



# Copernicus Assisted Inland Water Quality Emergency Monitoring Service



by

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## SUSTAINABLE DEVELOPMENT GOALS



- Support to SDGs 3, 6, 13, 15
- Become an evolution service element of the Copernicus Emergency Management Service (CEMS)
- Couple with EUROGEO activities
- Facilitate monitoring operation of water utilities & governmental agencies

## Emergency Management Service



Photo Credit: Héctor Garrido, Eloy Revilla, Rubén Rodríguez Olivares / EBD-CSIC

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# Finding the right niche – Keeping the balance

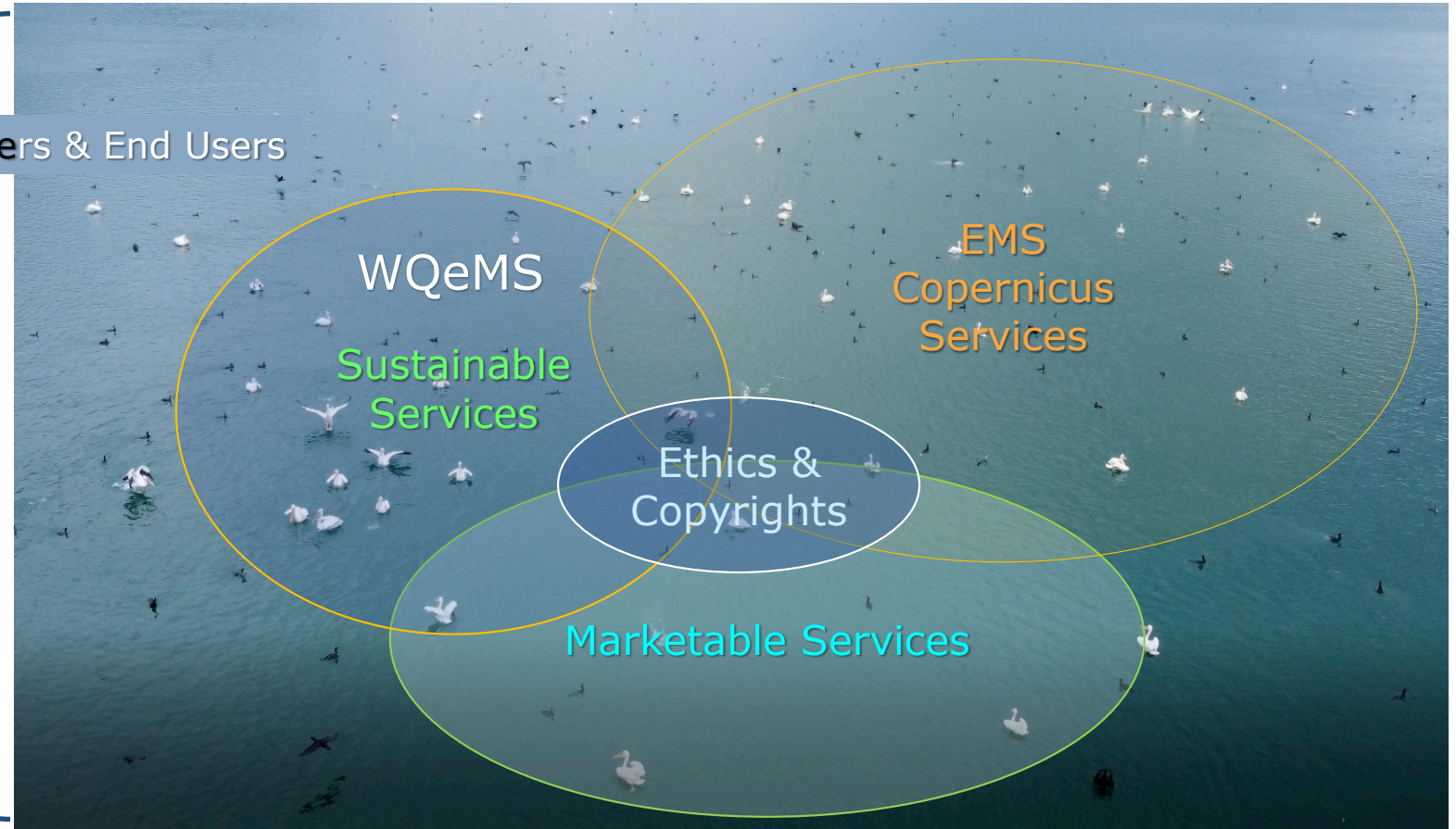


<https://wqems.eu/>



Water we drink...

Users & End Users



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# Expected service features



<https://wqems.eu/>



## RS product reliability and adaptability for the non-RS society users (experts and simple users)

Cross-scale

Uncertainty

Copyrights

Proven processes

Validation

User friendly interface

Framework conditions

Metadata quality

Easy to access products

Standardization

Analysis and reporting

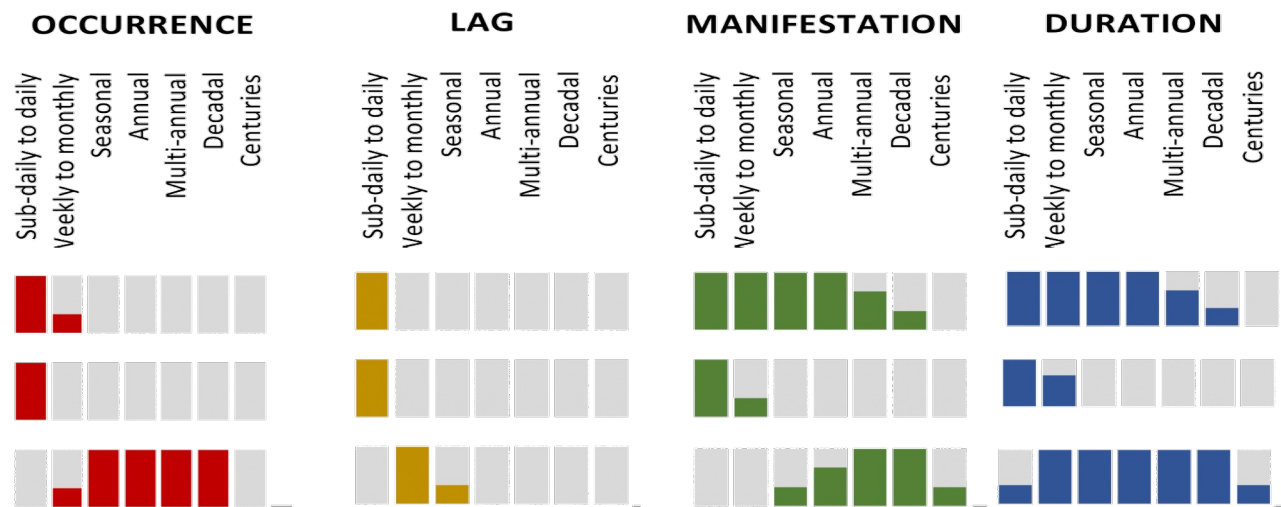
Delivery maintenance

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Water depth increase (dam failure)
Water depth increase (flooding)
Water depth increase (sea level fluctuation)



Term	Definition and associated information
Occurrence	The time span of the actual natural event or process or human activity
Lag	The time between commencement and detection
Manifestation	The time period of detectability
Duration	The time from commencement to completion of a natural event or process or human activity.



RESEARCH ARTICLE | [Open Access](#) |

## A globally relevant change taxonomy and evidence-based change framework for land monitoring

Richard M. Lucas , Sophia German, Graciela Metternicht, Rebecca K. Schmidt, Christopher J. Owers, Suzanne M. Prober, Anna E. Richards, Sally Tetreault-Campbell, Kristen J. Williams, Norman Mueller, Belle Tissot, Sean M. T. Chua, Alison Cowood, Terry Hills, Dayani Gunawardana, Alexis McIntyre, Sebastien Chognard, Clive Hurford, Carole Planque, Suvarna Punalekar, Daniel Clewley, Ruth Sonnenschein, Nicholas J. Murray, Ioannis Manakos, Palma Blonda, Kate Owers, Stephen Roxburgh, Heather Kay, Peter Bunting, Claire Horton ... [See fewer authors](#)

First published: 01 September 2022 | <https://doi.org/10.1111/gcb.16346>

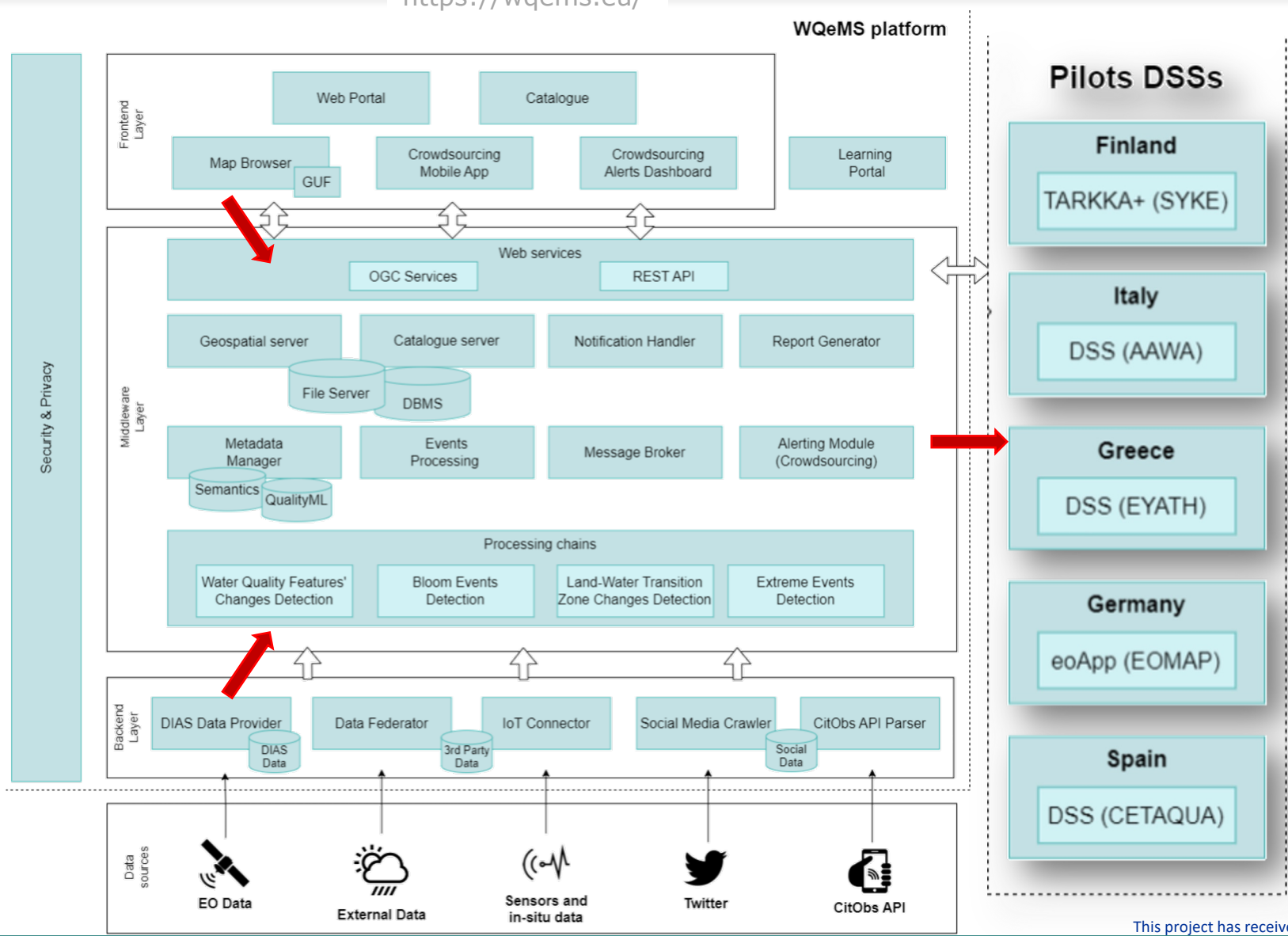


# A variety of DSSs at different level of technological maturity shall be served: a set of service subroutines have to be developed

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Shows to the points of the workflow, where EO data and their derivatives may be directly treated by the users or the service providers



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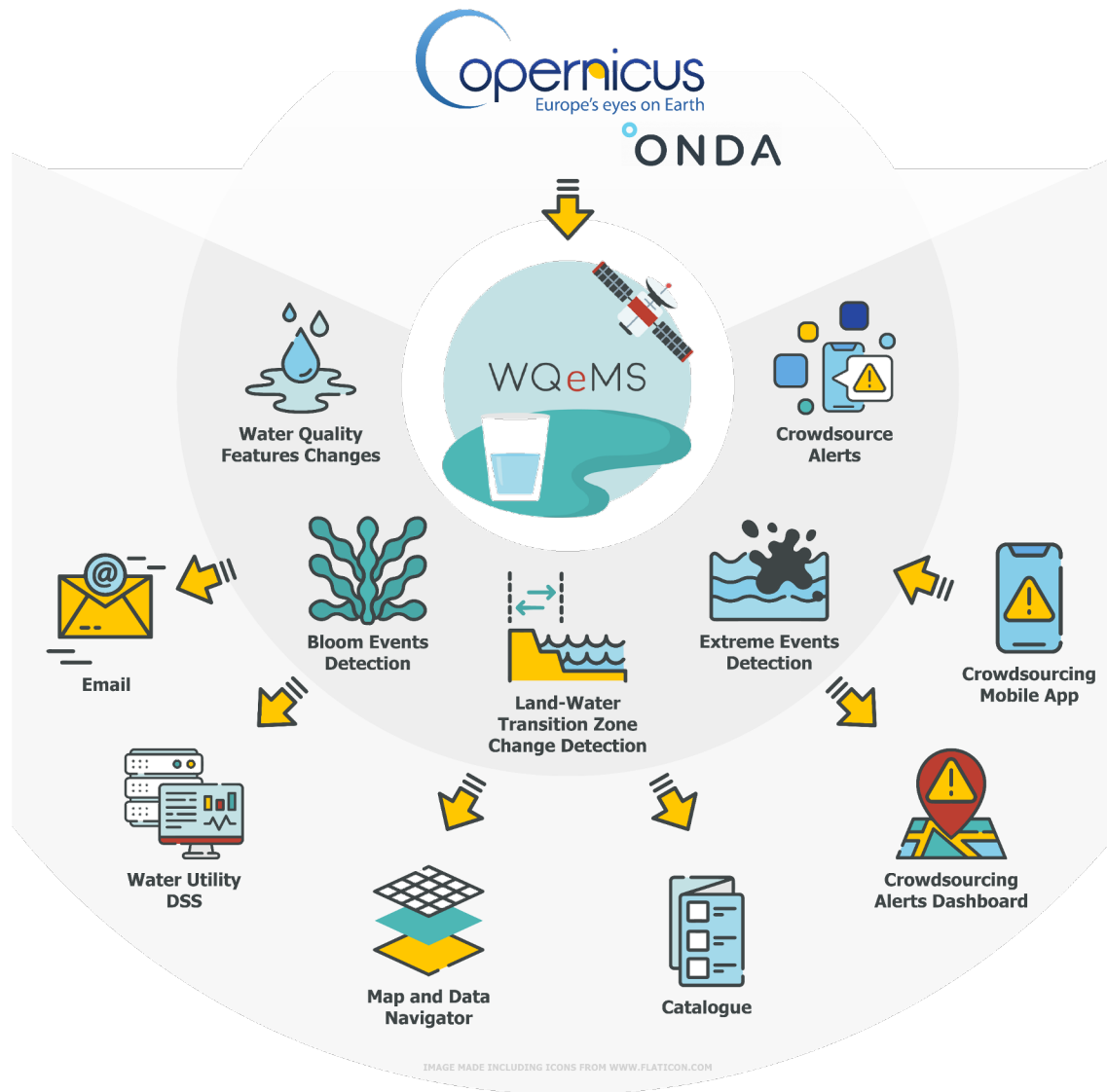




