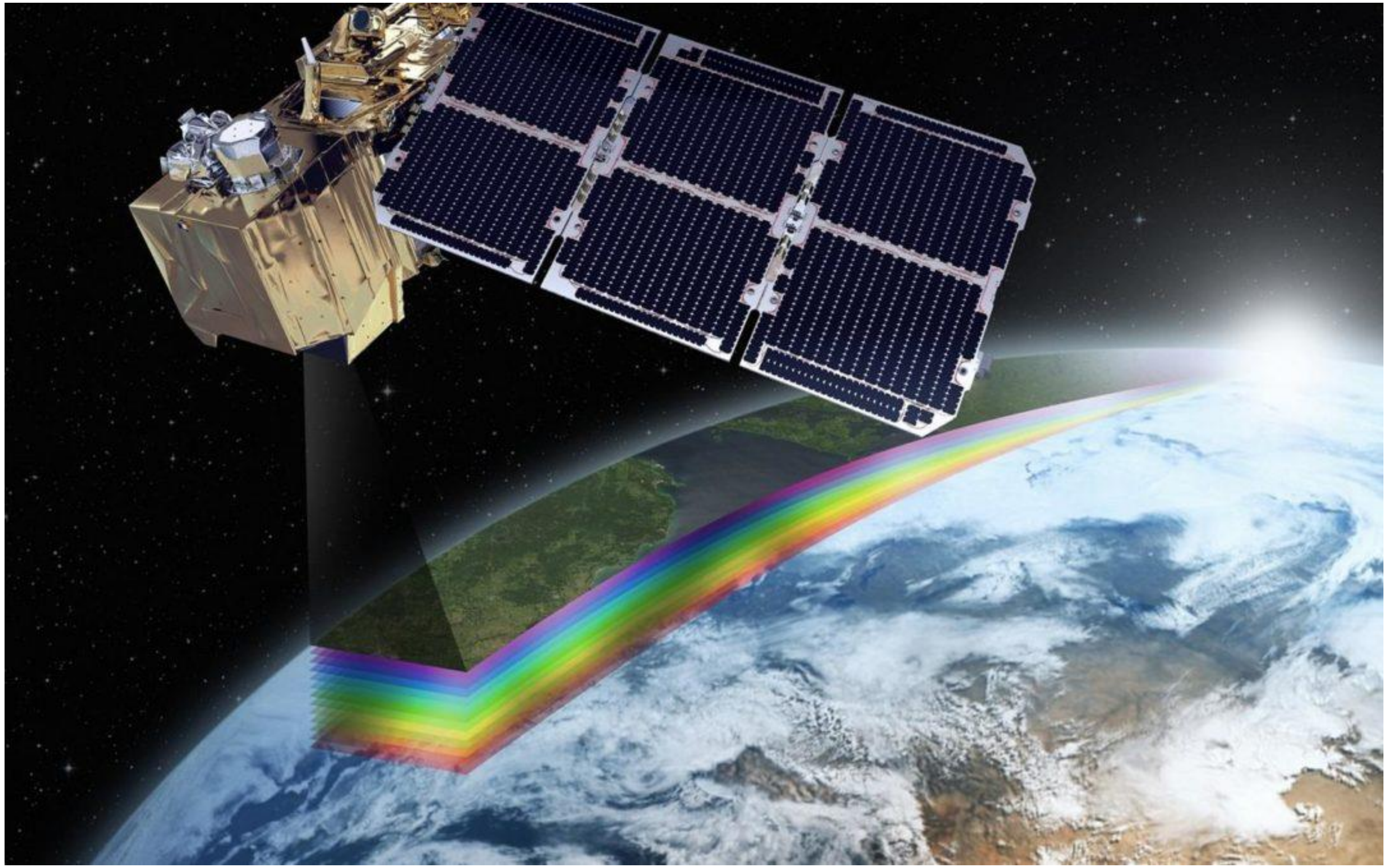
UNIVERSITÀ DEGLI STUDI DI TRIESTE



Course:

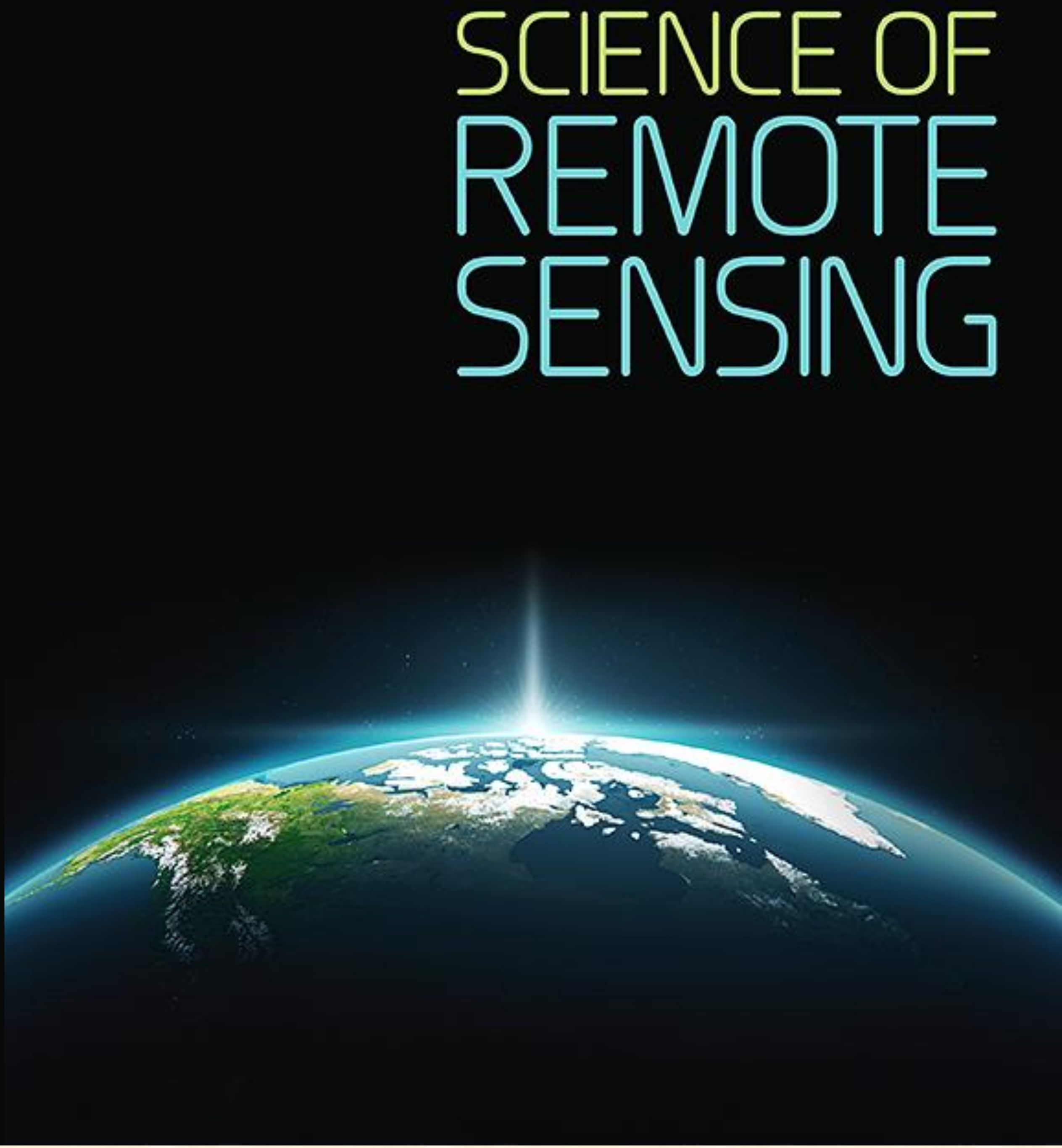
Remote Sensing of Global Changes

Dr. Francesco Petruzzellis

PhD student Valentina Olmo

Part 3

Methodologies for the interpretation and processing of remotely sensed images



Digital volume – Radiometric resolution

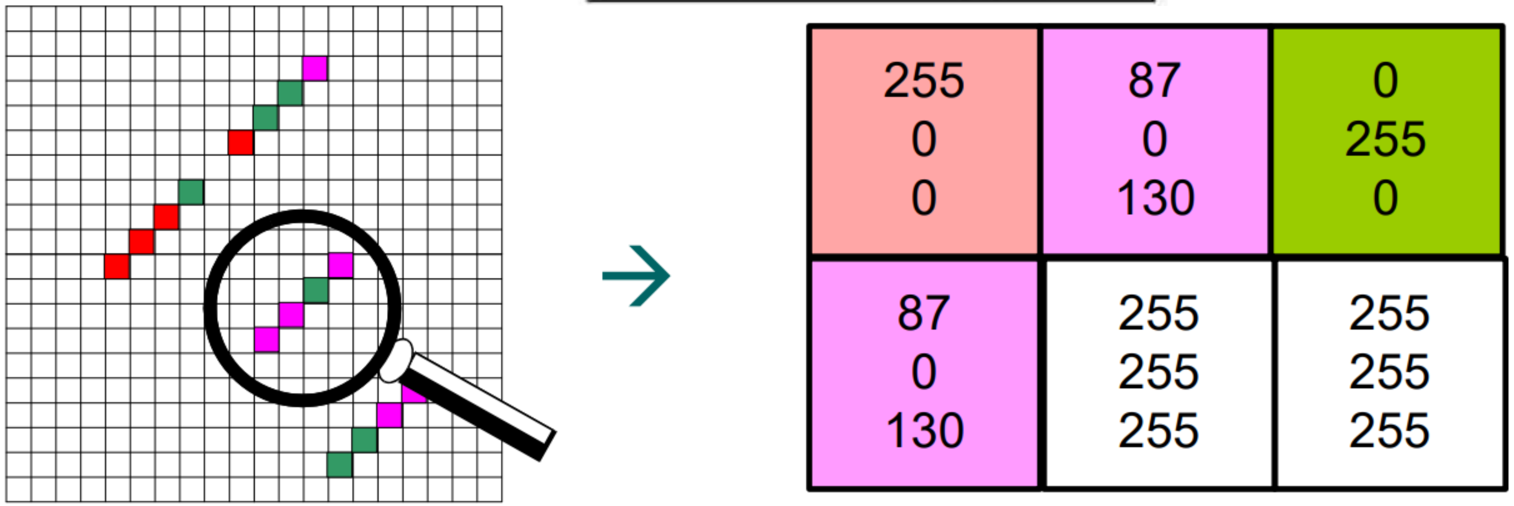
How much digital volume is occupied according to radiometric resolution?

Example:
Image 1024x768 pixel RGB 24-bit, meaning that each colour (RGB) could be represented by 8 bits

How many MB are occupied by the image?

1024x768x3 = 2359296 = 2.25 MB

1 byte = 8 bits
1 kilobyte = 1024 bytes
1 megabyte = 1024 kilobytes
1 gigabyte = 1024 megabytes
1 terabyte = 1024 gigabytes



You try:

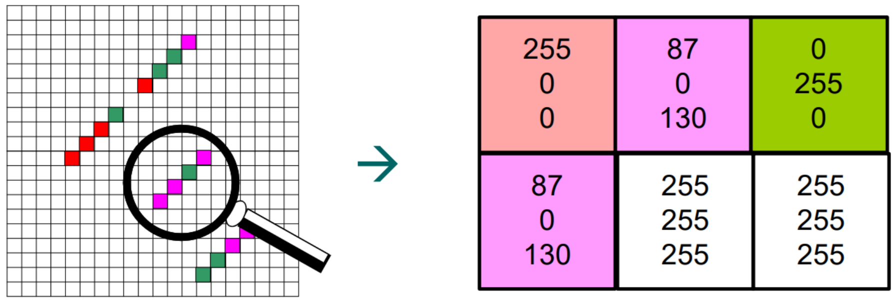
100x100 km tile, how many pixels? 100000x100000 pixels

For each band, how many MB, with 8, 16 and 24 bit?

8bit= 100000x100000x1 = 10000000000 bytes = 9.31 GB

16bit= 100000x100000x2 = 20000000000 bytes = 18.62 GB

24bit = 100000x100000x3 = 30000000000 bytes = 27.93 GB



Digital volume of multiband image = n total pixels + n bit to represent a pixel + palette dimensions (for RGB, $3x2^n$)

RGB 8bit = 3x256 = 768 bytes
RGB 16bit = 3x65546 = 196608 bytes = 0.18 MB

Like any numeric variable, basic statistical parameters:

1. Mean

$$\overline{DN_k} = \frac{\sum_{i=1,n} DN_{i,k}}{n_k}$$

Target band

N pixel in image

2. Standard deviation

$$SD_k = \sqrt{\frac{\sum_{i=1,n} (DL_{i,k} - \overline{DL_k})^2}{(n_k - 1)}}$$

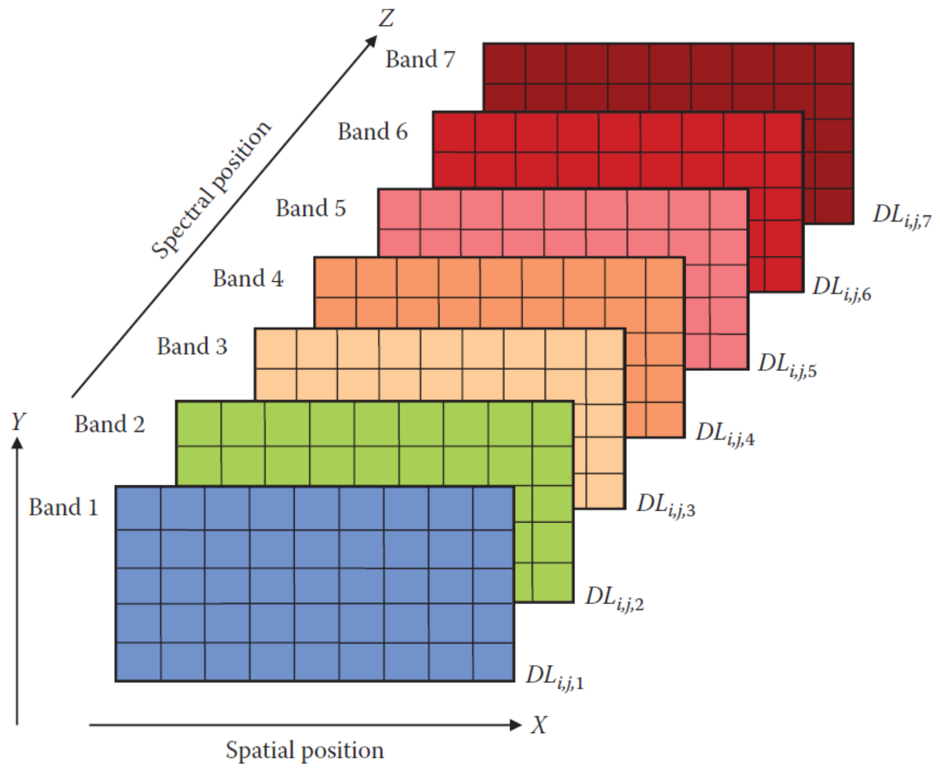
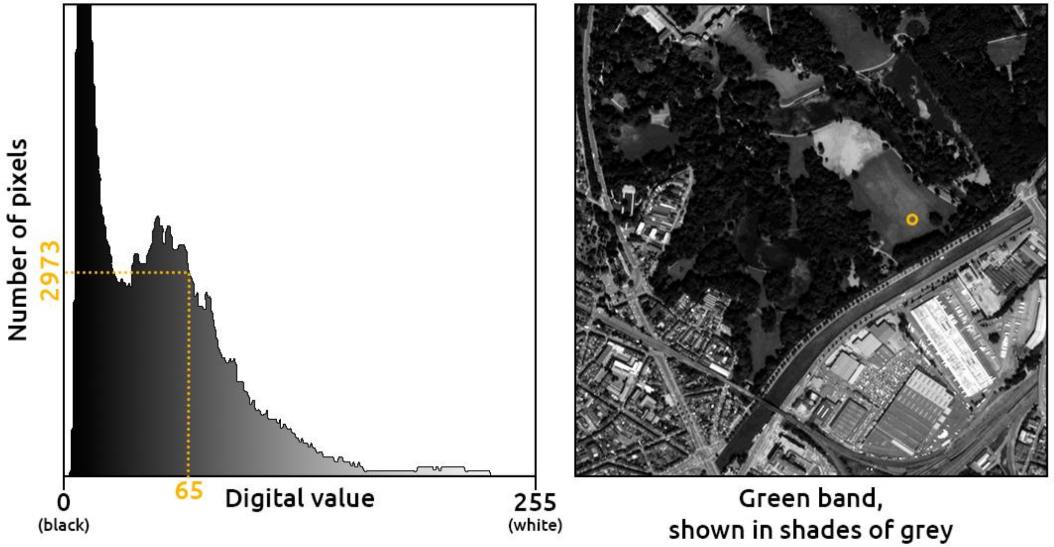


Image statistics and analysis



https://eo.belspo.be/en/remote-sensing-images

It is possible to compute the **histogram** for each band, which describes the distribution of DNs in the image.

$$RF(DN_i) = \frac{F(DN_i)}{\sum_{t=1,m} DN_i}$$

The **histogram** provides a first evaluation of the data distribution of each band.

The center indicates the dominant brightness of each band (mean), while its width is related to band variability (SD).

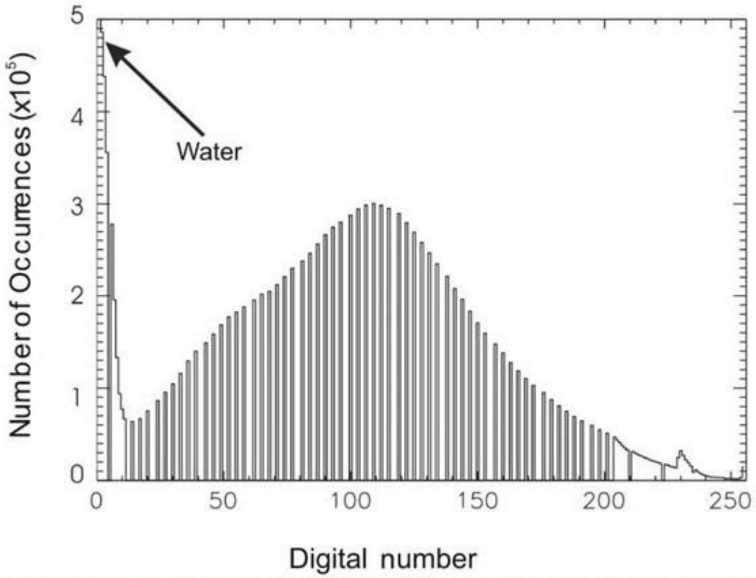


IMAGE ENHANCEMENTS

The process of image (or contrast) enhancement attempts to **adjust the radiometric resolution** of the image to the capabilities of the display system.

Two possible situations:

1. Range of DNs in the image is lower than the range of brightness display values

↓

CONTRAST STRETCHING

2. Image has a higher number of DNs than can be visualized.

↓

COLOUR COMPRESSION

Definitions of contrast:

$$C_1 = \frac{DN_{max}}{DN_{min}}$$

$$C_2 = DN_{max} - DN_{min}$$

$$C_3 = SD_{DN}$$

Stretching operations should provide higher contrast, increasing any of the three measures.

Colour compression implies maintaining the visual quality of the colour images with a significant reduction of the file size.

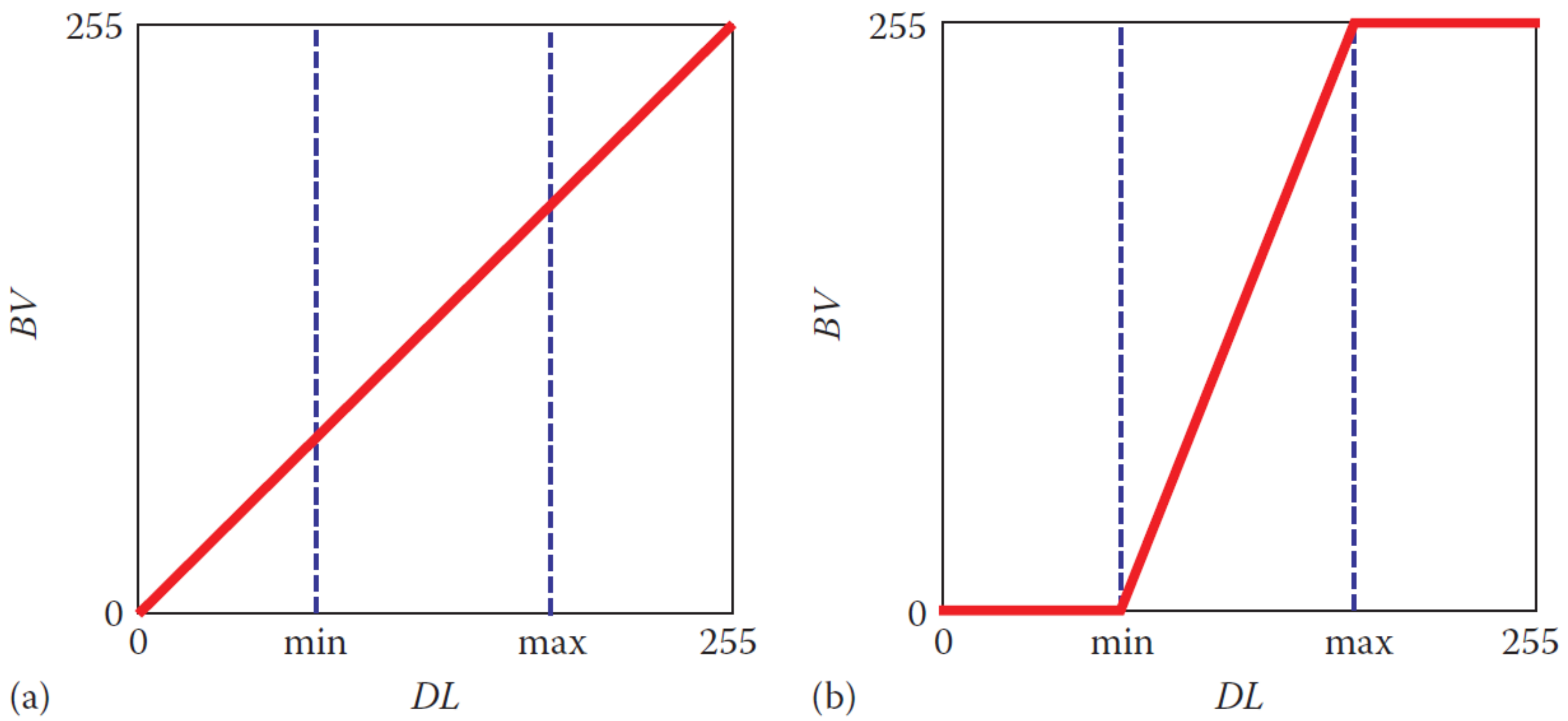
Lookup table (LUT): is a numeric matrix that shoes the brightness values (BVs) on the screen that will be assigned to each DN in the image.

The order of the row indicates the input DN

The value in the table expresses the BV that will display that DN. In this case, the higher the BV is, the more R, G and B the pixel will be.

