ENHANCE

Enabling One Health Coastal Management through advanced AI over Marine Copernicus and citizen science data

EUSPA AI week 2026

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EUSPA European Union Agency for the Space Programme

ENHANCE 5 Key Innovations

- **OneHealth Approach** (human, animal & environmental) for coastal management
- **Data Open Exchange Platform** for comprehensive monitoring
- **OneHealth AI-powered Toolkit** for monitoring marine coastal ecosystems
- **Interactive risk maps** with integrated early warnings system
- Fostering of stakeholder engagement through **Living Labs** and custom activities

Case Studies

Barcelona Beaches & Ebro Delta, Spain

Context: Address challenges posed urban wastewater pollution, agriculture, and aquaculture
Challenge: AI Models for biodiversity & habitat prediction

Pagasitikos Gulf, Greece

Context: Evaluate the effects of climate-induced flooding on ecosystem and coastal communities
Challenge: AI Models for HAB Risk Assessment

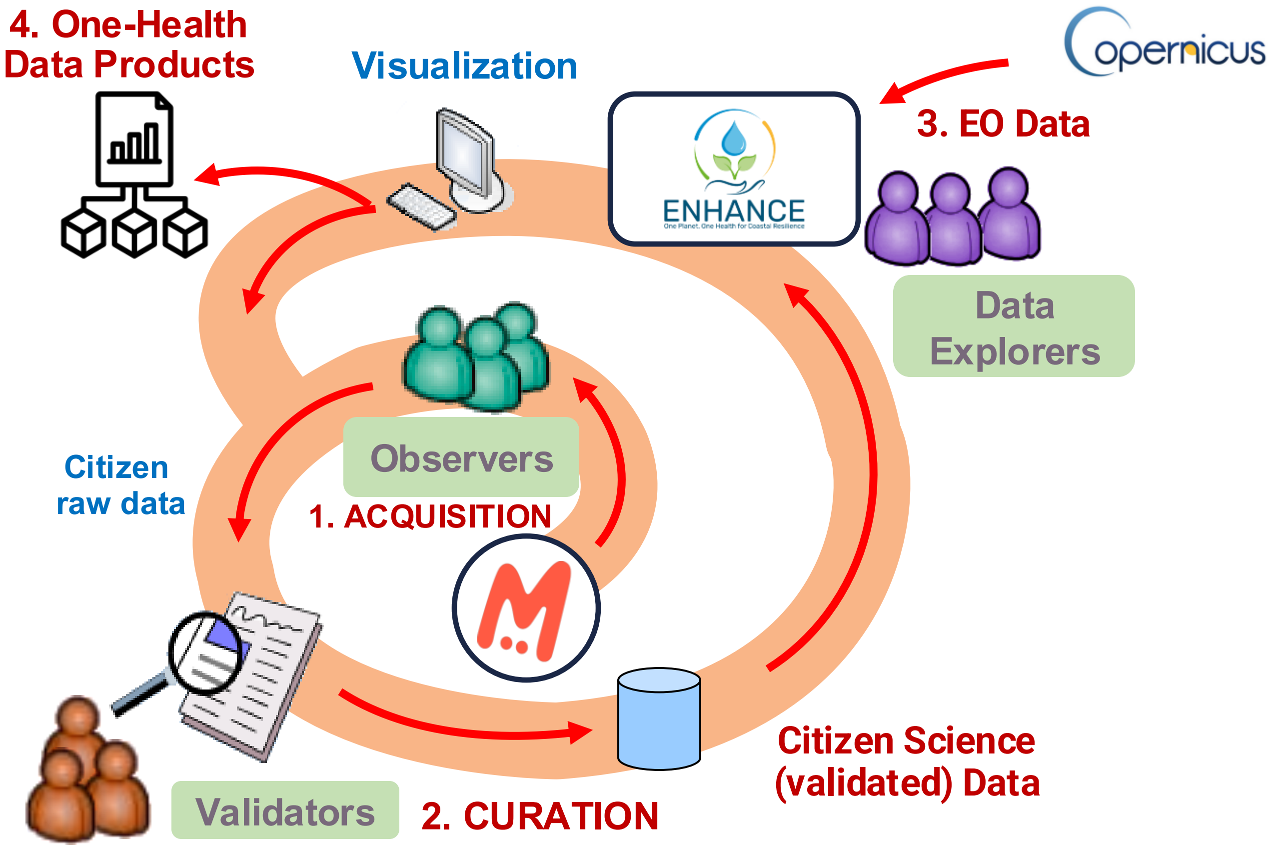
Common challenge: Chlorophyll-a & Turbidity Estimation with Copernicus data

