



Sentinel 2 data and a fuzzy algorithm for mapping burned areas and fire severity in the Vesuvio National Park, Italy

Erika Piaser, Giovanna Sona, Matteo Sali, Mirco Boschetti, Pietro Alessandro Brivio, Gloria Bordogna and Daniela Stroppiana



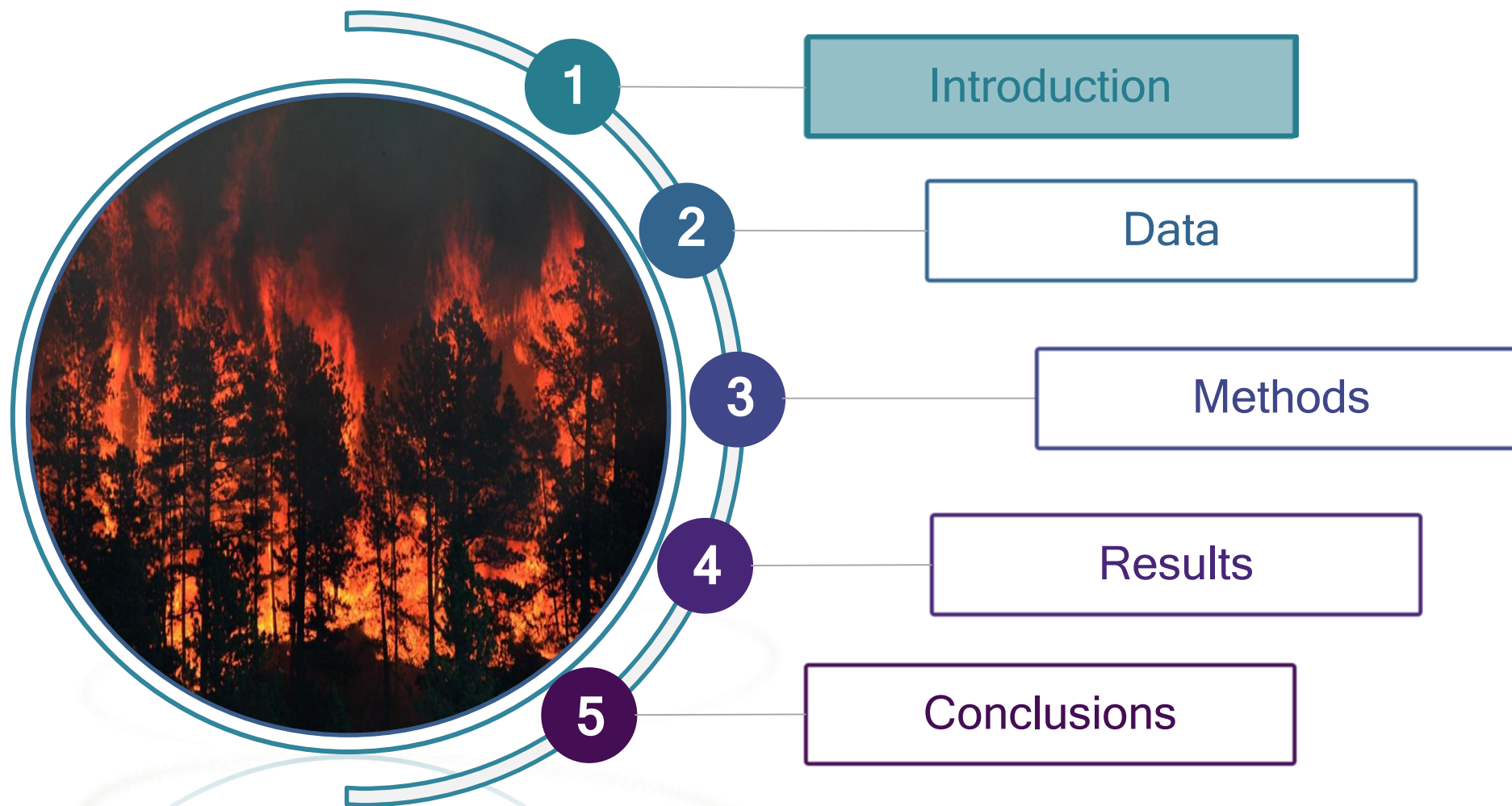


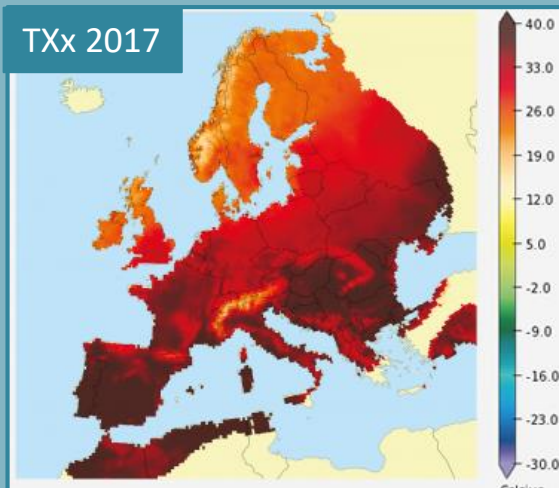
Image credit: *The San Diego Union Tribune* (Meg Oliphant)



INTRODUCTION: fire season 2017

Fire season with significant severe fires in southern Europe

TXx 2017



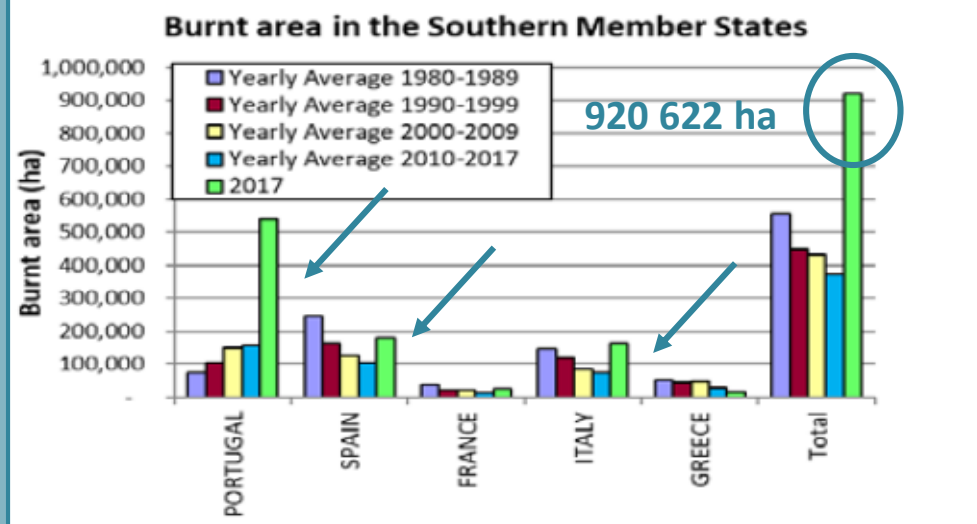
European State of the Climate 2017 (ECMWF, C3S, CAMS)

Climatic conditions

- Temperature above seasonal average
- Dry and hot conditions

Large forest fire

- Increased burned areas
- Increased average fire size
- Increase number of severe fires



EFFIS "Forest Fires in Europe, Middle East and North Africa 2017"



