Ecosystem services assessment using hyperspectral images

5^e Colloque Groupe Hyperspectral SFPT-GH

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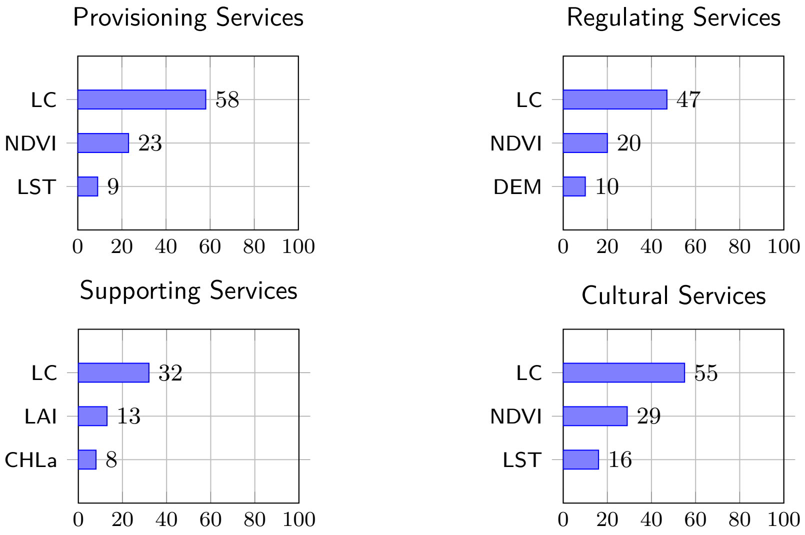
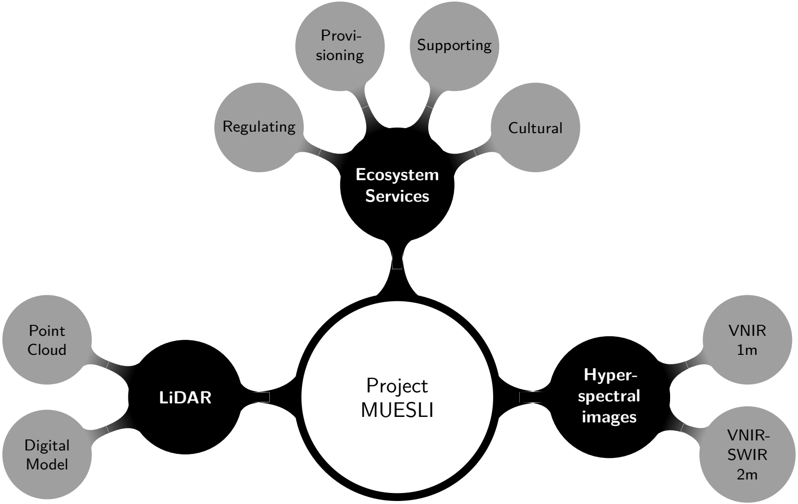
- Remote sensing mapping

ES assessment with remote sensing [AAD15]



Project MUESLI

Multiscale Mapping of Ecosystem Services by Very High Spatial Resolution Hyperspectral and Lidar Remote Sensing Imagery



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  3. Additional topographic data, e.g., LiDAR, LST, . . .
- In this talk: *Hyperspectral images*
  - Spectral unmixing to infer spectral heterogeneity
  - Correlation with regulation and production services

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- Variant: first reduce the dimension (PCA, ...)

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- Clusters estimated through the *PCA+Kmeans* pipeline applied on the whole image.

Curse of dimensionality

- Euclidean distance may fail to correctly assess the similarity between samples [AHK01]

$$\frac{d_M(\mathbf{x}) - d_m(\mathbf{x})}{d_M(\mathbf{x})} \rightarrow_p 0$$

for all Minkowski norm: $\|\mathbf{x}\| = \left(\sum_{i=1}^{d} |x_i|^p\right)^{1/p}$.

