

1ST INTERNATIONAL SYMPOSIUM ON CATCH IDENTIFICATION TECHNOLOGIES

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Real-time automatic total catch monitoring

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MINISTERIO DE AGRICULTURA, PESCA Y ALIMENTACIÓN

MINISTERIO DE CIENCIA E INNOVACIÓN



1. MOTIVATION

- The successful implementation of the Common Fisheries Policy (CFP) depends, at a large extent, on the **capacity to quantify total catches on board commercial vessels**.
- Because of the large number of fishing vessels and the high number of trips to be monitored, **classic monitoring methods**, mainly based on inspections, **are not effective** → **The use of electronic devices** to quantify fishing catches is gaining relevance.
- The **data provided** by such devices, in combination with mathematical models, may be used to **assess the state of the different fishing stocks and to optimize the fishing activity**.
- Increasingly though, technology has quickly developed during the last years to provide **vision and artificial intelligence-based, remote Electronic Monitoring (REM or EM systems)**, at lower costs, and with more potential to cover large areas than traditional monitoring strategies.

1. MOTIVATION

The Advantages of REM

for wildlife, fishers, retailers & consumers

End discarding
Efficient monitoring of the net hauling & fish sorting process will encourage fishers to fish more selectively & discard less.

Healthier ocean
Helps to facilitate stock recoveries and support marine ecosystems, teeming with life, which will absorb more carbon from the atmosphere.

Deter overfishing & illegal fishing activities
Will be used to support stronger enforcement tools & reward fishers who are using best practices at sea.

Improved scientific data
REM can capture widespread data to provide a full picture of fishing activity & help us better understand our seas.

Protects wildlife
Helps to monitor & reduce bycatch levels and reduce impacts on marine wildlife such as sharks, seabirds & cetaceans.

Confident fishers
Data supports decisions on stock management, enabling fishers to adopt sustainable harvest strategies.

Confident consumers, responsible retailers
Provides fishers with verifiable evidence of what they are seeing, haul-by-haul, to evidence responsible practices at sea.

Safeguards Marine Protected Areas (MPAs)
GPS, sensors & video can monitor fishing gear and help protect key marine habitats & help us understand the impacts of fishing on wildlife.



Data Trends
Patterns relating to fishing gear issues, fish stocks, & biological data can be identified over a long-time scale.

AI tools
Can identify specific species for conservation surveys & verify whether species are subject to landing obligation.

Increased and improved data
Rather than a 'snapshot' of sampling, REM captures video data of all hauls which can be stored & reviewed at a later date.

Meeting marine conservation targets
REM systems can help fish stocks to recovery by encouraging more selective fishing & minimise impacts on marine wildlife & habitats.

Non-biased data
In comparison to traditional methods where fishers & observers can interpret the catch information differently.

Cheaper data
REM systems allow data to be gathered at a fraction of the cost in comparison to traditional systems.

Faster access and response to data
Managers can respond quicker to events & give fishers the best opportunities based on what they are currently experiencing.

Mitigation use
REM reveals if fishers are following mitigation measures & whether it is working to help reduce wildlife bycatch.

SOURCE: <https://www.mcsuk.org/ocean-emergency/sustainable-seafood/our-sustainable-seafood-work/transparentsea/>

2. THE iOBSERVER CONCEPT



- Its main objective is to **automatically identify and quantify the whole catch on board fishing vessels.**
- It is installed over the conveyor belt, just before the fishing separation zone, taking images of everything that crosses the conveyor belt during fish separation. The recognition software automatically analyzes every image, identifies all individuals, estimates their length and generates a catch report.

- **Steel waterproof case**
 - ✓ Dimensions: 40x23x26cm; Weight: 18kg Touch screen
- **Industrial camera**
- **Industrial computer:** Image recognition software **Lighting system:** Led strip lights (diffuser films)



3. THE iOBSERVER VERSIONS

1st PROTOTYPE

Developed within the **LIFE iSEAS project** (LIFE13 ENV/ES/000131)

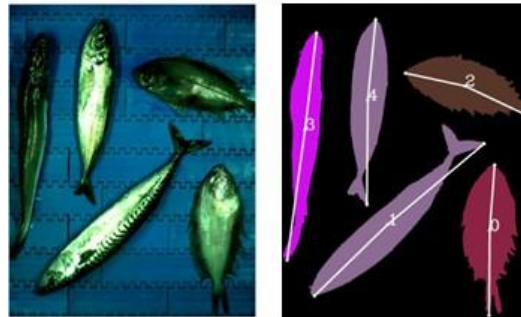


- **Image recognition software** for 17 species based on parameters: **color, texture, shape**.
- It has been intensively tested in *10 oceanographic campaigns* (170.000 images acquired) and on board **3 commercial vessels on 9 fishing trips** in Portugal and Northwest Cantabrian Sea (around 35.000 images acquired)

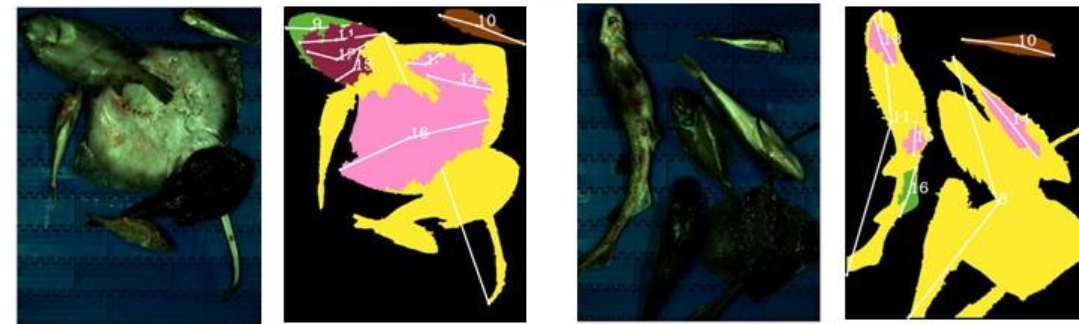
- **Main problems**

- ✓ Similar species
- ✓ Overlapped individuals
- ✓ Lighting problems

Separated individuals



Overlapped individuals



3. THE iOBSERVER VERSIONS

2nd PROTOTYPE

Development under the **SICAPTOR project** of the Pleamar Program (Fundación Biodiversidad) co-funded by the EMFF (European Maritime and Fisheries Fund)



- **Image recognition software** for 14 target species (ICES regions 8c/9a, including similar species) based on **DEEP LEARNING ALGORITHMS**

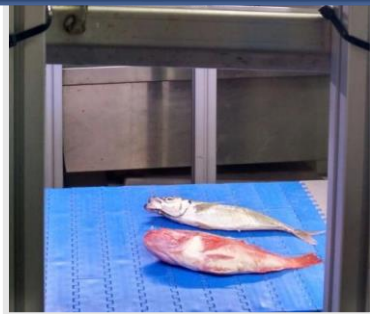
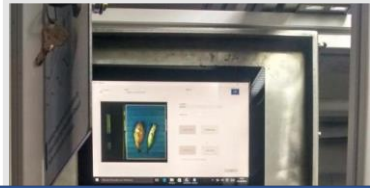
FAO 3A Code	Scientific name	Common name
BIB	<i>Trisopterus luscus</i>	Pouting
GUG	<i>Trigla gurnardus</i>	Grey gurnard
GUN	<i>Trigla lyra</i>	Piper gurnard
GUR	<i>Aspitrigla cuculus</i>	Red gurnard
GUU	<i>Chelidonichthys lucerna</i>	Tub gurnard
HKE	<i>Merluccius merluccius</i>	Hake
HOM	<i>Trachurus trachurus</i>	Horse mackerel
LDB	<i>Lepidorhombus boscii</i>	Four spot megrim
MEG	<i>Lepidorhombus whiffiagonis</i>	Megrim
MAC	<i>Scomber scombrus</i>	Atlantic mackerel
RJC	<i>Raja clavata</i>	Thornback ray
RJM	<i>Raja montagui</i>	Spotted ray
RJN	<i>Leucoraja naevus</i>	Cuckoo ray
WHB	<i>Micromesistius poutassou</i>	Blue whiting

