H2020-TWINN-2015. Grant Agreement no 691936	
Project full title:	Remote Sensing Science Center for Cultural Heritage
Project acronym:	ATHENA
Work Package	WP4
Deliverable	D4.8 Material virtual training

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Call:	Work programme **H2020** under **“Spreading Excellence and Widening Participation”, call: H2020-TWINN-2015: Twinning** (Coordination and Support Action).	
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Work Package (WP):	**WP4**	
Deliverable (D):	**D4.8 Material virtual training**	
Due date of deliverable:	**November 2018**	**Version: 1**
Author(s):	**Diofantos G. Hadjimitsis, Argyro Nisantzi, Kyriakos Themistocleous, Christodoulos Mettas, Evagoras Evagorou, Athos Agapiou, Vasiliki Lysandrou, Christiana Papoutsa, Andreas Christofe, Marios Tzouvaras**	
Contributor(s):	**Rosa Lasaponara, Nicola Masini, Thomas Krauss, Gunter Schreier**	
Start date of project:	**1/12/2015**	Duration: **36 months**

Document Sign-off				
Nature	**Name**	**Role**	**Partner**	**Date**
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REVIEWED	Rosa Lasaponara, Nicola Masini, Thomas Krauss, Gunter Schreier	Advance partners	CNR & DLR	19/11/2018
APPROVED	Diofantos G. Hadjimitsis	Project Coordinator	CUT	29/11/2018

Dissemination Level		
PU	Public	√
CO	Confidential, only for members of the consortium (including the Agency Services)	☐

Work Package: 4 – Training and knowledge transfer Deliverable: D4.8 - Material virtual training				
Sections to be protected	Description	Owner	Access Rights	
			Period	Type*
none				

Table of Contents

1. Summary

Work package 4 focused on the training and knowledge transfer between the existing personnel of the Remote Sensing Lab of the Cyprus University of Technology and experts from the high performing partners' institutions. The current deliverable consists precisely of the specific training/knowledge transfer activity of the virtual trainings that have took place throughout the project.

The deliverable provides a brief description for each virtual training, all relative information as per topic, participants, date etc. Also, the material produced by each trainer, is also hereunder displayed.

The topics of virtual trainings focused on the analysis of hyperspectral images, the use of remote sensing for looting monitoring and the multi-temporal remote sensing analyses. In addition, the fourth virtual training was focused on the Integration of RS data for Cultural Heritage management in the Copernicus Era.

2. Material from the Virtual Trainings

2.1 VIRTUAL TRAINING 1: "HYPERSPECTRAL PROCESSING"

2.1.1 Description

The first virtual training carried out by Dr. Daniele Cerra from DLR and was performed on the 16th of February 2016, using the skype platform. The training was entitled "Hyperspectral processing", with a special focus on the analysis of hyperspectral images. Two presentations were provided for this virtual training, addressing basic concepts and band collection for the analysis of hyperspectral images.

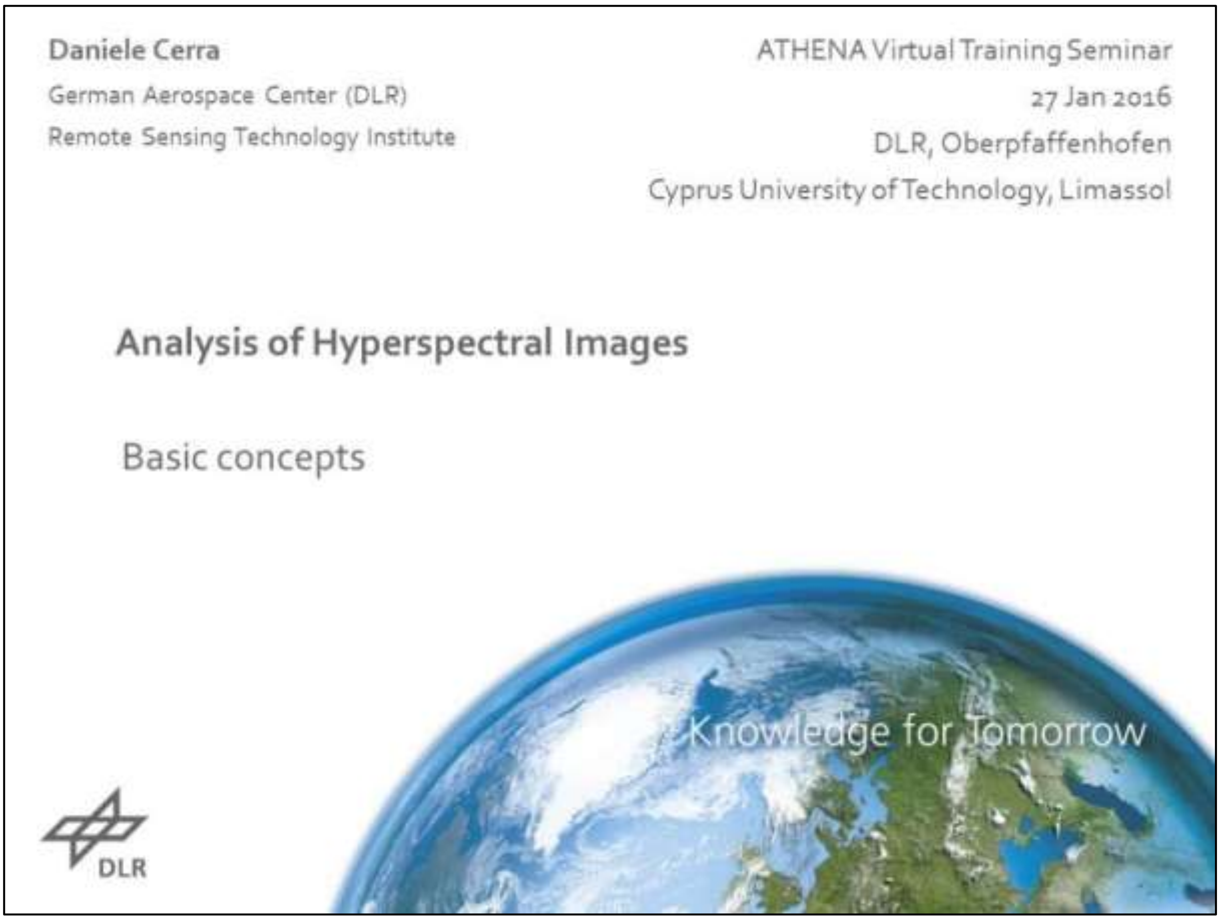
2.1.2 Participants

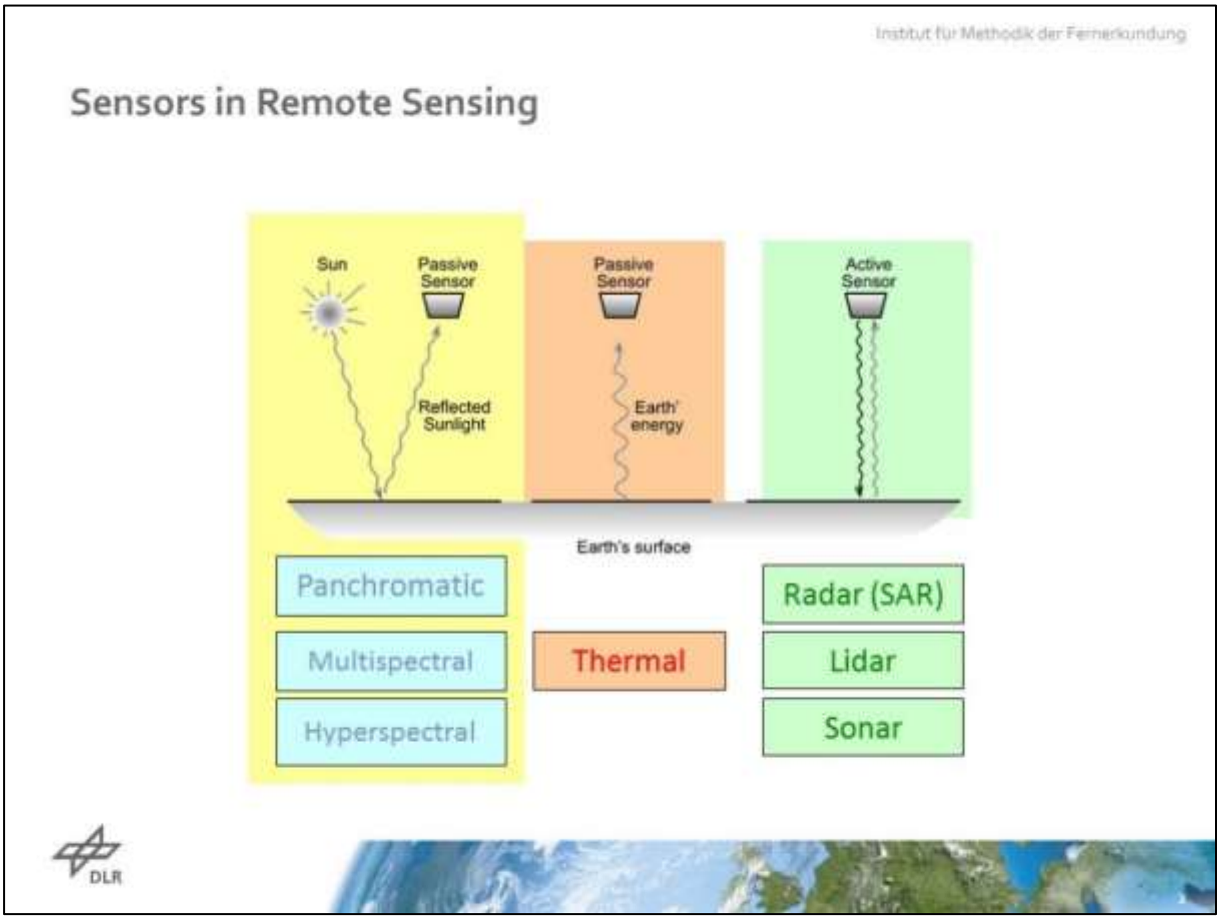
No.	Name	Role	Institution
1	Daniele Cerra	Trainer	DLR
2	Vasiliki Lysandrou	Trainee	CUT
3	Athos Agapiou	Trainee	CUT
4	Christodoulos Mettas	Trainee	CUT
5	Branca Cuca	Trainee	CUT
6	Kyriakos Themistocleous	Trainee	CUT
7	Evagoras Evagorou	Trainee	CUT
8	Argyro Nisantzi	Trainee	CUT

Group photograph at the end of the training at the premises of the Cyprus University of Technology

2.1.3 Presentation 1: "Analysis of Hyperspectral images – Basic concepts"

Hereunder the first presentation on the topic "Analysis of Hyperspectral images – Basic concepts" is given.

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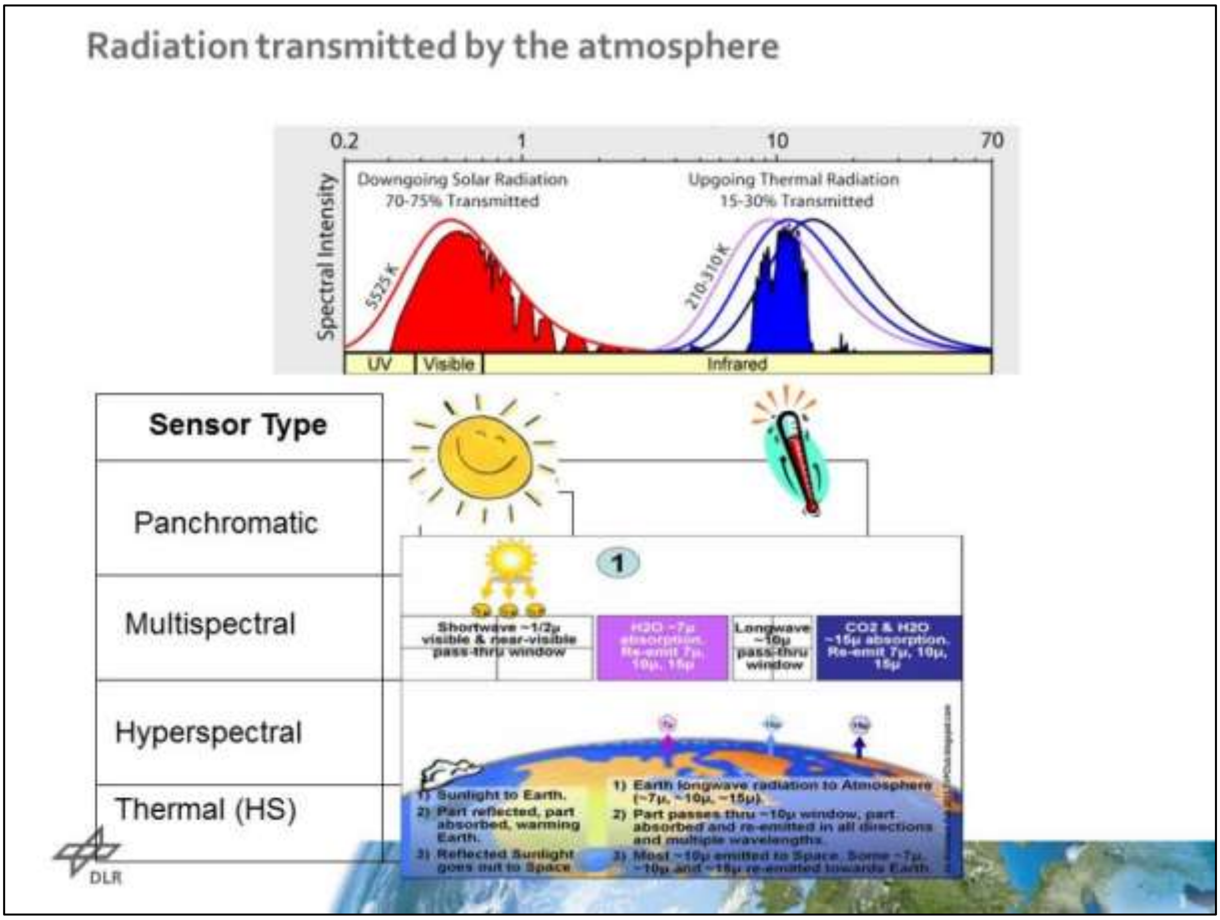
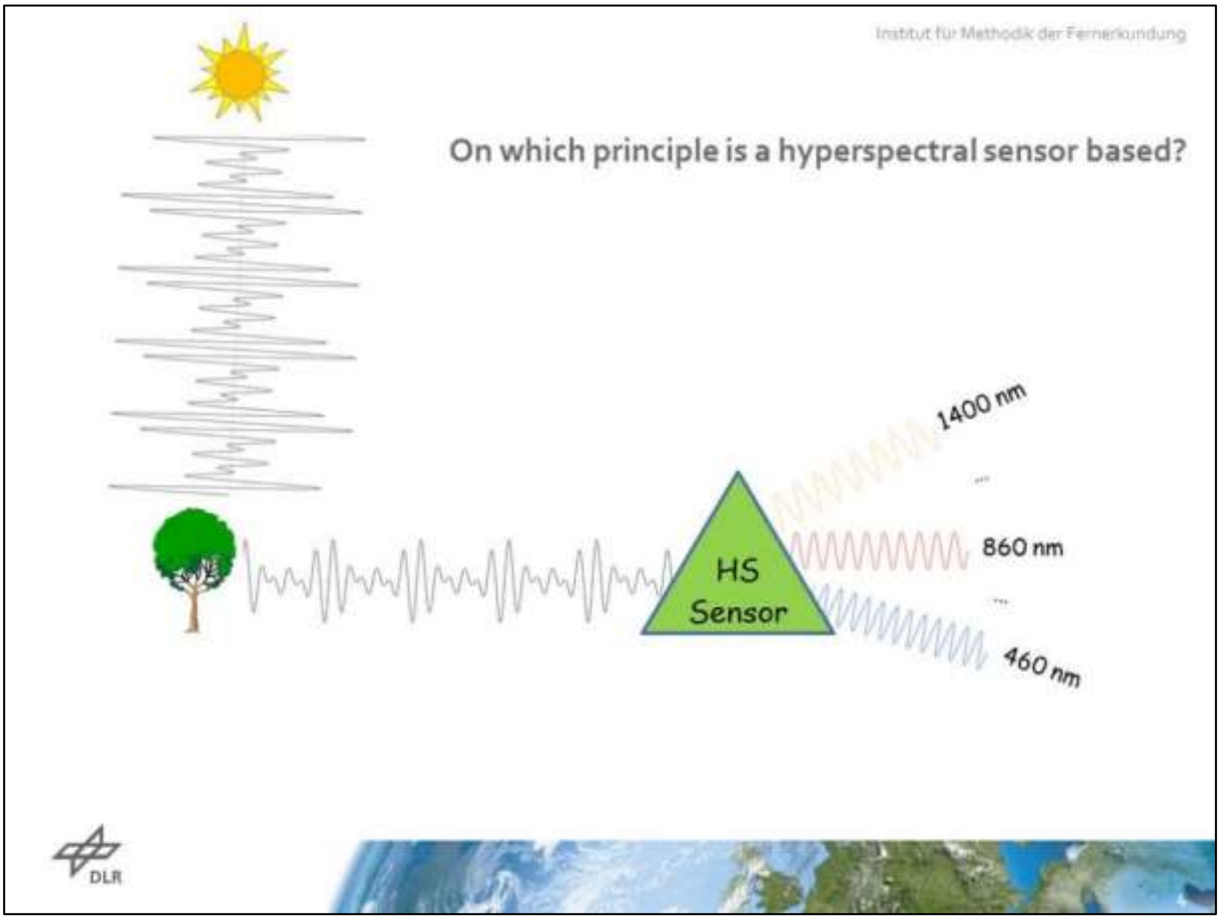
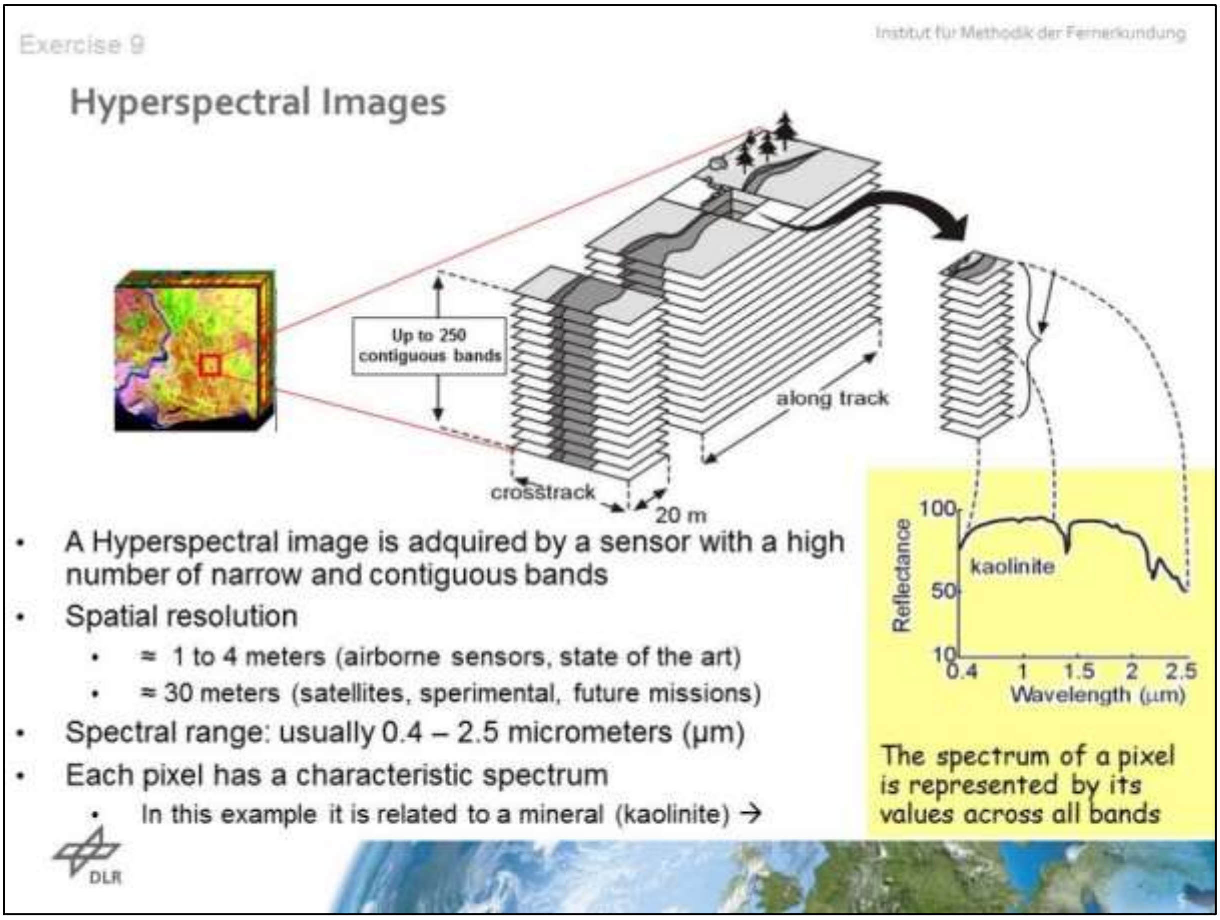
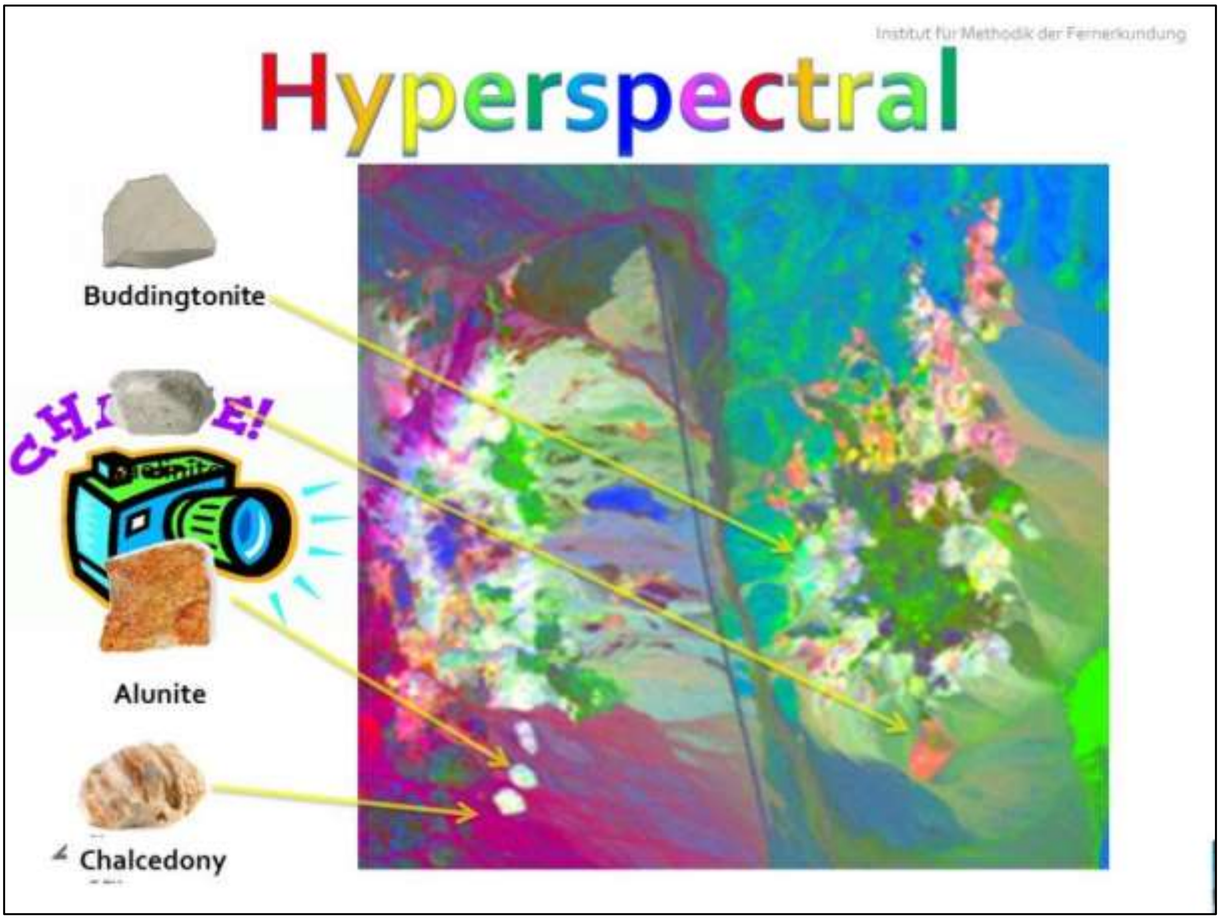
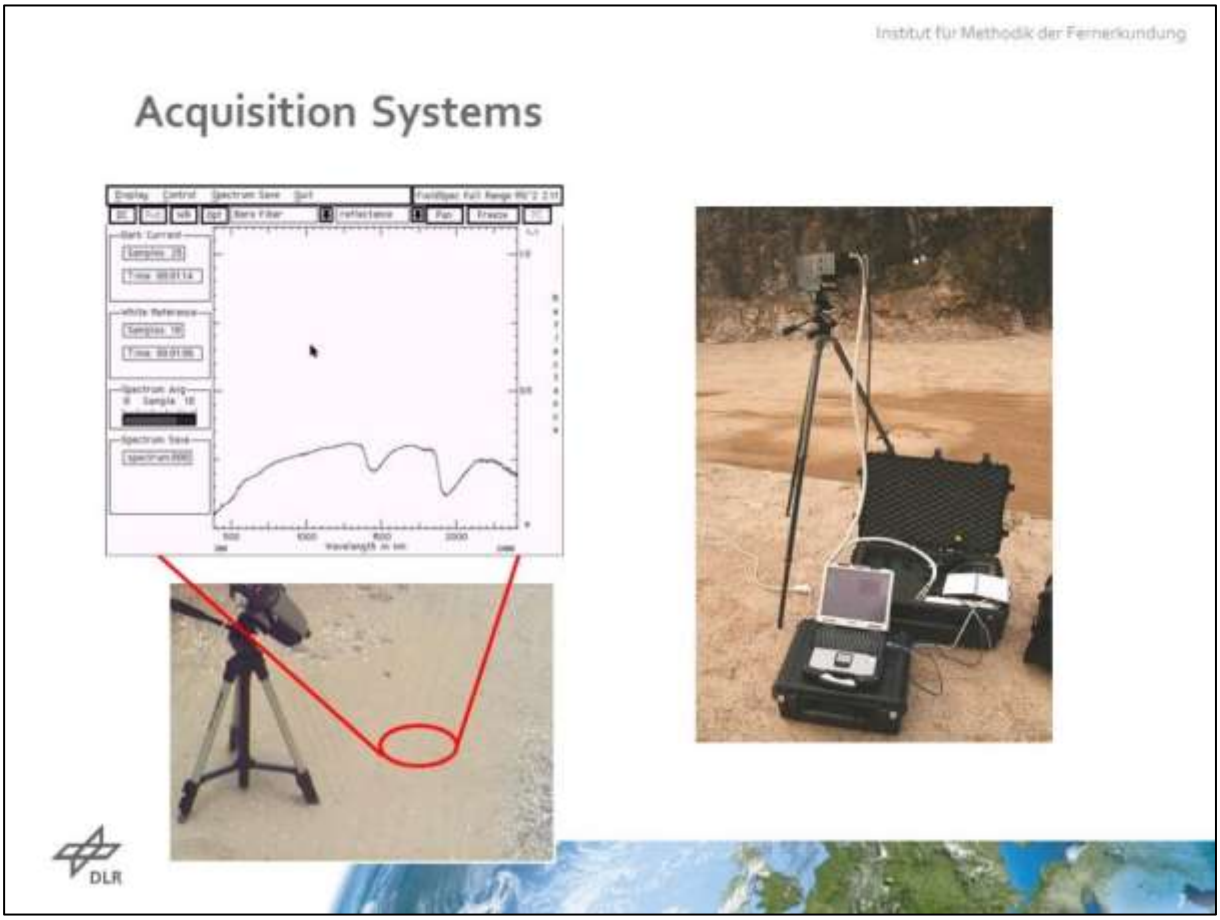
Sensors in Remote Sensing
Sun
Passive Sensor
Reflected Sunlight
Passive Sensor
Earth' energy
Active Sensor
Earth's surface
Panchromatic
Multispectral
Hyperspectral
Thermal
Radar (SAR)
Lidar
Sonar
DLR


Radiation transmitted by the atmosphere
0.2
1
10
70
Spectral Intensity
Downgoing Solar Radiation
70-75% Transmitted
Upgoing Thermal Radiation
15-30% Transmitted
5525 K
210-310 K
UV
Visible
Infrared
Sensor Type
Panchromatic
Multispectral
Hyperspectral
Thermal (HS)
1
DLR


Institut für Methodik der Fernerkundung
On which principle is a hyperspectral sensor based?
HS Sensor
1400 nm
860 nm
460 nm
DLR


Exercise 9
Institut für Methodik der Fernerkundung
Hyperspectral Images
Up to 250 contiguous bands
along track
crosstrack
20 m
100
50
10
Reflectance
kaolinite
0.4 1 1.5 2 2.5
Wavelength (µm)
The spectrum of a pixel is represented by its values across all bands
• A Hyperspectral image is adquired by a sensor with a high number of narrow and contiguous bands
• Spatial resolution
• ≈ 1 to 4 meters (airborne sensors, state of the art)
• ≈ 30 meters (satellites, sperimental, future missions)
• Spectral range: usually 0.4 – 2.5 micrometers (µm)
• Each pixel has a characteristic spectrum
• In this example it is related to a mineral (kaolinite) →
DLR


Institut für Methodik der Fernerkundung
Hyperspectral
Buddingtonite
Alunite
Chalcedony


Institut für Methodik der Fernerkundung
Acquisition Systems
DLR

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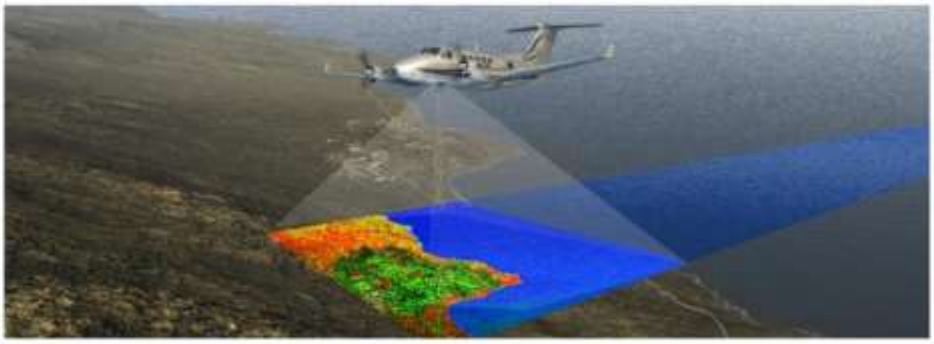
Acquisition Systems



DLR

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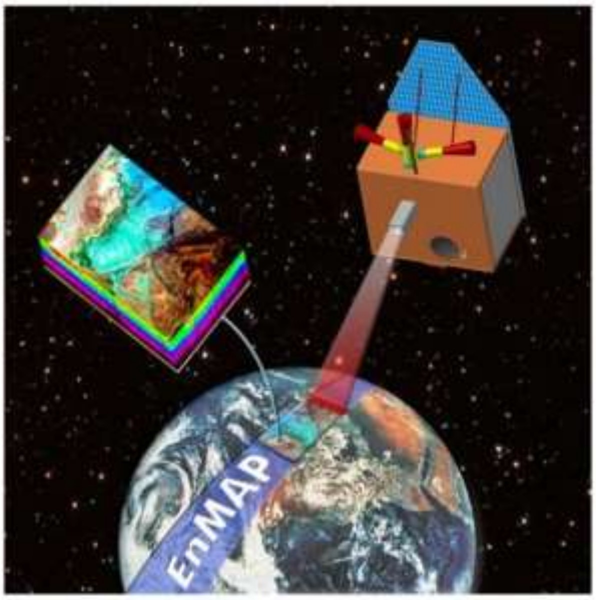
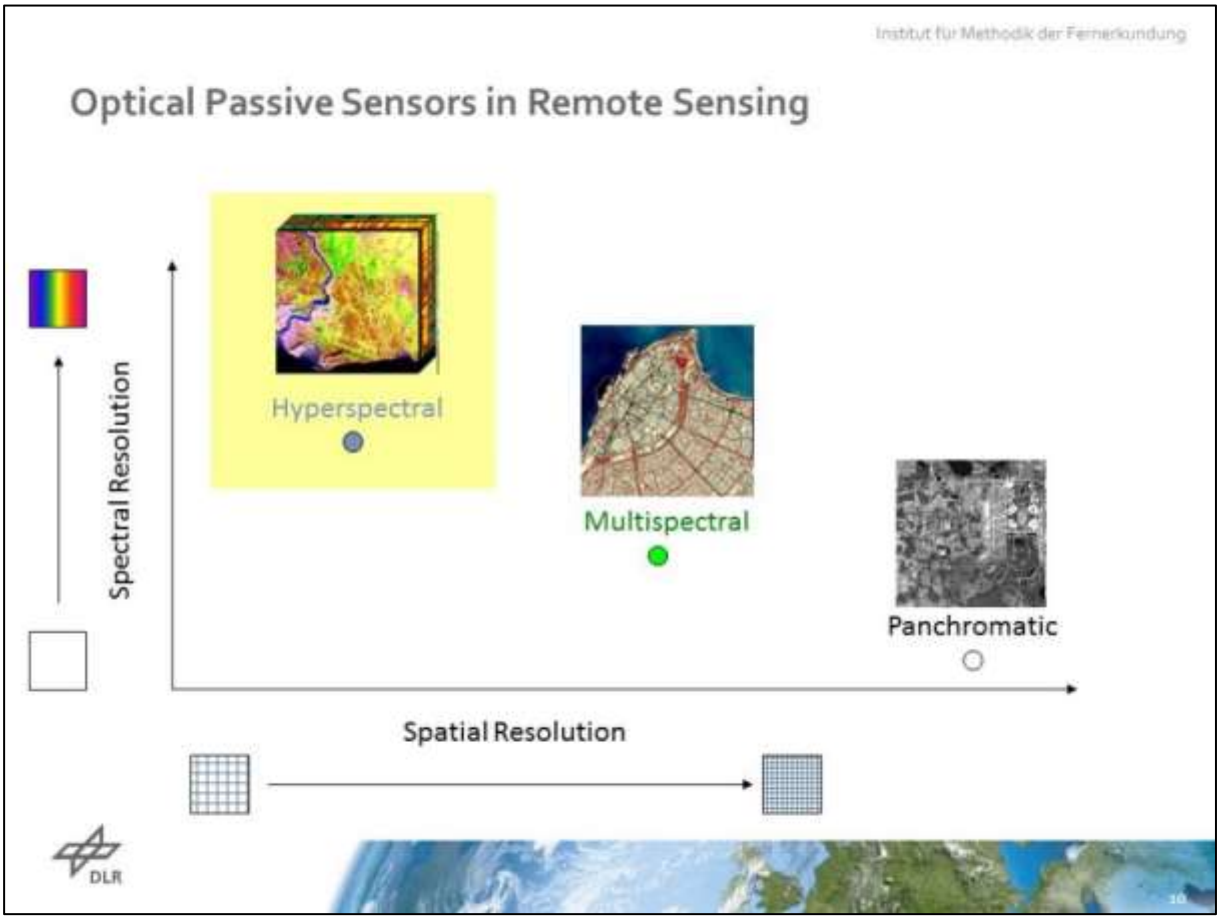
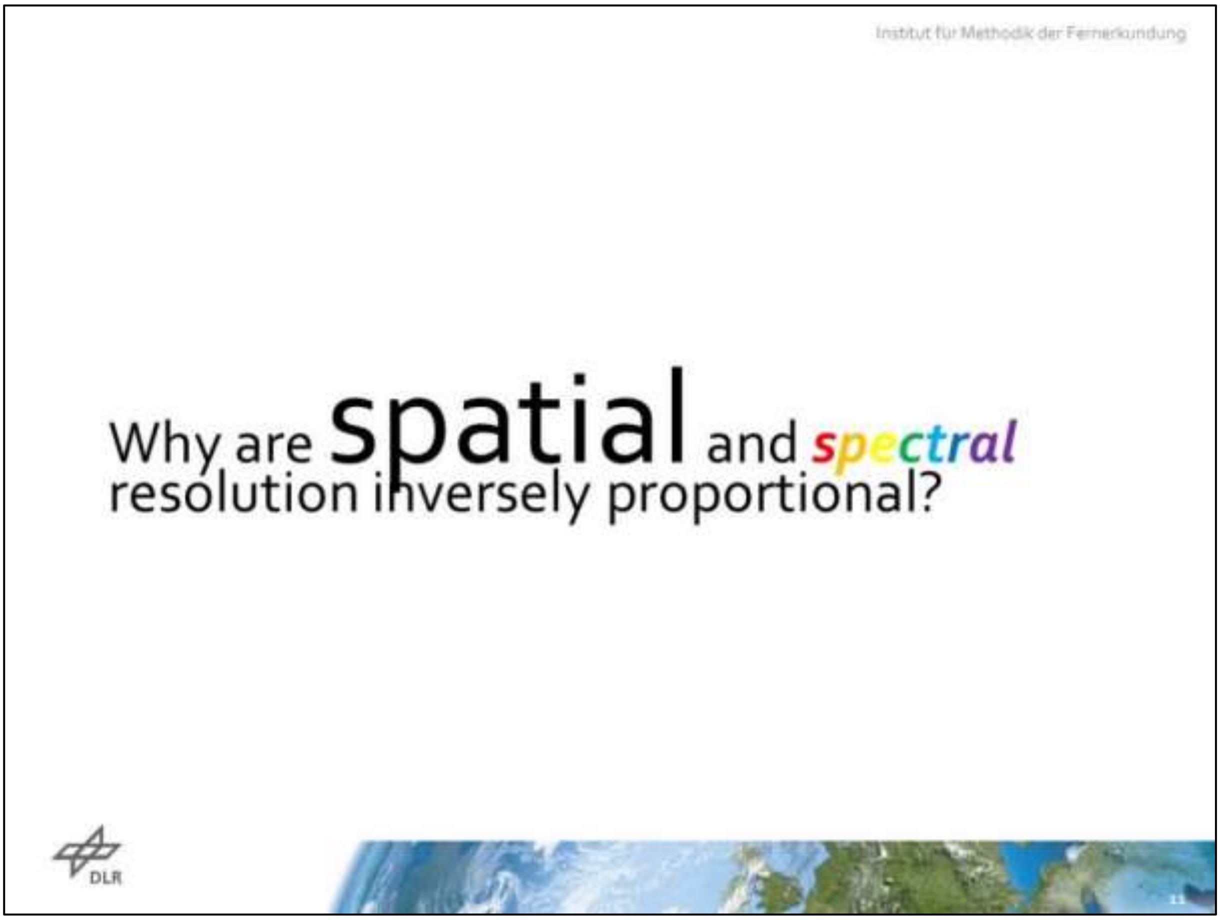
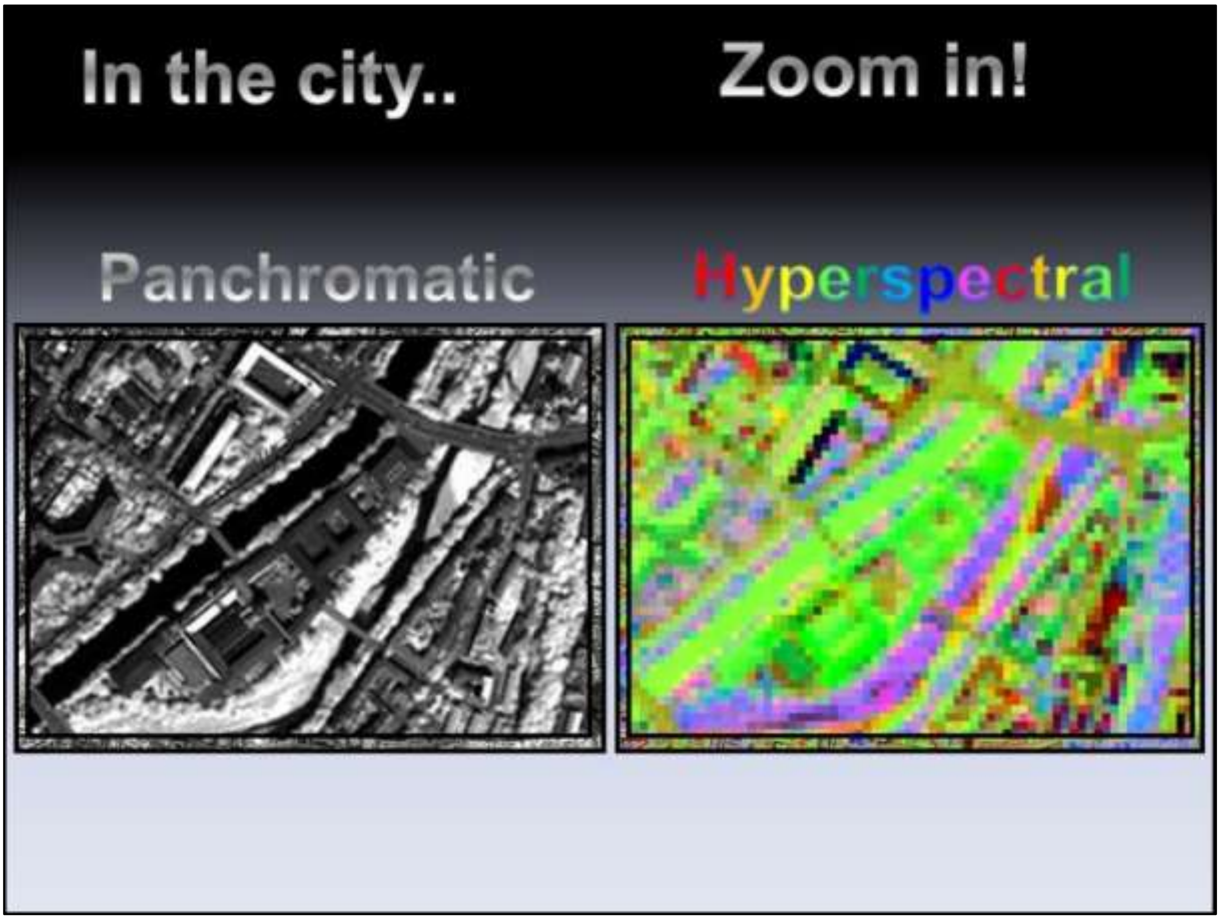
Acquisition Systems

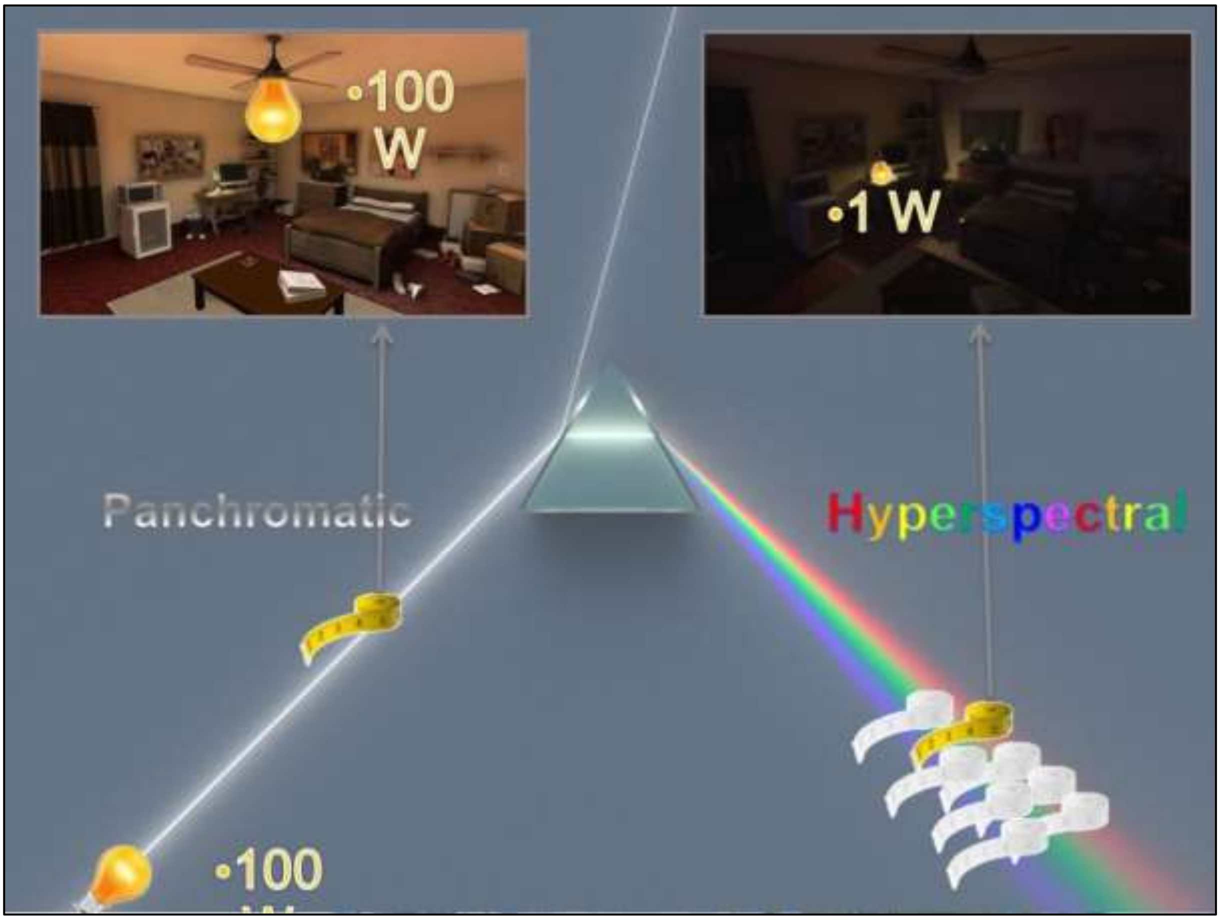


DLR


Institut für Methodik der Fernerkundung
Optical Passive Sensors in Remote Sensing
Hyperspectral
Multispectral
Panchromatic
Spectral Resolution
Spatial Resolution
DLR


Institut für Methodik der Fernerkundung
Why are spatial and spectral resolution inversely proportional?
DLR


In the city..
Zoom in!
Panchromatic
Hyperspectral


•100 W
•1 W
Panchromatic
Hyperspectral
•100

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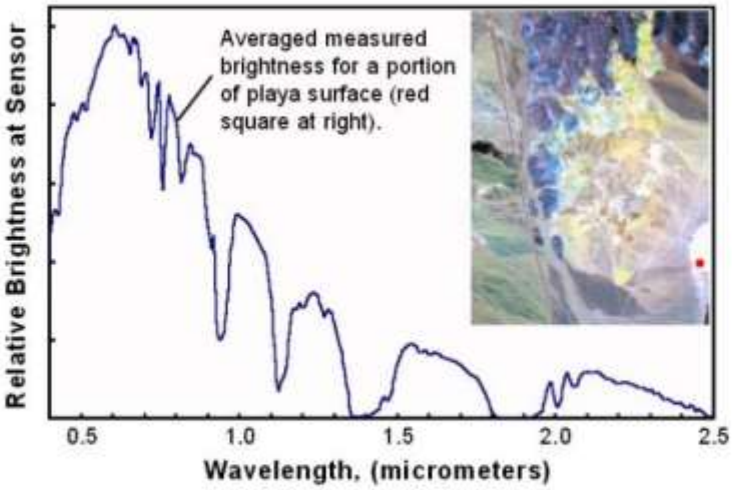
From radiance to reflectance



- If we want to know which fraction of the incoming solar energy is reflected by each band, we have to process the radiance values (amount of light/radiation measured in each band)

DLR

Figure by TNTmips

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From radiance to reflectance

- The solar energy is not constant across all the bands! We must correct this

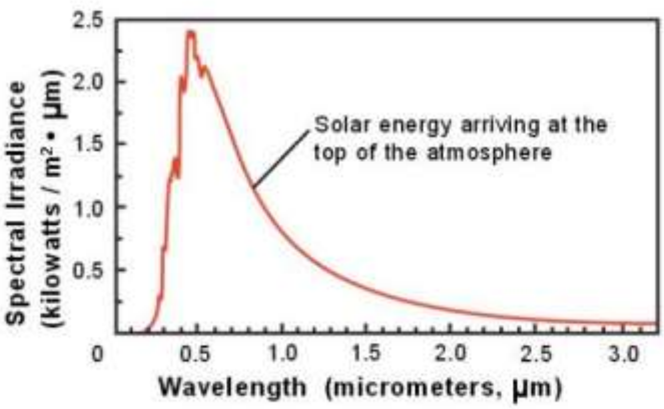

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Figure by TNTmips

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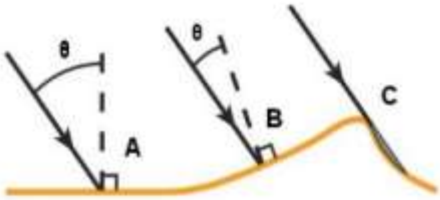
From radiance to reflectance

- Geometric effects / shadows



Illumination differences can arise from differing incidence angles (θ) as for **A** and **B**, or from shadowing (**C**).

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Figure by TNTmips

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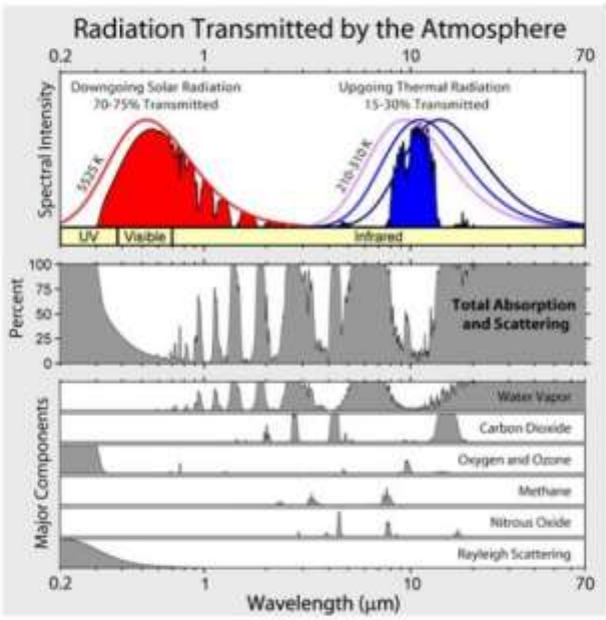
From radiance to reflectance

- Atmospheric effects



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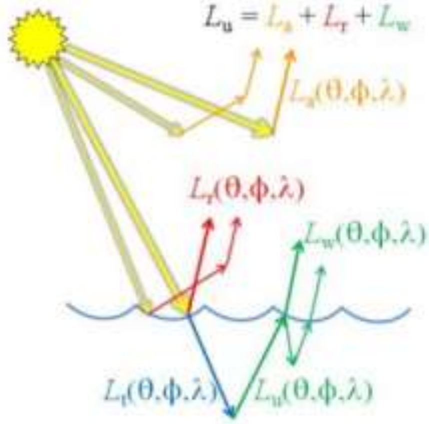
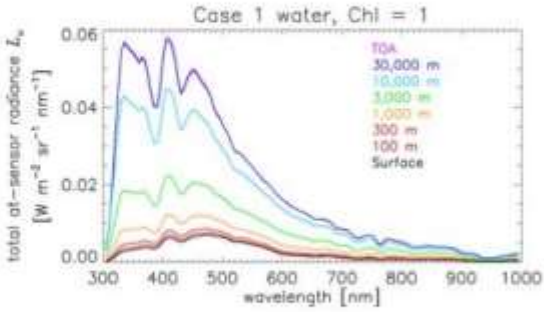
Why is the sky blue?

– Atmospheric path radiance → *La*





– Less important at long waves (infrared), more evident at short wavelengths

Figure by Ocean Optics

From radiance to reflectance

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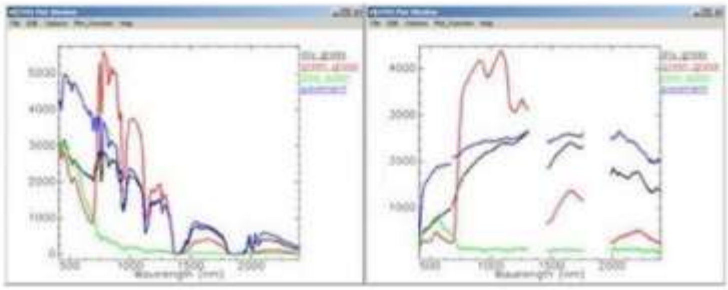


– After correcting all these aspects, we can convert each pixel value into the fraction of reflected energy for each band (from 0 to 1).

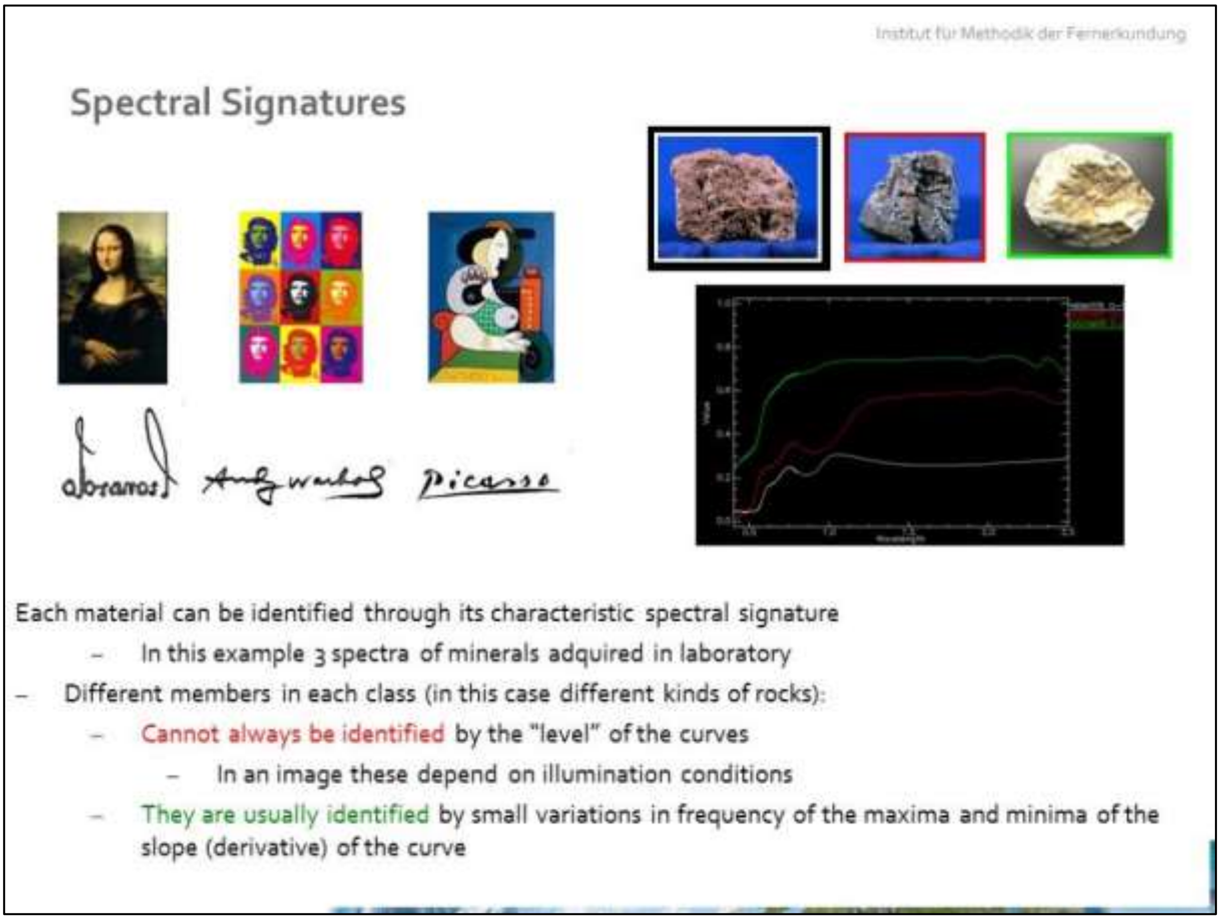
– To do this there are a lot of different methods

  – We are not going to see them in detail

– It is not mandatory to do this (only if we need to work with physical values)

– For statistical operations we can also use the data in radiance

Figure courtesy of Exelis VIS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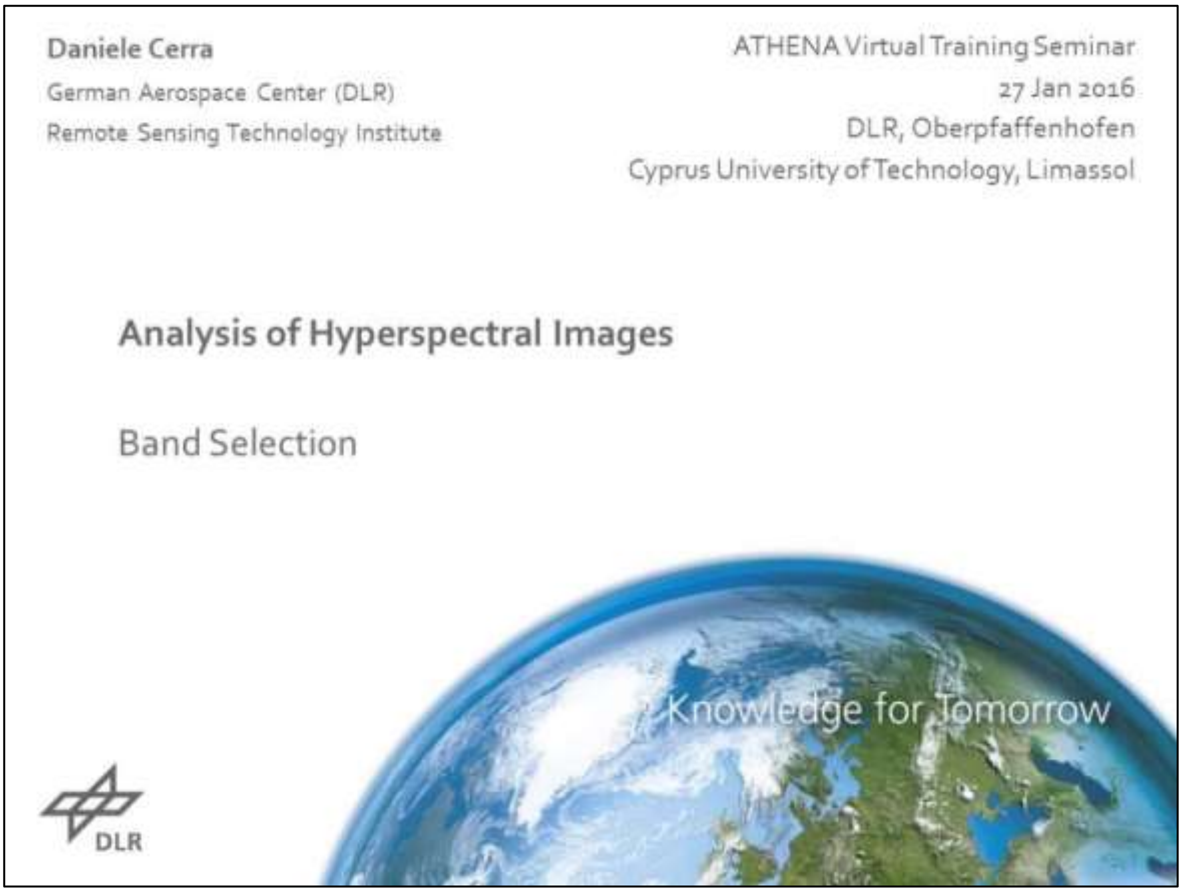
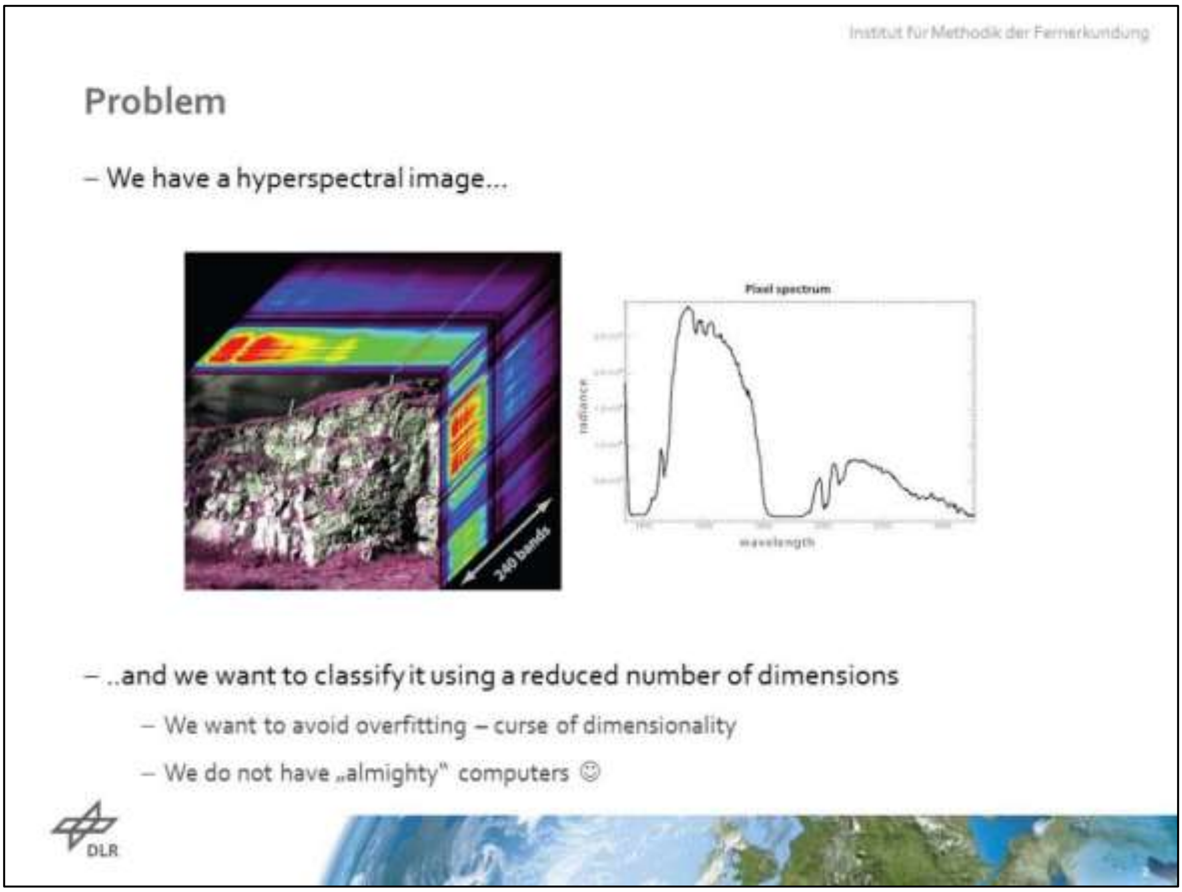
Spectral Signatures
Each material can be identified through its characteristic spectral signature
– In this example 3 spectra of minerals adquired in laboratory
– Different members in each class (in this case different kinds of rocks):
– Cannot always be identified by the "level" of the curves
– In an image these depend on illumination conditions
– They are usually identified by small variations in frequency of the maxima and minima of the slope (derivative) of the curve

2.1.4 Presentation 2: “Analysis of Hyperspectral images – Band selection”





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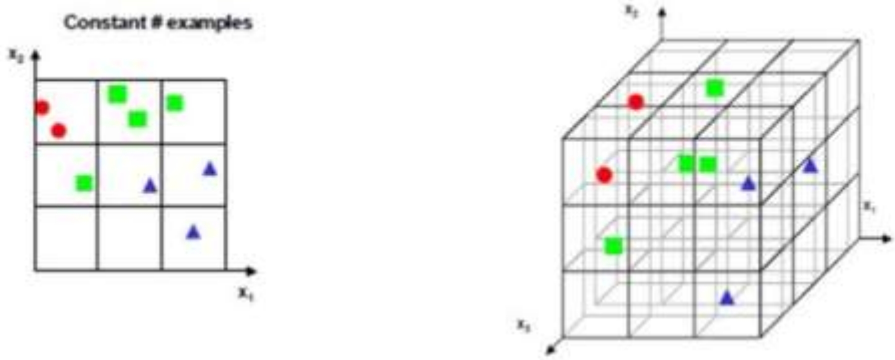
Curse of Dimensionality

– Classification problem: 3 classes



DLR

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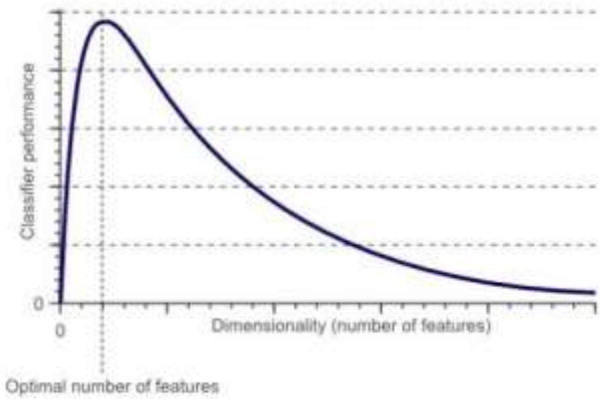
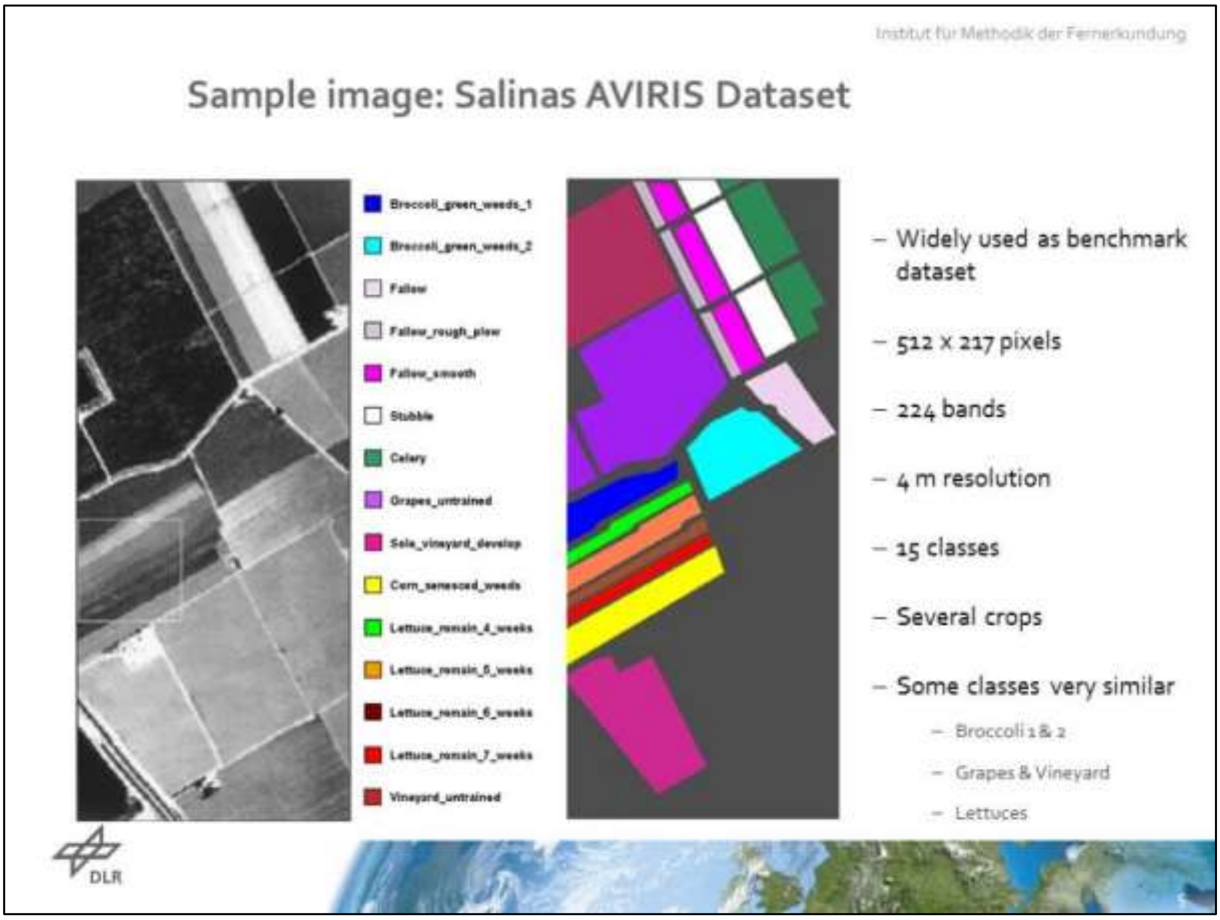
Curse of Dimensionality

– Classification problem



DLR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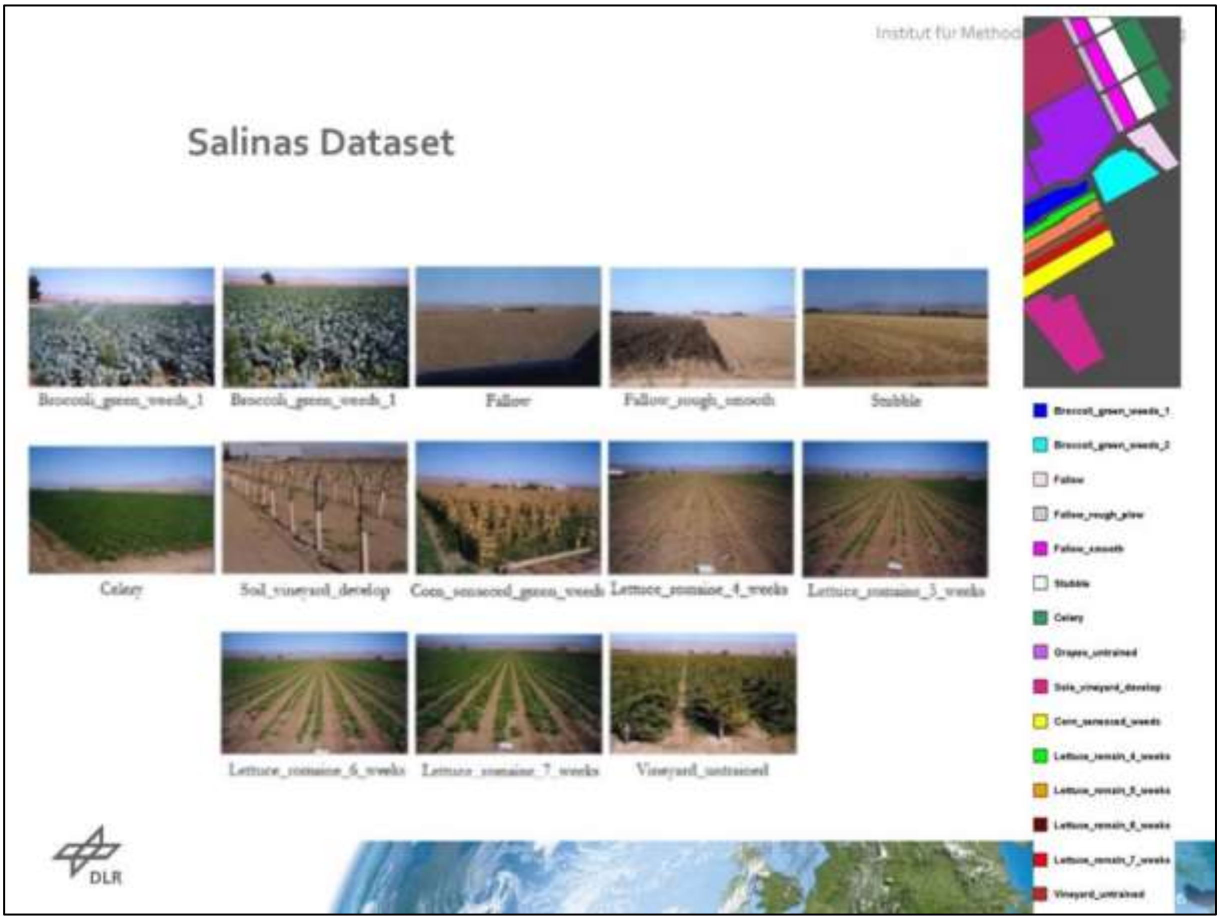
Sample image: Salinas AVIRIS Dataset
Broccoli_green_weeds_1
Broccoli_green_weeds_2
Fallow
Fallow_rough_plow
Fallow_smooth
Stubble
Celery
Grapes_untrained
Soil_vineyard_develop
Corn_senesced_weeds
Lettuce_romain_4_weeks
Lettuce_romain_5_weeks
Lettuce_romain_6_weeks
Lettuce_romain_7_weeks
Vineyard_untrained
– Widely used as benchmark dataset
– 512 x 217 pixels
– 224 bands
– 4 m resolution
– 15 classes
– Several crops
– Some classes very similar
– Broccoli 1 & 2
– Grapes & Vineyard
– Lettuces
DLR


Salinas Dataset
Fallow
Stubble
Celery
DLR

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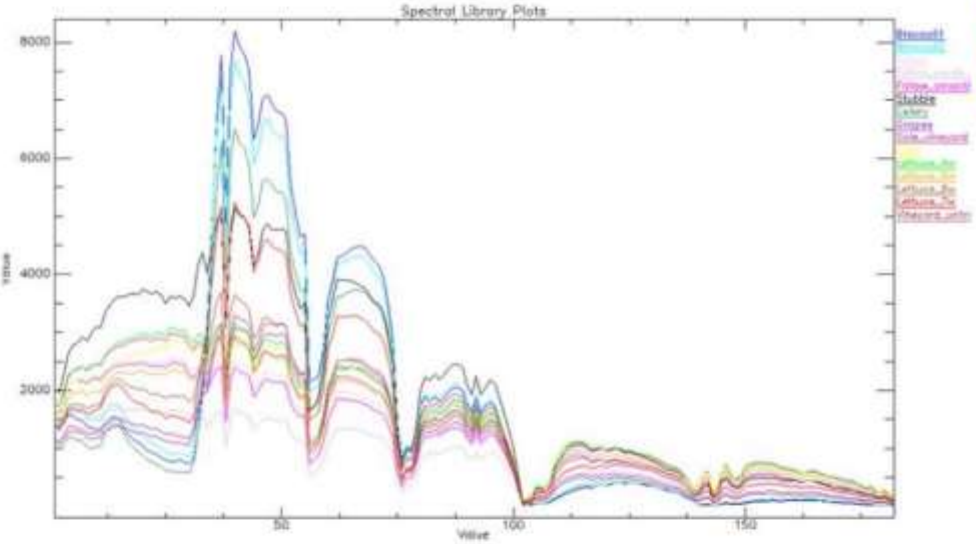
Sample Spectra



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Problem

- How to select the "best" bands?
- For example, we want to select 10 bands
- Let's see how...

