Earth Observation Laboratory
GeoInformation PhD Programme
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Automatic buildings extraction from hyperspectral data and its application to urban thermography

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Summary

-Introduction: the importance of automatic classification in Earth Observation

-Self Organising Map (SOM): Kohonen's artificial neural networks

-Used Imagery

-Methodology

-Results

-Application to urban thermography

-Conclusions and further studies

Automatic classification techniques it is necessary due to increasing amount of remotely-sensed data. It allows:

- To reduce the human assistance in the data analysis
- To earn time on the entire image processing chain
- To retrieve information in Near Real Time

Google Earth

AHS 25 June 2008

City changes everyday!

The importance of automatic classification in Earth Observation (3/3)

The concept behind this study is to identify buildings automatically (Del Frate et al. 2008) and to calculate their temperature masking out the other land cover classes, i.e., vegetation, asphalt.

The exclusive analysis of the spectral response of each pixel is not exhaustive to highlight them and the use of textural information allows to extract building with an higher accuracy.

Self Organising Map (SOM): Kohonen's artificial neural networks (1/2)

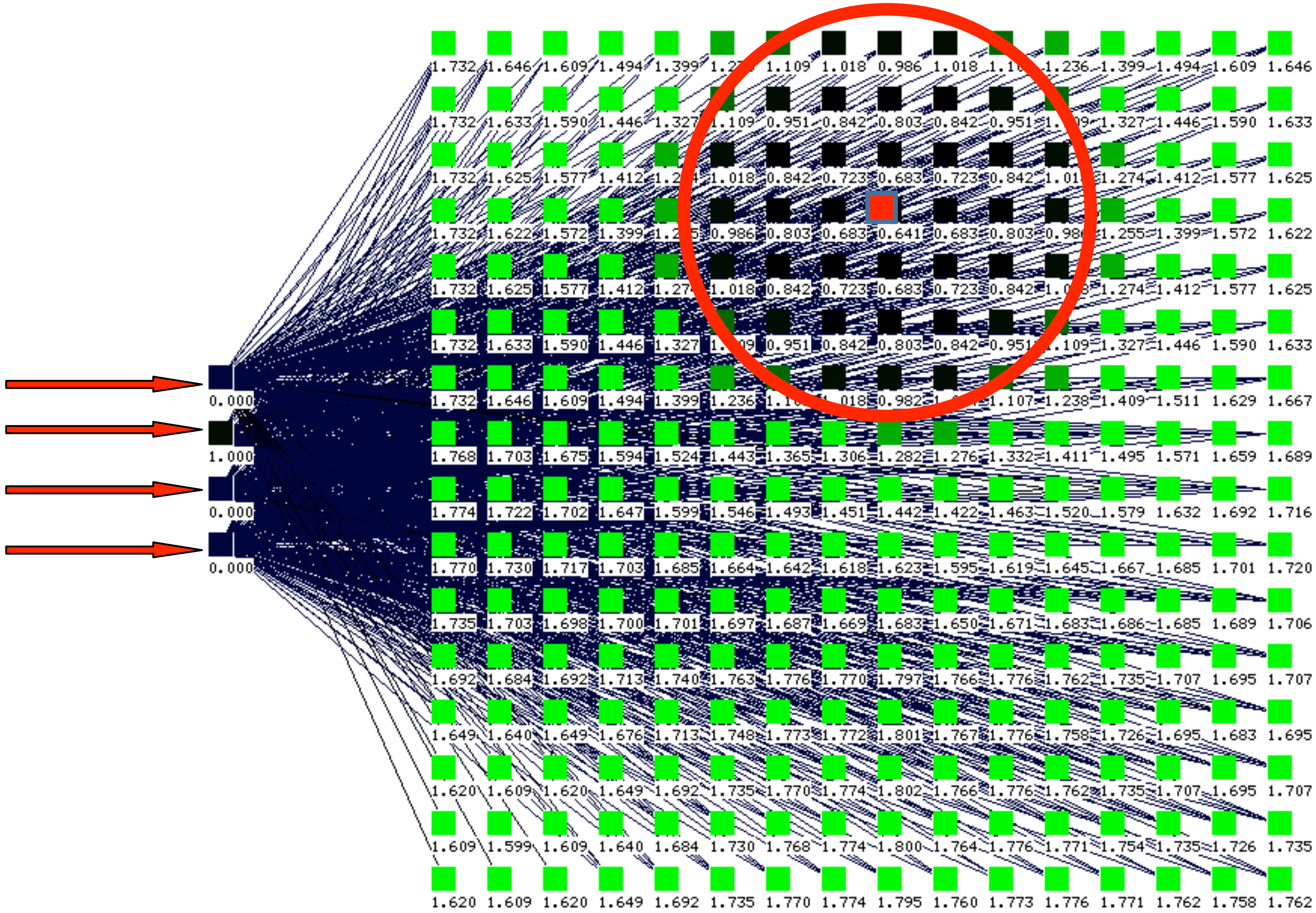
Kohonen's networks (Self Organising Map) can automatically form one- or many-dimensional maps of intrinsic features of the input data.