Building Trustworthy AI models for Biodiversity
(Barcelona Beaches & Ebro Delta, Spain)

From citizen observations to EO-based habitat prediction

Andreu Fornós Bautista, CSIC

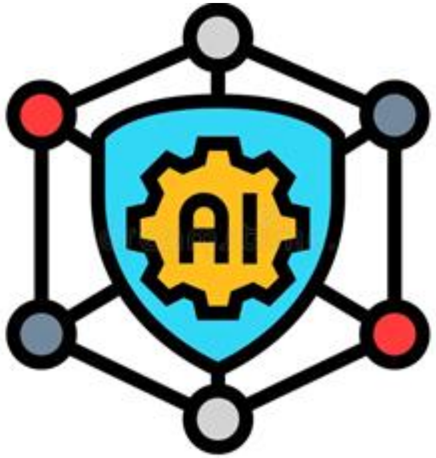
Leveraging Citizen Science & Copernicus data



- Citizen science data (mainly images for **subaquatic species**) collected are the starting point
- Citizen observations are validated using **trustworthy AI**
- Proxy indicators like **turbidity and Chlorophyll-a** (extracted by Copernicus data) can further validate the presence or absence of species

Baseline for AI usage: Trustworthy AI

- **Privacy and consent by design (RBAC)**
- **Auditability (logs)**
- **Security (OIDC, encryption, ...)**



Baseline for AI usage: AI Model HUB

Place to register and serve community registered AI models

- **Search** for AI models: Find internal and external AI models
- **Use** AI models for image inference
- **Register** your own AI models: Make your models available to the community

Citizen Science Data

MINKA

Citizen science community of people that take voluntary **observations of Flora and Fauna**

Key concepts:

- **+2.000 users**
- **+600.000 observations**
- Mainly **subaquatic species**
- Observations have **GPS coordinates and timestamp**
- Community identification workflow: **Human in the loop**

Earth observation Data

Earth observation component of the European Union's space program

- **Sentinel-2**: water color, turbidity, shoreline change, vegetation indices, ...

- **CMEMS**: chlorophyll-a, nutrients, oxygen, pollution indicators, ...

Product 1: Basic AI models for the HUB

We have integrated 4 models:

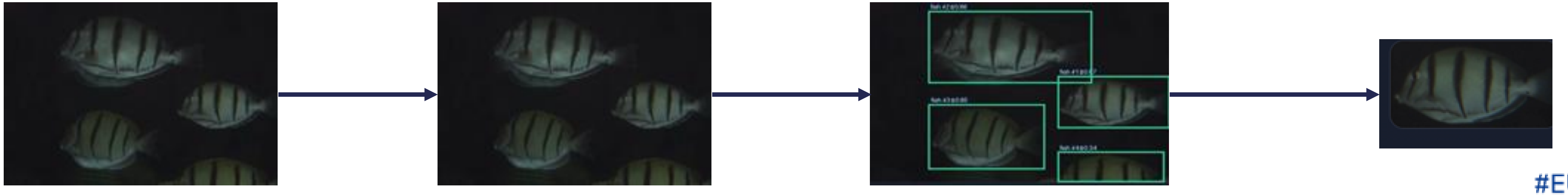
1. **Pl@ntNet**: Focused on plant image inference
2. **FishAI**: Demo AI model focused on subaquatic image inference
3. **SegmentationAI**: Demo AI model focused on segmentation of subaquatic images
4. **Set of kingdom specific models**

Product 2: Hierarchical AI

Multi-model composition with routing

- **Leverage multiple AI models** in the Models HUB for inference
- Much better performance than holistic classification models
- Example of an actual Hierarchical AI pipeline:

KINGDOM AI MODEL → ANIMALIA AI MODEL → SEGMENTATION AI MODEL → FishAI



Product 3: Hybrid AI

MINKA Community + AI Models HUB = Hybrid AI

Key enablers:

- **Human in the loop**: Community of people discussing flora and fauna classifications → **Continuous improvement loop**

- **Reputation system**: For AI models and for Citizens

- **Re-training mechanisms**: AI models can be retrained with the Human feedback

Product 4: Habitat prediction

Spatial habitat predictions by fusing validated species observations with Copernicus data

Key enablers:

- **Geolocated fauna and flora classified images**
- **Copernicus data layers:** Sentinel-2 and CMEMS
- In-situ data and the ability to corroborate habitat predictions

AI Models for HAB Risk Assessment

(Pagasitikos Gulf, Greece)

Chlorophyll-a & Turbidity Estimation with Sentinel-2

Dr. Evmorfia Bataka, UTH

Why monitor Chl-a and turbidity?

Key monitoring needs in coastal gulfs

- Track **eutrophication risk** and phytoplankton dynamics using chlorophyll-a as a proxy.
- Detect **turbidity changes** linked to sediment resuspension, runoff and coastal processes.
- Complement in **situ campaigns**: spatial coverage + repeatable observations.
- Support **early warning**: identify hotspots and rapid changes after events.

Optical water quality

Measured through surface reflectance

In situ is essential

Calibration, QA/QC, and validation

Sentinel-2 advantage

10–20 m pixels for narrow coastlines

Operational outputs

Maps + trends + anomalies

Why monitor Chl-a and turbidity?

- AI adds value when optics are complex:
  - Learns nonlinear interactions
  - Adapts to local water type with local ground truth (in-situ data)
  - Gives uncertainty flags for “out-of-domain” scenes

Study design: Pagasitikos Gulf

Sampling Plan

- 39 fixed stations (same coordinates each campaign)
- 24 campaigns (˜monthly) → 39 × 24 = 936 in situ records (before filtering)
- Matchup layer: 0–1 m (best reflects satellite surface signal)
- Prefer stations >200 m from shore to limit adjacency effects
- Record: date/time, sea state, sky conditions (for matchup QA)

Validation-friendly schedule

Train Holdout

Location Context

Inputs: Sentinel-2 + in situ data

Sentinel-2 MSI (Level-1C → Level-2A)

- Use Level-1C tiles as input (georeferenced, no atmospheric correction).
- Resample bands to 20 m to align red-edge bands (e.g., 705 nm).
- Atmospheric correction: C2RCC (C2X mode for turbid waters) or ACOLITE.

In situ measurements (surface layer)

- Chlorophyll-a (mg/m³) and turbidity (NTU) at 0–1 m depth.
- Repeatable station coordinates + time stamps (matchup fidelity).
- QA/QC: flags for outliers, equipment issues, extreme weather.

Matchup window
Aim for same-day sampling near overpass; otherwise flag ±1 day (and test sensitivity).

Phase-based process

Phase 0
Design stations + field protocol

Phase 1
Select Sentinel-2 scenes

Phase 2
SNAP preprocessing (C2X)

Phase 3
3×3 extraction + QC filtering

Phase 4
Build matchup database

Phase 5
Calibrate/ validate models

Atmospheric correction: C2RCC (C2X mode) → water-leaving reflectance

Matchups: station-centered 3×3 pixels to reduce noise + outliers

Model selection by R^2 + RMSE/NRMSE
AI extension: replace “linear fit” with supervised ML (RF / SVM / ANN), keeping the linear index as a baseline.

Phase 2: Preprocessing in SNAP (C2RCC / C2X)

Processing

1. **Download Sentinel-2 Level-1C tiles (cloud-free preferred).**
   L1C is georeferenced but not atmospherically corrected.

2. **Resample all bands to 20 m.**
   Ensures red-edge bands align with visible bands.

3. **Subset to Pagasitikos AOI.**
   Speeds processing and reduces storage.

4. **Atmospheric correction with C2RCC (C2X for turbid waters).**
   Outputs water-leaving reflectance (Level-2A).