BV (blue)	*BV* (green)	*BV* (red)
1	1	1
2	2	2
3	3	3
...	...	...
255	255	255

Lookup table (LUT) can be also represented as bivariate graph, where the DN of the image are displayed in the x-axis and BV is represented on y-axis.



CONTRAST ENHANCEMENT:

Applied when the range of DNs in the image is lower than the range of brightness display values.

Used adjusting the original DN distribution to the capabilities of the display system, improving image contrast.

Usually, even if a sensor has a 8-bit radiometric resolution, in most images the original data distribution do not cover the entire range of available BVs. In a monoband image, this means that a large range of grey tones are not used, and the image has a low contrast.

Three different ways:

1. Linear Contrast Enhancement (or Linear Stretch)

2. Histogram Equalization

3. Special Contrast Stretch

Linear Contrast Enhancement (or Linear Stretch)

The raw histogram in Fig (b) shows poor contrast.

Fig (d) is the stretched image, and displays higher contrast. Look at the stretched histogram in Fig (c).

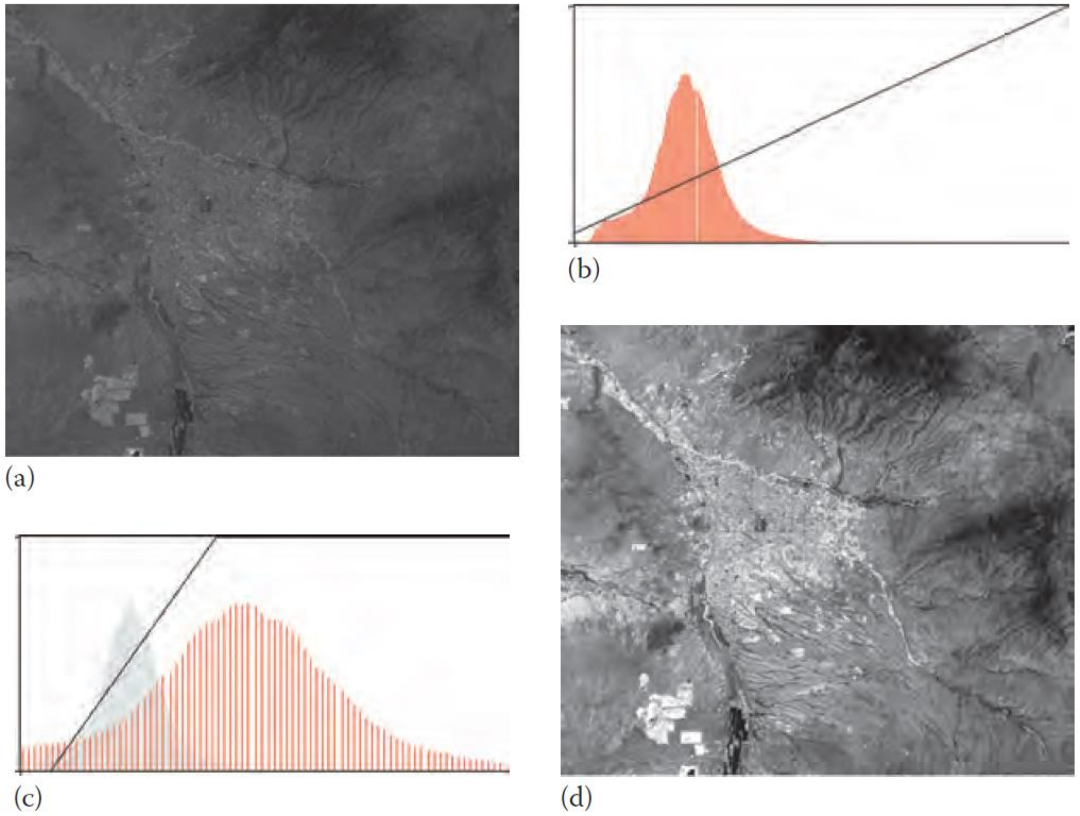
In this case, linear transformation:

$$BV = b + g\ DN$$

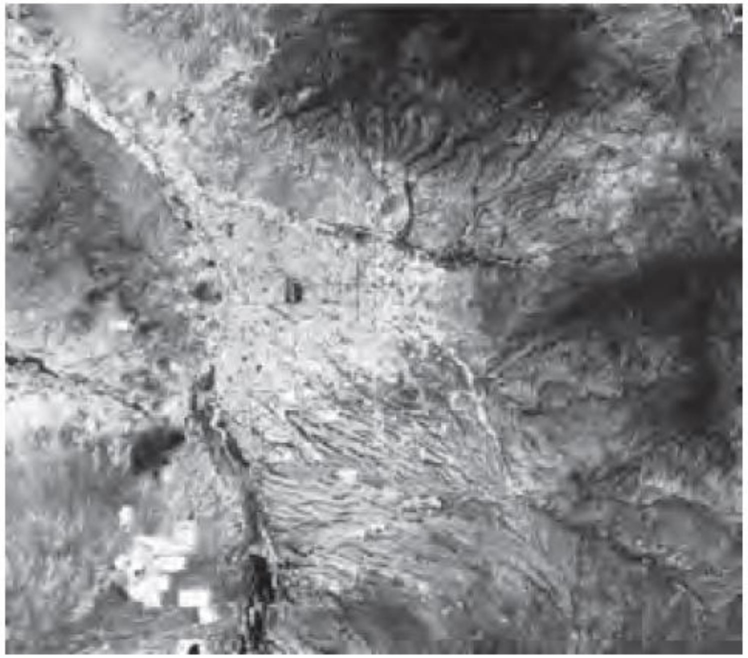
b = bias (intercept on y-axis)
g = gain (slope)

$$0 = b + g\ DN_{min}$$
$$255 = b + g\ DN_{max}$$

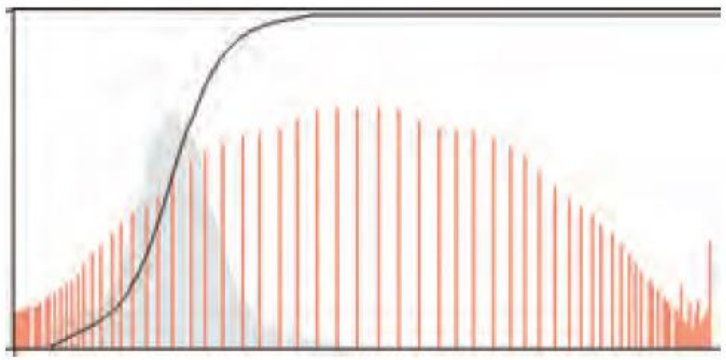
$$g = \frac{255}{DN_{max} - DN_{min}} \qquad b = \frac{-255 * DN_{min}}{DN_{max} - DN_{min}}$$



Instead of using DN_{max} and DN_{min}, the user can select different thresholds to fit the equation (e.g. certain percentiles).



(a)



(b)

Histogram equalization

The values are stretched according to their actual frequency distribution.

DNs with higher number of pixels will occupy a proportionally larger range in the enhanced image than those with lower frequency.

Fig (b) is the stretched histogram. The graphical profile of the LUT is not a straight line but a curved line, similar to cumulative distribution function of the original DNs.

Special Contrast Stretch

The idea is to restrict the contrast to a specific range of the DN

This could be helpful to enhane a specific feature on Earth's surface.

It is based either on:

- Setting a min and a max considering the DNs range of a selected feature
- By restricting the histogram equalization into a certain range

The feature of interest is enhanced at the expense of other areas in the image.

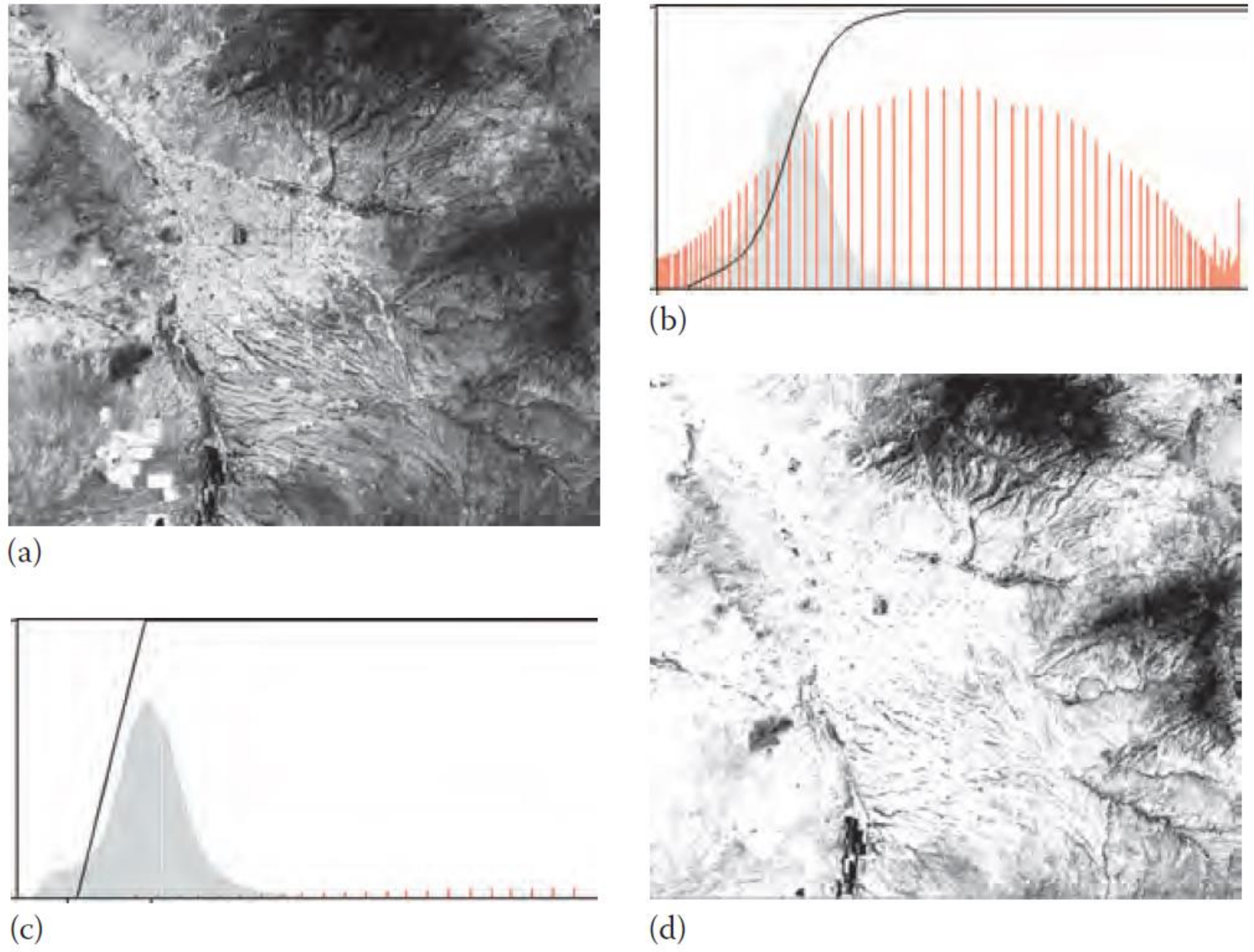
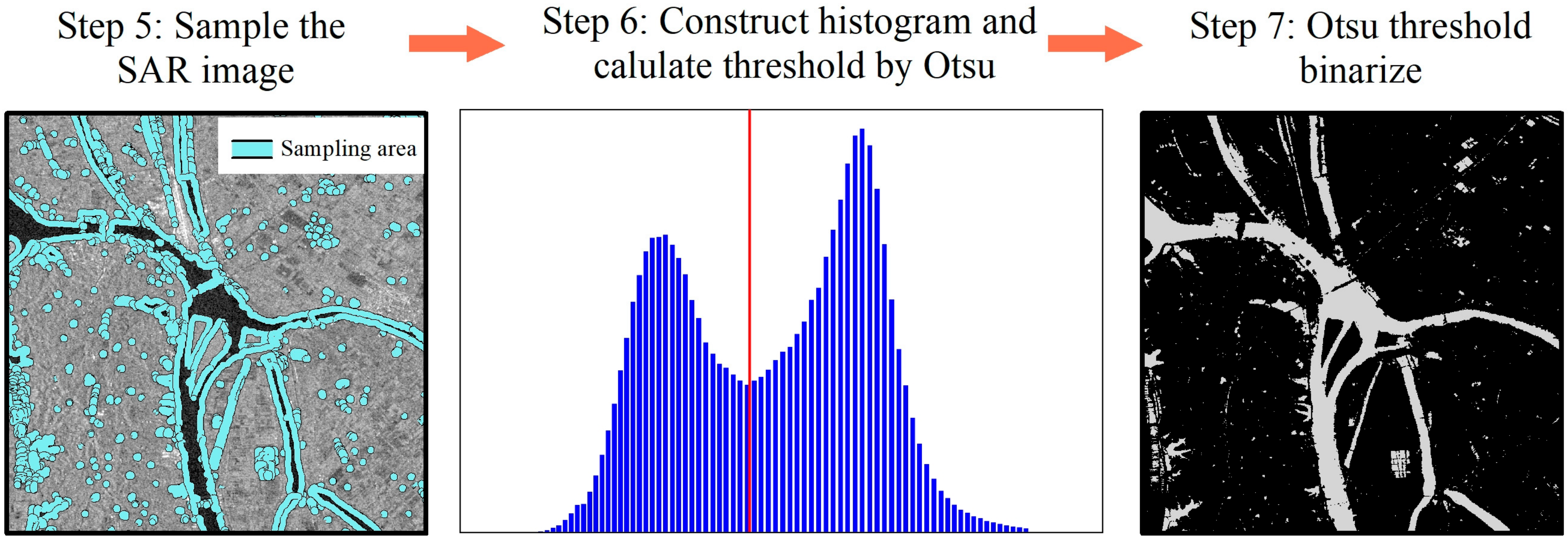


IMAGE ENHANCEMENTS

Special case of Special Contrast Stretch is the creation of a binary image (b/w image)

1 = white = pixel related to the feature of interest
0 = black = other pixels



CONTRAST COMPRESSION

<u>CONTRAST COMPRESSION:</u>

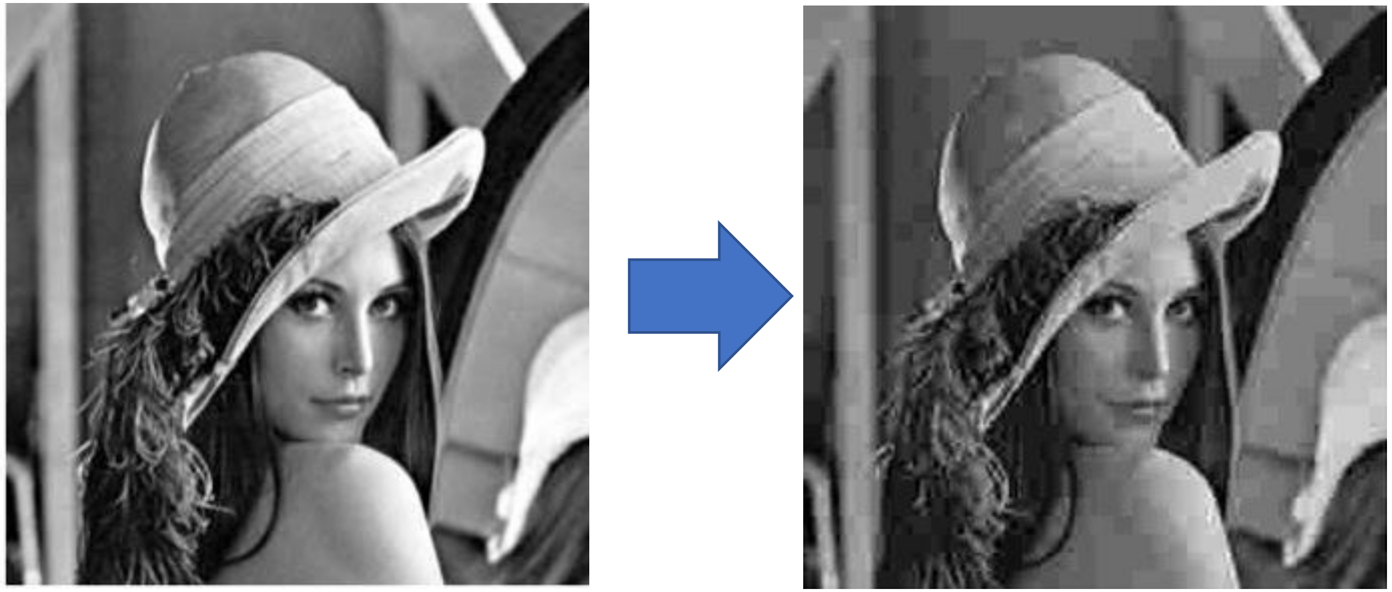
Applied when the range of the sensor exceeds the number of available BVs.

<u>It consists in the compression of original DNs range</u>.

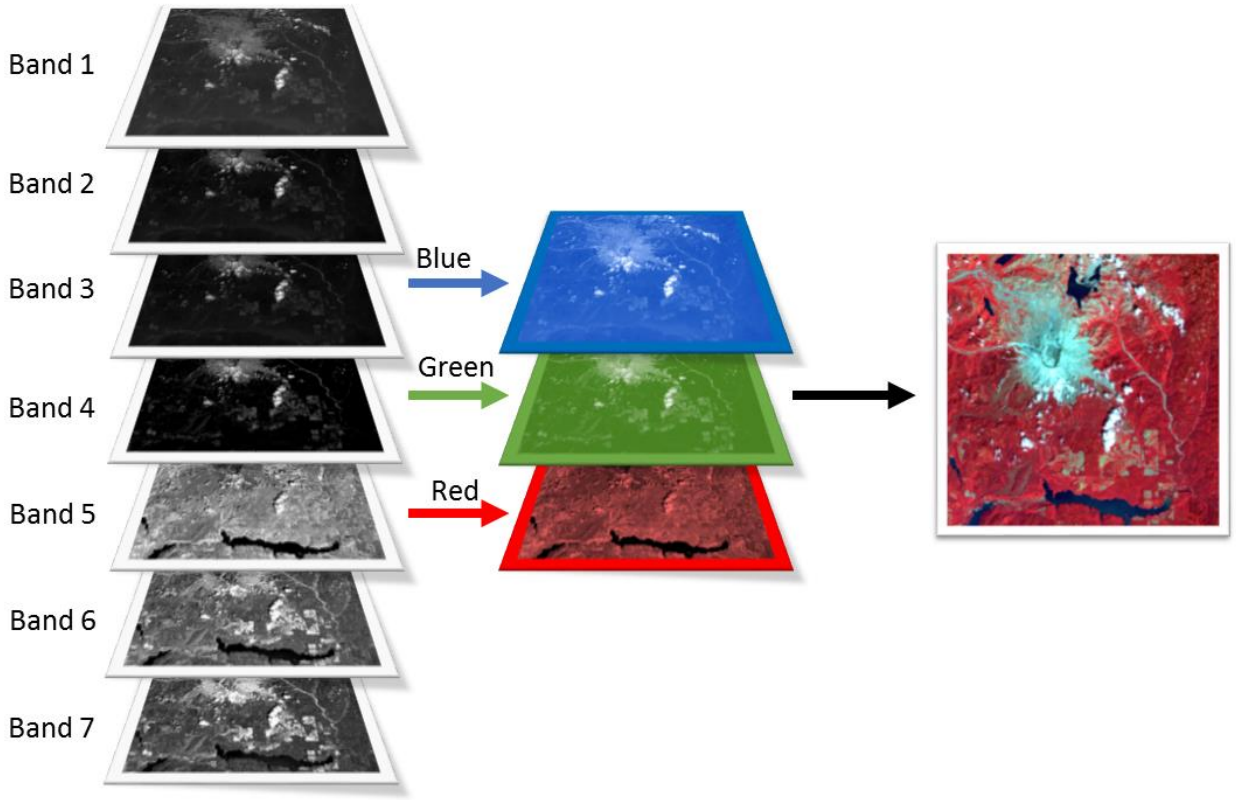
Most common approach:
Reducing the DNs range to a number of reduced intervals selected from the histogram.

Might be:
- Intervals of equal width
- Intervals of equal frequency
- Intervals manually selected

Or more elaborated algorithms exists:
- LZW
- JPEG (accepts 24 bits, 20:1 compression)
- PNG (24 bits but lower compression)



COLOR COMPOSITES



From multispectral data, it is possible to display RGB images, assigning one band to each colour.

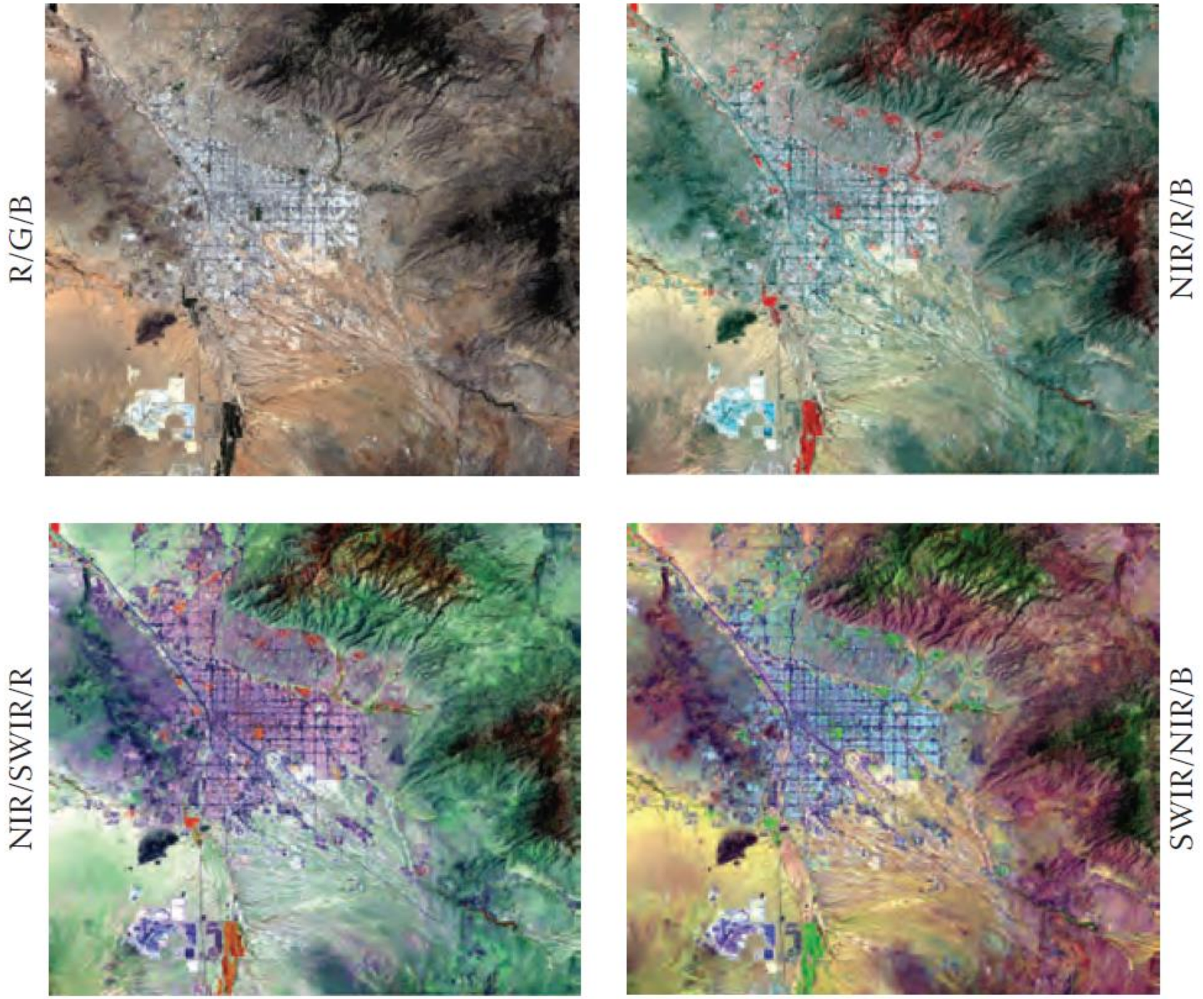
In total three bands can be chosen and assigned to R, G and B colour respectively.