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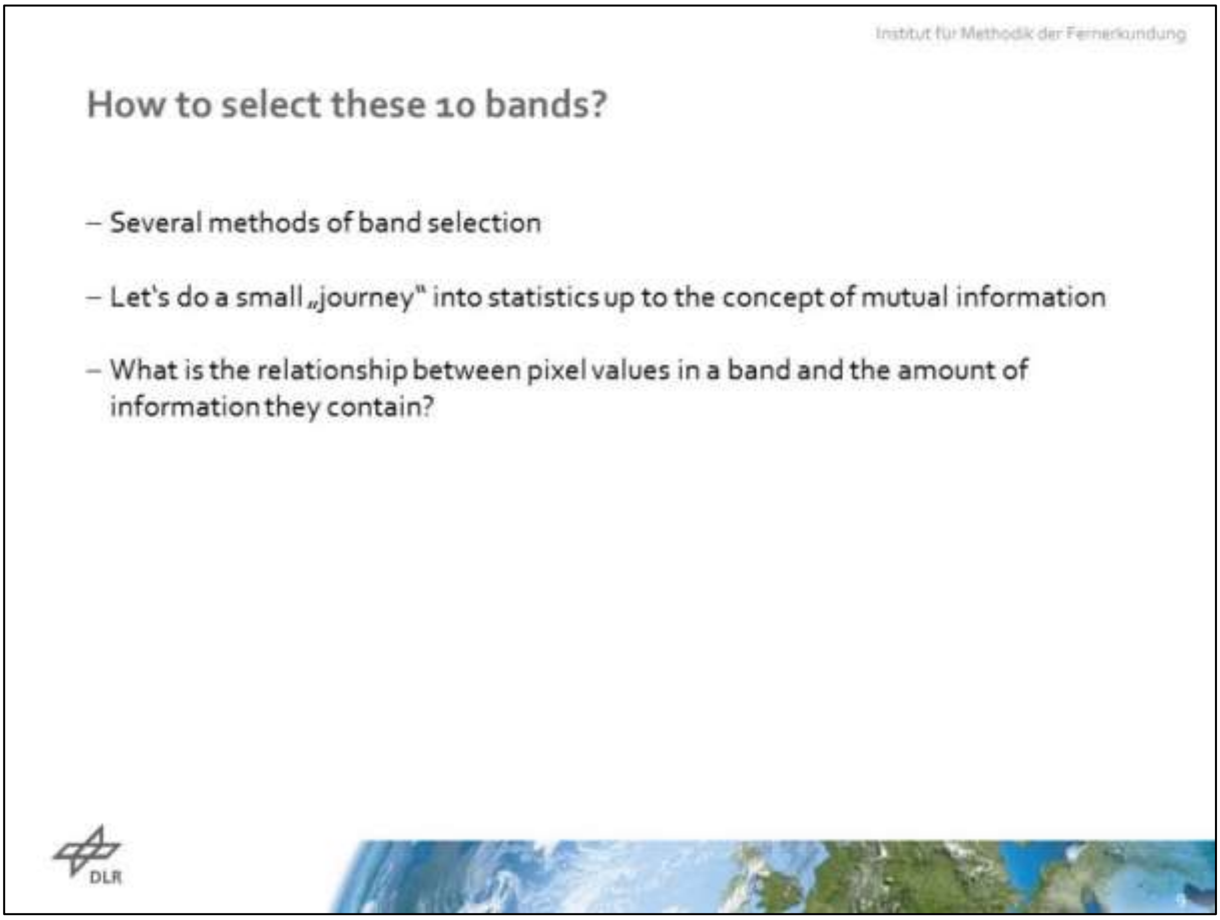
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How to select these 10 bands?
– Several methods of band selection
– Let's do a small „journey" into statistics up to the concept of mutual information
– What is the relationship between pixel values in a band and the amount of information they contain?
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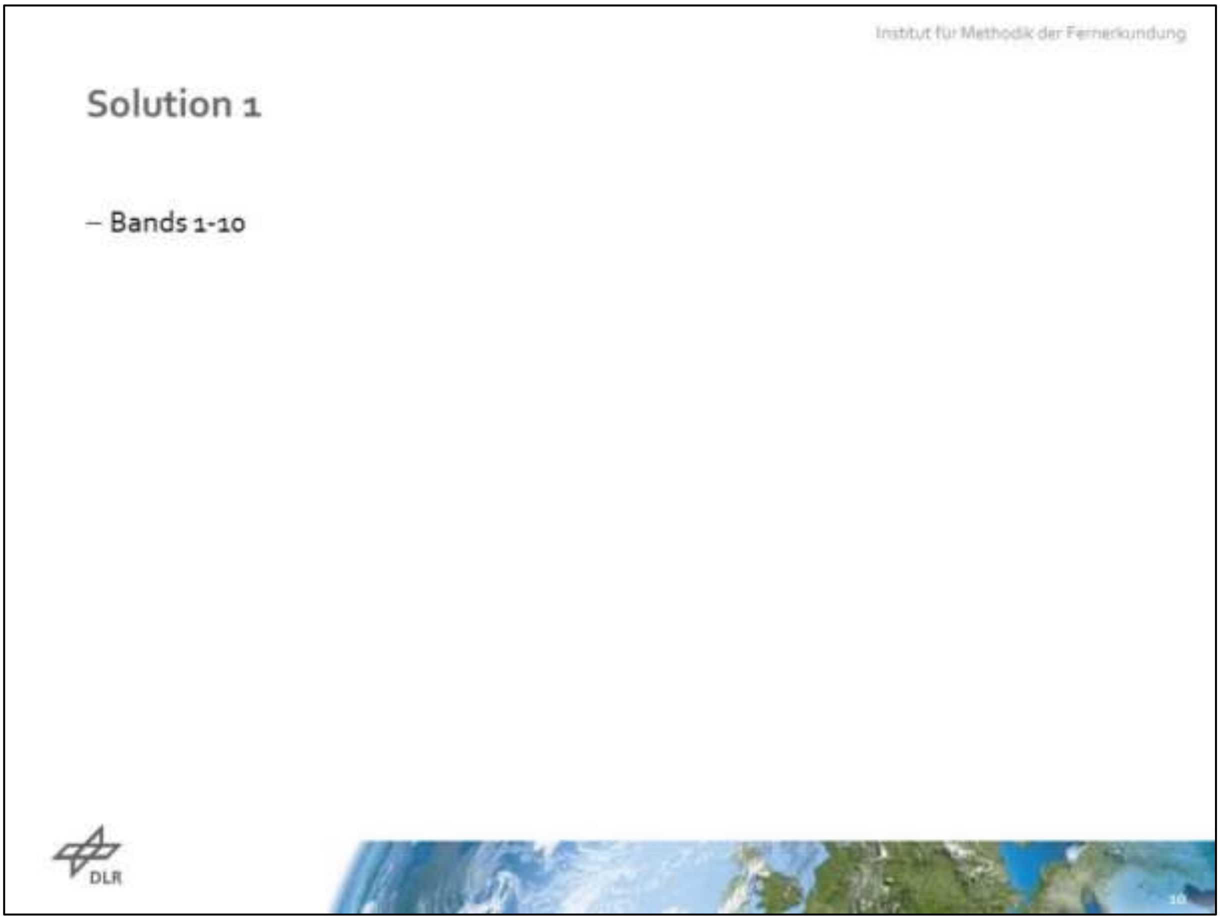
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Solution 1
– Bands 1-10
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Really?

Band 1

- Noisy bands are not used in the analysis
- Why are there noisy bands?

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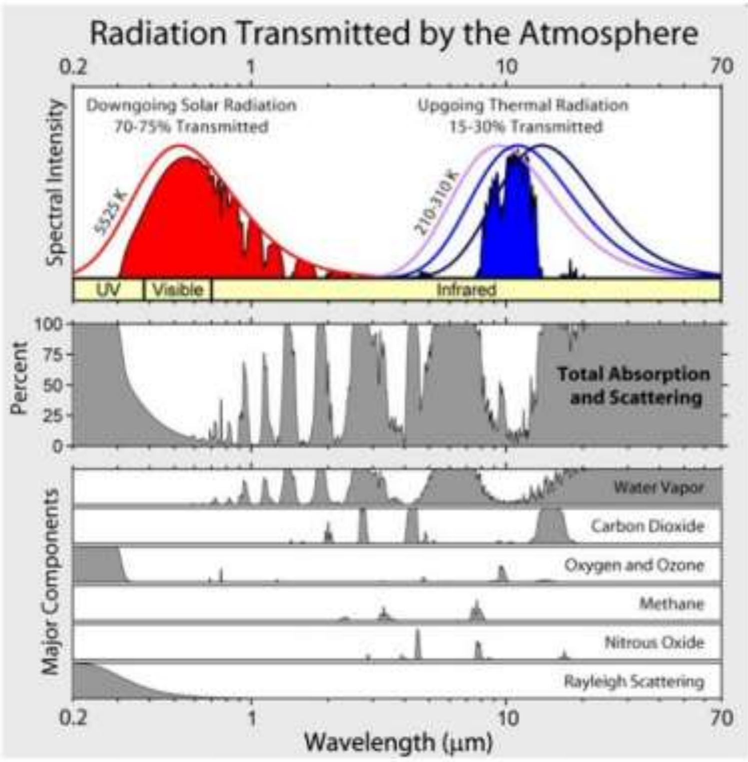

DLR

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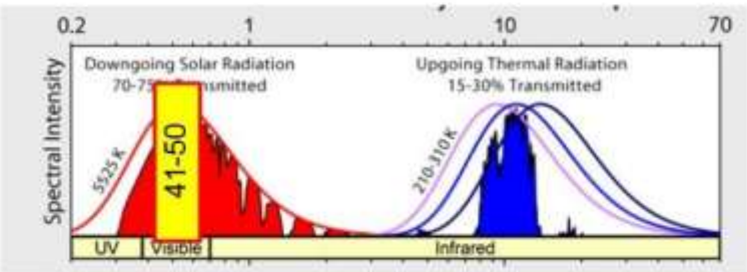
Solution 2

- Bands 41-50
  - In the range with the best Signal-to-Noise Ratio (SNR)



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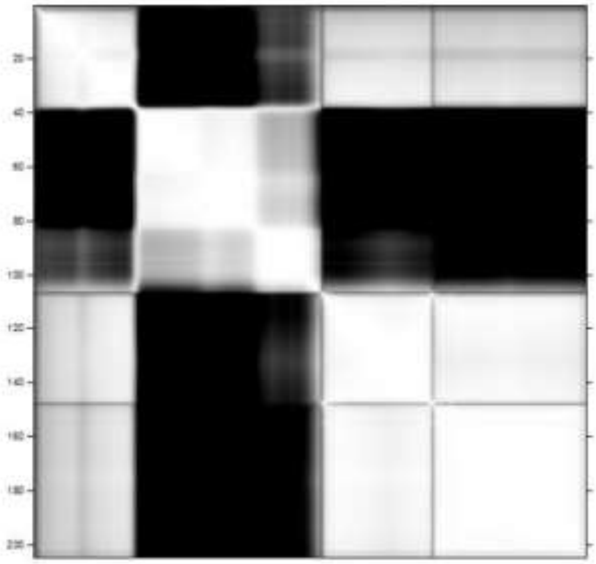
Correlation between bands



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Mean

	Score x	$x-\bar{x}$	$(x-\bar{x})^2$
1	3		
2	5		
3	7		
4	10		
5	10		
Totals	35		

- The mean is 35/5=7.

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Standard Deviation

	Score x	$x-\bar{x}$	$(x-\bar{x})^2$
1	3	3-7=-4	
2	5	5-7=-2	
3	7	7-7=0	
4	10	10-7=3	
5	10	10-7=3	
Totals	35	12	

- The (population) SD is the square root of the squared mean value of the difference from the mean:

- Sdev(X) = $\sqrt{\frac{4^2+2^2+0^2+3^2+3^2}{5}} = 2.76$

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Variance

	Score X	$X-\bar{X}$	$(X-\bar{X})^2$
1	3	3-7=-4	16
2	5	5-7=-2	4
3	7	7-7=0	0
4	10	10-7=3	9
5	10	10-7=3	9
Totals	35		38

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Variance

	Score X	$X-\bar{X}$	$(X-\bar{X})^2$
1	3	3-7=-4	16
2	5	5-7=-2	4
3	7	7-7=0	0
4	10	10-7=3	9
5	10	10-7=3	9
Totals	35		38

$$s^2 = \frac{\sum\left(x-\bar{X}\right)^2}{n} = \frac{38}{5} = 7.6$$

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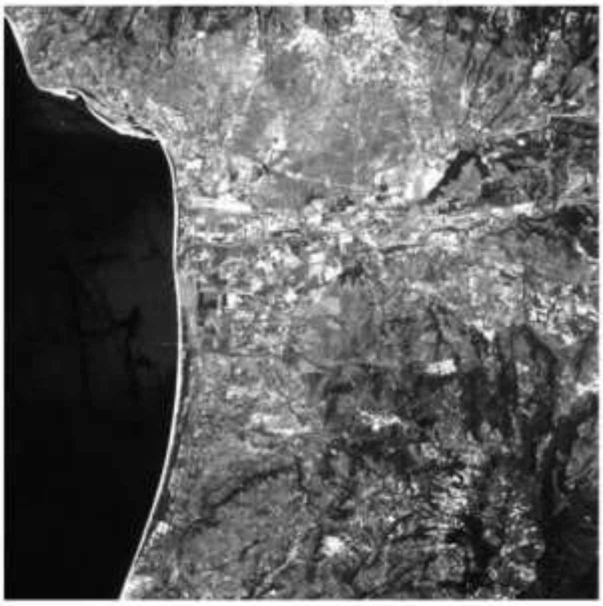
Example



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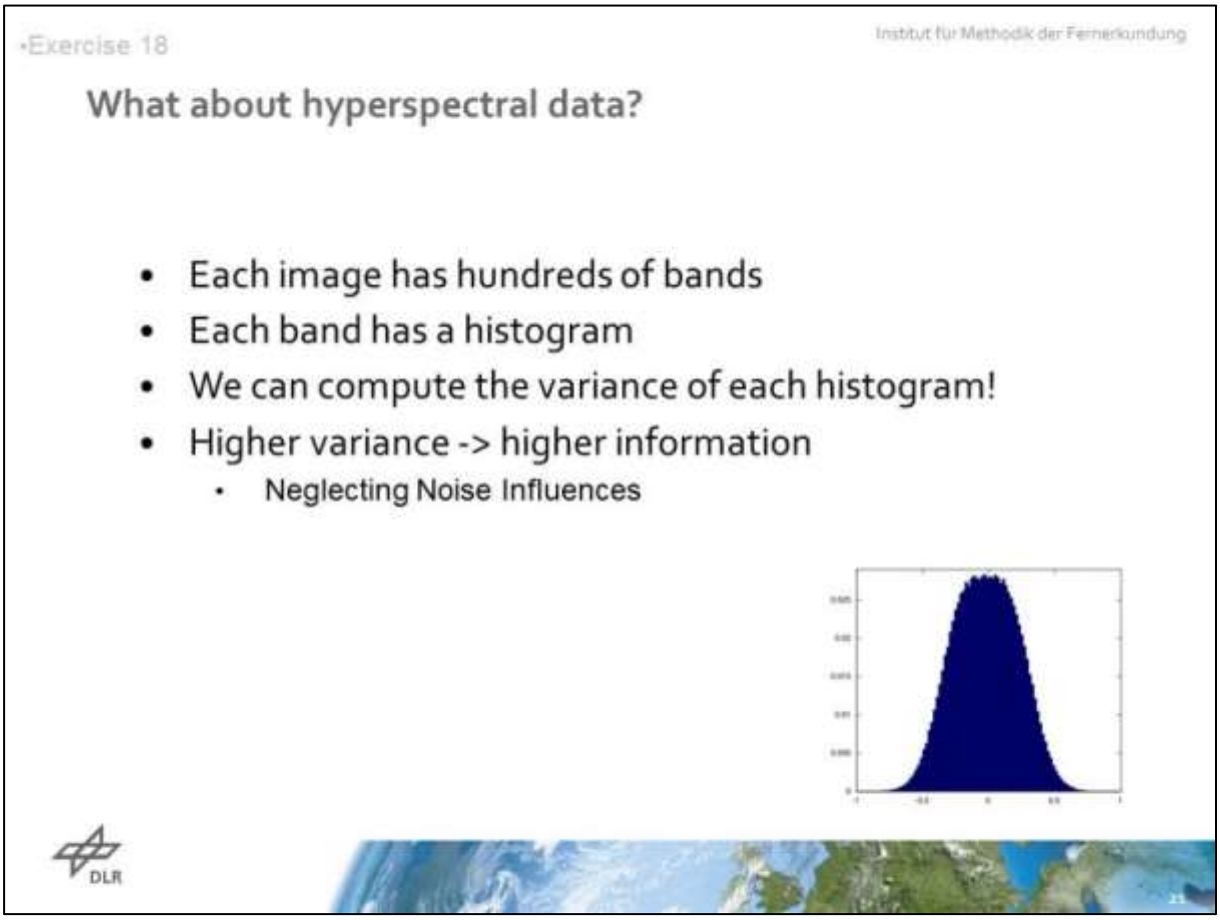
Local Variance in a 7x7 Sliding Window

DLR


Exercise 18
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What about hyperspectral data?
• Each image has hundreds of bands
• Each band has a histogram
• We can compute the variance of each histogram!
• Higher variance -> higher information
• Neglecting Noise Influences
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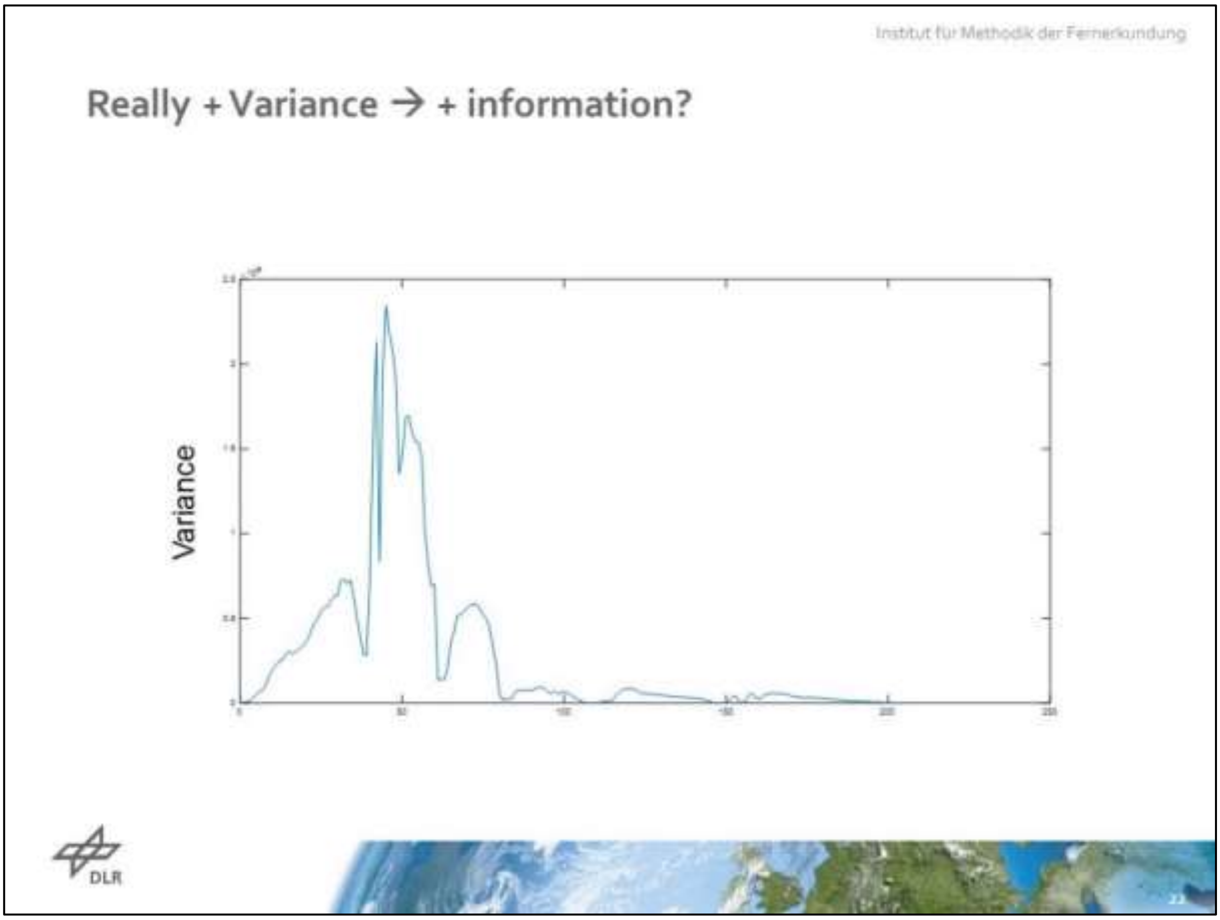
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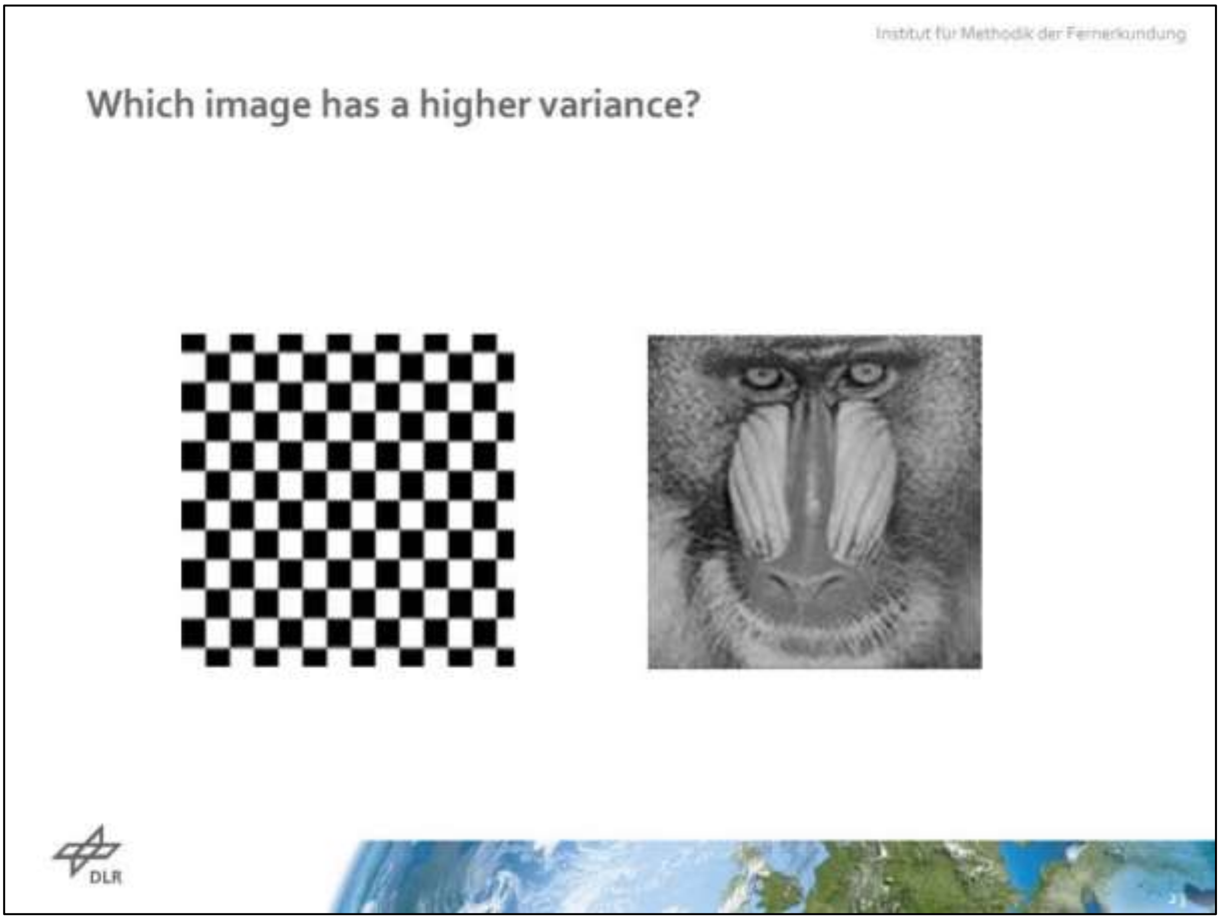
Really + Variance → + information?
Variance
DLR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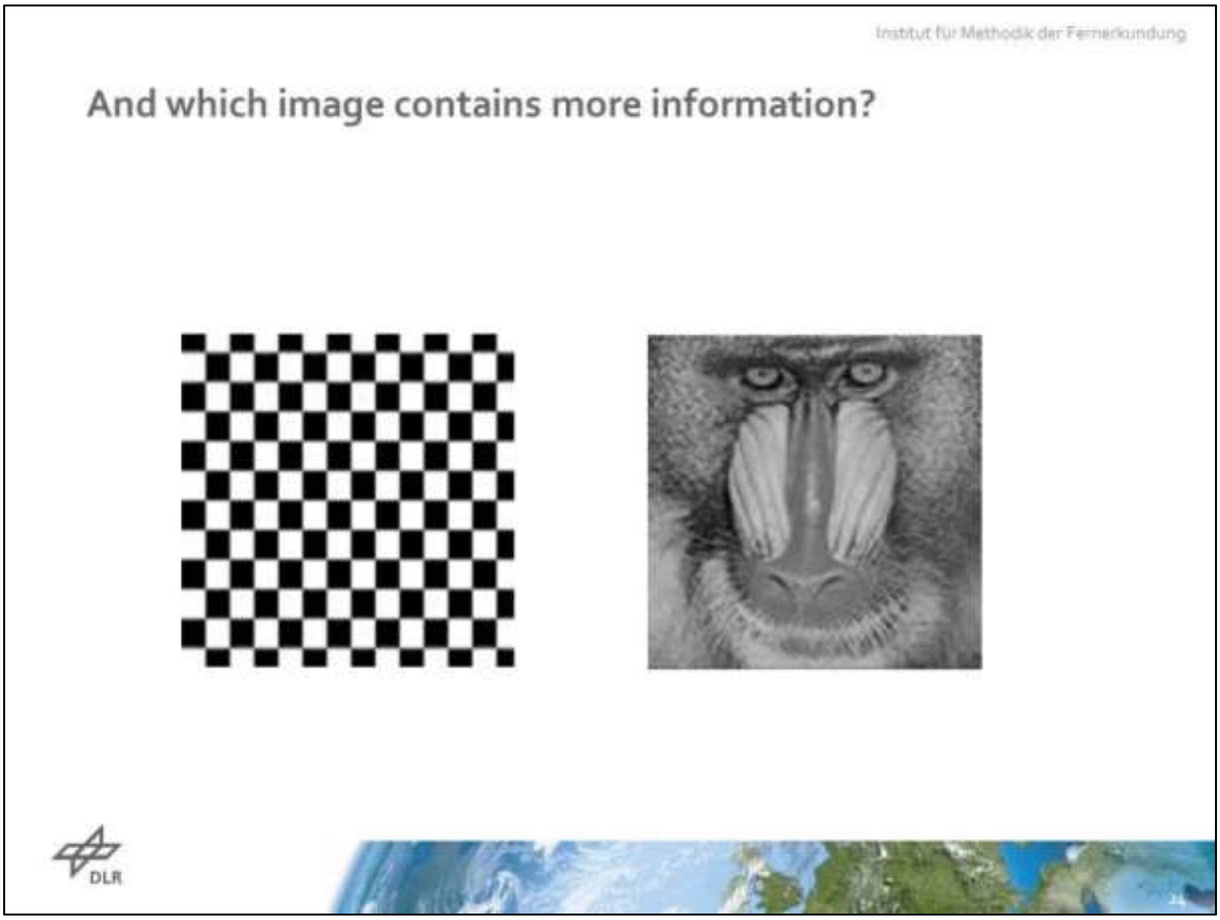
Which image has a higher variance?
DLR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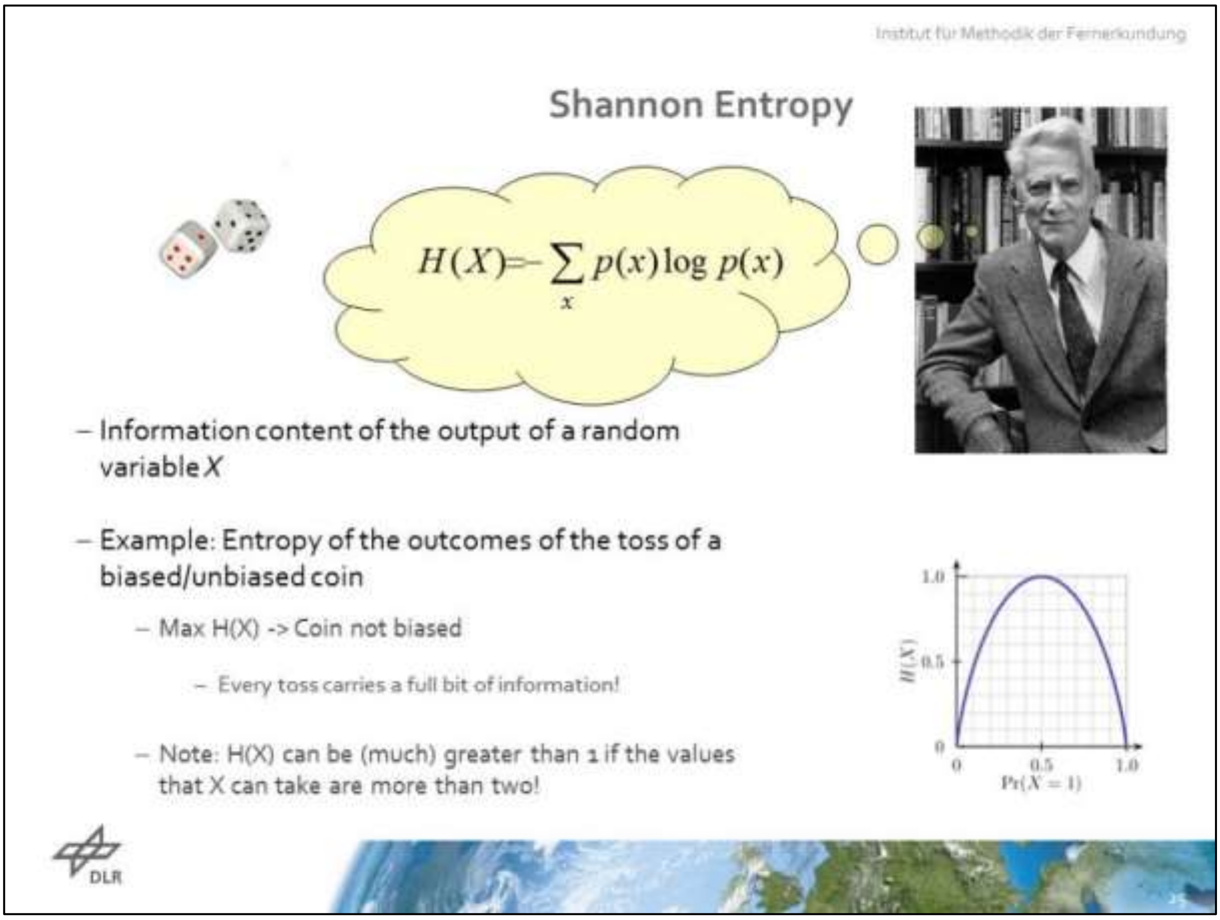
And which image contains more information?
DLR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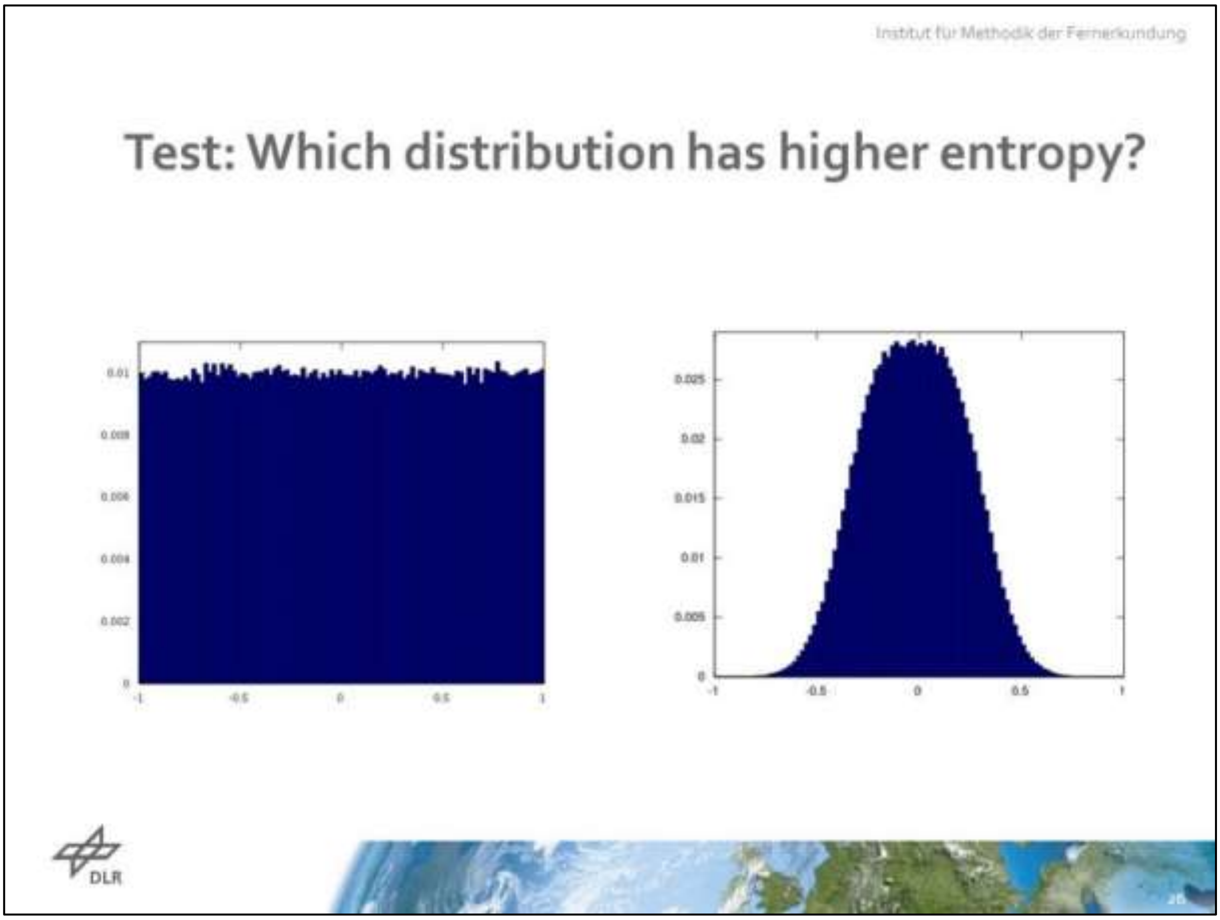
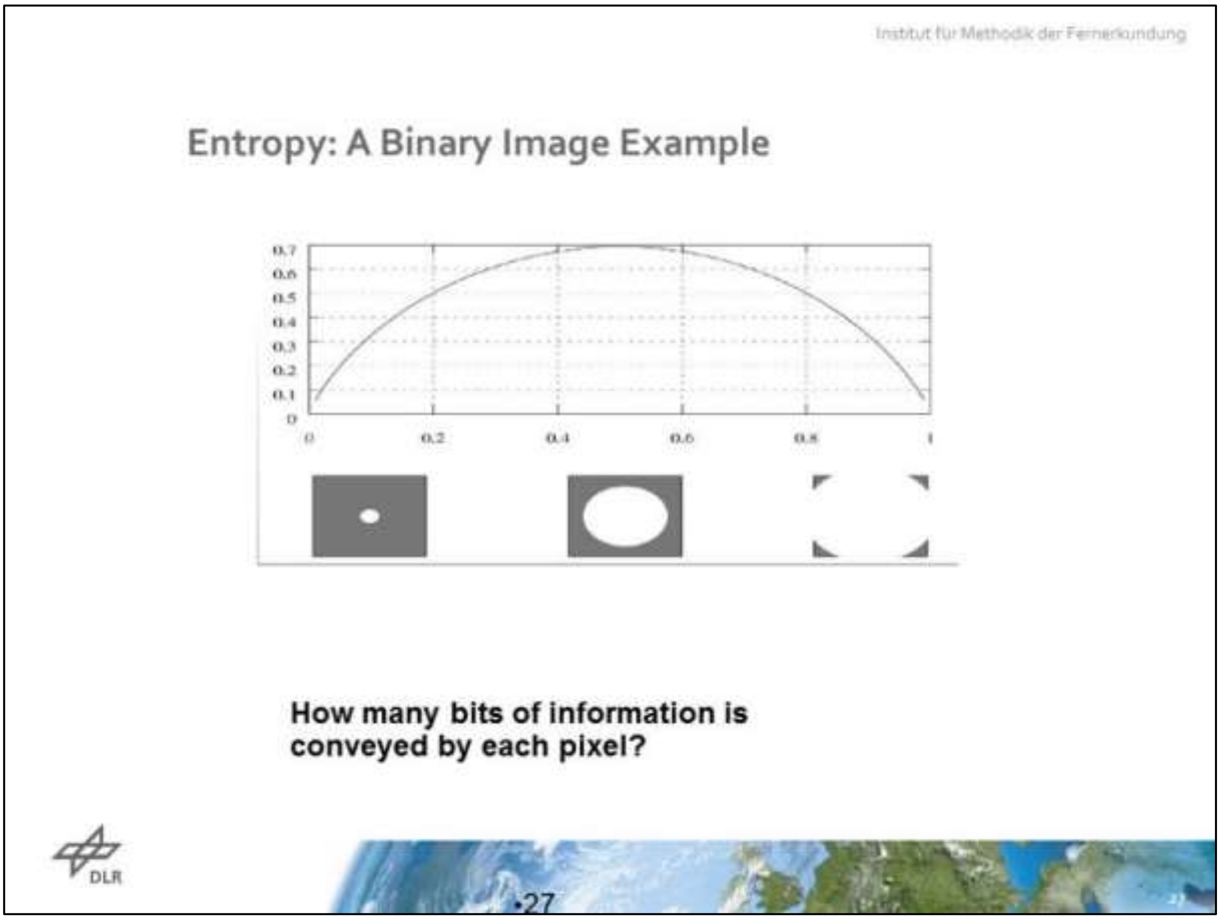
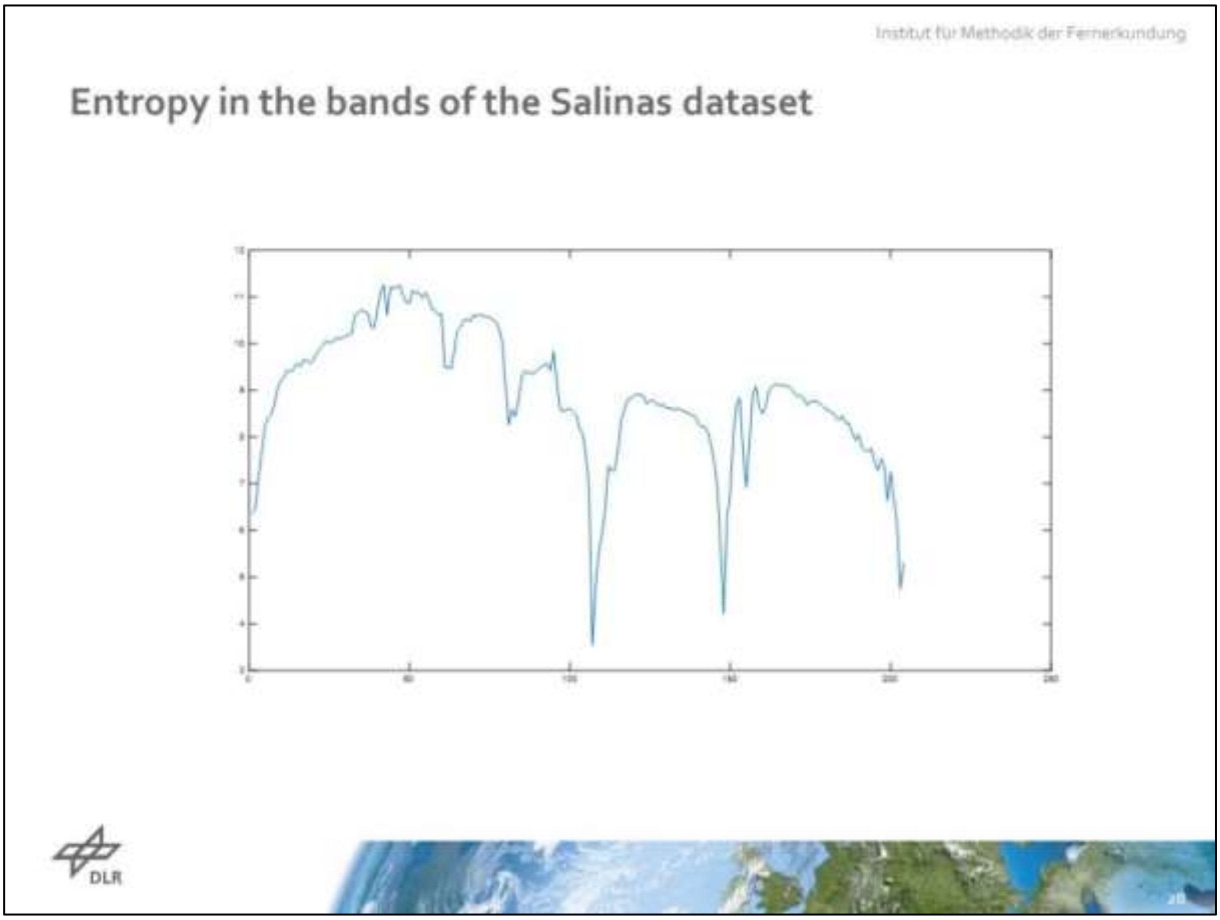
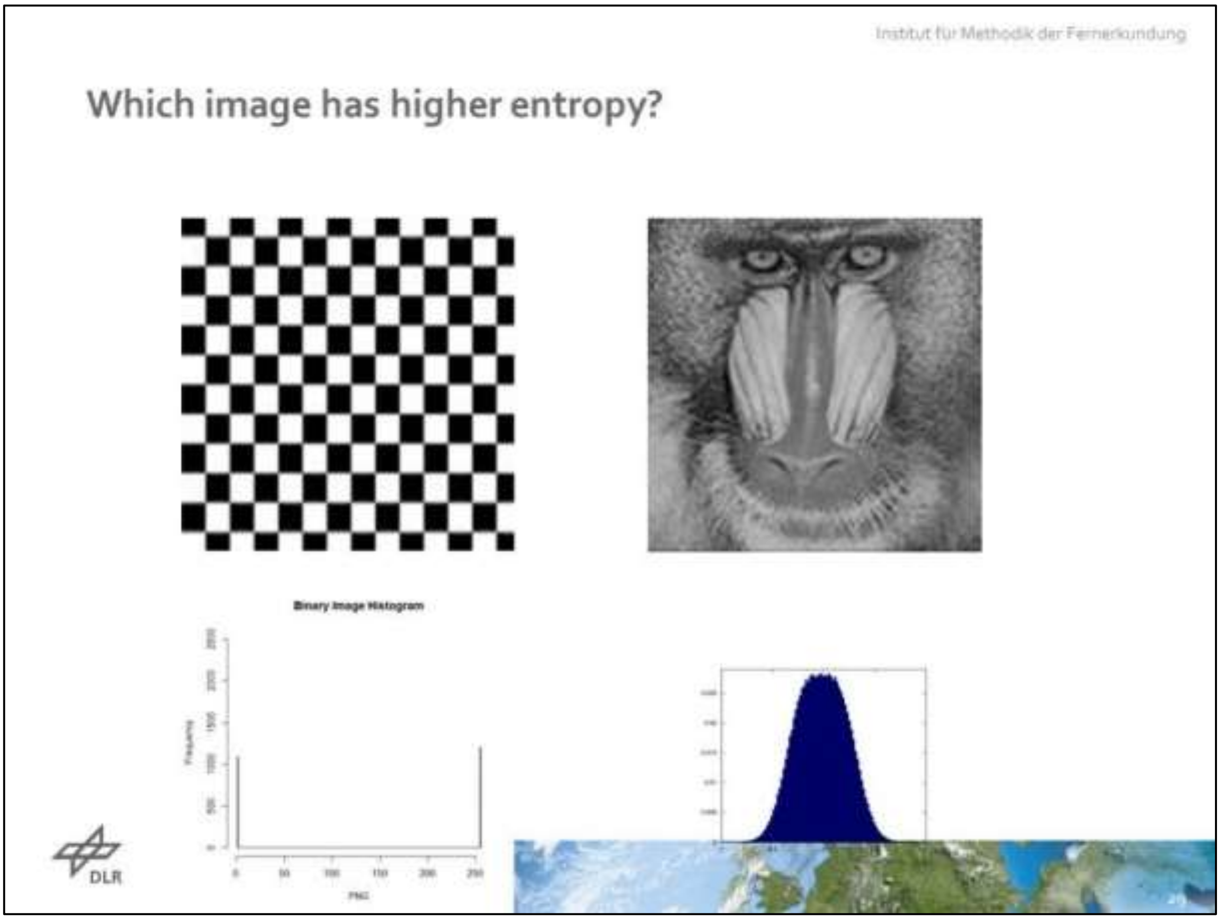
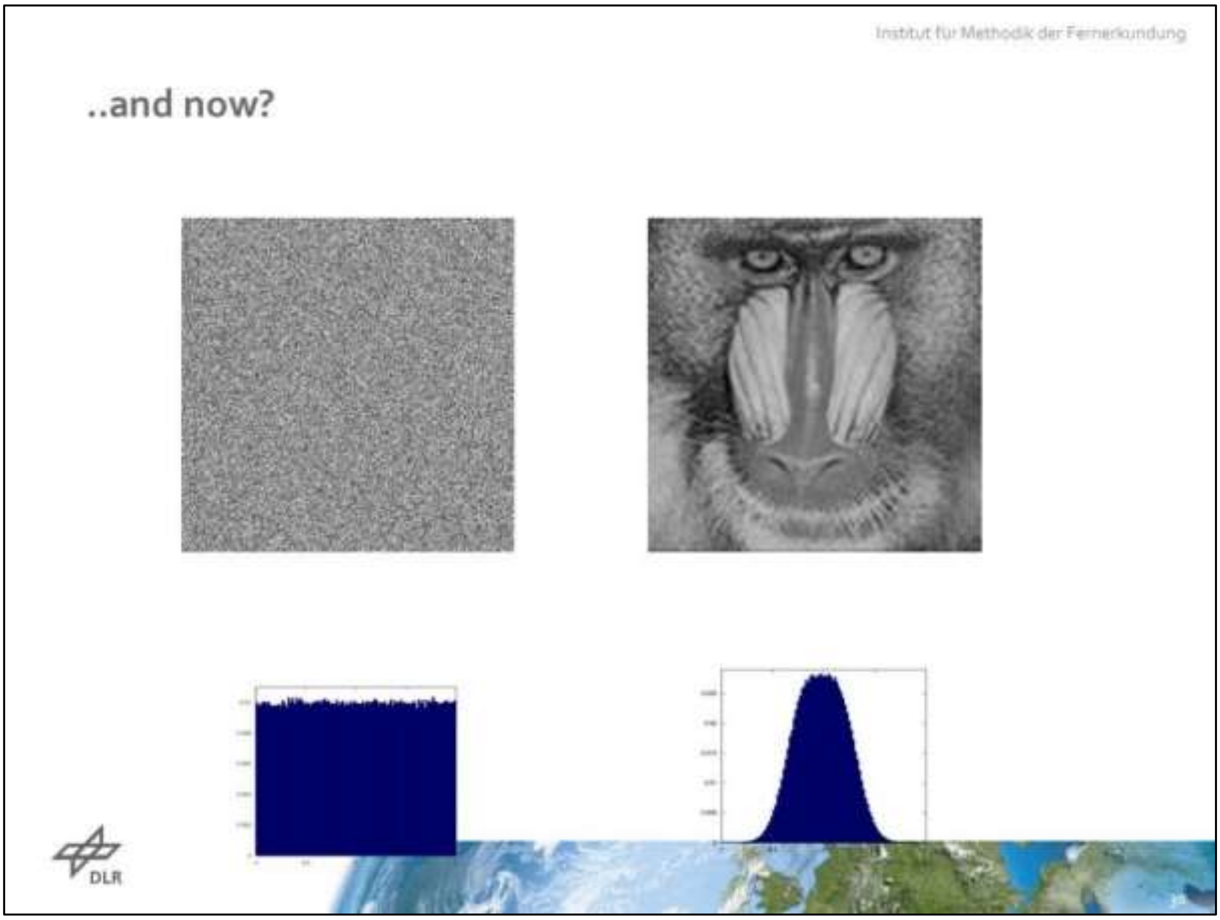
Shannon Entropy
$H(X) = -\sum_x p(x) \log p(x)$
– Information content of the output of a random variable X
– Example: Entropy of the outcomes of the toss of a biased/unbiased coin
– Max H(X) -> Coin not biased
– Every toss carries a full bit of information!
– Note: H(X) can be (much) greater than 1 if the values that X can take are more than two!
1.0
0.5
0
$H(X)$
0
0.5
1.0
$\Pr(X = 1)$
DLR

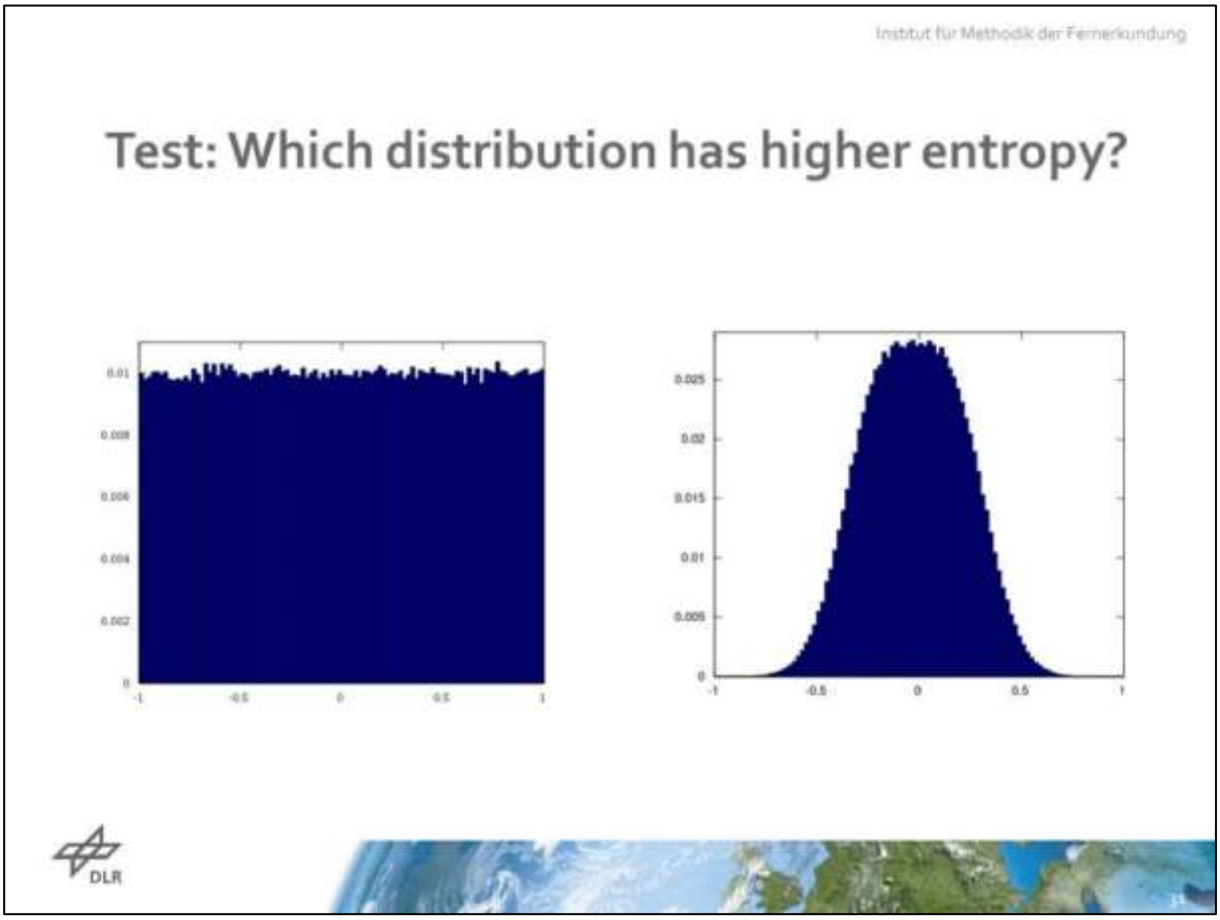

Institut für Methodik der Fernerkundung
Test: Which distribution has higher entropy?
0.01
0.008
0.006
0.004
0.002
0
-1
-0.5
0
0.5
1
0.025
0.02
0.015
0.01
0.005
0
-1
-0.5
0
0.5
1
DLR

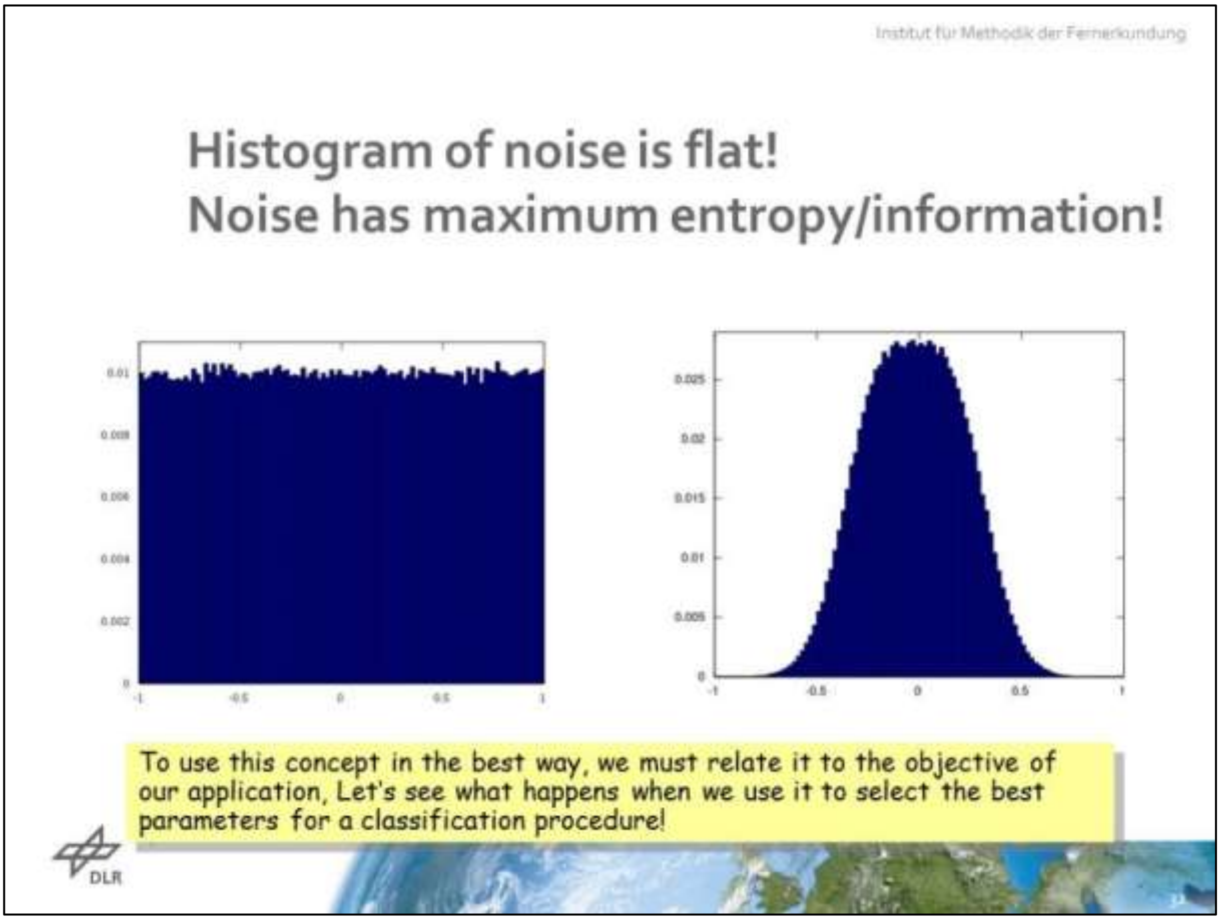

Institut für Methodik der Fernerkundung
Entropy: A Binary Image Example
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
0.2
0.4
0.6
0.8
1
How many bits of information is conveyed by each pixel?
DLR
•27


Institut für Methodik der Fernerkundung
Entropy in the bands of the Salinas dataset
DLR


Institut für Methodik der Fernerkundung
Which image has higher entropy?
Binary Image Histogram
DLR


Institut für Methodik der Fernerkundung
..and now?
DLR


Institut für Methodik der Fernerkundung
Test: Which distribution has higher entropy?
DLR


Institut für Methodik der Fernerkundung
Histogram of noise is flat!
Noise has maximum entropy/information!
To use this concept in the best way, we must relate it to the objective of our application, Let's see what happens when we use it to select the best parameters for a classification procedure!
DLR

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Entropy → Mutual Information

Basic Property of a signal → Dependence on another variable

Unsupervised → Supervised Information Quantification

DLR

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Pixel	Value in band 1	Value in band 2	Value in band 3	Class
X:100, Y:120	10	30	50	Broccoli
X:50, Y:100	25	130	50	Fallow
X:16, Y:12	13	12	48	Grapes
X:200, Y:420	5	70	49	Corn

Which band is better to separate these classes? Which one will give me the maximum information gain? And which one would only make things more difficult?

DLR

•Exercise 20

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Mutual Information

(can be expressed in terms of probability)

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \left(\frac{p(x,y)}{p(x)\,p(y)} \right),$$

DLR

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Small Test

- Suppose we have the following random variables
  - x = "is the temperature below 0 degrees?" → (0 = no, 1 = yes)
  - y = "do I have ice or water?" → (0 = ice, 1 = water)
  - z = "is it snowing outside?"→ (0 = no, 1 = yes)
  - w = „Are the Simpsons today on Pro7?"→ (0 = no, 1 = yes)
- How do you expect the mutual information to be between:
  - X and Y
  - X and Z
  - Y and Z
  - X and W

DLR

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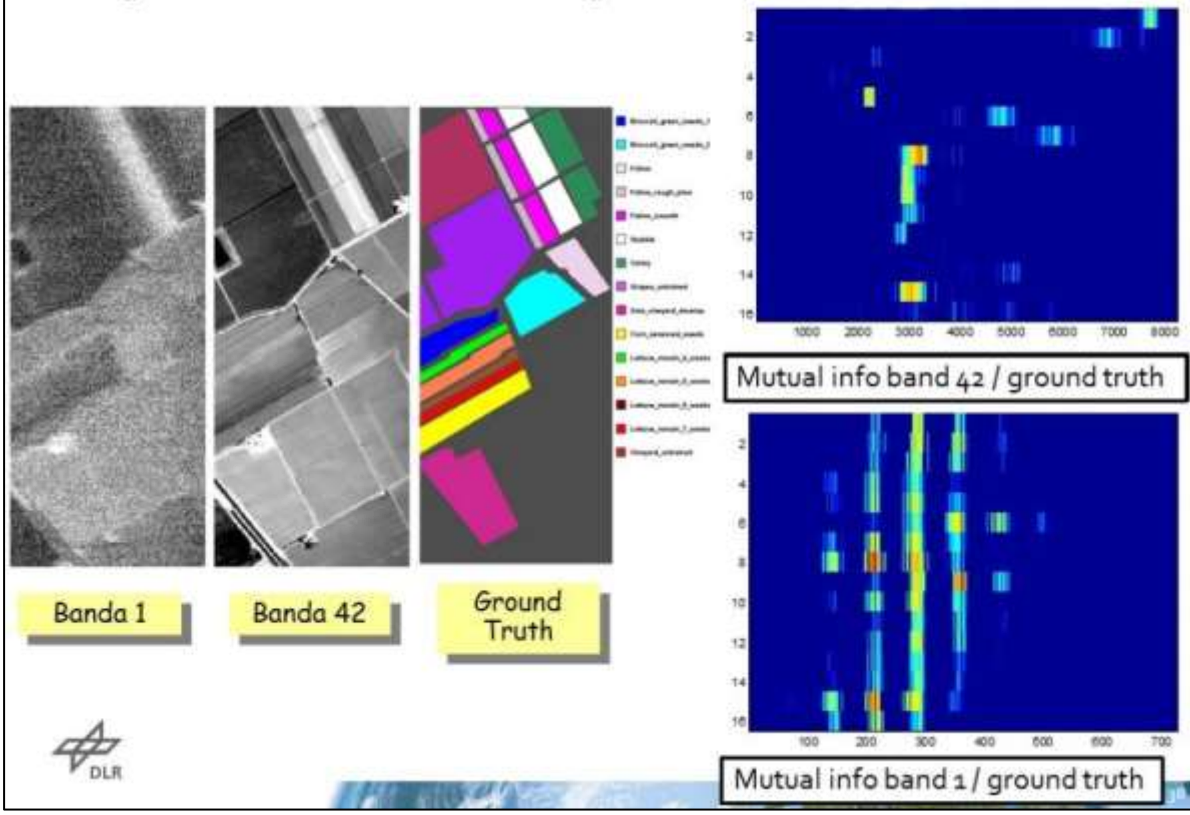
Mutual Information for HS data analysis

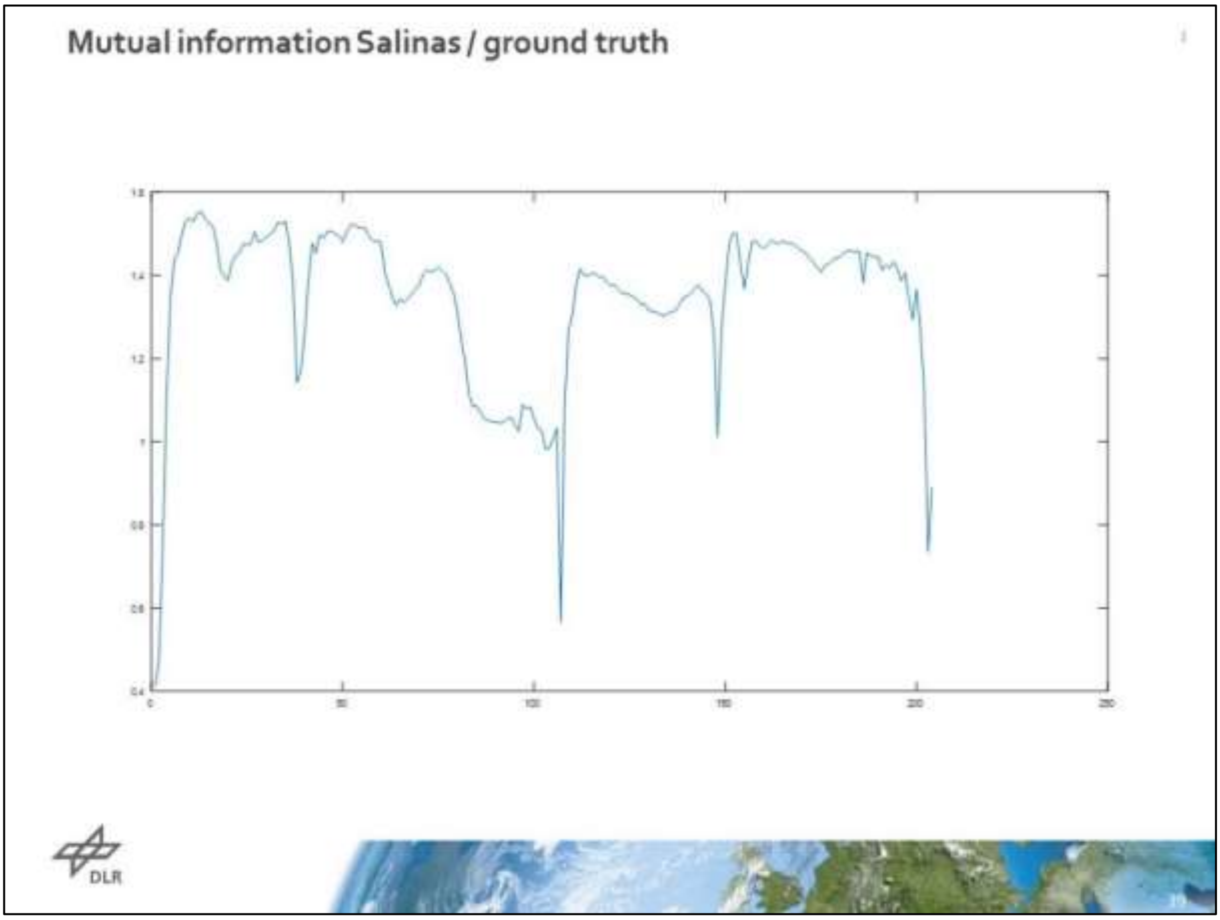
- What we REALLY want is how to select bands which are good to classify a specific dataset.
- The MI is great at finding correspondences between variables, even if their values are very different!
    - For example it has been used in our department to improve coregistration between radar and optical data, which are completely different!!

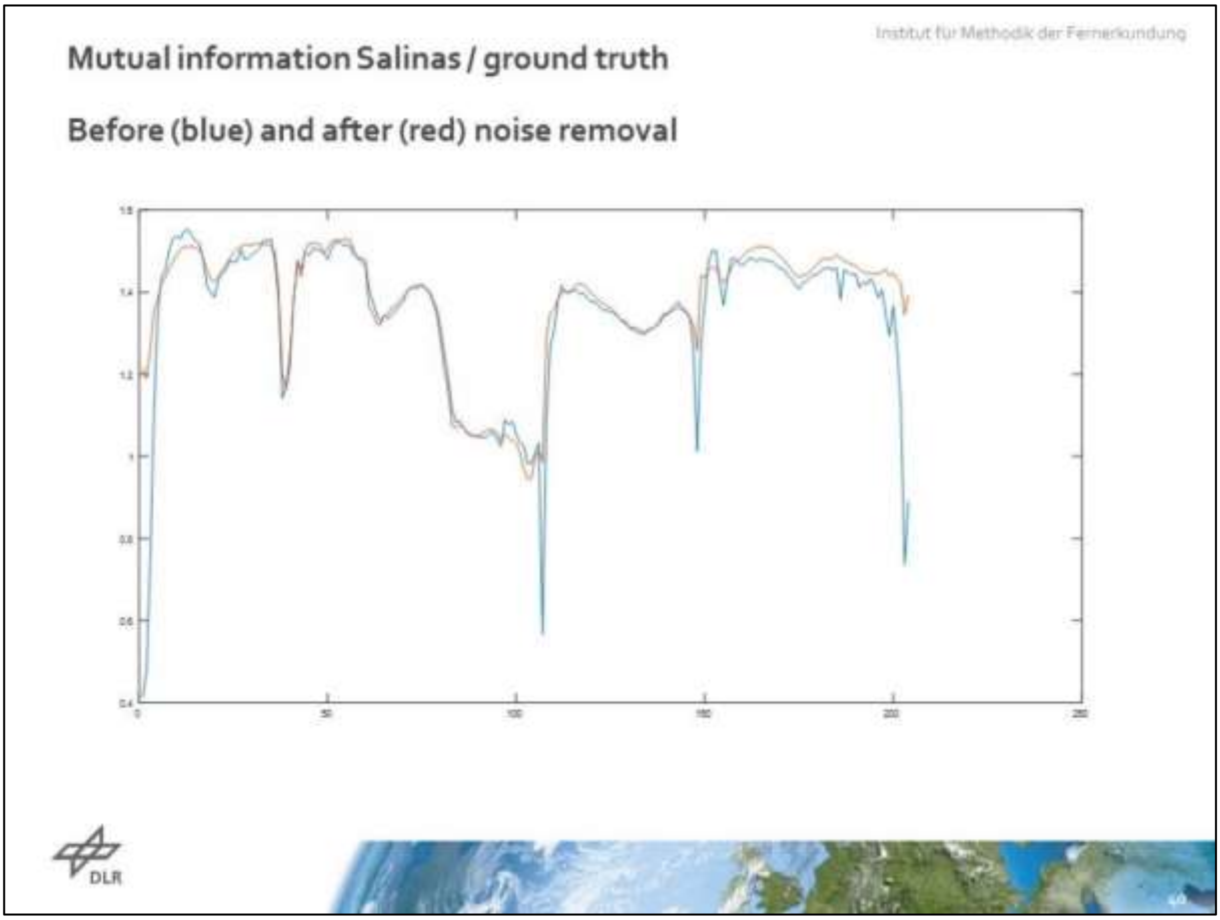
DLR

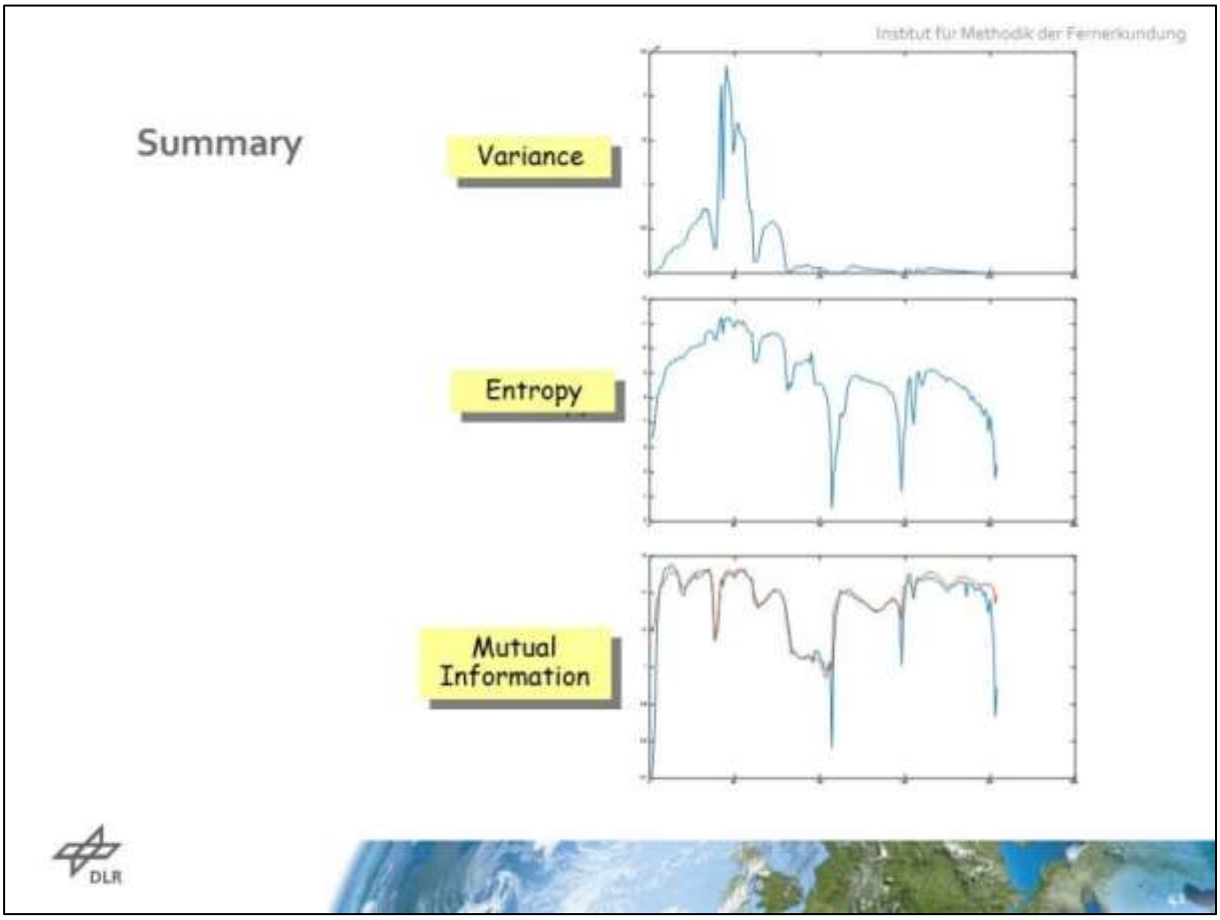
The mutual information between any two bands in the Salinas dataset and the ground truth are based on these joint distributions…

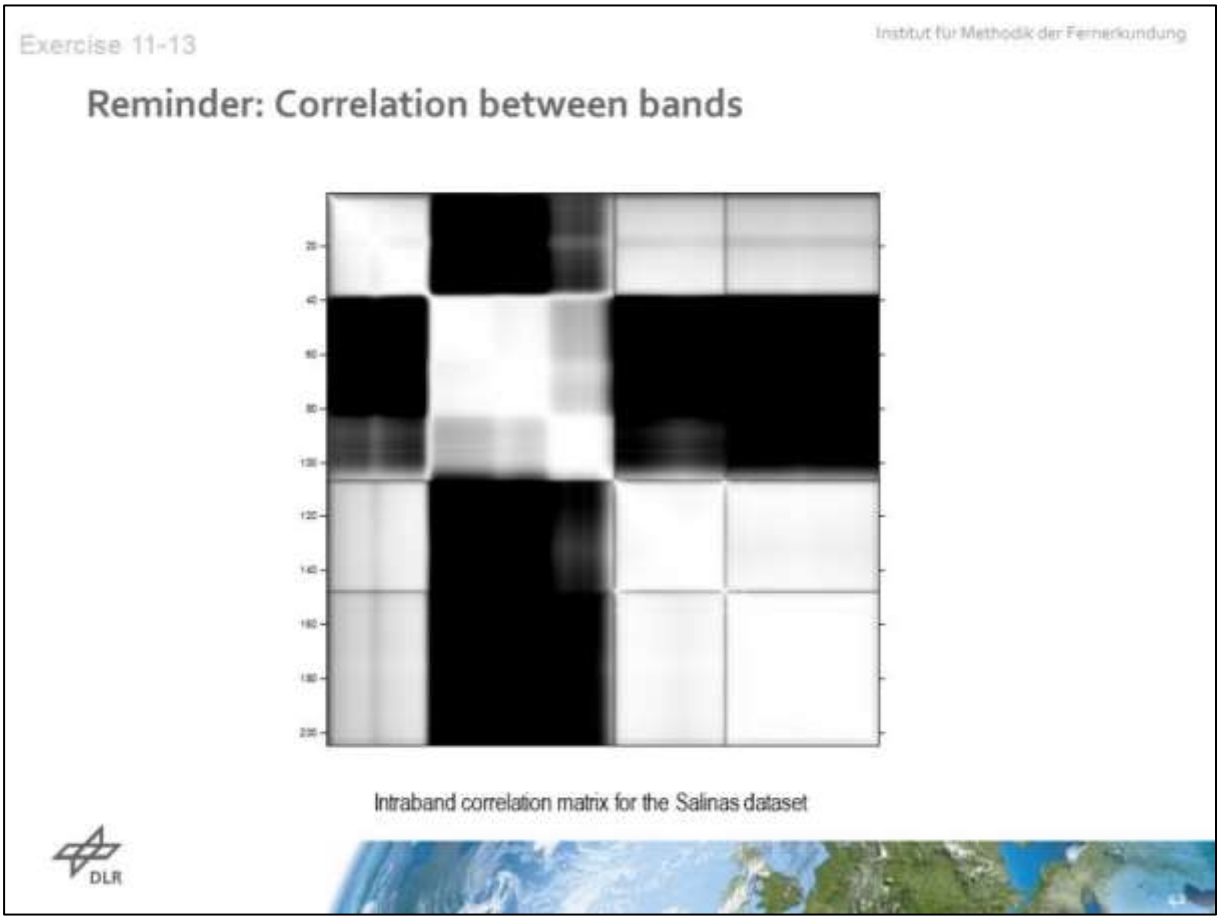


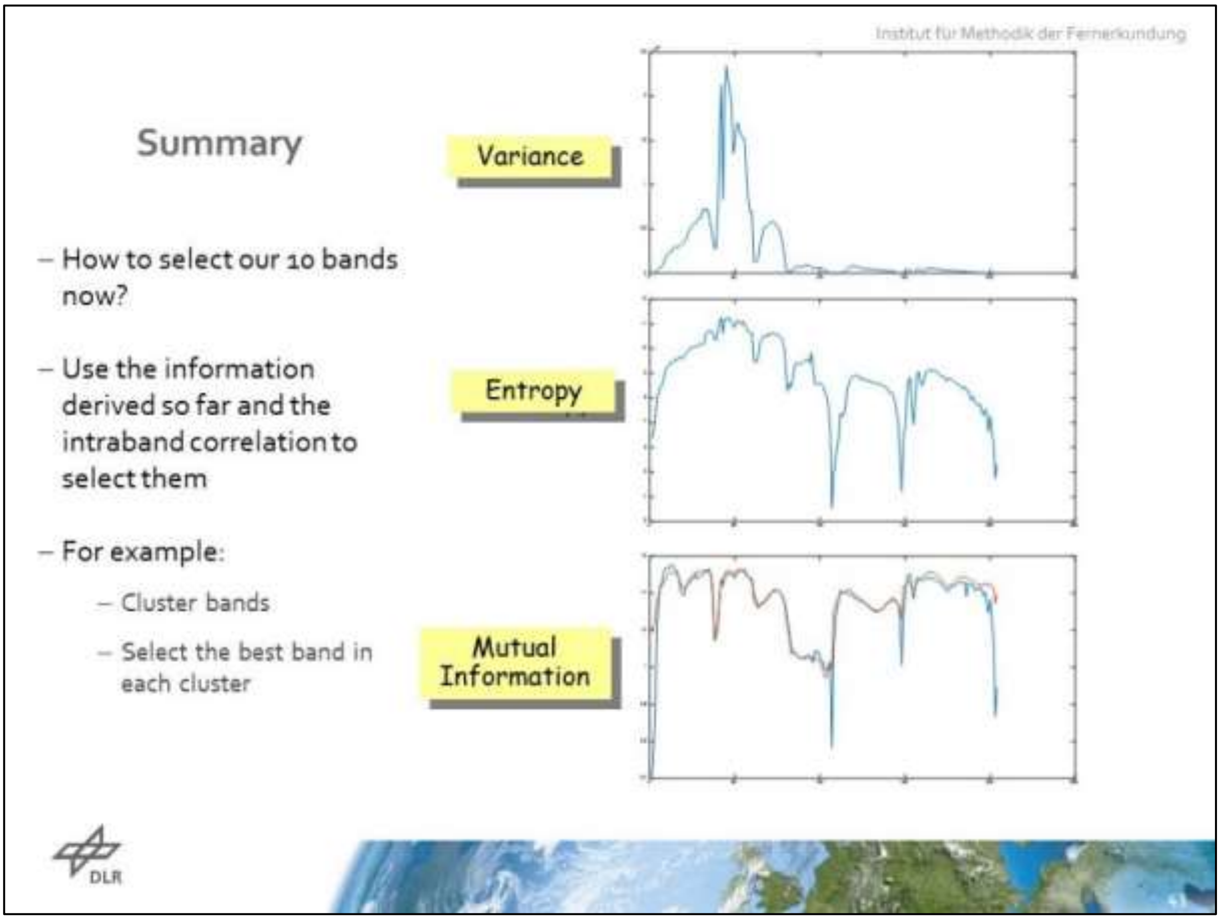
DLR

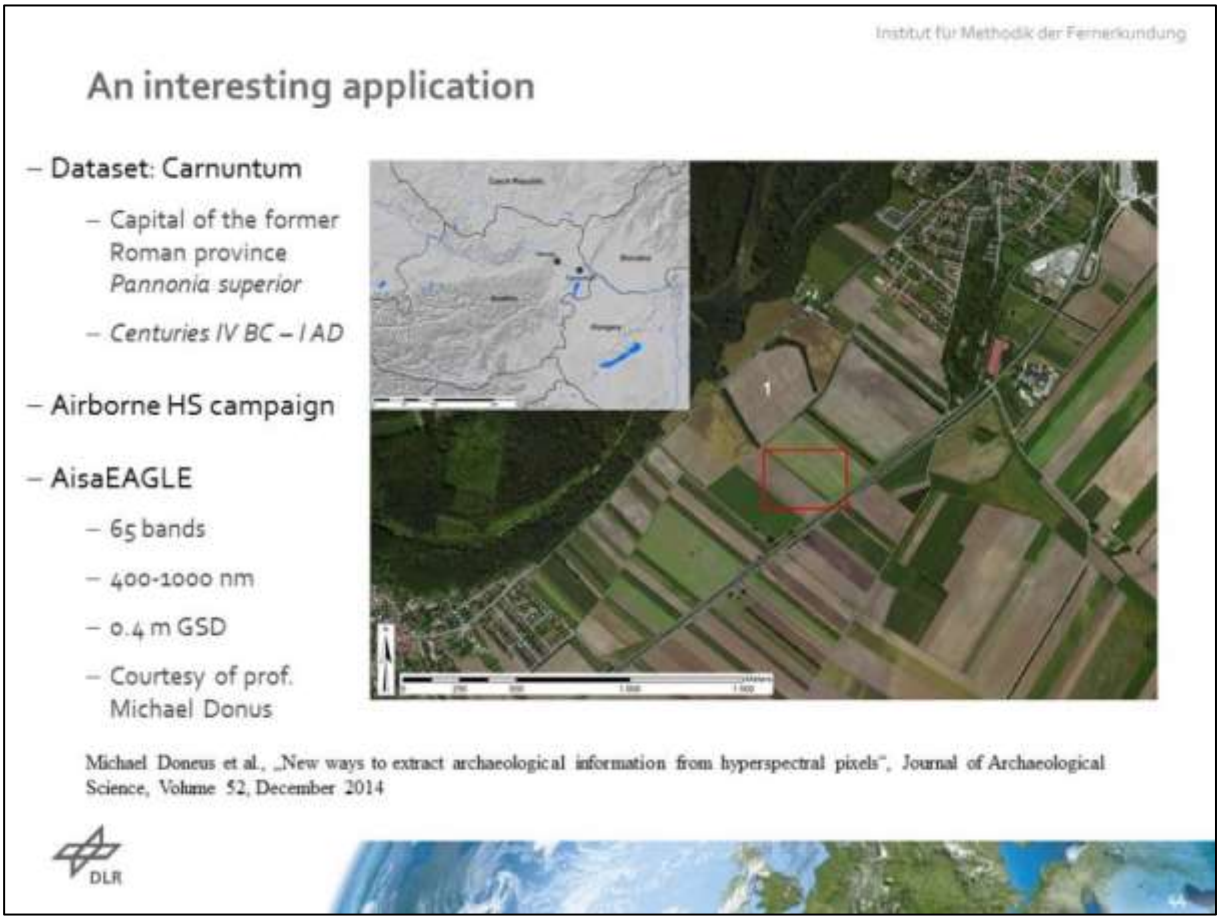

Mutual information Salinas / ground truth
DLR


Institut für Methodik der Fernerkundung
Mutual information Salinas / ground truth
Before (blue) and after (red) noise removal
DLR


Institut für Methodik der Fernerkundung
Summary
Variance
Entropy
Mutual Information
DLR


Exercise 11-13
Institut für Methodik der Fernerkundung
Reminder: Correlation between bands
Intraband correlation matrix for the Salinas dataset
DLR


Institut für Methodik der Fernerkundung
Summary
– How to select our 10 bands now?
– Use the information derived so far and the intraband correlation to select them
– For example:
– Cluster bands
– Select the best band in each cluster
Variance
Entropy
Mutual Information
DLR


Institut für Methodik der Fernerkundung
An interesting application
– Dataset: Carnuntum
– Capital of the former Roman province *Pannonia superior*
– *Centuries IV BC – I AD*
– Airborne HS campaign
– AisaEAGLE
– 65 bands
– 400-1000 nm
– 0.4 m GSD
– Courtesy of prof. Michael Donus
Michael Doneus et al., „New ways to extract archaeological information from hyperspectral pixels", Journal of Archaeological Science, Volume 52, December 2014
DLR

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How to highlight crop marks?