# the WQeMS platform



<https://wqems.eu/>



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# WQeMS platform interaction with the user



<https://wqems.eu/>



**1**

Send requests for data products on dates interval (on demand or continuous monitoring)

**2**

Access the generated data products (both GeoTIFF and metadata)

**3**

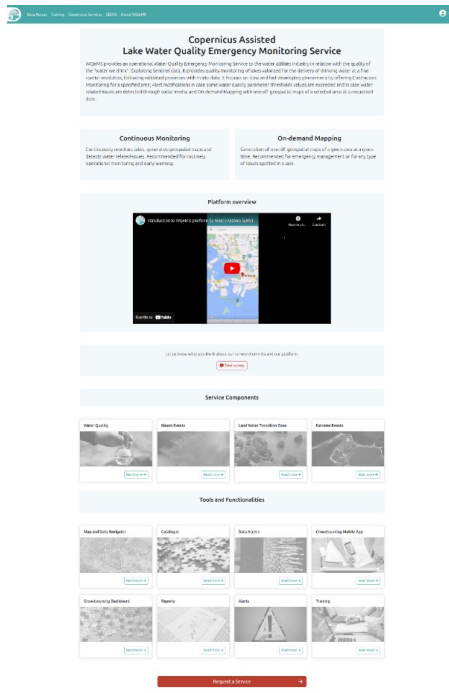
Get statistical data (i.e. time-series) obtained analysing the tiff files generated for the area of interest

**4**

Request a PDF report for a water body to be sent by email

**5**

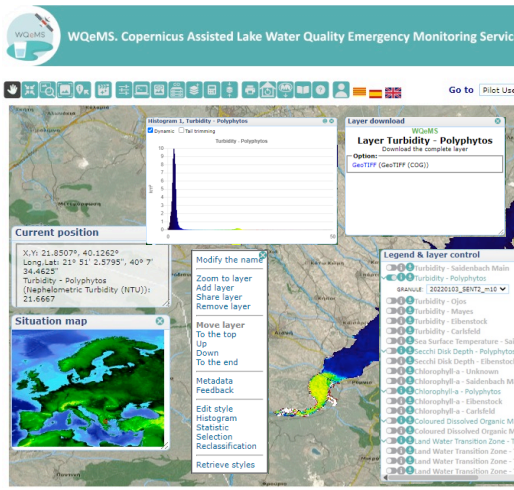
Configure the platform to send alert notifications by email or to HTTP API of an external system



OGC WMS  
GeoServer

HTTP File Server  
FTP Server

WQeMS: RestAPI  
Alert Configuration APIs  
Measure Type APIs  
Social Alert Type APIs



**WARNING: YOU HAVE A NEW ALERT FROM THE WQEMS PLATFORM**

You have a new alert generated by your alert configuration **Polyphytos Alert Configuration** related to the water body **polyphytos**.

The alert was generated for the following reasons:

The condition you set has happened. The measured value of Mean Spatial Value of Turbidity is 3.21 NTU which is greater than 1.4262 NTU.

See more details:

- Map and Data Navigator: <https://www.ogc3.grumets.cat/wqems/>
- HTTP File Server: [https://cog-wqems.ops.lecce.it/water-quality/tur/polyphytos/waterquality-tur\\_polyphytos\\_20220103\\_SENT2\\_m10-WQeMS.tif](https://cog-wqems.ops.lecce.it/water-quality/tur/polyphytos/waterquality-tur_polyphytos_20220103_SENT2_m10-WQeMS.tif)

WQeMS project - Grant Agreement No 101004157

**Rules**

Select a phenomena: Water Quality - Turbidity

Select a measure: Mean Spatial Value of Turbidity

Select a relationship: greater than

Value: 40

Unit: ntu

Buttons: Delete Rule, Add Rule

WQeMS framework enablers services EO research

This project has received funding from the European Union's Horizon 2020 Research and Innovation Action programme under Grant Agreement No 101004157







- **Facilitate the adoption of EO monitoring services in the water utilities' operations**
- **Increased awareness of the water utilities** in relation to water-related issues (early warning, fast response to phenomena)
- Fast and automated services: The platform is realized adopting **cloud micro-services approach, ensuring scalability and extensibility**
- **Federated approach** – enable new service providers to easily extend the WQeMS platform service portfolio
- **Adopting both standard and modern protocols for the interconnection of systems (i.e. APIs, OGC Web Services)**

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# WQeMS service components



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Service	Sub-service
Water Quality	Turbidity
	Chlorophyll-a
	Coloured Dissolved Organic
	Secchi Disk Depth
	Sea Surface Temperature
Bloom Event Detection	Harmful Algae Bloom Indicator
Land Water Transition Zone	Two Dates
	Hydroperiod
Extreme Event Detection	Oil Spill
	Muddy Water Flood



There are three different types of output data (for each service component) managed by the platform: **GeoTiff** files, **statistical data** in json format, and **metadata** in xml format

### Metadata

An XML file describing the metadata of each GeoTiff image.

For example, some parameters are: the file size, the HTTP link to the file, the Data Provider, and so on.

### GeoTiff

A raster layer that contains data about a specific feature monitored by each service.

### Statistical Data

A JSON that contains some statistical values associated with the GeoTiff image,

such as mean value, maximum value, median, and so on

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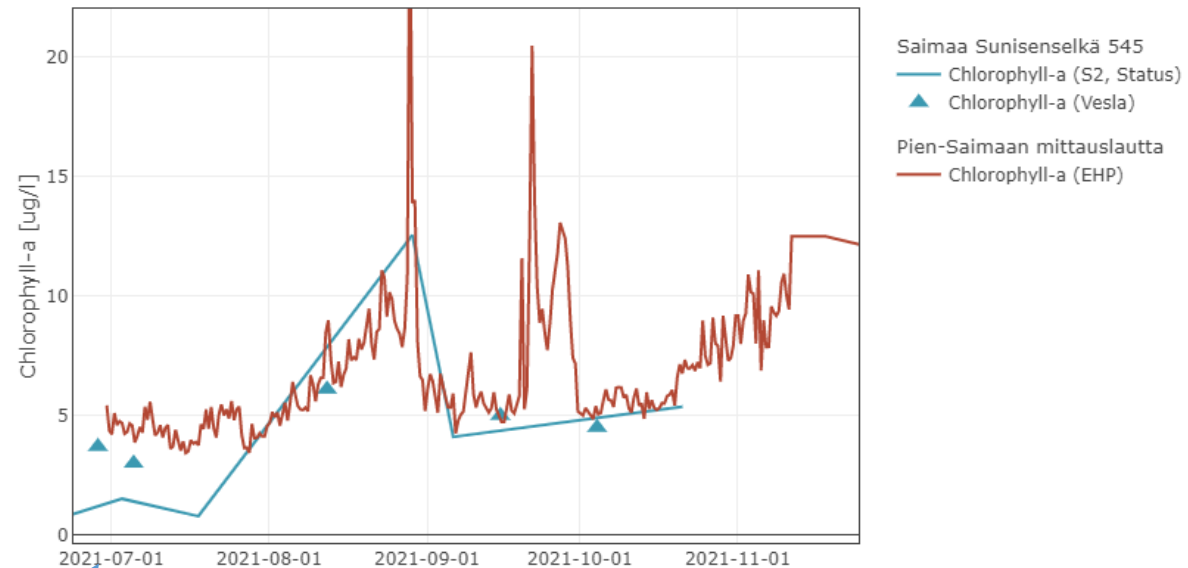
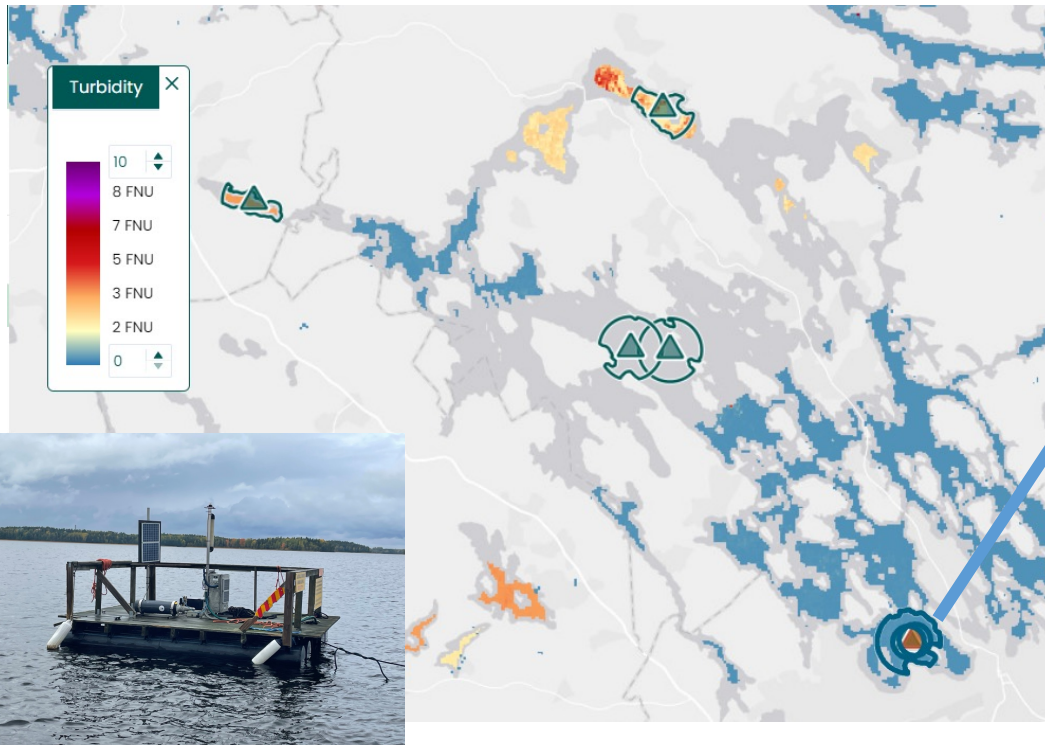
# (SC1) Water Quality Features



<https://wqems.eu/>

Comparison of in situ and satellite observations about water quality

Learning from the free and open water quality information through Syke's TARKKA web application and EOMAP's Modular Inversion Processor



Chl-a values observed at the location of the automated station with Sentinel-2 satellite (S2, blue line), laboratory samples (Vesla, blue triangles) and automated instruments (EHP, red line)

Location of the automated water quality monitoring station

**Innovation:** Expansion of known workflows and techniques for the needs of the water utility industry.

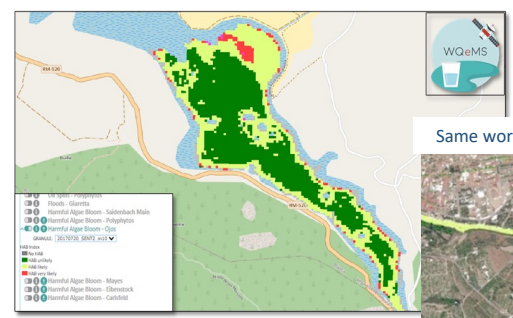
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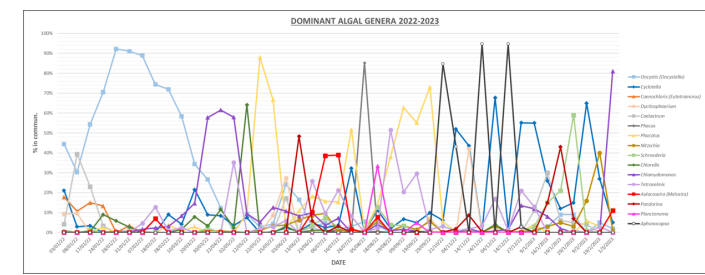
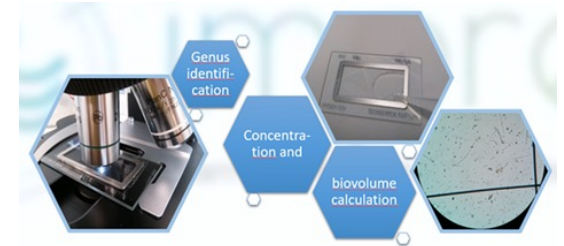


- In situ sampling (Azud de Ojós and DWTP Reservoir) to adjust the values detected in the Sentinel-2 images.
- Historical data of algal monitoring are used to test performance of hyperspectral images.



## Innovation:

- **Detection of potentially harmful cyanobacteria blooms**
- **Worldwide data even for small water bodies (< 1ha)**
- **For emergency and baseline scenarios**
- Tested (in GR, DE, FI) and in an operational DSS in Spain ...using **different type of sensors and data sources** (it combines data from satellite and in-situ online monitoring station; data from regional water basin agency and national weather agency, etc.)
- ...able to provide **forecast of cyanobacteria risk from coupled models** based on machine learning methods
- ...in a form that has been **co-created with and for the Drinking Water Plant Operator** that is using it since 2021

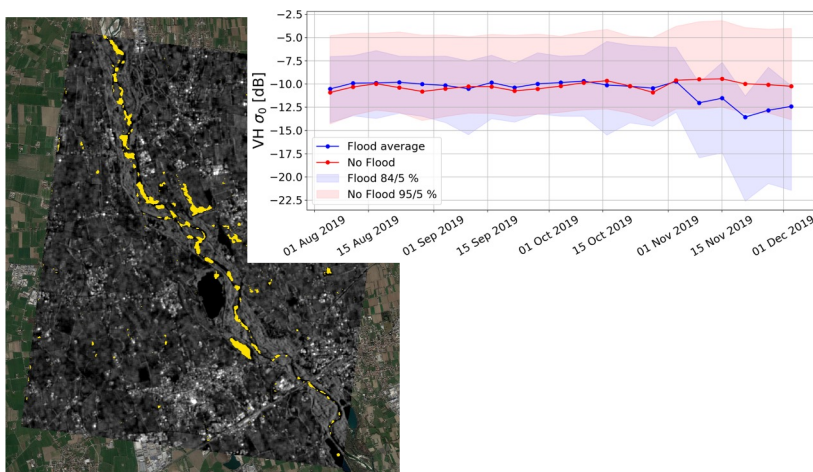


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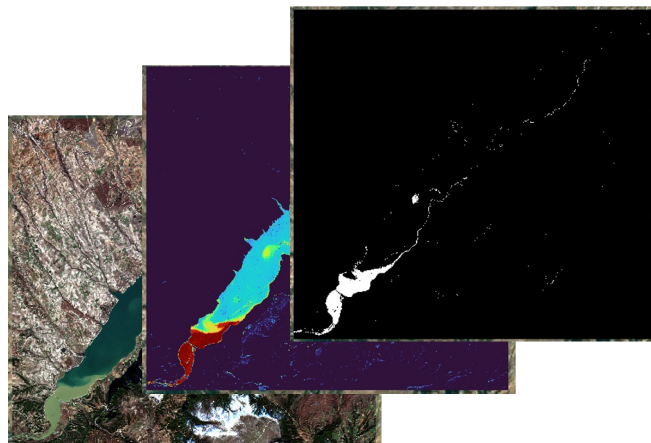
**Flood** sub-service maps extreme flood events using **Sentinel-1** every **~6 days** (both satellites) with a **10m** pixel size based on **Deep Learning**