The data are presented in mixed random order to the self-organizing network: SOM are able of learning complicated hierarchical relations of high-dimensional spaces through many simulations.

In image processing, SOMs are used to identify pixels relationships so as to provide re-organized output cluster/classes (Kohonen, 1995).

The weights will be computed such that topologically close nodes are sensitive to inputs that are physically similar.

Self Organising Map (SOM): Kohonen's artificial neural networks (2/2)



$$w_j(t+1) = w_j(t) + \eta \cdot \lambda_{cj}\left(x(t) - w_j(t)\right)$$

Where w is the neuron weight, λ is the neighborhood function (from 0 to 1) η is the learning rate (it decreases during the learning process) and x is the input

Used Imagery

AHS image acquired for the DESIREX 2008 campaign, which involved taking airborne and ground measurements with infrared sensors.

-flight date 25 June 2008, at 11:11 am
-flight height ≈ 1850 m above sea level

Airborne Hyperspectral Scanner (AHS) is an imaging line-scanner radiometer, installed on a CASA-212 200 series aircraft owned by Spain's National Institute for Aerospace Technology (INTA).
The AHS has 80 spectral channels available in the visible, shortwave infrared and thermal infrared with a resolution of ≈ 3 meters (case study).

http://www.uv.es/desirex/
http://www.esa.int/esaEO/SEMW3IWIPIF_index_0.html

Methodology

AHS Raw files

Georeferenced with IGM and radiance converted with calibration coefficients

AHS at-sensor radiance image

Band selection

AHS RGB + NIR bands

GLCM
<u>Grey Level Co-occurrence *Matrix*</u>

AHS
- RGB + NIR
- Homogeneity 3 x 3 (band 2)
-Homogeneity 5 x 5

Linearisation

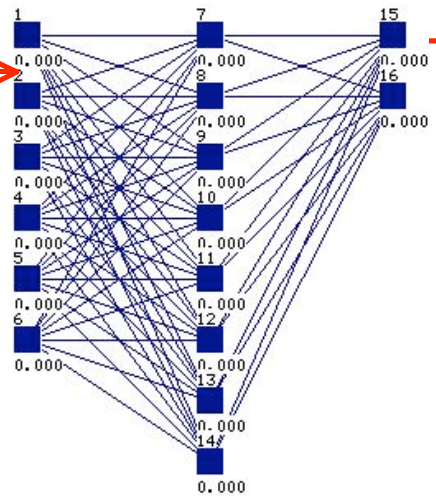
AHS Input dataset for SOM

Kohonen MAP 5 x 5

