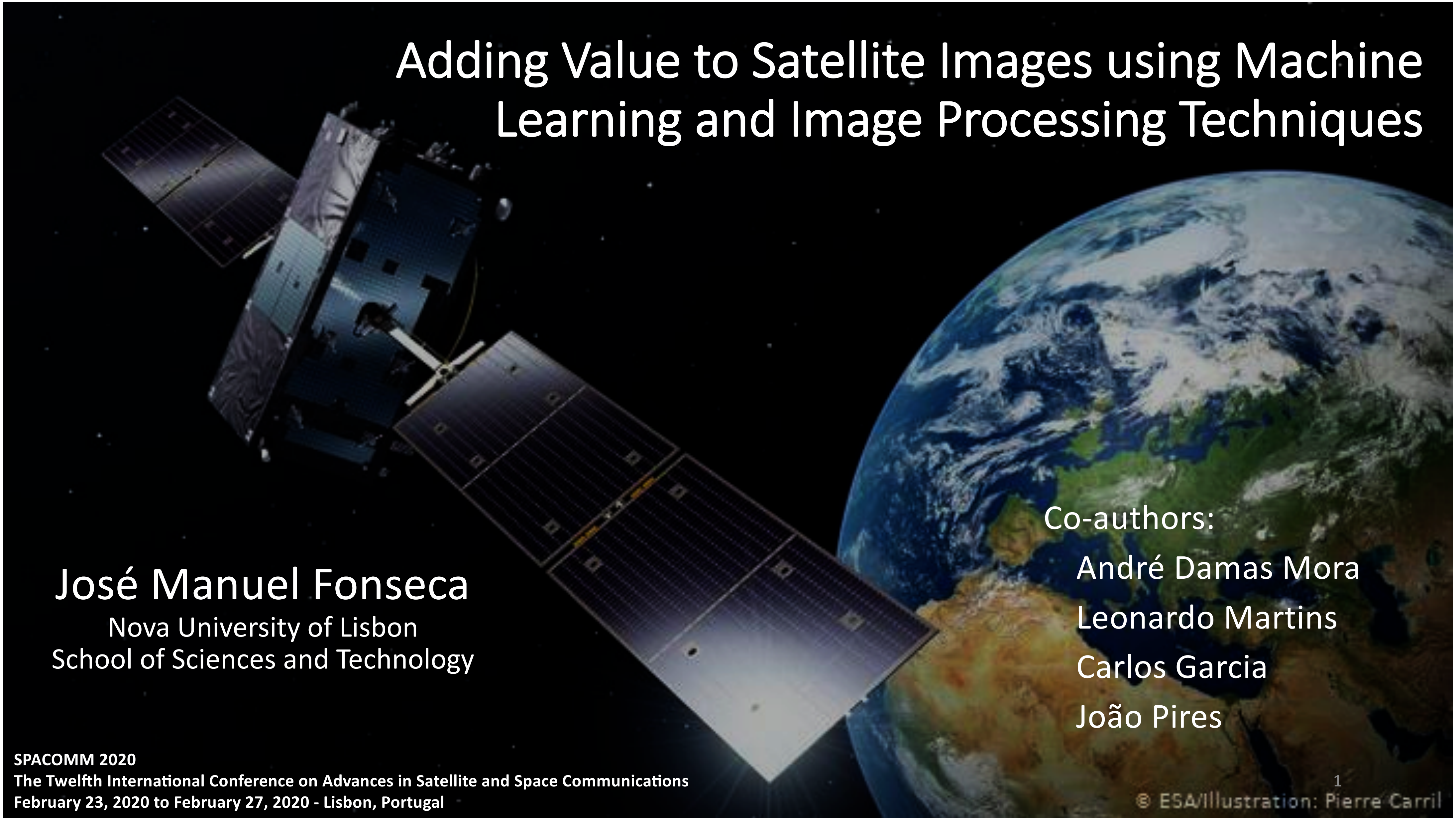
Adding Value to Satellite Images using Machine Learning and Image Processing Techniques



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João Pires

SPACOMM 2020
The Twelfth International Conference on Advances in Satellite and Space Communications
February 23, 2020 to February 27, 2020 - Lisbon, Portugal

The NOVA University

- Faculty of Sciences and Technology
- Faculty of Social and Human Sciences
- School of Business and Economics
- Medical School
- Faculty of Law
- Information Management School
- Institute of Tropical Medicine
- Institute of Chemistry and Biology António Xavier
- Public Health School

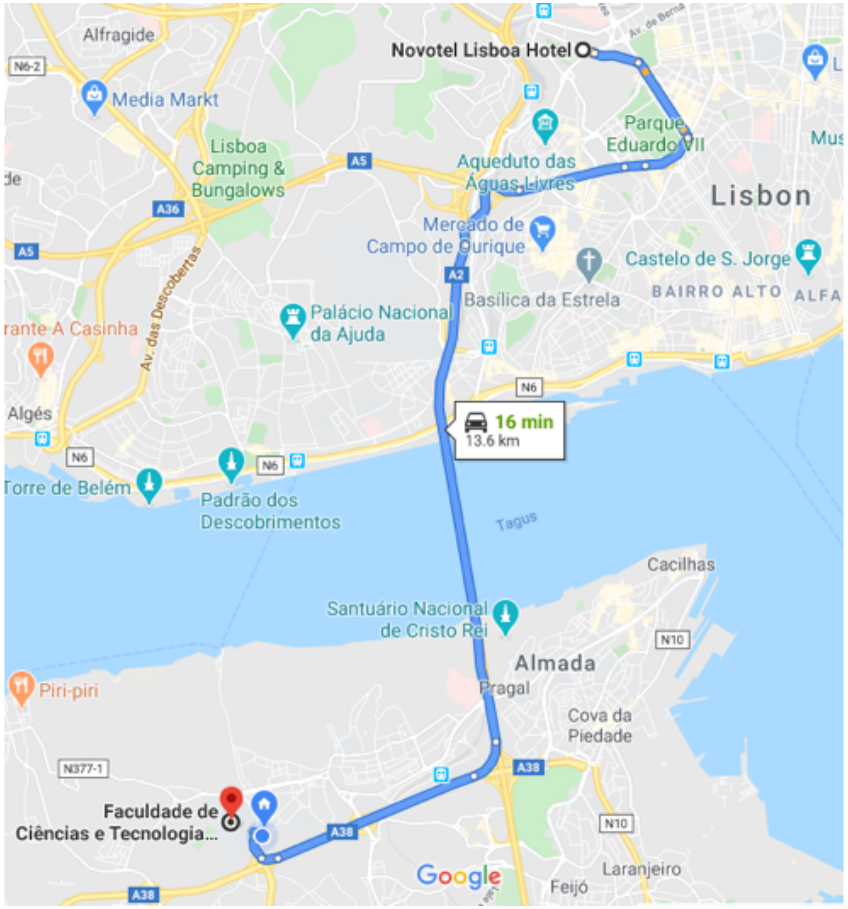
The Faculty of Sciences and Technology of NOVA Lisbon

- Monte da Caparica, Portugal (15Km from Lisbon downtown)
- 30 ha Campus
- 8500 students - 1100 new students every year
- 1500 MSc and PhD students
- 16 research centers
- 540 professors 170 staff members
- 14 Departments and 8 support services

FACULDADE DE CIÊNCIAS E TECNOLOGIA
UNIVERSIDADE NOVA DE LISBOA




Campus location (south side of the Tagus river)

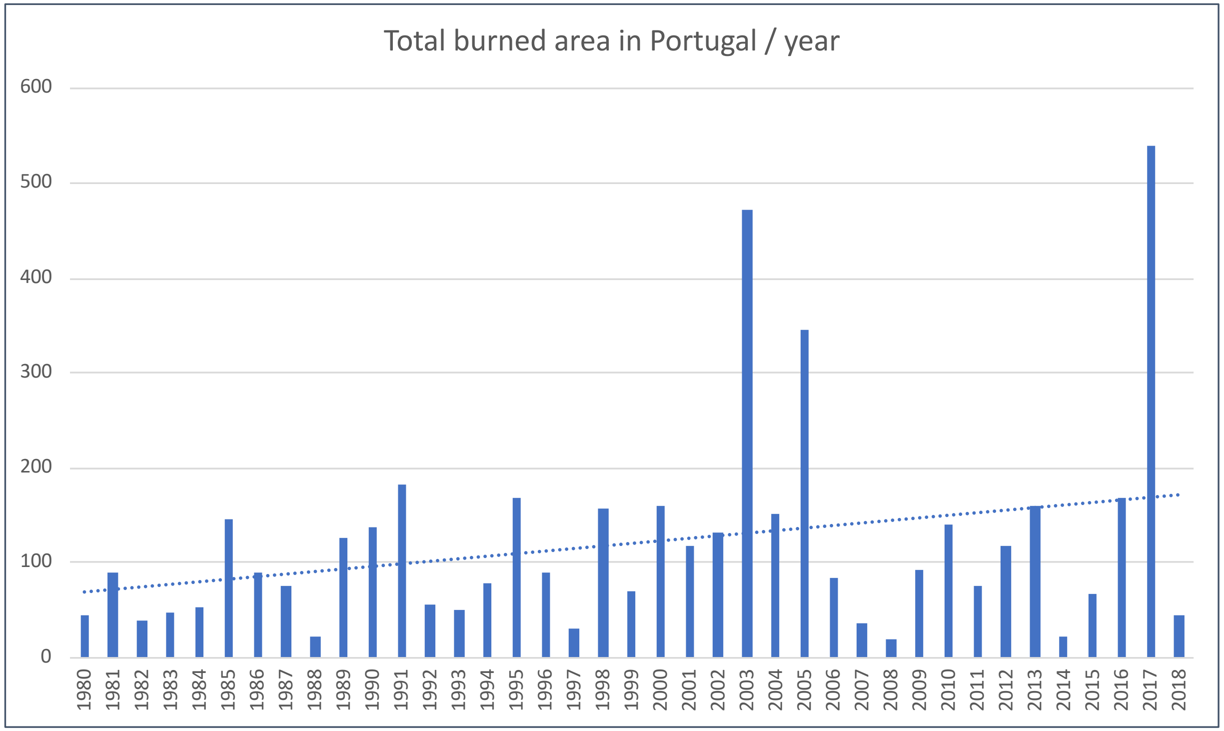


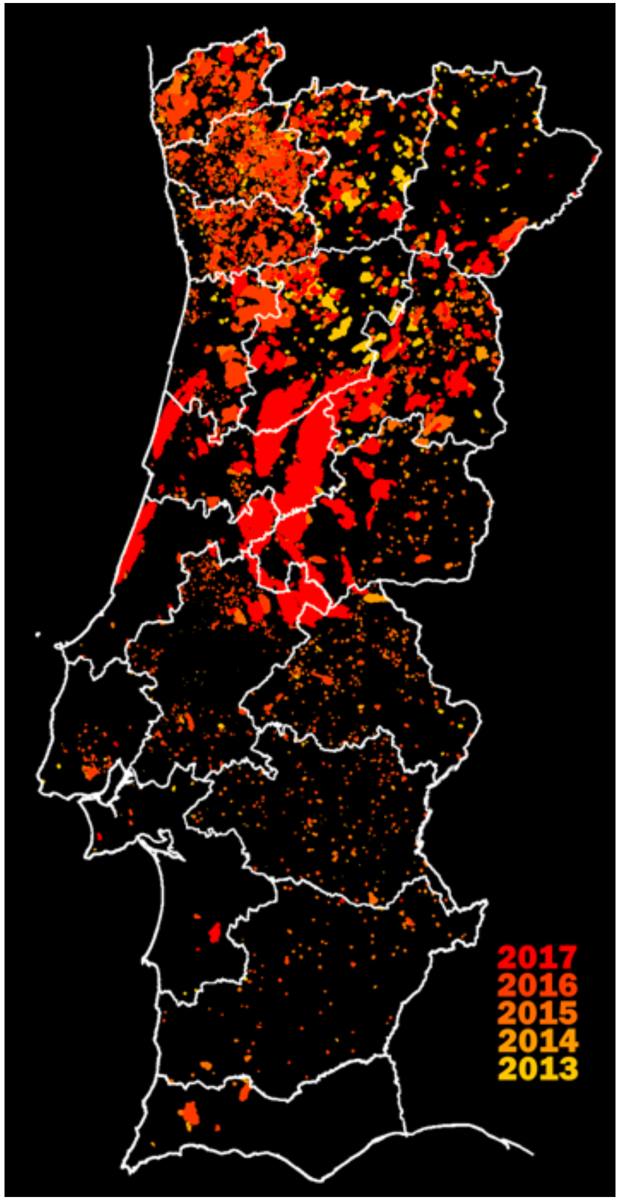
The “25 de Abril” bridge

The Campus of FCT-NOVA

Fires in Portugal

Burned area in Portugal





The New York Times

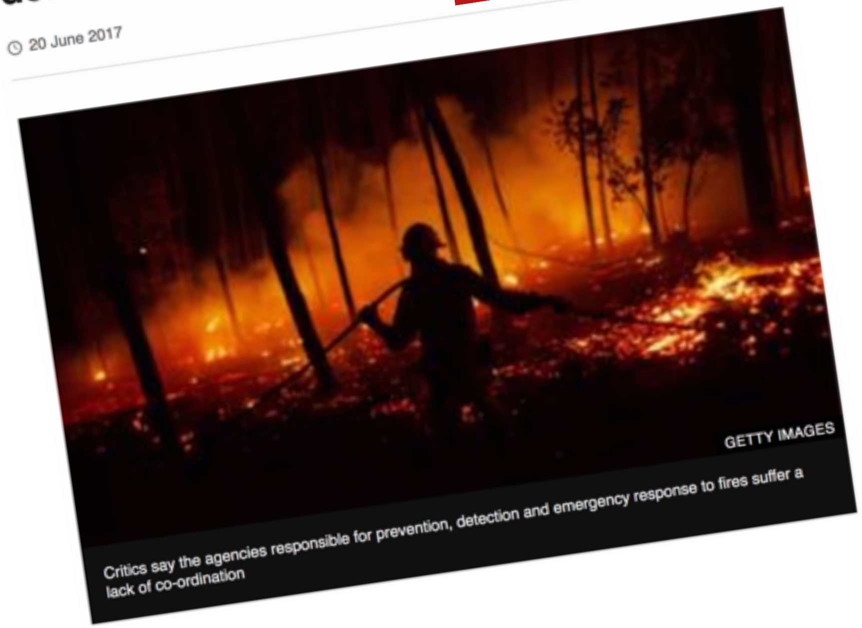
Portugal Fires Kill More Than 60, Including Drivers Trapped in Cars

BBC NEWS

Portugal wildfires: Why are they so deadly?