**Innovation:**

- Explicitly exploits time series patterns
- Uses deep learning
- **AOI-invariant model**

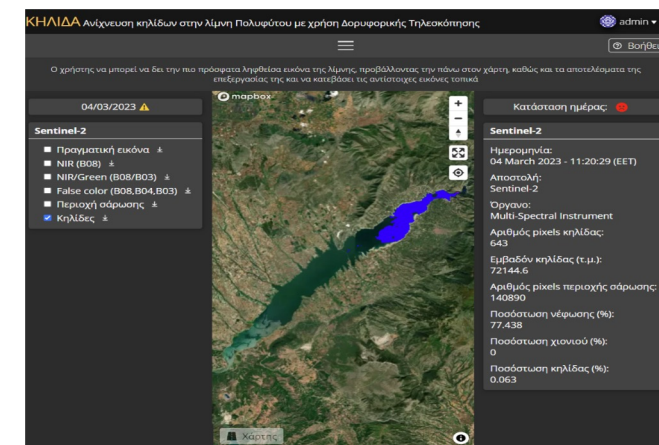
**Muddy water** sub-service maps muddy waters (extreme suspended sediment values in the water) using **Sentinel-2** every **~5 days** with **10m** pixel size based on **Ensemble Machine Learning**



**Innovation:**

- Unique muddy water mapping service using machine learning

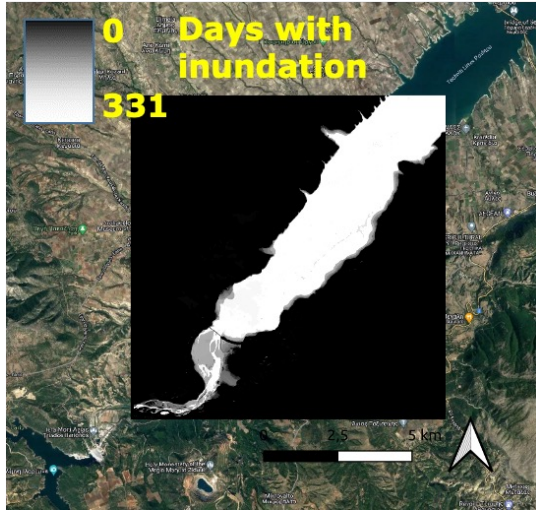
**Oil spill** sub-service maps potential hydrocarbons using **Sentinel-2** every **~5 days** with **10m** pixel size based on **Deep Learning**



**Innovation:**

- Unique hydrocarbon mapping service for inland waters using deep learning & optical data





Three modes for two-dates service:

- S2 mode: Only Sentinel 2 data
- S2-S1: Based on the user dates, the products (either S2 or S1), whose acquisition date is the closest to the user preference, will be used for the processing.
- S1 mode: Only Sentinel 1 data

Two modes for hydroperiod service:

- S2 mode
- S2-S1 mode



Polyphytos Lake (subset), land to water change detection between: 21-10-2017 and 02-12-2017

## Innovation:

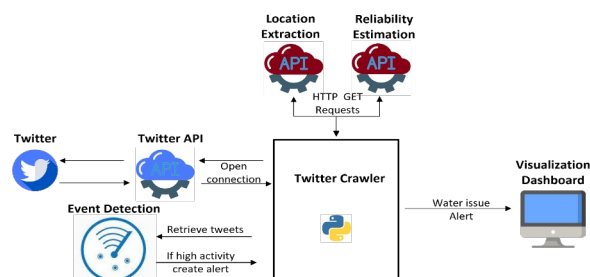
- **Proven and adapted workflows at multiple sites across Europe** reaching up to **98% accuracies** (multiple alternative methods for various scenery types)
- Exploitation of **both optical and radar data to enhance frequency of information** retrieval with proven credible results
- **Fully unsupervised performance**





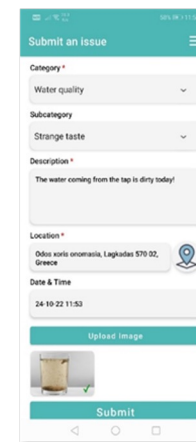
The Social Media Crawler collects water related tweets from Twitter in real time.

- Analysis of each retrieved tweet:
  1. Extract tweet location from text
  2. Estimate whether tweet is fake or not
- Detect water related events based on Twitter activity and location.



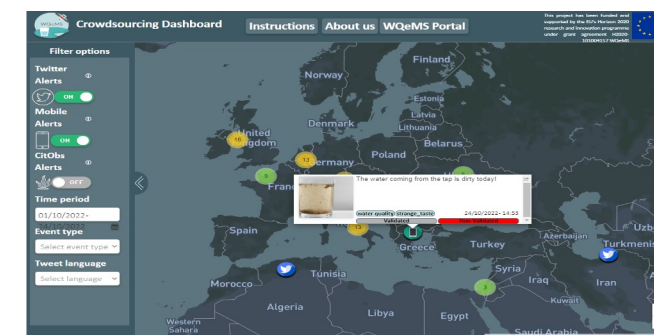
**Innovation:** Analyzes **large volumes of crowdsource water related information in real time** and provides potential water issues that need to be investigated.

The Crowdsourcing Mobile App allows citizens to post water related complaints through their smartphone.



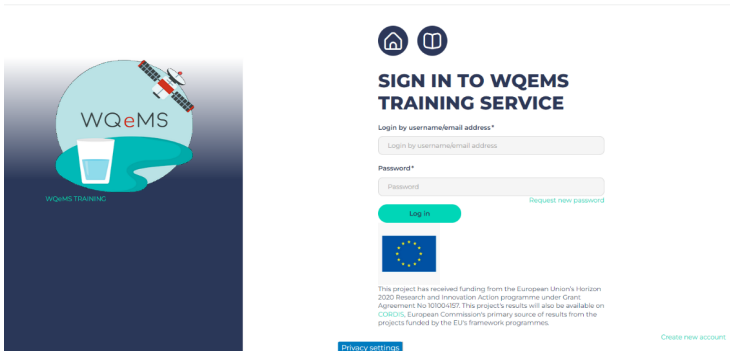
**Innovation:** Enables a more efficient and **streamlined way for water utilities to receive and handle complaints** and improving the quality of service and customer satisfaction.

The Crowdsourcing Dashboard visualizes the alerts collected from multiple sources including alerts generated by social media crawlers and complaints submitted through the crowdsourcing mobile app



**Innovation:** The crowdsourcing Dashboard combines and **visualizes data from multiple sources**, enabling quick identification and responding to emerging issues.





## WQeMS e-Training Platform

( <https://wqems.phoebeinnovations.com> )

### Content

- Understanding Copernicus data and services
- Technical aspects in earth observation services
- Inland water features' estimation services enabled by earth observation
- Use-cases and applications



### Training guidance

- **Training Pathway 1: Full-range training**
- **Training Pathway 2:** Familiar with background knowledge; Requiring **strong WQeMS-related skills for specific services**
- **Training Pathway 3:** Training to **attract interest of domain experts**
- **Training Pathway 4:** Focusing on **Academia**
- **Training Pathway 5:** Focusing on **Industry**

### Innovation:

- **Dedicated training pathways** through the material per level of competence and target audience.
- **Facilitate the acquisition of required skills and competences** by WQeMS users, related to the operation and **content interpretation of the developed solutions.**
- Help **sustain the operation of the WQeMS platform beyond project duration.**

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# (SC7) Metadata & Feedback

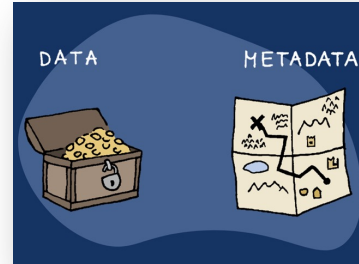


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WQeMS follows the FAIR principles: Data should be **Findable, Accessible, Interoperable and Reusable** to the greatest extent possible

- How to decide that a dataset is useful for our purposes (fit per purpose)?
- How to choose the best dataset in terms of the quality of the data?
- How policy makers can know better the results of policy and monitoring?

↓  
METADATA!



## Innovation:

- **New keywords that describe the dataset in a way to bring it closer to management, monitoring and policy**, following the GEO Essential Water Variables, i.e. "Lakes/reservoir levels", "Water Quality", "Water use/demand", "Evaporation", etc. and the UN Sustainable Development Indicators, i.e. Target 6.3.
- **Quality parameters included in the metadata based on QualityML dictionary.**

```
<gmd:errorStatistic>
  <gco:CharacterString>https://www.qualityml.org/1.0/metrics/RootMeanSquareError</gco:CharacterString>
</gmd:errorStatistic>
```

- All Metadata is **uploaded to the GeoNetwork catalogue and also allows connection to the GEO yellow pages**
- Metadata is also available through **the interoperable WQeMS Map and Data Navigator, by which feedback to the dataset can be provided.**

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# Main innovation elements



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- Use of multi-sensor-fusion technologies
- Spatial and temporal resolution, and product consistency
- Treatment of small (also uneven shaped) open surface water reservoirs
- Minimization and documentation of uncertainty
- Ontology and semantics of water quality supporting regulations
- Metadata tool documentation
- Interoperability with existing Decision Support Systems and multiple DIAS
- Cloud based micro-services structure
- Federated approach, enabling further service providers to expand WQeMS service portfolio



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research in  
WQeMS

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- framework
- enablers
- services
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# Focusing on SC4: Land-Water Transition Zone



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## Land-Water Transition Zone Change Detection

Hydroperiod

On-demand

Start Date

mm/dd/yyyy

End Date

mm/dd/yyyy

Multispectral Data **i**

Multispectral + Radar Data **i**

Two Dates

On-demand

Start Date

mm/dd/yyyy

End Date

mm/dd/yyyy

Multispectral Data **i**

Multispectral + Radar Data **i**

Radar Data **i**



Inundation maps and hydroperiods are produced

→ **WITHOUT** user input

→ with spaceborne data use **ONLY**

→ **Interoperable with existing applied international workflows and norms**





## Sentinel-2 data:

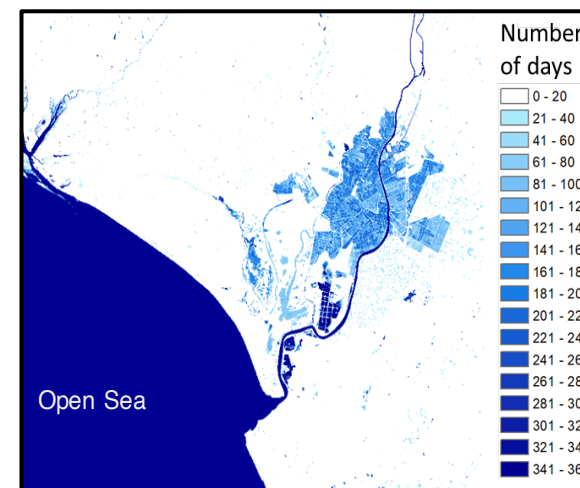
- **Adv.:** High accuracy in inundation mapping
- **Lim.:** Available and useful in non-regular time intervals throughout the year, because of cloud presence in the study area

## Sentinel-1 data:

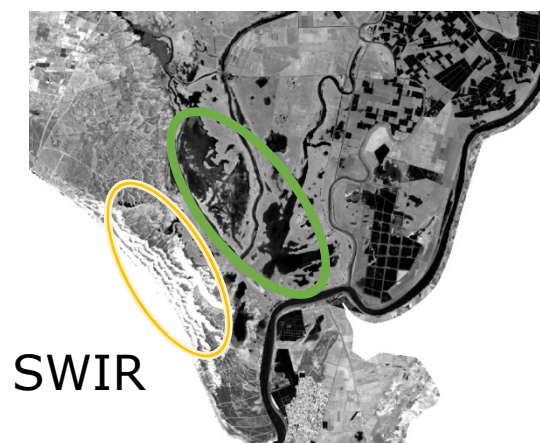
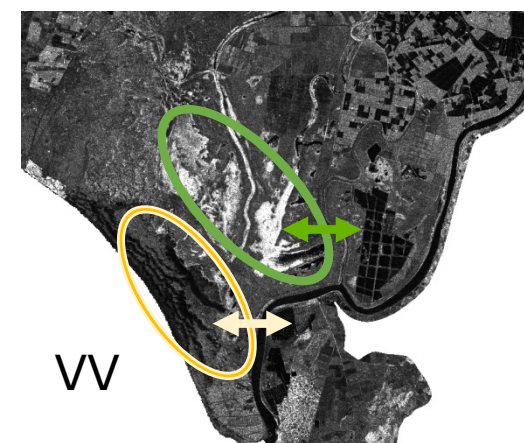
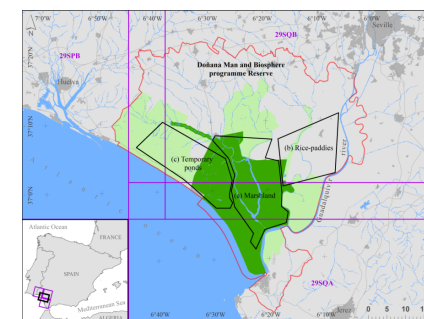
- **Adv.:** Available independently to weather conditions
- **Lim.:**
  - Specific regions (i.e. **sand dunes, bare ground**) may be misregistered as inundated due to low backscatter
  - **Emergent vegetation** that appears bright in S1 images confuses the water detection in SAR data.

