



***ELABORAZIONE DI IMMAGINI SATELLITARI
TRAMITE
TECNICHE DI DEEP LEARNING PER IL
MONITORAGGIO DI AREE
AMBIENTALI***

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Outline

- ❑ Introduction to Remote Sensing
- ❑ Database
 - Sentinel-2 Database for Land Cover Classification
- ❑ Procedure for automatic classification of Sentinel-2 images
 - Instance Selection
- ❑ Results
 - Pixel-wise Land Cover Classification (SVM & RF)
- ❑ Partnership with Planetek

Introduction to Remote Sensing

Remote Sensing (RS):

- the acquisition of information about a region of interest without any physical contact

Social and Economic Impact of RS:

- Crop production forecast
- Environmental monitoring
- Management of hazards
- Population estimates



Kilauea Volcano lava flow from fissures near Leilani Estates - May 23rd, 2018 - Nat. col.-NIR/SWIR + IR highlights - Contains modified Copernicus Sentinel data [2018], processed by Pierre Markuse



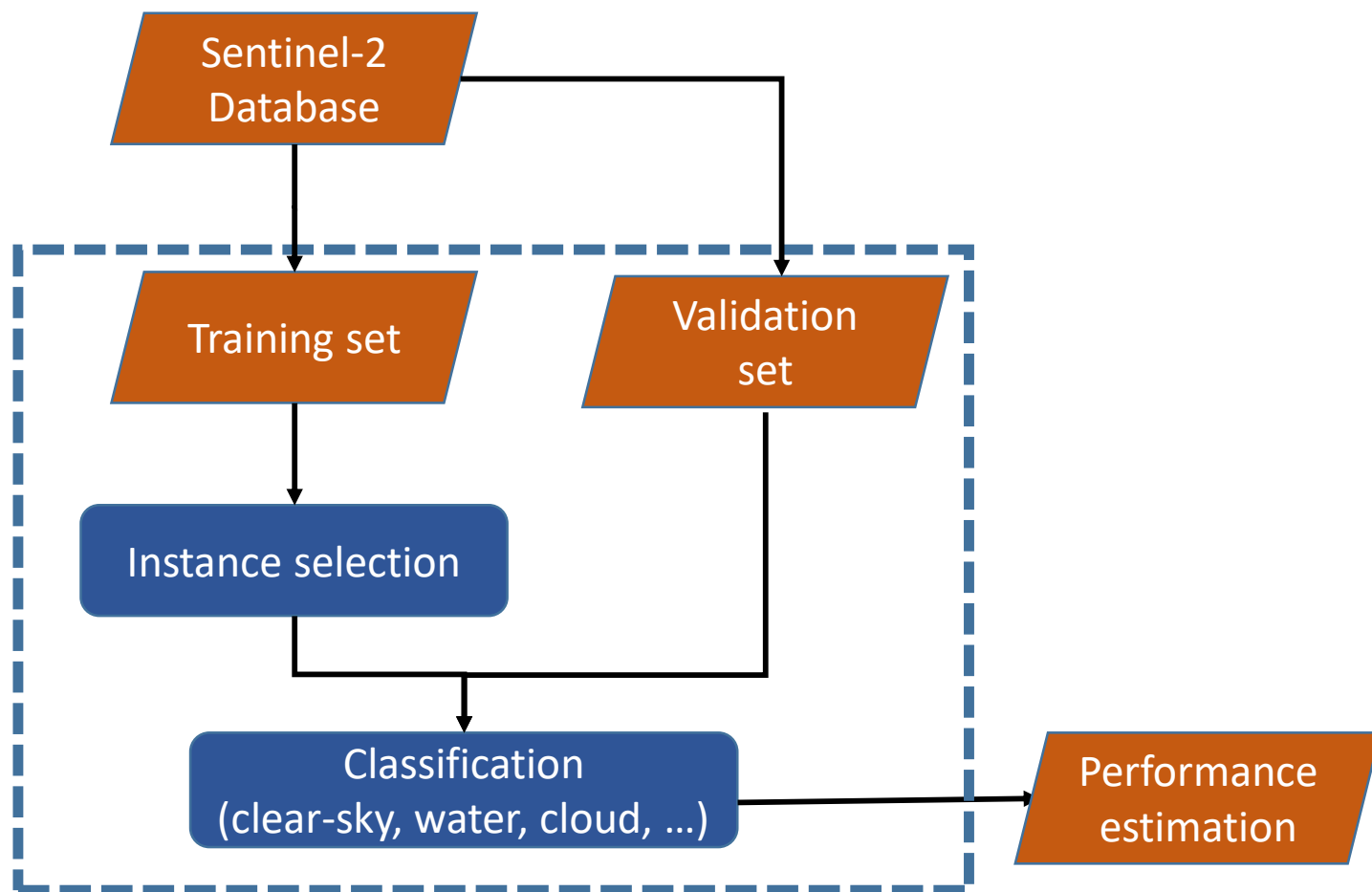
Sentinel-2 Database for Land Cover Classification



