Hyperspectral data and MaxEnTES algorithm: perspectives for novel application products

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The background

Planck formula: $B_i(\lambda_i, T) = \int_{(\Delta\lambda)_i} \frac{c_1}{\lambda_i^5} \frac{1}{\exp\left(\frac{c_2}{\lambda_i T}\right) - 1} d\lambda_i, \; c_1 = 2hc^2, \; c_2 = \frac{hc}{k}$

Measured radiance in the *i*-th channel: $L_i = \varepsilon_i(\lambda_i) B_i(\lambda_i, T)$

N values $\varepsilon_i(\lambda_i)$ for emissivity
+
Temperature value
→ **ill-posed problem**

Solutions → using *a priori* assumptions:

- Model Emittance Calculation (Kahle *et al*., 1980),
- Grey Body Emissivity (Barducci *et al*., 1996),
- Emissivity Spectrum Normalization (ESN) or Optimum Band Selection (OBS): selection of the maximum brightness temperature band (Warner *et al*., 1990)

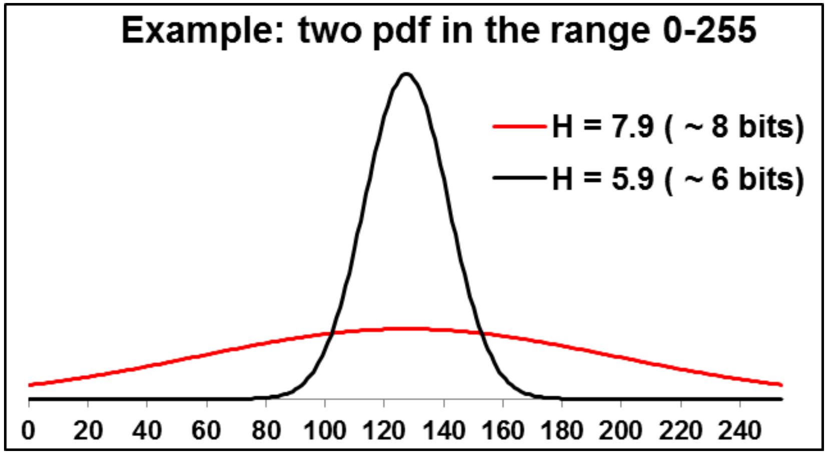
THE METHOD

The MaxEnTES approach

Entropy H as estimate of information

Given a probability distribution function $p(x_i)$, the (information) **entropy** H estimates the number of “bits” for coding p without loosing information:

$$H = -\sum_i p(x_i) \log \, p(x_i)$$



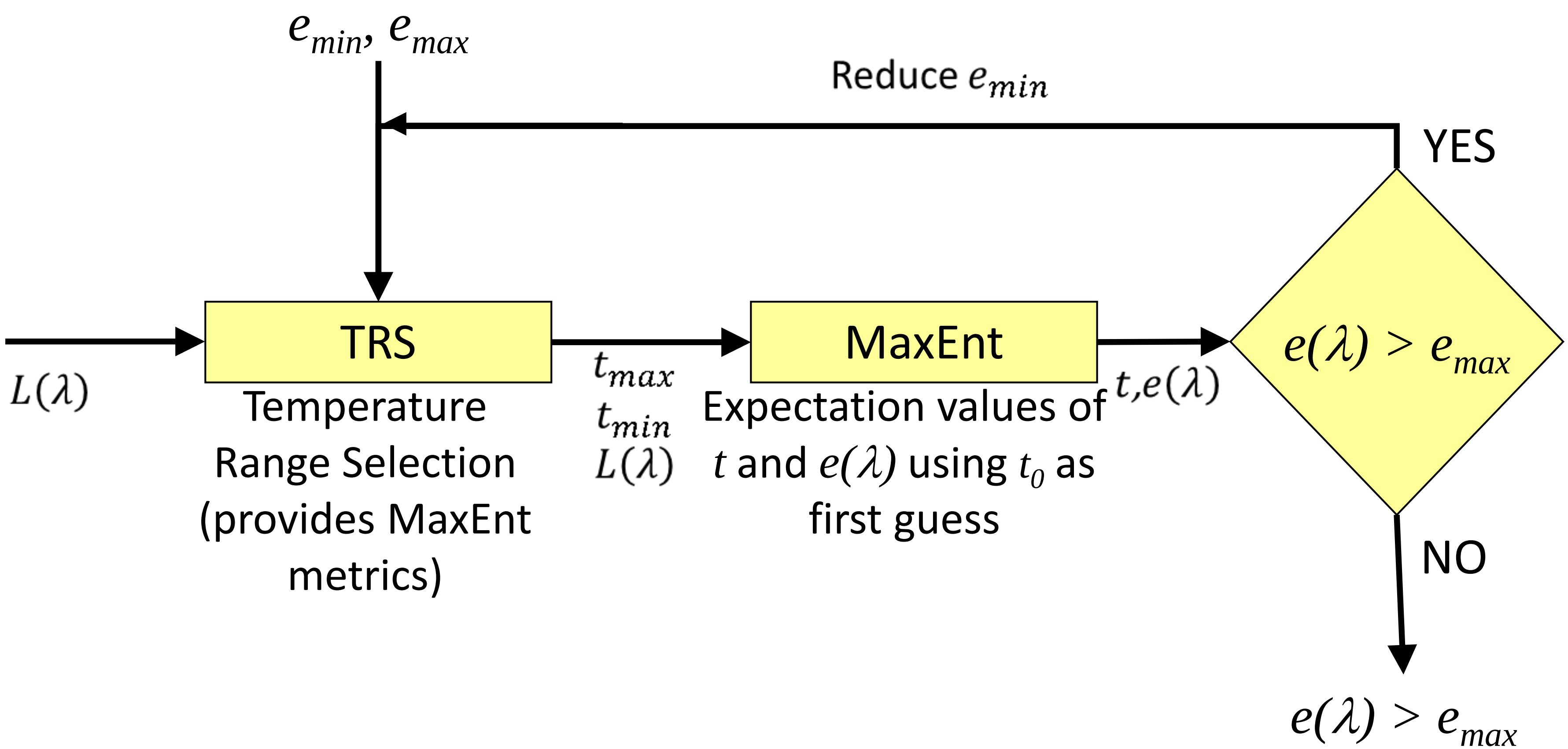
H measures the amount of **information** (i.e. **bits** if $\log_2$ is used)