Share

20 June 2017



Critics say the agencies responsible for prevention, detection and emergency response to fires suffer a lack of co-ordination

The Guardian

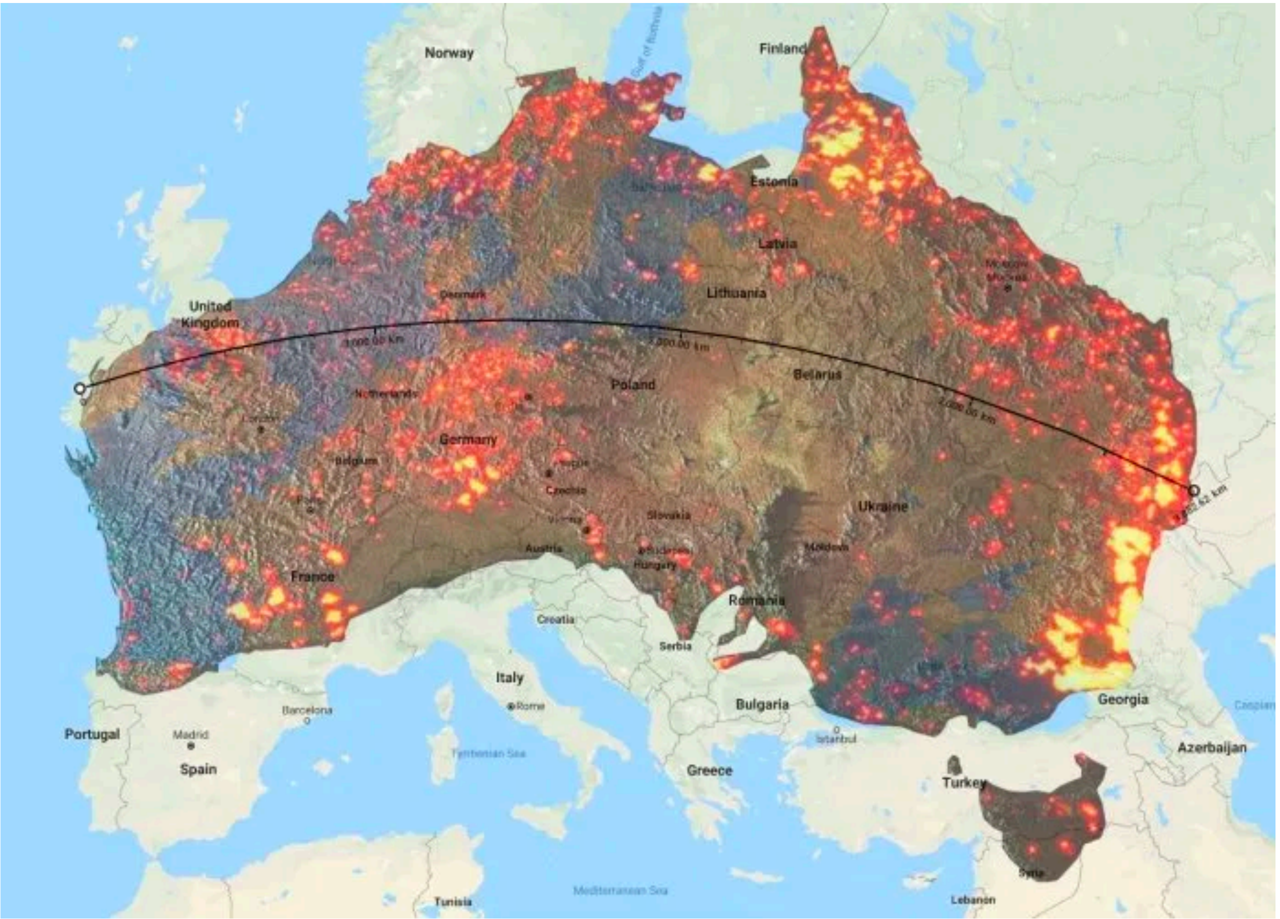
Portugal forest fires under control after more than 60 deaths

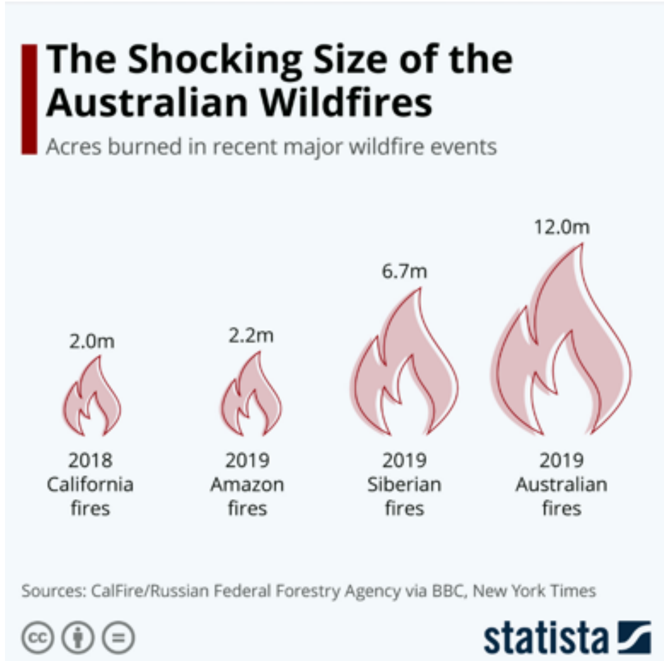
Officials say some fires could reignite after huge blaze ravaged tens of thousands of hectares around Pedrógão Grande

A firefighter lights a controlled fire to bring wildfires under control. Photograph: Tiago Petinga/EPA

17th June 2017 - 66 deads
15th October 2017 – 45 deads

Australia 2019/2020





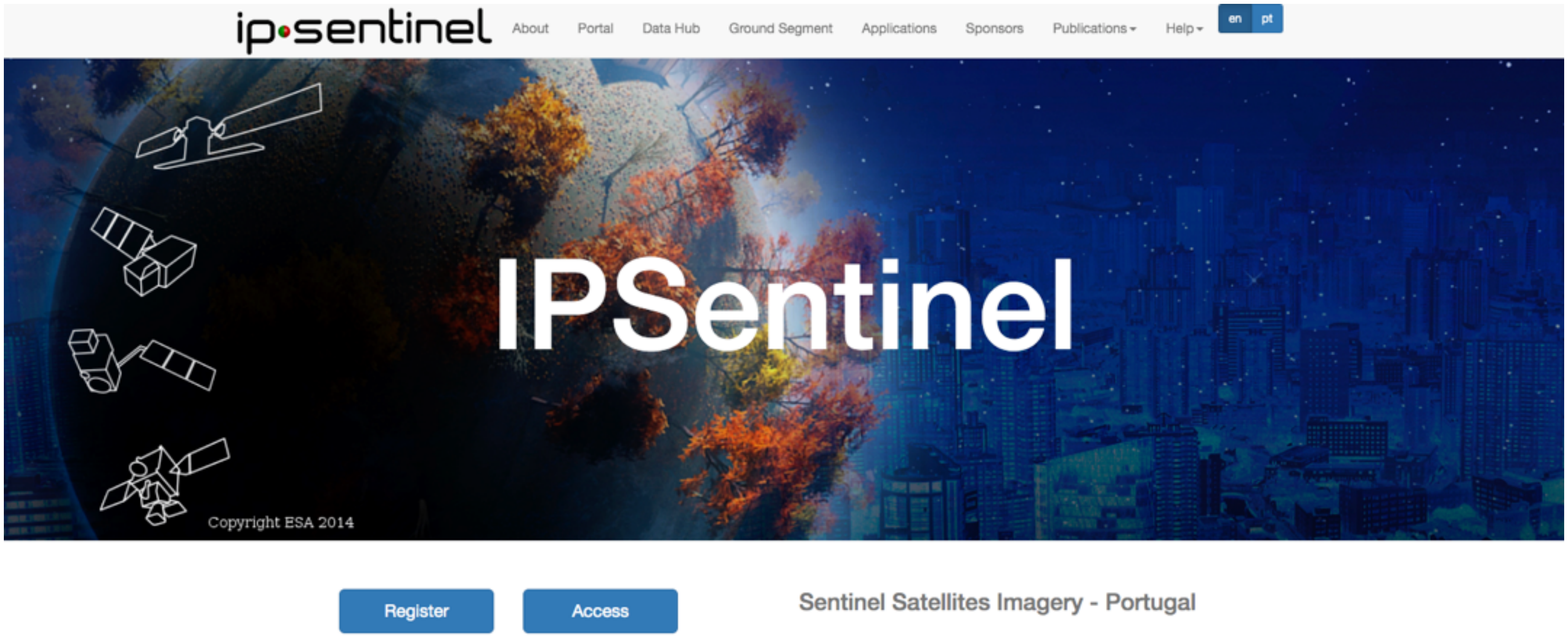
- 186,000 square kilometres burnt
- Over 5,900 buildings destroyed
- At least 34 people killed

Satellite image processing

The Copernicus constellation

- Copernicus Sentinel-1
  - Sentinel-1A and Sentinel-1B were launched on 3 April 2014 and on 25 April 2016
  - All-weather, day and night radar imagery for land and ocean services
- Copernicus Sentinel-2 – revisit time of **5 days** – **free access**
  - Sentinel-2A and Sentinel-2B were launched on 22 June 2015 and on 7 March 2017
  - High-resolution optical imagery for land services
  - Examples: vegetation, soil and water cover, inland waterways and coastal areas.
  - Sentinel 2C and 2D are planned to launch in 2020 and 2021 (cut revisit time)
- Copernicus Sentinel-3
  - Sentinel-3A and Sentinel-3B were launched on 16 February 2016 and on 25 April 2018
  - High-accuracy optical, radar and altimetry data for marine and land services.
  - Examples: sea-surface topography, sea- and land-surface temperature, ocean colour and land colour with high-end accuracy and reliability.
  - EUMETSAT operates the marine mission while ESA delivers the land mission.
- Copernicus Sentinel 5p - air pollution monitorization
- Sentinel 4 and 6 still to be launched

IPSentinel- Portuguese infrastructure for storing and providing images of Sentinel satellites



https://ipsentinel.pt/

Sentinel-2 bands

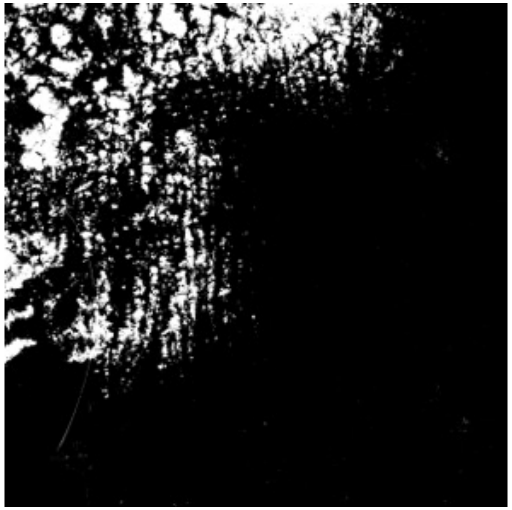
Band	Resolution	Central Wavelength	Description
B1	60 m	443 nm	Ultra blue (Coastal and Aerosol)
B2	10 m	490 nm	Blue
B3	10 m	560 nm	Green
B4	10 m	665 nm	Red
B5	20 m	705 nm	Visible and Near Infrared (VNIR)
B6	20 m	740 nm	Visible and Near Infrared (VNIR)
B7	20 m	783 nm	Visible and Near Infrared (VNIR)
B8	10 m	842 nm	Visible and Near Infrared (VNIR)
B8a	20 m	865 nm	Visible and Near Infrared (VNIR)
B9	60 m	940 nm	Short Wave Infrared (SWIR)
B10	60 m	1375 nm	Short Wave Infrared (SWIR)
B11	20 m	1610 nm	Short Wave Infrared (SWIR)
B12	20 m	2190 nm	Short Wave Infrared (SWIR)