- ❑ 108 Sentinel-2 L1C TOA reflectance images
- ❑ ~ 5 million **hand labelled** pixels
- ❑ ~ 30 countries

- ❑ Six Semantic labels
 - Clear sky
 - Water
 - Shadow
 - Cirrus
 - Cloud
 - Snow

Procedure for automatic classification of satellite optical images

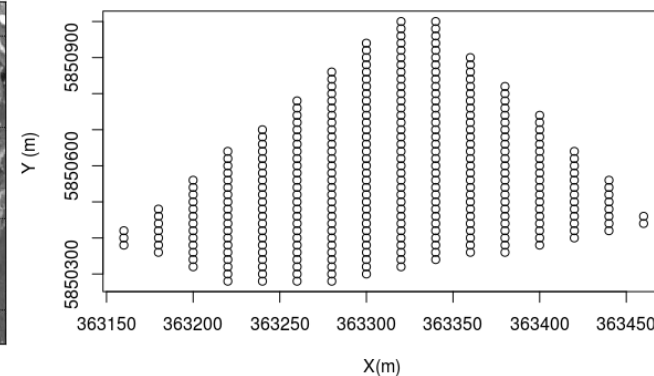
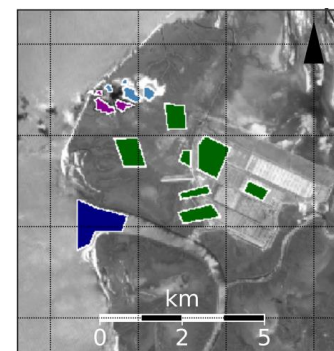
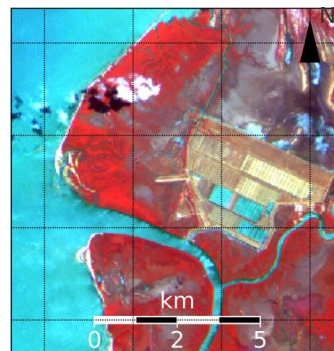


- ❑ 5- fold cross validation
- ❑ Instance selection performed by uniform sampling of the training set to speed up the pipeline
- ❑ Classification performed by SVM, RF and MLP

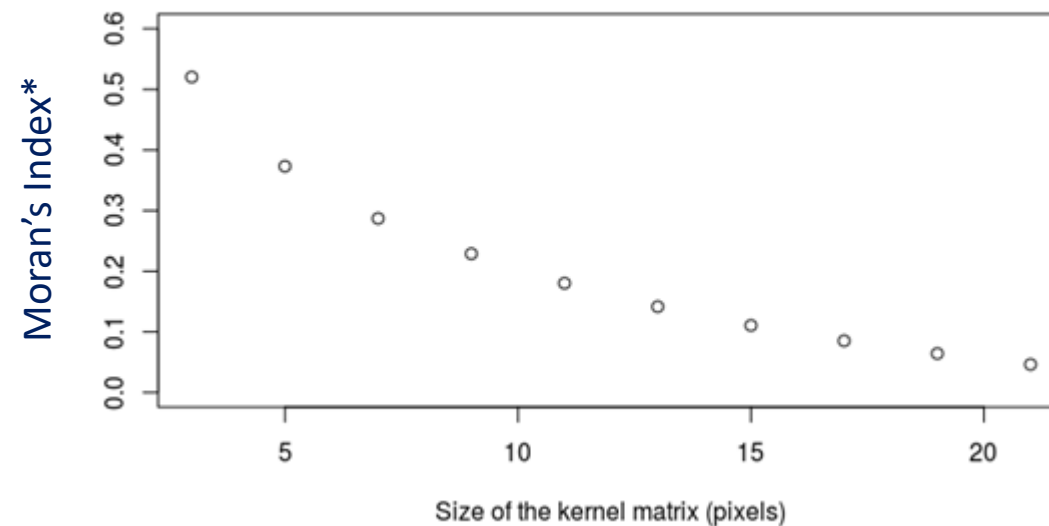


Instance Selection – Motivation

- ❑ The database consists of pixels characterized by **highly correlated** reflectance spectra by construction as can be show by Moran’s Index*
- ❑ Spatial autocorrelation statistics like Moran’s I measure the degree of dependency among observation of a certain feature in a geographic space*



