>>> Introduction to hyperspectral remote sensing imagery
>>> GRSS Summer School

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- Associated to the DYNAFOR lab
- IEEE GRSS:
  - Senior Member
  - Member of the *GRSS Chapter Committee*
  - IEEE JSTARS Associated Editor

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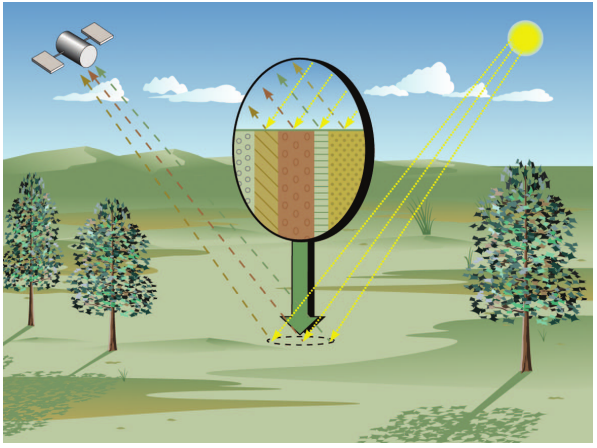
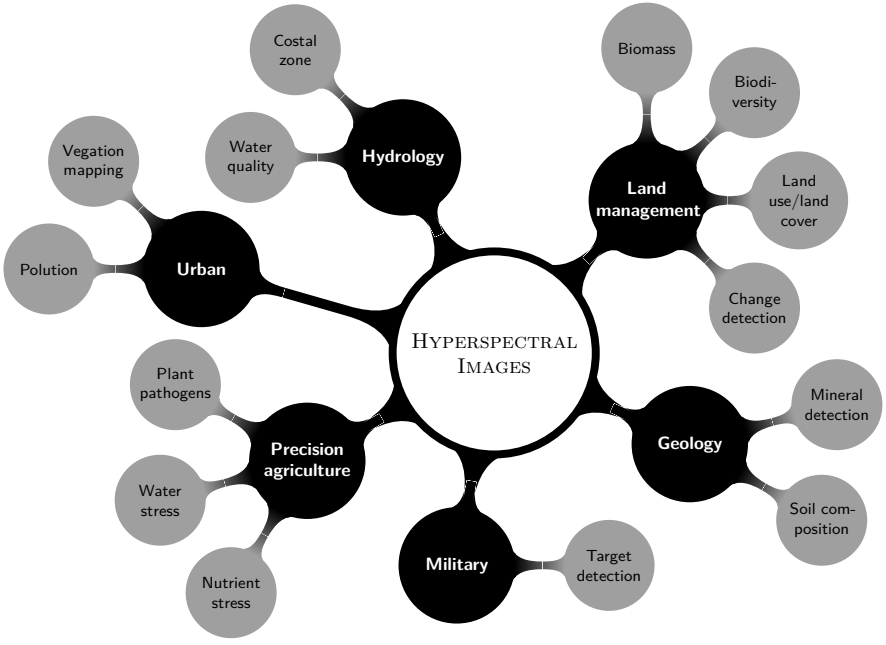
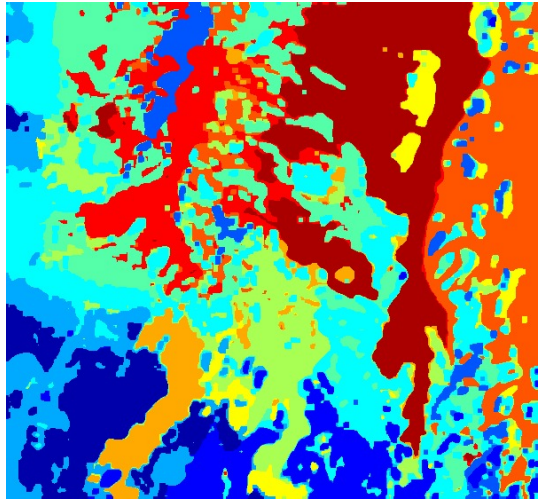


] *Image taken from [KM02].*

- Remote sensing provides information about landscapes.
- This information is carried out by the *electromagnetic energy* and is usually formated in terms of *digital image data*.
- This information can be used
  - To *update* and to *supervise* landscapes in known areas,
  - To *get prior* information about landscapes of unknown areas.

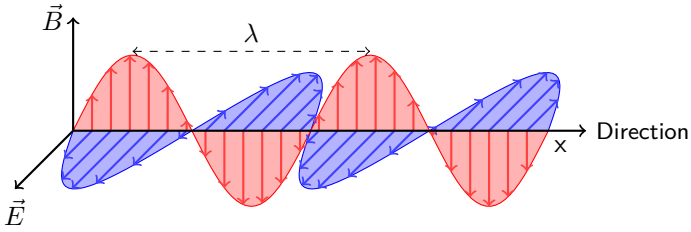

Hyperspectral Images
Hydrology
Costal zone
Water quality
Urban
Vegation mapping
Polution
Land management
Biomass
Biodi-versity
Land use/land cover
Change detection
Precision agriculture
Plant pathogens
Water stress
Nutrient stress
Geology
Mineral detection
Soil com-position
Military
Target detection