Recognition of 2 types of building clusters with min distance

Clustered image
- Buildings 1
- Buildings 2
- no buildings

Selection of 20000 pixels for training sites
1)Building
2)No Building



Classification with the trained neural network

Final classified Image with
- Buildings
- No Buildings

Standard signature 1/2

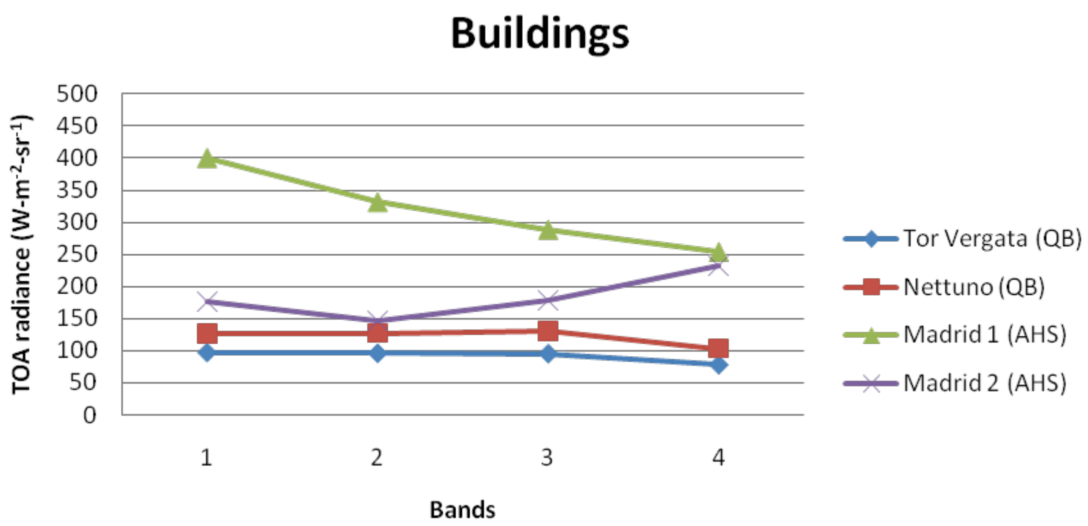
Spectral signature is not enough!

Different spectral signatures for the same class in different images could mean:
- different view angle (and sun angle);
- different atmospheric effects;
- different intrinsic composition of the class surface, especially in high resolution image.

Use of textural features for:

1) Calculation of the mean value of building clusters (for labelling)
RGB + NIR + Homogeneity 3 x 3 b2 + Homogeneity 5 x 5 b2 (Linearised)
2) Pixel classification

Standard signature 2/2



The homogeneity value for building class is **0.8** for window 3 x 3 and it decreases to **0.7-0.6** for window 5 x 5 (its value does not depends on the overall amount of radiance but only from the spatial relationship between pixels)

May the selected signatures (RGB + NIR + Homogenity 3 x 3 and Homogeneity 5 x 5) of different AHS images, taken at the same latitude (i.e. Madrid and Athens), at a similar height (around 2000 meters) in the same period of the year (Summer, for thermography), be similar?

Results (1/2)

Overall accuracy = **83.7%**
(without texture, the accuracy decreases to 78 %)

Ground Truth (Percent)			
Class	Buildings	No buildings	Total
Buildings	86.96	19.48	53.22
No buildings	13.04	80.52	46.78
	100.00	100.00	100.00

Results (2/2)

There are some misclassification error with roads and bare soil

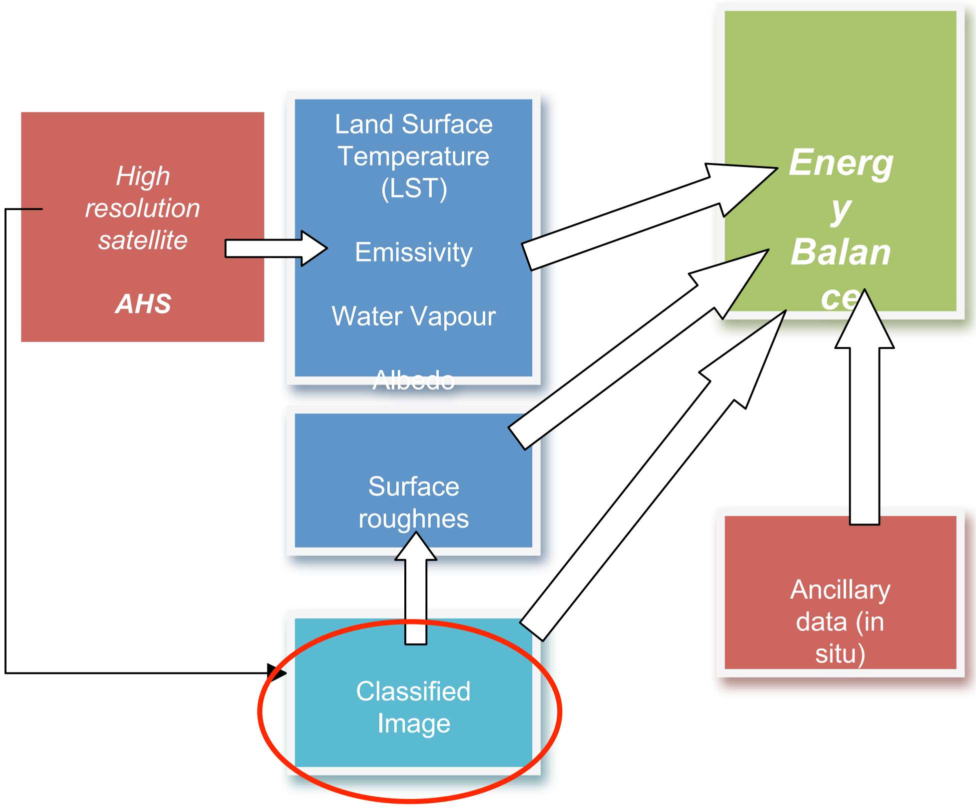
Application to urban thermography (1/3)