The most common composite is
FALSE COLOR or INFRARED COLOR COMPOSITE: NIR bands are assigned to R, red bands are assigned to G and green bands are assigned to B.

This is used to map vegetation, water bodies, urban areas, ecc.

Of course, any combination is possible.

COLOR COMPOSITES



	Landsat 8-9	Sentinel-2
Natural colours	4,3,2	4,3,2
False Colour Infrared	5,4,3	8,4,3
Land/Water	5,6,4	11,8,4
Vegetation analysis	6,5,4	11,8A,5
False colour (urban)	7,6,4	12,11,4
Agriculture	6,5,2	11,8A,2
False c. (TIR, SWIR, Green)	10,7,3	

It is possible to apply quantitative criteria to choose the best band combination for colour composites

OIF = Optimum Index Factor. It evaluates the variances within each bands and the correlations between bands

$$OIF = \frac{\sum_{k=1,3} s_k}{\sum_{j=1,3} \left| r_j \right|}$$

Standard deviation of k-band

Correlation coefficient between each pair of the selected bands

PSEUDOCOLORS

<u>Use of color even with single band is available.</u>

Since only one band is being used, we use the term pseudocolor.

It is possible to display pseudocolors by creating a LUT where a single DN is represented in different values of RGB.

Pseudocolors are generally used:

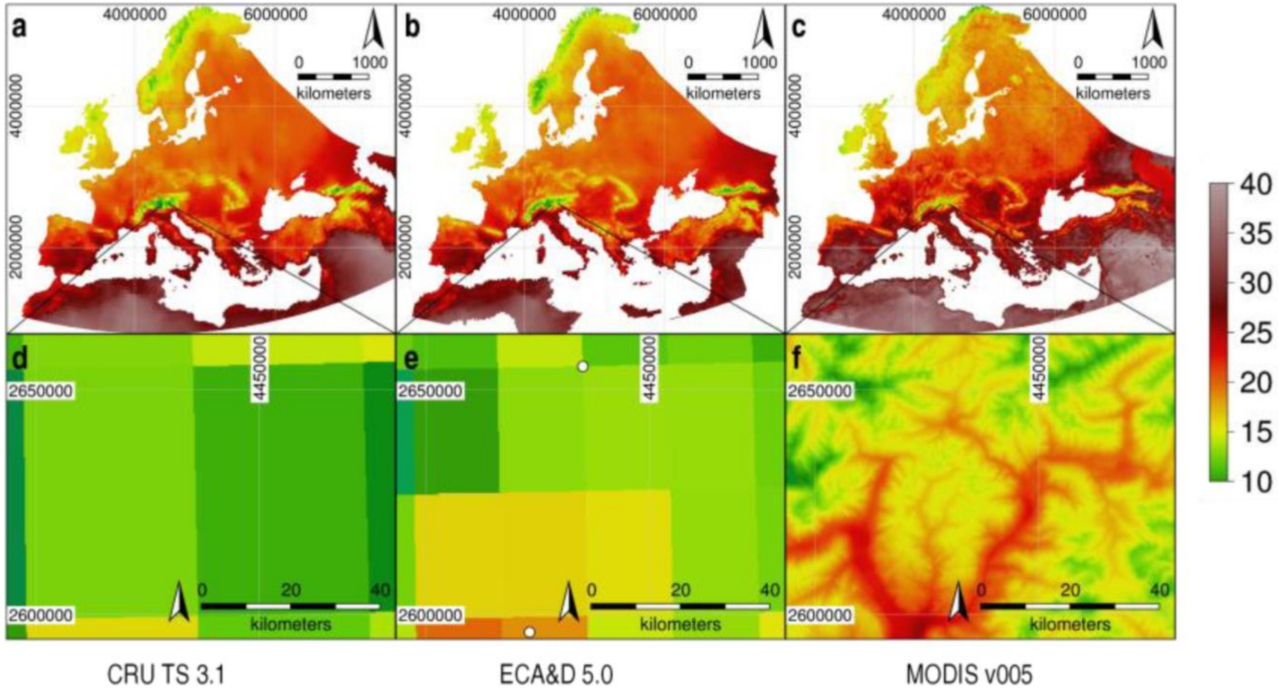
- When a color scheme is needed for a classified image
- To enhance a single-band image, by substituting the gray levels with color tones.

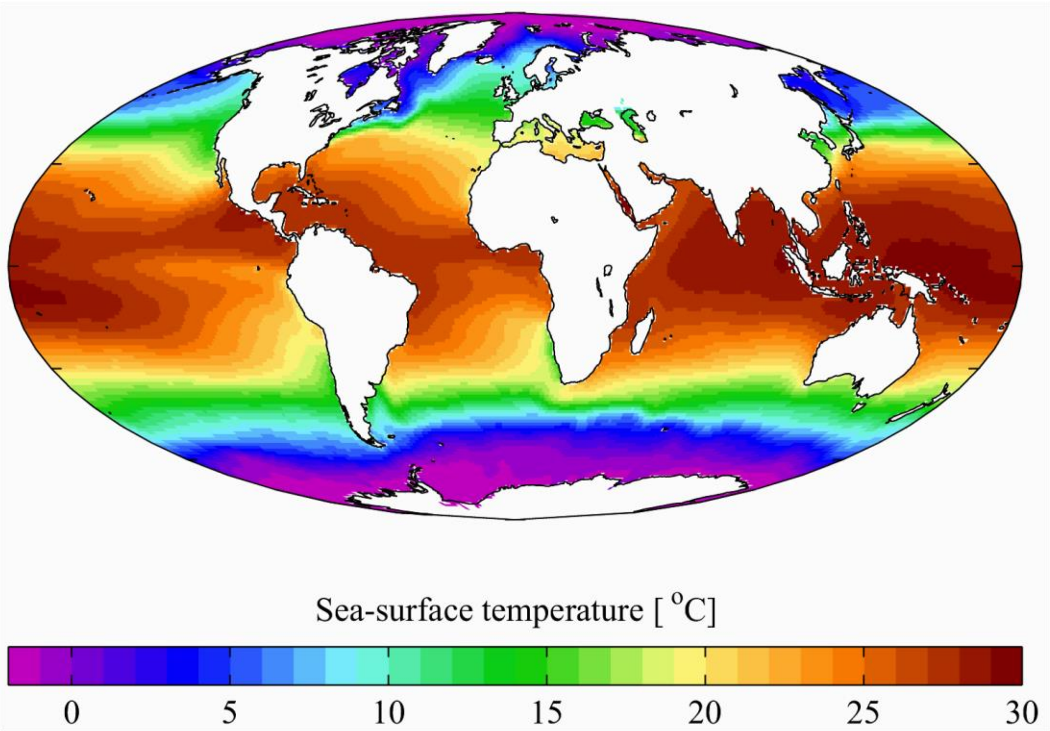
TABLE 6.3

Example of a Lookup Table for a Classified Image

DL	*BV* Red	*BV* Green	*BV* Blue	Resulting Color
0	0	0	0	Black
1	255	0	0	Red
2	0	255	0	Green
3	0	0	255	Blue
4	0	255	255	Cyan
5	255	255	0	Yellow
6	255	127	0	Ochre
7	127	127	127	Gray
8	255	0	127	Pink

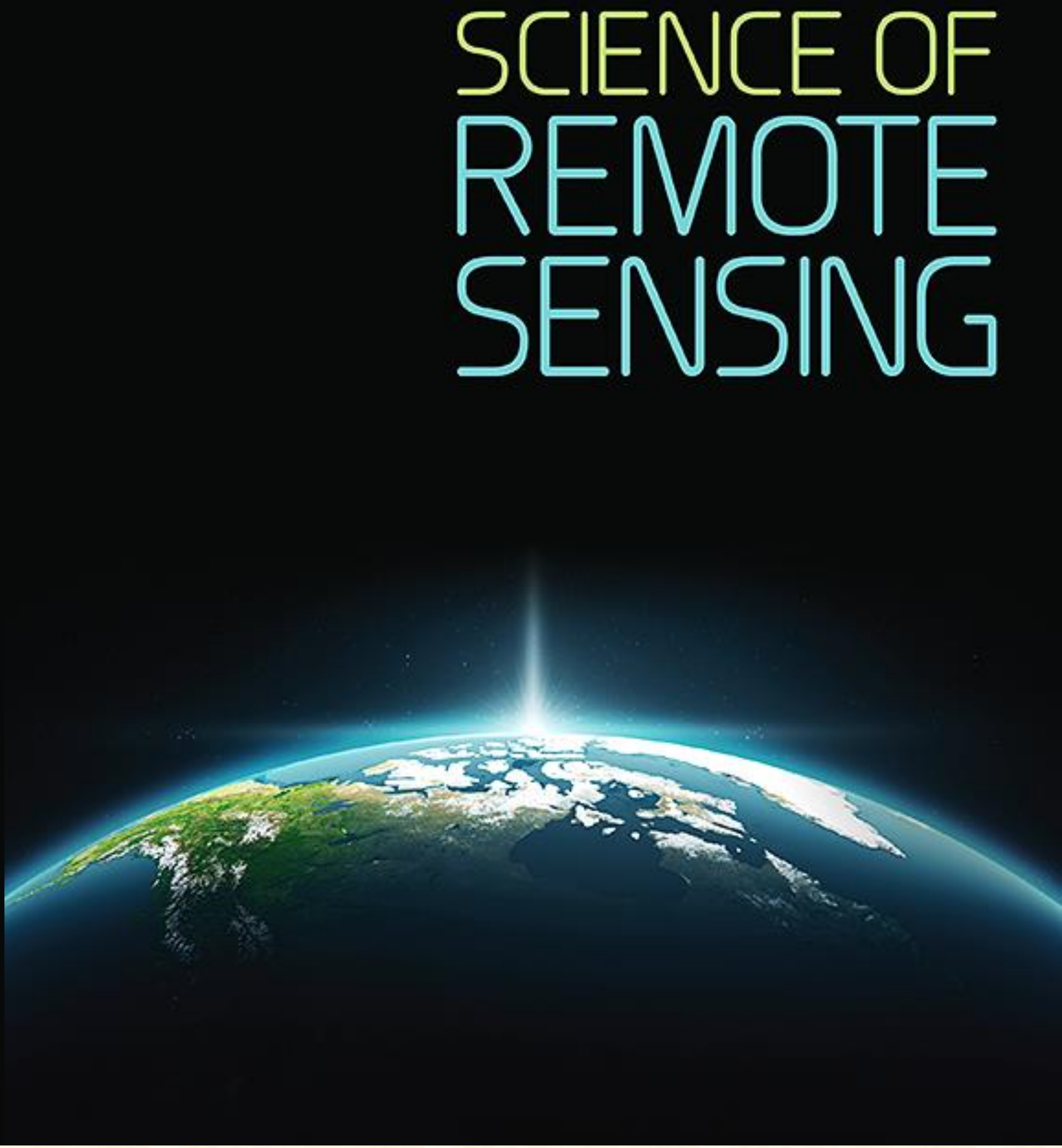
PSEUDOCOLORS





Part 3

Analyzing EO Satellites Images



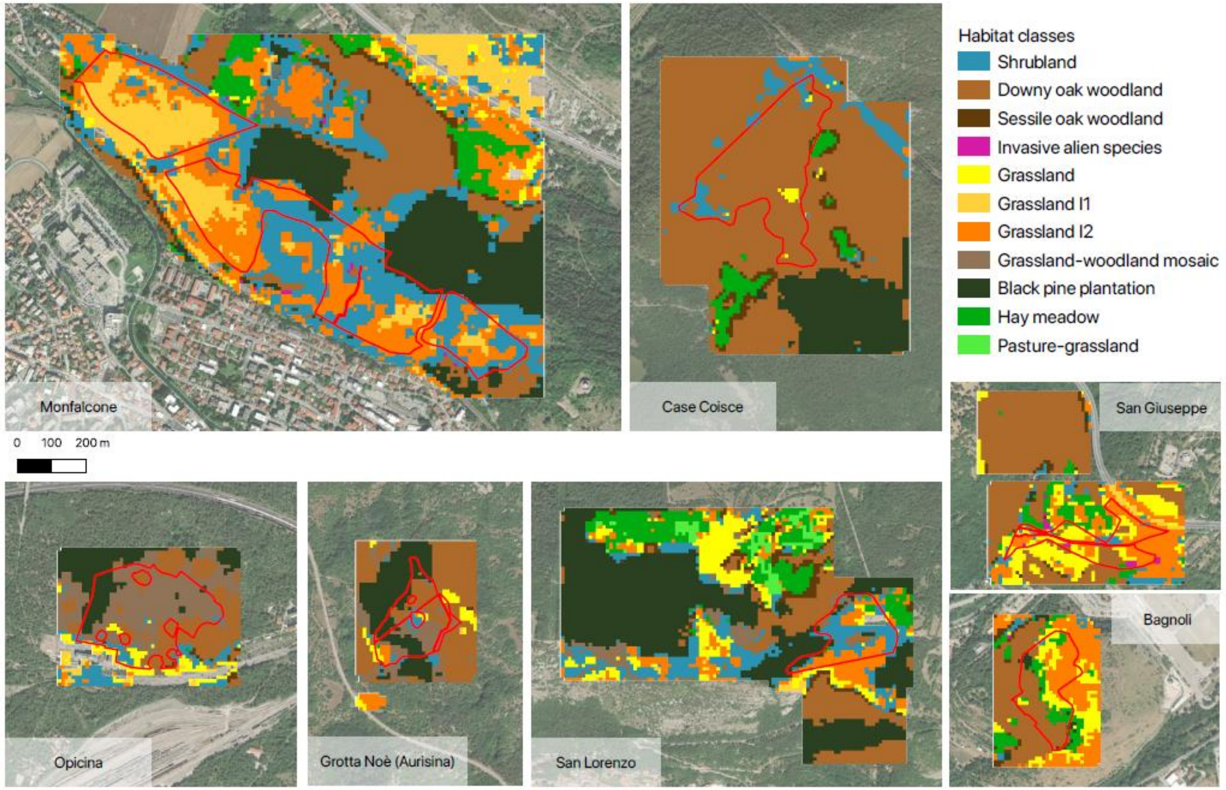
ANALYZING EO SATELLITES IMAGES

Different approaches to use RS data to study global changes:

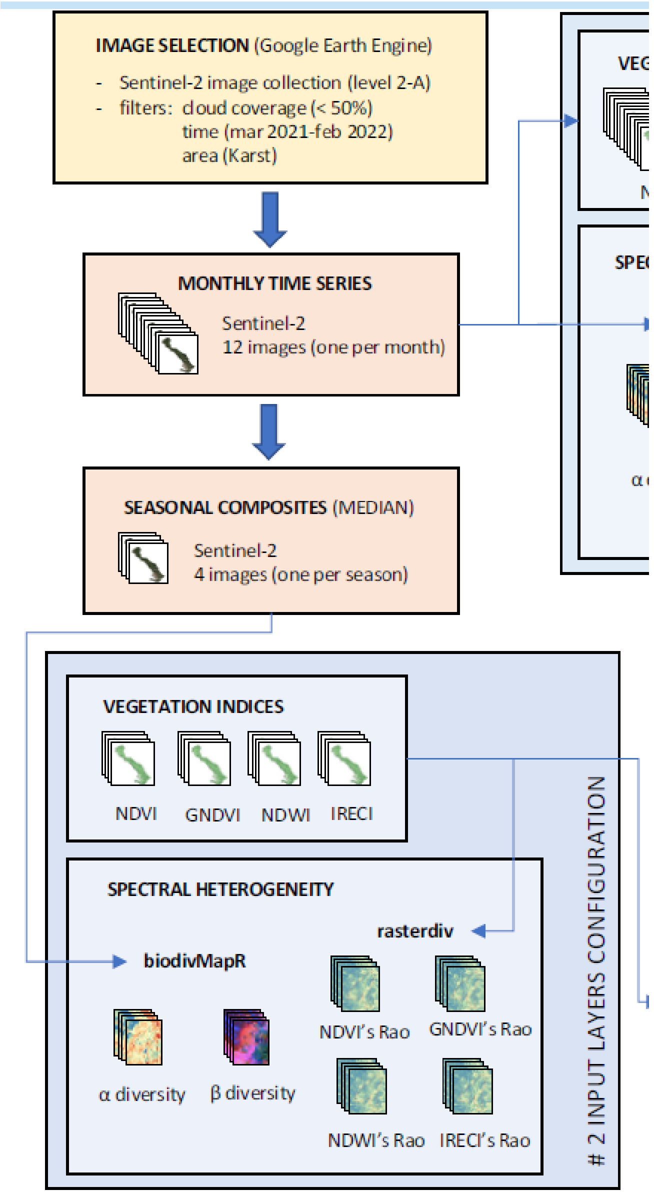
1. CLASSIFICATION

Process that assigns each element of the image to a certain category through digital interpretation.

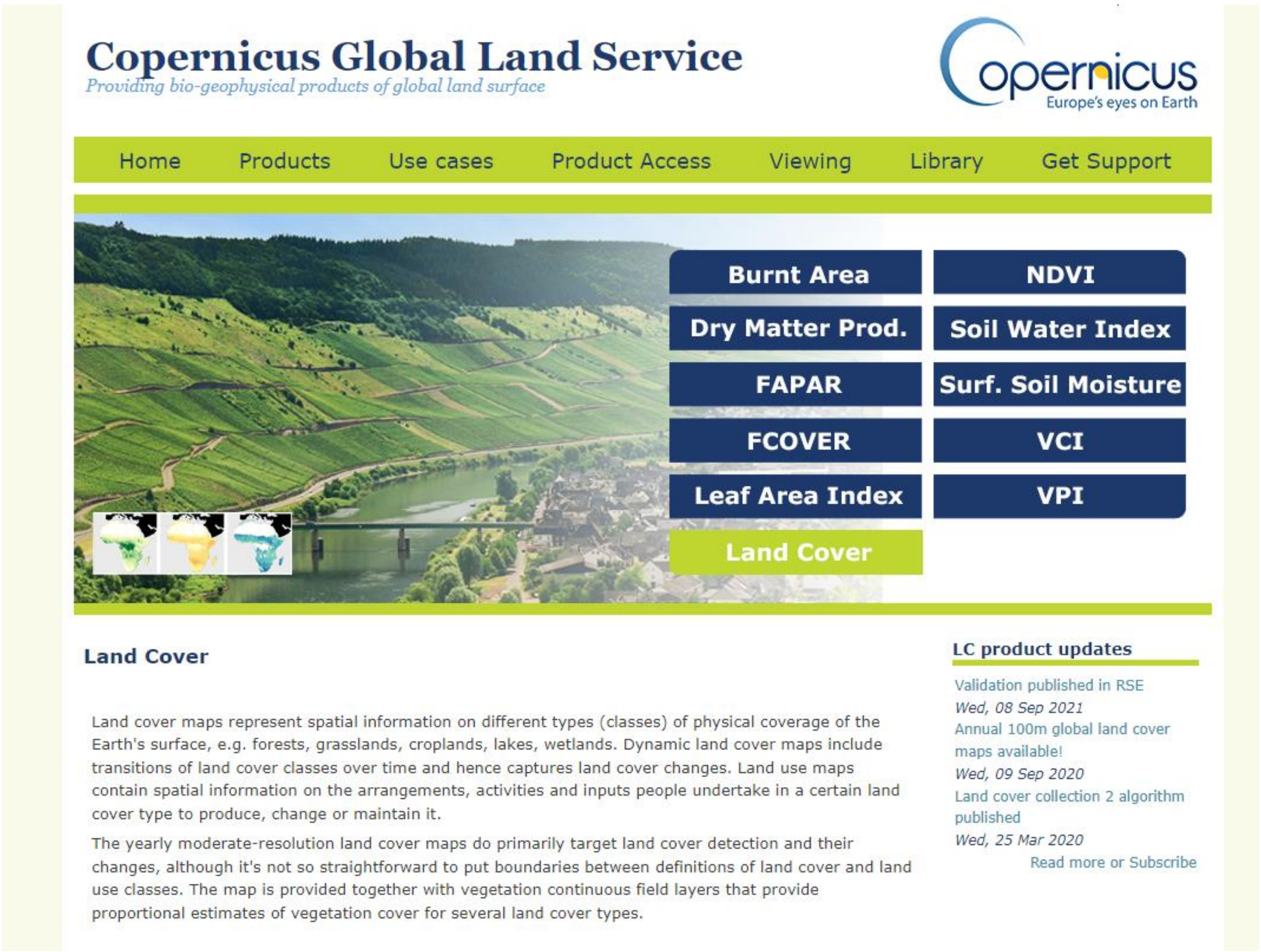
Converting numerical values in categories



Pafumi et al. In Preparation



ANALYZING EO SATELLITES IMAGES



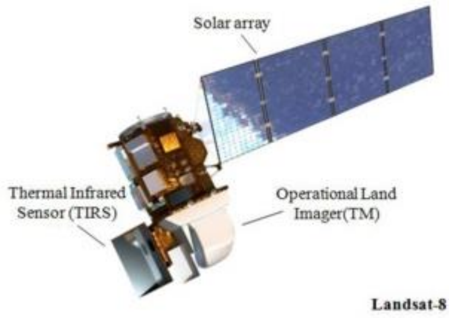
https://land.copernicus.eu/global/products/lc