- Three different algorithms, based on **deep learning**, were developed:
 - Species identification (Detection – bounding box)
 - Species identification (Instance segmentation)
 - Length estimation (Regression)
- These algorithms **use input data to learn** from them:
 - Inputs are images of the fishes
 - Learning algorithm (Artificial Neural Network) contains a number of parameters that are tuned minimizing the error between inputs and prediction algorithms

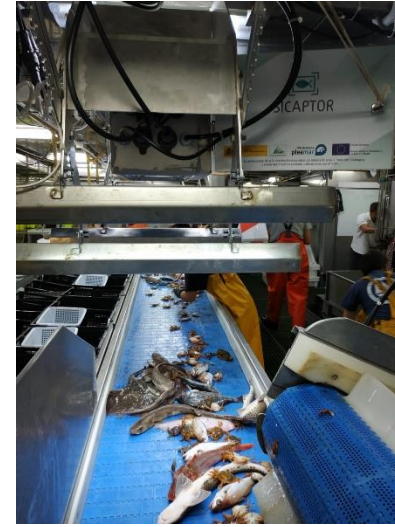
3. THE iOBSERVER VERSIONS

2nd PROTOTYPE INSTALLATIONS

It has been tested in 1 oceanographic campaign and on board 3 commercial vessels on 30 fishing trips in Portugal and Northwest Cantabrian Sea



Oceanographic vessels



Commercial vessels



3. THE iOBSERVER VERSIONS

2nd PROTOTYPE

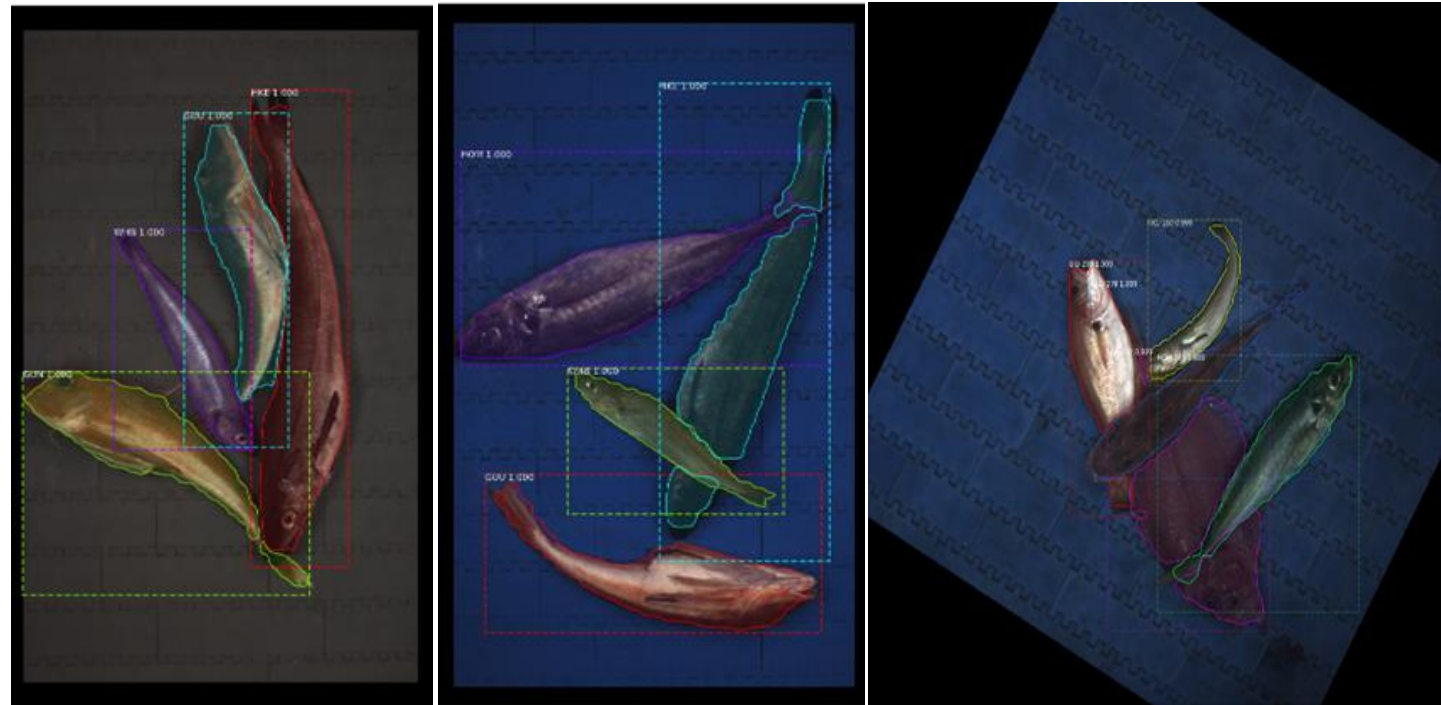
ON SHORE IMAGES WITH LOW OVERLAPPING

Species identification algorithm

Type of images on the test set

- Same conditions as training/validation pictures
- Maximum overlapping area 15%
- Images were labelled by a human observer (objective and non objective species)

Identification results



3. THE iOBSERVER VERSIONS

2nd PROTOTYPE

ON SHORE IMAGES WITH LOW OVERLAPPING

Species identification algorithm

Type of images on the test set

- Recall: % of correct identifications → **98% (average)**
- Precision: % of correct identifications among the positives → **95% (average)**

Confusion matrix

Predictions	Ground Truth															
	000 (62) 90.3	BIB (55) 96.4	GUG (52) 94.2	GUN (57) 100.0	GUR (29) 96.6	GUU (116) 93.1	HKE (136) 94.1	HOM (80) 98.8	LDB (60) 91.7	MAC (34) 100.0	MEG (66) 98.5	RJC (32) 100.0	RJM (3) 100.0	RJN (5) 80.0	WHB (112) 92.9	BG (2) 0.0
000 (59)	94.9	1.7	0.0	0.0	0.0	0.0	0.0	0.0	1.7	0.0	0.0	0.0	0.0	0.0	1.7	0.0
BIB (54)	0.0	98.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.9	0
GUG (50)	0.0	0.0	98.0	0.0	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
GUN (60)	0.0	0.0	0.0	95.0	0.0	3.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.7	0.0
GUR (29)	0.0	0.0	0.0	0.0	96.6	3.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
GUU (110)	0.0	0.0	0.0	0.0	0.9	98.2	0.0	0.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
HKE (129)	0.8	0.0	0.0	0.0	0.0	0.0	99.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
HOM (80)	0.0	0.0	0.0	0.0	0.0	1.2	0.0	98.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
LDB (59)	3.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	93.2	0.0	1.7	0.0	0.0	0.0	0.0	1.7
MAC (34)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
MEG (65)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0
RJC (32)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0
RJM (3)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
RJN (4)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0
WHB (106)	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	98.1	0.9
BG (27)	11.1	3.7	11.1	0.0	0.0	14.8	22.2	0.0	14.8	0.0	0.0	0.0	0.0	3.7	18.5	0.0

3. THE iOBSERVER VERSIONS

2nd PROTOTYPE

ON SHORE IMAGES WITH LOW OVERLAPPING

Length estimation algorithm

Type of images on the test set

- Same conditions as training/validation pictures
- Maximum overlapping area 15%
- Images were labelled by a human observer (objective and non objective species)

RESULTS

Species	MAE (mm)	MAPE (%)	Species	MAE (mm)	MAPE (%)
BIB	6	3.0	LDB	10	4.5
GUG	7	3.3	MAC	9	2.6
GUN	11	3.3	MEG	7	2.5
GUR	6	2.9	RJC	15	5.4
GUU	7	2.3	RJM	6	1.3
HKE	15	5.0	RJN	12	2.1
HOM	11	3.4	WHB	8	3.2