April 8th, 2017

0 1 2 km

July 12th, 2017



August 26th, 2017

0 1 2 km

Fires in the Vesuvio National Park observed by Sentinel-2

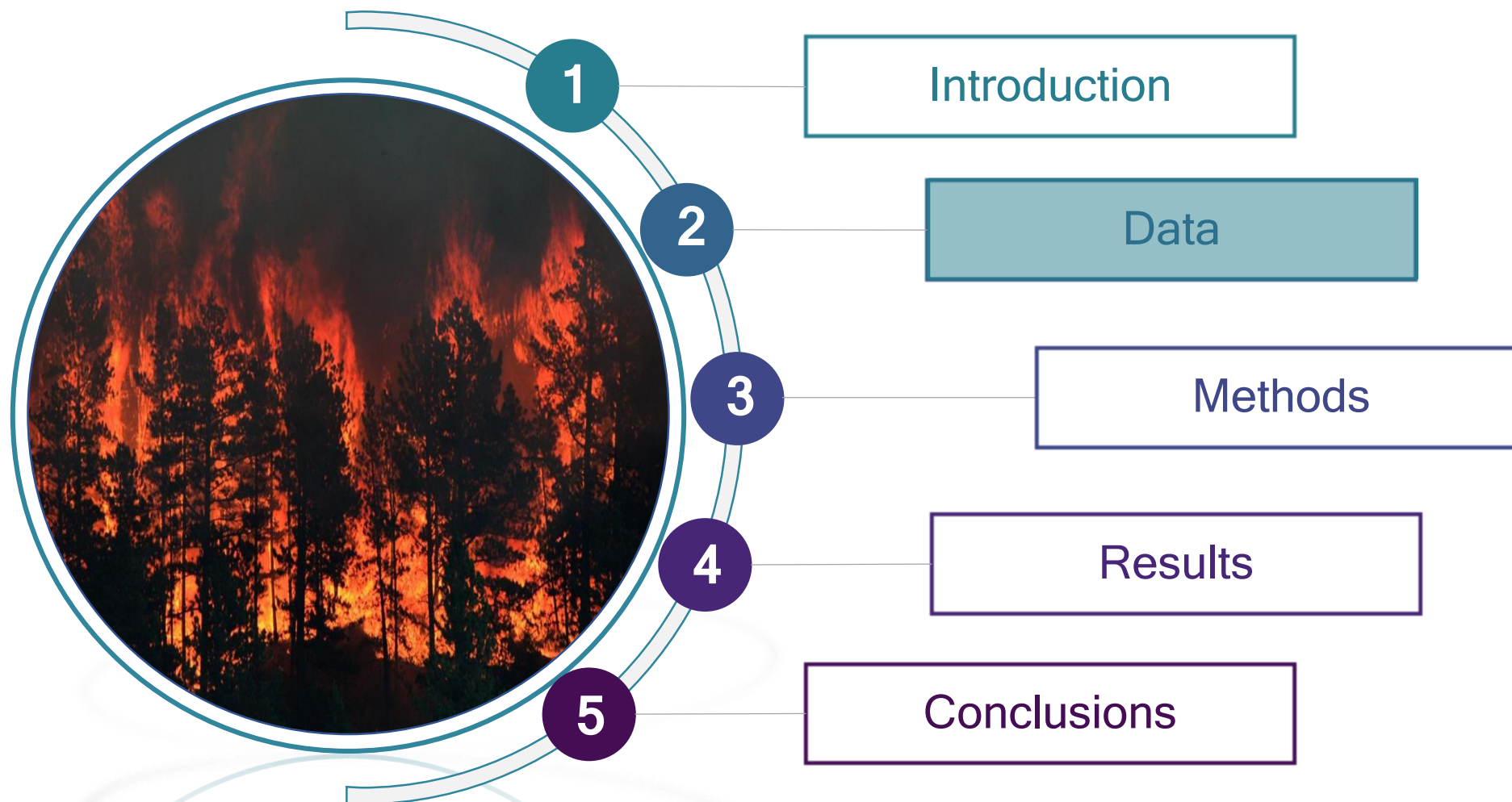


Image credit: *The San Diego Union Tribune* (Meg Oliphant)

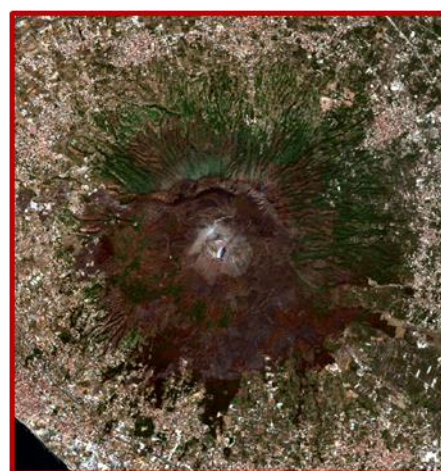


Data: Sentinel-2 imagery

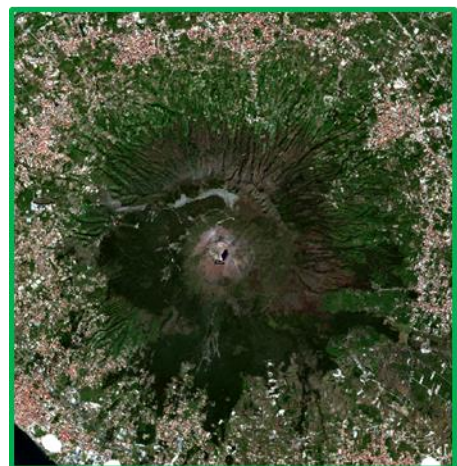
Post-evento: July 17



Post-evento: August 26



Pre-evento: April 8



Sentinel-2

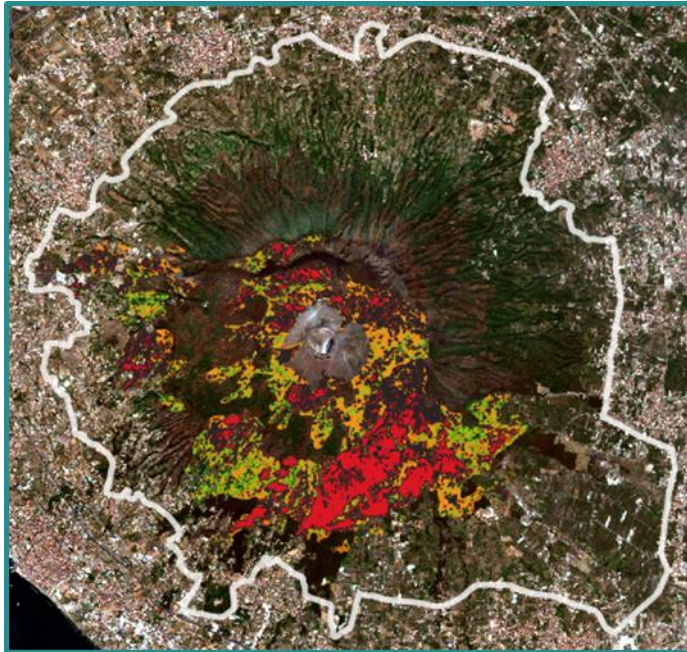
- Sentinel-2A (from June 2015) and Sentinel-2B (from March 2017)
- MSI 13 spectral bands with variable spatial resolution (10, 20 e 60 m)
- Temporal frequency (combined A&B) 5 days

S-2 data downloaded and processed with **Sen2r** (Ranghetti & Busetto, 2019)

0 1 2 km

BANDE SPETTRALI	RISOLUZIONE GEOMETRICA [m]
Banda 1-Coastal aerosol	60
Banda 2-Blue	10
Banda 3-Green	10
Banda 4-Red	10
Banda 5-Red Edge 1	20
Banda 6-Red Edge 2	20
Banda 7-Red Edge 3	20
Banda 8- NIR	10
Banda 8A- NIR	20
Banda 9-Water vapor	60
Banda 10-SWIR-Cirrus	60
Banda 11-SWIR1	20
Banda 12-SWIR2	20

Copernicus EMSR213



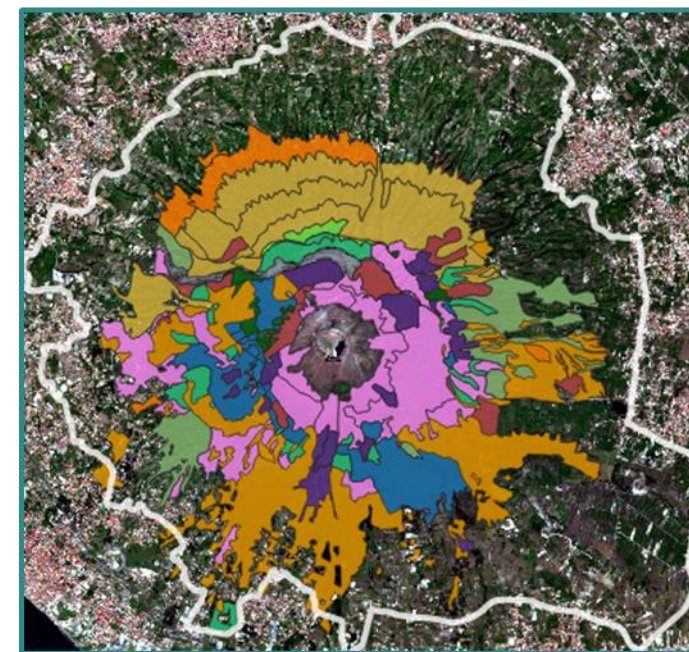
- Derived from high resolution GeoEye-2 images (0.5 m) acquired on **July 14 (2017)**
- Three «fire severity» levels (fire damage levels)

■ Slightly Damaged (SD)
■ Completely Destroyed (CD)
■ Highly Damaged (HD)

0 1 2 km

1. **Training sample**
2. **Algorithm validation**

Forest type map (Cona et al. 2005)



- Pinete di pino domestico (A)
- Pinete di pino marittimo (B)
- Pinete di pino nero (C)
- Pinete miste (D)
- Leccete (E)
- Querceti (F)
- Castagneti (G)
- Boschi misti (H)
- Boscaglie miste cespugliose (I)
- Robinieti (L)
- Arbusteti (M)