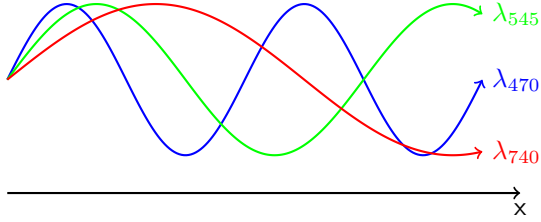
Classes

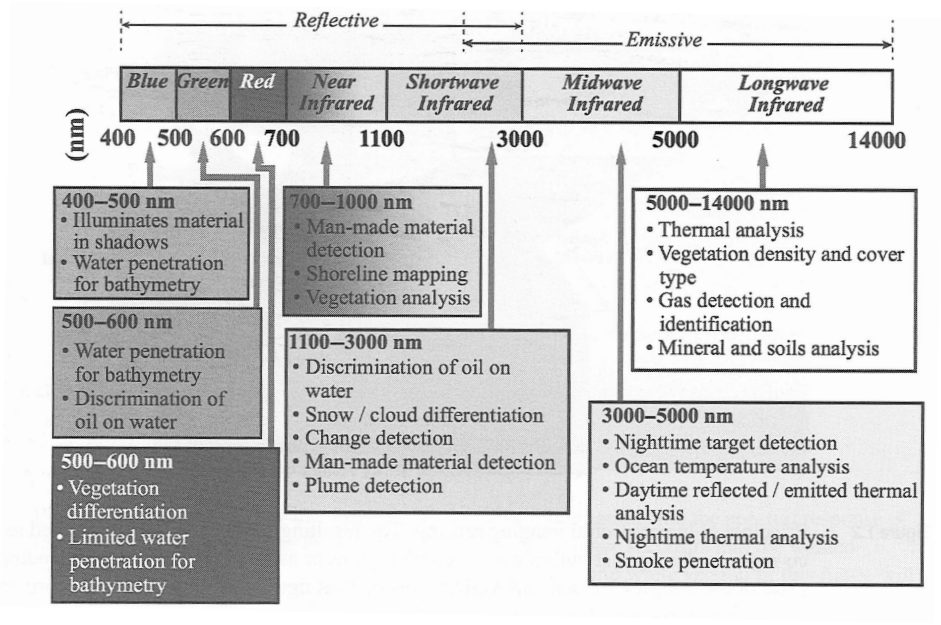
Lava 1970, Lava 1980 I, Lava 1980 II, Lava 1991 I, Lava 1991 II, Lava moss cover, hyaloclastite formation, Tephra lava, Rhyolite, Scoria, Firn-glacier ice, Snow.

>>> Outline



- An electromagnetic wave is a pertubation of the electric and magnetic field which propagates throught space.
- $\vec{E}$: Electric field. $\vec{B}$: Magnetic field.
- Wavelength (λ): *Minimal distance between 2 points of the space for which $\vec{E}$ and $\vec{B}$ recover the same values.*

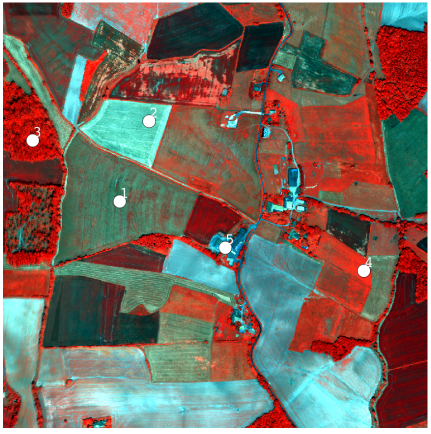


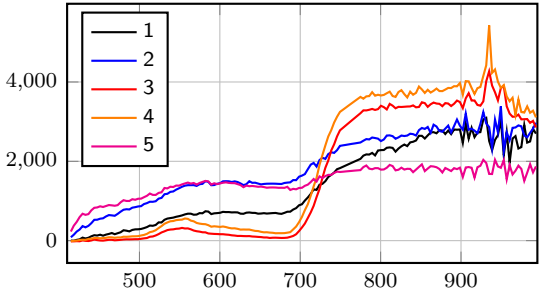

Reflective
Emissive
Blue
Green
Red
Near Infrared
Shortwave Infrared
Midwave Infrared
Longwave Infrared
(nm)
400
500
600
700
1100
3000
5000
14000
400–500 nm
• Illuminates material in shadows
• Water penetration for bathymetry
500–600 nm
• Water penetration for bathymetry
• Discrimination of oil on water
500–600 nm
• Vegetation differentiation
• Limited water penetration for bathymetry
700–1000 nm
• Man-made material detection
• Shoreline mapping
• Vegetation analysis
1100–3000 nm
• Discrimination of oil on water
• Snow / cloud differentiation
• Change detection
• Man-made material detection
• Plume detection
3000–5000 nm
• Nighttime target detection
• Ocean temperature analysis
• Daytime reflected / emitted thermal analysis
• Nighttime thermal analysis
• Smoke penetration
5000–14000 nm
• Thermal analysis
• Vegetation density and cover type
• Gas detection and identification
• Mineral and soils analysis

From [MLC16].

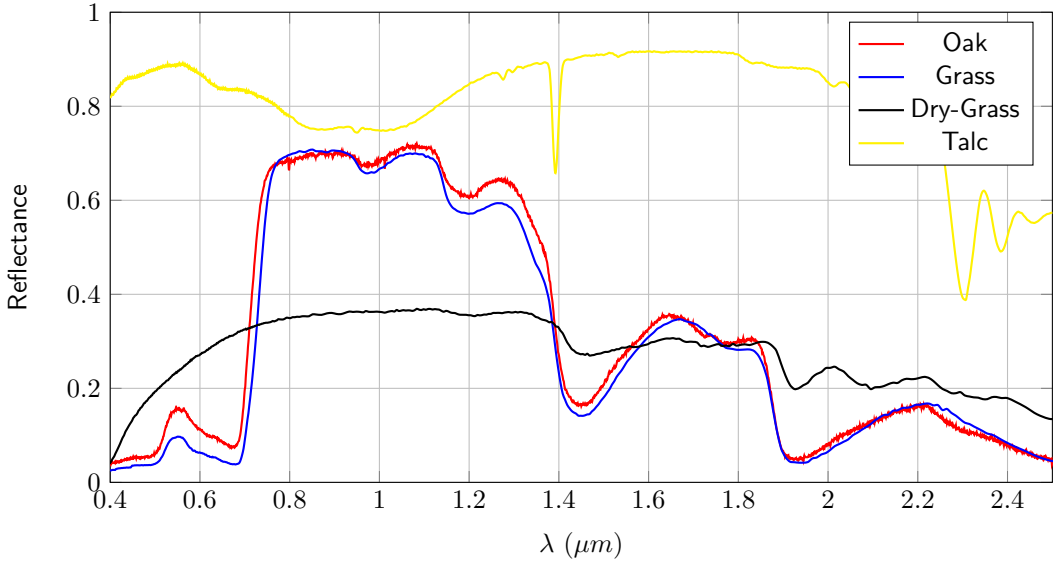
Reflectance:

- ⋆ Capacity of a given surface to reflect the incident light,
- ⋆ It is specific to each material.