DLR

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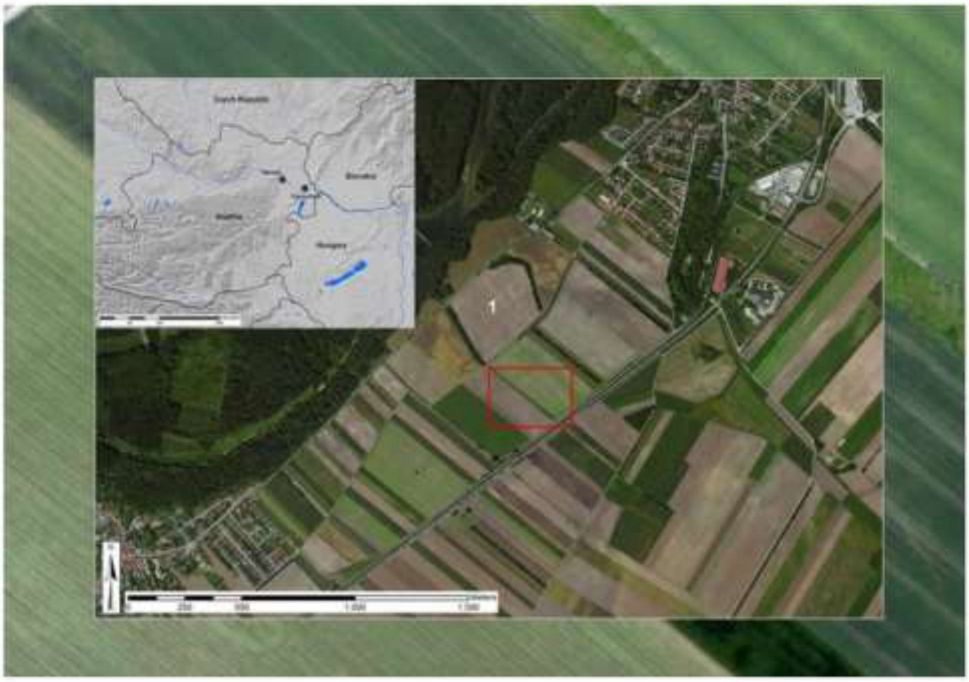
Not always that easy...



DLR


Institut für Methodik der Fernerkundung
Not always that easy...
B
RGB True Color Composite
DLR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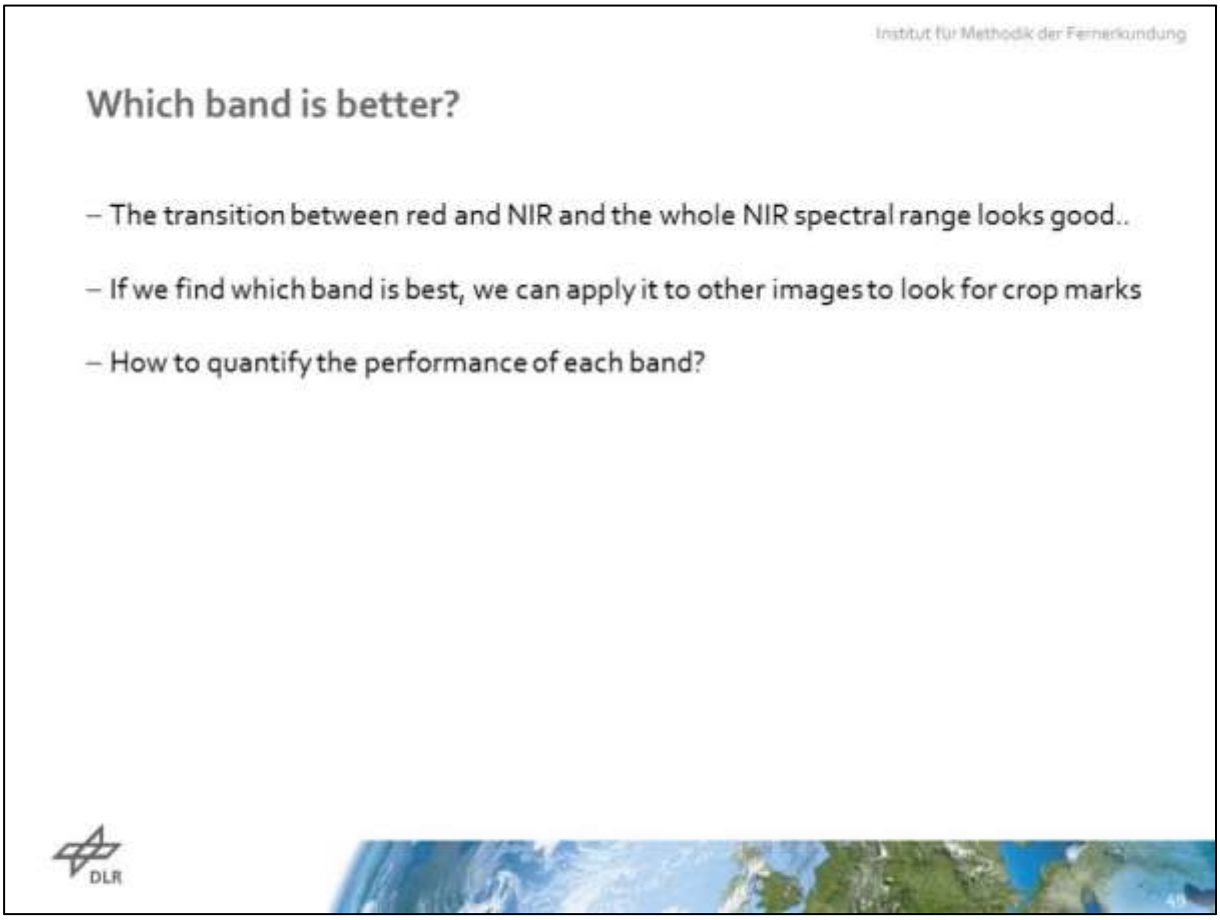
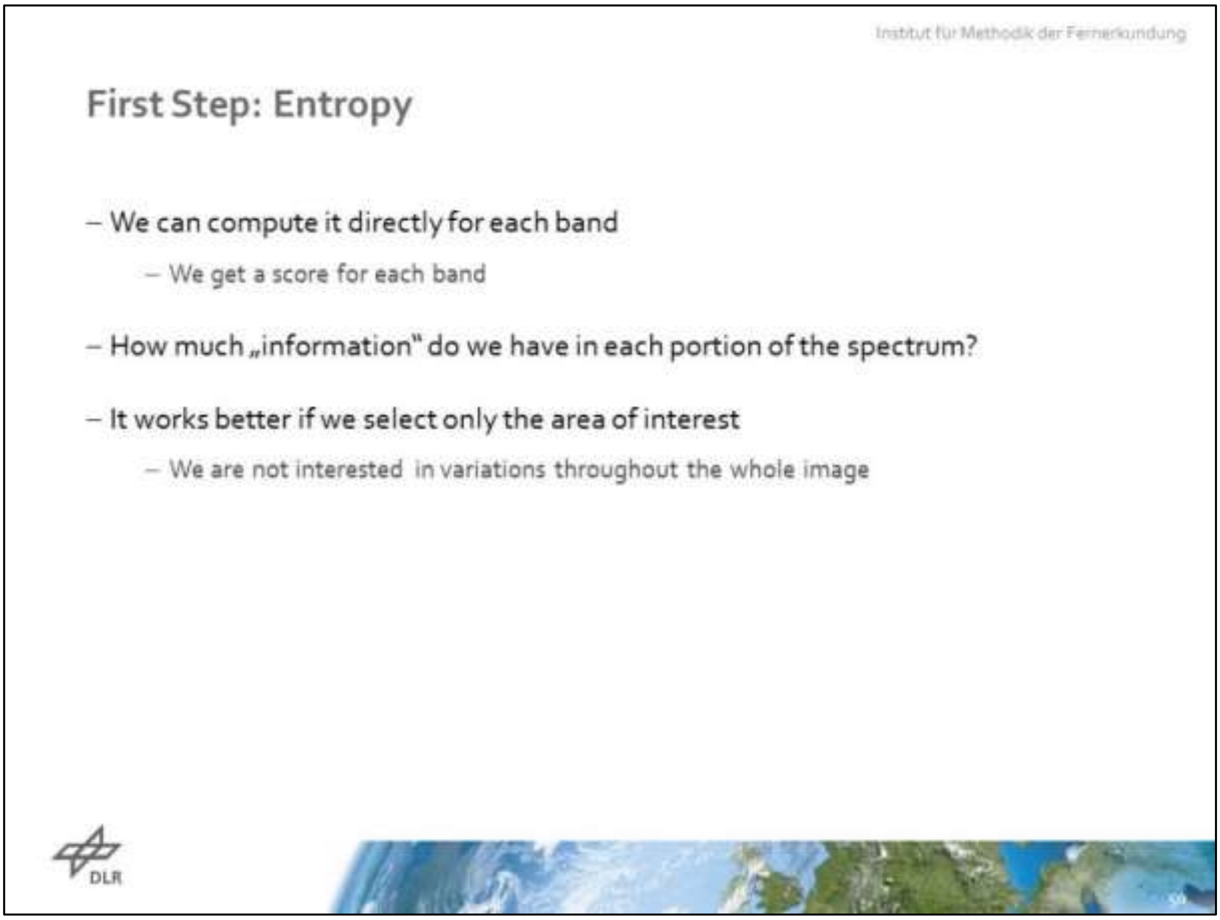
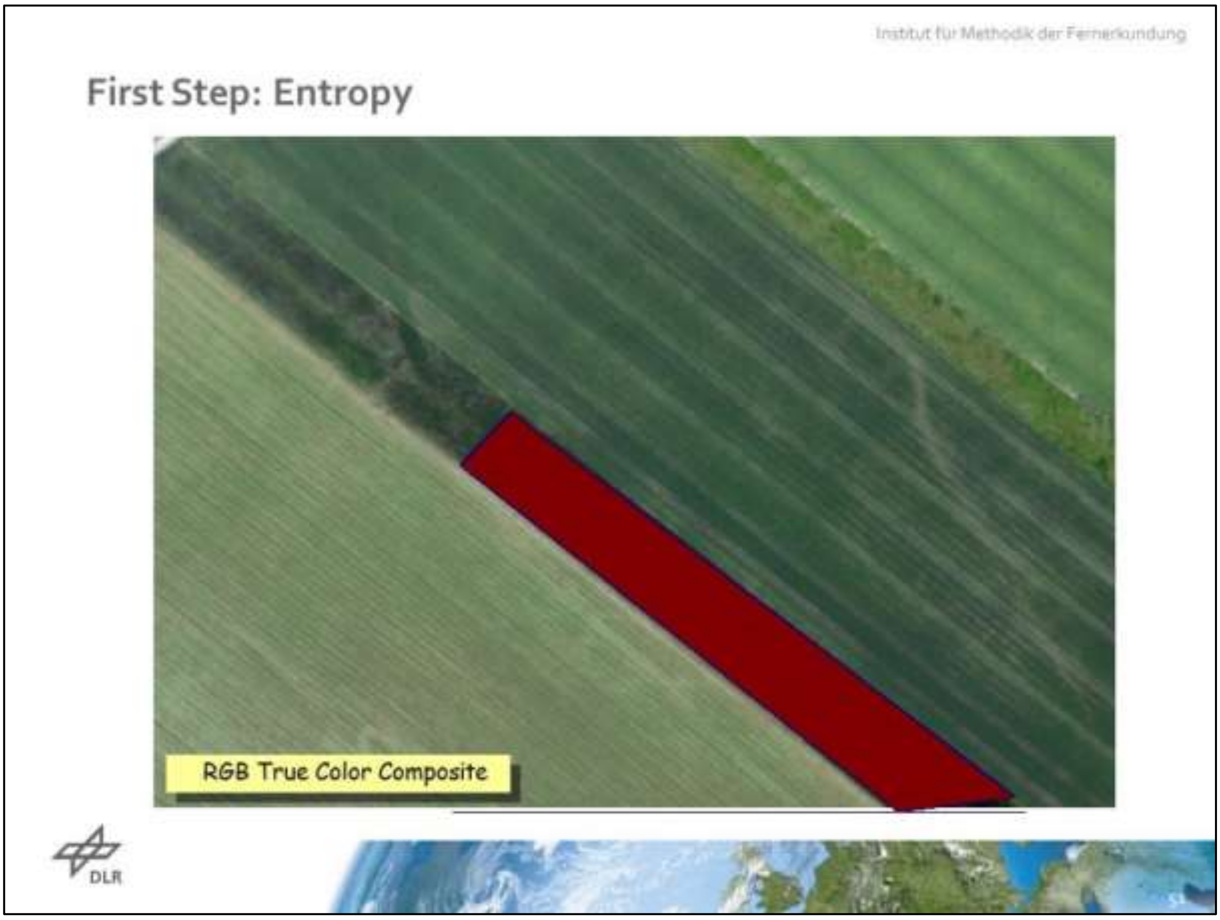
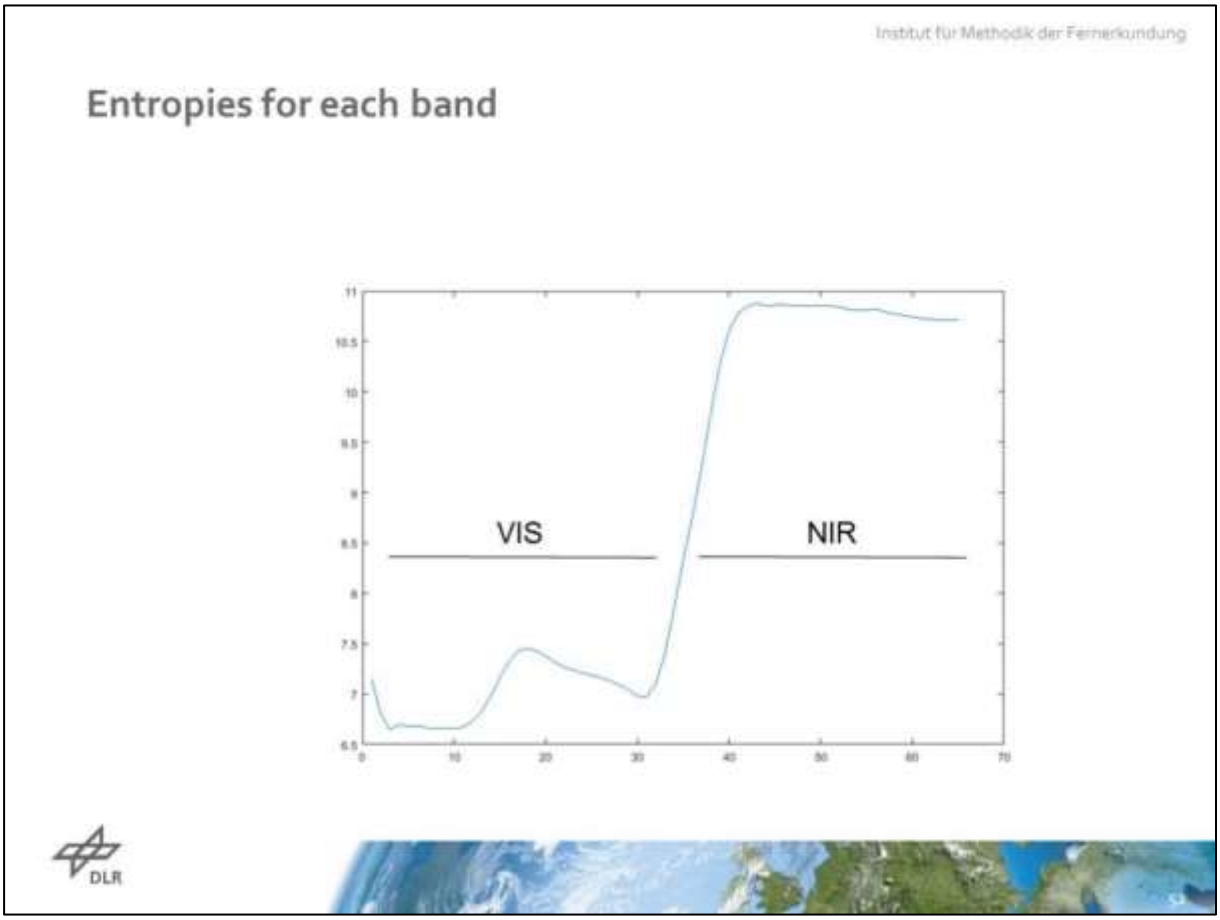
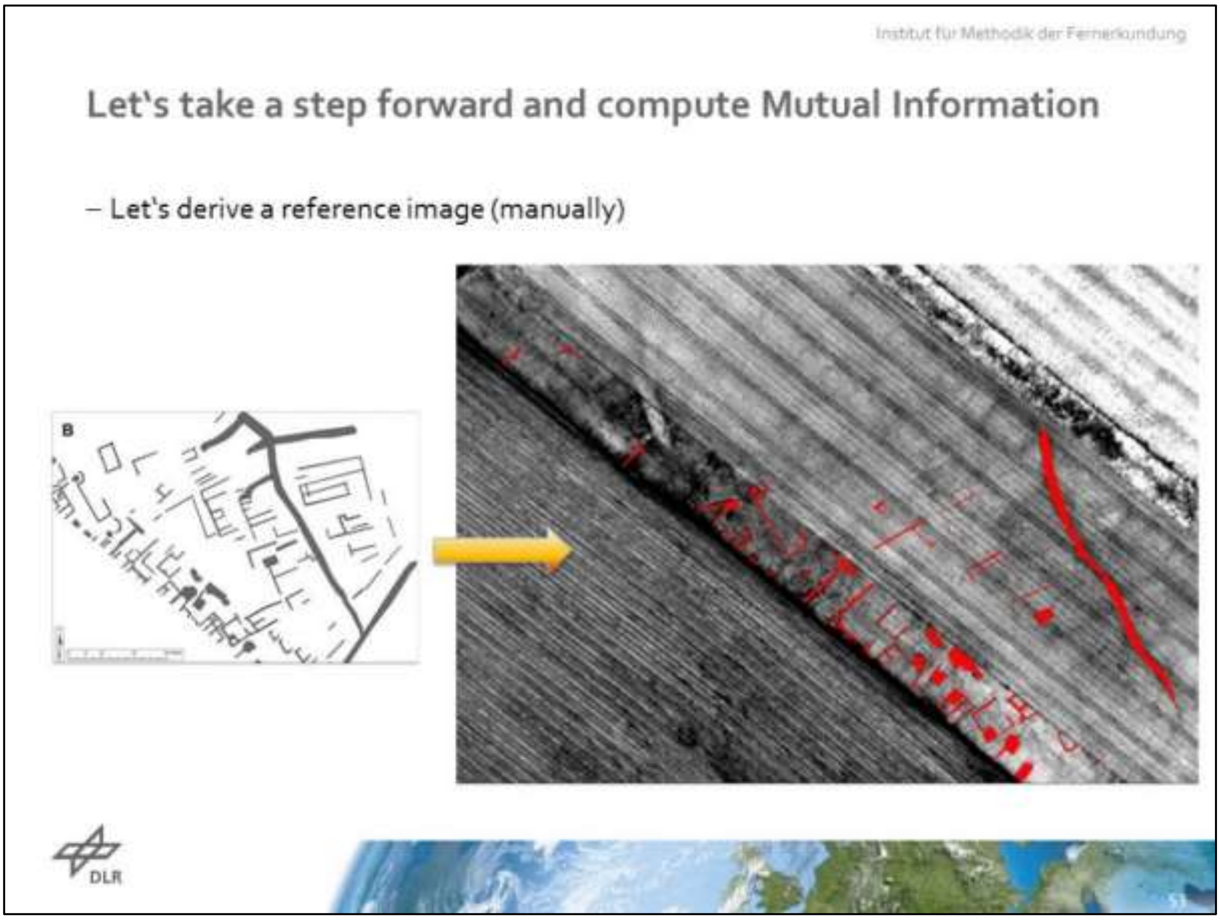
Which band is better?
– Let's have a look at all available bands...
DLR

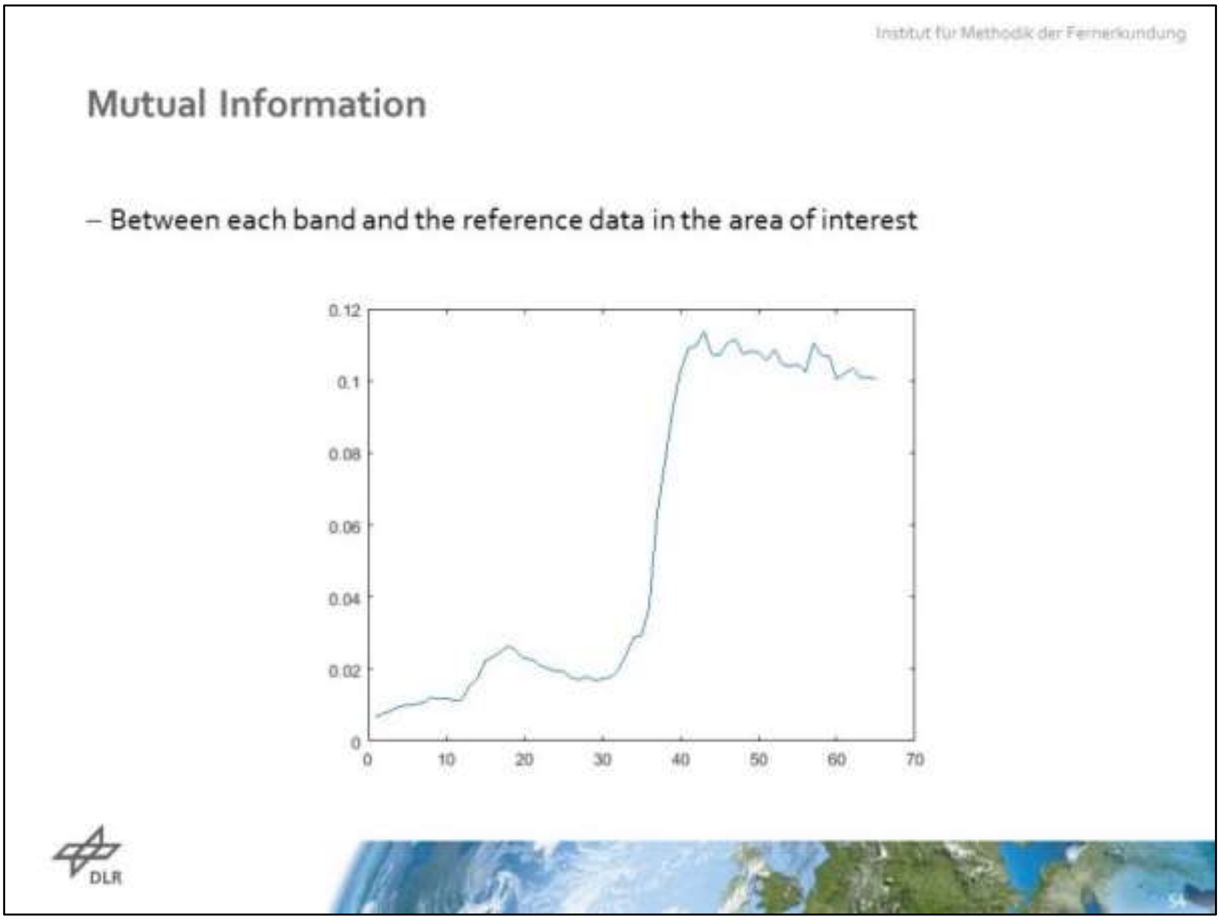

Institut für Methodik der Fernerkundung
Which band is better?
– The transition between red and NIR and the whole NIR spectral range looks good..
– If we find which band is best, we can apply it to other images to look for crop marks
– How to quantify the performance of each band?
DLR

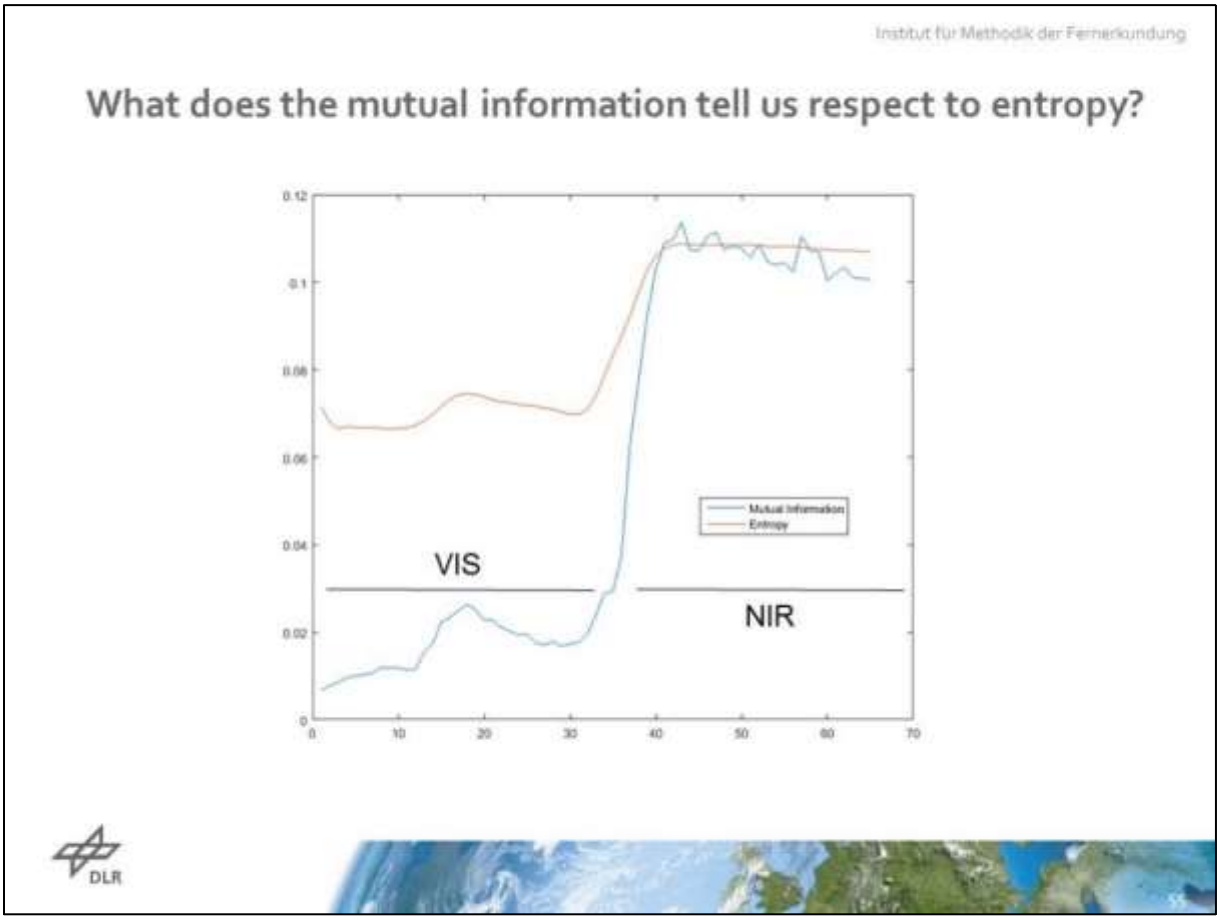

Institut für Methodik der Fernerkundung
First Step: Entropy
– We can compute it directly for each band
– We get a score for each band
– How much „information" do we have in each portion of the spectrum?
– It works better if we select only the area of interest
– We are not interested in variations throughout the whole image
DLR

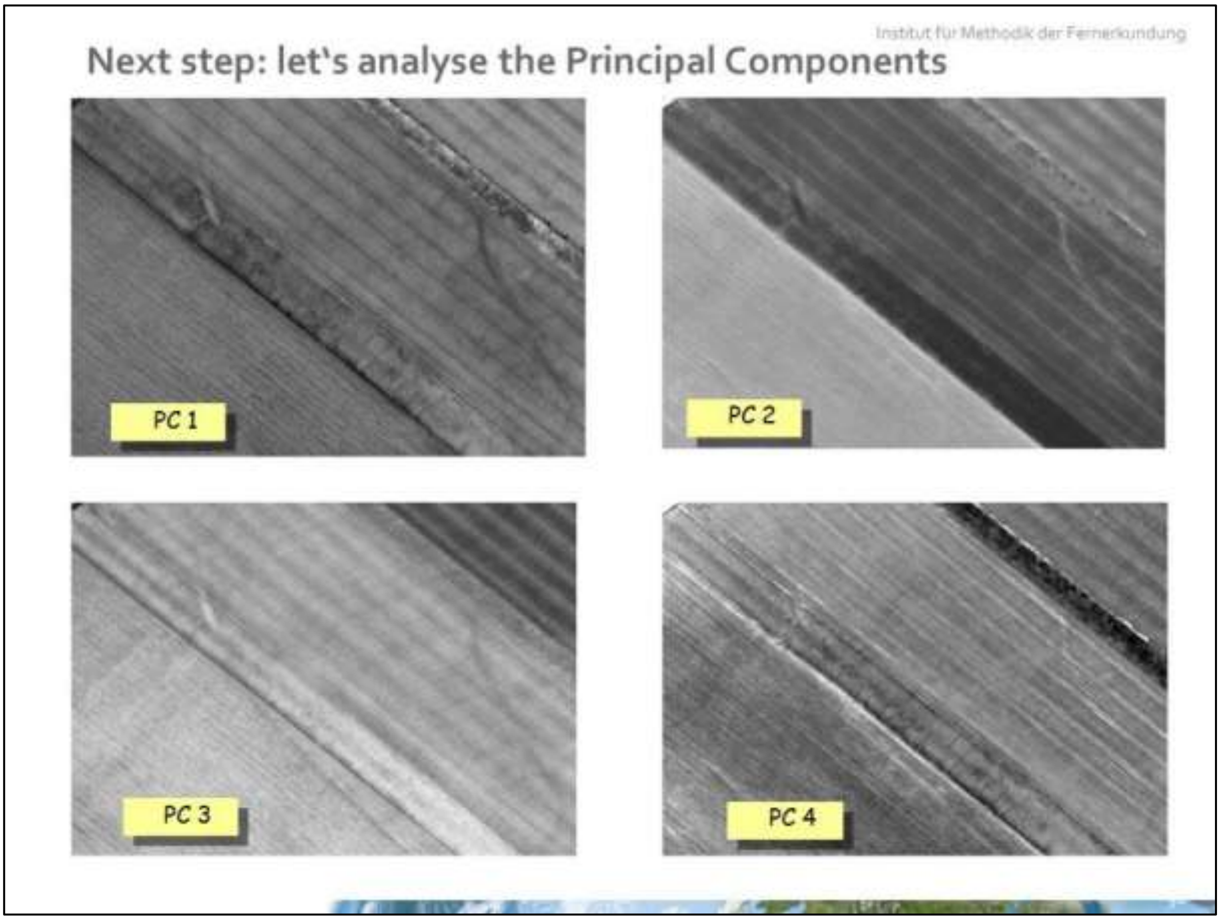

Institut für Methodik der Fernerkundung
First Step: Entropy
RGB True Color Composite
DLR

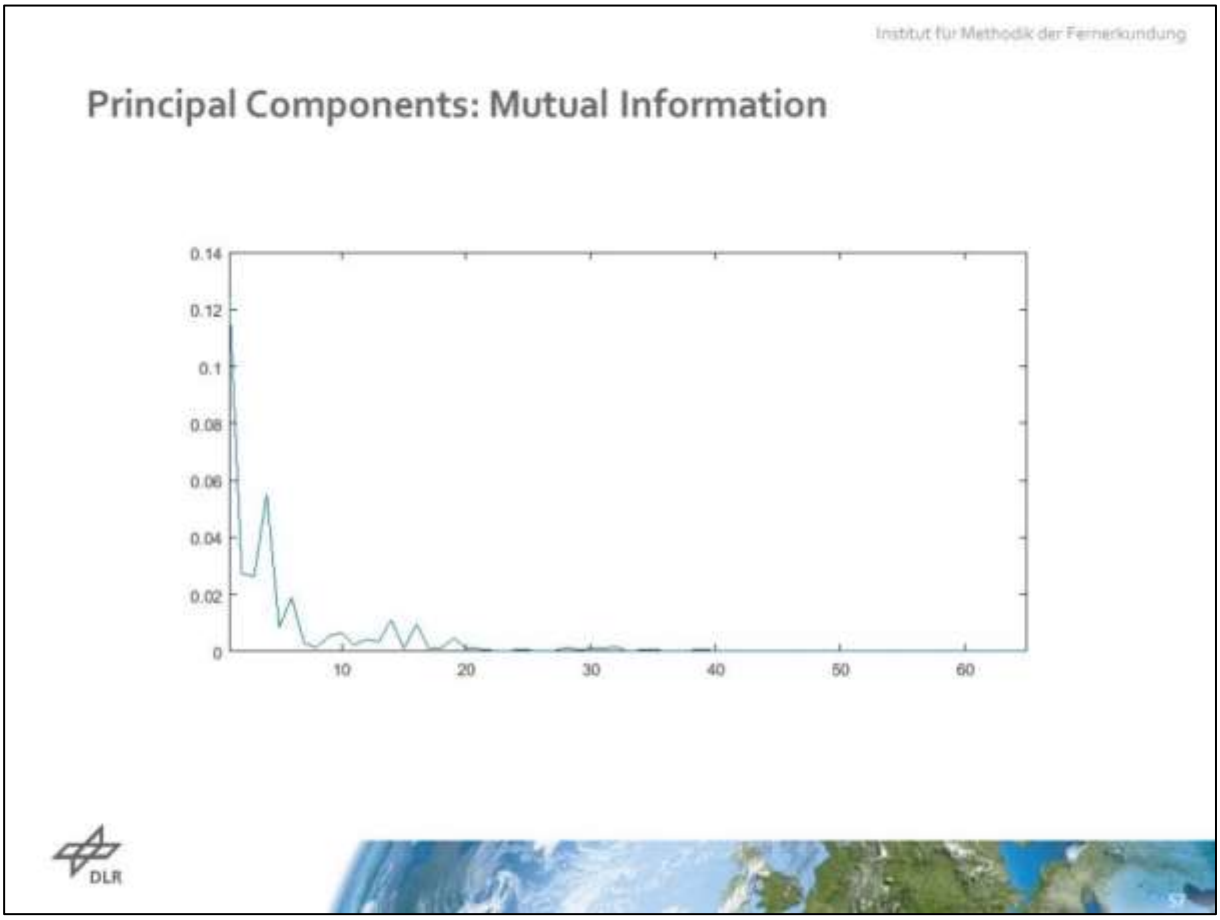

Institut für Methodik der Fernerkundung
Entropies for each band
VIS
NIR
DLR

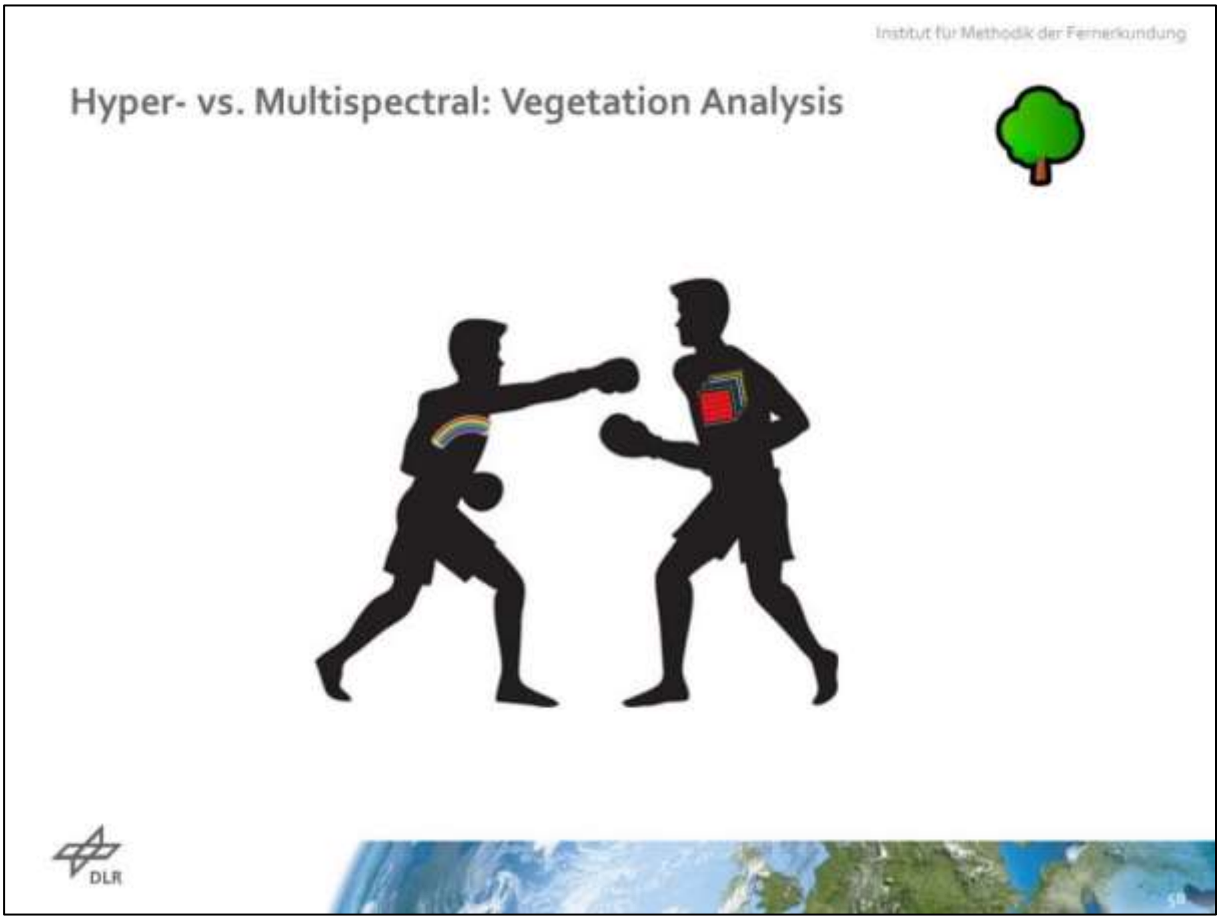

Institut für Methodik der Fernerkundung
Let's take a step forward and compute Mutual Information
– Let's derive a reference image (manually)
B
DLR

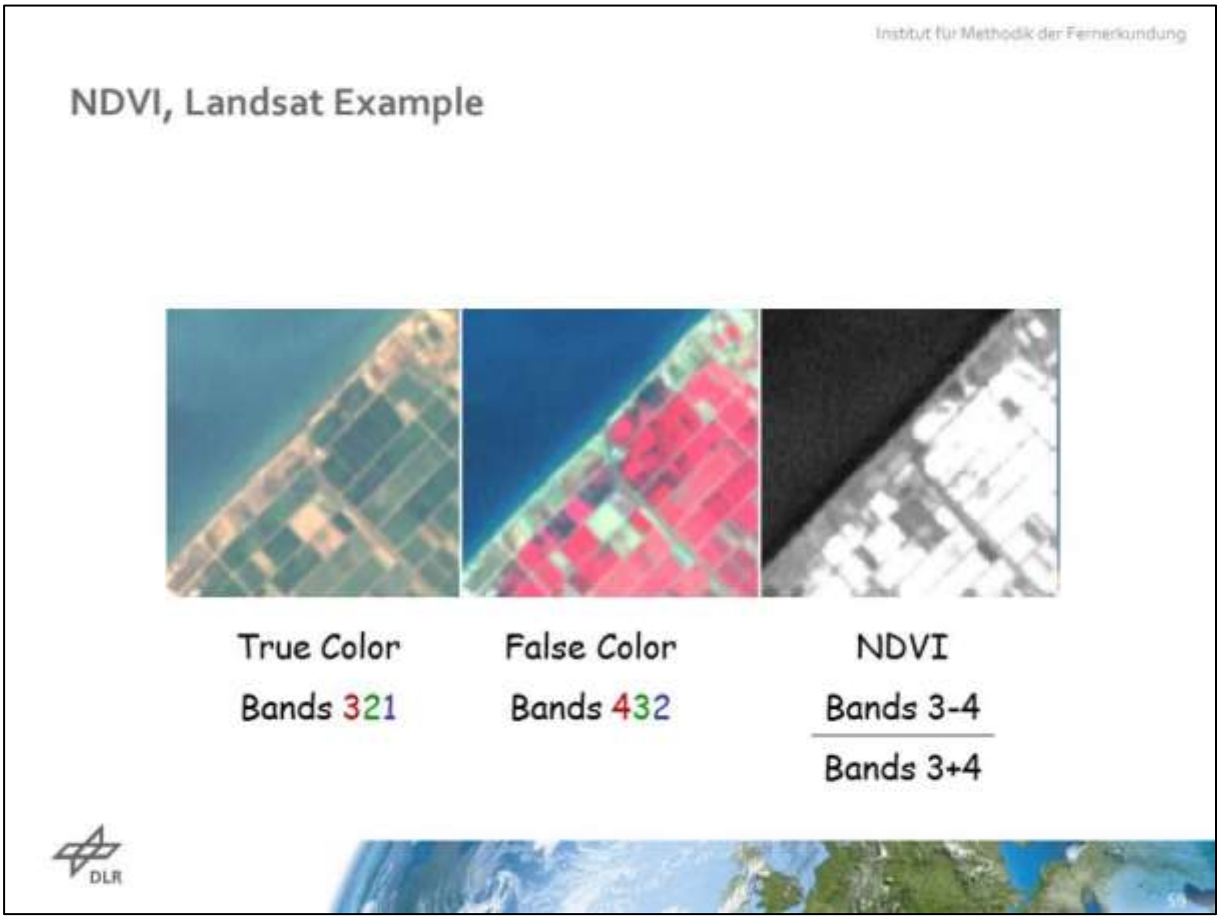

Institut für Methodik der Fernerkundung
Mutual Information
– Between each band and the reference data in the area of interest
0.12
0.1
0.08
0.06
0.04
0.02
0
0
10
20
30
40
50
60
70
DLR

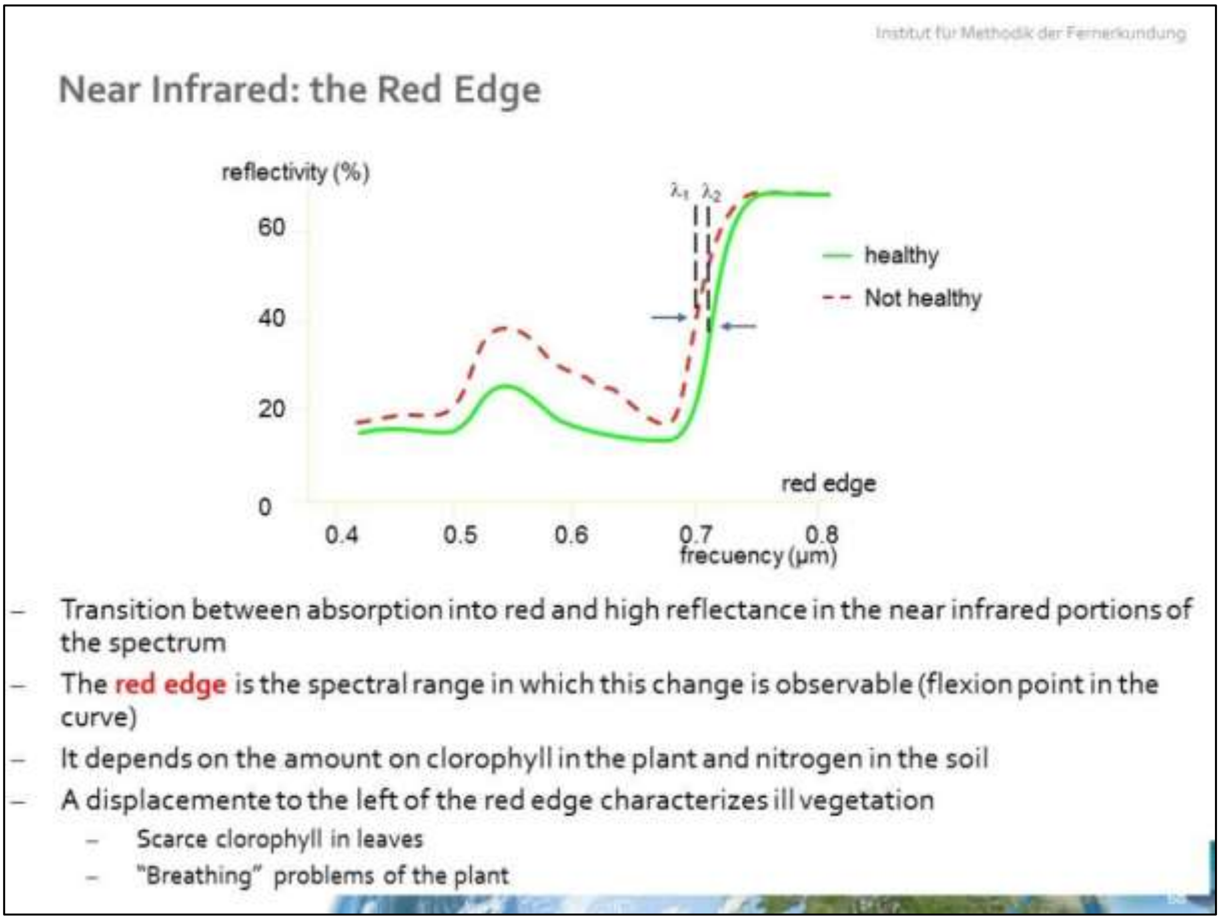

Institut für Methodik der Fernerkundung
What does the mutual information tell us respect to entropy?
0.12
0.1
0.08
0.06
0.04
0.02
0
0
10
20
30
40
50
60
70
Mutual Information
Entropy
VIS
NIR
DLR


Institut für Methodik der Fernerkundung
Next step: let‘s analyse the Principal Components
PC 1
PC 2
PC 3
PC 4

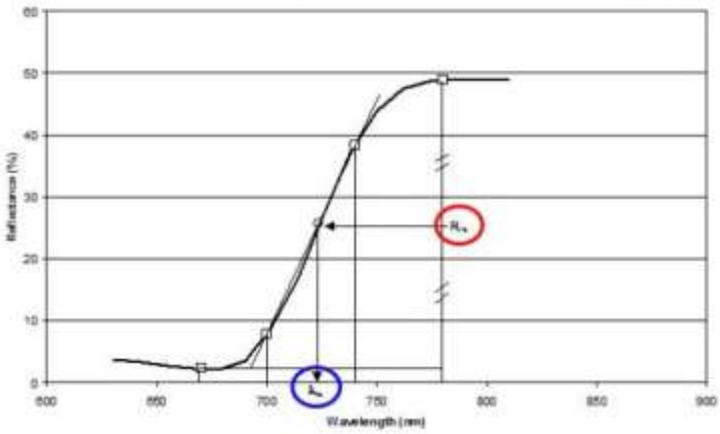

Institut für Methodik der Fernerkundung
Principal Components: Mutual Information
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
10
20
30
40
50
60
DLR


Institut für Methodik der Fernerkundung
Hyper- vs. Multispectral: Vegetation Analysis
DLR


Institut für Methodik der Fernerkundung
NDVI, Landsat Example
True Color
Bands 321
False Color
Bands 432
NDVI
Bands 3-4
Bands 3+4
DLR

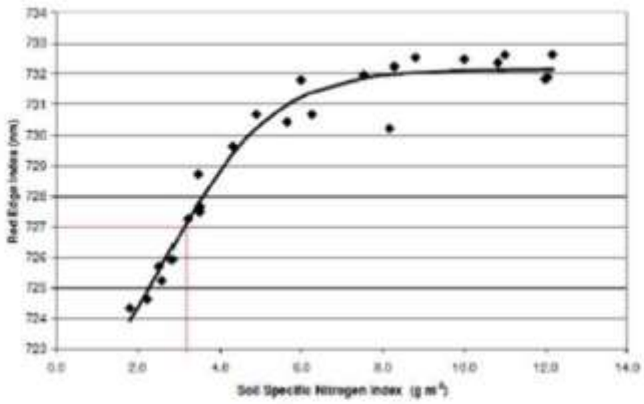

Institut für Methodik der Fernerkundung
Near Infrared: the Red Edge
reflectivity (%)
60
40
20
0
0.4
0.5
0.6
0.7
0.8
frecuency (μm)
healthy
Not healthy
red edge
– Transition between absorption into red and high reflectance in the near infrared portions of the spectrum
– The red edge is the spectral range in which this change is observable (flexion point in the curve)
– It depends on the amount on clorophyll in the plant and nitrogen in the soil
– A displacemente to the left of the red edge characterizes ill vegetation
– Scarce clorophyll in leaves
– "Breathing" problems of the plant

Example: How to compute the red edge position?



- Compute reflectivity in the inflection point in the spectrum x
  - $RE(x) = (R1(x) + R2(x))\,/\,2$
  - $R1(x)$ and $R2(x)$ are the reflectances at 670 and 780 nm
- Compute the red edge frequency position by the following equation:
  - $\lambda = 700 + 40\,((RE(x) - R3(x))\,/\,(R4(x) - R3(x)))$
  - $R3(x)$ and $R4(x)$ are reflectances at 700 and 740 nm

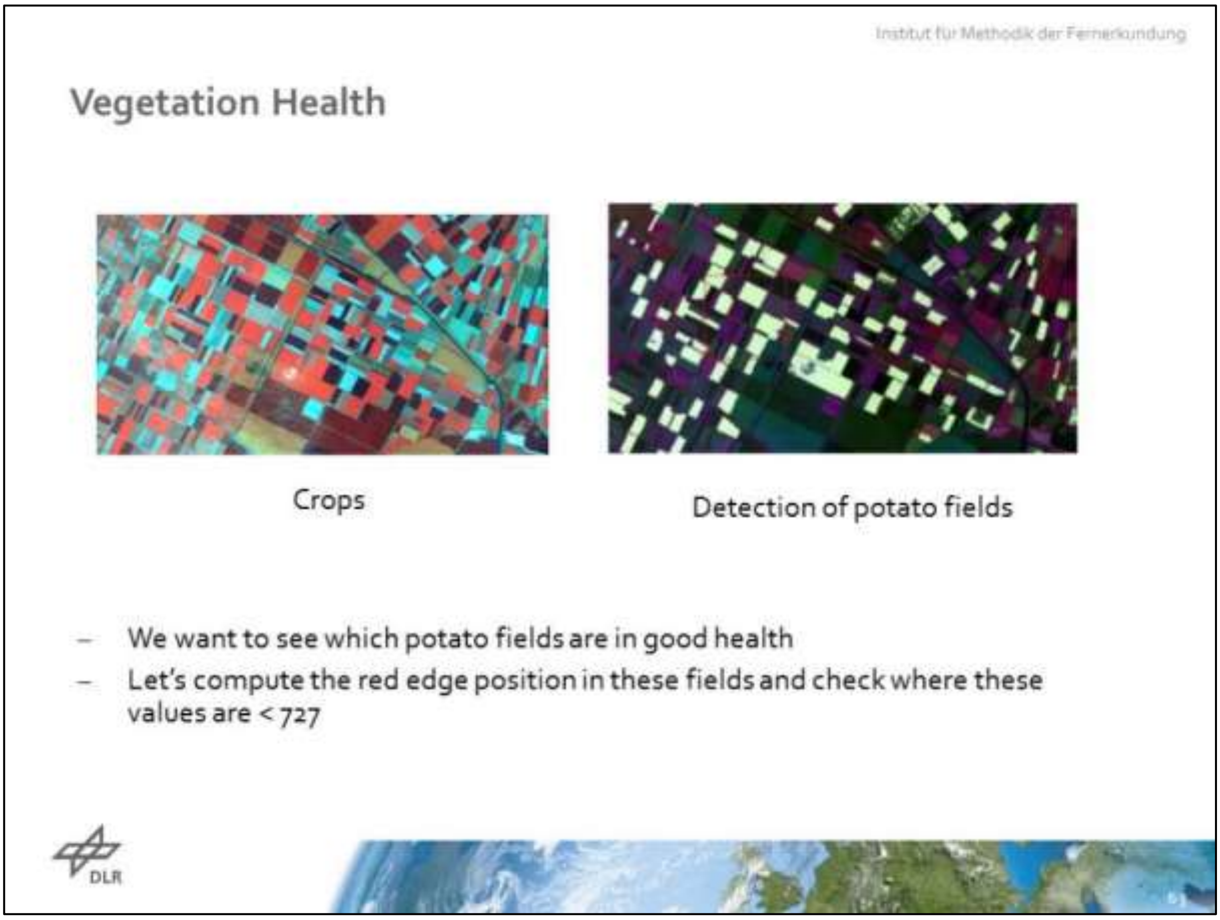
For which red edge values is the vegetation not in good health?

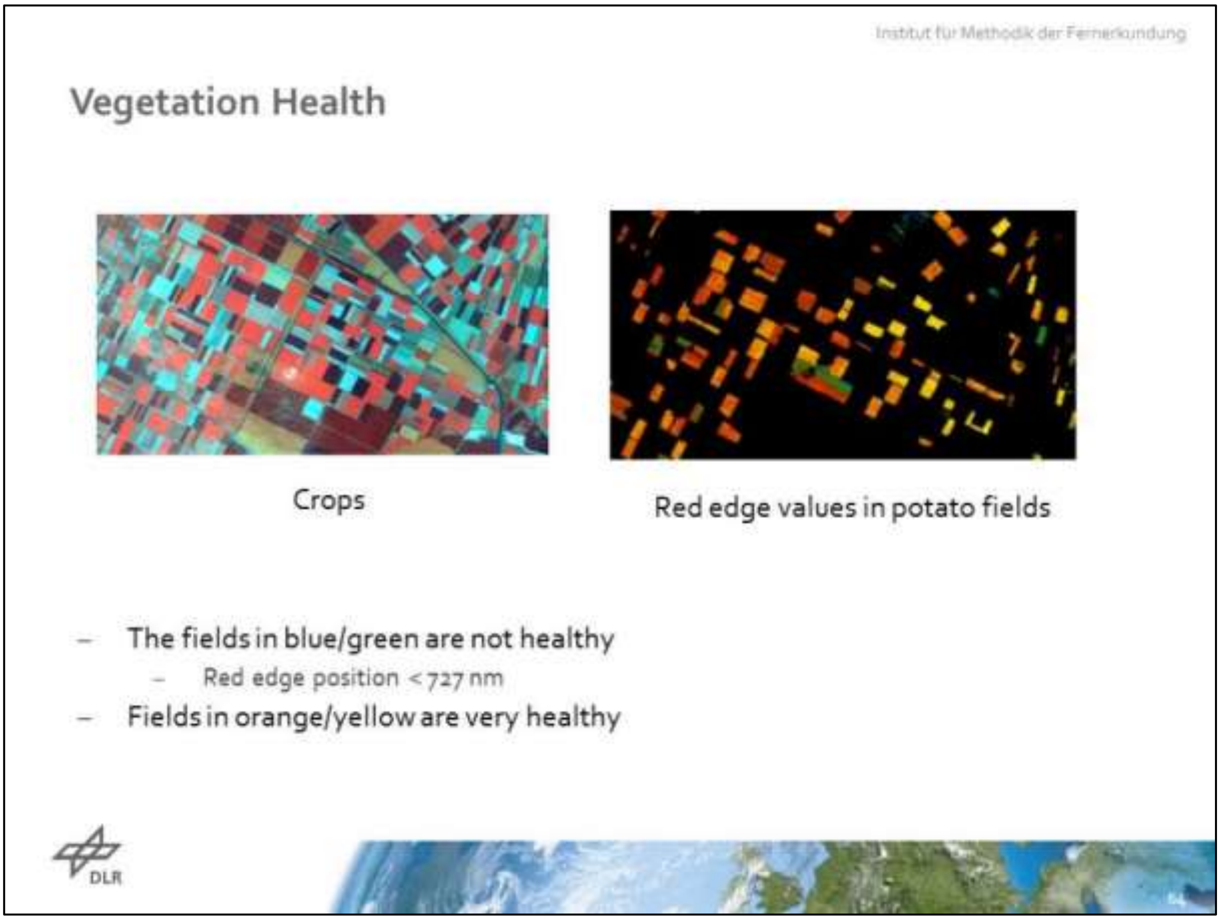


Red edge index as function of the Soil Specific Nitrogen Index for a potato crop

- Lack of nitrogen in the soil indicates respiratory problems of the plants
  - For potato fields this happens for values < 3.5
  - We have these values for red edge values < 727

DLR


Institut für Methodik der Fernerkundung
Vegetation Health
Crops
Detection of potato fields
– We want to see which potato fields are in good health
– Let's compute the red edge position in these fields and check where these values are < 727
DLR


Institut für Methodik der Fernerkundung
Vegetation Health
Crops
Red edge values in potato fields
– The fields in blue/green are not healthy
– Red edge position < 727 nm
– Fields in orange/yellow are very healthy
DLR

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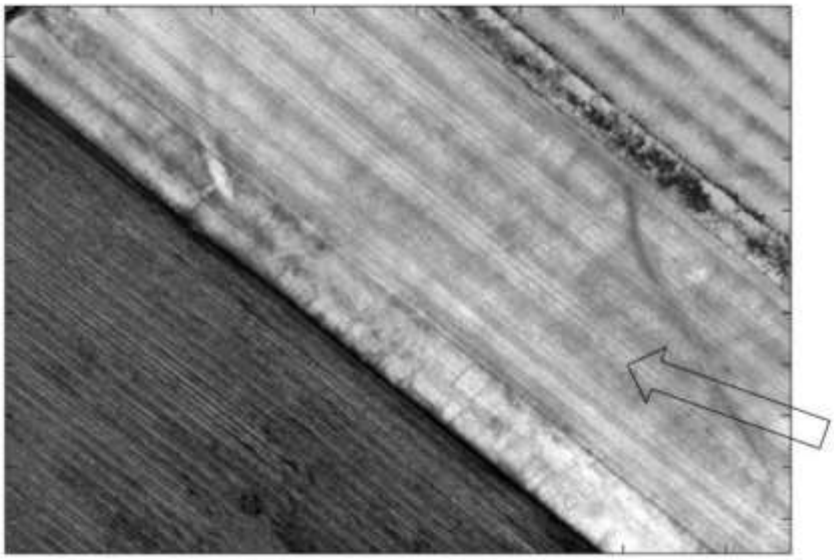
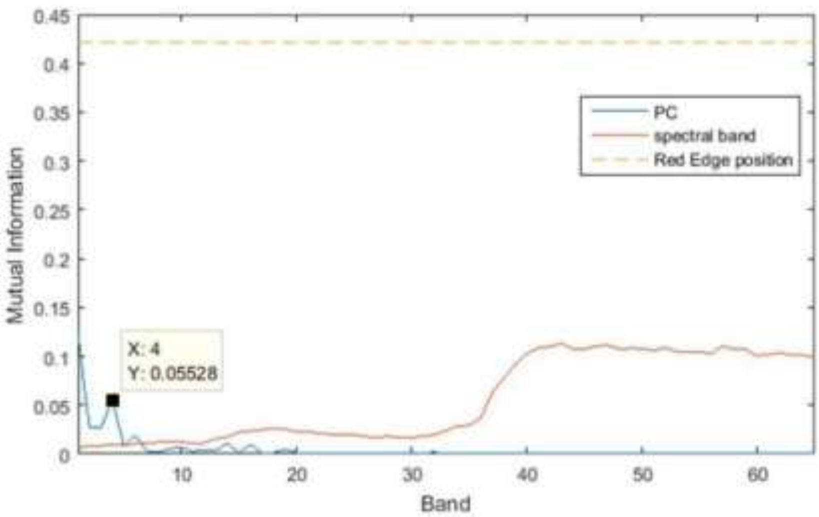
Back to our example: Red Edge image



Institut für Methodik der Fernerkundung

Summary (Mutual Information)

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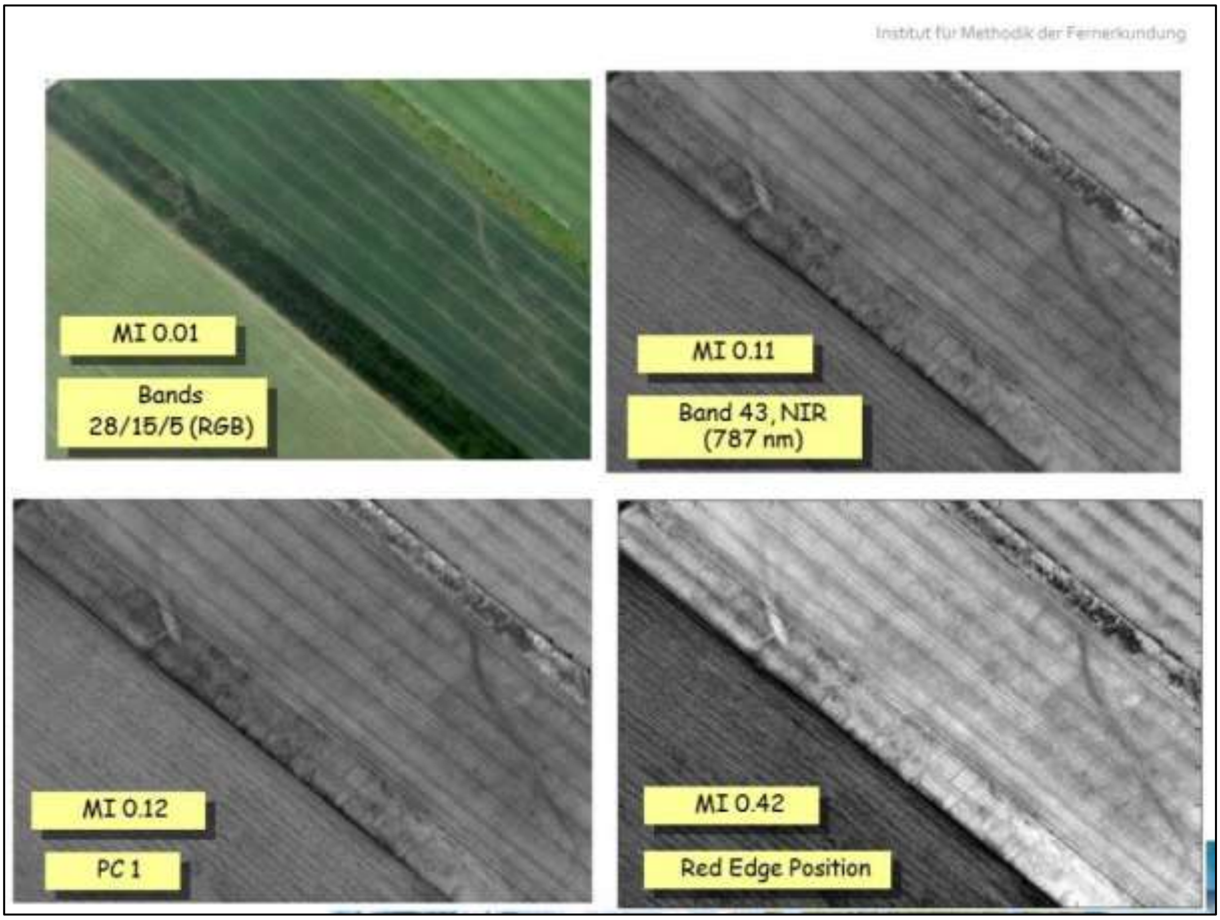
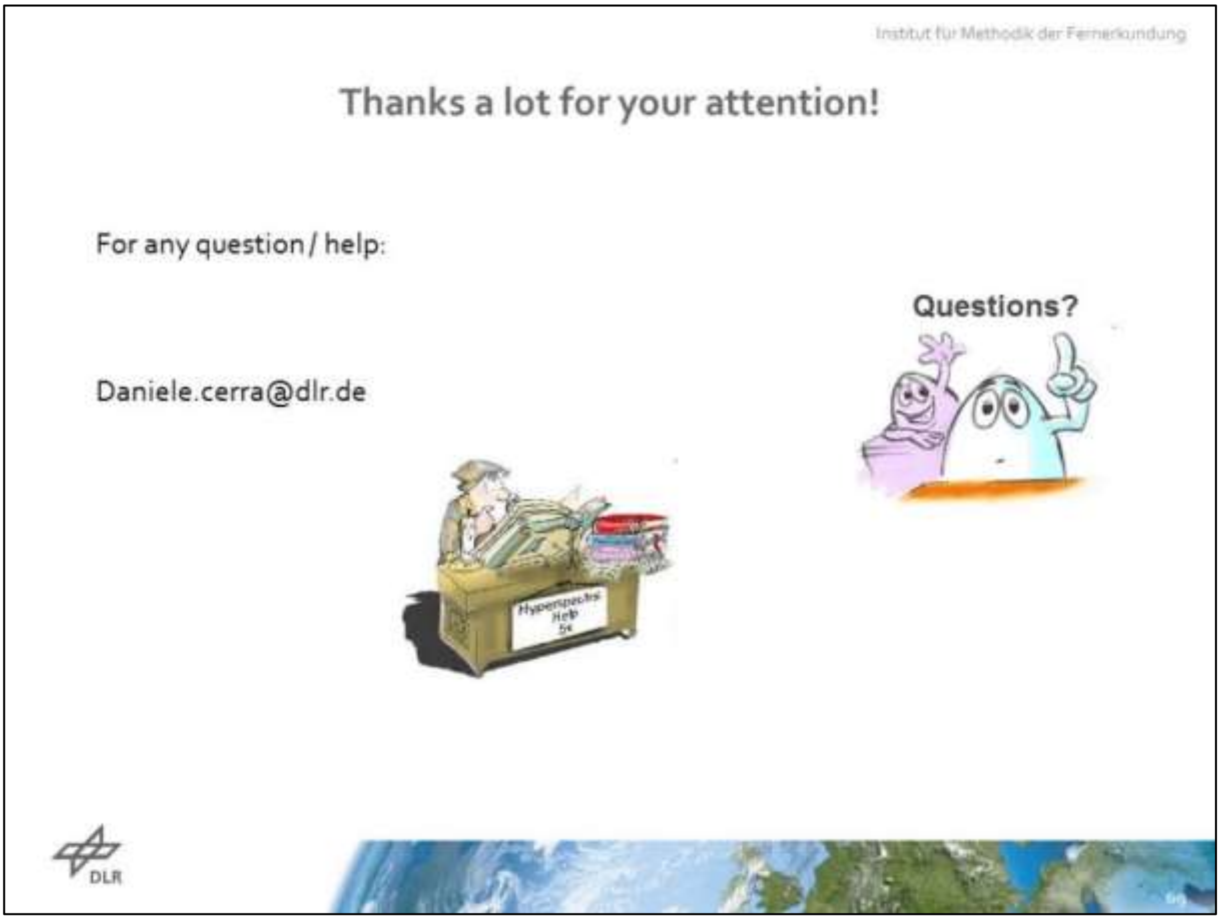
Mutual Info with what..?
DLR


Institut für Methodik der Fernerkundung
MI 0.01
Bands 28/15/5 (RGB)
MI 0.11
Band 43, NIR (787 nm)
MI 0.12
PC 1
MI 0.42
Red Edge Position


Institut für Methodik der Fernerkundung
Thanks a lot for your attention!
For any question / help:
Daniele.cerra@dlr.de
Questions?
DLR

2.2 VIRTUAL TRAINING 2: "MULTI-TEMPORAL REMOTE SENSING ANALYSES"

2.2.1 Description

The second virtual training was a two-day training event and it was performed physically, at the premises of the Cyprus University of Technology, in the Remote Sensing and Geo-Environment Laboratory. The training was carried out on the 6th and 7th of October 2016. The DLR trainer Dr. Ursula Gessner has developed and explained with case studies of performed or on going research, issues related to the multi-temporal remote sensing analysis, demonstrating the potential use of optical datasets for large scale applications and phenological studies.

The two-day training was followed by researches of the ATHENA project, as well as from PhD students of the Department of Civil Engineering and Geomatics of the CUT.