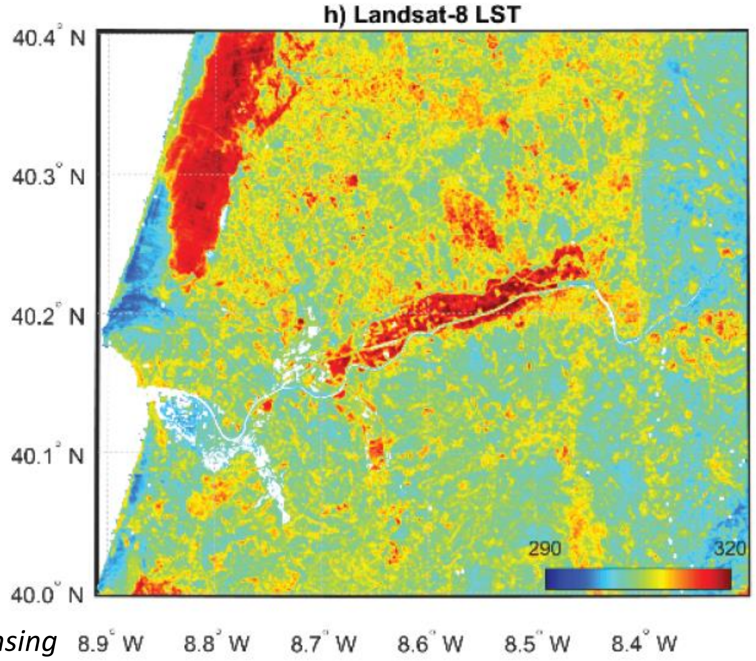
2. GENERATION OF CONTINUOUS VARIABLES

Generate spatial distribution of a biophysical variable derived from the sensor though empirical or physical models

Converting raw digital values into biophysical values

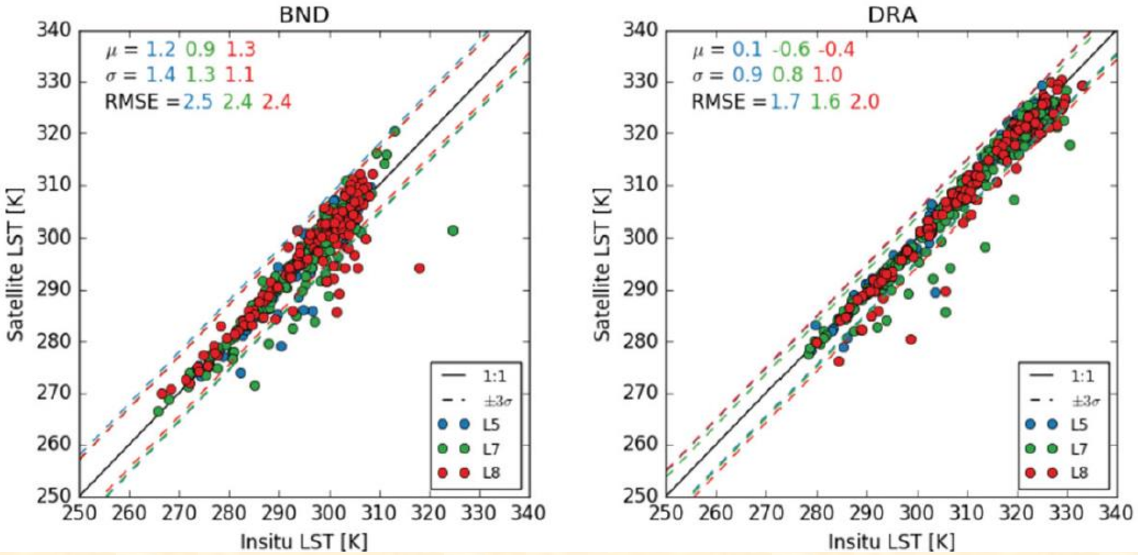
LST = Land Surface Temperature





Ermida et al. 2020 Remote Sensing

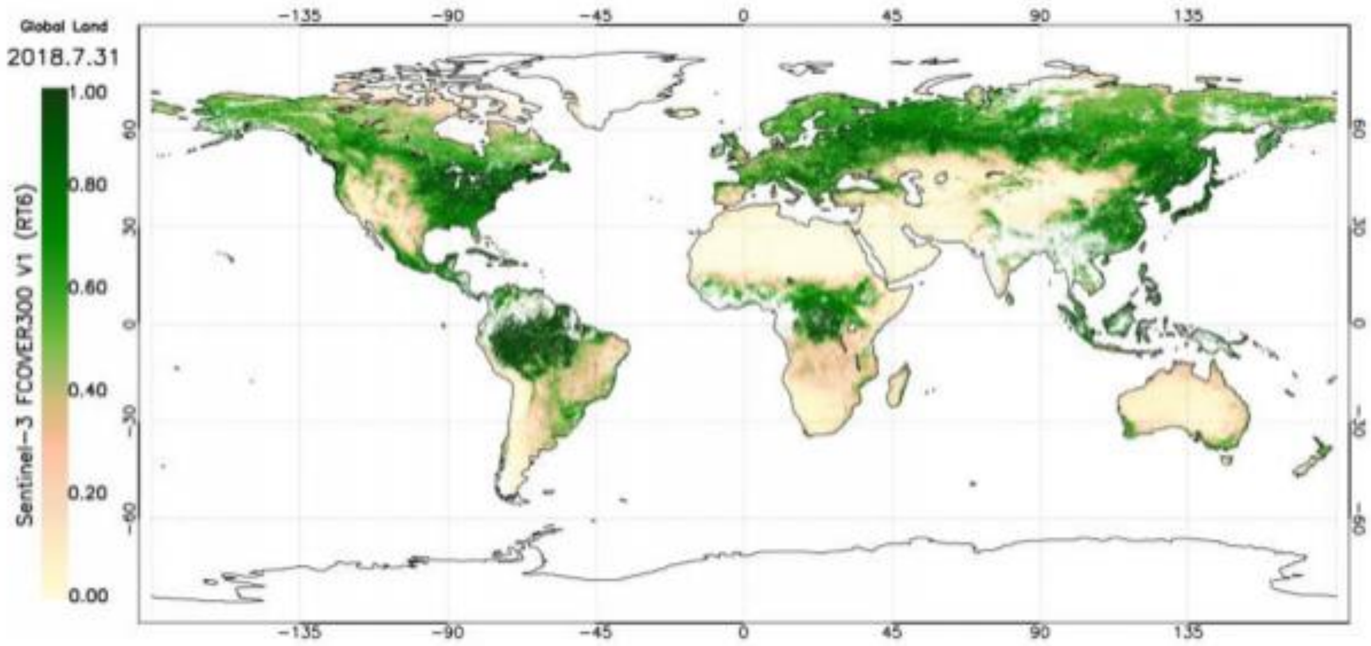
BAND	SPECTRAL	WAVELEN. [μm]	GEOM. [m]	SENSOR
1	aerosols	0.435 – 0.451	30	OLI
2	blue	0.452 – 0.512	30	OLI
3	green	0.533 – 0.590	30	OLI
4	red	0.636 – 0.673	30	OLI
5	NIR	0.851 – 0.879	30	OLI
6	SWIR-1	1.566 – 1.651	30	OLI
7	SWIR-2	2.107 – 2.294	30	OLI
8	pan	0.503 – 0.676	15	OLI
9	cirrus	1.363 – 1.384	30	OLI
10	TIR-1	10.600 – 11.190	100	TIRS
11	TIR-2	11.500 – 12.510	100	TIRS

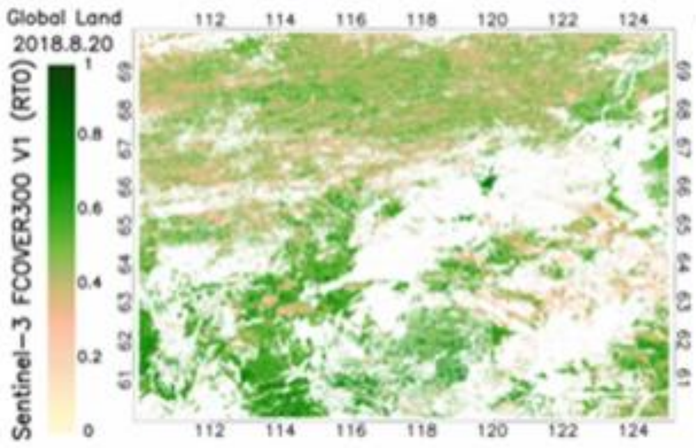


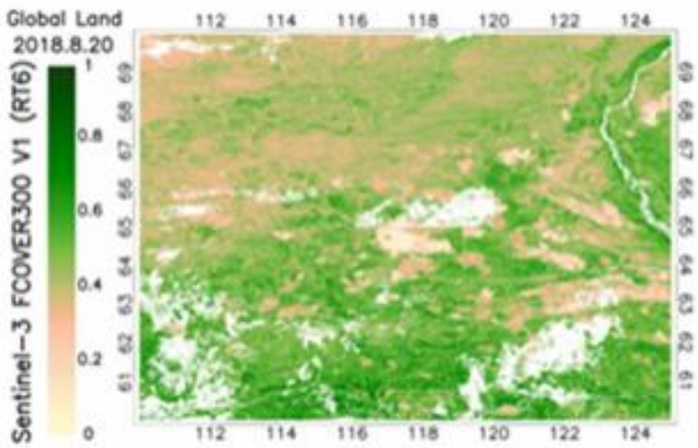
Vegetation biophysical variables:

FCOVER = Fraction of green vegetation cover

https://land.copernicus.eu/global/products/fcover







remote sensing MDPI

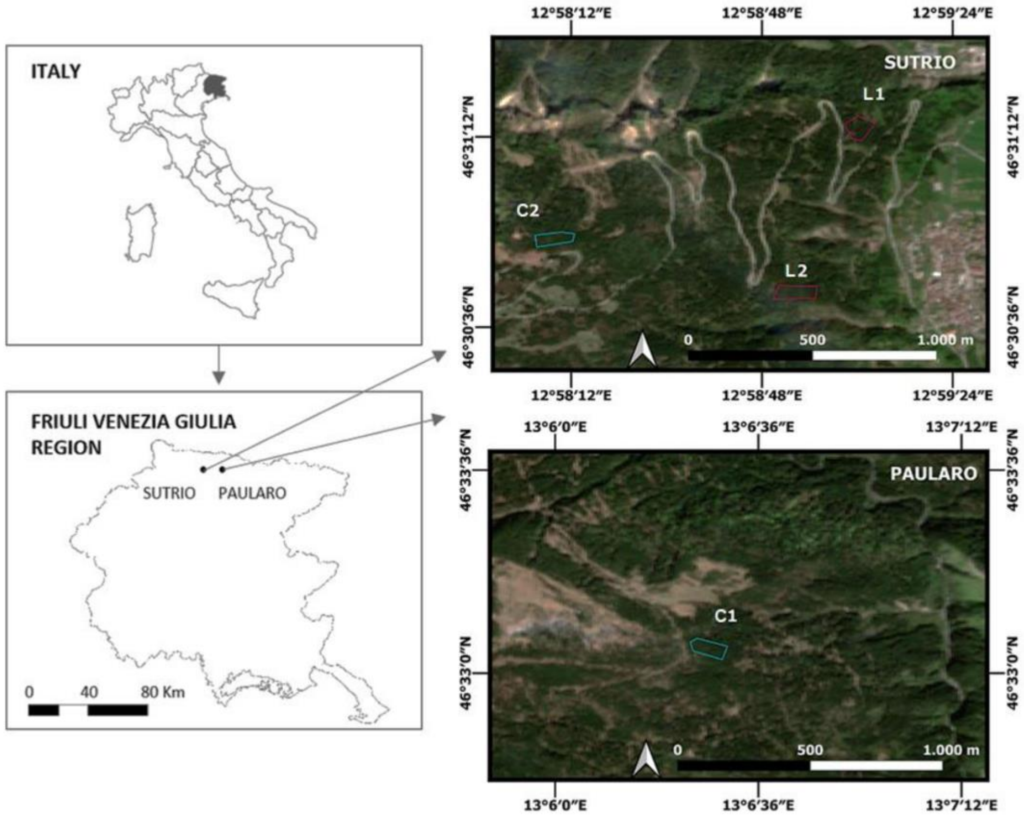
Article

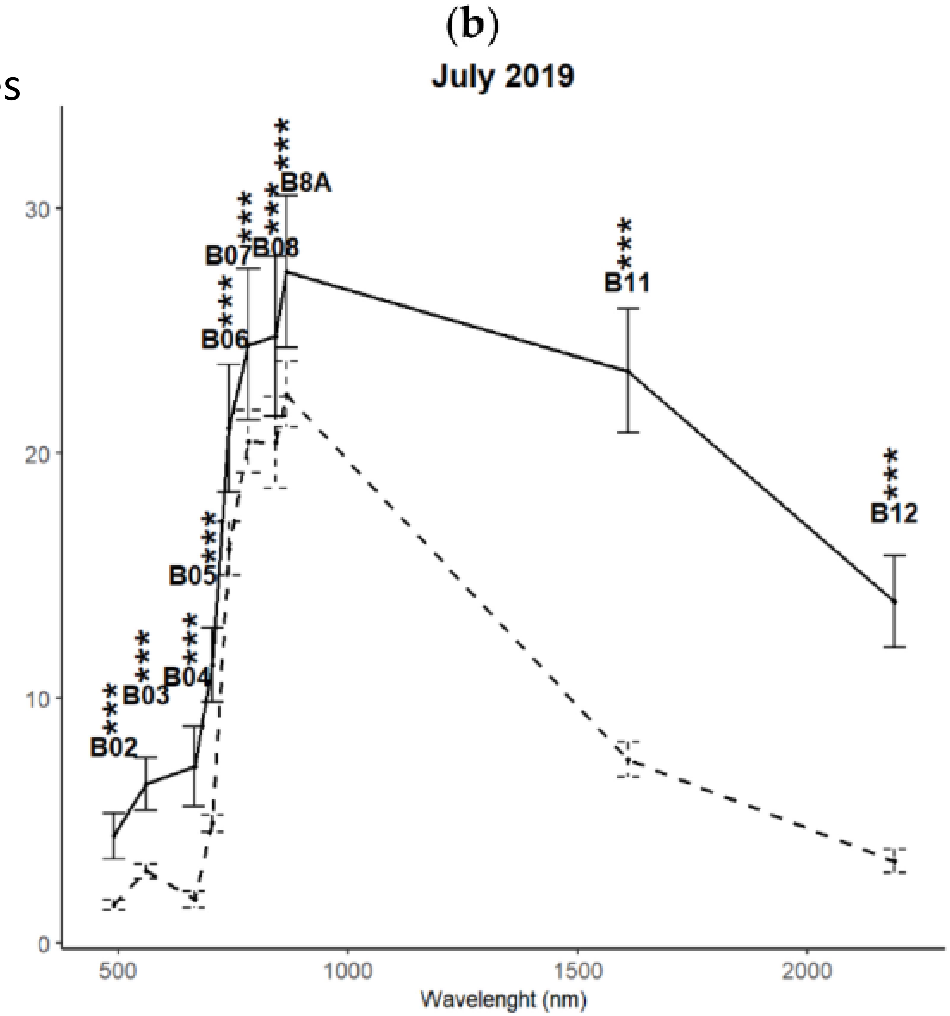
Use of Sentinel-2 Satellite Data for Windthrows Monitoring and Delimiting: The Case of "Vaia" Storm in Friuli Venezia Giulia Region (North-Eastern Italy)

3. CHANGE DETECTION

Quantification of changes occurred between two or more images

Could be performed on both classified images or biophysical variables





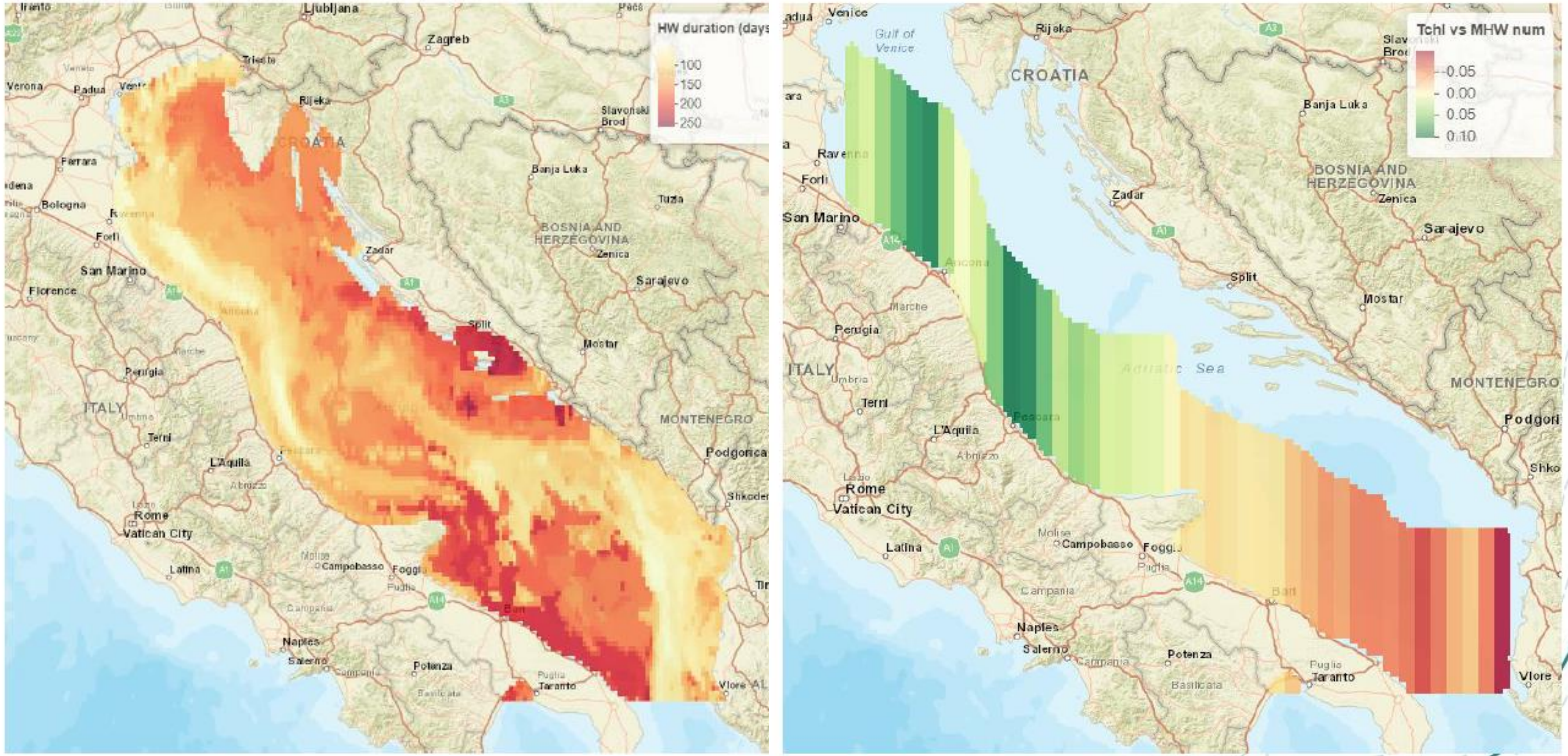
4. SPATIAL PATTERNS

Measure spatial properties of an object as: size, connectivity, shape.

ADRIATIC SEA MHW TRENDS

Bevilacqua et al. In Preparation

MHW = Marine Heatwaves



Chl content

GENERATION OF CONTINUOUS VARIABLES

- Transforming satellite measurements into biophysical variables

- The estimation of any variables relies on the physical relationship that links the surface properties with the radiance or reflectance measured by the sensor

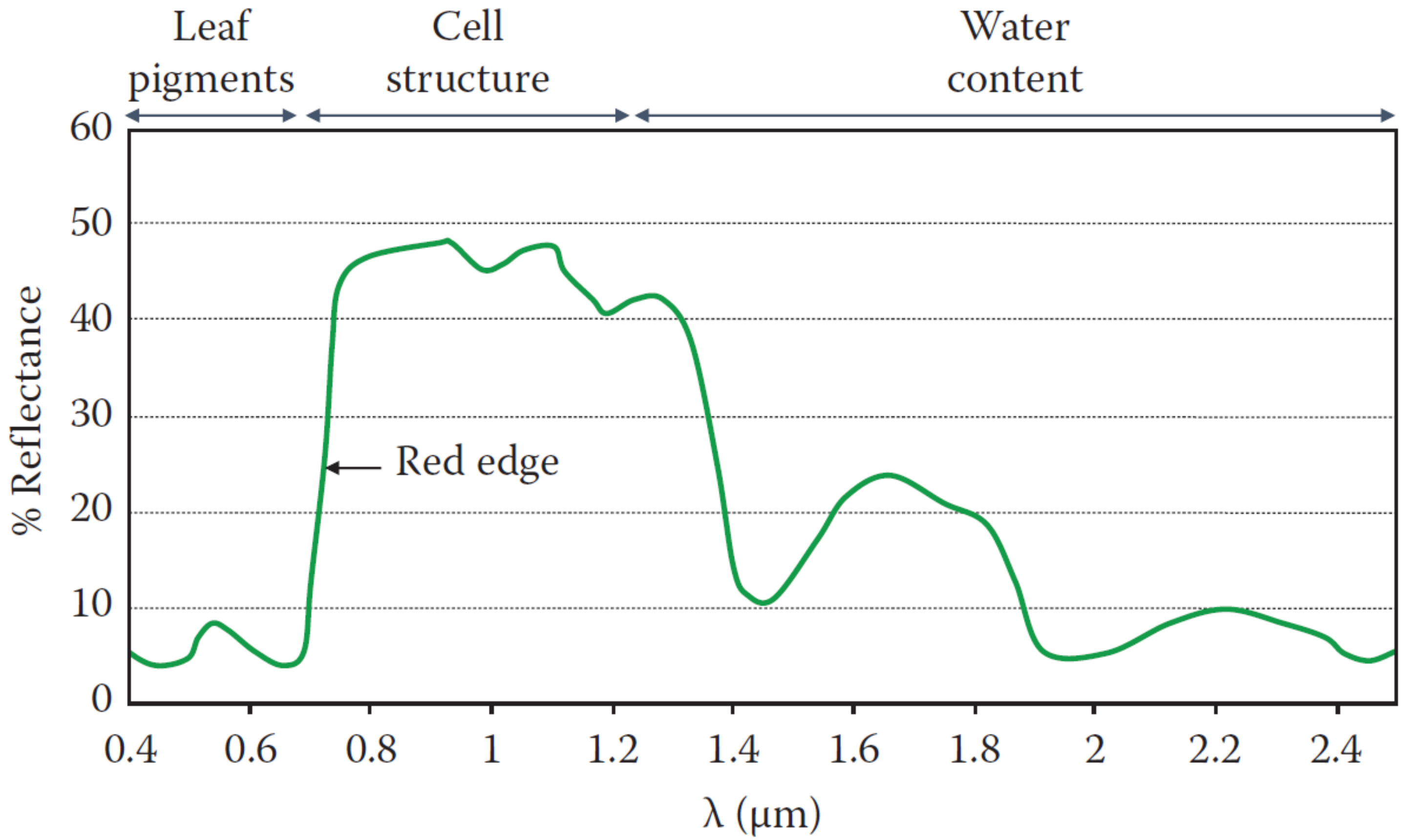
- Two different variables types:

1. **PRIMARY VARIABLES**: directly measured by the satellite.
    - Spectral radiances
    - Spectral reflectance
    - Land Surface T° in the TIR region
    - Surface backscatter coefficients in the microwave (MW) region
    - Heights through LiDAR measurements