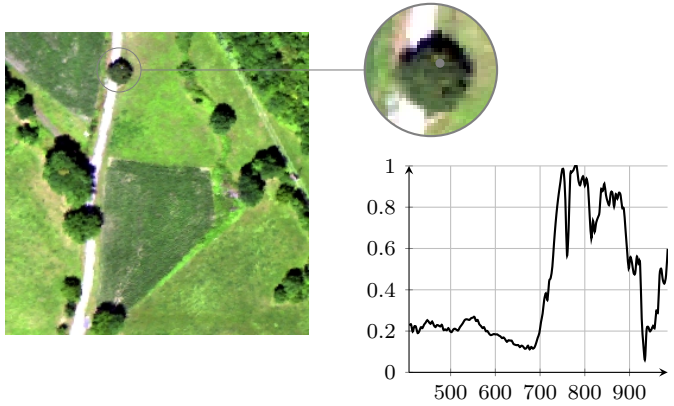




Spectral reflectance curves or spectral signature: Radiometric identity card



A remote sensing image is a sampling of a spatial, spectral and temporel process.



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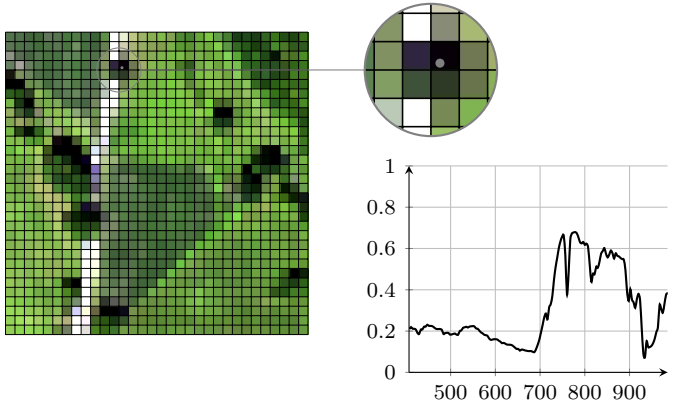

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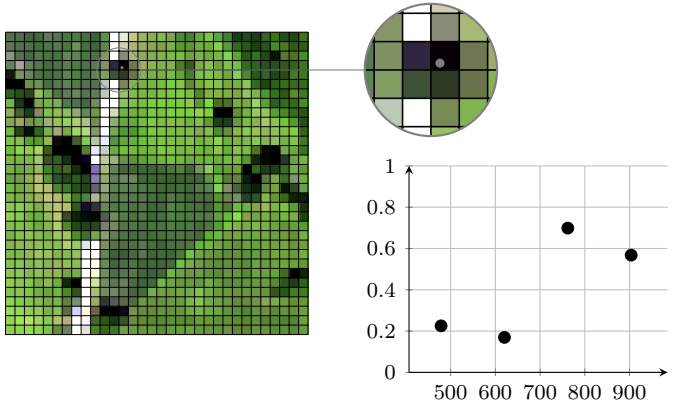

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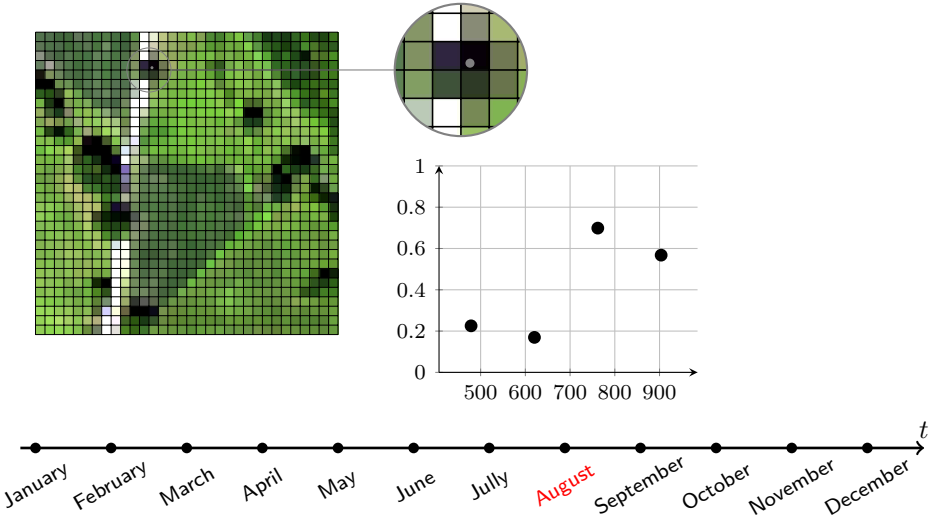


