NOVEMBER 6, 2026

METHODS FOR THE JOINT ANALYSIS OF SPECIES PRESENCE, FROM PASSIVE ACOUSTIC MONITORING, AND THEIR ENVIRONMENT

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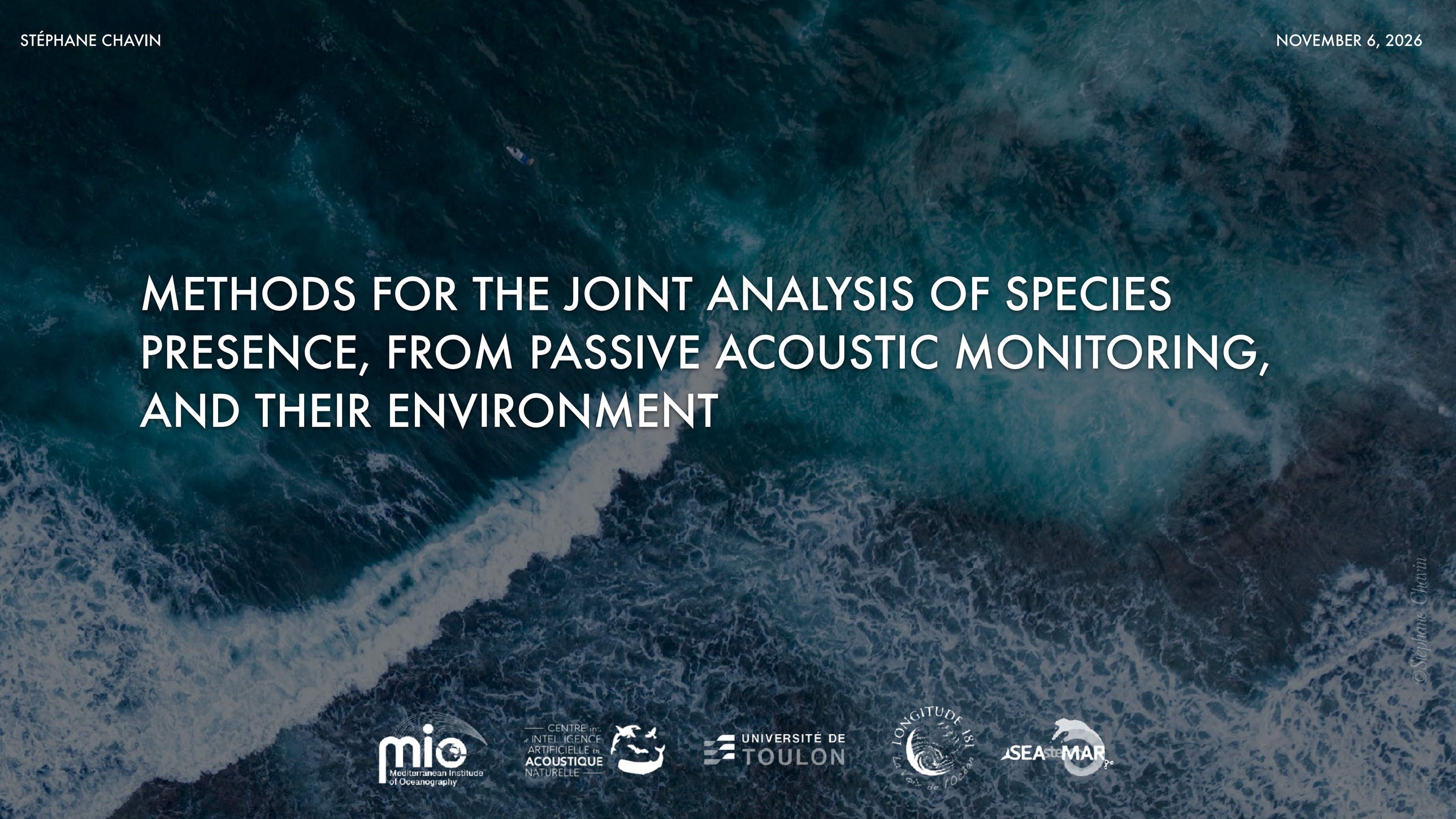
Presented by Stéphane Chavin



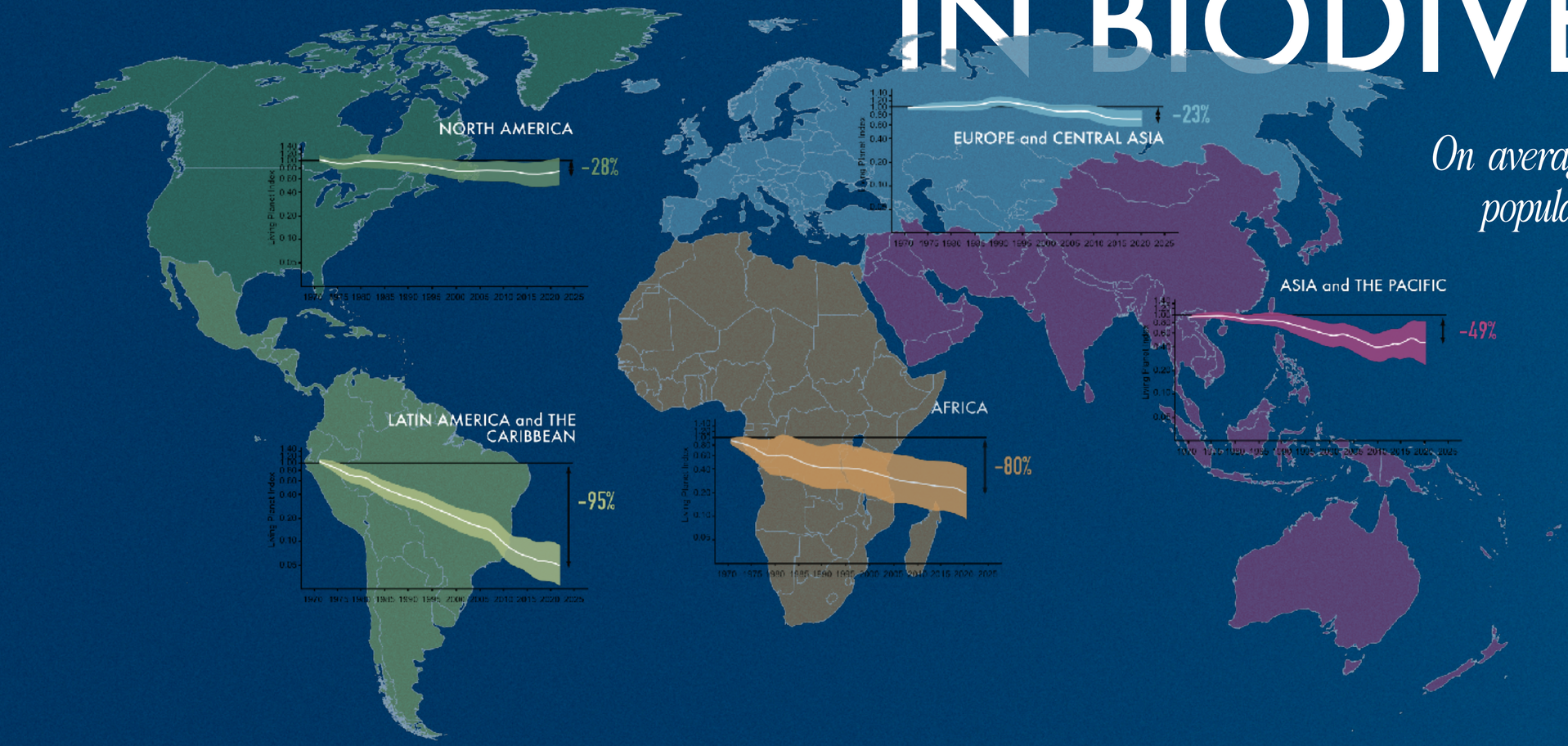
STÉPHANE CHAVIN

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A GLOBAL DECREASE IN BIODIVERSITY



On average, the size of the monitored population has decreased by 73% over the past 50 years

85 % for freshwater ecosystem, 69% for terrestrial and 56% in marine populations

- *Changes in land use* — *e.g. deforestation, converting wild lands for agriculture = fragment or destroy natural habitat*
- *Overexploitation* — *e.g. overfishing, overhunting = impact species faster than they can reproduce*
- *Climate change* — *e.g. changing seasonal patterns, rising temperature = too fast for the species to adapt*
- *Pollutions* — *e.g. plastics, chemicals, fertilizers = destroy habitat and can be a poison for species*

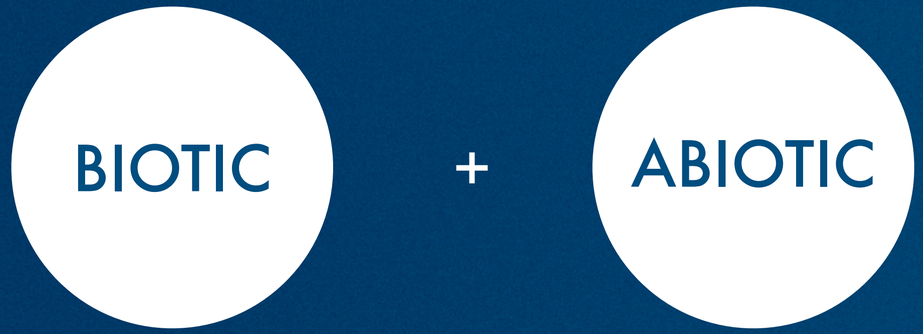
WHAT CAN SCIENCE DO ?

- *Monitoring*
  e.g. eDNA, remote sensing, bioacoustics
- *Conservation strategies*
  e.g. habitat restoration, new protected areas
- *Systemic policy changes*
  e.g. nature driven governance



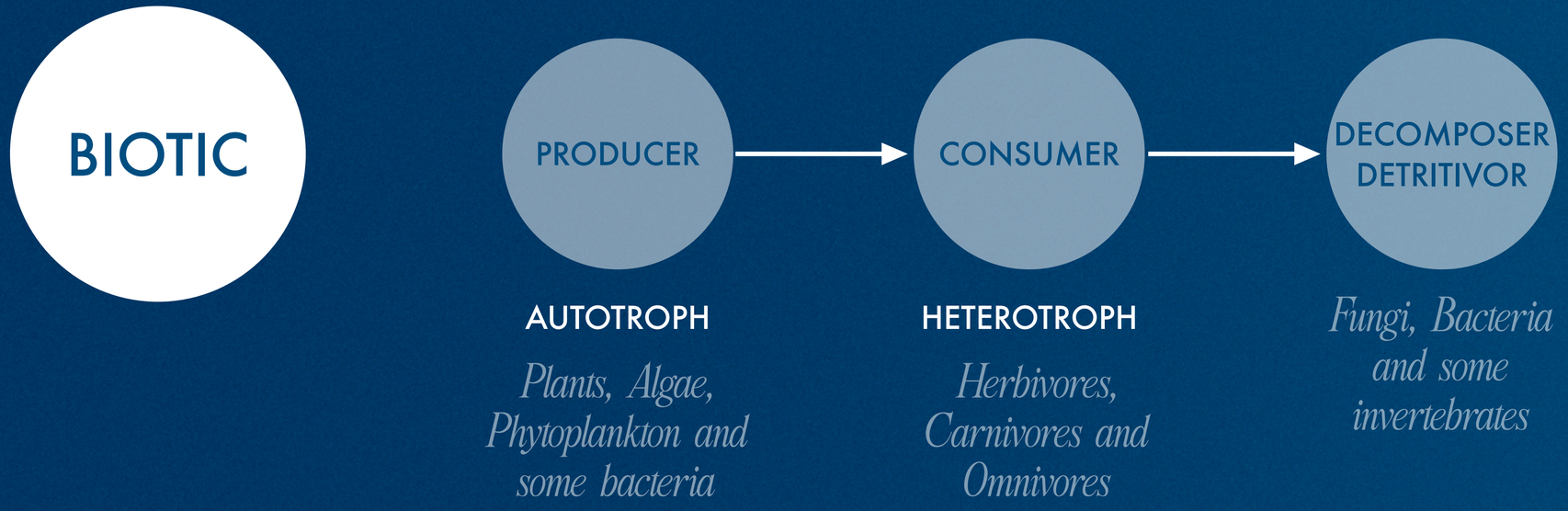
©Stéphane Chauvin

THE ENVIRONMENT



THE ENVIRONMENT

- *biotic component*

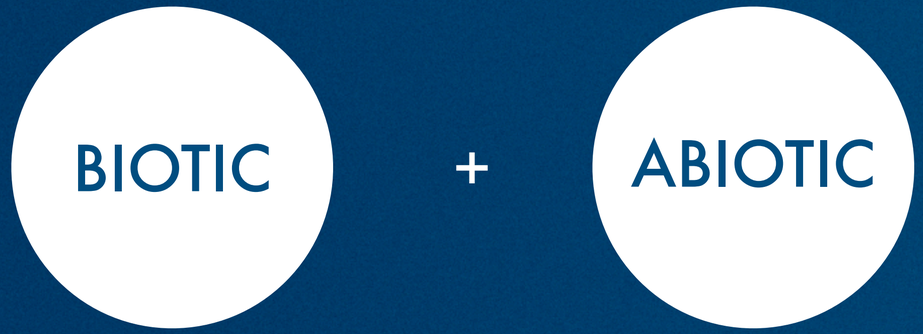


THE ENVIRONMENT

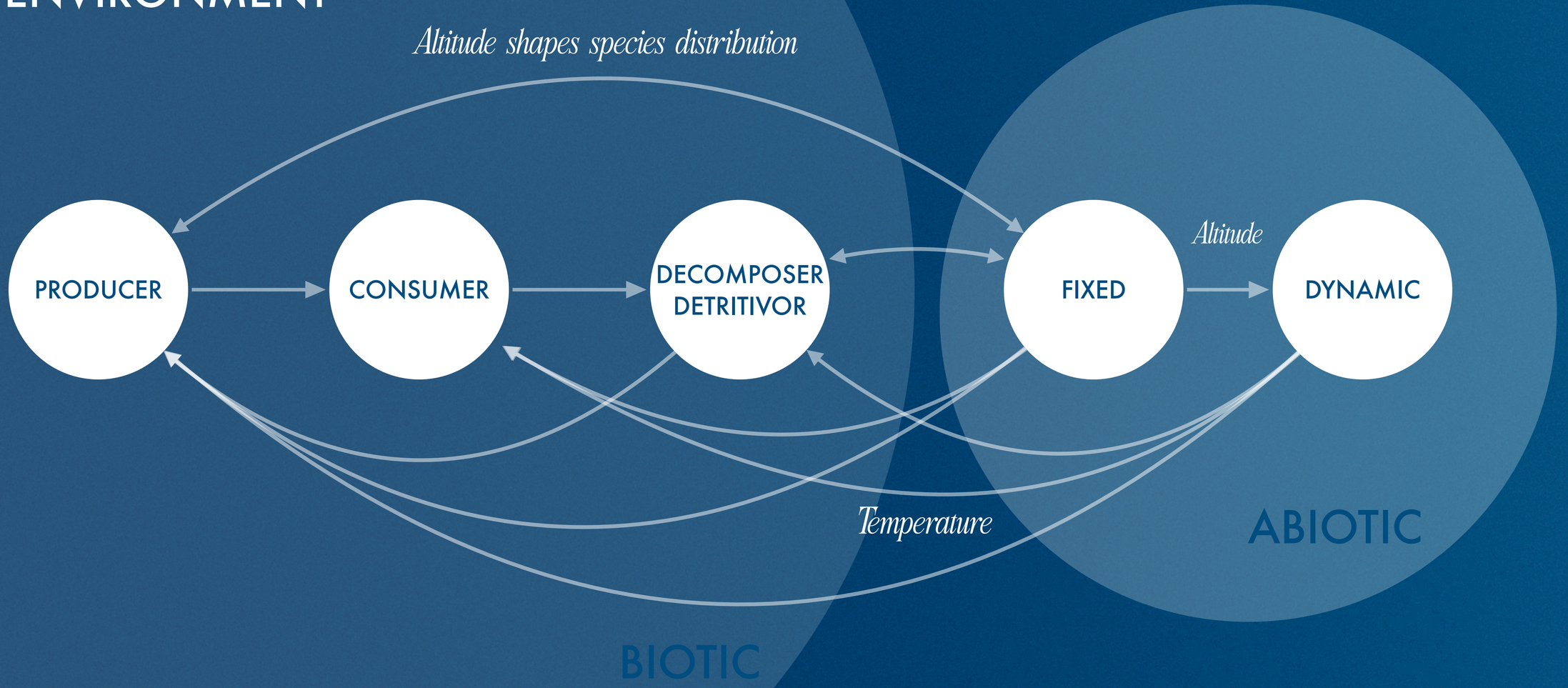
- *abiotic component*

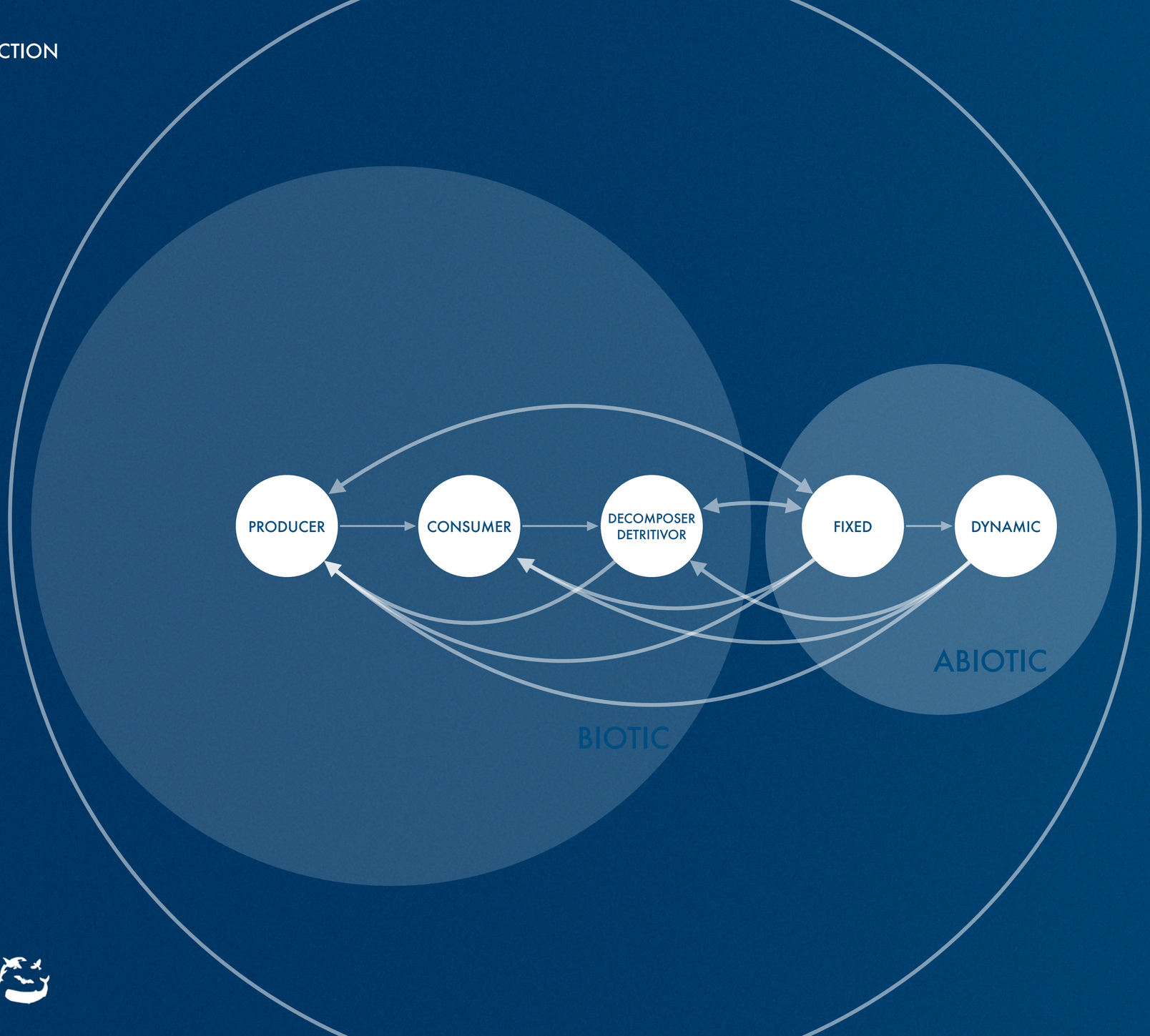


THE ENVIRONMENT



THE ENVIRONMENT





= AN ECOYSTSEM

The interactions between living beings and their environments = interdependence of each one

→ *Influence*

WHAT DO WE HAVE TO DO ?

HOW ?