Moran Index vs size of Neighbourhood (feature B2)



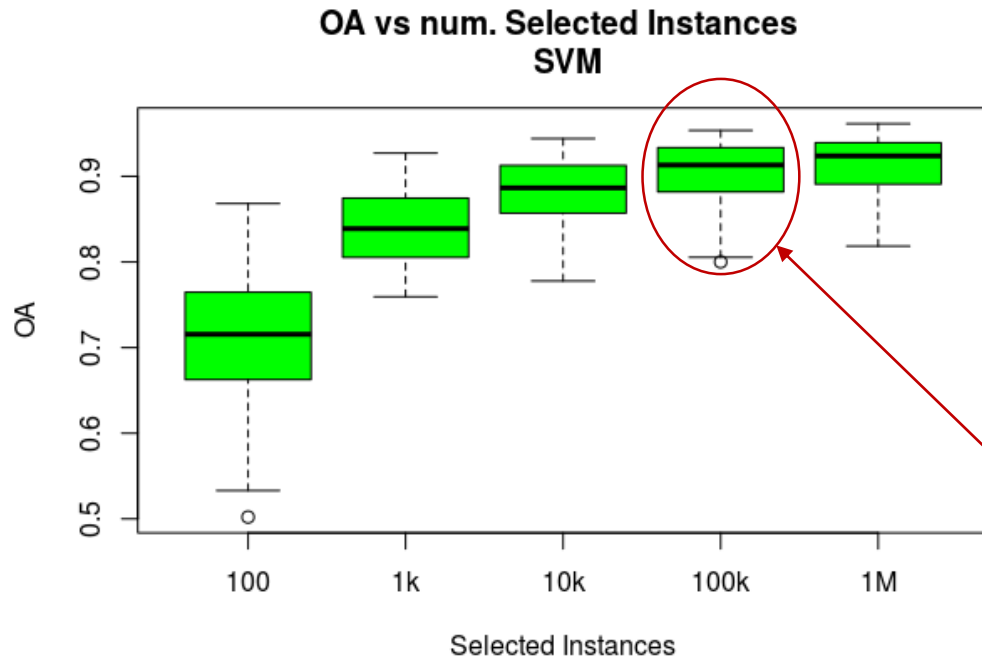
$$I_m = \frac{n}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

$0 < I_m < 1$, positive correlation

*Moran, P.A.P. (1950) , “Notes on Continuous Stochastic Phenomena” *Biometrika*, Volume 37, Issue 1-2.

Land Cover Classification – SVM

- Each pixel is described by 13 reflectance spectra



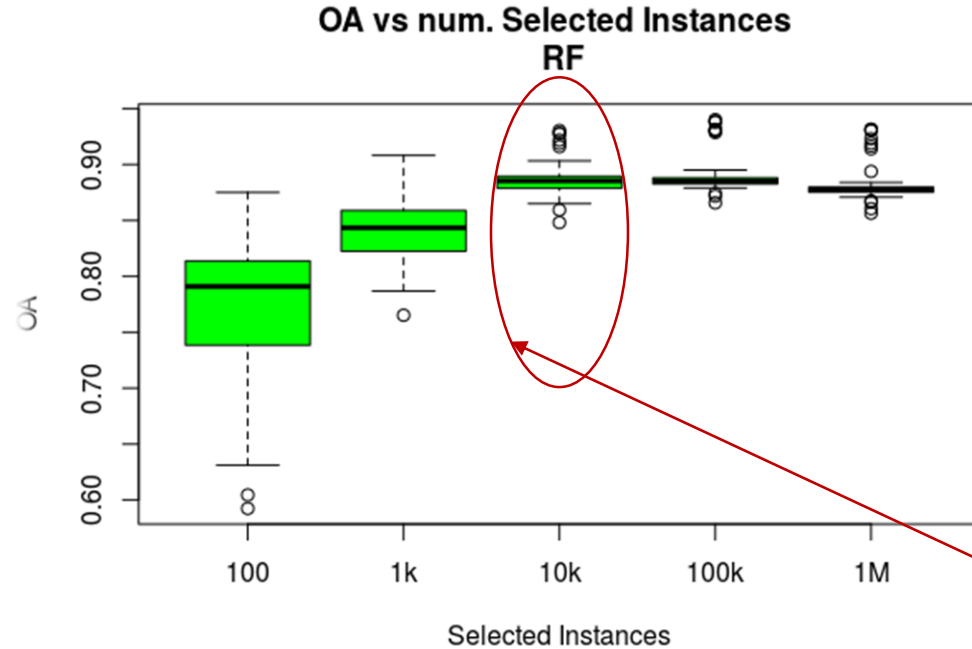
Predicted	Actual					
	clear	water	shadow	cirrus	cloud	snow
clear	83.7		7.9	5.2	0.7	
water		94.8	2.4			
shadow	9.6	5	87.6	3.9	0.1	0.1
cirrus	5.9	0.1	1.1	86.2	2.1	0.1
cloud	0.8		0.1	3.3	97.2	0.1
snow			0.9	1.4		99.7