Image automatic classification can represent an important issue in LST retrieval and Energy Balance Model. It contributes to:

- assign the parameters of the Energy balance model for the specific reference surface <u>(i.e., building heat transfer model parameters have to be applied on building cover class)</u>

- add information to extreme difference of temperature considering the surface where such differences are measured

- extract a roughness map

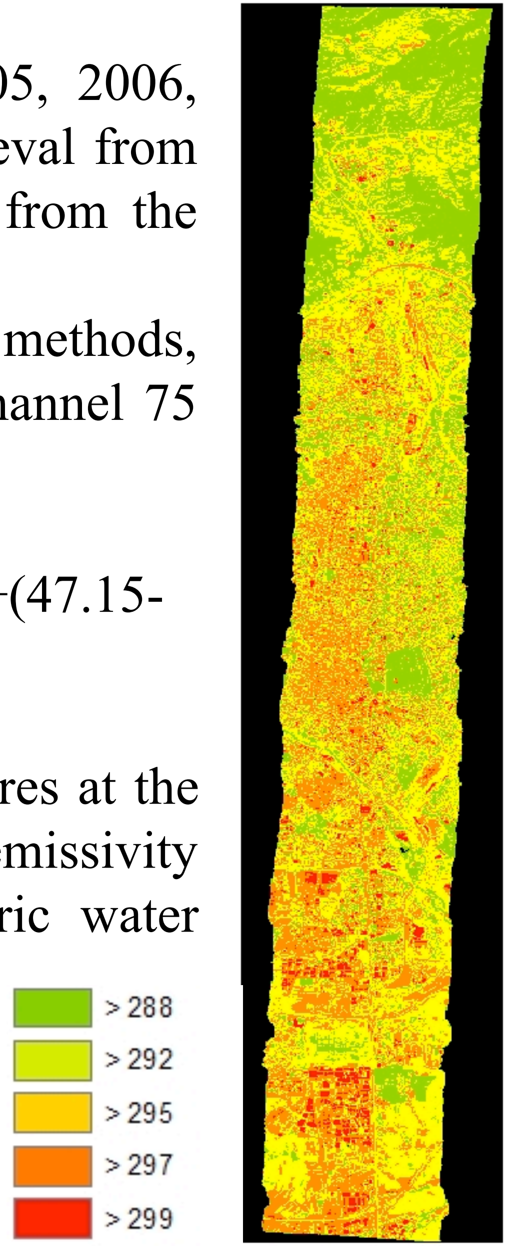


Application to urban thermography (2/3)

From the studies of Sobrino and Jiménez-Muñoz (2005, 2006, 2008), on temperature, emissivity and water vapour retrieval from hyperspectral data, a method to calculate LST directly from the data has been re-adapted and implemented.
This algorithm is based on two-channel or split-window methods, which use a combination between two thermal bands: channel 75 and channel 79.