2.2.2 Agenda and participants

Agenda

ATHENA-Training "Multi-Temporal Remote Sensing Analyses"

6-7 October 2016, CUT, Limassol, Cyprus

Conducted by Ursula Gessner, DLR

Thursday, October 6	
	12:30-13:30 Lunch
13:30-14:45	- Introduction - Time series in earth observation: o Suitable sensors and missions o Types of EO time series & variables o Data access
	14:45-15:15 Coffee Break
15:15-16:30	- Time series processing – theoretical background and methods o Time series components and characteristics o Handling of outliers/noise incl. smoothing /filtering methods o Analysis of multi-year developments (trends, complex developments) o Analysis of seasonality I (seasonal statistics, number of seasons)

Friday, October 7	
9:30-10:45	- Time series processing – theoretical background and methods o Analysis of seasonality II (land surface phenology) o Data fusion
	10:45-11:15 Coffee Break
11:15-12:30	- Examples for EO applications based on time series (examples from DLR research and activities)
	12:30-13:30 Lunch
13:30-14:45	- Use Cases: o Inundation/flood dynamics: theoretical background and practical exercise with SAR data o Land surface phenology: theoretical background and practical exercise with optical data
	14:45-15:15 Coffee Break
15:15-16:30	- Discussion of presented aspects - Identification of interesting aspects for joint studies - Ideas for joint journal paper /conference presentation

H2020-TWINN-2015 - Remote Sensing Science Center for Cultural Heritage - A T H E N A
2nd Virtual Training
Topic: Multi-Temporal Remote Sensing Analyses - Trainer: Ursula Gessner (DLR)
Friday, 7th October, 2016
Cyprus University of Technology, Limassol - Cyprus

List of participants

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12				
13				
14				
15				

2

ATHENA Remote Sensing Science Center for Cultural Heritage

European Commission | HORIZON 2020

CYPRUS UNIVERSITY OF TECHNOLOGY 2004 · DLR	H2020-TWINN-2015 - Remote Sensing Science Center for Cultural Heritage - A T H E N A 2nd Virtual Training Topic: Multi-Temporal Remote Sensing Analyses - Trainer: Ursula Gessner (DLR) Wednesday, 6th October, 2016 Cyprus University of Technology, Limassol - Cyprus

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10	Ursula Gessner	DLR	ursula.gessner@dlr.de	
11	Rodanthi MAMOURI	CUT	rodelise.mamouri@cut.ac.cy	
12				
13				
14				
15				

2

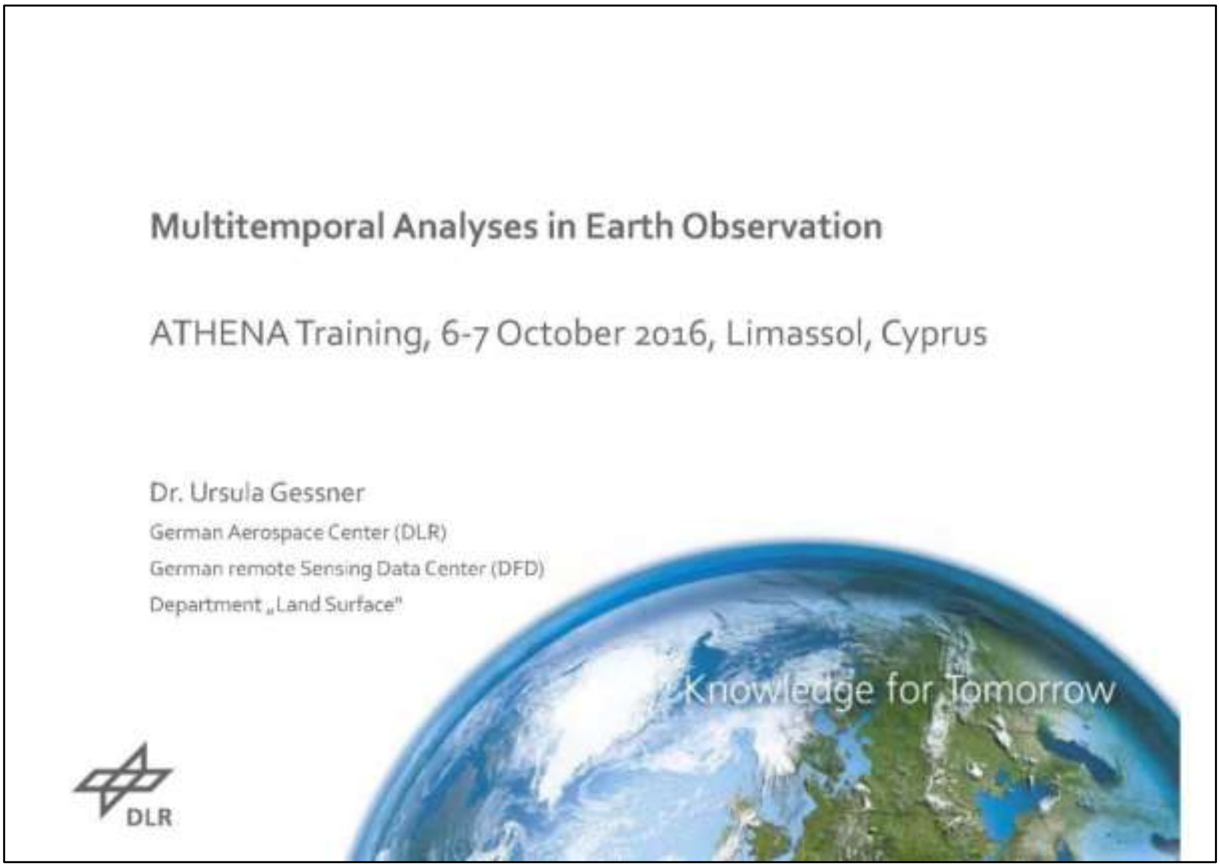
Group photo during and after the 2nd virtual training

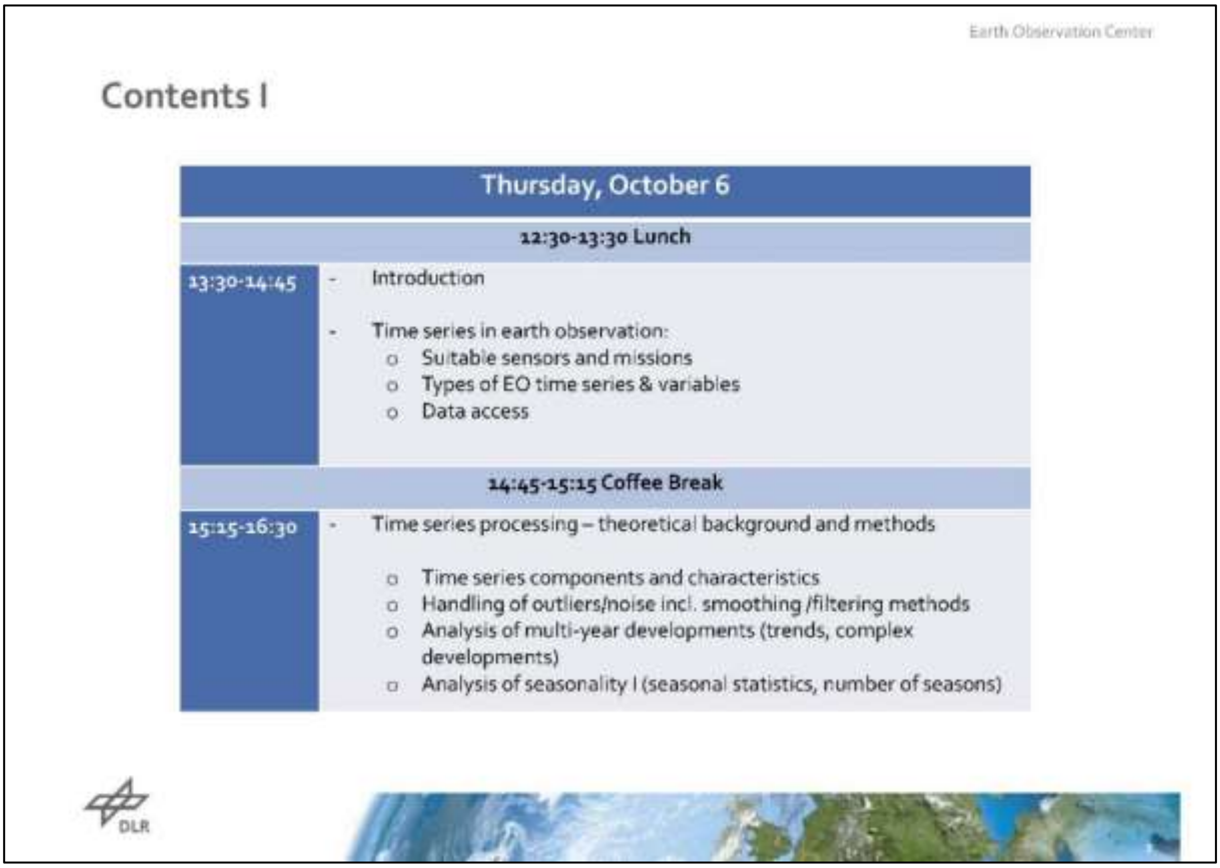
2.2.3 Presentations on "Multitemporal analyses in Earth Observation"

The sum up, the presentations made by Dr. Ursula Gessner regarding multitemporal analyses in Earth Observation contained the following:

- Time series in earth observation:
  - Suitable sensors and missions
  - Types of EO time series & variables
  - Data access
- Time series processing – theoretical background and methods
  - Time series components and characteristics
  - Handling of outliers/noise incl. smoothing /filtering methods
  - Analysis of multi-year developments (trends, complex developments)
  - Analysis of seasonality I (seasonal statistics, number of seasons)
  - Analysis of seasonality II (land surface phenology)
  - Data fusion
  - Examples for EO applications based on time series

Hereunder the presentation slights are provided, including theoretical concepts, examples of applications, literature etc.





Contents I

Thursday, October 6	
12:30-13:30 Lunch	
13:30-14:45	- Introduction - Time series in earth observation: o Suitable sensors and missions o Types of EO time series & variables o Data access
14:45-15:15 Coffee Break	
15:15-16:30	- Time series processing – theoretical background and methods o Time series components and characteristics o Handling of outliers/noise incl. smoothing /filtering methods o Analysis of multi-year developments (trends, complex developments) o Analysis of seasonality I (seasonal statistics, number of seasons)

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Contents II

Friday, October 7	
9:30-10:45	- Time series processing – theoretical background and methods o Analysis of seasonality II (land surface phenology) o Data fusion
10:45-11:15 Coffee Break	
11:15-12:30	- Examples for EO applications based on time series (examples from DLR research and activities)
12:30-13:30 Lunch	
13:30-14:45	- Use Cases: o Inundation/flood dynamics: theoretical background and practical exercise with SAR data o Land surface phenology: theoretical background and practical exercise with optical data
14:45-15:15 Coffee Break	
15:15-16:30	- Discussion of presented aspects - Identification of interesting aspects for joint studies - Ideas for joint journal paper /conference presentation

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TIME SERIES IN EARTH OBSERVATION

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EO TIME SERIES PRODUCTS – EXAMPLES

-> demonstration of animations of EO-based time series

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Earth Observation Time Series

A time series…

- …is *"a sequence of values collected over time on a particular variable"* (Haan, 1977).
- …can consist of the values of a variable observed at:
  - discrete times (e.g. spectral information recorded at overpass of EO-sensor)
  - averaged over a given time interval (e.g. vegetation index value averaged over the period of 8-days as done for MODIS products)
  - recorded continuously with time (not common for EO, e.g. hygrographs in museums)

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Earth Observation Time Series Variables

Categories of EO time series variables:	Examples
Spectral variables	• Top of atmosphere reflectance • Bottom of atmosphere reflectance • Albedo • ...
Indices	• Vegetation indices (NDVI, EVI, (M)SAVI, etc.) • Soil water indices (SWI, etc.) • Wetness indices (Tasseled Cap Wetness, NDWI, etc.) • Snow indices (NDSI, etc.) • ...
Biogeophysical variables	• Land/sea surface temperature (LST/SST) • Leaf Area Index (LAI) • Chlorophyll content • Atmospheric SO_2 content • Phenological dates • ...
Thematic information	• Presence/absence of single land use/cover classes (e.g. water, urban, forest, etc.) • Sub-pixel fraction of cover type (e.g. tree cover) • ...
Spatial pattern information	• Pixel based texture measures (variance, entropy, contrast, mean etc. in a filter window) • Spatial features of objects (size, compactness, contour length etc.) • Relational features (e.g. neighbouhood, isolation/fragmentation, connectivity etc.) • ...

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Major EO Satellites with Optical/Multispectral Sensors

Major EO Satellites with Radar and Passive Microwave sensing instruments

Major EO Satellites with Thermal Sensors

Figures from Kuenzer et al. (2014) Earth observation satellite sensors for biodiversity monitoring: potentials and bottlenecks, IJRS, 6599-6647.

-> Removed for copyright reasons

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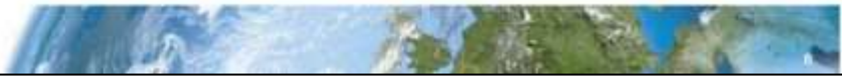

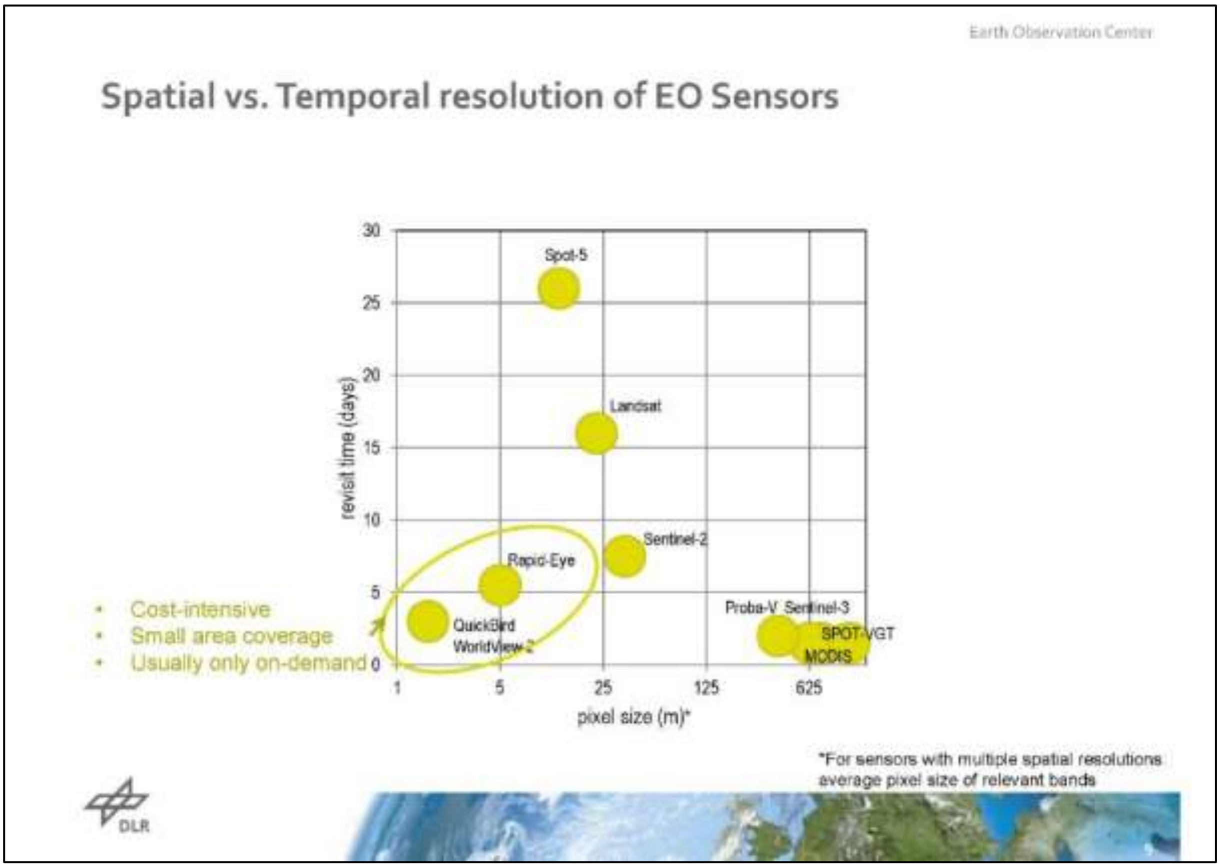
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Spatial vs. Temporal resolution of EO Sensors
revisit time (days)
30
25
20
15
10
5
0
1
5
25
125
625
pixel size (m)*
Spot-5
Landsat
Sentinel-2
Rapid-Eye
QuickBird
WorldView-2
Proba-V
Sentinel-3
SPOT-VGT
MODIS
Cost-intensive
Small area coverage
Usually only on-demand
*For sensors with multiple spatial resolutions average pixel size of relevant bands
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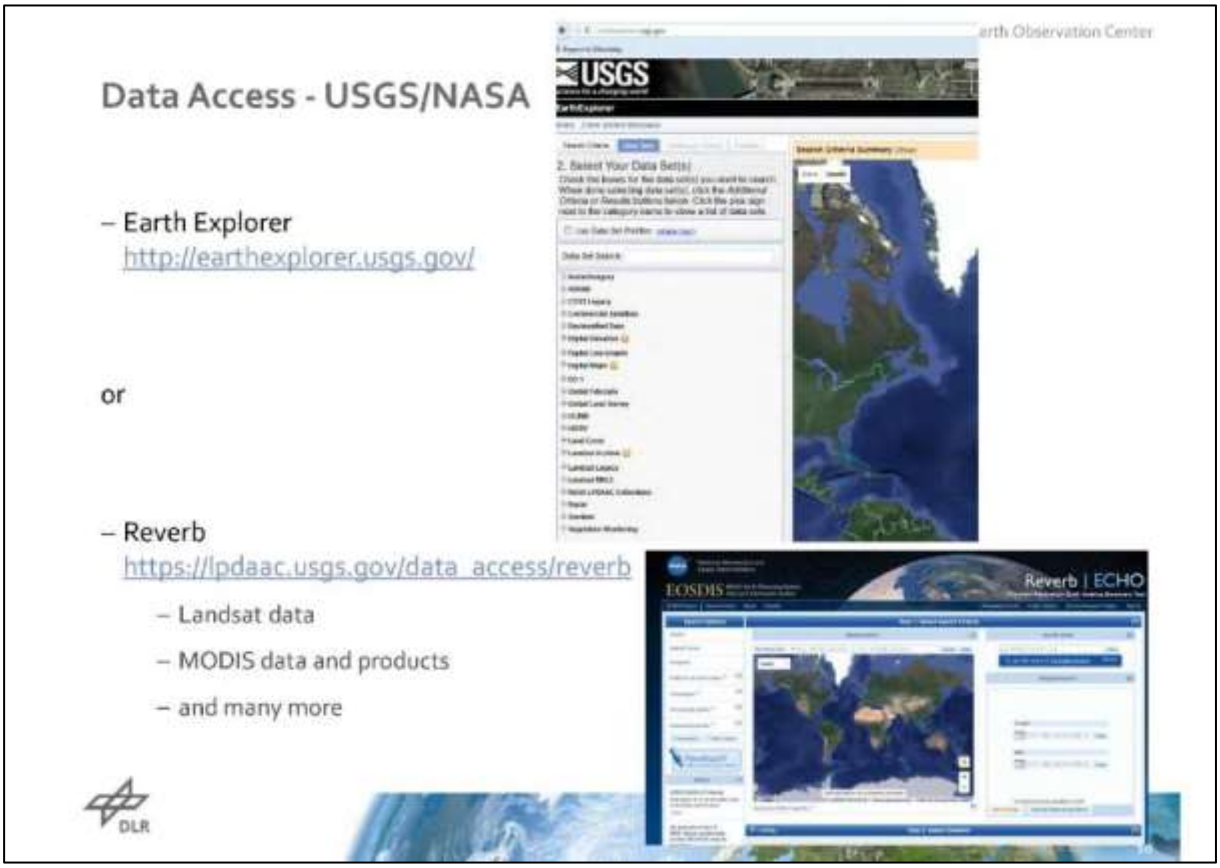
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Data Access - USGS/NASA
– Earth Explorer
http://earthexplorer.usgs.gov/
or
– Reverb
https://lpdaac.usgs.gov/data_access/reverb
– Landsat data
– MODIS data and products
– and many more
USGS
EOSDIS
Reverb | ECHO
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Data Access Sentinel Data - Examples

- Sentinel Data Hub:
  https://scihub.copernicus.eu
- Collaborative Data Hubs (National Data Hubs) currently under development for multiple countries, e.g.:
  - DLR in Germany (CODE-DE)
  - NOA in Greece
- Amazon Web Services
  http://sentinel-pds.s3-website.eu-central-1.amazonaws.com/
- USGS Earth Explorer
  http://earthexplorer.usgs.gov/

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EXEMPLARY WORKFLOWS FOR DATA DOWNLOAD

I. Sentinel Data Access – Sentinel Scientific Data Hub
II. Download of MODIS data via Reverb
III. Download Landsat data via EarthExplorer

→ see supplementary material for participants

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TIME SERIES PROCESSING – THEORETICAL BACKGROUND & METHODS

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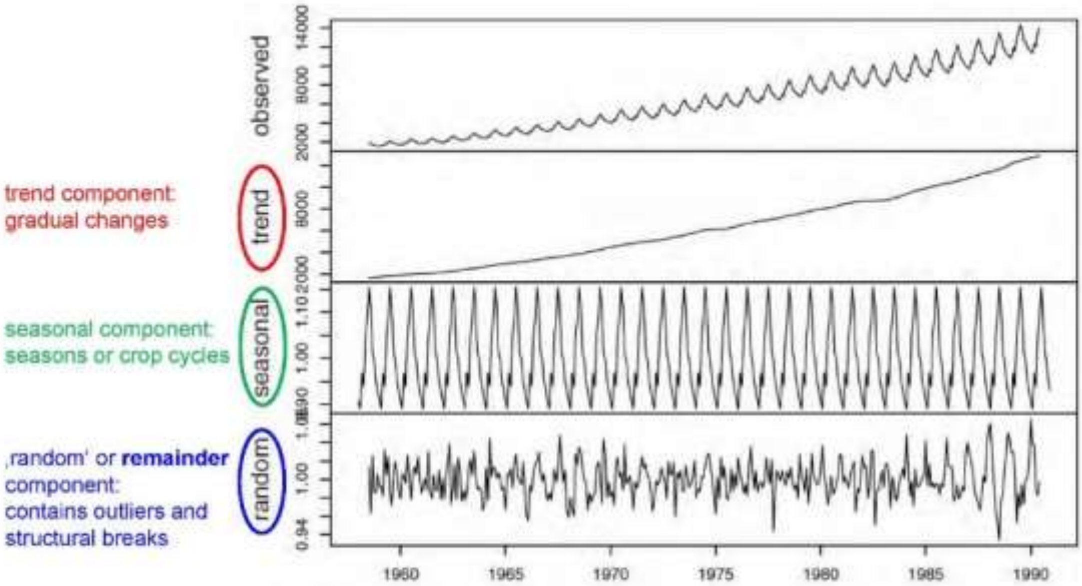
Time Series Components & Decomposition



adapted after: Cowpertwaite & Metcalfe (2009)

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EO time series – handling of outliers & ‚noise'

Reasons for outliers / noise in optical EO time series

- Atmospheric effects
- Clouds / haze
- Sun-sensor-geometry
- Sensor failures
- (pre-)processing errors

Not related to land surface characteristics

-> shall be removed by noise removal procedures

- Floods
- Bushfires
- (short) snow cover

Related to actual land surface characteristics. No noise!

-> can nevertheless be removed by noise removal procedures!

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EO time series – handling of outliers & ‚noise'

1. **Outlier identification and respective weighting of time series values**
2. Temporal filtering /smooting (with outliers removed or weighted according to 1.)

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EO time series – handling of outliers & ‚noise'

1. **Outlier identification and respective weighting of time series values**

   – based on quality information layers
   -> available for some time series products, e.g. for most MODIS products

Bit No.	Parameter Name	Bit Comb.	Sur_refl_qc_500m
31	adjacency correction performed	1	yes
		0	no
30	atmospheric correction performed	1	yes
		0	no
26–29	band 7 data quality four bit range	0000	highest quality
		1000	dead detector; data interpolated in L1B
		1001	solar zenith >= 86 degrees
		1010	solar zenith >= 85 and < 86 degrees
		1011	missing input
		1100	internal constant used in place of climatological data for at least one atmospheric constant
		1101	correction out of bounds pixel constrained to extreme allowable value
		1110	L1B data faulty
		1111	not processed due to deep ocean or clouds
22–25	band 6 data quality four bit range		SAME AS BAND ABOVE
18–21	band 5 data quality		SAME AS BAND ABOVE

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EO time series – handling of outliers & ‚noise'

1. **Outlier identification and respective weighting of time series values**

   – based on quality information layers
   -> available for some time series products, e.g. for most MODIS products

   – Based on statistics / rulesets, e.g.:
     – a value is classified /weighted as an outlier if
       – it deviates more than a deviation threshold from the median in a moving window and/or
       – it is lower (higher) than the mean value of its immediate neighbors minus (plus) a threshold value
       – or similar…
     – Weights are assigned based on an STL decomposition (Cleveland et al. 1990).

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EO time series – handling of outliers & ‚noise'

1. Outlier identification and respective weighting of time series values
2. **Temporal filtering /smooting (with outliers removed or weighted according to 1)**

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EO time series – handling of outliers & ‚noise'

1. Outlier identification and respective weighting of time series values
2. **Temporal filtering /smooting (with outliers removed or weighted according to 1)**
   - **Moving average:**
     replace each data value by a linear combination /mean of nearby values in a window
   - **Savitzky-Golay filter:**
     Least squares fit to a quadratic polynomial of the form:
     $$f(t) = c_1 + c_2 t + c_3 t^2$$
     Polynomial is fit to values in a moving window and cental value is replaced by fitted value
   - Fit to **asymmetric Gaussian** and **double logistic** functions
   - General option when fitting smoothing functions to EO data:
     Fitting to the upper envelope

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TIMESAT - Smoothing

- Adaptive Savitzky-Golay filtering: Replacement of each data value by a linear combination of nearby values in a window

  For each data value $y_i, i = 1, \ldots, N$ they fit a quadratic polynomial $f(t) = c_1 + c_2 t + c_3 t^2$ to all $2n + 1$ points in the moving window and replace values

- Fits to asymmetric Gaussians and double logistic functions: Local model functions are fit to data in intervals around maxima and minima in the time-series

  General form of local model functions: $f(t) \equiv f(t; \mathbf{c}, \mathbf{x}) = c_1 + c_2 g(t; \mathbf{x})$

  Where linear parameters c_n determine base level and amplitude and non-linear parameters x_n determine shape of basis function $g(t; x)$

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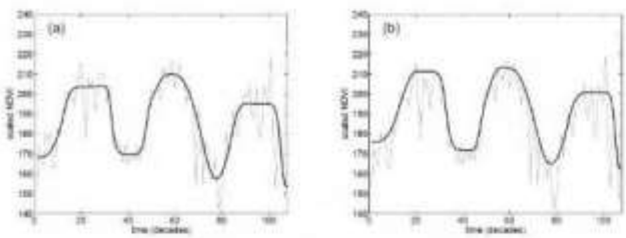
EO time series – handling of outliers & ‚noise'

Fitting to the upper envelope

- Background:
  - Outliers / noise in vegetation index time series are usually associated with a decrease in the index value (e.g. cloud effects, atmospheric influence)
  - Therefore, an adaption of the smoothed / filtered time series to the higher rather than the lower values of a time series is oftentimes favoured.

- Method:
  1) A function (e.g. Gaussian, quadratic polynomial) is fitted to a time series
  2) Data values of the original time series that are below the respective fitted function are given a lower weight
  3) Function is fitted a second time, with values weighted according to step 2)
  4) 2-3 can be repeated



Eklundh & Jönsson (2015)

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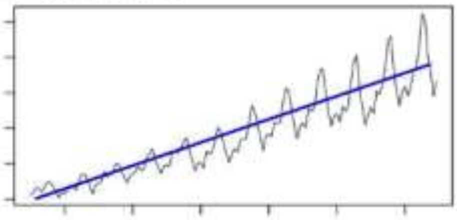
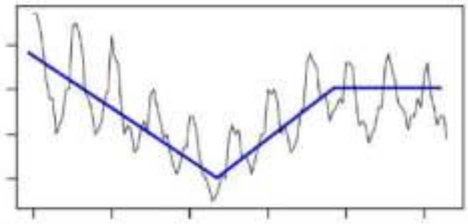
Analysis of multi-year temporal development (Trends)

- Linear trend analyses



- Methods accounting for discontinuous development / breaks, e.g.:
  - BFAST
  - LandTrendR



Figures adapted after:
Cowpertwaite & Metcalfe (2009)

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Trend Analysis of EO data

- When analysing EO time series for trends, several particularities of these datasets have to be considered:
  - Usually short time series
  - Sometimes high level of noise
  - Overlay of multiple noise effects and actual land surface dynamics / characteristics
  - Autocorrelation
  - Etc.
- Good overview on statistical particularities for EO time series analyses in:

De Beurs, K. M., & Henebry, G. M. (2005). A statistical framework for the analysis of long image time series. *International Journal of Remote Sensing*, *26*, 1551–1573.

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BFAST - Breaks For Additive Season and Trend

BFAST iteratively estimates the time and number of abrupt changes within time series, and characterizes change by its magnitude and direction. The algorithm can be extended to label detected changes with information on the parameters of the fitted piecewise linear models.

– An additive decomposition model is used to iteratively fit a piecewise linear trend and a seasonal model.

– Similarly, the seasonal component is fixed between breakpoints, but can vary across breakpoints.

-> m breakpoints in the trend component AND p seasonal breakpoints are identified

– seasonal breakpoints may occur at different times from the breakpoints in the trend component

Verbesselt et al. 2010

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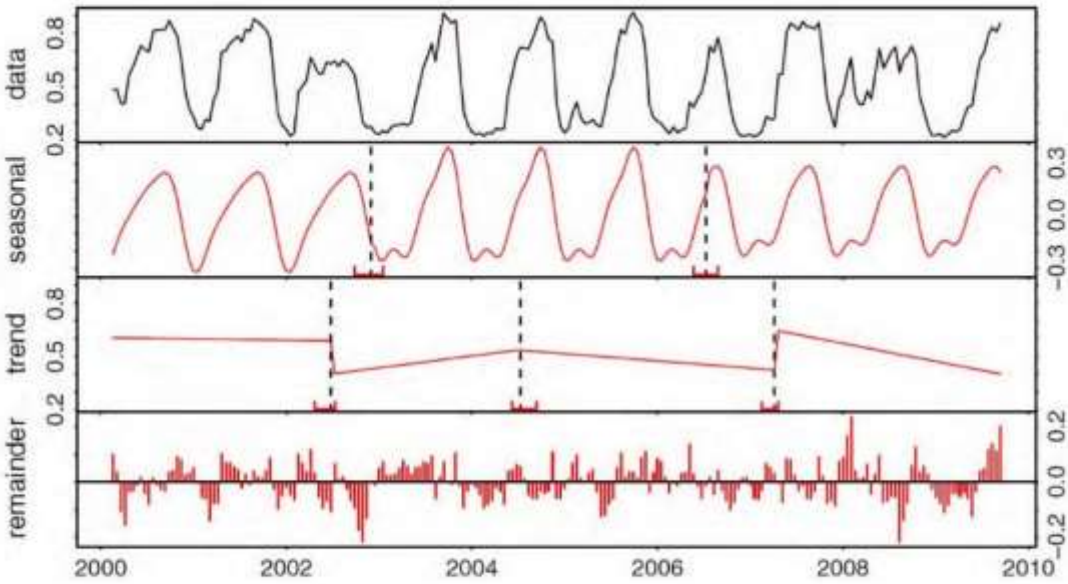
BFAST - Breaks For Additive Season and Trend



Verbesselt et al. 2010

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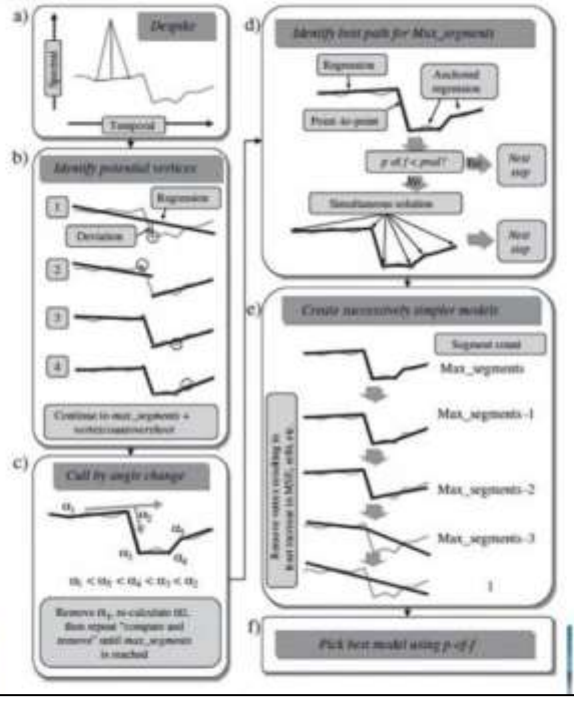
LandTrendR - identify periods of stability and change in Landsat data

– Pre-processing of multitemporal Landsat data
  -> Landsat data stack

– Identify straightline segments in a single pixel's trajectory:

  a. Elimination of spikes
  b. Identification of potential transition points (vertices)
  c. Removal of extraneous vertices
  d. Identification of best path through the vertices
  e. Sequential simplification of the time series
  f. Selection of the best model fit using a simple fitting statistic

Details: Kennedy et al. (2010)



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LandTrendR - identify periods of stability and change in Landsat data

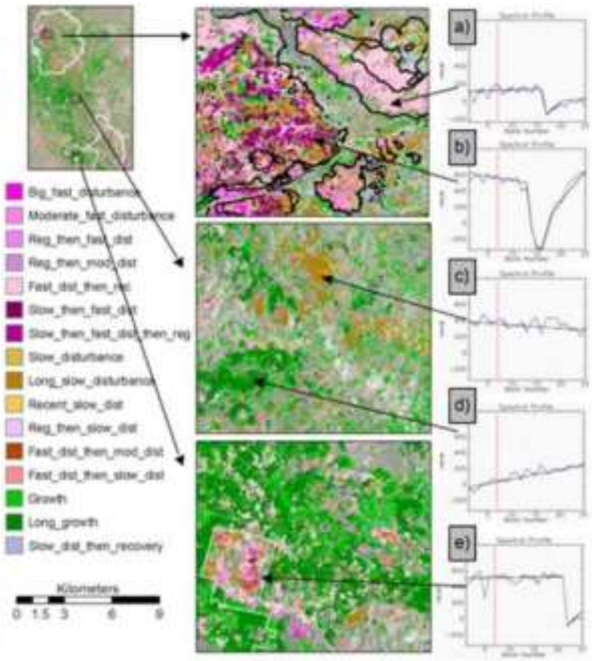
– Pre-processing of multitemporal Landsat data
  -> Landsat data stack

– Identify straightline segments in a single pixel's trajectory

– Segments and their fitted functions can be summarized in maps in different ways.

  Example: label change that has occurred in each pixel according to characteristic sequences of change over time

Details: Kennedy et al. (2010)



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Temporary tree cover loss Mekong Basin

2001-2011, MODIS 500m

Figures from Leinenkugel, P., Wolters, M., Oppelt, N. & Kuenzer, C. (2015). Tree cover and forest cover dynamics in the Mekong Basin from 2001 to 2011. Remote Sensing of Environment, 158, pp 376-392

-> Removed for copyright reasons

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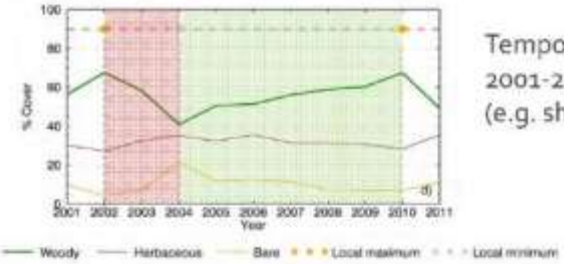
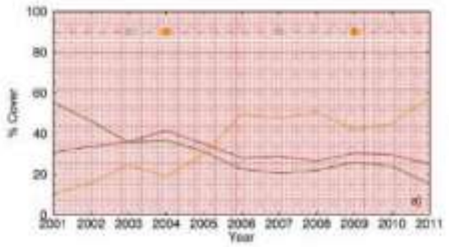
Temporal patterns of tree cover changes

Leinenkugel, P., Kuenzer, C., Wolters, M., & Oppelt, N. (2014). Sensitivity analysis for predicting continuous fields of tree cover and fractional land cover distributions in cloud prone areas. International Journal of Remote Sensing, 35, 1-23.



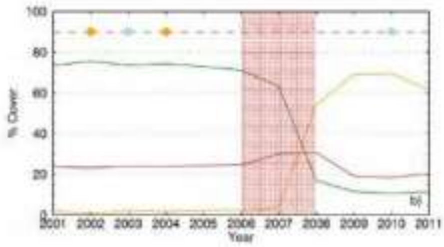
Temporal trajectory between 2001-2011 for one single pixel: (e.g. shifting cultivation, plantations)

Characterisation of the tree cover trajectory on the basis of the Gini-Index:



Gradual decrease

Low Gini Index



Abrupt decrease

High Gini Index

Analyses of Seasonality in EO time series

- Calculation of suitable **seasonal/annual statistics** (mean, median, variance, amplitude, integrals etc.) of the values of a variable in a time series
  - basis for trend analyses
  - usage as feature e.g. for land use/cover classification

- Determination of **number of seasons** per year

- Analysis of **Land Surface Phenology**

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Analyses of Seasonality in EO time series

Determination of number of seasons

Different approaches possible, e.g.:

- In Timesat Software (Eklundh & Jönsson, 2015):
  - de-trended data values (ti; yi), i = 1, 2,..,N for all years in the time-series are fit to a model function:

    $f(t) = c1 + c2 \sin(\omega t) + c3 \cos(\omega t) + c4 \sin(2\omega t) + c4 \cos(2\omega t)$

    where $\omega = 6\pi/N$.
  - fitting delivers a primary maximum, and possibly a secondary maximum.
  - amplitude ratio between the 2^{nd} maximum and the 1^{st} maximum > user defined threshold: -> 2 annual seasons, otherwise: 1 annual season

- Harmonic analysis
  - predefine one, two harmonics
  - Determine best fit

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Determination of number of seasons for rice mapping

Aqua/Terra MODIS time series 2000-2015

Figures from P. Leinenkugel, K. Clauss, C. Kuenzer (2015). Spatio-temporal analysis of cropping systems based on 15 years of MODIS data. Did rice cultivation intensified in the Mekong Delta? Remote Sensing. (submitted)

-> Removed as not yet published

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Analyses of Seasonality in EO time series

- Calculation of suitable **seasonal/annual statistics** (mean, median, variance, amplitude, integrals etc.) of the values of a variable in a time series
  - basis for trend analyses
  - usage as feature e.g. for land use/cover classification
- Determination of **number of seasons** per year
- Analysis of **Land Surface Phenology**

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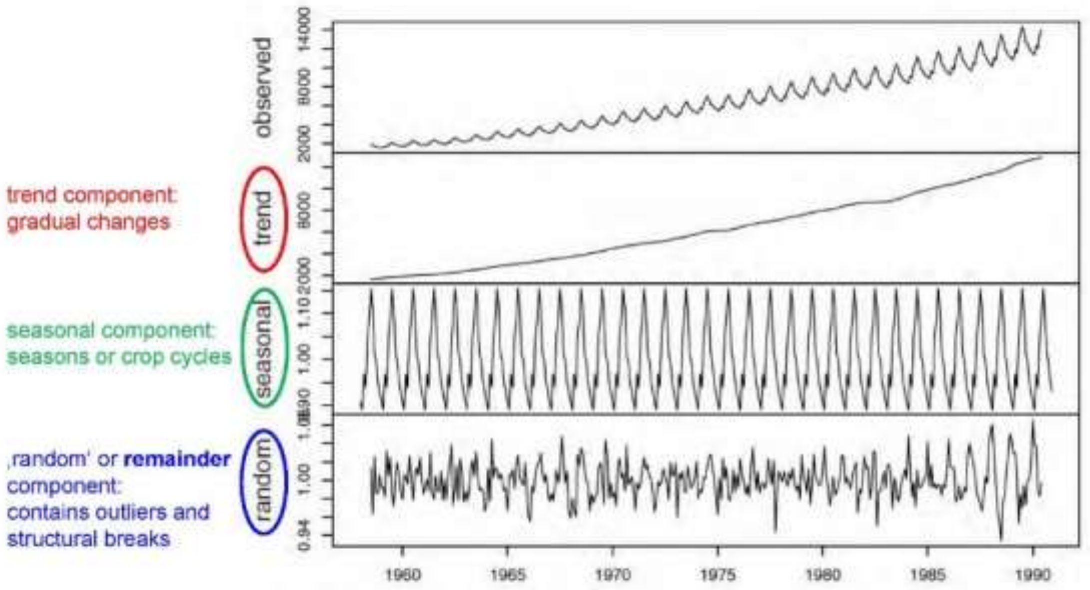
Time Series Components & Decomposition



adapted after: Cowpertwaite & Metcalfe (2009)

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Analyses of Seasonality in EO time series

- Calculation of suitable **seasonal/annual statistics** (mean, median, variance, amplitude, integrals etc.) of the values of a variable in a time series
  - basis for trend analyses
  - usage as feature e.g. for land use/cover classification

- Determination of **number of seasons** per year

- Analysis of Land Surface Phenology

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Phenology

Phenology analyzes life cycle events of plants and animals.

examples:

- when do cherry trees blossom?
- when do the leaves of oak trees turn yellow?
- when is barley in grainfilling stage?
- when do storks breed?

Phenology is usually studied at plant / animal level.

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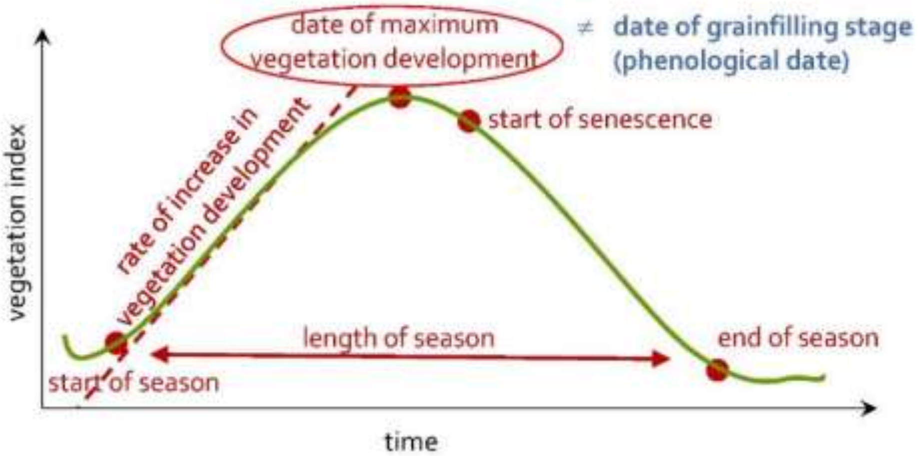
Land Surface Phenology (LSP)

The spatio-temporal development of vegetated land surfaces as detected from remote sensors

-> reflects phenology of mixtures of land covers or plant communities

SEASONALITY PARAMETERS



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Land Surface Phenology (LSP)

Relevance:

- Differentiation of land use/cover types (e.g. crop types, irrigation, forests, etc.)
- Detection of differences in soil moisture availability (e.g. due to differences in soil type/depth, differences in management practices, buried structures etc.)
- Identification of climate change/variability related changes in vegetation activitiy
- Land degradation assessments (shortening / failure of growing season, etc.)
- Ecosystem services assessment (e.g. timing of flowering vs. activity periods of pollinators, timing of fodder availability, etc.)

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Delineation of seasonality parameters from EO data

Seasonality parameters can be extracted from EO time series data for example using the TIMESAT software (Eklundh & Jönsson, 2015)

http://web.nateko.lu.se/timesat/timesat.asp

TIMESAT Workflow:

- Outlier removal / weighting
- Temporal filtering / smoothing
- Identification of number of seasons
- Identification of 11 seasonality parameters

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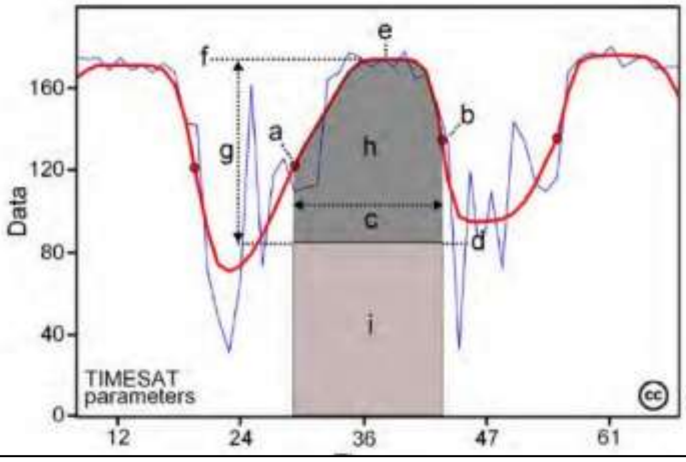
TIMESAT – Seasonality parameters

1. Time for the start of the season (a)
2. Time for the end of the season (b)
3. Length of the season (c)
4. Base level (d)
5. Time for the mid of the season (e)
6. Largest data value for the fitted function (f)
7. Seasonal amplitude (g)
8. Rate of increase at the beginning of the season
9. Rate of decrease at the end of the season
10. Large seasonal integral (h)
11. Small seasonal integral (h+i)



(Eklundh & Jönsson, 2015)

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TIMESAT – Seasonality parameters

1. Time for the start of the season: time for which the left edge has increased to a user defined level measured from the left minimum level.
2. Time for the end of the season: time for which the right edge has decreased to a user defined level measured from the right minimum level.
3. Length of the season: time from the start to the end of the season.
4. Base level: given as the average of the left and right minimum values.
5. Time for the mid of the season: computed as the mean value of the times for which, respectively, the left edge has increased to the 80 % level and the right edge has decreased to the 80 % level.
6. Largest data value for the fitted function during the season
7. Seasonal amplitude: difference between the maximum value and the base level.
8. Rate of increase at the beginning of the season: calculated as the ratio of the difference between the left 20 % and 80 % levels and the corresponding time difference.
9. Rate of decrease at the end of the season: calculated as the absolute value of the ratio of the difference between the right 20 % and 80 % levels and the corresponding time difference.
10. Large seasonal integral: integral of the function describing the season from the season start to the season end.
11. Small seasonal integral: integral of the difference between the function describing the season and the base level from season start to season end.

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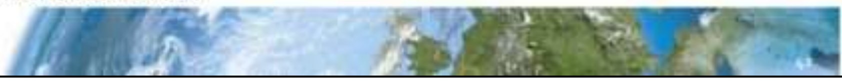

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Land Surface Phenology – Mekong Basin

Figures from Leinenkugel, P., Kuenzer, C., Oppelt, N., & Dech, S. (2013). Characterisation of land surface phenology and land cover based on moderate-resolution satellite data in cloud prone areas — A novel product for the Mekong Basin. Remote Sensing of Environment, 136, 180–198.

-> Removed for copyright reasons

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Start and end of season Africa

based on MODIS 500m reflectances

Figures from Winkler K.

-> Removed as not yet published

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Land Surface Phenology and Bushfires

Figures from Gessner, U.; Knauer, K.; Kuenzer, C. and Dech, S. (2015): Land surface phenology in a West African savannah: impact of land use, land cover and fire. In: C. Kuenzer & S. Dech, ed., 'Remote Sensing Time Series revealing Land Surface Dynamics'. Springer, Berlin, pp. 203-223.

-> Removed for copyright reasons

Large integral

Start of season

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Large integral for different fire frequencies and land cover types

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Land cover classification of the Mekong Delta

Figures from Leinenkugel, P., Kuenzer, C., Oppelt, N., & Dech, S. (2013). Characterisation of land surface phenology and land cover based on moderate-resolution satellite data in cloud prone areas — A novel product for the Mekong Basin. Remote Sensing of Environment, 136, 180–198.

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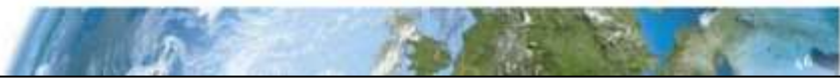

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Data fusion approaches

- Fusion of EO data with different spatial, temporal and spectral characteristics:
  1. **Fusion of spectral (index) information prior to thematic analysis**
     - pan-sharpening
     - time series fusion

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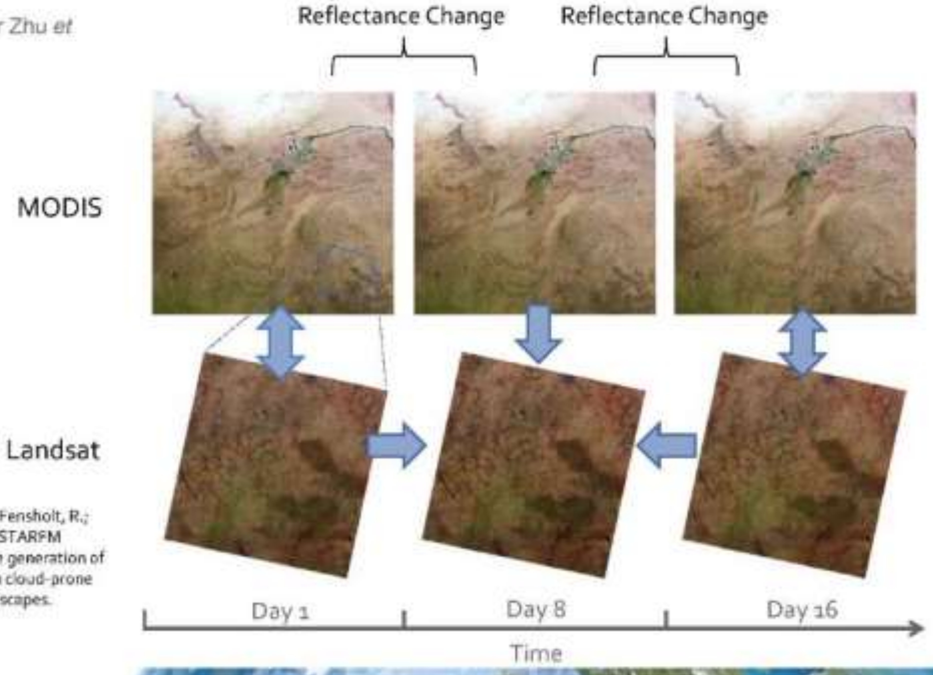
Time series fusion - ESTARFM framework

Modified after Zhu *et al.* (2010)



Knauer, K.; Gessner, U.; Fensholt, R.; Kuenzer, C. (2016): An ESTARFM fusion framework for the generation of large-scale time series in cloud-prone and heterogeneous landscapes. Remote Sensing 8, 425.

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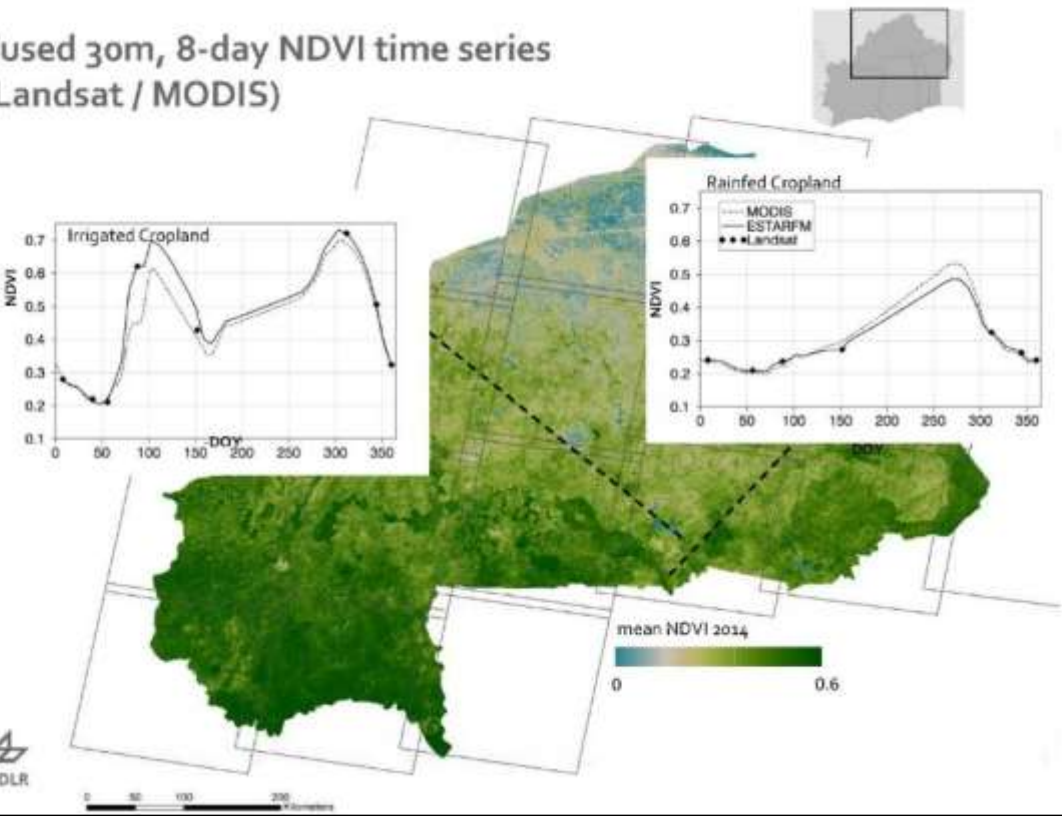
Fused 30m, 8-day NDVI time series (Landsat / MODIS)



Knauer, K.; Gessner, U.; Fensholt, R.; Kuenzer, C. (2016): An ESTARFM fusion framework for the generation of large-scale time series in cloud-prone and heterogeneous landscapes. Remote Sensing 8, 425

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Data fusion approaches

– Fusion of EO data with different spatial, temporal and spectral characteristics:

1. Fusion of spectral (index) information prior to thematic analysis
2. **Fusion of thematic information derived from different sensors in one value-added product**

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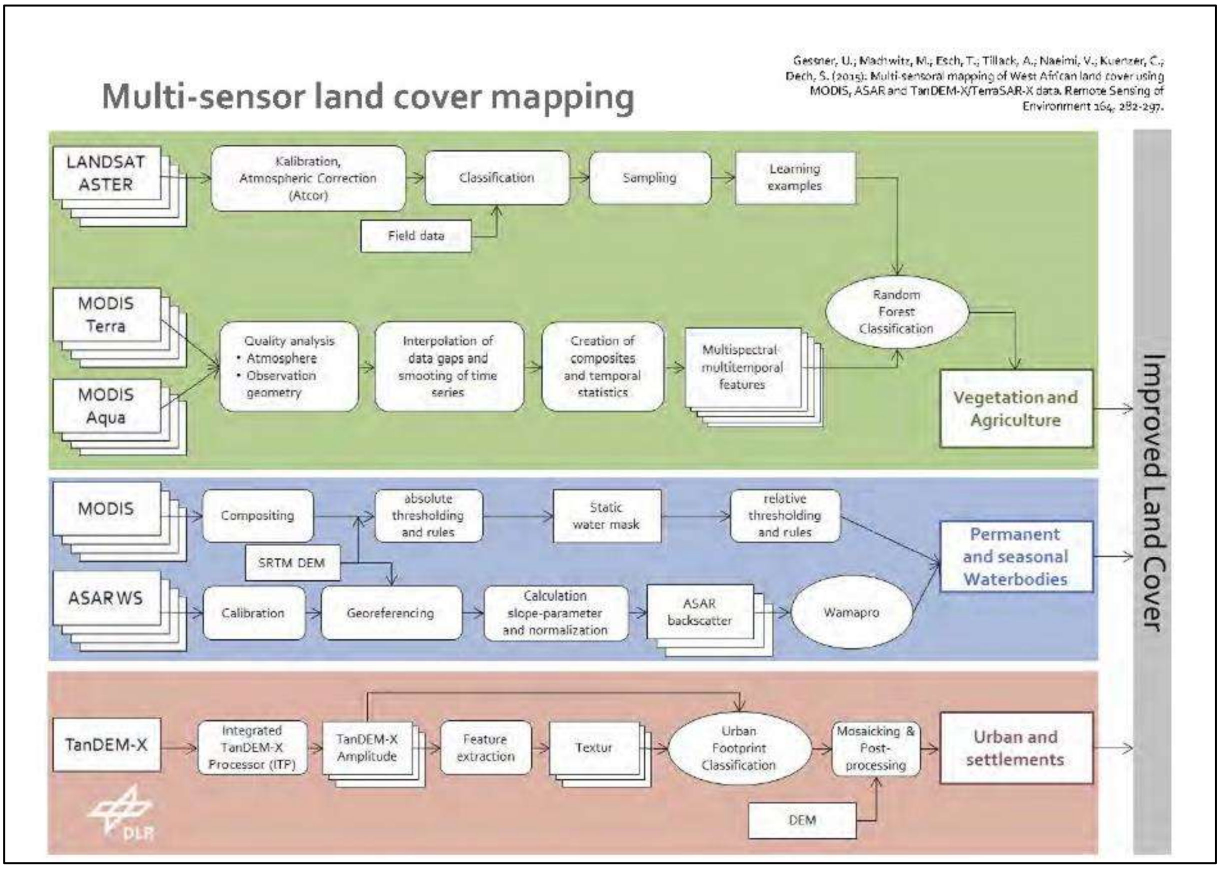
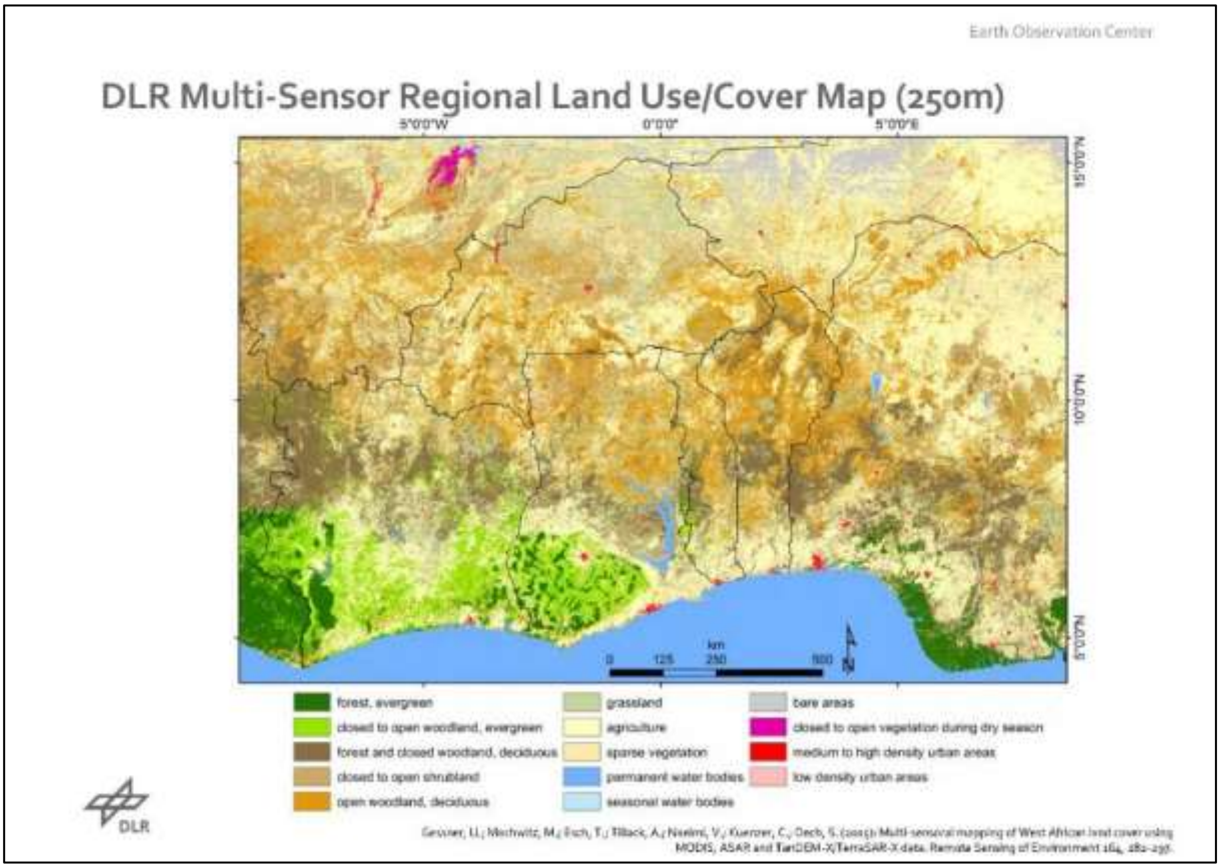
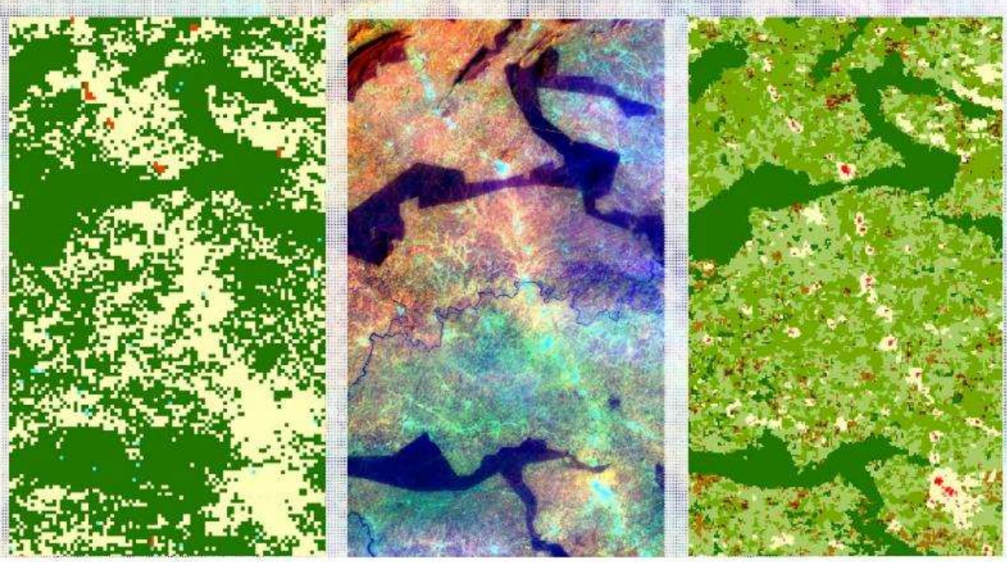

Multi-sensor land cover mapping
Gessner, U.; Machwitz, M.; Esch, T.; Tillack, A.; Naeimi, V.; Kuenzer, C.; Dech, S. (2015): Multi-sensoral mapping of West African land cover using MODIS, ASAR and TanDEM-X/TerraSAR-X data. Remote Sensing of Environment 164, 282-297.
LANDSAT ASTER
Kalibration, Atmospheric Correction (Atcor)
Classification
Sampling
Learning examples
Field data
MODIS Terra
MODIS Aqua
Quality analysis
• Atmosphere
• Observation geometry
Interpolation of data gaps and smoothing of time series
Creation of composites and temporal statistics
Multispectral multitemporal features
Random Forest Classification
Vegetation and Agriculture
MODIS
Compositing
absolute thresholding and rules
Static water mask
relative thresholding and rules
SRTM DEM
ASAR WS
Calibration
Georeferencing
Calculation slope-parameter and normalization
ASAR backscatter
Wamapro
Permanent and seasonal Waterbodies
TanDEM-X
Integrated TanDEM-X Processor (ITP)
TanDEM-X Amplitude
Feature extraction
Textur
Urban Footprint Classification
Mosaicking & Post-processing
DEM
Urban and settlements
Improved Land Cover
DLR


Earth Observation Center
DLR Multi-Sensor Regional Land Use/Cover Map (250m)
5°0'0"W
0°0'0"
5°0'0"E
15°0'0"N
10°0'0"N
5°0'0"N
km
0
125
250
500
N
forest, evergreen
closed to open woodland, evergreen
forest and closed woodland, deciduous
closed to open shrubland
open woodland, deciduous
grassland
agriculture
sparse vegetation
permanent water bodies
seasonal water bodies
bare areas
closed to open vegetation during dry season
medium to high density urban areas
low density urban areas
DLR



Global Standard (MODIS) | Landsat | WASCAL-DLR-Product (MODIS, ASAR, TanDEM-X)

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Anomalies

Prerequisites:

– long time series -> for defining typical (average) conditions

– Thorough outlier removal

Options:

– Absolute anomaly

– Relative anomalies (in relation to typical variability / mean value)

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Meteorological and agricultural drought indices

El Nino 2015/2016 (situation Nov. 2015)

Figures from Winkler K.

-> Removed as not yet published

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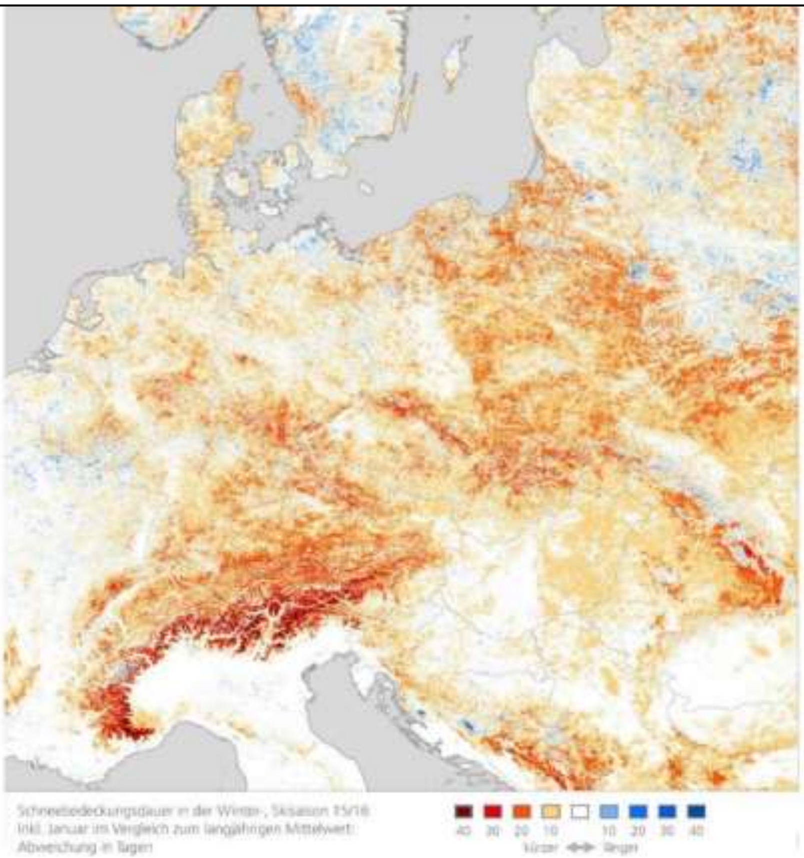
Anomaly in snow cover duration in winter 2015/2016



Source:
Dietz et al. (2016)
[illegible]

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Selected Literature

- Haan, C.T. (1977): Statistical Methods in Hydrology. Iowa State University Press, Iowa, 378 pp.
- Cowpertwaite, P.S.P. & Metcalfe, A.V. (2009): Introductory Time Series with R. Springer, Heidelberg/London/New York, 254pp.
- Kuenzer, C., Dech, S., Wagner, W. (2015): Remote Sensing Time Series - Revealing Land Surface Dynamics. Springer, Heidelberg/London/New York, 441pp.
- De Beurs, K. M., & Henebry, G. M. (2005). A statistical framework for the analysis of long image time series. *International Journal of Remote Sensing*, 26, 1551–1573.
- Donner, R. V.; Barbosa, S. M. (2008): Nonlinear Time Series Analysis in the Geosciences. Springer, Heidelberg/London/New York, 390pp.
- Cohen, W. B.; Yang, Z.; Kennedy, R. (2010): Detecting trends in forest disturbance and recovery using yearly Landsat time series: 2. TimeSync — Tools for calibration and validation. Remote Sensing of Environment 114, 2911-2924.
- Joensson, P. and Eklund, L. (2004): TIMESAT—a program for analyzing time-series of satellite sensor data. Computers & Geosciences 30, 833–845.
- Joensson, P. and Eklund, L. (2002): Seasonality Extraction by Function Fitting to Time-Series of Satellite Sensor Data. IEEE Transactions on Geosciences and Remote Sensing, Vol. 40, 8, 1824-1832.

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Literature

- Verbesselt, J.; Hyndman, R.; Zeileis, A.; Culvenor, D. (2010): Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. Remote Sensing of Environment 114, 2970-2980.
- Zhu, X.; Chen, J.; Gao, F.; Chen, X.; Masek; J. G. (2010): An enhanced spatial and temporal adaptive reflectance fusion model for complex heterogeneous regions. Remote Sensing of Environment 114, 2970-2980.
- Beurs, de, K.M. and Henebry, G.M. (2004): Land surface phenology, climatic variation, and institutional change: Analyzing agricultural land cover change in Kazakhstan. Remote Sensing of Environment 89, 497-509.
- Duy Ba Nguyen, Kersten Clauss, Senmao Cao, Vahid Naeimi, Claudia Kuenzer and Wolfgang Wagner (2015). Mapping Rice Seasonality in the Mekong Delta with Multi-Year Envisat ASAR WSM Data. Remote Sensing, 7 (12), 15868-15893.
- Kennedy, R.; Yang, Z.; Cohen, W. B. (2010): Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation. Remote Sensing of Environment 114, 2897-2910.
- Eklund, L. and Joensson, P. (2015): TIMESAT 3.2 with parallel processing - Software Manual. Lund and Malmö University, Sweden.

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2.3 VIRTUAL TRAINING 3: "SATELLITE MONITORING FOR ARCHAEOLOGICAL LOOTING"

2.3.1 Description

The third virtual training was again performed physically instead of remotely. Dr. Nicola Masini from IBAM-CNR and Dr. Rosa Lasaponara from IMAA-CNR, were hosted by the Cyprus University of technology in Limassol, Cyprus. The training was carried out on the 1st of September 2017 and focused on the use of remote sensing for monitoring archaeological looting, displaying paradigms from countries beyond Europe.

Basic overview of Looting and its monitoring from space

Relevance of the training activities in the framework of the ATHENA project

Cyprus due to its geographical position has always been the crossroad between three continents: Europe, Africa, and Asia, the bridge between east and west. With the various wars and conflicts in the Middle east area, remote sensing techniques seem to be the most efficient, time effective way for monitoring CH's destruction even documenting CH prior its total extinction, as well as to monitor archaeological looting activities which represent one of the main risks affecting archaeological heritage throughout the world.

Actions oriented to prevent looting can be supported by satellite technologies which can provide reliable information to: (i) detect and quantify looting phenomenon even over large areas, (ii) set up tools to undertake monitoring also for remote areas or sites not accessible due to war or other limiting factors.

Recently, looting activities that have exponentially increased in the Middle East since the beginning of the conflict in Syria. in the middle east areas. To face this UNESCO and UNITED National provided additional efforts and adopted new actions to condemn and contrast looting activities The United Nations Security Council, on 12 February 2015, adopted the Resolution 2199 that condemns the destruction of cultural heritage and adopts legally binding measures to counter illicit trafficking of antiquities and cultural objects.

Basic overview of Looting and CH monitoring from space

The preservation of cultural heritage and landscape is today a strategic priority not only to assure cultural treasure and evidences of the human past to future generations, but also to exploit them as a strategic and valuable economic asset, if inspired to sustainable development strategies. This is an extremely important key factor for the countries which are owners of an extraordinary cultural legacy, which is particular fragile due to its specific characteristics and specific risks at which CH is continuously exposed. Taking advantage of large-spatial coverage, high-spectral and sensitivity satellite remote sensing can be usefully adopted for contrasting looting. Satellite technologies offer a suitable chance to quantify and analyse this phenomenon, especially in those countries, from Southern America to Middle East, where the surveillance on site is not much effective and time consuming or non-practicable due to military or political restrictions.

The training activities organized by CNR and carried out by Rosa Lasaponara and Nicola Masini were focused on the characterization of the looting phenomenon from a multi-faced prospective (as detailed below). In particular, the training activities were focused on the use of high spatial resolution satellite and aerial optical images and Lidar acquisition to quantitatively assess looting. An overview of methodologies and data processing for the identification and quantification of looting features (using both single date and multitemporal satellite images) were discussed for several study areas.

