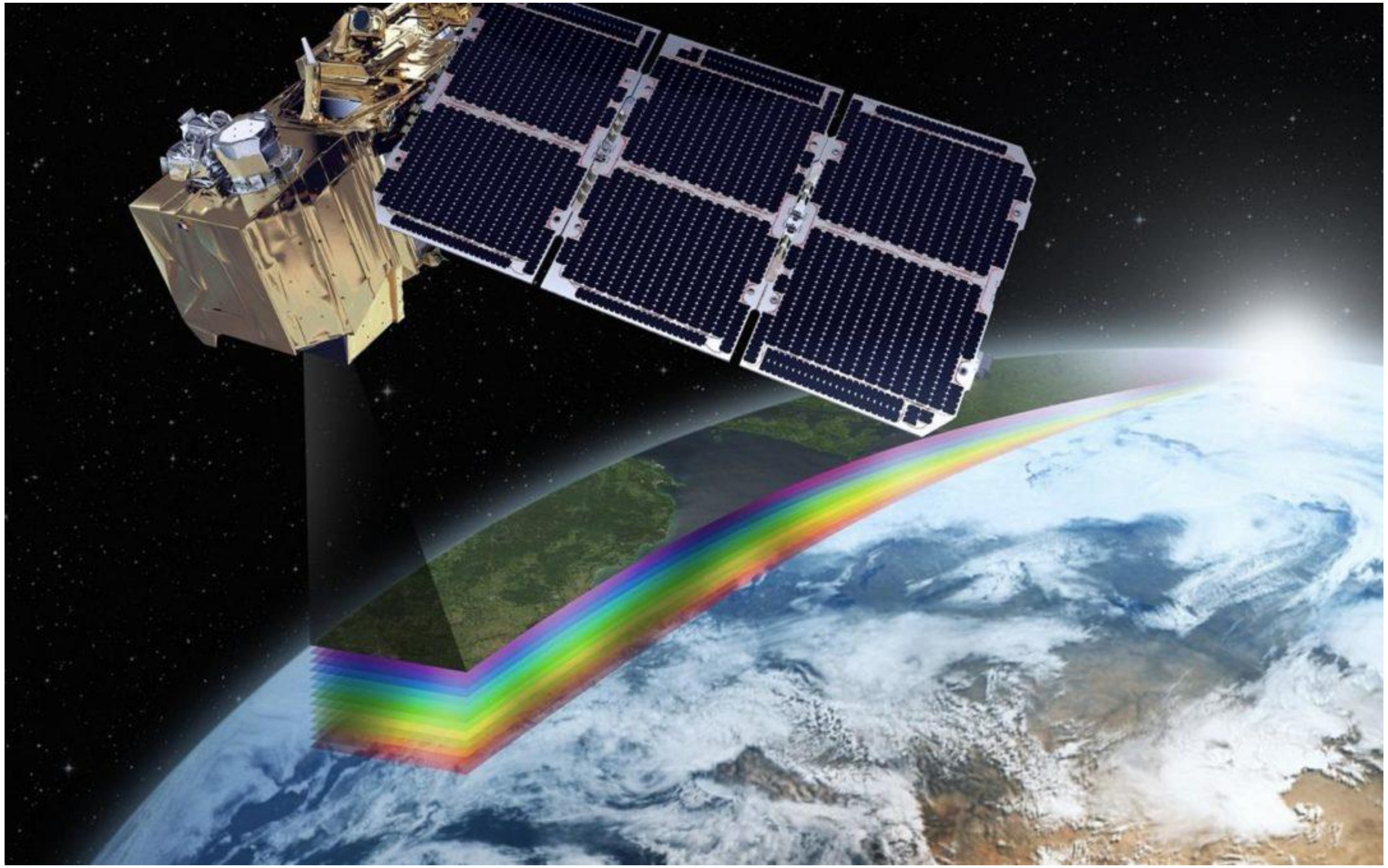
UNIVERSITÀ DEGLI STUDI DI TRIESTE



Course:

Remote Sensing of Global Changes

Dr. Francesco Petruzzellis

PhD student Valentina Olmo

Part 4

Remote Sensing of Biodiversity – Study cases

SCIENCE OF REMOTE SENSING

UNIVERSITÀ
DEGLI STUDI DI TRIESTE

DIPARTIMENTO DI
SCIENZE DELLA VITA

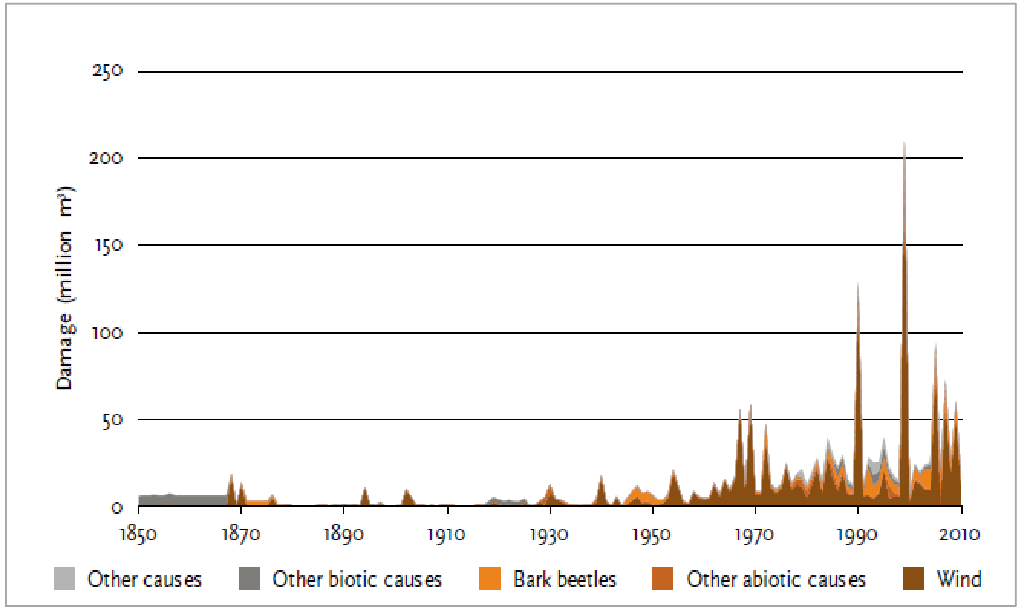
Use of Sentinel satellite data for windthrows monitoring and delimiting: the case of “Vaia” storm in Friuli Venezia Giulia (North-Eastern Italy)

Valentina Olmo

STORM-ASSOCIATED DAMAGE IN FORESTS

In **Europe**

1/2 of forest damages is due to extremely intense winds



Total damage occurring in European forests (million m^3) due to different disturbances. (Modified from: Schelhaas 2008).

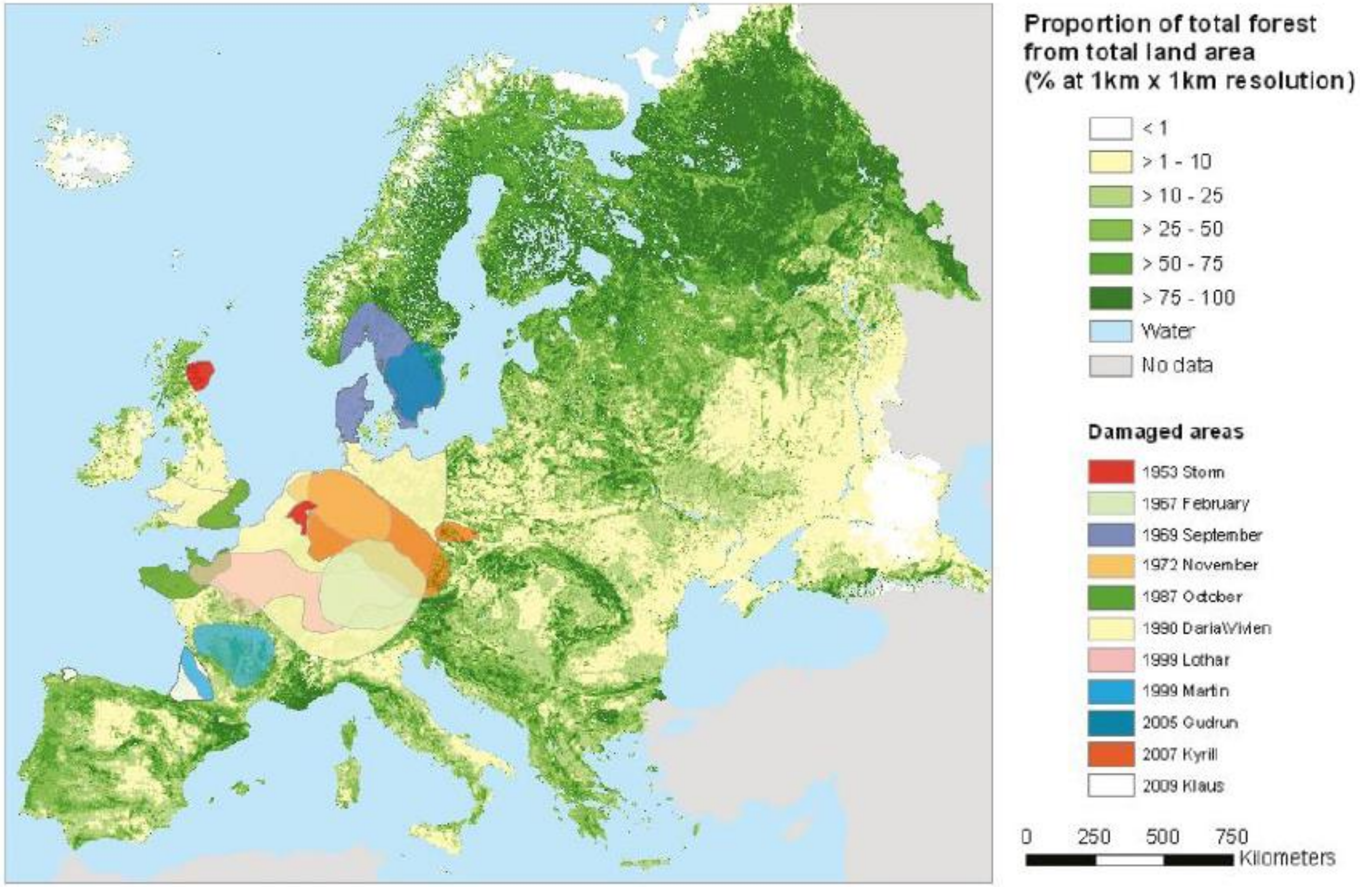
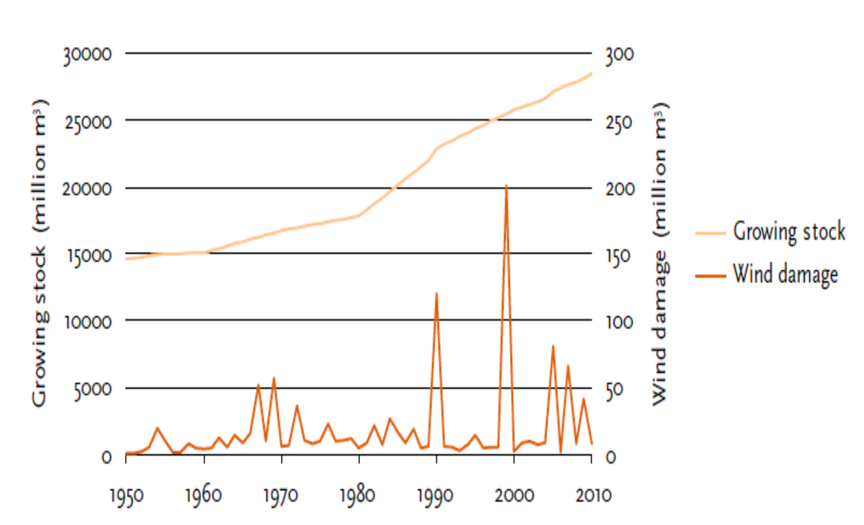


Figure 4: Estimated areas affected by selected storms. From: Gardiner et al., 2010.

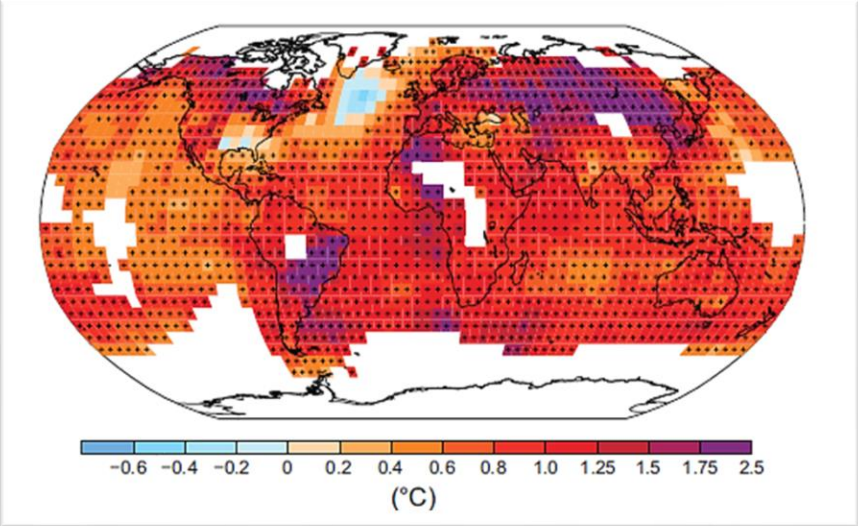
Damage increase causes:

1. Forest management

2. Climate change



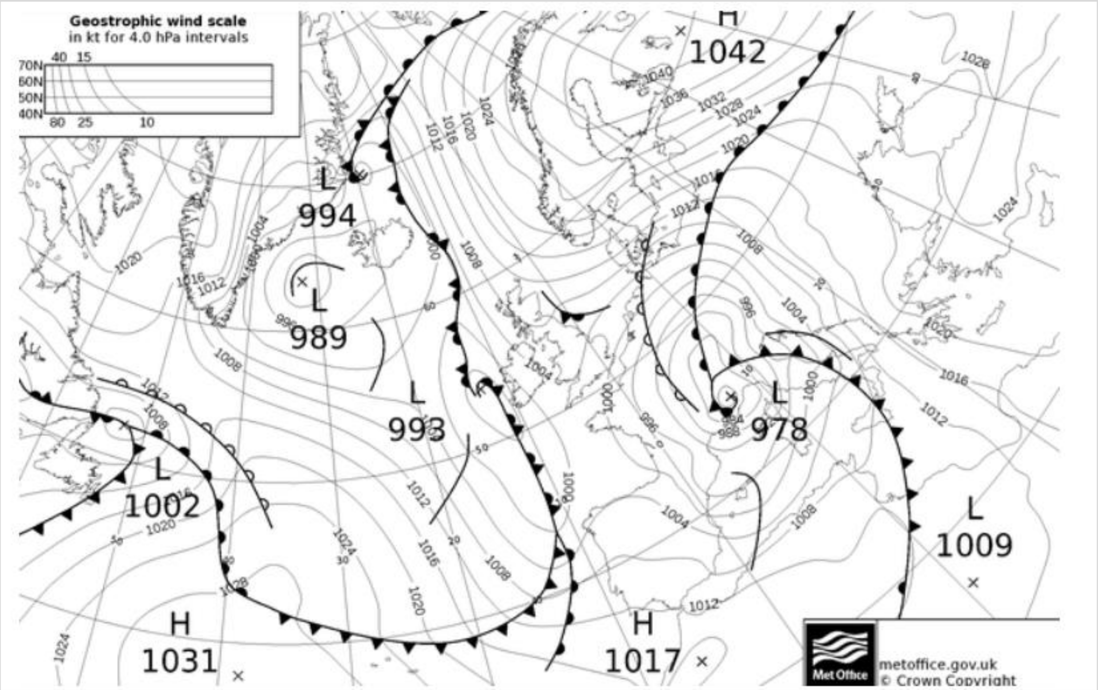
Development of growing stock and damage caused by storms in the period 1950–2010. From: Gardiner et al., 2013.



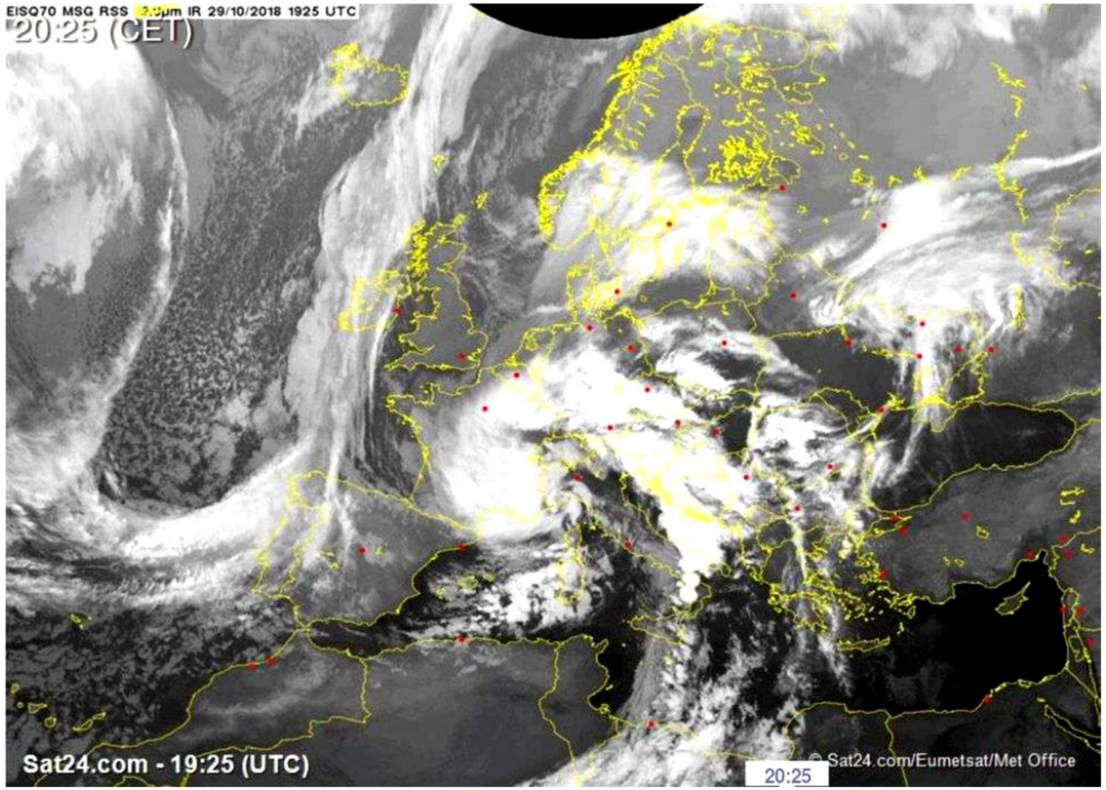
Observed change in surface temperature 1901-2012. From: IPCC, 2013.

Vaia

Saturday 27th - Tuesday 30th October 2018



Geostrophic wind map on October 29, 18 UTC. (From: MetOffice).



Vaia storm from Meteosat-11 satellite infrared channel on October 29, 8:25 PM.(From: Eumetasat).

Vaia

Saturday 27th - Tuesday 30th October 2018

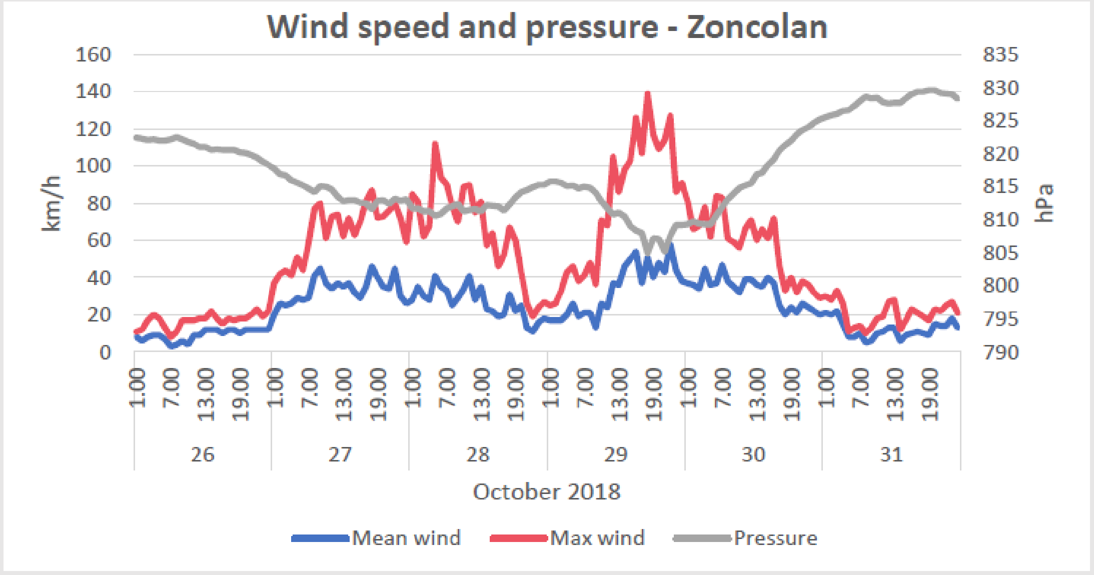


Figure 22: Wind mean and maximum speed and pressure at Zoncolan climatic station.

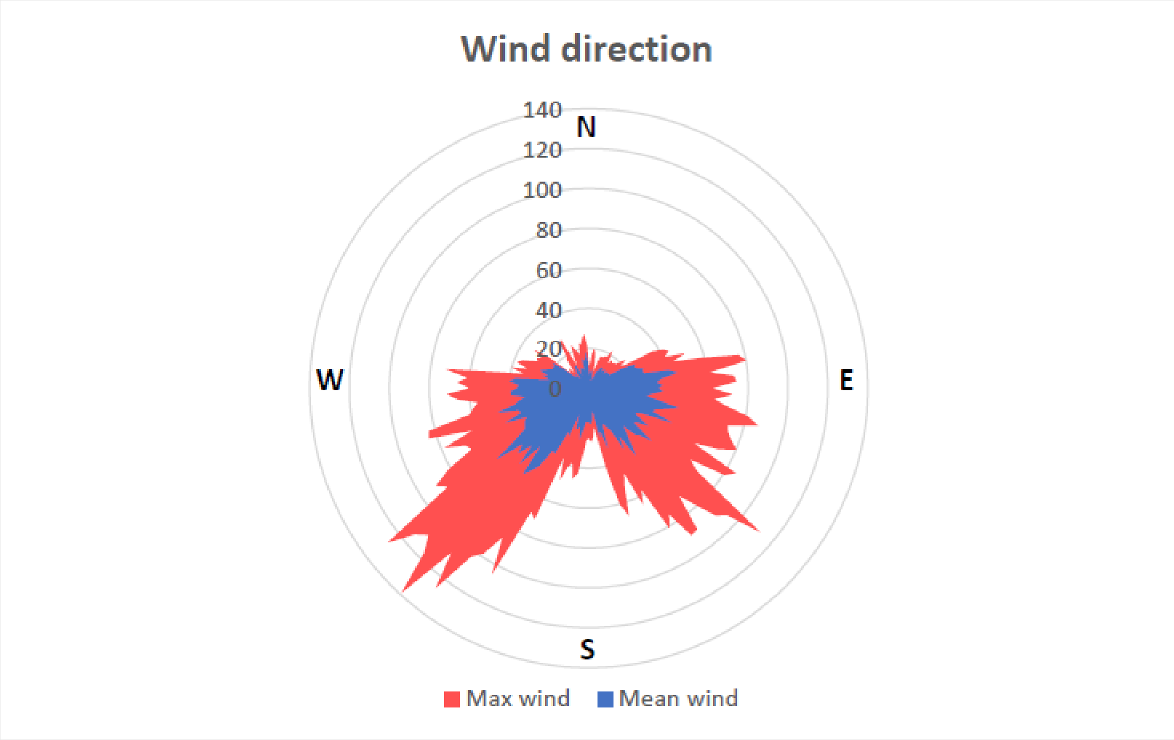


Figure 23: Direction of mean and maximum wind speed (km/h) at Zoncolan climatic station

VAIA ESTIMATED DAMAGE

8 million $\mathbf{m^3}$

loss of standing trees

42,500 ha

of damaged forests
(3340 ha in FVG)

494

municipalities hit

Chirici et al. 2019

RADAR INSTRUMENT

sentinel-1 → Structural information

MULTISPECTRAL INSTRUMENT

sentinel-2 → Biophysical information

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)

Valentina Olmo [1,2], Enrico Tordoni [3], Francesco Petruzzellis [1,2], Giovanni Bacaro [2,*] and Alfredo Altobelli [2]

Aims

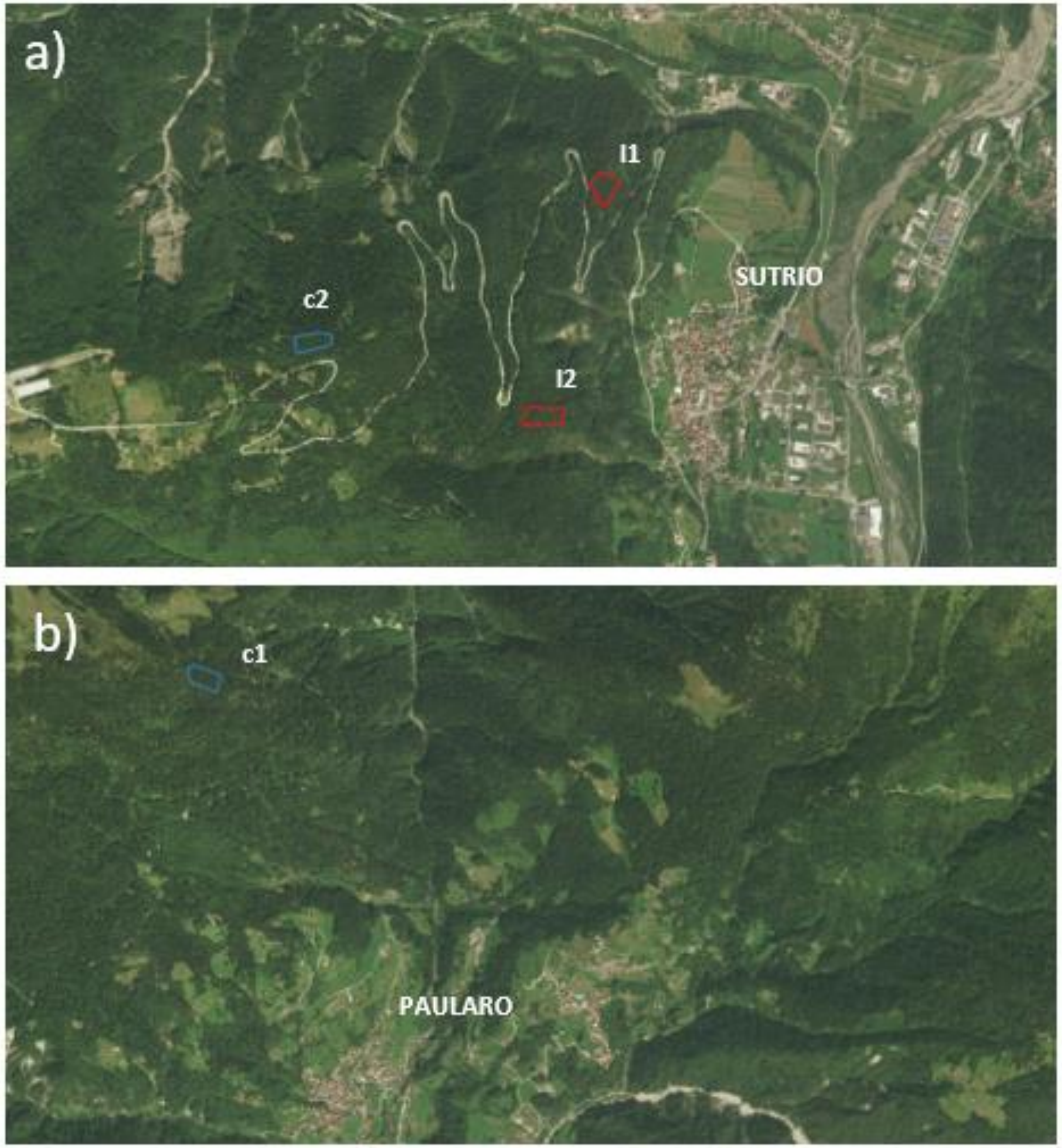
1. Monitor immediate and long-term ecological effects
2. Determine the best bands transformations (indices)
3. Produce a windthrow map of Friuli-Venezia Giulia region

Materials and Methods

STUDY AREAS

2 windthrown and
2 control sites

- Similar lithology
- 10.000 m^2
- S or E exposition
- > 40% slope
- 750 m - 1250 m a.s.l.
- *Picea abies* and *Abies alba*



Scale: 1:25000.