## Opportunity:

- Improve accuracy of Sentinel-1 based inundation maps fusing information from Sentinel-2 based masks



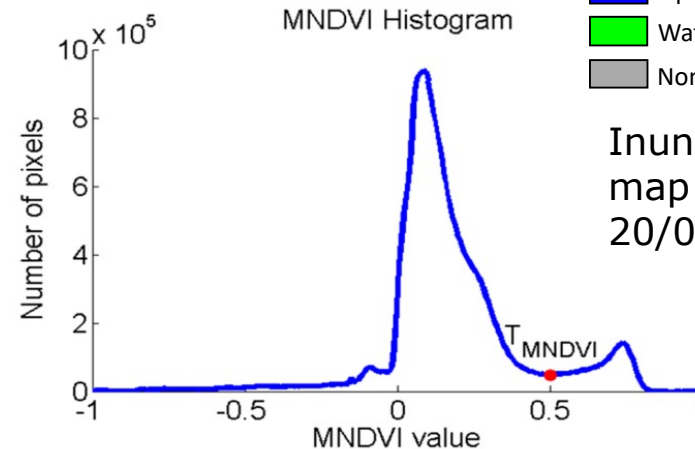
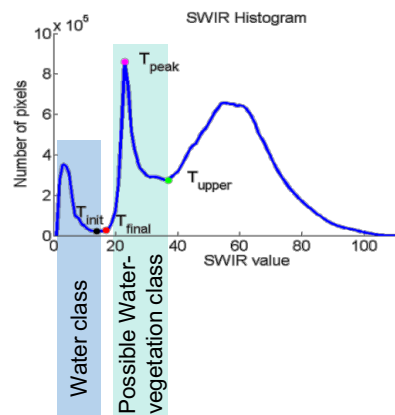
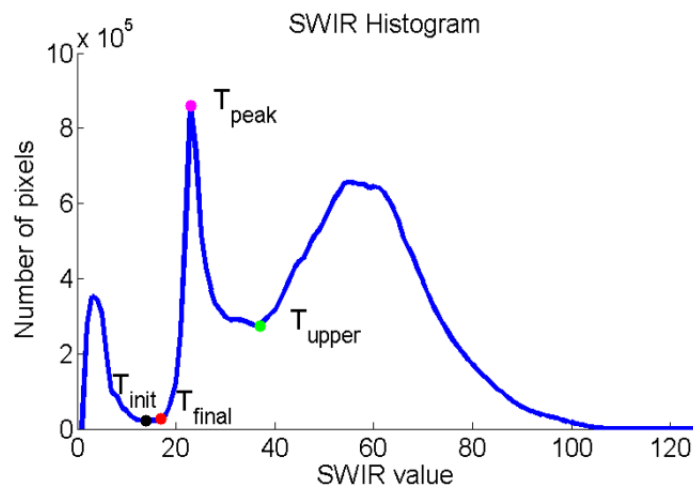
Hydro-period generated for 2016-2017 using Sentinel-2A data



## Methodology in a nutshell

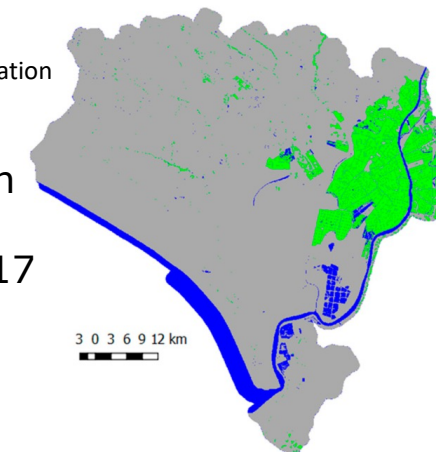
- Initial threshold  $T_{init}$ , corresponding to the first deep valley of the **SWIR** histogram, separates coarsely inundated / non-inundated pixels
- Sentinel-2 image is segmented into non-overlapping segments
- Expanding patches are set around the centroids of segments with high percentage of inundated pixels, and the median of the "splitting" thresholds of all patches is the optimal threshold per segment. Final threshold  $T_{final}$ , estimated as the median of optimal thresholds, separates the **open-water subclass**.
- In parallel, a TMNDVI threshold, corresponding to the first valley greater than 0.4 on the MNDVI histogram, is detected.
- $T_{final}$  in combination with  $T_{upper}$  and TMNDVI are used for estimating the water-vegetation subclass.

Kordelas GA, Manakos I, Aragonés D, Díaz-Delgado R, Bustamante J. Fast and Automatic Data-Driven Thresholding for Inundation Mapping with Sentinel-2 Data. *Remote Sensing*. 2018; 10(6):910. <https://doi.org/10.3390/rs10060910>



■ Open-water  
■ Water-vegetation  
■ Non-water

Inundation map on 20/08/2017





# Inundation mapping: Transferable results



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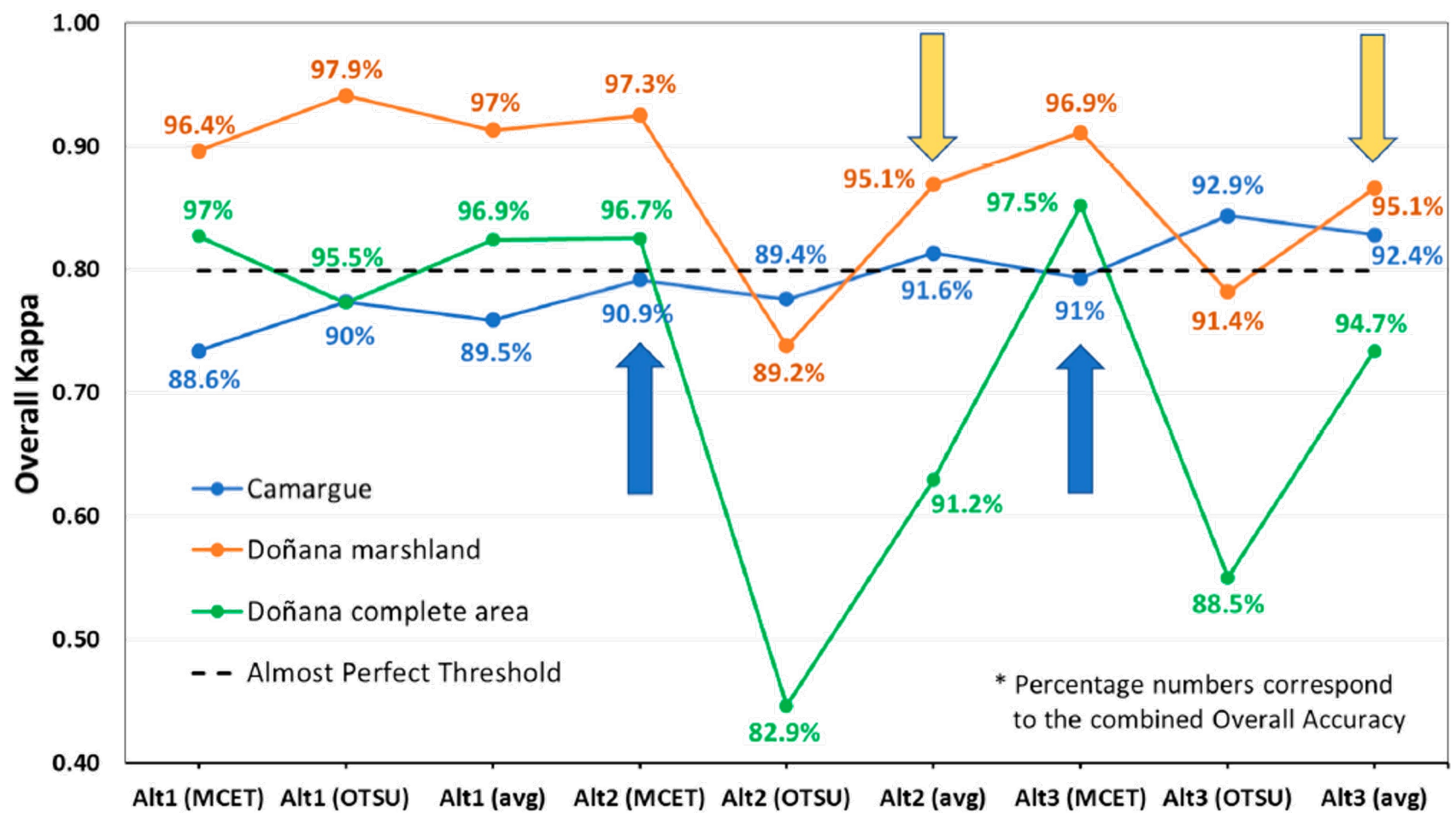


The **modified automatic local thresholding unsupervised** methodology\*:

1. Detects water class, by estimating automatically a threshold on:
  1. Alt1: SWIR1 - Band 11 ( $\lambda = 1610$  nm),
  2. Alt2: The product (per pixel multiplication) of Band 12 ( $\lambda = 2190$  nm, SWIR 2) and Band 8A ( $\lambda = 865$  nm) (Band 12 \* Band 8A),
  3. Alt3: The product of Band 11 (SWIR 1) and Band 8A (Band 11 \* Band 8A)
2. For the **estimation of splitting thresholds**, the following approaches were tested:
  1. MCET algorithm,
  2. Otsu's algorithm,
  3. Average of 1 and 2

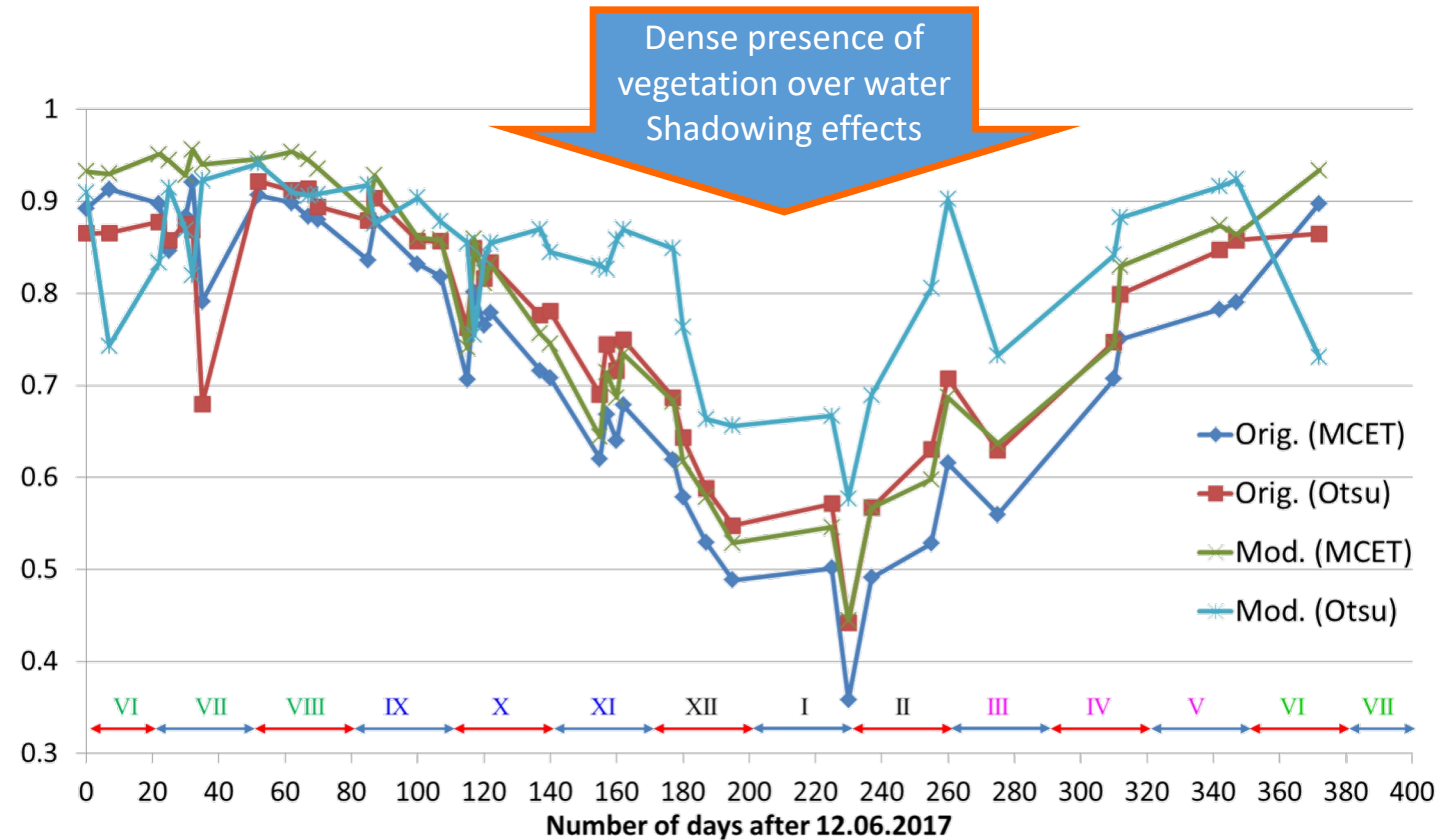
\* Kordelas GA, Manakos I, Lefebvre G, Poulin B. Automatic Inundation Mapping Using Sentinel-2 Data Applicable to Both Camargue and Doñana Biosphere Reserves. *Remote Sensing*. 2019; 11(19):2251. <https://doi.org/10.3390/rs11192251>

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\* Percentage numbers correspond to the combined Overall Accuracy





**Kappa coefficient variation between 12.06.2017 and 16.06.2018 in Camarque area, France**

## Mean Overall Accuracy (Mean kappa):

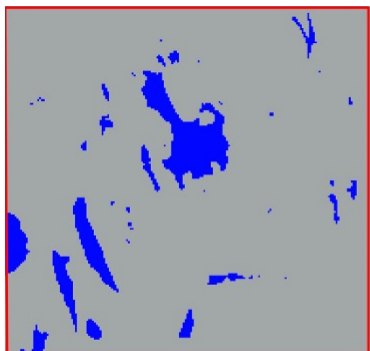
- Original + MCET: 88.0% (0.72)
- Original + Otsu : 89.5% (0.76)
- Modified + MCET: 90.4% (0.78)
- Modified + Otsu : 92.1% (0.83)



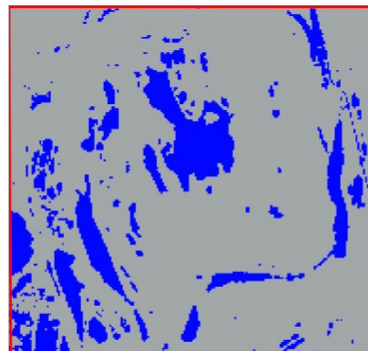




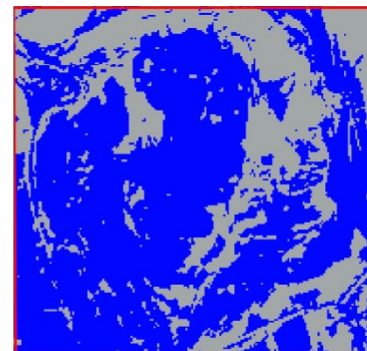
**Underestimation  
example  
of automatic  
thresholding in  
halophilous scrubs**



Original Thresholding (MCET)

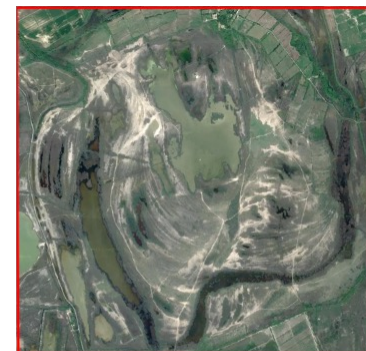


Modified Thresholding (Otsu)



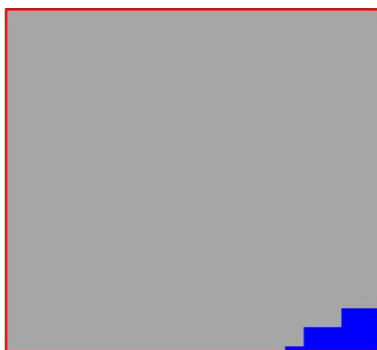
Strict Thresholding

**correct**

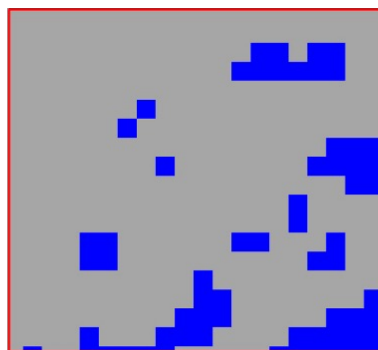


Google Image

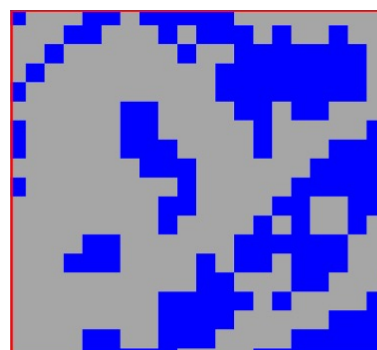
**Overestimation  
example  
of strict thresholding in  
urban areas due to  
shadow presence**



Original Thresholding (MCET)



Modified Thresholding (Otsu)