- *Monitoring*
  e.g. eDNA, remote sensing, bioacoustics

→ Collecting data on field, searching for elusive or new species

- *Conservation strategies*
  e.g. habitat restoration, new protected areas

→ Identifying habitat and species preferences

- *Systemic policy changes*
  e.g. nature driven governance

→ Identifying the risks and presenting results with solutions

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HUMPBACK WHALE

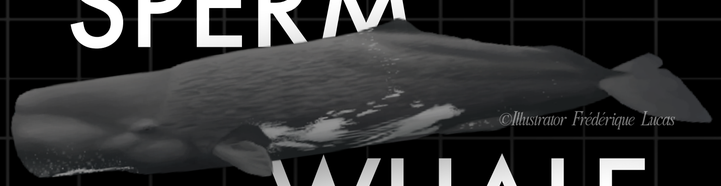


METHODS FOR THE JOINT ANALYSIS OF SPECIES PRESENCE, FROM PASSIVE ACOUSTIC MONITORING, AND THEIR ENVIRONMENT

HUMPBACK WHALE



SPERM WHALE



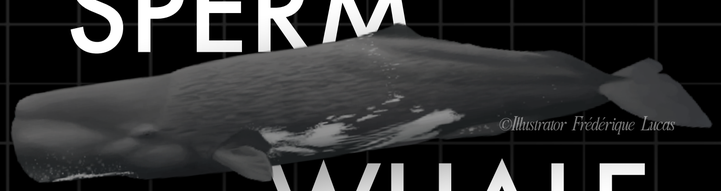
CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

METHODS FOR THE JOINT ANALYSIS OF SPECIES PRESENCE, FROM PASSIVE ACOUSTIC MONITORING, AND THEIR ENVIRONMENT

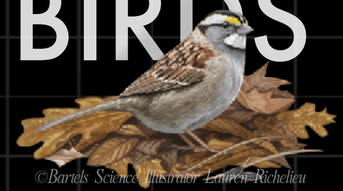
HUMPBACK WHALE



SPERM WHALE



BIRDS



CENTRE interdisciplinaire d'INTELLIGENCE ARTIFICIELLE en ACOUSTIQUE NATURELLE

- *some context about*

HUMPBACK WHALE

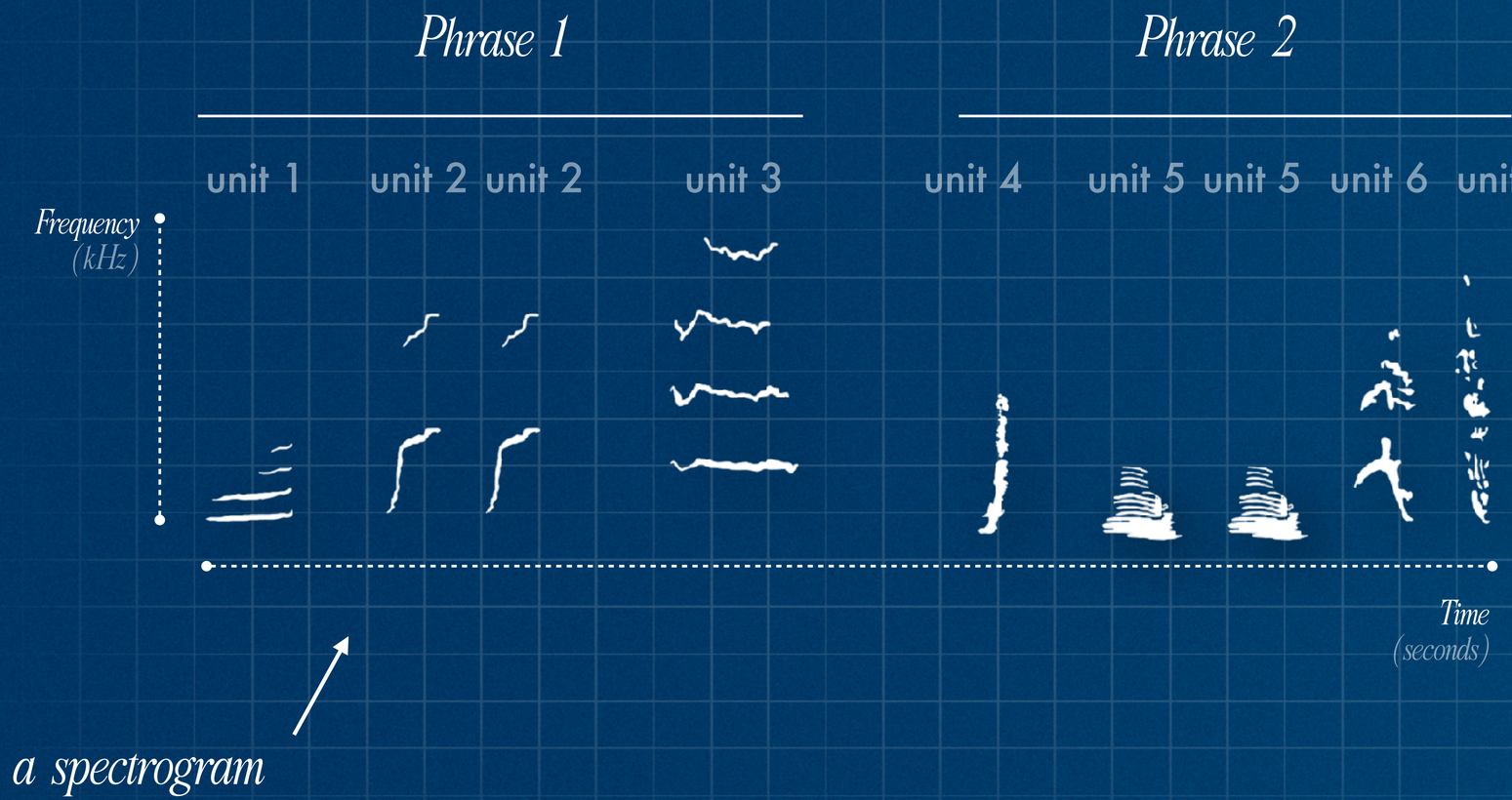
Megaptera novaeangliae



©Illustrator Frédérique Lucas

- *Use sound for communication and as display of competitive fitness during breeding season*
- *Mature male produces complex and organised sequences of vocalisations called song* [3]
- *Migrates from poles (feeding area) to the tropics (breeding area) to breeding*

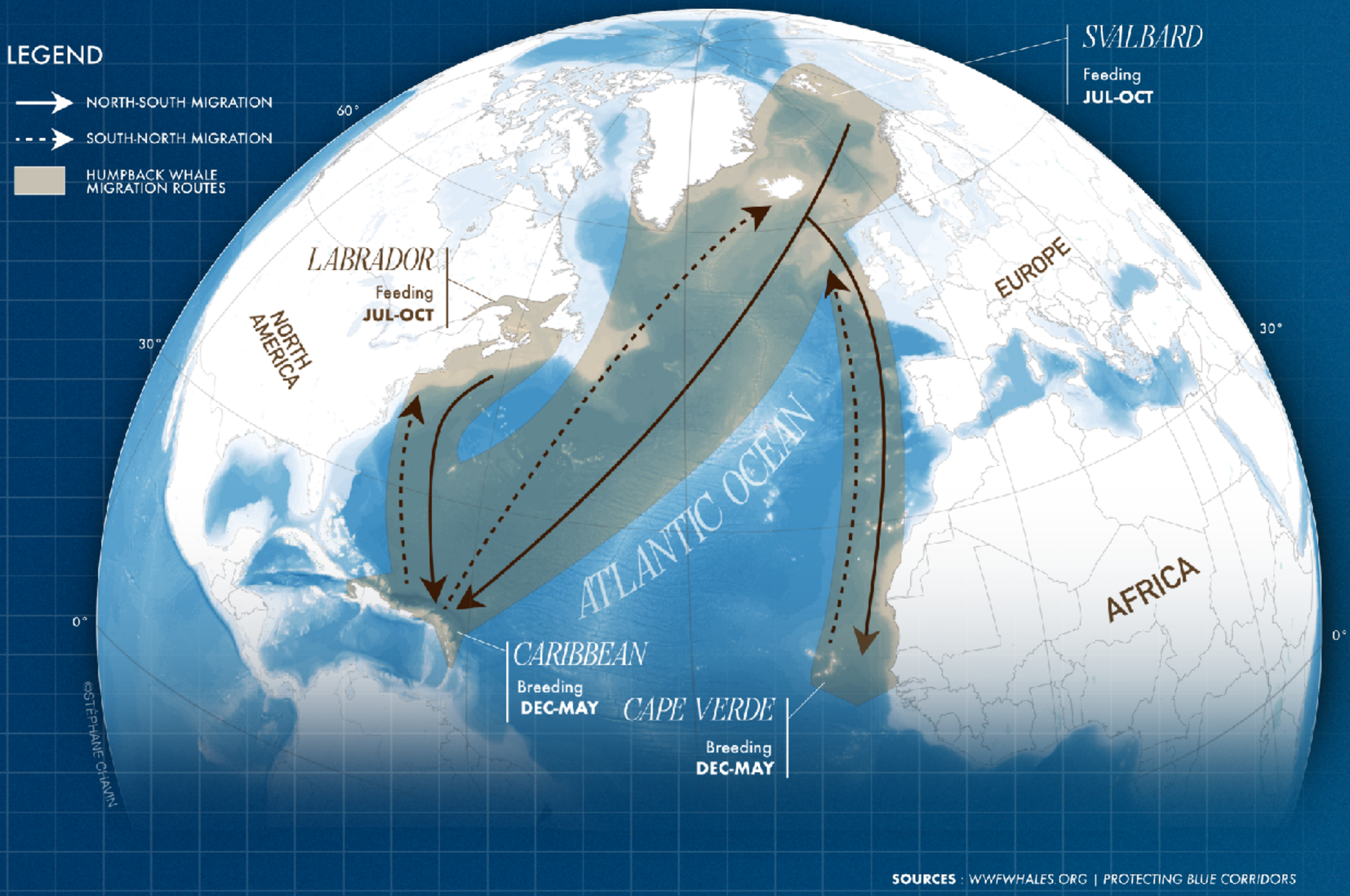
HUMPBACK WHALE SONG [3]



a spectrogram

- **Unit** : *usually less than 3 seconds*
- **Phrase** : *composed of 3 to 6 units*
- **Theme** : *multiple phrases*
- **Song** : *succession of themes (30 minutes)*

North Atlantic population : Migrates to the Caribbean or Cape Verde from December until May.

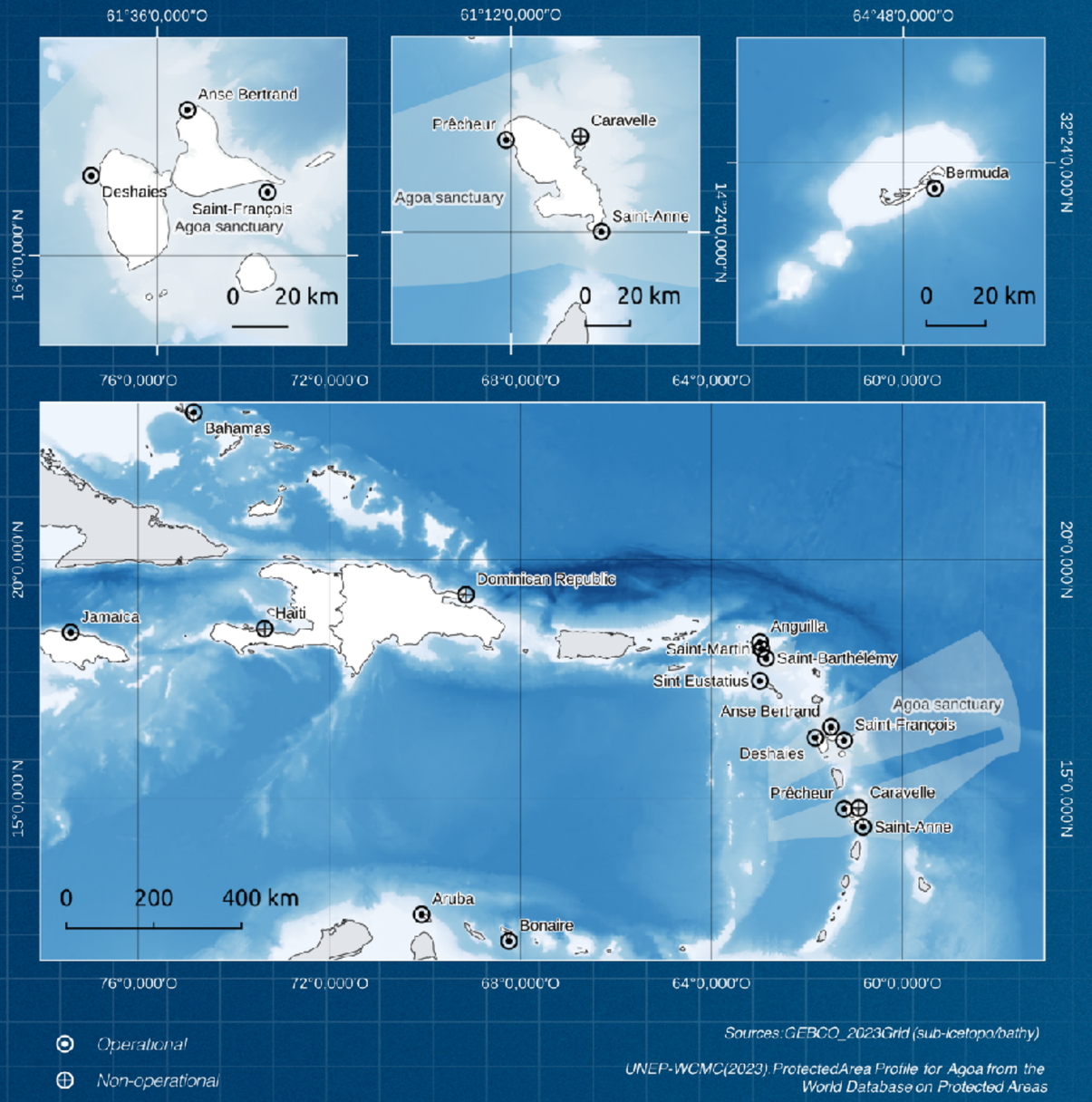


Migration routes of the North Atlantic population

- *Between December 2020 and the end of 2022, 17 Autonomous Recording Units (ARUs) placed across the Caribbean*

= *Passive Acoustic Monitoring (PAM)*

- *~20m depth, it records 1 minute every 6 minutes (duty cycle : 1 ON/5 OFF)*
- *~ 10 000 hours of recordings*



Interreg Caraïbes
Fonds européen de développement régional

CARI'MAM

CENTRE int. d'INTELLIGENCE ARTIFICIELLE en ACOUSTIQUE NATURELLE

D H G D



HUMPBACK WHALE SONG, *Guadeloupe*

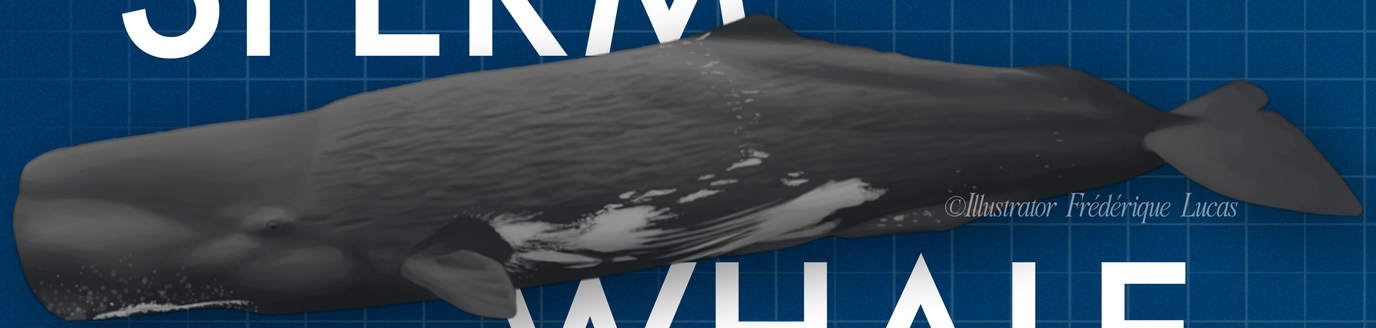
CENTRE INT. D'INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

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- *some context about*

SPERM WHALE

Physeter macrocephalus



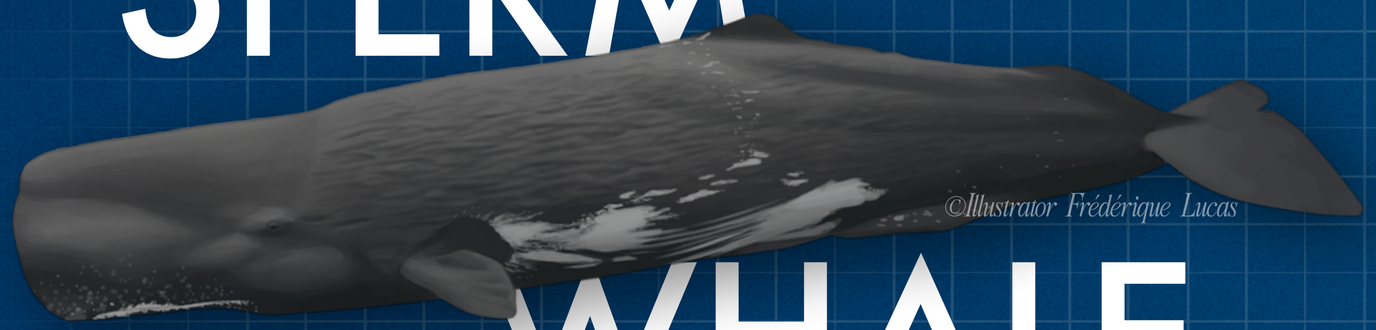
©Illustrator Frédérique Lucas

- *Produces various sound, for different purposes : echolocation clicks, codas, creak...*
- *Population in the Mediterranean Sea*

- *some context about*

SPERM WHALE

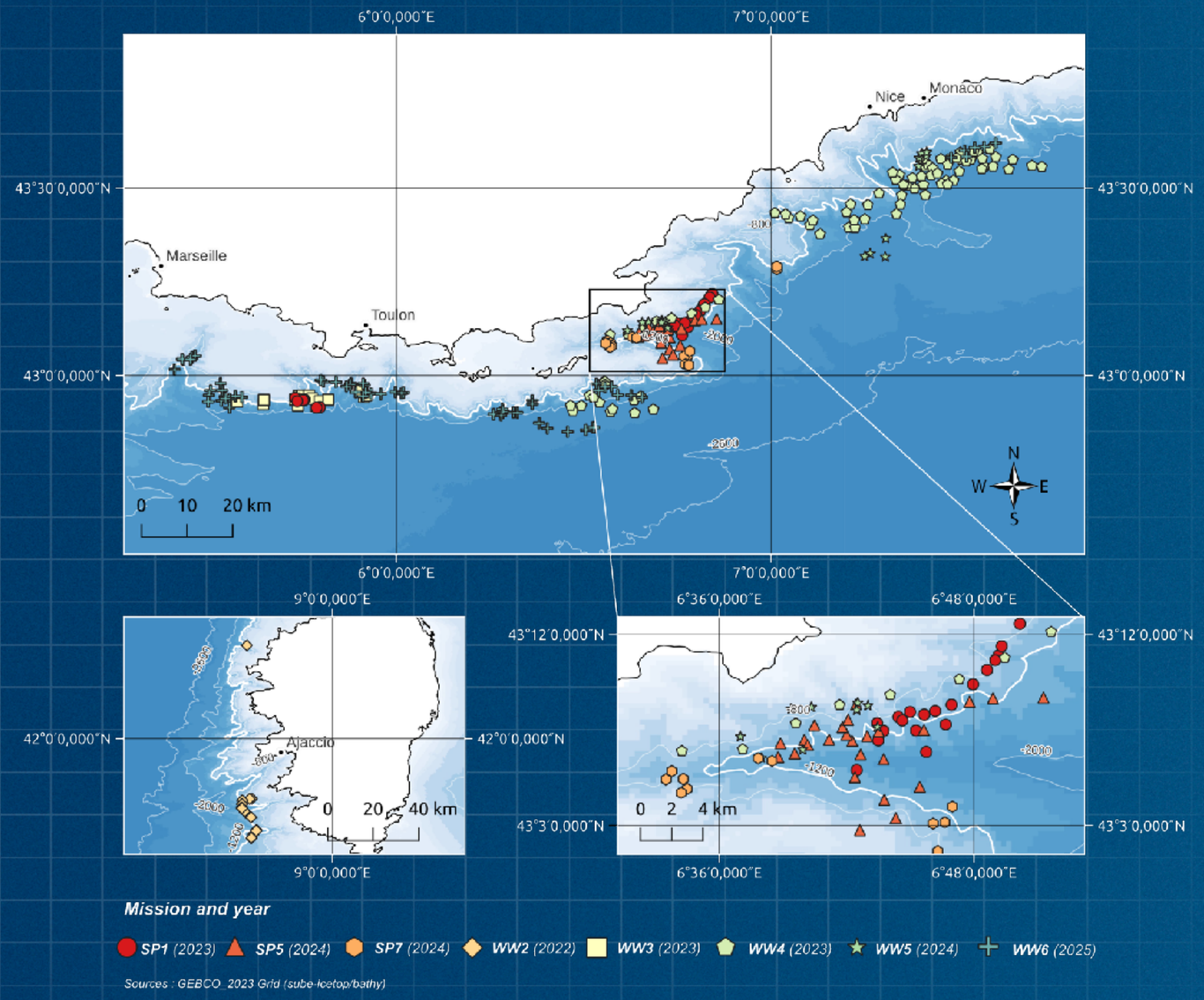
Physeter macrocephalus



©Illustrator Frédérique Lucas

- *Produces various sound, for different purposes : echolocation clicks, codas, creak...*
- *Population in the Mediterranean Sea*
  ~ 20 km from here (University of Toulon)