p_k peaked→ H small (needed *less* bits for coding it)

E. T Jaynes[*] introduces (1957) the MaxEnt principle: **Maximum entropy** “represents the **most honest description of our state of knowledge**”

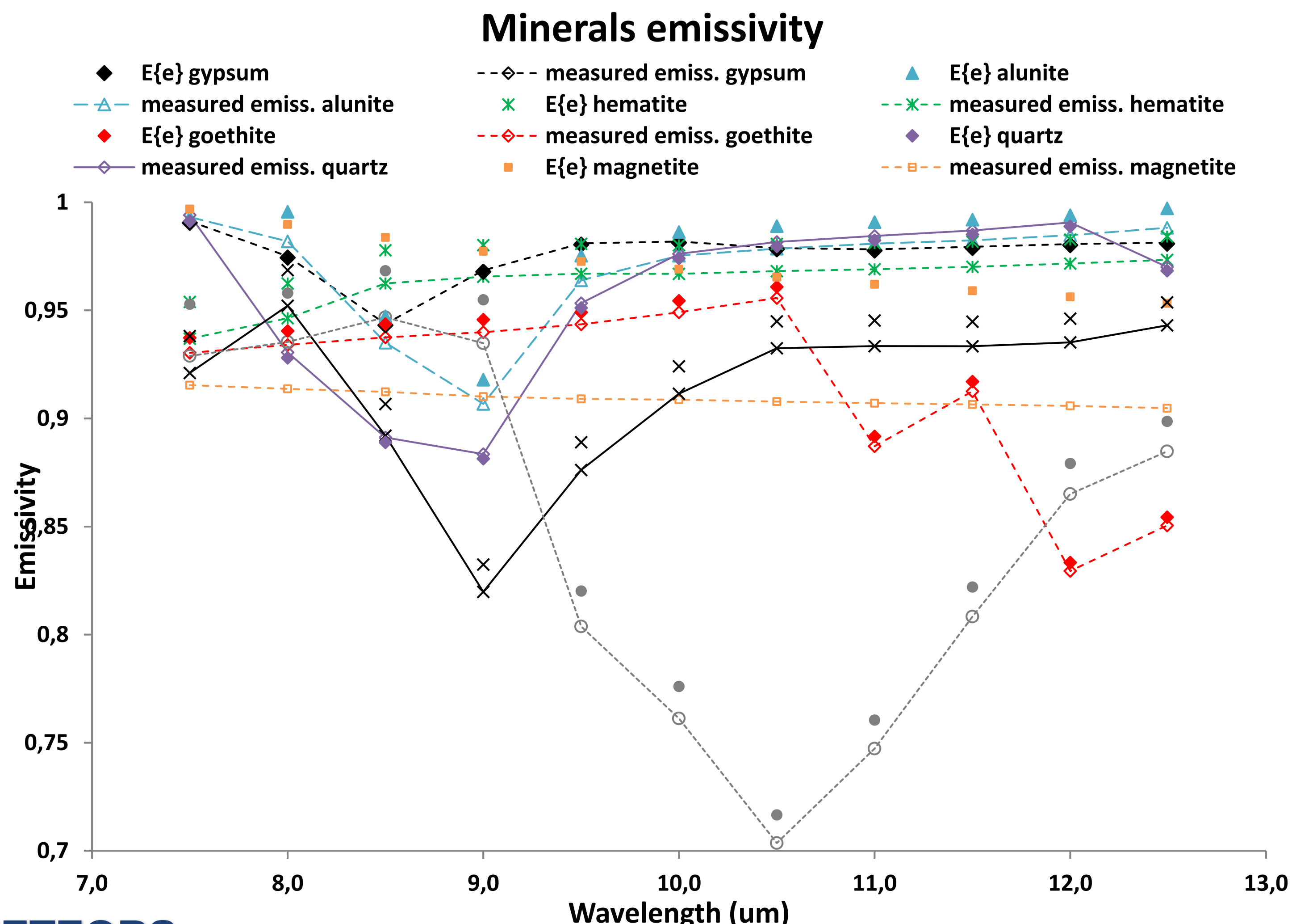
(*) E. T Jaynes, “Information theory and statistical mechanics,” *Phys. Rev.*, vol. 106, no. 4, pp. 620–630, May 1957.