SENTINEL missions

- 2 identical satellites phased at 180°
- Near-polar, sun-synchronous orbit
- 10-12 days repeat cycle (each)

sentinel-1

Radar imaging (band-C)

Products:

- Interferometric Wide Swath
- Level-1 Ground Range Detected
- High Resolution

→ Dual-polarisation modes (VV+VH)

→ Spatial res. 10m

sentinel-2

Multispectral imaging

Products:

- Level 2A

→ 13 bands

→ Spatial res. 10-20-60m

8

Vegetation indices

Index	Name	Reference
$GNDVI=\frac{B8-B3}{B8+B3}$	Green Normalized Difference Vegetation Index	Gitelson et al., 1996
$IRECI=\frac{B7-B4}{B5/B6}$	Inverted Red-Edge Chlorophyll Index	Frampton et al., 2013
$NDREDI=\frac{B5-B2}{B5+B2}$	Normalized Difference Red-Edge Blue Index	Einzmann et al., 2017
$NDVI=\frac{B8-B4}{B8+B4}$	Normalized Difference Vegetation Index	Rouse et al., 1974
$NDWI=\frac{B8-B11}{B8+B11}$	Normalized Difference Water Index 11	Chen et al., 2005
$NDWI8A=\frac{B8A-B11}{B8A+B11}$	Normalized Difference Water Index 11 with 8A band	
$PSRI=\frac{B4-B2}{B6}$	Plant Senescence Reflectance Index	Merzlyak et al., 1999
$SLAVI=\frac{B8}{B4+B12}$	Specific Leaf Area Vegetation Index	Lymburner et al., 2000

REMOTE SENSING DATA PROCESSING

sentinel-1

Sentinel-1
9 dates

SNAP
Radiometric calibration
Speckle filtering
Terrain correction
Db conversion

GRASS GIS

VV & VH
4 sites

R software environment

sentinel-2

Sentinel-2
9 dates

GRASS GIS

8 Vis
4 sites

R software environment

CHANGE DETECTION PROCESSING

Image differencing

Pre = 23rd of October 2018

Post = 4th of November 2018

sentinel-1

$$\mathbf{WI} = (\sigma^0_{VV,\,post} - \sigma^0_{VV,\,pre}) + (\sigma^0_{VH,\,post} - \sigma^0_{VH,\,pre})$$

Ruetschi et al. (2019)

→ Habitat map → **a** (index) = 2,9; **n** (pixels) = 27

CHANGE DETECTION PROCESSING

Image differencing

Pre = 21st of April 2018

Post = 21st of April 2019

sentinel-2

$$\boldsymbol{NDWI8A_{diff}} = NDWI8A_{pre} - NDWI8A_{post}$$

SCL mask

pre = 4

post = 4 & 5

Habitat map

a (index) = 0,15

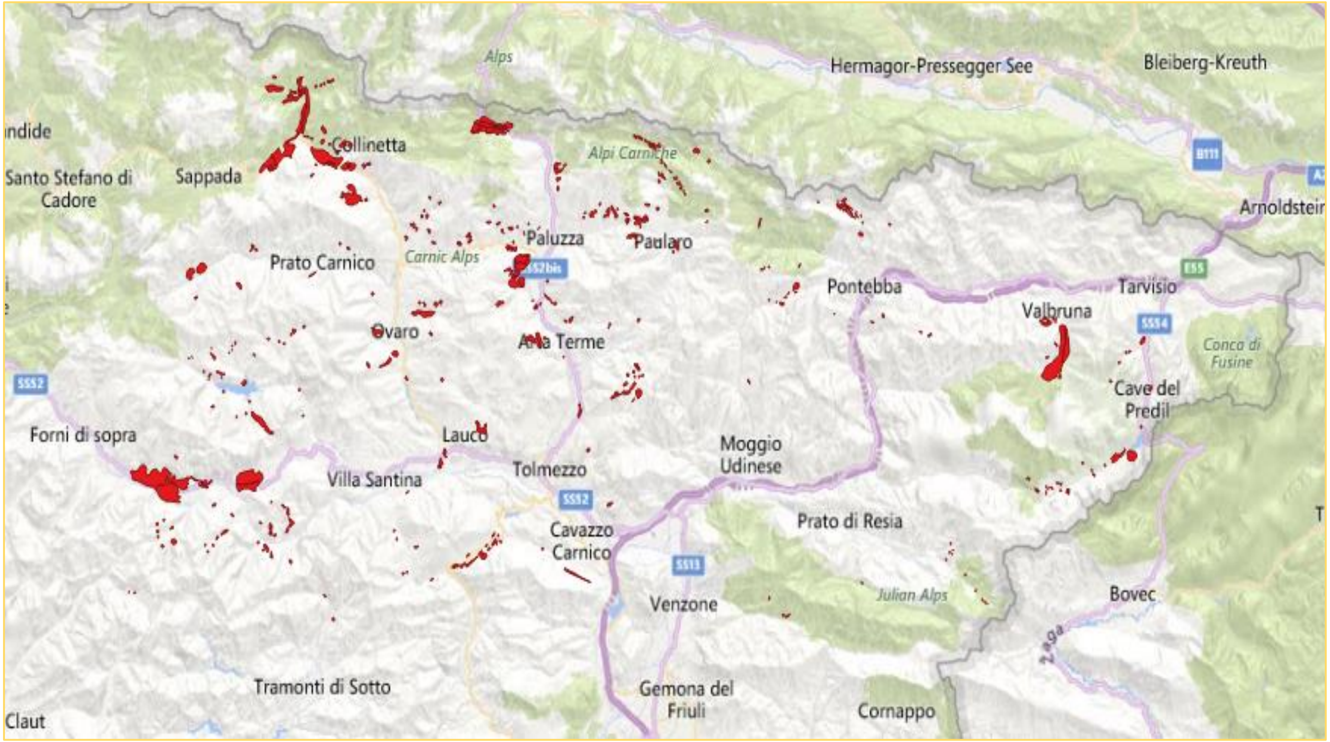
n (pixels) = 2

MAP VALIDATION

1. Field assessments
2. Visual inspections & spatial statistics

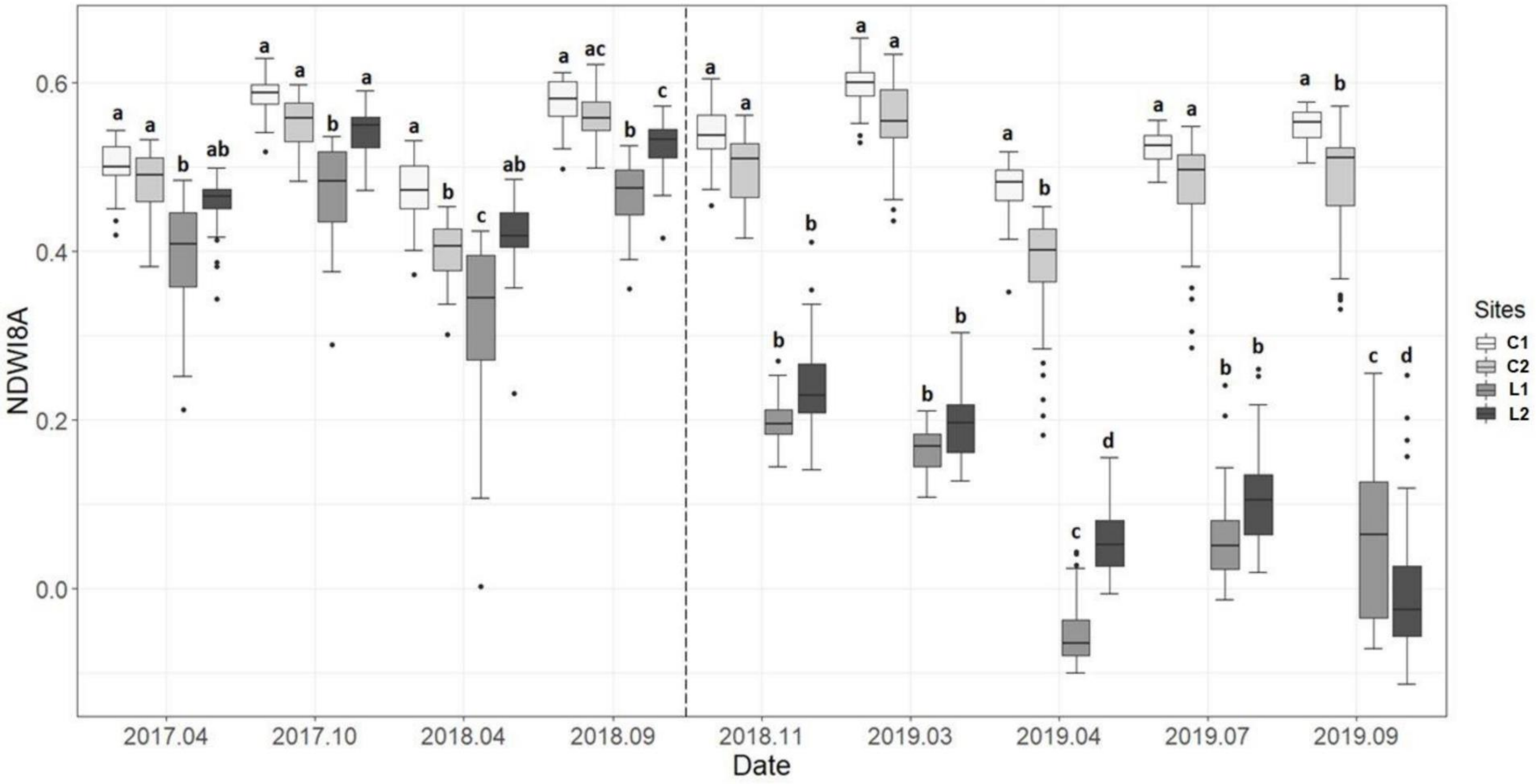
Reference map:

Regional Forest System



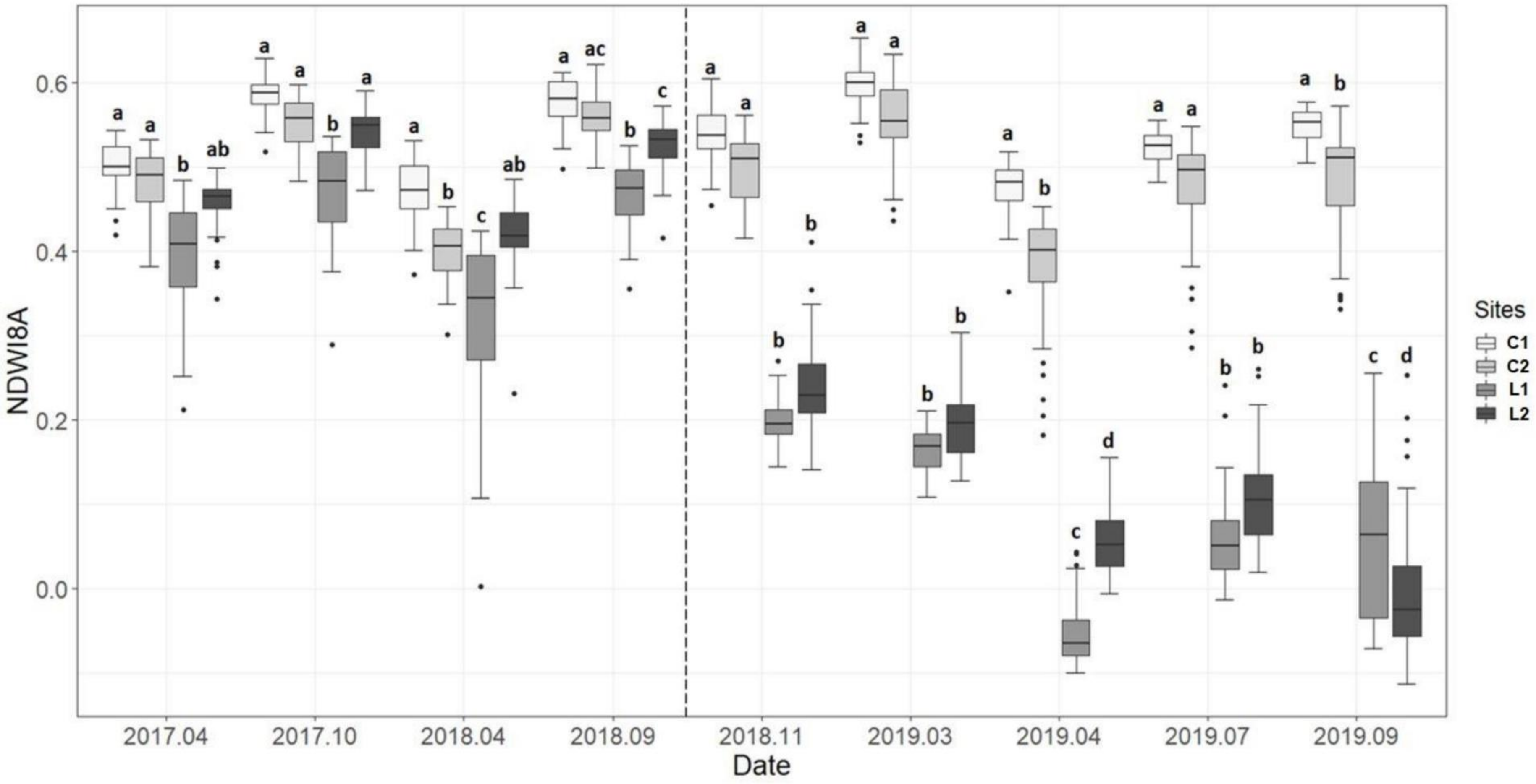
Results

SENTINEL-2 TEMPORAL PROFILES



$$\text{NDWI8A} = \frac{B8A - B11}{B8A + B11}$$

Date
21 April 2017
08 October 2017
21 April 2018
26 September 2018
15 November 2018
05 March 2019
21 April 2019
23 July 2019
13 September 2019



Similar profiles

$$NDWI = \frac{B8 - B11}{B8 + B11}$$

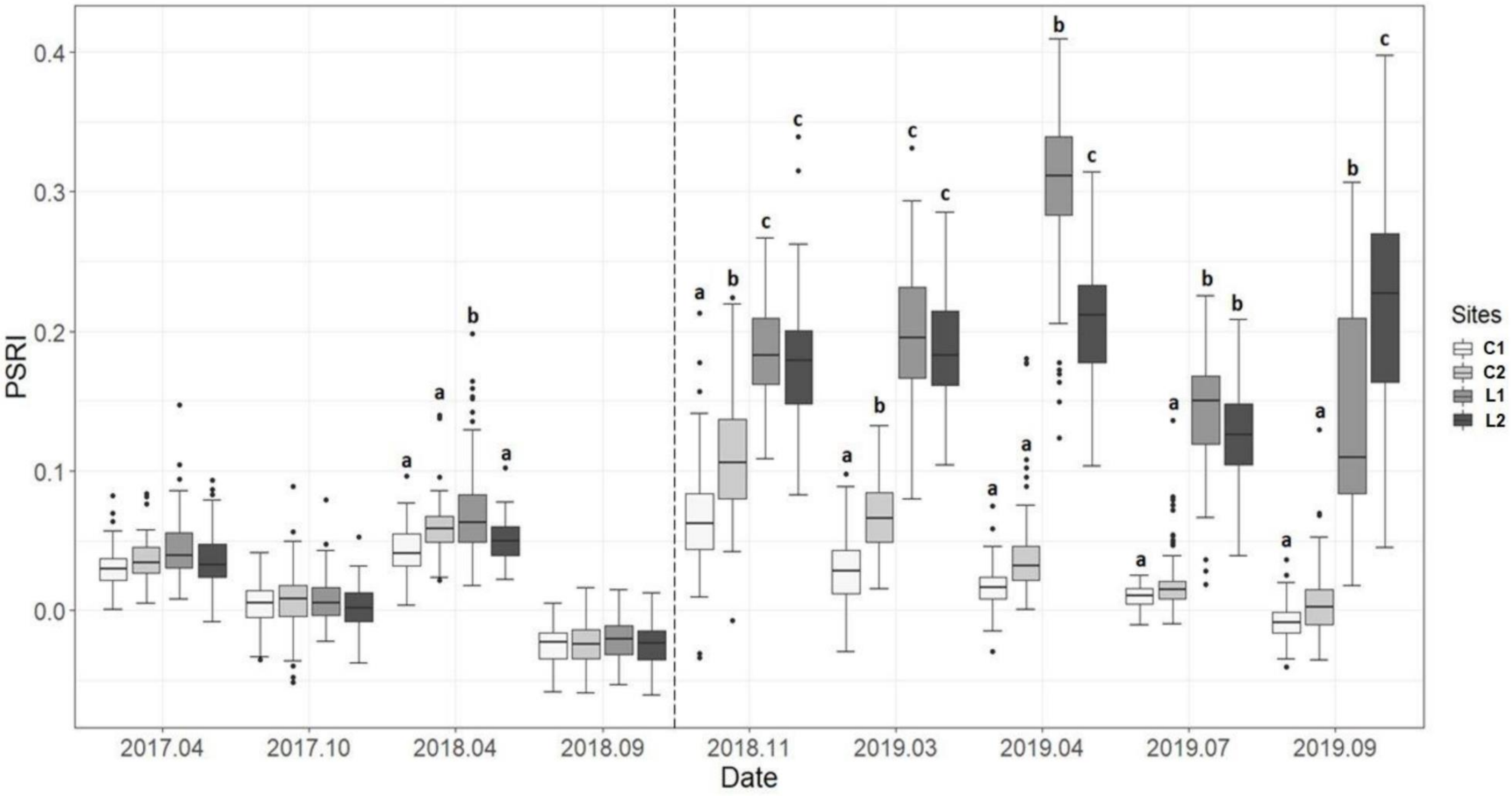
$$NDVI = \frac{B8 - B4}{B8 + B4}$$

$$PSRI = \frac{B4 - B2}{B6}$$

$$SLAVI = \frac{B8}{B4 + B12}$$

$$GNDVI = \frac{B8 - B3}{B8 + B3}$$

SENTINEL-2 TEMPORAL PROFILES



Similar profiles

$$NDWI = \frac{B8 - B11}{B8 + B11}$$

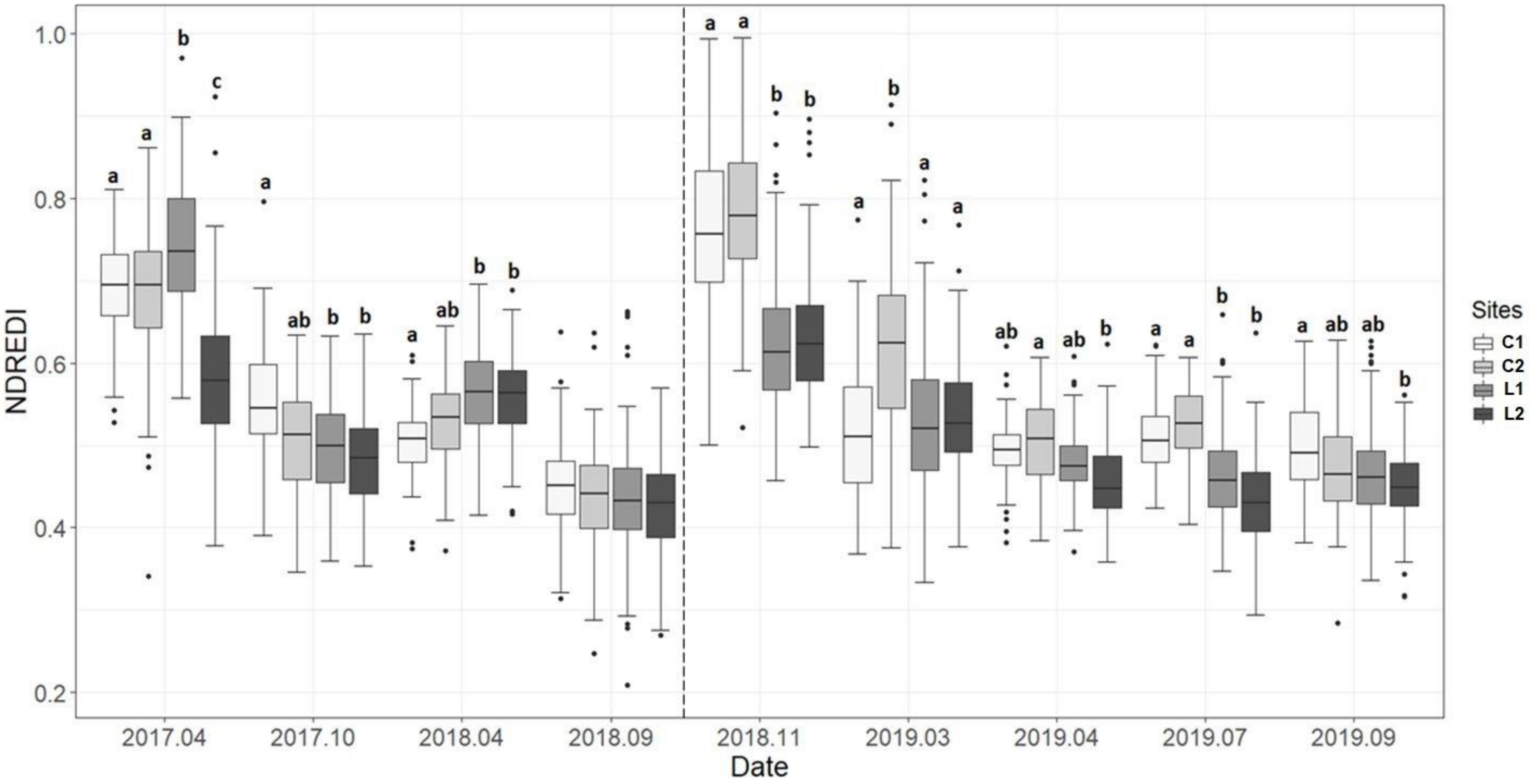
$$NDVI = \frac{B8 - B4}{B8 + B4}$$

$$PSRI = \frac{B4 - B2}{B6}$$

$$SLAVI = \frac{B8}{B4 + B12}$$

$$GNDVI = \frac{B8 - B3}{B8 + B3}$$

SENTINEL-2 TEMPORAL PROFILES



Different profiles

$$IRECI = \frac{B7 - B4}{B5/B6}$$

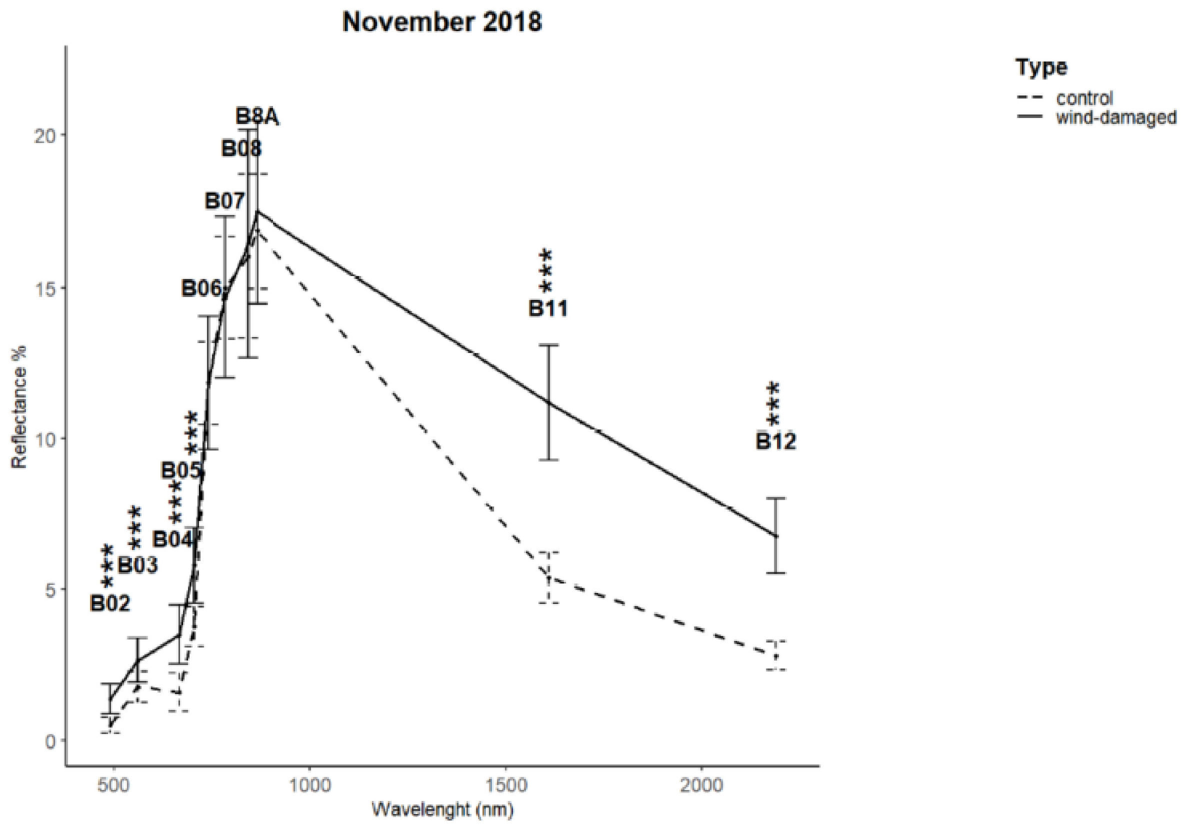
$$NDREDI = \frac{B5 - B2}{B5 + B2}$$

SENTINEL-2 VEGETATION INDICES PERFORMANCE

Index	Coefficient		SE	*p*-Value	R^2
NDWI8A	Intercept	0.49	0.007	***	0.80
	Treatment	−0.388	0.011	***	
NDWI	Intercept	0.473	0.021	***	0.77
	Treatment	−0.4	0.006	***	
NDVI	Intercept	0.841	0.01	***	0.76
	Treatment	−0.29	0.007	***	
PSRI	Intercept	0.025	0.003	***	0.69
	Treatment	0.163	0.005	***	
SLAVI	Intercept	4.122	0.062	***	0.65
	Treatment	−2.813	0.106	***	
GNDVI	Intercept	0.774	0.003	***	0.60
	Treatment	−0.145	0.005	***	
IRECI	Intercept	−0.048	0.003	***	0.32
	Treatment	−0.108	0.006	***	
NDREDI	Intercept	0.55	0.006	***	0.03
	Treatment	−0.043	0.01	***	

Generalized Least Square (GLS) models outputs and performance

SENTINEL-2 SPECTRAL SIGNATURES



Statistical analysis:
GLS+ post hoc pairwise comparison

PERFORMANCE

$$NDWI8A=\frac{B8A-B11}{B8A+B11}$$

$$NDWI=\frac{B8-B11}{B8+B11}$$

$$NDVI=\frac{B8-B4}{B8+B4}$$

$$PSRI=\frac{B4-B2}{B6}$$

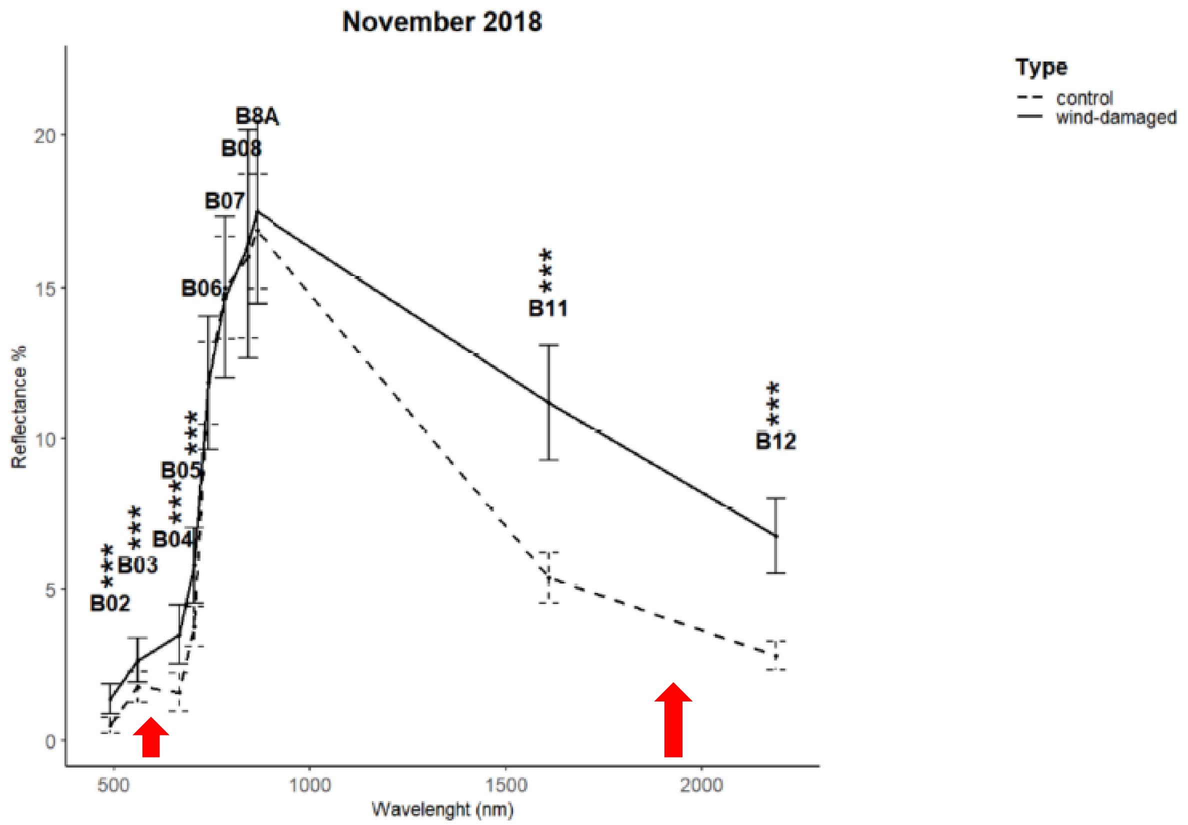
$$SLAVI=\frac{B8}{B4+B12}$$

$$GNDVI=\frac{B8-B3}{B8+B3}$$

$$IRECI=\frac{B7-B4}{B5/B6}$$

$$NDREDI=\frac{B5-B2}{B5+B2}$$

SENTINEL-2 SPECTRAL SIGNATURES



Statistical analysis:
GLS+ post hoc pairwise comparison

PERFORMANCE

NDWI8A=$\frac{B8A-B11}{B8A+B11}$

NDWI=$\frac{B8-B11}{B8+B11}$

NDVI=$\frac{B8-B4}{B8+B4}$

PSRI=$\frac{B4-B2}{B6}$

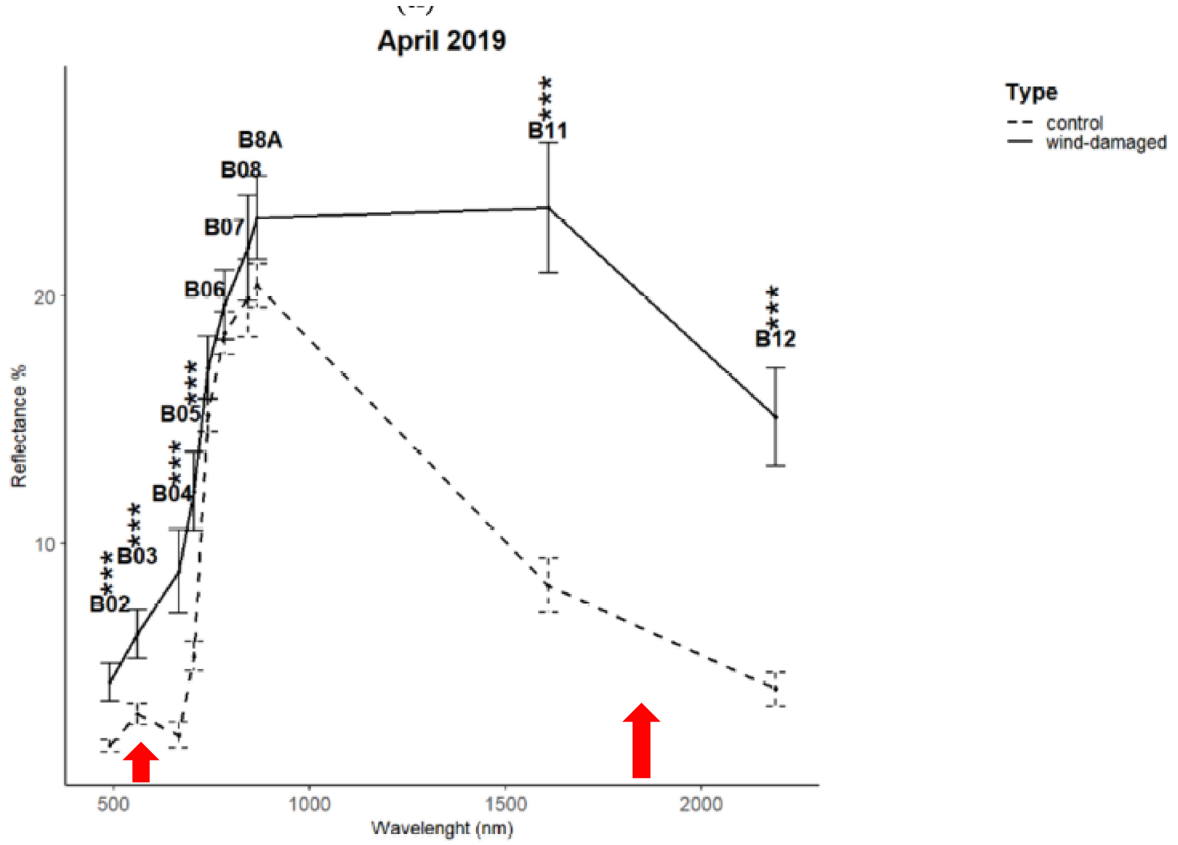
SLAVI=$\frac{B8}{B4+B12}$

GNDVI=$\frac{B8-B3}{B8+B3}$

IRECI=$\frac{B7-B4}{B5/B6}$

NDREDI=$\frac{B5-B2}{B5+B2}$

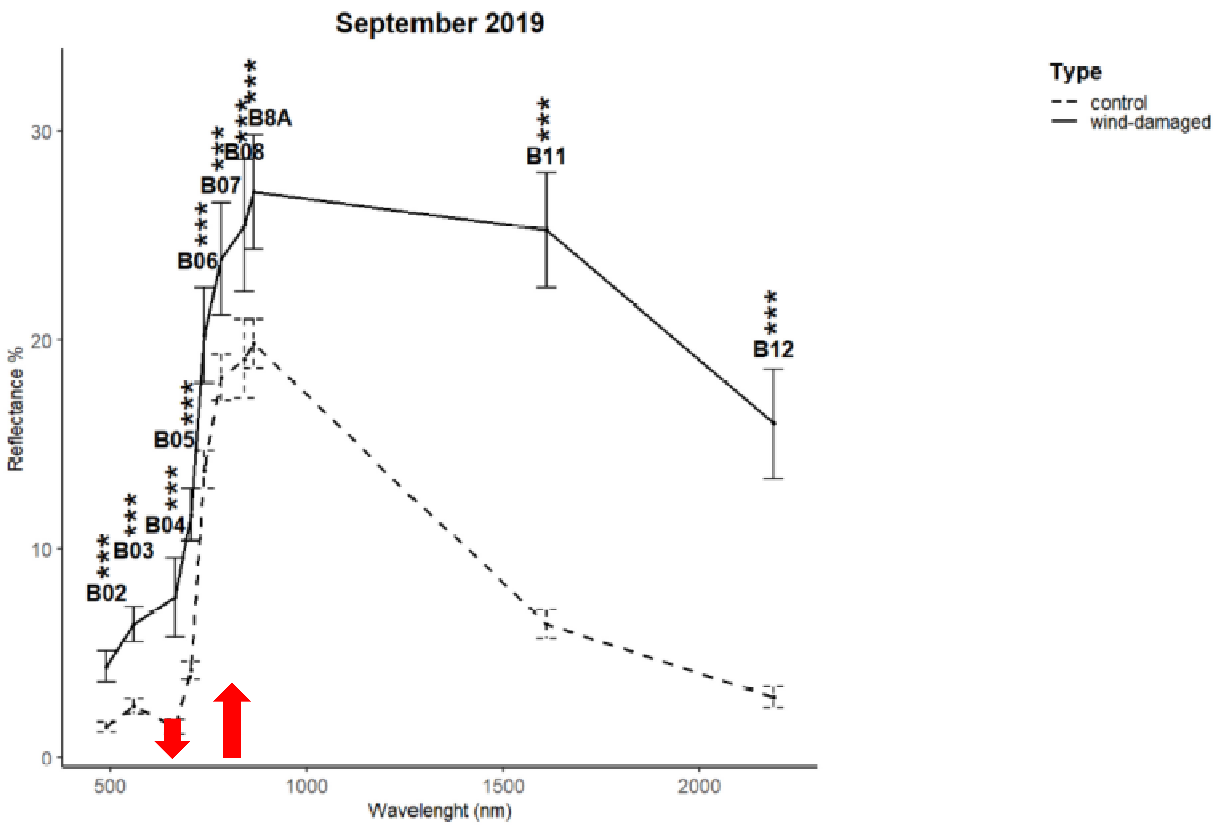
SENTINEL-2 SPECTRAL SIGNATURES



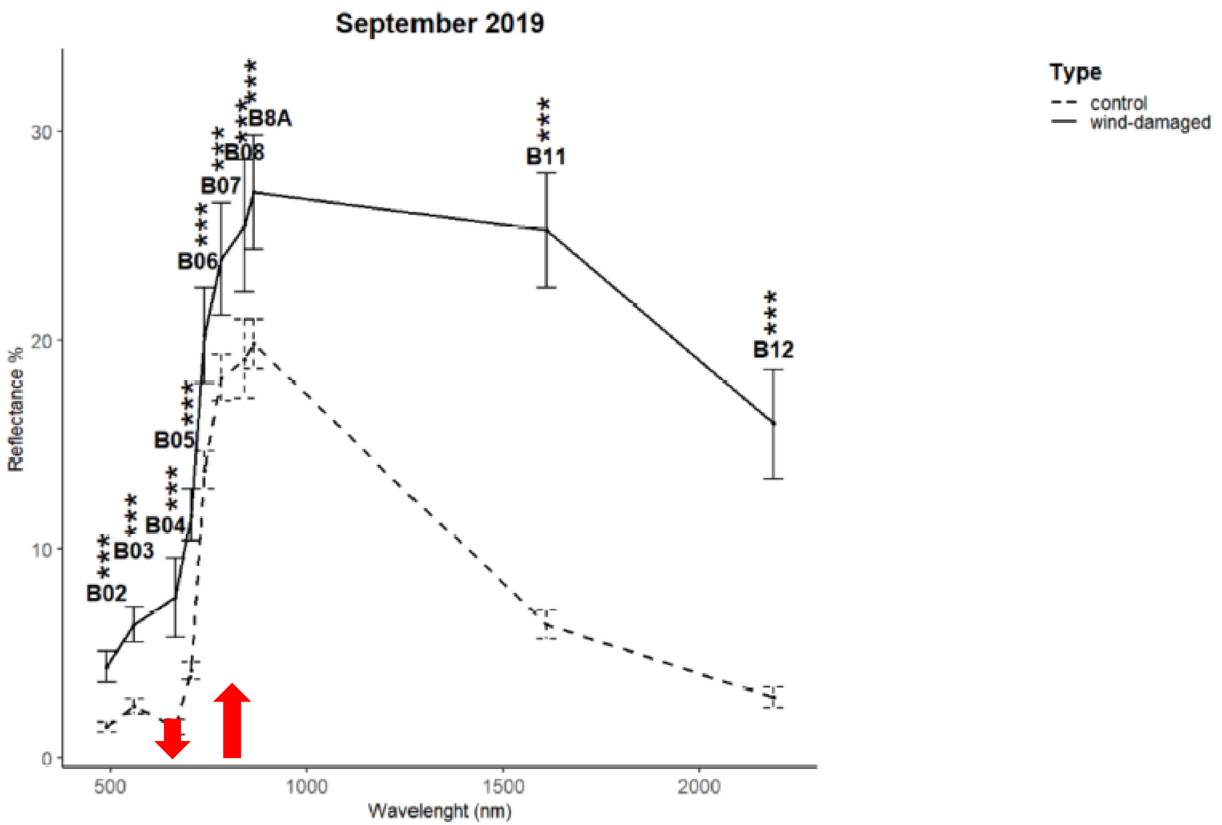
Statistical analysis:
GLS+ post hoc pairwise comparison