- *Protocol : Searching for sperm whale using acoustic; Photographing the fluke; Recording multiple dives with underwater acoustic array*
- *232 dives between 2022 and 2025 from 8 missions*
- *Almost all the observations are between Marseille and Monaco*



- *some context about*

BIRDS



©Bartels Science Illustrator Lauren Richelieu

- *Uses sound for different purpose : during breeding season or to defend a territory (e.g. : song), communication (e.g. : call)* [5]

species can :

  - *be residents*
  - *do short-distance migration*
  - *do long distance migration*
  - *...*

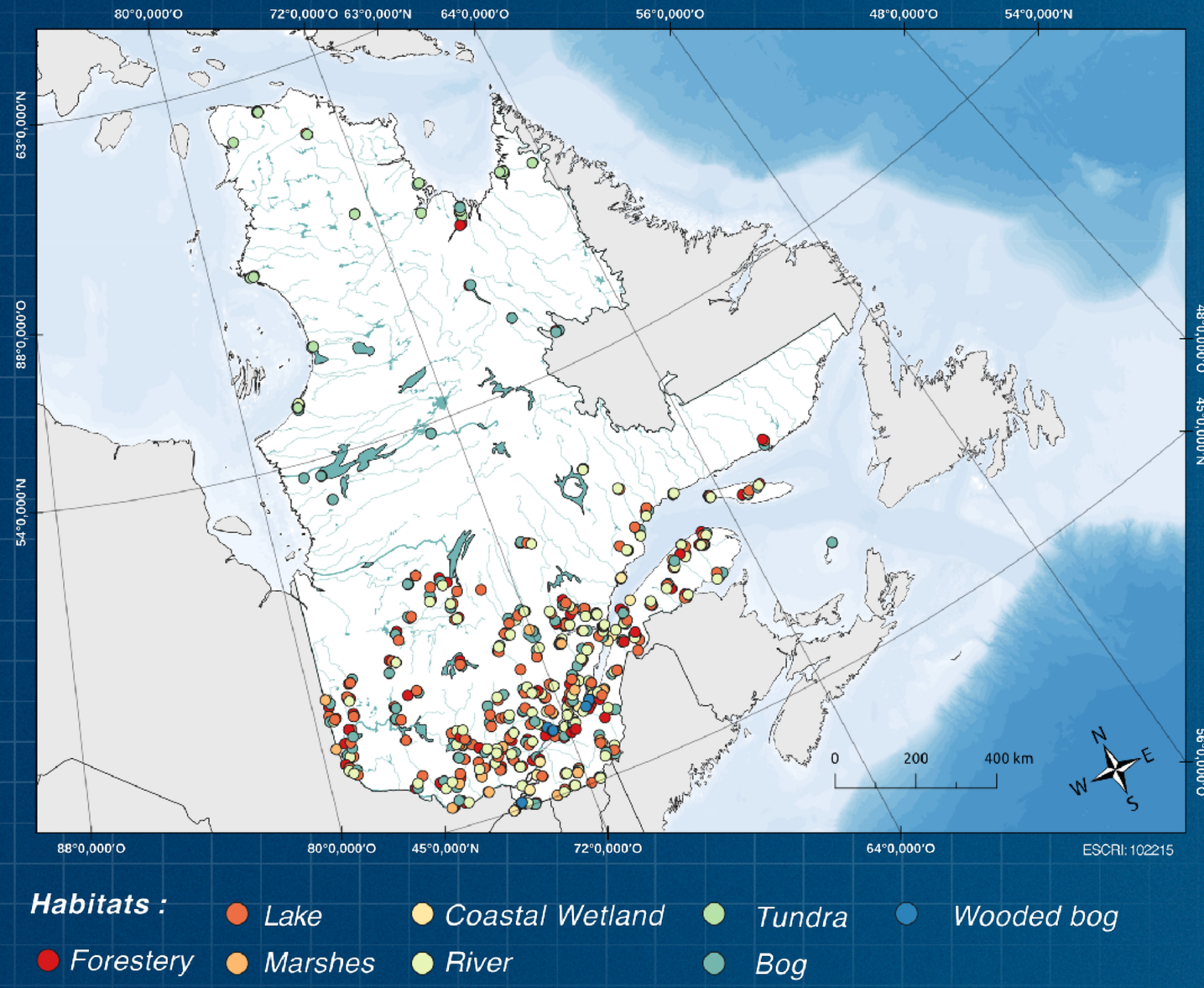
- *Migrations are induced by endogenous annual rhythm linked to the photoperiod and other parameters* [6]

Spring migration generally occurs between March and June going through different flyway



Map of the different flyways of birds in the Northern America continent [7]

- *Started in 2016 until now*
- *Over 200 different ARUs in various habitats*
- *Between 15-minutes and 1-hour recordings at specific time of the day*



Environnement, Lutte contre les changements climatiques, Faunes et Parcs
Québec

CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE



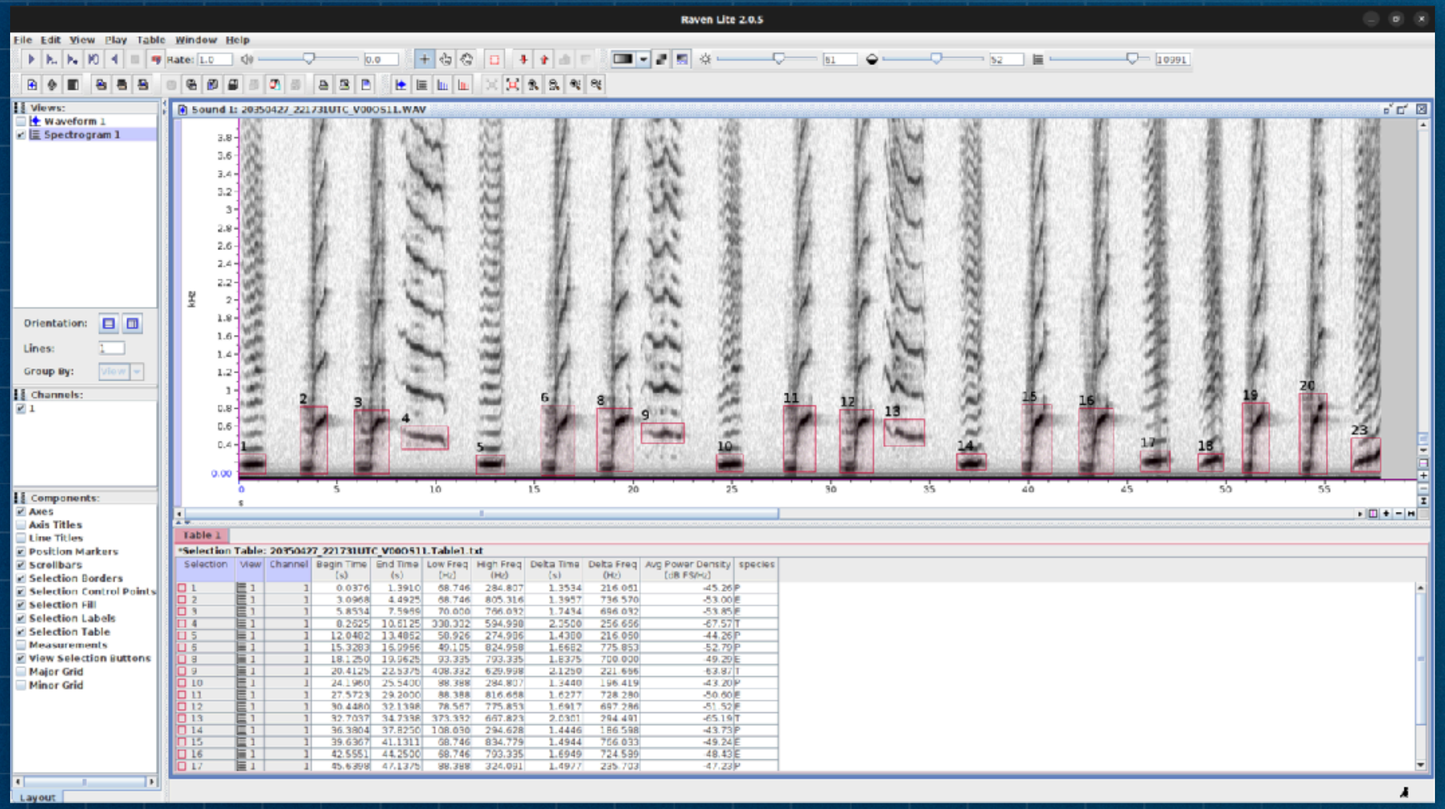
BIRD CHORUS

©Stephane Chauvin, Indonesia

CENTRE INT. D'INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

HOW CAN WE DETECT SPECIES IN A RECORDING ?

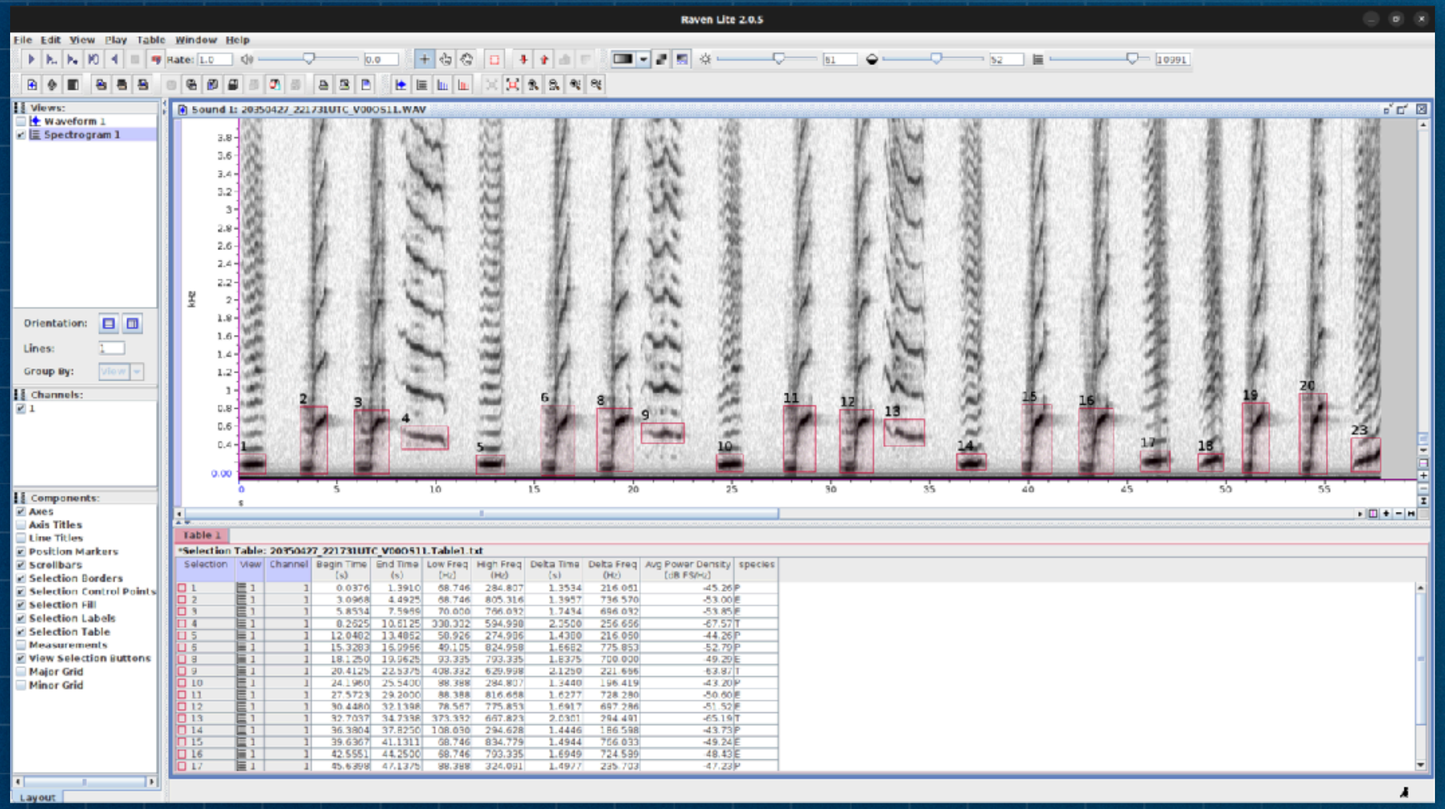
- *manually analysed by experts*



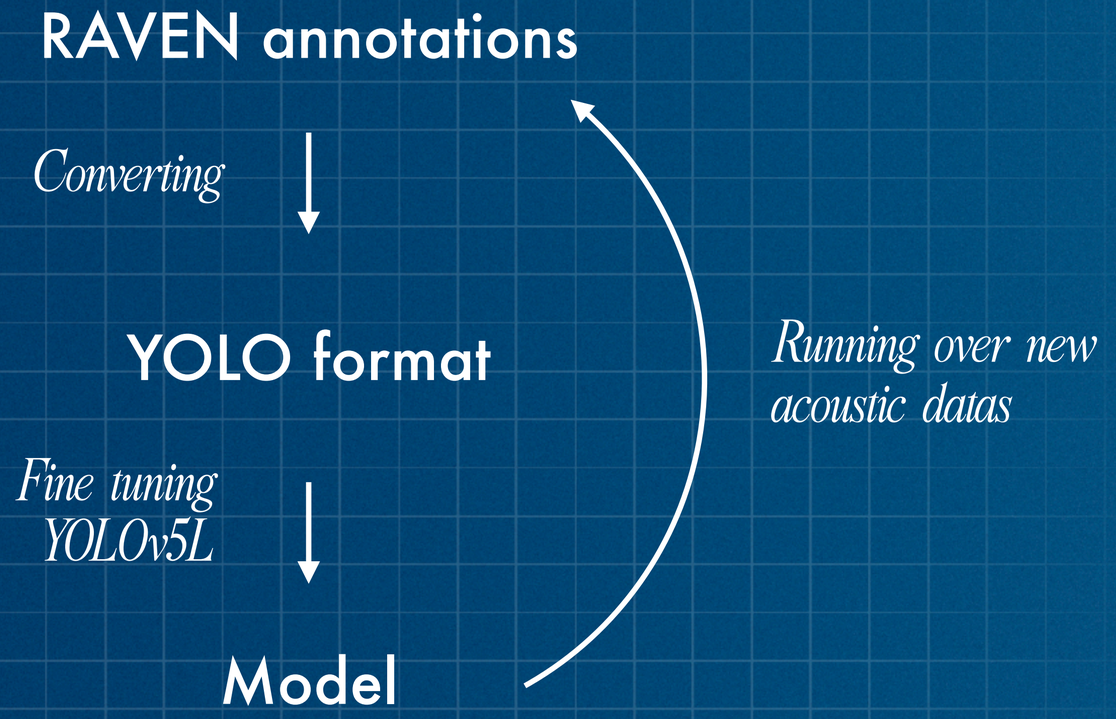
Raven annotation software

- *manually analysed by experts*

Québec = 341 000 files which would take approximately 20 years to listen entirely 24/7



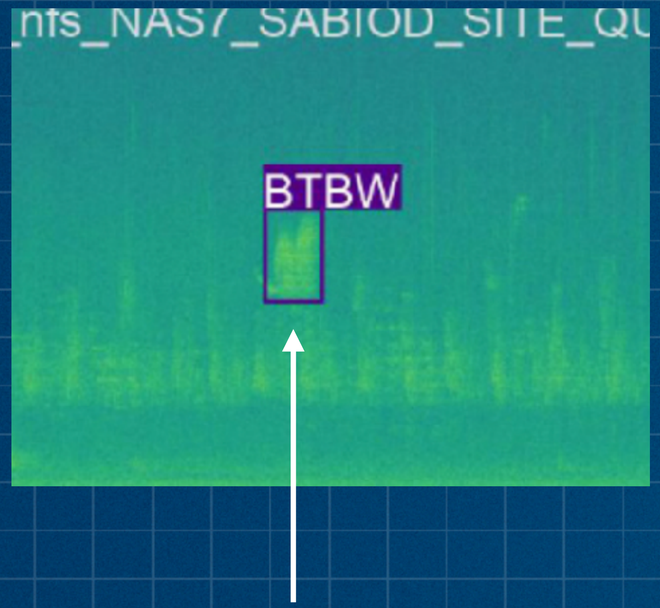
- *A full pipeline to adapt Raven or LabelMe annotations into a format to train a YOLO model* [8]
- *YOLO (You Only Look Once) is a deep learning model that is used for object detection and requires boxed annotations*



- *A full pipeline to adapt Raven or LabelMe annotations into a format to train a YOLO model* [8]
- *YOLO (You Only Look Once) is a deep learning model that is used for object detection and requires boxed annotations*

Ground Truth

15-seconds spectrogram

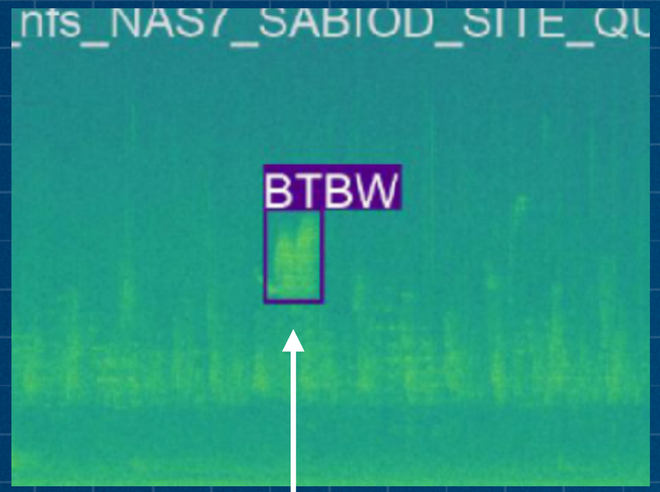


Black-throated blue warbler

- *A full pipeline to adapt Raven or LabelMe annotations into a format to train a YOLO model* [8]
- *YOLO (You Only Look Once) is a deep learning model that is used for object detection and requires boxed annotations*

Ground Truth

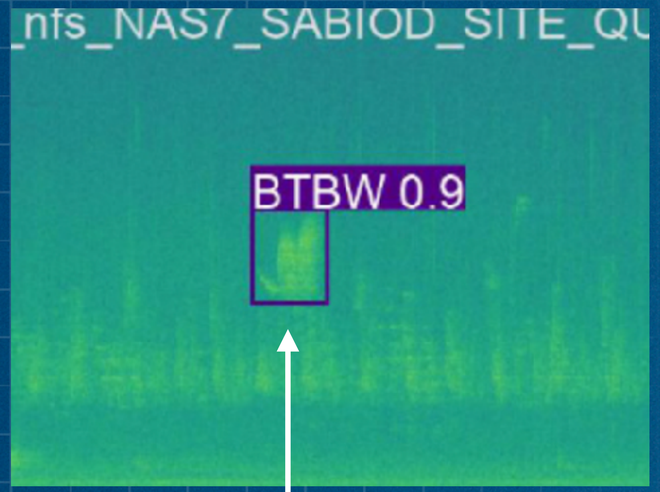
15-seconds spectrogram



Black-throated blue warbler

Model's prediction

15-seconds spectrogram

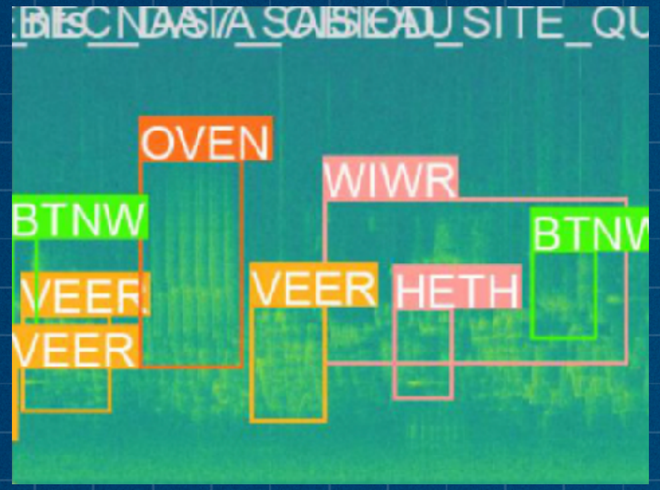


Black-throated blue warbler with 90% confidence

- *A full pipeline to adapt Raven or LabelMe annotations into a format to train a YOLO model* [8]
- *YOLO (You Only Look Once) is a deep learning model that is used for object detection and requires boxed annotations*