MaxEnTES algorithm scheme



THE PERFORMANCES

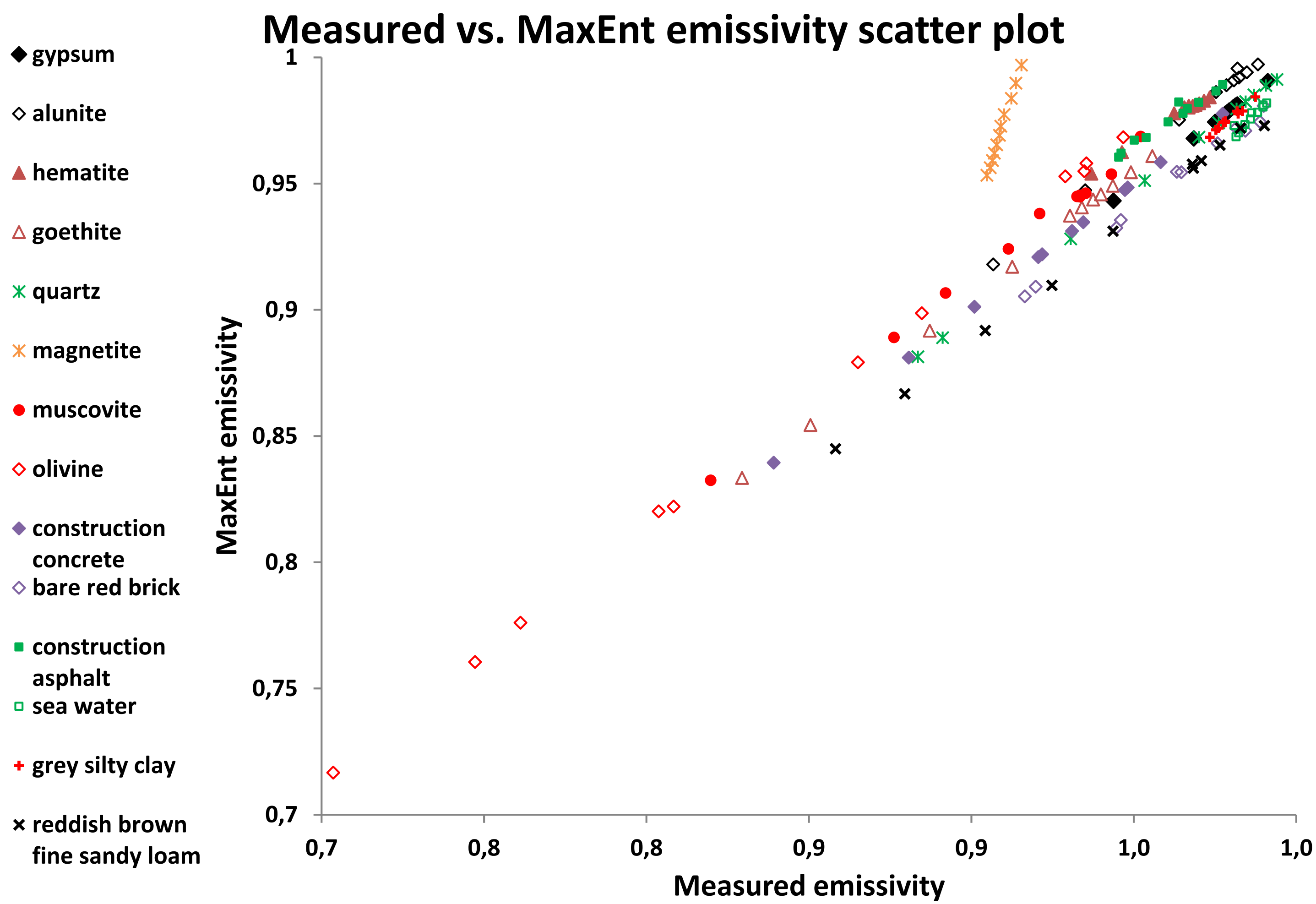
MaxEnTES applied to simulated data: *measured vs. retrieved*