3. Results

SENTINEL-2 SPECTRAL SIGNATURES



Statistical analysis:
GLS+ post hoc pairwise comparison



Statistical analysis:
GLS+ post hoc pairwise comparison

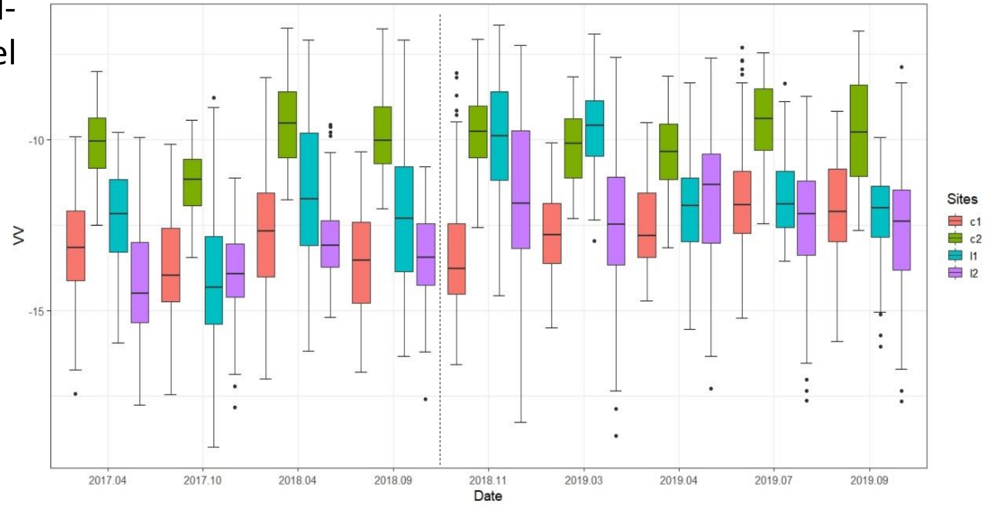
SENTINEL-1 TEMPORAL PROFILES & PERFORMACE

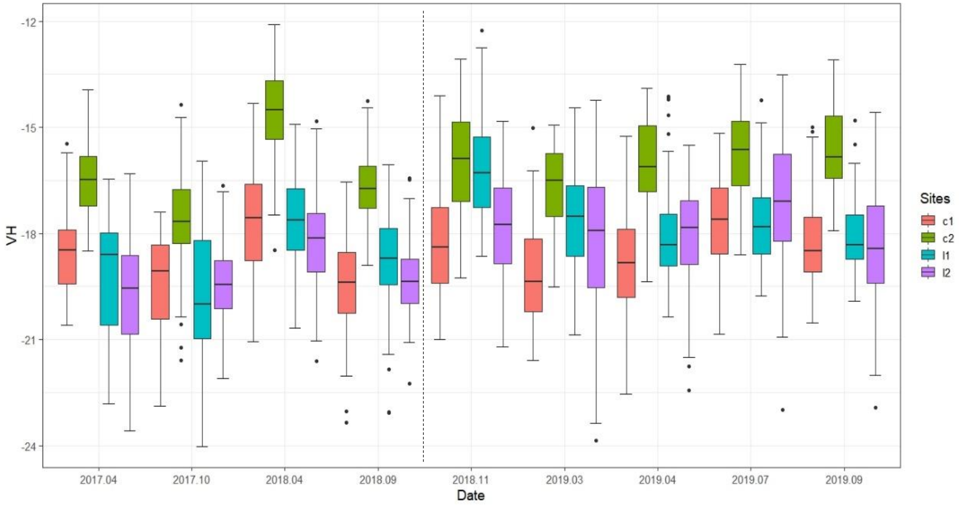
Backscatter	Coefficient		SE	P. value	R^2
VV	Intercept	-11.764	0.261	***	0.009
	Treatment	-0.462	0.089	***	
VH	Intercept	-17.726	0.274	***	0.013
	Treatment	-0.470	0.076	***	

Radar-affecting parameters	
System-dependent	• Resolution • Polarization (HH, VV, HV, VH) • Wavelength/Frequency (X, C, L, and P bands) • Incidence angle
Target-dependent	• Surface roughness (relative to wavelength) • Structure (size, orientation, surface pattern) • Dielectric constant (moisture content) • Slope angle/orientation

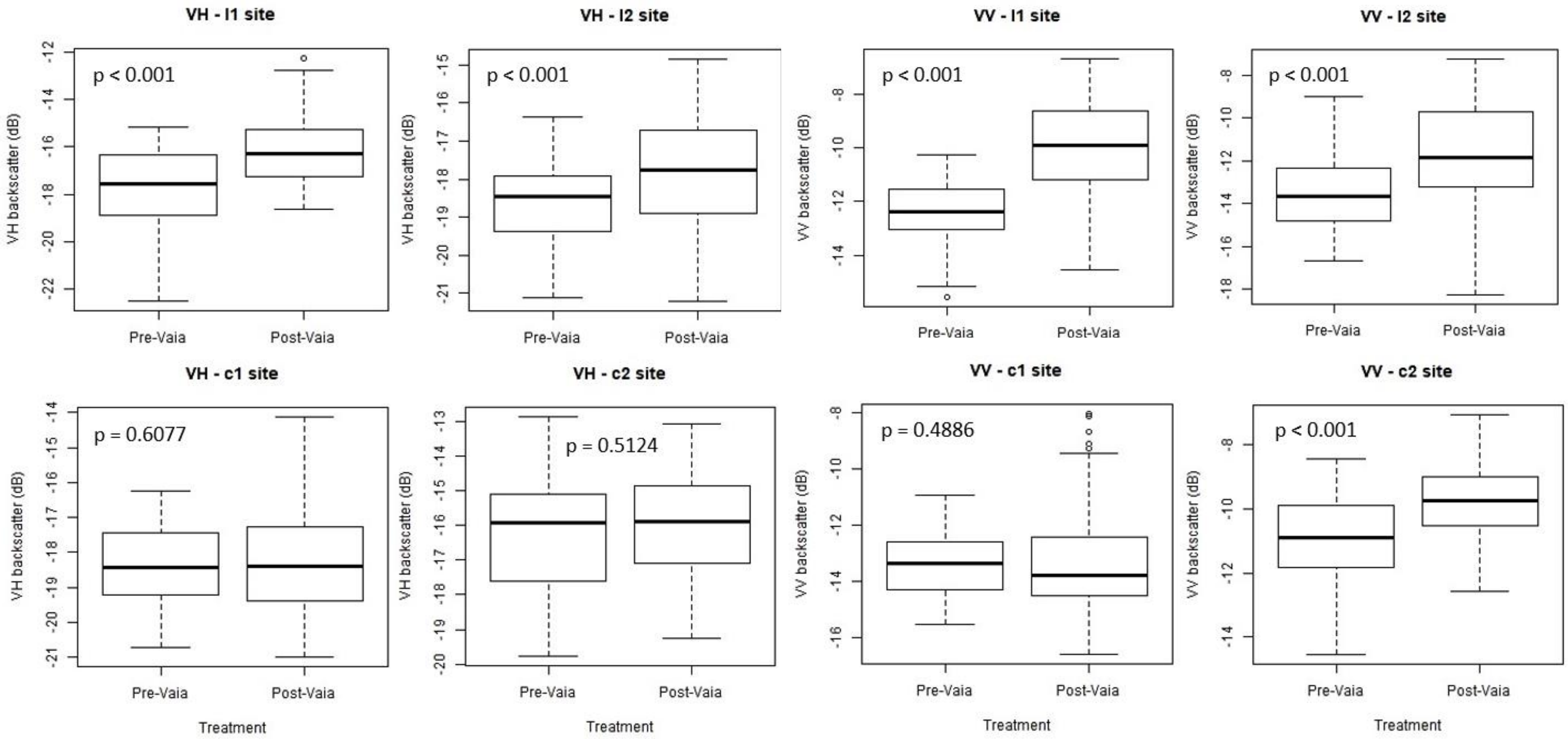
Table 12: Parameters affecting radar imagery