Cloud detection – sentinel scl mask

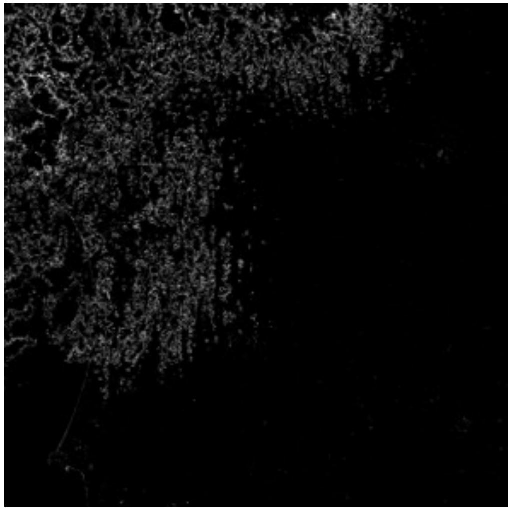
- Sentinel-2 provides Level-2 products: – scene classification mask
- Level 2A-processing is split into two parts:
  - Scene Classification (SC) - pixel classification map
    - Cloud
    - Cloud shadows
    - Vegetation
    - Soils/deserts
    - Water
    - Snow
  - Atmospheric Correction (S2AC) aims at transforming TOA (top of atmosphere) to BOA(bottom of atmosphere) reflectance.
- For our work, values 3, 8, 9 e 10 were considered “clouds”

Label	Classification
0	NO_DATA
1	SATURATED_OR_DEFECTIVE
2	DARK_AREA_PIXELS
3	CLOUD_SHADOWS
4	VEGETATION
5	NOT_VEGETATED
6	WATER
7	UNCLASSIFIED
8	CLOUD_MEDIUM_PROBABILITY
9	CLOUD_HIGH_PROBABILITY
10	THIN_CIRRUS
11	SNOW

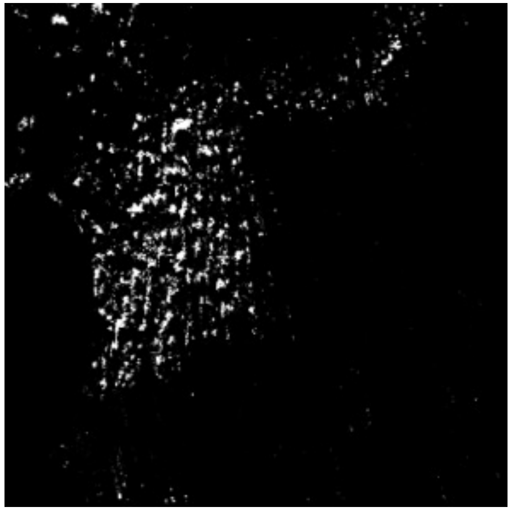
Scene classification values



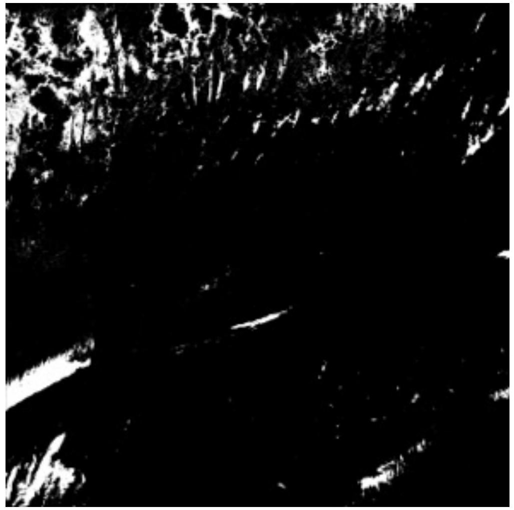
Clouds High Probability (9)



Clouds Medium Probability (8)

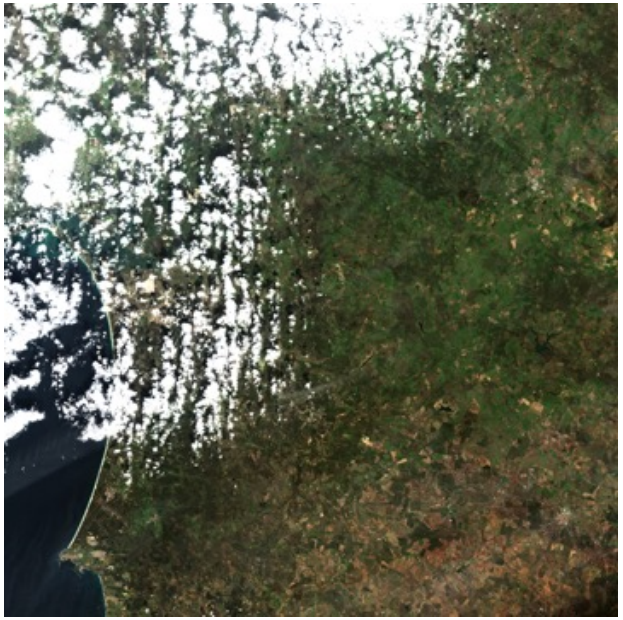


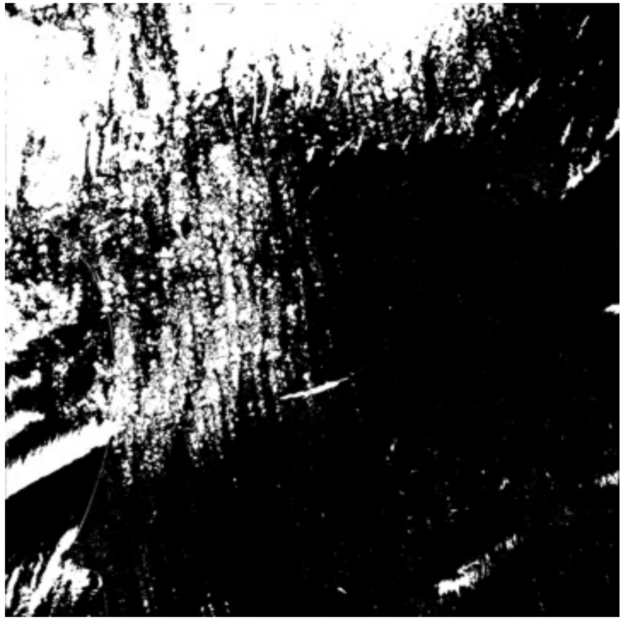
Cloud Shadows (3)



Cloud Thin Cirrus (10)

RGB Image





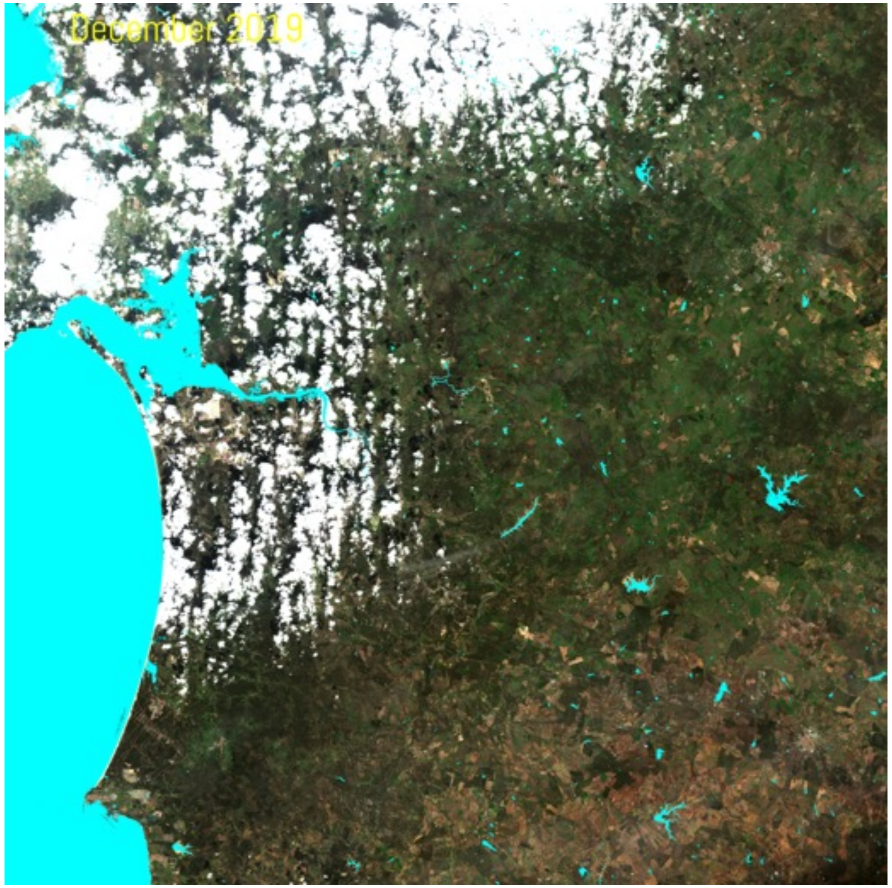
Resulting Cloud Mask Image

Water detection

Automatic detection and evaluation of water bodies

Does Sentinel-2 indentify water (code 6)?

Sentinel-2 water detection



Our water detection

Sentinel-2 bands and indexes used for water classification

	Band	Resolution	Central Wavelength	Description
	B1	60 m	443 nm	Ultra blue (Coastal and Aerosol)
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	B11	20 m	1610 nm	Short Wave Infrared (SWIR)
	B12	20 m	2190 nm	Short Wave Infrared (SWIR)

Calculated indexes:

Normalized Difference Vegetation Index – **NDVI** = (B8 – B4) / (B8 + B4)
Normalized Difference Water Index – **NDWI** = (B8 – B12) / (B8 + 12)
Modified Normalized Difference Water Index – **MNDWI1** = (B3-B11) / (B3+B11)
Modified Normalized Difference Water Index – **MNDWI2** = (B3-B12) / (B3+B12)

Water classifier

- Inputs:
  - Sentinel-2 bands: 1,2,3,4,5,6,7,8,9,11,12
  - Ndvi
  - Ndwi
  - Mndwi1
  - Mndwi2
- CART Decision Tree (Matlab)
- Trainning set: 15 000 000 pixels from 12 months - 1 250 000 pixels from each month
- The Ground Truth: the COS - Land-Cover Land-Use maps

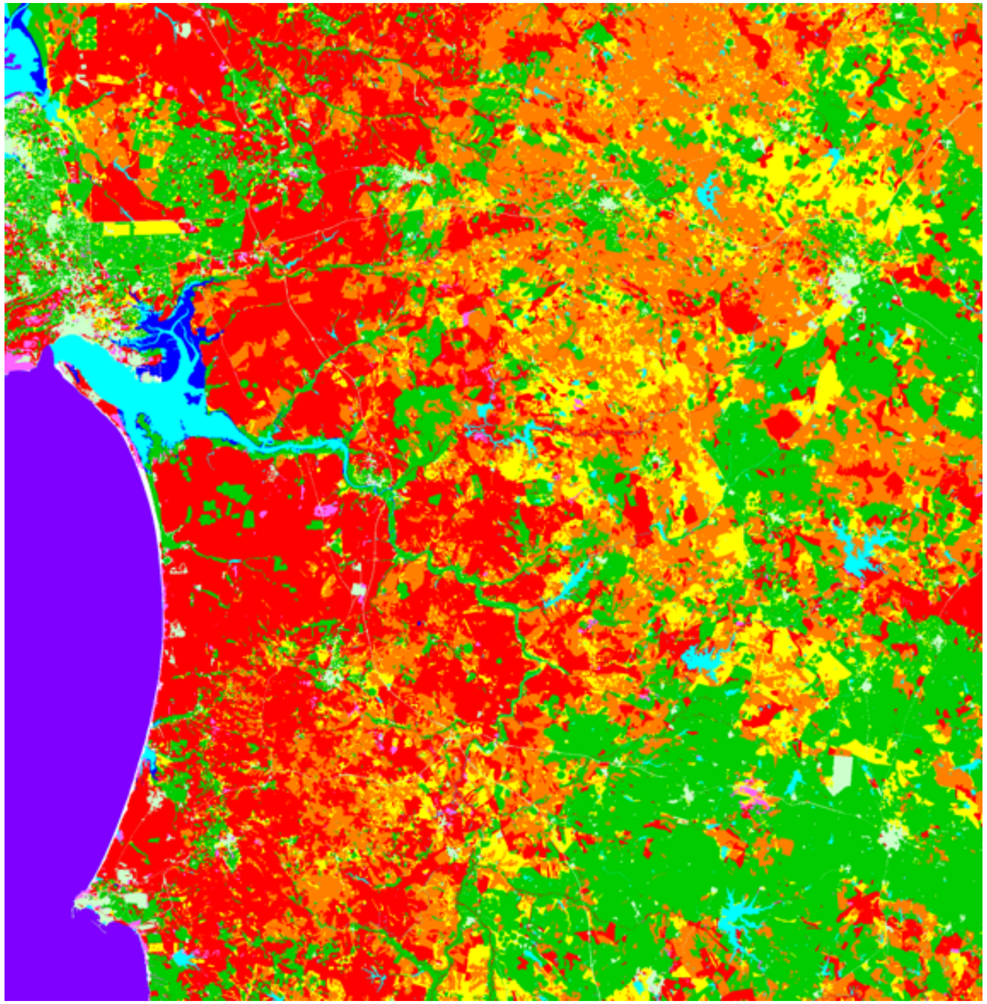
Water detection

The Ground Truth

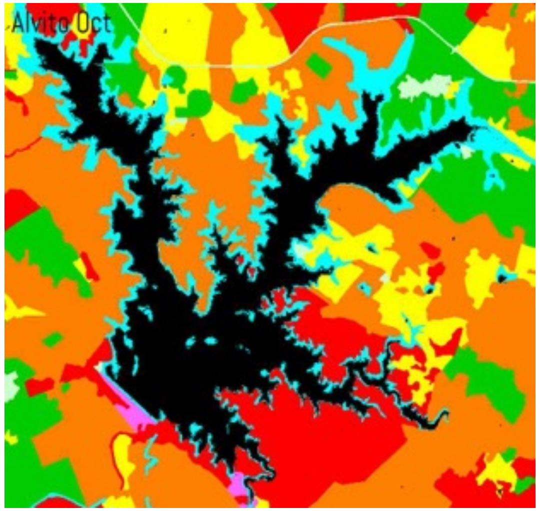
- COS – Land using occupation map periodically updated by DGT – Direção Geral do Território (3 years cycle)
- Portuguese COS has 10 mega-classes:

0 - Ocean
1 - Artificialized territories
2 - Agriculture
3 – Grassland
4 - Agroforestry areas
5 – Forests
6 – Bushland
7 - Open spaces or little vegetation
8 - Wetlands
9 - Water Bodies

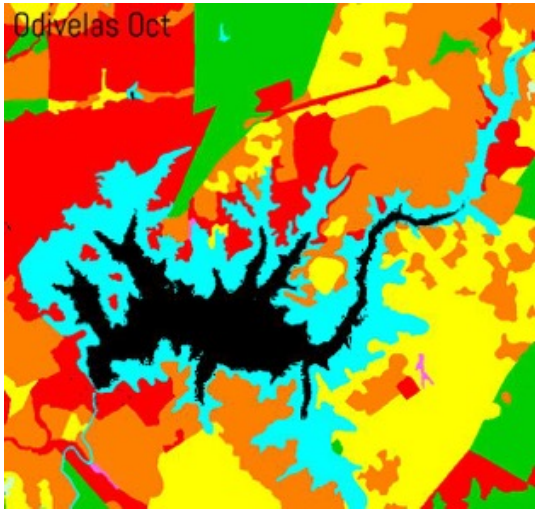
Classes 0, 8 and 9 are considered water



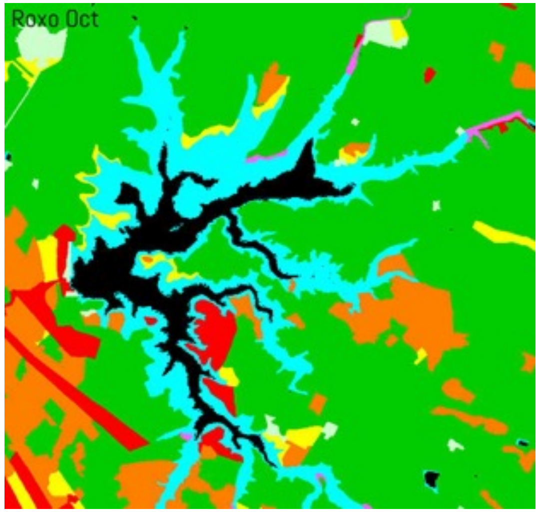
The ground truth problem



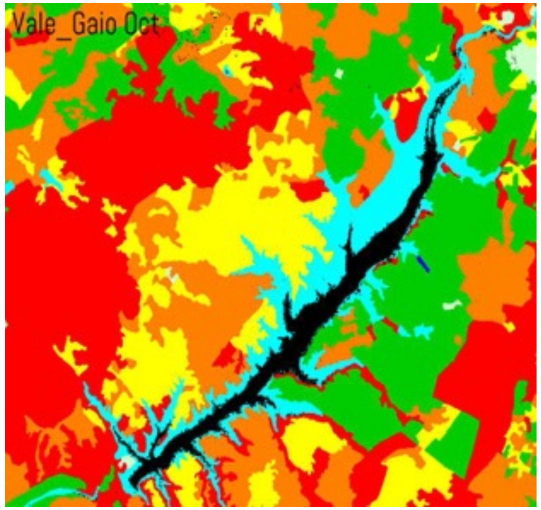
Alvito dam - October 2019



Odivelas dam - October 2019



Roxo dam - October 2019

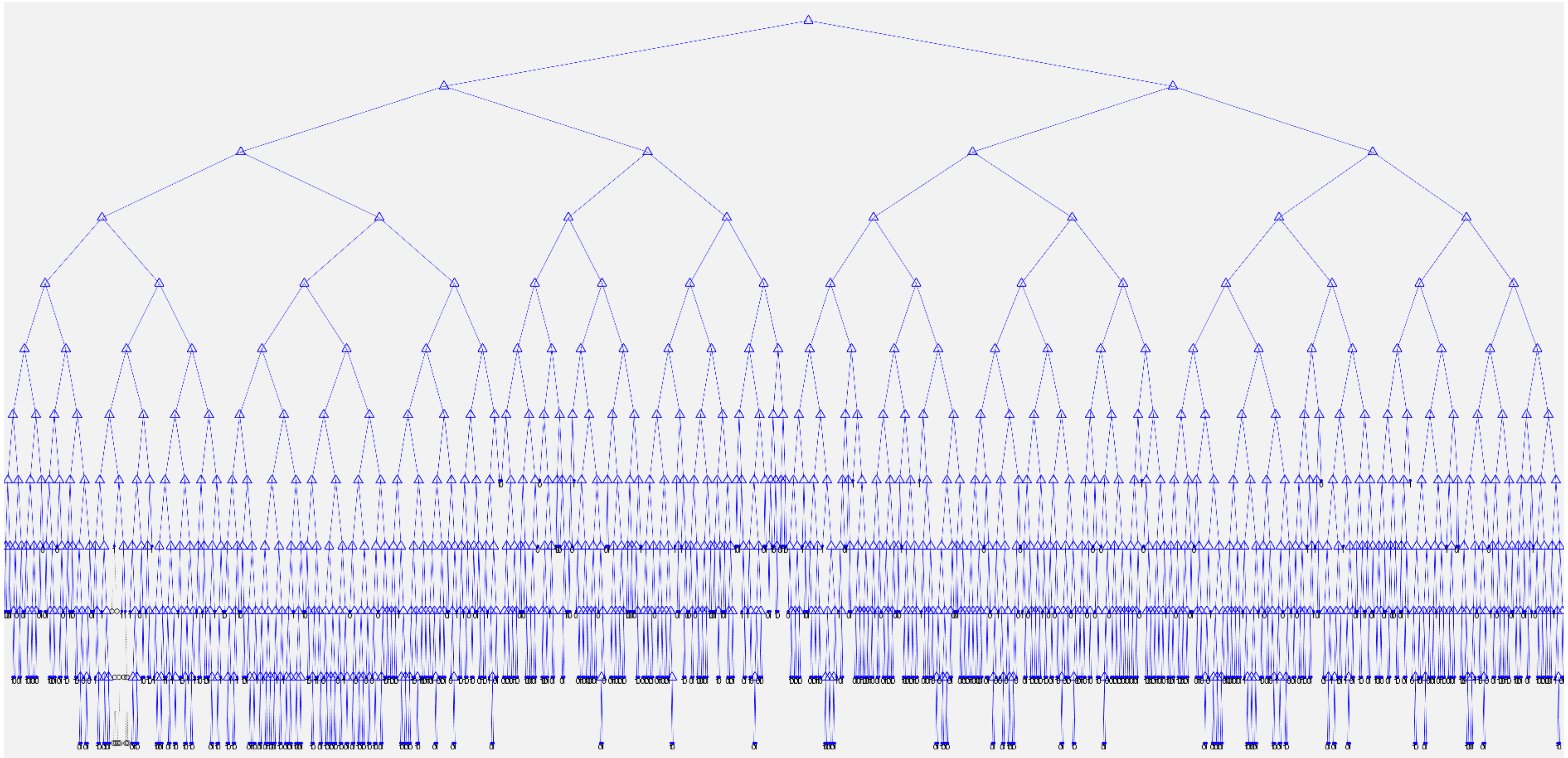


Vale Gaio dam - October 2019

Water bodies according to COS

Real water bodies

A complex decision tree… that works



How shall we train the classifier?

Test	Train: Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Global
Jan	98,96	94,13	86,63	74,22	47,88	98,05	85,32	83,86	48,47	98,76	98,62	98,83	98,89
Feb	98,9	98,97	98,74	96,05	96,42	98,46	97,51	94,16	98,17	98,69	98,87	98,77	98,91
Mar	93,79	93,74	99,06	93,43	94,15	94,1	93,33	92,67	93,52	93,36	93,99	94,03	99,05
Apr	98,91	98,89	98,99	99,15	99,08	99,04	98,98	98,57	98,69	98,78	99,04	98,95	99,14
May	98,31	98,31	98,82	98,78	99,08	98,93	98,73	98,47	98,56	98,46	98,76	98,53	99,04
Jun	95,97	97,67	90,43	96,02	85,29	98,79	88,77	95,06	25,2	97,92	98,4	98,23	98,67
Jul	98,55	98,44	98,68	98,95	98,93	98,96	99,01	98,67	98,87	98,61	98,84	98,78	98,98
Aug	98,67	98,54	98,63	98,9	98,8	98,87	98,86	98,88	98,66	98,65	98,79	98,74	98,92
Sep	98,57	98,71	98,05	98,81	98,84	98,79	98,81	91,89	98,83	98,56	98,74	98,61	98,89
Oct	98,31	75,85	66,15	85,64	82,09	97,74	89,11	82,48	38,02	98,82	98,27	98,5	98,72
Nov	98,57	89,19	71,27	79,93	67,45	97,59	91,91	85,17	46,18	98,51	98,77	98,62	98,81
Dec	98,74	91,85	79,69	69,54	57,44	98,34	90,43	84,95	46,68	98,68	98,64	98,9	98,81