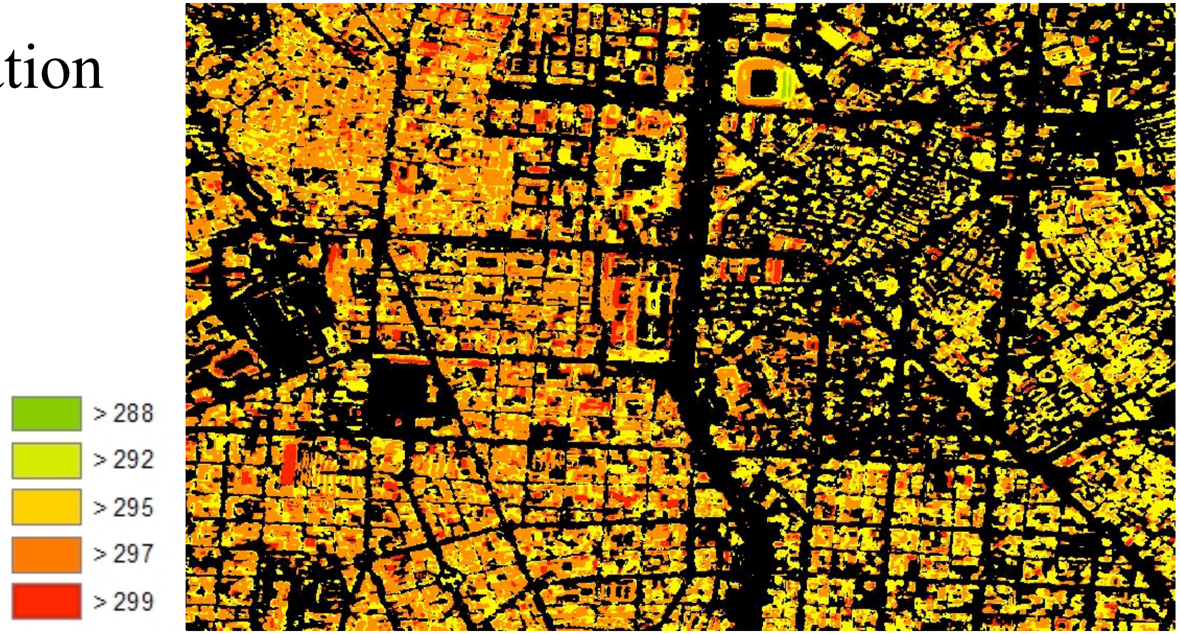
$$LST = T_{75} + 0.485(T_{75-} T_{79}) + 0.0068(T_{75-} T_{79})^2 + 0.0798 + (47.15-10.80W)(1-\varepsilon) + (-49.05+21.53W)\,\Delta\varepsilon$$

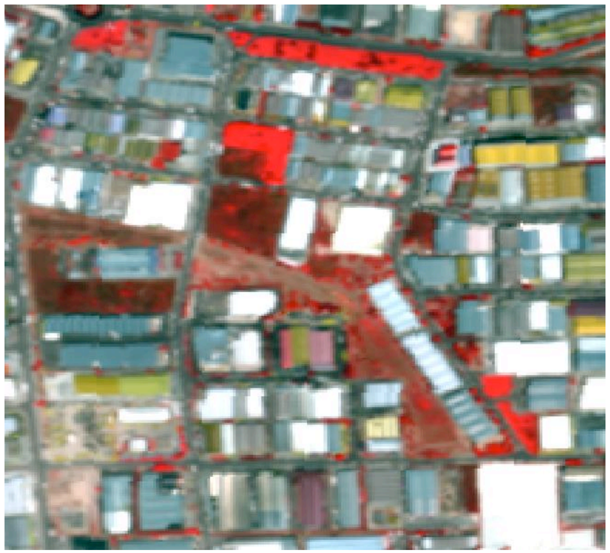
where T_{75} and T_{79} are the at-sensor brightness temperatures at the SW bands (in Kelvin), ε is the mean emissivity, $\Delta\varepsilon$ is the emissivity difference, $\Delta\varepsilon = \varepsilon_{75}+\varepsilon_{79}$ and W is the total atmospheric water vapour content (in g cm^{-2}).