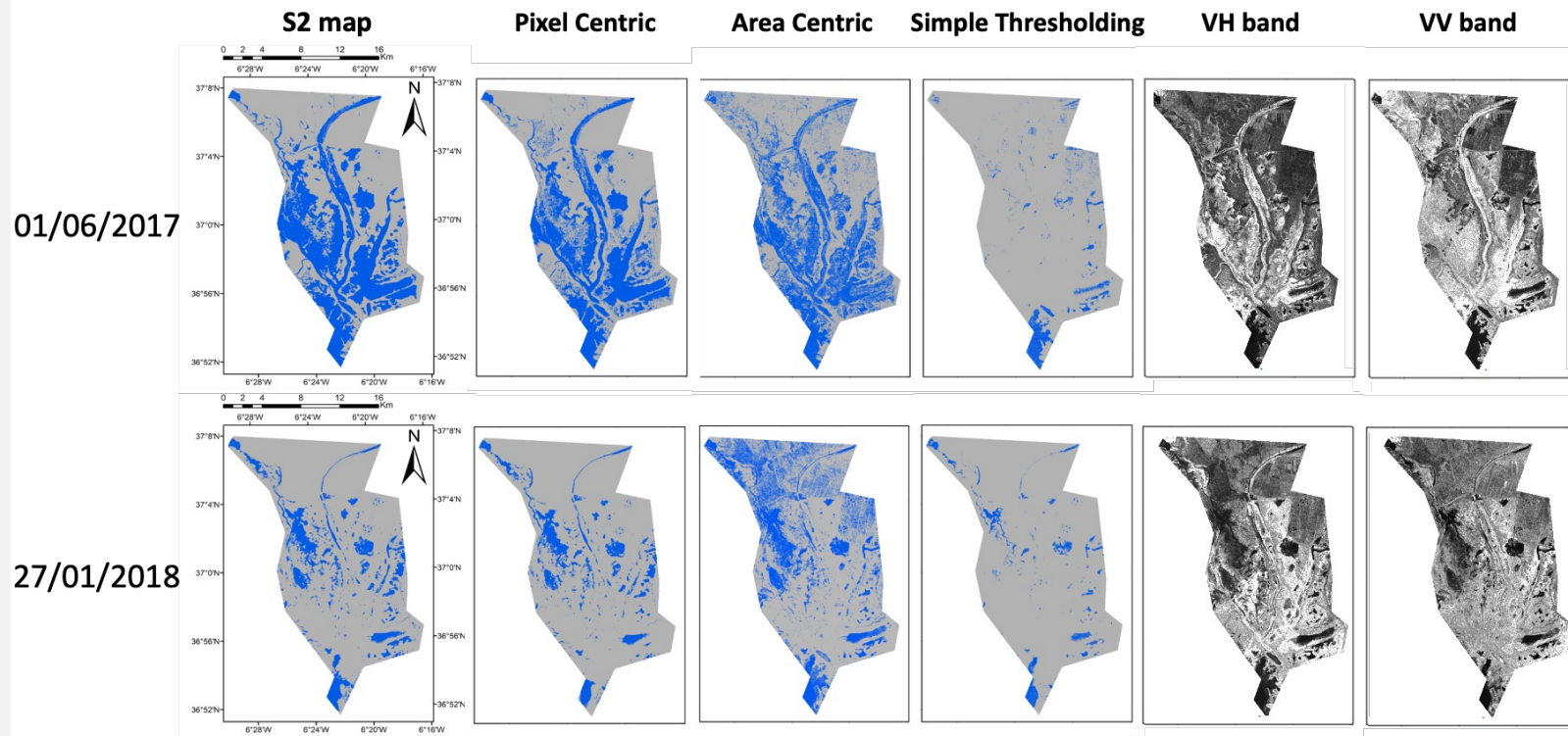
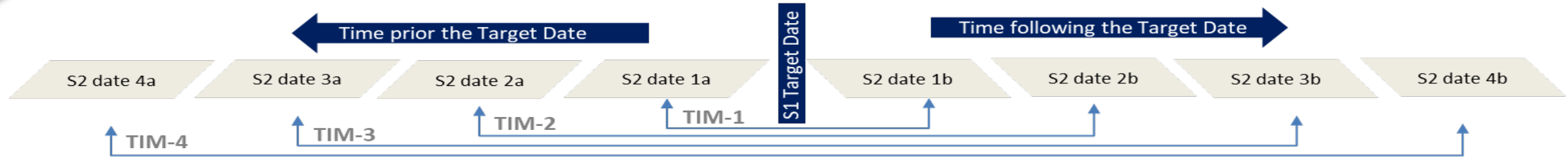
Strict Thresholding

**correct**



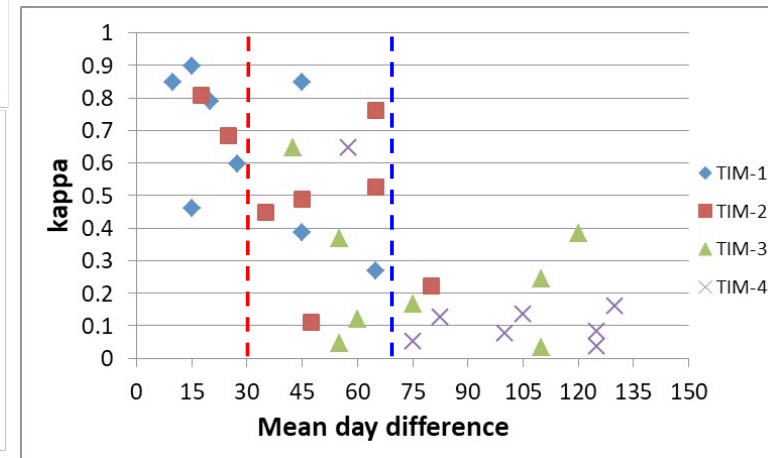
Google Image





Average  $k$ :

- **TIM-1: 0.64**
- **TIM-2: 0.51**
- TIM-3: 0.25
- TIM-4: 0.16
- Area Centric : 0.45
- Simple Thresholding : 0.23



**correct**

I. Manakos, G. Kordelas, K. Marini, Fusion of Sentinel-1 data with Sentinel-2 products to overcome non-favourable atmospheric conditions for the delineation of inundation maps", 2019, European Journal of Remote Sensing, DOI: 10.1080/22797254.2019.1596757

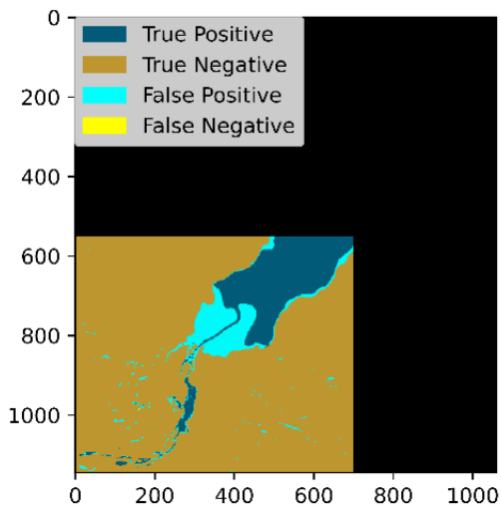




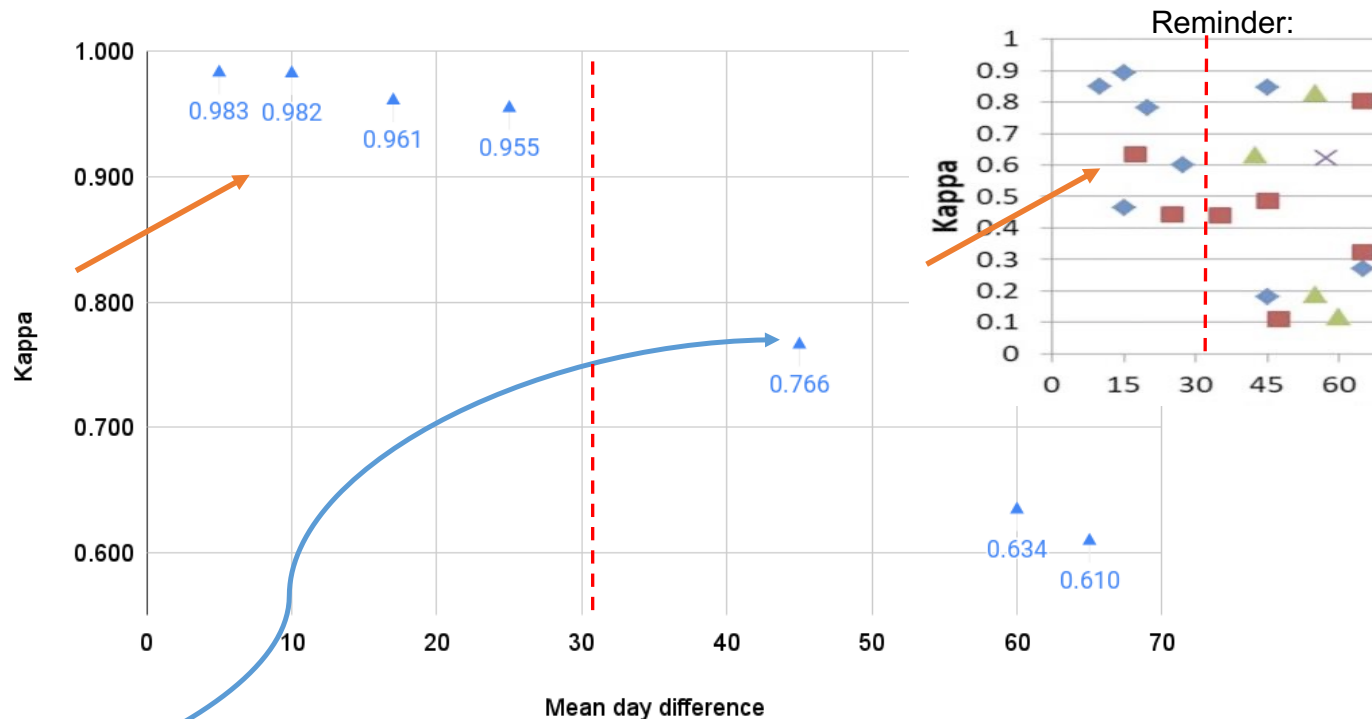
# Inundation mapping: lakes vs. wetlands results



<https://wqems.eu/>



Target date: 16-10-2019  
 S2 reference maps:  
 16-09-2019 | 15-12-2019  
**mdd: 45**



... performs better than Donana due to the size of the area and the complexity of the landscape elements; thus, becoming more appropriate for the open water reservoirs used by the water utilities

The **mean day difference (mdd)** is calculated by the mean difference between the two S2 reference inundation maps and the target date.

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# Inundation mapping: the time (and spatial) change effect



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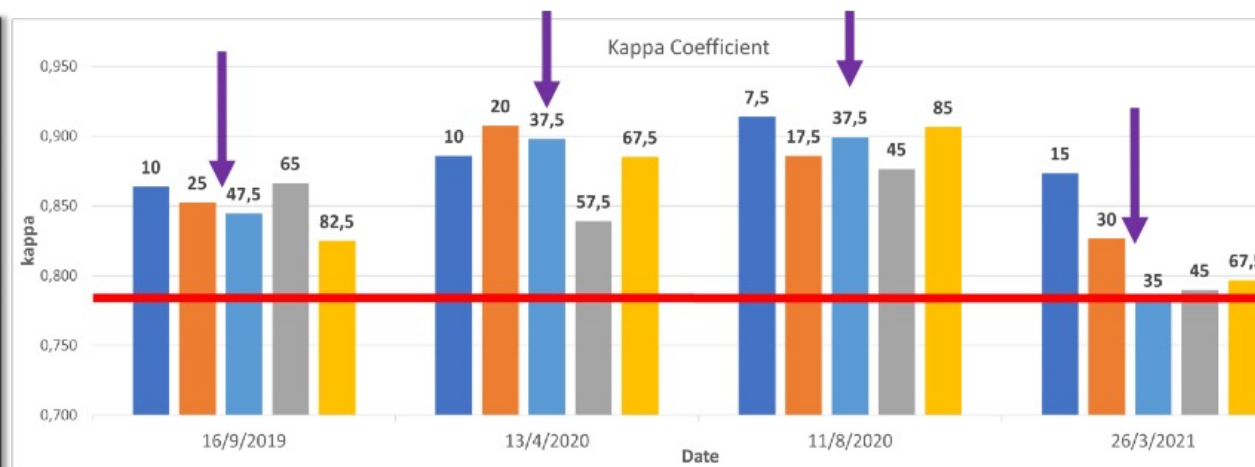
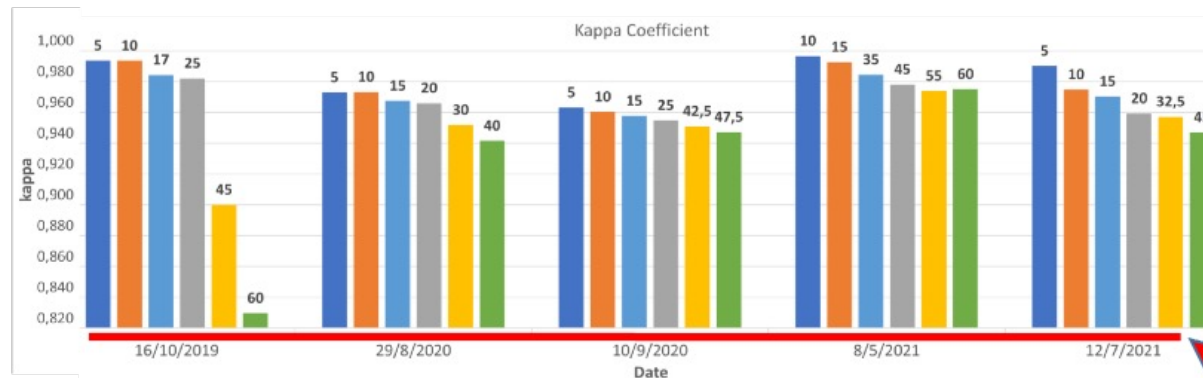
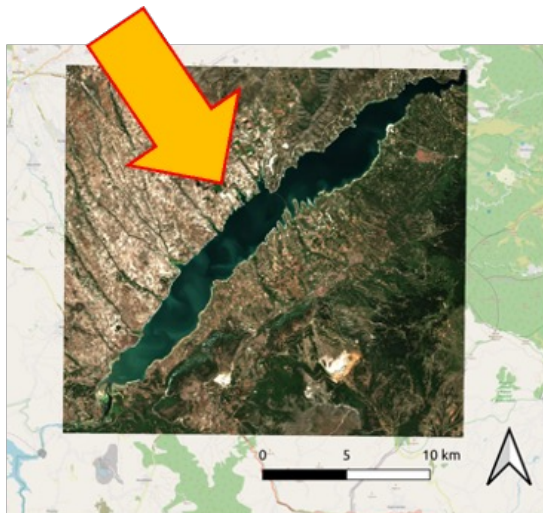


Polyphytos  
(slow  
water level  
changes)



vs.