- Spatial resolution: *Ability to distinguish two closed objects.*

2 m/pixel 1m/pixel

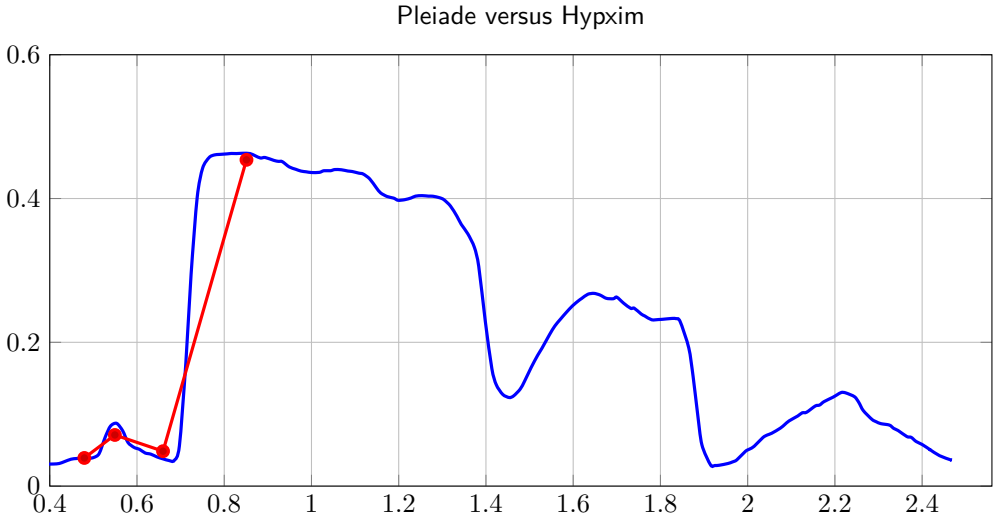
- Radiometric resolution: *Smallest difference in intensity that the sensor can record.*

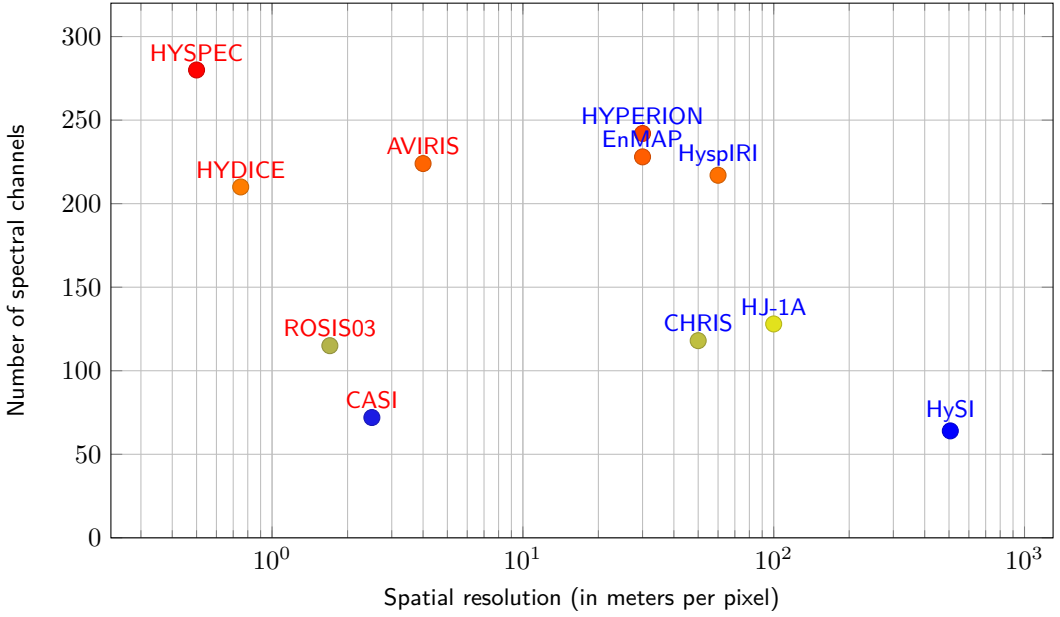
Coding	Quantification	Exemple: 6.666666
8 bits	256	7
16 bits	65536	6.67

- Spectral resolution: *Width of each band of the spectrum that can be collected.*

Image Type	Number of bands
Panchromatic	1
Multispectral	~ 10
Hyperspectral	> 100
Ultraspectral	> 100

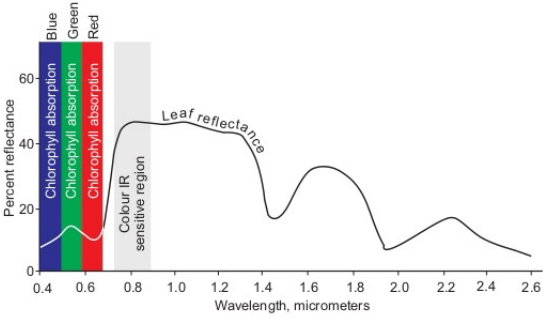
- Spatial and spectral resolution are linked: difficult to have high spatial *and* spectral resolution at the same time.


Pleiade versus Hypxim
0.6
0.4
0.2
0
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2
2.4


HYSPEC
HYDICE
AVIRIS
HYPERION
EnMAP
HyspIRI
ROSIS03
CASI
CHRIS
HJ-1A
HySI
Number of spectral channels
Spatial resolution (in meters per pixel)
300
250
200
150
100
50
0
10^0
10^1
10^2
10^3