0 1 2 km

1. **Identify forested areas within the Park**
2. **Training sample**

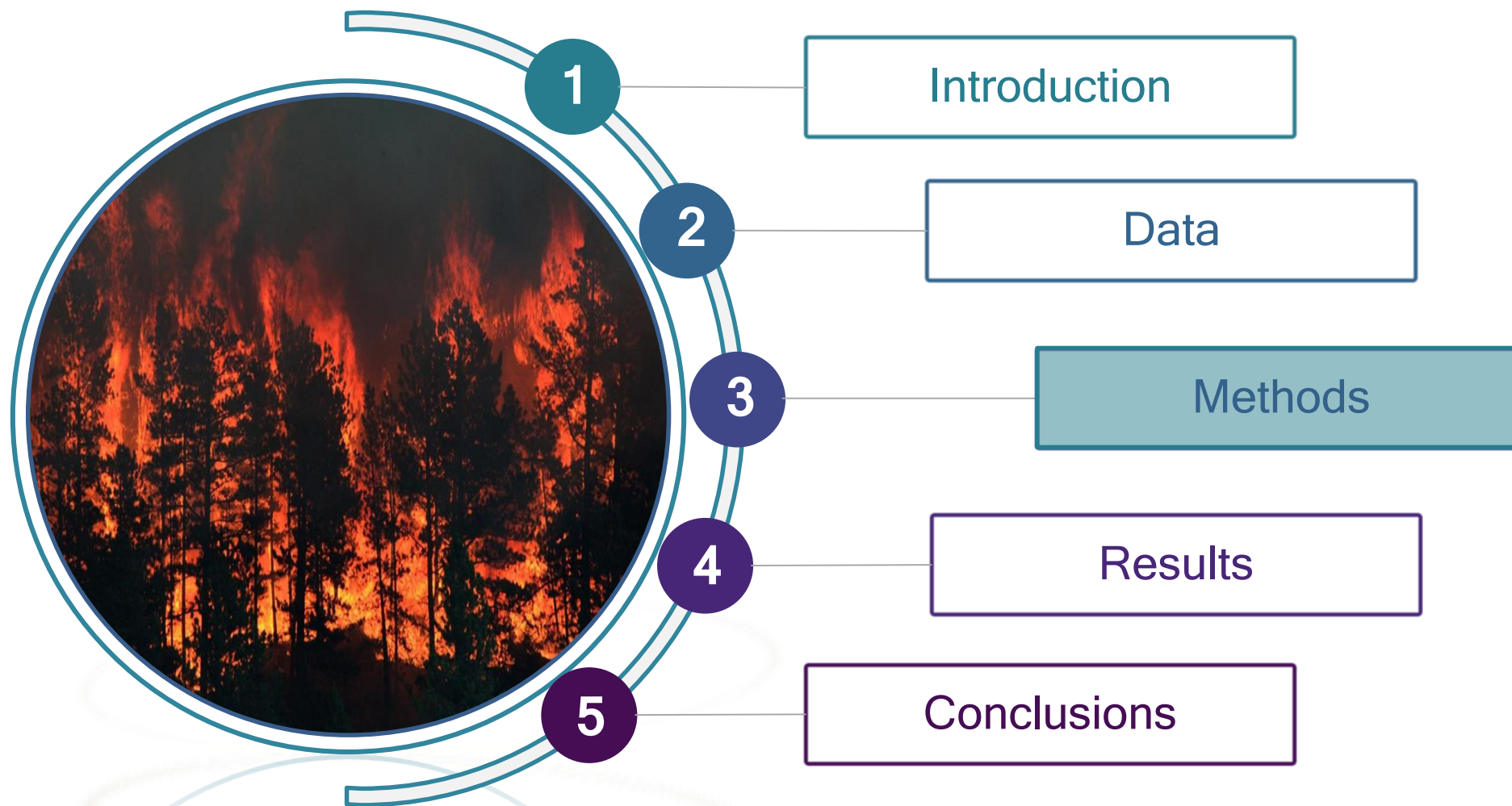
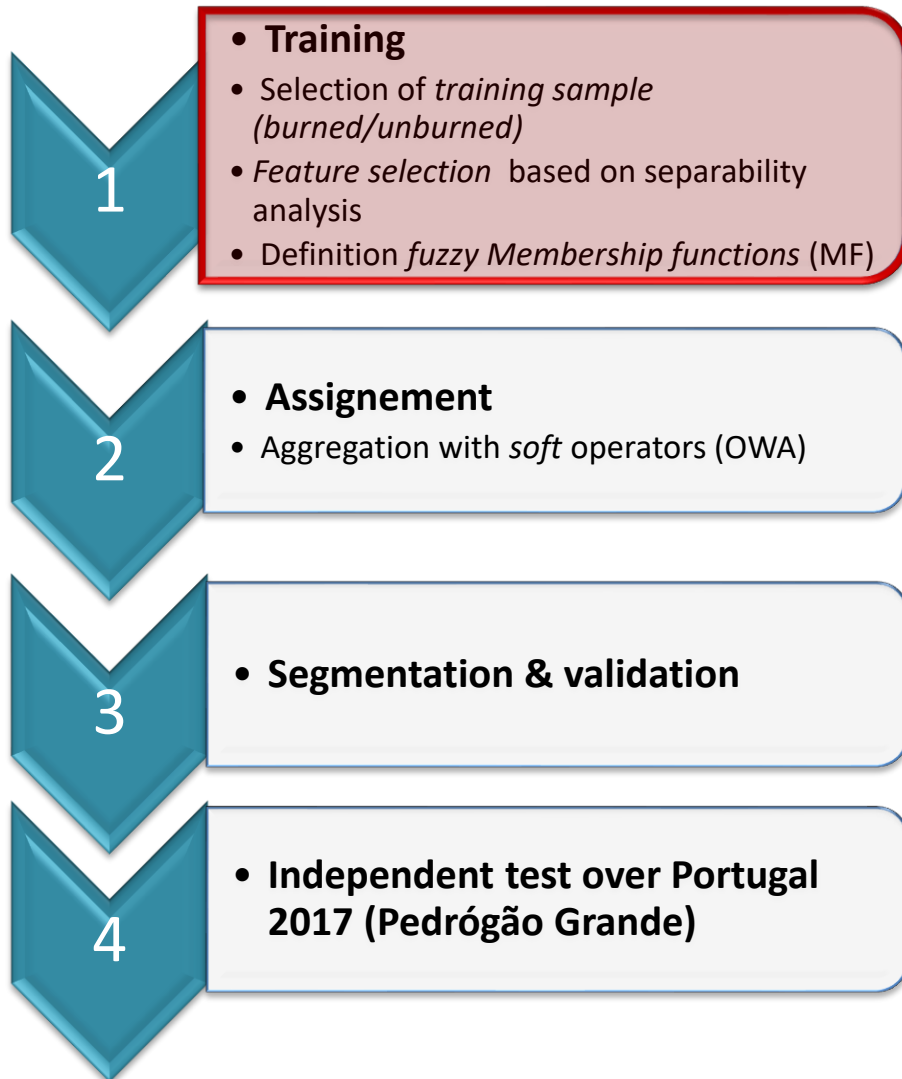
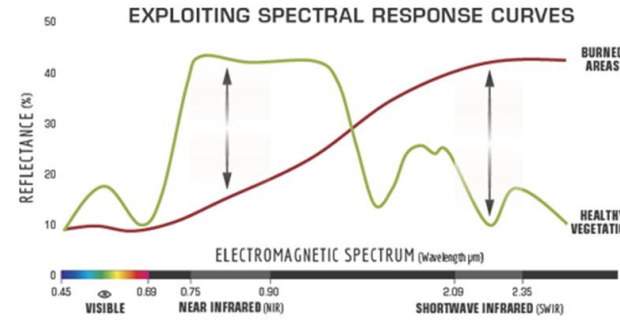


Image credit: *The San Diego Union Tribune* (Meg Oliphant)

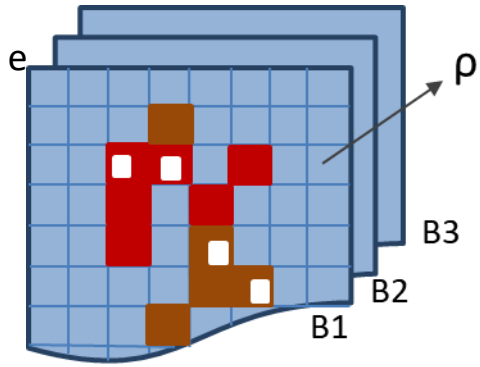




1. *Training sample* for classes «Burned» e «Unburned»



Fonte: US Forest Service



Features «POST» event

Features «DELTA»
(temporal difference)

2. Extraction of density distribution (Kernel) for each class and *feature*

3. *Feature selection*: separability analysis with **metric M** (Boschetti, 2014)

$$M = \left| \frac{\mu_1 - \mu_2}{\sigma_1 + \sigma_2} \right|$$

$M > 1$ classes can be discriminated

1 Training

- Selection of *training sample* (burned/unburned)
- *Feature selection* based on separability analysis
- Definition *fuzzy Membership functions* (MF)

2 Assignment

- Aggregation with *soft operators* (OWA)

3 Segmentation & validation

- Independent test over Portugal 2017 (Pedrógão Grande)

Reflectance (ρ)
or reflectance difference ($\Delta\rho$)

Membership Degree (MD)



$0 < MD < 1$

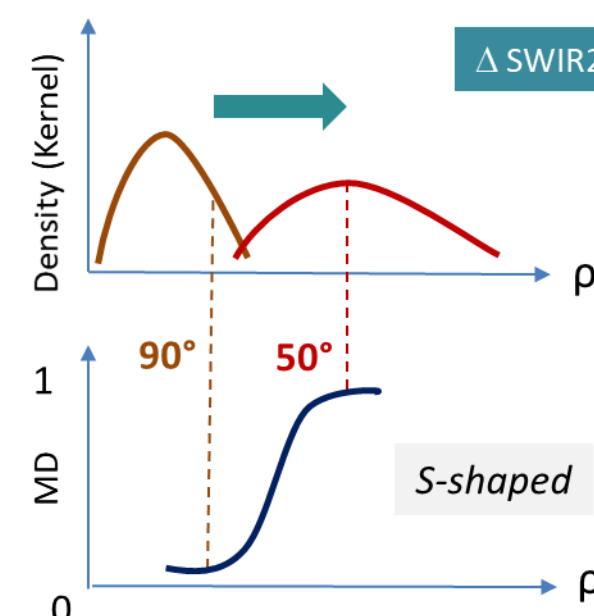
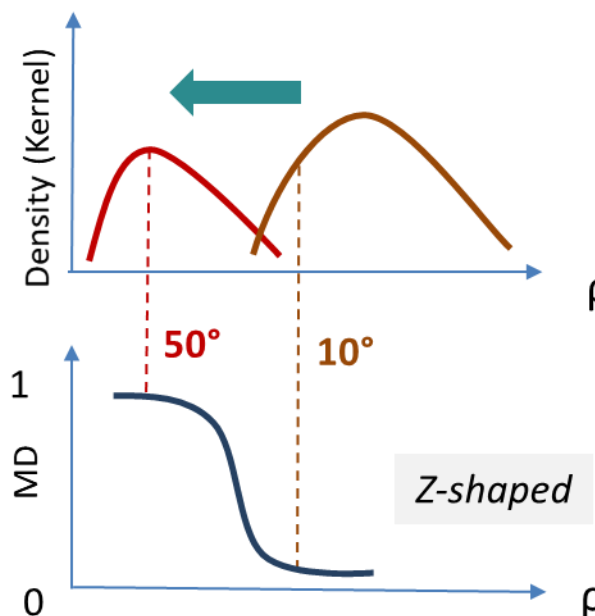