Moreover, advanced data processing based on both autocorrelation statistics and unsupervised classification have been presented, applied and discussed for significant study areas, as Dura Europos; selected in Syria. The main topic were deeply focalized on the following:

1. Looting as a complex problem
   - ✓ black market of looted items
   - ✓ social and anthropological view of looters;

2. Looting features from above: physical and spectral characteristics
   - ✓ Looting from optical satellite data
   - ✓ Looting from SAR satellite data
   - ✓ Looting from LIDAR
   - ✓ Looting from UAV optical image

3. An overview of looting
   - ✓ Looting in the diverse continents from Middle East to Peru, from Asia to Europe:
   - ✓ Looting mapping and quantification
   - ✓ Visual inspection, Crowd sourcing and automatic data processing to map and quantify looting

4. Data processing from looting feature extraction
   - ✓ Classification to automatically detect looting in desert environment
   - ✓ LISA approach to enhance looting features

5. Practical applications

2.3.2 Agenda and Participants

Detailed training program

- **Lectures/presentations**

Lesson 1: An overview of Looting and international black market (Nicola Masini)

Lesson 2: Looting features and monitoring tools (Nicola Masini)

Lesson 3: An overview of Looting activities thought the world (Rosa Lasaponara)

Lesson 4: Looting from space: from visual inspection to automatic recognition and mapping (Rosa Lasaponara)

- **Practical exercise**

Satellite data for study areas selected in Syria-Dura Europos

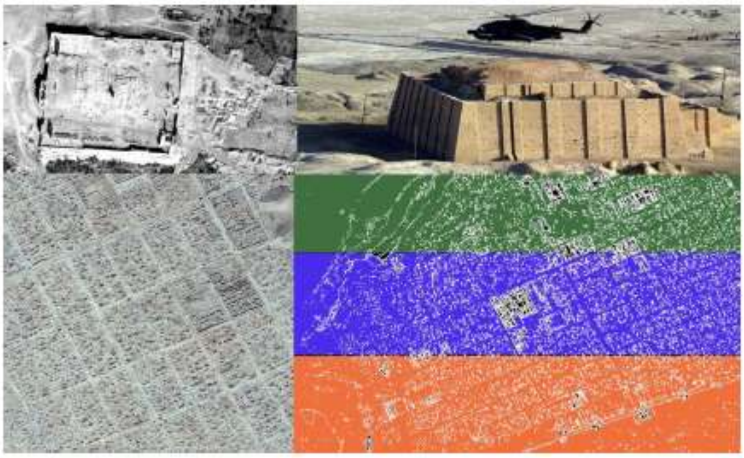
Software: open (snap) and commercial ENVI

ATHENA-Training

"Archaeological looting: Ancient problems and New approaches based on Remote Sensing"

1st September 2017, CUT, Limassol, Cyprus

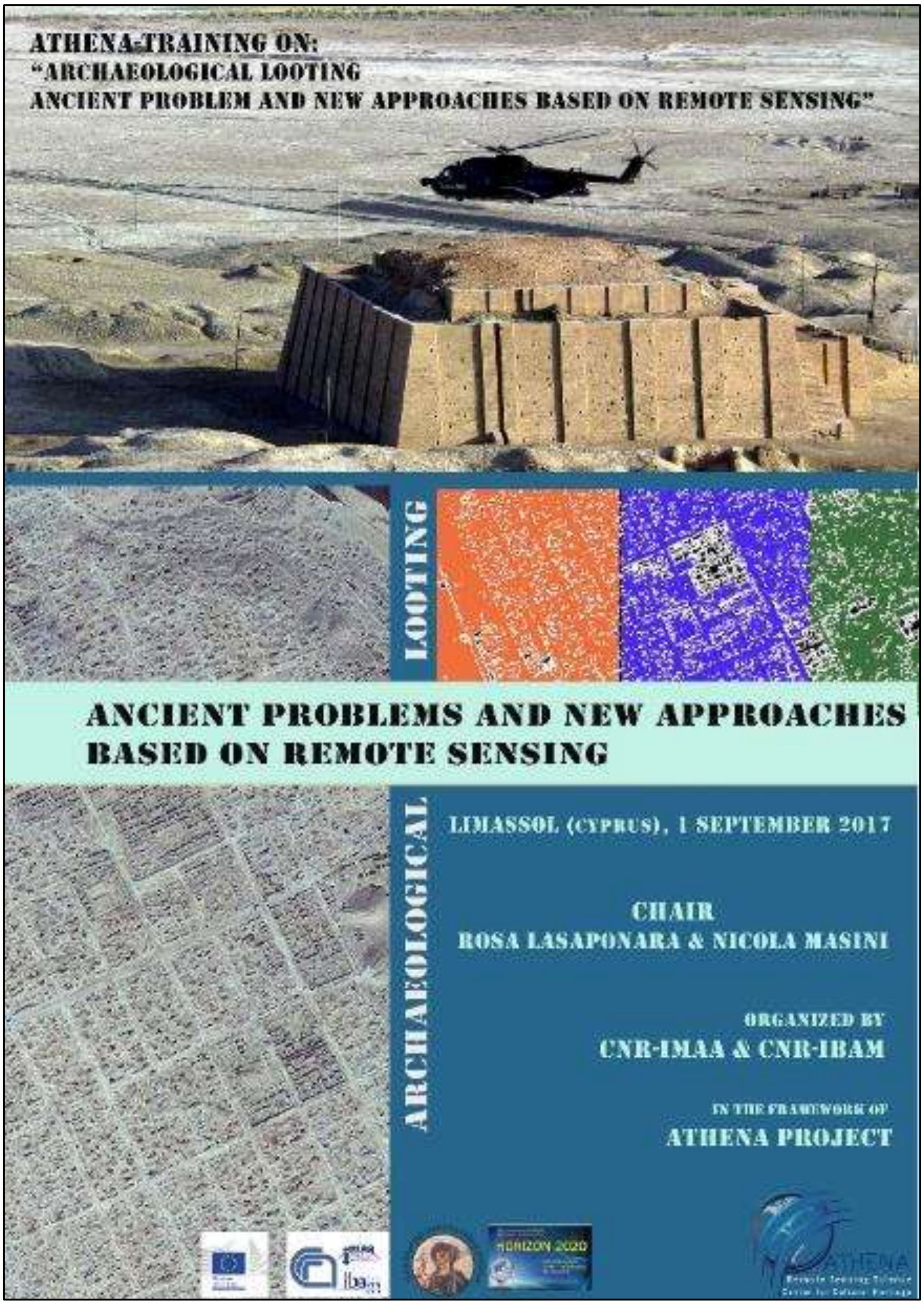
Conducted by Dr. Rosa Lasaponara and Dr. Nicola Masini



Agenda

Friday, September 1st	
9:30-10:30	- Archaeological looting disturbance : ethics and strategies for contrasting and monitoring
10:30-11:30	- EO technologies for looting observation, quantification and mapping
11.30-12.30	- State of Art of EO based approaches for looting monitoring
12:30-13:30 Lunch	
13:30-14:30	- Looting feature extraction : ALFEA method by Lasaponara & Masini
14.30-15:30	- Tutorial (study cases)
15:30-16:30	- Discussion of presented aspects - Identification of interesting aspects for joint studies - Ideas for joint journal paper /conference presentation

4th virtual training: Agenda



4th virtual training: Flyer

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Cyprus University of Technology

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H2020-TWINN-2015 - Remote Sensing Science Center for Cultural Heritage - A T H E N A
Topic: Archaeological looting: Ancient problems and New approaches based on Remote Sensing
Trainers: Dr. Rosa Lasaponara and Dr. Nicola Masini
Date: Friday, 1st September, 2017
Venue: CUT - Limassol, Cyprus

List of participants

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3	Andreas Christofe	CUT	andreas.christofe@cut.ac.cy	
4	Georgios Leventis	CUT	georgios.leventis@cut.ac.cy	
5	Antria Nicolaou	CUT	ac.nikolaou@cut.ac.cy	
6	VASILIKI LYSANDROU	CUT	vasiliki.lysandrou@cut.ac.cy	

1

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10	Rodothi Mamouri	CUT	rodanthi.mamouri@cut.ac.cy	
11				
12				
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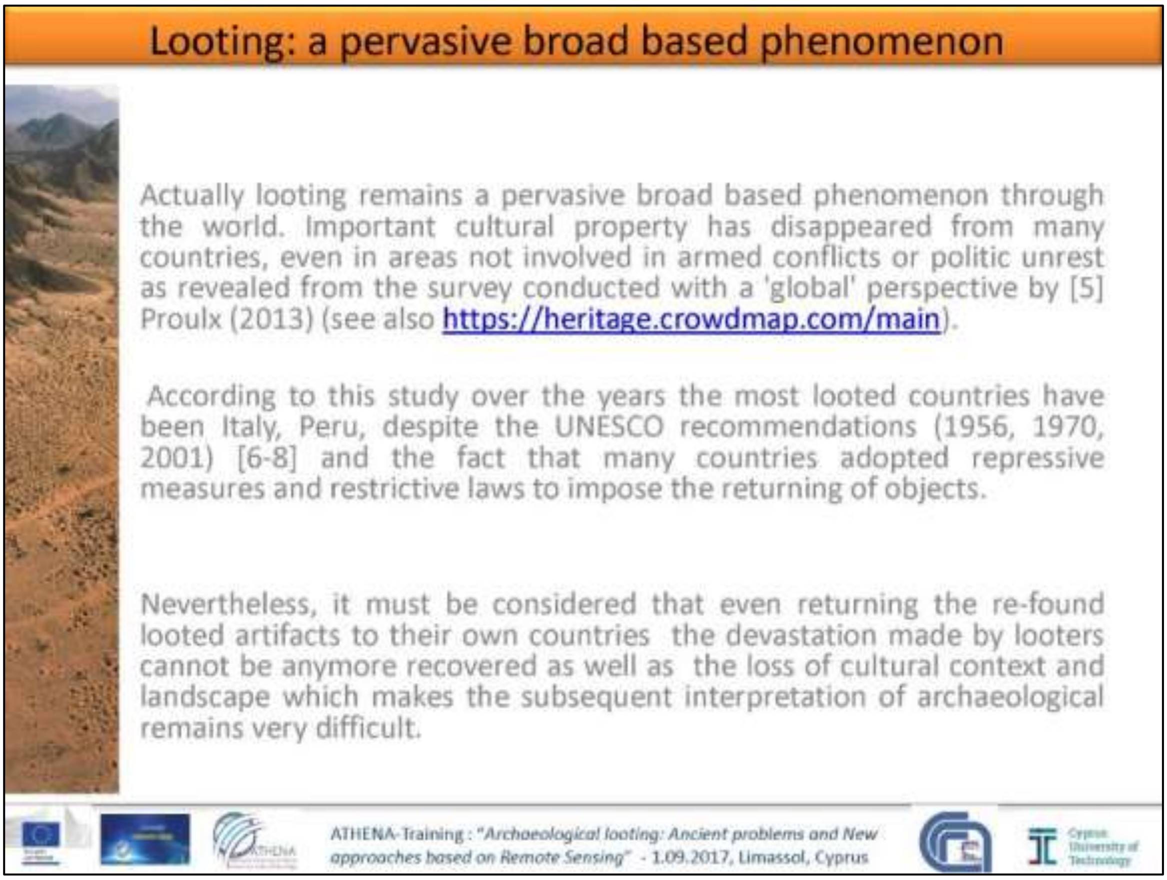
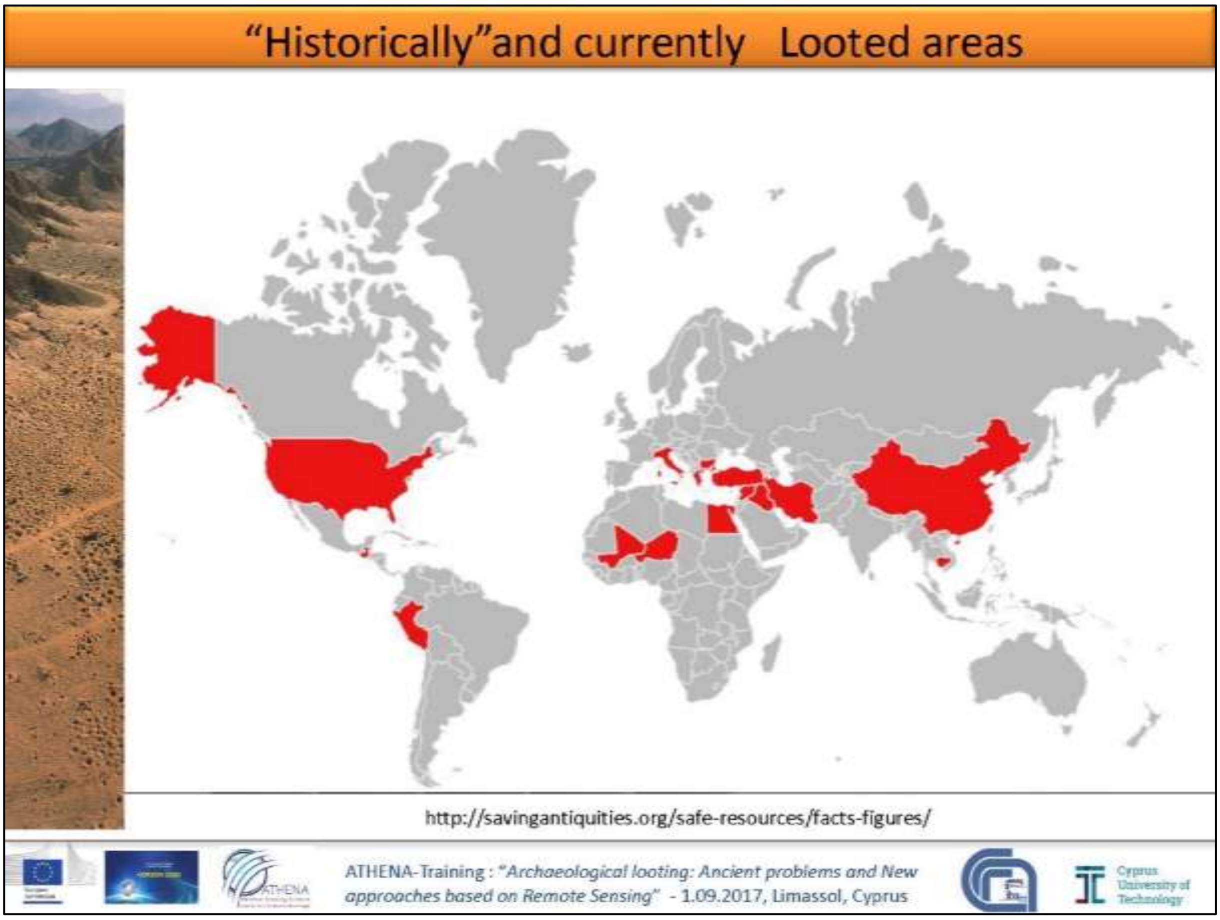
Photos during the 3rd Virtual Training at the premises of the Cyprus University of Technology

2.3.3 Presentations on "Archaeological looting. Ancient problems and new approaches based on remote sensing"




"Historically"and currently Looted areas
http://savingantiquities.org/safe-resources/facts-figures/
ATHENA-Training : "Archaeological looting: Ancient problems and New approaches based on Remote Sensing" - 1.09.2017, Limassol, Cyprus
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Looting in China
TOUR PAPHOS like never before!
BOOK NOW
https://www.theguardian.com/world/2012/jan/01/china-tomb-raiders-destroy-relics
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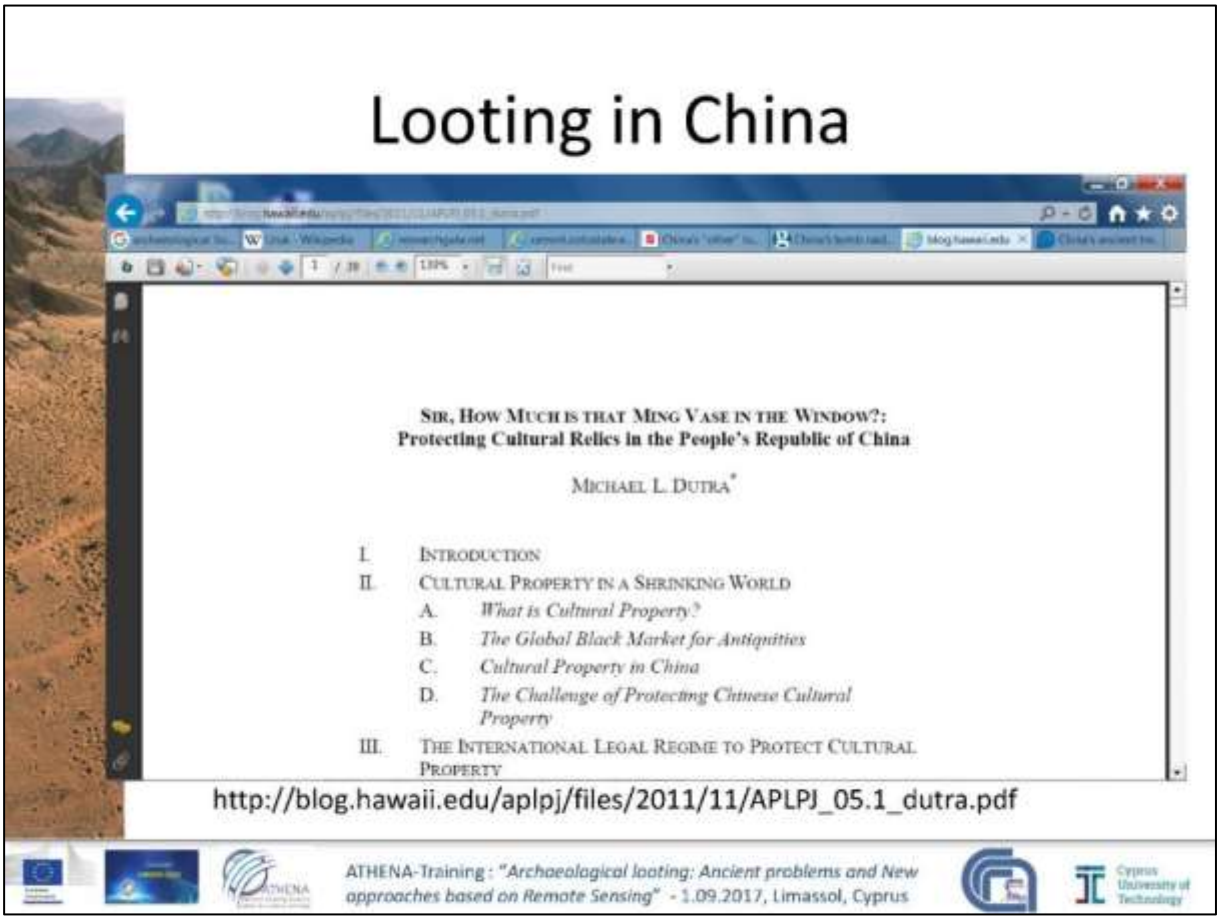
Cyprus University of Technology


Looting in China
SIR, HOW MUCH IS THAT MING VASE IN THE WINDOW?:
Protecting Cultural Relics in the People's Republic of China
MICHAEL L. DUTRA*
I. INTRODUCTION
II. CULTURAL PROPERTY IN A SHRINKING WORLD
A. What is Cultural Property?
B. The Global Black Market for Antiquities
C. Cultural Property in China
D. The Challenge of Protecting Chinese Cultural Property
III. THE INTERNATIONAL LEGAL REGIME TO PROTECT CULTURAL PROPERTY
http://blog.hawaii.edu/aplpj/files/2011/11/APLPJ_05.1_dutra.pdf
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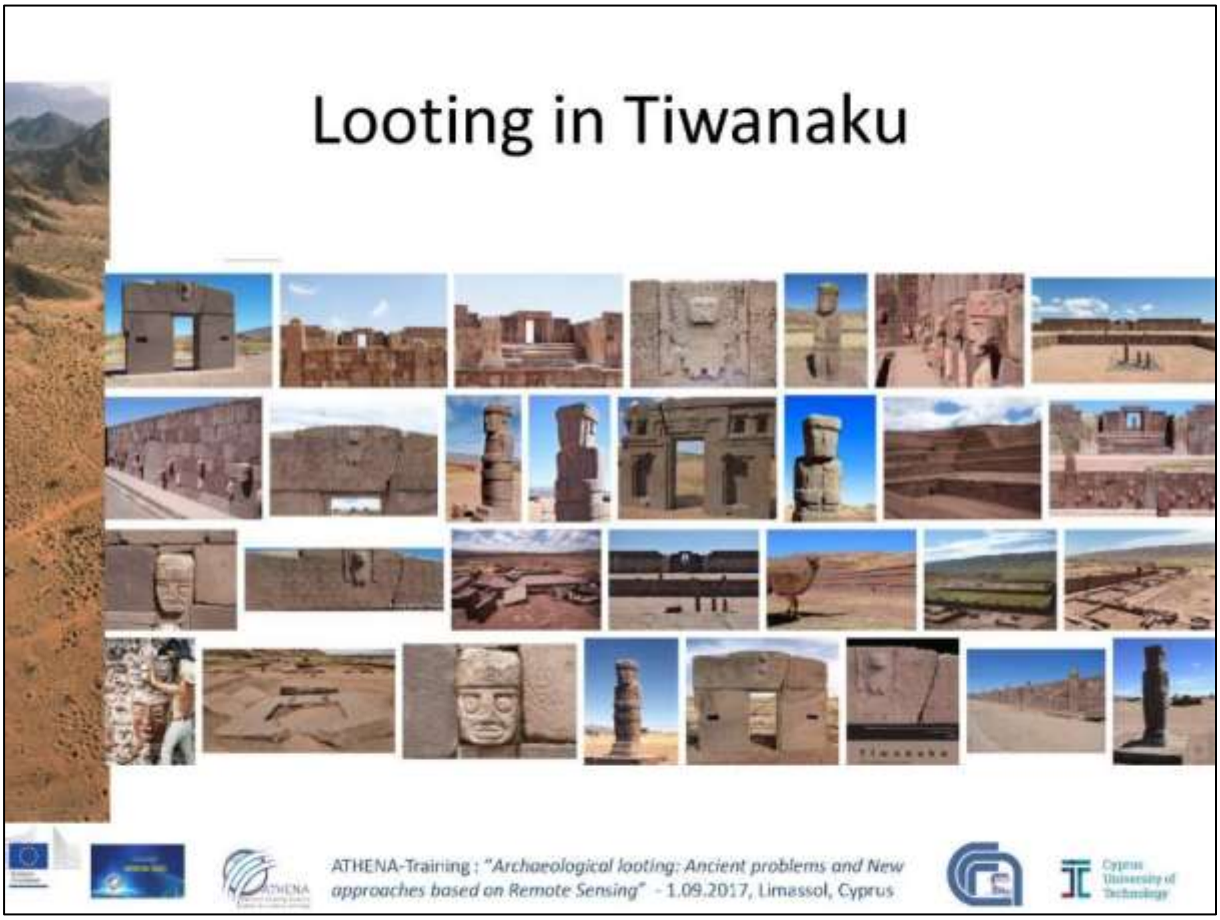
Looting in China
ATHENA-Training : "Archaeological looting: Ancient problems and New approaches based on Remote Sensing" - 1.09.2017, Limassol, Cyprus


Looting in Tiwanaku
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Looting in Tiwanaku
Anonymous Swiss Collector
Relics for Sale at Tiwanaku [Bolivia, from La Razón]
https://www.anonymousswisscollector.com/2012/11/relics-for-sale-at-tiwanaku-bolivia.html
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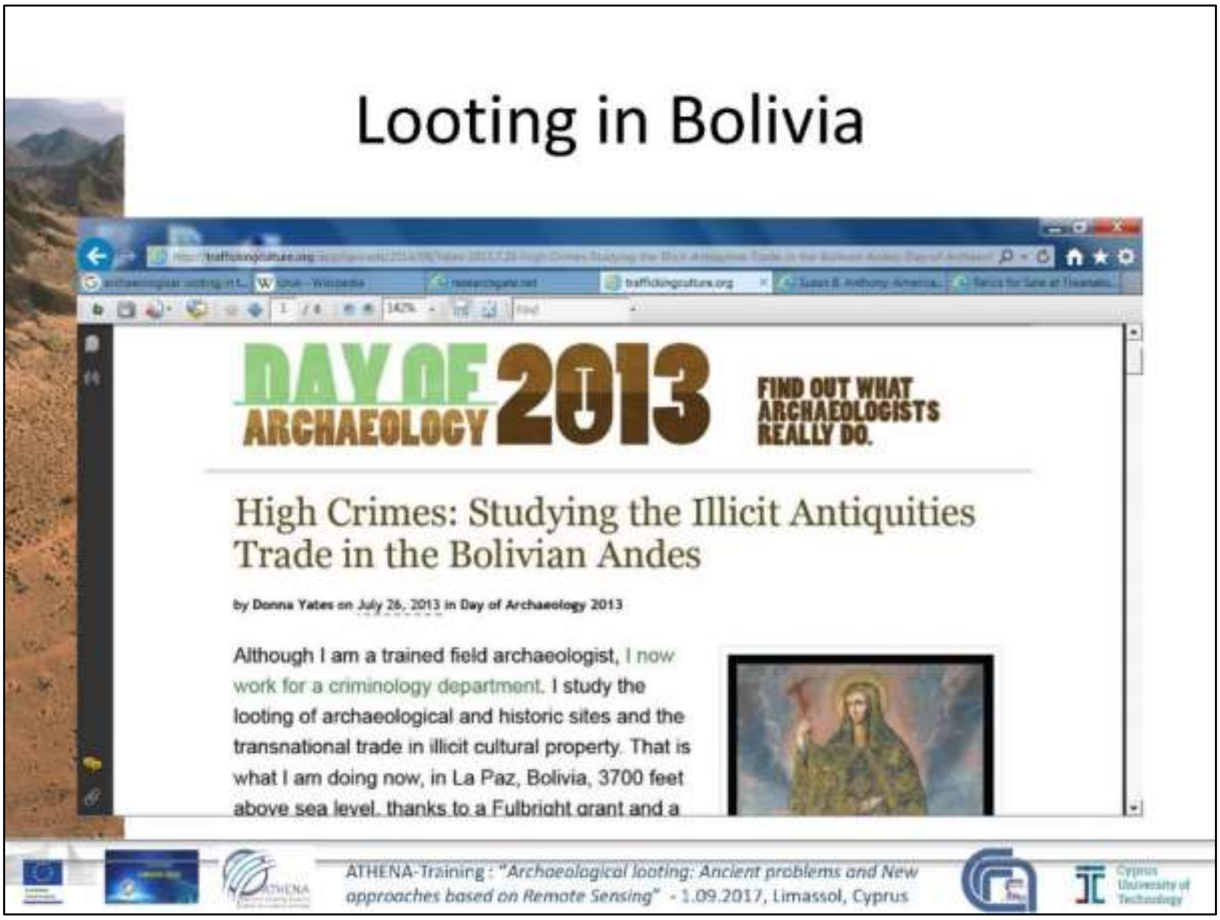
Looting in Bolivia
DAY OF ARCHAEOLOGY 2013
FIND OUT WHAT ARCHAEOLOGISTS REALLY DO.
High Crimes: Studying the Illicit Antiquities Trade in the Bolivian Andes
by Donna Yates on July 26, 2013 in Day of Archaeology 2013
Although I am a trained field archaeologist, I now work for a criminology department. I study the looting of archaeological and historic sites and the transnational trade in illicit cultural property. That is what I am doing now, in La Paz, Bolivia, 3700 feet above sea level, thanks to a Fulbright grant and a
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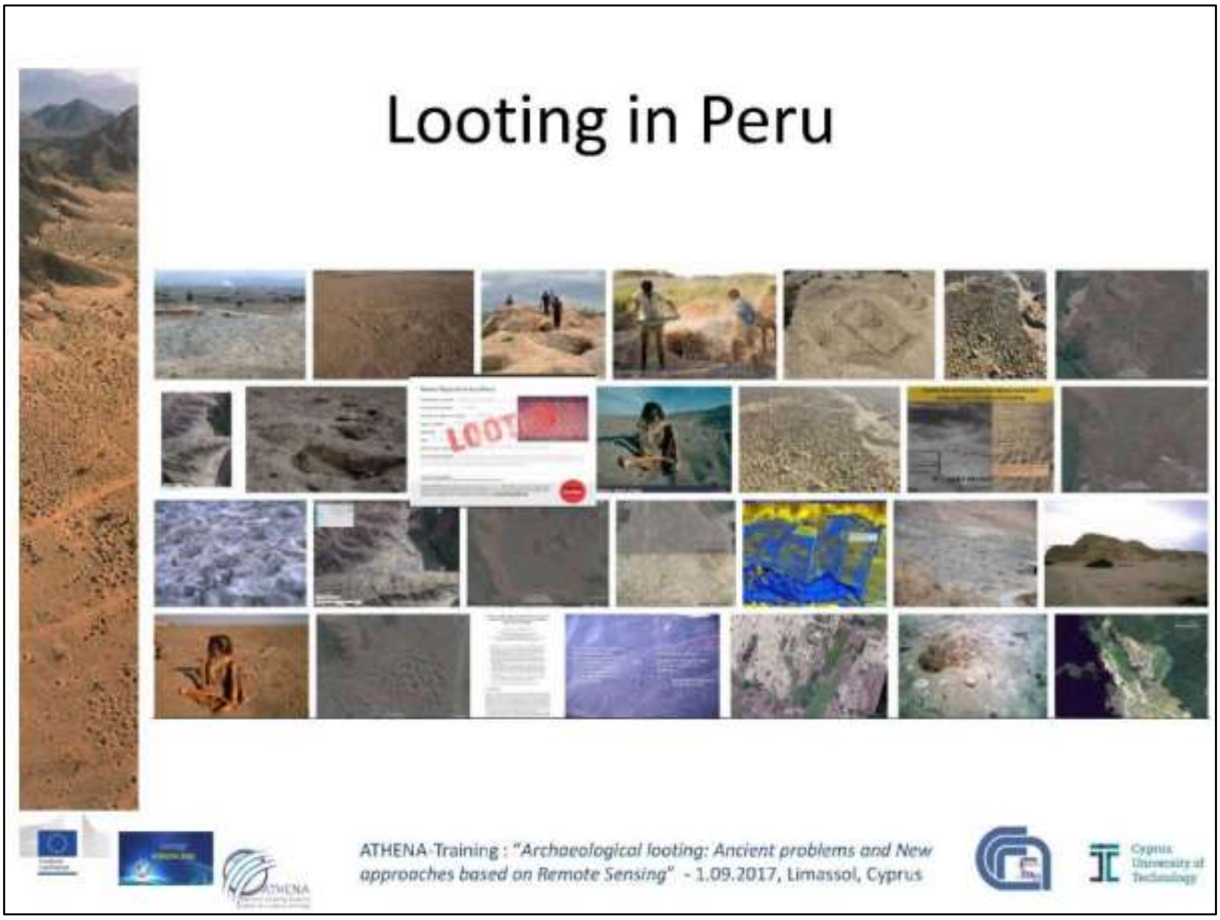
Looting in Peru
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Looting in Italy
The Italian States: Occupation
POLICE
HSI
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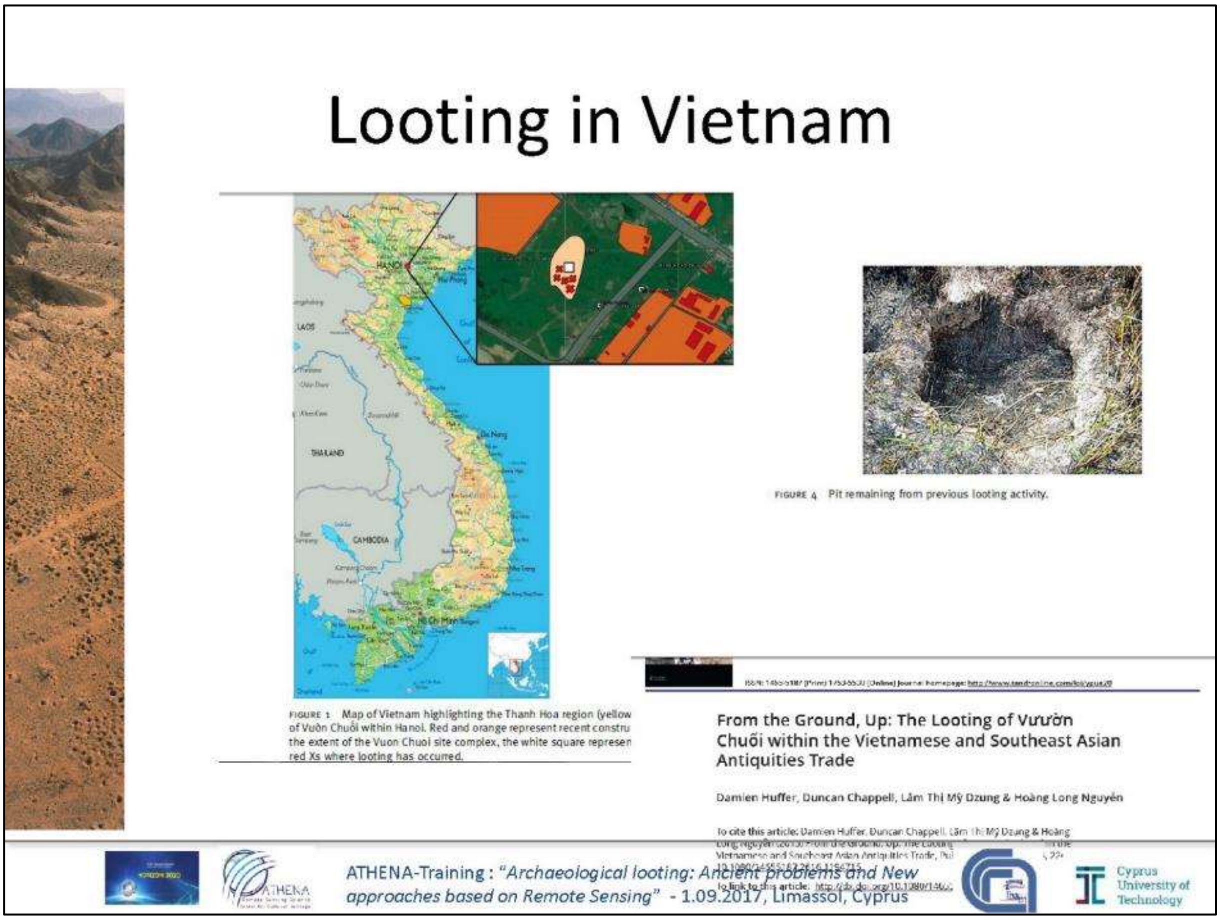
Looting in Vietnam
FIGURE 1 Map of Vietnam highlighting the Thanh Hoa region (yellow of Vuòn Chuối within Hanoi. Red and orange represent recent constru the extent of the Vuon Chuoi site complex, the white square represen red Xs where looting has occurred.
FIGURE 4 Pit remaining from previous looting activity.
From the Ground, Up: The Looting of Vườn Chuối within the Vietnamese and Southeast Asian Antiquities Trade
Damien Huffer, Duncan Chappell, Lâm Thị Mỹ Dzung & Hoàng Long Nguyễn
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Looting in Jordan

Contreras and Brodie Satellite Imagery Use in Investigating Looting of Archaeological Sites in Jordan

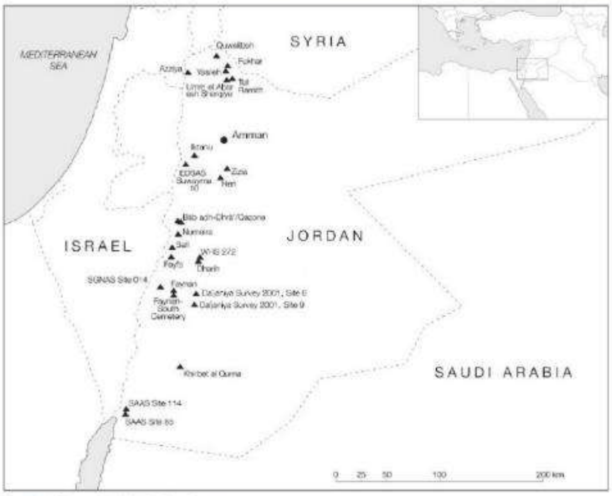

Figure 1 Sites evaluated for looting damage.

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Contreras and Brodie Satellite Imagery Use in Investigating Looting of Archaeological Sites in Jordan

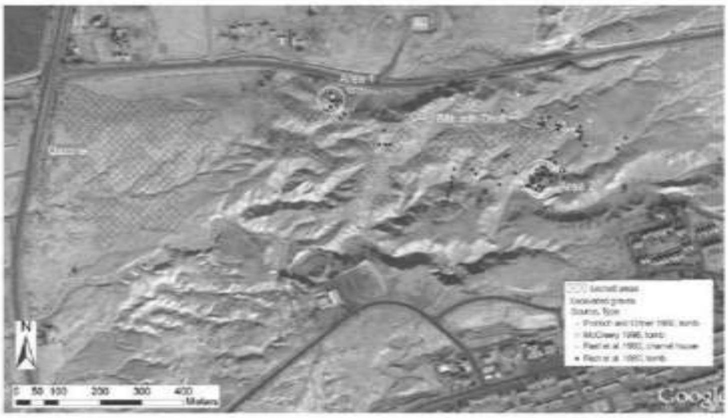

Figure 2 Google Earth image of Bāb adh-Dhrā' (2007), showing damage from looting and areas excavated.

Methodology

Two methods of prospecting for looted areas were employed, both utilizing the DAAHL database. First, the DAAHL database was filtered for cemetery sites—deemed the most likely targets for looters because of the availability of intact ceramics and other saleable grave goods—and the resulting collection of 406 sites was downloaded as a .kml file (a geographic location and associated display information in keyhole markup language) that could be imported directly into Google Earth. The areas immediately surrounding each of these sites were inspected for signs of obvious and extensive looting, visible as pitting on aerial and/or satellite images (highly contrasting intermingled dark and light pixels, distinct from the basically monochromatic, unmodified landscape) (FIG. 2). This was possible because Google Earth incorporates sub-meter/pixel QuickBird imagery for much of Jordan. The correspondence between pitting identified on images and looting on the ground was established from areas previously documented as badly damaged by looting (Bāb adh-Dhrā' and Khirbat Qazone, as described below, and also Safi; Papadopoulos et al. 2001; Politis 1994, 1998a, 1998b, 1999, 2002; Politis et al. 2005; Politis et al. 2007). Where looting was identified, the location was marked with a rough polygon and noted for later evaluation. In total, 18 sites with indications of looting were identified using this method. The relatively low number of looted cemeteries identified should not, however, be taken as an indication of the scarcity of looting. JADIS includes reports of few isolated burials, and only relatively extensive looting

Courtesy by Daniel A. Contreras, Neil Brodie. The Utility of Public Available Satellite Imagery for Investigating Looting of Archaeological Sites in Jordan
Article in Journal of Field Archaeology · March 2010

DOI: 10.1179/009346910X12707320296838

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Looting in Jordan

Contreras and Brodie Satellite Imagery Use in Investigating Looting of Archaeological Sites in Jordan

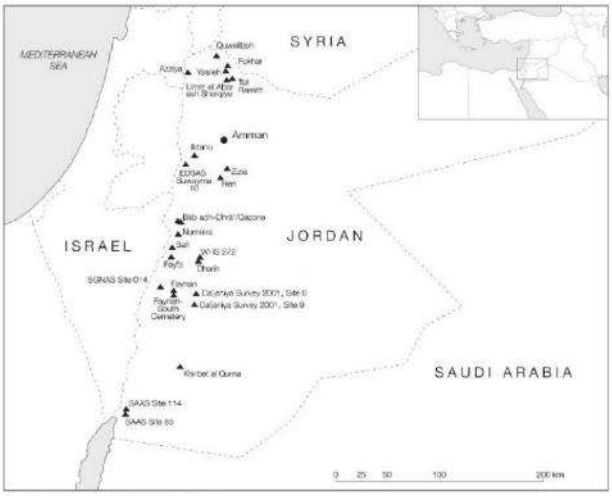

Figure 1 Sites evaluated for looting damage.

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Looting underwater treasures

http://www.haaretz.com/archaeology/1.77747

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War and Looting

Figure 2. Some archaeological sites looted in Iraq during the second Gulf War: Abbas al Kurdi (upper left), Sifr (upper right), Jokha (lower left), and Tell Medinah (lower right)

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Looting detection by visual inspection in Iraq by Stone (2008)

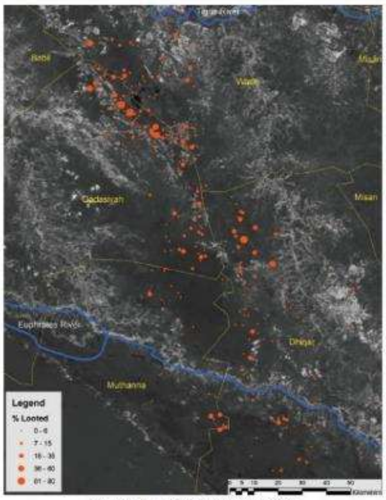

Figure 4. Looting visible in recent imagery. Image by Elizabeth Stone.

Courtesy by Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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War and Looting
http://www.nationalgeographic.com.au/people/iconic-ancient-sites-ravaged-in-isis-last-stand-in-iraq.aspx
EXPLORE VIDEOS NEWS TV WIN MORE
NATIONAL GEOGRAPHIC
Recently released satellite imagery of archaeological sites around the northern Iraqi city of Mosul has revealed extensive destruction at two capital cities of ancient Mesopotamia, according to researchers with the American Schools of Oriental Research Cultural Heritage Initiatives (ASOR CHI).
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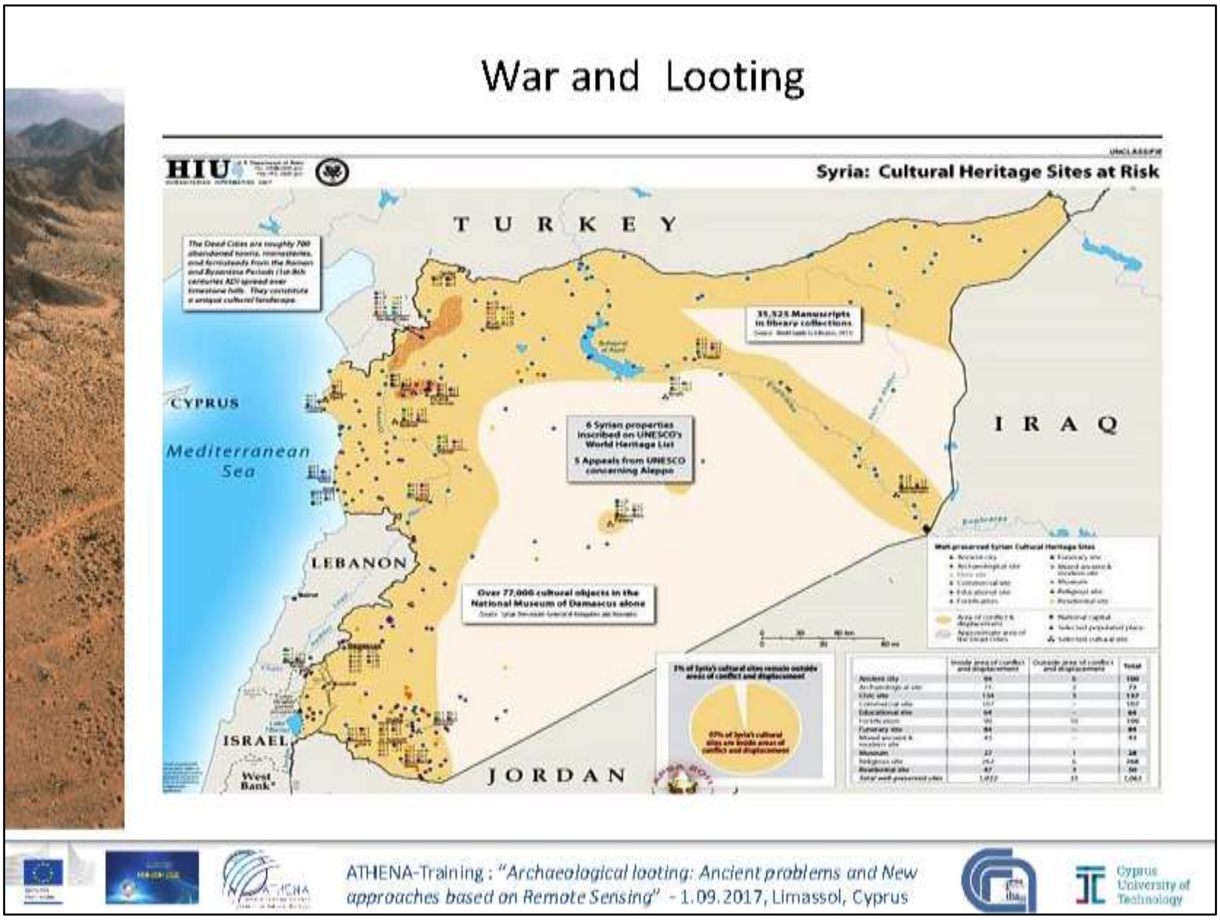
War and Looting
HIU
Syria: Cultural Heritage Sites at Risk
TURKEY
IRAQ
CYPRUS
Mediterranean Sea
LEBANON
ISRAEL
JORDAN
West Bank*
35,525 Manuscripts in library collections
6 Syrian properties inscribed on UNESCO's World Heritage List
5 Appeals from UNESCO concerning Aleppo
Over 77,000 cultural objects in the National Museum of Damascus alone
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Looting: a pervasive broad based phenomenon

Proulx B.B. 2013. "Archaeological site looting in global prespective. Nature, scope and frequency." *American Journal of Archaeology* (117): 111-125.

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On the monitoring of archaeological looting and damage

- In order to monitor archaeological looting and damage since the thirties of the 20th century aerial surveillance has been a common tool appreciated by archaeologists and conservators as it permits not only the discovery of unknown sites but also the monitoring of know sites and the estimation of risk factors, such as environmental (landslides, flooding) and man-made (i.e. the impact of urban and industrial infrastructures) issues.
- Results from some recent investigations have shown that Very High resolution (VHR) satellite imagery are of great help in the remote surveying of archaeological heritage for the identification of the areas of archaeological interest as well as for of looting and the quantification of damage
- https://www.aaas.org/page/ancient-history-modern-destruction-assessing-current-status-syria-s-world-heritage-sites-using

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On the monitoring of archaeological looting and damage

- Results from some recent investigations have shown that Very High resolution (VHR) satellite imagery are of great help in the remote surveying of archaeological heritage for the identification of areas of archaeological interest affected by looting and the quantification of damage in Syria (Casana and Panahipour 2014; AAS 2015), in Iraq (Stone 2015), in Peru (Contreras 2010; Lasaponara et al. 2014).
- Up to now, only a few contributions have been specifically focused on data processing for the extraction of looting /devastation features based on optical (Lasaponara et al. 2014; Van Ess et al. 2006; Lasaponara and Masini 2010; Cerra et al. 2016) or SAR (Tapete et al. 2016) remote sensing.
- In particular, van Hees et al. (2006) used a semiautomatic object oriented approach based on the segmentation and subsequent supervised classification, applied to the archaeological site of Uruk-Warka in Iraq (Van Ess et al. 2006).
- Lasaponara & Masini (2010) introduced for the first time the use of local spatial association indicators (LISA) for the identification of looting patterns, near Nasca in Southern Peru. This approach was later coupling LISA with usupervised classifications for the automatic extraction of looting features in Ventarron (Northern Peru) (Lasaponara et al. 2014).
- Cerra et al. (2016) obtained change maps in two archaeological sites in Syria and in Iraq by analysing texture features, extracted through Gabor filters, and differences in brightness values.

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On the monitoring of archaeological looting and damage

- Visual inspection
- Semiautomatic Processing
- Automatic processing

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Monitoring illegal excavation based on visual inspection of VHR satellite data for UNESCO- UNOSAT

- https://www.theatlantic.com/photo/2016/02/the-looting-of-syrias-archaeological-treasures/459996/
- http://www.livescience.com/56141-looting-artifacts-from-syria-to-us.html
- https://www.aaas.org/page/ancient-history-modern-destruction-assessing-status-syria-s-tentative-world-heritage-sites-7
- http://www.unesco.org/new/en/safeguarding-syrian-cultural-heritage/
- http://www.unesco.org/new/en/phnompenh/culture/tangible-cultural-heritage/prevention-of-looting-and-illicit-traffic-of-cultural-property

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Visual inspection of google earth

TerraWatchers initiative

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Looting detection by visual inspection in Iraq by Stone (2015)

•Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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Looting detection by visual inspection in Iraq by Stone (2015)

"Iraq had experienced site looting in the past– indeed it is largely as a result of this activity that the world's museums have Mesopotamian collections, but in the decades before 1990 a strong system of site protection was in place and the local population was sufficiently prosperous to have little interest in acquiring antiquities for sale. Two unrelated events changed everything in 1990.

One was the Iraqi invasion of Kuwait and its aftermath–including the Shiite uprising; the second was the filling of the lake behind the Ataturk dam in Turkey which initiated a decrease in the water critical for irrigation in southern Iraq (Beaumont 1998).

The net result was an impoverishment of the population of the south due to reductions in both agricultural production and support from the central government. It is thus perhaps not surprising that the local population began to turn to an alternate source of income: the retrieval and sale of antiquities. " (Stone , 2015)

•Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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Looting detection by visual inspection in Iraq by Stone (2015)

Figure 1a (top). Site 1217 on February 27, 2003.Figure 1b (middle).
Figure 1b (middle)Site 1217 on June 10, 2003.
Figure 1c (bottom). Site 1217 on January 18, 2015.
Photographs courtesy of of the Digital Globe Corporation.

Courtesy by Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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Looting detection by visual inspection in Iraq by Stone (2015)

Stone (2015) has re-examined 1,465 of the surveyed archaeological sites that had been used in the earlier project (Stone , 2003).

For each site, the current situation was compared with that in 2003 (see Table 1).

Determining the exact location of each site, using GIS to measure their sizes based on the imagery, and using the published surface survey data to assess the date of the most accessible archaeological remains had already been accomplished for the 2003 looting survey

Courtesy by Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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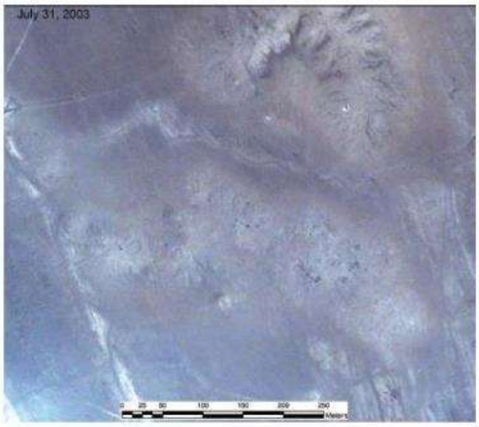
Looting detection by visual inspection in Iraq by Stone (2015)



Courtesy by Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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Looting detection by visual inspection in Iraq by Stone (2015

Sites with Evidence for >10% Looting						
Period of Occupation	February 2003 Sites	February 2003 %	Summer 2003 Sites	Summer 2003 %	Summer 2015 Sites	Summer 2015 %
Early Ubaid	0	0.00	0	0.00	0	0.00
Late Ubaid	0	0.00	1	0.33	0	0.00
Early Uruk	3	4.35	3	1.00	2	3.23
Middle Uruk	0	0.00	1	0.33	0	0.00
Late Uruk	9	13.04	19	6.36	4	6.45
Jemdet-Nasr	2	2.90	14	4.68	2	3.23
Early Dynastic I	0	0.00	14	4.58	3	4.84
Early Dynastic II	0	0.00	7	2.34	2	3.23
Early Dynastic III	0	0.00	0	0.00	0	0.00
Akkadian	0	0.00	3	1.00	3	4.84
Ur III/Isin-Larsa	6	8.70	27	9.03	9	14.52
Old Babylonian	6	8.70	24	8.03	5	8.06
Kassite	3	4.35	25	8.36	3	4.84
Middle Babylonian	3	4.35	17	5.69	3	4.84
Neo-Babylonian	1	1.45	5	1.67	1	1.61
Achaemenid	3	4.35	24	8.03	4	6.45
Parthian	11	15.94	56	18.73	11	17.74
Sassanian	8	11.59	34	11.37	6	9.68

Courtesy by Stone E. C. 2015. "An Update on the Looting of Archaeological Sites in Iraq." *Near Eastern Archaeology*, 78 (3): 178-186.

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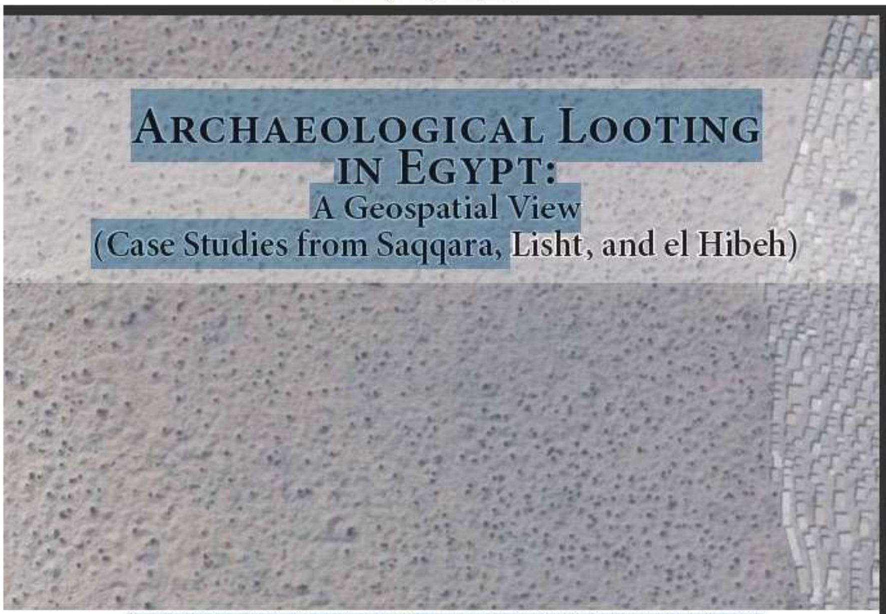
Looting detection by visual inspection in Egypt by Parcak (2015)


ARCHAEOLOGICAL LOOTING IN EGYPT:
A Geospatial View
(Case Studies from Saqqara, Lisht, and el Hibeh)

Thousands of looting pits visible from space at the site of Abusir El Malek, a Late Period–Ptolemaic Period cemetery (near Fayoum, Egypt). Imagery courtesy of Google Earth.

Sarah Parcak

Sarah Parcak 2015 Archaeological Looting in Egypt: A Geospatial View (Case Studies from Saqqara, Lisht, andel Hibeh) Near Eastern Archaeology, Vol. 78, No. 3, Special Issue: The Cultural Heritage Crisis in the Middle East (September 2015), pp. 196-203

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Looting detection by visual inspection in Egypt by Parcak (2015

Sarah Parcak 2015 Archaeological Looting in Egypt: A Geospatial View (Case Studies from Saqqara, Lisht, andel Hibeh) Near Eastern Archaeology, Vol. 78, No. 3, Special Issue: The Cultural Heritage Crisis in the Middle East (September 2015), pp. 196-203

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Looting identification by Visual Inspection in Syria by Casana J. 2015

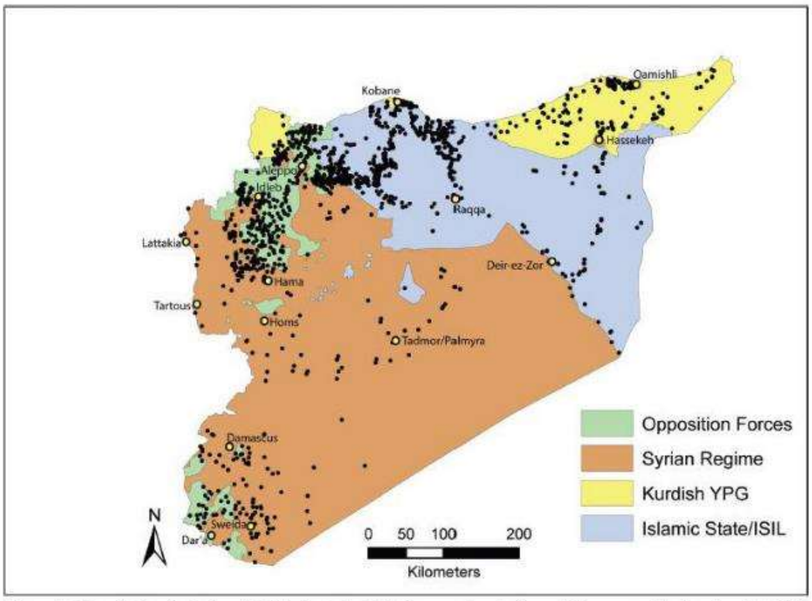

Figure 5a (above). Map illustrating all 1,289 sites included in the current analysis overlaid on areas of factional control within Syria as of early 2015, as mapped by the Strategic Needs Analysis Project (SNAP 2015).

- Courtesy by Casana J. 2015. "Satellite Imagery-Based Analysis of Archaeological Looting in Syria." *Near Eastern Archaeology* 8, (3): 142-152.

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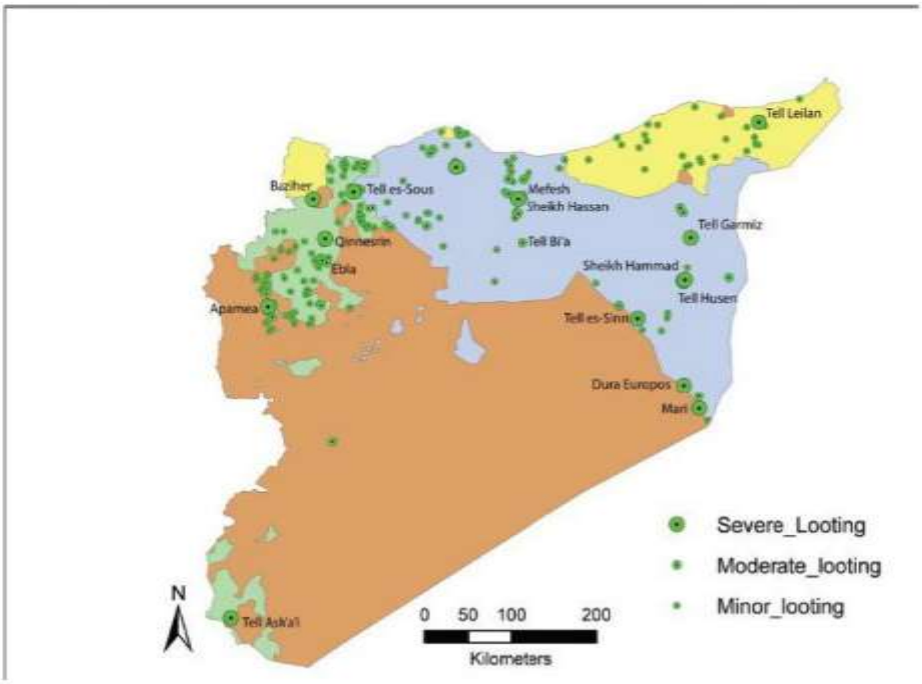
Looting identification by Visual Inspection in Syria by Casana J. 2015



Courtesy by Casana J. 2015. "Satellite Imagery-Based Analysis of Archaeological Looting in Syria." *Near Eastern Archaeology* 8, (3): 142-152

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Apamea looting using enanched TERRA-SAR

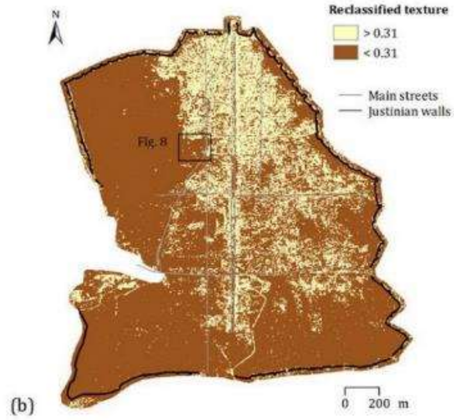

Fig. 7. (a) Texture map of the TerraSAR-X ST scene of 22nd October 2014, obtained by applying a kernel of 9 × 9 pixels and Gaussian weighting. The texture-based extent of looting is highlighted in yellow. Green and orange polygons show the location of the sample areas used to extract texture values in un-looted and looted areas. (b) Reclassified texture map, with location of the area zoomed in Fig. 8.

Courtesy by Tapete D., F. Cigna, D.N.M. Donoghue 2016. "'Looting marks' in space-borne SAR imagery: Measuring rates of archaeological looting in Apamea (Syria) with TerraSAR-X Staring Spotlight." *Remote Sensing of Environment* (178): 42–58.

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Visual Inspection based on enanched VHR satellite data in Peru (Lasaponara &Masini 2012, Lasaponara et al 2012)

- Lasaponara & Masini (2010) introduced for the first time the use of local spatial association indicators (LISA) for the identification of looting patterns, near Nasca in Southern Peru.

- This approach was later improved coupling LISA with un-supervised classifications for the automatic extraction of looting features in Ventarron (Northern Peru) (Lasaponara et al. 2014).

Lasaponara R. and N. Masini 2010. "Facing the archaeological looting in Peru by local spatial autocorrelation statistics of Very high resolution satellite imagery." In Taniar D. et al (Eds), *Proceedings of ICSSA, The 2010 International Conference on Computational Science and its Application* (Fukuoka-Japan, March 23 – 26, 2010), Springer, Berlin, 261-269.
Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0. 177-193, doi: 10.1007/978-90-481-8801-7_8.
Lasaponara R., G. Leucci, N. Masini, R. Persico 2014. "Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru" *Journal of Archaeological Science* 42: 216-230 http://dx.doi.org/10.1016/j.jas.2013.10.032

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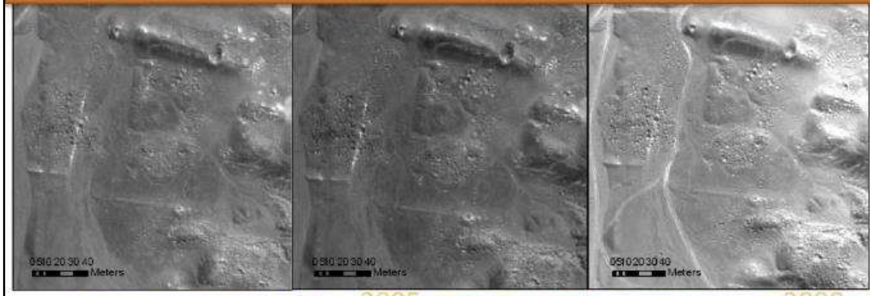
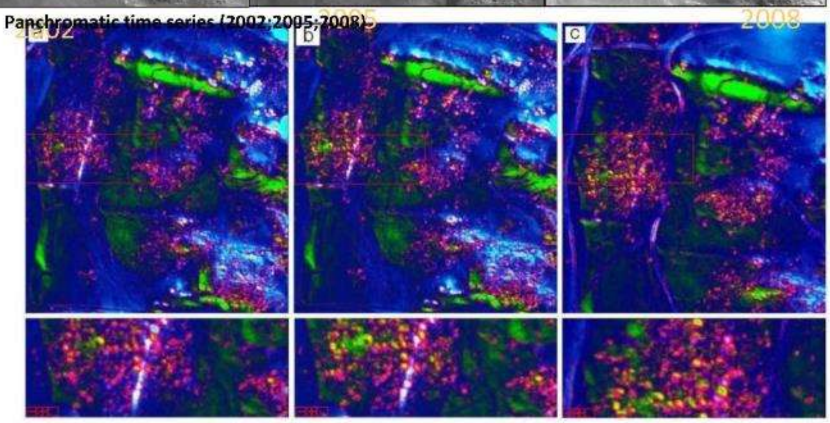
Geospatial analyses for Monitoring of illegal excavation in Peru (Lasaponara and Masini 2012)



Panchromatic time series (2002;2005;2008)

The improvement obtained by LISA application is still more evident if we compare the panchromatic satellite time series with the correspondent time series processed by local spatial autocorrelation statistics



CAHUACHI (NASCA)

The multitemporal comparison of the three RGB images clearly shows an increasing number of pits from 2002 to 2008 and, therefore, the **intensification of the looting phenomenon over the years.**

RGB composition of LISA (R:Geary; G: Moran; B: Getis) applied to panchromatic images of 2002 QB (a), 2005 QB (b) and 2008 WW1 (c). RGB composition emphasize pits enhancing their edges (circled with magenta).

Lasaponara R. and N. Masini 2010. "Facing the archaeological looting in Peru by local spatial autocorrelation statistics of Very high resolution satellite imagery." In Taniar D. et al (Eds), *Proceedings of ICSSA*, The 2010 International Conference on Computational Science and its Application (Fukuoka Japan, March 23 – 26, 2010), Springer, Berlin, 261-269.
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Lasaponara R., G. Leucci, N. Masini, R. Persico 2014. "Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru" *Journal of Archaeological Science* 42: 216-230 http://dx.doi.org/10.1016/j.jas.2013.10.032

Semi automatic

Van Hees et al. (2006) used a semiautomatic object oriented approach based on the segmentation and subsequent supervised classification, applied to the archaeological site of Uruk-Warka in Iraq (Van Ess et al. 2006).

Van Ess M., H. Becker, J. Fassbinder, R. Kiefl, I. Lingenfelder, G. Schreier, A. Zevenbergen 2006. "Detection of Looting Activities at Archaeological Sites in Iraq Using Ikonos Imagery." Angewandte Geoinformatik, Beiträge zum (18), Heidelberg: Wiechmann-Verlag 668–678

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Satellite based Automatic identification of looting

Lasaponara & Masini (2010) introduced for the first time the use of local spatial association indicators (LISA) for the identification of looting patterns, near Nasca in Southern Peru.

This approach was later coupling LISA with un-supervised classifications for the automatic extraction of looting features in Ventarron (Northern Peru) (Lasaponara et al. 2014).

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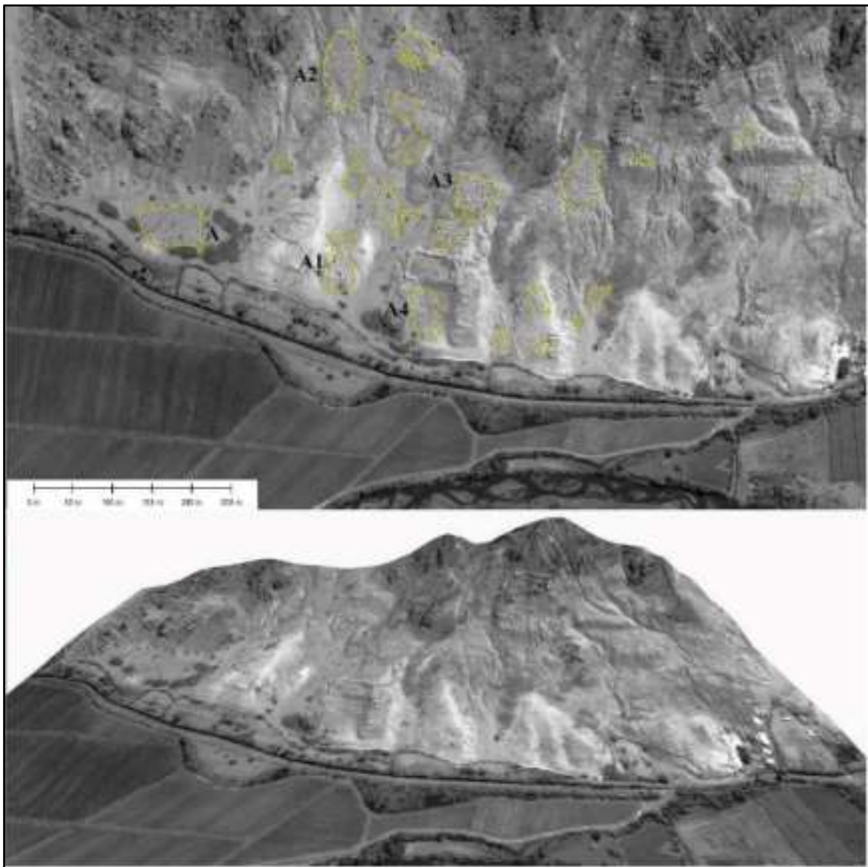
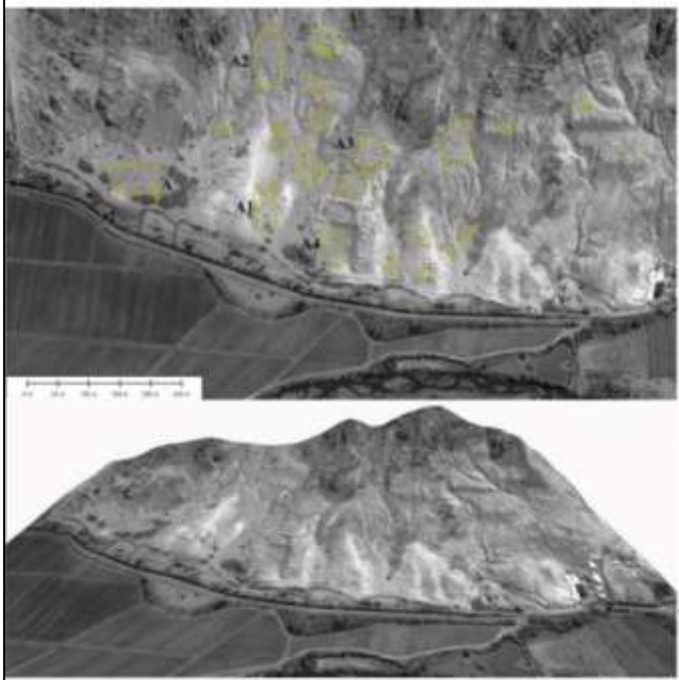


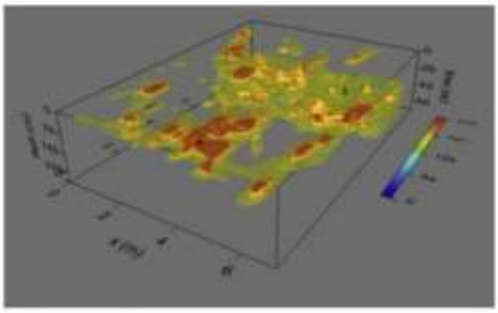
ITACA mission (Peru):

Ceremonial Centre of Ventarron: MONITORING

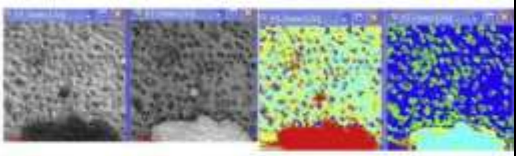
SATELLITE-BASED MONITORING OF ARCHAEOLOGICAL LOOTING IN PERU

VENTARRON (LAMBAYEQUE)



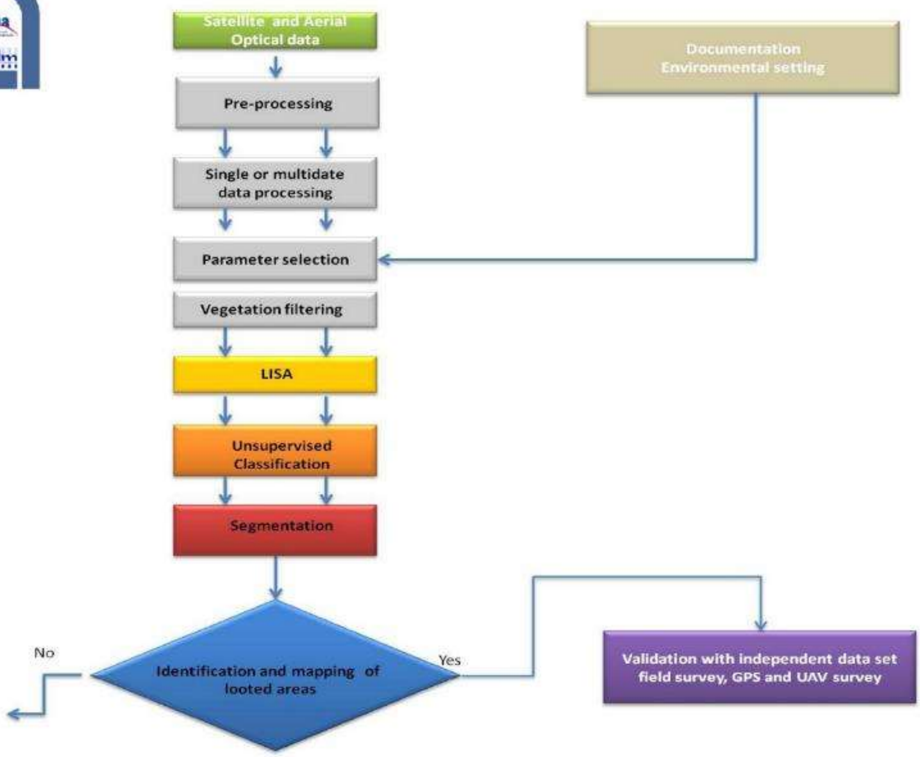


Georadar 3d map of a looted tomb



Automatic extraction of looting features using Satellite multitemporal imagery in Lasaponara et al 2014

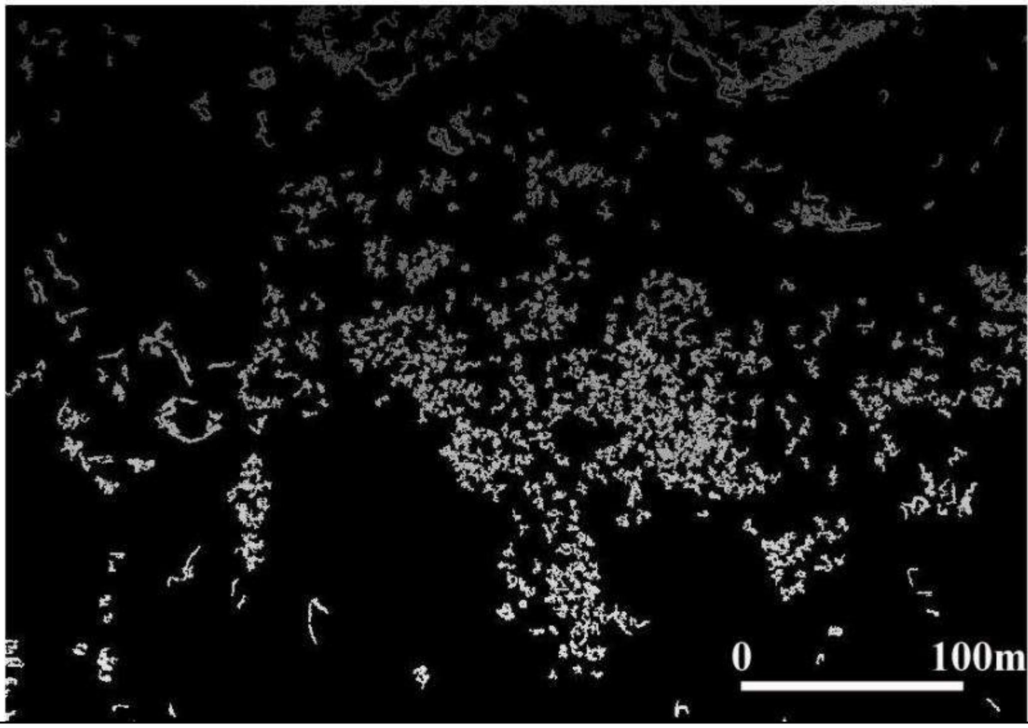
Lasaponara R., Leucci G., Masini N., Persico R. 2014. Investigating archaeological looting using satellite images and georadar: the experience in Lambayeque in North Peru. ***Journal of Archaeological Science***, 42, 216-230



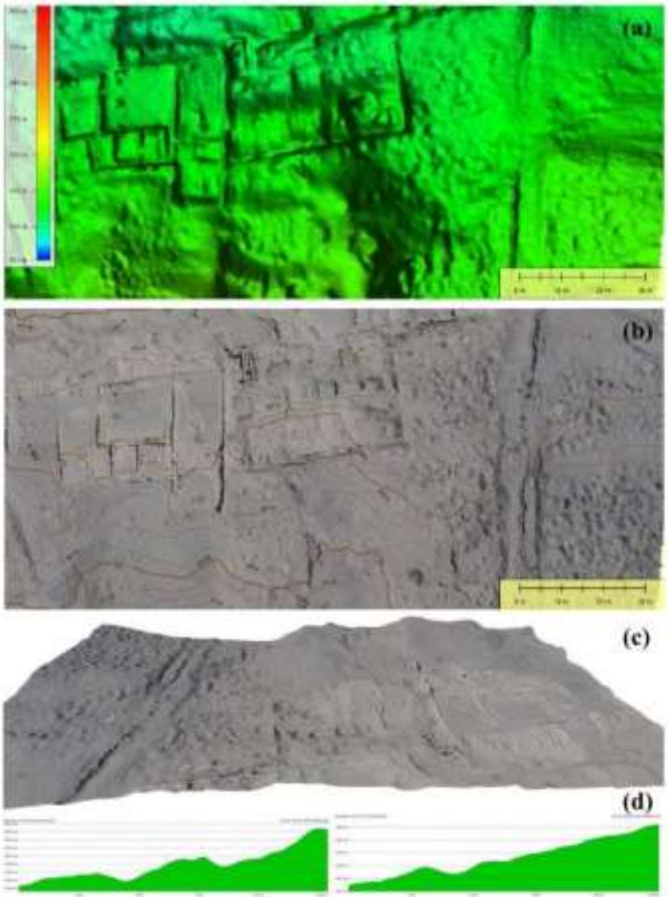
Lasaponara R. and Masini N., 2016 (in press) **Combat illegal excavations in Cahuachi: ancient problems and modern technologies in "Ancient NASCA world: New Insights from Science and Archaelogy" Springer Book**

Test areas

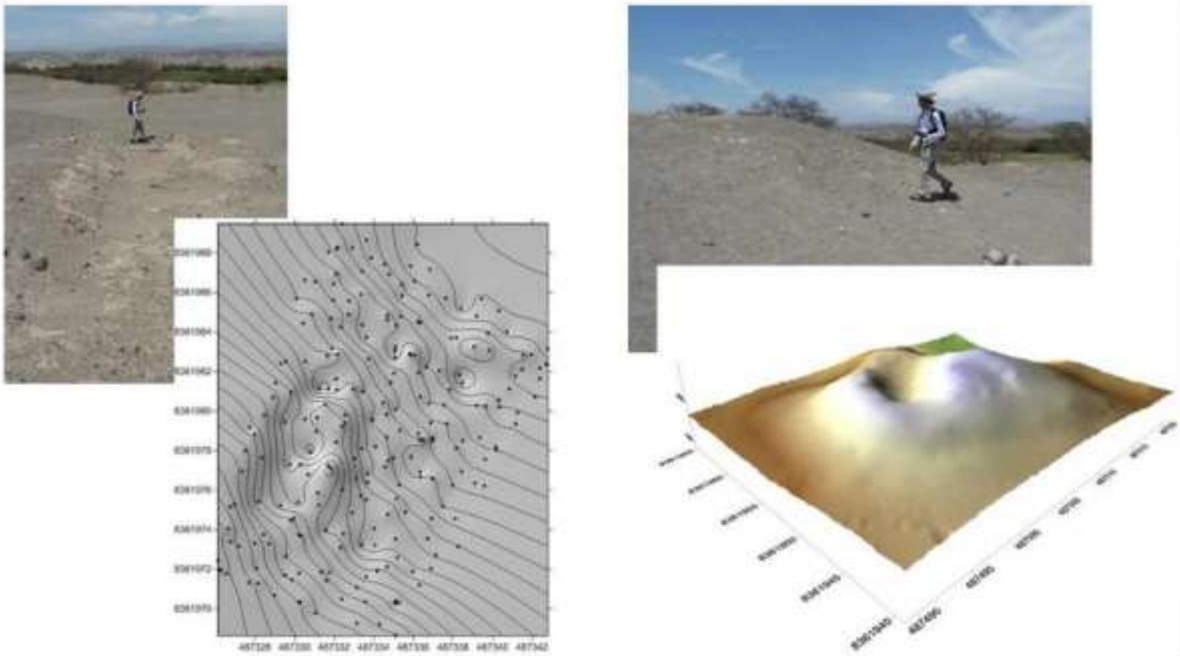
Results from segmentation (zoom of a subset)



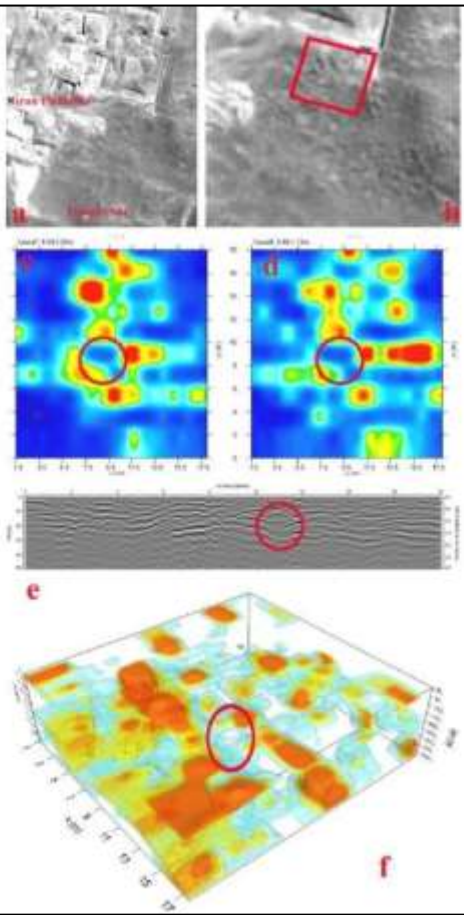
Drone survey



Field survey



Geophysical survey



Archaeological looting: one of the most a serious threats

Archaeological looting is recognized as one of the most a serious threats to cultural resources throughout the world in both recorded and unrecorded sites.

Many problems are associated with illegal excavations among them: (i) damaging of archaeological sites, (ii) loss of artefacts, (iii) destruction of the context of artefacts and therefore irreplaceable loss of valuable information, (iv) and denying this cultural heritage to new generation (Atwood 2006).

To contrast illegal excavations, satellite data processing procedure can enhance and easier identify, classify and map spatial patterns linked to looting activities

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DON'T POCKET THE PAST
Protect Historic and Archaeological Sites
Thank you for your attention !!
CATASTROPHE!
The Looting and Destruction of Iraq's Past
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2.3.4 Presentation of “Looting from space: from visual inspection to automatic recognition and mapping”

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- Edge enhancement
- Texture analysis
- Classification
- Change detection

Visual Interpretation

Advantages of Visual Interpretation:

1. Human brain is the best data processor for information extraction, thus **can do much more complex operations that computers can not match**.
2. Interpreters expertise can be part of the input

Disadvantages:

1. We can only see three bands at a time. Can not process more at a time.
2. **Time consuming and costly. Can not be automated,**
3. **thus not applicable for large projects.**
3. Requires training and experience to do a good work.

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Advantages of Computer-Aided Classifications

1. Can be **automated for large area application**
2. Better consistency
3. Can process as many images with as many bands as necessary
4. **Image processing experience are required** for

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Remote Sensing in Archaeology

I. Optical Satellite remote Sensing in Archaeology : an overview

1. **Remote Sensing in Archaeology: from visual data interpretation to digital data manipulation** - *Rosa Lasaponara and Nicola Masini*

2. **Image enhancement, feature extraction and geospatial analysis in an archaeological perspective**
Rosa Lasaponara and Nicola Masini

3. **Pattern recognition and classification using VHR data for archaeological research**
Rosa Lasaponara and Nicola Masini

4. **On the enhancement of archaeological marks by Pan-sharpening techniques**
Rosa Lasaponara and Nicola Masini

NAZCA CEREMONIAL CENTRE OF CAHUACHI

Looters' holes : small and circular pits (0.7-3 m diameter) filled with sand, and by scattered remains

1. Lasaponara R. and N. Masini 2010. "Facing the archaeological looting in Peru by local spatial autocorrelation statistics of Very high resolution satellite imagery." In Taniar D. et al (Eds), *Proceedings of ICSSA*, The 2010 International Conference on Computational Science and its Application (Fukuoka-Japan, March 23 – 26, 2010), Springer, Berlin, 261-269.

2. Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8.