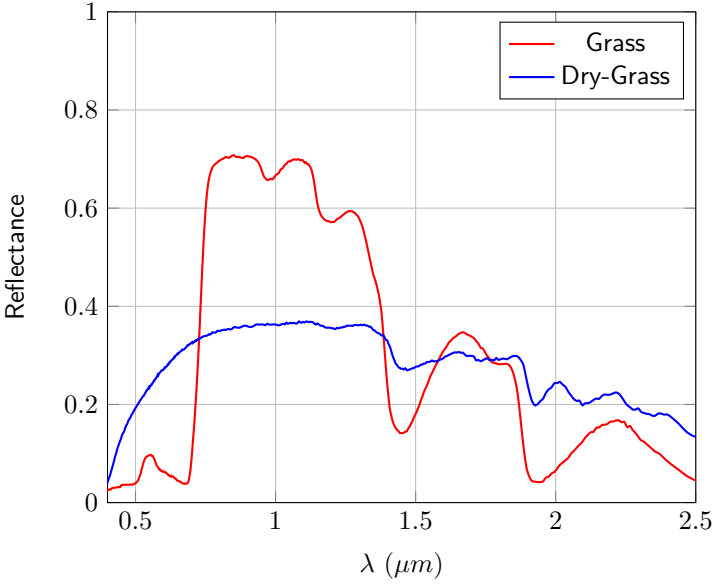
Healthy vegetation (high photosynthesis)

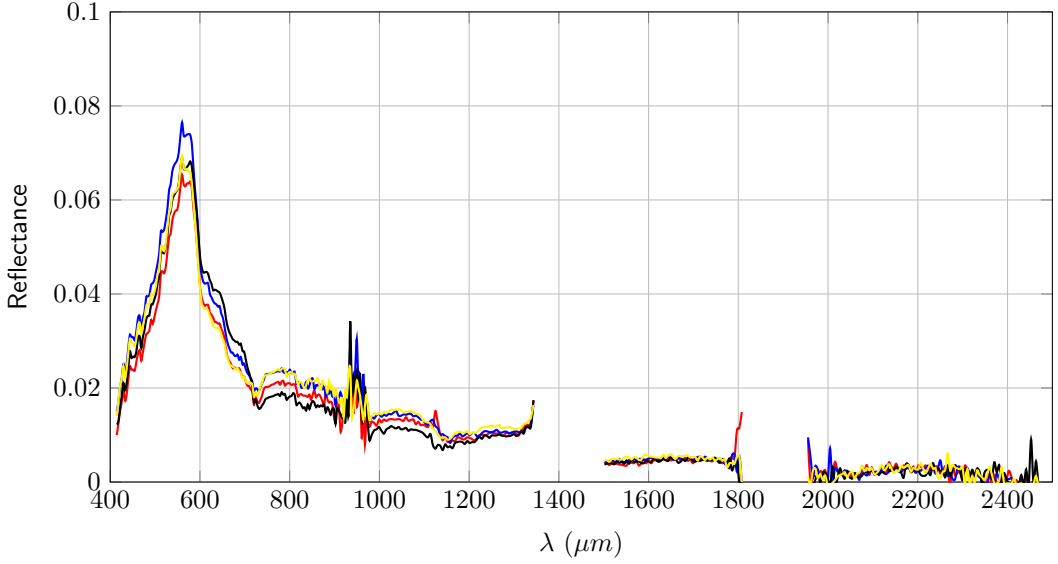
- ⋆ Absorption in *blue* and *red* domain,
- ⋆ *Visible* to *near infrared*: increase of the reflectance,
- ⋆ *Mid infrared*: depends on the free water in the leafs.