$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$

Funzione logistica

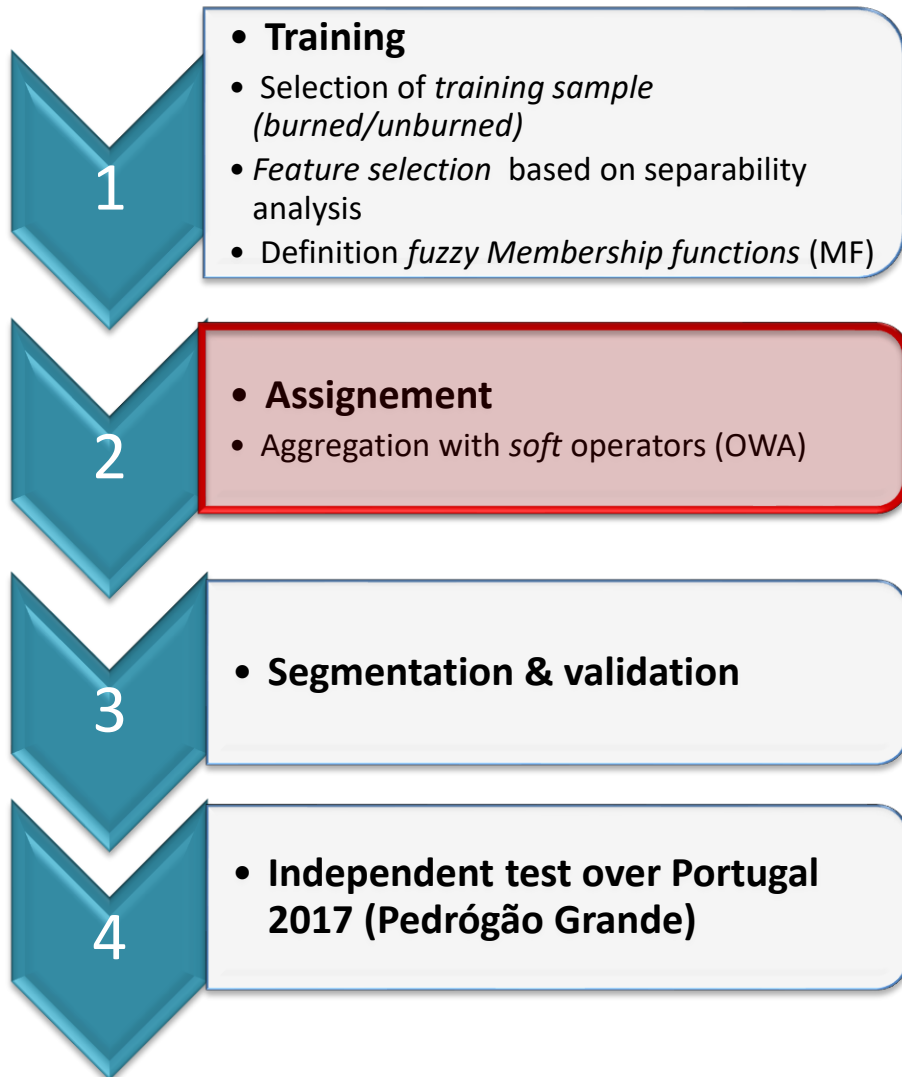
Slope

Inflection point

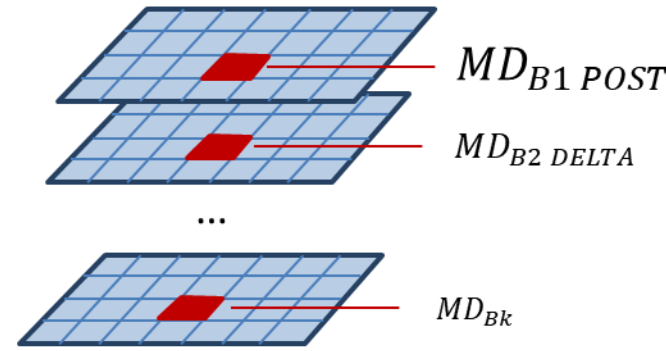


Δ SWIR2

(Roteta et al., 2019)

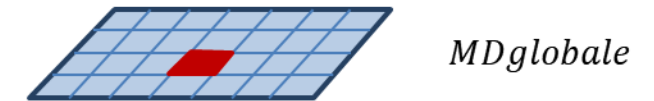


Mappa delle EVIDENZE PARZIALI



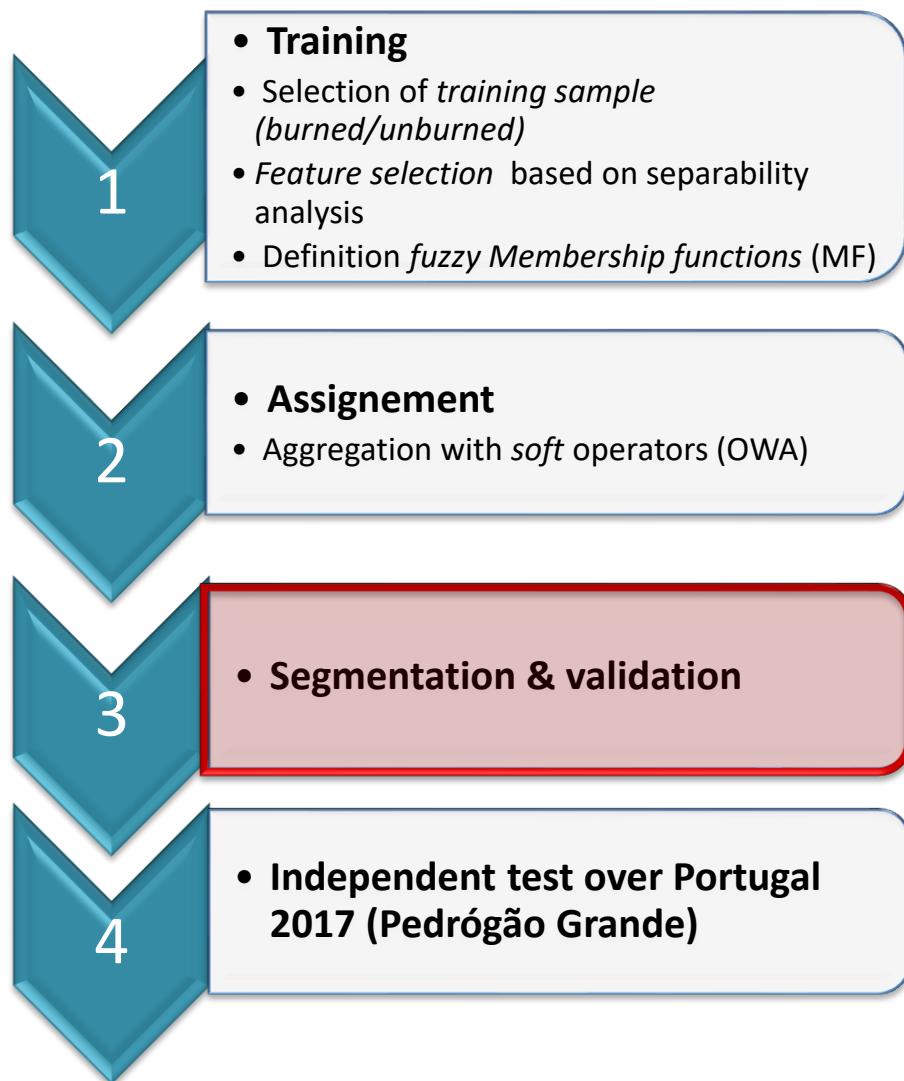
$k = \text{features selezionate mediante separabilità}$

Mappa di EVIDENZA GLOBALE



1. $W_{OR} = [1, 0, 0, \dots, k]$ (Pessimistic approach)
2. $W_{quasi OR} = [0.5, 0.5, 0, \dots, k]$ (Partial pessimistic approach)
3. $W_{Average} = \left[\frac{1}{k}, \frac{1}{k}, \dots \right]$ (Average approach)
4. $W_{quasi And} = [0, 0, \dots, 0.5, 0.5]$ (Partial optimistic approach)
5. $W_{And} = [0, 0, \dots, 0, 1]$ (Optimistic approach)

METHODS: binary maps and validation



Segmentation

Global evidence $\xrightarrow{\text{Threshold } TH}$ Binary map *burned/unburned*