January 2019

February 2019

March 2019

Apr 2019

May 2019

June 2019

July 2019

August 2019

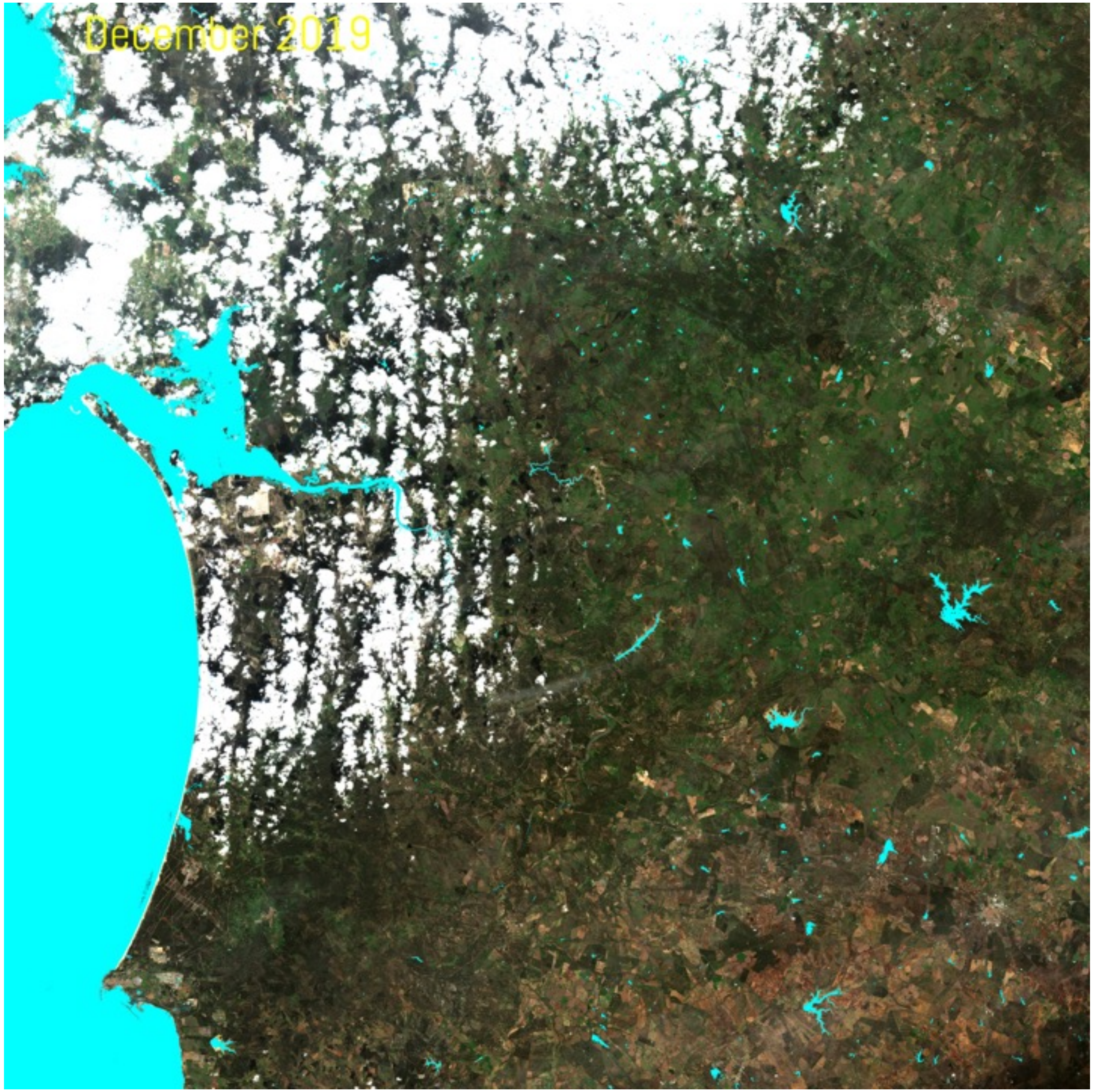
September 2019

October 2019

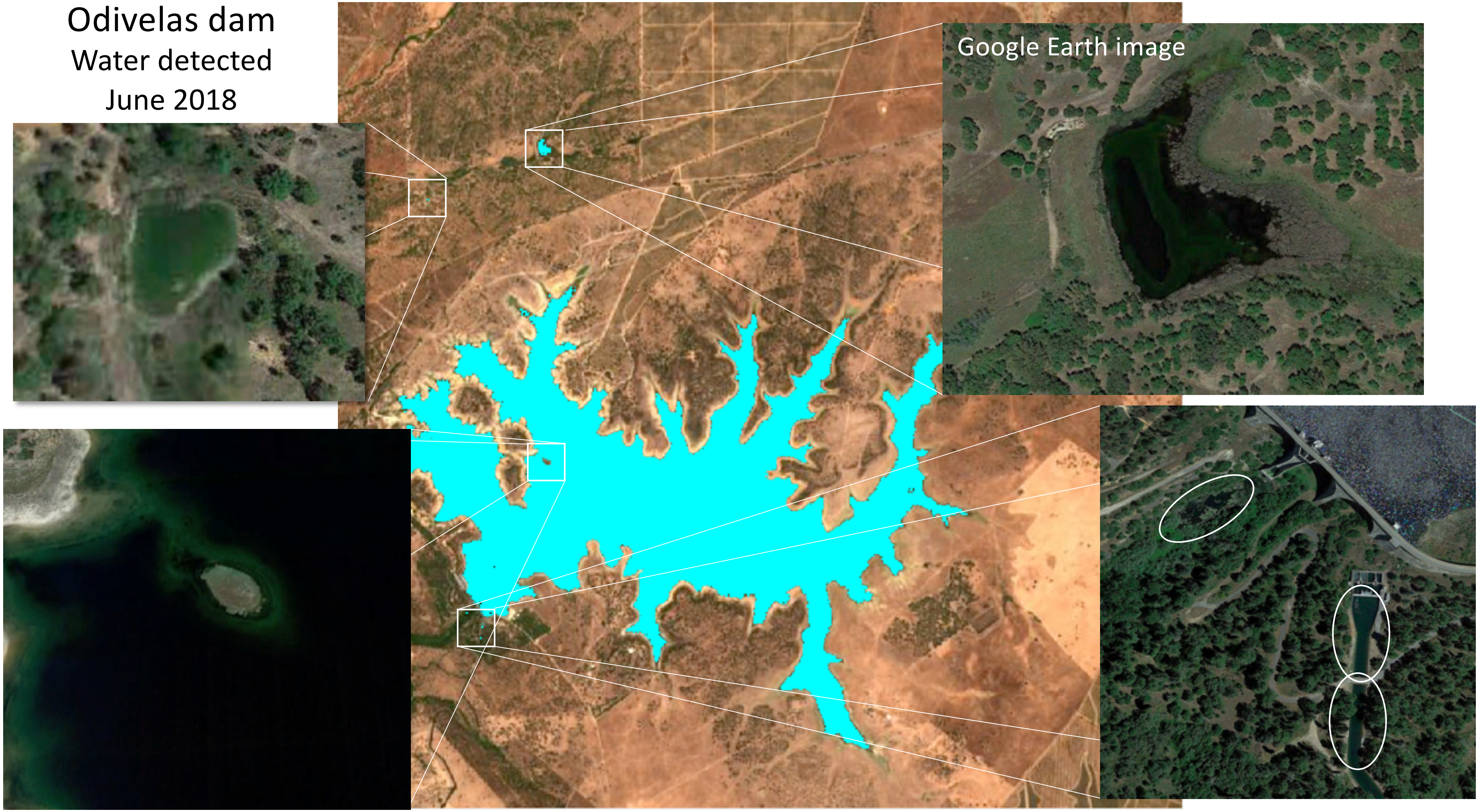
November 2019

December 2019

Water detection during 2019

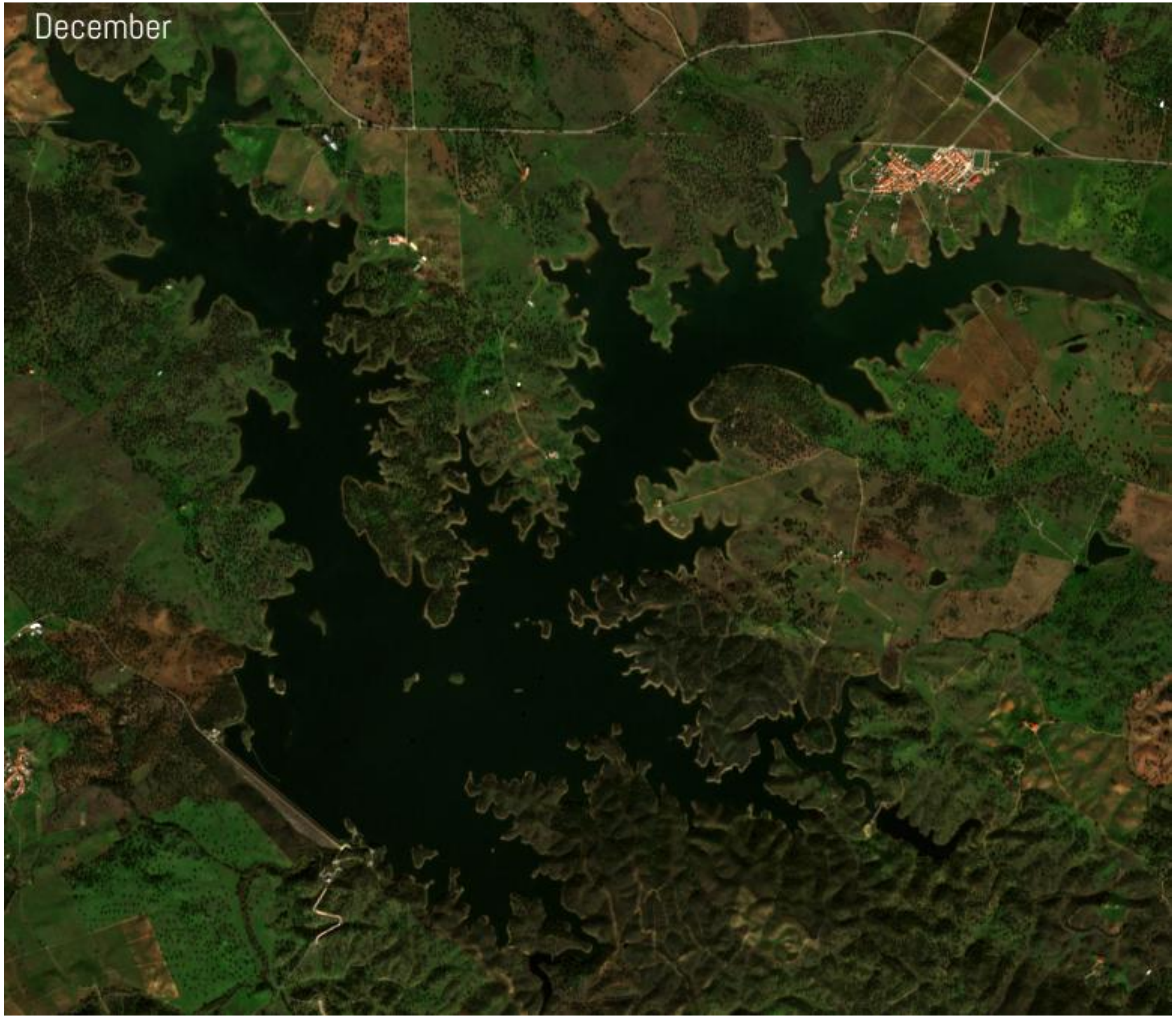


Odivelas dam
Water detected
June 2018

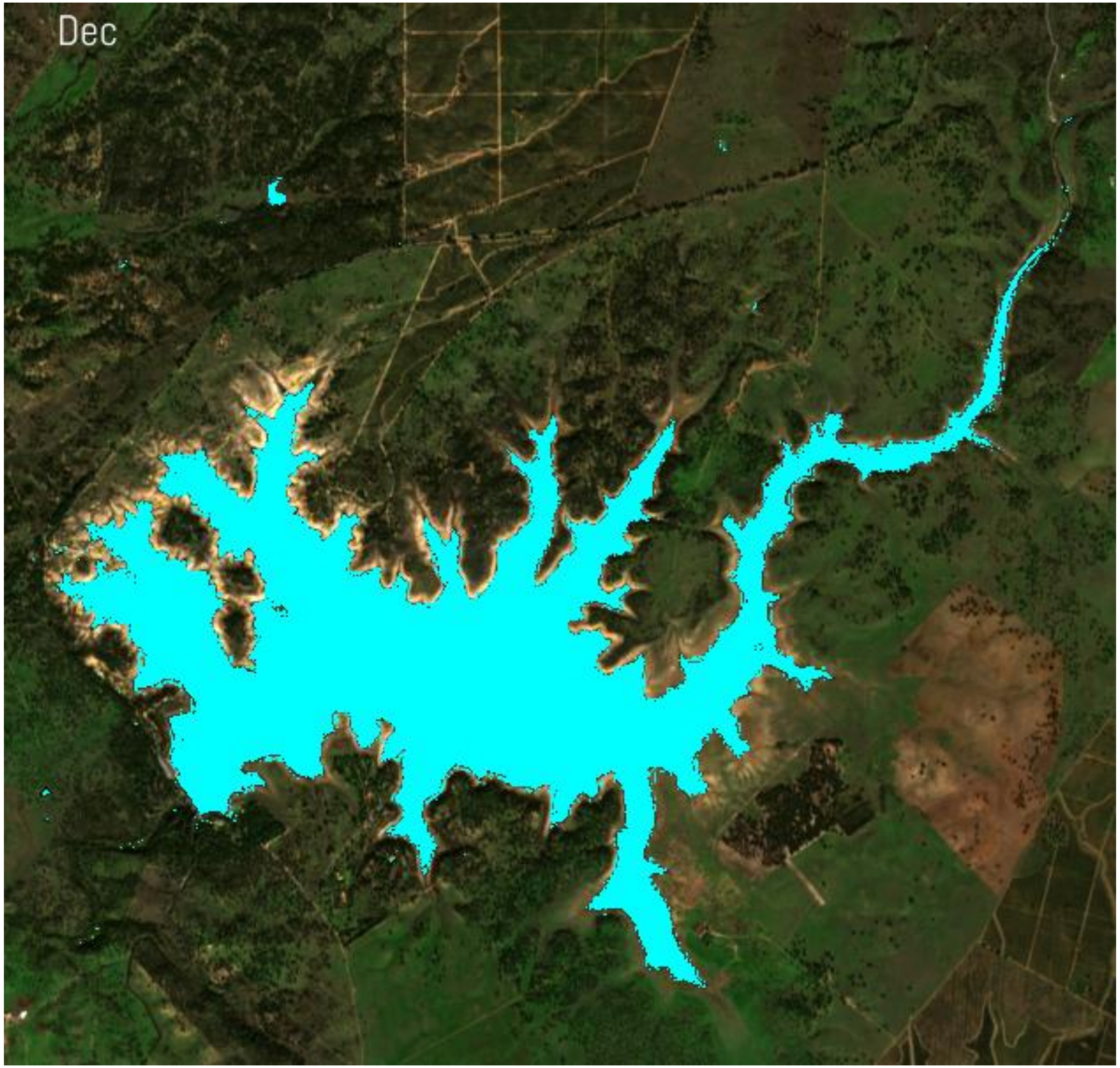


Alvito Dam example

Is water always water?