2. **SECONDARY VARIABLES**: inferred or derived from models.
    - Chlorophyll content
    - Water content
    - Leaf Area Index (LAI)
    - Fraction of photosynthetically active radiation absorbed by plants (fAPAR)
    - Soil moisture
    - Evapotranspiration (ET)

GENERATION OF CONTINUOUS VARIABLES

- For secondary variables, it is necessary to model the relationship between satellite and actual biophysical variables measurements
- Any empirical or theoretical model should be based on theoretical relationship between the parameter being estimated and radiances or reflectance measured by the sensor
- Model must be then validated on the ground



1. **INDUCTIVE OR EMPIRICAL MODELs**
   - These models fit a numerical relationship between the parameter to be estimated and the satellite measurements based on in situ observations

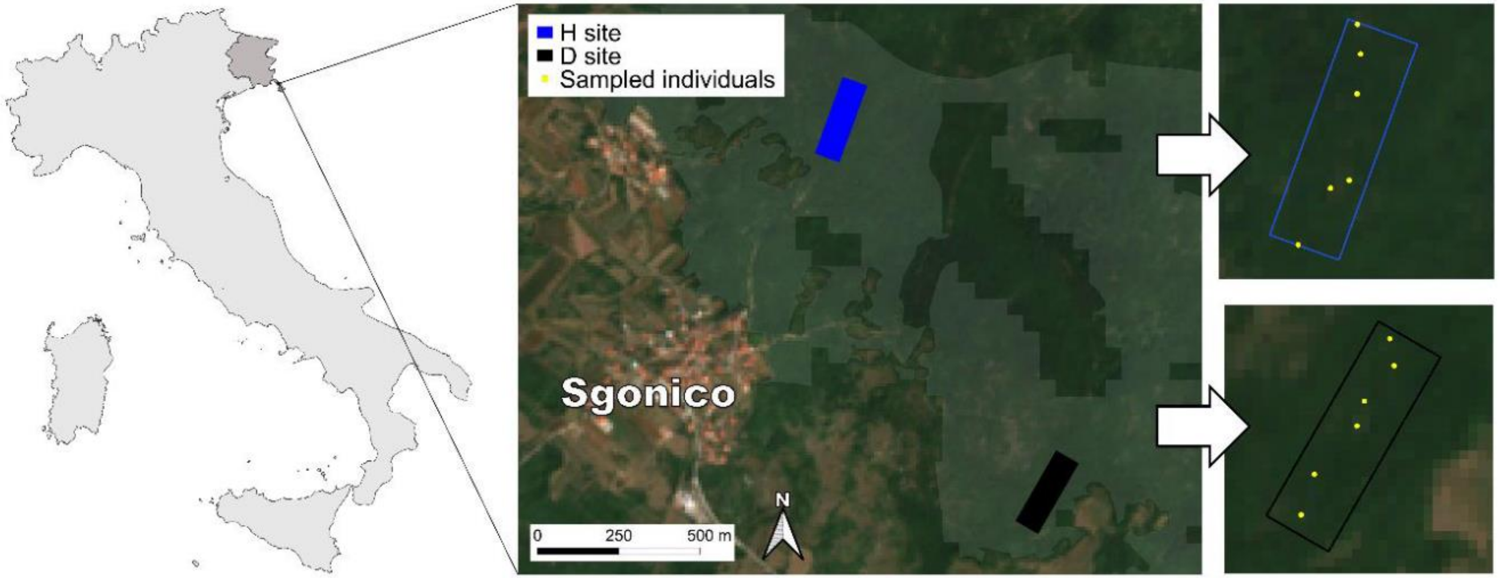
   - The satellite image must be calibrated
   - Require simultaneous field data collection


forests MDPI

Article

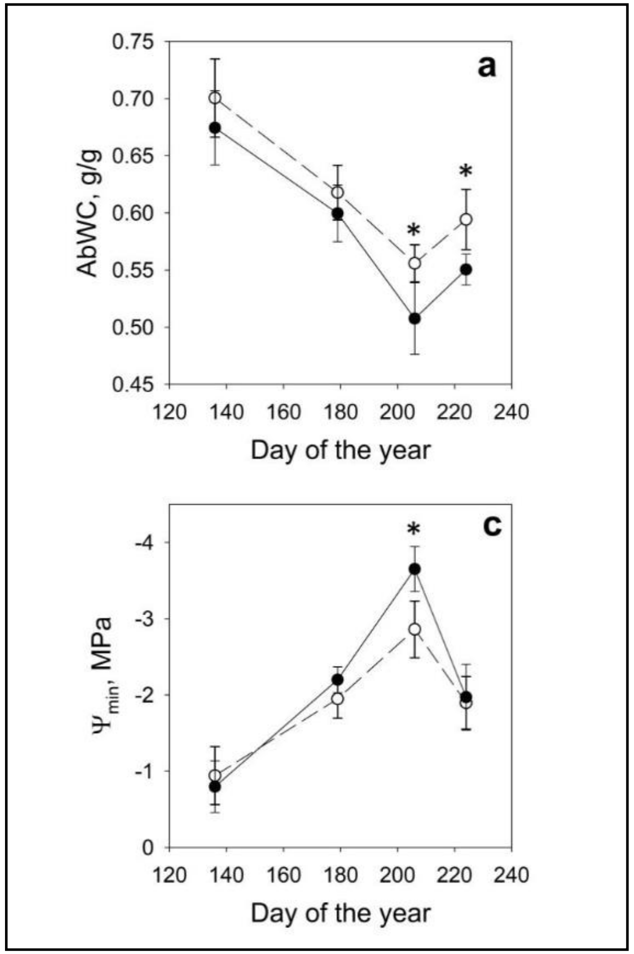
Correlation of Field-Measured and Remotely Sensed Plant Water Status as a Tool to Monitor the Risk of Drought-Induced Forest Decline

Daniel Marusig, Francesco Petruzzellis, Martina Tomasella, Rossella Napolitano, Alfredo Altobelli and Andrea Nardini *

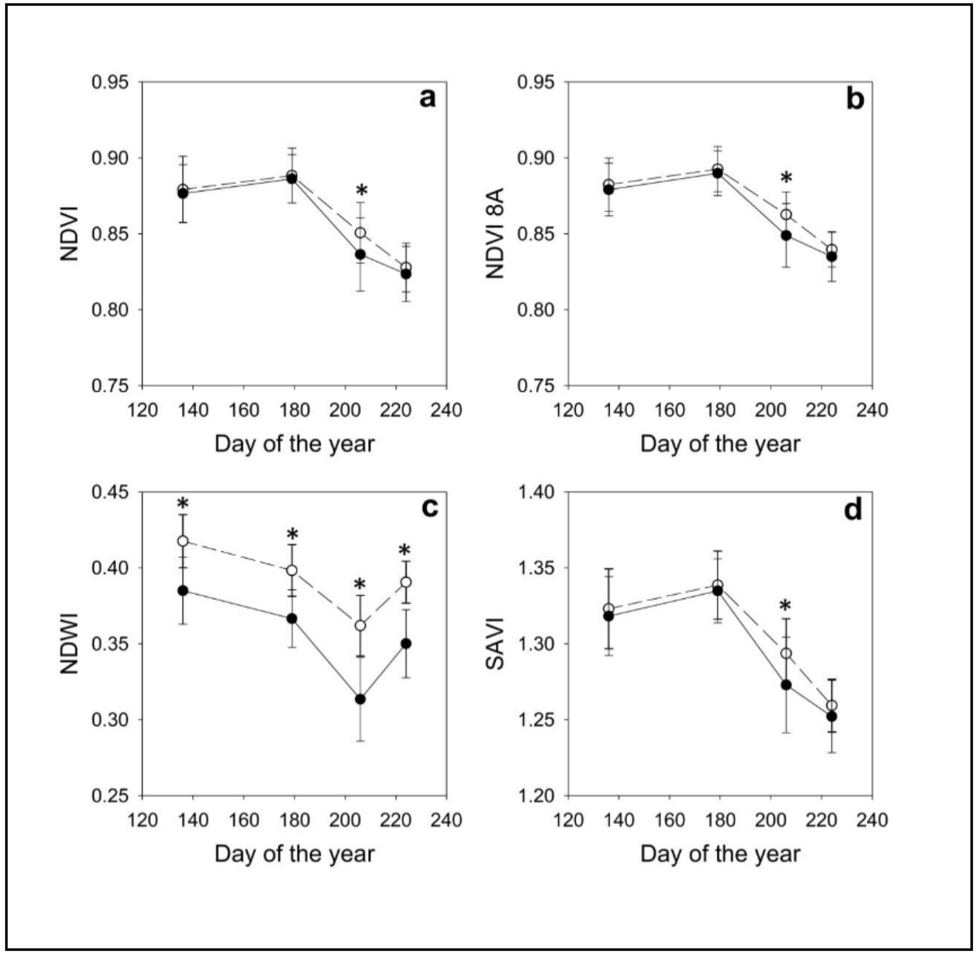


GENERATION OF CONTINUOUS VARIABLES

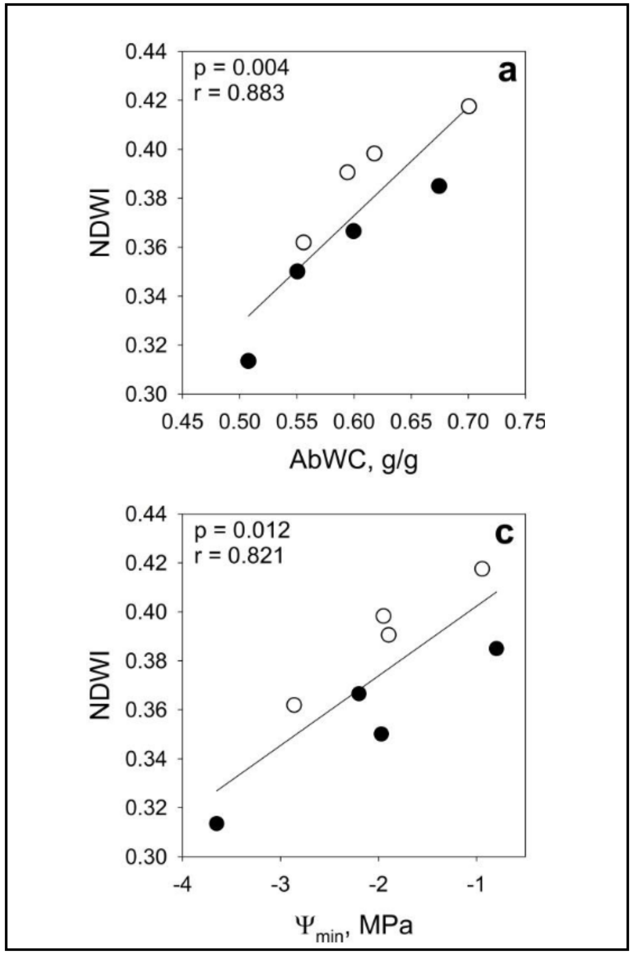
Field measurements



Satellite measurements



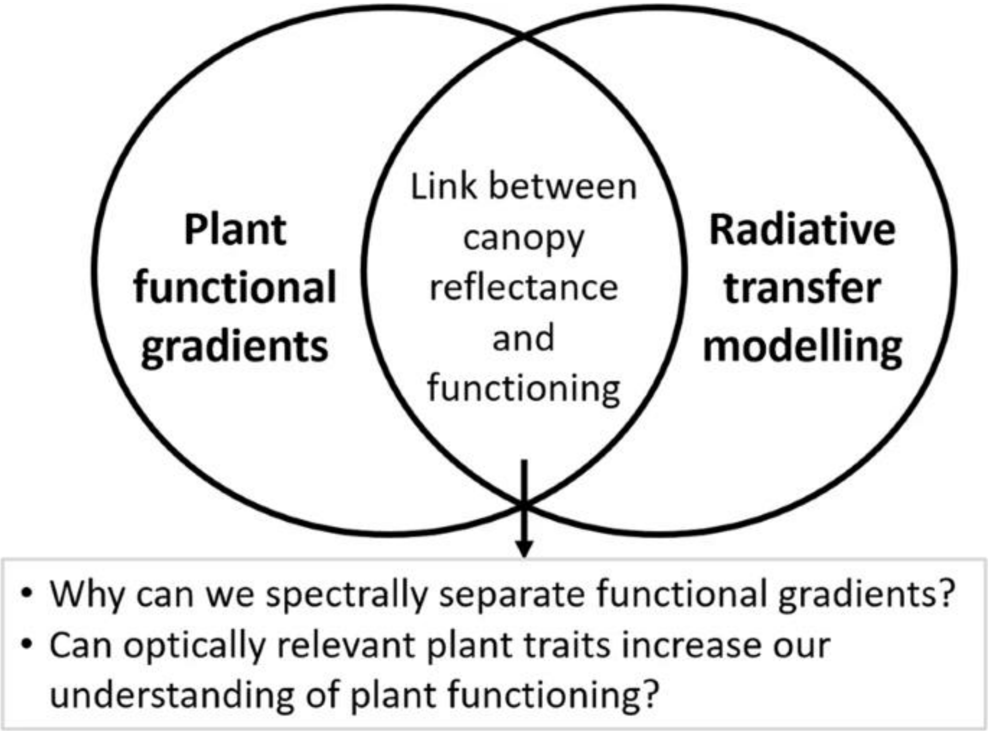
Calibration



2. DEDUCTIVE OR THEORETICAL MODELs

- These models establish general relationships between the required parameter and satellite measurements

- Example: Radiative Transfer Models (RTMs)
- Relates incident radiation to vegetation canopies trough angular, structural biochemical and biophysics characteristics



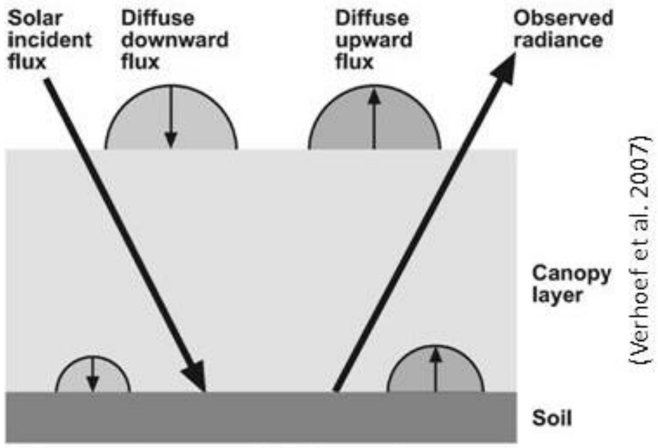
Kattenborn and Schmidtlein et al. 2029 Scientific Report

PROSAIL

Combines 4-stream canopy model **SAIL**

Calculates the diffuse and direct reflectance and transmittance of the whole canopy using:

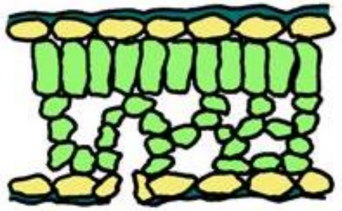
- Solar/viewing angle
- Leaf area index (m^2/m^2)
- Leaf angle distribution
- Soil reflectance
- Leaf reflectance/transmittance

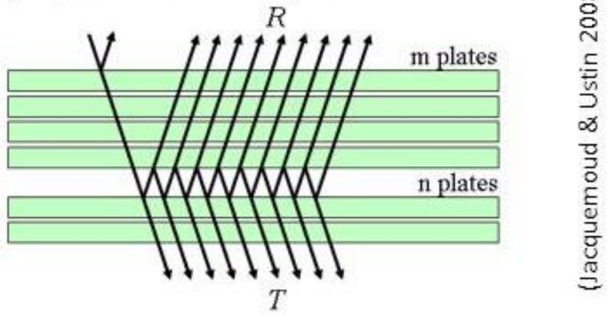


with leaf optics model **PROSPECT**

Calculates the reflectance and transmittance of a single leaf using a plate model dependent on:

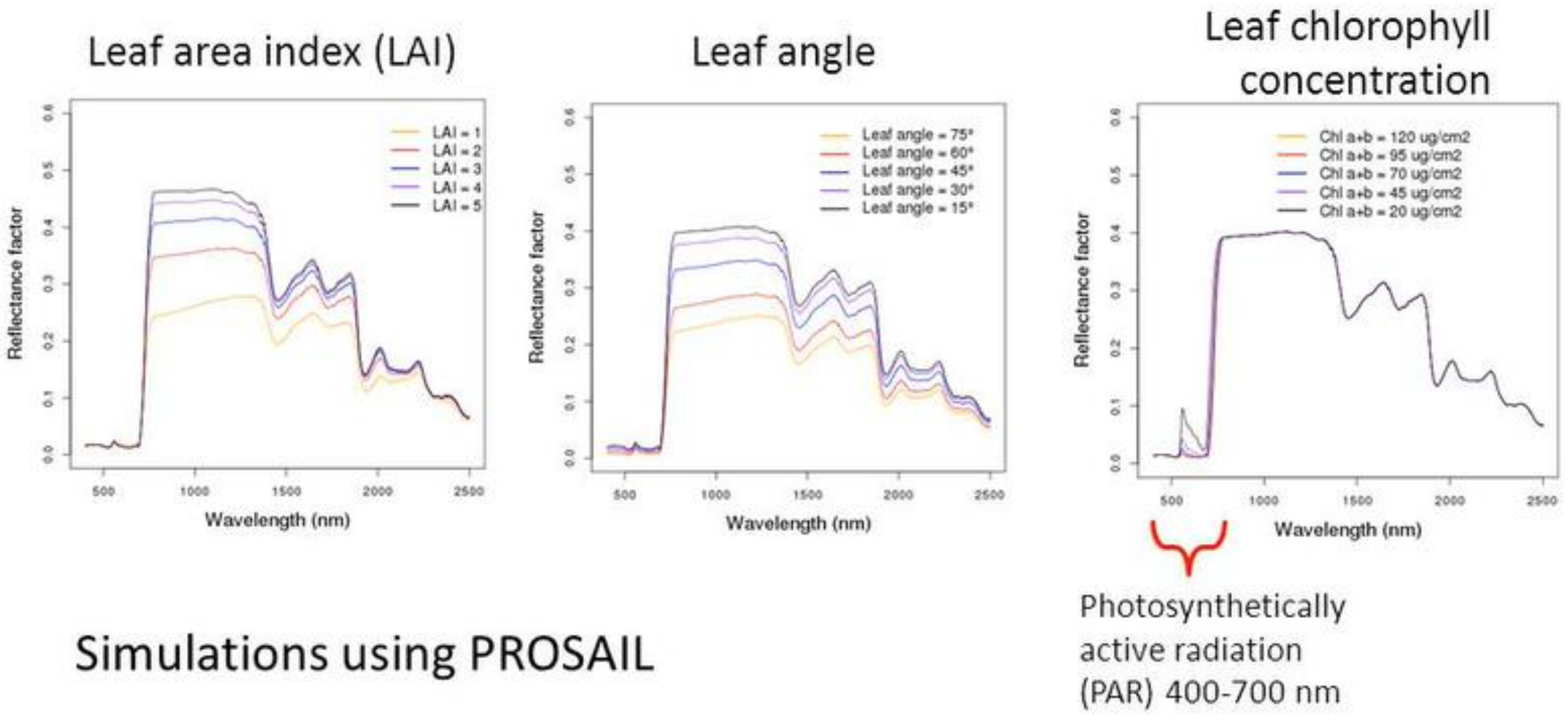
- Internal leaf mesophyll structure
- Chlorphyll a+b and carotenoid content (μg/cm^2)
- Dry matter content (g/cm^2)
- Equivalent water thickness (cm)
- Brown pigment





University of Reading
National Centre for Earth Observation
NATURAL ENVIRONMENT RESEARCH COUNCIL
UCL

From radiative transfer model INVERSION it is possible to estimate plant traits



GENERATION OF CONTINUOUS VARIABLES

Hauser et al. 2021 Remote Sensing of Environment

Sentinel-2

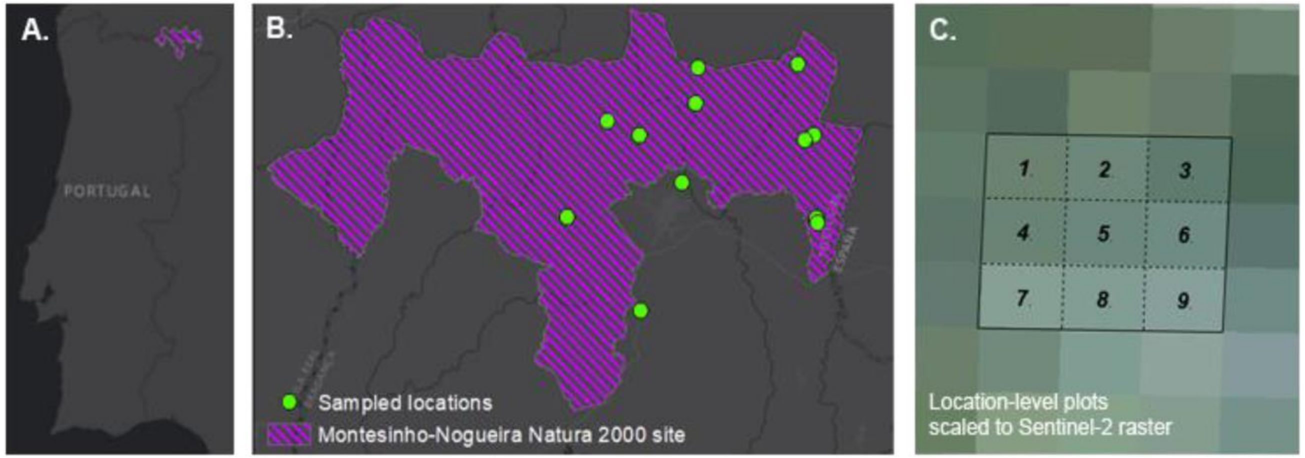
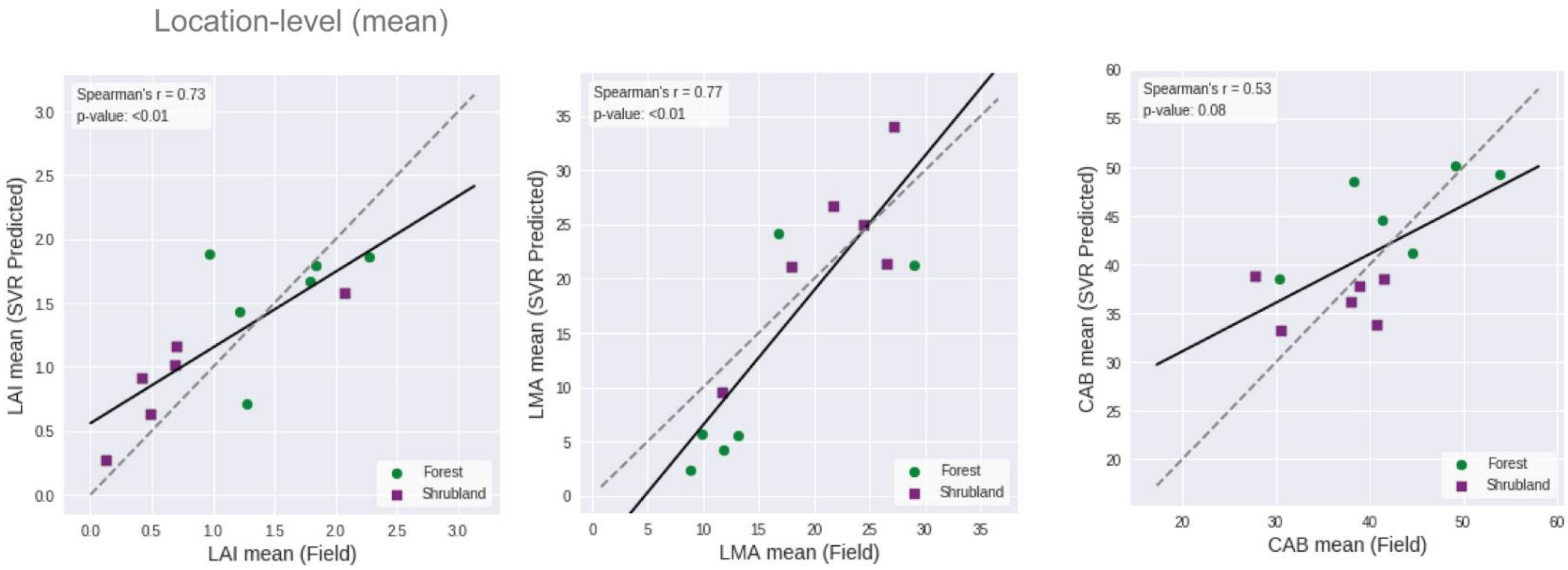


Table 1

Ranges of variable input parameters of the PROSAIL model used to generate the LUTs.