Giaretta  
(incl.  
Brenta  
river with  
fast water  
level  
changes)



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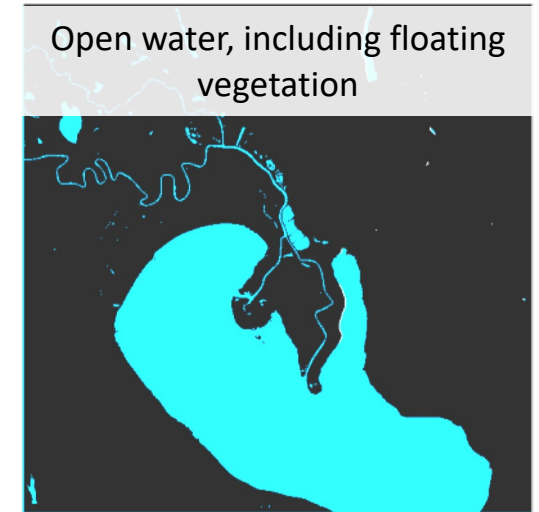
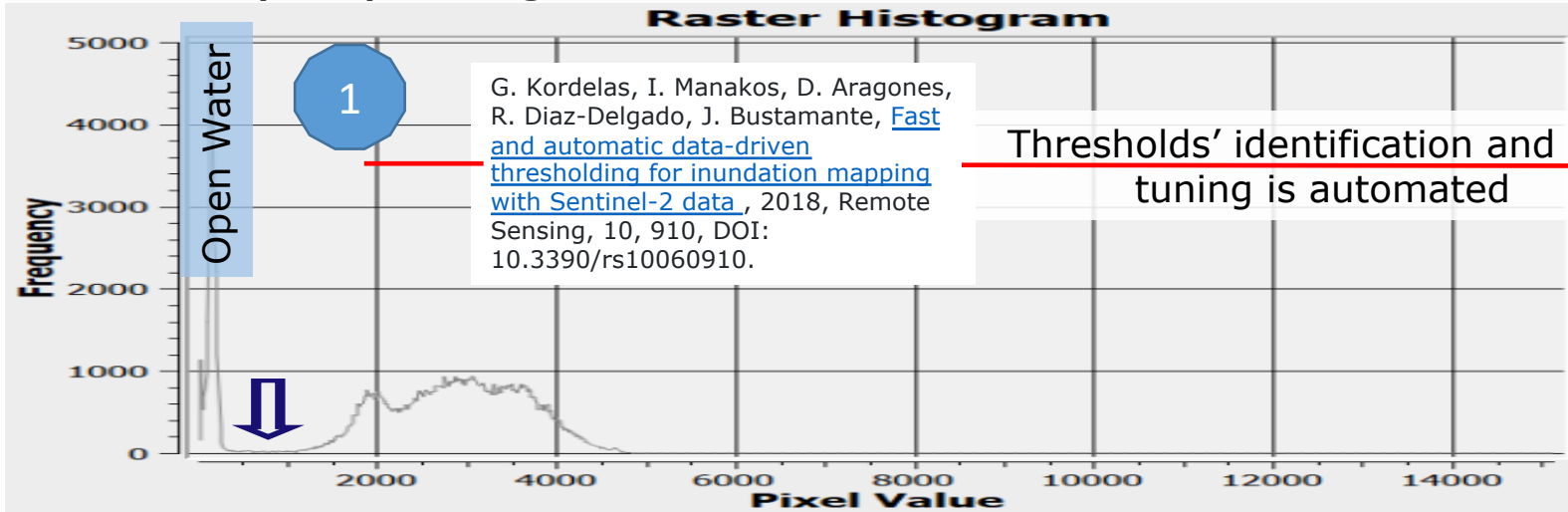


# Floating vegetation mapping: 1<sup>st</sup> attempts (part I)

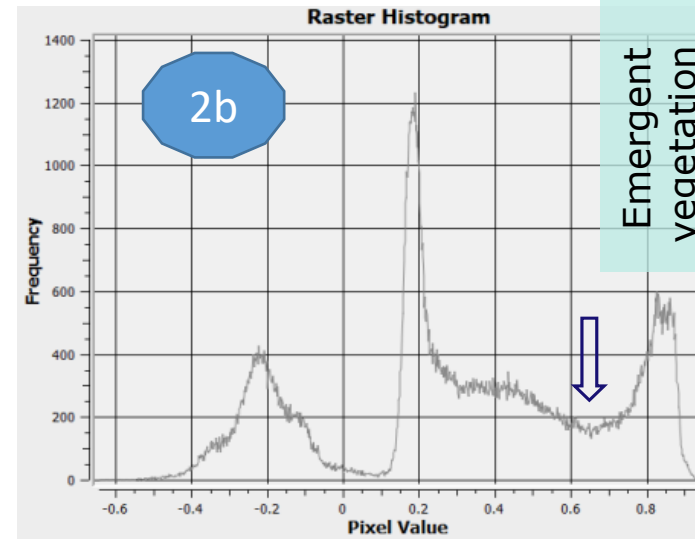
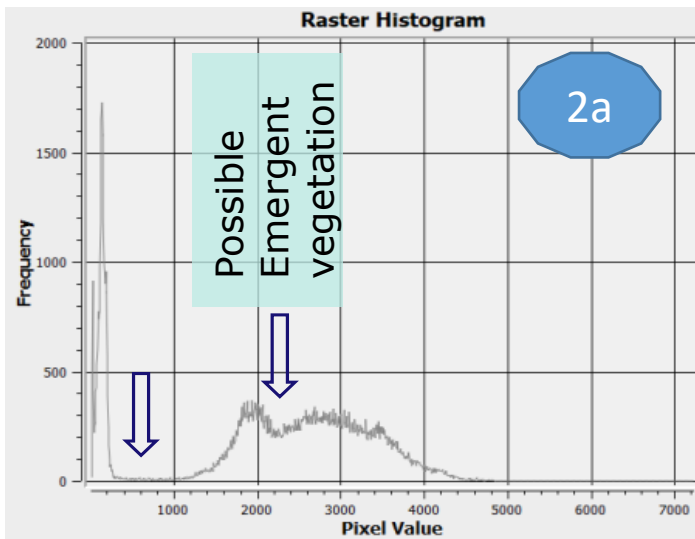


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## SWIR (B11) histogram



## NDVI histogram



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3

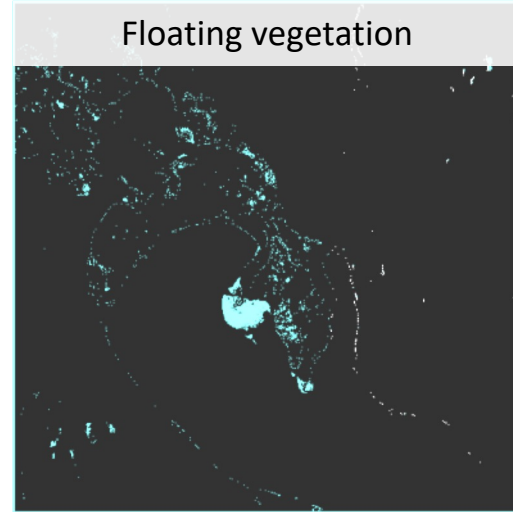
Conditions:

$$B05/ B11 \in (0.6, 1.5)$$

$$NDWI \in (0.2, 0.45)$$

$$B12 \in (100, 900)$$

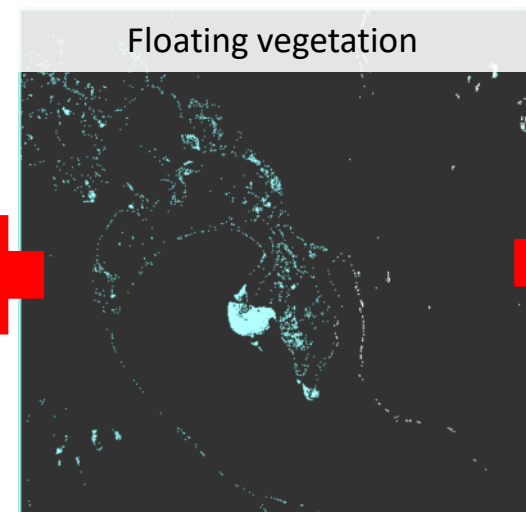
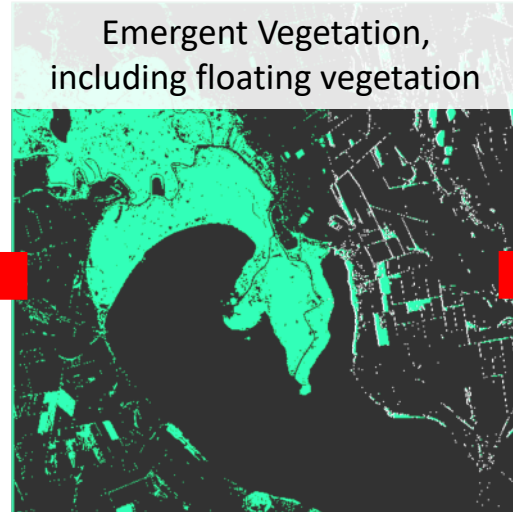
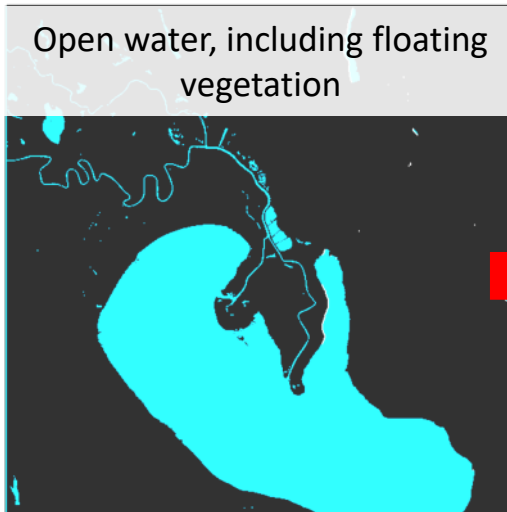
Thresholds' identification could become automated →



4

Combine the 1,2 &3

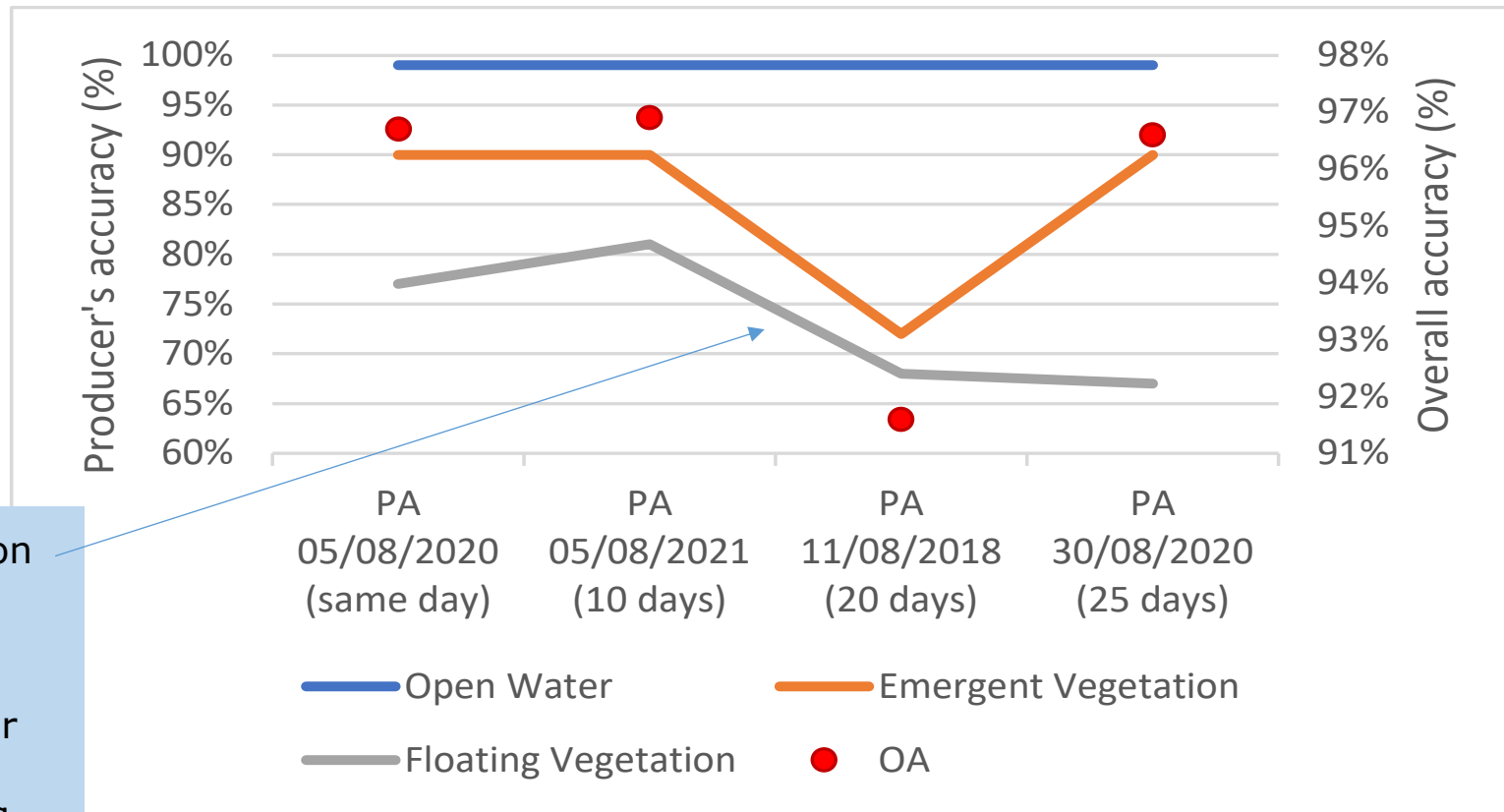
1. Where is Open water is Open water
2. Where is Emergent vegetation is Emergent vegetation
3. Where is Floating vegetation, keep it & overwrite pixels of (1.) & ( 2.)



Area of interest boundaries: the more specific the better the result as land cover synthesis influences thresholds' identification



Overall high OA (> 91%) at all dates is in this case misleading for the performance of the approach in each class, as the assessed dataset is imbalanced (surface extent per class).