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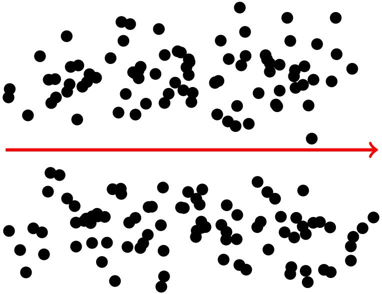
- PCA loses information and is usually not adapted to hyperspectral images [CB03]



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Linear mixture model

- Each pixel is a convex linear combination of endmembers (pure spectra):

$$\mathbf{x} = \sum_{j=1}^{s} \alpha_j \mathbf{s}_j + \mathbf{e}$$

  - $\mathbf{s}_j$ is the j^{th} endmember,
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- Matrix formulation:

$$\mathbf{x} = \mathbf{S}\boldsymbol{\alpha} + \mathbf{e}$$

where $\mathbf{S} = \left[\mathbf{s}_1, \ldots, \mathbf{s}_s\right]$.

LMM based heterogenity measure

- Mean distance between endmembers

$$H(p) = \frac{1}{s_p}\text{Trace}\big(\bar{\mathbf{S}}\bar{\mathbf{S}}^\top\big)$$

where $\bar{\mathbf{S}}$ is the centered matrix of endmembers.

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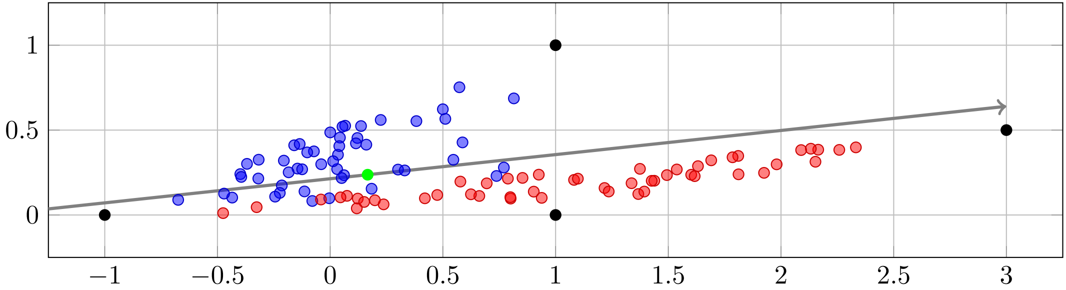
- α-diversity computed on abundance features rather than PCA features

$$\tilde{\mathbf{x}} = [\alpha_1, \ldots, \alpha_s]$$

with $s \ll d$.

  - PCA: minimizes a reconstruction error using an *orthogonal* basis
  - LMM: minimizes a reconstruction error using a *physically interpretable non-orthogonal* basis

Illustration



First PC accounts for 92% of the cummulative variance

Outline

Data collection

- HySpec (2m/pixel) acquired June 8/9, 2016.

Domain	Beginning	End
1	400	1340
2	1550	1800
3	1980	2400

- 27 crop plots of radius 500 m were sampled during February to August 2016.

Provisionning	Control
Yield	Aphid low rate
Average Ear Weight	Aphid Hight rate
Thousand Seed Weight	Seeds rate
Density	Eggs rate

Simulations

- Unmixing strategy
  - Vertex Component Analysis (VCA) are used to extract a large number of endmembers (36)
  - Sparse unmixing [IBP11]: only endmembers whose abundances are different from 0 are considered *present* in the plot and variation of illumination is accounted for.
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- Competitive strategies

Method	Acronym
Mean distance to the centroids	MDC
Mean distance to the endmembers	MDE
Abundances-based entropy	AE
Spectral species distribution using PCA	SSD-PCA
Spectral species distribution using abundances	SSD-A