Overall Accuracy (OA) = #correctly labeled pixels / #total pixels

Overall accuracy = 0.92 ± 0.03

Land Cover Classification – RF

- Each pixel is described by 13 reflectance spectra



	clear	water	shadow	cirrus	cloud	snow
clear	95.1		9.6	20.5		
water	0.2	79.7	1.1			
shadow	4	20.3	87.9	0.8		
cirrus	0.1		0.3	30.1	0.8	2.6
cloud	0.6		0.6	46.5	99.2	2.1
snow			0.5	2		95.3
	clear	water	shadow	cirrus	cloud	snow

Actual

Overall Accuracy (OA) = #correctly labeled pixels / #total pixels

Overall accuracy = 0.89 ± 0.01

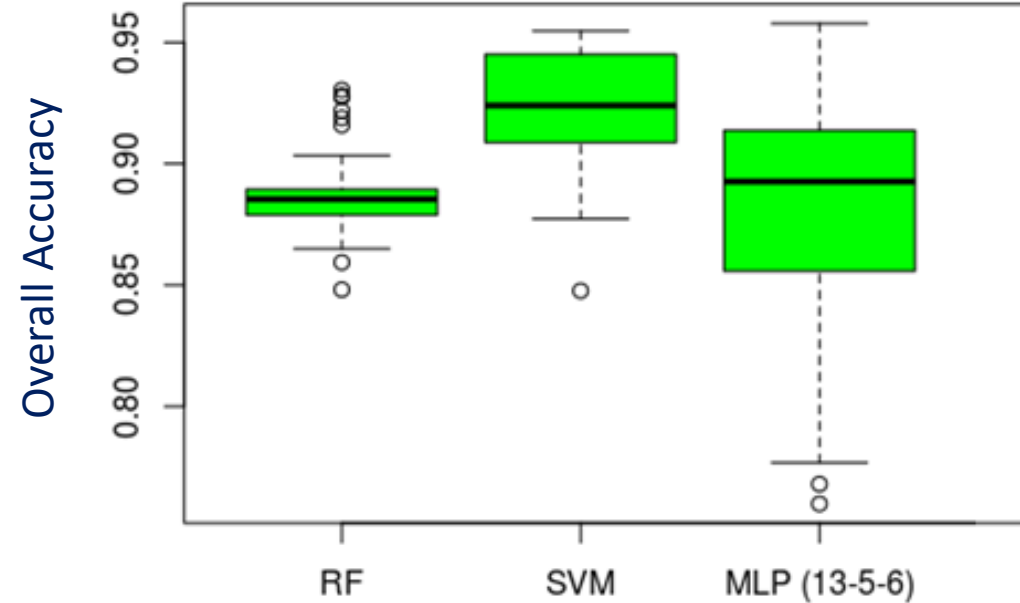
LC Classification – Comparison between classifiers

Overall Accuracy

MLP: 0.88 ± 0.04

RF: 0.89 ± 0.01

SVM: 0.92 ± 0.03



Conclusions

- ✓ SVM is the most accurate classifier
- ✓ RF is the most robust classifier
- ✓ RF is most effective in detecting clear-sky and cloud pixels
- ✓ SVM is most effective in detecting snow, water and cirrus pixels

Future developments

- Ensemble Classifier
- Deep Learning Techniques (based on DBN or DNN)

Partnership with Planetek

- ✓ Development of a procedure to automatically detect buildings in very high resolution satellite images of urban areas

Conferences

- The ESA Earth Observation Φ -week Open Science and Future EO, Frascati, ESRIN, 12-16/11/2018 (poster)

Change detection of Build-up areas exploiting multiple classification approaches in VHR images