- Maximum error: 5.4%
- Mean absolute error: 9.2 mm
- Resolution used by biologists is around 5 or 10 mm

3. THE iOBSERVER VERSIONS

2nd PROTOTYPE

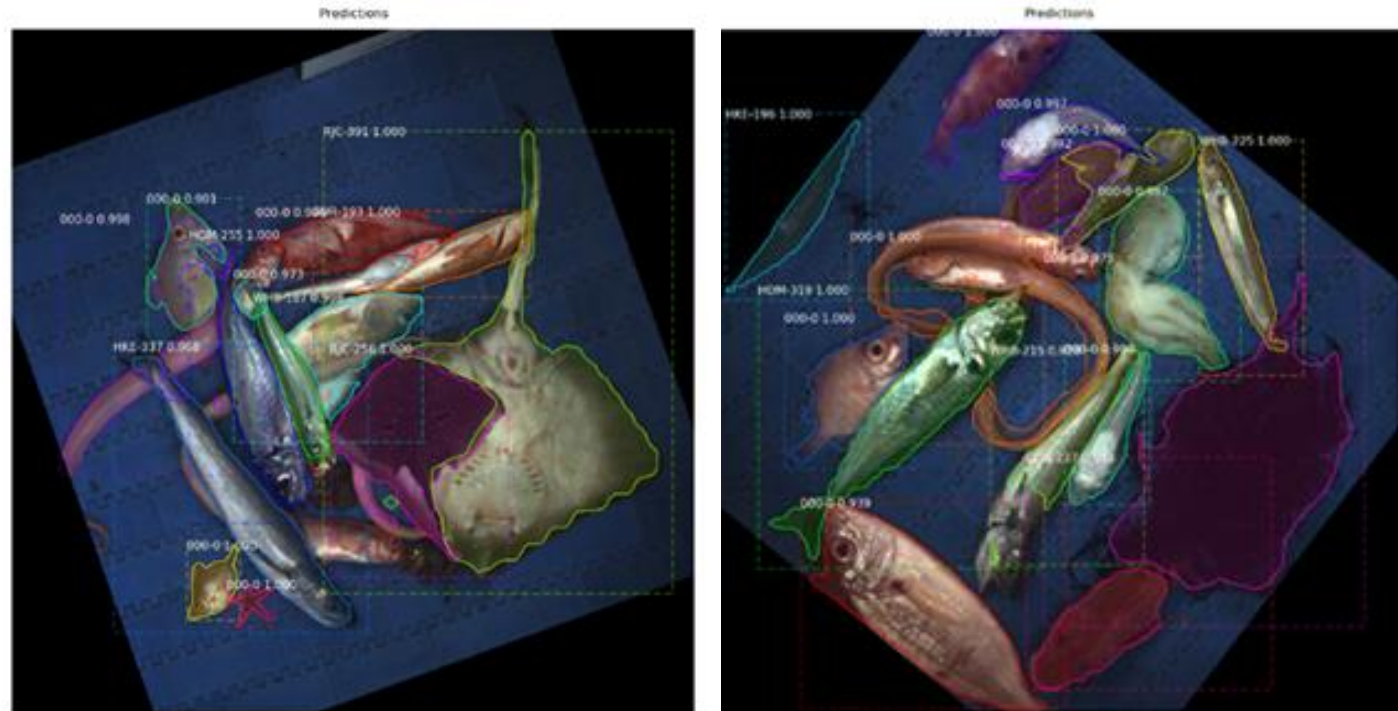
ON SHORE/ON BOARD IMAGES WITH MODERATE OVERLAPPING

Species identification algorithm

Type of images on the test set

- Images with a larger degree of overlapping
- Objective species were labelled by a human observer
- Non-objective species were not labelled

Identification results



3. THE iOBSERVER VERSIONS

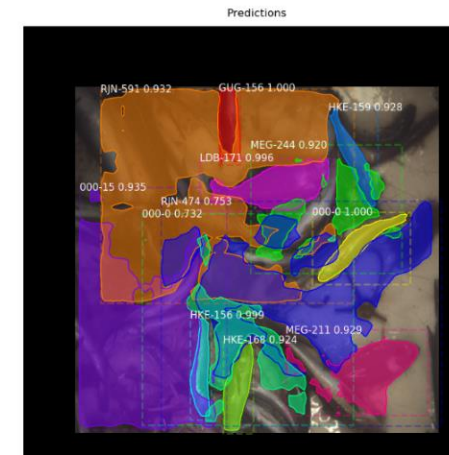
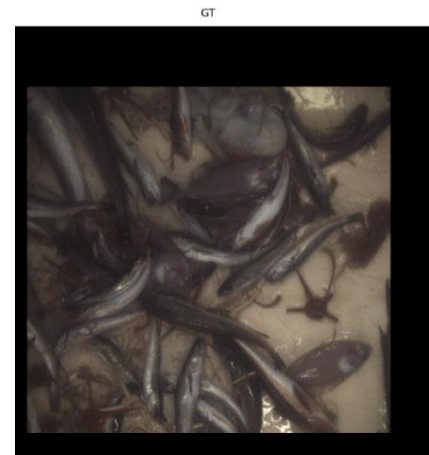
2nd PROTOTYPE

Species identification algorithm

Type of images on the test set

- Commercial vessel
- Worse lighting conditions, water accumulation, white conveyor belt
- Images were not labelled (no confusion matrix)
- Human observer:
 - a) Weight per species

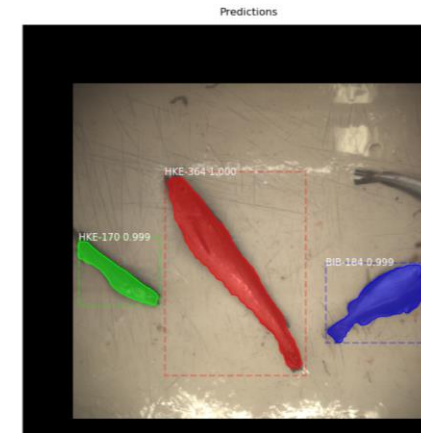
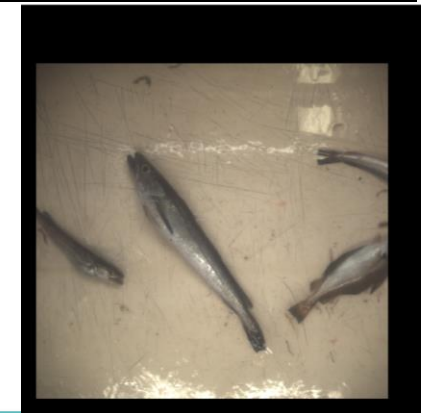
COMMERCIAL VESSELS WITH HIGH OVERLAPPING