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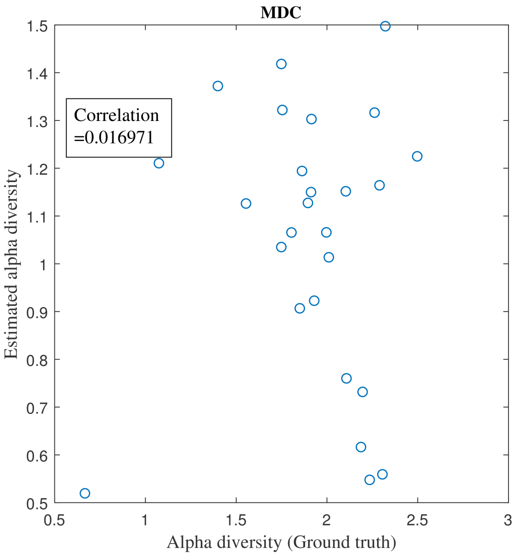
Global α-diversity



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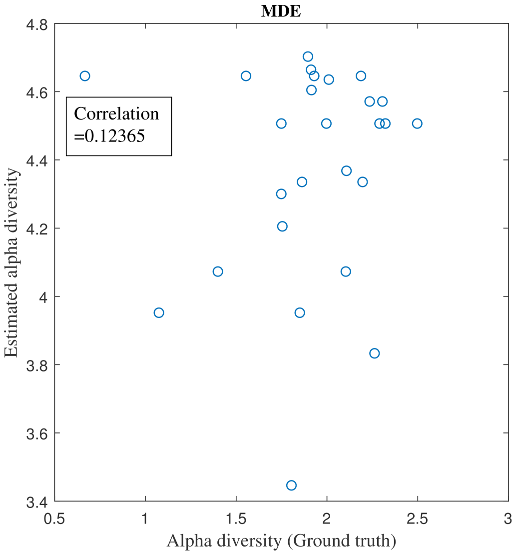

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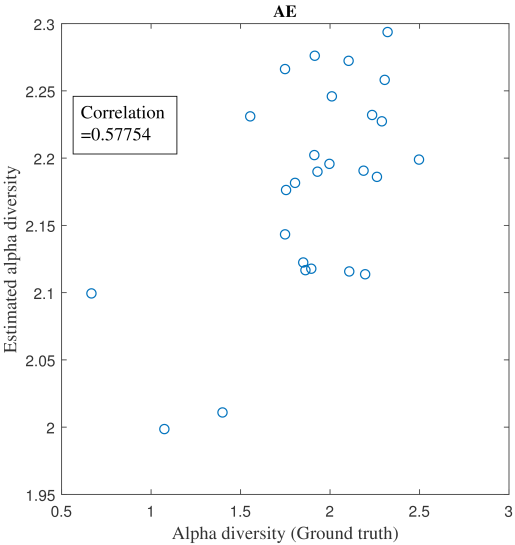

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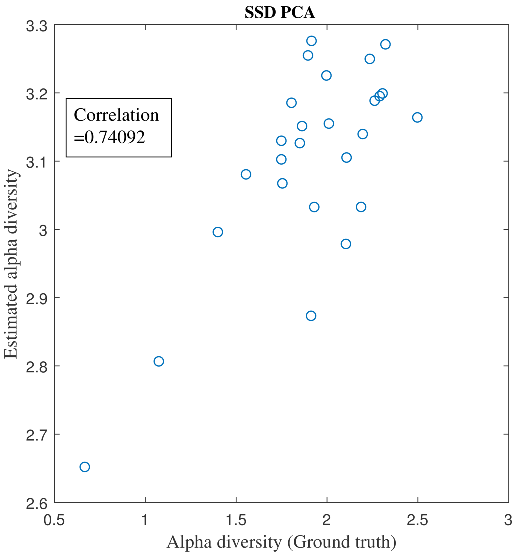