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ORGANIZATIONS:

1: DIPARTIMENTO INTERATENEO DI FISICA "M. MERLIN", UNIVERSITA' DEGLI STUDI DI BARI ALDO MORO, BARI, ITALY
2: PLANETEK ITALIA S.R.L., ITALY
3: LABORATORY OF REMOTE SENSING, NATIONAL UNIVERSITY OF ATHENS, ATHENS, GREECE



PhD Courses

- ✓ How to prepare a technical speech in English
- ✓ Management and knowledge of european research and promotion of research results
- ✓ Programming with Python for Data Science
- ✓ Image and Signal Processing
- ✓ Introduction to Parallel Computing and GPU Programming using CUDA
- ✓ Interpolation Methods and Techniques for Experimental Data Analysis
- × Introduction to C++ programming

Seminaries

1. "Cycle of lectures on SM and BSM models". Bari, Dipartimento Interateneo di Fisica, Prof. S Khalil - Director of the Center for Theoretical Physics Zewail City for Science and Technology, Egypt. 20-23/03/2018

Thank you for your attention !

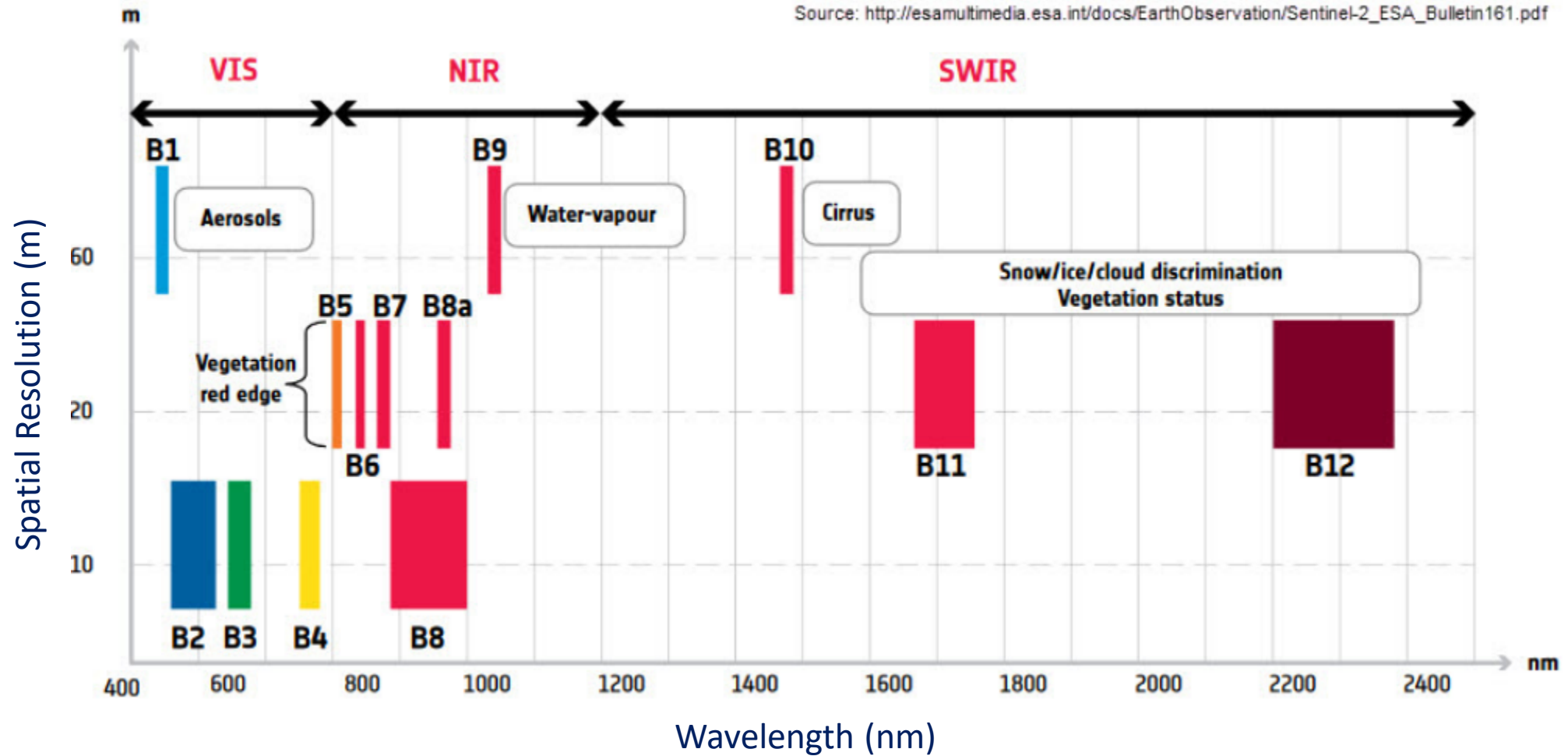
Any Questions?