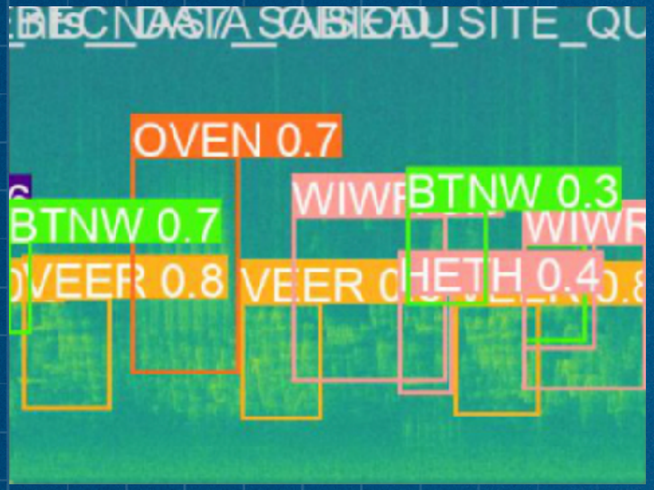
Ground Truth

15-seconds spectrogram



Model's prediction

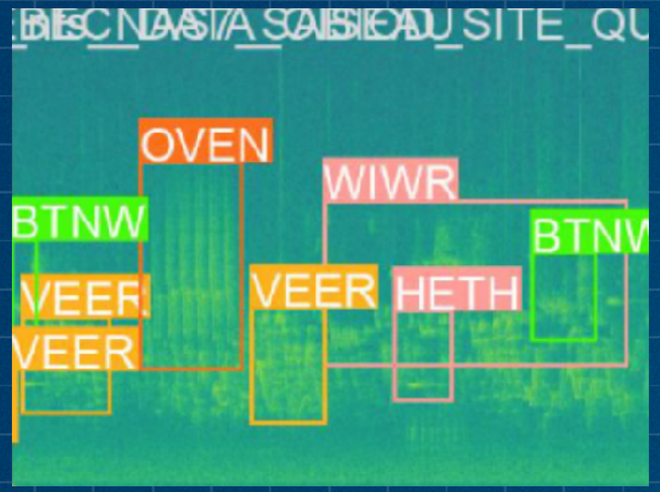
15-seconds spectrogram



- *A full pipeline to adapt Raven or LabelMe annotations into a format to train a YOLO model* [8]
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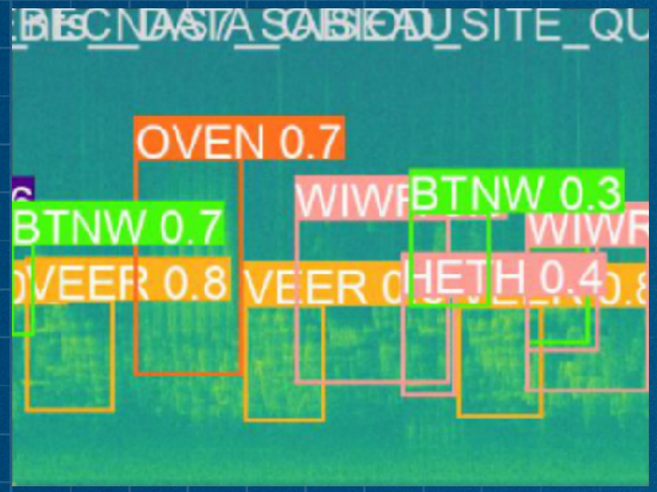
Ground Truth

15-seconds spectrogram



Model's prediction

15-seconds spectrogram



= Québec dataset's can be analysed in 45 days

1. LABELS

- *23 units for humpback whale*
- *27 bird species*

2. ANNOTATION

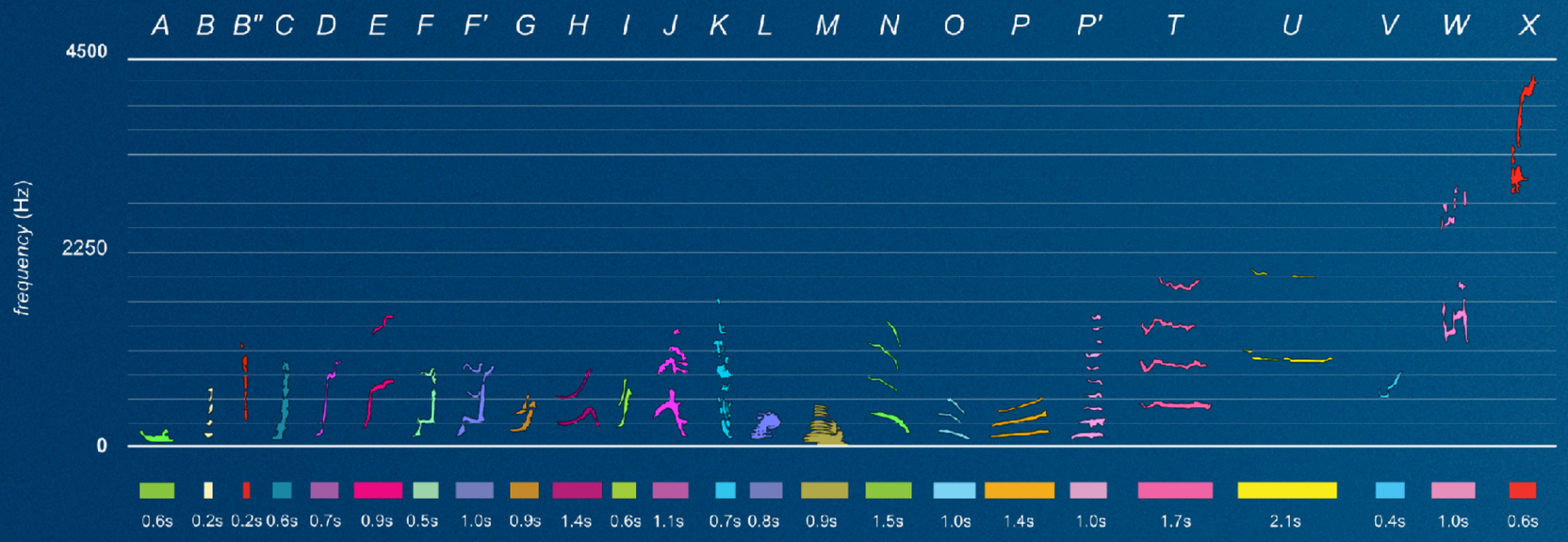
- *Raven bounding boxes*

3. ACTIVE LEARNING LOOPS

- *Increase the training set with more and various examples*

4. EVALUATION

- *Evaluate the model using different metrics and compare to other architectures*



Vocal repertoire of the Humpback whale North Atlantic population between 2020 and 2022

MODELS EVALUATION

$$mAP = \frac{1}{N} \sum_{i=1}^{n} AP_i$$

$$AP = \sum_{i=1}^{n-1} (r_{i+1} - r_i) \times p_{interp}(r_{i+1})$$

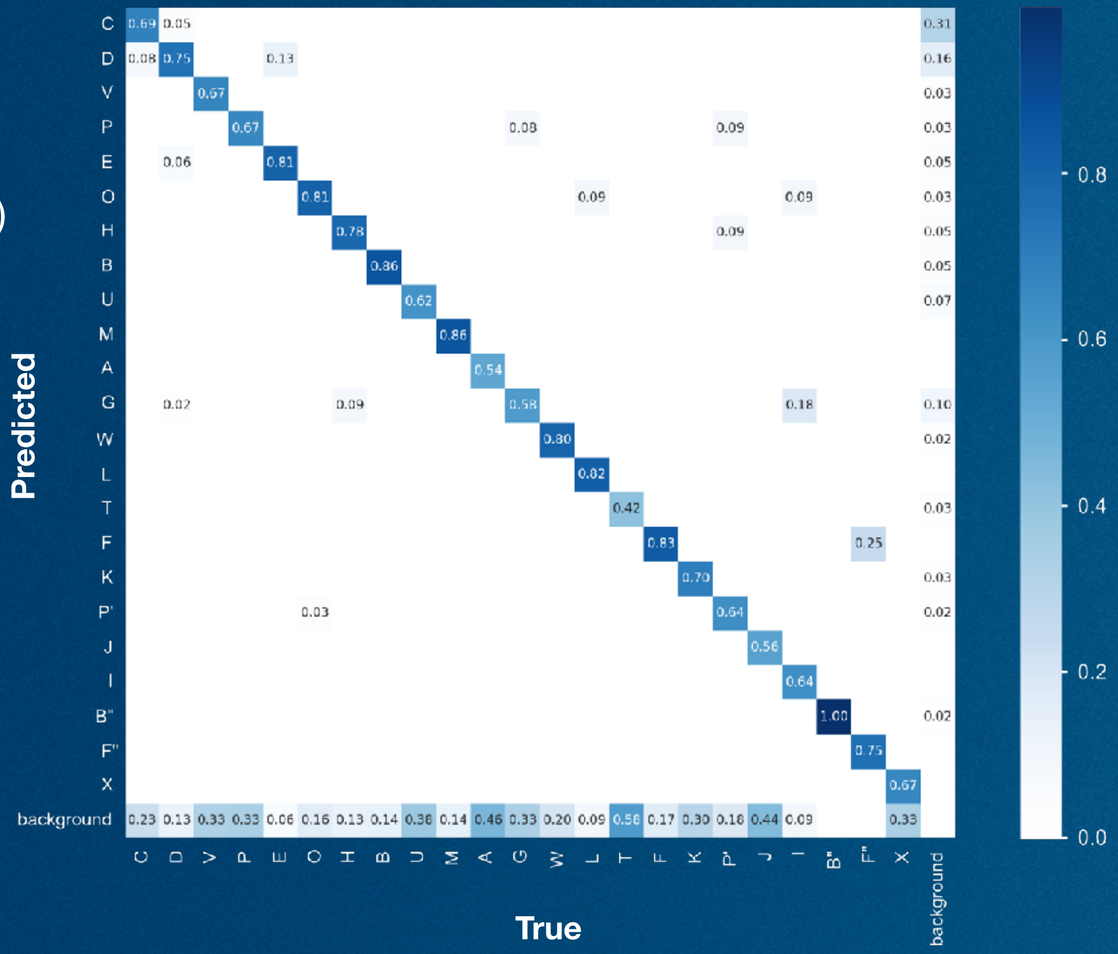
Humpback whale model :

- *mAP@50 of 74% for 23 units*
- *Low confusion between units*

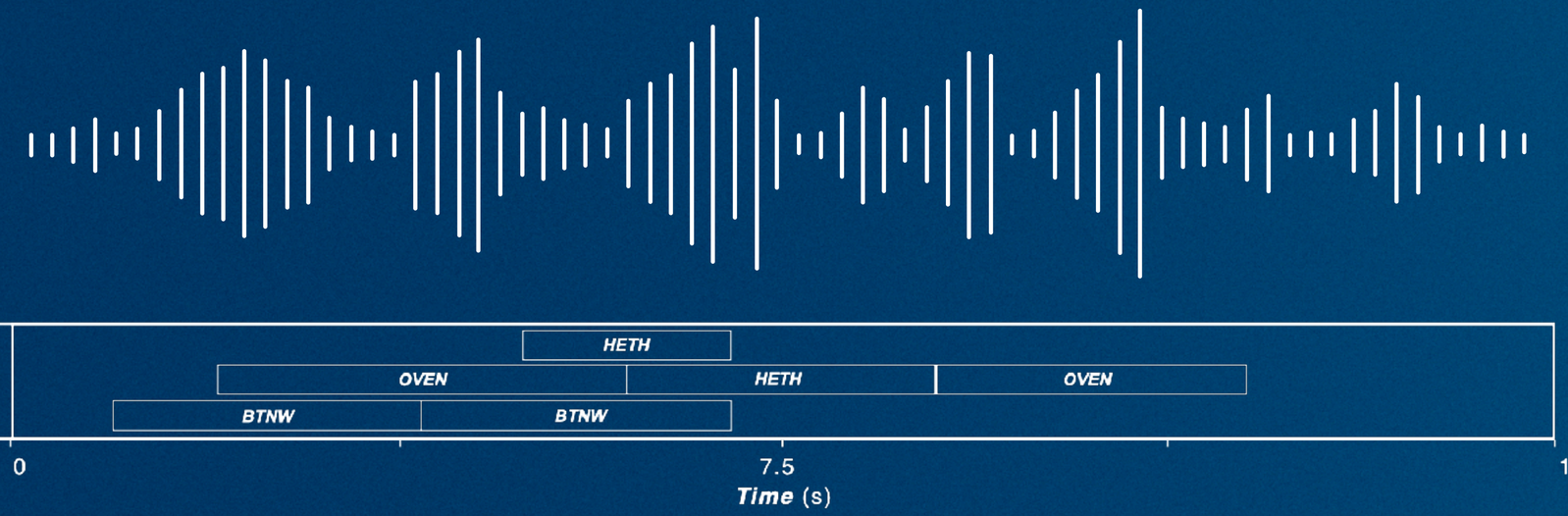
Bird model :

- *mAP@50 of 82% for 27 species*
- *Better scores than BirdNET, even in high chorus scenarios*

Humpback whale confusion matrix



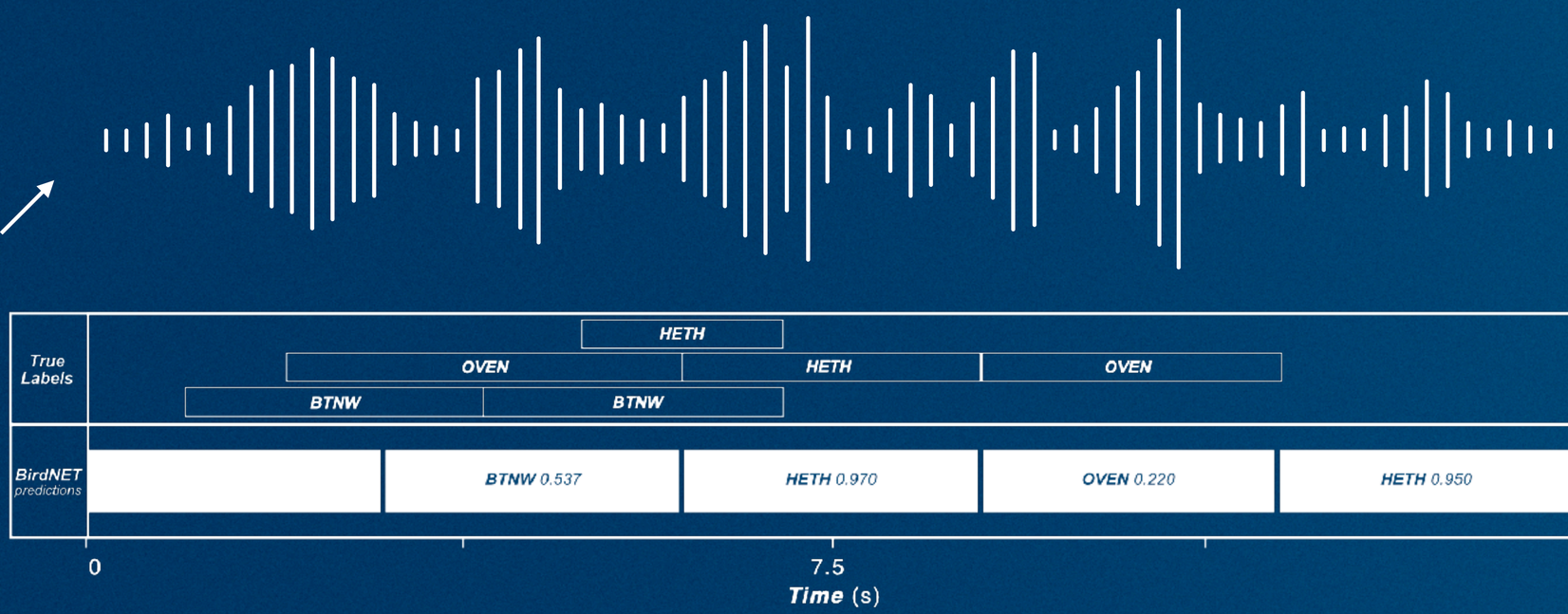
15 seconds audio signal



TRUE LABELS / EXPERTS

Start time, end time and species
Highly precise, but time consuming

15 seconds audio signal



TRUE LABELS / EXPERTS

Start time, end time and species
Highly precise, but time consuming

BirdNET [9]

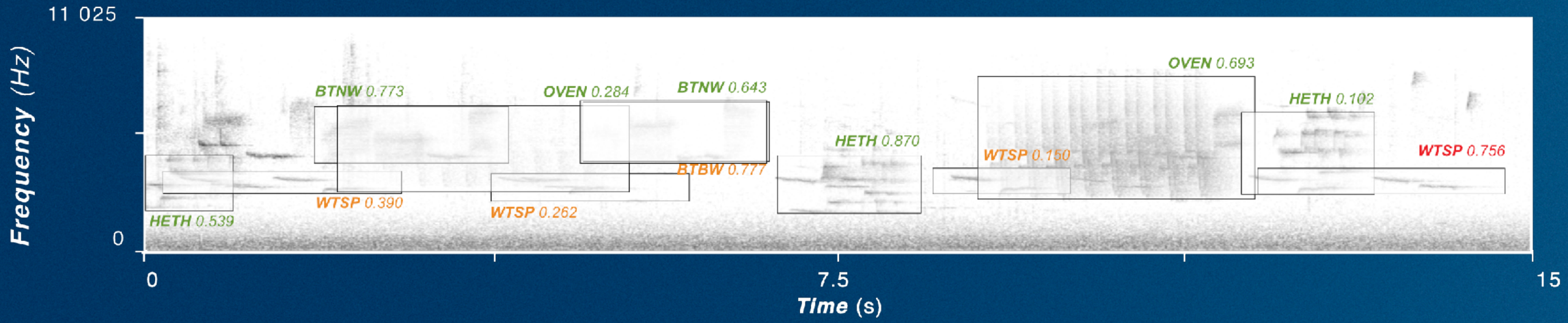
Confidence every 3 seconds associated to each species (over 6000 species)
Fast but less informations and less precision

OUR MODEL [10]

Correct prediction

Correctly removed due to low confidence

Error with high confidence



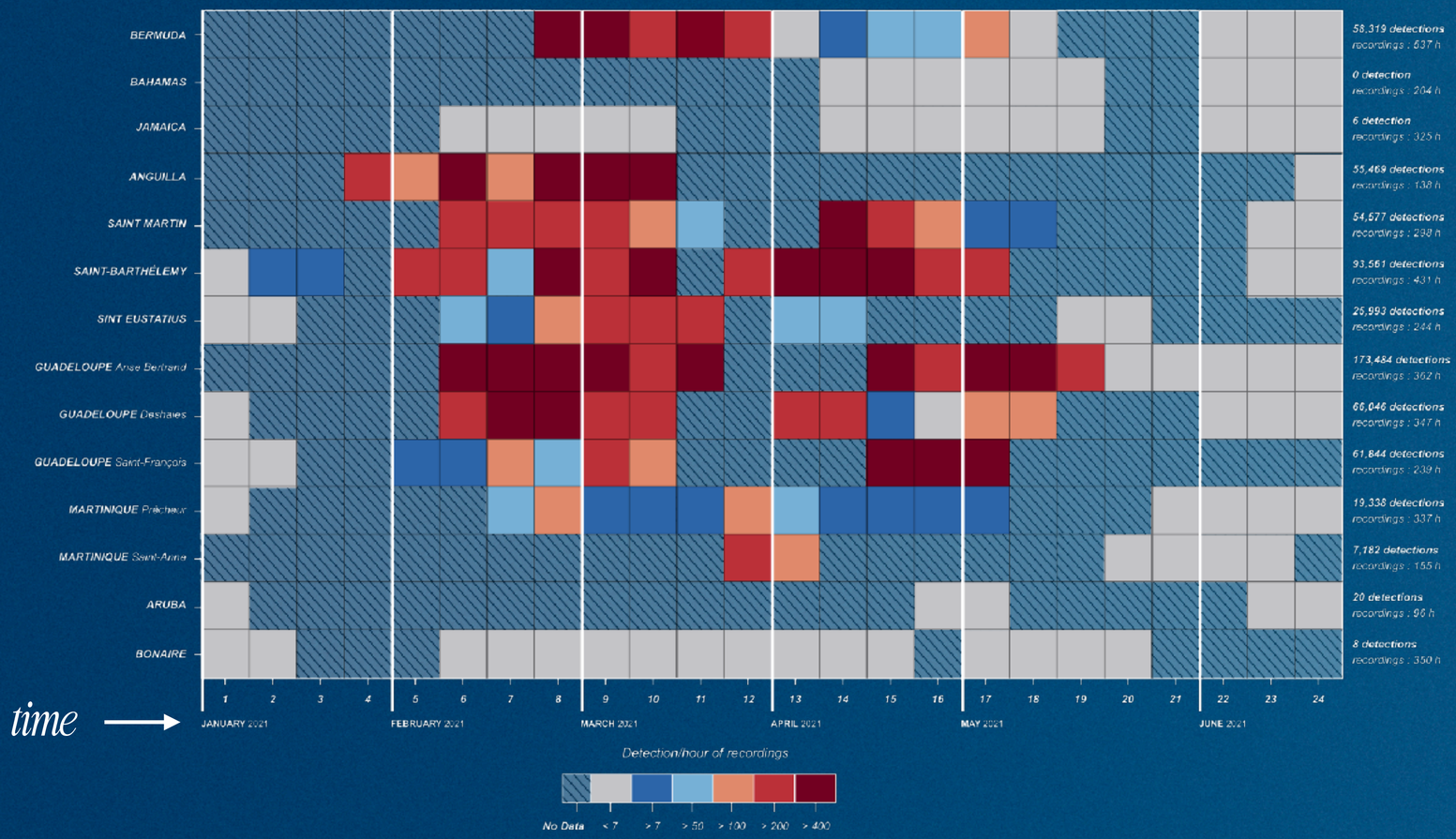
Begin Time (s)	End Time (s)	Duration (s)	Minimum Frequency (Hz)	Maximum Frequency (Hz)	Confidence	Species
0.00	0.96	0.96	1929	4524	0.539	**HETH** (Hermit trush)
0.21	2.79	2.58	2779	3812	0.390	**WTSP** (White-throated sparrow)
1.82	3.93	2.11	4203	6844	0.773	**BTNW** (Black-throated Green Warbler)
2.08	5.22	3.14	2871	6890	0.284	**WTSP** (White-throated sparrow)
...						