Linear mixed-effects model (LMMs) outputs





SENTINEL-1 TEMPORAL PROFILES

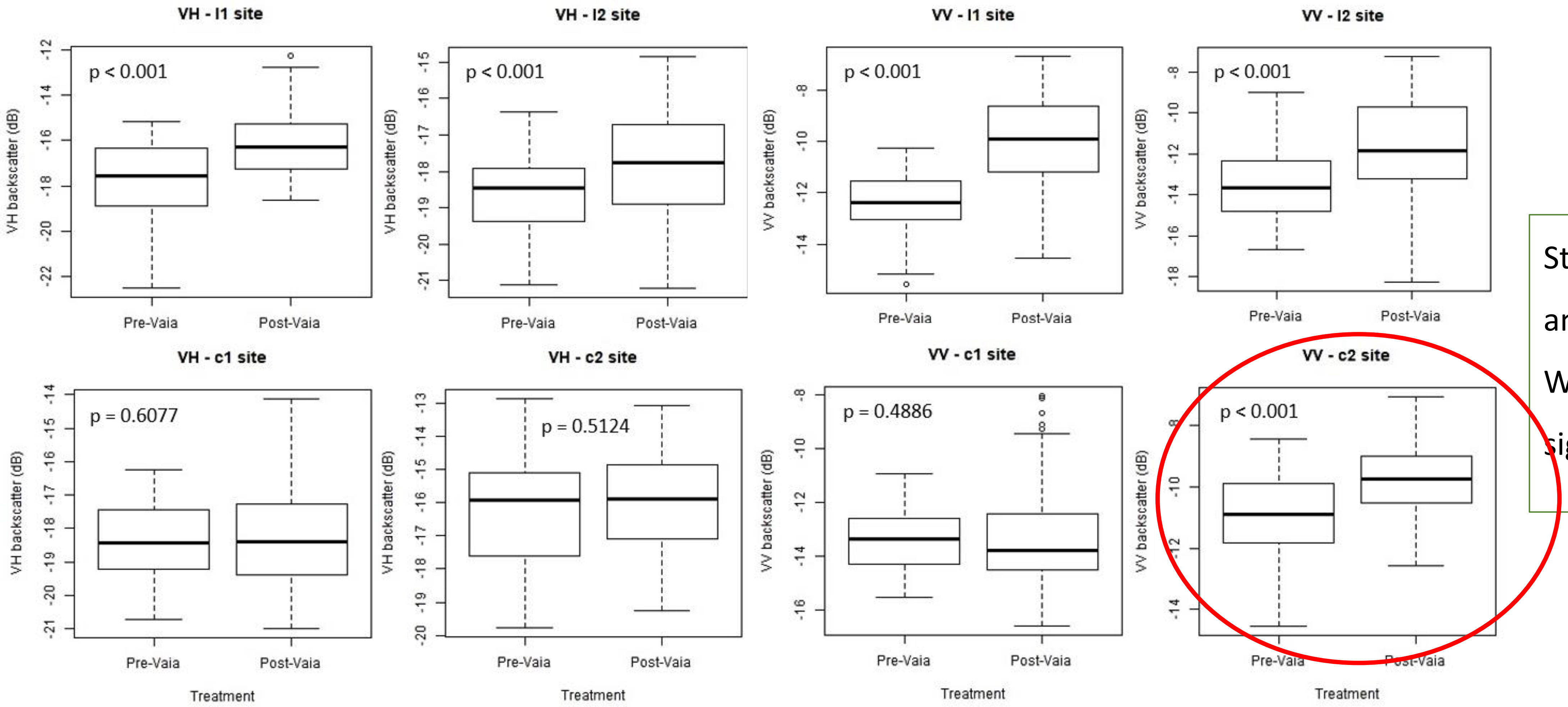


Statistical analysis: Wilcoxon signed rank test

Short-term monitoring

3. Results

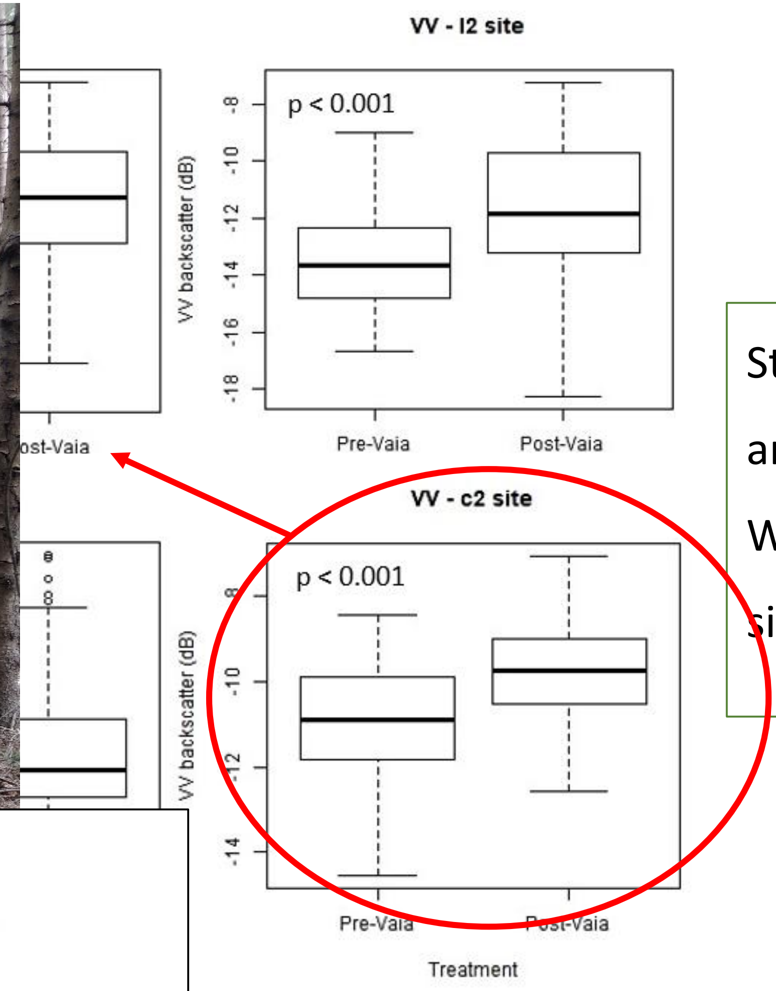
SENTINEL-1 TEMPORAL PROFILES

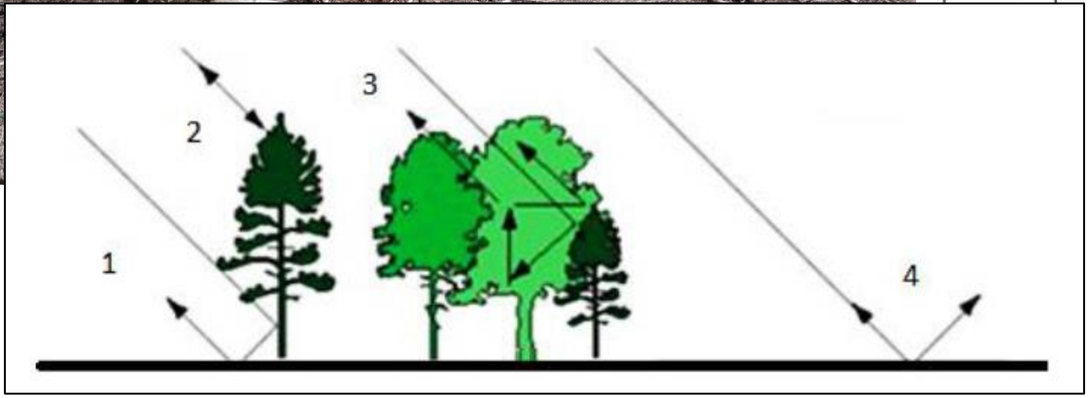


Statistical analysis: Wilcoxon signed rank test

Short-term monitoring

SENTINEL-1 TEMPORAL PROFILES



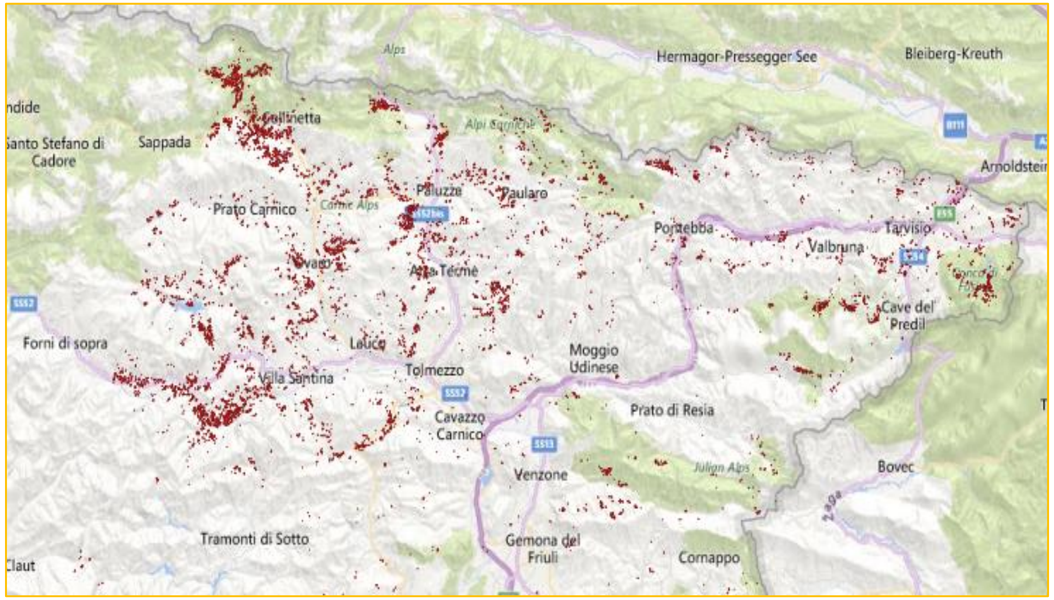


Statistical analysis: Wilcoxon signed rank test

SENTINEL-2 CHANGE DETECTION

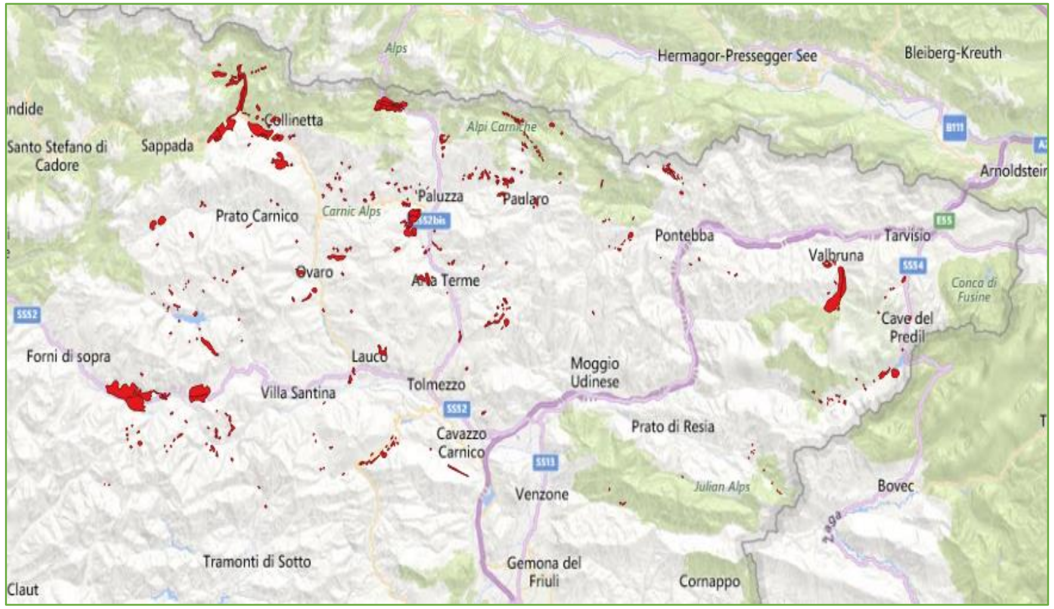
NDWI8A
vegetation index
differencing

2545 ha

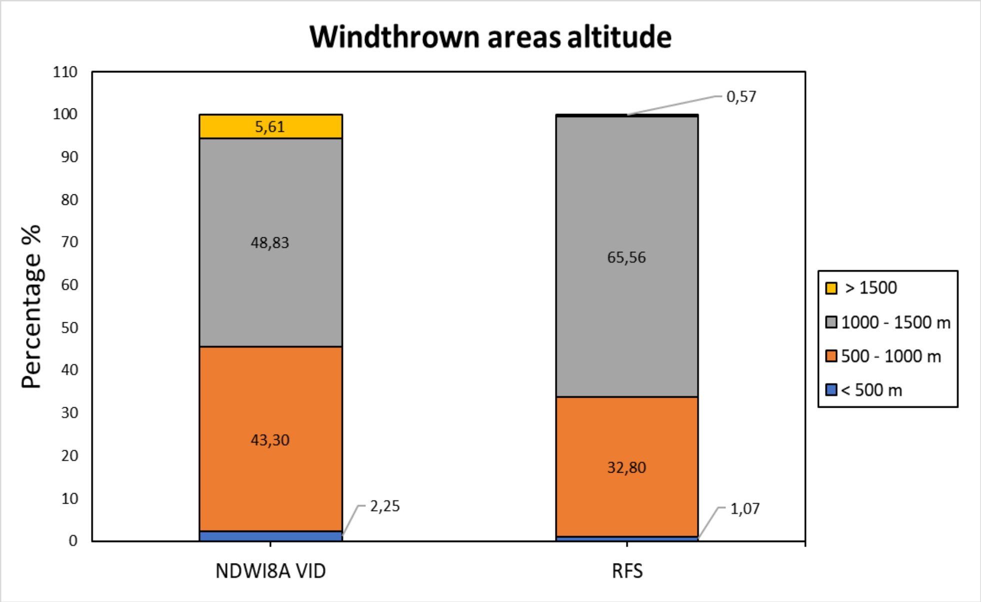


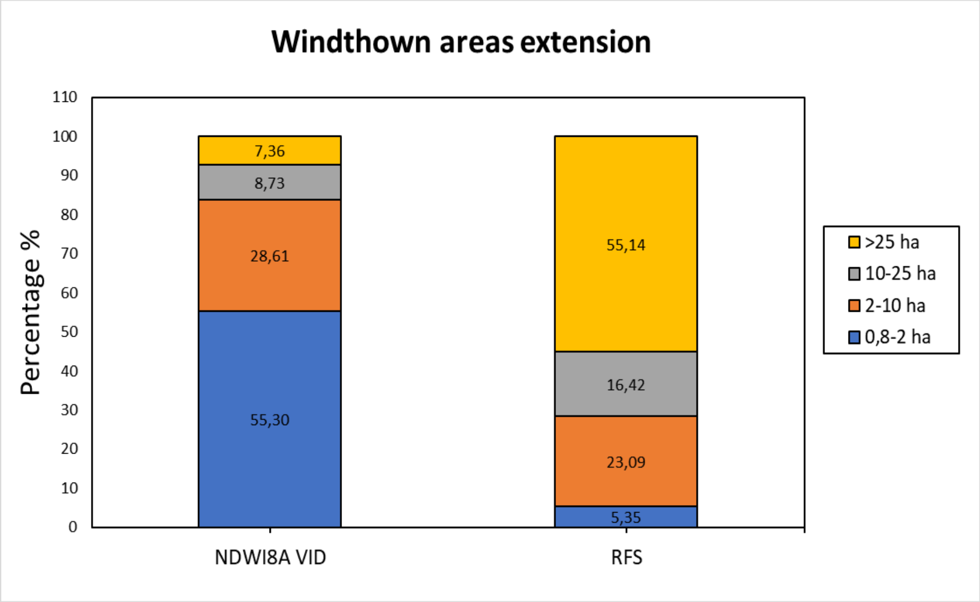
Regional Forest Service

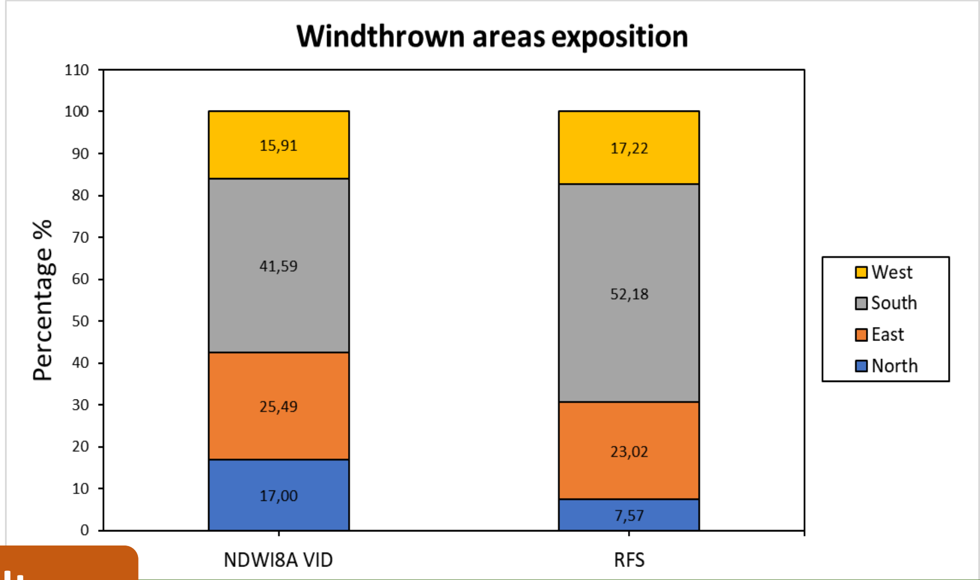
3184 ha

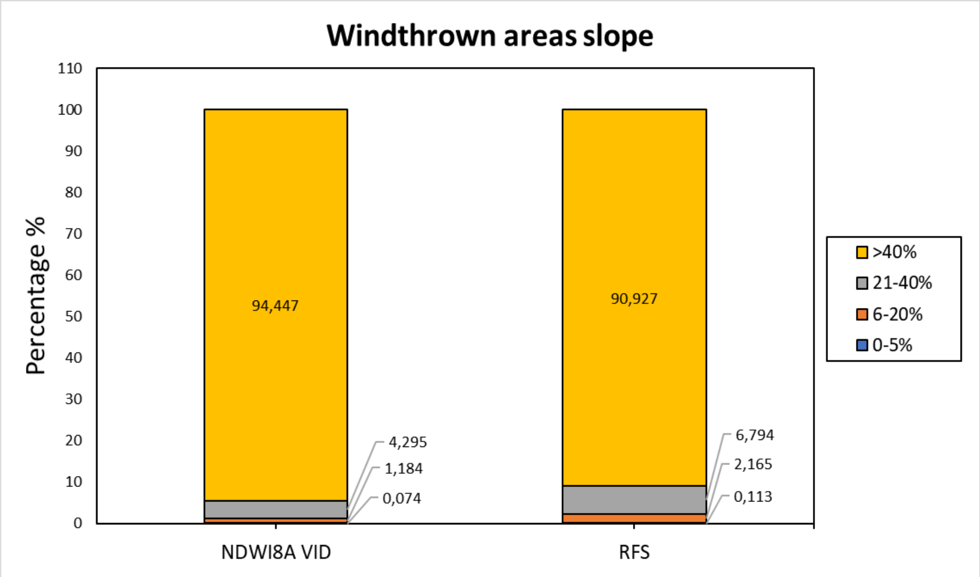


SENTINEL-2 CHANGE DETECTION

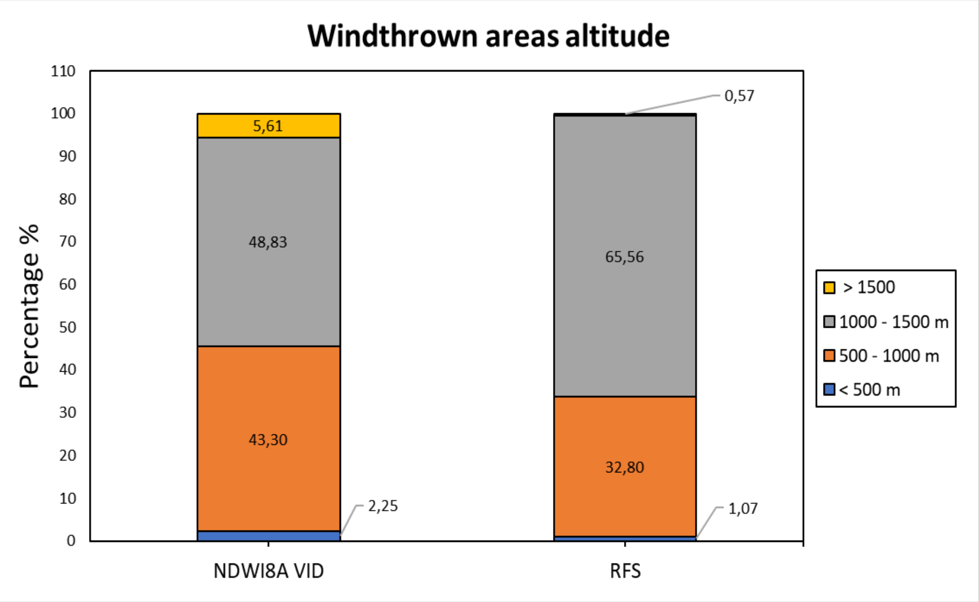


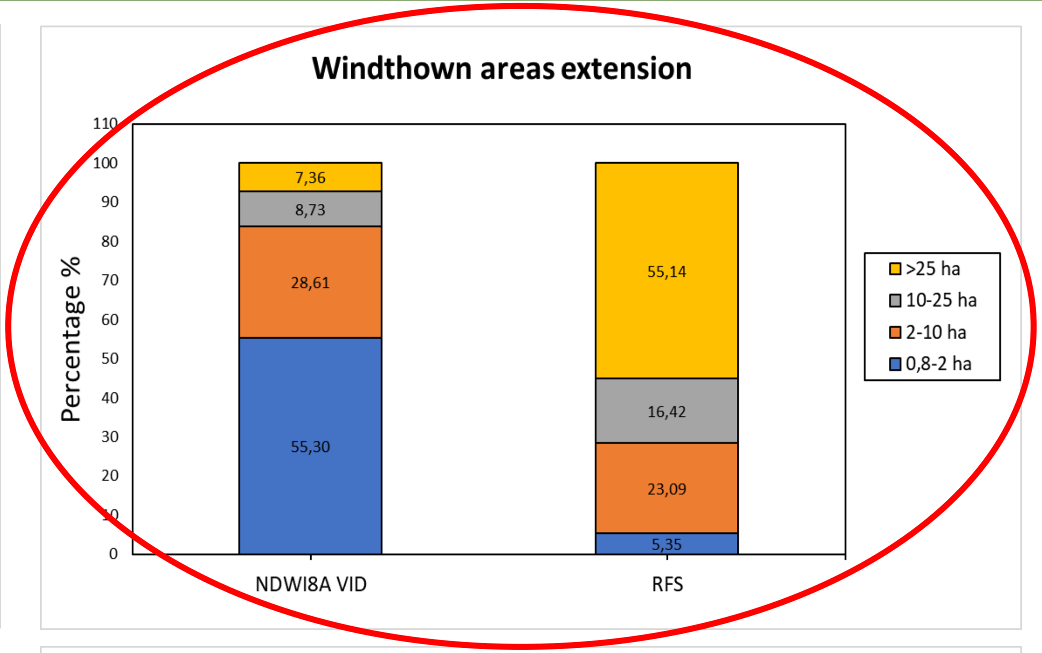


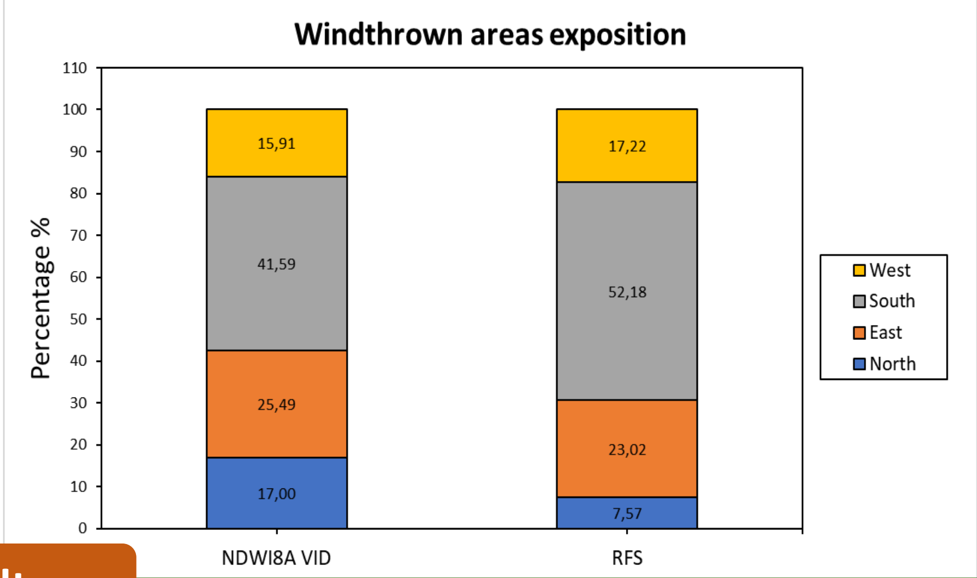


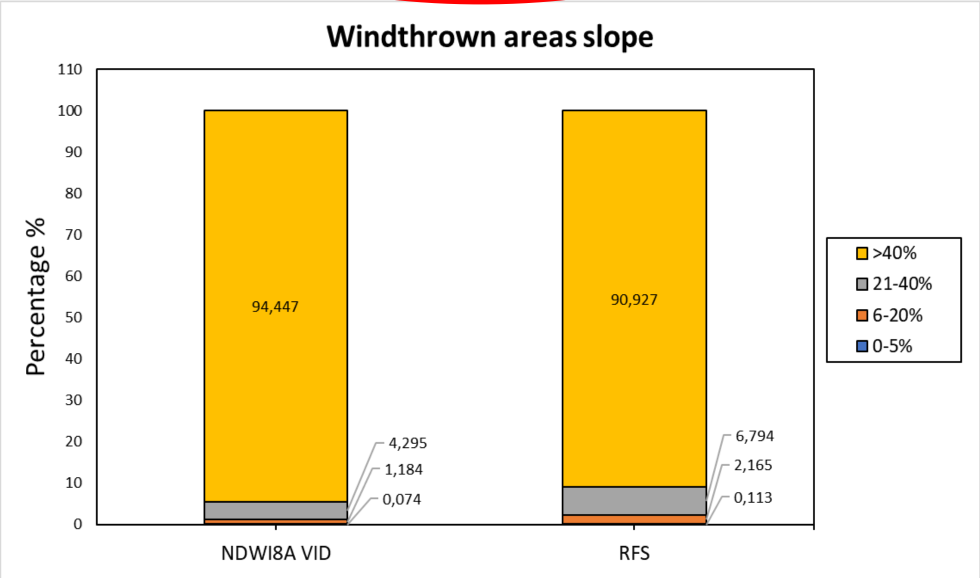


SENTINEL-2 CHANGE DETECTION



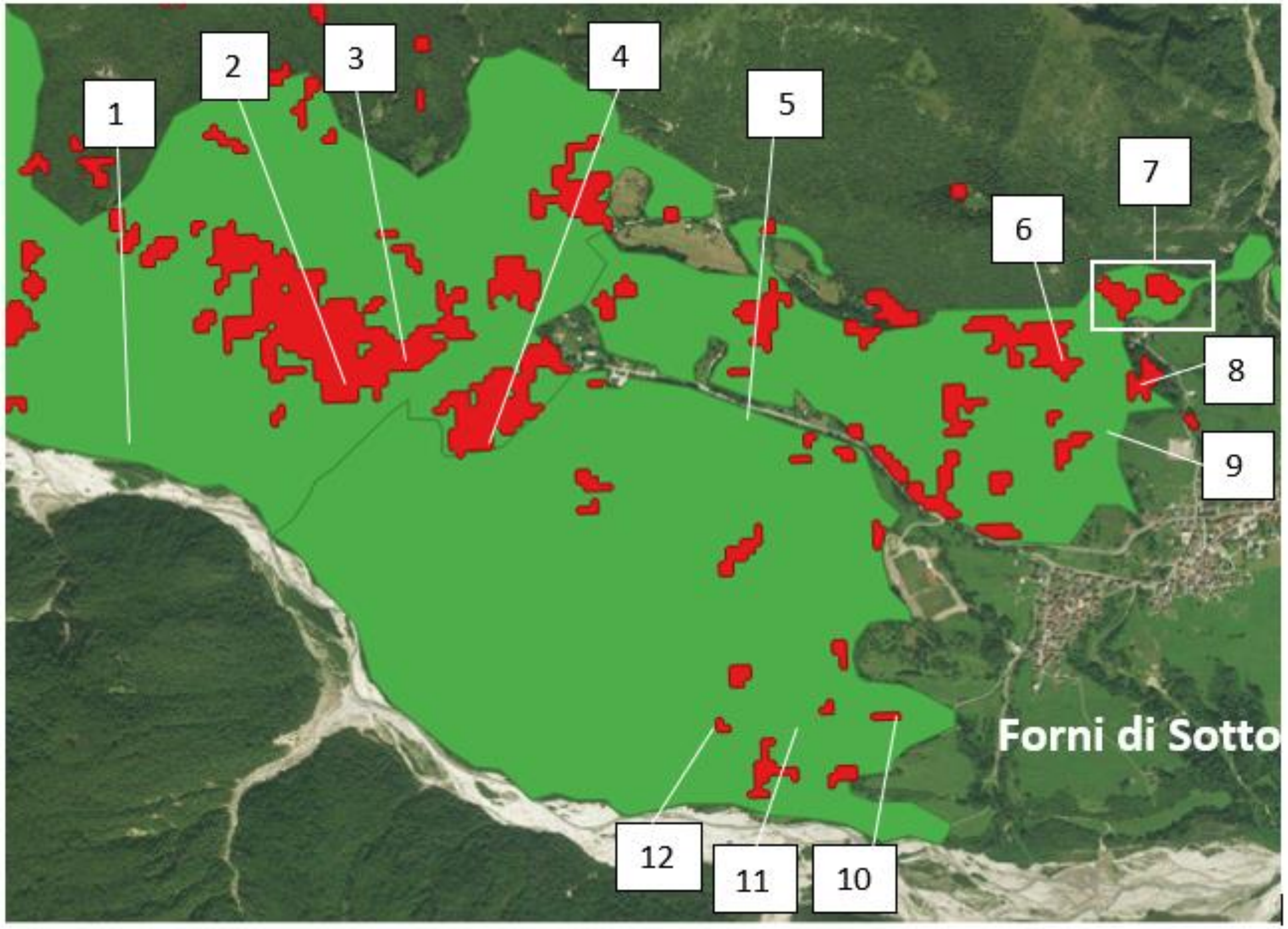




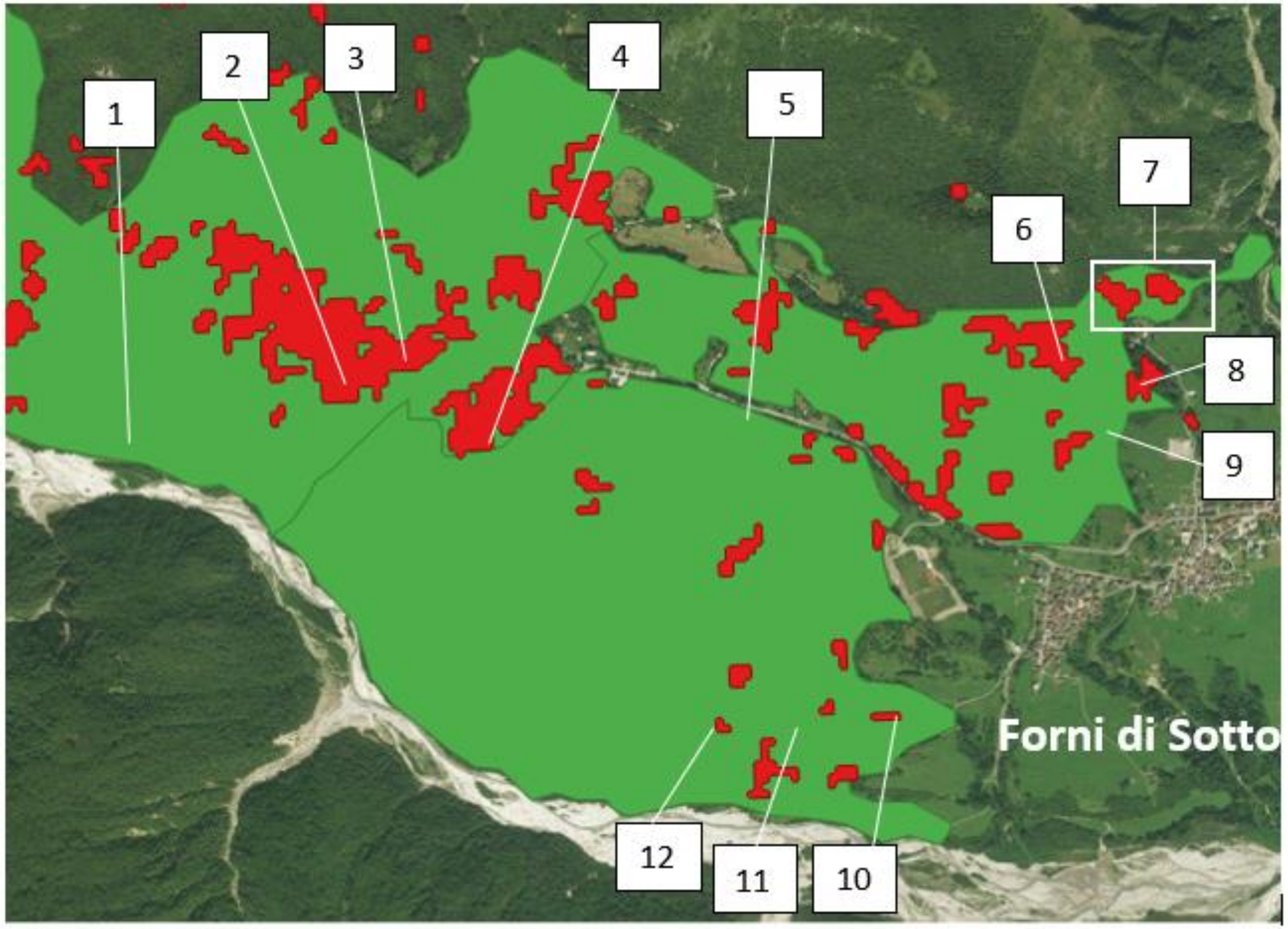


3. Results

SENTINEL-2 CHANGE DETECTION



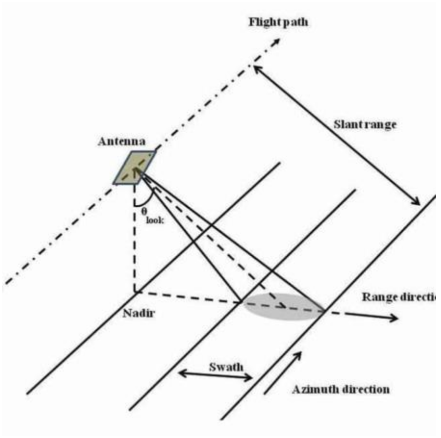
SENTINEL-2 CHANGE DETECTION

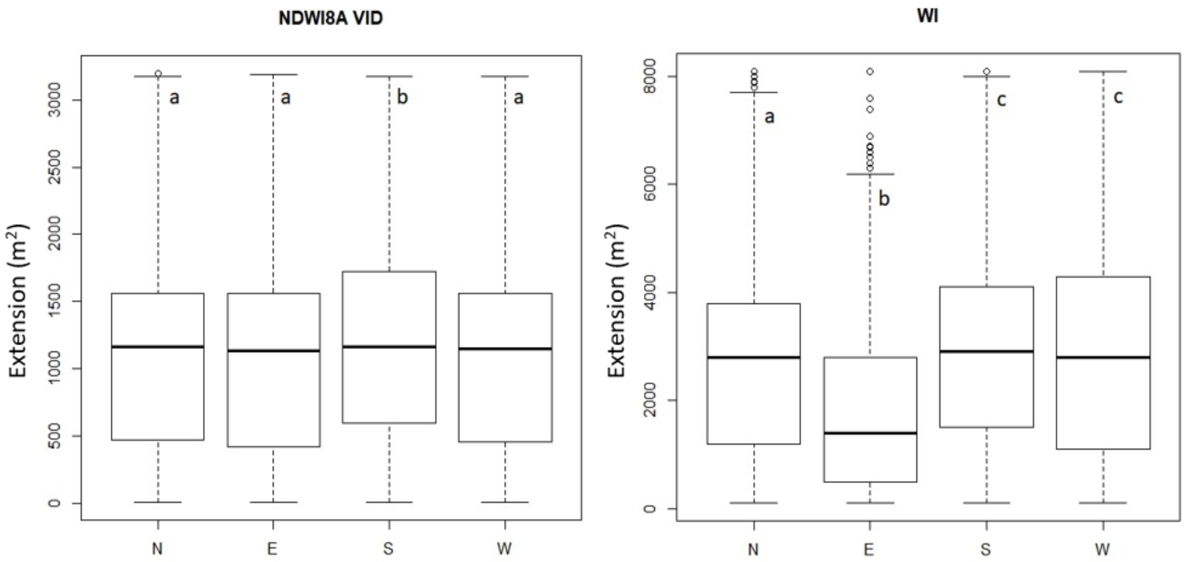


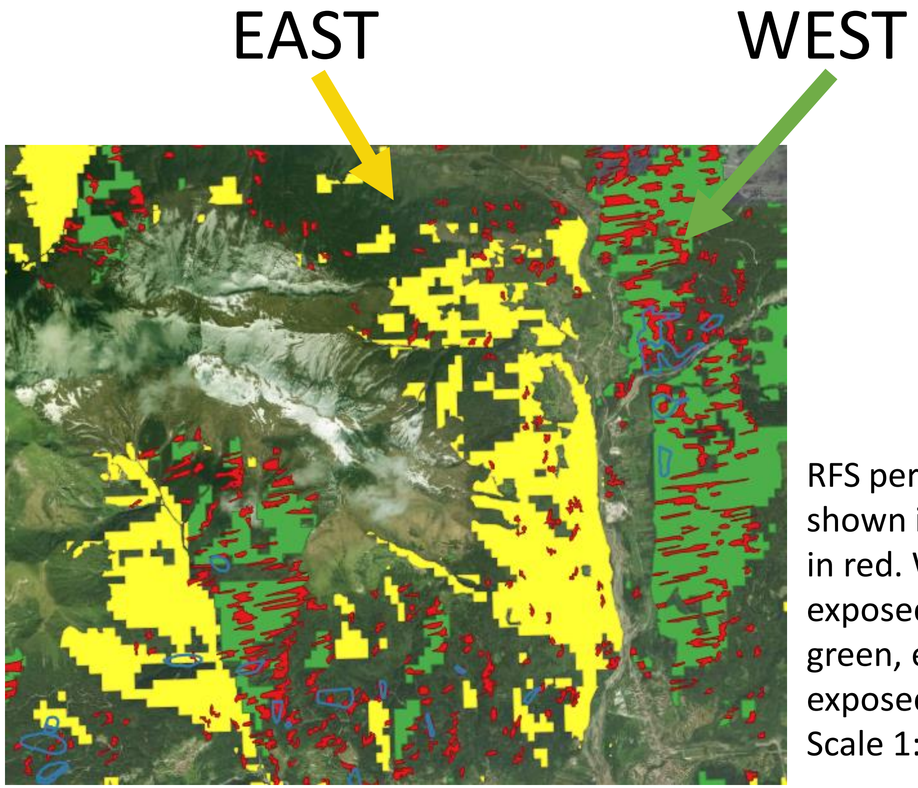
SENTINEL-1 CHANGE DETECTION

West exposed damaged areas:

RFS = 17%
NDWI8A VID = 16%
WI =35%







RFS perimeters are shown in blue, WI in red. West exposed areas in green, east exposed in yellow. Scale 1:65000.

Statistical analysis:
Kruskall-Wallis non-parametric rank test + post hoc pairwise comparison

Conclusions

RADAR

- Windthrows have short-term effects on radar backscatter
- WI detection method → Strong topologic effects due to FVG Alps geometry

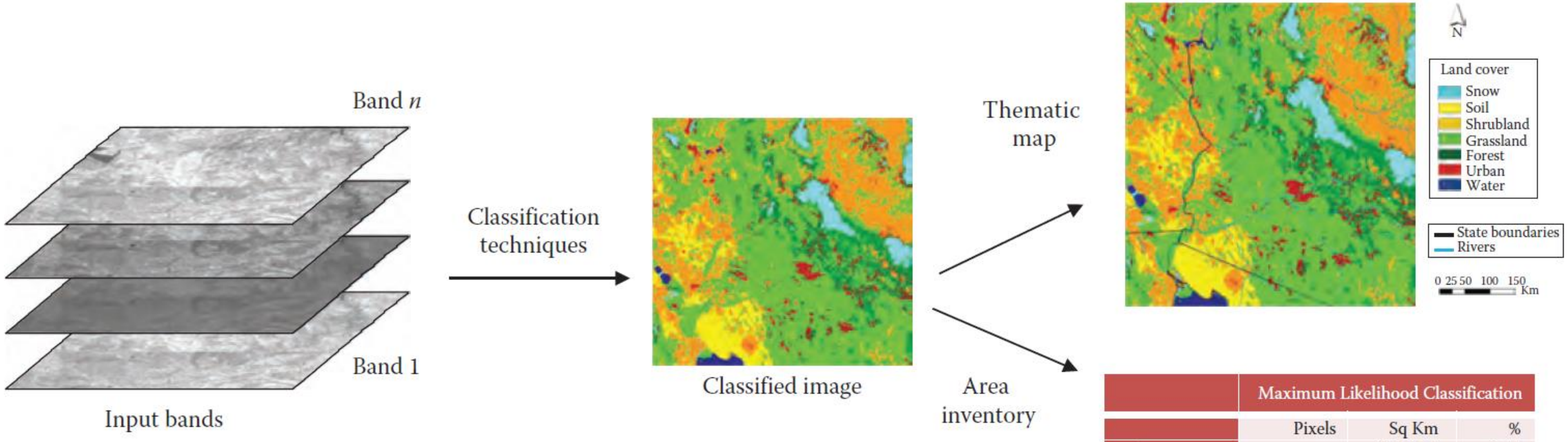
MULTISPECTRAL

- NDWI8A → Best index for windthrow-caused forest die-off & successions monitoring
- NDWI8A VID detection method → Safe, accurate, easy, cost-effective for areal damage

Thank you for the attention

IMAGE CLASSIFICATION

- Generation of thematic maps is a very common objective of digital image processing
- Goal = assigning each pixel to one of the target categories



	Maximum Likelihood Classification		
	Pixels	Sq Km	%
Soil	73945	18486.25	4.68
Snow	110697	27674.25	7.00
Herbaceous	686120	171530.00	43.41
Shrublands	438187	109546.75	27.72
Forested	166335	41583.75	10.52
Urban	89905	22476.25	5.69
Water	15517	3879.25	0.98
Total	1580706	395176.50	100.00

IMAGE CLASSIFICATION

- The output image will no longer represent a quantitative measurement
- Each pixel will have a DN which will represent a numeric label that identifies a category
- Classified image can be transformed into thematic maps by assigning a proper patch or colour key
- Classification methods are based on spectral information, but also on the spatial and temporal dimensions of the images.
- Three major phases:
    1. **TRAINING**: digital definition of the categories based on sample pixels
    2. **ASSIGNMENT**: allocation of the whole image to one of the categories
    3. **RESULTS** ASSESSMENT: calculation of metrics to quantify the robustness of the classification

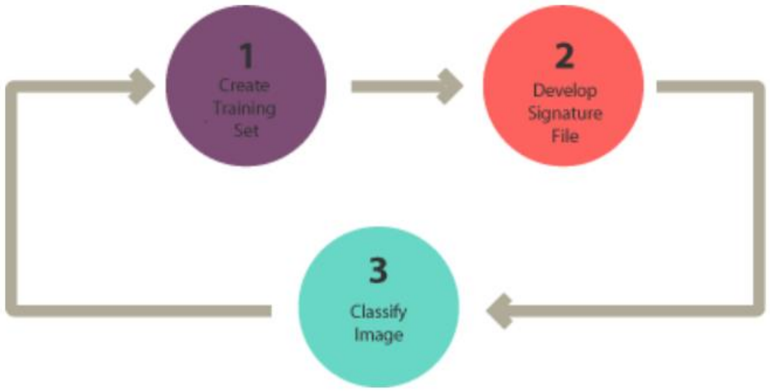


IMAGE CLASSIFICATION

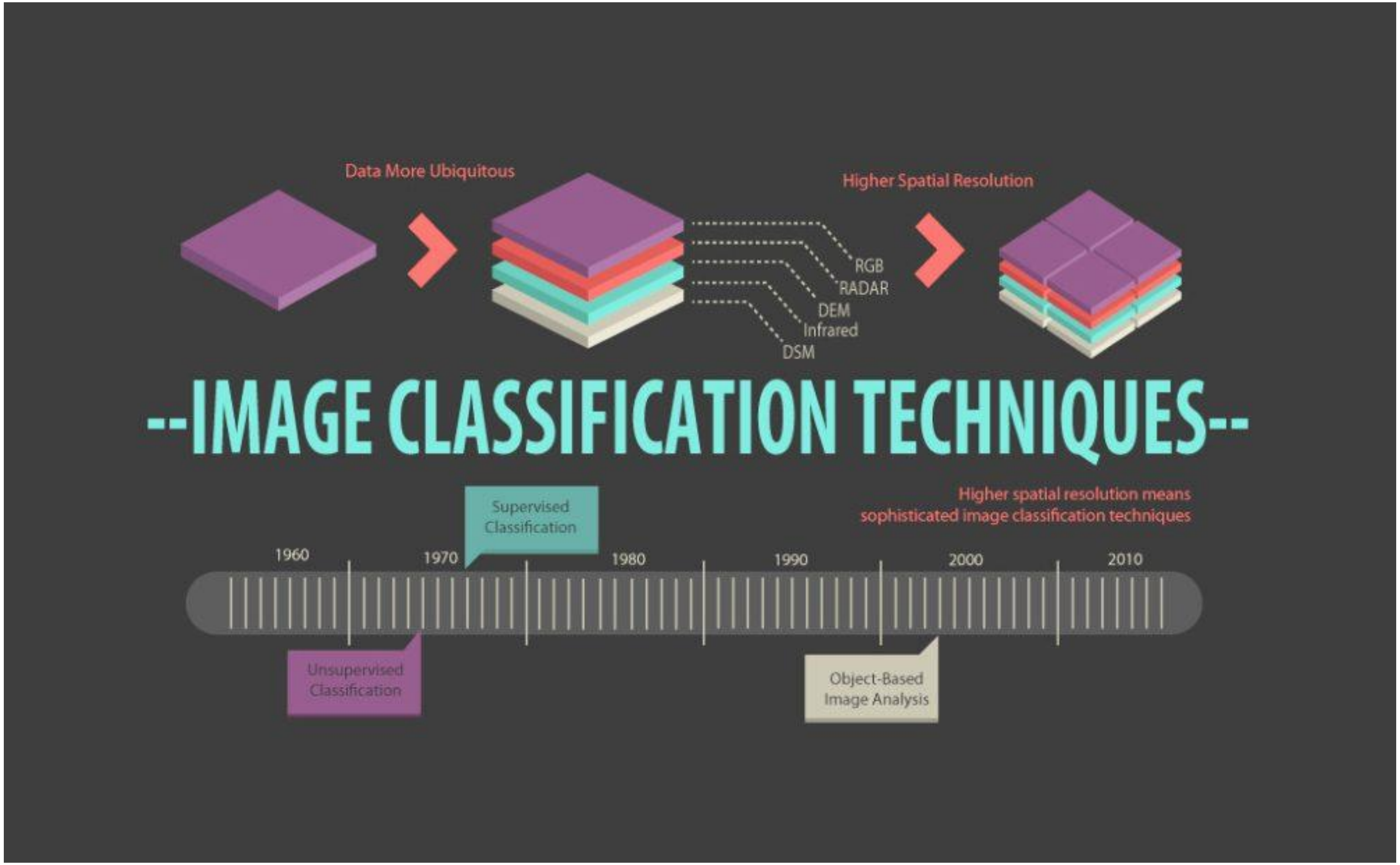


IMAGE CLASSIFICATION

Supervised classification:

Based on
sex/music/style/rockiness…

Is this singer Ozzy Osbourne?

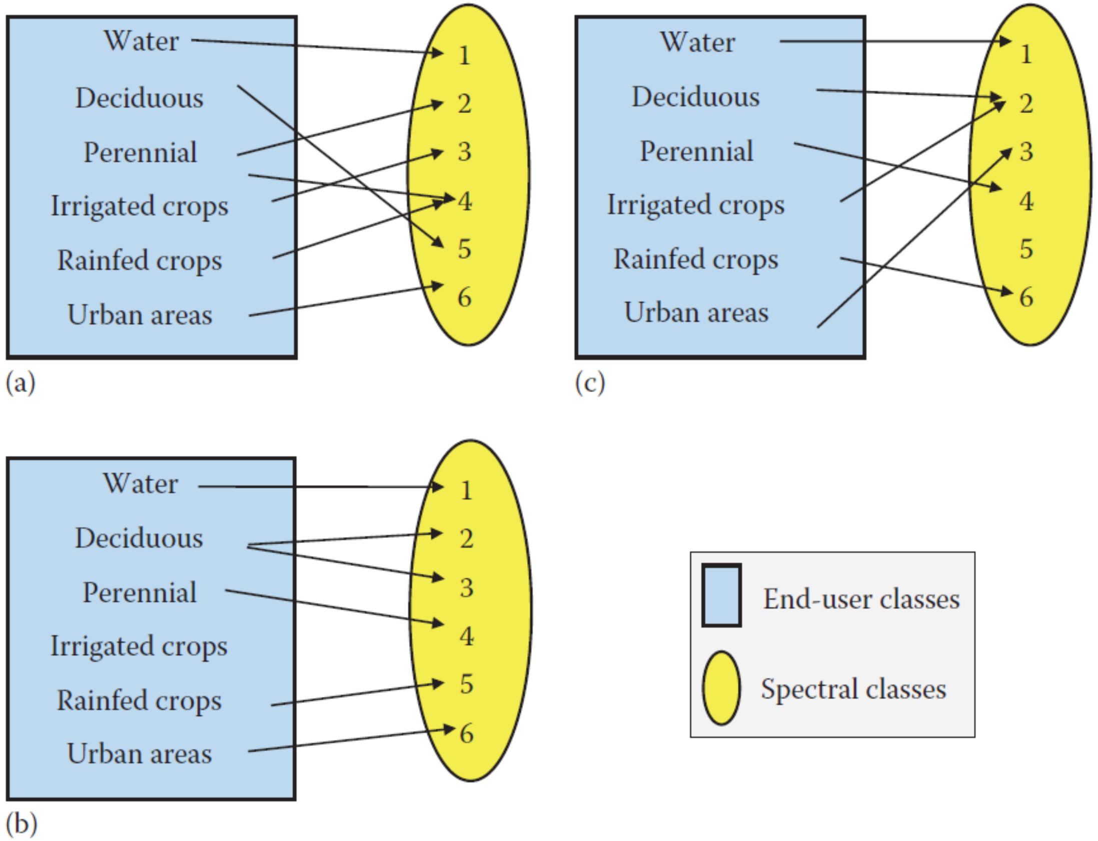
Unsupervised classification:

How different singers can be
classified in your Spotify playlist?