Backup Slides

Sensors on board Sentinel-2 Satellites

Source: http://esamultimedia.esa.int/docs/EarthObservation/Sentinel-2_ESA_Bulletin161.pdf



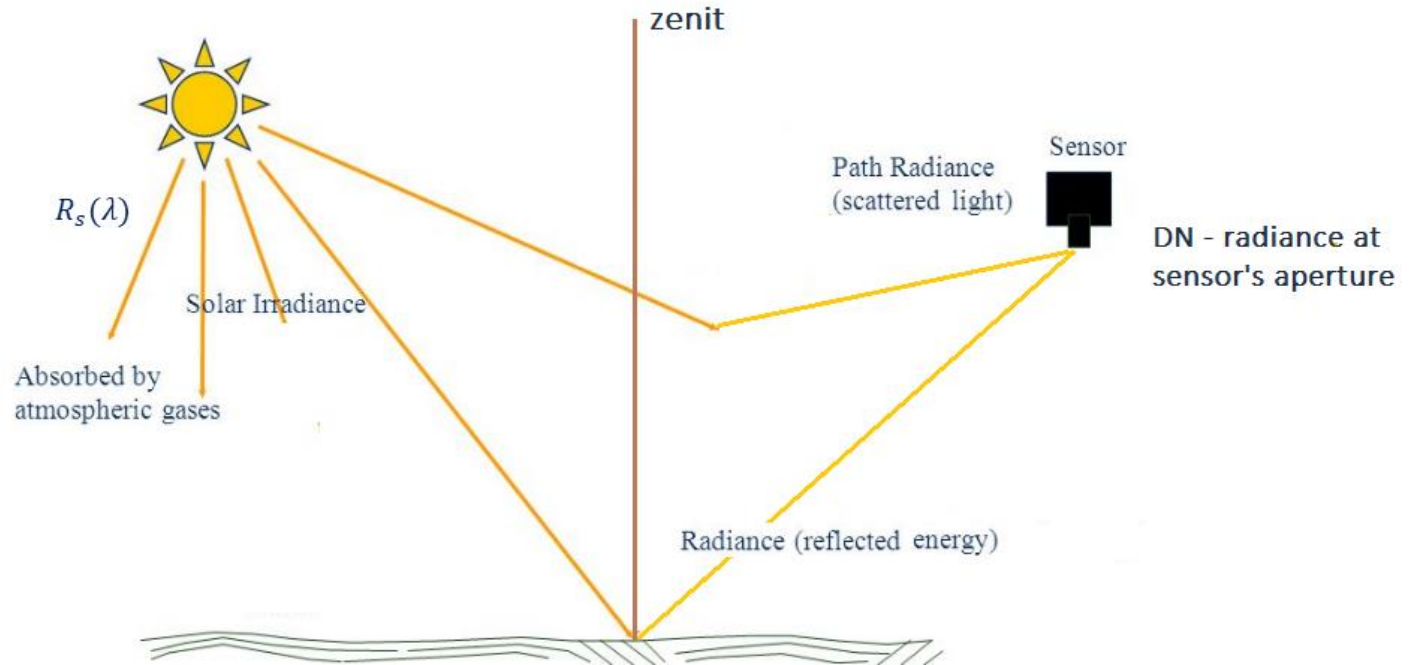
Recovery of TOA reflectances

- Recovery of Top-of-atmosphere reflectance ρ_k

$$\rho_k(i, j) = \frac{\pi \times DN(i, j)}{A_k \times E_{s,k} \times \cos(\theta_s(i, j))} \times d(t)$$

With

- A_k calibration coefficient
- $E_{s,k} = \int d\lambda T_k(\lambda) R_s(\lambda)$ extra-terrestrial solar spectrum
- $DN(i, j)$ radiance at sensor's aperture (i.e. radiance leaving the ground * transmission factor + path radiance)
- $\theta_s(i, j)$ sun zenith angle
- $d(t) = (1 - \varepsilon \times \cos(\omega(t - 2)))^2$
correction for the sun-Earth distance variation



LC Classification – Proposal