Recording location

+ *300 000 detections between 2021 and 2022 in 14 stations* [11]

FINDINGS :

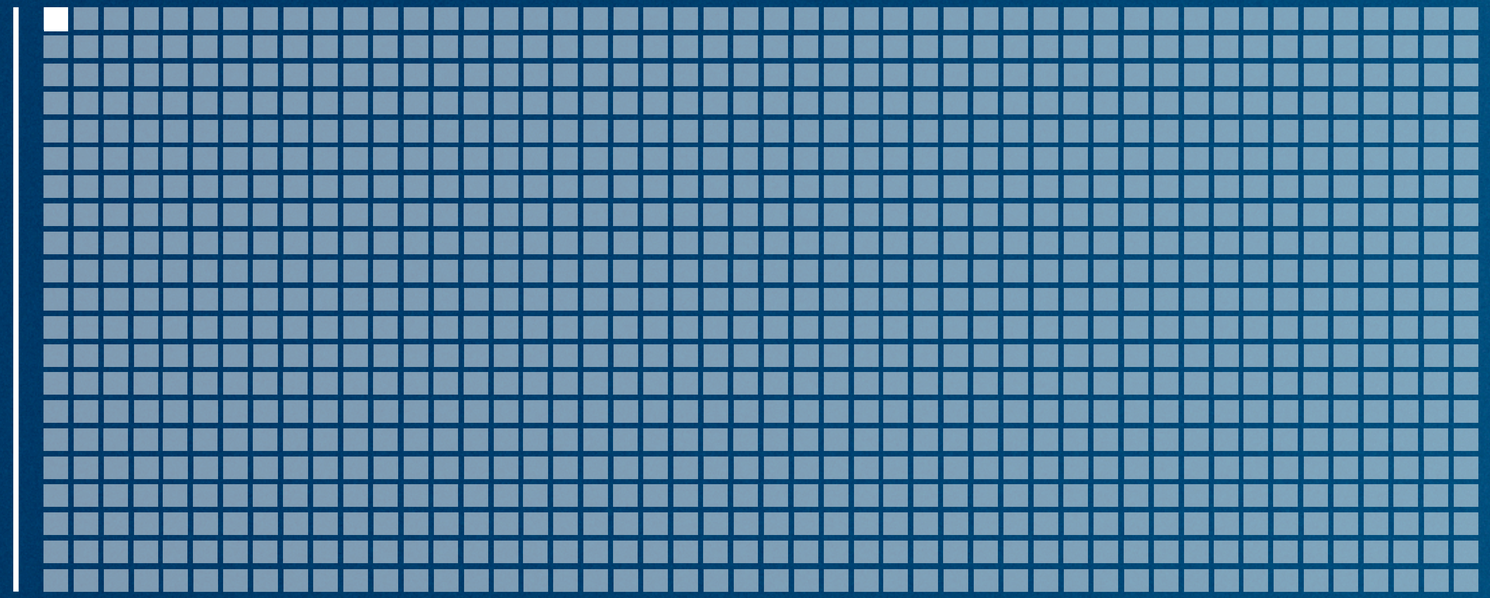
- *Verified the seasonal migration period*



- *29 795 annotations (22.5 hours of recordings)*
- *~22 million detections from 2016 to 2025 in 16 different regions of Québec*

29 795 annotations → ■

~22 million detections



HOW TO ANALYSE THESE RESULTS TO UNDERSTAND SPECIES PREFERENCES ?

(How to map species distribution ?)

SPECIES DISTRIBUTION MODELING (SDM)

MAXENT MODELS [12]

- *Presence only models*
- *Generate background points*
- *Use averaged environmental layers*

↓

SPERM WHALE

GENERALISED ADDITIVE MODELS (GAM) [13]

- *Presence-absence models*
- *Can take the environmental layers for each of the observation periods*

↓

HUMPBACK WHALE & BIRDS

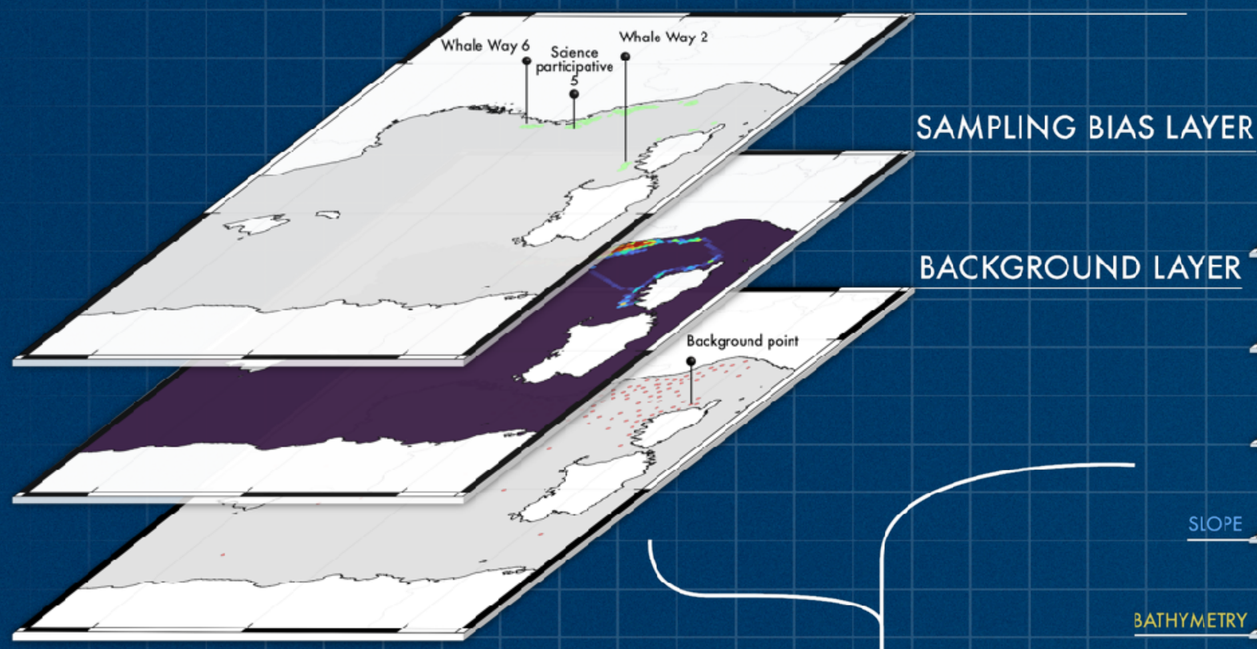
MAXENT MODEL

SAMPLES

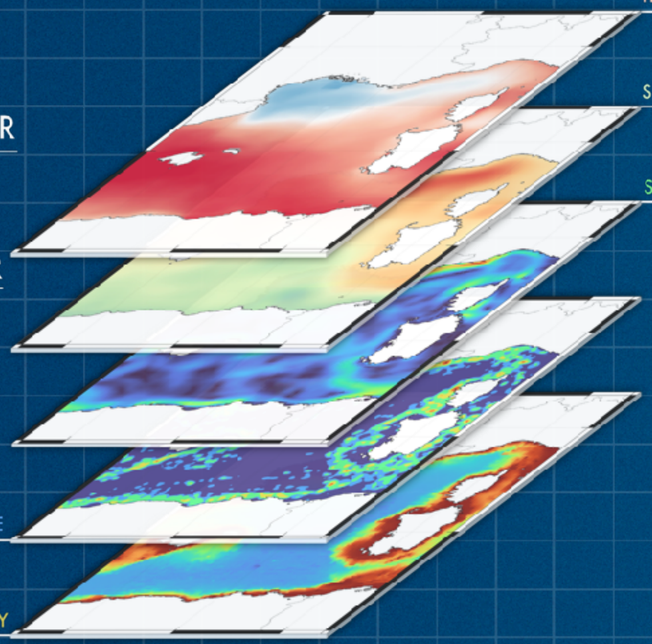
PRESENCE LAYER

SAMPLING BIAS LAYER

BACKGROUND LAYER



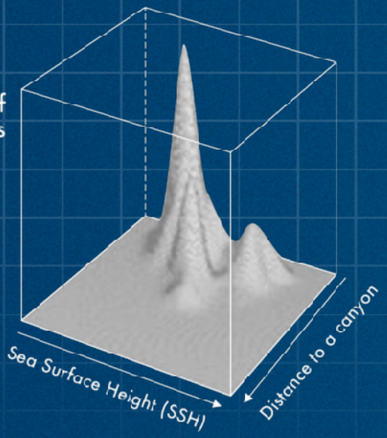
VARIABLES



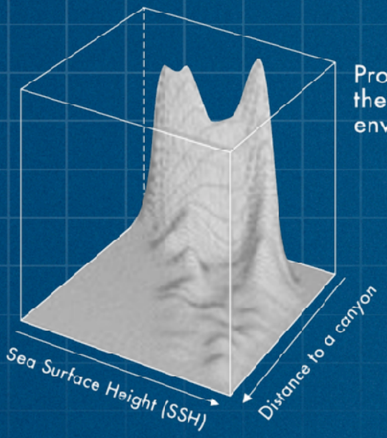
Averaged values between May and October from Copernicus

MaxENT optimisation

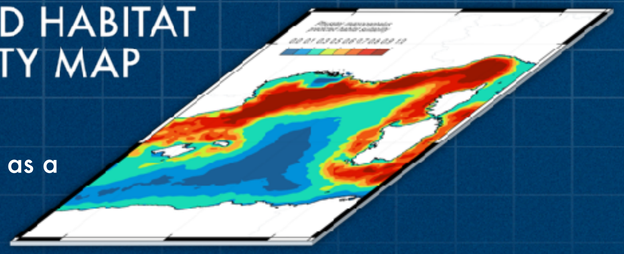
Probability density of the presences



Probability density of the available environment



PREDICTED HABITAT SUITABILITY MAP

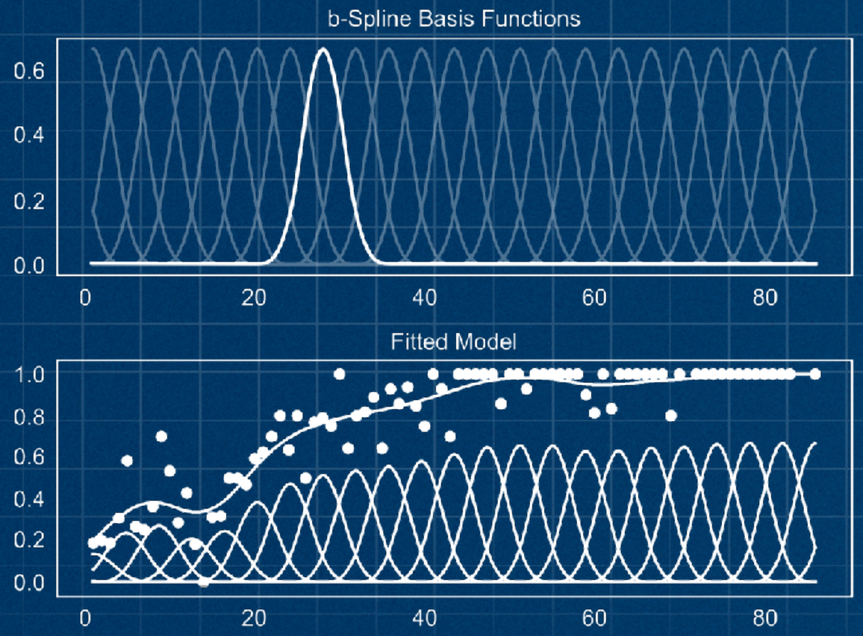


+ value of the Area Under the Curve (AUC) True positive rate as a function of False positive rate

GAMs

parameters in the model

Humpback whale Detection rate (detection/hour of recording)	Temperature	Salinity	Chlorophyll concentration	Week number	Date
150	25.2	36.0	0.08	12	2021-03-24
220	25.6	36.5	0.09	13	2021-04-01
33	27.6	34.5	0.12	2	2021-01-12
75	24.5	35.0	0.16	27	2021-07-08

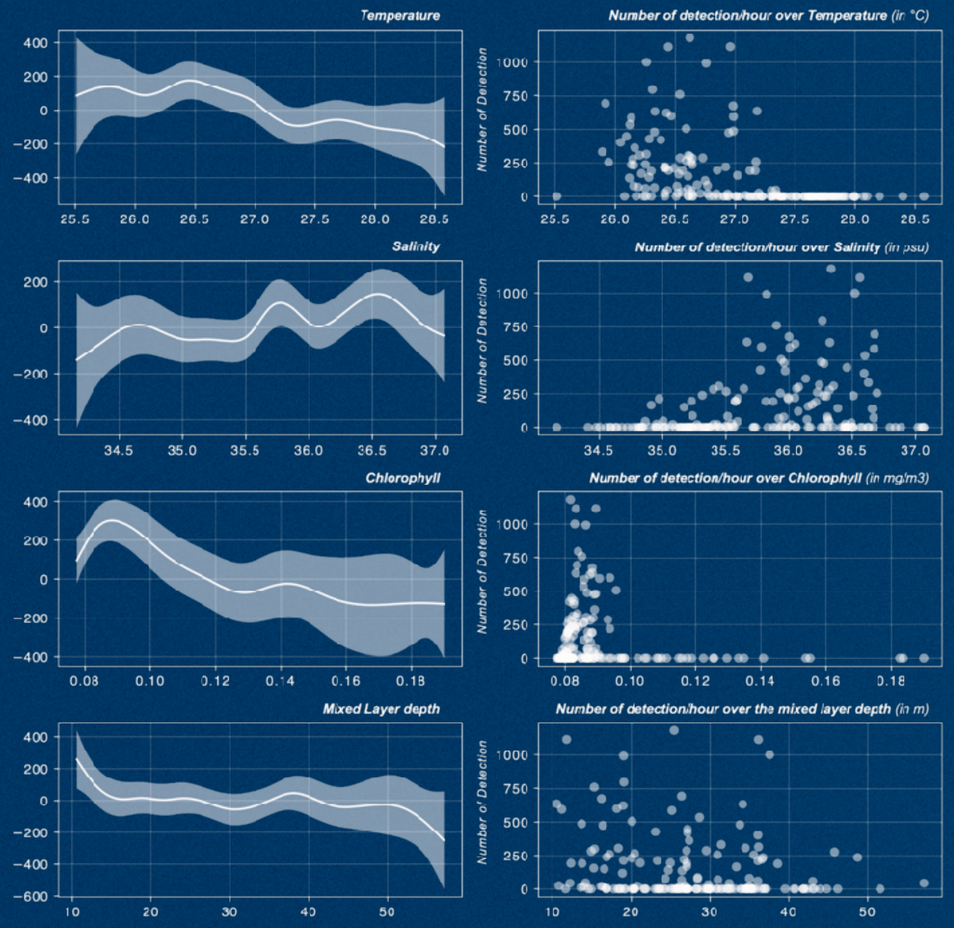


Optimise all polynomial segments = finding the relation between the detection rate and each of the environmental variables