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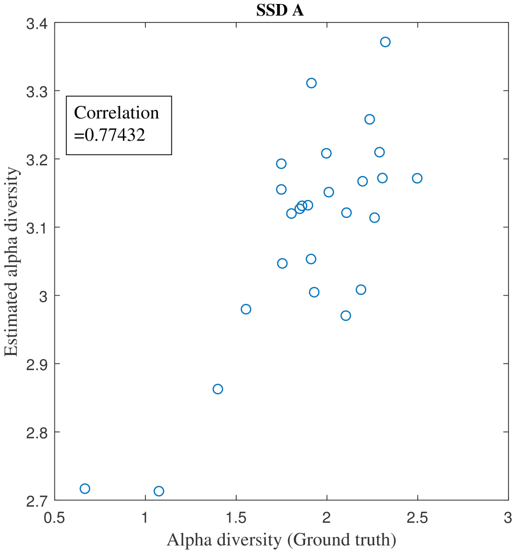
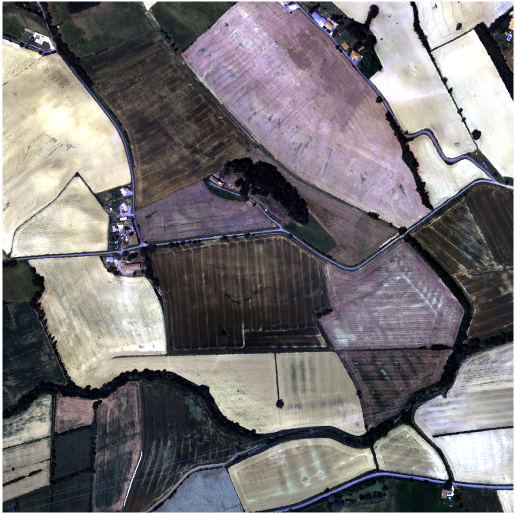
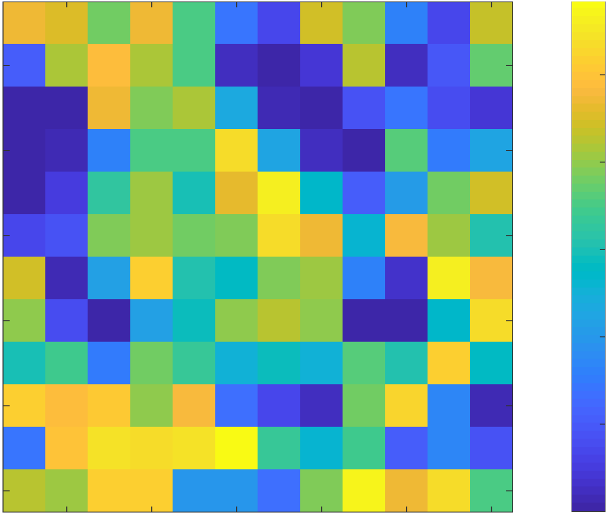
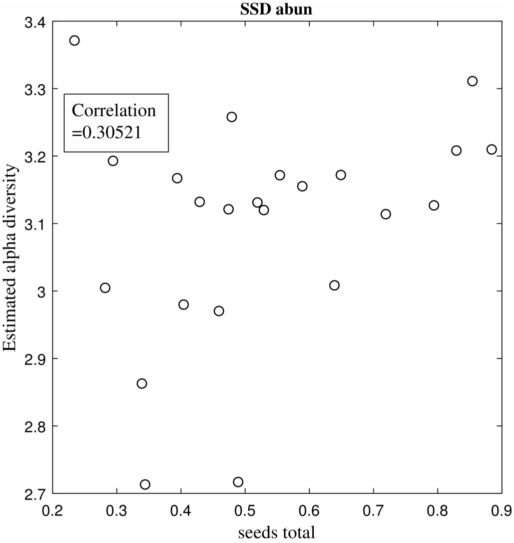


Local α-diversity





Ecosystem services



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  - Can abundances *and* endmembers be informative together ?
- How to incorporate LiDAR:
  - In the unmixing process ?
  - In the explanatory model ?

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