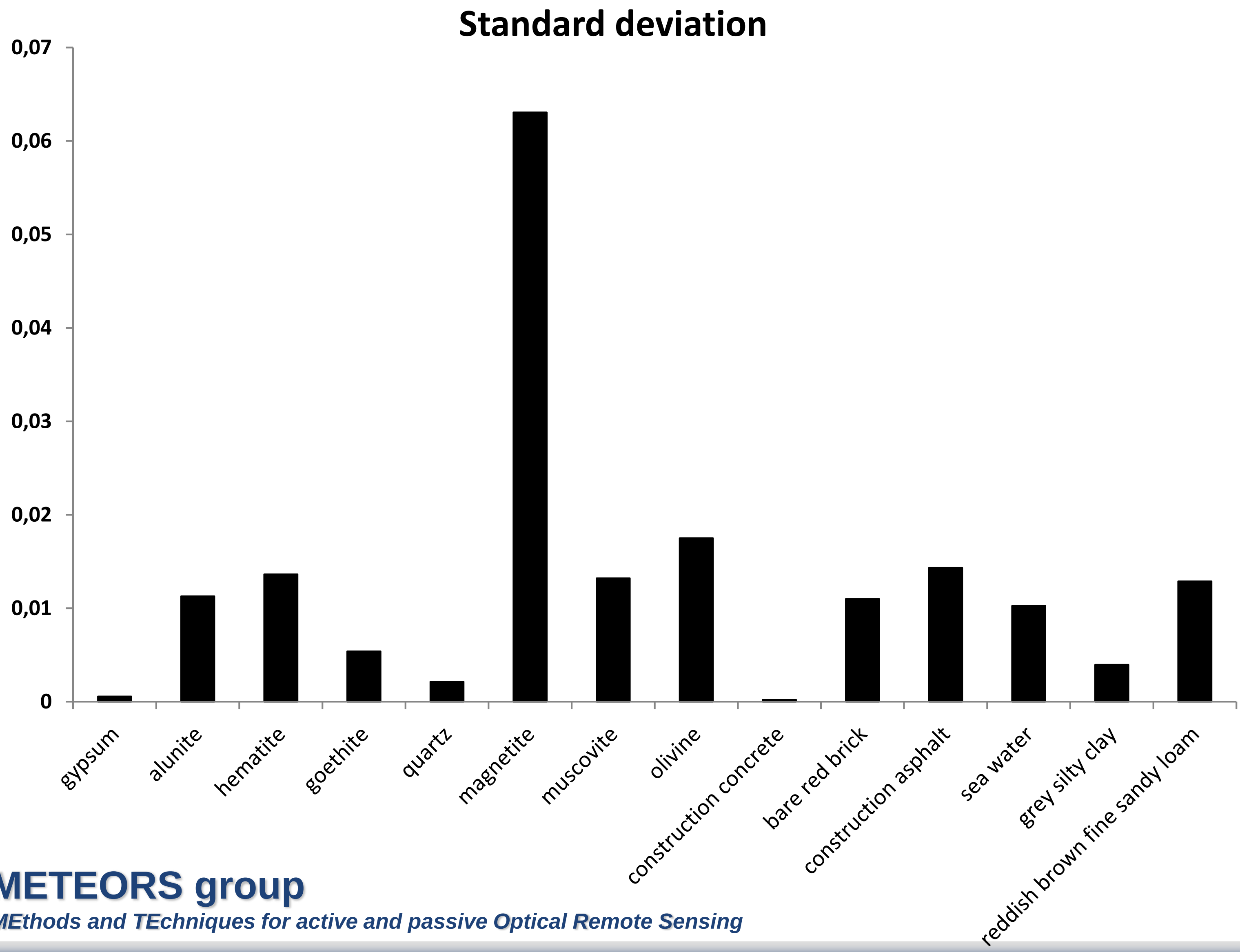
METEORS group

MEthods and TEchniques for active and passive Optical Remote Sensing

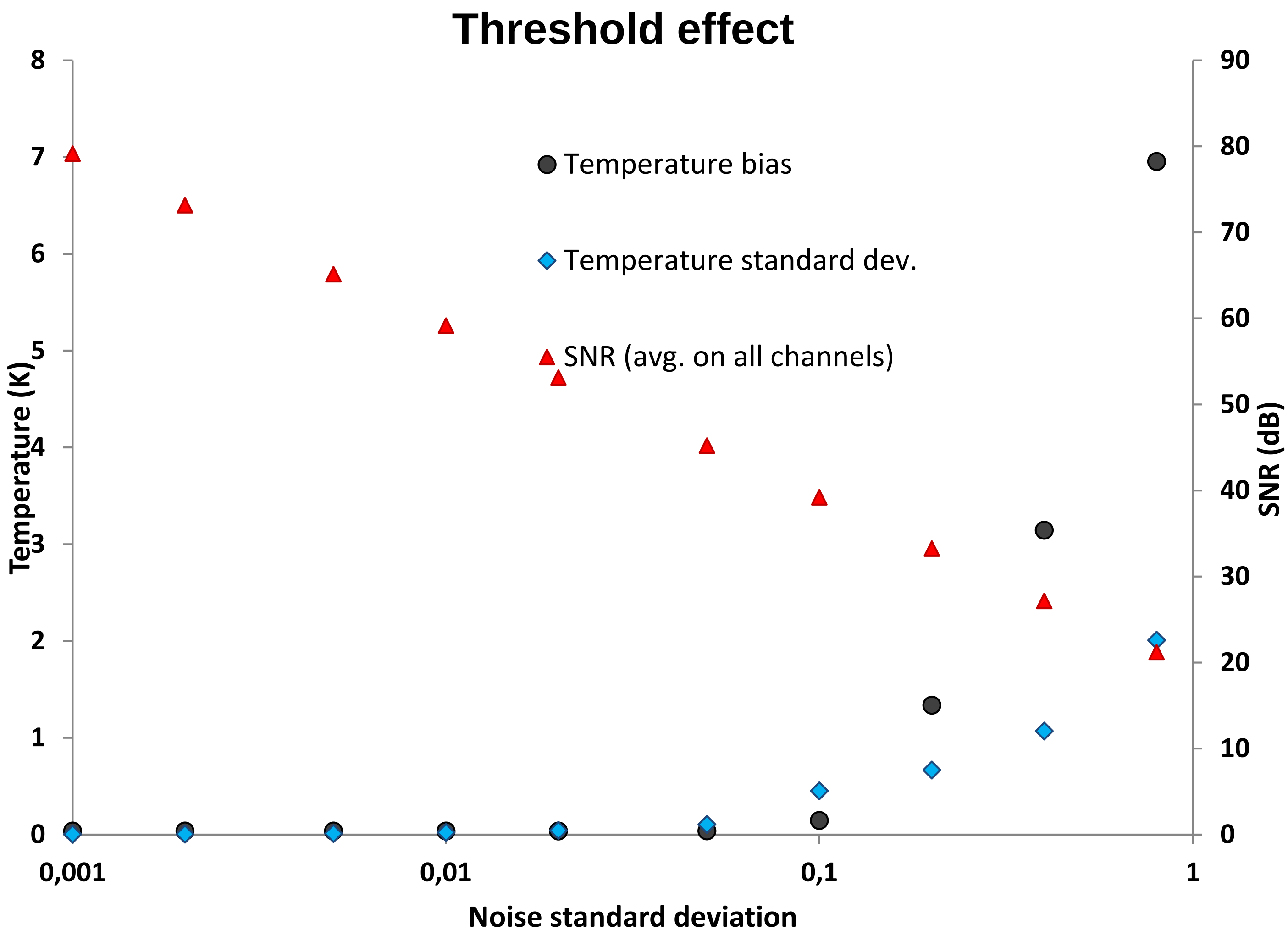
MaxEnTES applied to simulated data: *performances*