Domain	Parameter	Symbol	Unit	Distribution	Range
Leaf	Leaf structural parameter	N	–	Uniform	1.4–1.7
	Chlorophyll a + b content	CAB	$\mu g/cm^2$	Gaussian	10–60
	Equivalent water thickness	EWT	g/cm^2	Uniform	0.001–0.045
	Leaf dry mass per area	LMA	g/cm^2	Uniform	0.001–0.040
	Brown pigments content	Cbrown	–	Fixed	0.01
Canopy	Leaf area index	LAI	m^2/m^2	Gaussian	0.01–3.5
	Mean leaf inclination angle	ALA	deg	Uniform	30–70
	Hot spot size parameter	hot	m/m	Fixed	0.01
Abiotic	Ratio of diffuse to total incident radiation	SKYL	–	Fixed	18%
	Soil brightness	psoil	–	Fixed	Spectroradiometer
Positional	Solar zenith	tts	o	Fixed	Sentinel-2 geometry
	Observer zenith	tto	o	Fixed	Sentinel-2 geometry
	Relative azimuth	phi	o	Fixed	Sentinel-2 geometry

GENERATION OF CONTINUOUS VARIABLES



2. DEDUCTIVE OR THEORETICAL MODELs

- They also have limitations, as they need to be tested and constrained by actual data to find uncertainties and improve their performance

- These models are generally preferred to inductive models because of the mechanistic relationships between spectral data and biophysical variables and because they are more extendable in space and time

3. INTERMEDIATE APPROACHES

- Defined as semi-empirical models
- First step: physical modelling
- Second step: empirical adjustement

GENERATION OF CONTINUOUS VARIABLES

Beyond the previous complex approaches, there are simplified methods to generate continuous variables from remotely sensed data.

1. **PRINCIPAL COMPONENT ANALYSIS**
2. **SPECTRAL VEGETATION INDICES (VIs)**
3. **SPECTRAL MIXTURE ANALYSIS**
4. **ADVANCED SATELLITES PRODUCTS**

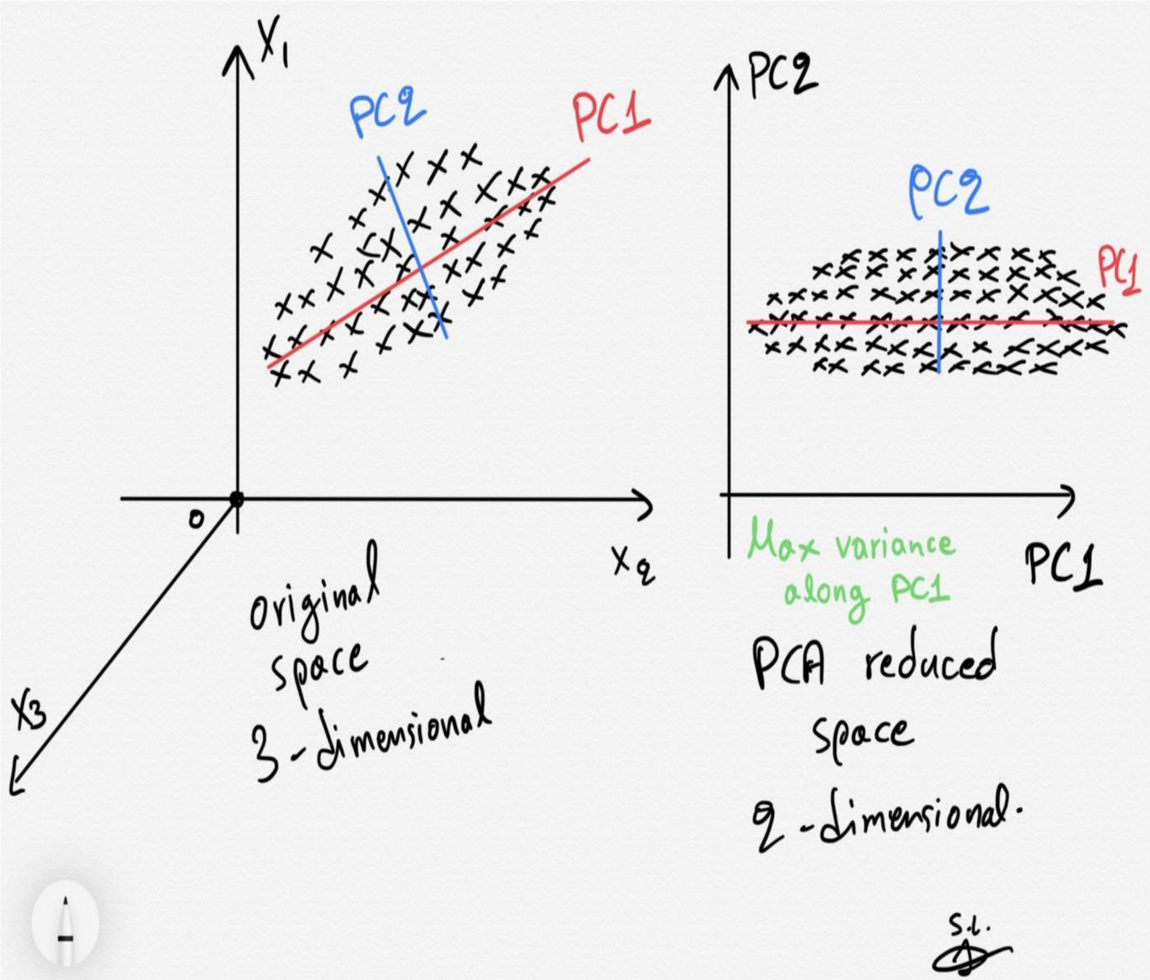
PRINCIPAL COMPONENT ANALYSIS (PCA)

This is a type of analysis used when dealing with multivariate data.

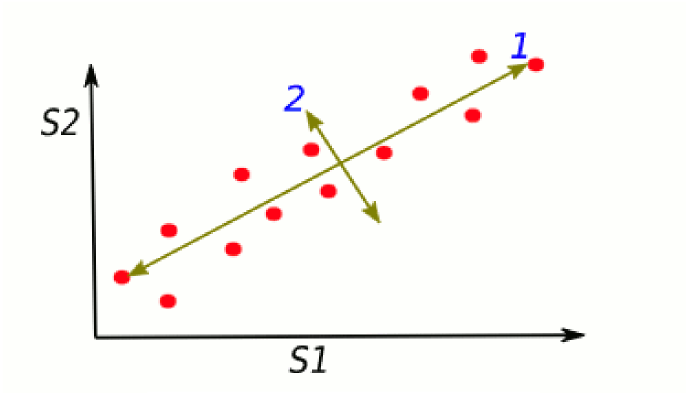
Multispectral data, which usually contains redundant information

This analysis perform a **DIMENSIONALITY REDUCTION**, by removing redundant spectral information present in the multiband images.

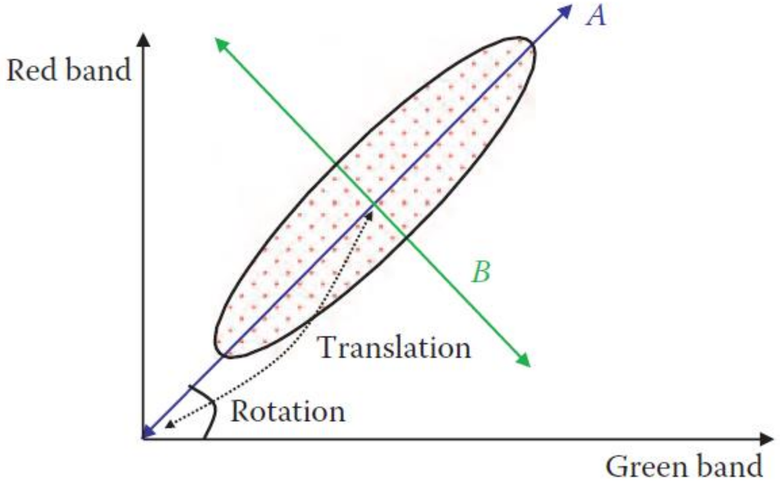
without losing a significant amount of original information.

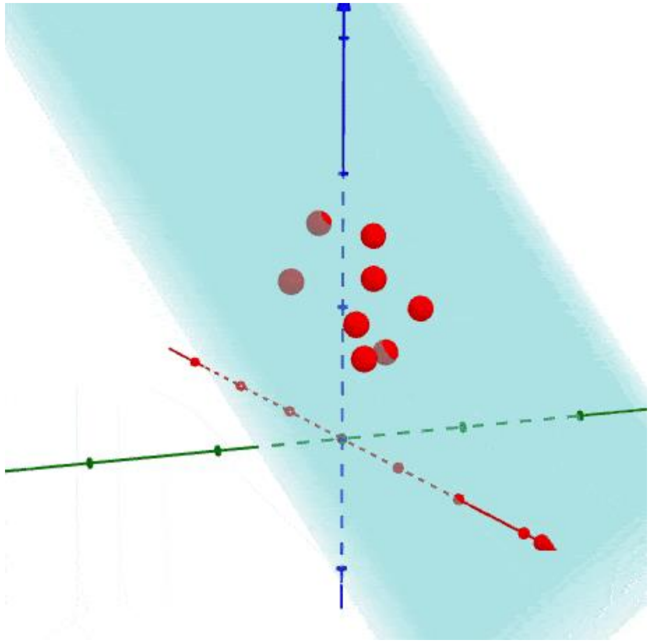


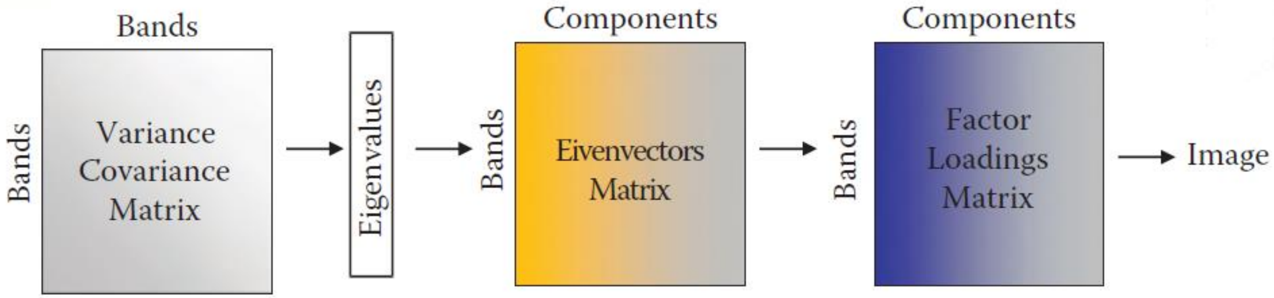
PRINCIPAL COMPONENT ANALYSIS (PCA)



$$PC_1 = a_{1i}DL_i + a_{1k}DL_k$$







From distance matrix...

Eigenvalues are calculated for each component (n components = n bands)...

Selection of components (=PCs) to be retrieved for following analyses

Eigenvalues are proportional to the length of the associated components, which is related to the original information thy retained.

PRINCIPAL COMPONENT ANALYSIS (PCA)

The PCs are obtained in such a way that eigenvalues decreases progressively from the first to the last ones, since the objective is to maximize successively the variance extracted in the analysis.

$$V_j = \frac{\lambda_j}{\sum_{j=1,p} \lambda_j}$$

Variance of j-component (V_j)

Eigenvalue associated to j-component (λ_j)

We can calculate the relationship between each band with each component, in order to interpret the meaning of the new variables (= the principal components) that have been calculated.

$$r_{i,j} = \frac{a_{i,j}\sqrt{\lambda_j}}{s_i}$$

Eigenvector of j-component in i-band ($a_{i,j}$)

Eigenvalue associated to j-component (λ_j)

Correlation coefficient between j-component and i-band ($r_{i,j}$)

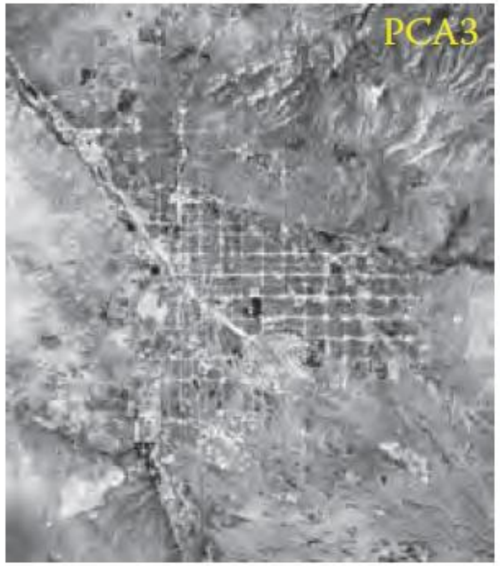
Standard deviation of i-band (s_i)

TABLE 7.1
Variance–Covariance Matrix of the Tucson Image

	B1	B2	B3	B4	B5	B7
B1	1443.30					
B2	443.07	243.85				
B3	1043.43	414.51	1166.48			
B4	859.79	260.55	503.65	630.02		
B5	999.67	319.26	665.64	664.89	741.61	
B7	1020.65	342.95	1065.25	492.80	642.28	1039.70

TABLE 7.2
Eigenvector Matrix of the Tucson Image

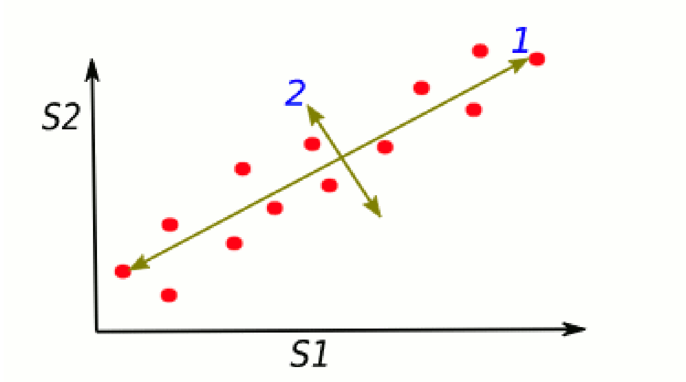
	B1	B2	B3	B4	B5	B7	λ	Variance (%)
CP1	0.552	0.188	0.465	0.320	0.380	0.444	4477.44	85.04
CP2	0.285	–0.017	–0.546	0.503	0.385	–0.468	613.23	11.65
CP3	0.250	–0.847	–0.252	–0.033	–0.063	0.389	112.82	2.14

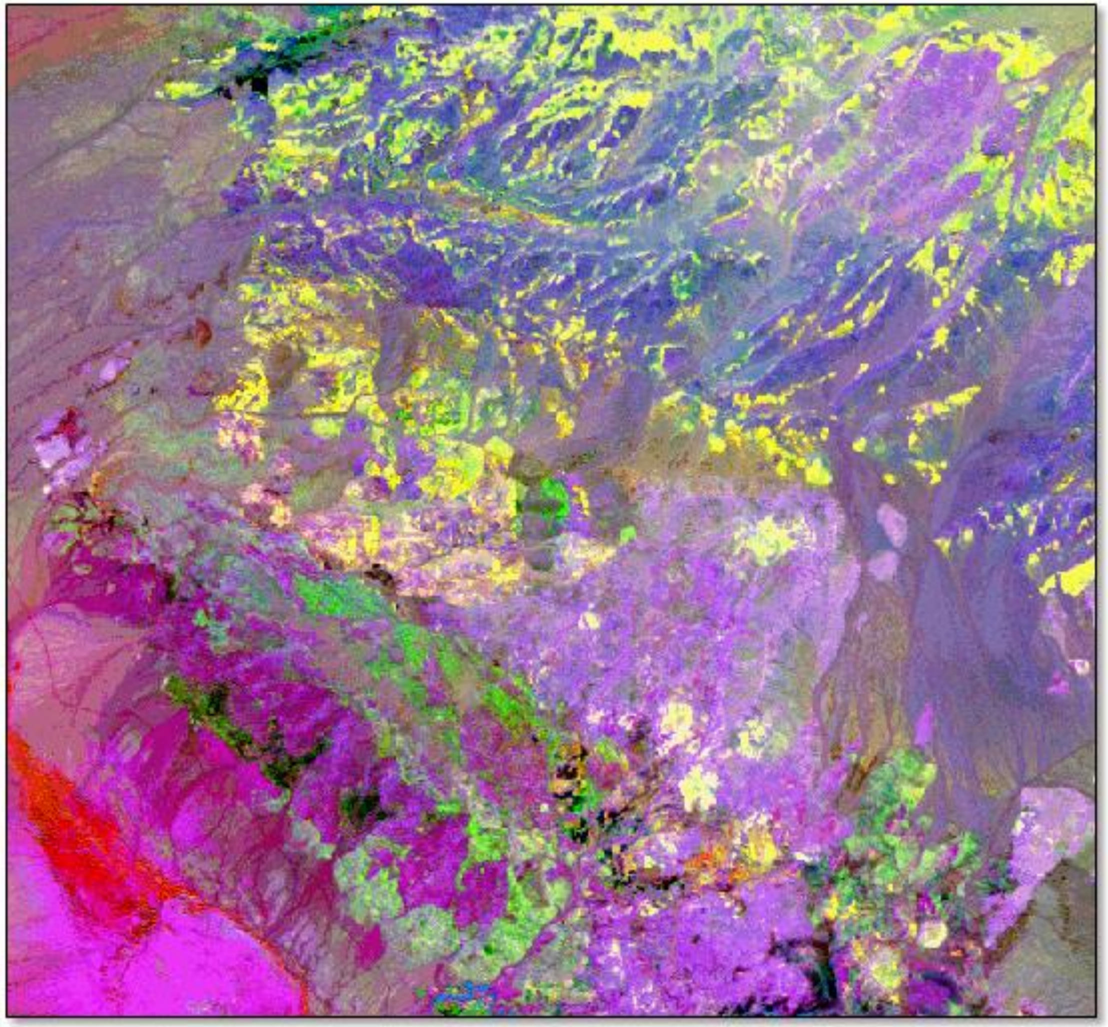


How can these information be used?

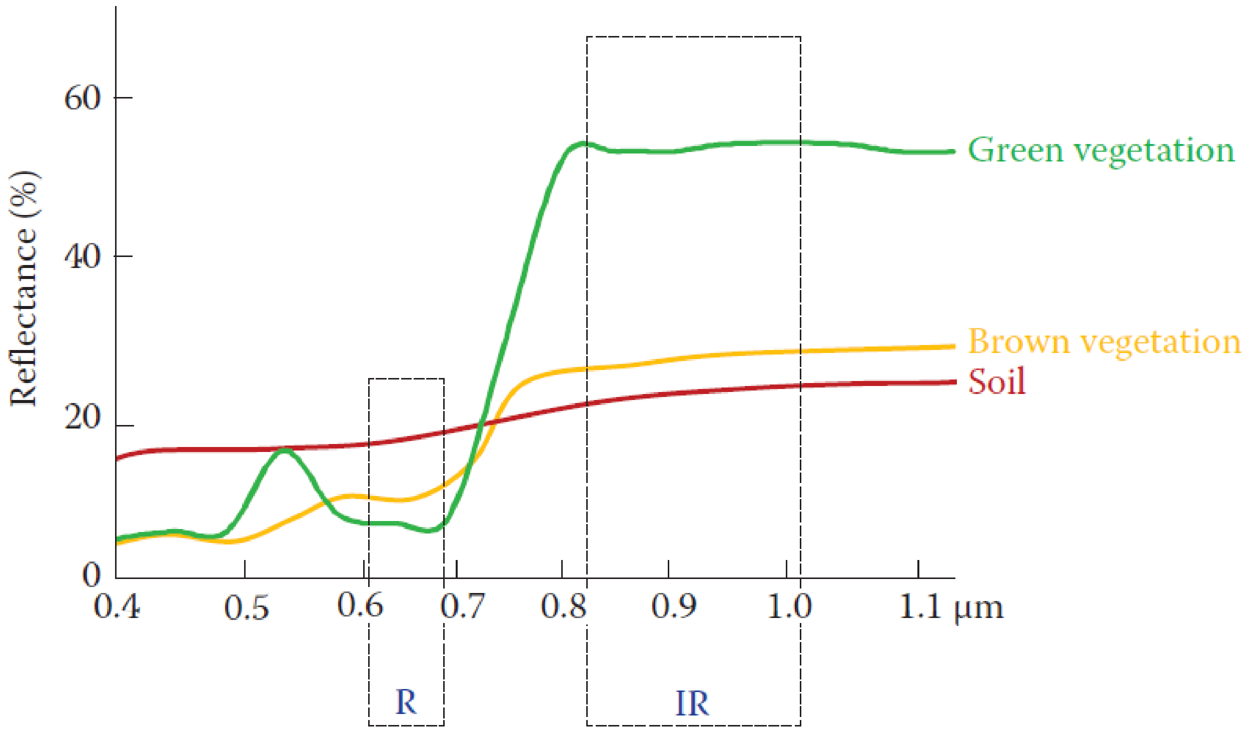
PCA scores = coordinates of each pixel/spatial unit in the space created by the retained PCs)

- Visual inspection: generate images and check which features can be discriminated
- Use PCs with the highest variance explained for multitemporal classification
- Use PCs' scores to detect changes between two or more dates





SPECTRAL VEGETATION INDICES (VIs)



The calculation of VIs is a simple and robust technique to extract quantitative information on the amount of vegetation or greenness.