Supervised classification:

It requires a priori knowledge of the area that helps in selecting the samples for each category

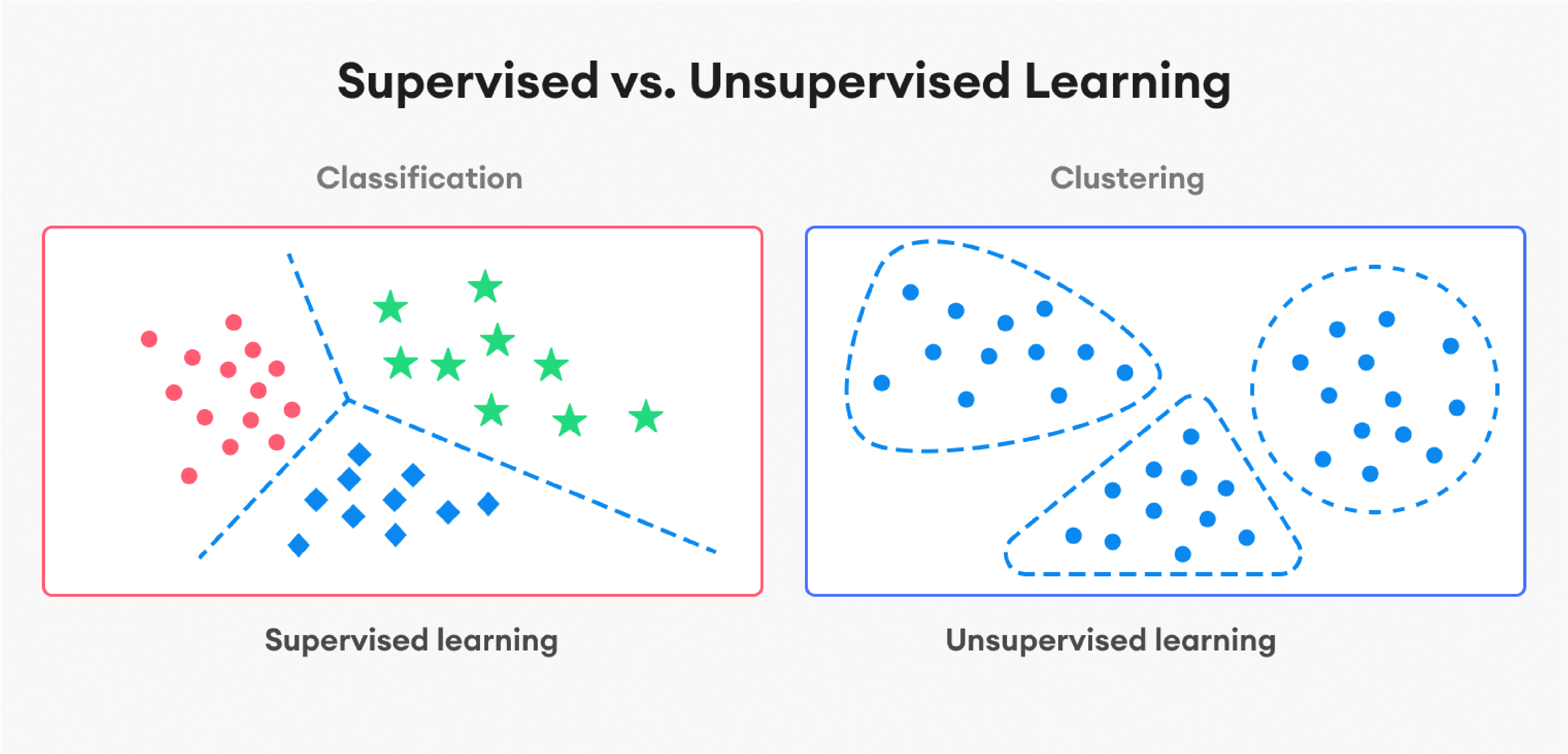
Assign the univocal correspondance between end-user classes and spectral classess

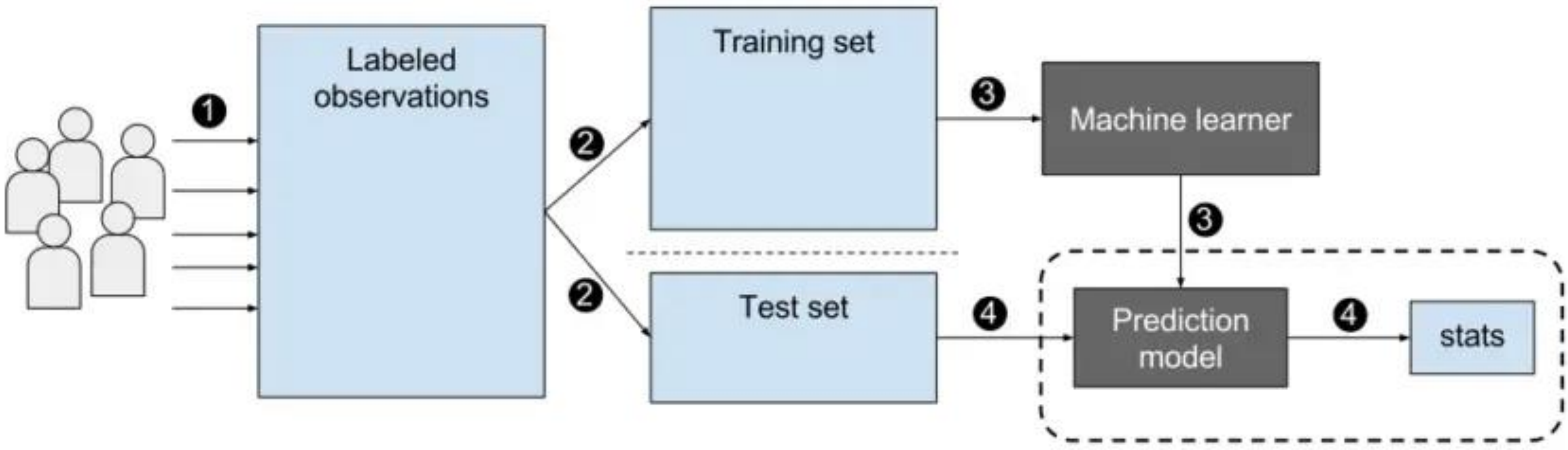


Unsupervised classification:

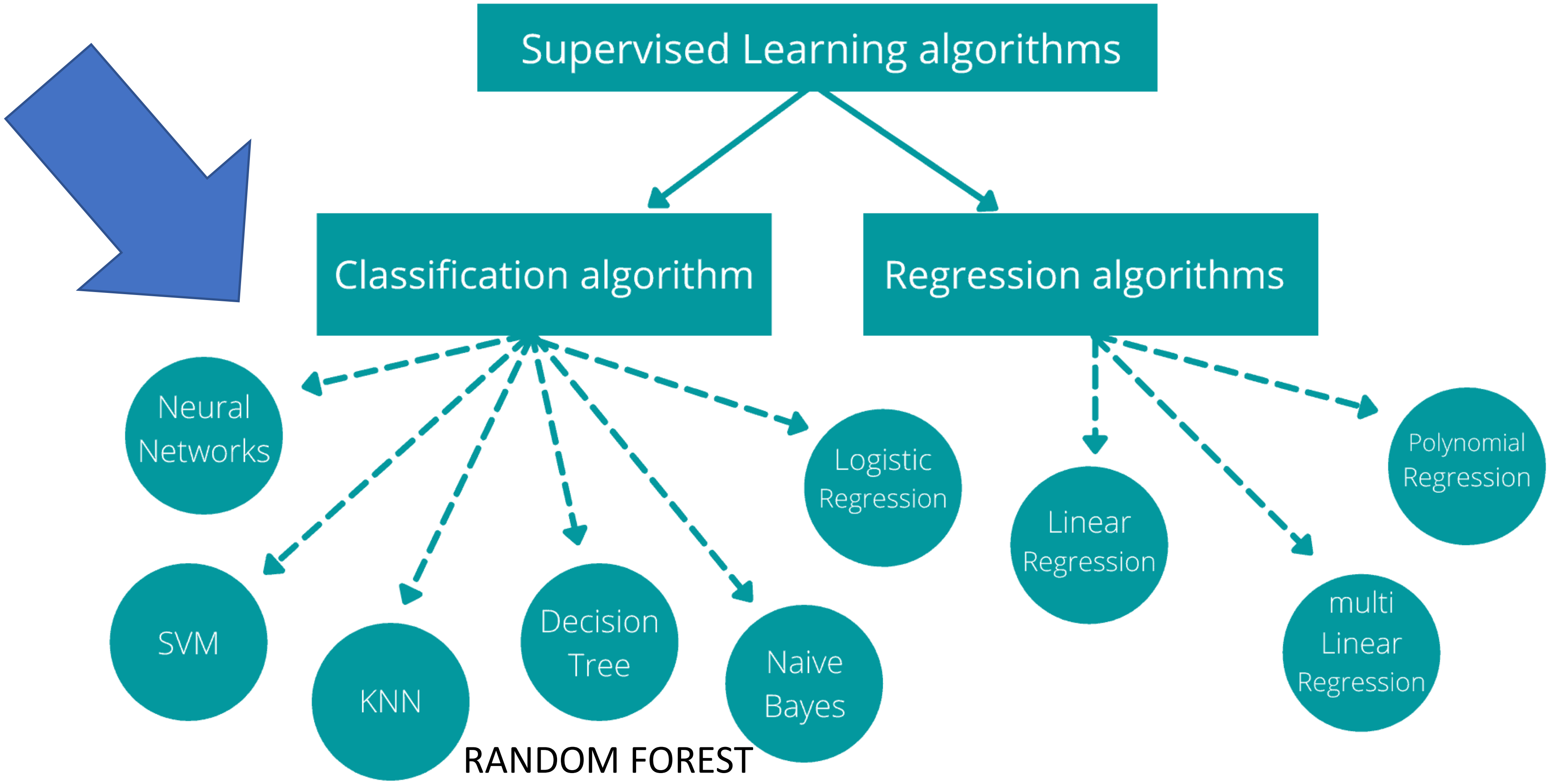
Automatic searches to find the clusters of homogeneous within the image

Later, the user needs to find correspondances between spectral groups and target categories


Supervised vs. Unsupervised Learning
Classification
Clustering
Supervised learning
Unsupervised learning



…..a priori Knowledge!!!


Supervised Learning algorithms
Classification algorithm
Regression algorithms
Neural Networks
SVM
KNN
Decision Tree
Naive Bayes
Logistic Regression
Linear Regression
multi Linear Regression
Polynomial Regression
RANDOM FOREST

Application of Random Forest

Remote Sensing

Used in ETM devices to acquire images of the earth's surface.

Accuracy is higher and training time is less

Object Detection

Multiclass object detection is done using Random Forest algorithms

Provides better detection in complicated environments

Kinect

Random Forest is used in a game console called Kinect

Tracks body movements and recreates it in the game

IMAGE CLASSIFICATION – SUPERVISED CLASSIFICATION

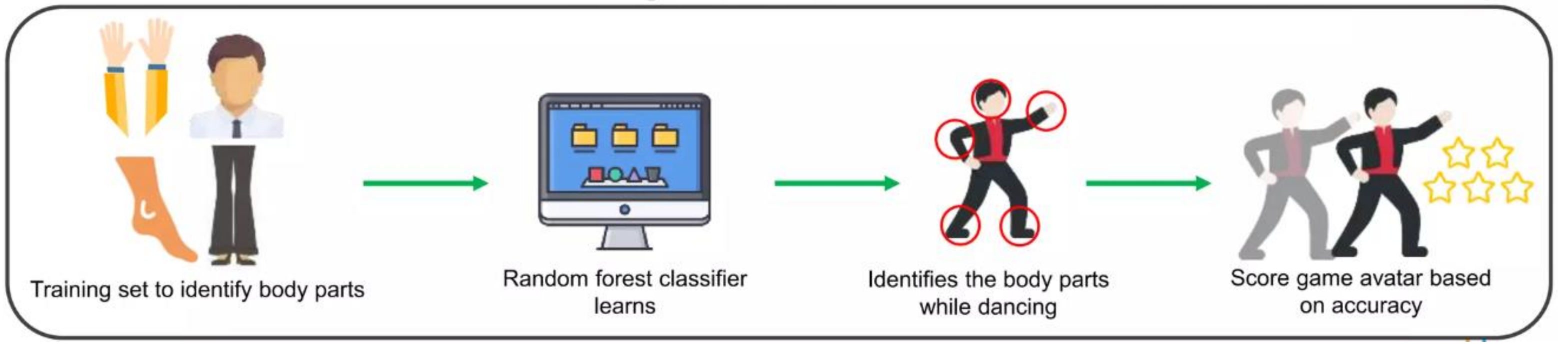
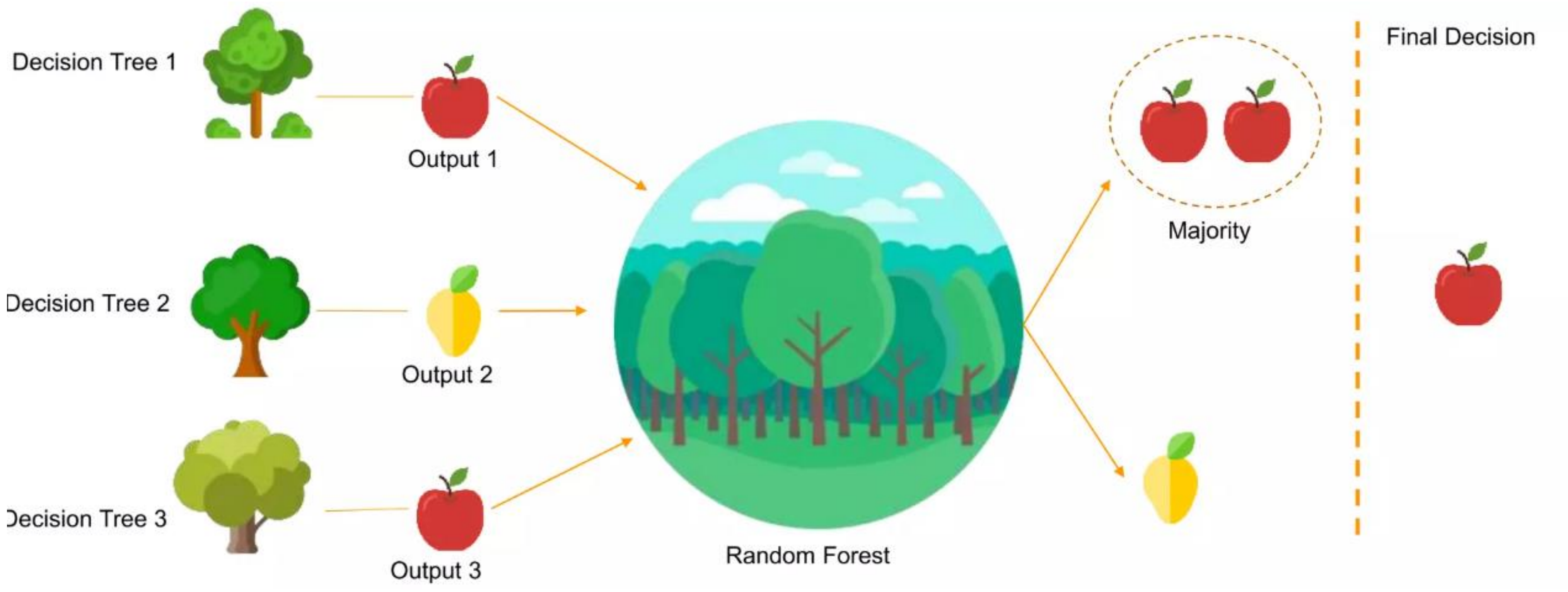
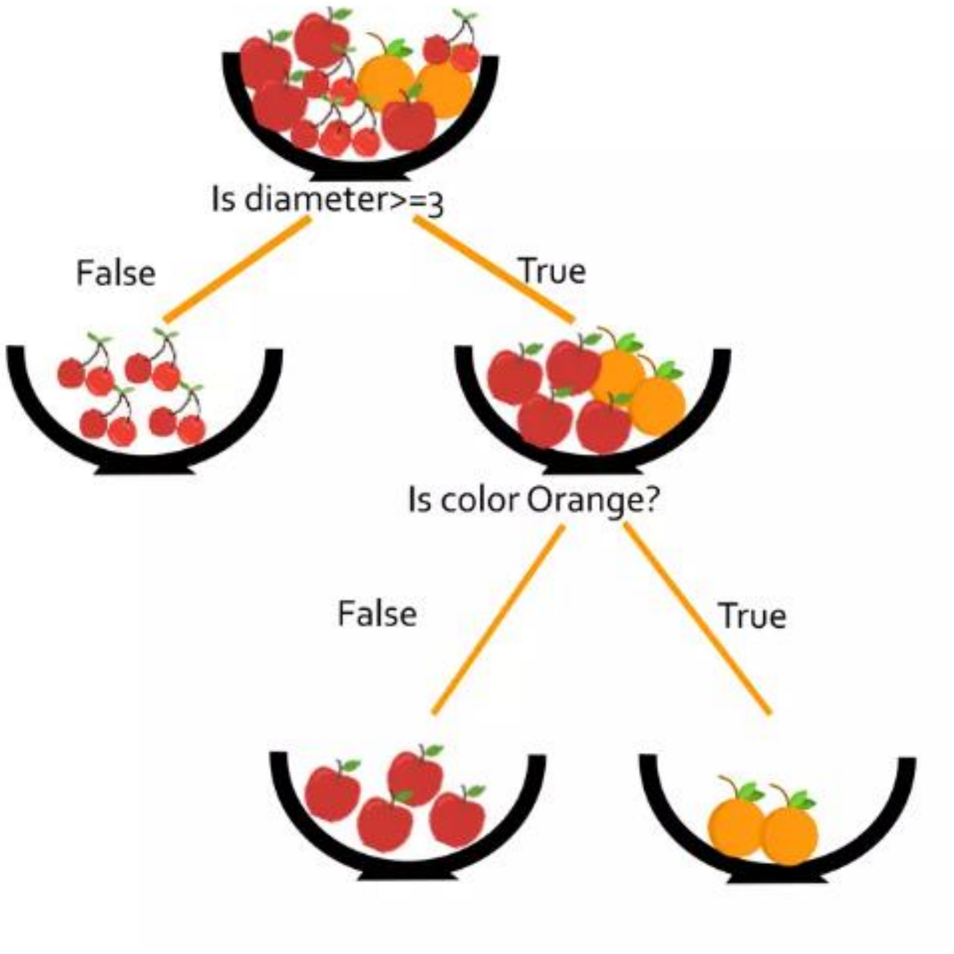


IMAGE CLASSIFICATION – SUPERVISED CLASSIFICATION

- Random Forest is a method that constructs multiple decision trees during training phase.
- The decision of the majority of the trees is chosen by the random forest as the final decision.



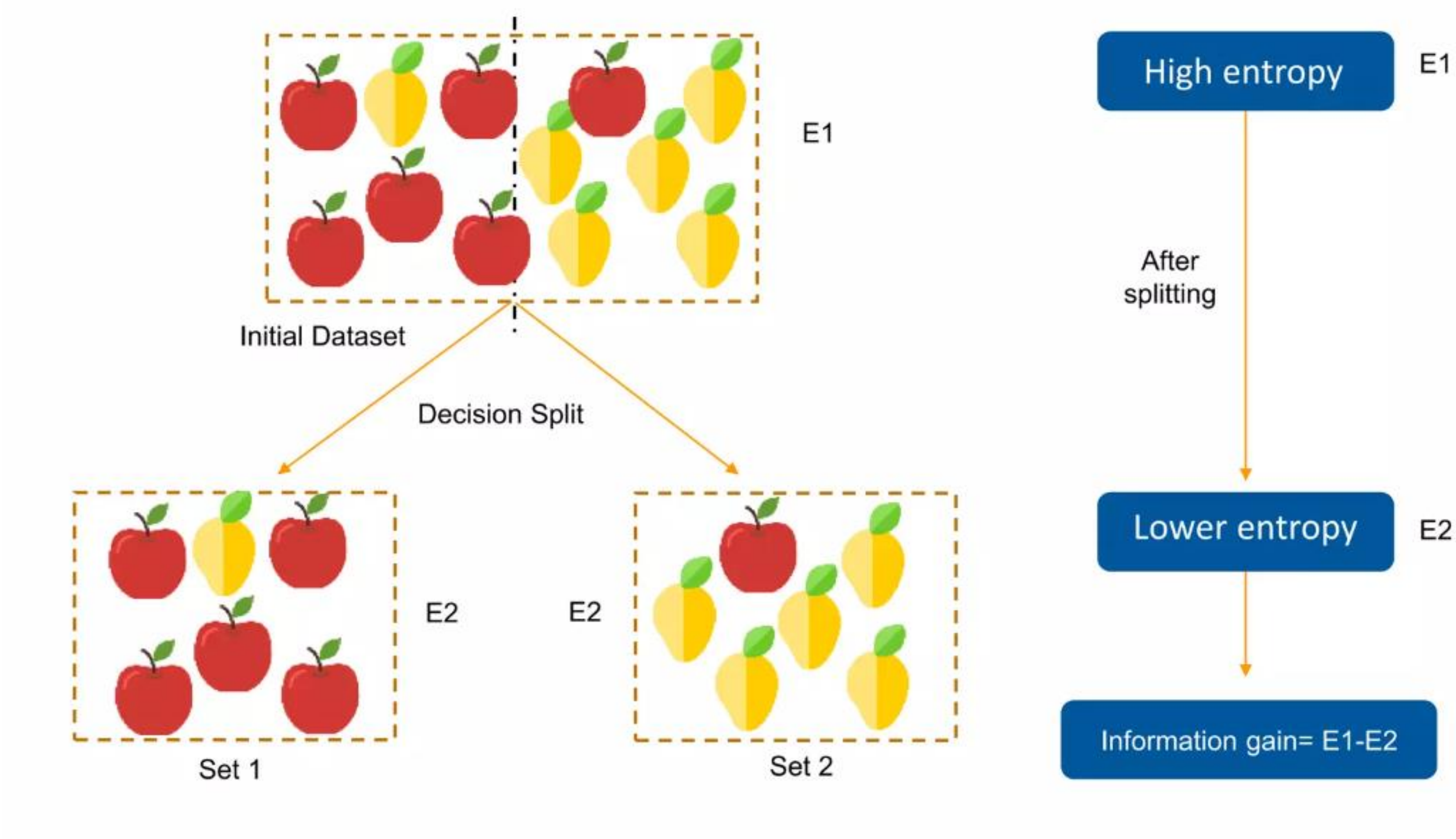


Decision Tree:

- The decision tree is a tree shaped diagram used to determine a course of action.
- Each branch of the tree represents a possible decision, occurrence or reaction\

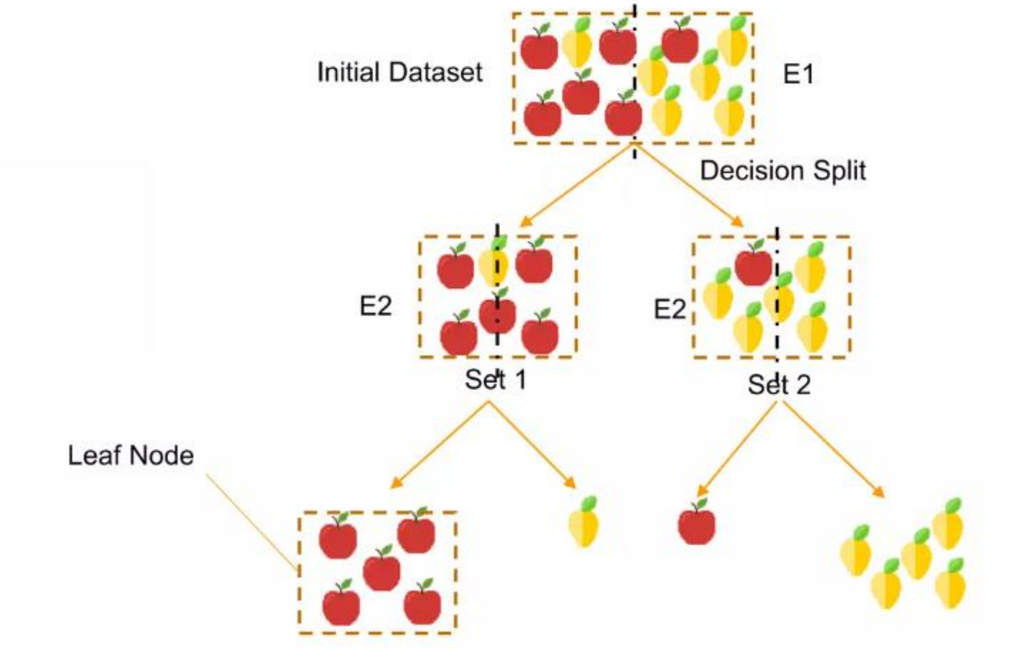
1. Entropy
    - Measure of randomness

2. Information gain
    - Is the measure of the decrease or randomness after the data is split



3. Leaf node: carries the classification or the decision

4. Decision node: intermediate decision, have 2 sub-branches



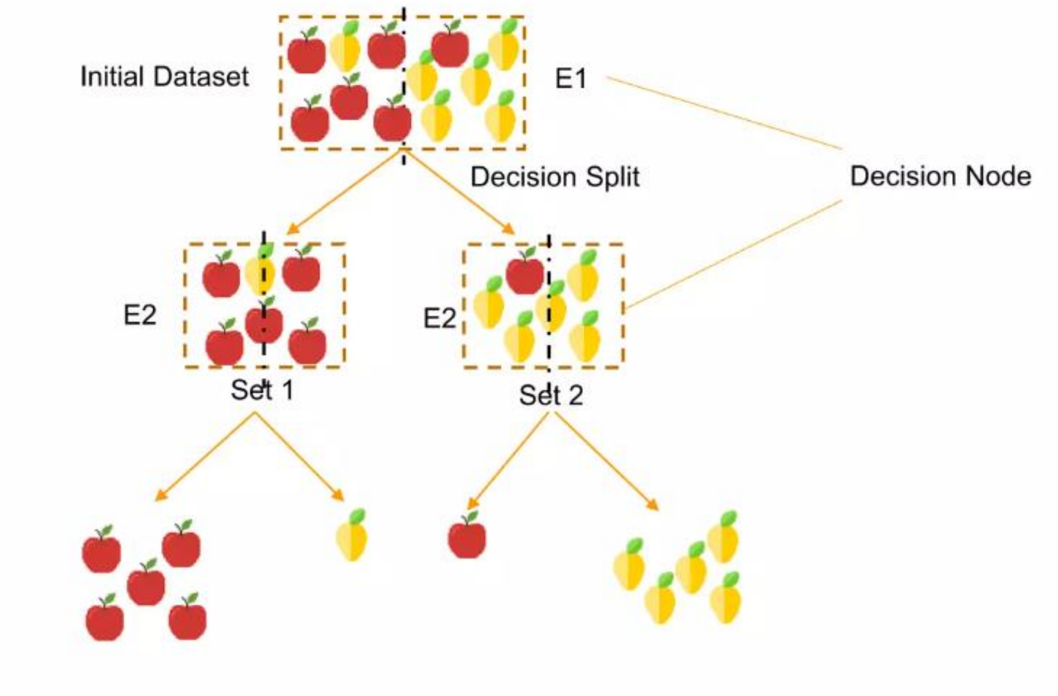


IMAGE CLASSIFICATION – SUPERVISED CLASSIFICATION

Problem statement

To classify the different types of fruits in the bowl based on different features

The dataset(bowl) is looking quite messy and the entropy is high in this case

Training Dataset

Color	Diameter	Label
Red	3	Apple
Yellow	3	Lemon
Purple	1	Grapes
Red	3	Apple
Yellow	3	Lemon
Purple	1	Grapes

How to split the data

We have to frame the conditions that split the data in such a way that the information gain is the highest

Conditions

Color== purple?

Diameter=3

Color== Yellow?

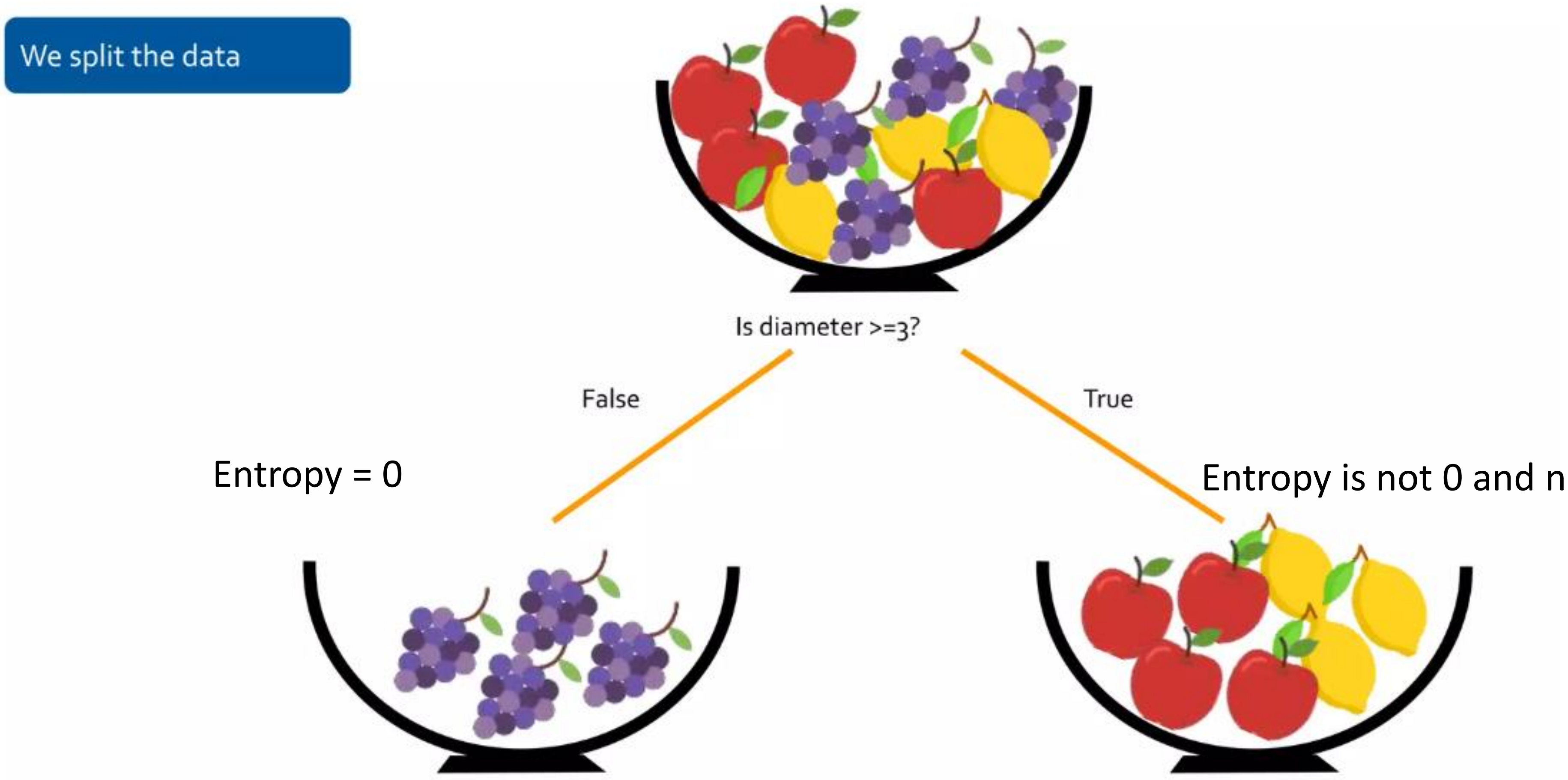
Color== Red?