MaxEnTES applied to simulated data: *performances*



MaxEnTES applied to simulated data: *performances*



MaxEnTES applied to MIVIS images: *dataset*

MIVIS dataset:

- **location**: Alps mountains (Italy)
- **date and time**: July 1999, 10:55 local time
- **ground height**: between 1 km and 2 km
- **radiometric calibration**: on board black body
- **atmospheric correction**:

$$L(\lambda)=\varepsilon(\lambda)B(T,\lambda)e^{-\tau(\lambda)}+\frac{\rho_0}{\pi}S_\downarrow(\lambda)e^{-\tau(\lambda)}+S_\uparrow(\lambda)\varepsilon(\lambda)$$

MaxEnTES input — groud reflected — to-sensor transmittance — atmospheric emission

with:

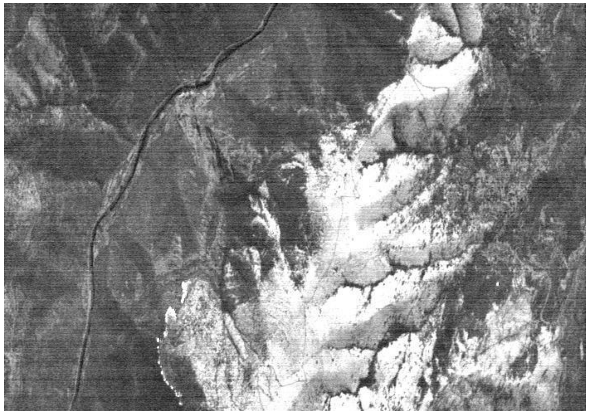
τ: ground to sensor optical thickness

ρ_0: average ground reflectance

$S_\uparrow$, $S_\uparrow$: up-welling, down-welling irradiance

Ground emitted radiance 8.38 µm

Band index	Wavelength (µm)	FWHM (µm)
#93	8.37776	0.153924
#94	8.7507	0.1483
#95	9.17875	0.159724
#96	9.57371	0.155506
#97	10.0028	0.149747
#98	10.4292	0.174995
#99	10.9272	0.176988
#100	11.4201	0.166759
#101	11.9046	0.16783
#102	12.4171	0.18534

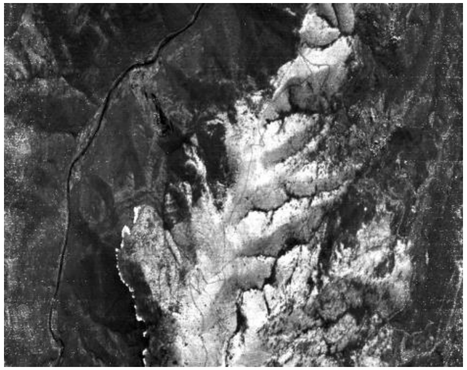


Ground emitted radiance 12.42 µm

MaxEnTES applied to MIVIS images: *comparison with other methods*

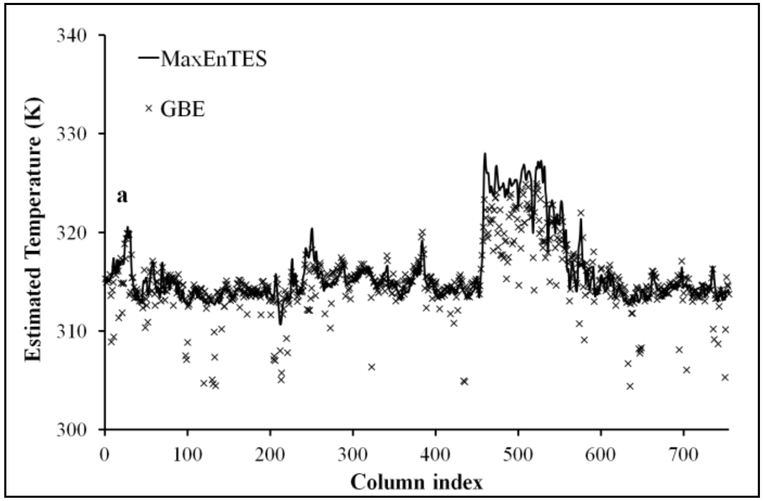
Estimated temperature for the MIVIS dataset