= it comes with a R^2 value for the fitted model

RESULTS : Humpback whale

2. VARIABLE PARAMETER



Temperature

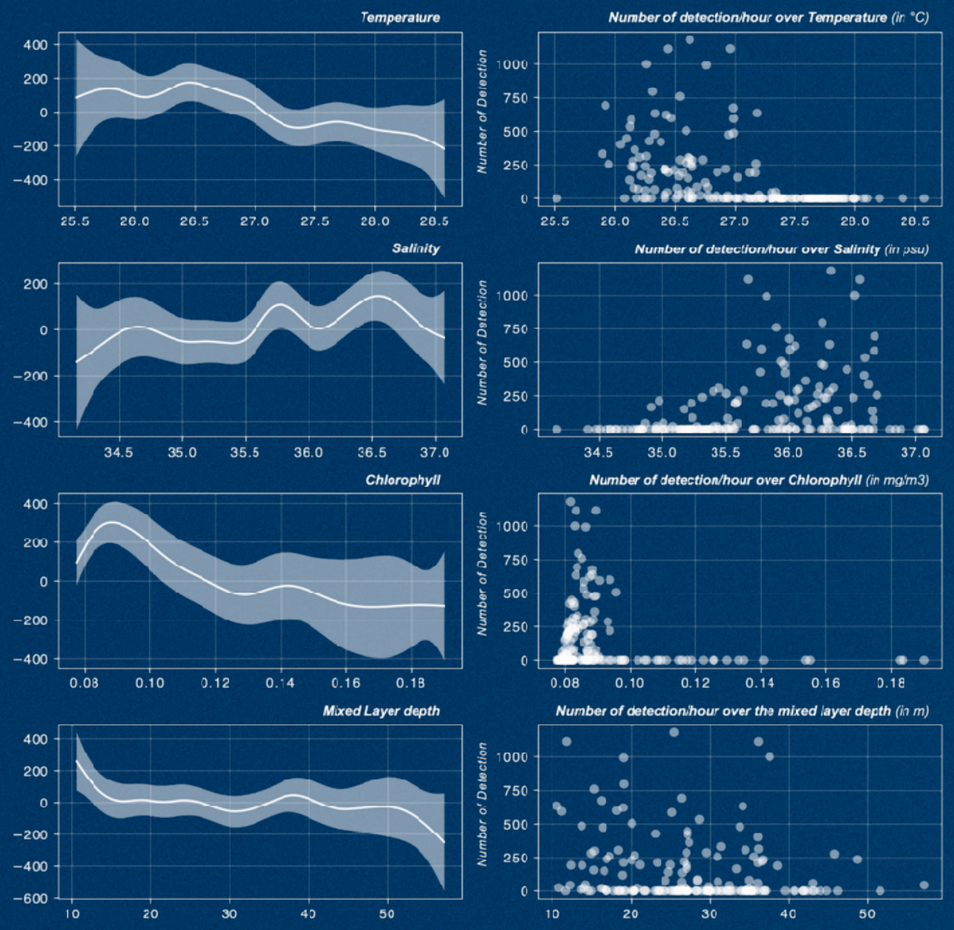
R^2 *value of the model : 53%*

Salinity

Chlorophyll concentration

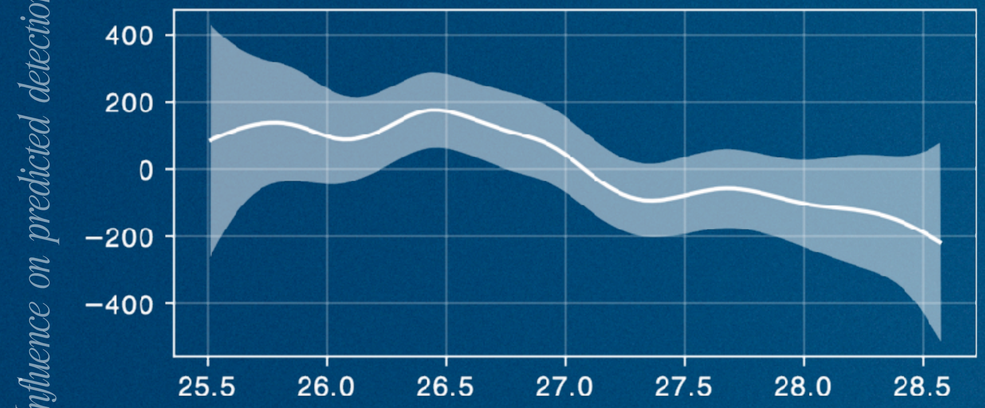
Mixed Layer depth

RESULTS : Humpback whale



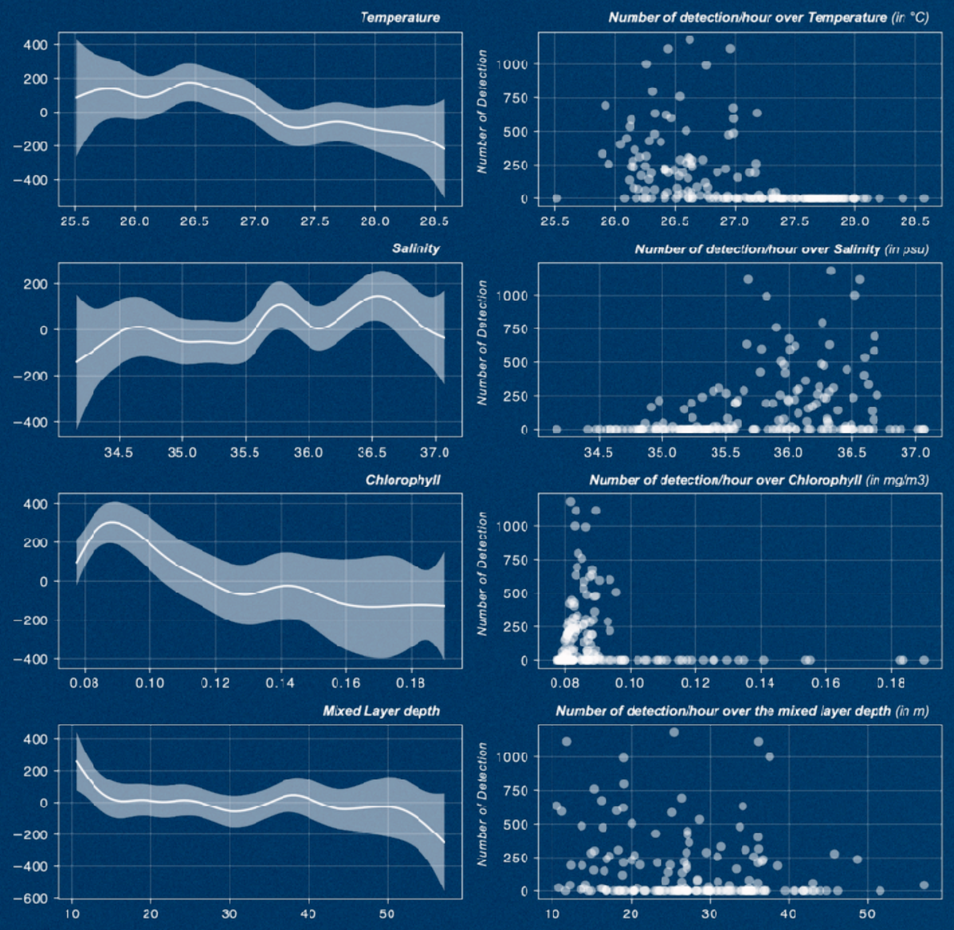
2. VARIABLE PARAMETER

Temperature

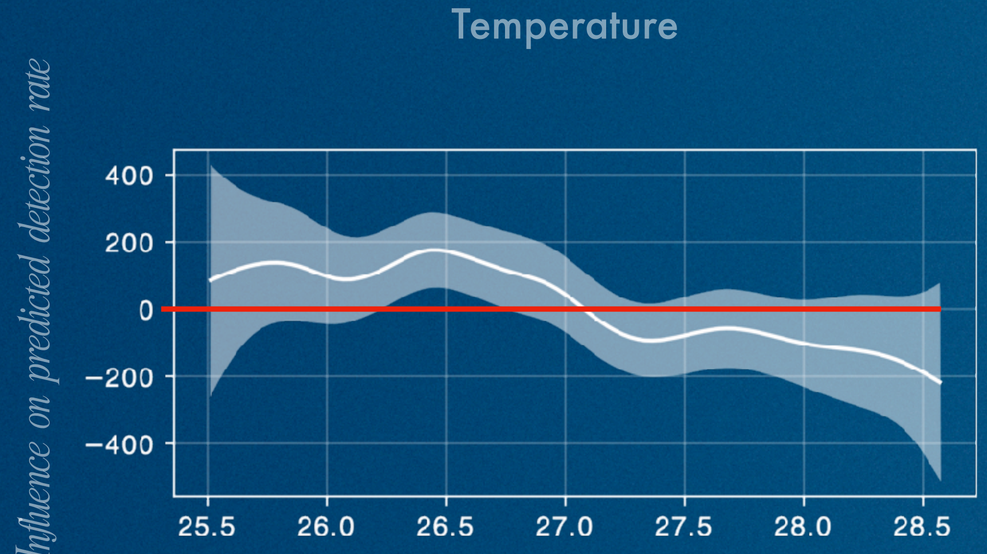


CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

RESULTS : Humpback whale

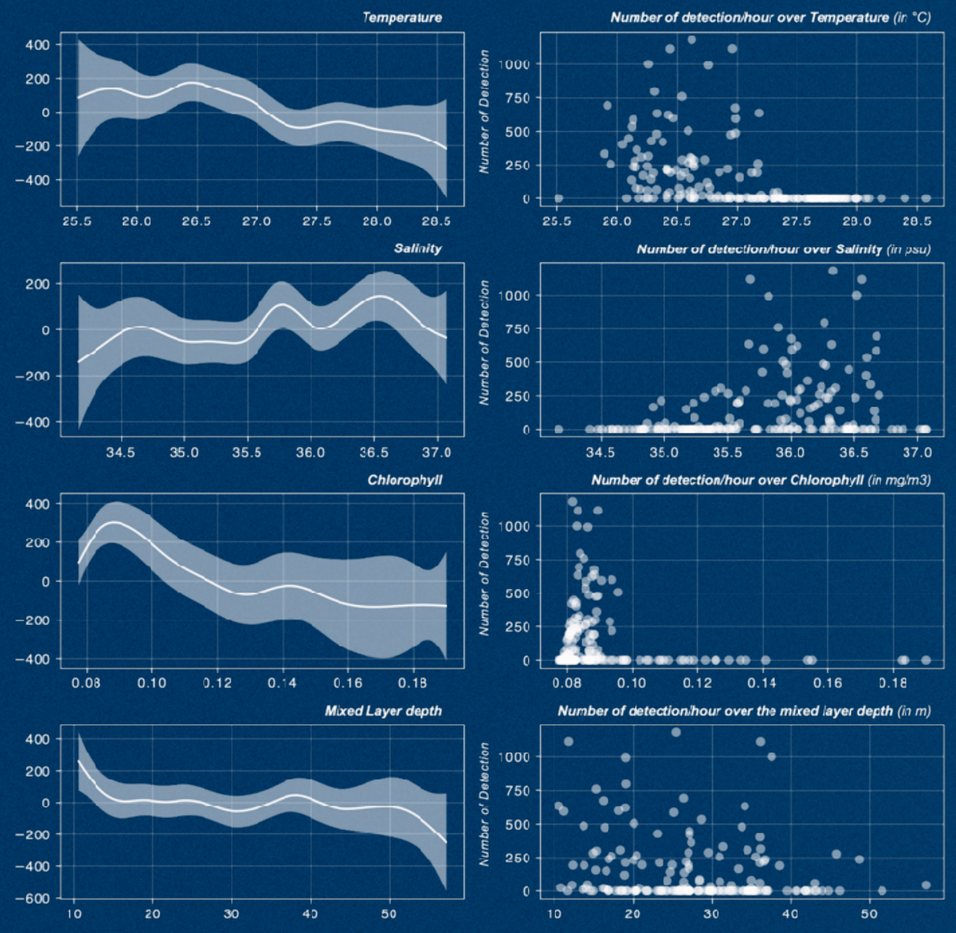


2. VARIABLE PARAMETER

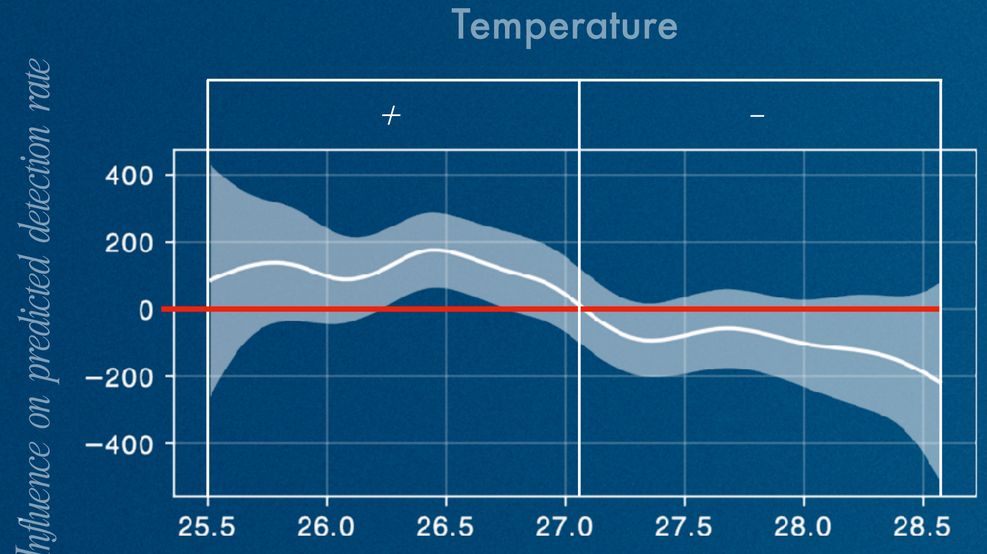


CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

RESULTS : Humpback whale



2. VARIABLE PARAMETER



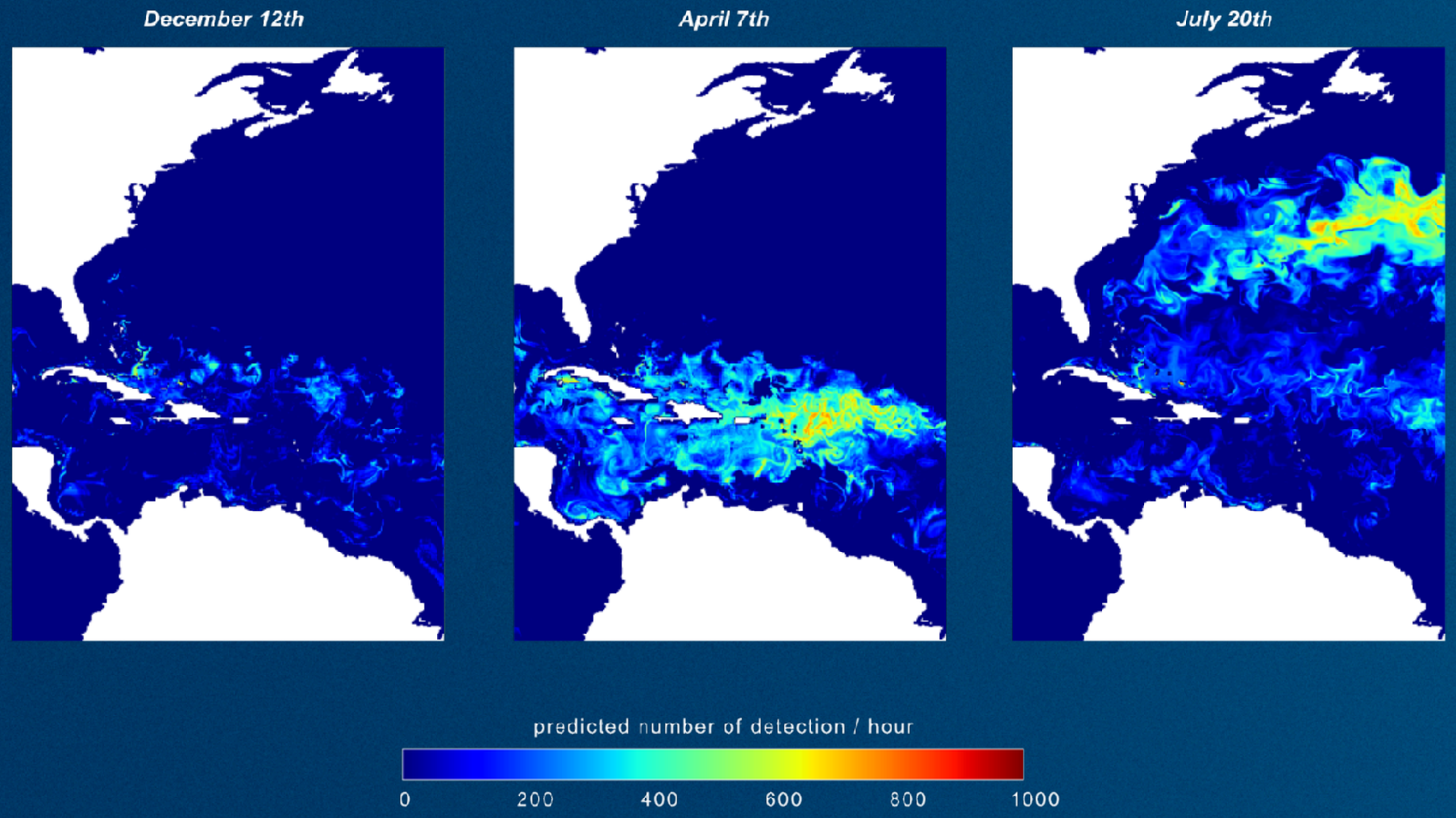
Potential link between Temperature and the presence of humpback whale on breeding ground :
decrease when the temperature > 27.1°C

=> Similar observations in the literature

CENTRE interdisciplinaire d'INTELLIGENCE ARTIFICIELLE en ACOUSTIQUE NATURELLE

RESULTS : Humpback whale

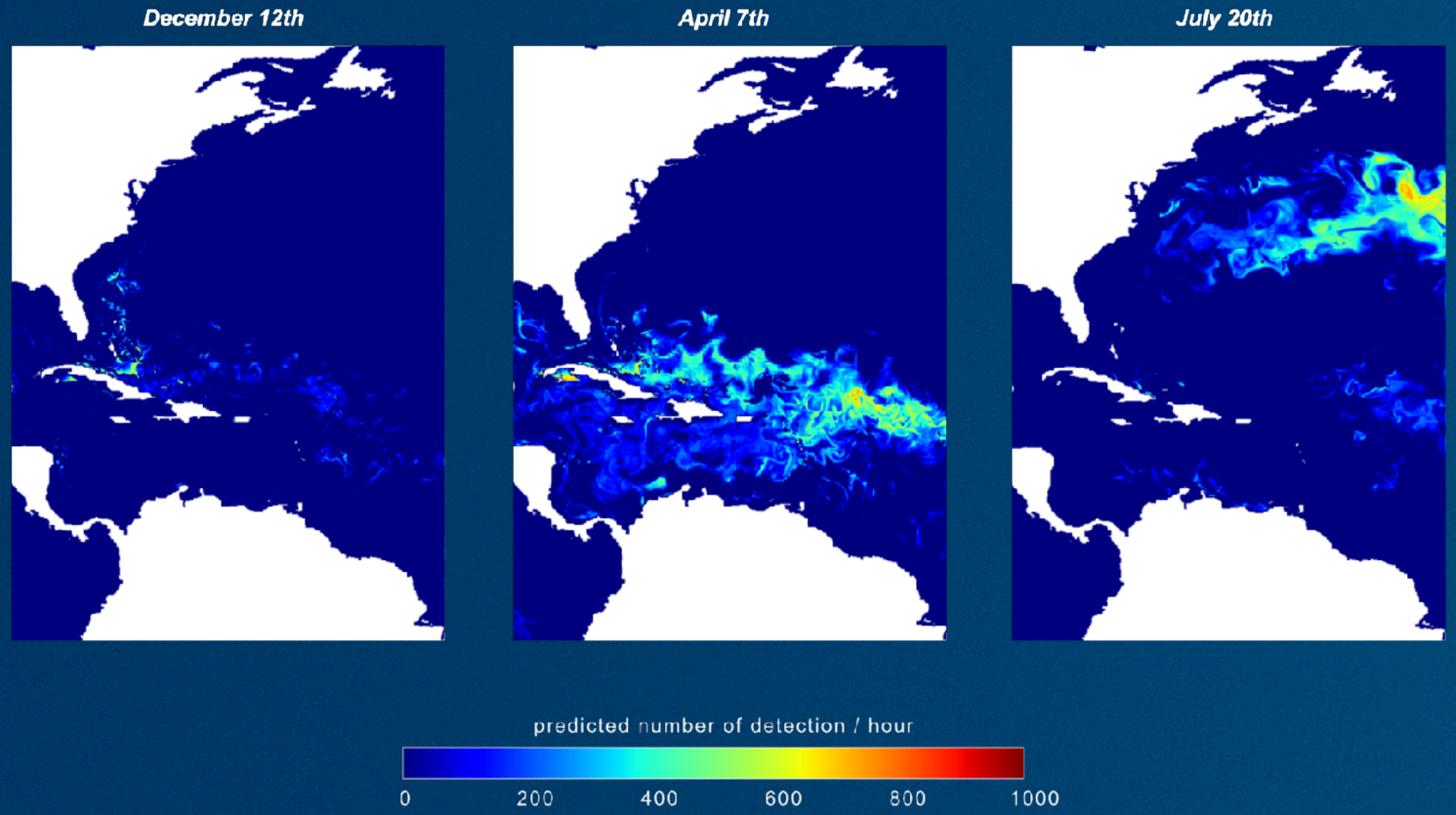
Before the breeding season



After the breeding season

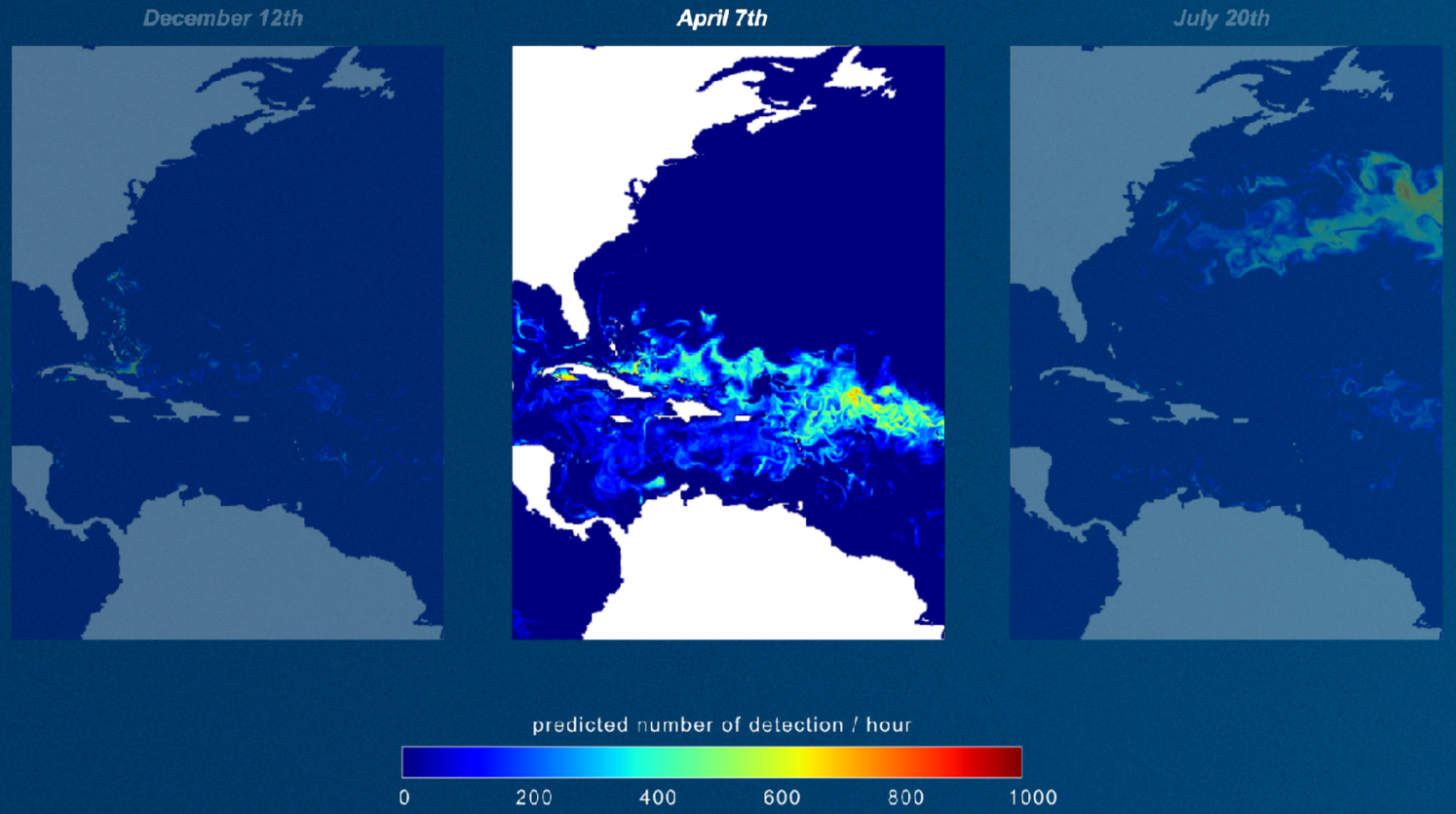
Predicted detection rate of Humpback whale between December 2020 and July 2021