3. Lasaponara R., G. Leucci, N. Masini, R. Persico 2014. "Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru" *Journal of Archaeological Science* 42: 216-230 http://dx.doi.org/10.1016/j.jas.2013.10.032

4. LasaponaraR, N Masini (2017) "Integrated tecnology for lotting Monitoring" The Ancient Nasca World: new Insight from science and technology, R Lasaponara, N Masini G Orefici Springer

5. LasaponaraR, N Masini 2017 "Space Based Monitroing of Archaeological Looting :An Overview in Peruvian Archaeological areas" *Proceedings of ICSSA*, The 2017 International Conference on Computational Science and its Application Trieste , Springer, Berlin,. 713-727

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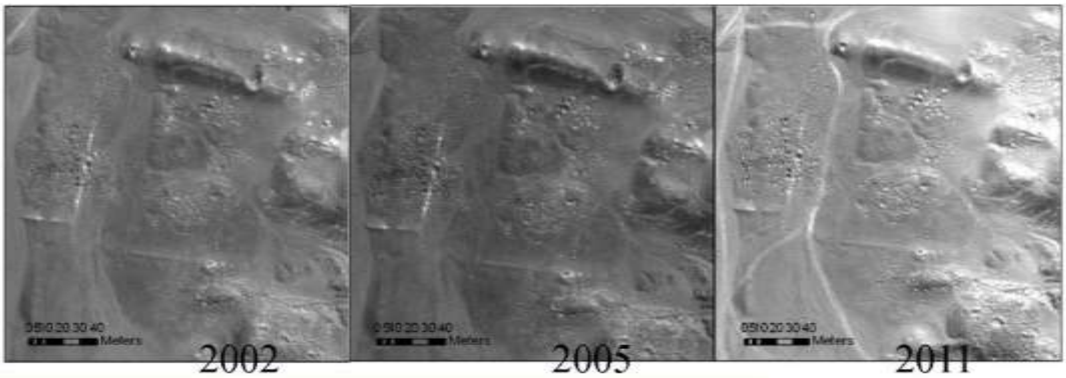


A time series of panchromatic and multispectral satellite images (2002-2005-2008-2011) allowed the mapping of looting over the years.

The reliability of the detection was evaluated by field surveys :

- ❑ Rate of success high for flat areas
- ❑ but …..**Unsatisfactory** for other areas (mound)

This suggested to use an approach, based on

-clustering methods such as local indices of spatial autocorrelation statistics (LISA)

- enhancement approach using Wavelet transforms

Satellite data

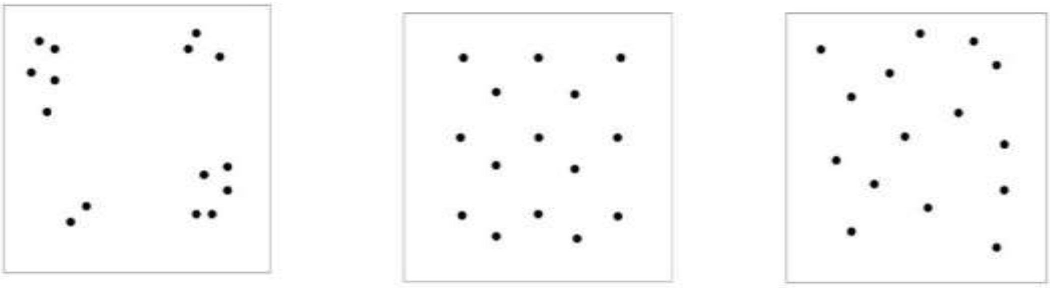
LISA Wavelet

LISA applied to Wavelet

Lasaponara R. and N. Masini 2010. "Facing the archaeological looting in Peru by local spatial autocorrelation statistics of Very high resolution satellite imagery." In Taniar D. et al (Eds), *Proceedings of ICSSA*, The 2010 International Conference on Computational Science and its Application (Fukuoka-Japan, March 23 – 26, 2010), Springer, Berlin, 261-269

Spatial Autocorrelation

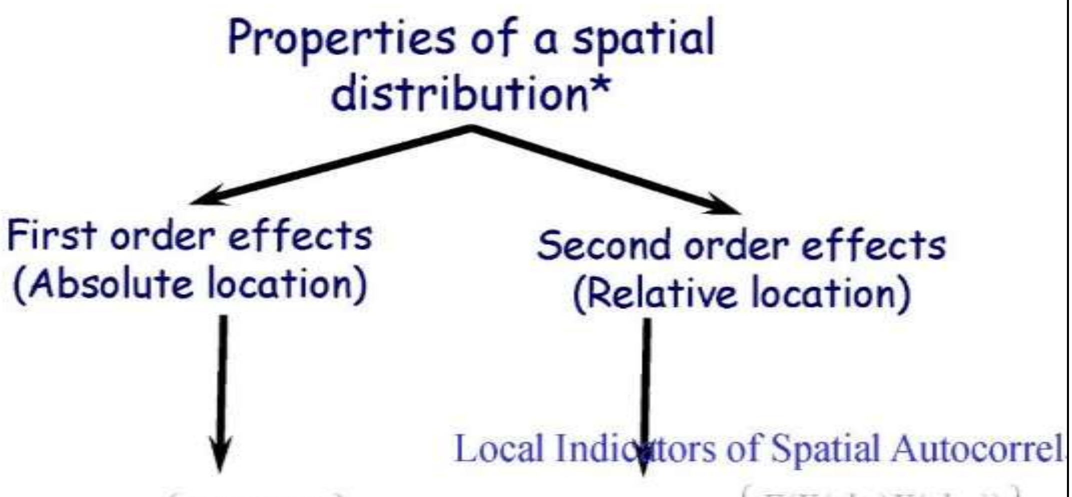
- called "event" the number of spatial occurrences in the considered variable,
- spatial autocorrelation measures the degree of dependency among events,
- considering at the same time their similarity and their distance relationships



Positive Autocorrelation (or attraction)	Negative Autocorrelation (or repulsion)	No Autocorrelation (or random)
Events : near and similar (clustered distribution)	between events when, even if they are near, they are not similar (uniform distribution)	no spatial effects, neither about the position of events, neither their properties

Lasaponara R. and N. Masini 2010. "Facing the archaeological looting in Peru by local spatial autocorrelation statistics of Very high resolution satellite imagery." In Taniar D. et al (Eds), *Proceedings of ICSSA*, The 2010 International Conference on Computational Science and its Application (Fukuoka-Japan, March 23 – 26, 2010), Springer, Berlin, 261-269

KDE: intensity and its measures



$$\hat{\lambda}_{\tau}(s) = \lim_{ds \to 0} \left\{ \frac{E(Y(ds))}{ds} \right\}$$

$$\gamma(s_i, s_j) = \lim_{ds_i, ds_j \to 0} \left\{ \frac{E(Y(ds_i)Y(ds_j))}{ds_i ds_j} \right\}$$

First order	Second order
Large scale variation in the mean value of a spatial process (global trend)	Small-scale variation around the gradient or Local dependence of a spatial process (local clustering)

Lasaponara R. and N. Masini 2010. "Facing the archaeological looting in Peru by local spatial autocorrelation statistics of Very high resolution satellite imagery." In Taniar D. et al (Eds), *Proceedings of ICSSA*, The 2010 International Conference on Computational Science and its Application (Fukuoka-Japan, March 23 – 26, 2010), Springer, Berlin, 261-269

Local Indicators of Spatial Autocorrelation (LISA)

LISA allow us to understand **where clustered pixels are**, by measuring **how much are homogeneous** features inside the fixed neighbourhood

Local Moran's index (Anselin, 1995).

$$I_i = \frac{(X_i - \bar{X})}{S_X^{\ 2}} \sum_{j=1}^{N} (w_{ij}(X_j - \bar{X}))$$

Clustering: Positive values indicate a cluster of similar values, while negative values imply no clustering (that is, high variability between neighboring pixels)

Local Geary's C index (Cliff & Ord, 1981)

$$C = \frac{n-1}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - X_j)^2}{2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}}$$

Detection of areas of **dissimilarity** of reflectance value, that is,
It is useful for detecting **edge areas** between clusters and other areas with dissimilar neighboring values

Getis and Ord's Gi index (Getis and Ord, 1992; Illian et al., 2008)

$$G_i(d) = \frac{\sum_{i=1}^{n} w_i(d)x_i - \bar{x}_i \sum_{i=1}^{n} w_i(d)}{S(i)\sqrt{\left[(N-1)\sum_{i=1}^{n} w_i(d) - \left(\sum_{i=1}^{n} w_i(d)\right)^2\right] \Big/ N-2}}$$

Hot spot: determination of concentrations of low values and high values

- N is the events number
- X_i ed X_j are the intensity values in the point i and j (with i≠j)
- $\bar{X}$ is the intensity mean
- w_{ij} is an element of the weights matrix

Spatial Autocorrelation (SA) in the context of image processing

1 the spatial event is the pixel

spatial autocorrelation statistics are calculated considering geographical coordinates of its centroid

2 Quantitative nature : spectral reflectance

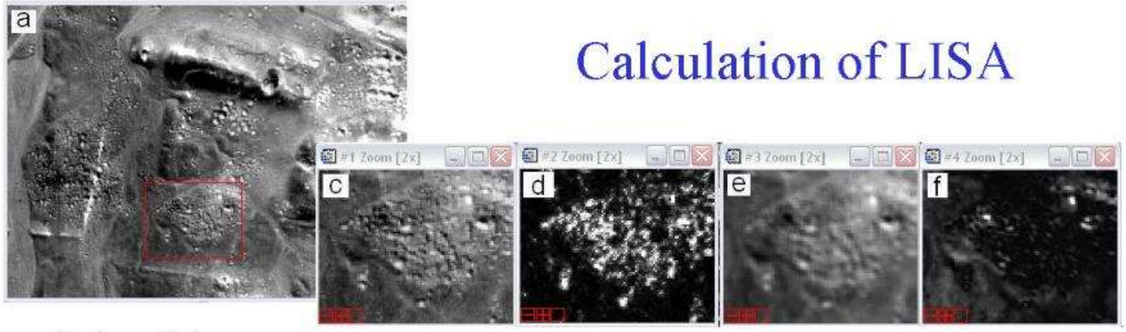
- Pixel reflectance value for each band
- SA measures the degree of dependency among spectral bands

3 Geometric nature : lag distance

- lag distance : the range over which autocorrelation will be calculated or the separation distance between events

Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8

Calculation of LISA

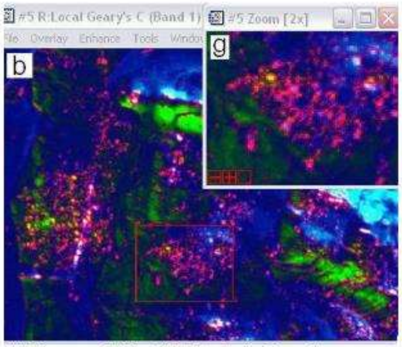


Panchromatic image (PAN) | Zoom of PAN | the Geary's C | Getis and Ord's Gi | Moran's I

RGB

Summary of analysis procedure

- ❑**1. Once lag distance** is found and
- ❑ 2. Assumed the **queen's contiguity**.
- ❑ **3. Local indicators** of spatial autocorrelation were calculated



Results :

❑ Geary index (d), allows to best represent the rough surface, so the pitting holes due to **its capability to detect dissimilarity**

❑ Getis and Ord Gi (e) needs a classification, before to be interpretated

Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8

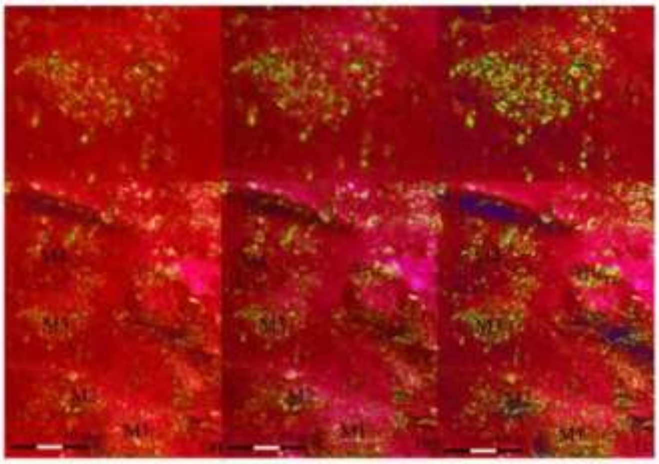
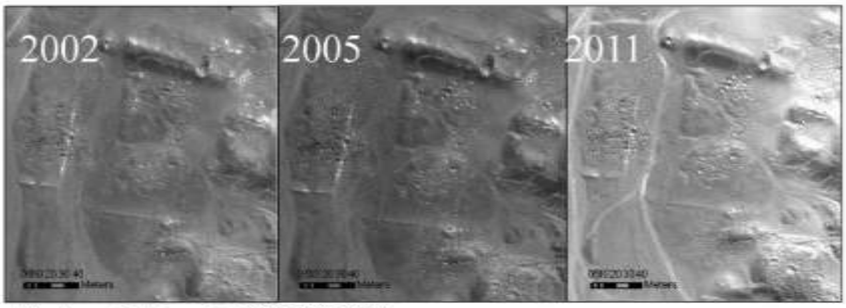


Figure 3. RGB composition of Moran, Getis and Geary indices (R:Moran; G:Getis; B:Geary) applied to panchromatic images of 2002 QB (a), 2005 QB (b) and 2008 WW1 (c). As in the previous figure 2 M1-M4 indicate mounds characterized by pits dug by grave looters; up of each figure a zoom of Mound M3 can be observed. RGB composition of Moran, Getis, and Geary indices emphasize pits enhancing their edges (yellow coloured). The multitemporal comparison of the three RGB images clearly show an increasing number of pits from 2002 to 2008 and, therefore, the intensification of the looting phenomenon over the years. ¶

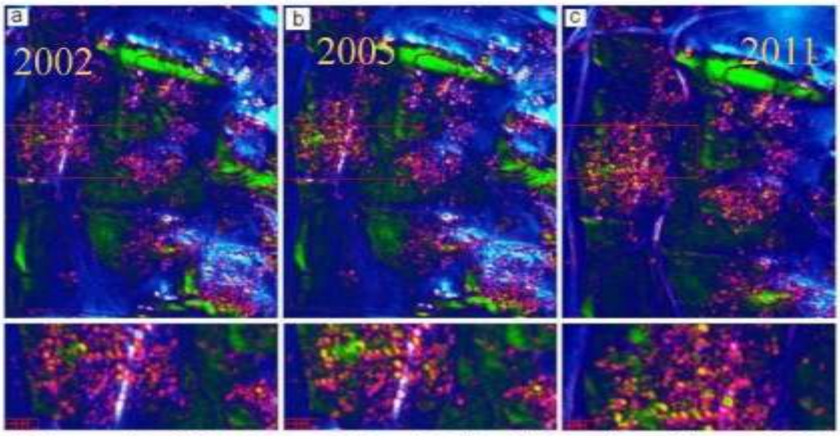
Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8

ATHENA-Training : *"Archaeological looting: Ancient problems and New approaches based on Remote Sensing"* - 1.09.2017, Limassol, Cyprus



Panchromatic time series (2002;2005;2008)

The improvement obtained by LISA application is still more evident if we compare the panchromatic satellite time series with the correspondent time series processed by local spatial autocorrelation statistics

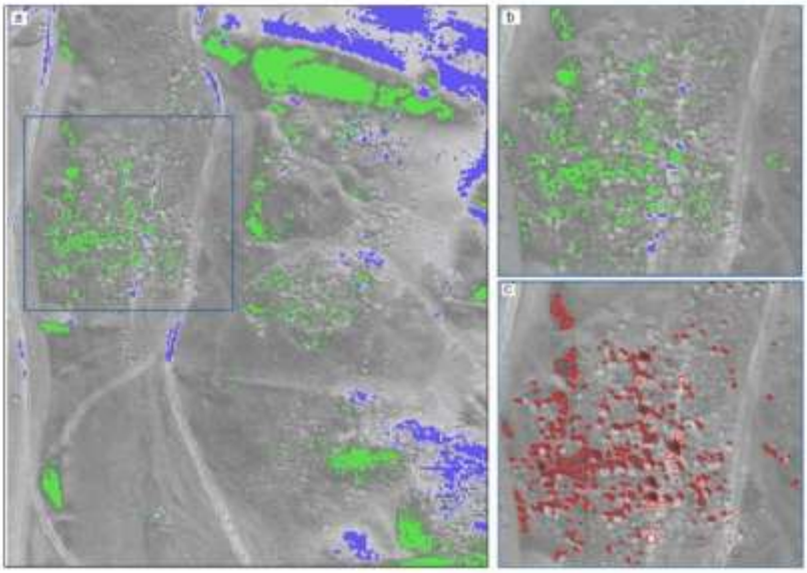


The multitemporal comparison of the three RGB images clearly shows an increasing number of pits from 2002 to 2011 and, therefore, the **intensification of the looting phenomenon over the years**.

RGB composition of LISA (R:Geary; G: Moran; B: Getis) applied to panchromatic images of 2002 QB (a), 2005 QB (b) and 2011 WW1 (c). RGB composition emphasize pits enhancing their edges (circled with magenta).

Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8

Getis & Ord's Gi



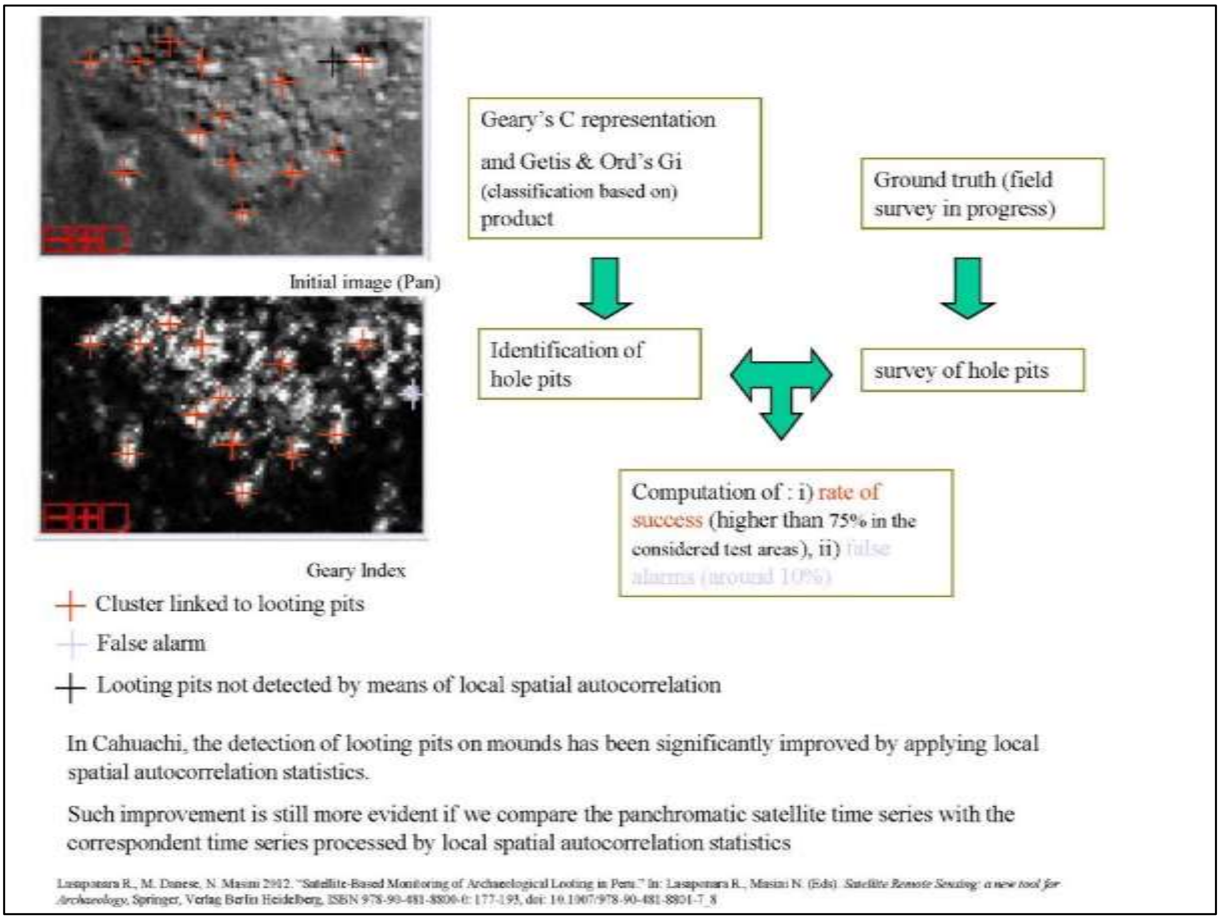
- ❑Clusters that show the best results are those characterized by low reflectance intensity & corresponding low Gi values or high reflectance intensity & corresponding high Gi values show positive spatial autocorrelation
- ❑These clusters were then converted to polygons with the aim to obtain the map of the looting phenomenon

❑ in Cahuachi corresponding values were found considering equal intervals as follow

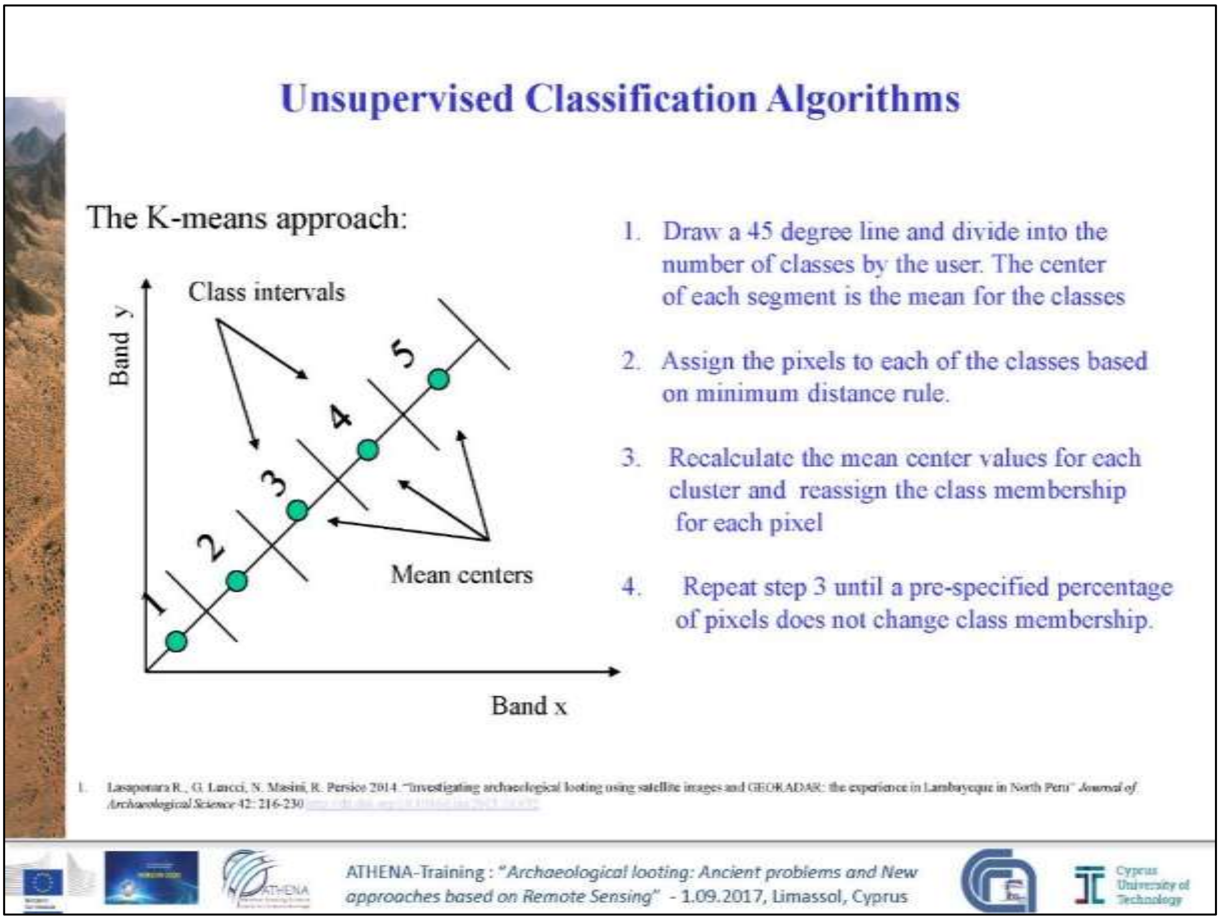
$G\max - G\min$ $\quad$ $I\max - I\min$

❑where I is the intensity, G is the index and n is the number of classes wanted in the classification

Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). *Satellite Remote Sensing: a new tool for Archaeology*, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8



Initial image (Pan)
Geary Index
Geary's C representation and Getis & Ord's Gi (classification based on) product
Ground truth (field survey in progress)
Identification of hole pits
survey of hole pits
Computation of : i) rate of success (higher than 75% in the considered test areas), ii) false alarms (around 10%)
Cluster linked to looting pits
False alarm
Looting pits not detected by means of local spatial autocorrelation
In Cahuachi, the detection of looting pits on mounds has been significantly improved by applying local spatial autocorrelation statistics.
Such improvement is still more evident if we compare the panchromatic satellite time series with the correspondent time series processed by local spatial autocorrelation statistics
Lasaponara R., M. Danese, N. Masini 2012. "Satellite-Based Monitoring of Archaeological Looting in Peru." In: Lasaponara R., Masini N. (Eds). Satellite Remote Sensing: a new tool for Archaeology, Springer, Verlag Berlin Heidelberg, ISBN 978-90-481-8800-0: 177-193, doi: 10.1007/978-90-481-8801-7_8



Unsupervised Classification Algorithms
The K-means approach:
Class intervals
Band y
Band x
Mean centers
1 2 3 4 5
1. Draw a 45 degree line and divide into the number of classes by the user. The center of each segment is the mean for the classes
2. Assign the pixels to each of the classes based on minimum distance rule.
3. Recalculate the mean center values for each cluster and reassign the class membership for each pixel
4. Repeat step 3 until a pre-specified percentage of pixels does not change class membership.
1. Lasaponara R., G. Leucci, N. Masini, R. Persico 2014. "Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru" Journal of Archaeological Science 42: 216-230
ATHENA-Training : "Archaeological looting: Ancient problems and New approaches based on Remote Sensing" - 1.09.2017, Limassol, Cyprus
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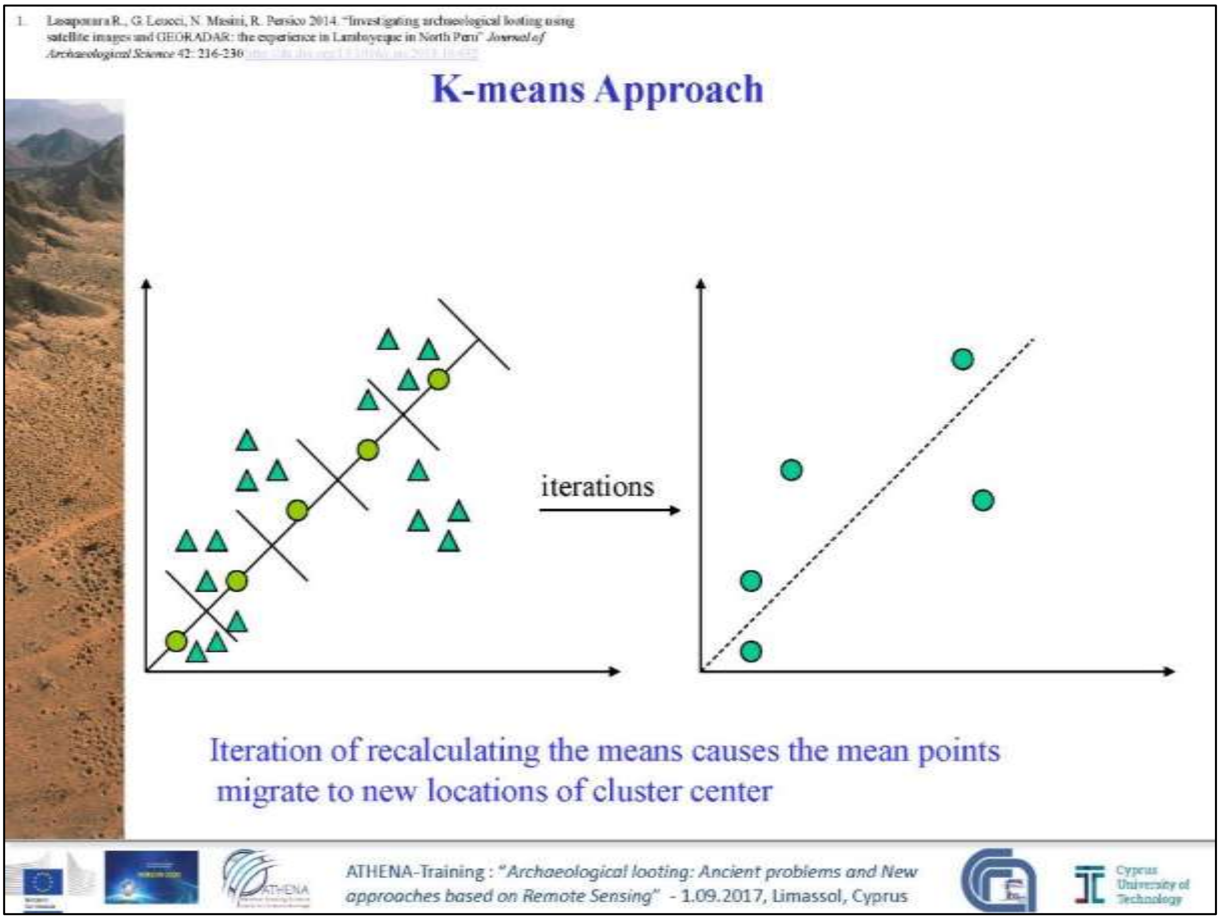

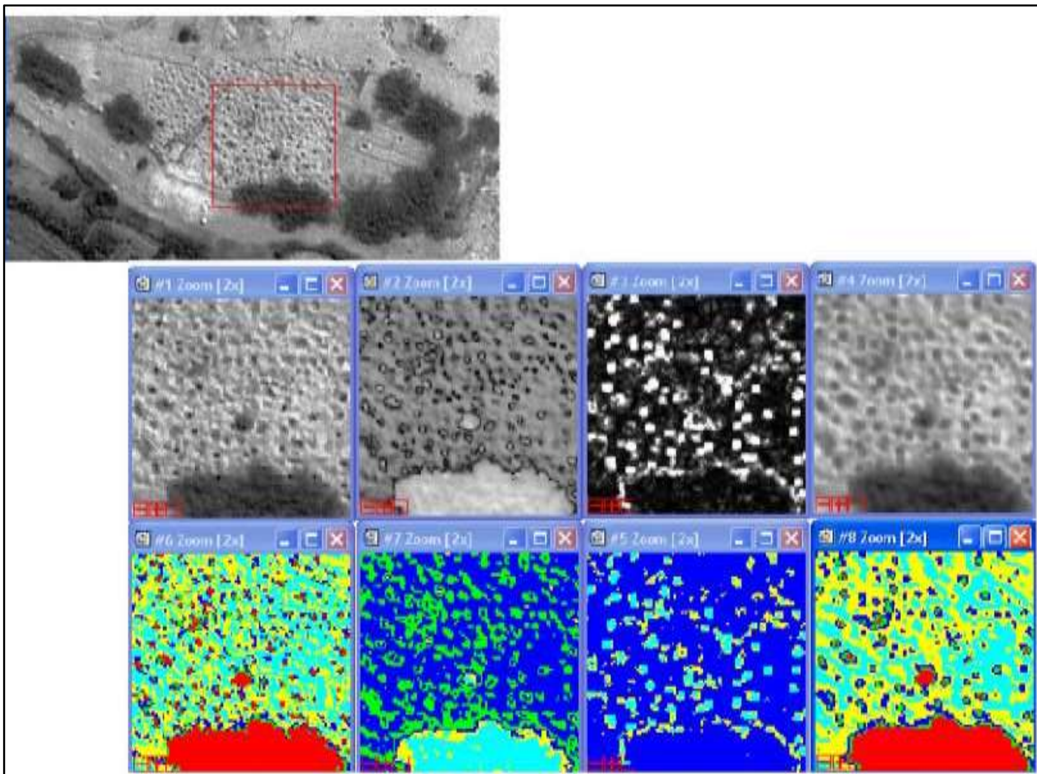

Area A in Cafetal. Upper: red pansharpened band; Medium, from left to right: zoomed detail of red pansharpened band, Moran, Geary and Getis applied to red band, respectively; lower, from left to right: Kmeans classification of the zoomed details

Lasaponara R., G. Leucci, N. Masini, R. Persico 2014. "Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru" *Journal of Archaeological Science* 42: 216-230

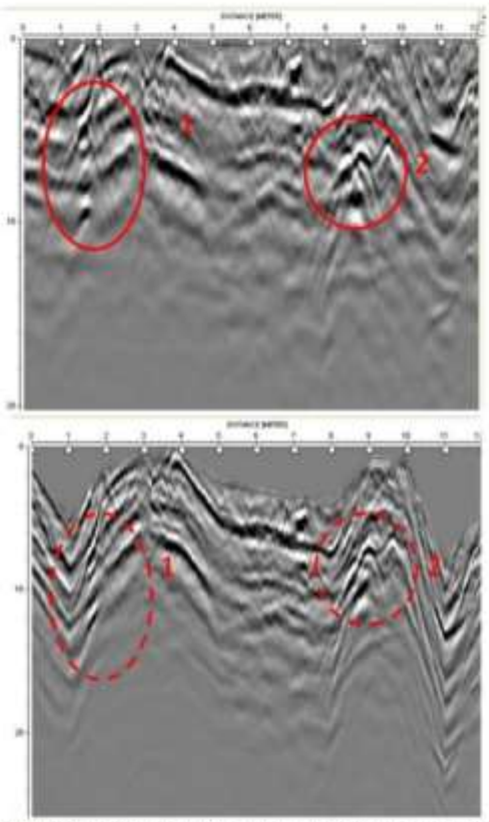

Fig. Processed GPR profile gathered in the archaeological site of Arenal. The abscissa is in meter, the ordinate in nanoseconds. Upper panel: without topographic correction. Lower panel: with topographic correction.

Lasaponara R., G. Leucci, N. Masini, R. Persico 2014. "Investigating archaeological looting using satellite images and GEORADAR: the experience in Lambayeque in North Peru" *Journal of Archaeological Science* 42: 216-230

2.4 VIRTUAL TRAINING 4: "INTEGRATION OF REMOTE SENSING DATA FOR PROTECTION AND PRESERVATION OF CULTURAL HERITAGE"

2.4.1 Description

The forth virtual training, focused on the use of Integration of Remote Sensing data for Cultural Heritage management in the Copernicus Era. The virtual training was carried out physically instead, at the CUT premises in Limassol-Cyprus, on the 3rd of September 2018. The trainers from the CNR (IBAM and IMAA) that offered lectures were Dr. Rosa Lasaponara, Dr. Nicola Masini, Dr. Francesco Soldovieri and Ms Ilaria Catabano.

During this training, the integrational use of Various remote sensing techniques and data, and the fusion of the results, has been presented and analyzed. A special focus was given also to the deformation depiction of monuments and sites through persistent scattered interferometry.

2.4.2 Agenda and participants

ATHENA 4th Virtual Training Agenda

ATHENA

Remote Sensing Science Center for Cultural Heritage

4th Virtual Training Agenda

Topic: Integration of RS data for Cultural Heritage management in the Copernicus Era

Date: 3 September, 2018

Venue: Dorothea Building, 3rd floor

Hosted by: Cyprus University of Technology

Trainers: Dr. Rosa Lasaponara (CNR-IMAA), Dr. Nicola Masini (IBAM-CNR)

Project Coordination Team

This project has received funding from the *European Union's Horizon 2020 research and innovation programme* under grant agreement No 691936. Work programme **H2020** under **"Spreading Excellence and Widening Participation", call: H2020-TWINN-2015: Twinning** (Coordination and Support Action).

ATHENA 4th Virtual Training Agenda

Monday 3rd September

09:10 – 09:20	**Registration**
09:20 – 09:30	**Welcoming**
09:30 – 10:30	**Data integration and fusion: state-of-the Art and future perspectives for archaeological prospection and architectural heritage monitoring**
10:30 - 11:00	Coffee break
11:00 – 12:00	**Data integration and fusion: state-of-the Art and future perspectives for archaeological prospection and architectural heritage monitoring**
12:00 - 12:30	Coffee break
12:30 – 14:00	**Case studies and applications**

END OF MEETING

Cyprus University of Technology

H2020-TWINN-2015 - Remote Sensing Science Center for Cultural Heritage - A T H E N A
Topic: 4th Virtual Training
Date: 3 September 2018
Venue: Dorothea Building, 3rd floor

List of participants

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ATHENA Remote Sensing Science Center for Cultural Heritage

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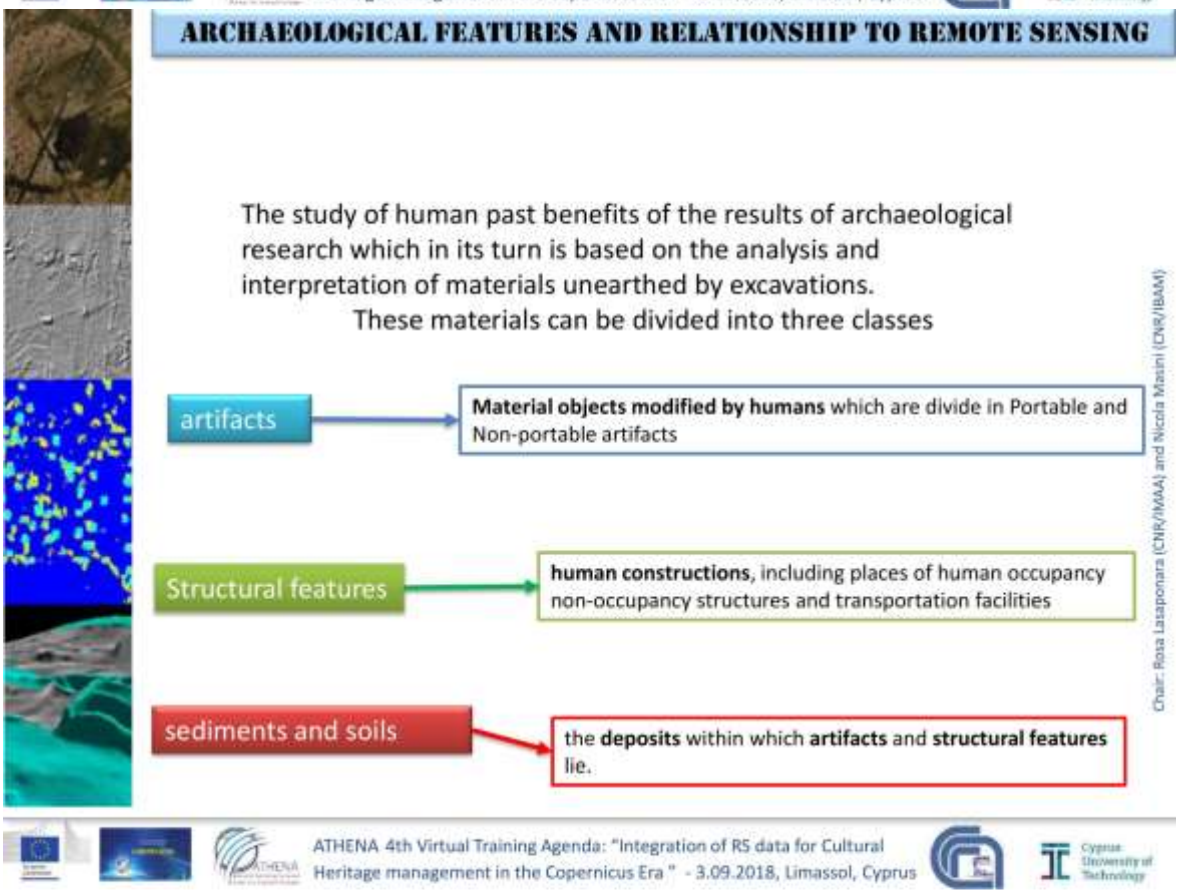
Photos during the 4th Virtual Training at the premises of the Cyprus University of Technology

2.4.3 Presentation of "Data integration and fusion: state-of-the art" and "Future perspectives for archaeological prospection and architectural heritage monitoring"

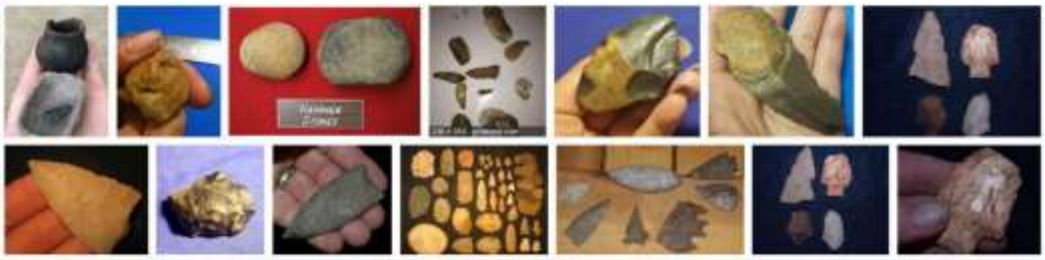


ARCHAEOLOGICAL FEATURES AND RELATIONSHIP TO REMTE SENSING

artifacts

Artifacts are material objects modified by humans

- **Portable artifacts** include smaller items that are easily moved, like tools employed in day-to-day activities (e.g., arrowheads, pots, knives).
- **Non-portable artifacts** include items not easily moved like cut posts, building timbers, shaped stones used in architectural constructions, and bricks.



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ARCHAEOLOGICAL FEATURES AND RELATIONSHIP TO REMTE SENSING

Structural features

Structural features result from the many types of human constructions, including:

- **places of human occupancy** (e.g., buildings, houses, storage facilities, public structures),
- **non-occupancy structures** (e.g., exterior hearths, subterranean storage pits, wells, fortification ditches)
- **transportation facilities** (e.g., roads, sidewalks).

Many structural features are composed of multiple, robust non-portable artifacts like stone blocks (e.g., a building foundation made of many individual bricks). Most structural features are reflected only by more subtle changes in deposits, for example when ditches, house pits, storage pits are filled in with sediments, or buried posts and wooden structures decompose into soil.

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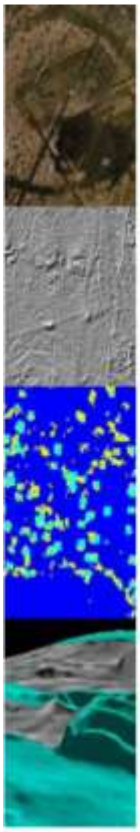

ARCHAEOLOGICAL FEATURES AND RELATIONSHIP TO REMTE SENSING

Sediments and soils

Sediments and soils are the deposits within which artifacts and structural features lie.

- Most sediments and soils result from **natural processes** such as eolian or alluvial deposition.
- Many sediments and soils within archaeological sites are **anthropogenic** or are created or altered by human activity such as
  - ***Additive deposit****: material accumulation* (places where refuse is dumped, and therefore rich in organic material like food waste, bones, discarded portable artifacts, ash from fires), *mounding activity* when soils are built up for burial mounds or in raised berms associated with ditch construction.
  - ***Deposit subtraction*** occurs when parts of natural or cultural deposits are **removed** by human activity as occurs in the construction of ditches or cellars.
  - Intensive firing such as from a hearth or a burned structural feature (e.g., a house) profoundly **increases soil magnetism**.
  - The simple act of **human occupation** subtly **raises the magnetic susceptibility of the soils** through the **addition of organic material** and the spreading of **fired earths** through a site area

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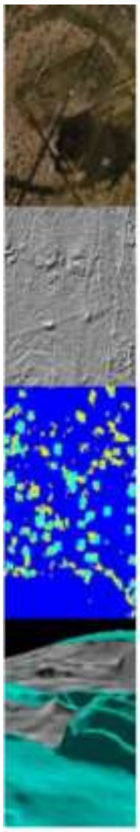

ARCHAEOLOGICAL FEATURES AND RELATIONSHIP TO REMTE SENSING

Remote Sensing could be used for identifying and imaging buried artifacts, structures, soil and sediments

However it is important to consider that:

1) No remote sensing sensor/technique is capable of detecting all the classes of archaeological features
2) Each RS sensor is sensitive to particular kinds of physical characteristics (magnetic susceptibility / emitted radiation (IRT)/ reflectance /radar backscattering etc..)
3) Remote Sensing provides indirect data of possible archaeological interest

The integration of sensors, data and RS products is necessary to detect a large variety of features and materials and charecterize potential anthropogenic layers

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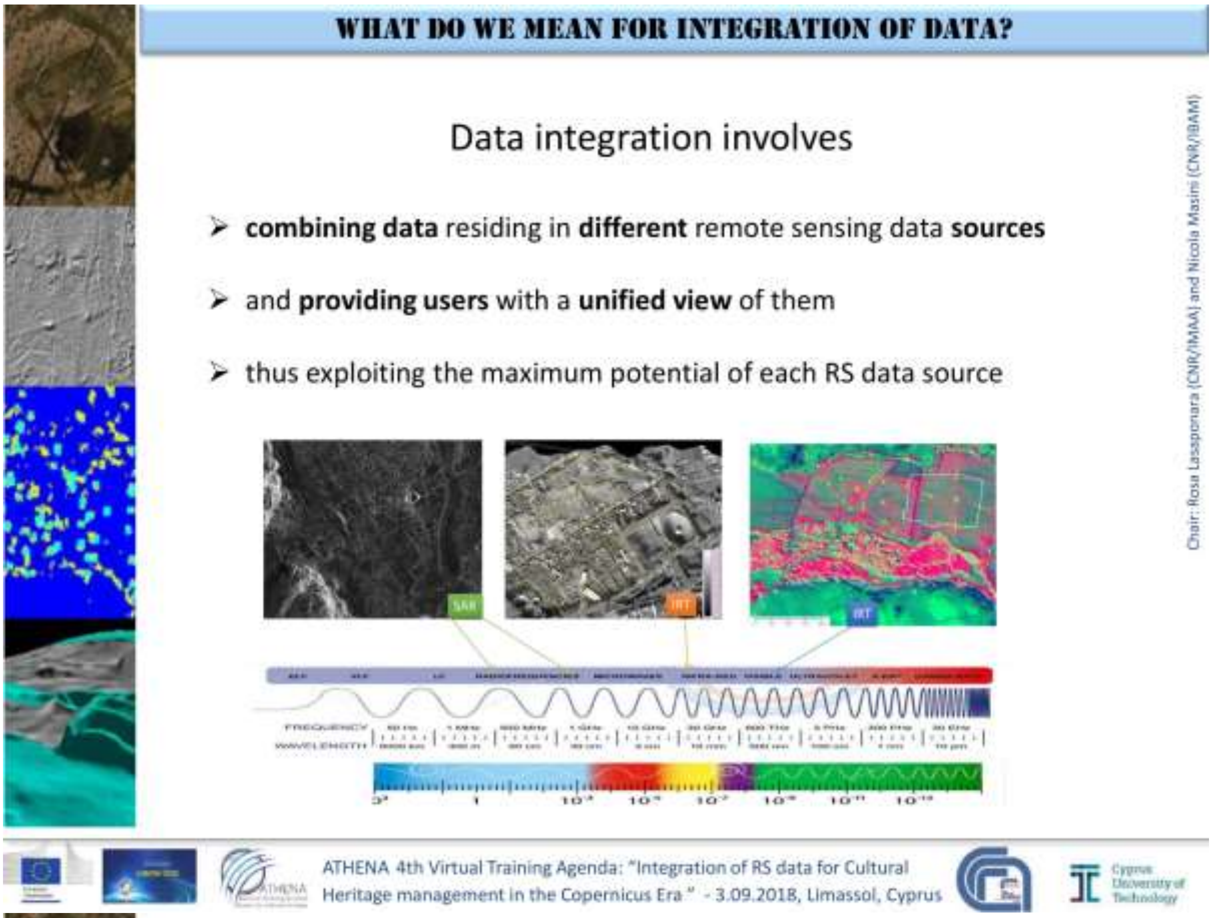
WHAT DO WE MEAN FOR INTEGRATION OF DATA?
Data integration involves
➢ combining data residing in different remote sensing data sources
➢ and providing users with a unified view of them
➢ thus exploiting the maximum potential of each RS data source
SAR
IRT
IRT
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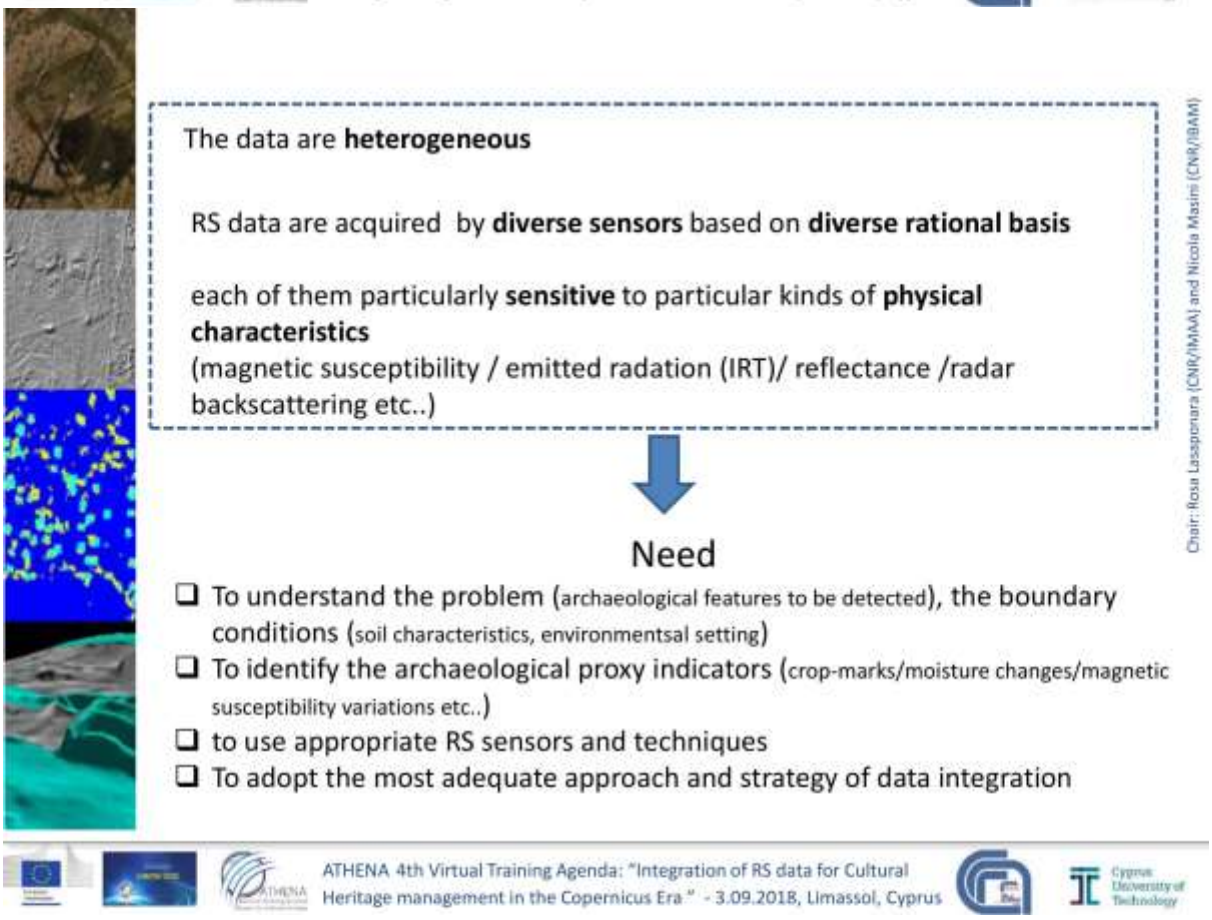
The data are heterogeneous
RS data are acquired by diverse sensors based on diverse rational basis
each of them particularly sensitive to particular kinds of physical characteristics
(magnetic susceptibility / emitted radiation (IRT)/ reflectance /radar backscattering etc..)
Need
❑ To understand the problem (archaeological features to be detected), the boundary conditions (soil characteristics, environmentsal setting)
❑ To identify the archaeological proxy indicators (crop-marks/moisture changes/magnetic susceptibility variations etc..)
❑ to use appropriate RS sensors and techniques
❑ To adopt the most adequate approach and strategy of data integration
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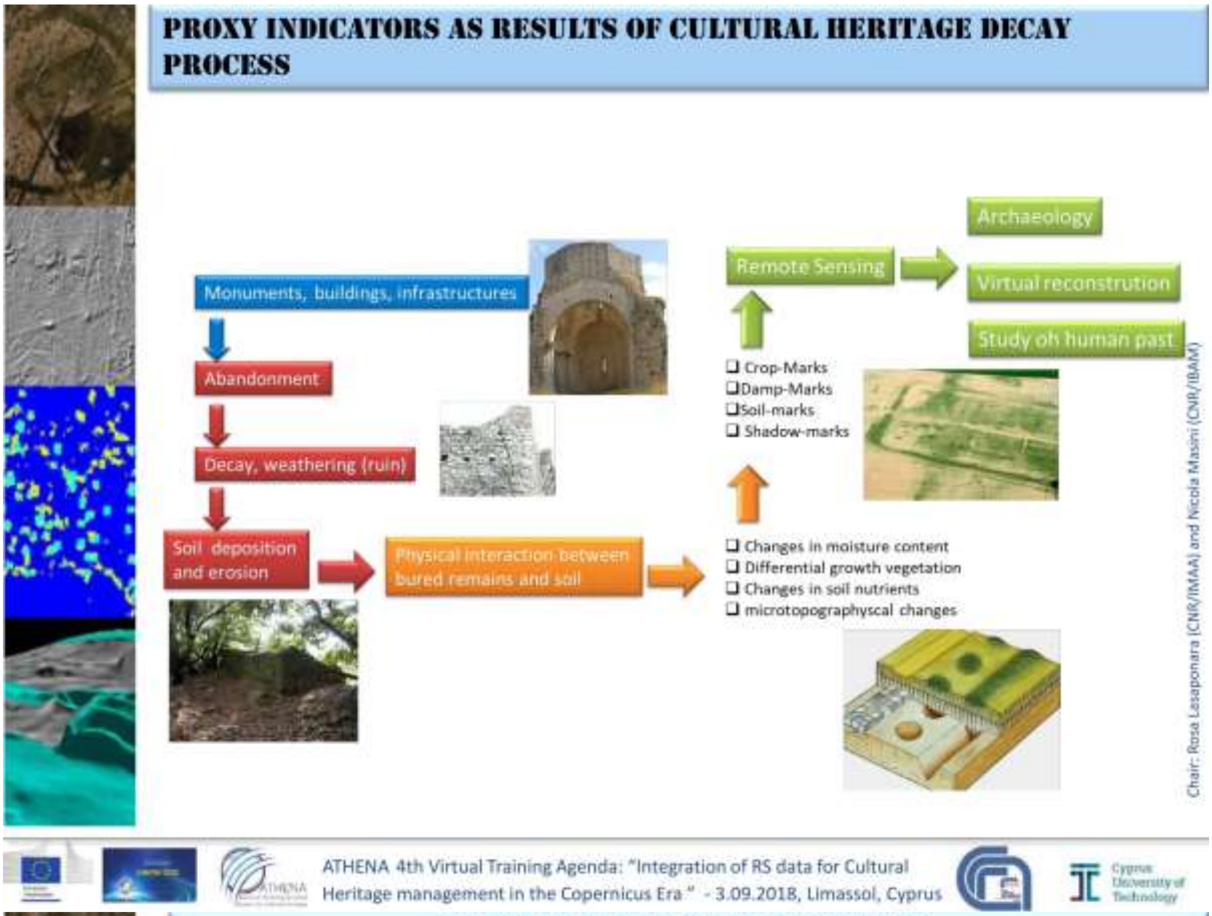
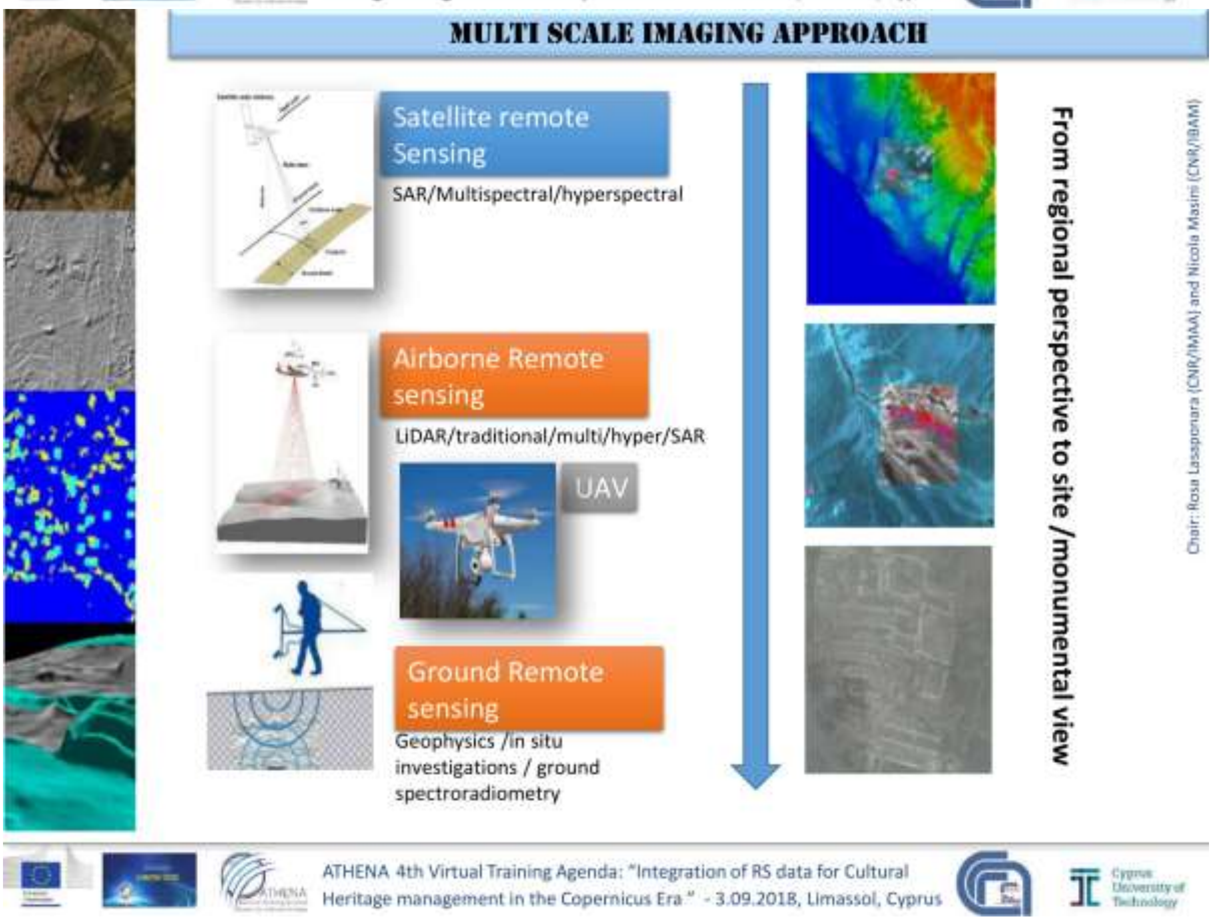

PROXY INDICATORS AS RESULTS OF CULTURAL HERITAGE DECAY PROCESS
Monuments, buildings, infrastructures
Abandonment
Decay, weathering (ruin)
Soil deposition and erosion
Physical interaction between bured remains and soil
Changes in moisture content
Differential growth vegetation
Changes in soil nutrients
microtopographyscal changes
Crop-Marks
Damp-Marks
Soil-marks
Shadow-marks
Remote Sensing
Archaeology
Virtual reconstrution
Study oh human past
Chair: Rosa Lasaponara (CNR/IMAA) and Nicola Masini (CNR/IBAM)
ATHENA 4th Virtual Training Agenda: "Integration of RS data for Cultural Heritage management in the Copernicus Era" - 3.09.2018, Limassol, Cyprus


MULTI SCALE IMAGING APPROACH
Satellite remote Sensing
SAR/Multispectral/hyperspectral
Airborne Remote sensing
LiDAR/traditional/multi/hyper/SAR
UAV
Ground Remote sensing
Geophysics /in situ investigations / ground spectroradiometry
From regional perspective to site /monumental view
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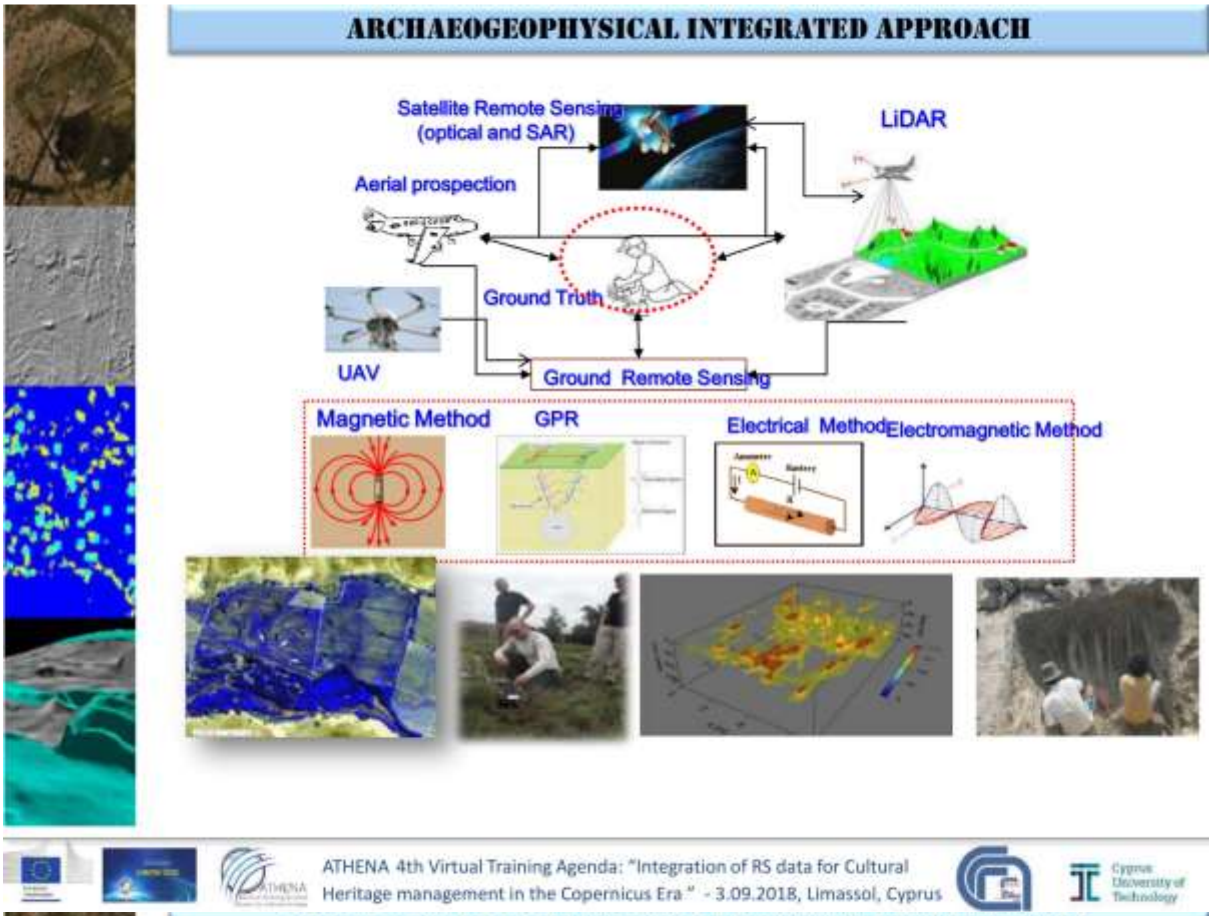
ARCHAEOGEOPHYSICAL INTEGRATED APPROACH
Satellite Remote Sensing (optical and SAR)
LiDAR
Aerial prospection
Ground Truth
UAV
Ground Remote Sensing
Magnetic Method
GPR
Electrical Method
Electromagnetic Method
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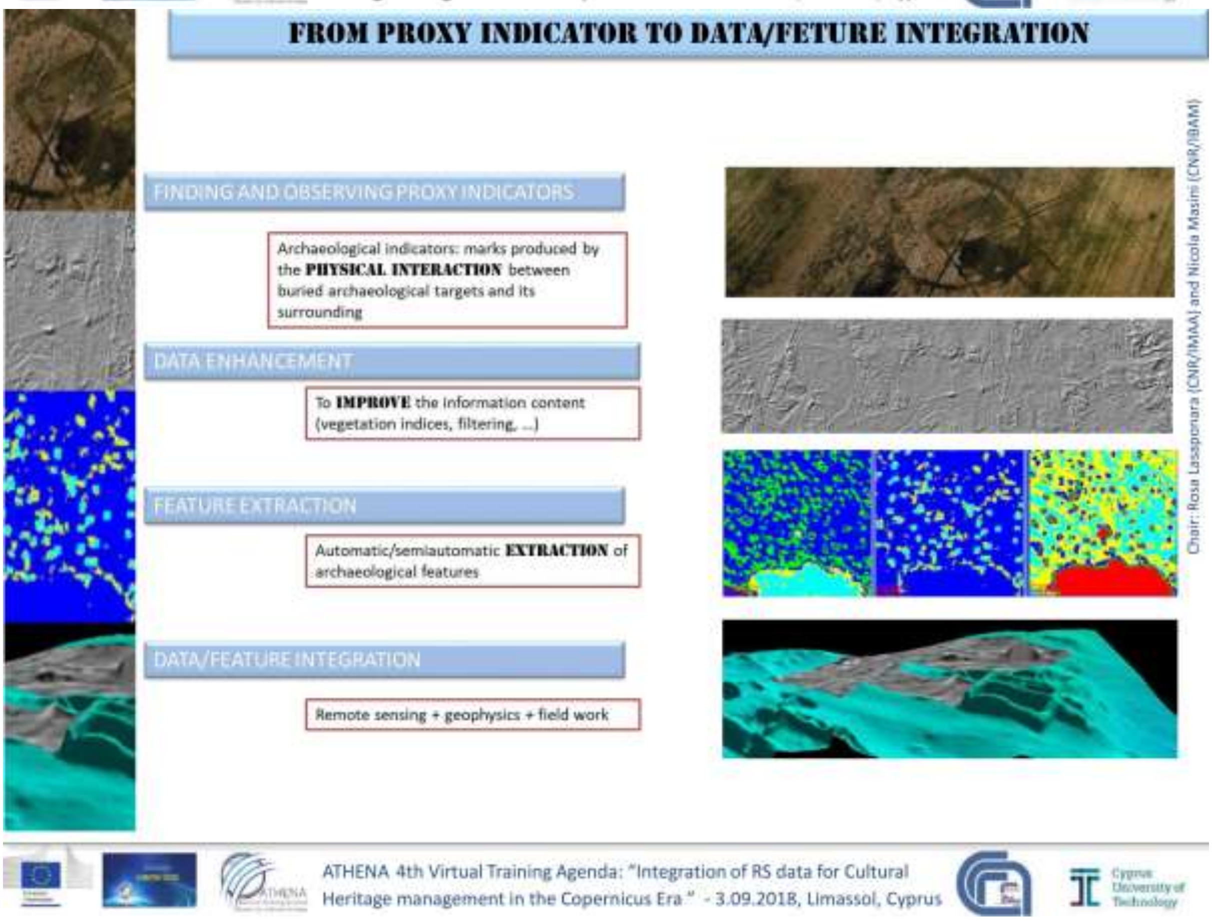
FROM PROXY INDICATOR TO DATA/FETURE INTEGRATION
FINDING AND OBSERVING PROXY INDICATORS
Archaeological indicators: marks produced by the PHYSICAL INTERACTION between buried archaeological targets and its surrounding
DATA ENHANCEMENT
To IMPROVE the information content (vegetation indices, filtering, ...)
FEATURE EXTRACTION
Automatic/semiautomatic EXTRACTION of archaeological features
DATA/FEATURE INTEGRATION
Remote sensing + geophysics + field work
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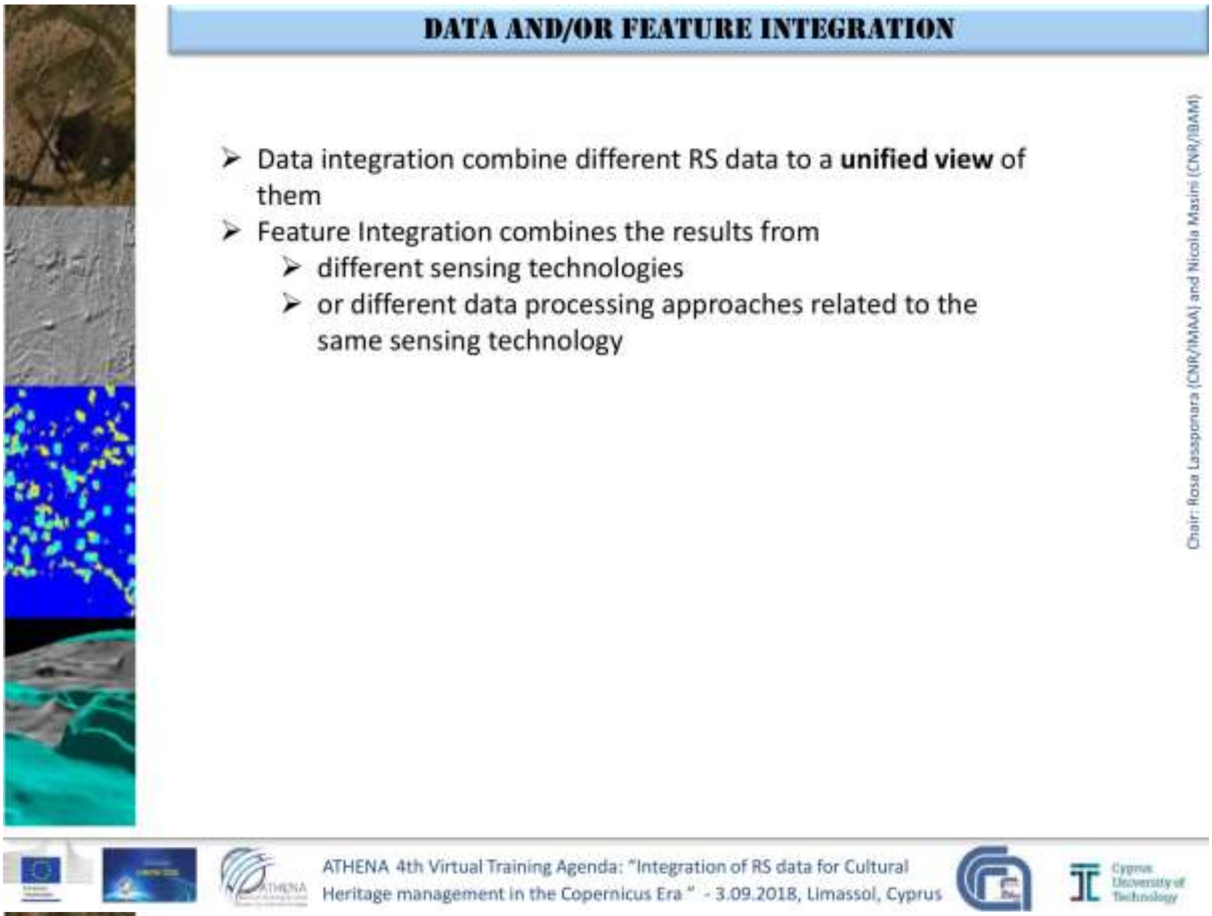
DATA AND/OR FEATURE INTEGRATION
➢ Data integration combine different RS data to a **unified view** of them
➢ Feature Integration combines the results from
➢ different sensing technologies
➢ or different data processing approaches related to the same sensing technology
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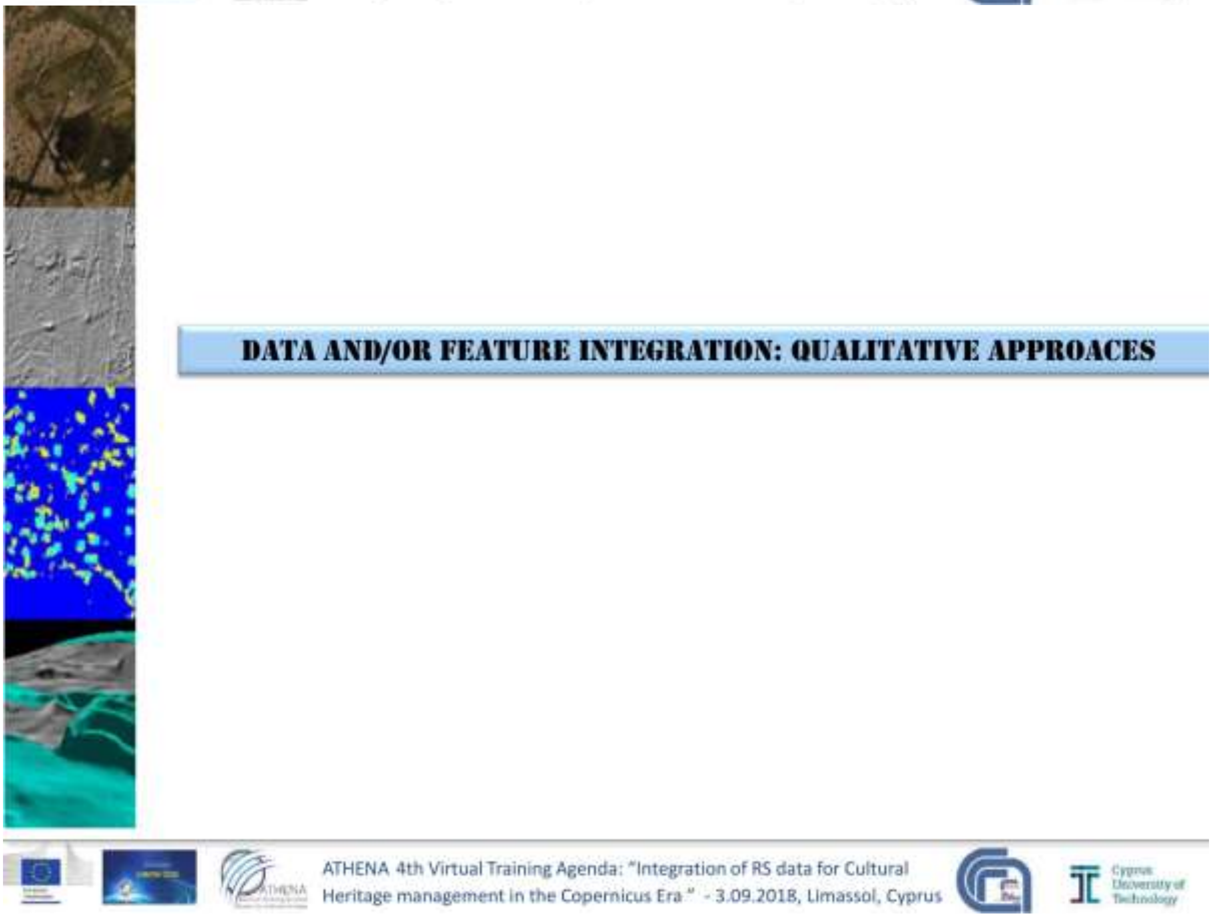
Cyprus University of Technology