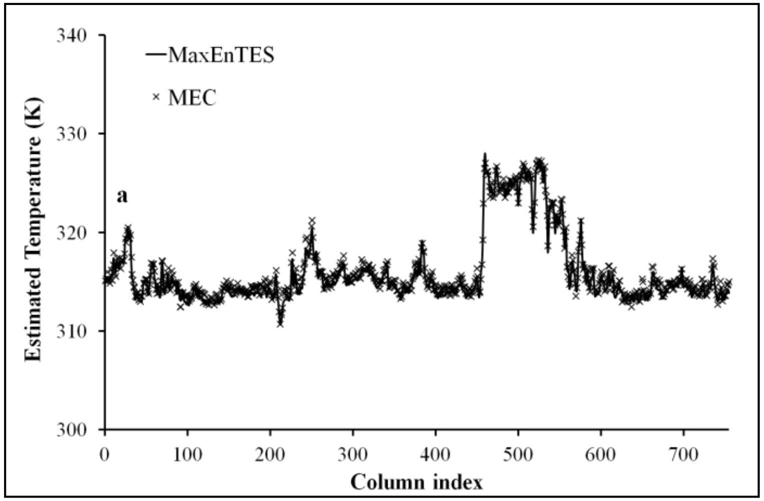
MaxEnTES



GBE

MEC

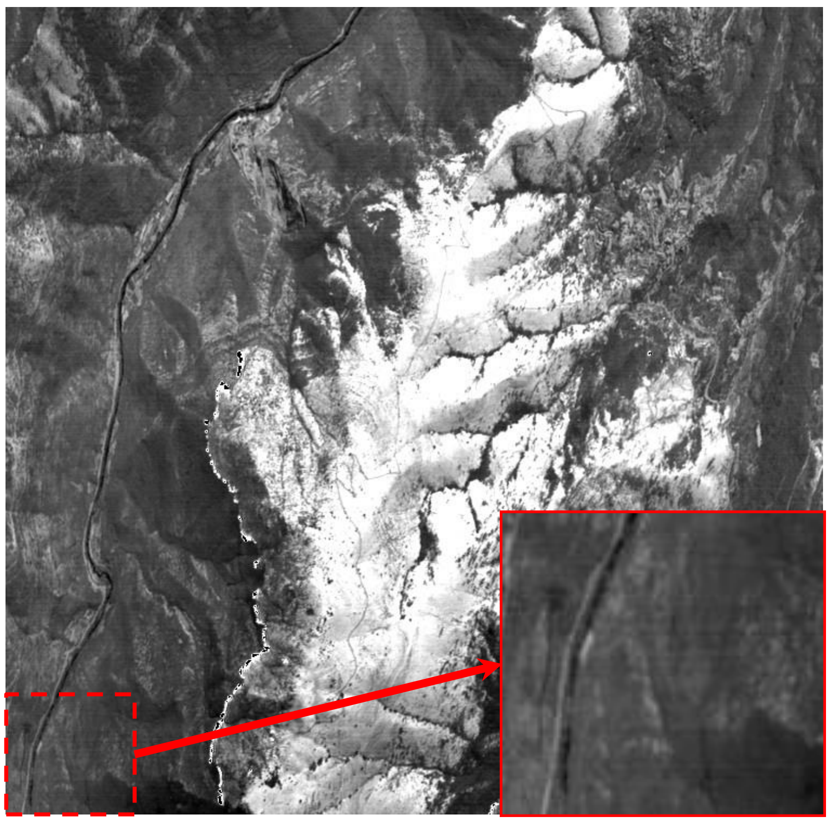


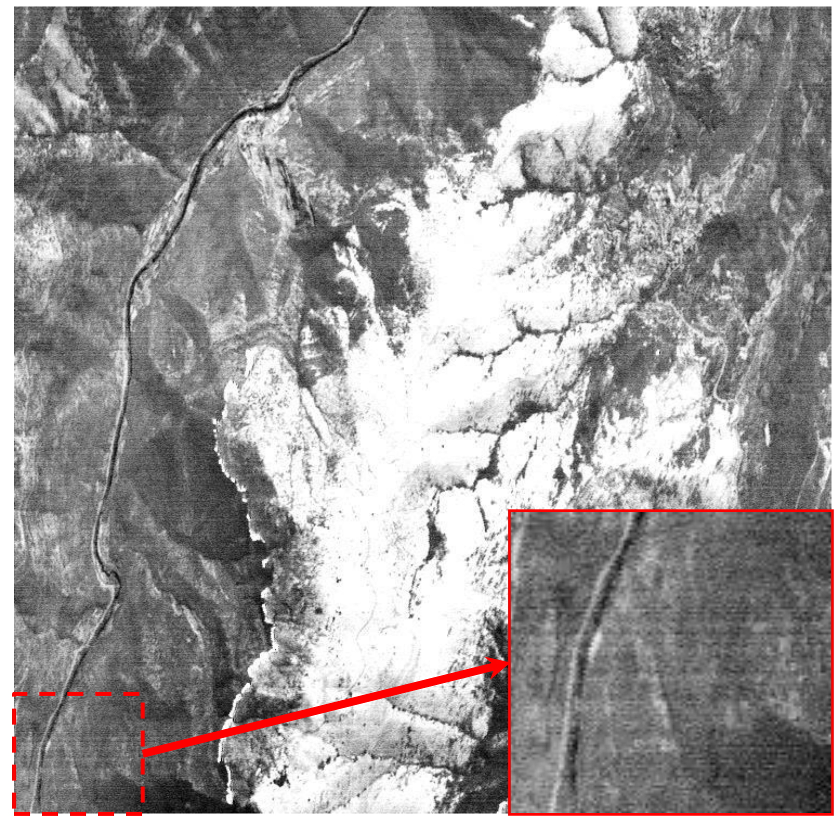


MaxEnTES applied to MIVIS data: *performances*

MaxEnTES / MEC comparison: ground temperature