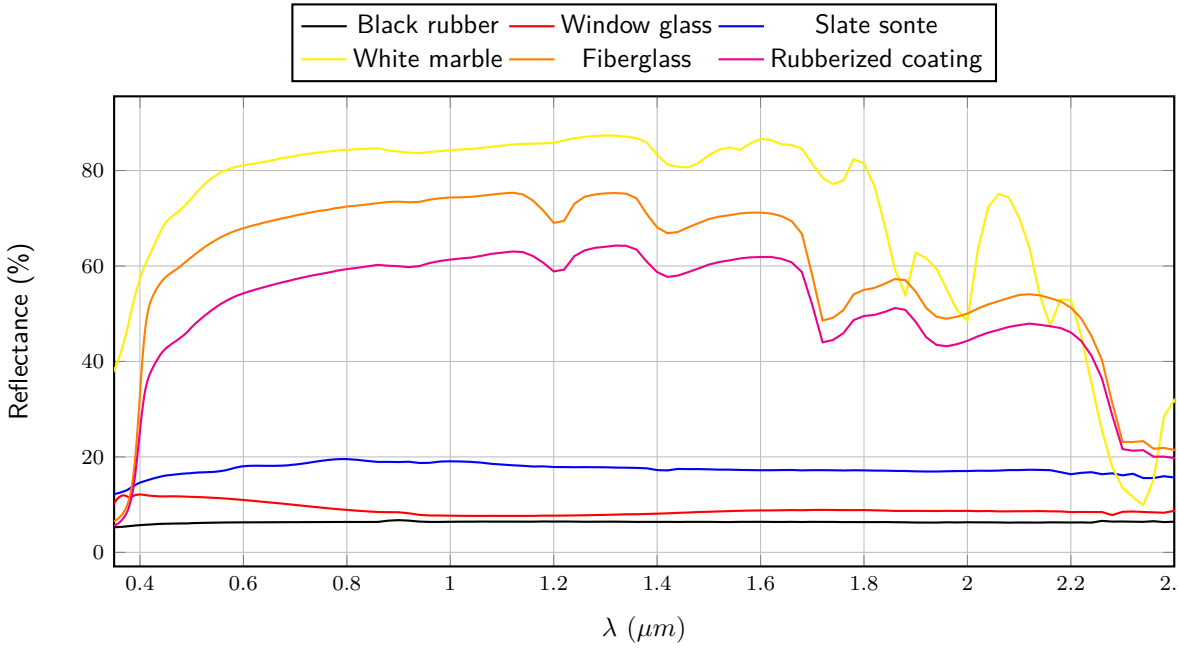


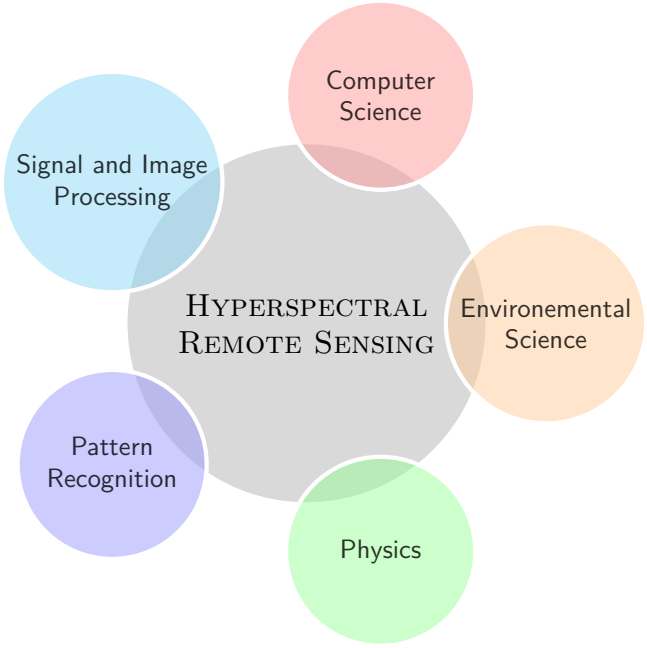
Factor modifying the reflectance

- ⋆ Leaf thickness,
- ⋆ Leaf age,
- ⋆ Water content,
- ⋆ Nitrogen content,
- ⋆ Health condition,
- ⋆ ...



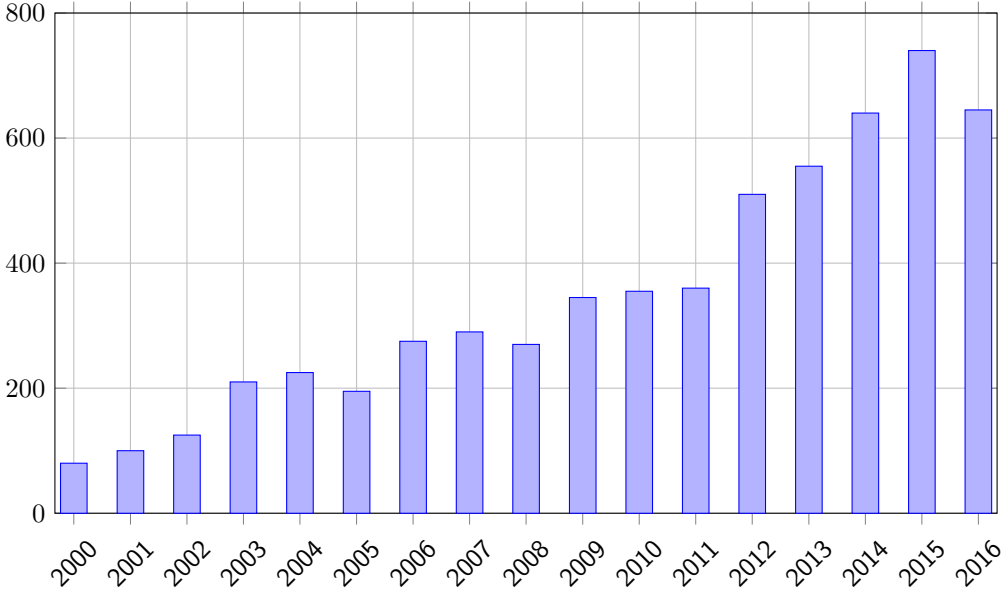

0.1
0.08
0.06
0.04
0.02
0
Reflectance
400
600
800
1000
1200
1400
1600
1800
2000
2200
2400
λ (μm)


Black rubber
Window glass
Slate sonte
White marble
Fiberglass
Rubberized coating
Reflectance (%)
0
20
40
60
80
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
2.2
2.4
λ (μm)

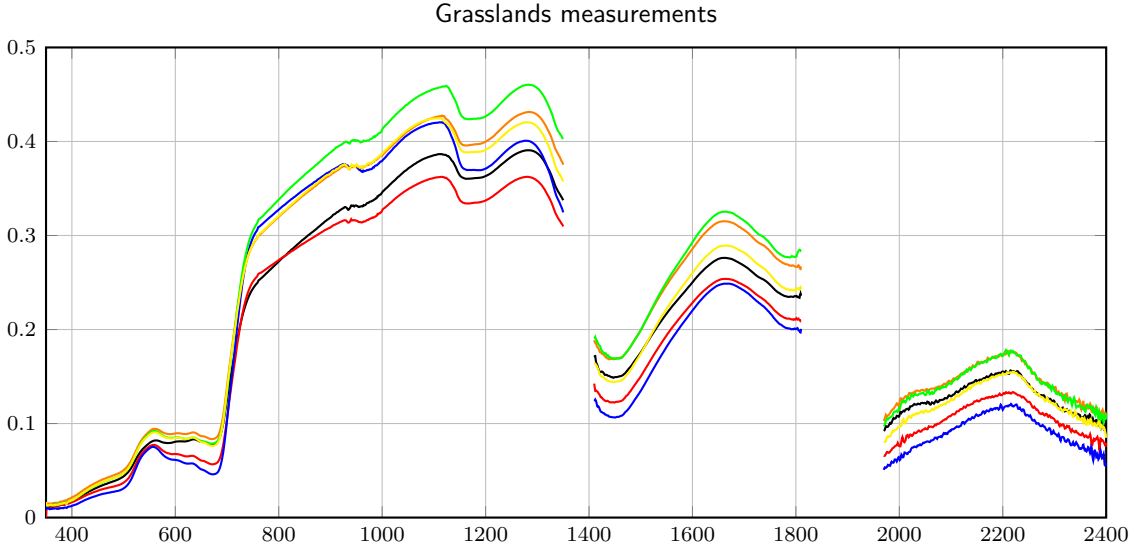

Computer Science
Signal and Image Processing
Hyperspectral Remote Sensing
Environemental Science
Pattern Recognition
Physics

- Transmission:
  - Compression.
- Pre-processing:
  - Geometric and atmospheric corrections,
  - Data fusion,
  - Feature extraction.
- Information extraction:
  - Classification/inversion,
  - Unmixing,
  - Target detection.