Diameter=1

Training Dataset

Color	Diameter	Label
Red	3	Apple
Yellow	3	Lemon
purple	1	Grapes
Red	3	Apple
Yellow	3	Lemon
purple	1	Grapes

IMAGE CLASSIFICATION – SUPERVISED CLASSIFICATION

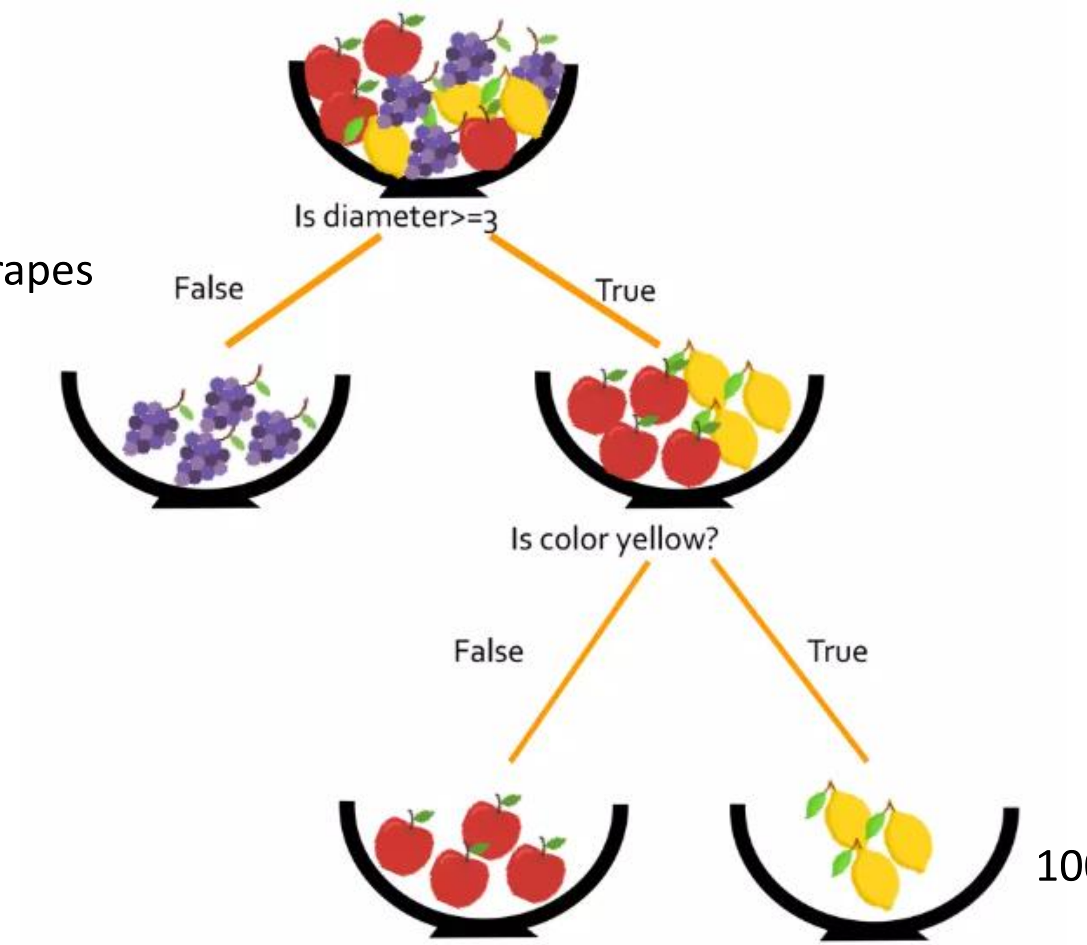


Entropy = 0

Entropy is not 0 and need to be splitted

IMAGE CLASSIFICATION – SUPERVISED CLASSIFICATION

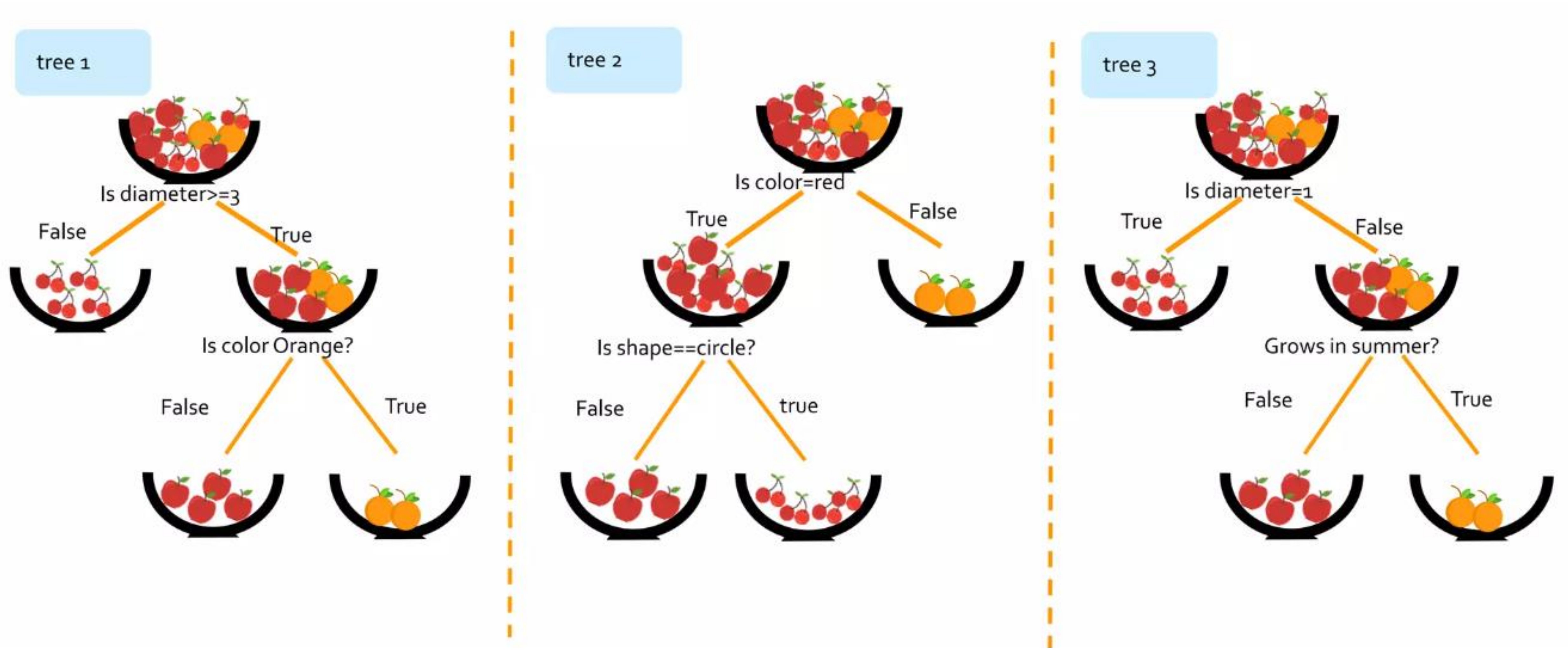
100% accuracy for grapes



100% accuracy for lemons

100% accuracy for apples

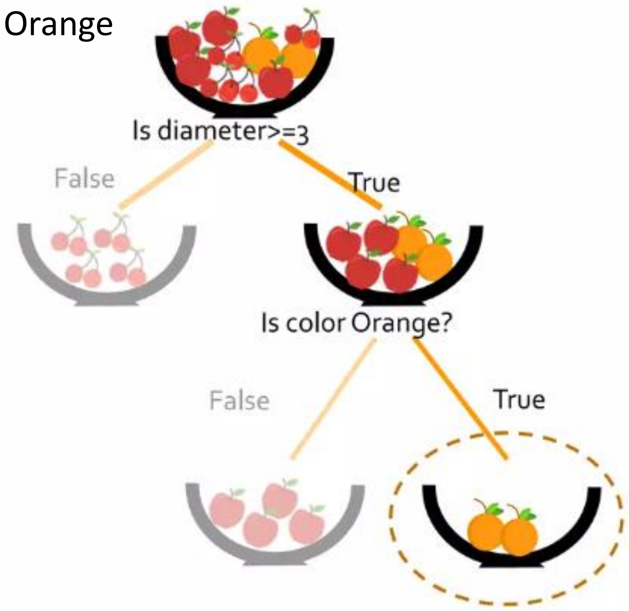
IMAGE CLASSIFICATION – Random Forest – How does it work?



How to classify this fruit?

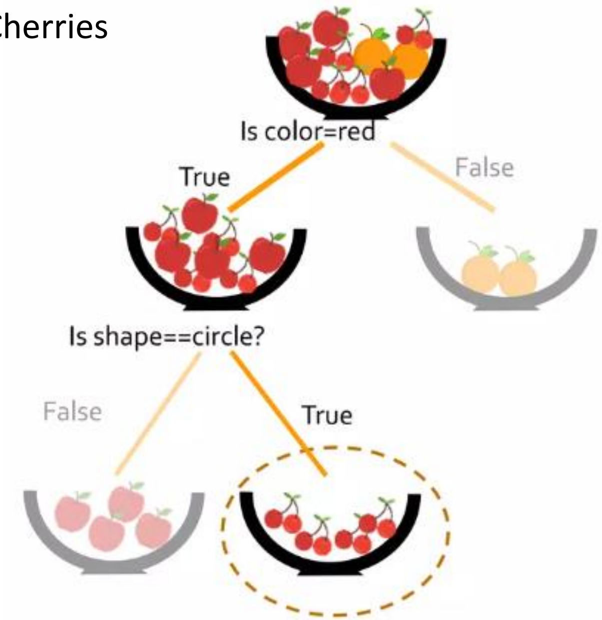
Tree 1
Diameter = 3
Color = orange

Result = Orange



Tree 2
Color = red
Shape = Circle

Result = Cherries



Tree 3
Diameter = 3
Color = orange

Result = Orange

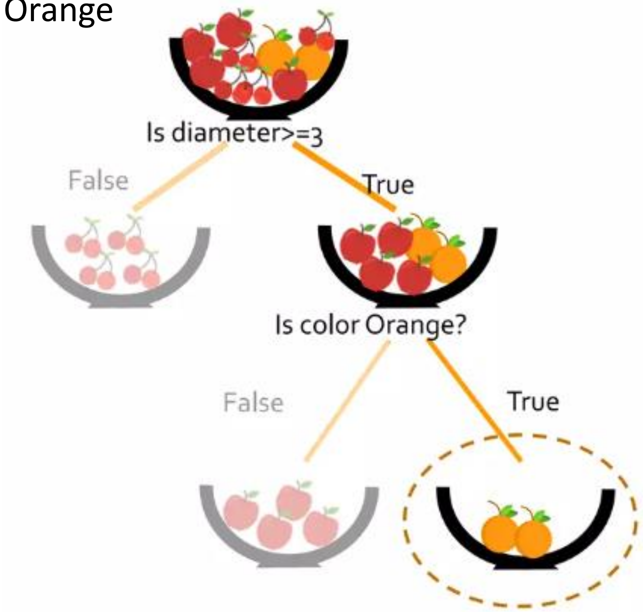
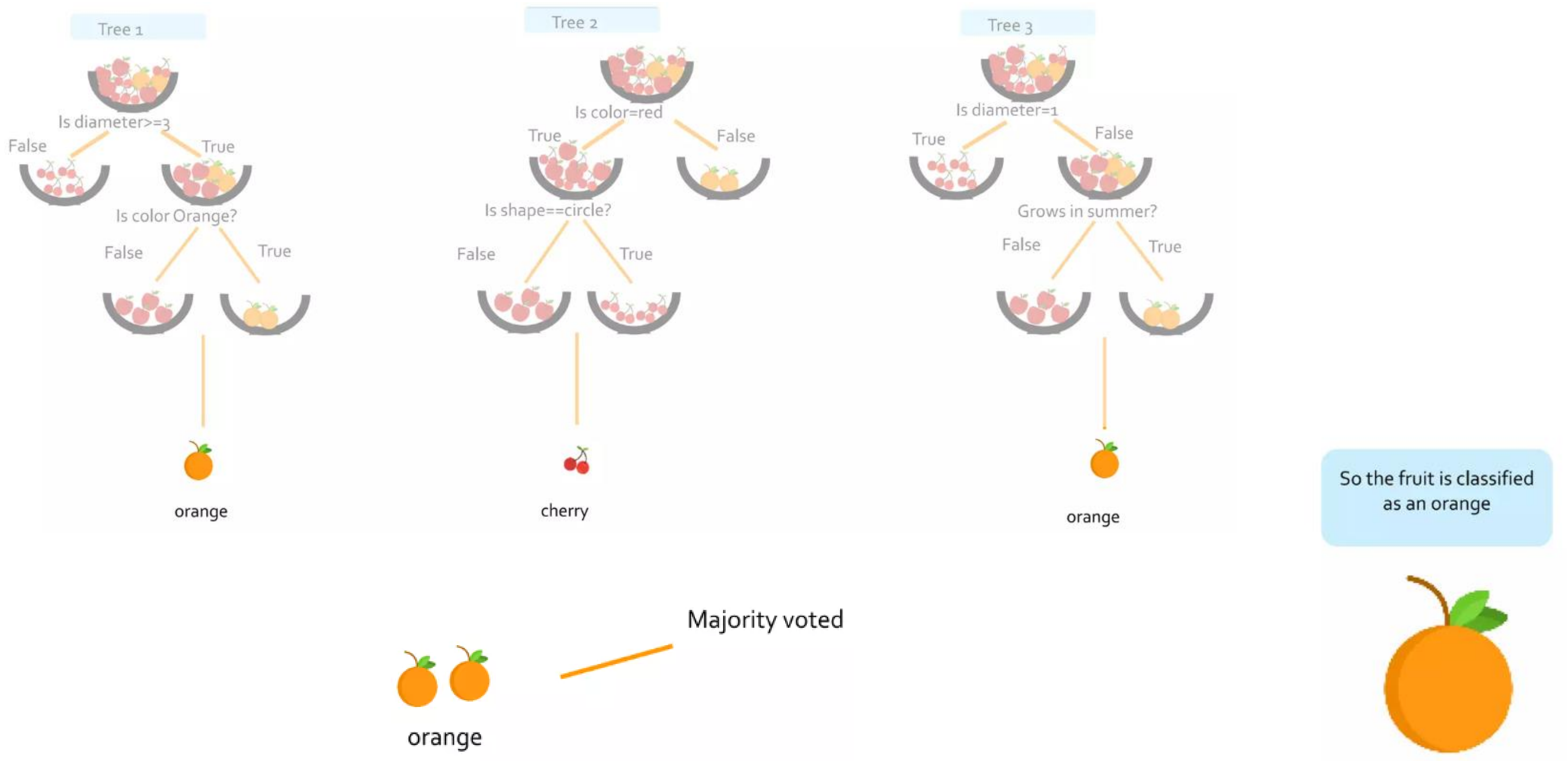
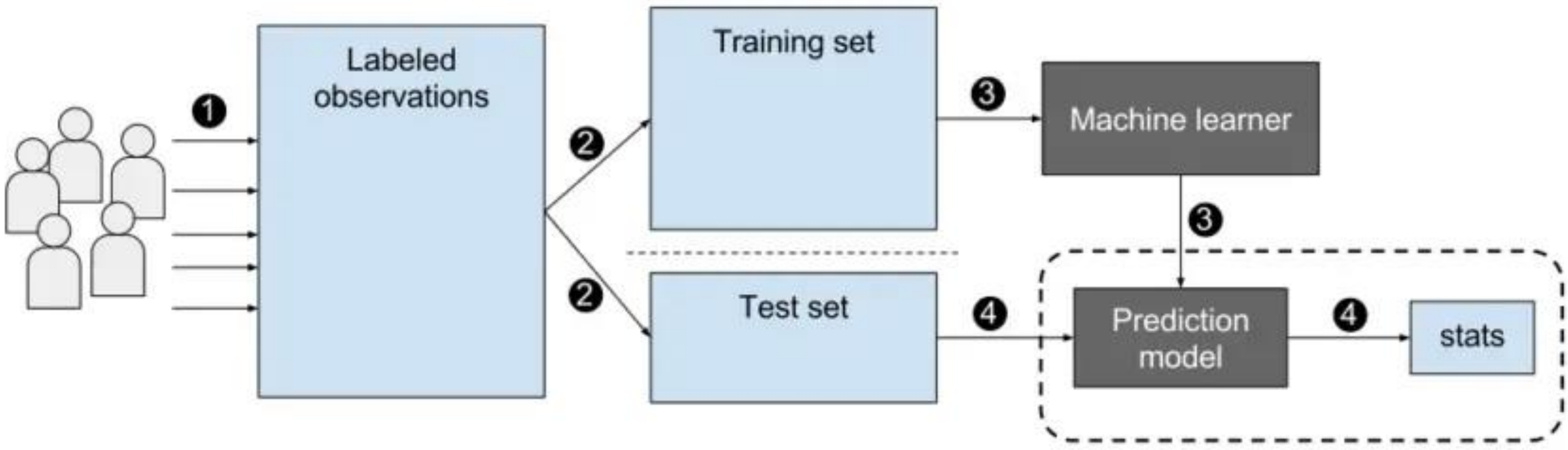


IMAGE CLASSIFICATION – SUPERVISED CLASSIFICATION





.....a priori Knowledge!!!

IMAGE CLASSIFICATION – UNSUPERVISED CLASSIFICATION

The most used unsupervised algorithms:

- ISODATA
- K-means

A K-means algorithm tries to group similar items in the form of clusters. The number of group is represented by K.

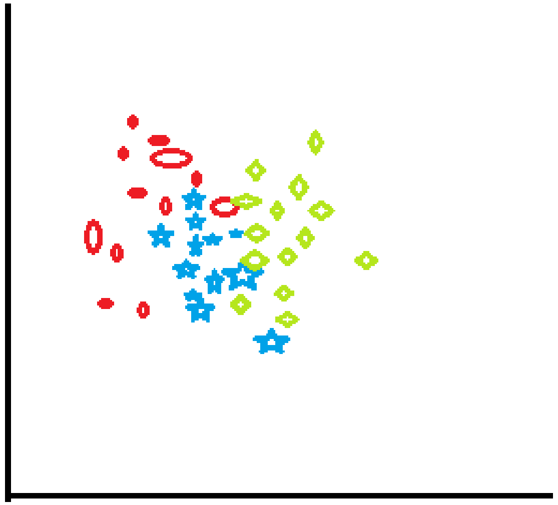


fig 1: before applying k-means clustering

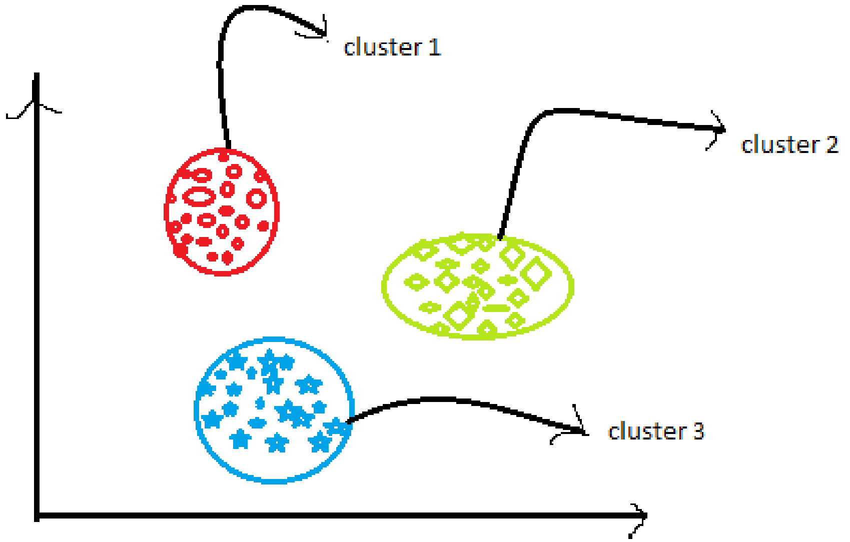


fig 2: After applying K-means clustering

IMAGE CLASSIFICATION – UNSUPERVISED CLASSIFICATION – k-means

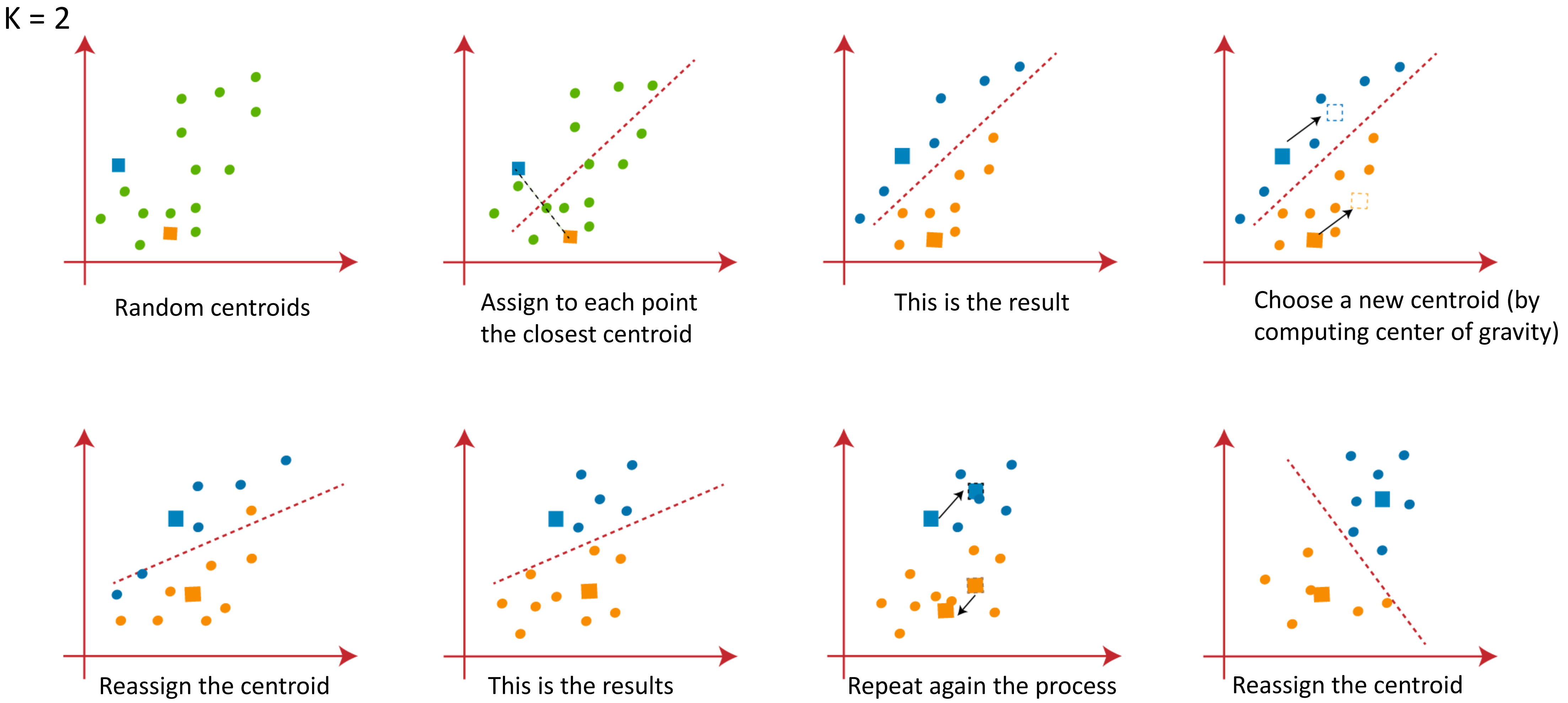
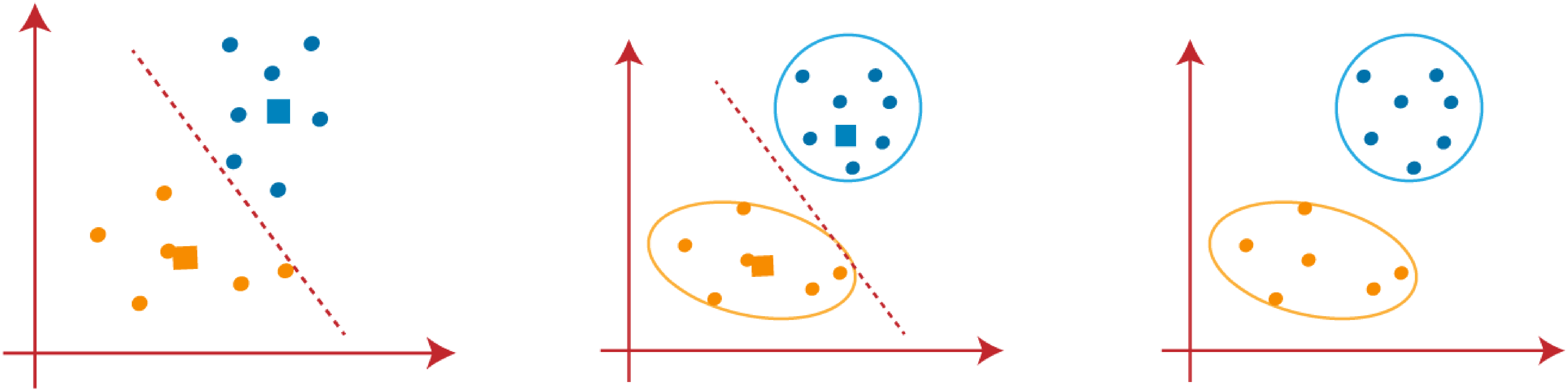


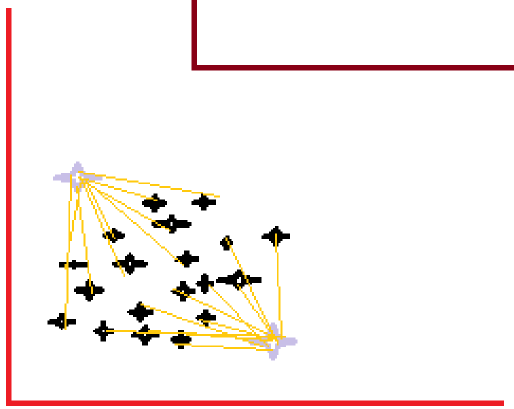
IMAGE CLASSIFICATION – UNSUPERVISED CLASSIFICATION – k-means



How to choose the parameter k?

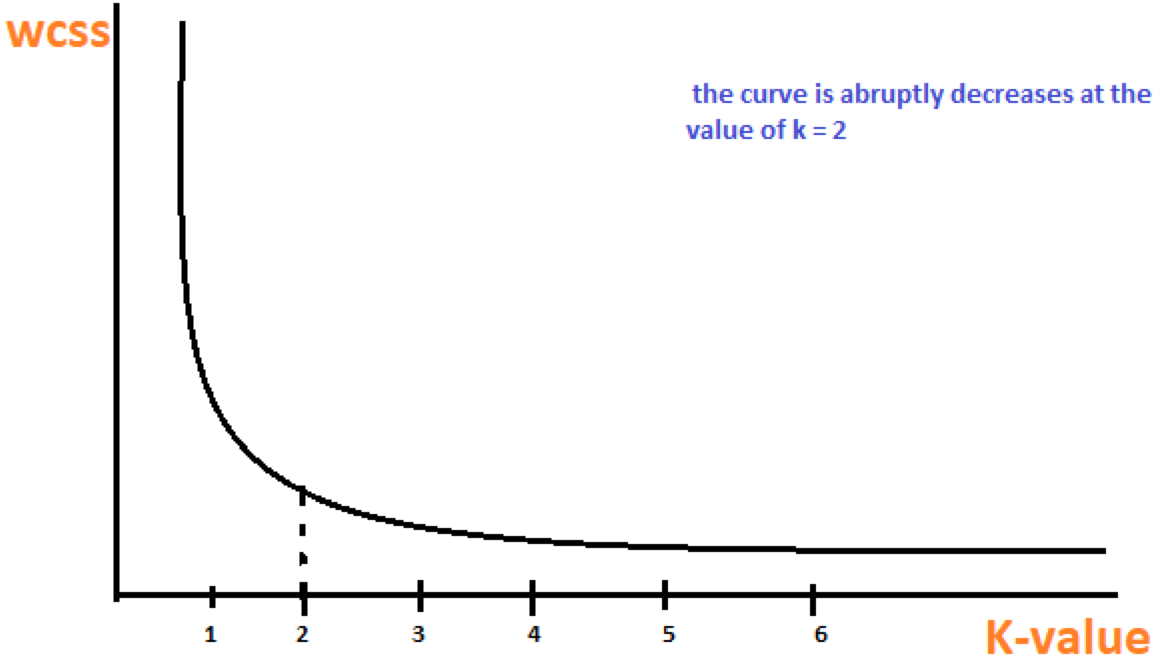
Elbow method

with in cluster sum of square (wss) = $\sum_{i=1}^{n} (Ci + Xi)^2$



when k = 1

wcss = high



UNIVERSITÀ DEGLI STUDI DI TRIESTE

Dipartimento di Scienze della Vita

Corso di Laurea in

Ecologia dei Cambiamenti Globali

Using remote sensing to map natural habitats: an integrated approach applied to the Classical Karst eco-mosaic

Emilia Pafumi

1. Introduction

1.1. Conservation of a semi-natural landscape: Karst eco-mosaic

millenary pasture activities

↓

evolution of Karst grassland

socio-economic changes after World War II

↓

pasture abandonment

↓

secondary succession and grassland decline

↓

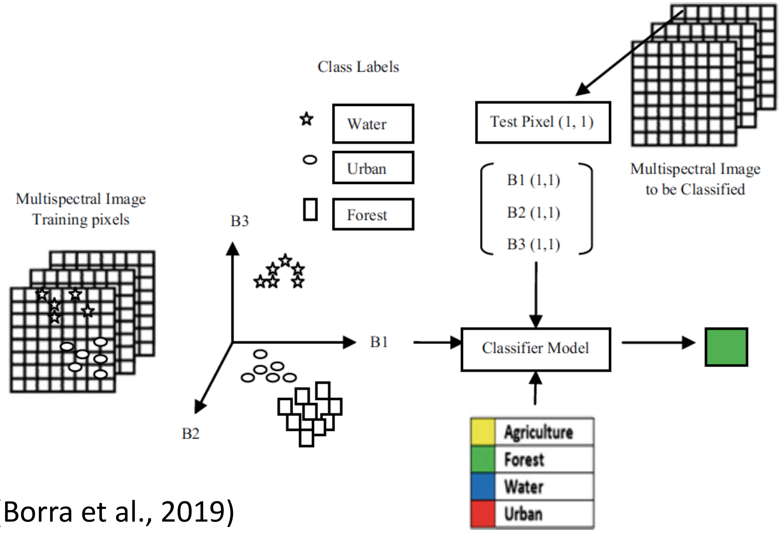
projects to reintroduce grazing: "Ecomosaico del Carso"

«Ecomosaico del Carso» project:

- aims at the restoration of Karst grassland and the management of woodland;
- restoration actions are starting in 2022;
- habitat mapping was required to characterize the initial conditions.

1.2. Habitat mapping: image classification

- Image classification = process of categorizing pixels into ground cover classes.
- The choice of the remote sensing input data influences the type of habitat that can be mapped.



(Borra et al., 2019)

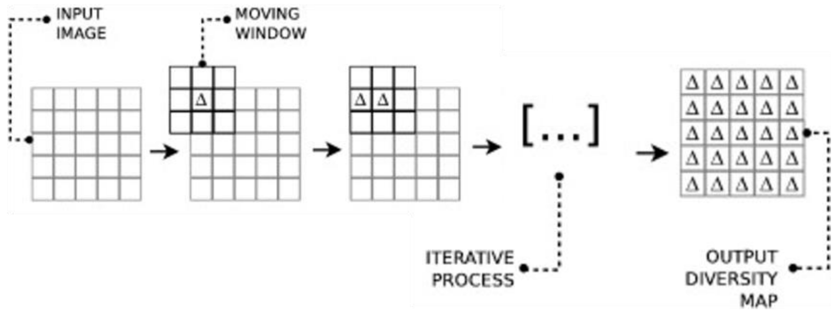
- Most common approaches:
  - single-date images
  - spectral reflectance bands or simple vegetation indices
- Open problem: these approaches are inadequate for mapping heterogeneous landscapes with small and spectrally similar habitat patches.

- Novel approaches:
  1) inclusion of multi-temporal data
  2) use of different indices, as spectral heterogeneity indices

1.3. Spectral heterogeneity

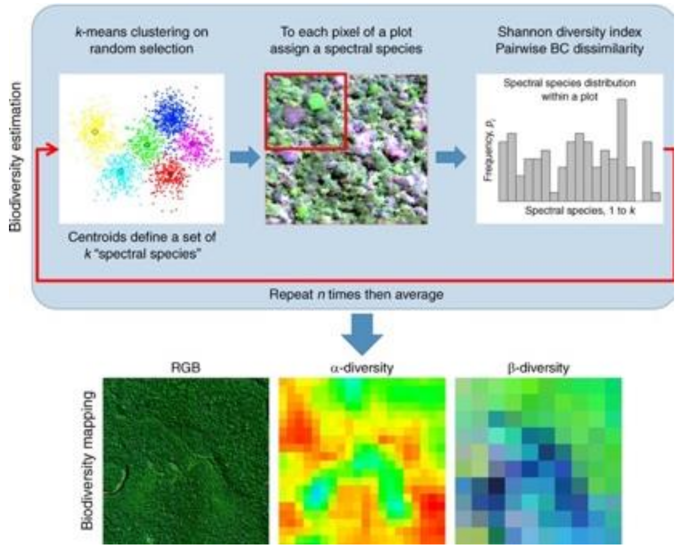
- Spectral heterogeneity = variation in the remote sensing signal
- Spectral Variation Hypothesis (Palmer et al., 2002): spectral heterogeneity is linked to species diversity
- Spectral heterogeneity indices:
  - Rao's Q index: relative abundance of pixel values and spectral distance among them
  - Spectral α- and β-diversity indices
- Possible use for habitat classification.

MOVING WINDOW APPROACH



(Rocchini et al, 2013)

SPECTRAL SPECIES APPROACH



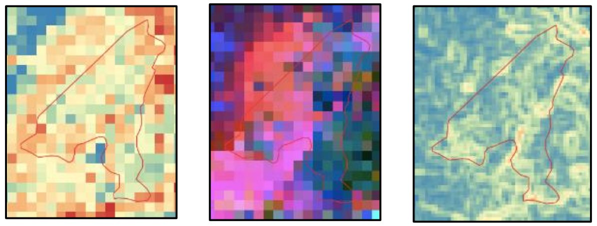
(Féret and Asner, 2014)

1.4. Aims of the study

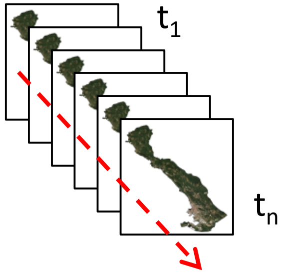
The aim of this study was to develop an integrated approach to map natural habitats in Karst eco-mosaic through remote sensing.