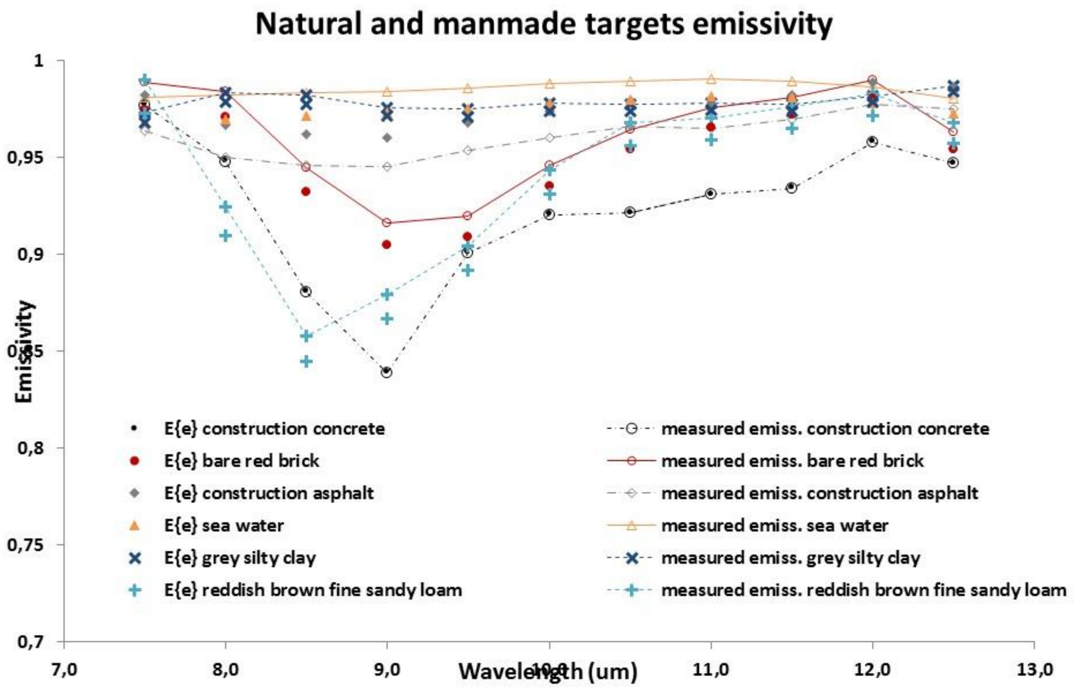
- MaxEnTES image is “softer” (noisy bands contribution is distributed along all data);
- MEC uses the temperature from an arbitrary band (at longer wavelength).