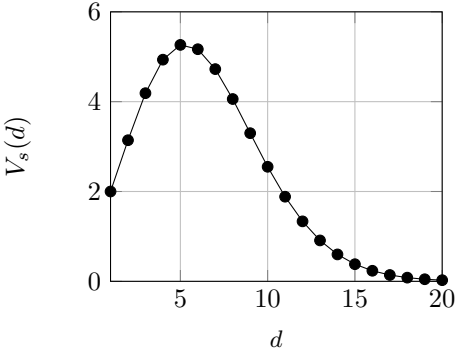
Number of published papers per year about "hyperspectral remote sensing" (*ISI Web of science*)

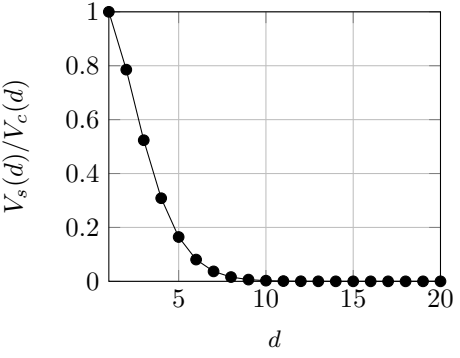


- Pattern recognition:
  - High dimensional data,
  - Spectral variability,
  - Reduce ground-thruth,
- Computer science:
  - Large volume of data
  - Real time constraints
- Thematic application:
  - Environmental issues
  - Military issues
  - Astrophysical issues


Grasslands measurements
0.5
0.4
0.3
0.2
0.1
0
400
600
800
1000
1200
1400
1600
1800
2000
2200
2400

- ⋆ High number of measurements d but limited number n of samples.
- ⋆ High dimensional space do not behave as low/moderate dimensional space [JL98]:
  - ⋆ Volume of an hypersphere: $V_s(d,r) = \frac{\pi^{d/2}}{\Gamma\left(\frac{d}{2}+1\right)} r^d$,
  - ⋆ Volume of an hypercube: $V_c(d,r) = (2r)^d$.

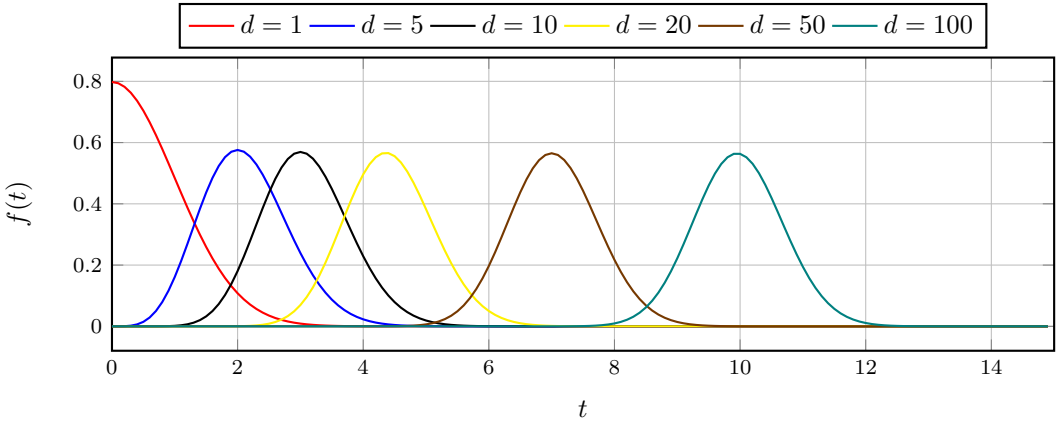




Consider a r.v. $\mathbf{x} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. The likelihood of $t = \|\mathbf{x}\|$ is given by

$$f(t) = \frac{t^{d-1} \exp(-t^2/2)}{2^{(d/2)-1}\Gamma(d/2)}$$

which is maximum for $t^* = \sqrt{d-1}$ [JL98].

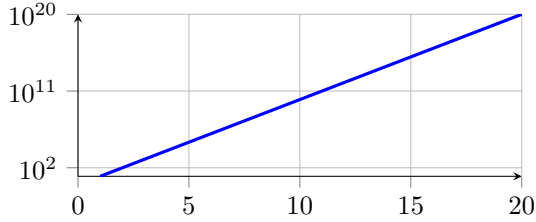


- ⋆ Concentration of measure phenomenon [AHK01]: if $\mathbf{x}$ r.v. with i.i.d variables

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

  for all Minkowski norm: $\|\mathbf{x}\| = \left(\sum_{i=1}^{d} |x_i|^p\right)^{1/p}$.
- ⋆ From [Don00]:
  - ⋆ Rate of convergence of estimators decreases when d increases,
  - ⋆ The number of model parameters increase w.r.t d.