Identification results

RESULTS

- Good if overlapping is not too high
- Bad with high overlapping



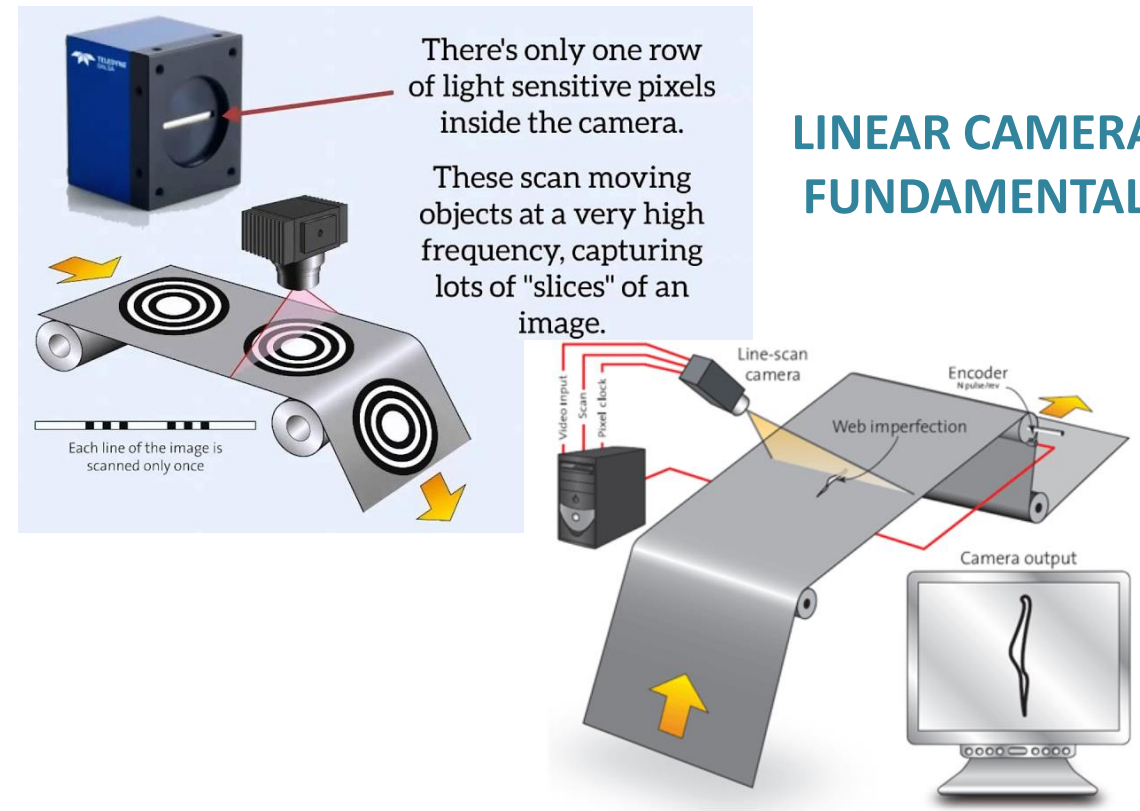
3. THE iOBSERVER VERSIONS

3rd PROTOTYPE

On-going Development under the **SICAPTOR2.0 project** of the Pleamar Program (Fundación Biodiversidad) co-funded by the EMFF (European Maritime and Fisheries Fund)



LINEAR CAMERAS FUNDAMENTALS



- To carry out the computations in a computer outside the iObserver:
 - ✓ Reduce size and weight of the iObserver
 - ✓ Increase computational capabilities (reduce cost)
- Explore the use of linear and matrix (+flux algorithm) cameras
 - ✓ Lower lightning requirements
 - ✓ But requires perfect coordination with belt movement required

3. THE iOBSERVER VERSIONS

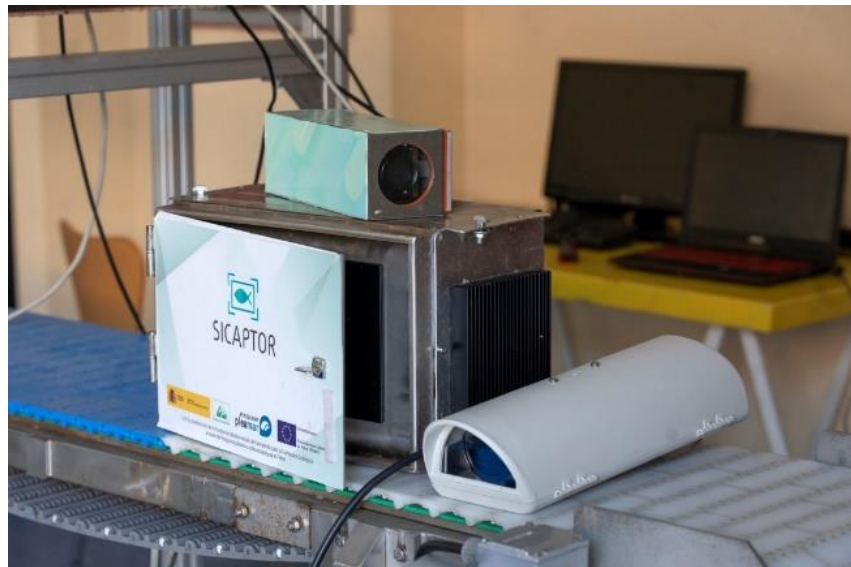
3rd PROTOTYPE

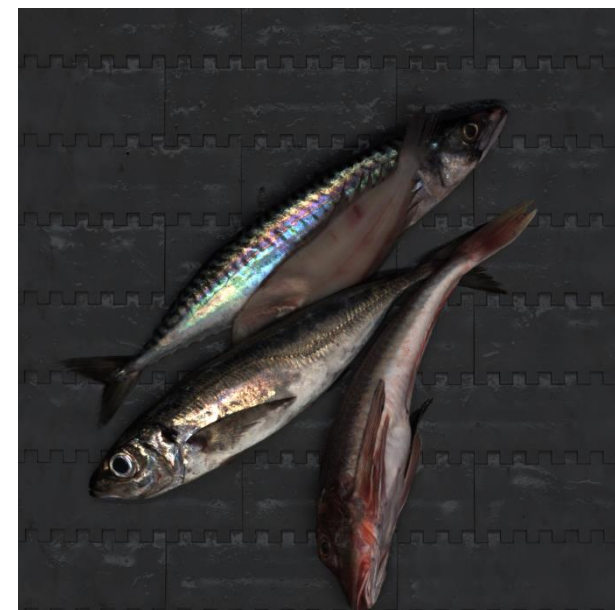
- ***Moving the processing hardware out of the case brings great benefits:***
 - a) It facilitates the development of much more powerful and standard solutions.
 - b) It is easily upgradeable.
 - c) Specialized hardware is not necessary, which implies **lower costs**.
 - d) The processing equipment can be used for other tasks (for example: REDBOX application for the management of hauls/trips, casts and catches).
 - e) The capture hardware update cycle (longer cycles) and the processing one (shorter cycles) are decoupled, resulting in long-term cost optimization.

3. THE iOBSERVER VERSIONS

	iObserver SICAPTOR	iObserver2.0 Linear	iObserver2.0 Matrix
TYPE OF CASE	Watertight stainless Steel IP68	Watertight stainless steel APG Serie 38S IP68 for food applications	Waterthight IP66
DIMENSIONS	400x230x260 mm	279x106x97 mm	466x127x113 mm
WEIGHT	18 kg	3 kg	2.7 kg
CAMERA	Matrix JAI GO-5000C, 5 MP resolutiond and a 1" color sensor	Linear 7.04um 2048x2-26kHz-Color-CMOS-GigE	Matrix JAI GO-5000C, 5 MP resolutiond and a 1" color sensor
COMPUTATION MODULE	Industrial computer inside de case	On the bridge	On the bridge
LIGHTING SYSTEM	4 LED linear spotlights (with diffuser films)	1-2 LED spotlights IP69K EFFI-FLEX-IPK69-30-000-TR-P3-LS (with diffuser films)	2 LED spotlights IP69K EFFI-FLEX-IPK69-30-000-TR-P3-LS (with diffuser films)

3. THE IOBSERVER VERSIONS





4. IMPLEMENTATION OF DEEP LEARNING ALGORITHMS IN iOBSERVER 2.0

- **Two differentiated categories of images were generated** both at testing inland facilities and on board the R/V Miguel Oliver (of the Spanish General Secretary of Fisheries) during the DESCARSEL0921 campaign:
 - **Training images.** These are images intended to train and calibrate the detection algorithms. That is why it is important that these present the maximum number of specimens of each target species, in the greatest number of positions, both of the specimen (ventral, dorsal, lateral, straight, curved...) and on the conveyor belt (centered , attached to the sides, corners, perpendicular, parallel, etc.). Two subsets of images were obtained from these:
 - a) Images of individual specimens, both target and non-target species.
 - b) Images with several specimens, some with overlap and others without overlap between them, both of target and non-target species.
 - **Images of complete hauls for calibration and evaluation of system results.** The objective of this set of images is to evaluate the performance of the system with real sets in conditions that can be reproduced on board a commercial vessel.