MaxEnTES temperature image


MEC temperature image

THE PERSPECTIVES

MaxEnTES Applications: URBAN ENVIRONMENTS

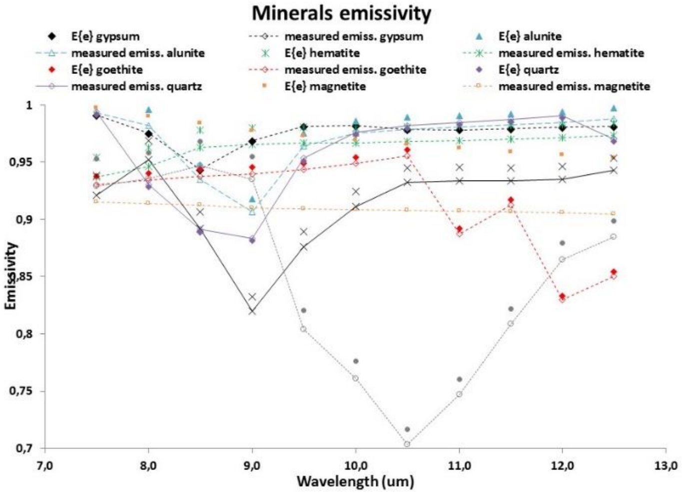


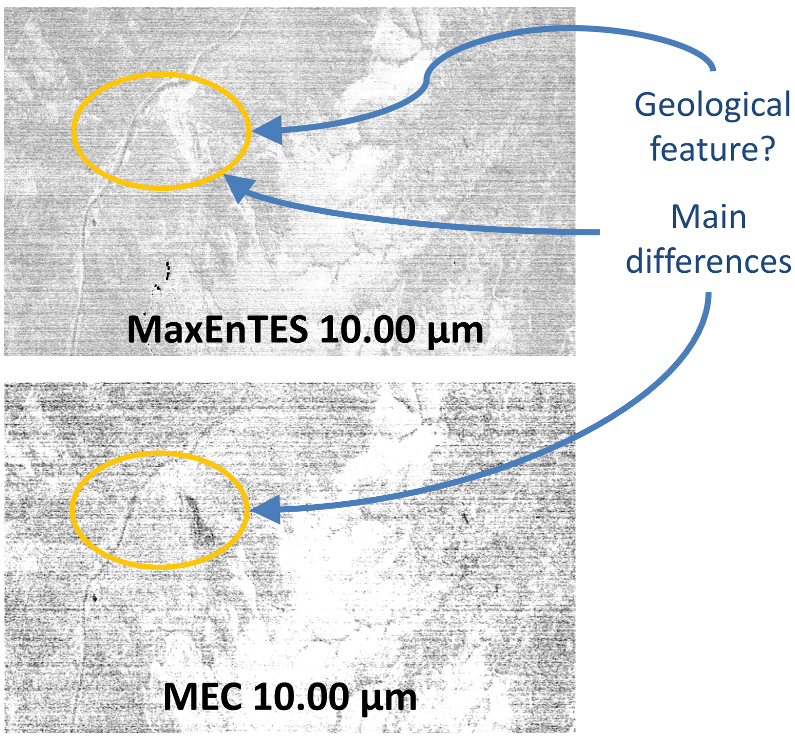
- Fragmented scenario
- Emissivity characterisation on man-made targets
- Reliable temperature mapping

⇨ *High spatial detail needed*

⇨ *Hypersharpening/ data integration with VNIR*

MaxEnTES Applications: GEOLOGICAL FEATURES

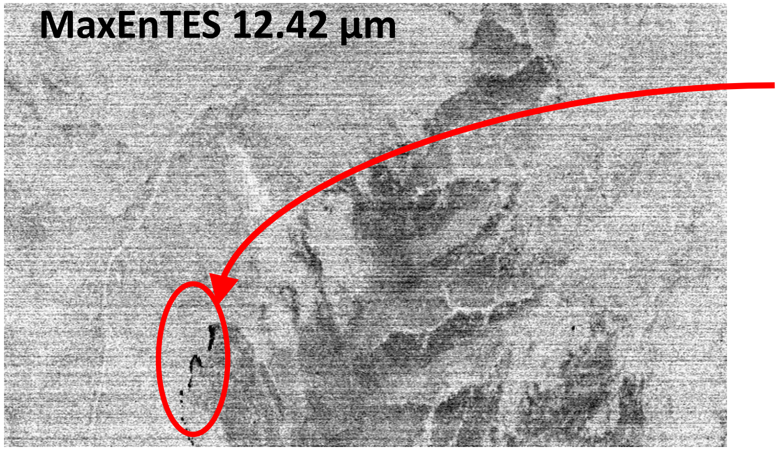




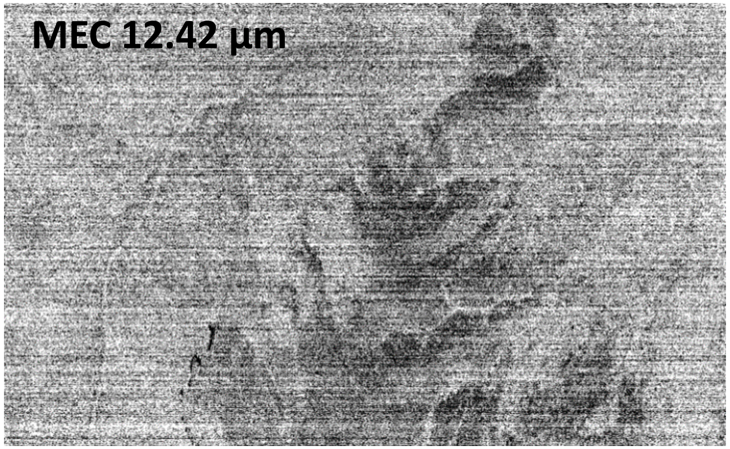
- TES not essential for natural targets, but useful for geological features characterisation based on emissivity spectral analysis

⇨ *High spatial detail not required*

MaxEnTES Applications: FIRES



Fire fronts



- Fires front detection
- Pros in case of saturated pixels
- Synergies with:
  - ⇨ *Hypersharpening*
  - ⇨ *Vegetation damage severity level using hyperspectral VNIR data*

CONCLUSIONS

MaxEnTES final considerations

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- No external hypothesis required for TES
- Results consistent with other methods
- Less noisy images
- Threshold effect vs. SNR
- Less sensitive to saturated pixels

⇨ **Emissivity of geological targets**

⇨ **Fire fronts detection**

⇨ **Emissivity of manmade targets in urban environment**