$MD > TH \rightarrow \text{«Burned»}$

$MD < TH \rightarrow \text{«Unburned»}$

Validation

$$OE = \frac{FN}{TP + FN}$$

Omission Error

$$CE = \frac{FP}{TP + FP}$$

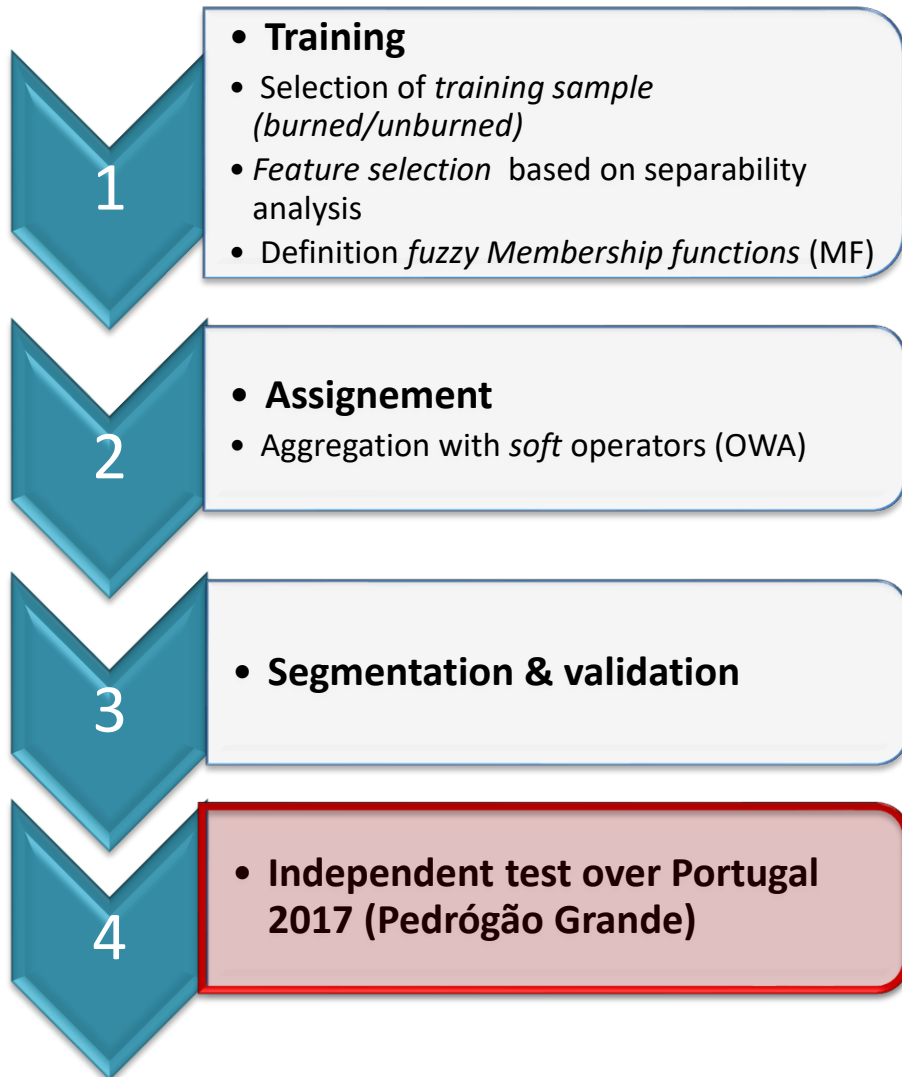
Commission Error

$$DC = \frac{2TP}{2TP + FP + FN}$$

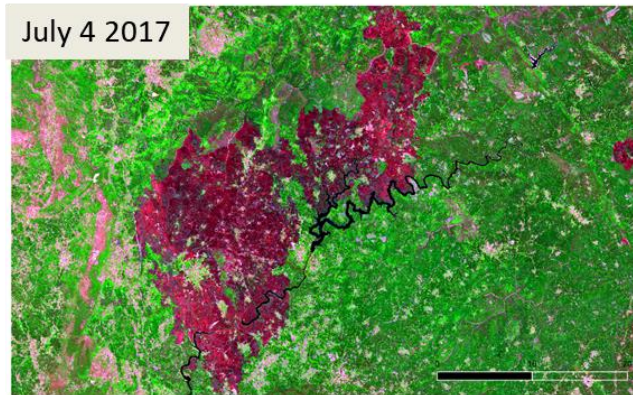
Dice coefficient

		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

Confusion matrix computed for variable TH
($0 < TH < 1$)



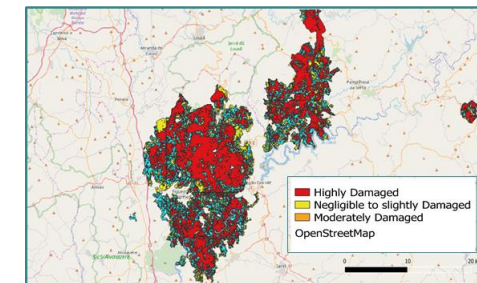
Sentinel-2 data over Portugal



RGB (11,8,4)

- This step aims at assessing **EXPORTABILITY** of the algorithm in different conditions (vegetation, fire severity) compared to those used for training the algorithm (Vesuvio National Park).
- The algorithm has been applied with no changes (input features, membership functions, OWA) to **Pedrógão Grande fire event** (June 17th, 2017)
- Two S-2 images (pre-fire and post-fire images)
- **Validation** by comparison with Copernicus maps of the event
- Accuracy metrics for TH in $[0, 1]$

Copernicus EMSR207



(Source: SPOT-7 June 20th, 2017)

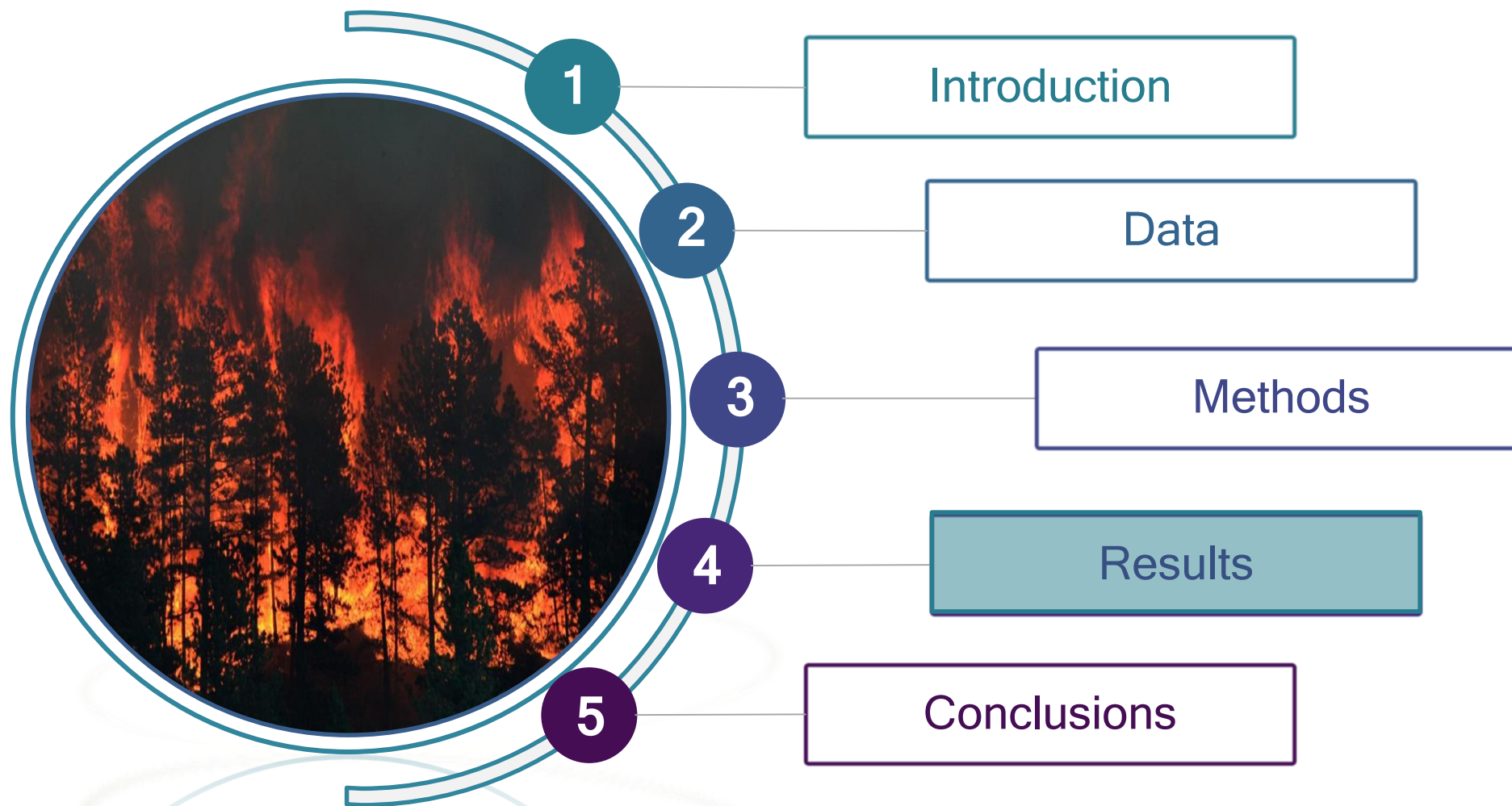
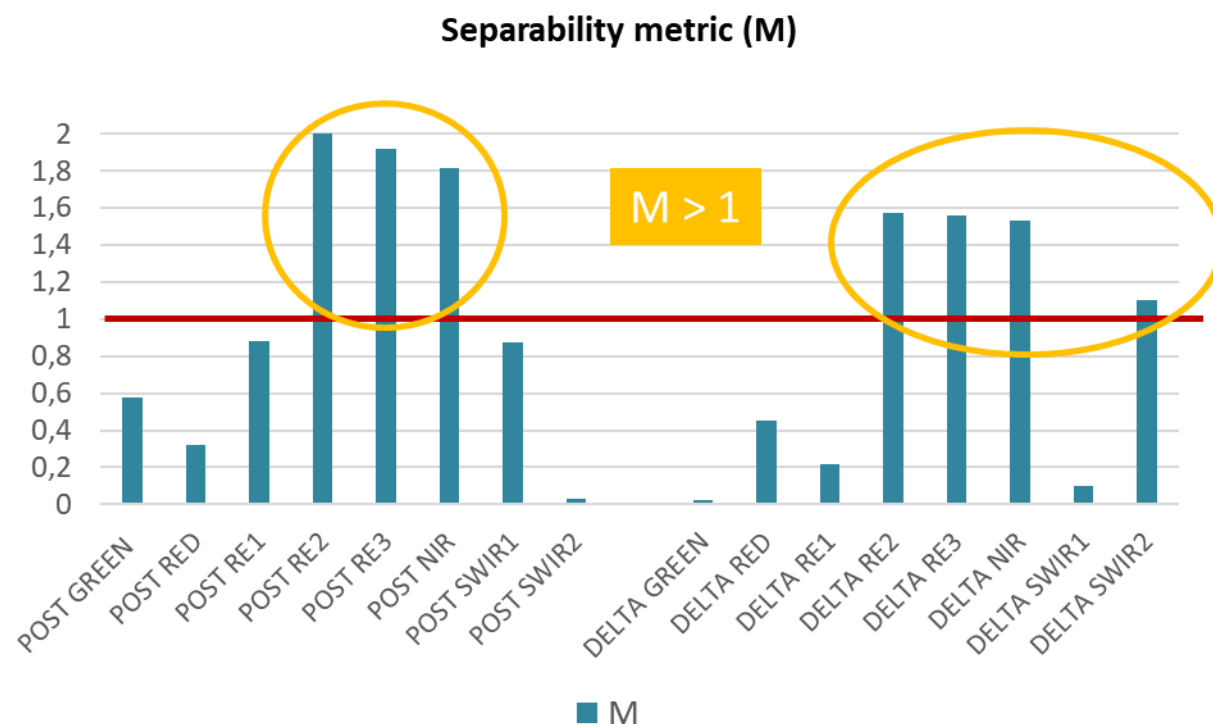