(i) Patches distribution change; and/ or  
 (ii) wind-induced density/ geometry change/ shift, and/ or  
 (iii) wave- or water-level-induced floating plant leaves moistening/ partial flooding



I. Manakos, E. Katsikis, S. Medinets, Y. Gazyetov, L. Alagialoglou, V. Medinets, Identification of Emergent and Floating Aquatic Vegetation Using an Unsupervised Thresholding Approach: A Case Study of the Dniester Delta in Ukraine, 9th International Conference on Geographical Information Systems Theory, Applications and Management, 25-27 April 2023, Prague, Czech Republic, DOI: 10.5220/0012024000003473

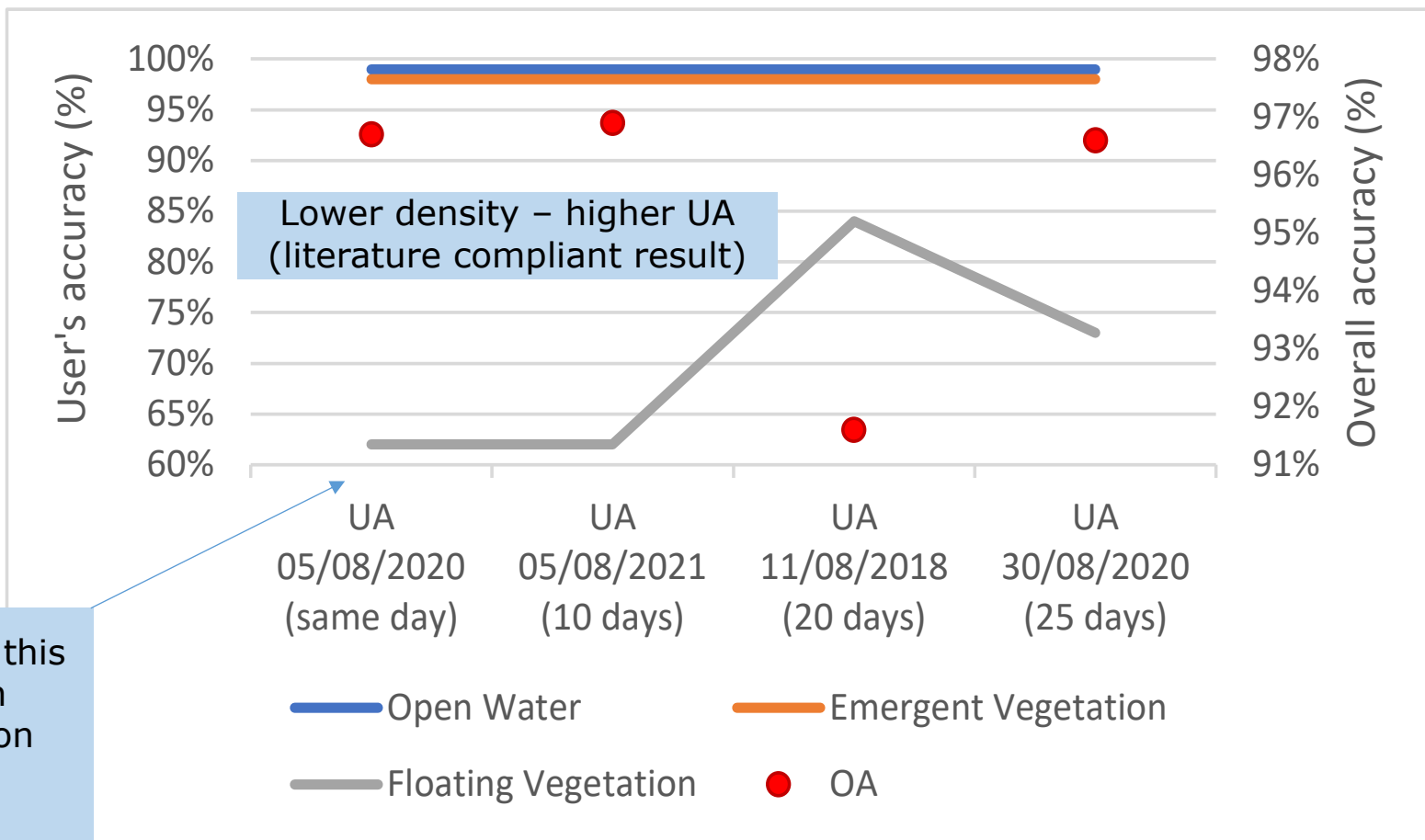




# Floating vegetation mapping: 1<sup>st</sup> attempts (part IV)



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Lower density – higher UA (literature compliant result)

It is registered that this type of classification error depends also on i) the floating vegetation species (water lilies/ chestnuts, else), and ii) the density-level

PUBLISHED next: Machine Learning for Identifying Emergent and Floating Aquatic Vegetation from Space: A Case Study in the Dniester Delta, Ukraine, SN Computer Science; with user's accuracy over 85% for the floating vegetation

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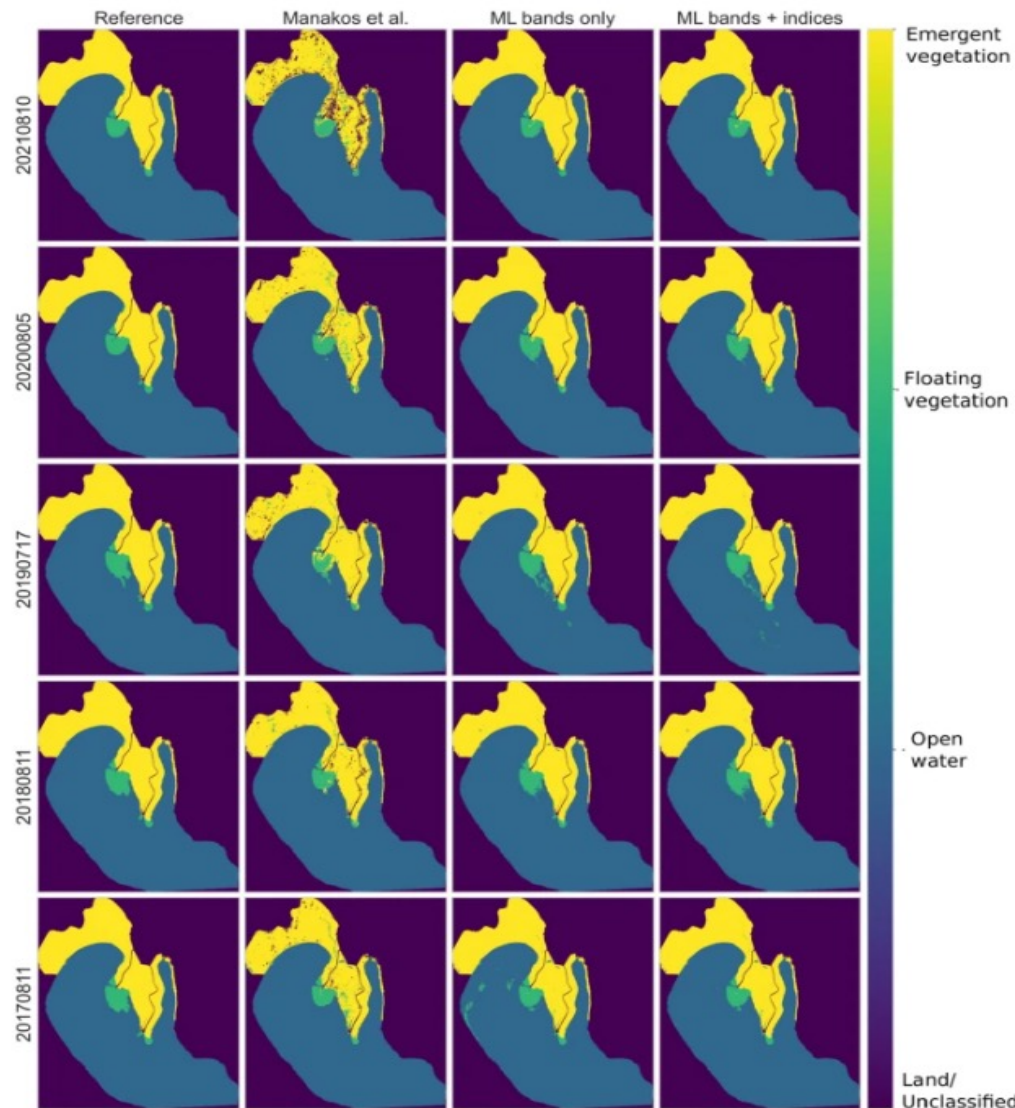
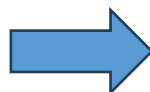
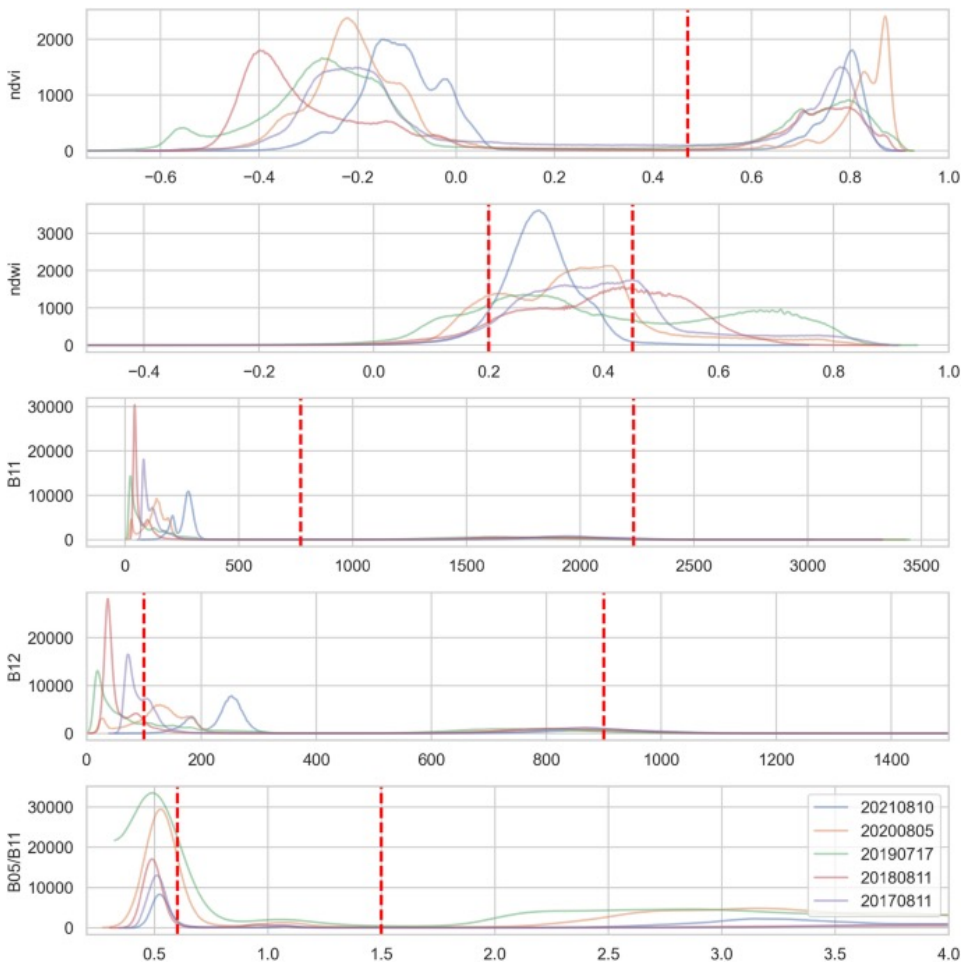


# Floating vegetation mapping: Machine learning approach (part I)



<https://wqems.eu/>

L. Alagioglou, I. Manakos, E. Katsikis, S. Medinets, Y. Gazyetov, V. Medinets, A. Delopoulos, Machine Learning for Identifying Emergent and Floating Aquatic Vegetation from Space: A Case Study in the Dniester Delta, Ukraine, 2024, SN Computer Science, DOI: 10.1007/s42979-024-02873-7.



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This project has received funding from the European Union's Horizon 2020 Research and Innovation Action programme under Grant Agreement No 101004157



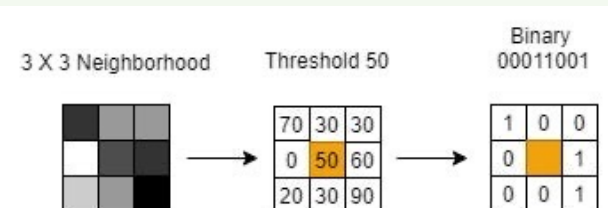


## Classification/ Evaluation

- Classifiers: Random Forest (RF), XGBoost
- A leave-one-date-out strategy: evaluating various ML models on a single date after they have been trained on all other dates, and this process is iteratively carried out for each date
- Metrics: F1-score, Recall (producer's accuracy), Precision (user's accuracy)

## Used Features

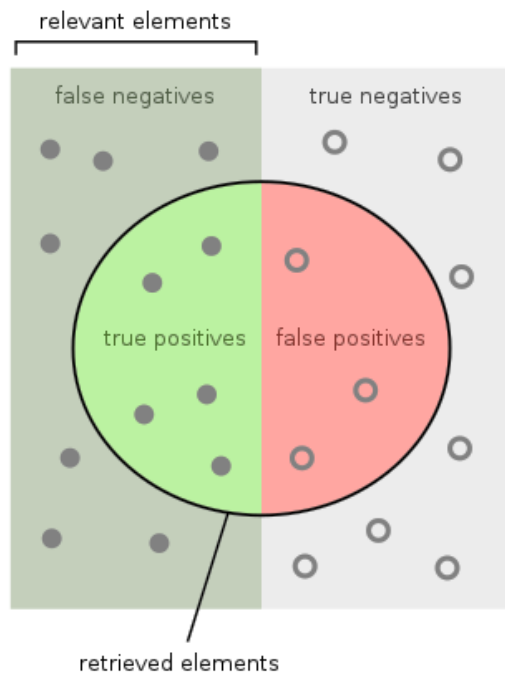
- the 12 bands of the Sentinel-2 L2A products
- additional features based on the domain knowledge acquired from our previous work (e.g., Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), ratio B05/B11)
- texture features for each band are derived using the Local Binary Pattern (LBP) method\*.



**Pattern = 00011001**  
**LBP = 1 + 8 + 16 = 25**

\* Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal Mach Intell. 2002;24(7):971-87.





How many retrieved items are relevant?

Precision =  $\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$

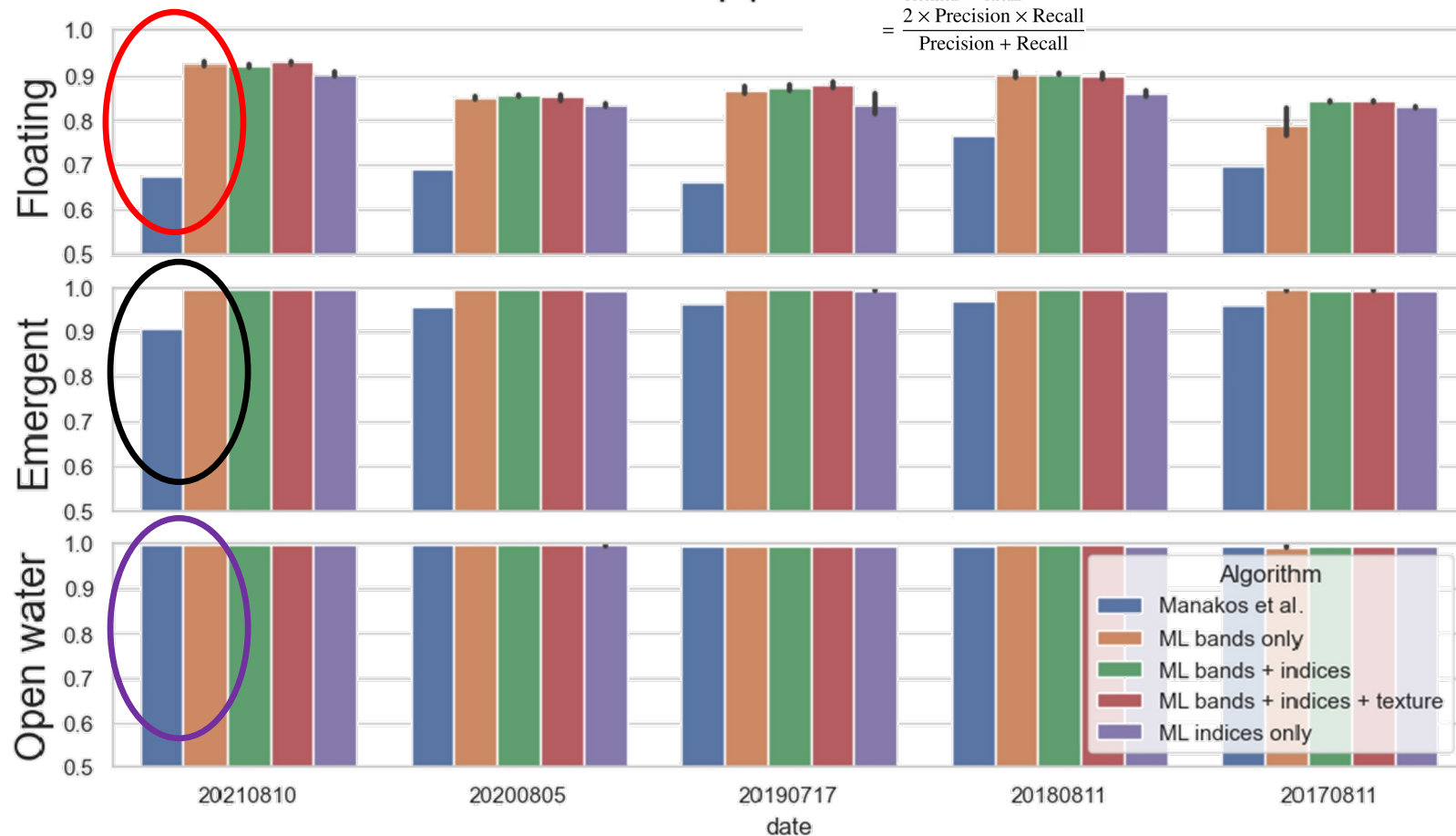
How many relevant items are retrieved?