4. IMPLEMENTATION OF DEEP LEARNING ALGORITHMS IN iOBSERVER 2.0

Instance segmentation algorithm with **Mask R-CNN** for the segmentation and identification of captured species

Regression algorithm with a **modified MobileNet-V1** convolutional neural network for fish length estimation

- **SICAPTOR: 15 identified classes** (14 target species, including size + Other species).
- **SICAPTOR 2.0: 31 identified classes** (14 target species, including size + 16 non-target species + Other species category).
- Using the test set, the **recall** obtained is 96% and the **accuracy** is 92%. Both accuracy and sensitivity drop very slightly compared to SICAPTOR → It is the price to pay for a much **more powerful algorithm**:
 - a) It allows to differentiate more than twice as many species.*
 - b) It works with both SICAPTOR matrix camera and SICAPTOR 2.0 linear camera images.*
 - c) The set of tests has been calculated incorporating a greater number of complex images with multiple fish and overlap.*

4. IMPLEMENTATION OF DEEP LEARNING ALGORITHMS IN IOBSERVER 2.0

- The **regression algorithm for size estimation** is created from a convolutional Network MobileNet-V1 trained from scratch, modified to include as input the results of the segmentation algorithm.
- This algorithm was adapted to work with the new version with 31 species of SICAPTOR 2.0 and was re-entangled by adding the new set of images.
- The **Mean Absolute Percentage Error (MAPE) obtained** is **3.1%**, calculated on the fraction of correct identifications of the target species; **the Mean Absolute Error (MAE)** is **9mm**, improving the results of previous versions.

	BIB	GUG	GUN	GUR	GUU	HKE	HOM	LDB	MAC	MEG	RJC	RJM	RJN	WHB
MAE (mm)	6	6	10	7	9	16	11	7	9	6	10	7	11	9
MAPE	2.7%	3.0%	3.4%	3.0%	2.9%	5.2%	3.2%	3.4%	2.8%	2.0%	3.5%	2.0%	2.0%	3.9%

4. IMPLEMENTATION OF DEEP LEARNING ALGORITHMS IN iOBSERVER 2.0

- As a **NOVELTY**, we are using different alternatives to apply multiple object tracking algorithms with segmentation, in the literature identified as **MOTS** (*Multiple Object Tracking and Segmentation*) with the idea of solving the problem of fish cut at the edges of each consecutive frame during the haul recording procedure and qualitative and quantitative analysis of each haul.

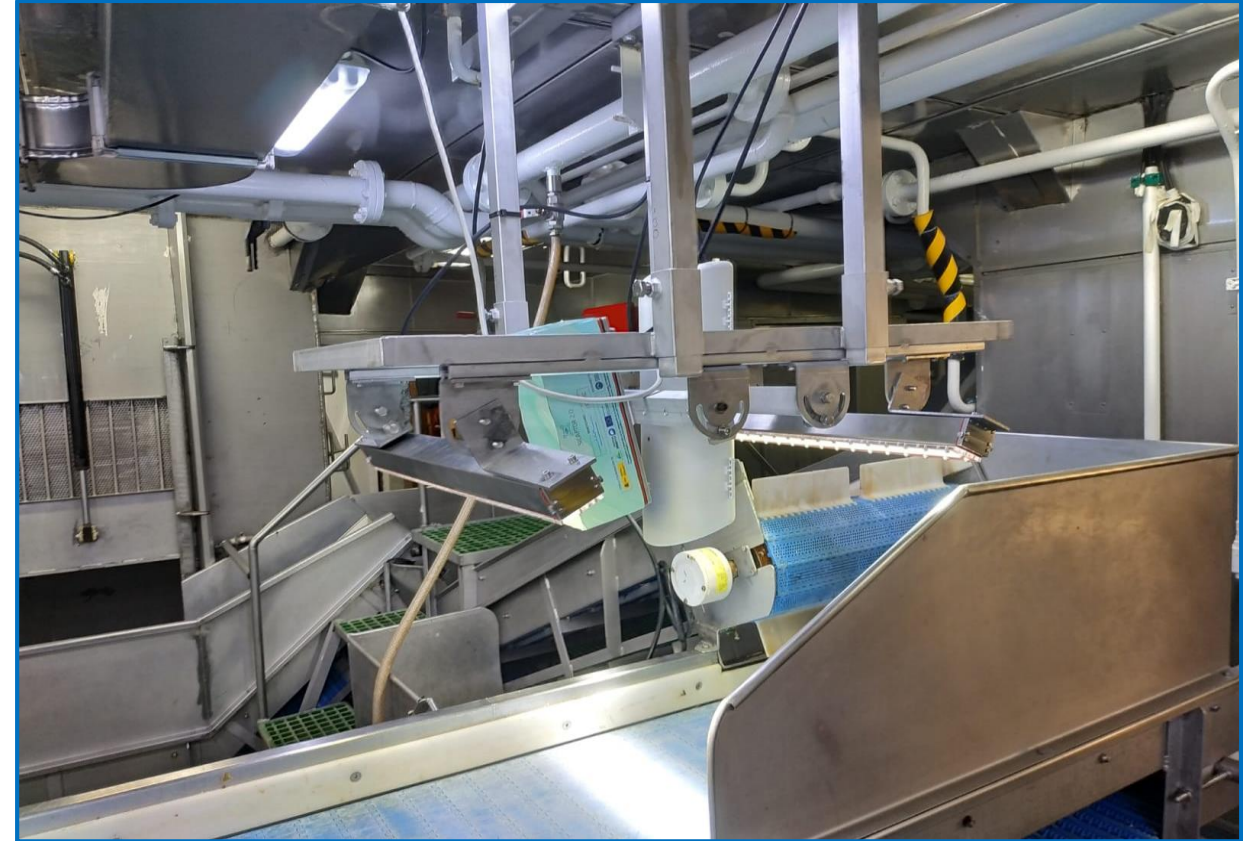


5. ON BOARD TESTS OF THE iOBSERVER2.0

- Carried out during the scientific campaigns DESCARSEL0921 and DESCARSEL0921 to study the selectivity during trawling operations and high survival of discards in the Cantabrian-Northwest Fishing Ground.
- Led by the Spanish Institute of Oceanography – Oceanographic Center of Vigo (IEO-CSIC).
- Carried out in On the R/V Miguel Oliver (of the Spanish General Secretary of Fisheries)
- September 2021 and 2022