The most used one involves the use of two bands:

- Red = R
- Near-InfraRed = NIR

Could you tell me why?

The goal is to combine R and NIR to enhance the vegetation signal.

SPECTRAL VEGETATION INDICES (VIs)

VIs can be used as direct measure of greenness, but can also be used as a proxy of biophysical variables:

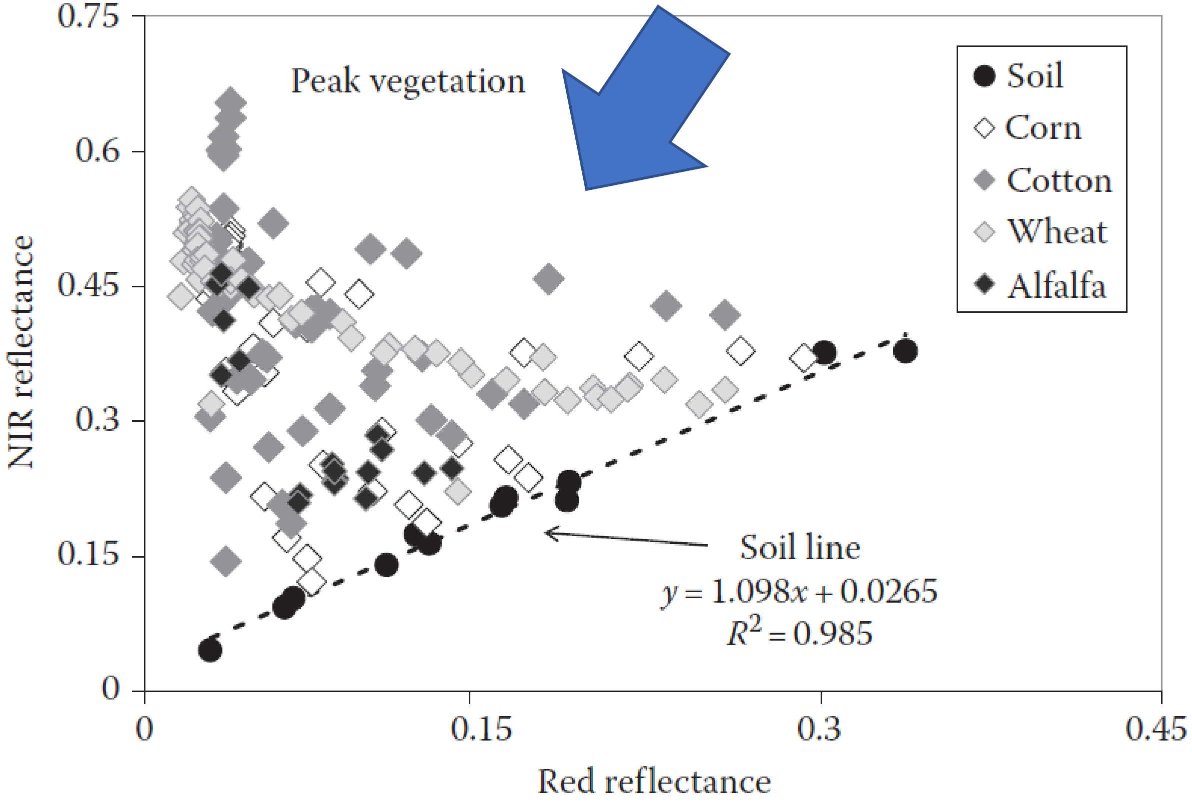
- Leaf Area Index
- fAPAR
- Green Vegetation Fraction (Fv)
- Biomass
- Photosynthesis

Indeed, greenness is a composite signal of leaf chlorophyll content, leaf area, canopy cover, canopy structure

↓

VI = "integrator" of many variables that together determine the photosynthetically active vegetation signal.

SPECTRAL VEGETATION INDICES (VIs)



Starting point = structure of vegetation spectra in R-NIR space

There is a **TRIANGULAR PATTERN**:

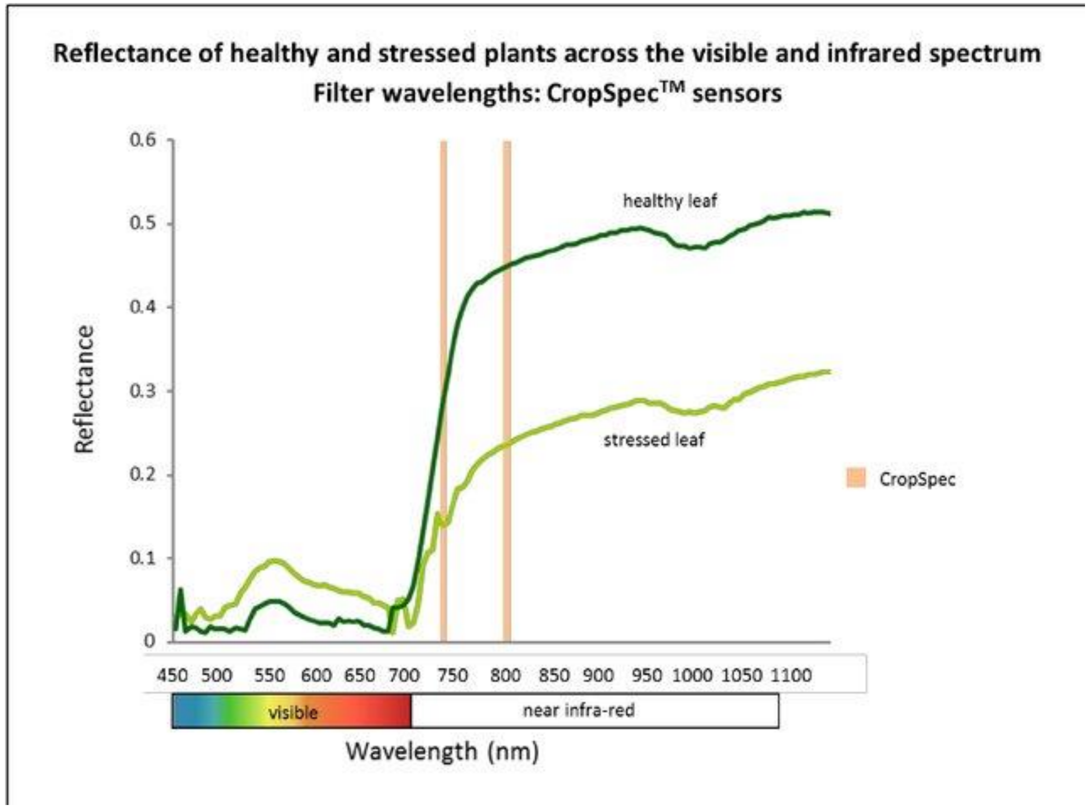
- One side is represented by the "soil line", which indicates the absence of vegetation
- Green apex of maximum NIR and minimum R

On these basis, the task of a VI is to quantify the amount of vegetation present in a pixel based on its position in the R-NIR space

Different ways to calculate VIs:

1. Band ratios
2. Normalized differences
3. Linear Band Combinations
4. Optimized band combinations

$$SR = \frac{\rho_{NIR}}{\rho_R}$$



SR = simple ratio, the most simple one

It allows separating healthy vegetation from non-vegetation cover types

The main limitation regards the fact that both low and stressed vegetation have reduced reflectance in NIR and higher in R

Low SR values may both indicate low quantity of vegetation and high amount of stressed vegetation.

Ratios are useful in their ability to reduce many forms of multiplicative noise:

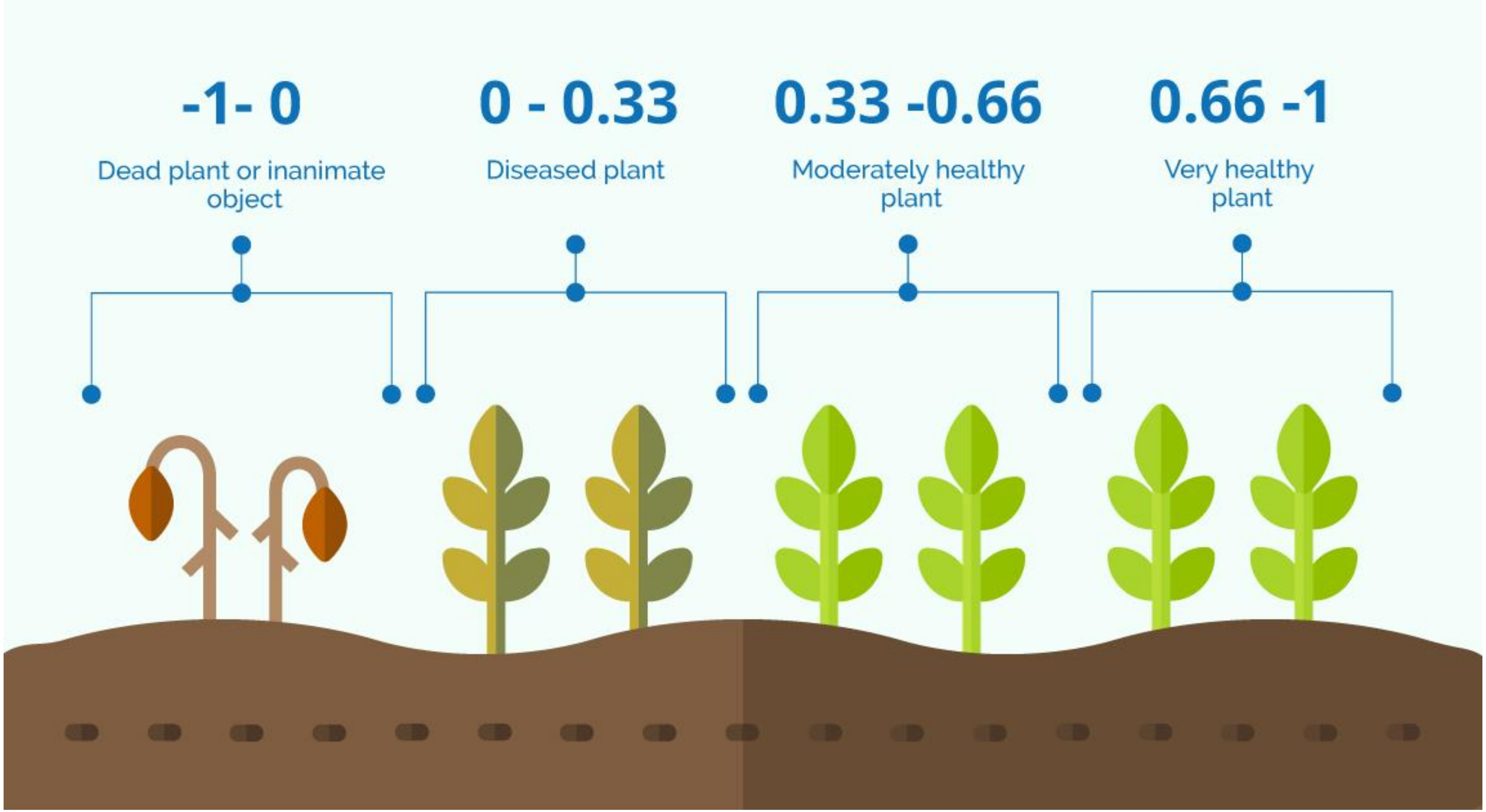
- illumination differences
- atmospheric attenuation
- cloud shadows
- topographic variations (slope, aspect)

$$NDVI = \frac{\rho_{NIR} - \rho_{R}}{\rho_{NIR} + \rho_{R}}$$

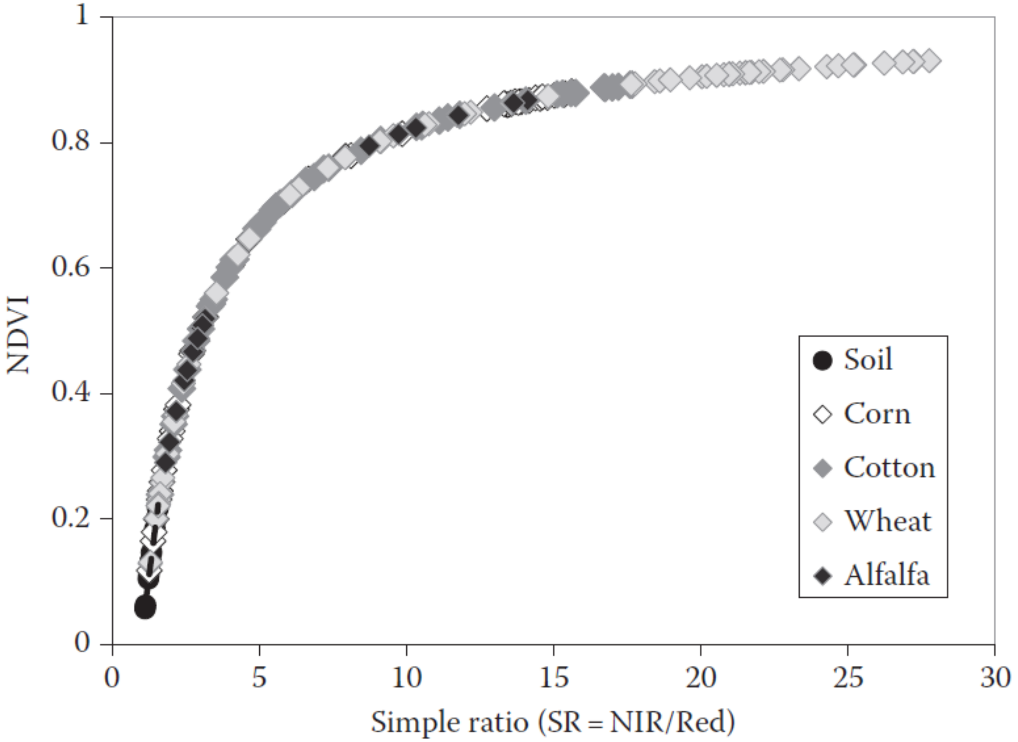
BAND	SPECTRAL	WAVELEN. [μm]	GEOM. [m]
1	aerosols	0.429 – 0.457	60
2	blue	0.451 – 0.539	10
3	green	0.538 – 0.585	10
4	red	0.641 – 0.689	10
5	red edge	0.695 – 0.715	20
6	red edge	0.731 – 0.749	20
7	red edge	0.769 – 0.797	20
8	NIR	0.784 – 0.900	10
8a	narrow NIR	0.855 – 0.875	20
9	water vapour	0.935 – 0.955	60
10	SWIR cirrus	1.365 – 1.385	60
11	SWIR	1.565 – 1.655	20
12	SWIR	2.100 – 2.280	20

NDVI = normalized different vegetation index

It ranges from -1 to 1+1


-1- 0
Dead plant or inanimate object
0 - 0.33
Diseased plant
0.33 -0.66
Moderately healthy plant
0.66 -1
Very healthy plant

SPECTRAL VEGETATION INDICES (VIs) – Normalized indices



Non linear relationship with SR, meaning that NDVI is highly sensitive to low and sparse vegetation.

When 0 < NDVI < 0.5, then 1 < SR < 3

But…

When 0.5 < NDVI < 0.9, then 3 < SR < 19

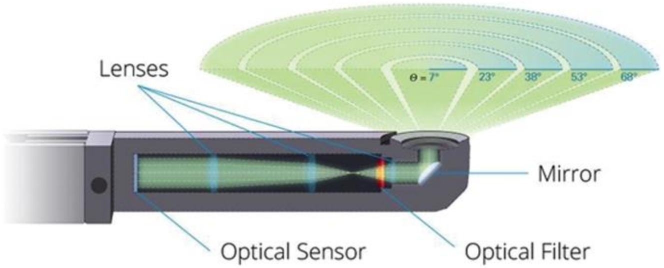
The advantages of NDVI are

- More stable
- Less sensitive to external variations

NDVI has been used as a proxy of several biophysical variables:

1. **Leaf Area Index (LAI)**: one of the fundamental vegetation biophysical variables. It is defined as the ratio between total canopy leaf area and its projected area on the ground.

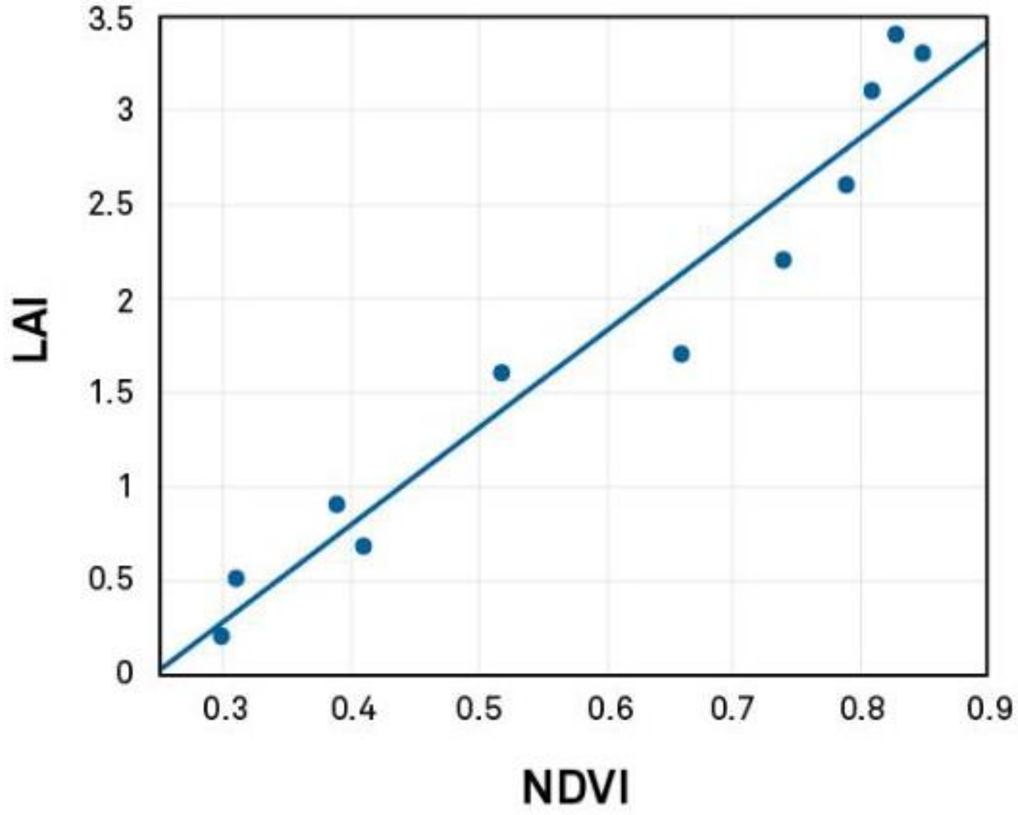
Hemispherical photos



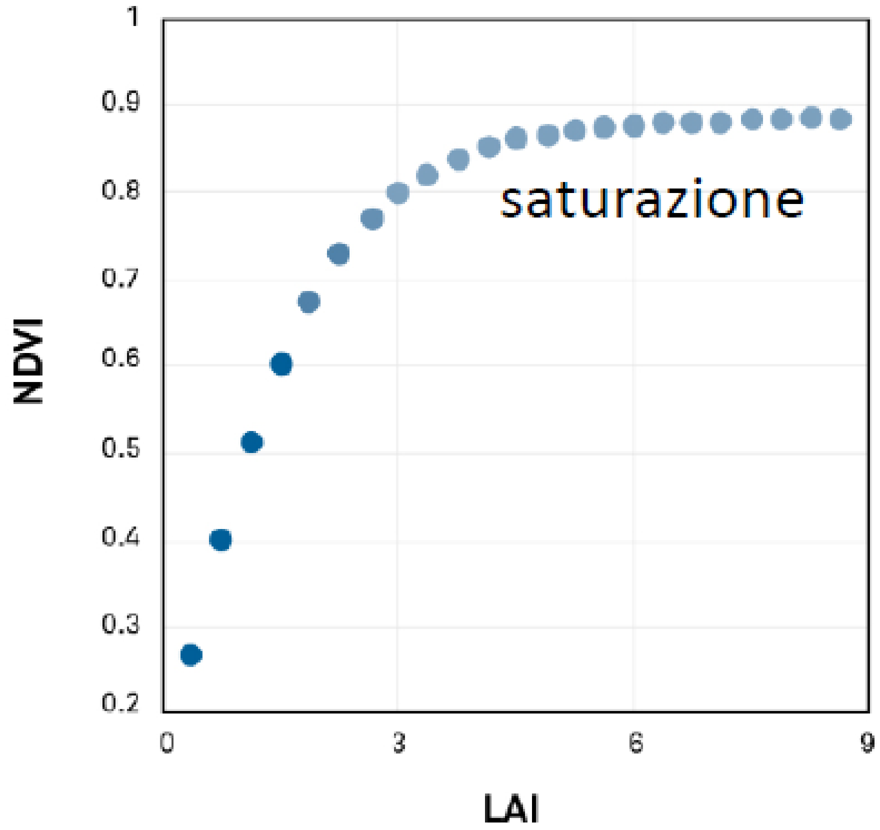
LAI 2200C Plant Canopy Analyzer

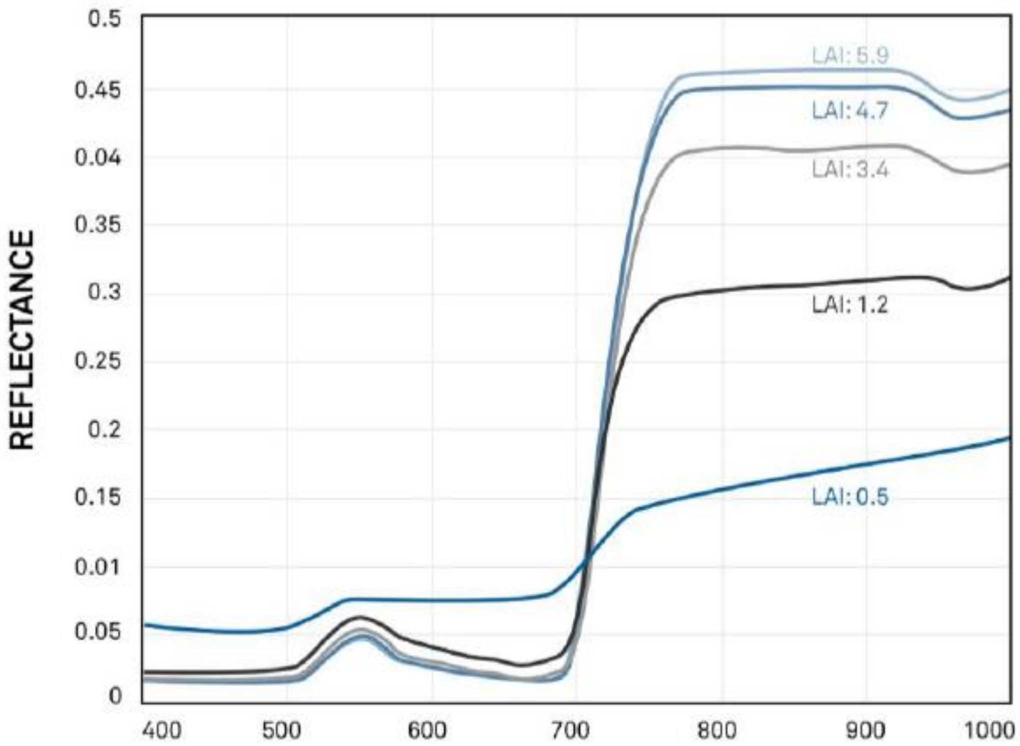
https://www.licor.com/env/products/leaf_area/LAI-2200C/applications

classe	LAI medio	dev std
acero-frassineto	3,56	±1,35
betuleto	4,45	±0,90
carpineto	3,75	±0,69
castagneto	4,09	±0,84
corileto	4,73	±0,57
faggeta	4,01	±1,06
ostrio-querceto	2,84	±0,83
pecceta	3,58	±0,98
piceo-faggeta	3,26	±0,61
rimboschimento	2,84	±1,83
rovereto	2,57	±0,55



SPECTRAL VEGETATION INDICES (VIs) – Normalized indices





Saturation!!! at high LAI values.