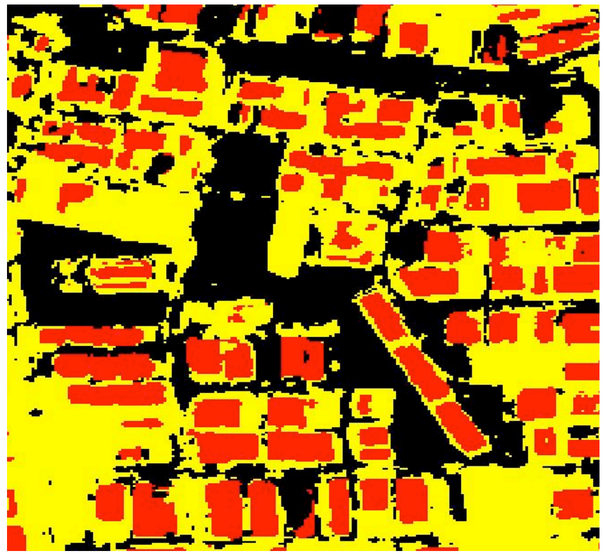
Application to urban thermography (3/3)

Building mask application





Industrial area where buildings have a temperature higher than 300 K



Conclusions and further studies

Goals

The developed method classifies buildings automatically with an accuracy of 83.7 % through Kohonen Self Organising Map

It extracted building signatures (spectral + textural) from a AHS image

The entire process allows to retreive Building Surface Temperature with high resolution from a single image (without other information, like radiosonde or land use map)

Next steps

Application to other images (i.e. Athens, from Thermopolis campaign)
http://www.esa.int/esaCP/SEMVNMH7KYF_index_0.html

Object analysis, starting from building and road recognition

Improving accuracy (analyzing building shadow contribution, filtering the spread pixels)

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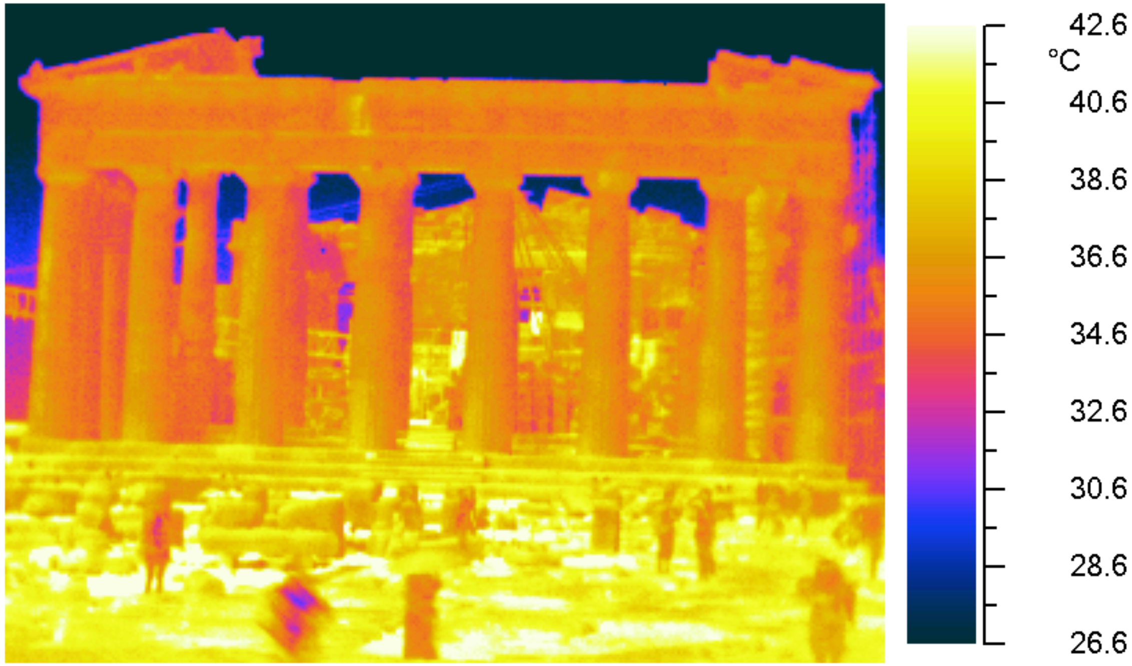
Thank you for your attention!



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