5. ON BOARD TESTS OF THE iOBSERVER2.0

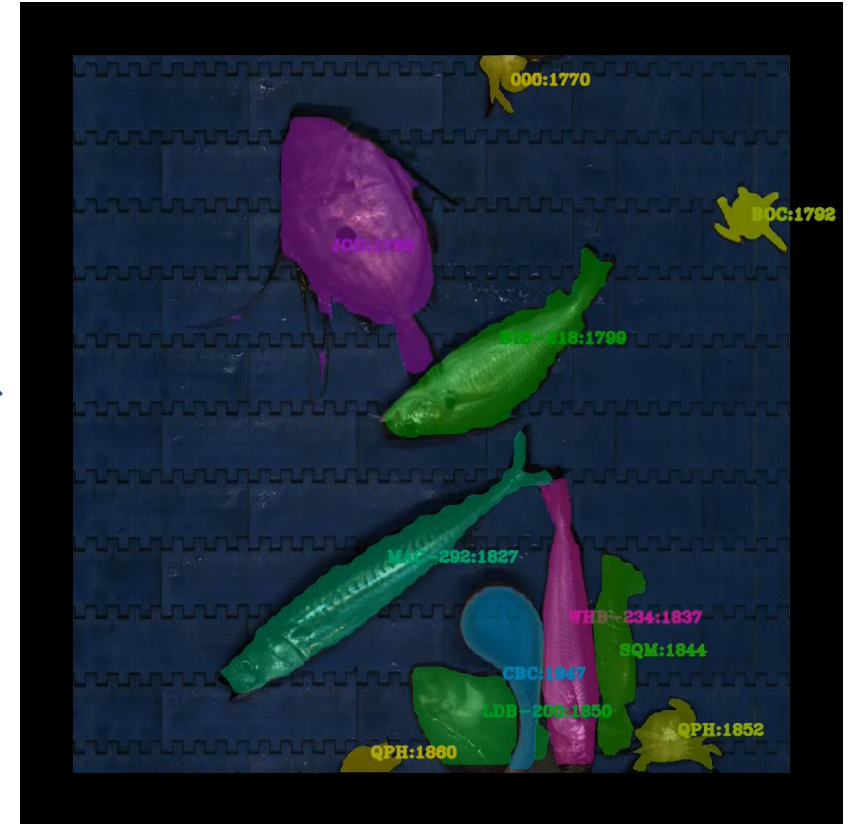


5. ON BOARD TESTS OF THE IOBSERVER2.0



5. ON BOARD TESTS OF THE IOBSERVER2.0

Deep learning recognition with multiple object tracking output



5. ON BOARD TESTS OF THE iOBSERVER2.0

DESCARSEL0921 iOBSERVER 2.0 results by species for codends and target species

Average WAPE 49%

spc	GT weight	Pred weight	WAPE	GT detected	True detection
BIB	46384	36825	31%	74%	93%
GUG	636	416	131%	17%	26%
GUN	1436	1066	52%	61%	83%
GUR	6186	5288	17%	84%	98%
GUU	2086	3693	82%	98%	55%
HKE	186763	193136	12%	96%	92%
HOM	88050	67893	25%	76%	99%
LDB	38753	28673	26%	74%	100%
MAC	18690	15101	22%	79%	98%
MEG	5846	12414	123%	94%	44%
WHB	127490	111069	17%	85%	98%
	522320	475574	49%	76%	81%

The model has difficulties with species with few individuals or with very similar appearance

GT Weight: observed weight (g)

Pred Weight: predicted weight (g)

WAPE: Weighted Average Percentage Error

GT detected: Fraction of observed weight correctly detected

True detected: Fraction of correct predicted weight

Grouping similar species: Average WAPE 20%

spc	GT weight	Pred weight	WAPE	GT detected	True detection
BIB	46384	36825	31%	74%	93%
GUX	10344	10463	22%	90%	89%
HKE	186763	193136	12%	96%	92%
HOM	88050	67893	25%	76%	99%
LEZ	44599	41087	11%	90%	98%
MAC	18690	15101	22%	79%	98%
WHB	127490	111069	17%	85%	98%
	522320	475574	20%	84%	95%

Results greatly improve by grouping similar species, such as gurnards and megrims, as in comercial classification.

5. ON BOARD TESTS OF THE iOBSERVER2.0

DESCARSEL0921 iOBSERVER 2.0 results per haul for codends and target species

Average WAPE 18%

haul	overlap	GT weight	Pred weight	WAPE	GT detected	True detection
5	4	44262	44225	6%	97%	97%
6	4	26484	24744	9%	92%	99%
9	8	42324	36636	33%	77%	89%
13	5	18674	16980	12%	89%	98%
14	2	12008	9926	24%	79%	96%
15	5	8968	8372	8%	93%	99%
16	2	29062	29951	8%	97%	95%
17	3	11110	9972	13%	88%	98%
18	6	7120	5938	20%	82%	98%
20	3	21064	18288	20%	83%	96%
21	5	55054	50630	19%	87%	94%
23	6	34757	23981	36%	66%	96%
24	5	9685	9106	14%	90%	96%
26	7	41558	39704	11%	92%	97%
27	7	43204	47600	24%	93%	84%
28	9	70340	55388	31%	74%	94%
31	3	46646	44133	21%	87%	92%
4.9		522320	475574	18%	86%	95%

GT Weight: observed weight (g)

Pred Weight: predicted weight (g)

WAPE: Weighted Average Percentage Error

GT detected: Fraction of observed weight correctly detected

True detected: Fraction of correct predicted weight

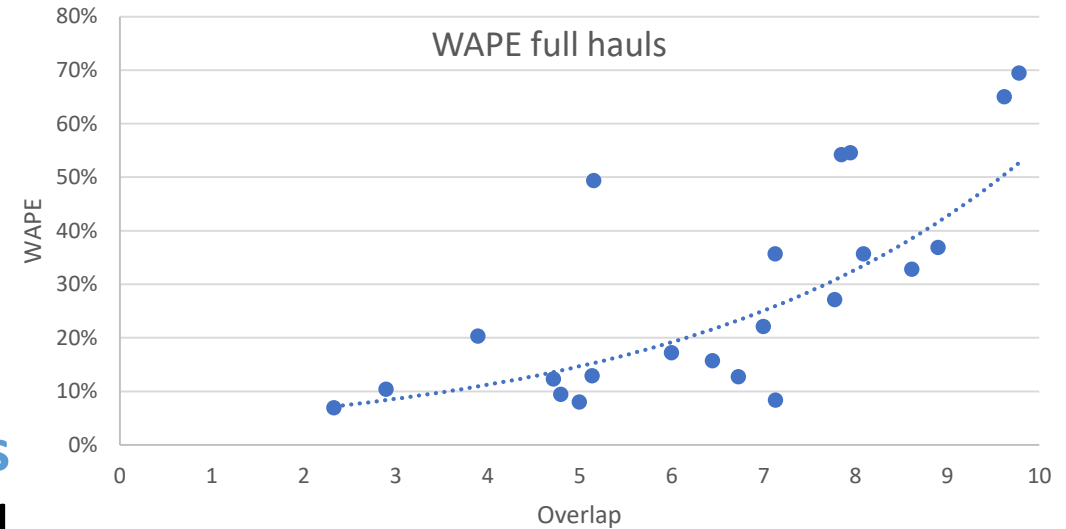
Grouping similar species: Average WAPE 16%

haul	overlap	GT weight	Pred weight	WAPE	GT detected	True detection
5	4	44262	44225	4%	98%	98%
6	4	26484	24744	8%	93%	99%
9	8	42324	36636	33%	77%	89%
13	5	18674	16980	9%	91%	100%
14	2	12008	9926	20%	81%	98%
15	5	8968	8372	8%	93%	99%
16	2	29062	29951	8%	97%	95%
17	3	11110	9972	13%	88%	98%
18	6	7120	5938	17%	83%	100%
20	3	21064	18288	13%	87%	100%
21	5	55054	50630	17%	88%	95%
23	6	34757	23981	32%	69%	100%
24	5	9685	9106	13%	91%	96%
26	7	41558	39704	10%	93%	97%
27	7	43204	47600	20%	95%	86%
28	9	70340	55388	27%	76%	96%
31	3	46646	44133	17%	89%	94%
4.9		522320	475574	16%	88%	97%

Calculating by haul, the weighted effect of the most abundant species improves the final result.

6. CONCLUSIONS AND ON-GOING/FUTURE WORK

- Promising results, but further research is needed.
- **The main obstacle is the high overlap of the fish** on the conveyor belt → Develop a mechanical fish separation system + collaboration of crews.
- **Increase and improve the catalog of annotations** by incorporating samples with a complete and balanced distribution by species and length.
- Improve and incorporate the latest advances in DL recognition algorithms.
- More tests on commercial ships.