DATA AND/OR FEATURE INTEGRATION: QUALITATIVE APPROACES
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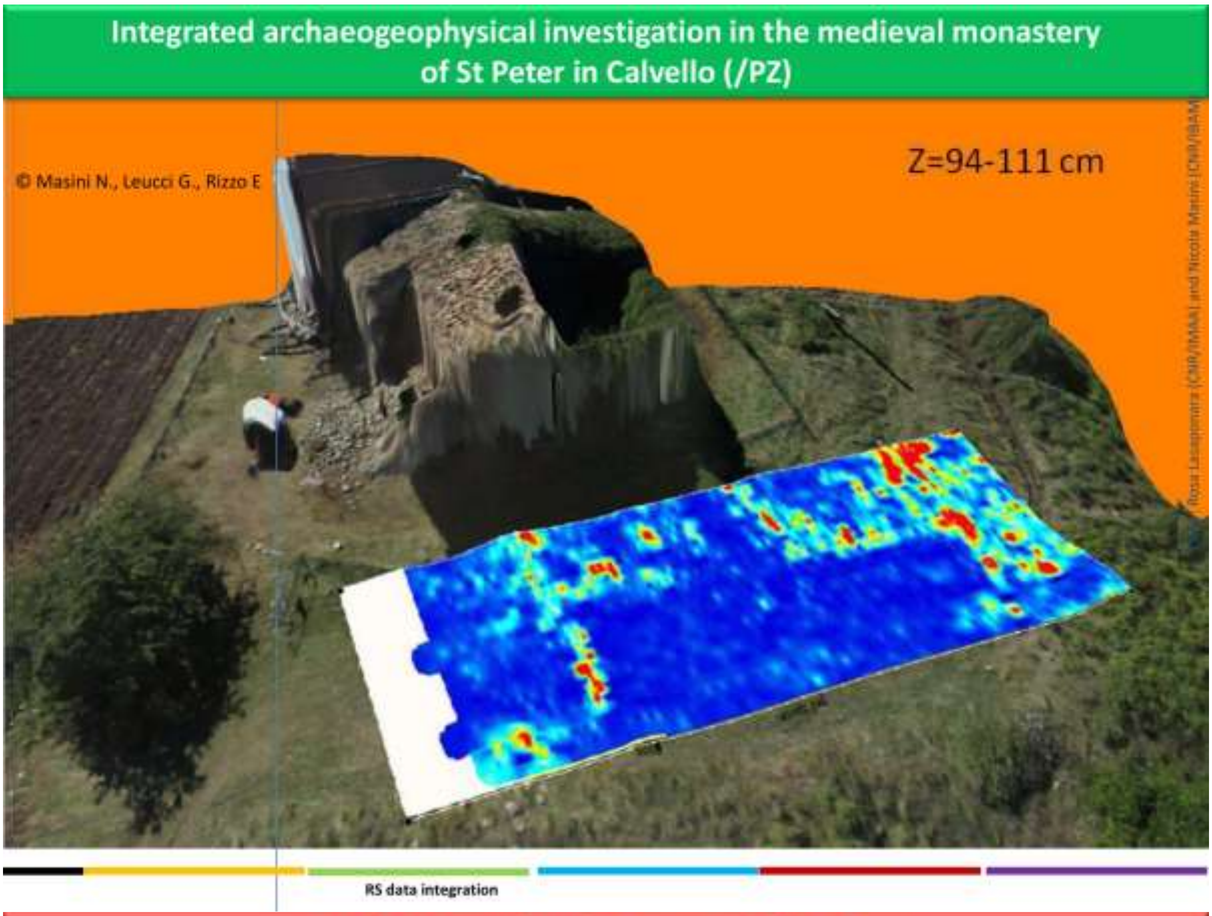
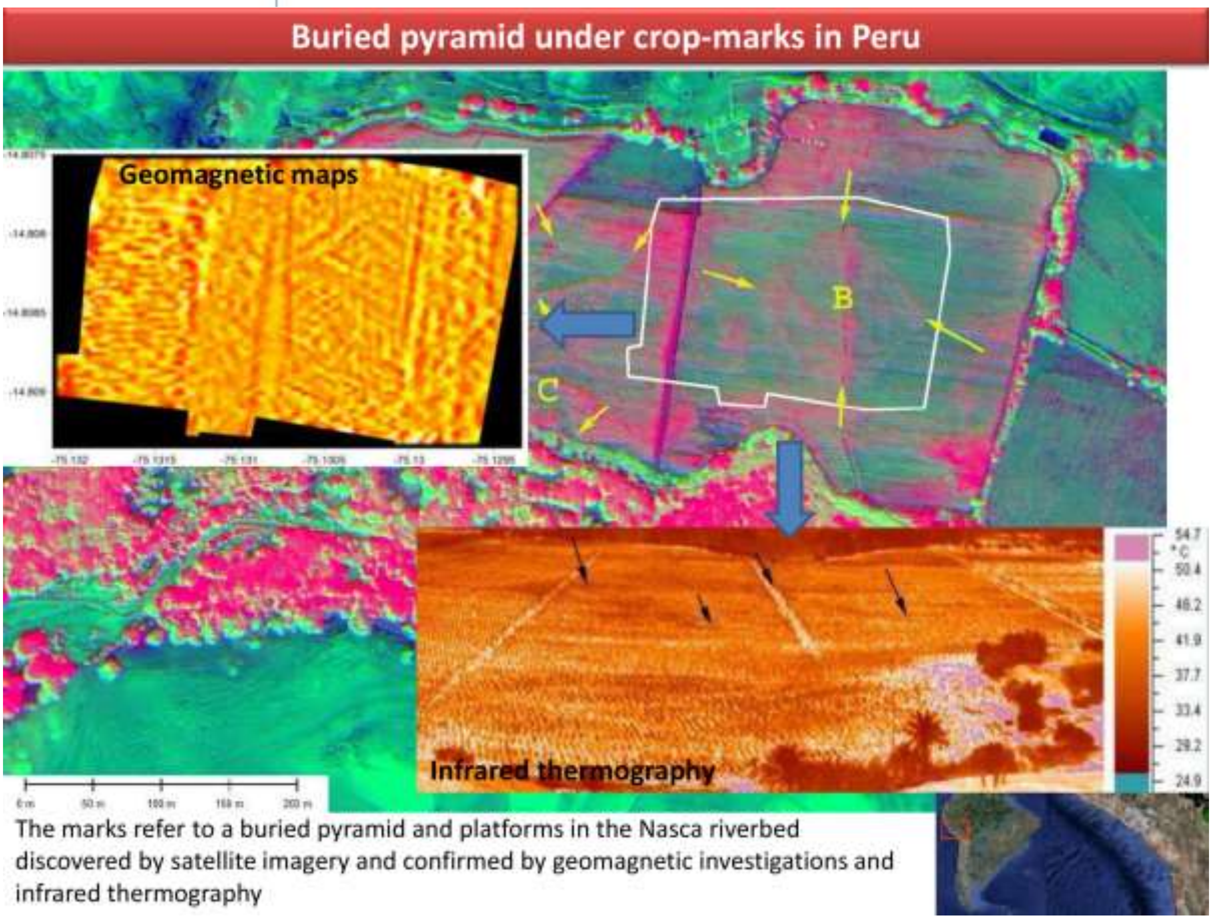
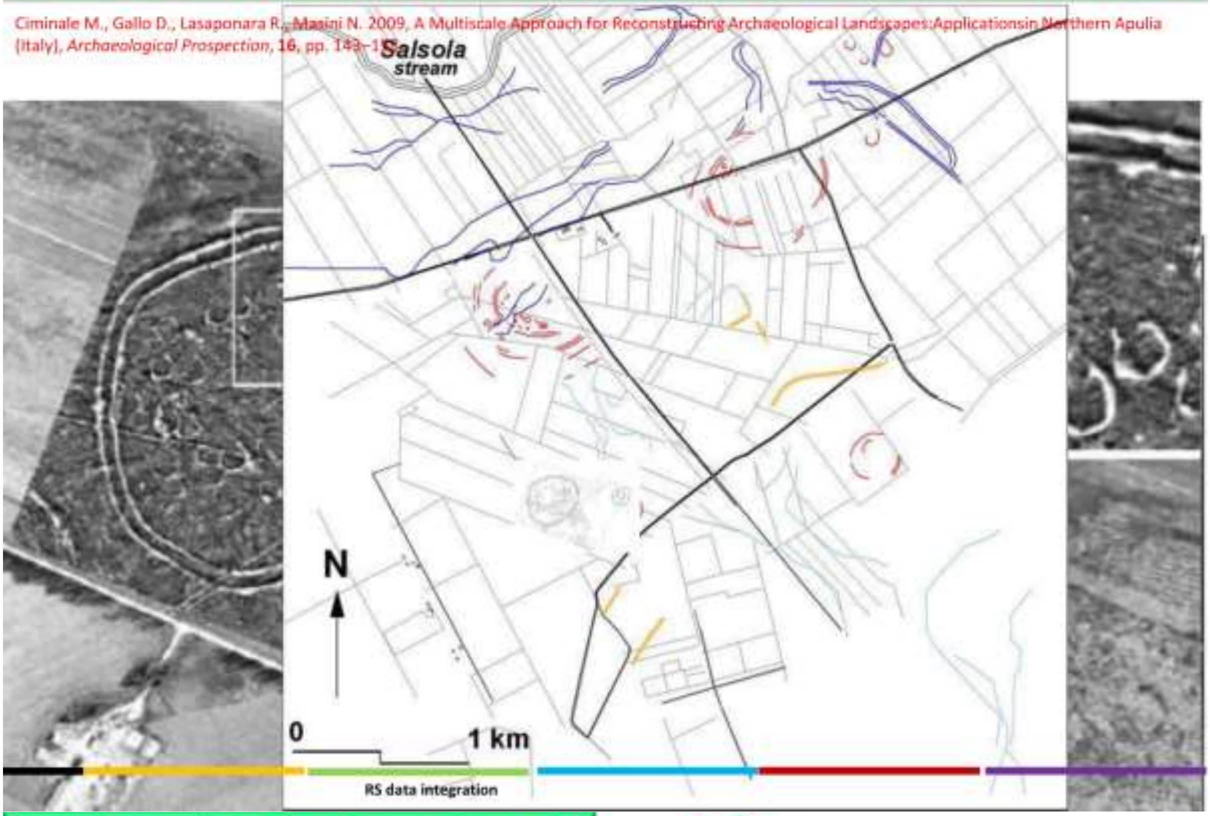

Integrated archaeogeophysical investigation in the medieval monastery of St Peter in Calvello (/PZ)
© Masini N., Leucci G., Rizzo E
Z=94-111 cm
RS data integration

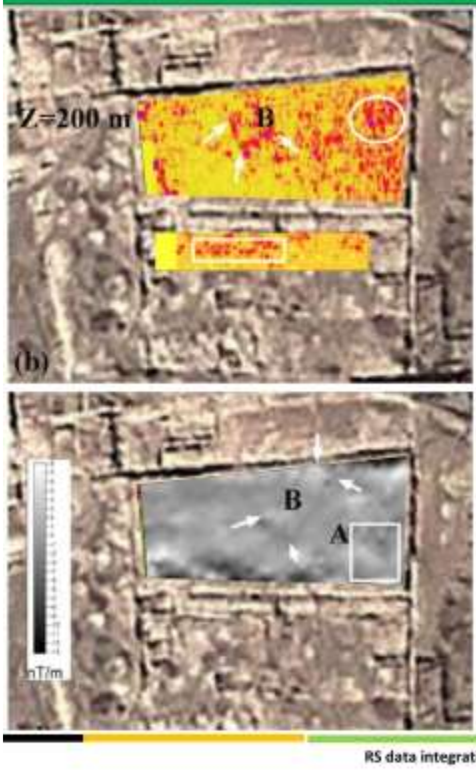

Buried pyramid under crop-marks in Peru
Geomagnetic maps
B
C
Infrared thermography
The marks refer to a buried pyramid and platforms in the Nasca riverbed discovered by satellite imagery and confirmed by geomagnetic investigations and infrared thermography

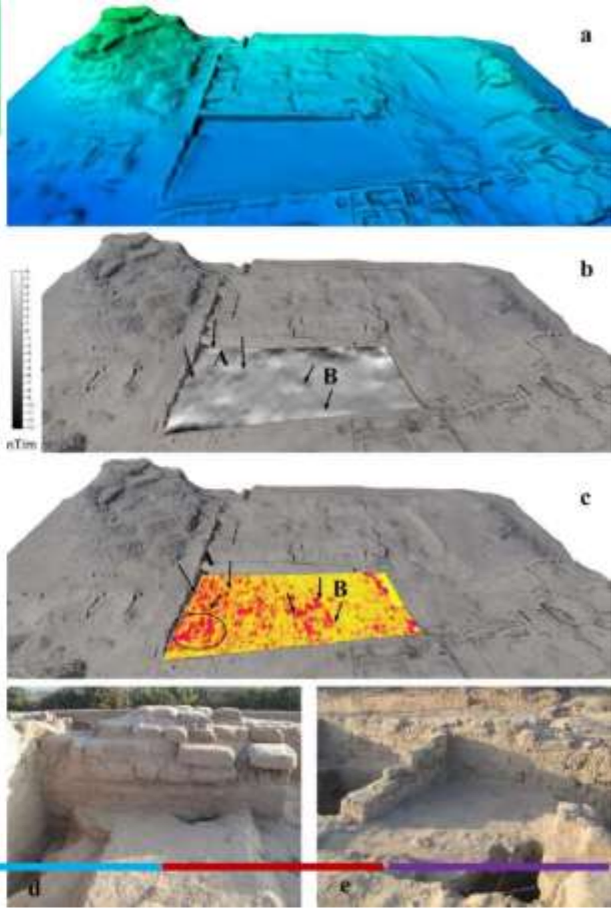
Integrated archaeogeophysical investigation in a neolithic settlement near Lucera (Apulia)

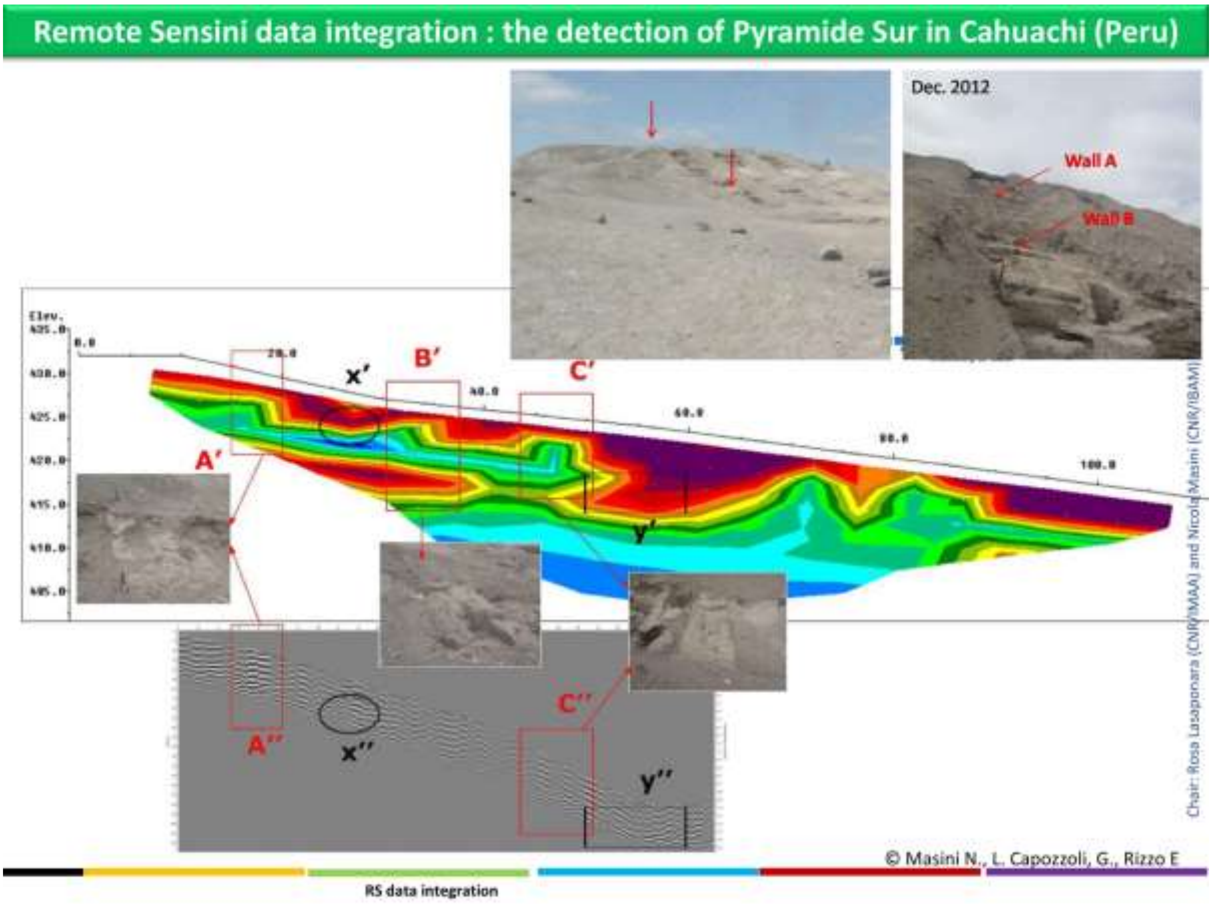
Ciminale M., Gallo D., Lasaponara R., Masini N. 2009, A Multiscale Approach for Reconstructing Archaeological Landscapes:Applicationsin Northern Apulia (Italy), *Archaeological Prospection*, 16, pp. 143–1

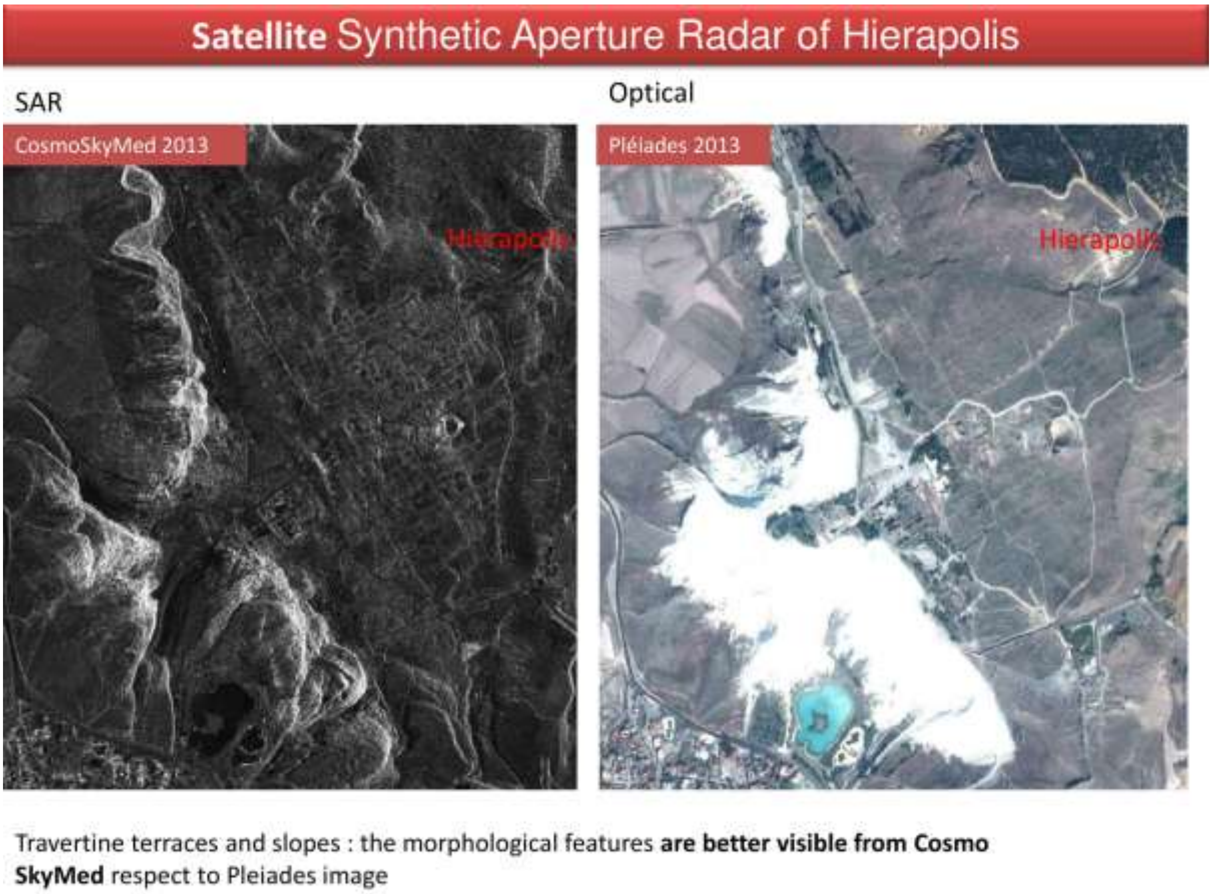


Remote sensing data integration : the detection in Paredones (Inca age) near Nasca (Peru)

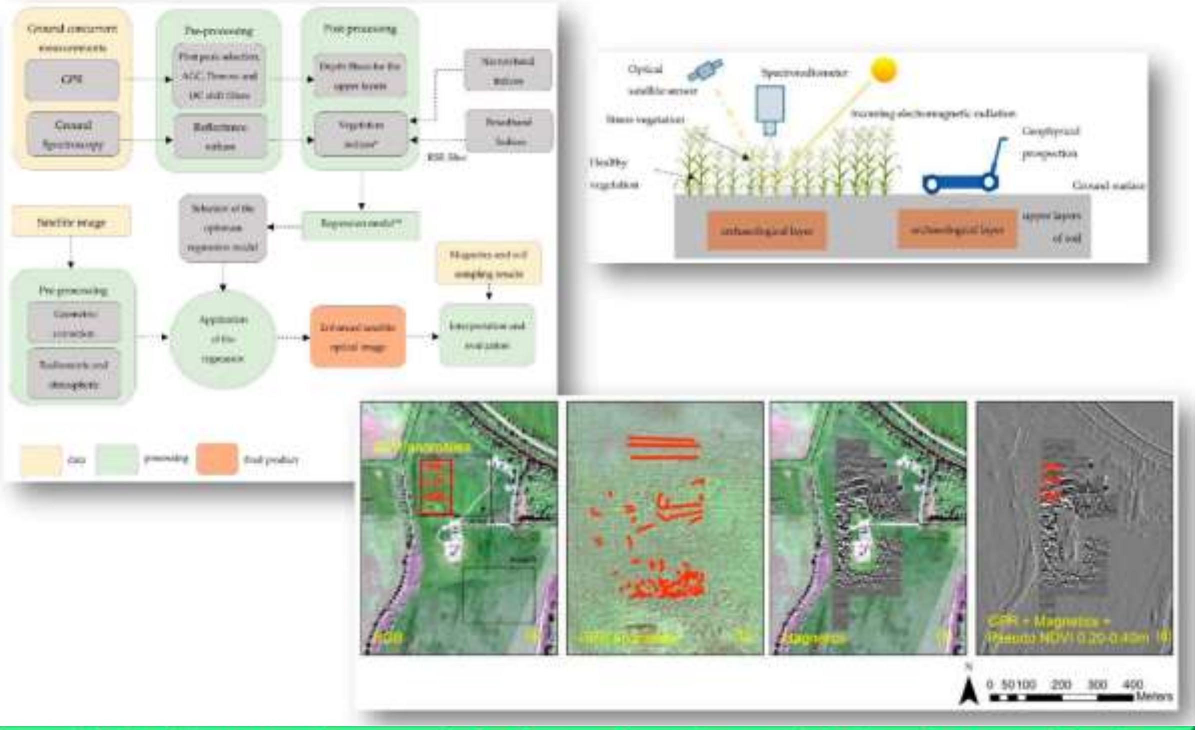




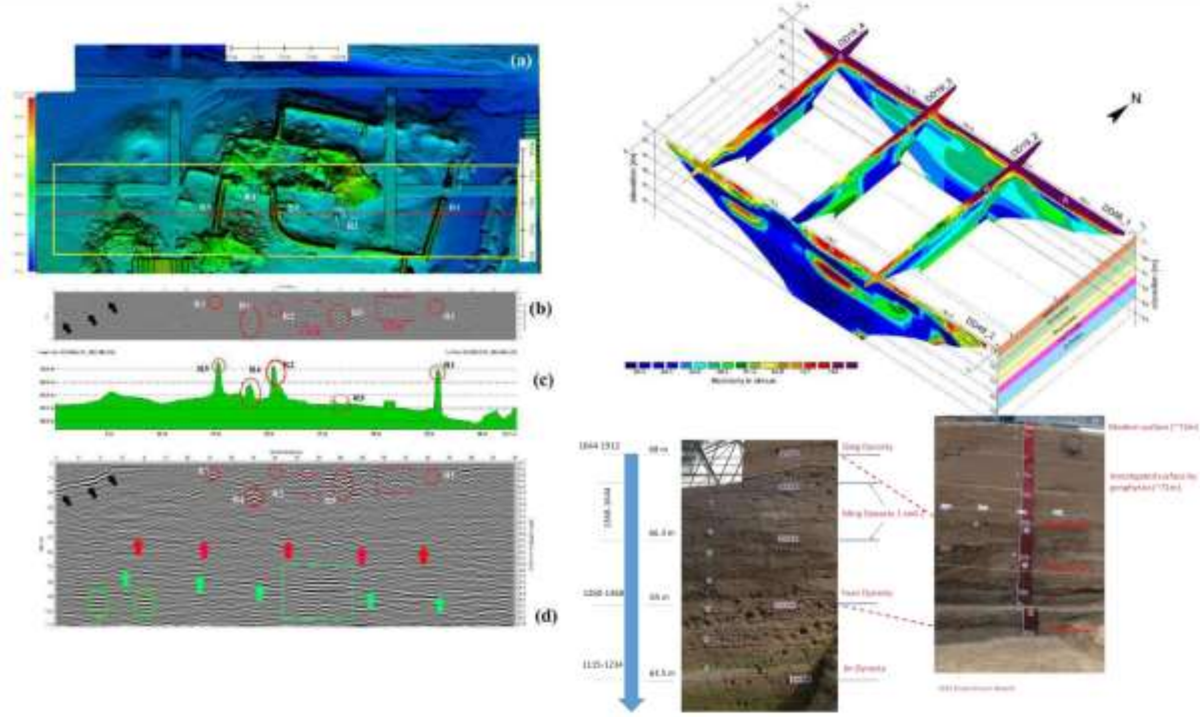

Remote Sensini data integration : the detection of Pyramide Sur in Cahuachi (Peru)
Dec. 2012
Wall A
Wall B
A′
B′
C′
x′
y′
A′′
x′′
C′′
y′′
Chair: Rosa Lasaponara (CNR/IMAA) and Nicola Masini (CNR/IBAM)
© Masini N., L. Capozzoli, G., Rizzo E
RS data integration


Satellite Synthetic Aperture Radar of Hierapolis
SAR
Optical
CosmoSkyMed 2013
Pléiades 2013
Hierapolis
Hierapolis
Travertine terraces and slopes : the morphological features **are better visible from Cosmo SkyMed** respect to Pleiades image

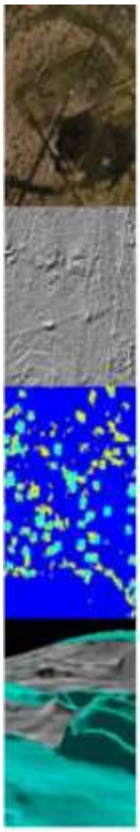
Fusion of satellite multispectral images based on ground-penetrating radar (GPR) data for the investigation of buried concealed archaeological remains (Agapiou et al. 2017)



Geophysical integrated approach for feture detection and dating: the case of Kaifeng in China



Masini et al. 2017, Towards an operational use of geophysics for Archaeology in Henan (China): Archaeogeophysical investigations, approach and results in Kaifeng



DATA AND/OR FEATURE INTEGRATION: QUANTITATIVE AND AUTOMATIC APPROACHES

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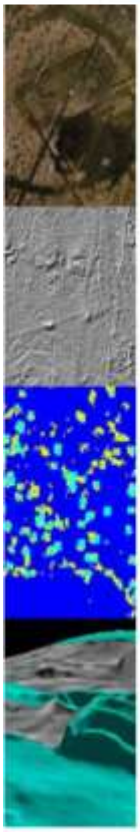
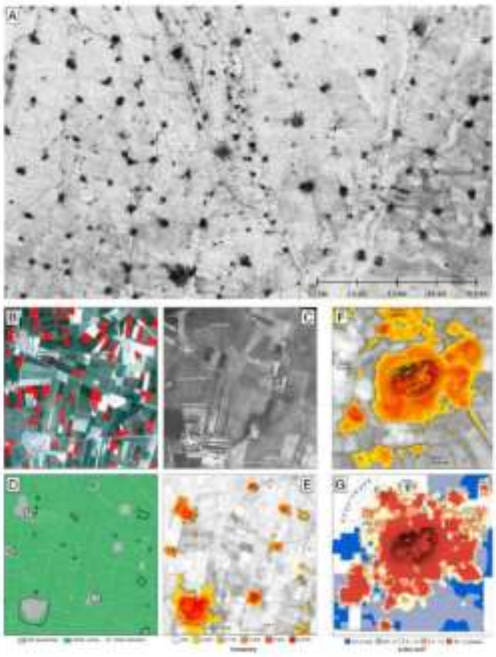


Mapping patterns of long-term settlement in Northern Mesopotamia at a large scale by Menze & Ur



remote sensing approach for comprehensively mapping the pattern of human settlement at large scale and establish the largest archaeological record for a landscape in Mesopotamia,

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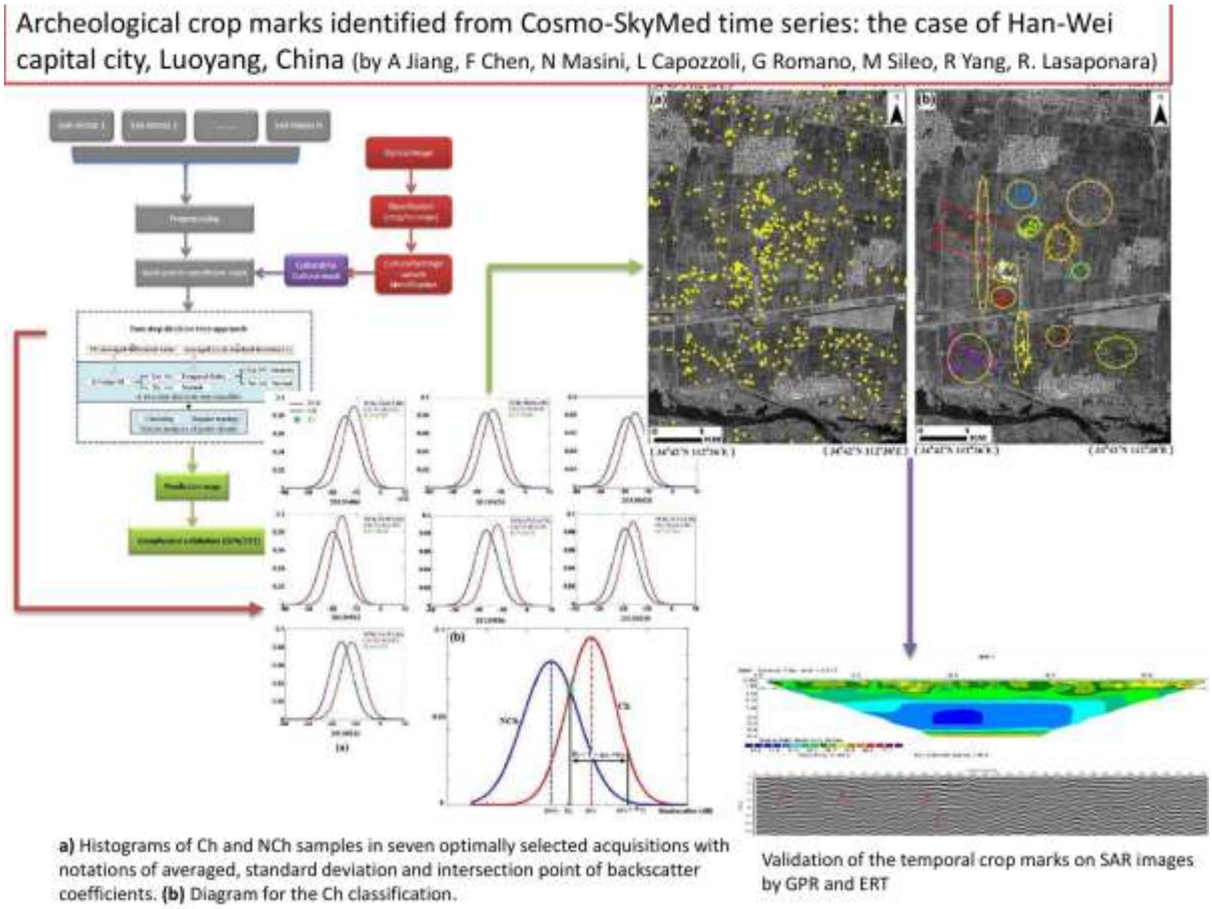
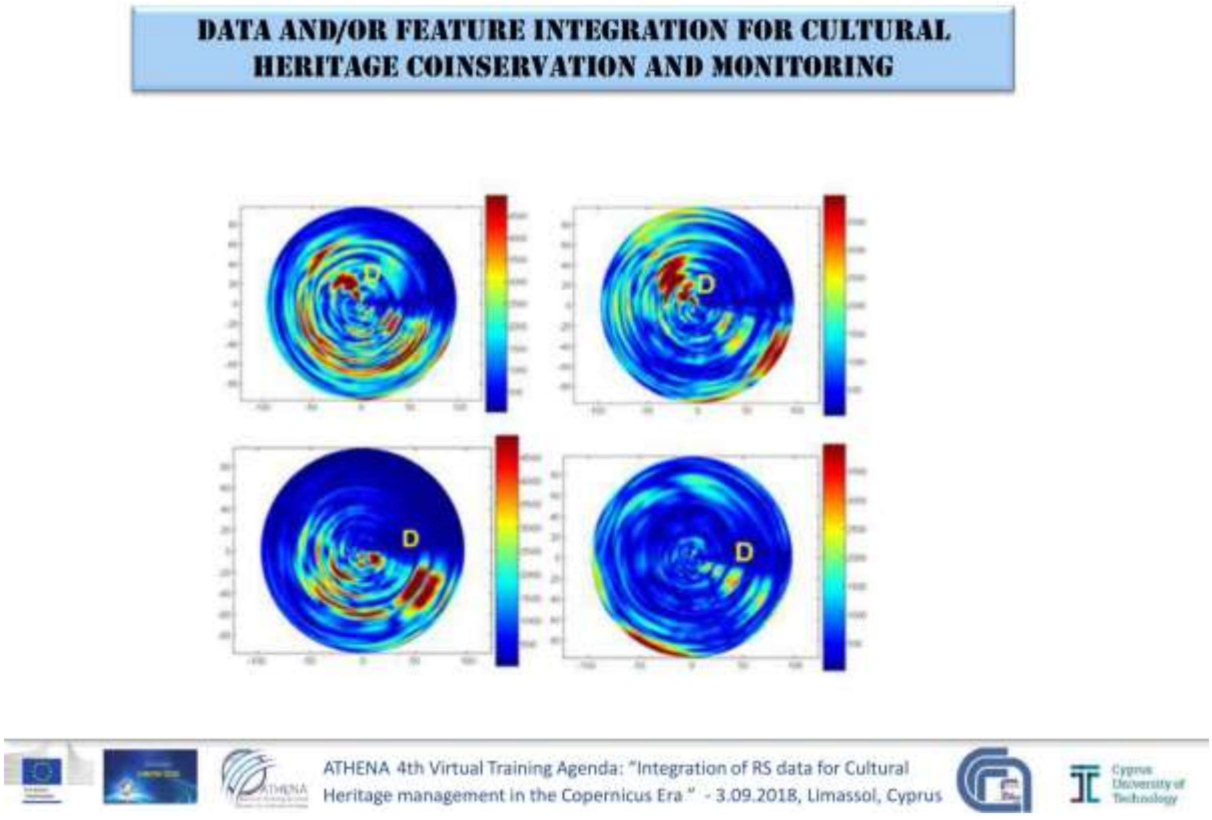

Archeological crop marks identified from Cosmo-SkyMed time series: the case of Han-Wei capital city, Luoyang, China (by A Jiang, F Chen, N Masini, L Capozzoli, G Romano, M Sileo, R Yang, R. Lasaponara)
a) Histograms of Ch and NCh samples in seven optimally selected acquisitions with notations of averaged, standard deviation and intersection point of backscatter coefficients. (b) Diagram for the Ch classification.
Validation of the temporal crop marks on SAR images by GPR and ERT


DATA AND/OR FEATURE INTEGRATION FOR CULTURAL HERITAGE COINSERVATION AND MONITORING
D
D
D
D
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CONSERVATION OF MONUMENTS

- ❑The conservation of monuments is the basis of any policy, strategy and measures aimed at the protection, enhancement and enjoyment.
- ❑It is an activity consisting of two phases : one **cognitive**, the other **operational**
- ❑The cognitive phase is aimed at the diagnosis of degradation pathologies (material decay, structural instability).
- ❑The diagnosis is the result of inter/multi-disciplinary investigations aimed to understand
    - ❖**materials** and **construction techniques**,
    - ❖mechanisms and causes of **degradation**,
    - ❖**boundary conditions** (environment and climate),
    - ❖conditions of **vulnerability**,
    - ❖**Anamnesis**: history of previous restorations and of the damages suffered in the past

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PRESERVATION OF ARCHAEOLOGICAL HERITAGE: CHARACTERISTICS

The conservation of archaeological heritage has some **peculiarities** respect to historical built heritage such as:

- **older** and, consequently, **a longer exposure** to **degradation** and **risk** factors
- conservative characteristics typical of the **ruins without** covering structures **protecting** them
- **Lack of use (**or reuse functional) makes **maintenance** a goal to be pursued with **higher costs respect to historical buildings**
- archaeological restoration is **extremely conservative** than architectural one
    - **additions** are **prohibited** except as minimal additions as part of an intervention anastylosis

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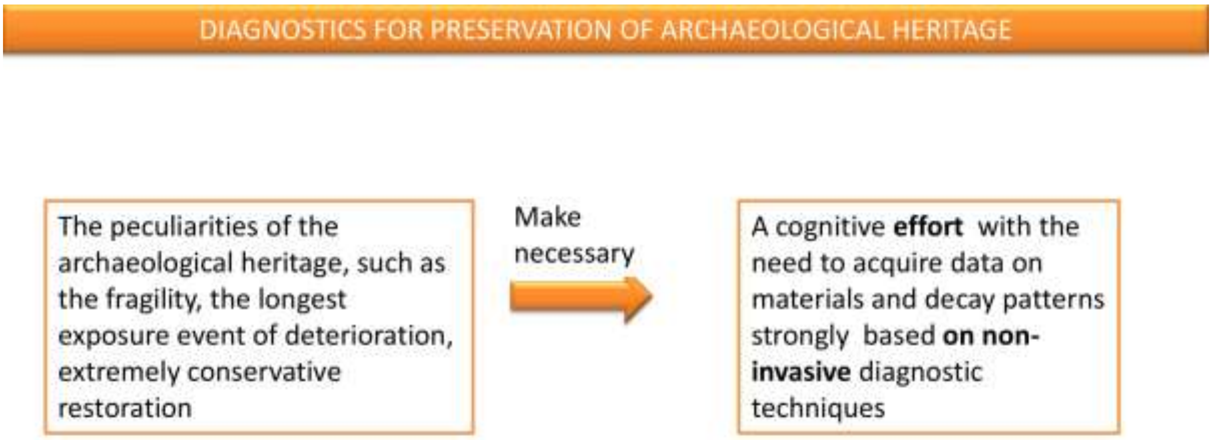
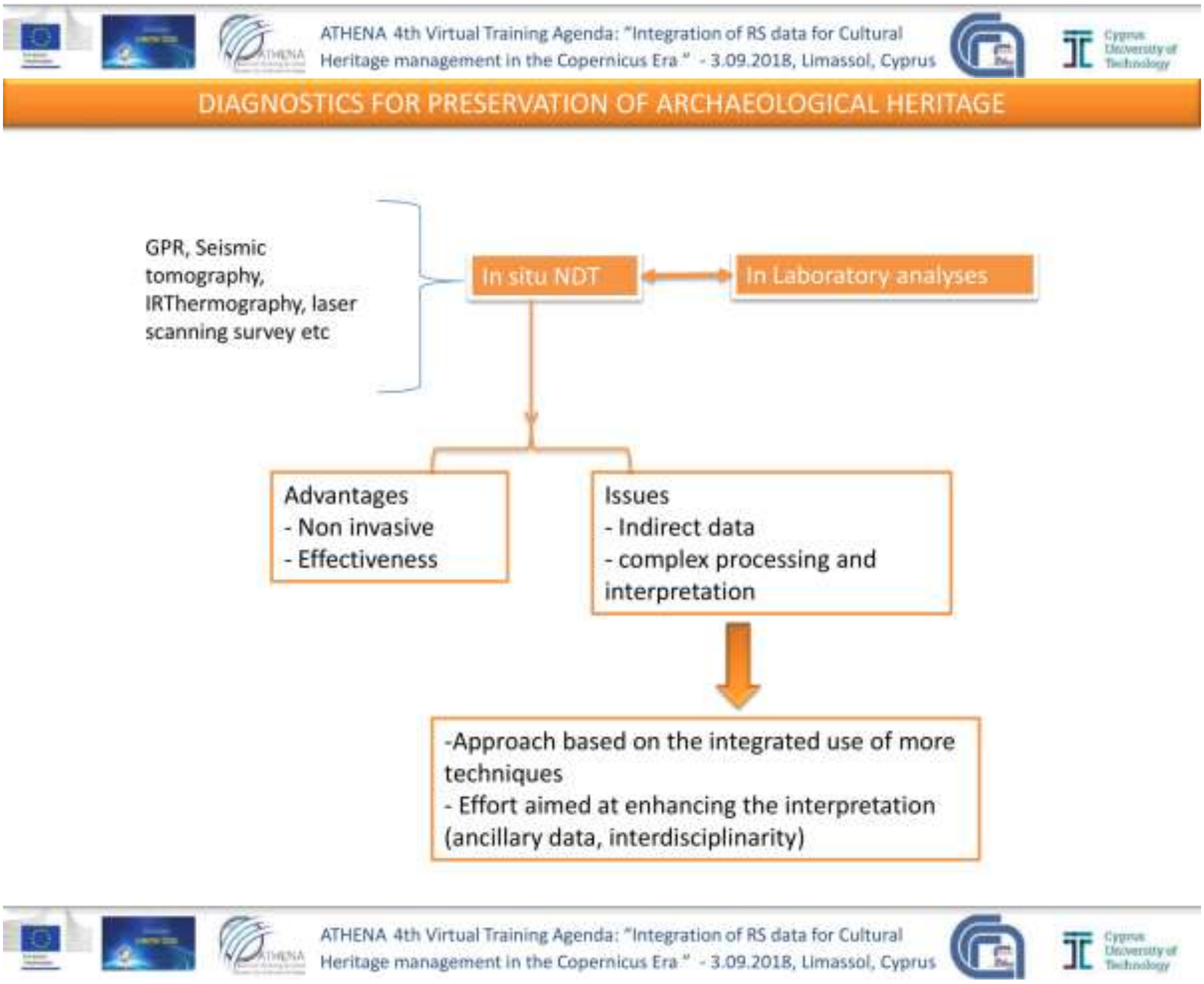

DIAGNOSTICS FOR PRESERVATION OF ARCHAEOLOGICAL HERITAGE
The peculiarities of the archaeological heritage, such as the fragility, the longest exposure event of deterioration, extremely conservative restoration
Make necessary
A cognitive **effort** with the need to acquire data on materials and decay patterns strongly based **on non-invasive** diagnostic techniques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DIAGNOSTICS FOR PRESERVATION OF ARCHAEOLOGICAL HERITAGE
GPR, Seismic tomography, IRThermography, laser scanning survey etc
In situ NDT
In Laboratory analyses
Advantages
- Non invasive
- Effectiveness
Issues
- Indirect data
- complex processing and interpretation
-Approach based on the integrated use of more techniques
- Effort aimed at enhancing the interpretation (ancillary data, interdisciplinarity)
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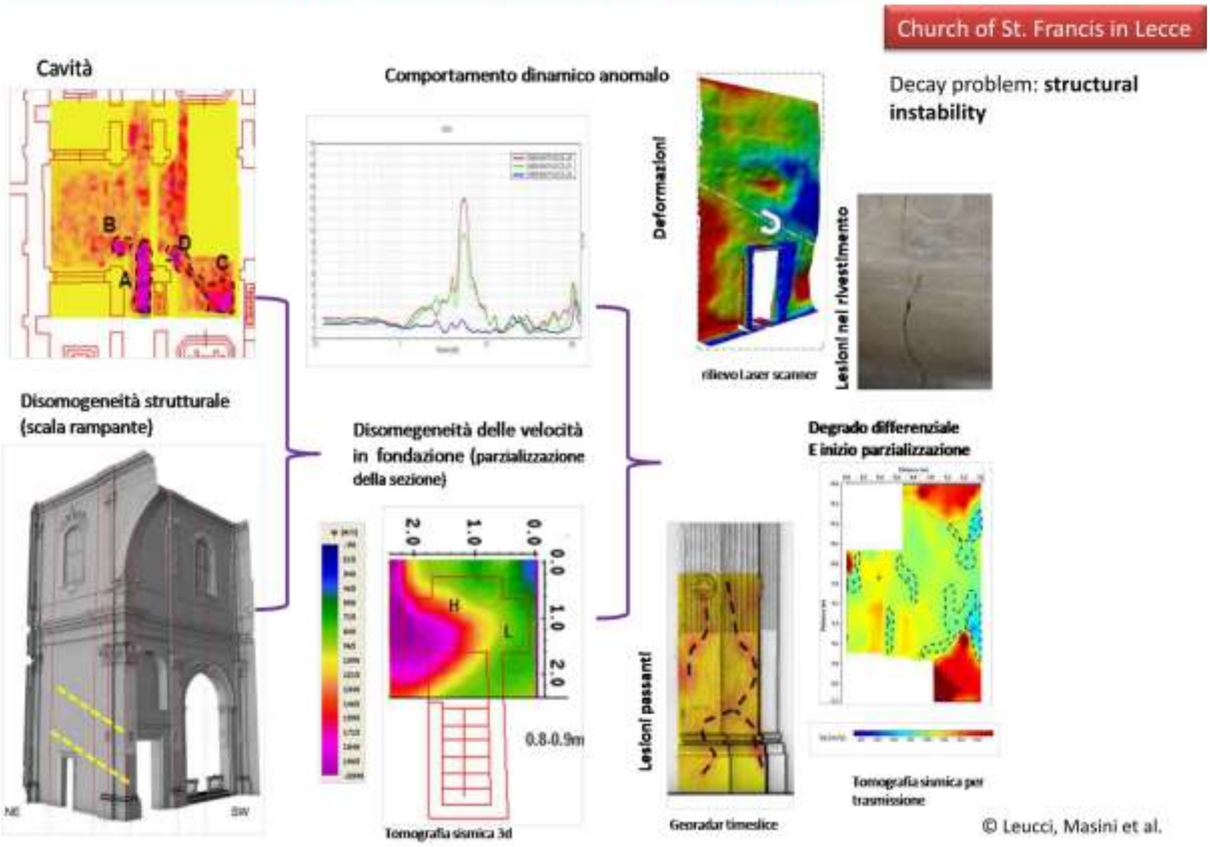
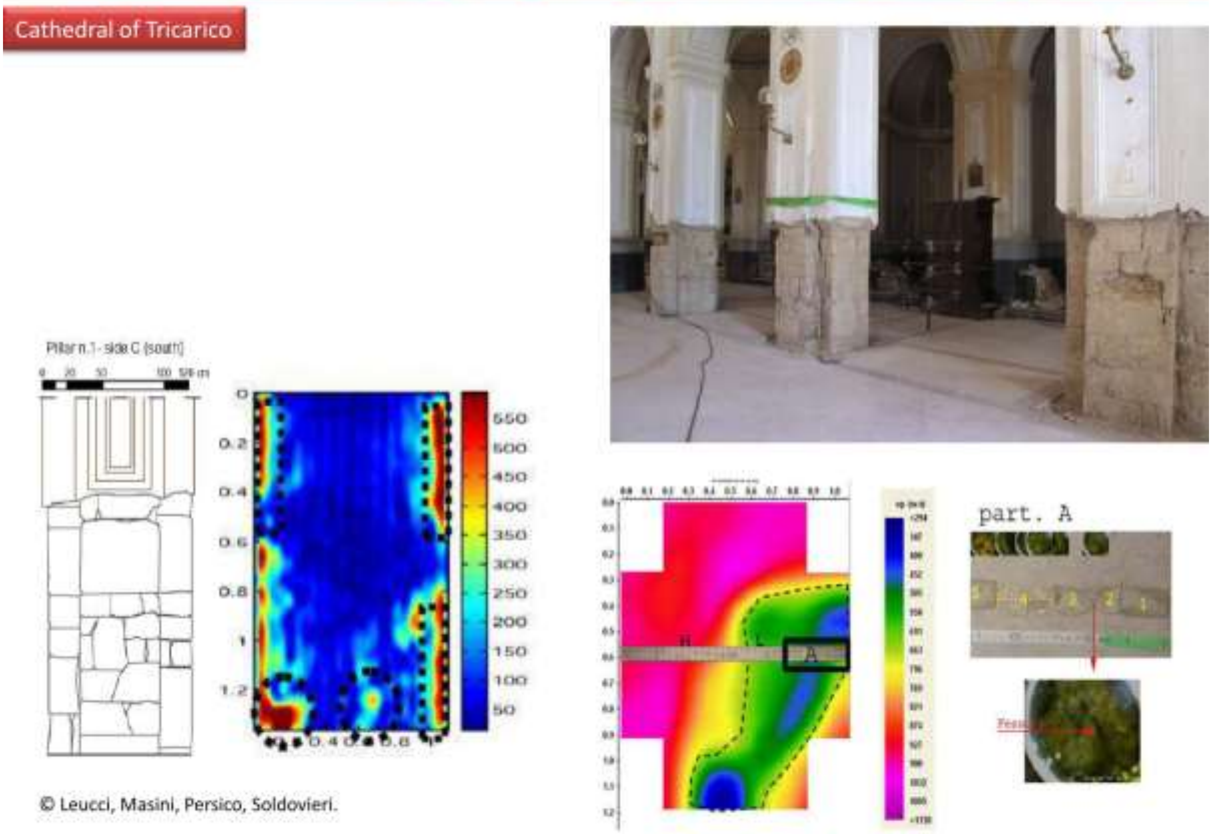
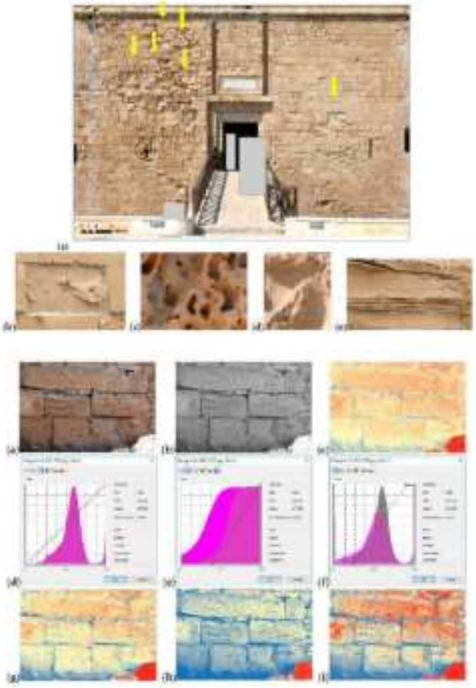
Approaches adopted for diagnostics investigations



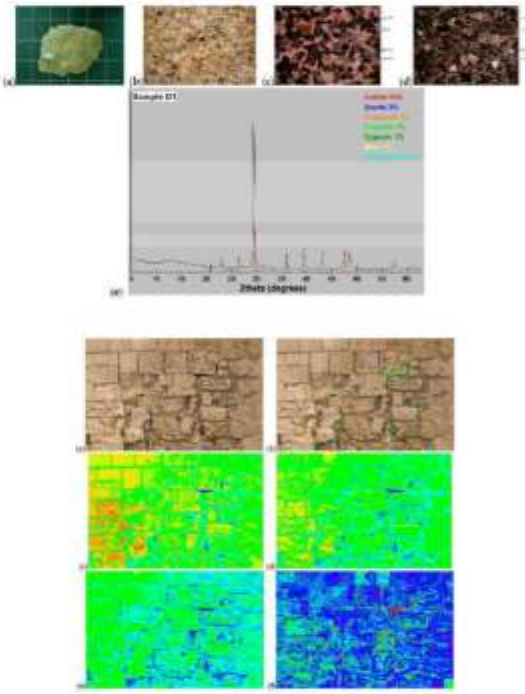
Integration of Georadar and Sonic tomography for imaging fractures and cracks



Integrated Investigation of Built Heritage Monuments: The Case Study of Paphos Harbour Castle, Cyprus (Vasiliki Lysandrou et al. 2018)

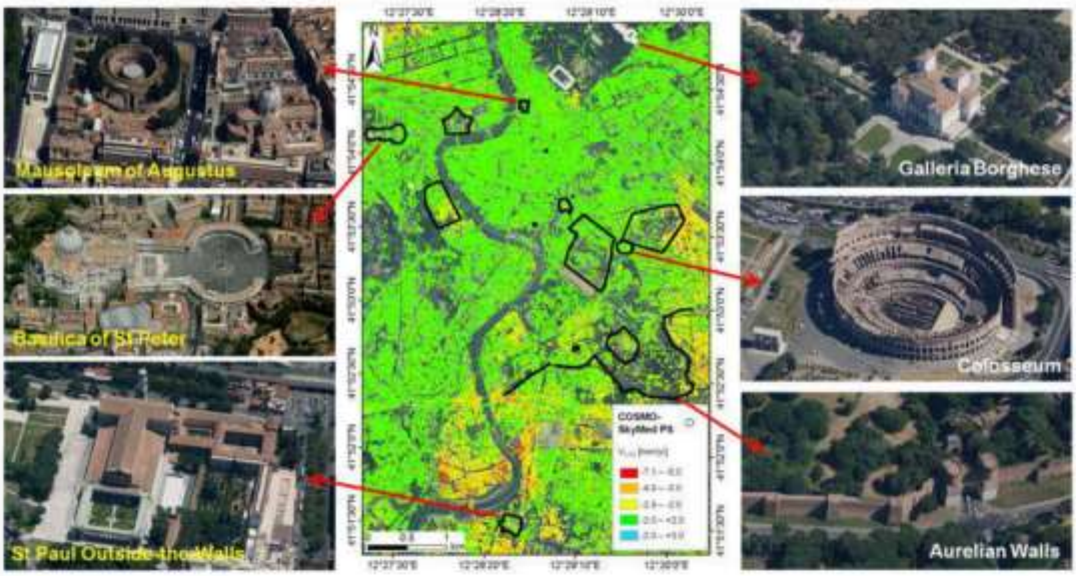


Identification of stone deterioration patterns



State of preservation of the main (north) façade of the castle using DIP techniques:

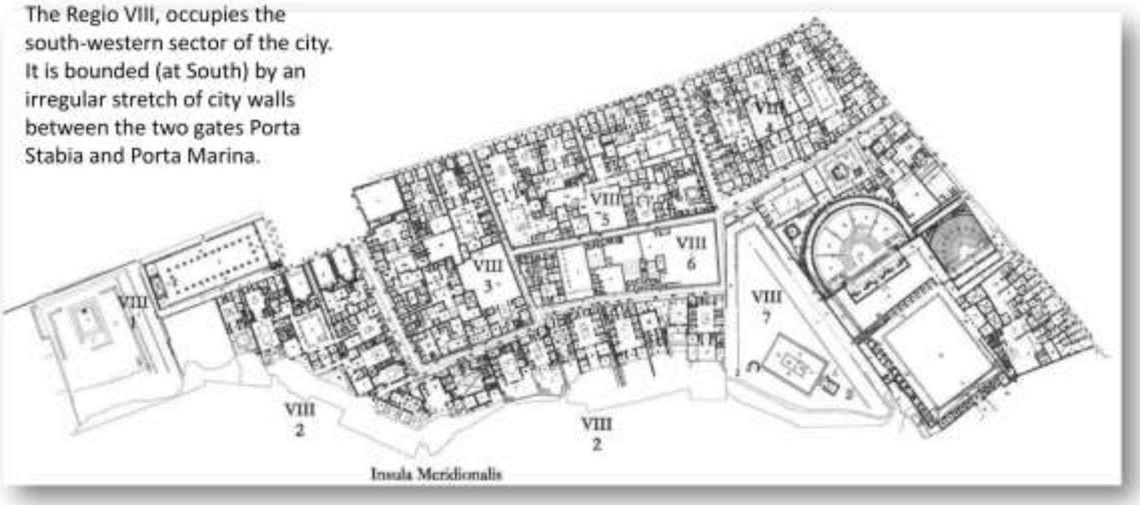
SUBSIDENCE MONITORING OF ROME BY SAR INTERFEROMETRY



Additional info in Francesca Cigna, Rosa Lasaponara, Nicola Masini, Pietro Milillo and Deodato Tapete **Persistent Scatterer Interferometry Processing of COSMO-SkyMed StripMap HIMAGE Time Series to Depict Deformation of the Historic Centre of Rome, Italy**
Remote Sens. **2014**, *6*(12), 12593-12618; doi:10.3390/rs61212593

Regio VIII in the archaeological area of Pompeii

The Regio VIII, occupies the south-western sector of the city. It is bounded (at South) by an irregular stretch of city walls between the two gates Porta Stabia and Porta Marina.



Regio VIII has a urban layout rather irregular, especially along the southern border, having to adapt to the edge of the lava outcrop on which the city stands.

Chronology

End of the 7th -late 4th century BC: Casa dei *Postumii*; Doric temple of the Triangular Forum (half of the sixth century BC); **3rd – 2nd century** : Great Theatre and Quadriportico o Caserma dei Gladiatori, Basilica; **1° cent BC-1° cent AD**: Odeion or Theatre Hall, restructuring of the domus with atrium built against the city walls on the southern slopes

Regio VIII in the archaeological area of Pompeii : some investigated area

Regio VIII : detail of insula 1,1: (Basilica)

Insula 2, 13 : domus

Triangula Forum : columns

Insula 2, 21 : domus of L. Aelius Magnus

Regio VIII in the archaeological area of Pompeii : Aims and object of investigation

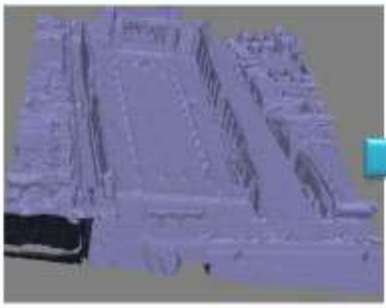
A) Masonry structures : investigation of bulding tecniques, decay patters (cracks, inhomogeneities, voids), survey of deformations

B) **Frescoes** : detection of detachments and inhomogeneities

C) **Wells and cisterns** : exploration and survey

Methodological approach

3d reconstruction of masonry structure geometry and deformations



3d-model provided from UAV-vased survey

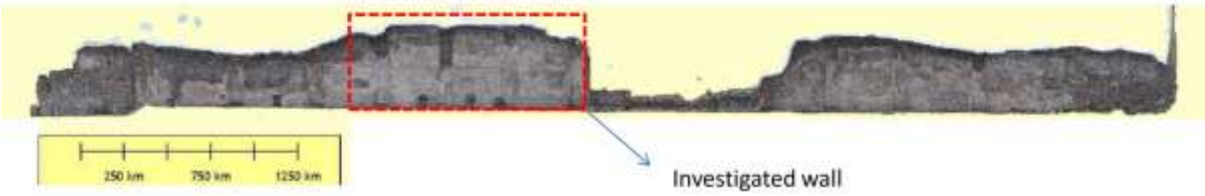
IRT

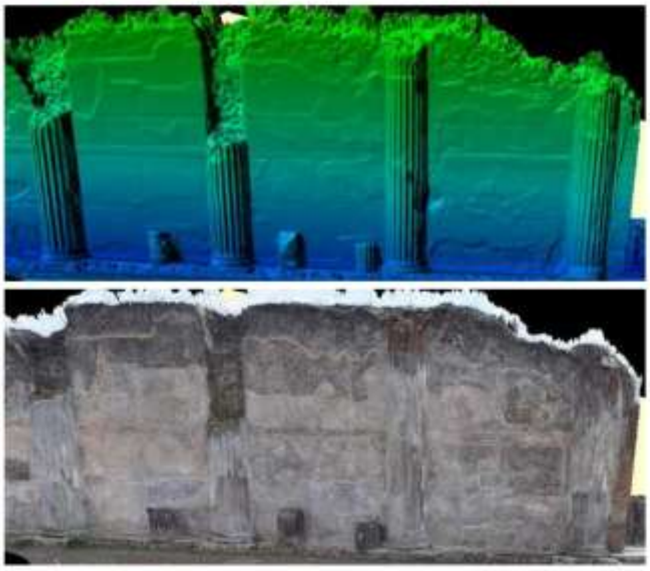
Video endoscopy

Validation with direct data

GPR, **Sonic** and (in case) **infrared** thermography data integration for the dection of buiding and decay features

Pompei: photogrammerical survey and the study of building techniques

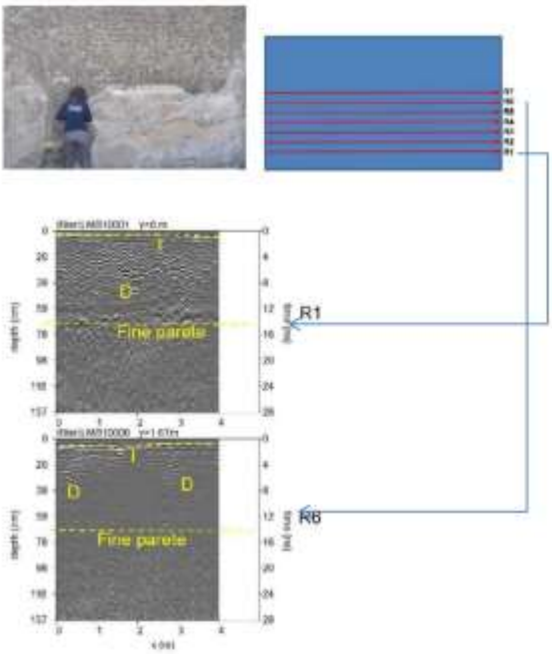


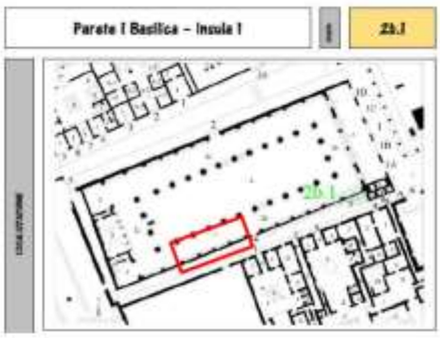


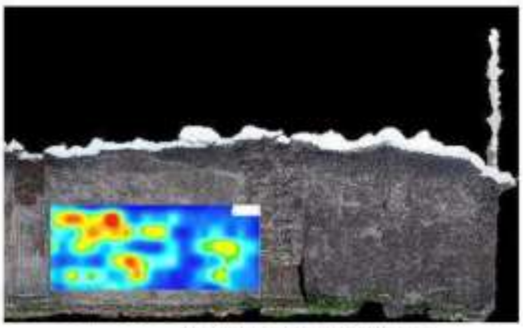
Building techniques:
The wall is made by irregular stone elements of Peperino with thickness equal to approximately 0.66 m. It is a wall at multiple body consisting of three layers (15+30+15 cm), of which the central one very well joined with the two adjacent. Layers of plaster of thickness varying from 3 to 7 cm, on both sides of the wall.

© Masini & Pecci

GPR investigation of walls of Basilica



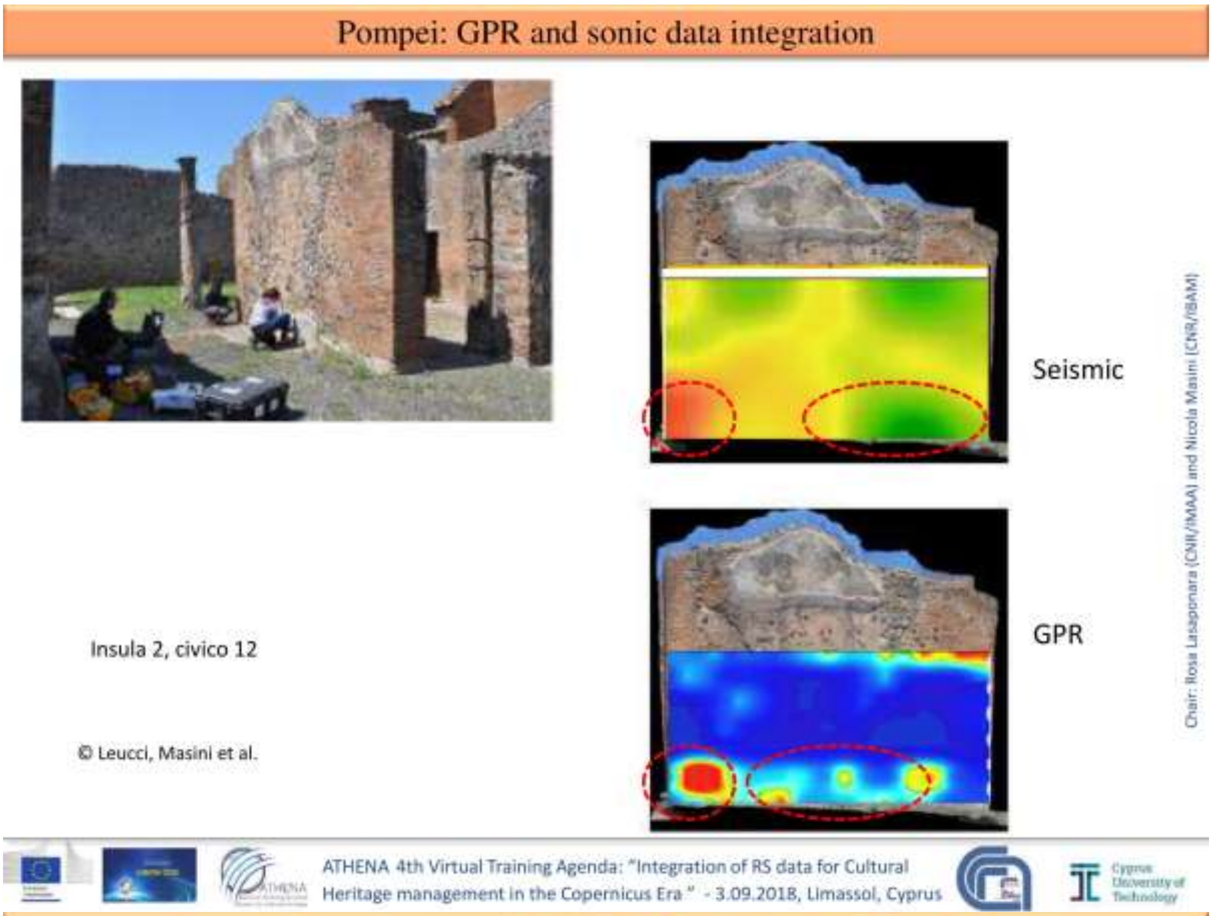




GPR slice at 8-12 cm depth

The data analysis showed the presence: of a number of defects attributable to the discontinuity (D) which are much more evident in the lower part (see Profile R1); the layer of plaster (I - yellow dashed line) of variable thickness between 1 and 3cm.

© Leucci, Masini, Scavone et al.


Pompei: GPR and sonic data integration
Seismic
GPR
Insula 2, civico 12
© Leucci, Masini et al.
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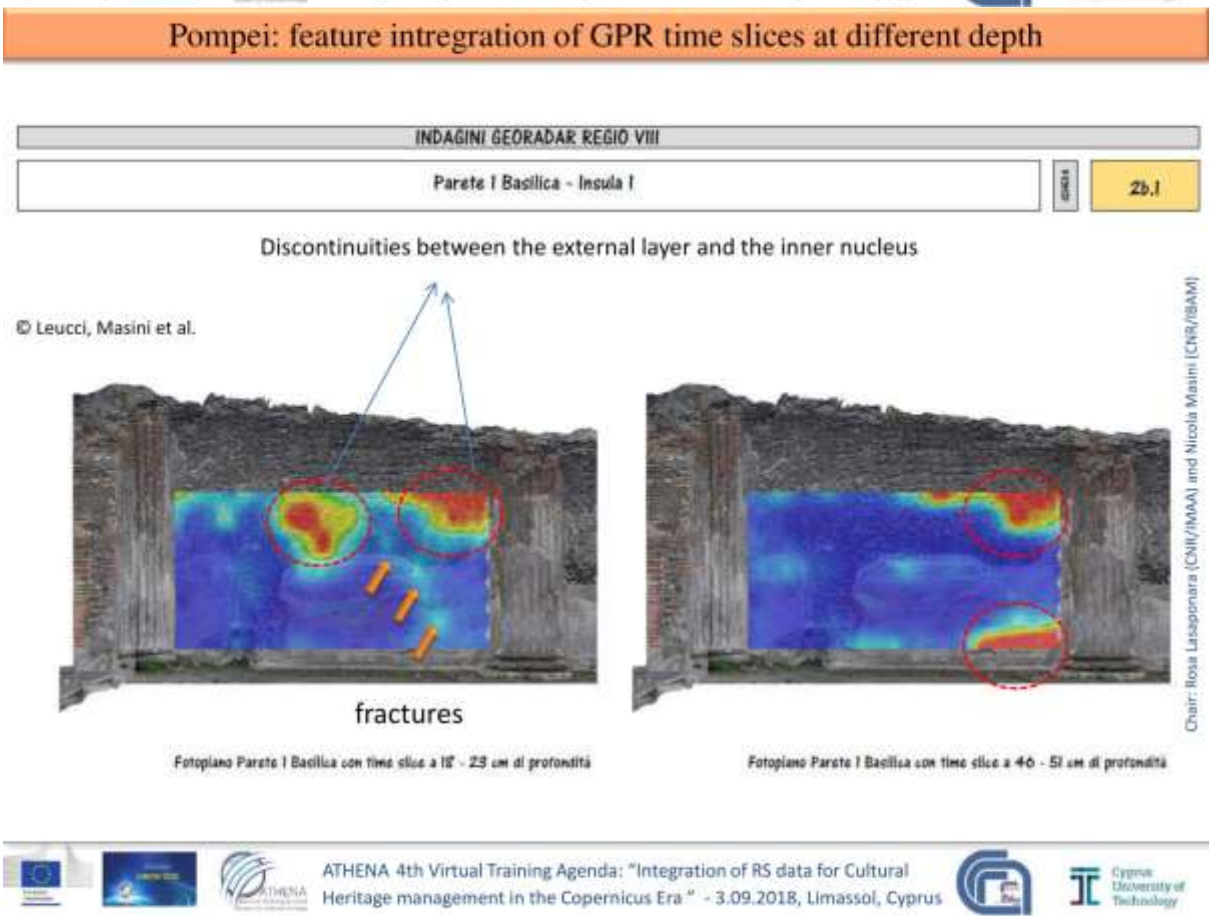
Pompei: feature intregration of GPR time slices at different depth
INDAGINI GEORADAR REGIO VIII
Parete I Basilica - Insula I
2b.I
Discontinuities between the external layer and the inner nucleus
© Leucci, Masini et al.
fractures
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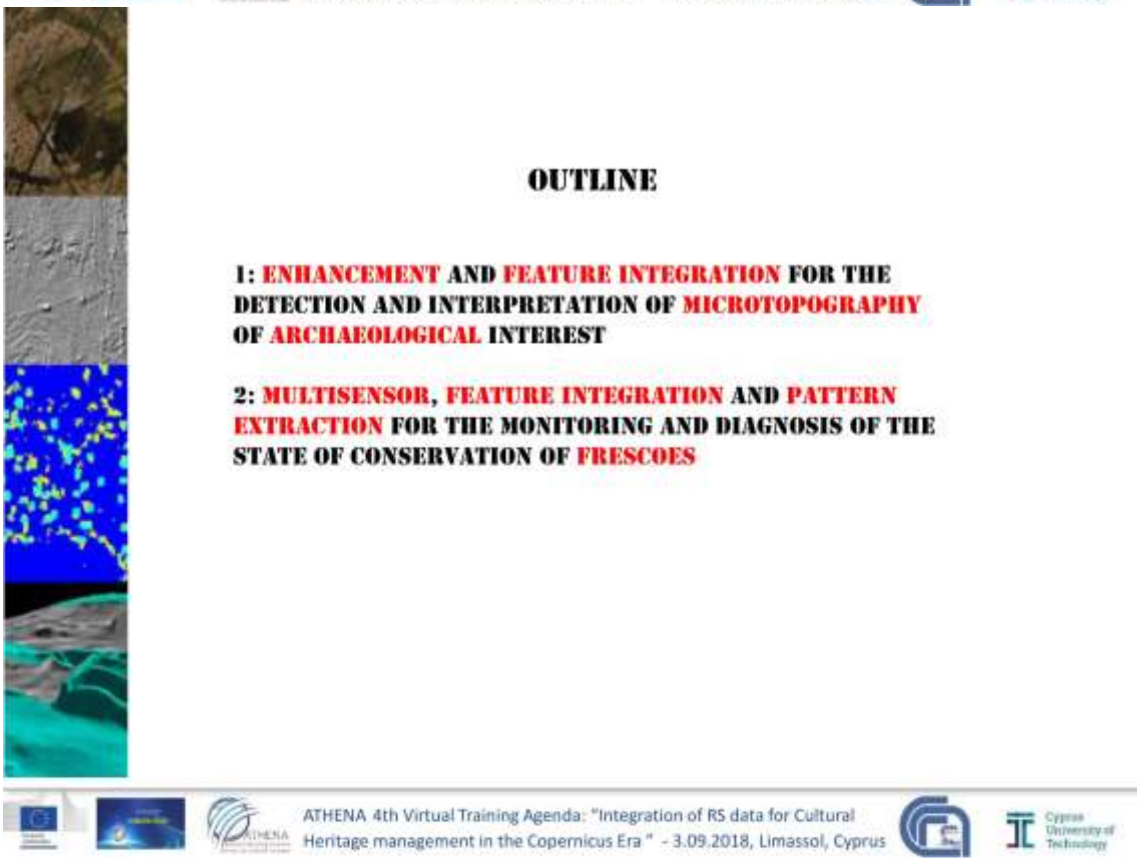
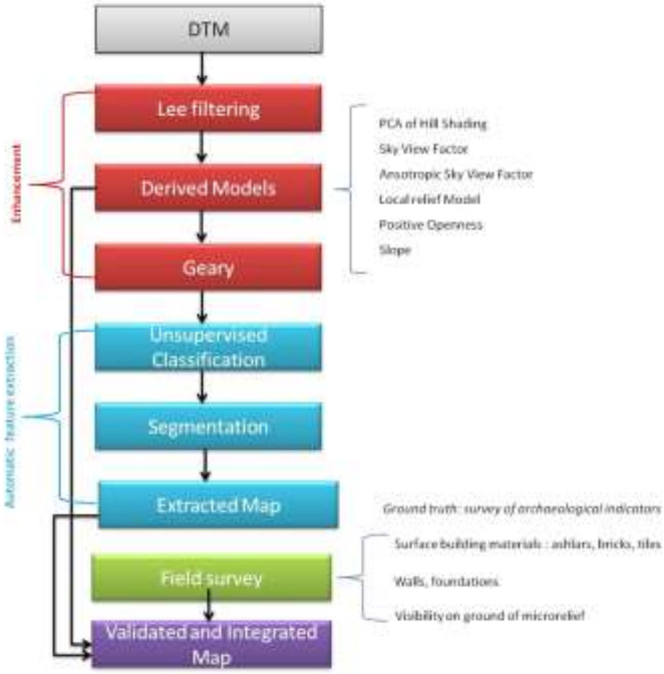
2.4.4 Presentation of the “Case studies and applications”



ENHANCEMENT AND FEATURE INTEGRATION OF ARCHAEOLOGICAL MICROTOPOGRAPHY



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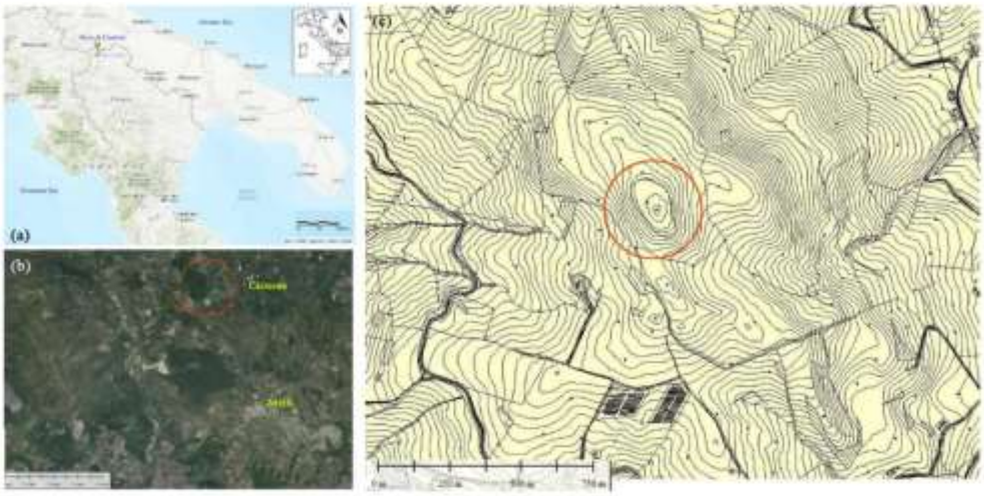
STUDY AREA



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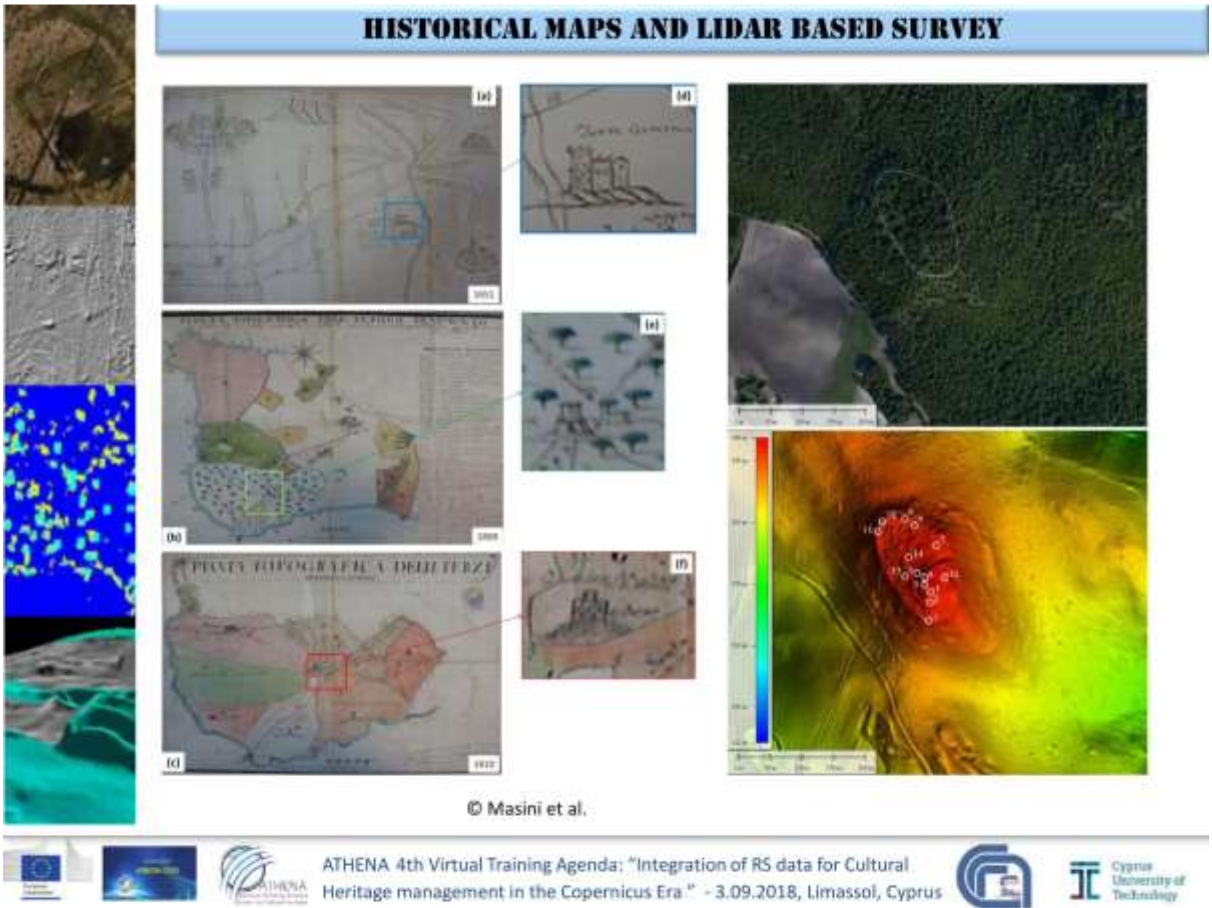
HISTORICAL MAPS AND LIDAR BASED SURVEY
© Masini et al.
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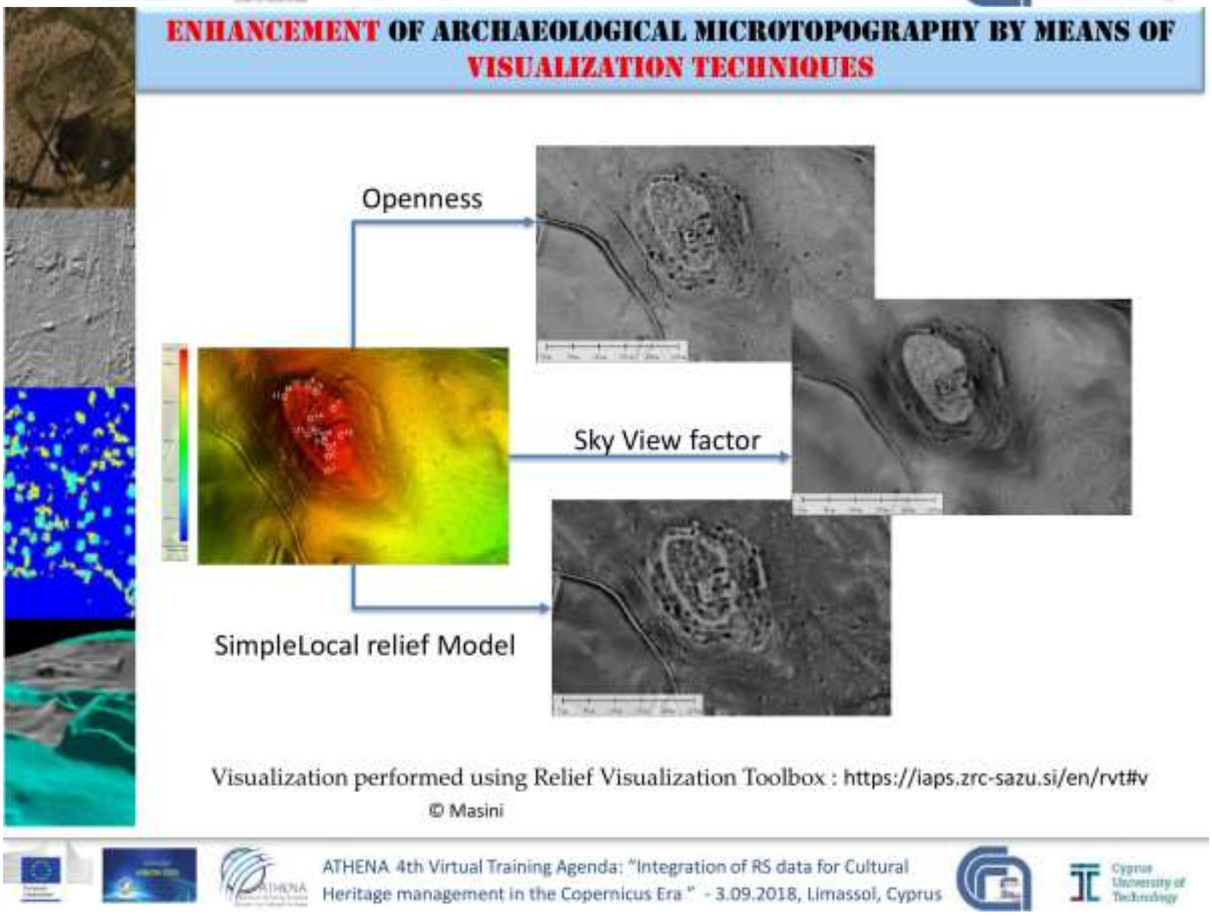
ENHANCEMENT OF ARCHAEOLOGICAL MICROTOPOGRAPHY BY MEANS OF VISUALIZATION TECHNIQUES
Openness
Sky View factor
SimpleLocal relief Model
Visualization performed using Relief Visualization Toolbox : https://iaps.zrc-sazu.si/en/rvt#v
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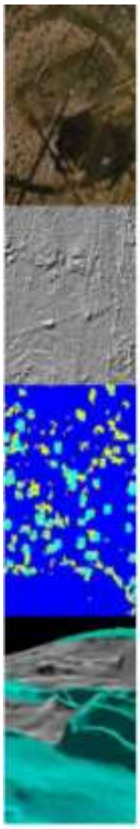
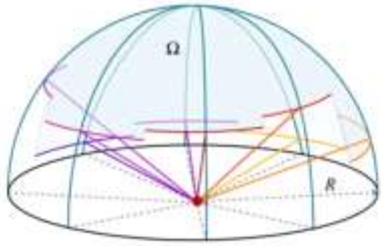
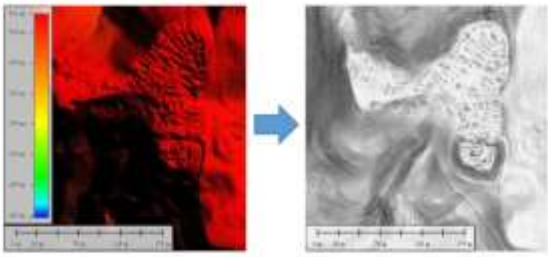


SKY VIEW FACTOR

- Sky View Factor (SVF) quantifies the portion of the sky visible from a certain point' within a certain radius
- SVF considers a homogeneous illumination from all directions above
- elevation angle is determined into multiple directions and to the given distance
- considers a hemisphere only
- values between 0 and 1





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Kokalj 2014

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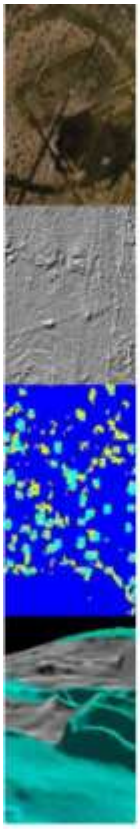
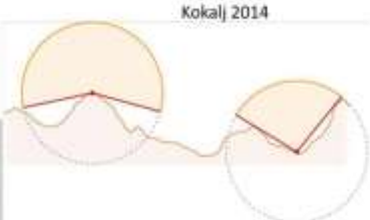
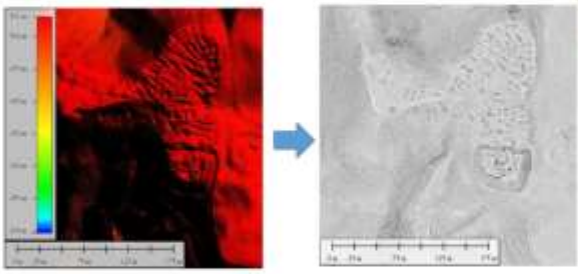


OPENNESS

Openness considers homogeneous illumination from all directions. It includes larger angles than SVF.
Openness highlights convexities namely ridges and crests.