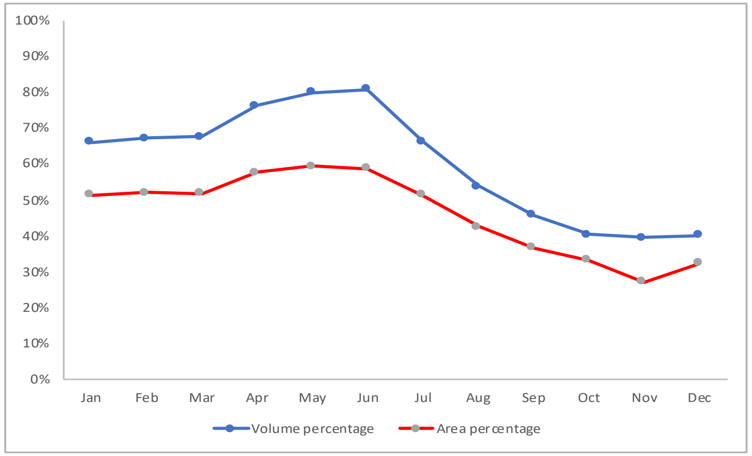


Odivelas dam
during 2019

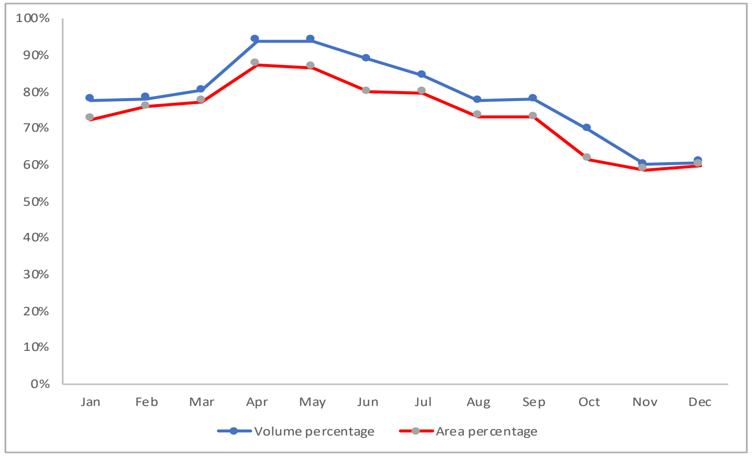


Estimated area vs Measured volume (2019)

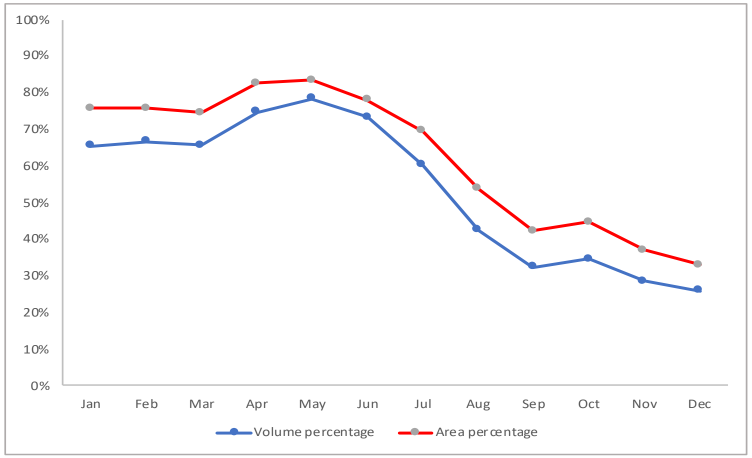
Odivelas dam



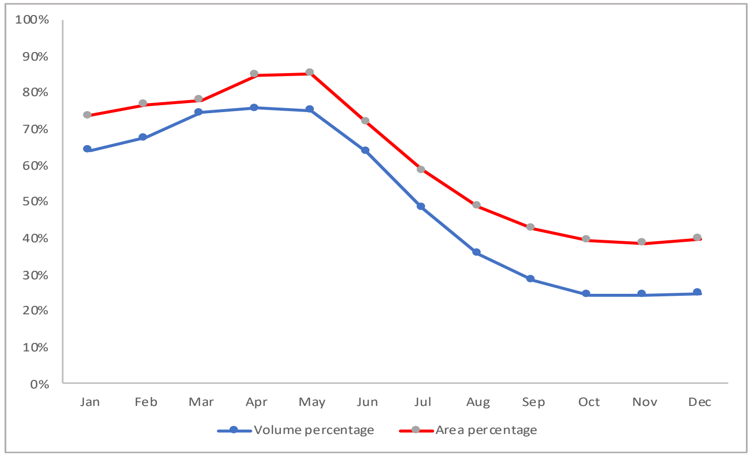
Alvito dam



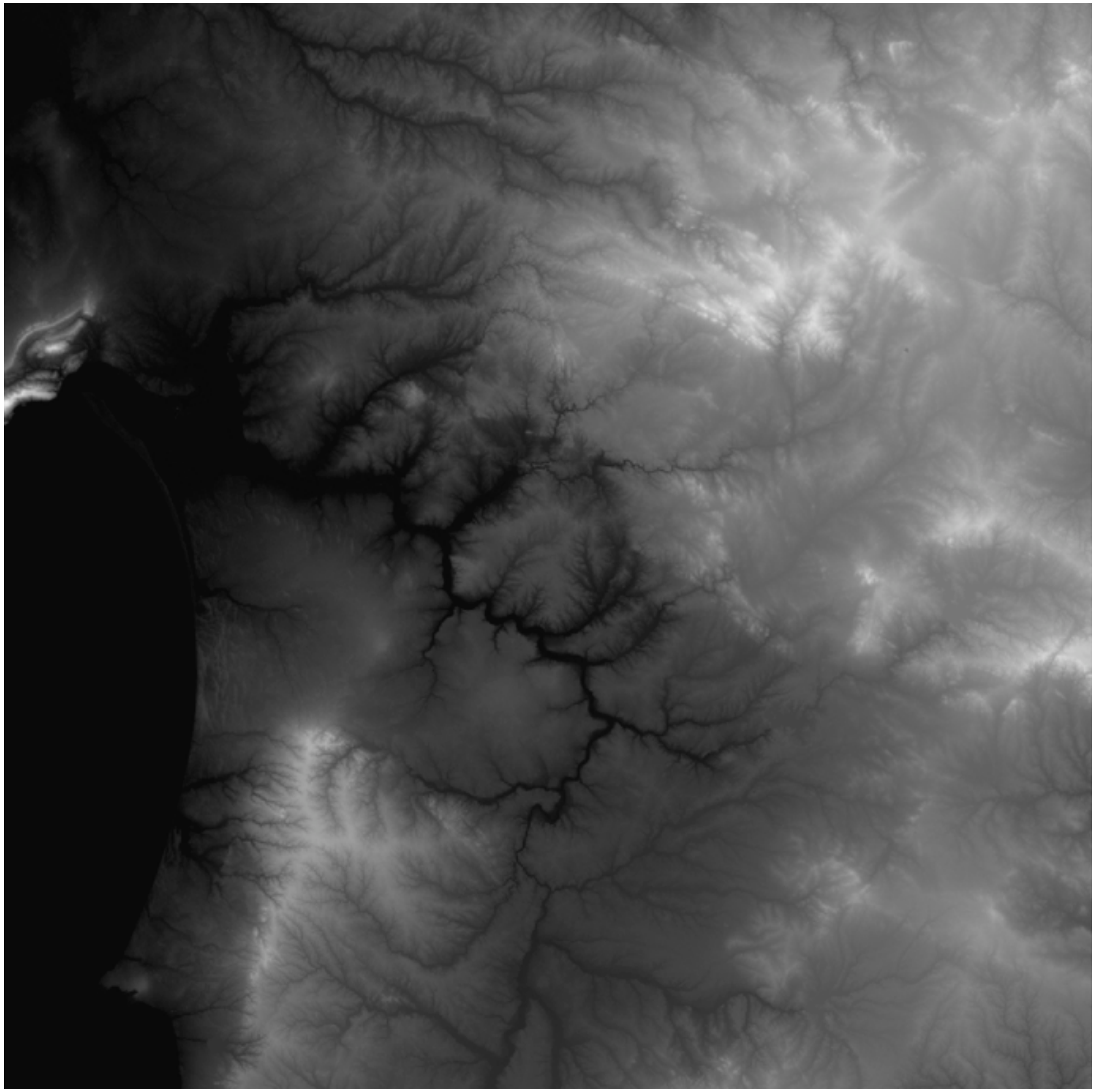
Roxo dam



Vale Gaio dam

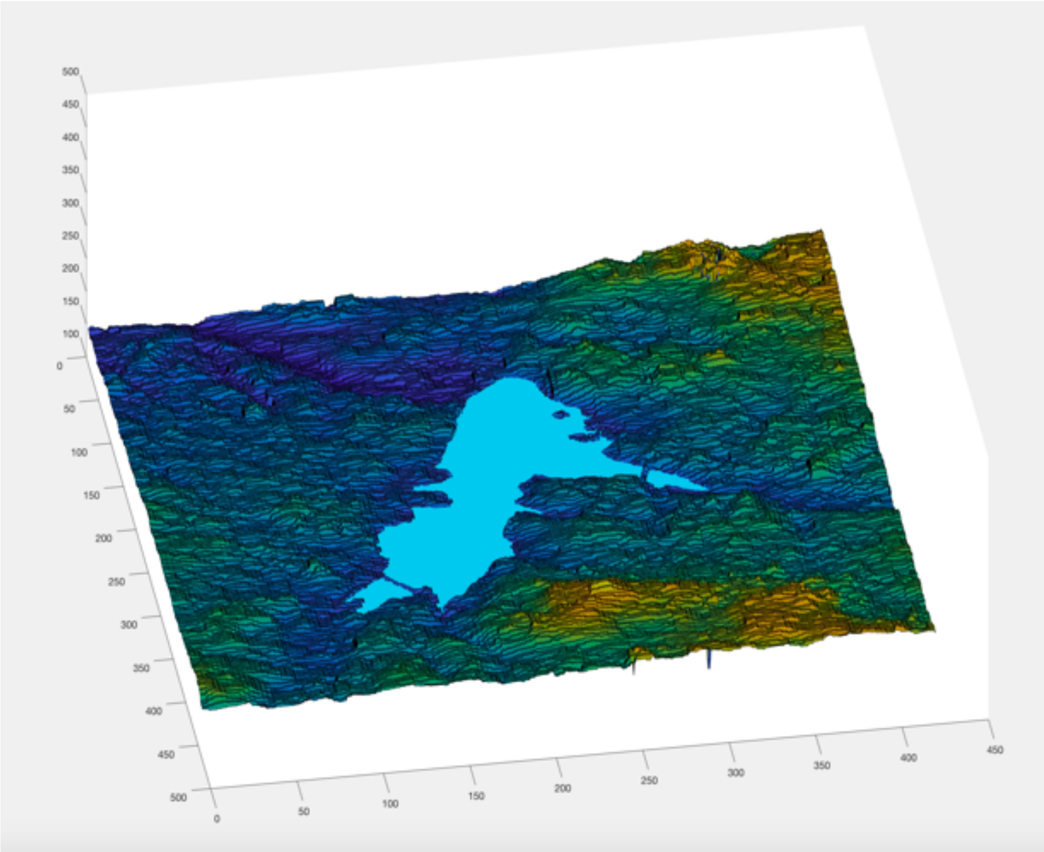


Digital Elevation Model by EarthData[1]



[1]https://earthdata.nasa.gov/

Water volume estimation based on Digital Elevation Model by EarthData[1]