NDVI is not a good proxy of LAI when vegetation is dense!

NDVI has been used as a proxy of several biophysical variables:

1. **Leaf Area Index (LAI)**: one of the fundamental vegetation biophysic
   as the ratio between total canopy leaf area and its projected area o

2. **Fractional vegetation cover (Fv)**: minimal saturation issue compare

3. **Fraction of photosynthetically active radiation absorbed by plants**

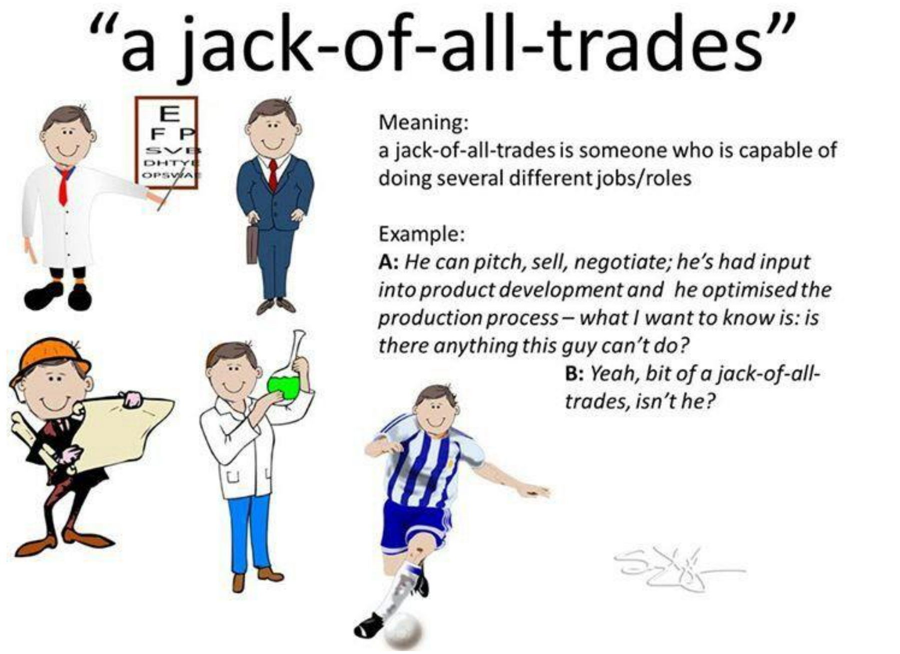
4. **Chlorophyll content**

5. **Water content**

6. **Net CO_2 flux**

7. **Gross and Primary productivity** of vegetation

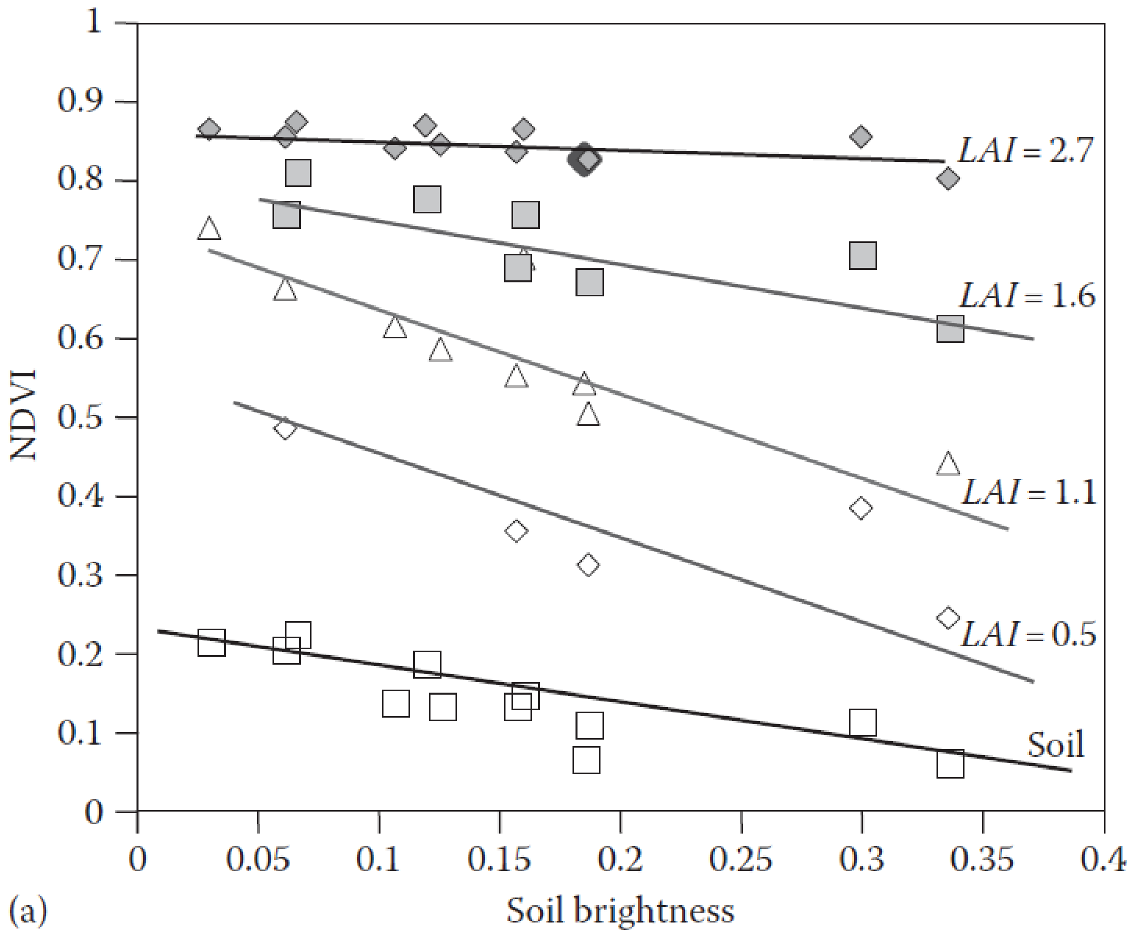
8. **Evapotranspiration**



SPECTRAL VEGETATION INDICES (VIs) – Optimized indices

Normalized indices have some disadvantages:

- Non-linear behaviour
- Sensitivity to soil brightness
- NDVI saturation at very high or very vegetation densities



Optimized indices introduced corrections, designed to measure NIR and R contrast of a pixel removing unwanted non-vegetation objects.

Soil correction factor: related to different optical penetration of R and NIR through vegetation canopy

$$SAVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R + L}(1+L)$$

Soil Adjusted Vegetation Index

BAND	SPECTRAL	WAVELEN. [μm]	GEOM. [m]
1	aerosols	0.429 – 0.457	60
2	blue	0.451 – 0.539	10
3	green	0.538 – 0.585	10
4	red	0.641 – 0.689	10
5	red edge	0.695 – 0.715	20
6	red edge	0.731 – 0.749	20
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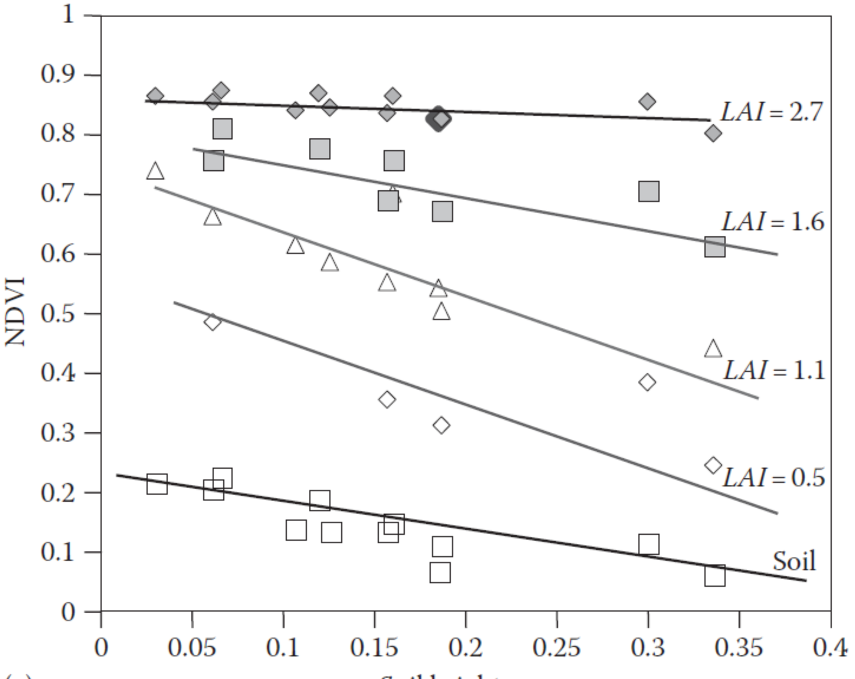
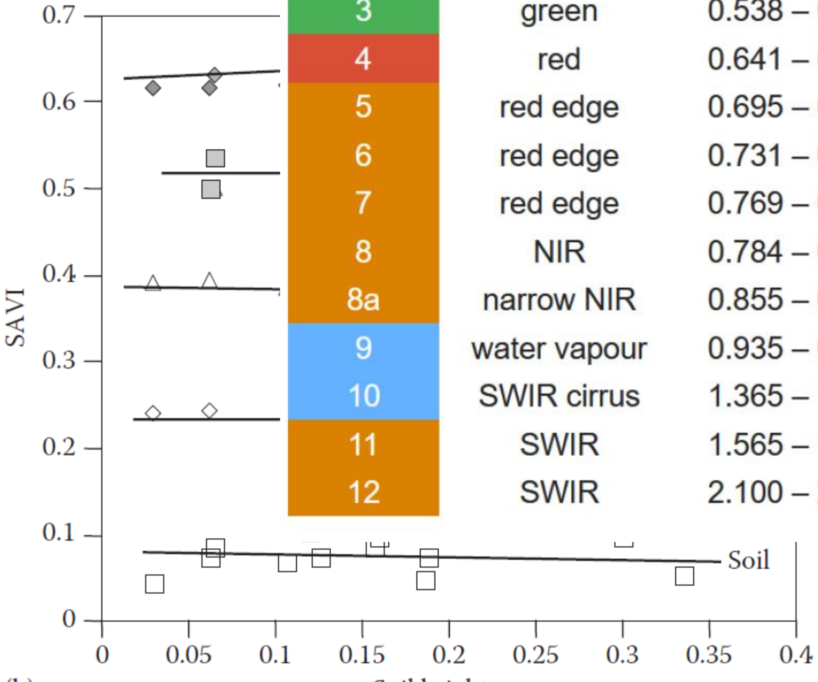
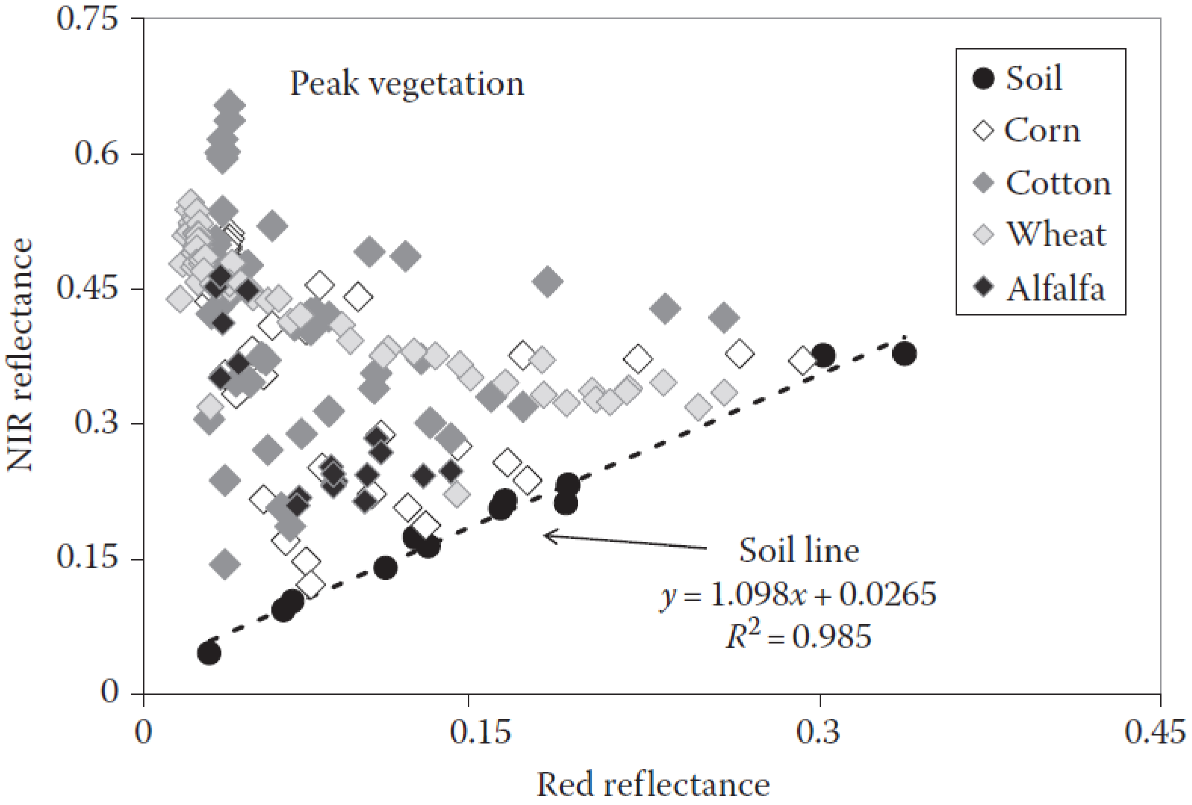


(a)



(b)



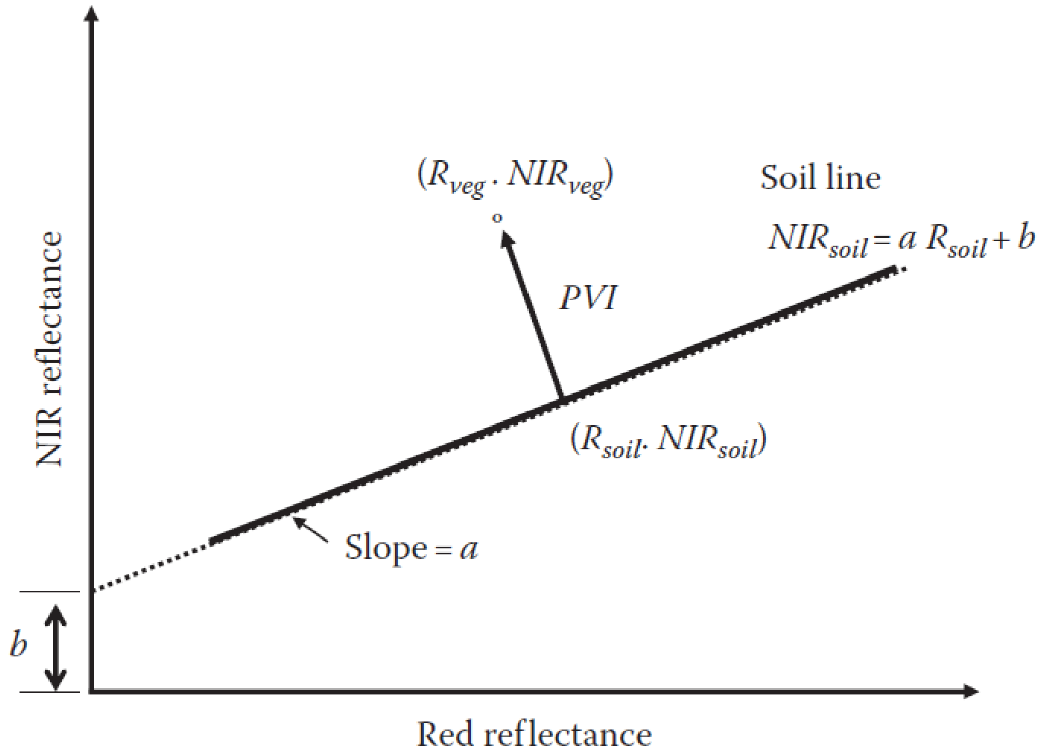
$$TSAVI = \frac{a(\rho_{NIR} - a\rho_R) - b}{a\rho_{NIR} + \rho_R + ab}$$

Correction using local-, regional- or global-based soil line. a and b are the coefficient of the linear equation in the figure.

In these VI, the contrast between R and NIR is measured by subtracting or linearly combining the R and NIR bands.

$$PVI = \frac{(\rho_{NIR} - a * \rho_R) - b)}{(1 + a^2)^{1/2}}$$

Perpendicular vegetation index



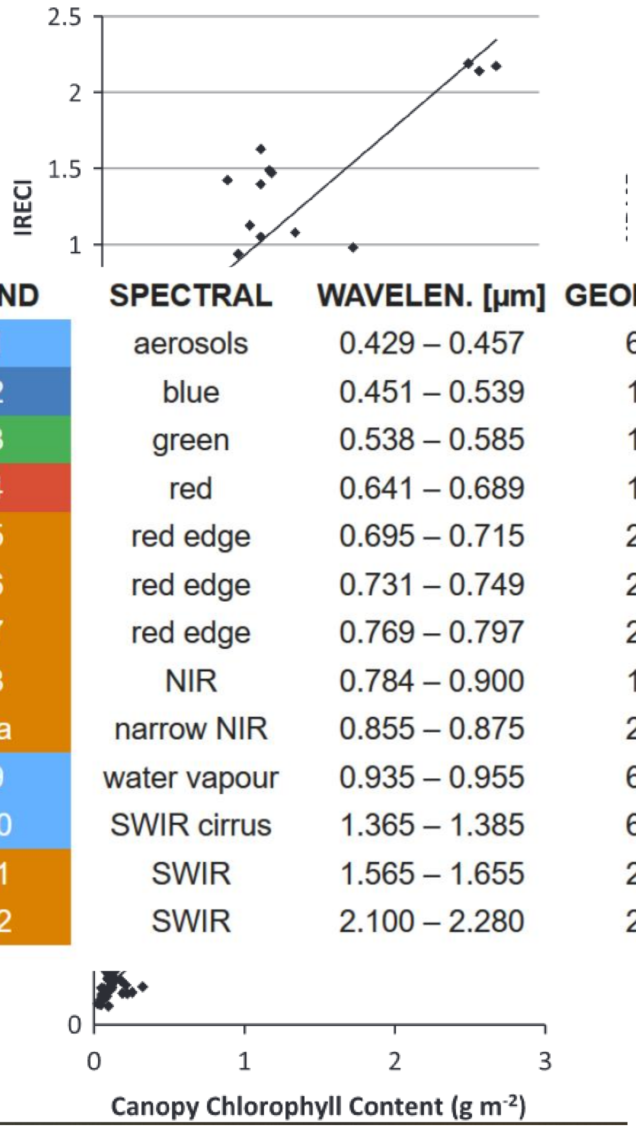
SPECTRAL VEGETATION INDICES (VIs) – Beyond NIR and R region

$$\mathrm{IRECI} = \frac{(\rho_{RE/NIR} - \rho_R)}{(\rho_{RE1}/\rho_{RE2})}$$

IRECI = Inverted Red-Edge Chlorophyll Index

It uses Red Edge bands, which combine the effects of strong chlorophyll absorption and leaf internal scattering

Frampton et al. 2013 ISPRS



BAND	SPECTRAL	WAVELEN. [µm]	GEOM. [m]
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7	red edge	0.769 – 0.797	20
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10	SWIR cirrus	1.365 – 1.385	60
11	SWIR	1.565 – 1.655	20
12	SWIR	2.100 – 2.280	20

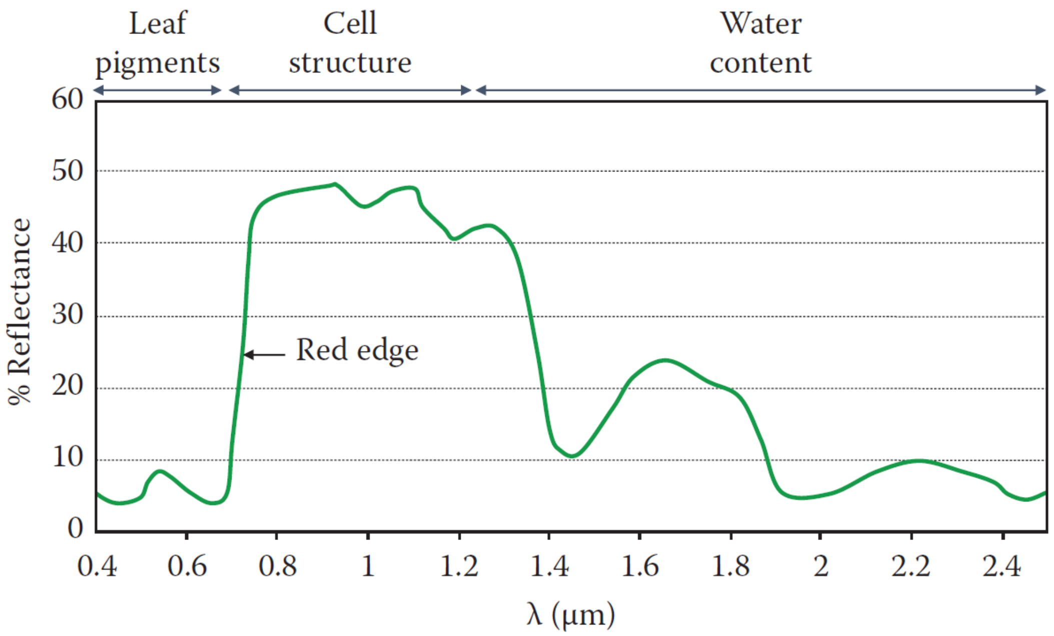
GNDVI = green NDVI

It uses the green band, and it is considered a proxy of the photosynthetic activity of the vegetation

$$GNDVI = \frac{(\rho_{NIR} - \rho_G)}{(\rho_{NIR} + \rho_G)}$$

Often used to asses water and nitrogen content

$$NDWI = \frac{(\rho_{NIR} - \rho_{SWIR})}{(\rho_{NIR} + \rho_{SWIR})}$$



https://www.indexdatabase.de/

https://custom-scripts.sentinel-hub.com/custom-scripts/sentinel-2/indexdb/