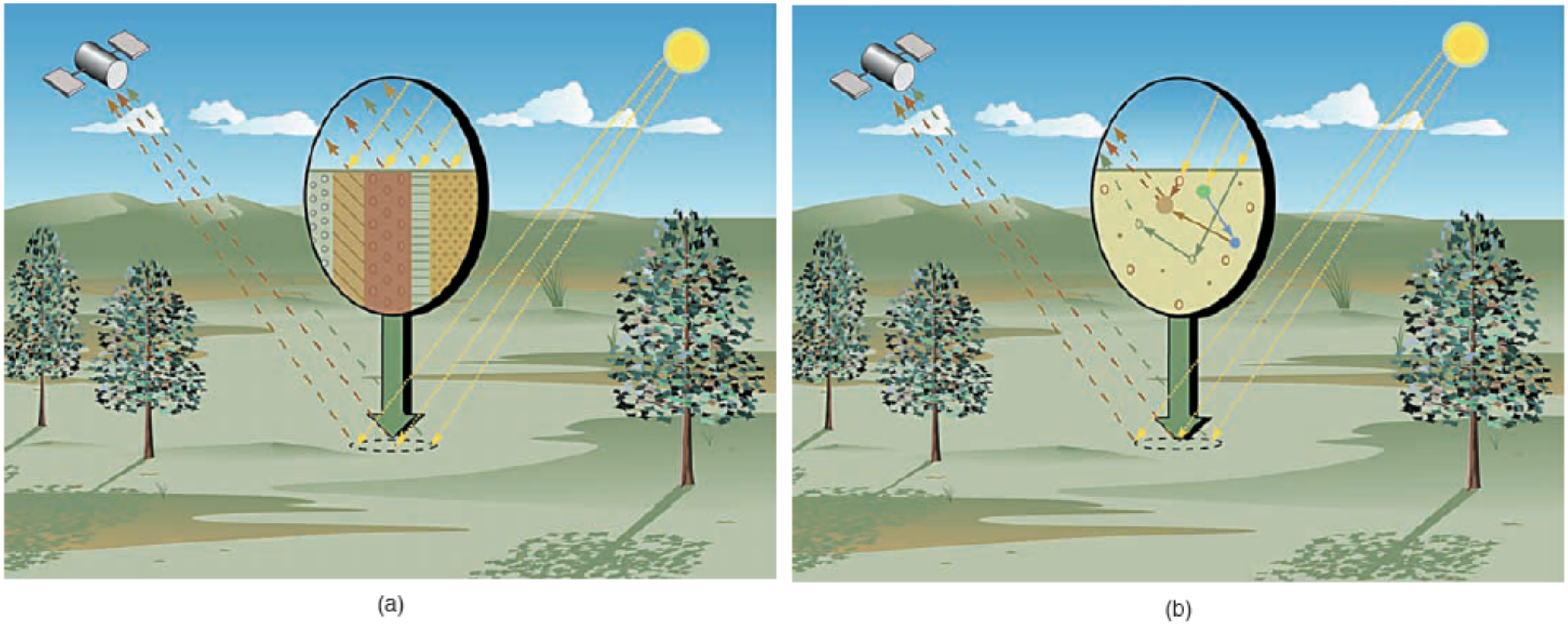
B. Nonlinear model

- when the endmember areas are very small and mixed (e.g. sand grains of different composition)
- Important for mineral studies and vegetation/canopy studies

Result is not ONE classification image but N classification images (N = number of endmembers), each showing the abundance (fraction planes) for each endmember