Output products

Water-leaving reflectance
(Rrs / reflectance bands)

Automatic products (C2RCC)
- Chl-a
- Total suspended solids

Validation strategy for 24 campaigns

Prefer time-blocked validation (by campaign)

Option A: Hold out 6 campaigns (season-balanced)

24 monthly campaigns → train on 18, validate on 6 (all stations in each held-out date).

Option B: Leave-One-Campaign-Out (LOCO-CV)

- 24 folds: each time hold out one campaign (all 39 stations).
- Report mean/median RMSE and NRMSE across folds.
- Add an optional "spatial transfer" test: hold out ~20% stations.

Report metrics

- R^2 (explained variance)
- RMSE (absolute error)
- NRMSE (relative error, %)
- Scatter plots and residual checks by season

Use the same metrics as the reference paper so results are directly comparable.

Phase 5: Model calibration (linear baseline + ML)

Baseline

Chl-a index
X = (R560 + R705) / (R560 + R665)
Fit: Chl-a = a·X + b (re-estimate a, b for Pagasitikos)

Turbidity index
X = (R705 · R705) / R490
Fit: Turbidity = a·X + b (re-estimate a, b for Pagasitikos)

Machine learning

- Inputs: reflectance bands (490, 560, 665, 705, 740, 783, 865) ± a few indices.
- Targets: Chl-a and turbidity (often log-transform for stability).
- Models: Random Forest / Gradient Boosting as robust starting points.
- Validation: split by campaign/date (avoid random leakage).
- Keep interpretability: report baseline linear model alongside ML.

Machine Learning Methodology

Goal: learn a nonlinear mapping from Sentinel-2 reflectance to Chl-a and turbidity (calibrated with in situ matchups).

1 **Assemble features (X)**
Mean reflectance from 3x3 window: 490, 560, 665, 705, 740, 783, 865 nm
+ a small set of stable indices.

2 **Preprocess + QC**
Cloud/cirrus/glint masking; remove outliers; keep only valid water pixels.
Transform targets (often log) and standardize features if needed.

3 **Train candidate models**
Start with robust regressors: Random Forest and Gradient Boosting.
Tune with a small grid; keep the linear index model as a baseline.

4 **Validate (avoid leakage)**
Split by campaign/date (e.g., leave-one-campaign-out CV).
Report R2, RMSE, NRMSE; check errors by season and turbidity range.

5 **Deploy + map**
Apply model pixel-wise to new Sentinel-2 scenes to produce maps.
Flag out-of-domain predictions using training feature ranges.

Outputs: maps, trends and event detection

Expected Pagasitikos products

Possible operational deliverables

- Monthly Chl-a and turbidity maps (cloud-masked).
- Station time series + anomalies vs seasonal baseline.
- Hotspot detection (near inflows/ports/coastal works).
- Model report: coefficients, metrics, and validity domain.
- Recalibration plan (e.g., annual or after regime shifts).

For Pagasitikos, maps are generated by applying the locally calibrated model pixel-wise.

Reference examples (Mar Menor)

Chlorophyll-*a* and turbidity estimations for Mar Menor lagoon

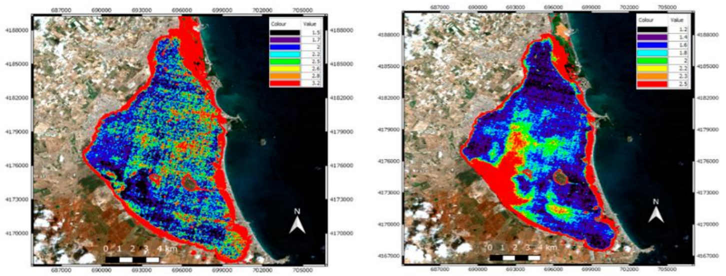


Figure 5. Thematic maps of Mar Menor, August 14, 2019. [Chl-*a*] (mg/m^3) map obtained with equation 1 (on the left) and turbidity (NTU) map obtained with equation 3 (on the right). *Mapa del Mar Menor del 14 de agosto, 2019. Mapa de [Chl-*a*] (mg/m^3) obtenido con la ecuación 1(a la izquierda) y el mapa de turbidez (NTU) obtenido con la ecuación 3 (a la derecha).*

Example thematic maps demonstrate spatial gradients and nearshore caveats (bottom reflectance).

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THANK YOU FOR YOUR TIME!

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