- Curse of dimensionality: Number of points to uniformly sample a unit hypercube (step=0.1)



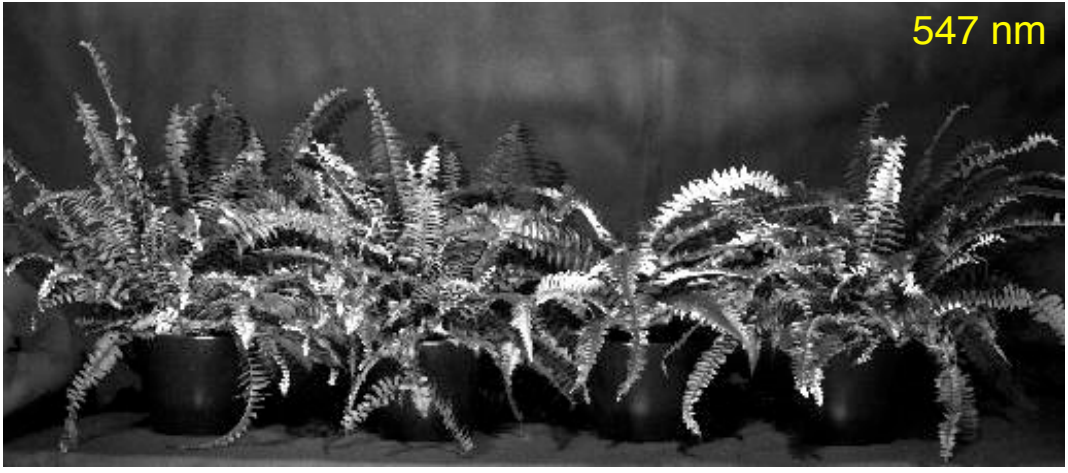
- Method based on *nearest neighbors* fail (with Euclidean distance)
- Hughes phenomenon [Hug68]:

  "With a fixed design pattern sample, recognition accuracy can first increase as the number of measurements made on a pattern increases, but decay with measurement complexity higher than some optimum value."

- Ill-posed problem:
  - Matrix inversion,
  - Determinant,
  - Overfitting ...

>>> Is there a fake ?

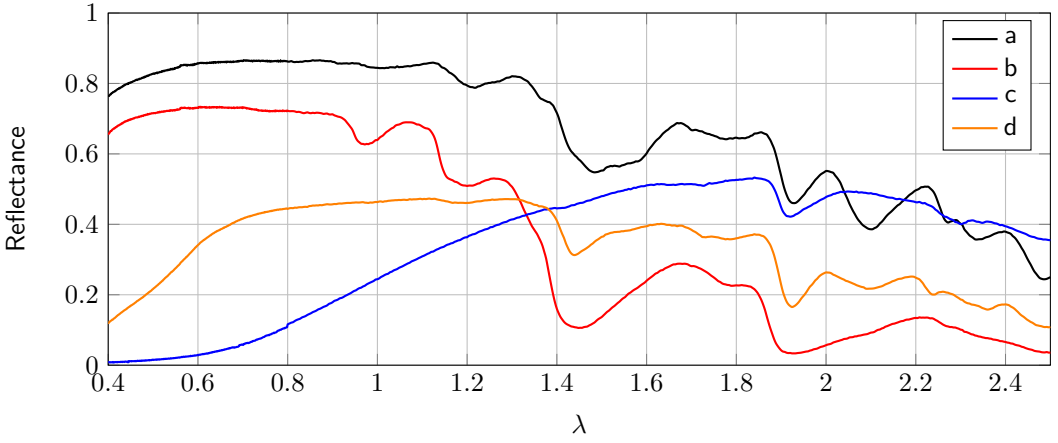

473 nm


547 nm


621 nm


681 nm


770 nm



There are two spectra of the same material (cotton), before and after drying. Which are they ?

What is the number of parameters to estimate for a Gaussian distribution

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- ⋆ The mean: d

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- ⋆ The mean: d
- ⋆ The covariance matrix: $d(d+1)/2$

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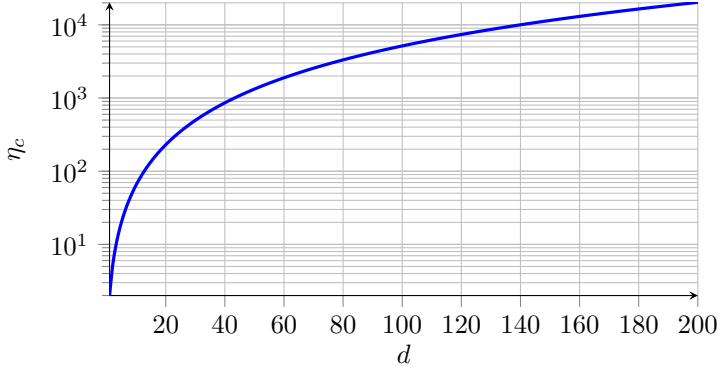
- ⋆ The mean: d
- ⋆ The covariance matrix: $d(d+1)/2$

Total: $d(d+3)/2 \approx d^2/2$



Aggarwal, Charu C., Alexander Hinneburg, and Daniel A. Keim. "On the Surprising Behavior of Distance Metrics in High Dimensional Space". In: *Database Theory — ICDT 2001: 8th International Conference London, UK, January 4–6, 2001 Proceedings*. Ed. by Jan Van den Bussche and Victor Vianu. Berlin, Heidelberg: Springer Berlin Heidelberg, 2001, pp. 420–434.

Donoho, D.L. "High-dimensional data analysis: the curses and blessing of dimensionality". In: *AMS Mathematical challenges of the 21st century*. 2000.

Hughes, G.F. "On the mean accuracy of statistical pattern recognizers". In: *IEEE Trans. Inf. Th.* IT-14 (Jan. 1968), pp. 55–63.

Jimenez, L.O. and D.A. Landgrebe. "Supervised classification in high-dimensional space: geometrical, statistical, and asymptotical properties of multivariate data". In: *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on* 28.1 (Feb. 1998), pp. 39–54.

Keshava, N. and J. F. Mustard. "Spectral unmixing". In: *IEEE Signal Processing Magazine* 19.1 (Jan. 2002), pp. 44–57.

Manolakis, D., R. Lockwood, and T. Cooley. *Hyperspectral Imaging Remote Sensing: Physics, Sensors, and Algorithms*. Cambridge University Press, 2016. ISBN: 9781316033401. URL: https://books.google.fr/books?id=Zeg8DQAAQBAJ.