Image credit: *The San Diego Union Tribune* (Meg Oliphant)



RESULTS: separability & density distribution

Training sample: 67 ROI, 3744 pixels



7 features were selected (those that showed $M > 1$): POST RE2, POST RE3, POST NIR, DELTA RE2, DELTA RE3, DELTA NIR e DELTA SWIR2



RESULTS: fuzzy membership functions (MF)

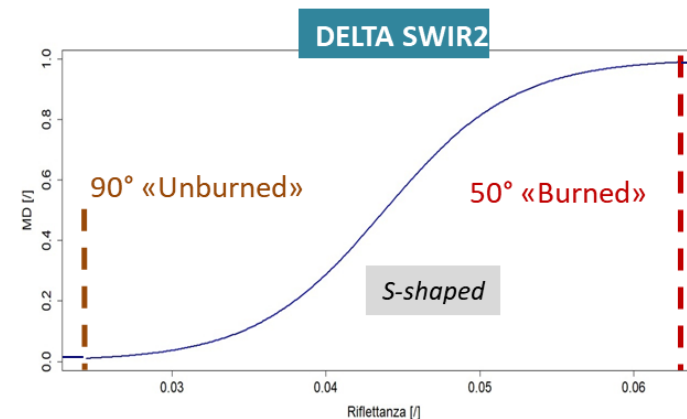
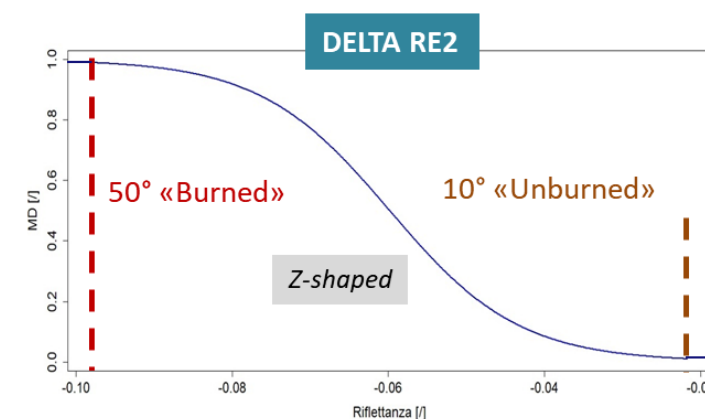
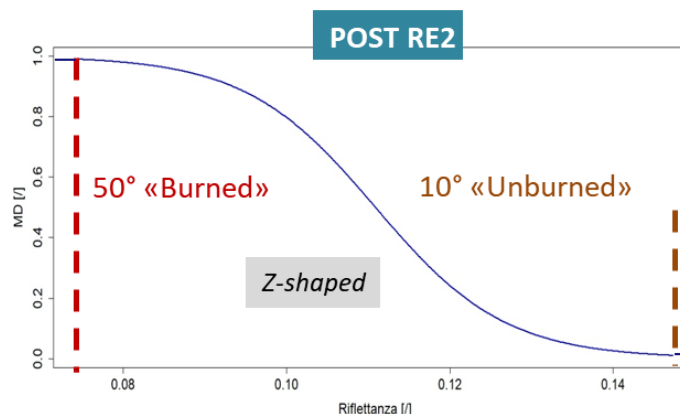
Logistic function

$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$



BANDE SPETTRALI	K	X0
POST RE2	-125.894	0.1109
POST RE3	-115.775	0.11659
POST NIR	-123.658	0.10986
DELTA RE2	-120.291	-0.0598
DELTA RE3	-93.7206	-0.07527
DELTA NIR	-87.1443	-0.08657
DELTA SWIR2	236.984	0.04381

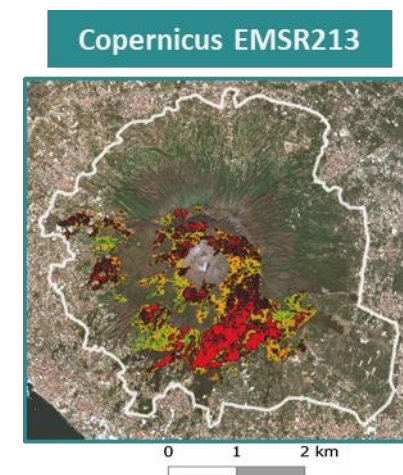
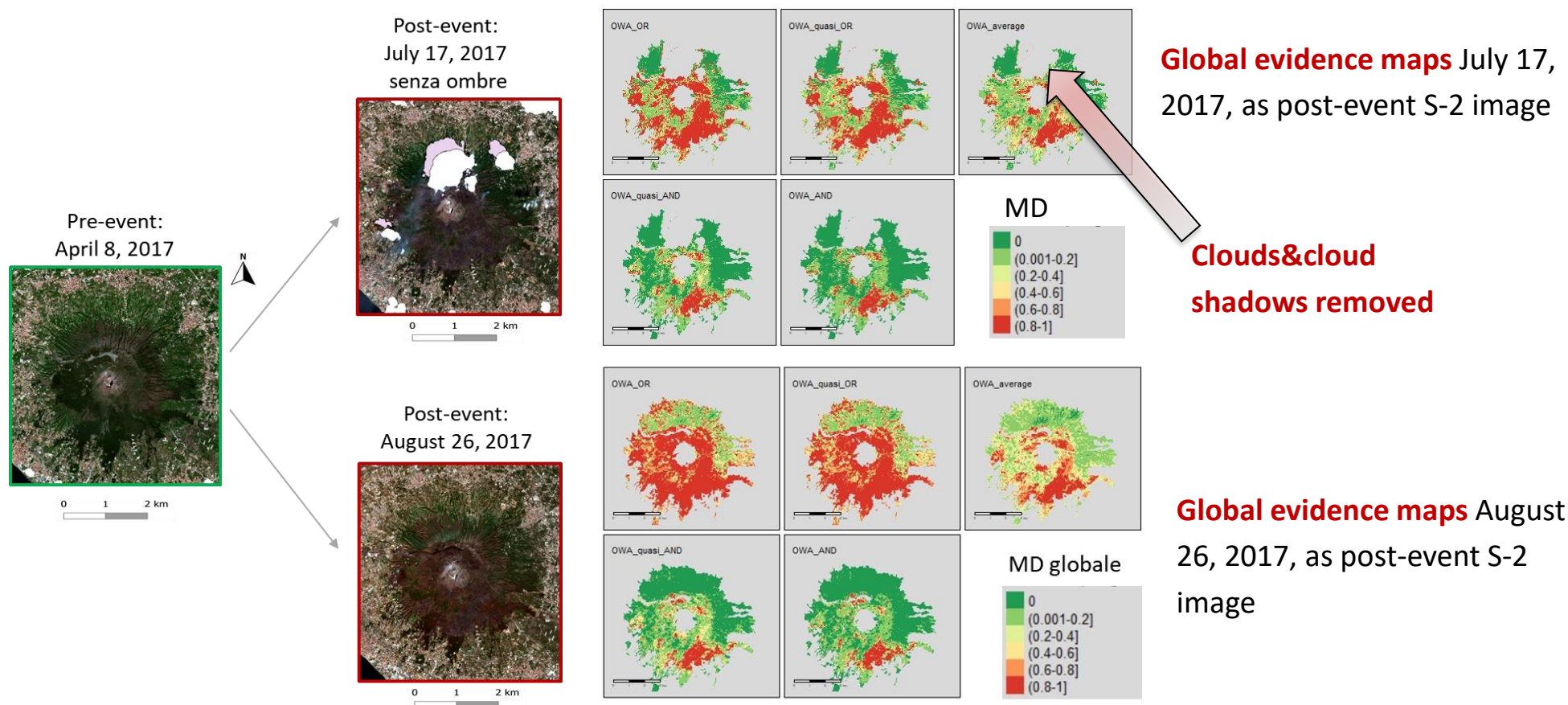
- Exploiting training and density distribution (percentiles) the two parameters of the logistic functions (K, X0) have been estimated
- Logistic function relies on two assumptions:
 $f(x) \rightarrow 1$ for $x \rightarrow -\infty$ (opposite for Δ SWIR2)
 $f(x) \rightarrow 0$ for $x \rightarrow +\infty$ (opposite for Δ SWIR2)