Specifically, the objectives were:

1) to quantify the importance of measures of spectral heterogeneity;



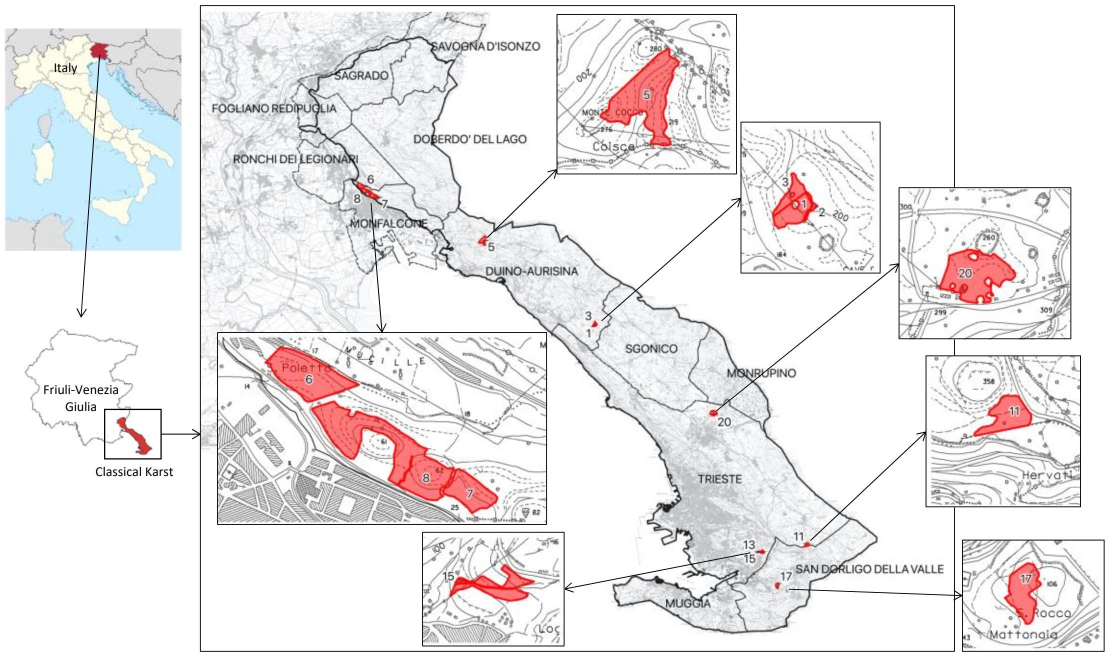
2) to provide a framework to include multi-temporal data.



2. Materials and methods

2.1. Field data collection

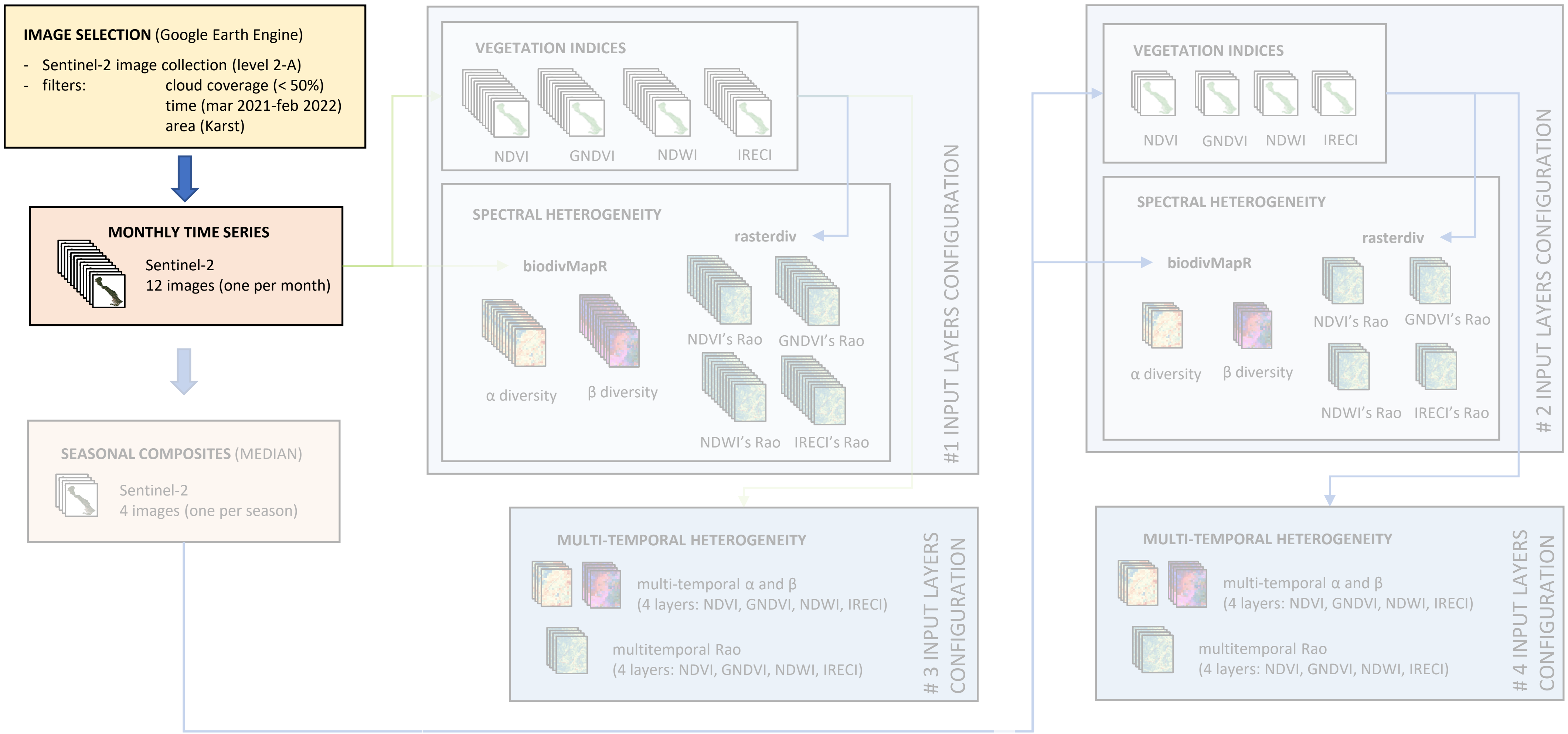
Study area: "Ecomosaico del Carso" project



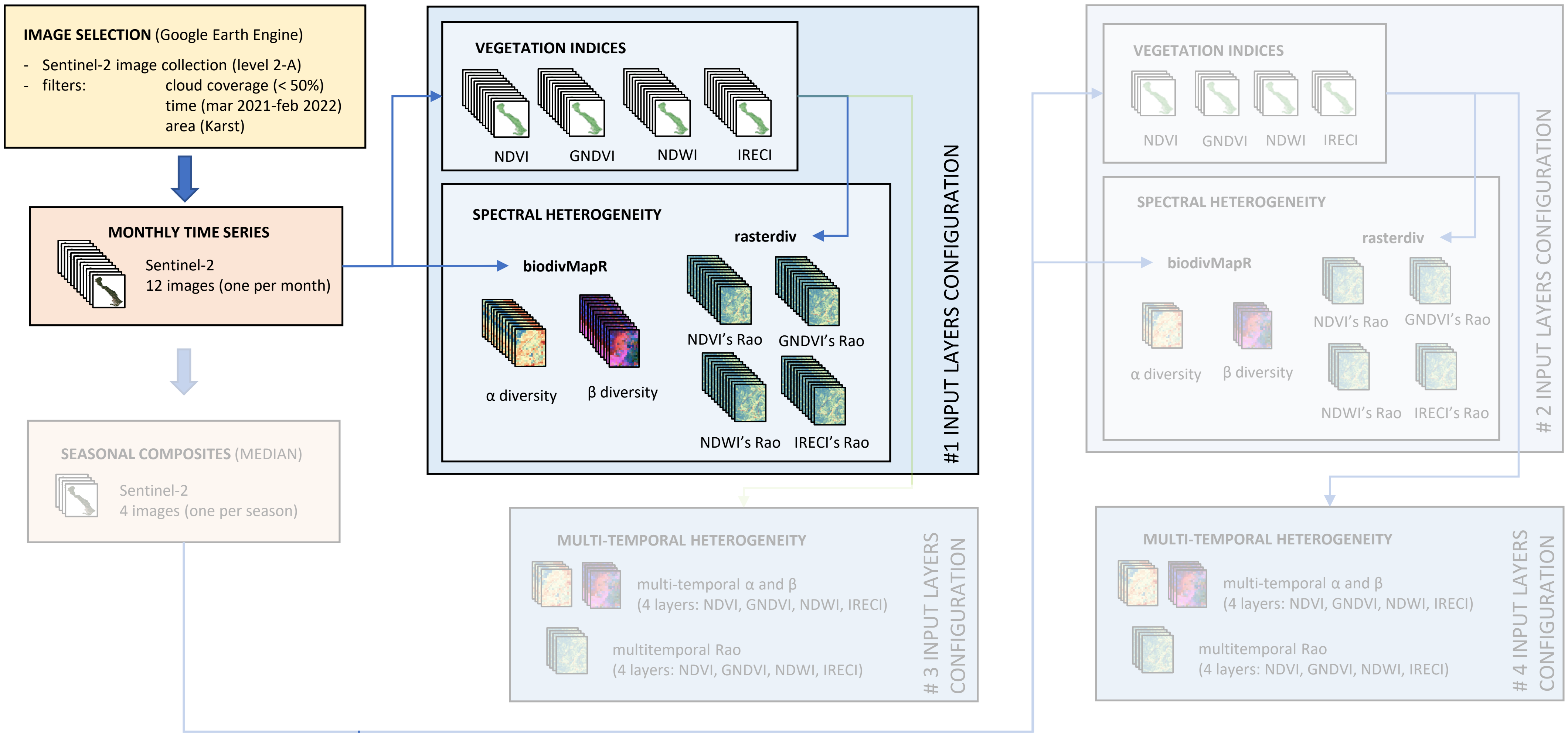
Field surveys (March - May 2022)

- habitat classes:
  1) fine classes: vegetation types based on Poldini (1989; 2009)
  2) coarse classes
- manually mapping → polygons in QGIS

2.2. Remote sensing data collection and processing



2.2. Remote sensing data collection and processing



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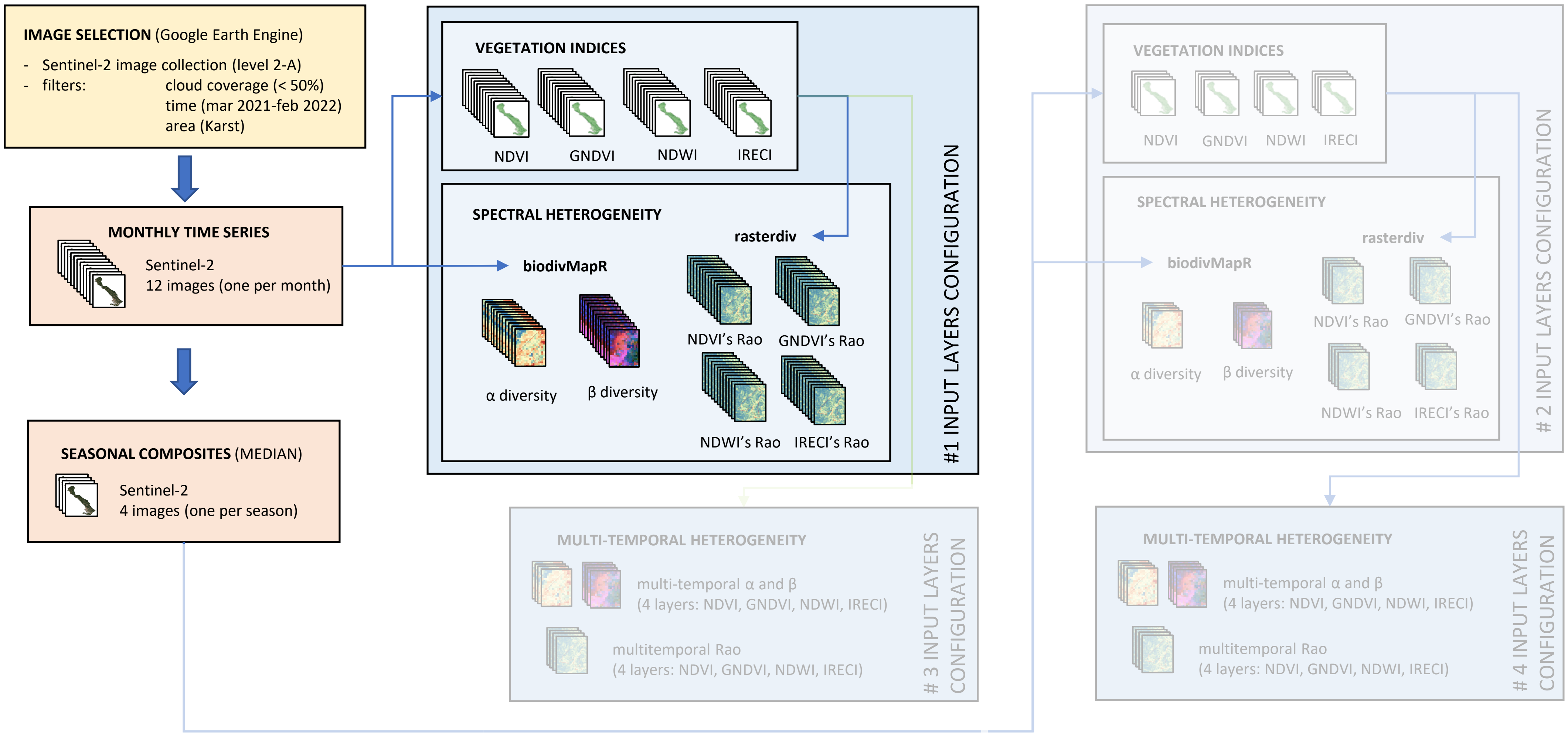

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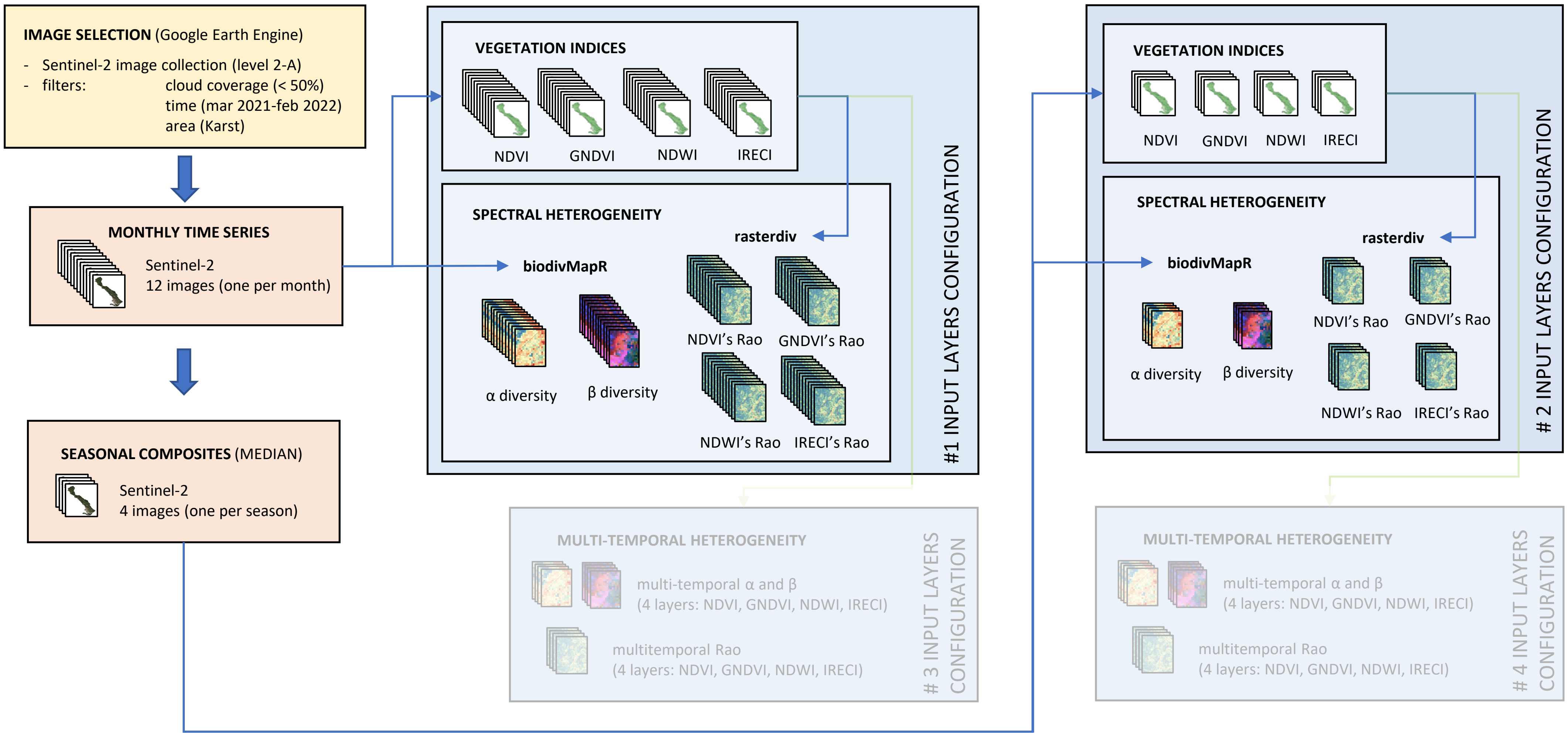

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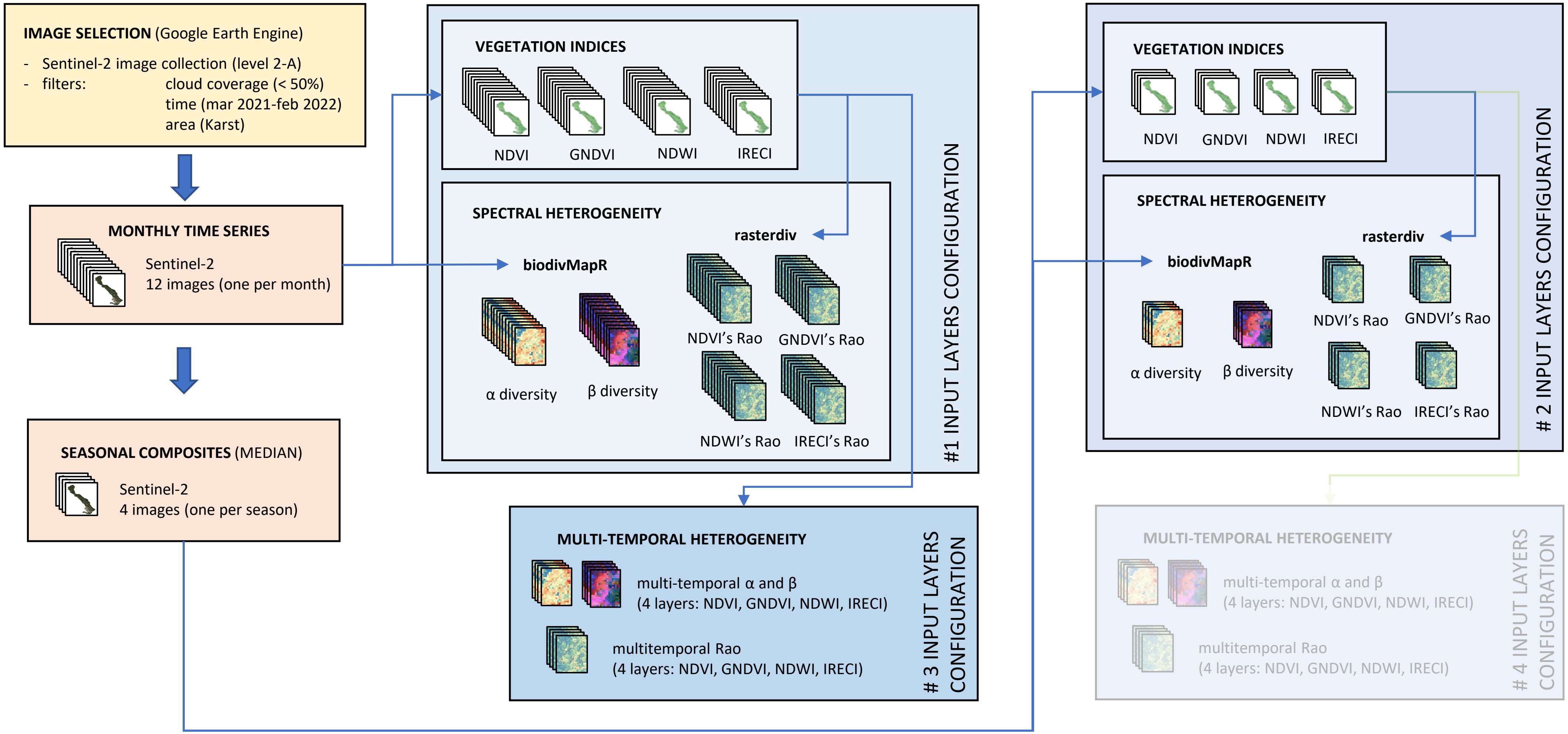

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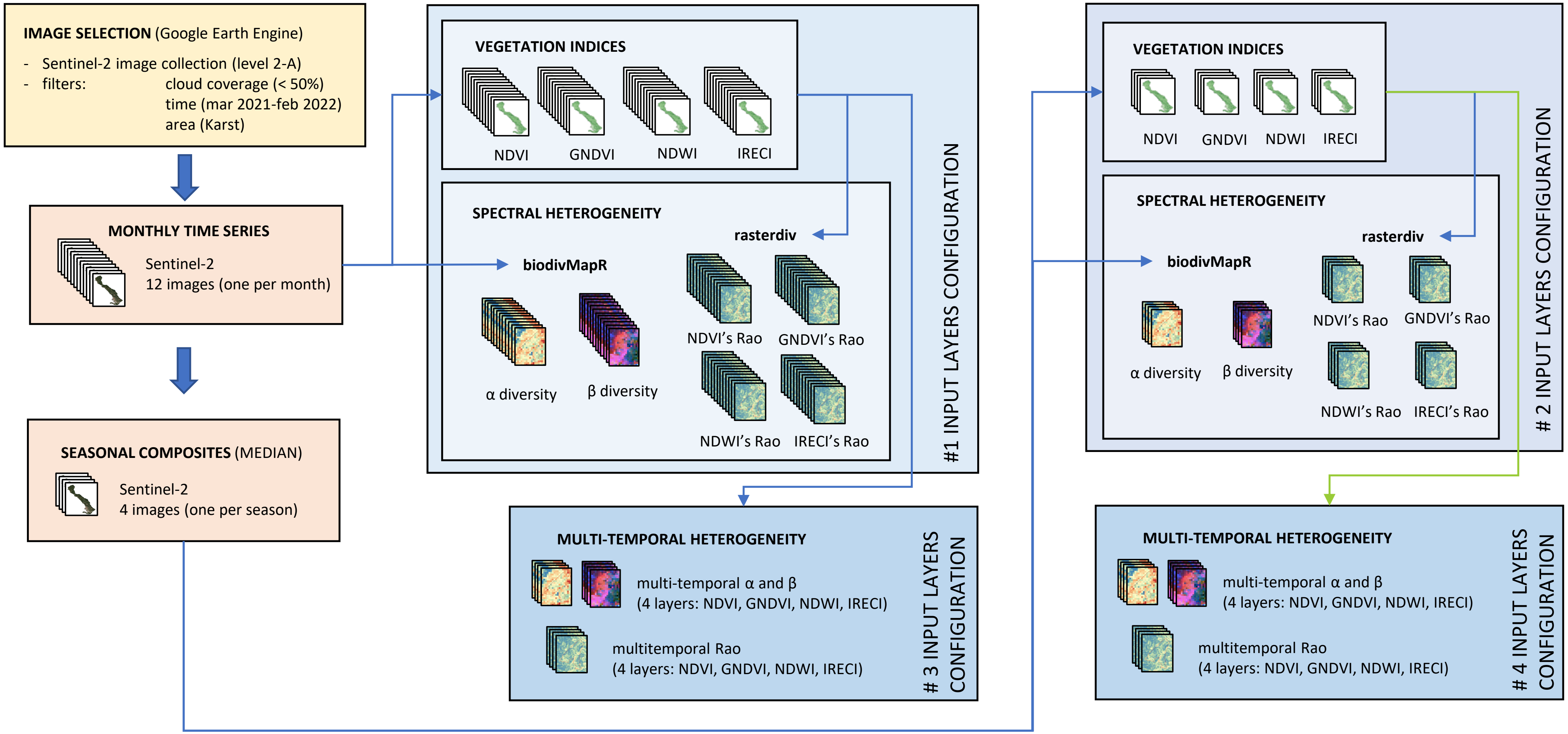
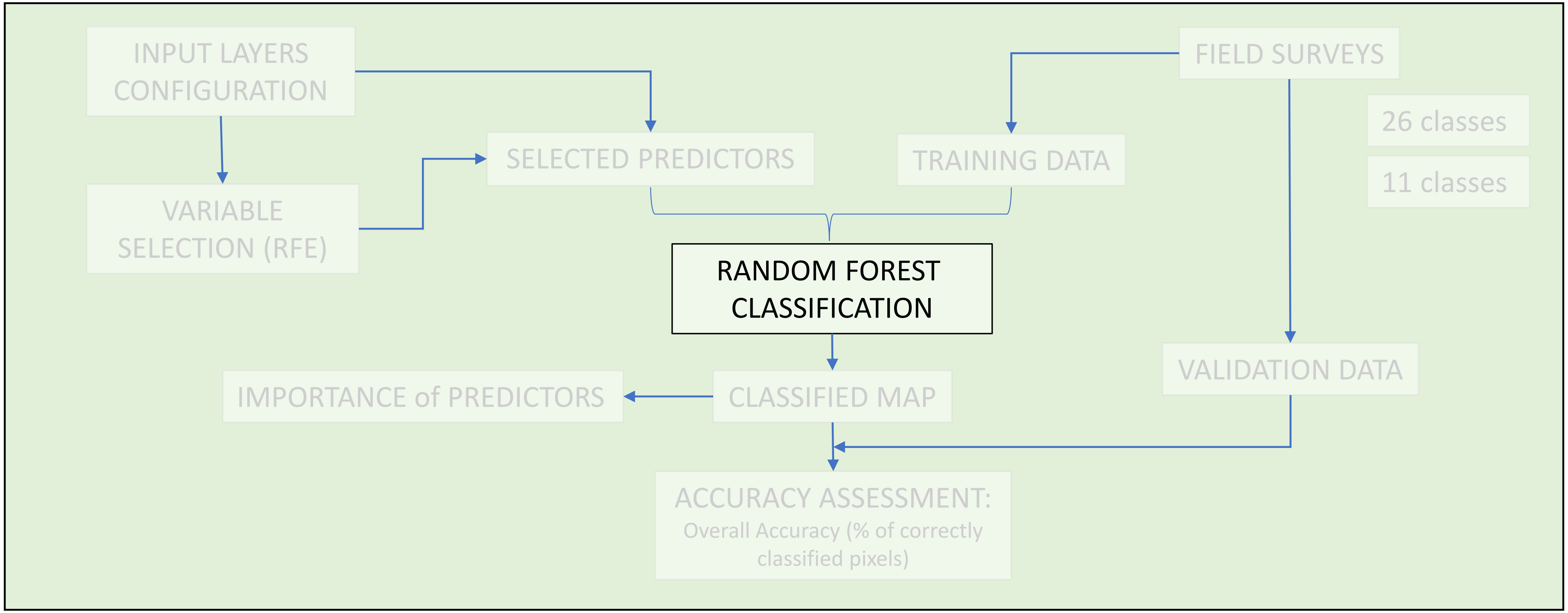


2.3. Image classifications



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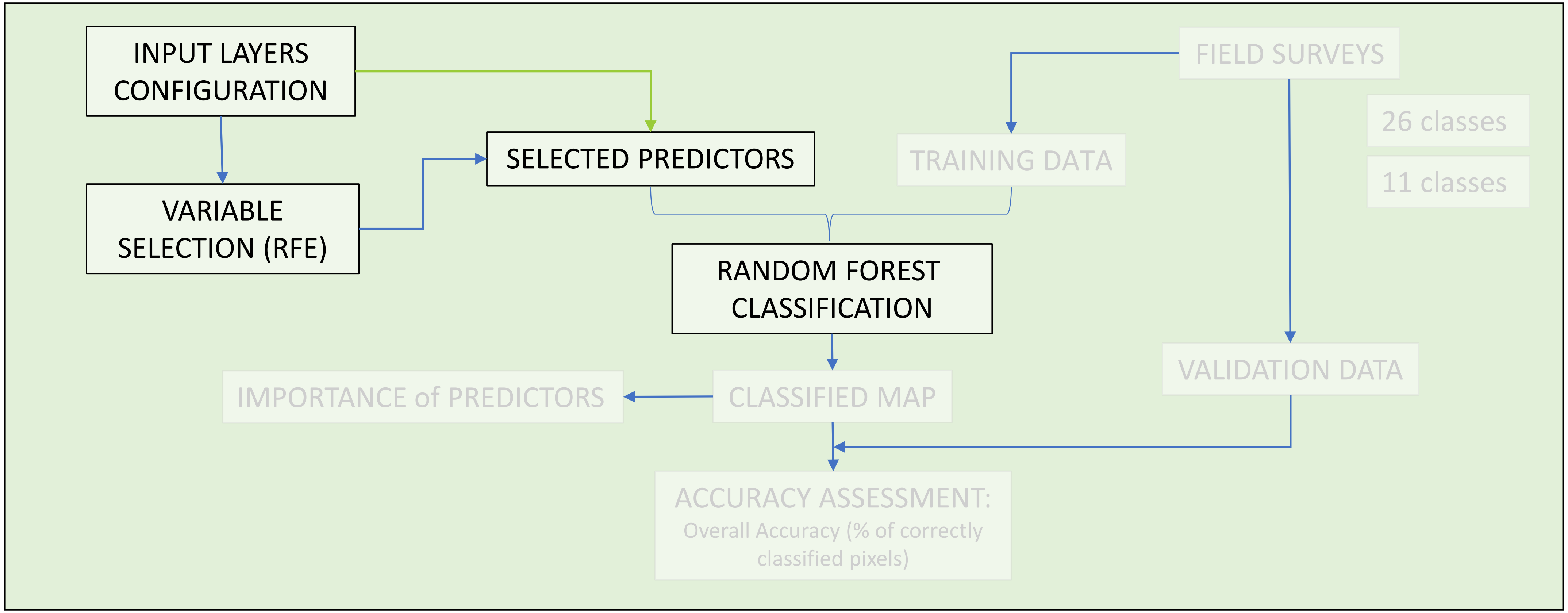

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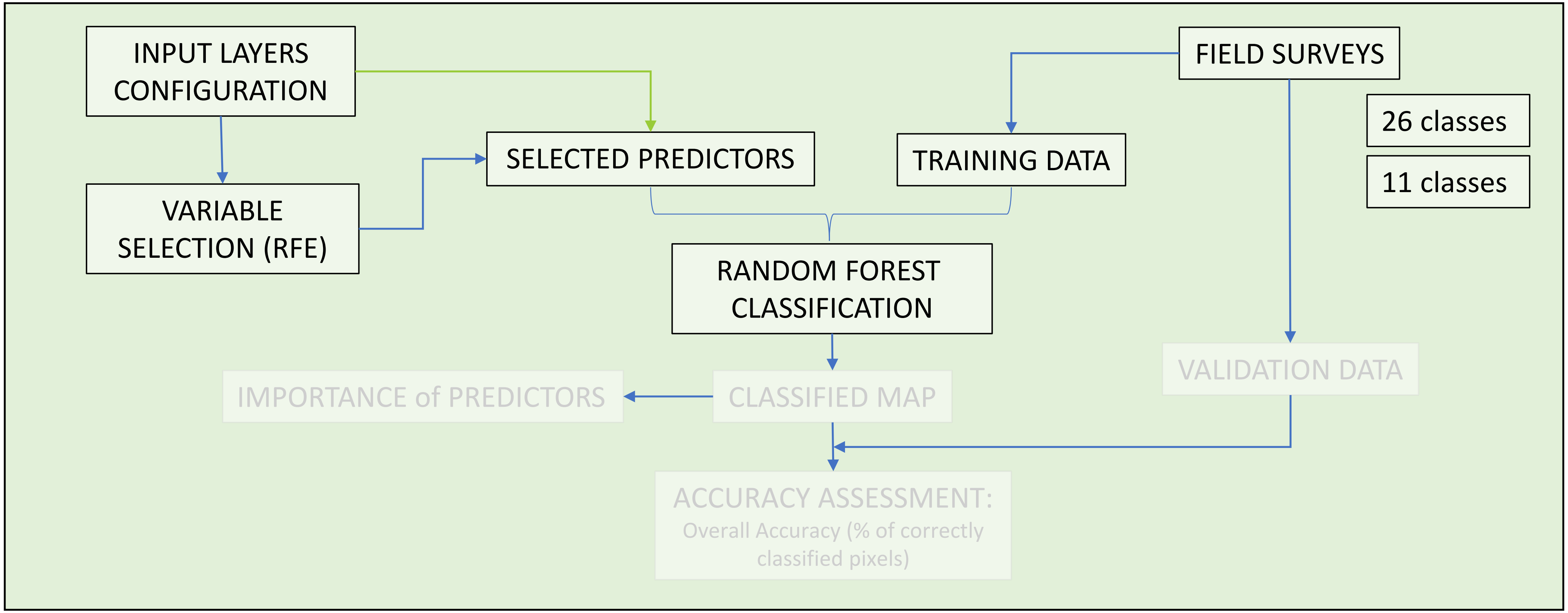