Kokalj 2014





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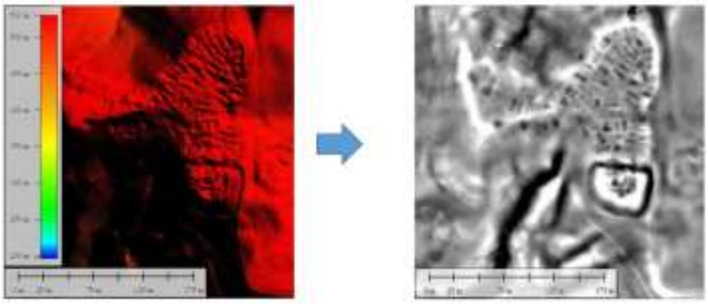
SIMPLE LOCAL RELIEF MODEL

Local Relief Model consists in filtering terrain surface out just leaving archaeological features and their relative elevation above or below the terrain. In this way it enhances the visibility of small-scale topographic features removing large-scale landscape forms from the DTM.

In particular, the LRM approach is based on the: (i) smoothing of DEM made applying low pass filter, (ii) its subtraction to the initial DEM, (iii) calculation of the zero meter contours from the difference model to obtain break lines, as well as the intersection of the break lines with the DEM



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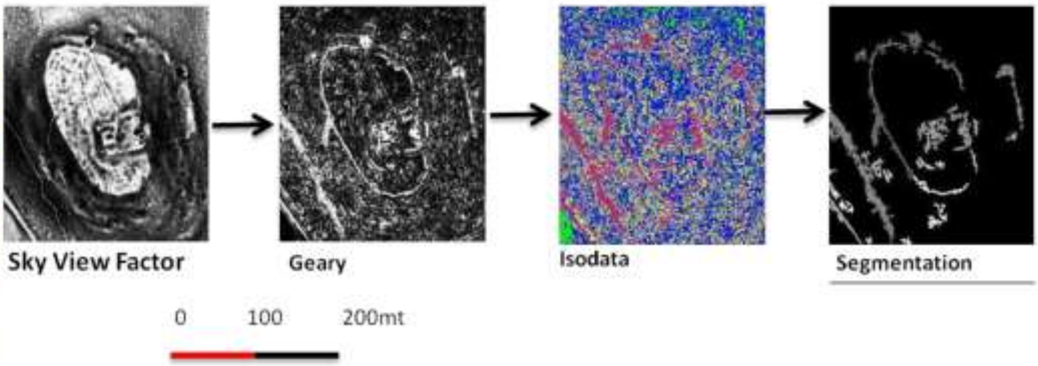
AUTOMATIC FEATURE EXTRACTION APPROACH APPLIED TO SKY VIEW FACTOR



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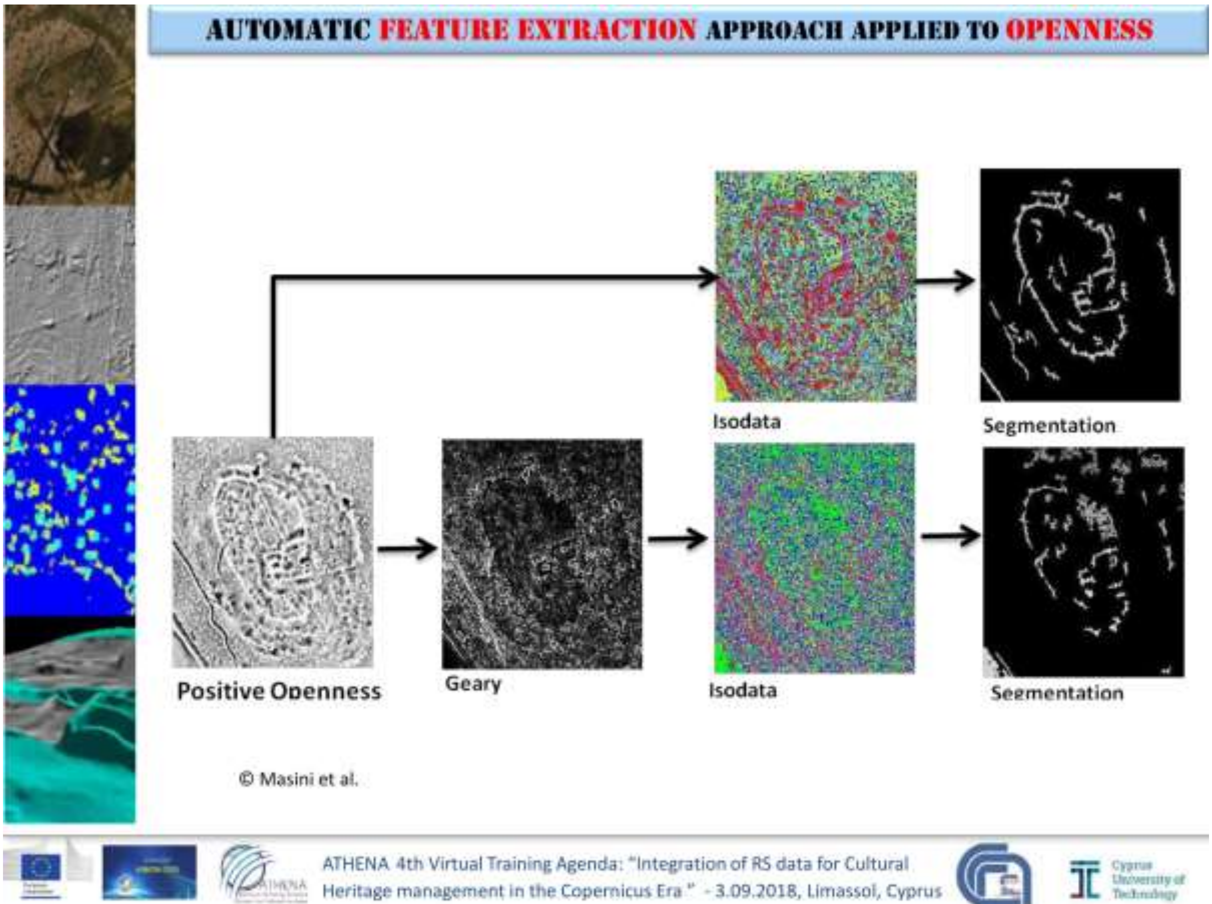
AUTOMATIC FEATURE EXTRACTION APPROACH APPLIED TO OPENNESS
Isodata
Segmentation
Positive Openness
Geary
Isodata
Segmentation
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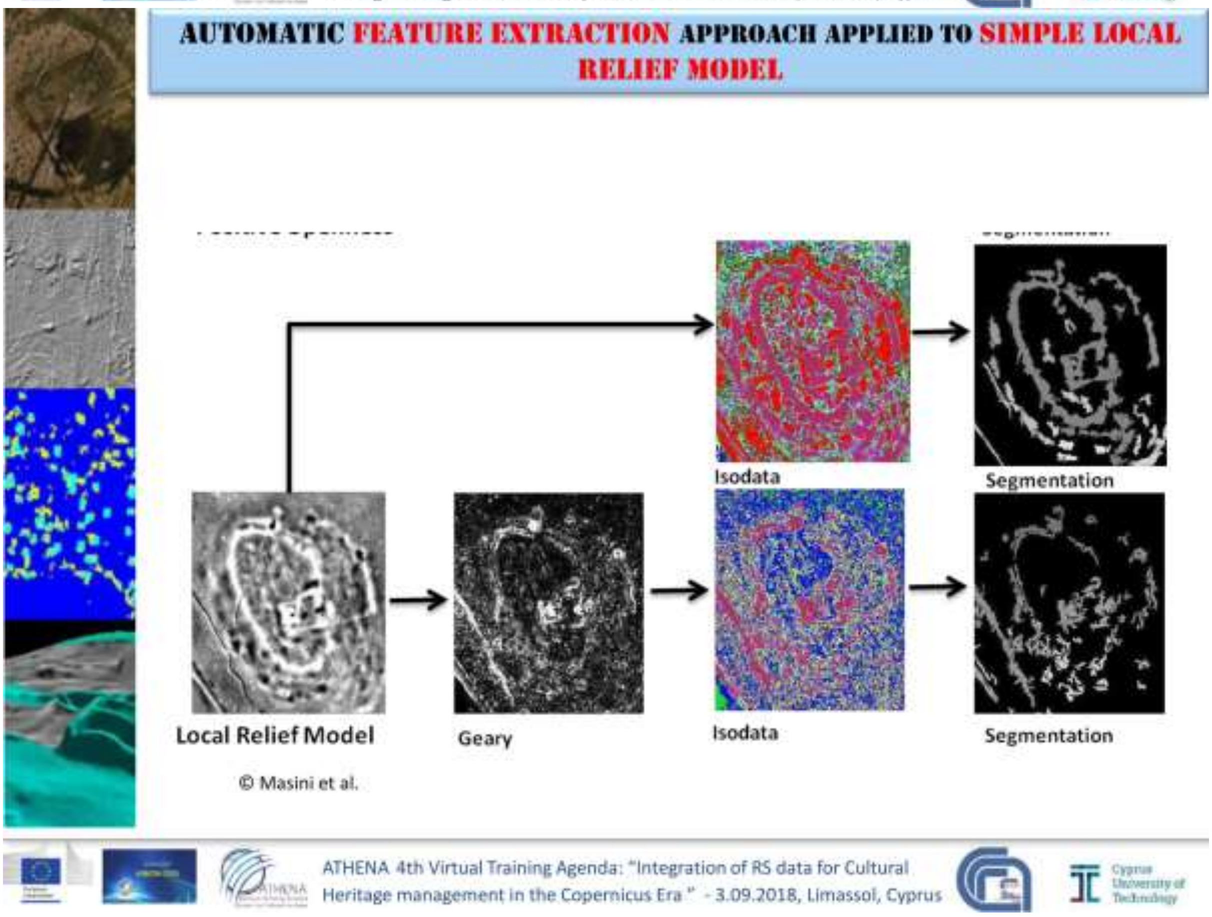
AUTOMATIC FEATURE EXTRACTION APPROACH APPLIED TO SIMPLE LOCAL RELIEF MODEL
Isodata
Segmentation
Local Relief Model
Geary
Isodata
Segmentation
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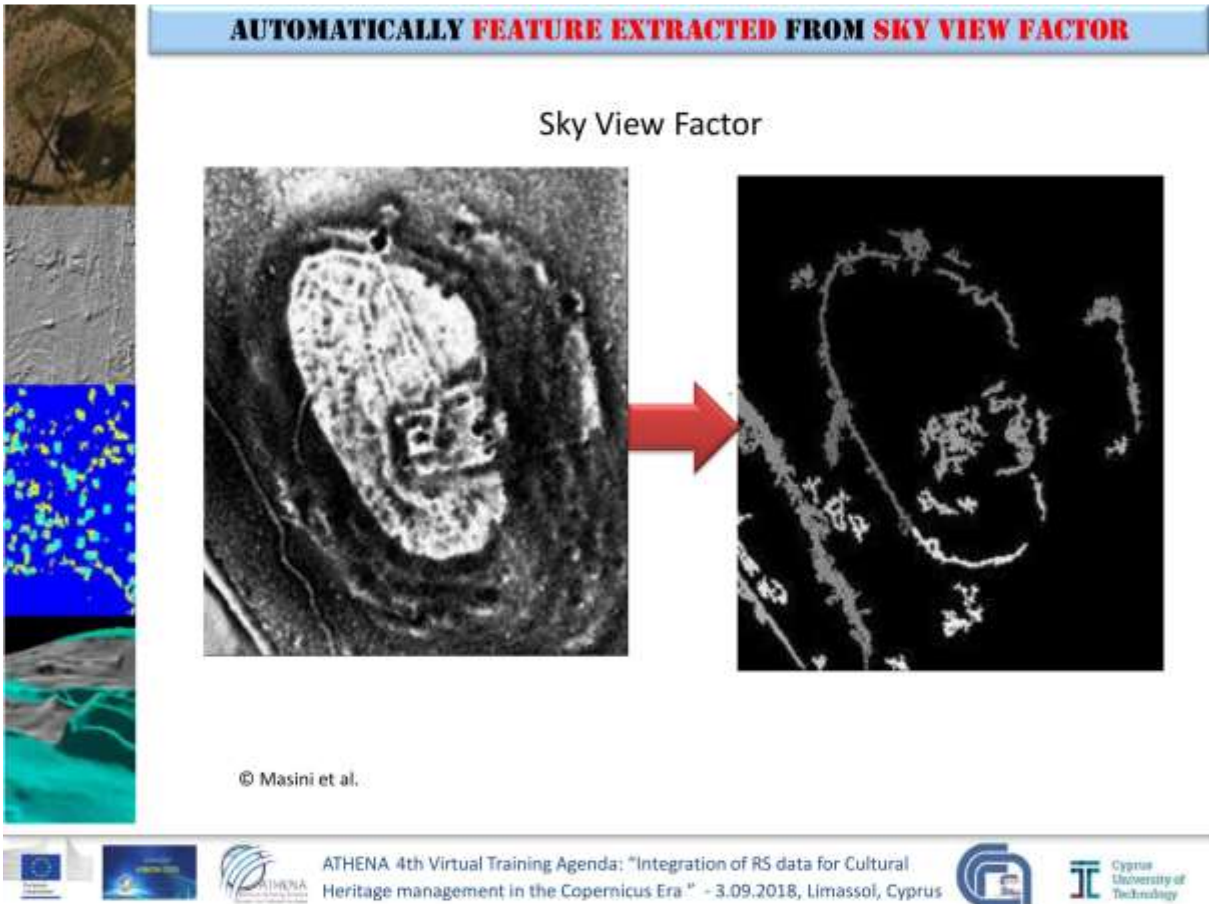
AUTOMATICALLY FEATURE EXTRACTED FROM SKY VIEW FACTOR
Sky View Factor
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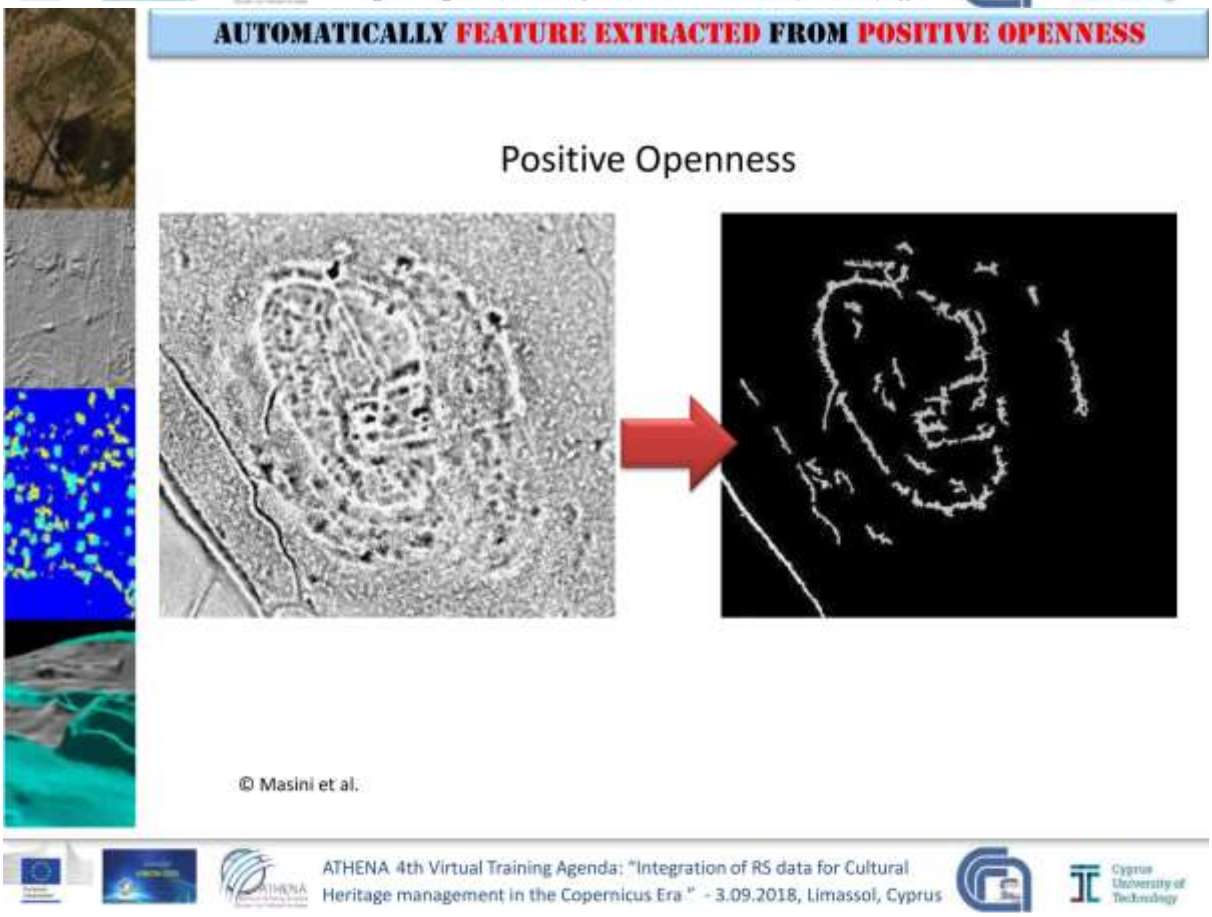
AUTOMATICALLY FEATURE EXTRACTED FROM POSITIVE OPENNESS
Positive Openness
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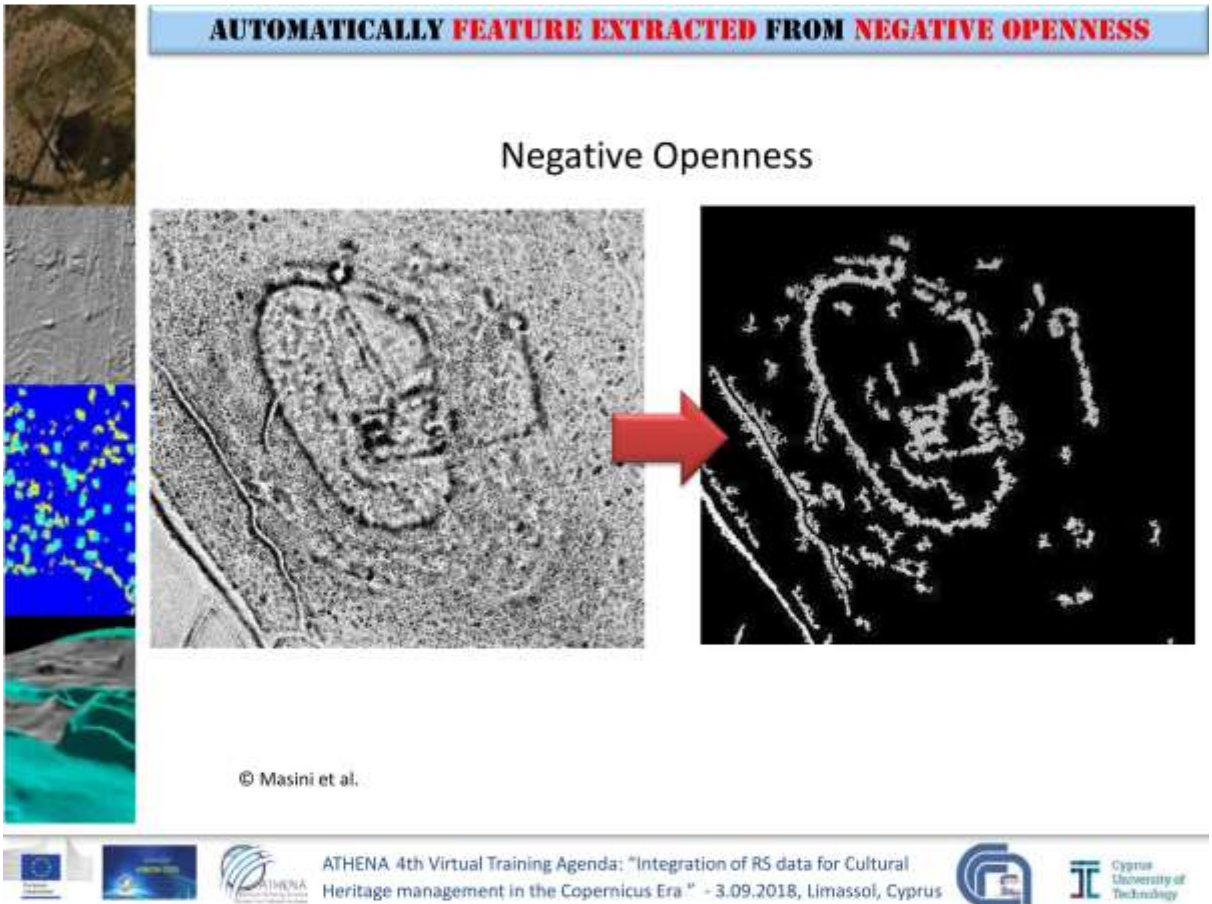
AUTOMATICALLY FEATURE EXTRACTED FROM NEGATIVE OPENNESS
Negative Openness
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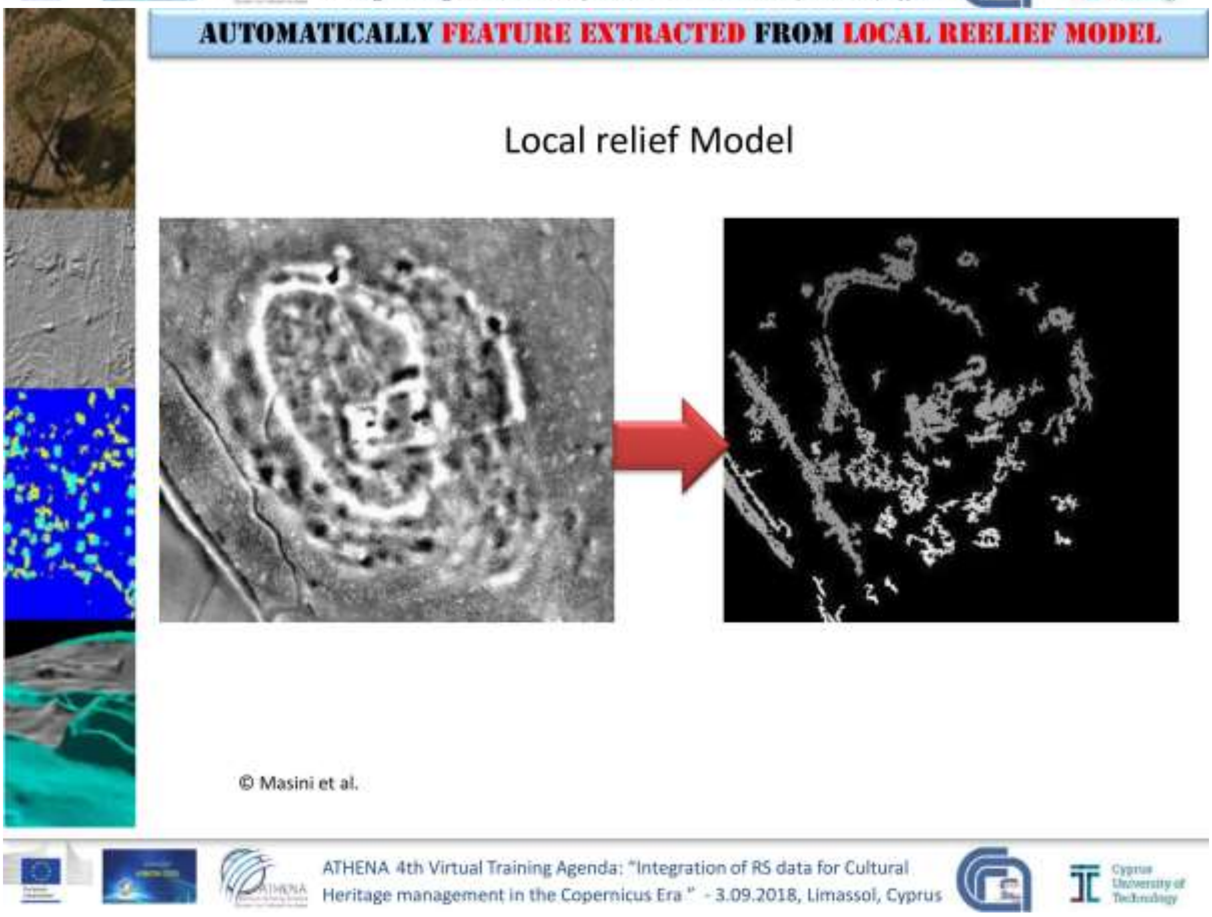
AUTOMATICALLY FEATURE EXTRACTED FROM LOCAL REELIEF MODEL
Local relief Model
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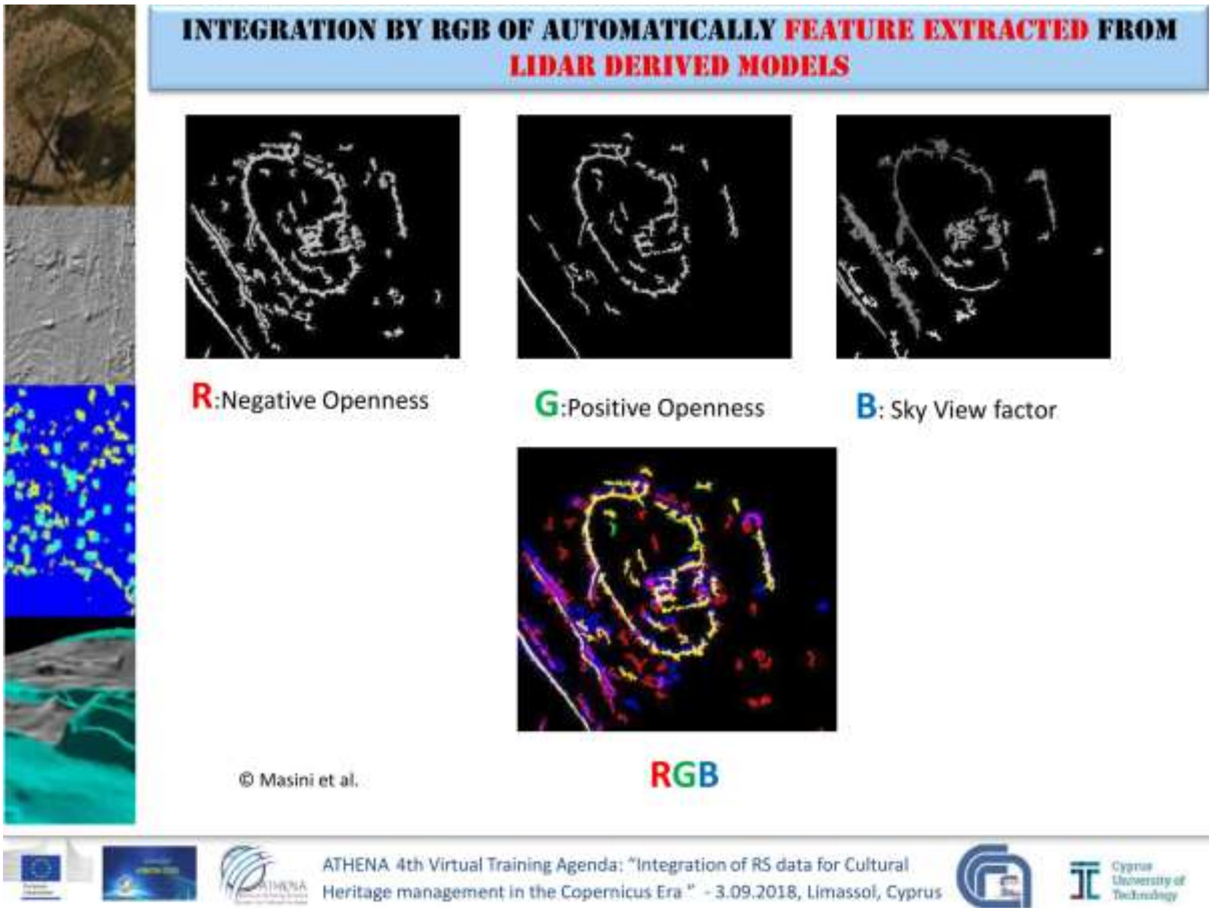
INTEGRATION BY RGB OF AUTOMATICALLY FEATURE EXTRACTED FROM LIDAR DERIVED MODELS
R:Negative Openness
G:Positive Openness
B: Sky View factor
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RGB
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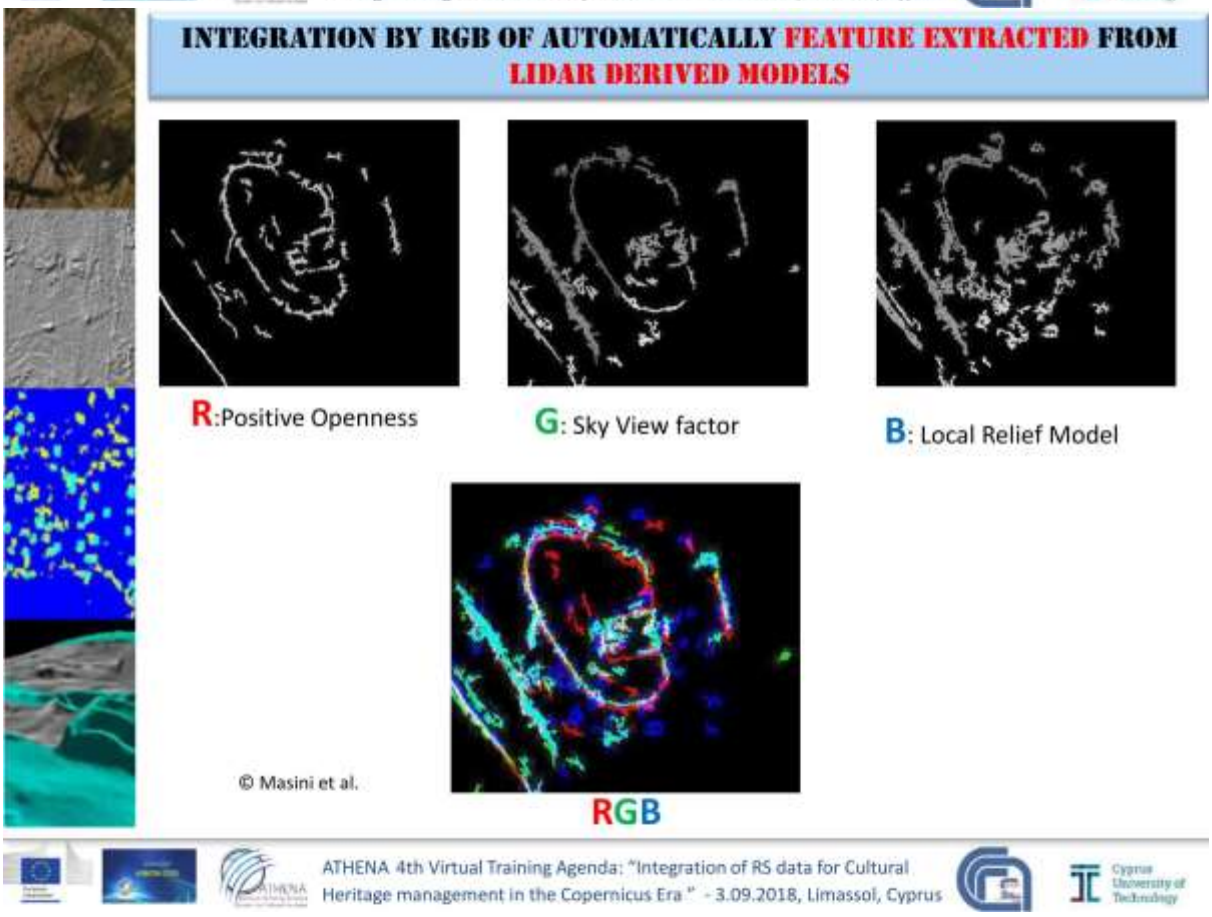
INTEGRATION BY RGB OF AUTOMATICALLY FEATURE EXTRACTED FROM LIDAR DERIVED MODELS
R:Positive Openness
G: Sky View factor
B: Local Relief Model
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RGB
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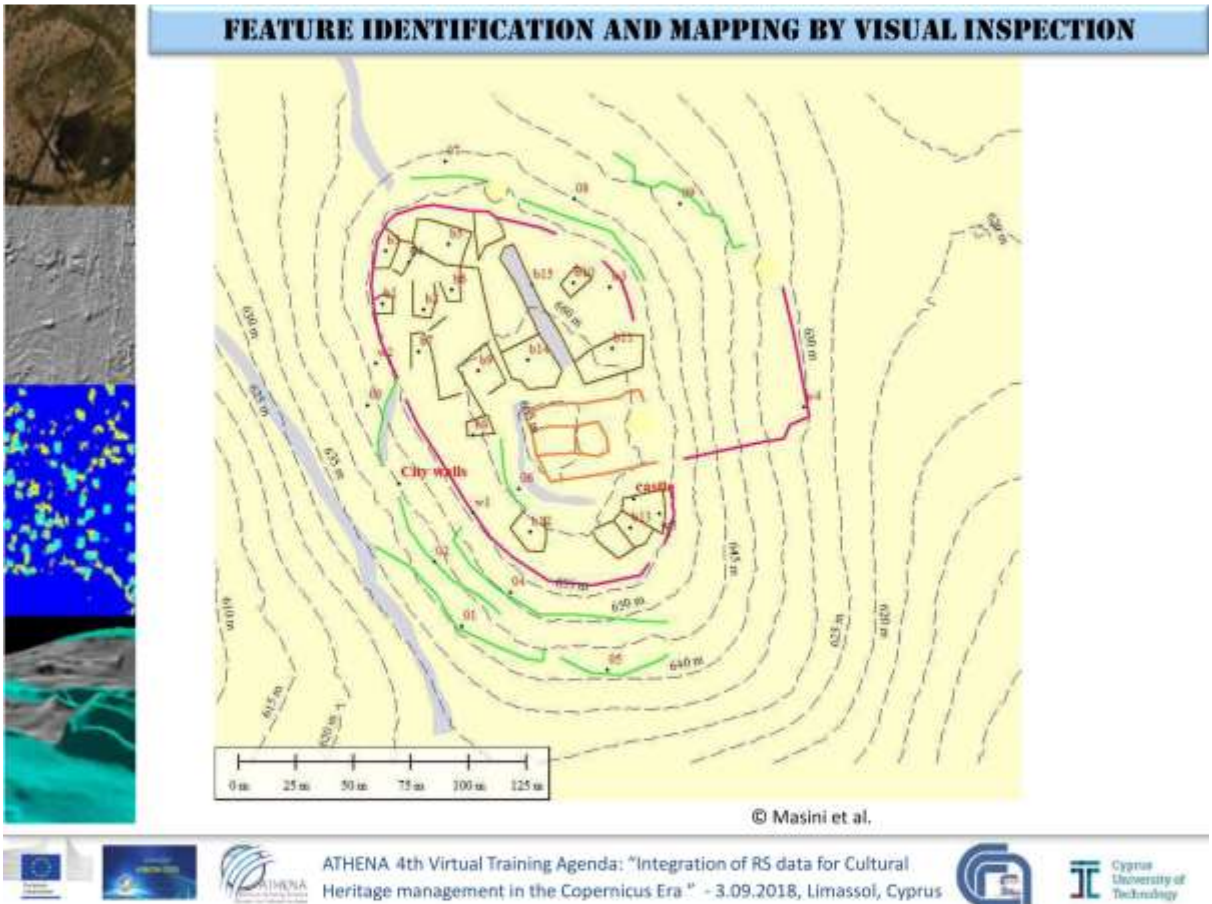
FEATURE IDENTIFICATION AND MAPPING BY VISUAL INSPECTION
City walls
castle
0 m 25 m 50 m 75 m 100 m 125 m
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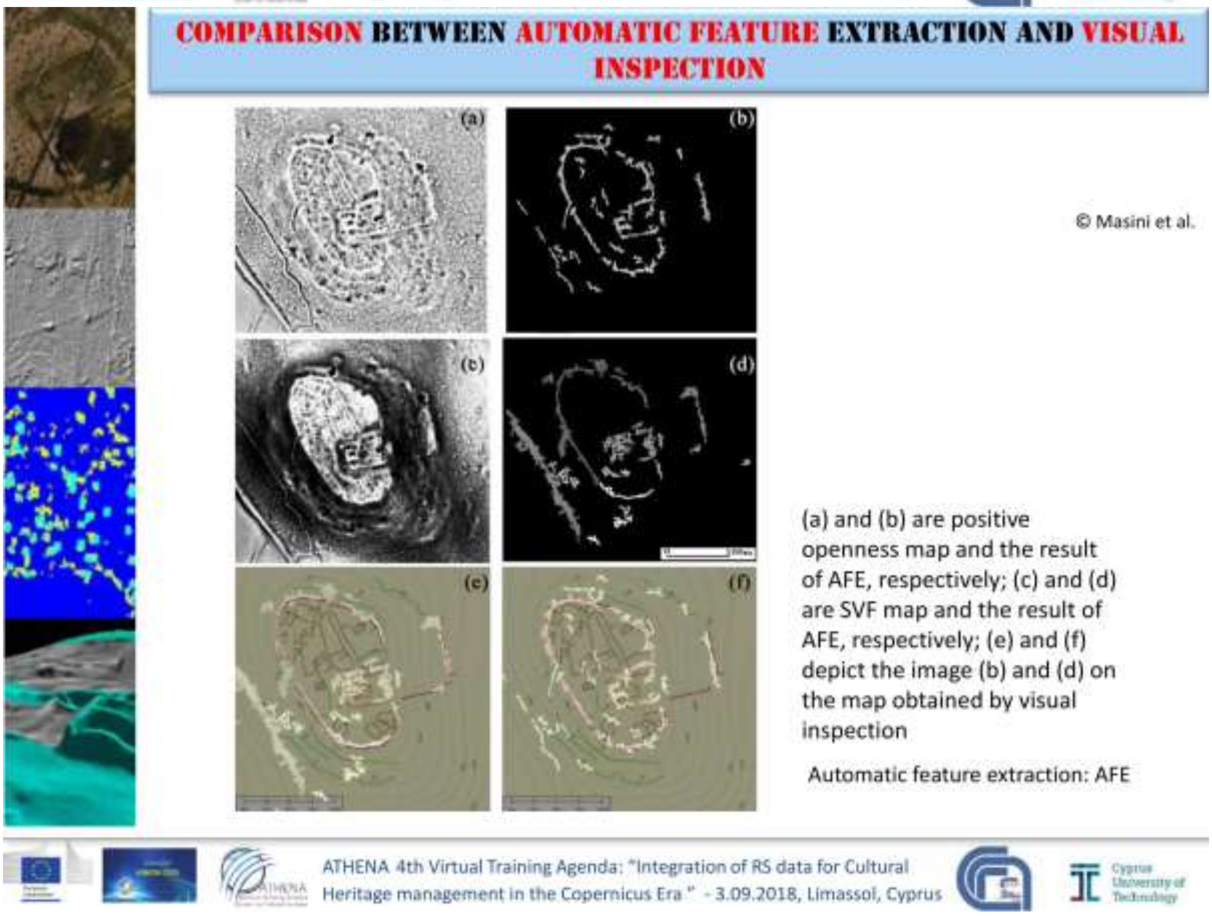
COMPARISON BETWEEN AUTOMATIC FEATURE EXTRACTION AND VISUAL INSPECTION
(a)
(b)
(c)
(d)
(e)
(f)
© Masini et al.
(a) and (b) are positive openness map and the result of AFE, respectively; (c) and (d) are SVF map and the result of AFE, respectively; (e) and (f) depict the image (b) and (d) on the map obtained by visual inspection
Automatic feature extraction: AFE
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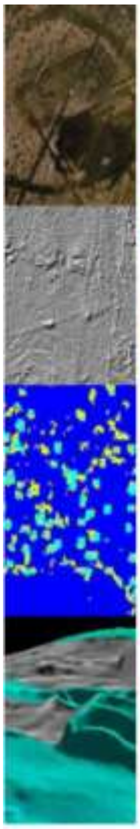
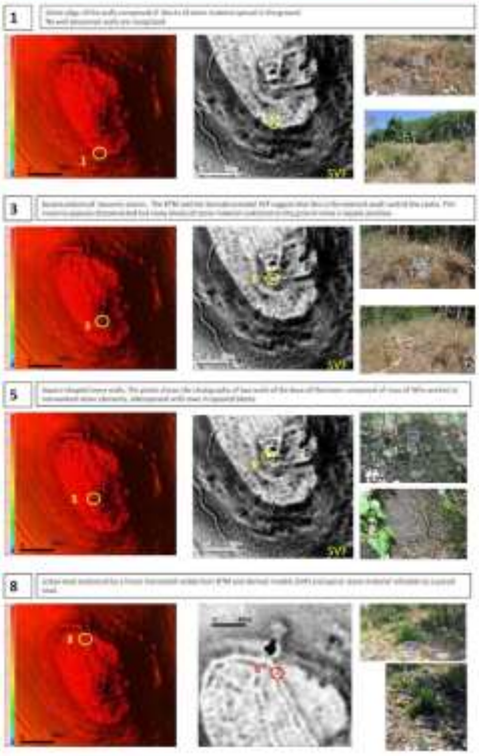


IN SITU VALIDATION



	AFE applied to Positive Openness			AFE applied to SVF	
	Total length (mt)	Features detected (mt; %)		Features detected (mt; %)	
City walls	469	438	93%	454	97%
Castle	222	190	86%	184	83%
Buildings	855	119	14%	32	4%
OAF	585	196	34%	117	20%
Total length	2131				

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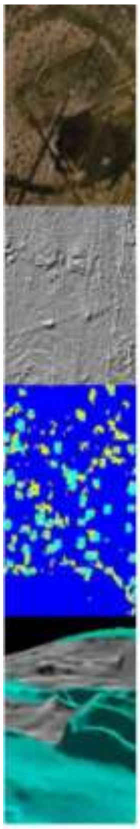

MULTISENSOR, FEATURE INTEGRATION AND PATTERN EXTRACTION FOR THE MONITORING AND DIAGNOSIS OF THE STATE OF CONSERVATION OF FRESCOES

A promising application field of remote sensing ands in-situ non invasive investigations is the monitoring and analysis of the state of conservation of works of art, such as wall paintings including frescoes.

To this aim, two are the issues to address:

I. the choice of the most appropriate sensing technology
II. and the analysis, integration and interpretation of data after their processing.

Feature Integration approach and Pattern extraction based on spatial analysis based for the interpretation of data coming from different non-invasive tests, to improve the extraction process of the pattern decay

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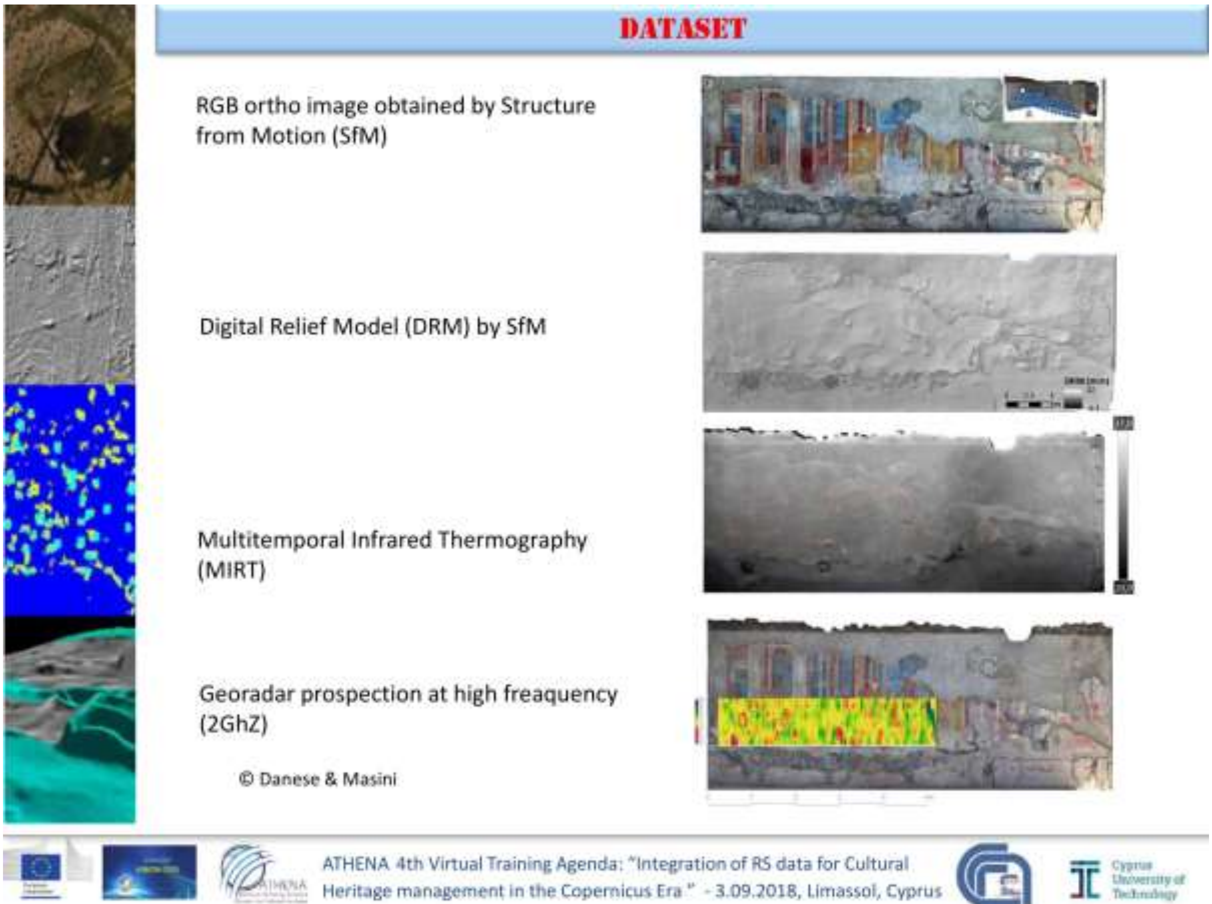
DATASET
RGB ortho image obtained by Structure from Motion (SfM)
Digital Relief Model (DRM) by SfM
Multitemporal Infrared Thermography (MIRT)
Georadar prospection at high freaquency (2GhZ)
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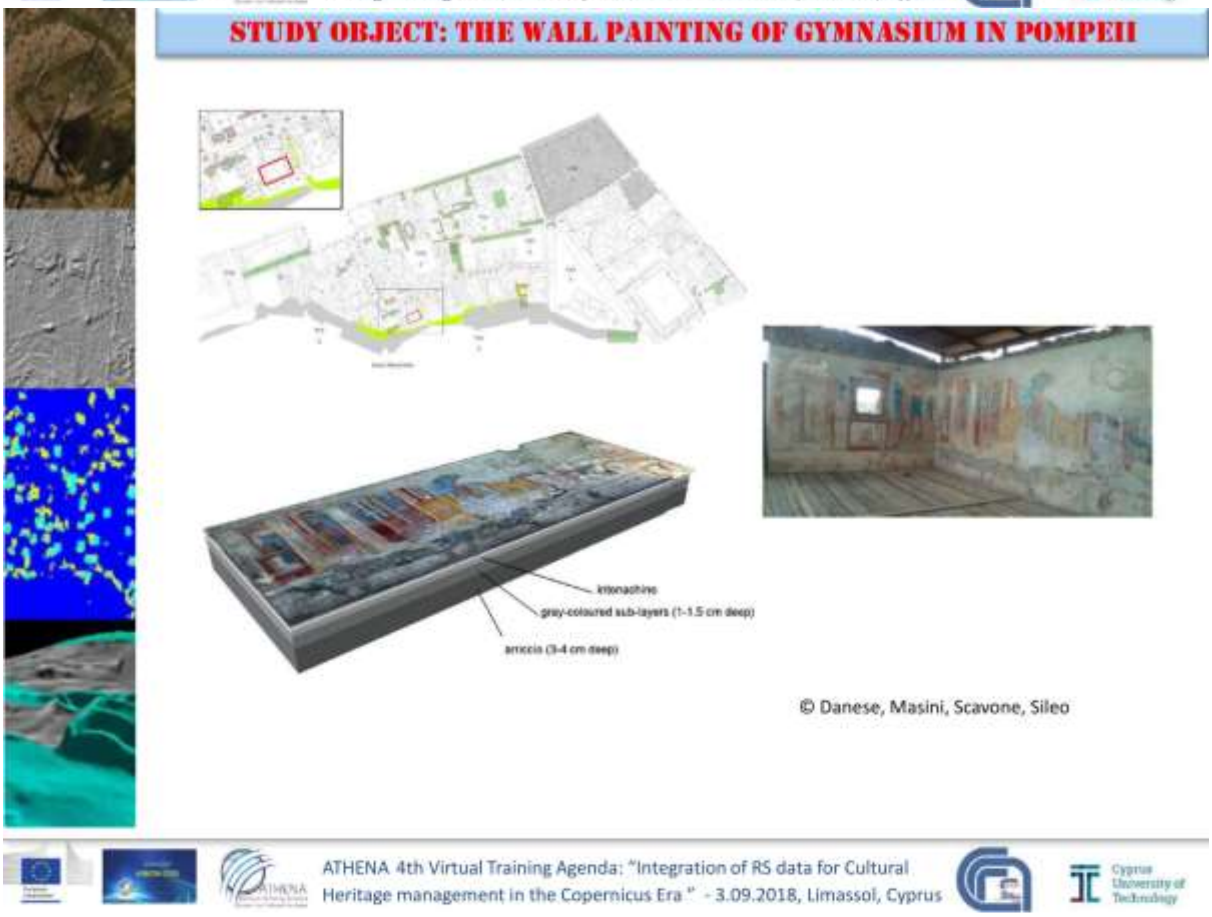
STUDY OBJECT: THE WALL PAINTING OF GYMNASIUM IN POMPEII
intonachino
gray-coloured sub-layers (1-1.5 cm deep)
arriccio (3-4 cm deep)
© Danese, Masini, Scavone, Sileo
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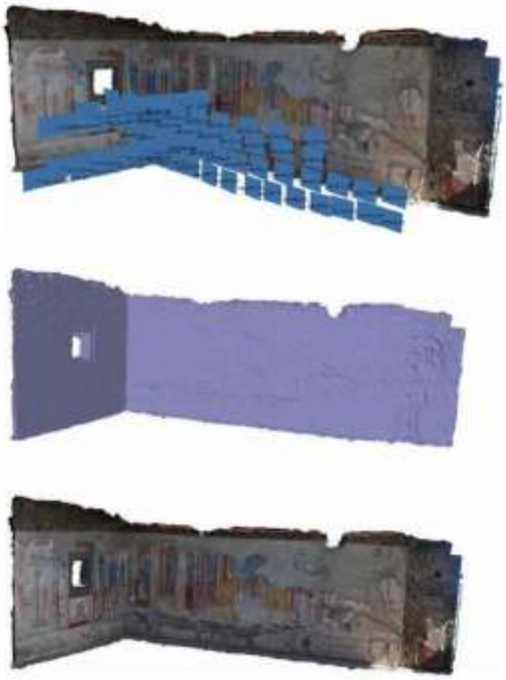

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3D mesh and textured model of the wall paintings in the Gymnasium

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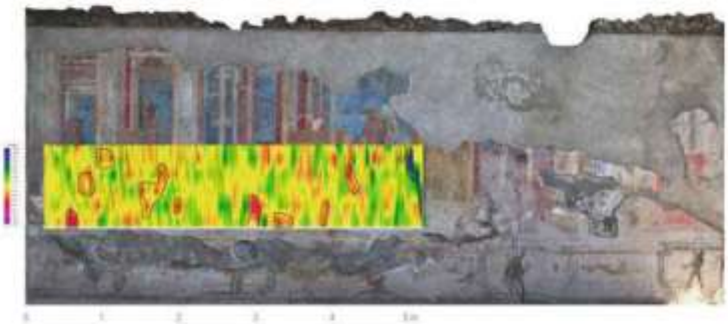
IRT prospections have been performed by using the passive method in an indoor environment. IRT images were collected with a FLIR SC660 sensor FPA (Focal Plane Array) uncooled microbolometer operating in the spectral range between 7.5 and 14 m.



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The GPR survey was performed with the Hi-Mod GPR of IDS using the antenna at 2-GHz frequency. The GPR antenna was moved on the painted surface by using a plastic panel against the wall. GPR data were collected with 512 samples per scan for a recording time window of 30 ns and a manual gain function

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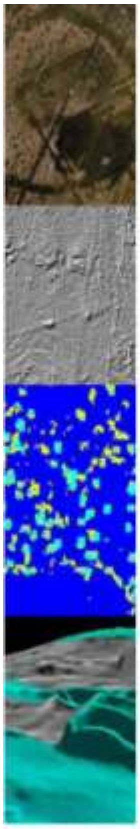

Table 1 Types of damage and their extensions found with the visual inspection

Code	Damage definition	Areas detected with visual interpretation (square meters)
0	Areas with the best state of conservation of the fresco	17.99
	Superficial decay:	
1	Salts	0.73
	Damage interesting all the stratigraphy, from the paint layer to deeper layers:	
2	Swelling	0.46
3	Detachment	0.89
4	Fracturing	0.65
5	Lack	10.55
6	Deep lack	0.15

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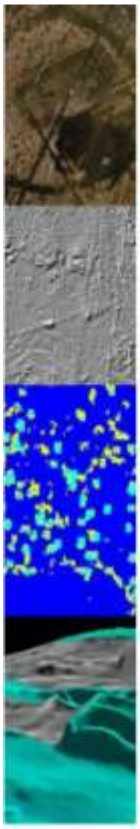

FEATURE INTEGRATION APPROACH BASED ON SPATIAL ANALYSIS

The fresco was considered as a vertical geographical space. Different type of spatial analysis was used to extract information from the RGB, the DRM, the MIRT and the GPR data

Spatial analysis studies the spatial distribution of phenomena, aggregation shapes and existing relationships, by considering their heterogeneity and their mutual dependency as indicated by spatial autocorrelation

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PATTERN EXTRACTION AND FEATURE INTEGRATION APPROACH BASED ON SPATIAL ANALYSIS

MAP ALGEBRA → **DRM**

It is a high level language for spatial modelling based on local, focal and zonal (Tomlin 1990) functions that, mixed together, allow constructing personal functions or personalized computation.

HOTSPOT ANALYSIS → **RGB; MIRT; GPR**

Hotspot analysis allows us to better understand distribution of existing data, by finding, with the research of spatial autocorrelation, areas, where there are group of pixels with local anomalies. In the case of a fresco, the presence of autocorrelation indicates the similarity properties of materials, such as its conservation state or beforehand the type of constituting material. index used was the Getis and Ord's Gi (1992), defined according to formula (1):

Geovisual Analytics → **MIRT**

Geovisual analytics allows us to explore, reduce and return prediction with techniques coming from visual data mining of geospatial information (Keim and Ward 2003) with the help and at the same time by improving the human visual ability to find patterns (MacEachren and Kraak 2001.
the **V-analytics software** was used (Andrienko and Andrienko 2005) to perform the **Self-organizing Maps (SOM)**

The **SOM** is a **neural network architecture** that allows **reducing the n-dimensionality** of the input data in a two-dimensional lattice. At the same time, it **maintains topological relationships of the original data set**. Through a **learning algorithm**, without supervision, it is useful for **pattern extraction**.

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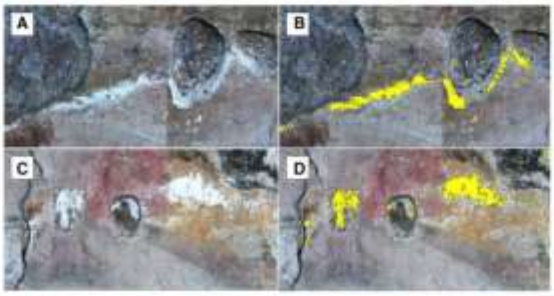
RESULTS: RGB LAYER ANALYSIS

The RGB obtained with SfM was converted through map algebra in HSV.

The V component (areas with $V \geq 0.85$) was useful for the extraction of salts over the paintings



Salt pattern extraction, two details (**a**, **c**) of the fresco with the corresponding distribution of salts found (in yellow **b**, **d**)

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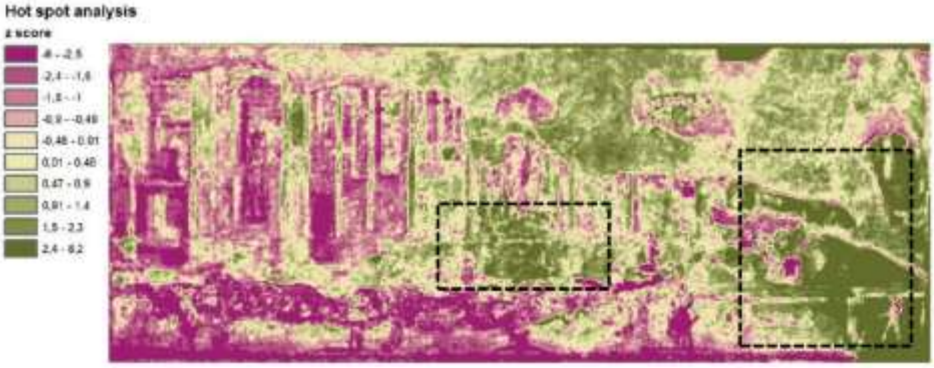
RESULTS: RGB LAYER ANALYSIS

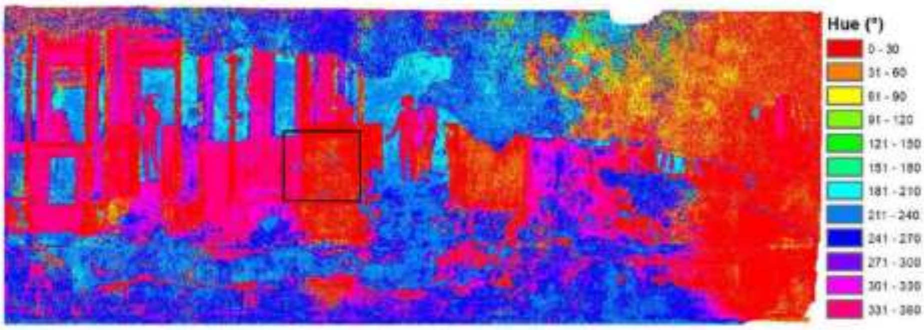
Moreover, the *V* raster was analyzed with **HOTSPOT ANALYSIS**, using as intensity the ***V*** value, Euclidean distance and the Distance bandwidth as methods for calculation of distances, proximity and weights matrixes



The green areas cluster areas affected by a progressive phenomenon of decoloration of the existing pictorial pigments, due a major exposure to the Sun and external agents .

RESULTS: RGB LAYER ANALYSIS

The *H* raster instead is useful to highlight areas with local detachment of pigments



Dominant color of pigments (H) highlights areas with local pigment detachment, as in the drawn rectangle

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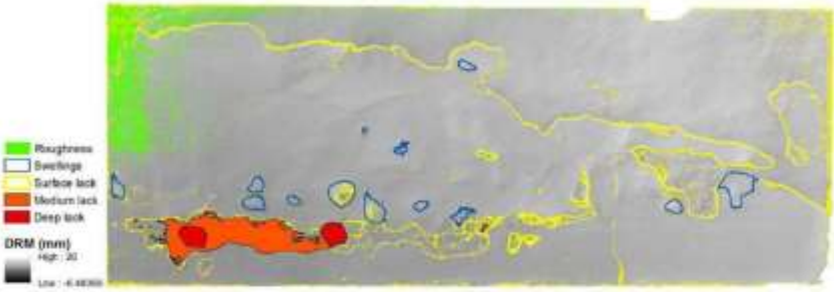
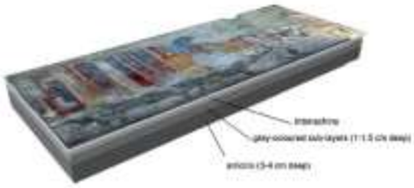
RESULTS: DIGITAL RELIEF MODEL (DRM) ANALYSIS

The DRM was analyzed with basic methods taken from **geomorphometry** that is **contour** and **slope** analysis.
By means of yhe contouring (with 0.2 mm of contour interval), classified in quantiles, after the elimination of outliers and by converting close lines in polygons, it was possible **to extract swellings, detachments and lacks**



Decay extraction from DRM

In particular lacks at **three different depths were detected**, corresponds to the three layer of frescoes



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RESULTS: DIGITAL RELIEF MODEL (DRM) ANALYSIS

Finally, it is interesting to observe the behaviour of the isolines: the areas covered by the surface lack have the same "elevation" of parts of the still painted areas (the cyano and the orange classes). The hypothesis is that these are the parts of the fresco, together with swelling, having a higher risk of new detachments

Contouring derived from DRM. The orange and the cyano classes could reveal areas more at risk

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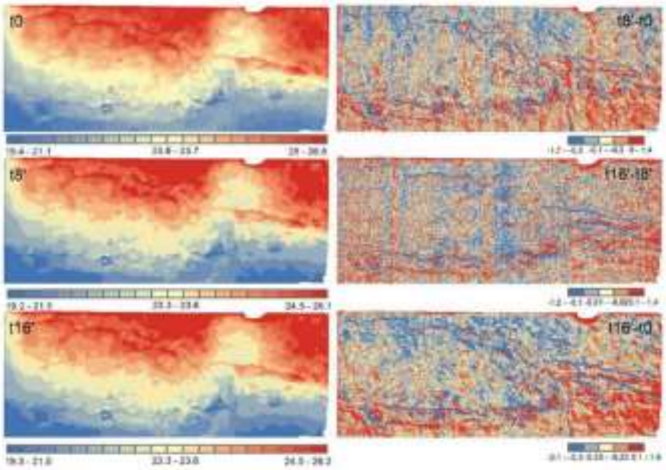
RESULTS: INFRARED THERMOGRAPHY (IRT) ANALYSIS

Three thermograms (t0', t8', t16') were preprocessed with **MAP ALGEBRA**, to calculate raster representing change over time. Three interval raster were obtained: t8'–t0', t16'–t8' and t16'–t0 and classified in 20 quantile classes.



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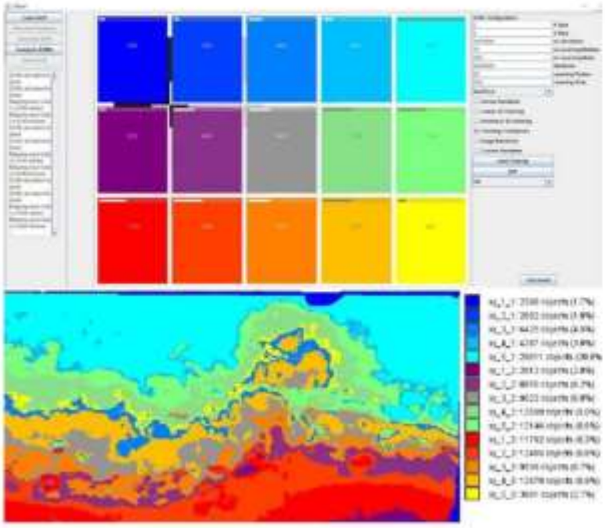
RESULTS: INFRARED THERMOGRAPHY (IRT) ANALYSIS

Due also to the total dimension of the MIRT data set (each IRT raster is characterized by 603 (column) × 235 (raw) × 3 (number of thermograms) = 425,115 pixels) we decided to analyze them with **SOM**. For the SOM a lattice of 5 * 3 elements was chosen.



Screenshot of the V-analytics with the obtained SOM and clusterization of MIRT

From the result obtained first, it was possible to highlight and extract the major efflorescence in a better way than in the visual interpretation

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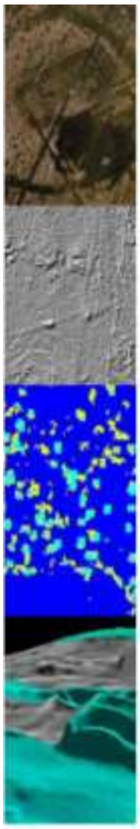
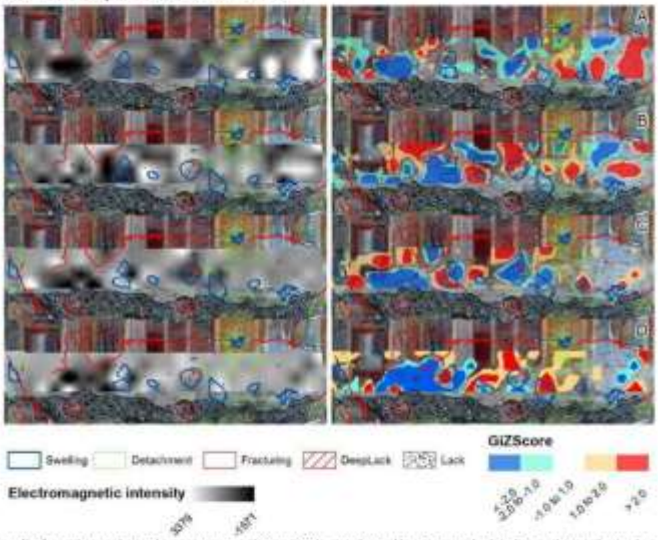


RESULTS: Ground Penetrating Radar (GPR) Data Set Analysis

The GPR data set was analyzed with **HOTSPOT ANALYSIS** applied to each time slice at the different depth. The hotspot analysis, overlayed with damaged areas, highlights, better than the simple classification of the GPR raster, with the lower (the blue one) and the hotter (red) clusters zones characterized, respectively, by a better or worst adherence. The reliability of this type of analysis over GPR data is offered by the time slice more superficial. In fact, it shows the same anomalies visually detected with IRT



GPR time slices (left column) and corresponding Getis and Ord's Gi result (right column) at the different depth: z = 2.5 mm (**a**), z = 1.5 mm (**b**), z = 3.5 mm (**c**), z = 5 mm (**d**)

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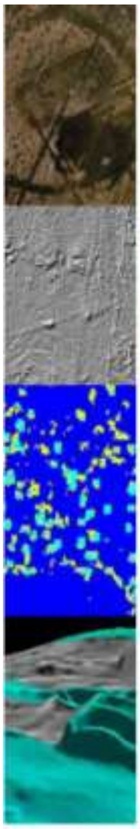
Cyprus University of Technology



THE FINAL DECAY MAP AND QUANTIFICATION

The final map with decay patterns and risk areas extracted with spatial analysis

Table 2 Types of damage and their extensions found with the spatial analysis

Code	Damage definition	Areas detected with visual interpretation (square meters)
0	Areas with the best state of conservation of the fresco	6.42
	Superficial decay:	
1	Salts	0.93
2	Areas with discoloration risk	6.62
3	Roughness	1.47
	Damage interesting all the stratigraphy, from the paint layer to deeper layers:	
4	Swelling	0.46
	Lack	
5	Surface	14.93
6	Medium	2.17
7	Deep lack	1.54
8	Areas with detachment risk	8.48
	Water capillary rising:	
9	Low	2.37
10	Medium	2.24
11	High	0.59

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Cyprus University of Technology

3. Overall

During the ATHENA project four virtual trainings have been organised and successfully implemented by the advanced partners (DLR and CNR) to the host institution (CUT). The virtual trainings were planned -when possible- when other actions of the project were also taking place, in an effort to maximize their overall impact and training outcomes.

The virtual trainings provided a very good opportunity to discuss various aspects of the use of remote sensing technologies for cultural heritage, while they pave the road for relevant scientific publications in conferences and journals.