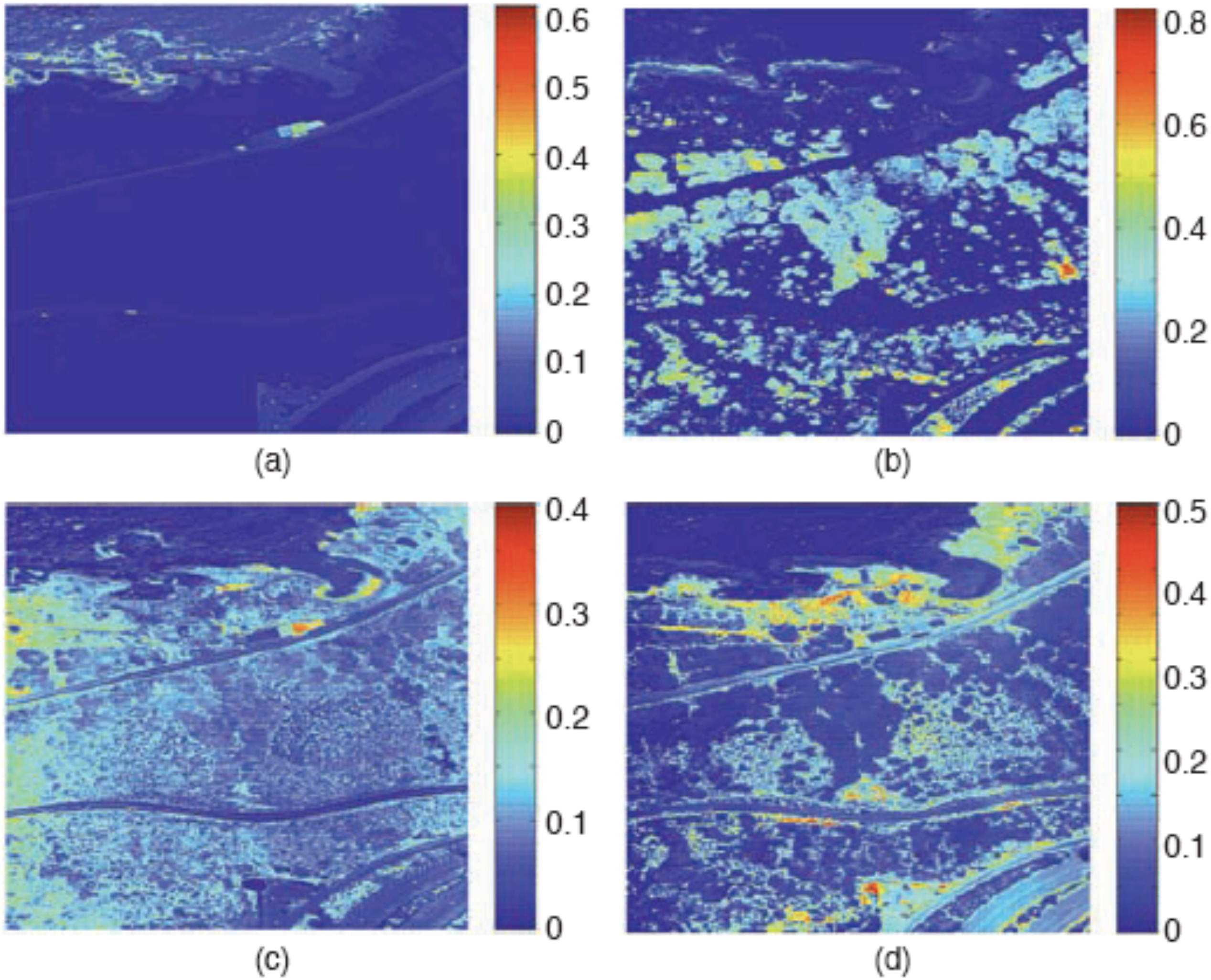
Spectral unmixing related to hyperspectral imaging (because many bands needed for unmixing.

Spectral Unmixing



Linear mixing (left) ; nonlinear mixing (right).

Spectral Unmixing



Fractional planes of 4 endmembers.

Spectral Unmixing

Linear unmixing. Consists often of 3 steps:

- reduction of number of bands (reduction of computations), e.g. by principal component analysis

- determination of endmembers (manual, automatic)

- determination of abundances
  - requires at least M bands (M = number of endspectra abundances)
  - usually a least squares approach is used