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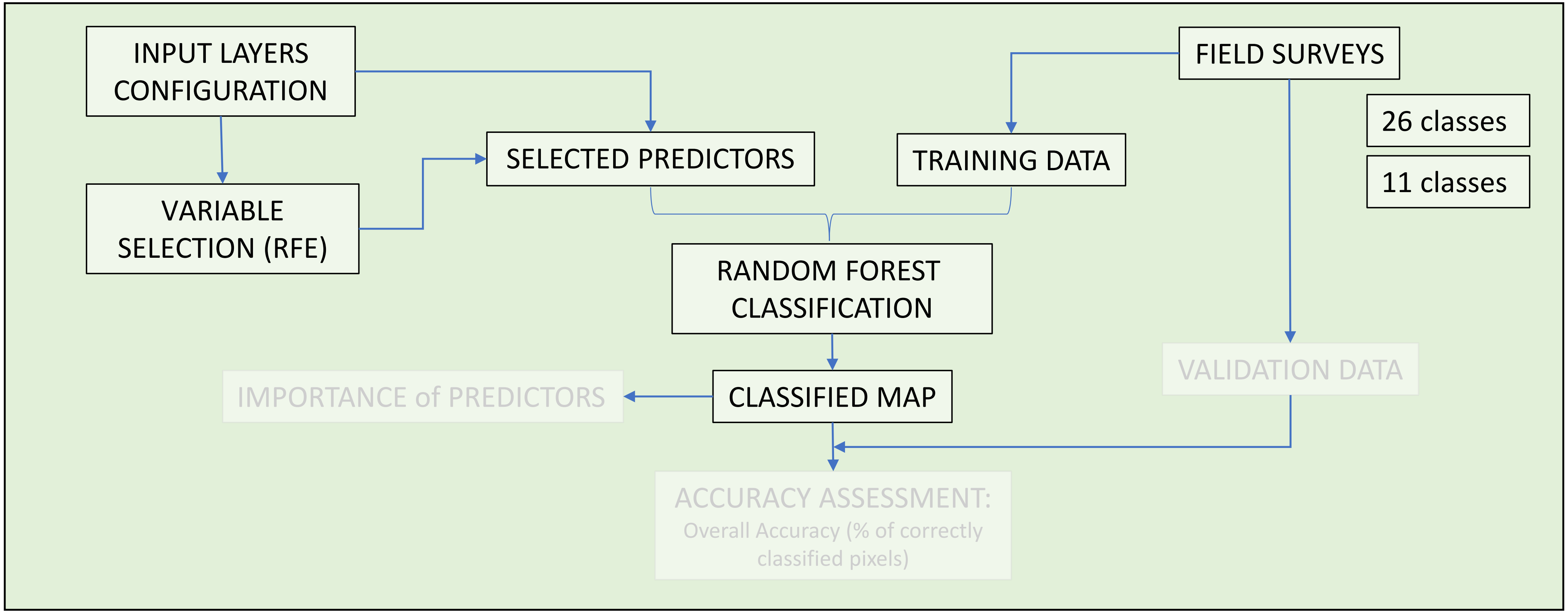

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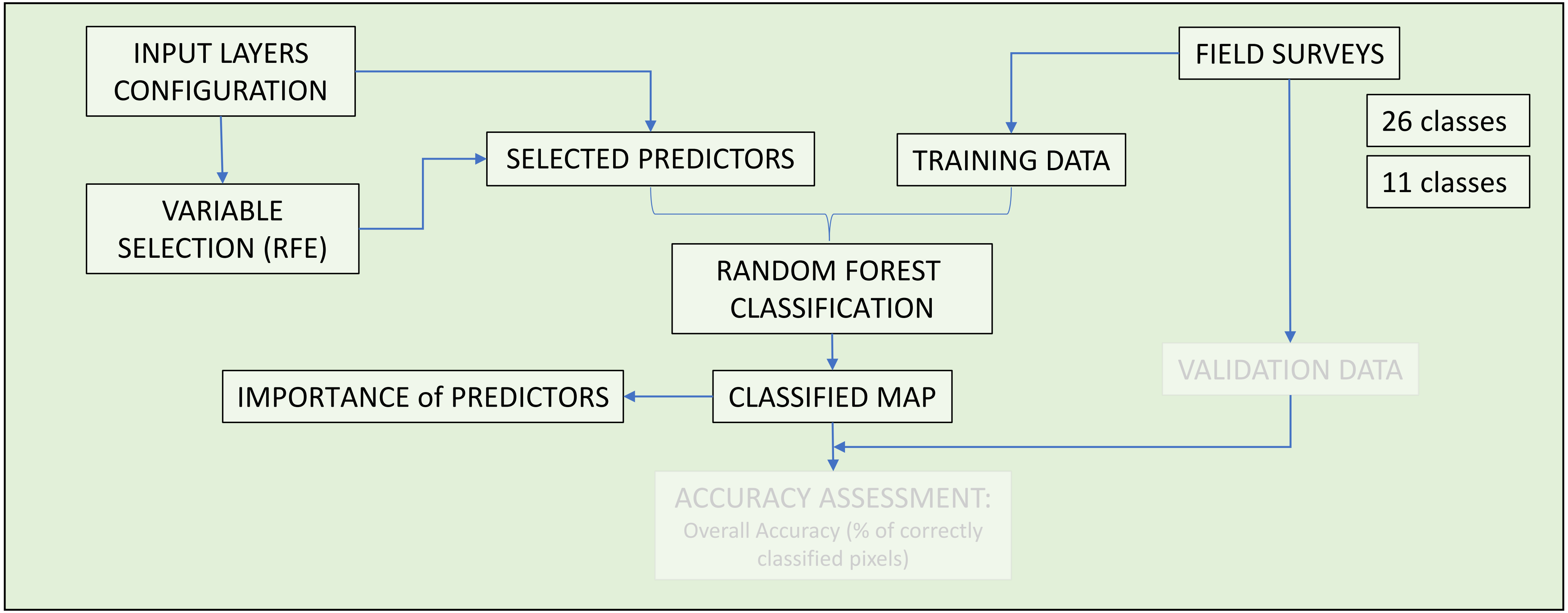

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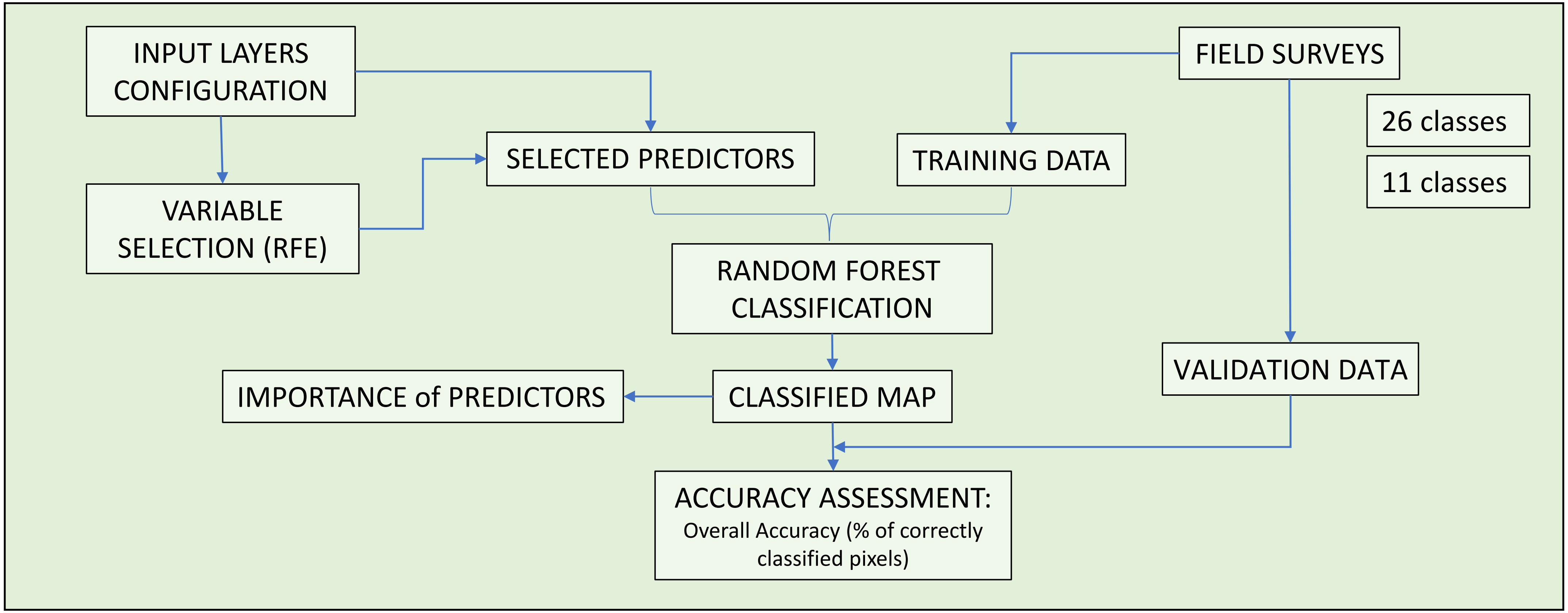
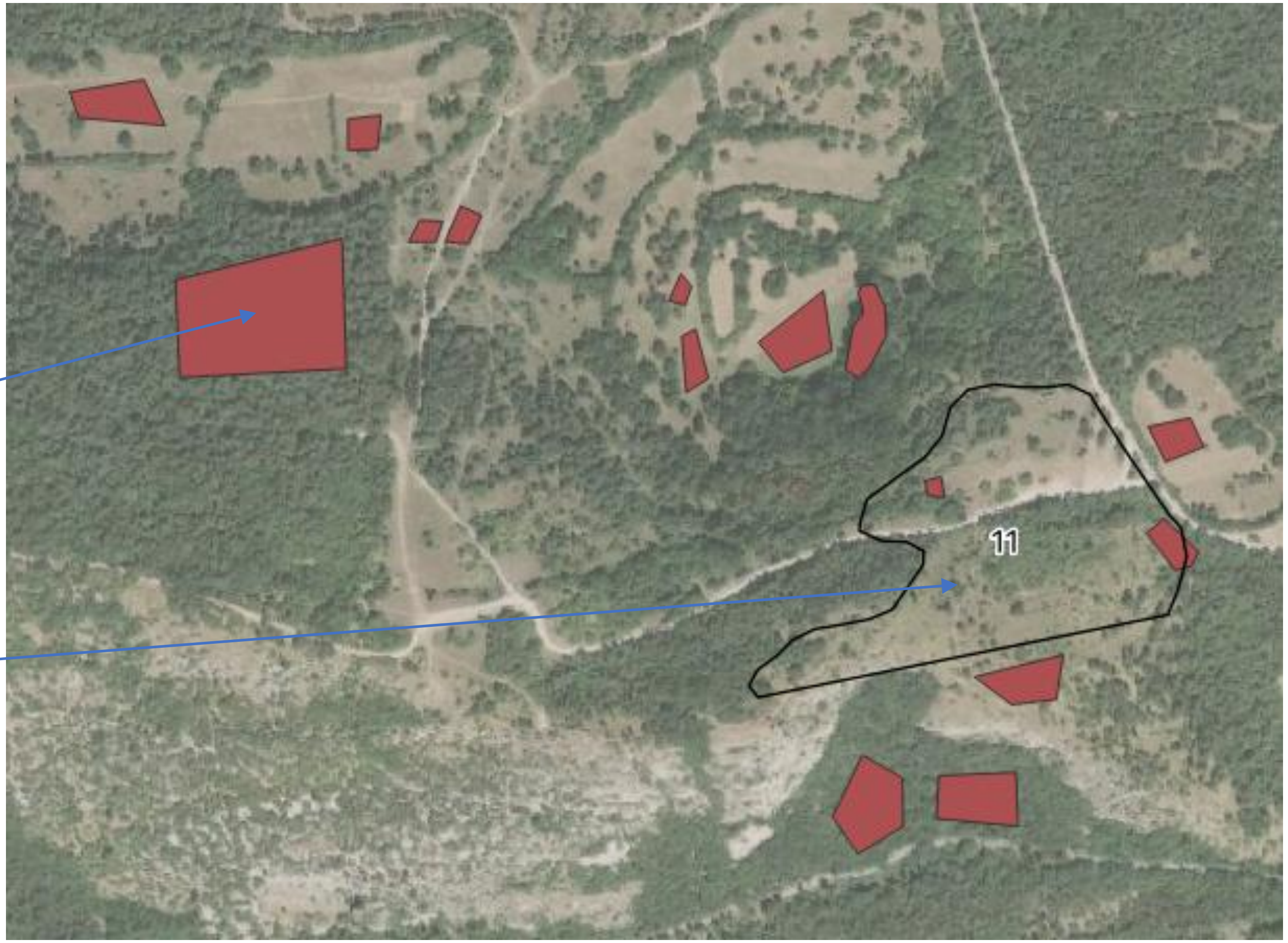


Training and validation data

Reference data were derived from field surveys:

- Training areas were chosen outside the study areas when possible and mapped on the field;
- Validation data points were randomly extracted from the QGIS polygons, after excluding the training areas.

Thus, training and validation data are independent, but the accuracy can be reduced.



3. Results and discussion

3.1. Field surveyed habitats

26 habitat classes	11 habitat classes
Pioneer shrubland on screes with *Ostrya carpinifolia*	Shrublands
Shrubland with *Cotinus coggygria*	
Pioneer thermophilous shrubland on screes	
Thermophilous Karst shrubland	
Shrubland with *Fraxinus ornus*	
Downy oak woodland: young	Downy oak woodland
Downy oak woodland: mature	
Sessile oak woodland	Sessile oak woodland
Grasslands (9 classes)	Grasslands (3 classes)
Grassland-woodland mosaic	Grassland-woodland mosaic
Pasture-grassland	Pasture-grassland
Hay meadow	Hay meadow
Black pine plantation	Black pine plantation
Grove with *Ailanthus altissima*	Invasive alien species
Grove with *Robinia pseudoacacia*	

Criteria for grassland classification:

TYPE of GRASSLAND


Thermophilous grassland


Mesophilous grassland


Flysch grassland

DEGREE of FELTING


Pure grassland


Grassland + patches *Sesleria autumnalis*


Mosaic grassland/*S. autumnalis*


Felted grassland

STAGE of SUCCESSION

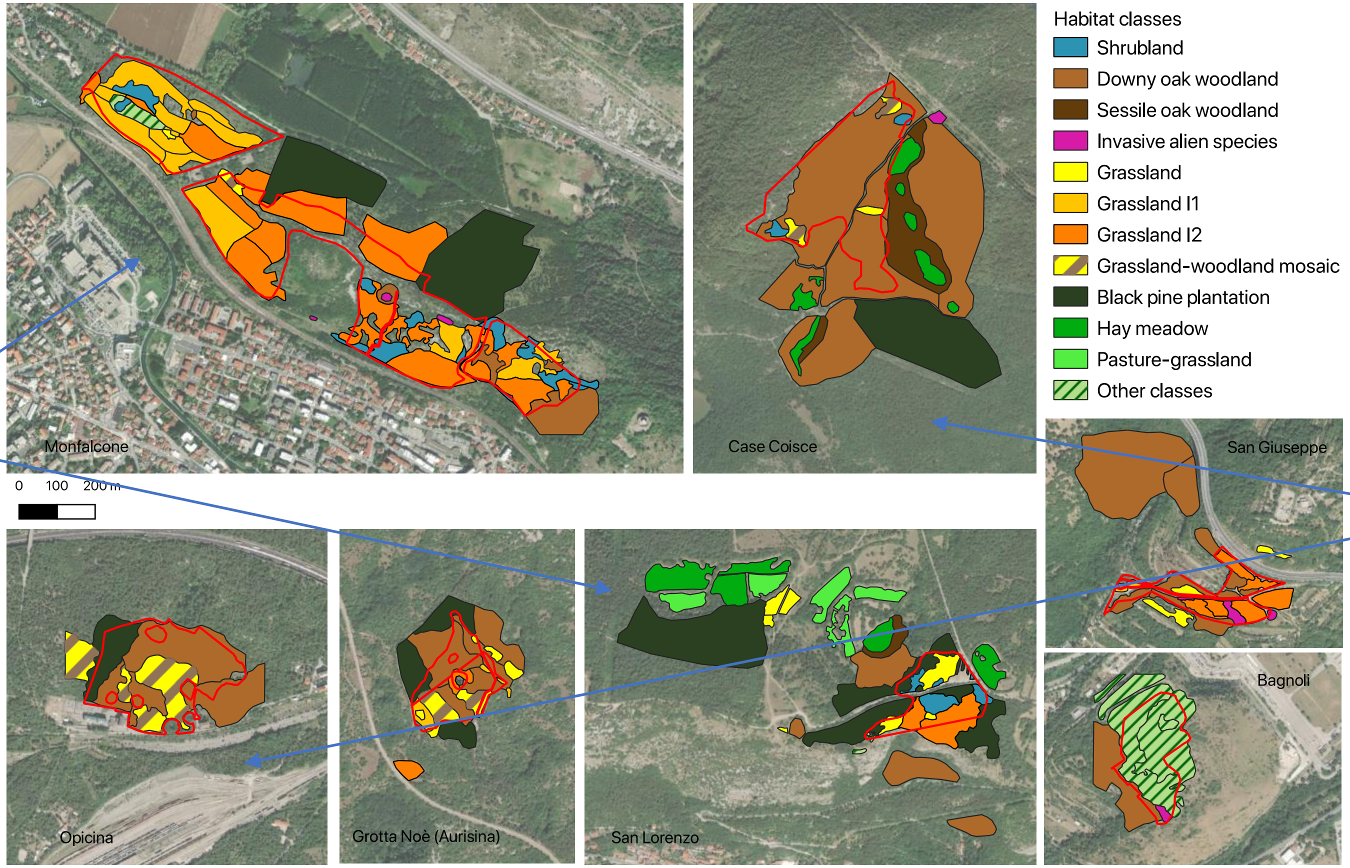

Grassland I-0


Grassland I-1


Grassland I-2

3.1. Field surveyed habitats

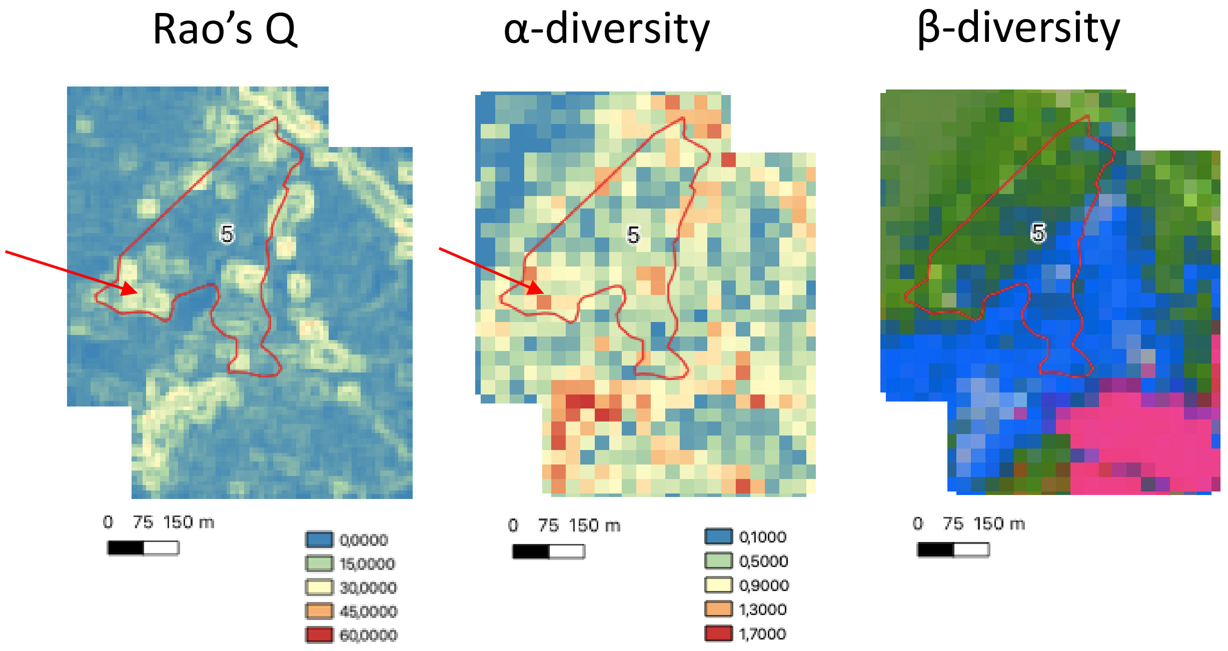
areas dominated by grasslands

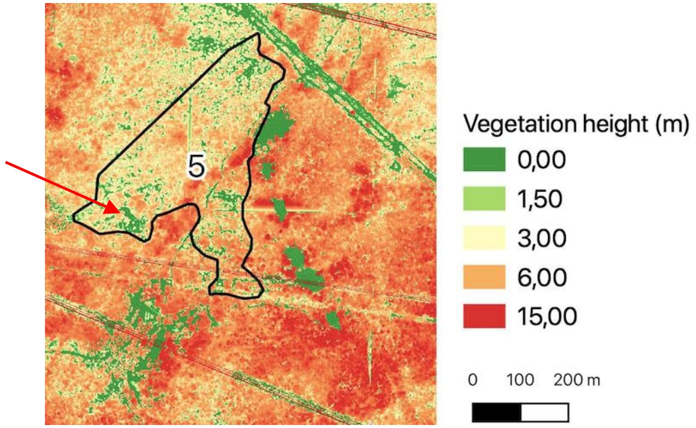


areas dominated by woodland

3.2. Remote sensing data

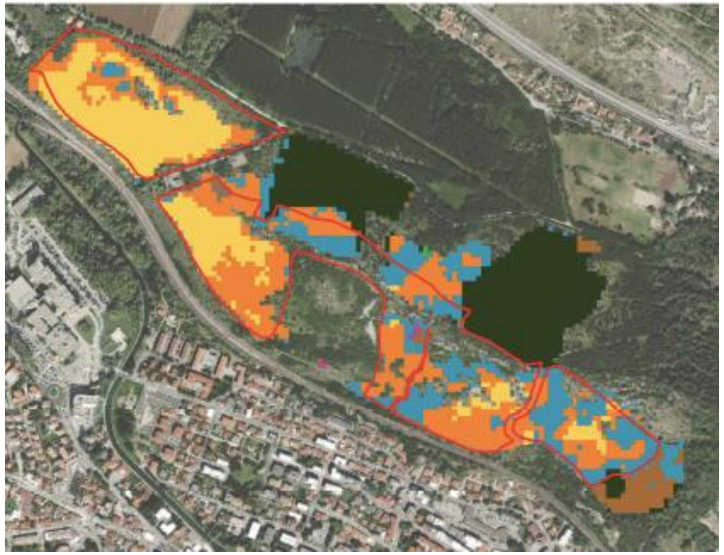
- 64 vegetation indices layers
- 176 spectral heterogeneity layers
- Areas with high spectral heterogeneity were generally areas with low vegetation



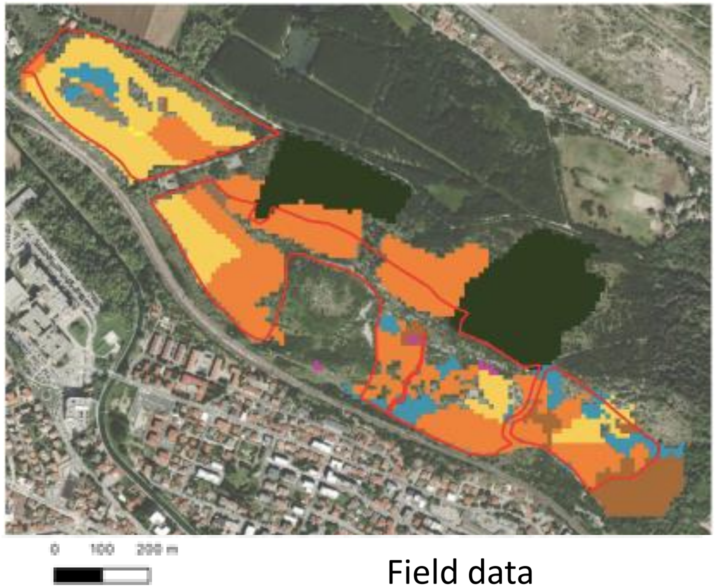


3.3. Image classifications

- Best input configuration: seasonal temporal configuration, 11 classes
- Best OA = 0.71



Best classification



Field data

Habitat classes
- Shrubland
- Downy oak woodland
- Sessile oak woodland
- Invasive alien species
- Grassland
- Grassland I1
- Grassland I2
- Grassland-woodland mosaic
- Black pine plantation
- Hay meadow
- Pasture-grassland

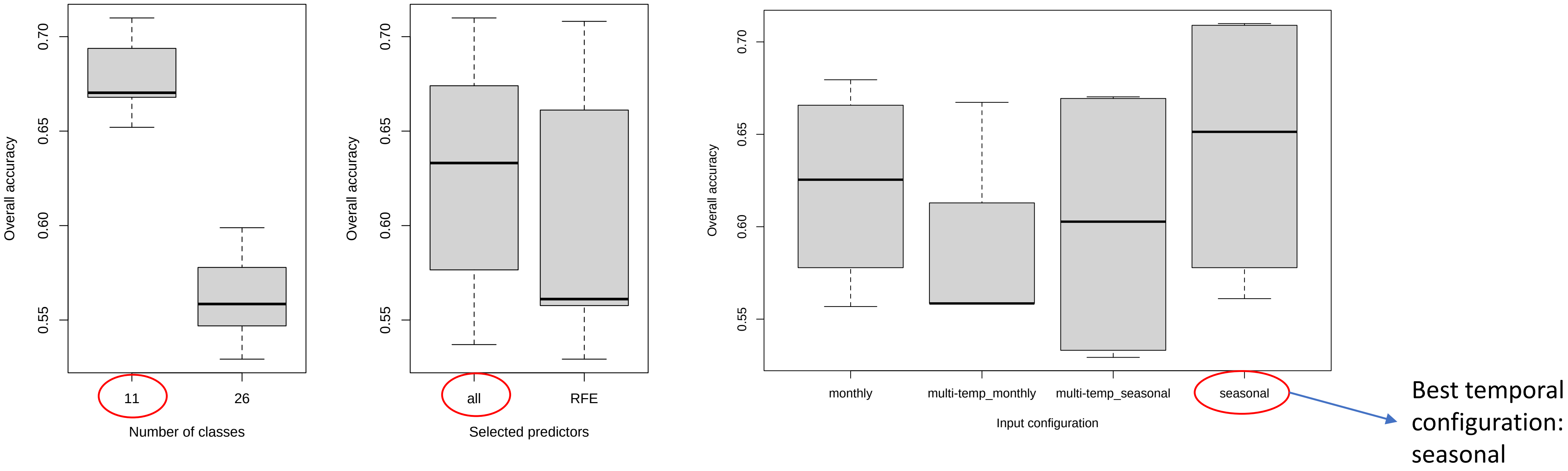
OA = 0.71 (with spectral heterogeneity) vs
OA = 0.66 (only vegetation indices)

- User's accuracy (UA) = the proportion of pixels classified as *i* that had reference class *i*
- Producer's accuracy (PA) = the proportion of pixels of reference class *i* that were correctly classified as *i*

Class	UA	PA
Shrubland	0.19	0.69
Downy oak woodland	0.86	0.76
Sessile oak woodland	0.43	0.19
Invasive alien species	–	0.00
Grassland I0	0.43	0.71
Grassland I1	0.66	0.76
Grassland I2	0.74	0.53
Grassland-woodland mosaic	0.34	0.48
Black pine plantation	0.84	0.89
Hay meadow	0.71	0.79
Pasture-grassland	0.75	0.27

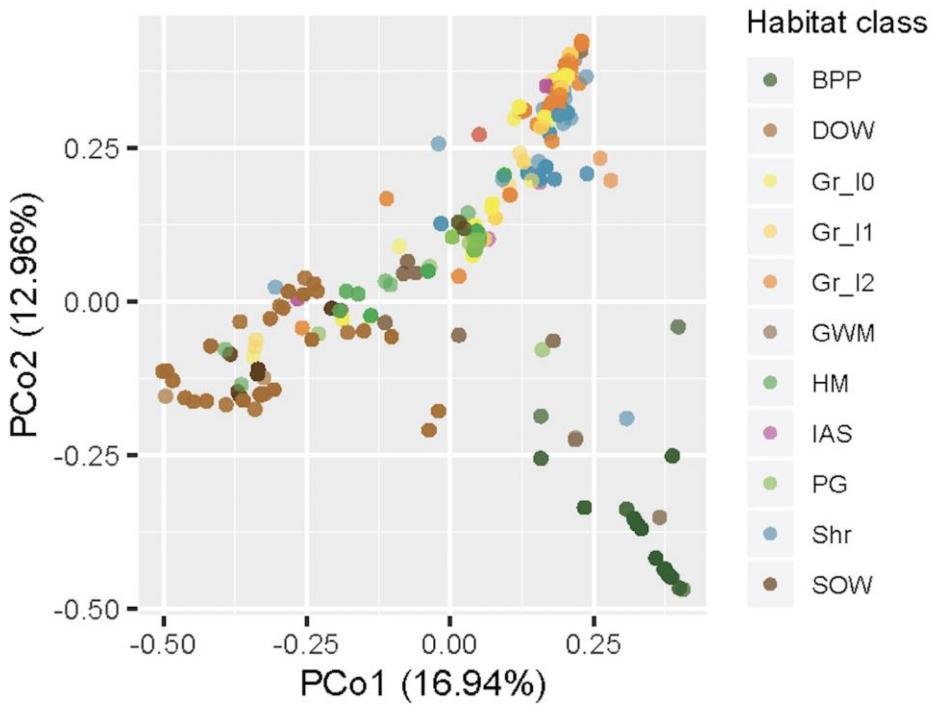
3.3. Image classifications

- Overall Accuracy (OA) = percent of correctly classified pixels

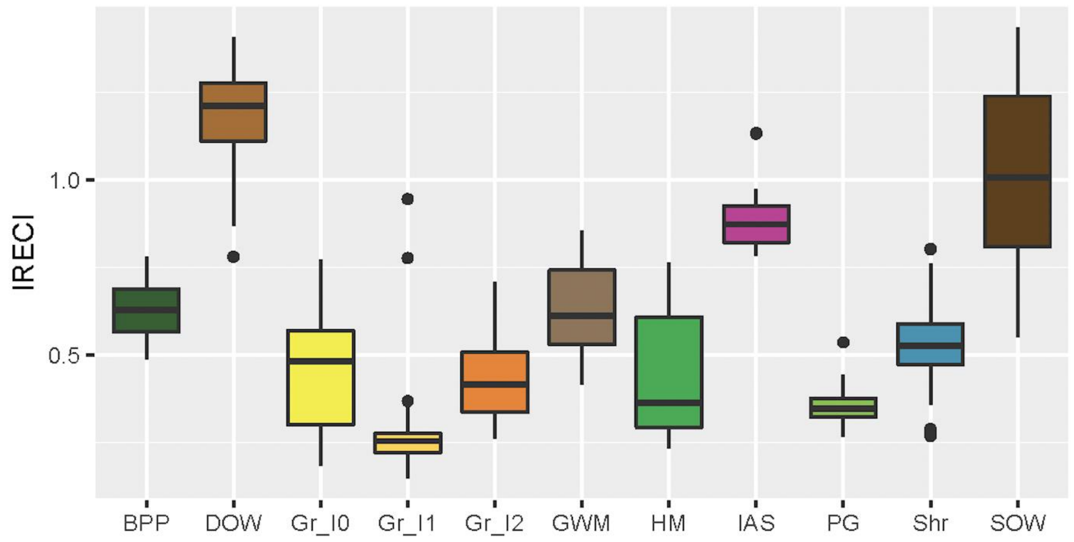


3.3. Image classifications – Important variables

- β-diversity (100.00%): dissimilarity among communities



- IRECI (97.58%): Red Edge bands → related to chlorophyll content and LAI (Frampton et al., 2013).



4. Conclusions

- The aims of this study were achieved:
    - natural habitats in Karst eco-mosaic were mapped with a good accuracy (0.71);
    - measures of spectral heterogeneity had an important role (especially β-diversity);
    - seasonal aggregation allowed to include multi-temporal data.
- Possible improvements: use of data with higher resolutions or different input configurations.
- This approach can be applied in the future to monitor "Ecomosaico del Carso" project over time.


Grazie per l'attenzione