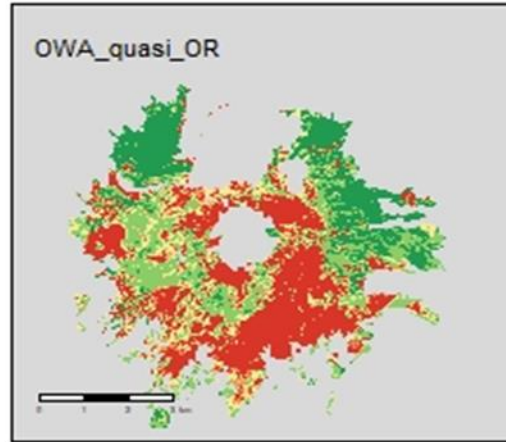
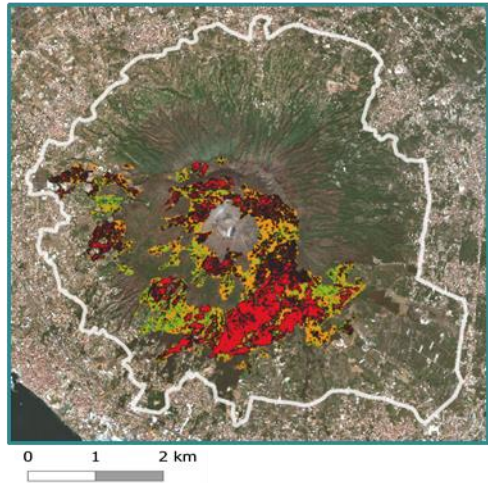
Opposite behaviour

RESULTS: global evidence maps

- **Global evidence maps** have been derived by combining pre-event S-2 image (April 8, 2017) with two post-event S-2 images: July 17 and August 26;
- **July 17 is the S-2 image closest in time to Copernicus reference** date (most suited for validation but with clouds and shadows). Clouds have been masked out during pre-processing and shadows have been masked out manually;
- **August 26 is cloud-free post-event image** (best signal, no atmospheric disturbance but later with respect to reference)

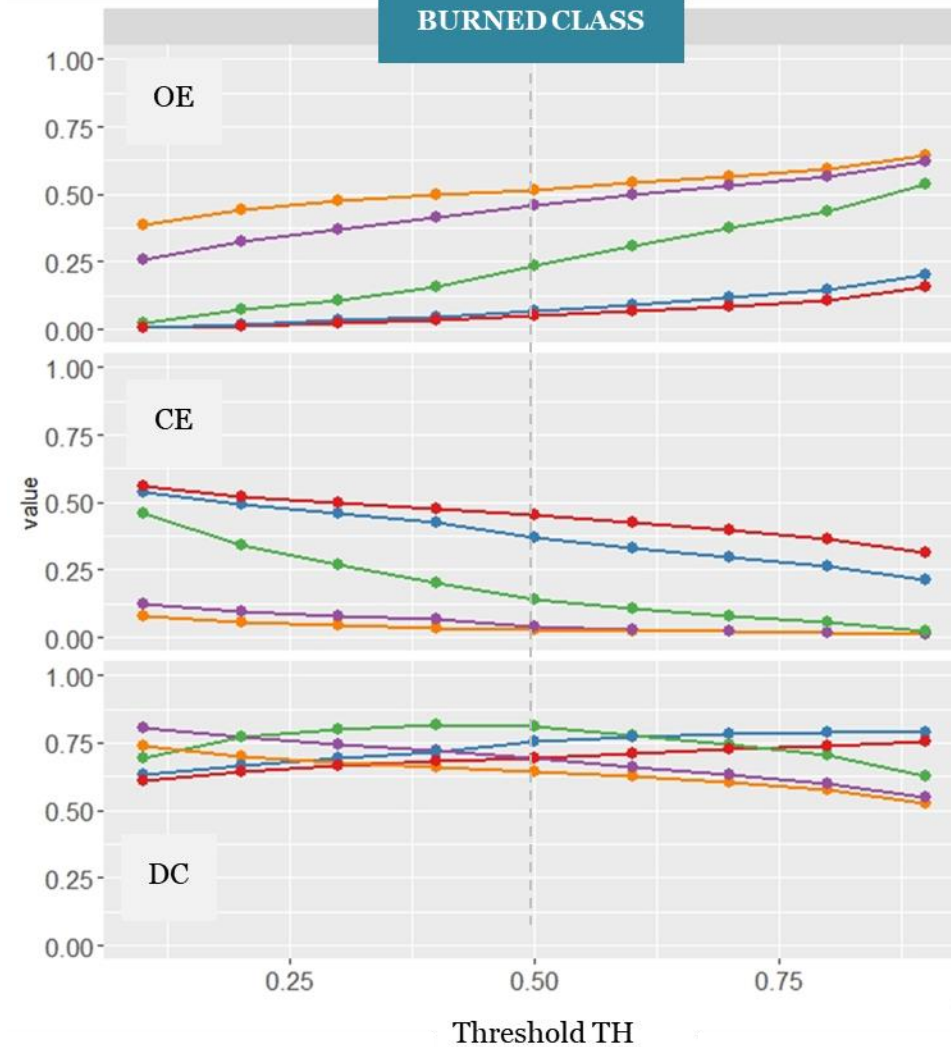


Copernicus EMSR213



- **Comparison of Copernicus (left) & Global evidence map** for OWA Almost OR (right)
- Global evidence map ranges in $[0, 1]$ showing the degree of **membership to burned class**
- Once threshold TH is fixed a binary burned/unburned map can be derived and compared to reference
- Accuracy metrics are computed from the confusion matrix for all OWAs (see graphs)

BURNED CLASS



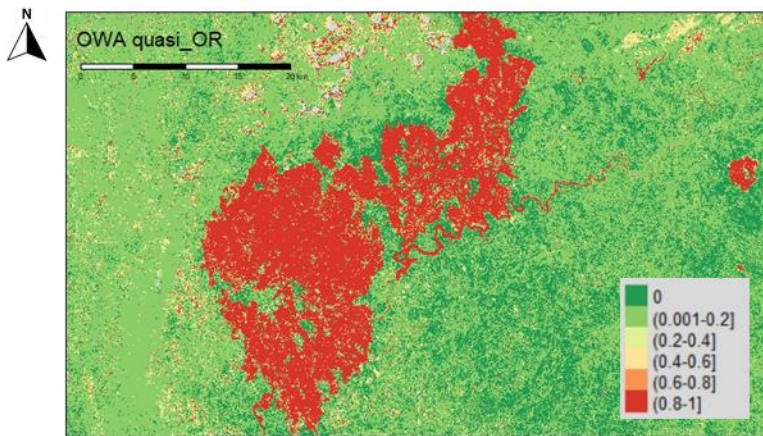
Post-event:
July 17 2017

owa

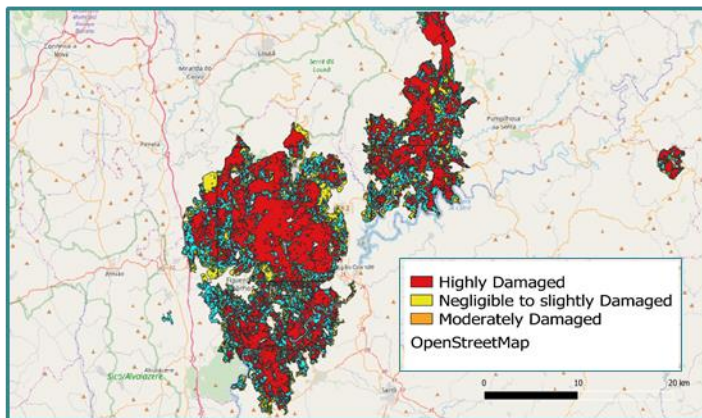
- OR
- quasi_OR
- average
- quasi_AND
- AND