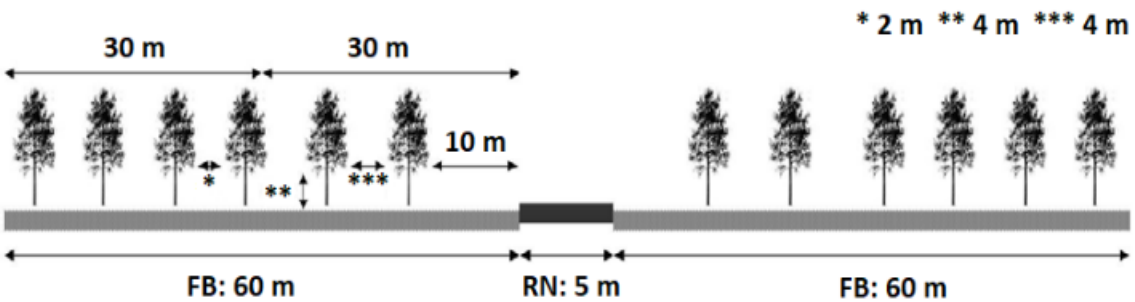
[1]https://earthdata.nasa.gov/

Fire breaks

Semi-automatic Fire Break Maintenance Operations Detection

Fire Break Maintenance Operations Detection

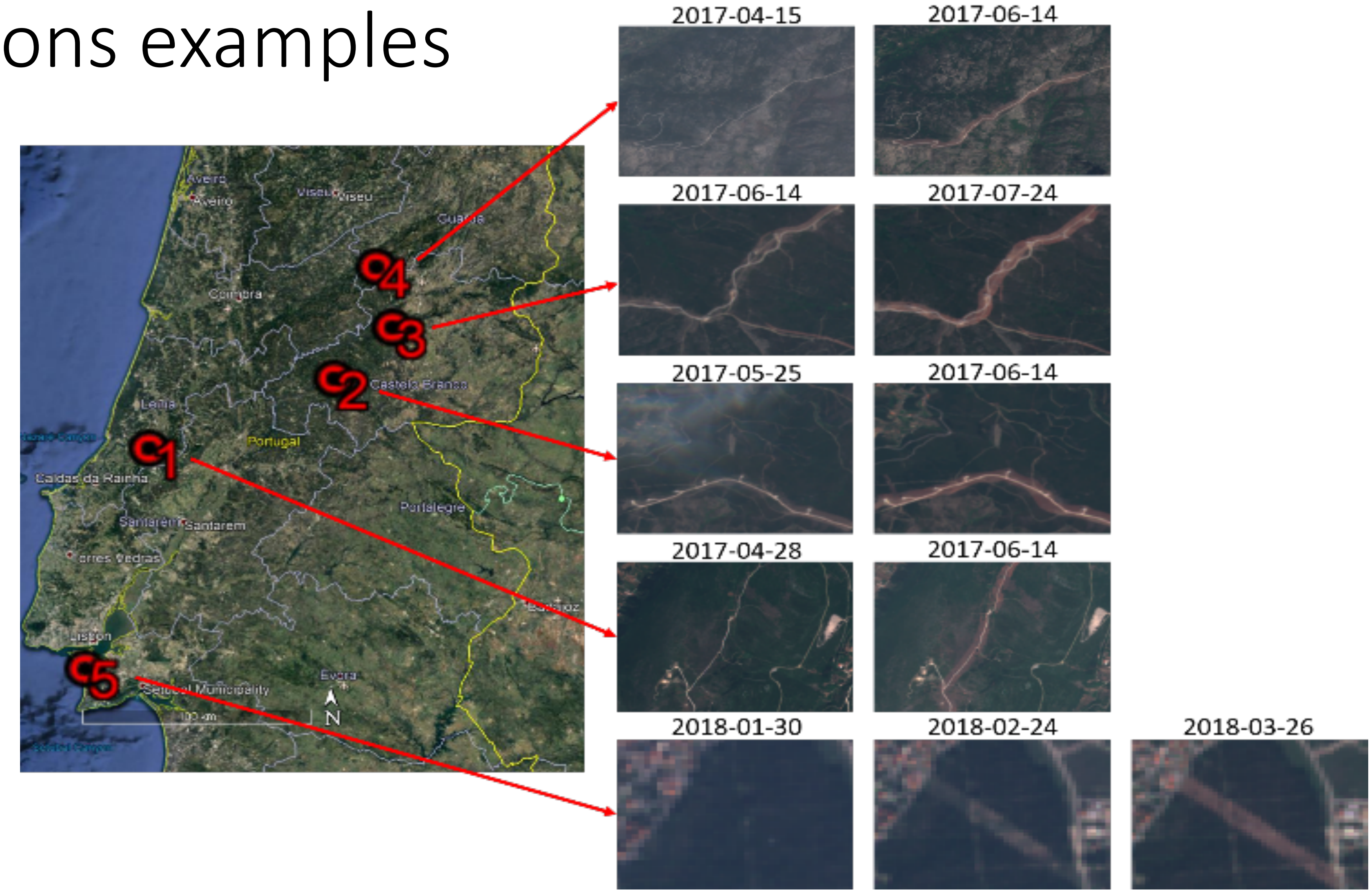
- The Portuguese Institute of Nature and Forest Conservation defined the Fire Breaks Network (11 125Km, 1 600Km already implemented)
- A Fire Break is a strip of land that has been strategically and artificially modified, where vegetation density is reduced to break up the continuity of fuel



- It acts as a barrier to slow or stop the progress of wildfire
- Its maintenance must be ensured and verified periodically

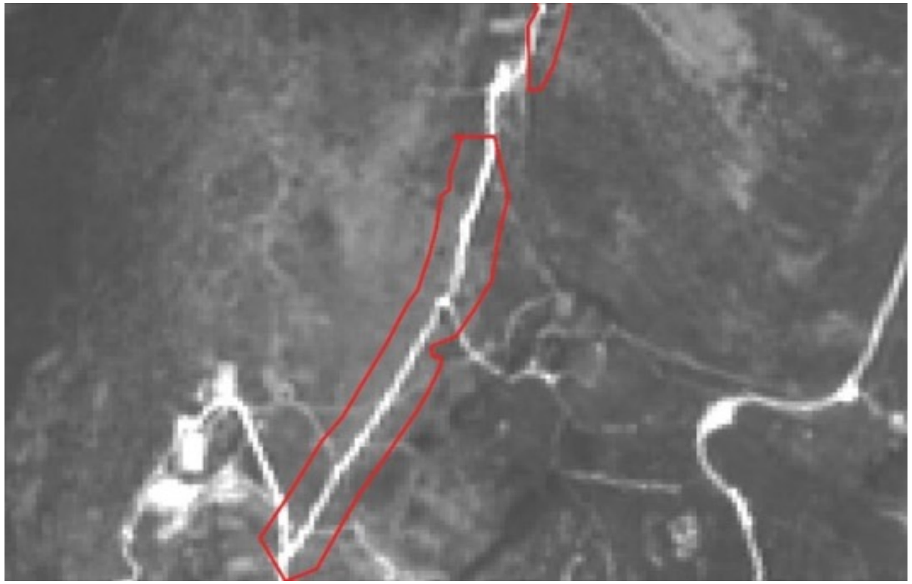
Operations examples

C1 – Serra dos Candeeiros
C2 – Sertã
C3 – Fundão
C4 – Seia
C5 - Marisol



Example of a maintenance operation

Band 04 image of intervention on a FB in Serra dos Candeeiros

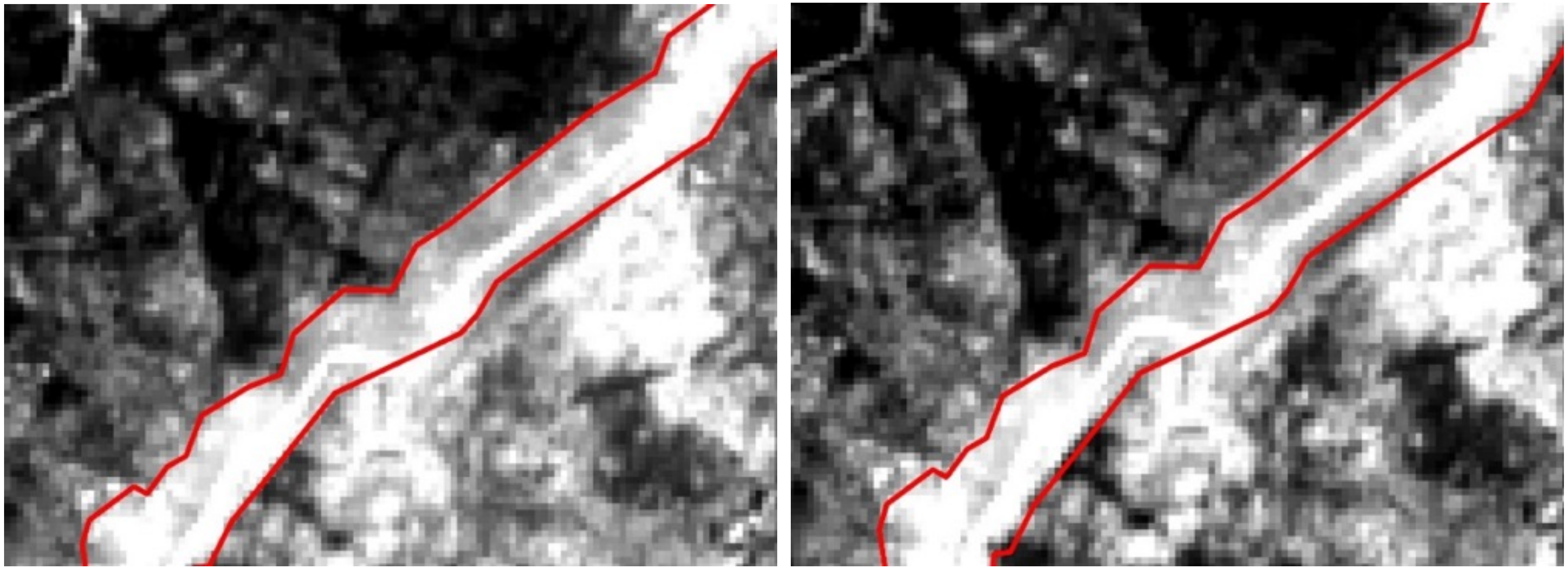


8 May 2017

4 July 2017

Fire break detection problems

- Geolocation error: translactional offset < 1.5 pixels
- Fire breaks between 60m and 125m are 6 to 12 pixels wide



Original Image

Corrected image
Estimated offset of 0.7 North/South and -0.11 East/West

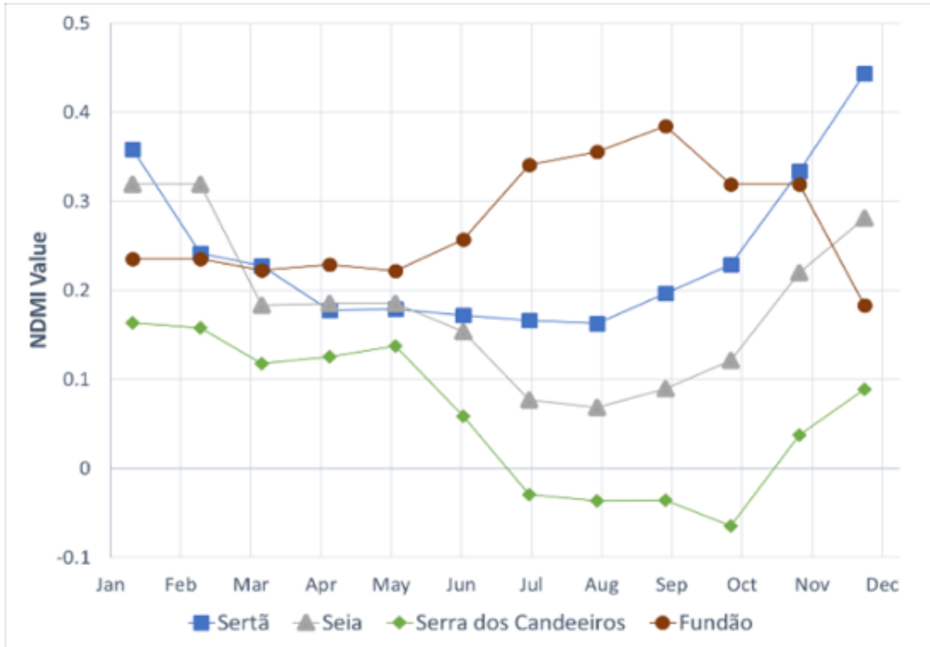
Bands and indices

Sentinel-2 bands: B02, B03, B04, B05, B07, B08, B8A, B11 and B12

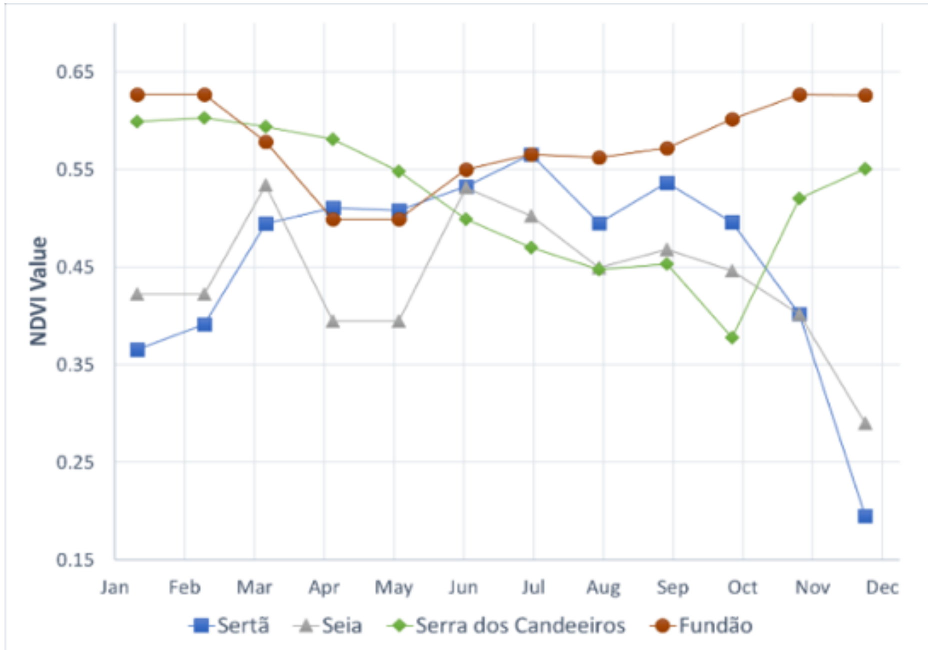
Calculated indices

Index	Description	Equation
NDMI	Normalized Difference Moist Index	$\frac{B08-B11}{B08+B11}$
NDVI	Normalized Difference Vegetation Index	$\frac{B08-B04}{B08+B04}$
RVI	Ratio Vegetation Index	$\frac{B04}{B08}$
NMDI	Normalized Multi-band Drought Index	$\frac{B8A-(B11-B12)}{B8A+(B11-B12)}$
NDI	Normalized Difference Index	$128\times\left(\frac{B03-B04}{B03+B04}+1\right)$
ExG	Excess of Green	$2\times B03-B04-B02$
ExR	Excess of Red	$1.3\times B04-B03$
ExGR	Excess of Green minus Excess of Red	$ExG-ExR$
MExG	Modified Excess	$0.441\times B04-0.811\times B03+0.383\times B02+18.78745$