Recall =  $\frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$

Source: [https://en.wikipedia.org/wiki/Precision\\_and\\_recall](https://en.wikipedia.org/wiki/Precision_and_recall)

The F1-score is a measure that harmoniously integrates UA and PA, yielding a single score that accounts for both false positives and false negatives.

$$F1 = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

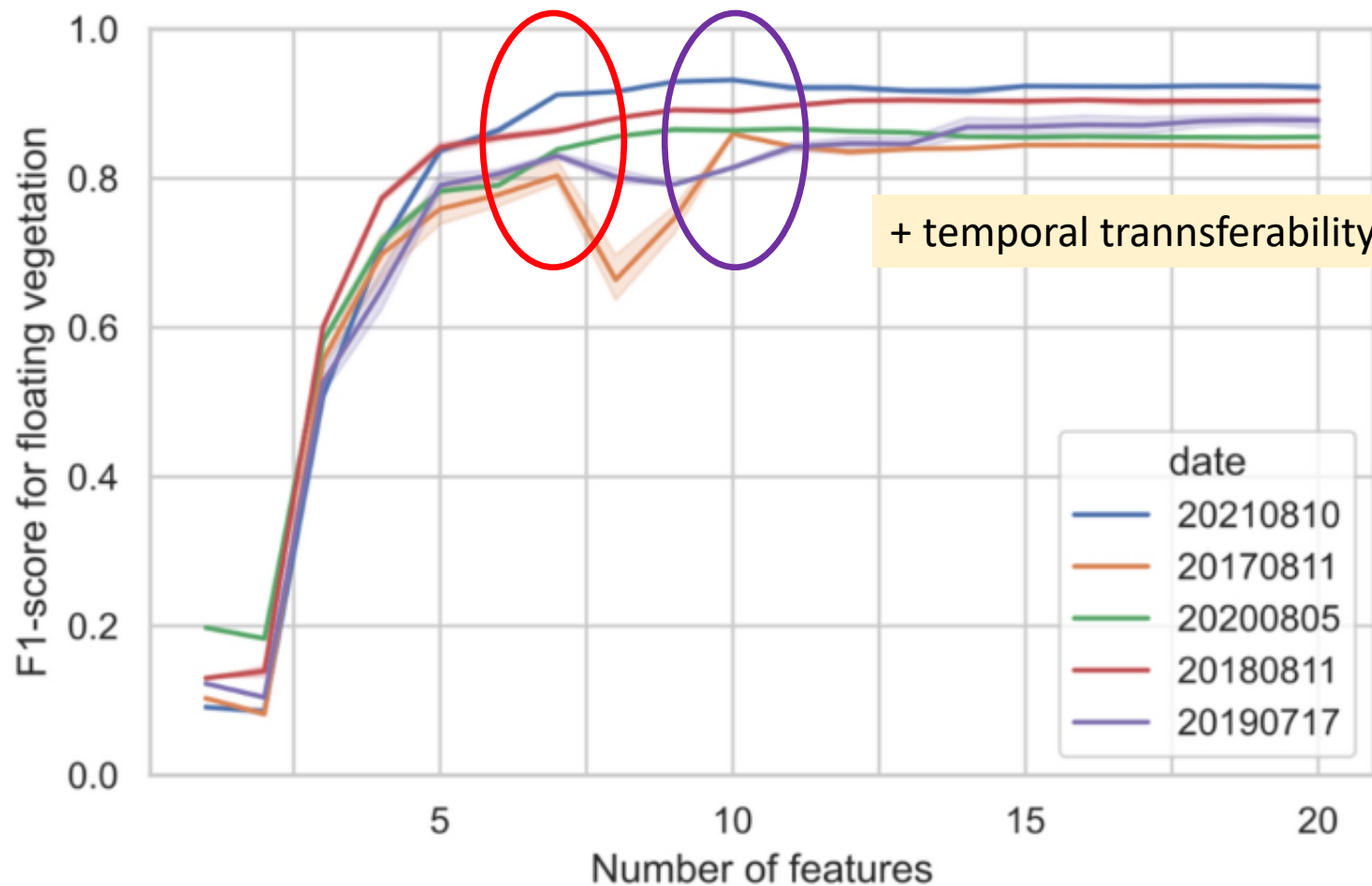




## Feature Importance Analysis

- the Max-Relevance Min-Redundancy (MRMR)\* algorithm was employed to quantify and rank the significance of features
- maximizing the relevance of features with the target class while simultaneously minimizing the redundancy among the features themselves

\* Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans Pattern Anal Mach Intell. 2002;24(7):971-87.





Algorithm	F1	Precision (UA)	Recall (PA)
ML bands + indices	<b>0.880 ± 0.031</b>	0.904 ± 0.049	<b>0.858 ± 0.037</b>
ML bands + indices + <b>texture</b>	<b>0.881 ± 0.032</b>	<b>0.912 ± 0.048</b>	0.853 ± 0.041
ML bands only	0.864 ± 0.055	0.867 ± 0.082	0.862 ± 0.037
ML indices only	0.852 ± 0.031	0.888 ± 0.051	0.822 ± 0.045
Manakos et al	0.697 ± 0.041	0.720 ± 0.099	0.690 ± 0.080

Improved from ~ 0.7 to > 0.85

Rank	Feature	Rank	Feature	Rank	Feature	Rank	Feature
1	B11	6	B07	11	B8A	16	<i>LBP<sub>B08</sub></i>
2	B12	7	B06	12	B02	17	<i>LBP<sub>B07</sub></i>
3	B09	8	B01	13	NDWI	18	<i>LBP<sub>B04</sub></i>
4	NDVI	9	B05	14	B03	19	<i>LBP<sub>B06</sub></i>
5	B08	10	B05/B11	15	B04	20	<i>LBP<sub>B02</sub></i>

Ranked low, but may offer a slight improvement still

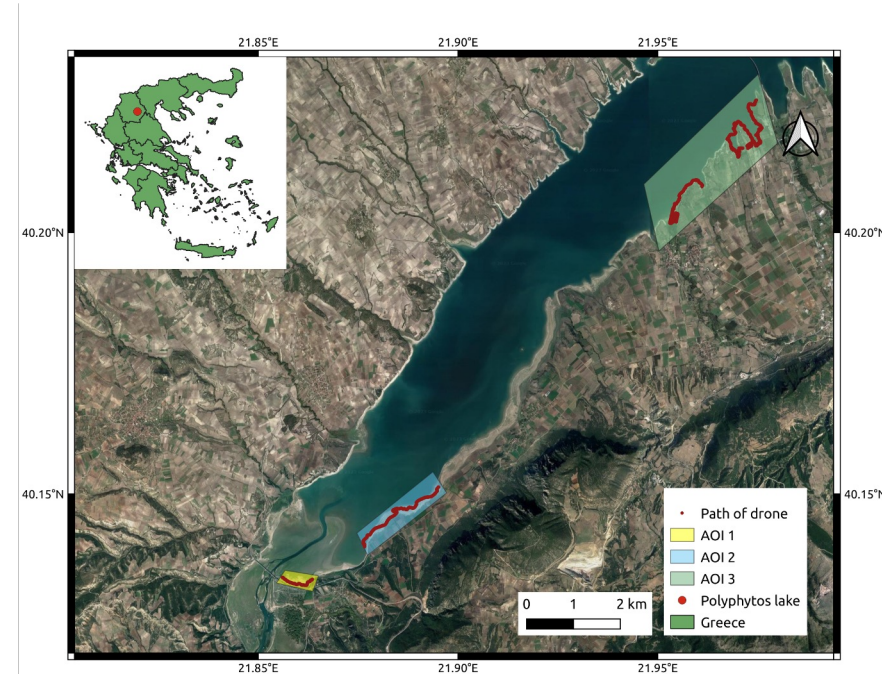




Assess the effectiveness of AI models in mapping and analyzing underwater aquatic vegetation (UVeg) comparing traditional ML algorithms based on handcrafted features and a pretrained foundation model using a range of remote sensing data including multispectral, satellite and aerial imagery.

## Data Sources:

- Air-borne images using the DJI Mini Pro UAV (3-6 cm resolution)
- Space-borne images: WorldView-2 (GSD: 1.8m) and Sentinel-2 (S2) (lowest GSD 10m)
- Annotations for S2 were extracted based on WorldView-2 imagery.



L. Alagialoglou, I. Manakos, S. Papadopoulou, R. Chadoulis, A. Kita, Mapping underwater aquatic vegetation using foundation models with air- and space-borne images: the case of Polyphytos Lake, 2023, Remote Sensing, Special Issue: Remote Sensing and Artificial Intelligence in Inland Waters, DOI: 10.3390/rs15164001





## Traditional ML models

- Pixel-based Logistic Regression
- Random Forest

Features: Spectral bands, total absorption, particle backscattering, diffuse attenuation coefficient, and Secchi disk depth (QAA-RGB algorithm\*)

## Foundation Model for Semantic Segmentation with Prompt-tuning

- Segment Anything (SAM)\*\*: Mask Autoencoder (MAE) Vision Transformer (ViT), pretrained on a large-scale dataset, fine-tuned with limited annotations

\*Pitarch, J.; Vanhellefont, Q. The QAA-RGB: A universal three-band absorption and backscattering retrieval algorithm for high resolution satellite sensors. Development and implementation in ACOLITE. Remote Sens. Environ. 2021, 265, 112667

\*\*Kirillov, A.; Mintun, E.; Ravi, N.; Mao, H.; Rolland, C.; Gustafson, L.; Xiao, T.; Whitehead, S.; Berg, A.C.; Lo, W.Y.; et al. Segment anything. arXiv 2023, arXiv:2304.02643

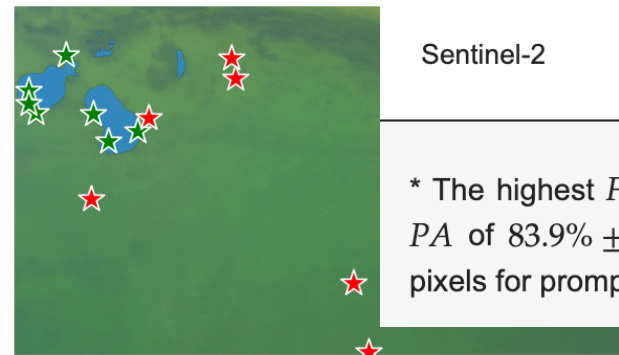
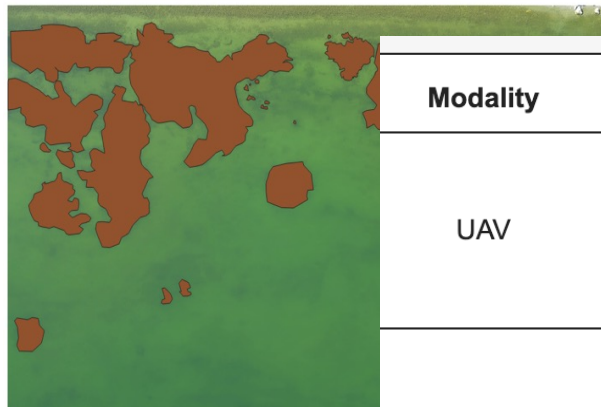
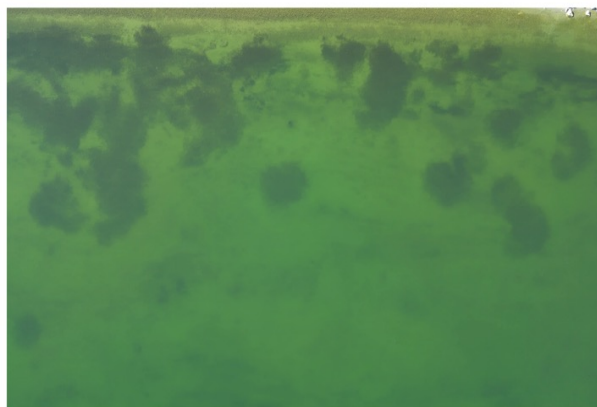




# Submerged vegetation mapping: 1<sup>st</sup> attempts with foundation models (III)



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Modality	ML Method	Size of Training Set	Dataset Size	F1	UA	PA
UAV	Log Regr	10-fold CV	~8M px	0.350	0.219	0.861
	RF	10-fold CV	~8M px	0.576	0.415	0.941
	SAM	20 px pairs	~8M px	<b>0.842 *</b>	<b>0.957</b>	<b>0.751</b>
World View 2	Log Regr	20-fold CV	~400k px	0.340	0.207	0.956
	RF	20-fold CV	~400k px	<b>0.472</b>	<b>0.328</b>	<b>0.845</b>
	SAM	8 px pairs	~400k px	0.264	0.157	0.834
Sentinel-2	Log Regr	40-fold CV	~14k px	0.184	0.103	0.890
	RF	40-fold CV	~14k px	<b>0.331</b>	<b>0.231</b>	<b>0.581</b>

\* The highest F1 score of  $86.5\% \pm 4.0\%$ , with corresponding UA of  $89.6\% \pm 5.8\%$  and PA of  $83.9\% \pm 4.8\%$ , is achieved for UAV images using 40 positive/negative pairs of pixels for prompting the SAM model.

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L. Alagialoglou, I. Manakos, S. Papadopoulou, R. Chadoulis, A. Kita, Mapping underwater aquatic vegetation using foundation models with air- and space-borne images: the case of Polyphytos Lake, 2023, Remote Sensing, Special Issue: Remote Sensing and Artificial Intelligence in Inland Waters, DOI: 10.3390/rs15164001

This project has received funding from the European Union's Horizon 2020 Research and Innovation Action programme under Grant Agreement No 101004157







## Results - Feature Importance Analysis

### **UAV Imagery:**

- Blue band most informative for single-feature classifier.
- Green + Blue bands combination nearly as effective as using all bands.

### **Sentinel-2 Bands:**

- Most informative: B07, B08, B01, B09.
- Effective combinations: B01-B07-B12 and B01-B07-B11.

### **WorldView-2 Analysis:**

- Green, RedEdge, Near Infrared1 bands most informative.
- Close-to-shore ("shallow pixels") analysis crucial for feature importance.





## Conclusions:

- SAM shows potential for high-resolution air-borne imagery but requires further adaptation to low resolution spaceborne data.
- Random Forest resulted in the best performance for WorldView-2 and Sentinel-2 data.
- Logistic Regression was successfully transferred to different locations in the lake.
- Feature Importance analysis provided valuable insights for future research by identifying significant bands for each data source (e.g., the Blue band was found the most informative for single-feature classifier and UAV imagery).

## Future Directions:

- Focus on adapting foundational models (e.g., SAM) to coarser resolution imagery.
- Explore one-shot prompt adaptation methods for better transferability and efficient segmentation across larger areas and different dates.





with a smile and vision

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Thank you  
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