$TH > 0.5$

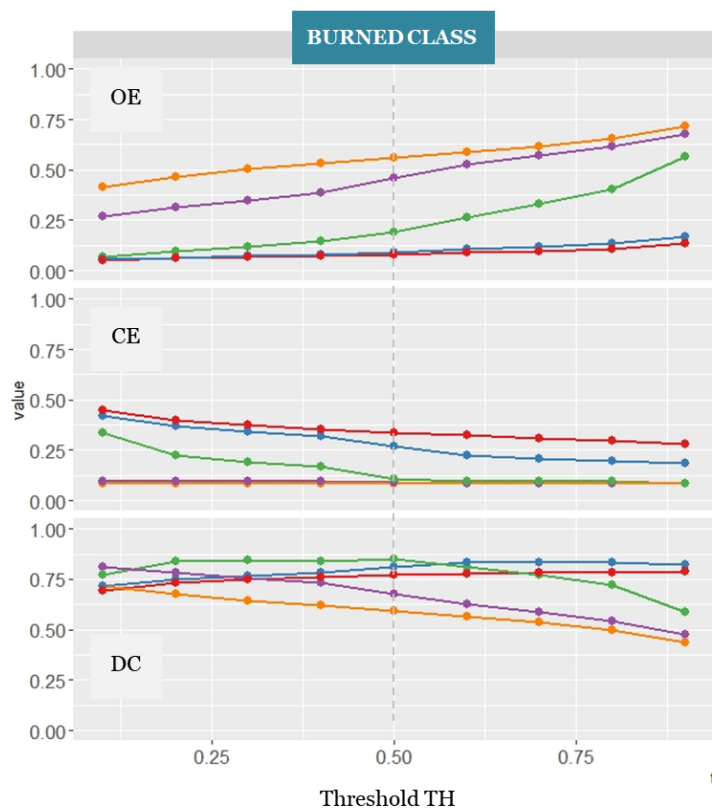
OE \rightarrow 10 – 23 %
CE \rightarrow 40 – 23 %
DC \rightarrow 75 – 85 %



Copernicus EMSR207



- Also for test area in Portugal (Pedrógão Grande) **global evidence maps** have been compared with **Copernicus** (in the figure only OWA Almost OR is shown as global evidence map)
- Graphs below show accuracy metrics for variable threshold TH values (x-axis) used for deriving the binary burned/unburned map



Pedrógão Grande

Comparison between accuracy metrics for testing and training area: range of values for TH > 0.5

Pedrógão Grande Vesuvio National Park

Per TH > 0.5

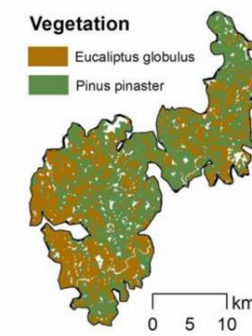
OE → 10 – 23 %
CE → 25 – 19 %
DC → 81 – 85 %

Per TH > 0.5

OE → 10 – 23 %
CE → 40 – 23 %
DC → 75 – 85 %

owa
— OR
— quasi_OR
— average
— quasi_AND
— AND

Lower commission error in Portugal probably due to more homogeneous vegetation and higher fire severity



Alfonso Fernández Manso et al., 2020

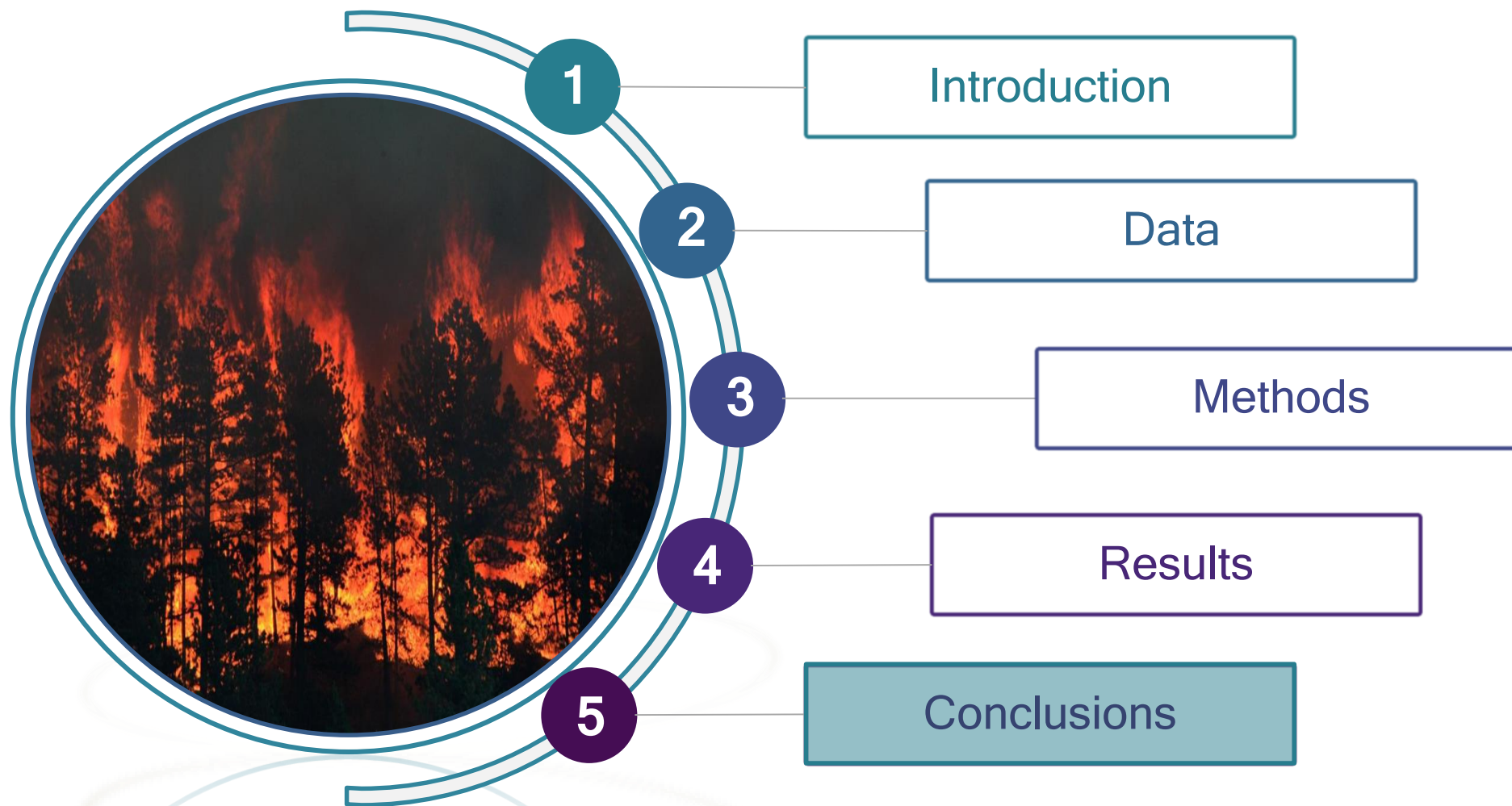
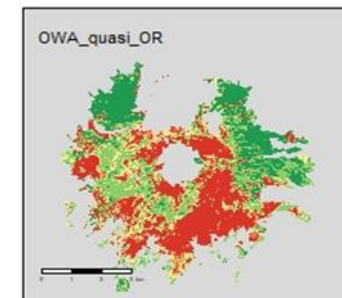
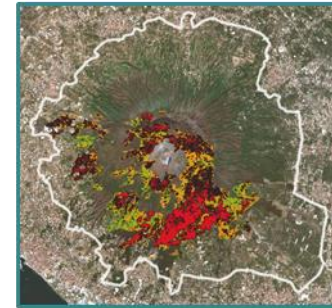


Image credit: *The San Diego Union Tribune* (Meg Oliphant)

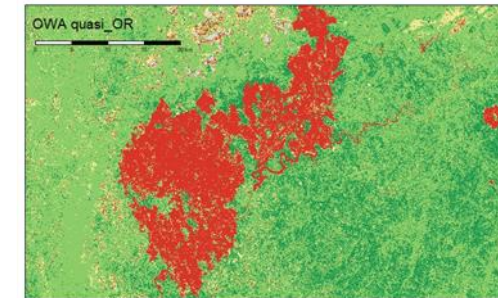
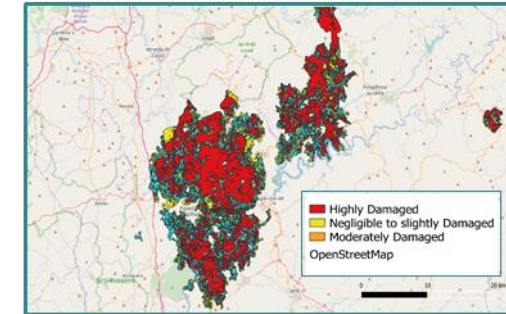


- Our results highlighted that the best **features** for discriminating **burned vs. unburned areas** are the same spectral bands generally used for monitoring **vegetation conditions and status** (Red Edge, NIR e SWIR2) expressed as both post-fire and temporal difference reflectance;
- Frequency of observation offered by Sentinel-2 is suitable for monitoring a dynamic (in space and time) phenomenon as **wildfires**;
- **The proposed algorithm** produces satisfactory results when compared to reference data Copernicus damage maps ($OE < 25\%$ e $23 < CE < 40\%$, per $TH > 0.5$);
- **Among inspected and tested OWA**, Almost_OR showed best results in both test and training areas.


Vesuvio National Park



Portugal (Pedrógão Grande)



- Algorithm improvement for **better discrimination** of surfaces with similar spectral signal, such as **cloud shadows and water**;
- The above objective can be achieved by integrating spectral information from thermal infrared bands (integration of Sentinel-3 data in a multi-source approach);
- **The fuzzy approach could integrated a Region Growing (RG) algorithm:** exploiting global evidence derived with different OWA (pessimistic and/or optimistic) could be used as seed and growing layers. Commission errors can be reduced;
- Contextual approach
- Active fires could be exploited for automatic definition of fuzzy membership functions so that site specific characteristics are described;
- Test with spectral indices (NDVI, NBR, EVI, SAVI)
- Multi-source approach by including information from SAR (Sentinel-1) for areas with persistent cloud cover



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