Vegetation index along the year

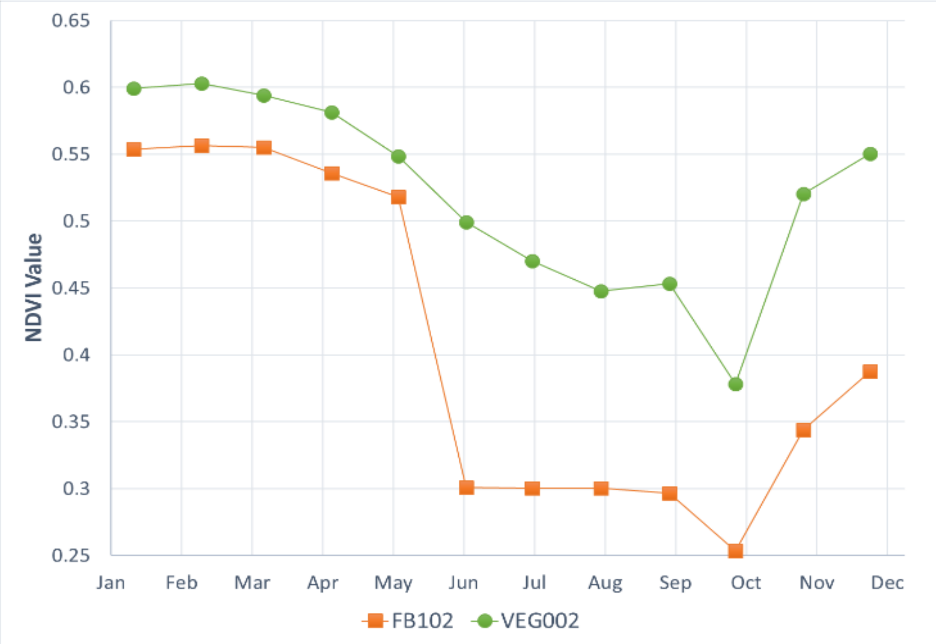


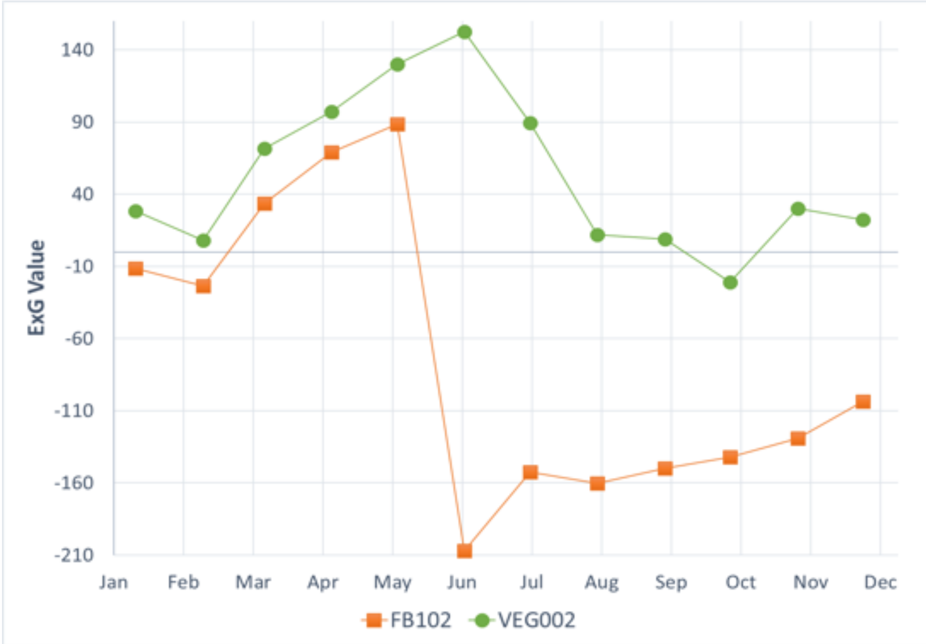
NDMI index



NDVI index

Comparison FB and VEG





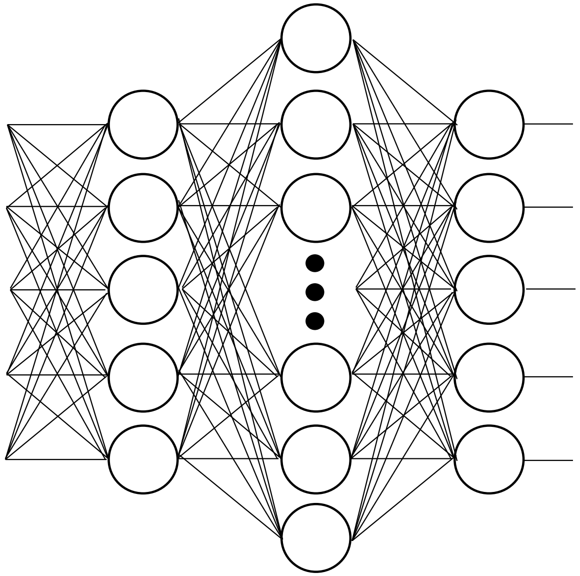
NDVI index

ExG index

ExG index is adequated for operation detection

Fire Break detection

- A Neural Network with one hidden layer varying the number of neurons in the interval [5,100] with steps of 5 was adopted
- Features were grouped for evaluation

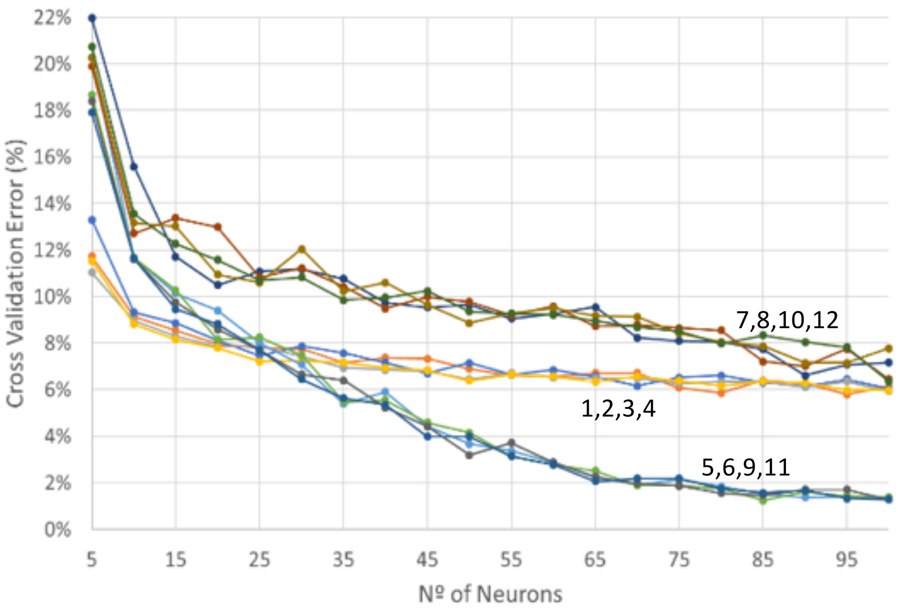


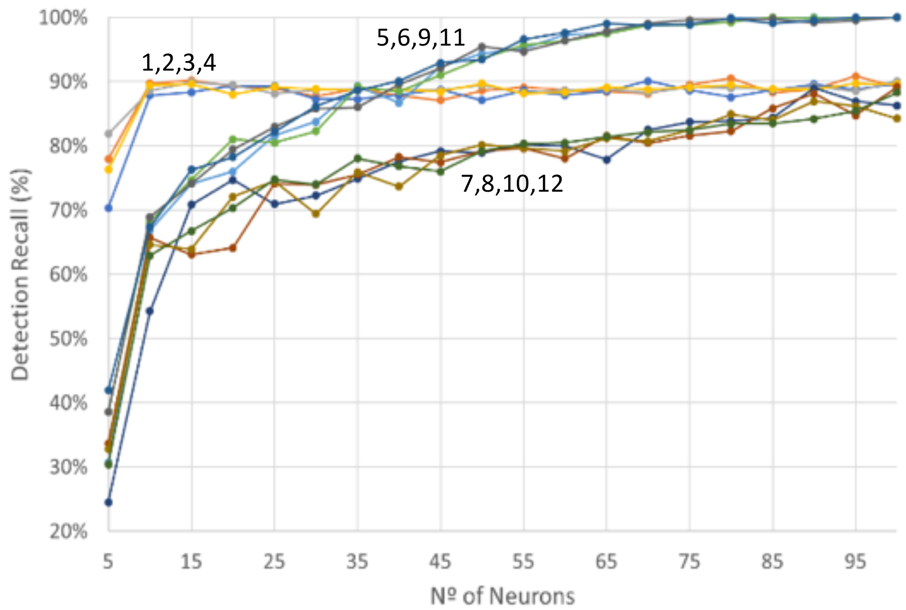
Group	Features
1	B05, ExG
2	B11, ExG
3	B05, ExG, NMDI
4	B11, ExG, NMDI
5	B05, ExG, ExR
6	B11, ExG, ExR
7	B05, ExG, ExGR
8	B11, ExG, ExGR
9	B05, ExG, ExR, NMDI
10	B05, ExG, ExGR, NMDI
11	B11, ExG, ExR, NMDI
12	B11, ExG, ExGR, NMDI

SelectKBest feature selection algorithm

Is network size important?

A neural network with 53 neurons on the hidden layer was choosen to classify based on Group 5





ExR is on all the best groups and only on those

Best feature groups

1	B05, ExG
2	B11, ExG
3	B05, ExG, NMDI
4	B11, ExG, NMDI

7	B05, ExG, ExGR
8	B11, ExG, ExGR
10	B05, ExG, ExGR, NMDI
12	B11, ExG, ExGR, NMDI

5	B05, ExG, ExR
6	B11, ExG, ExR
9	B05, ExG, ExR, NMDI
11	B11, ExG, ExR, NMDI

Classification results on maintenance operations

Classification results for the training dataset.

	Median Filter Data		Mean Filter Data	
Detection	Yes	No	Yes	No
Recall (%)	93	98	97	99
Precision (%)	94	98	89	97
F1-Score (%)	93	98	93	98
Relative Error (%)	3.1		3.3	

Classification results for the validation dataset (average of all generated classifiers).

	Median Filter Data		Mean Filter Data	
Detection	Yes	No	Yes	No
Recall (%)	87	97	77	98
Precision (%)	57	99	64	99
F1-Score (%)	68	98	70	99
Relative Error (%)	2.9		2.5	

False positives must be avoided (few positive examples available)

Conclusions

- Land-Cover Land-Use maps
  - Water detection and evaluation is accurate
  - Production of automatic simplified Land-Cover Land-Use maps is possible but very difficult (preliminary tests indicate errors in the order of 30% to 40% of the pixels)
  - Improve the classification by more adequate trainning set selection
- Fire Break Maintenance Operations Detection
  - The developed methodology produces acceptable results
  - Mean filtering is more conservative but median filter facilitates maintenance detection (but with tendency for more false positives)

Acknowledgments

- Our partners:
  - **DGT** – Direção Geral do Território
  - **IMS** – Information Management School
  - **ICNF** - Instituto da Conservação da Natureza e das Florestas
  - **ISA** - Instituto Superior de Agronomia

- This work was partially supported by grants:
  - IPSTERS – DSAIPA/AI/0100/2018 - *Sistema de reconhecimento terrestre do IPSentinel,*
  - *FORESTER - PCIF/SSI/0102/2017 - Rede de sensores combinada com modelação da propagação do fogo integrado num sistema de apoio à decisão para o combate a incêndios florestais*
  - *FUELMON – PTDC/CCI-COM/30344/2017 - Monitorização Remota de Corta-Fogos para Proteção de Fogos Florestai*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Machine Learning and Image Processing Techniques
Thank you for your attention
Questions?
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SPACOMM 2020
The Twelfth International Conference on Advances in Satellite and Space Communications
February 23, 2020 to February 27, 2020 - Lisbon, Portugal
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