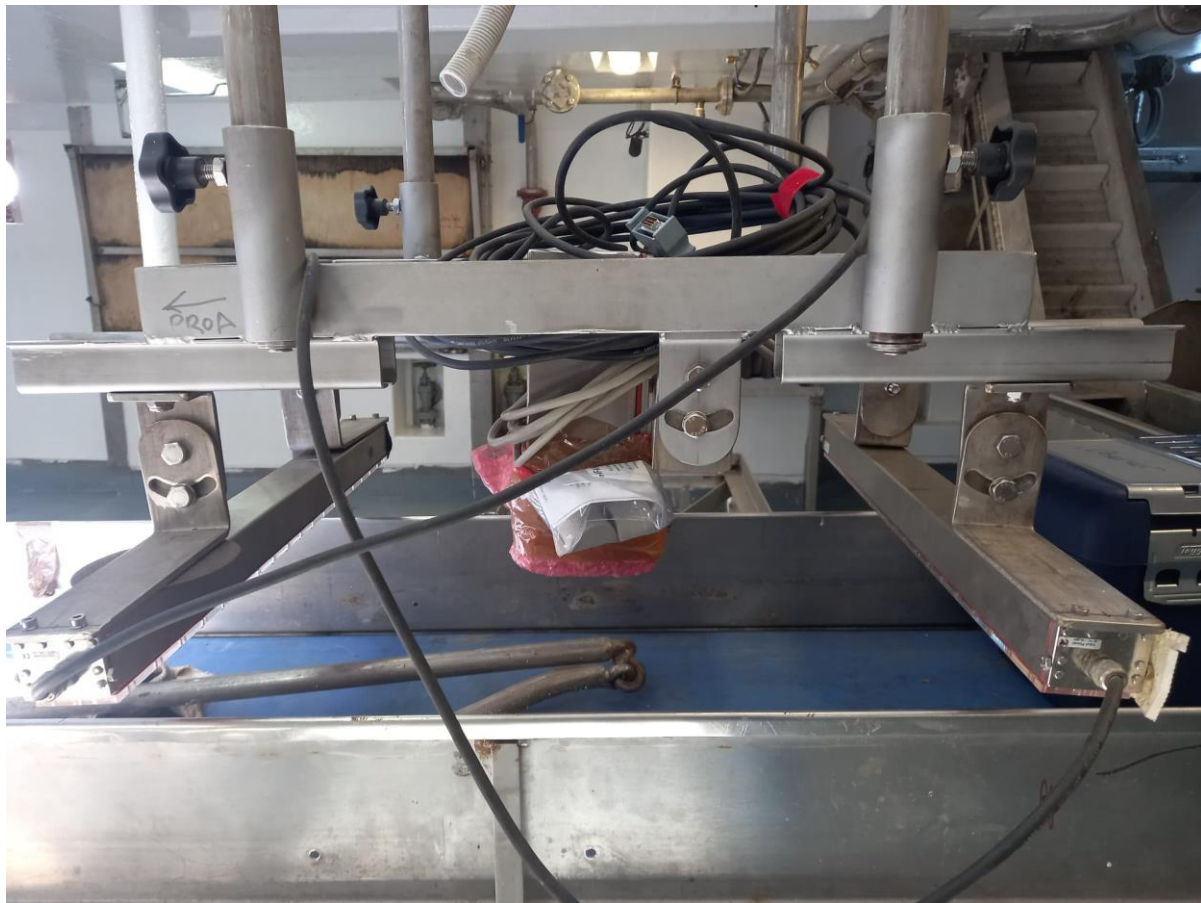


6. CONCLUSIONS AND ON-GOING/FUTURE WORK



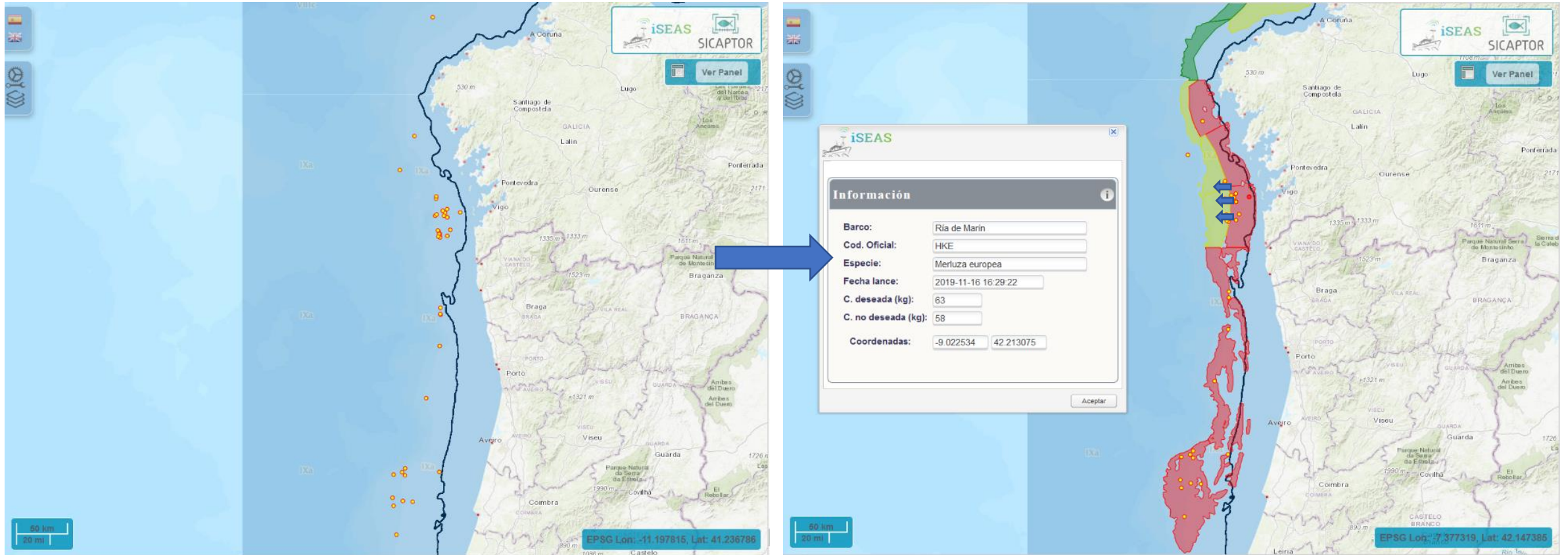
TO INTENSIVELY TEST OUR iOBSERVER2.0
ON REAL FISHING CONDITIONS – GALICIAN
BOTTOM TRAWLER

6. CONCLUSIONS AND ON-GOING/FUTURE WORK

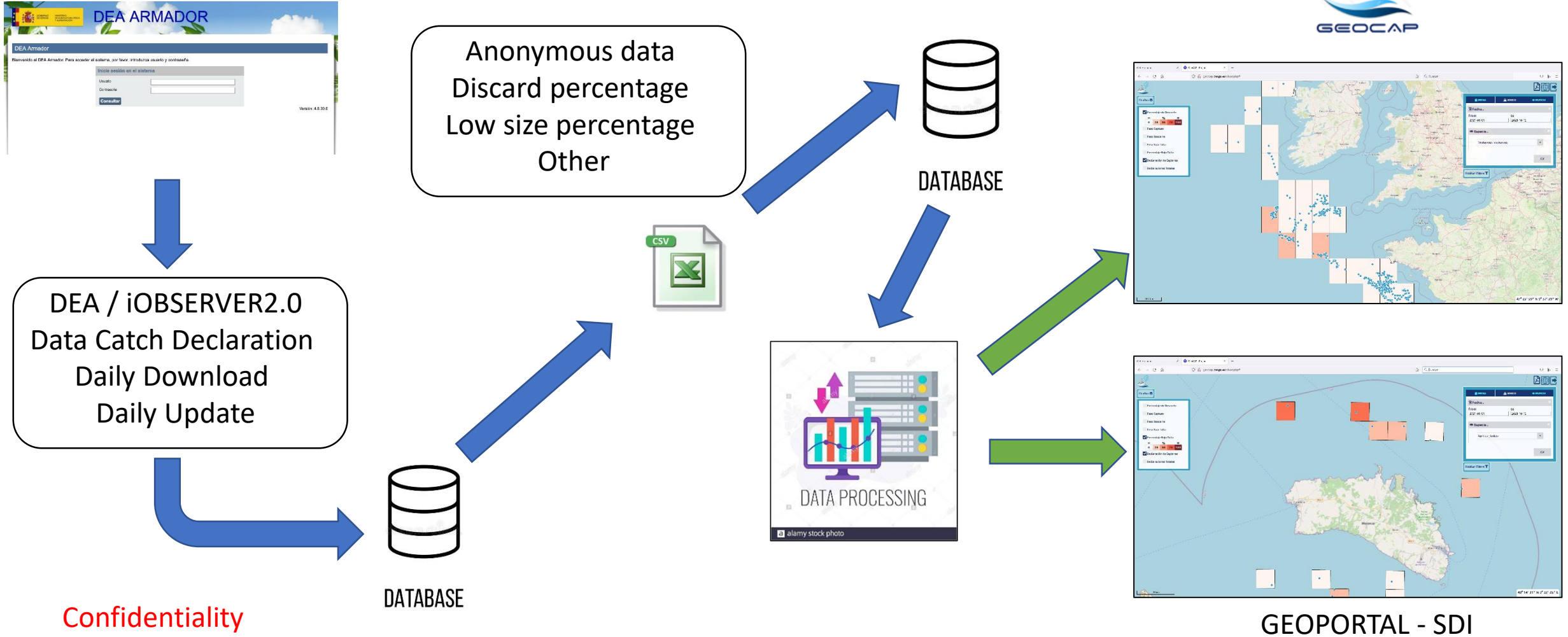


6. CONCLUSIONS AND ON-GOING/FUTURE WORK

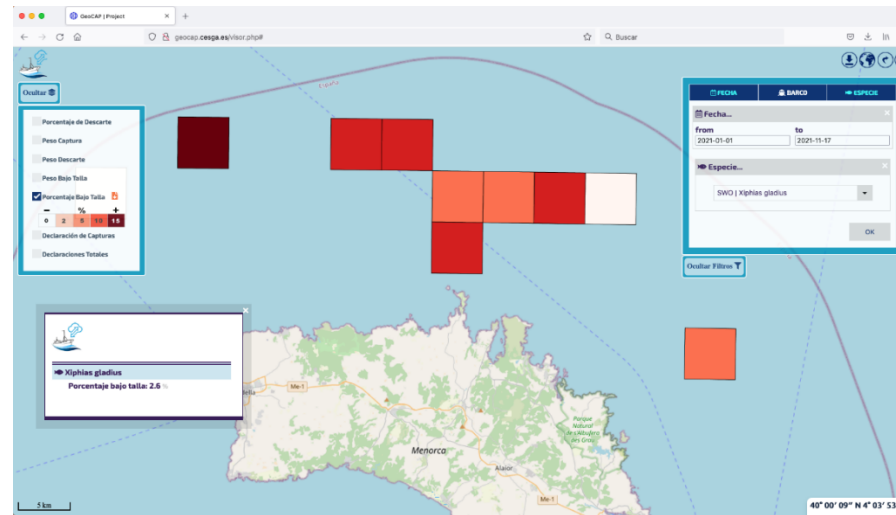
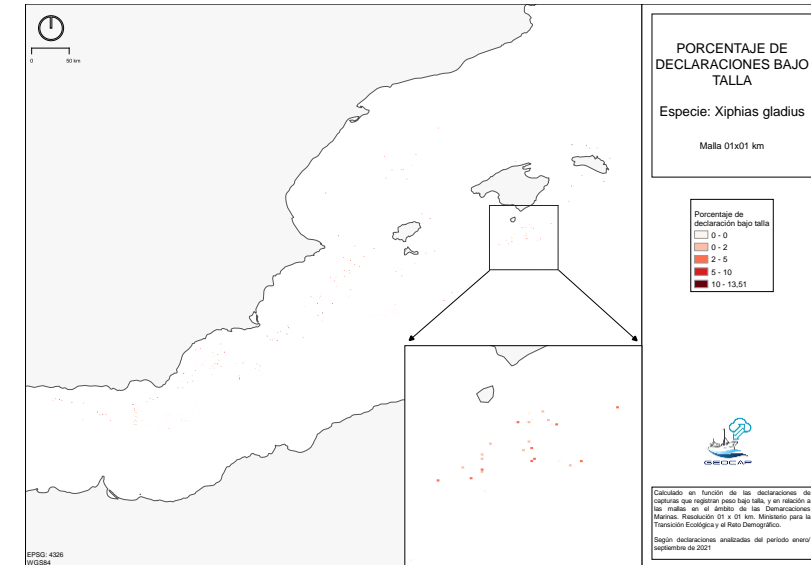
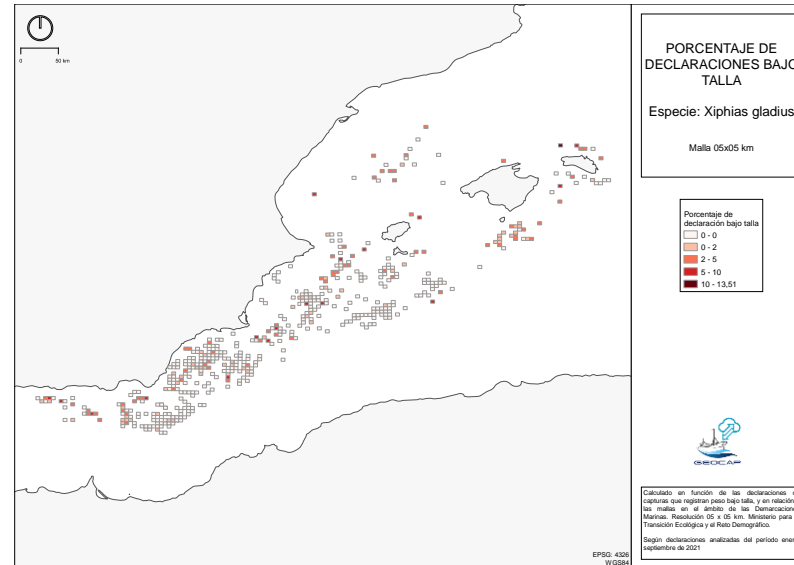
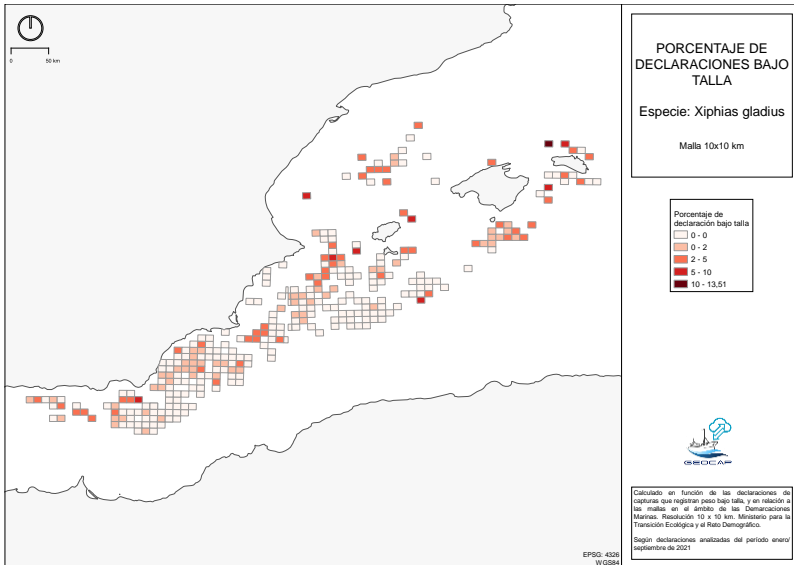
WHAT ARE DOING WITH THE FISHING/TOTAL CATCH DATA? – OUR PROPOSAL



6. CONCLUSIONS AND ON-GOING/FUTURE WORK



6. CONCLUSIONS AND ON-GOING/FUTURE WORK



Dates: 1/1/2021-17/11/2021

Species: SWO

Percentage under MCRS

Grid: 5km x 5km

1ST INTERNATIONAL SYMPOSIUM ON CATCH IDENTIFICATION TECHNOLOGIES

Bergen (Norway) - November, 1st-3rd



THANK YOU VERY MUCH FOR YOUR ATTENTION

This work has been carried out in part within the framework of the Agreement between the Ministry of Agriculture, Fisheries and Food and the State Agency Spanish Council for Scientific Research (IEO-CSIC), to promote fisheries research as a basis for sustainable fisheries management.



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#PlanDeRecuperacion
#NextGenerationEU



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