RESULTS : Humpback whale in SST +1 °C



Predicted detection rate of Humpback whale between December and July with +1°C on the SST

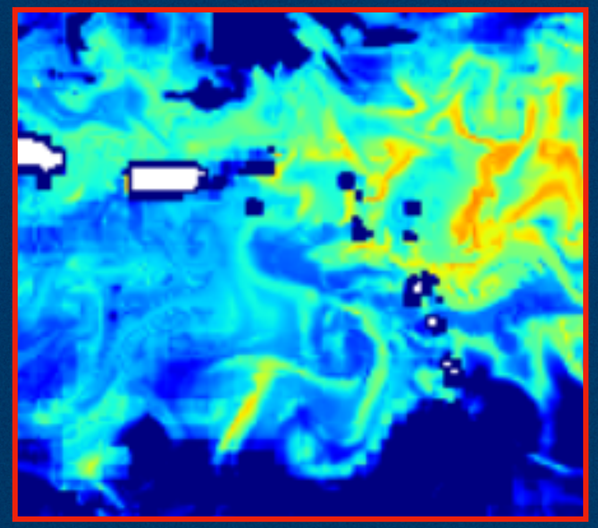
RESULTS : Humpback whale



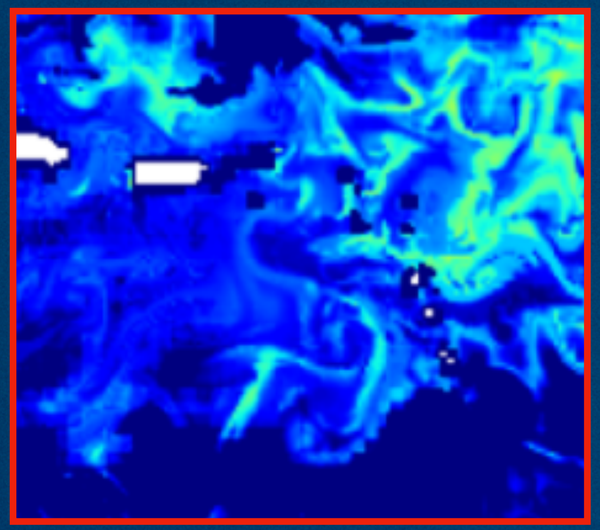
Predicted detection rate of Humpback whale between December and July with +1°C on the SST

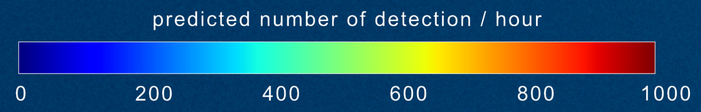
RESULTS : Humpback whale

Actual

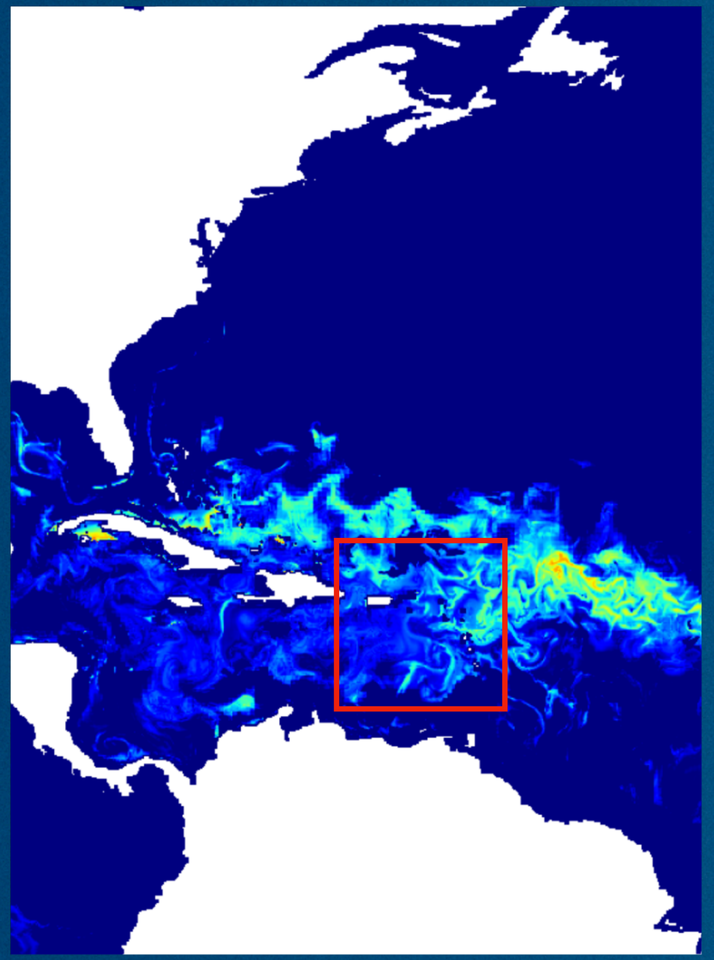


Actual +1 °C of SST

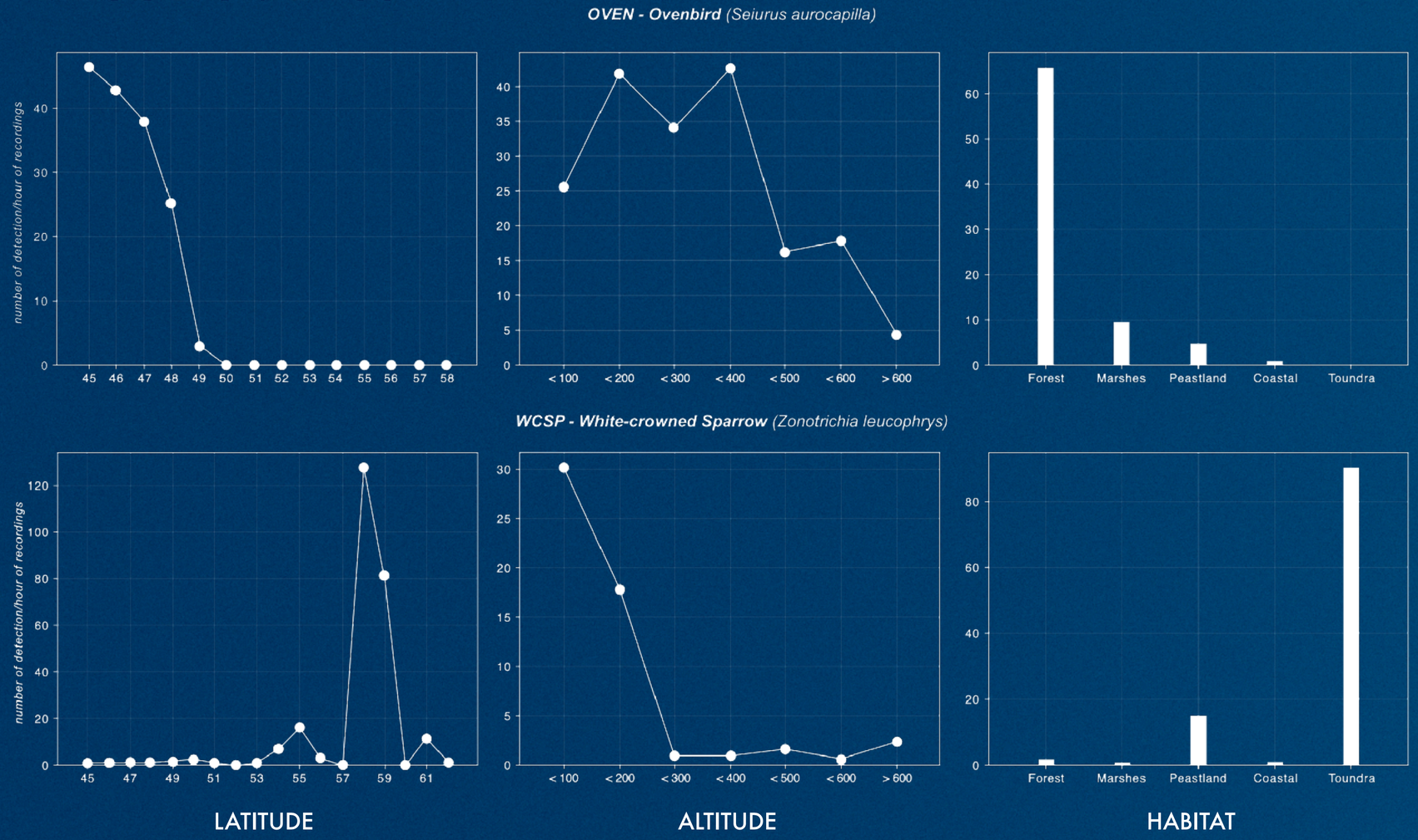




April 7th



RESULTS : Birds



LATITUDE ALTITUDE HABITAT

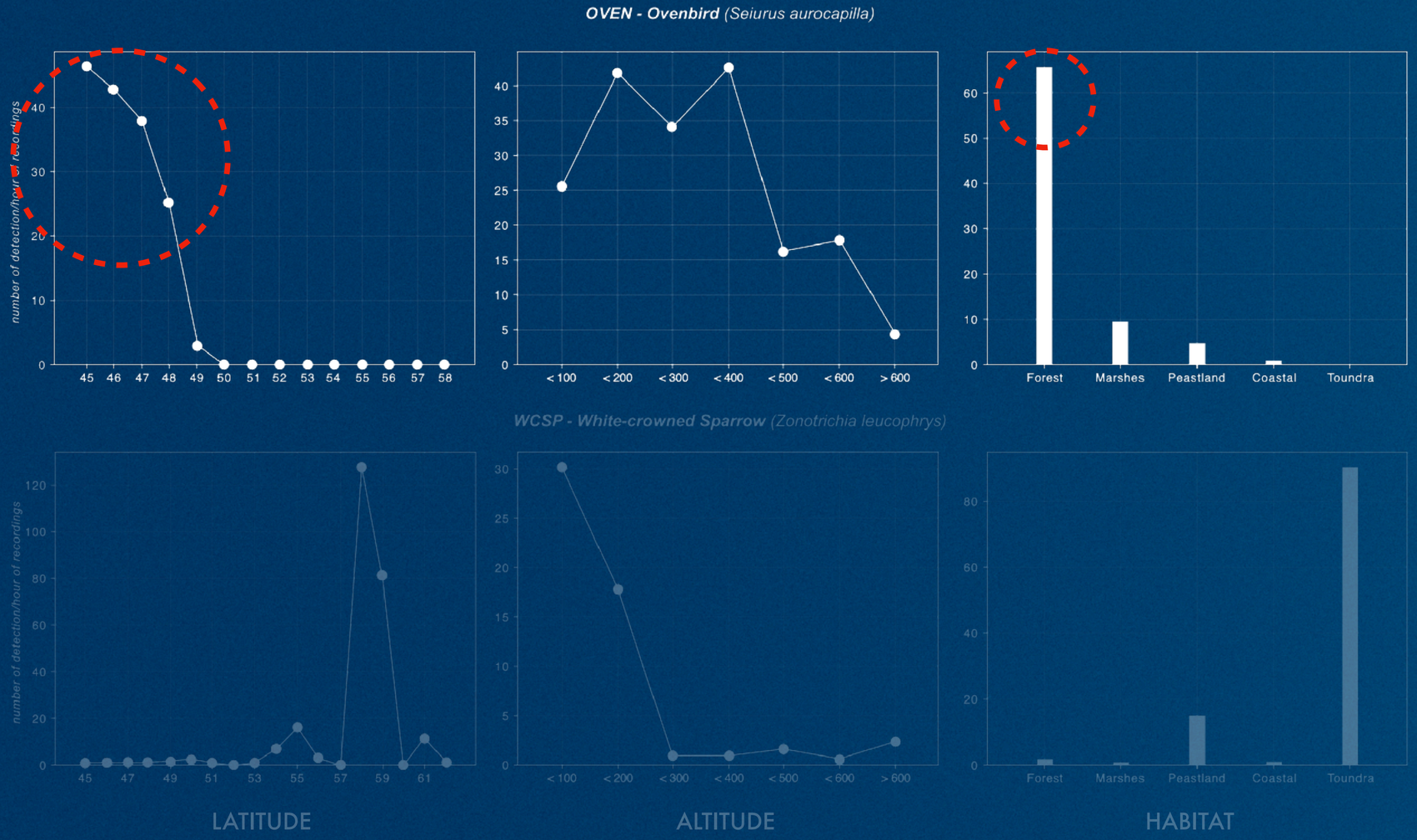
1. FIXED PARAMETER

Example for 2 of the 27 species :

Analysis of the number of detections per hour of recording at different fixed parameters

CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

RESULTS : Birds

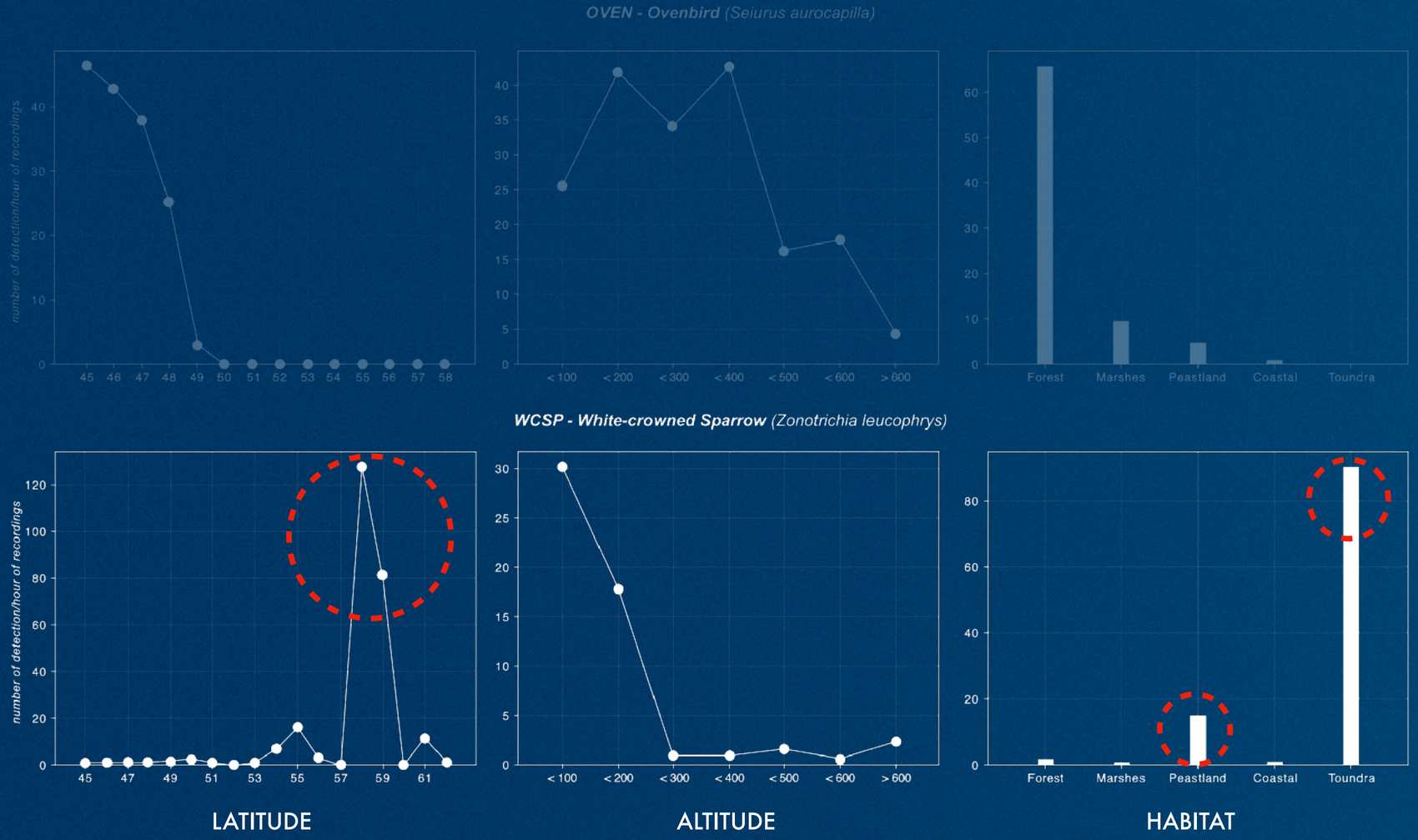


1. FIXED PARAMETER

Ovenbird : preferences for forest at lower latitudes = deciduous

White-crowned Sparrow : preferences for high latitude in tundra or peatland habitats

RESULTS : Birds



1. FIXED PARAMETER

Ovenbird : preferences for forest at lower latitudes = deciduous

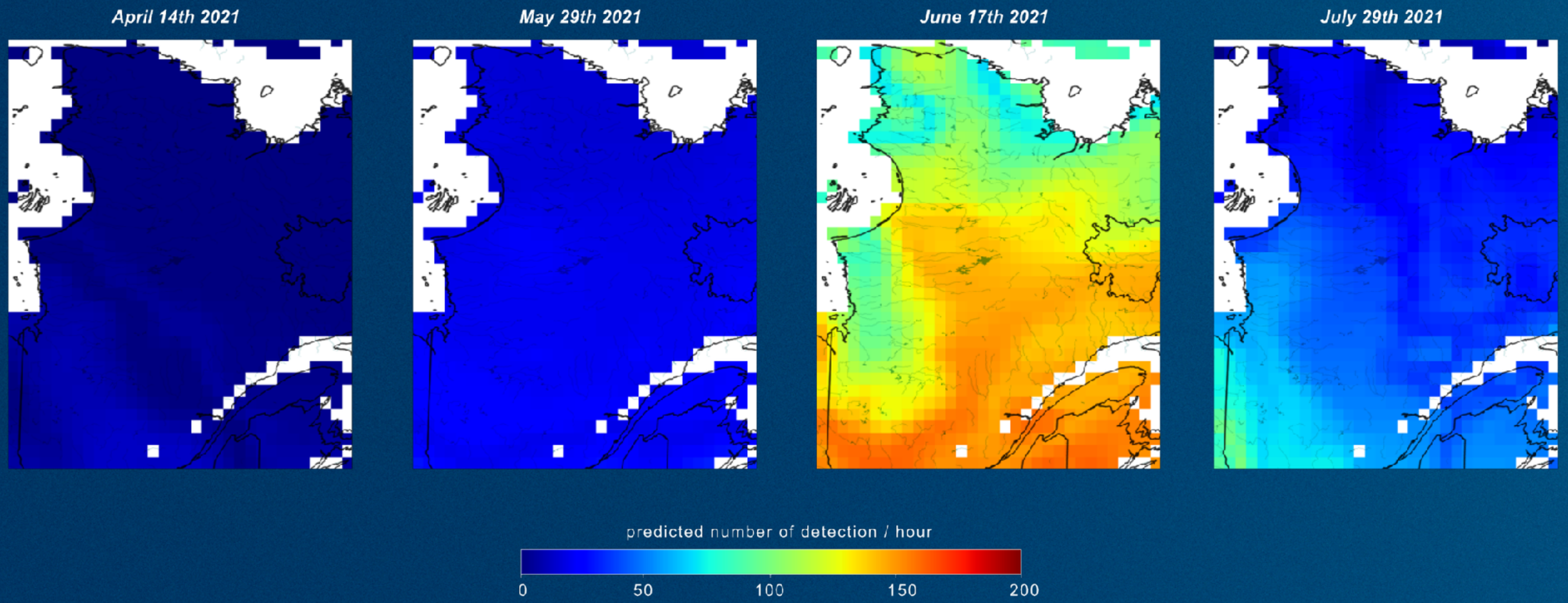
White-crowned Sparrow : preferences for high latitude in tundra or peatland habitats

CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

RESULTS : Birds

2. VARIABLE PARAMETER

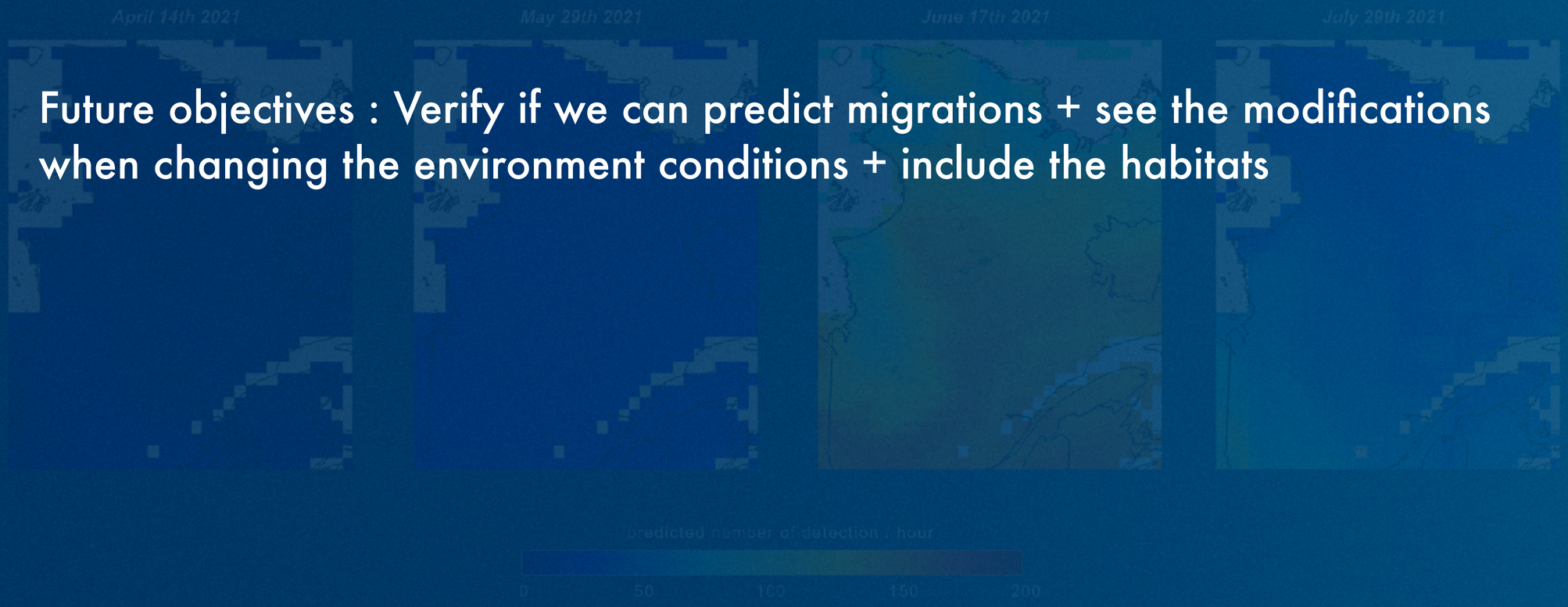
temperature, precipitation and wind intensity



RESULTS : Birds

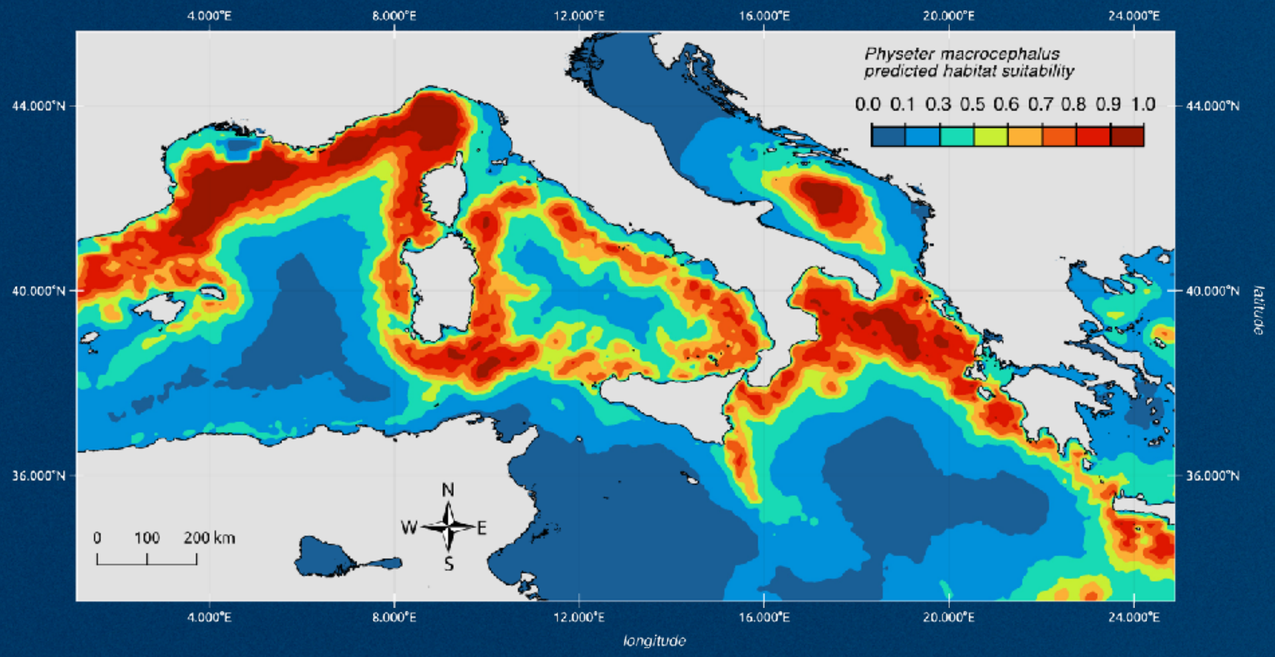
2. VARIABLE PARAMETER

temperature, precipitation and wind intensity



Future objectives : Verify if we can predict migrations + see the modifications when changing the environment conditions + include the habitats

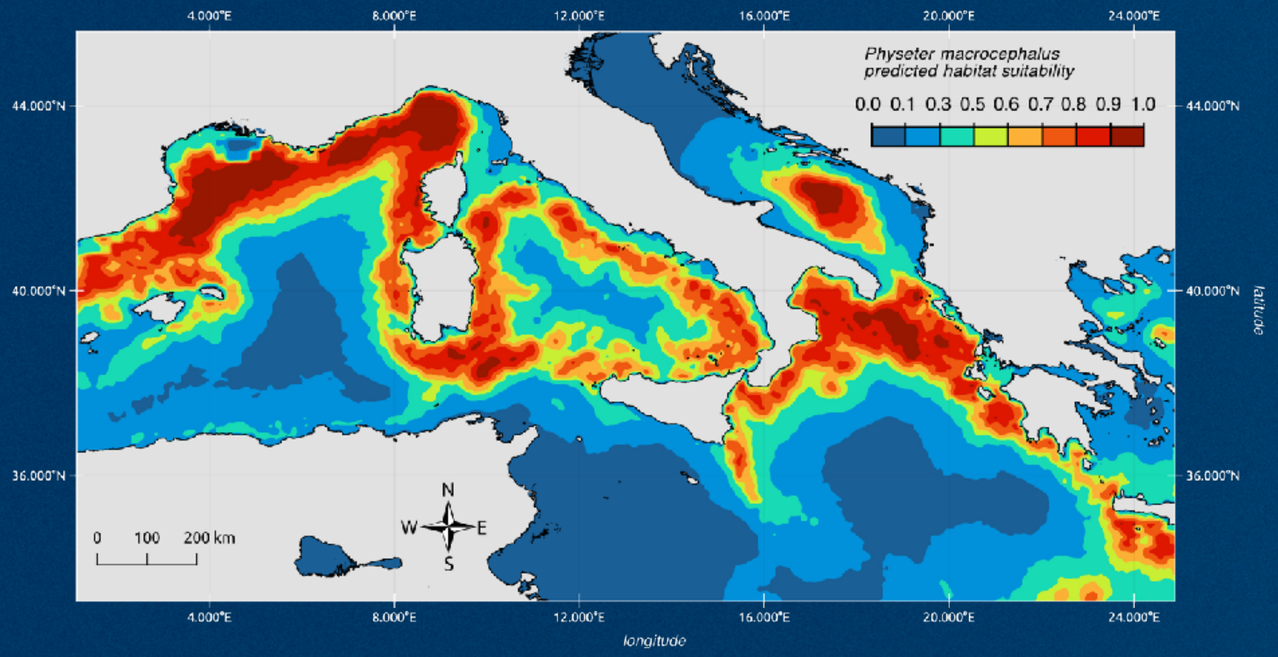
RESULTS : Sperm whale



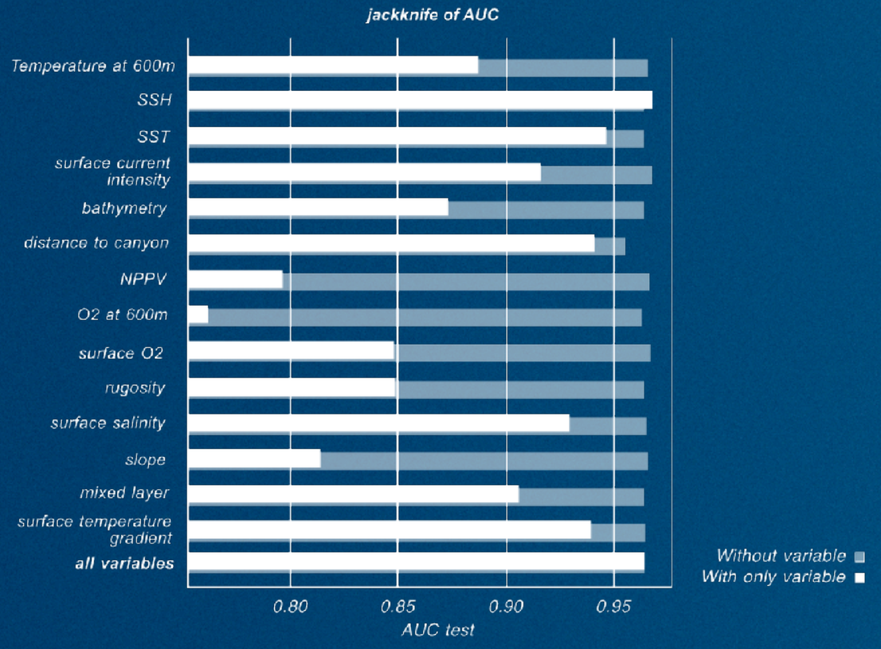
AUC of 96.5% over the test set (Ocean Biodiversity Information System dataset)

Predicted map of suitable habitat for sperm whale in the Mediterranean Sea along the impact of each parameters

RESULTS : Sperm whale

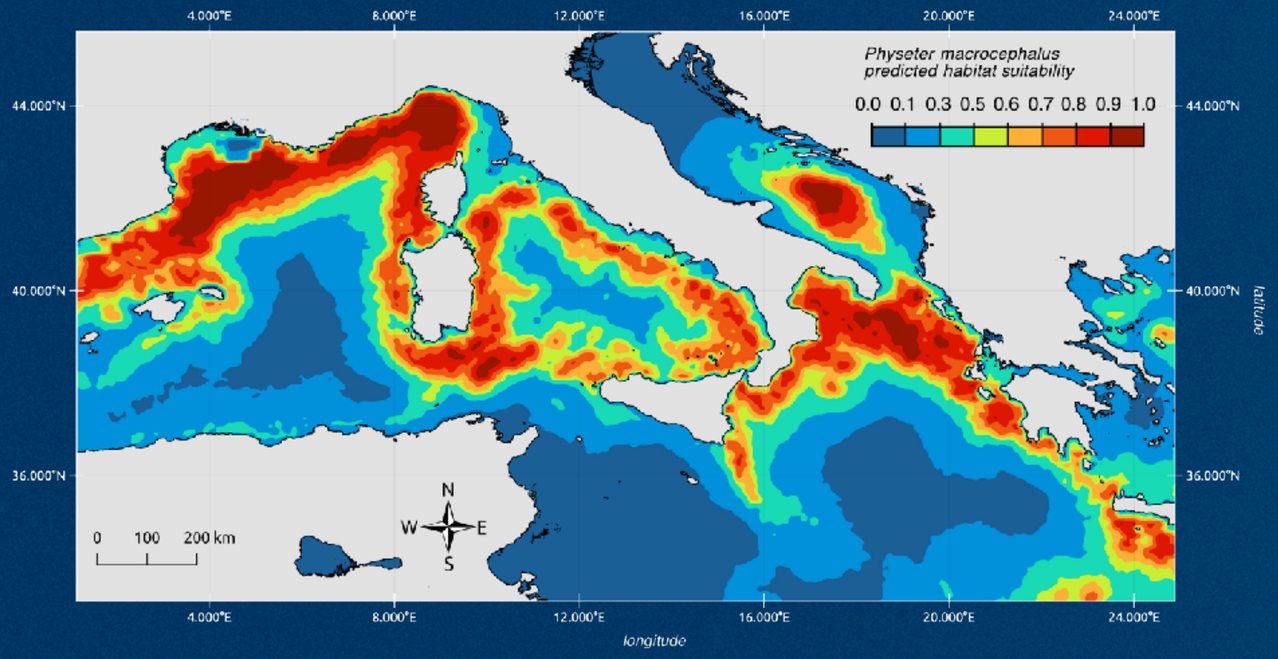


Contribution in the model

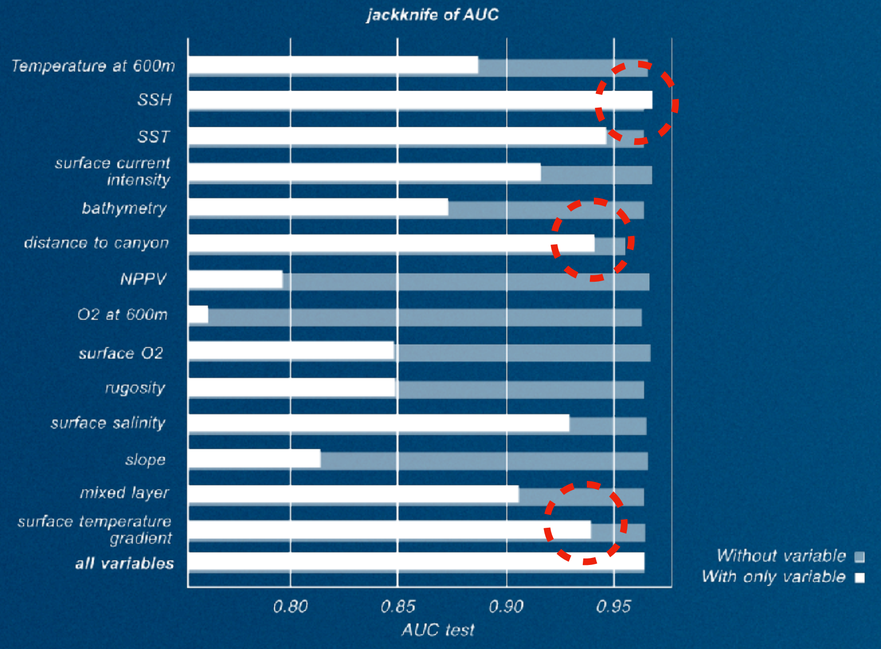


Predicted map of suitable habitat for sperm whale in the Mediterranean Sea along the impact of each parameters

RESULTS : Sperm whale

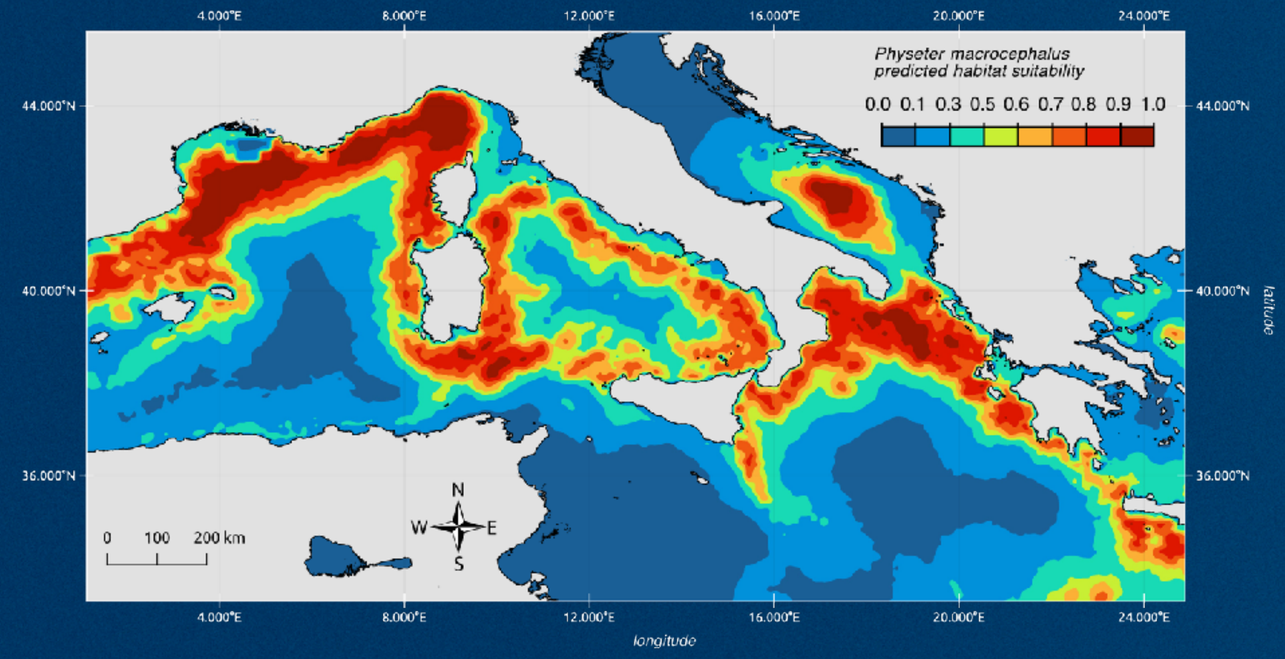


Contribution in the model

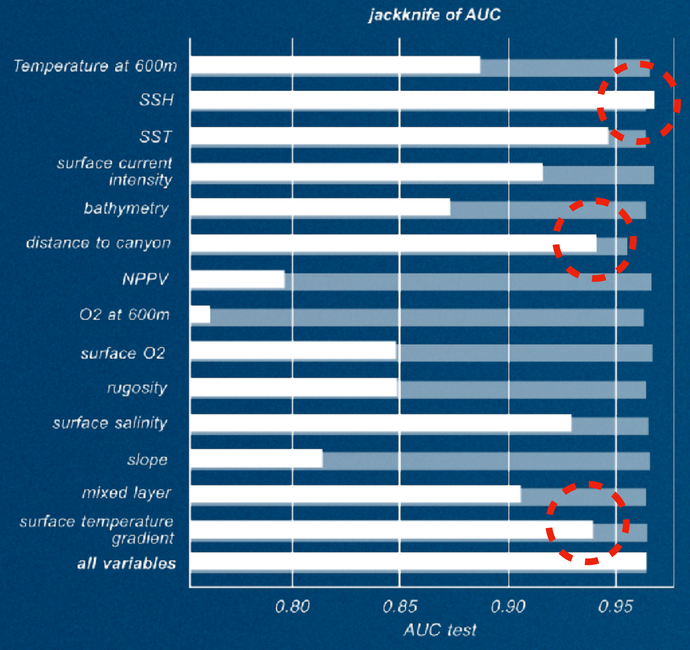


Predicted map of suitable habitat for sperm whale in the Mediterranean Sea along the impact of each parameters

RESULTS : Sperm whale



Contribution in the model



Influence on suitability

↗ *when lower SSH*

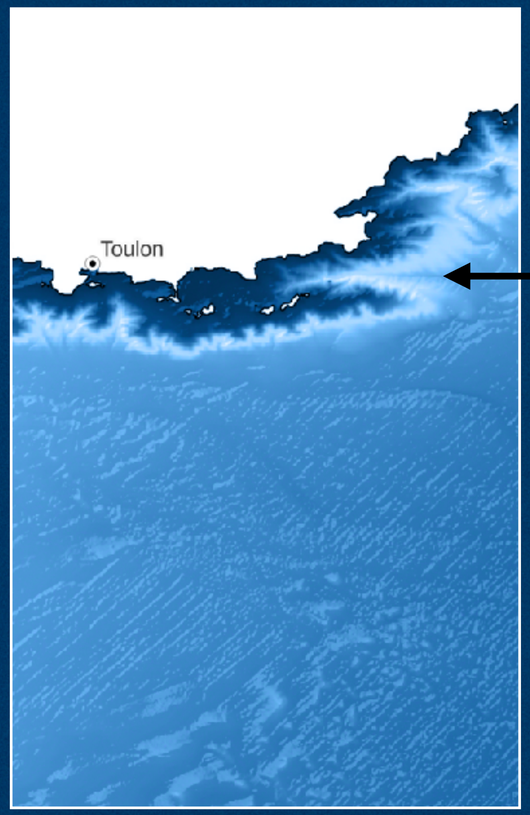
↗ *near canyons*

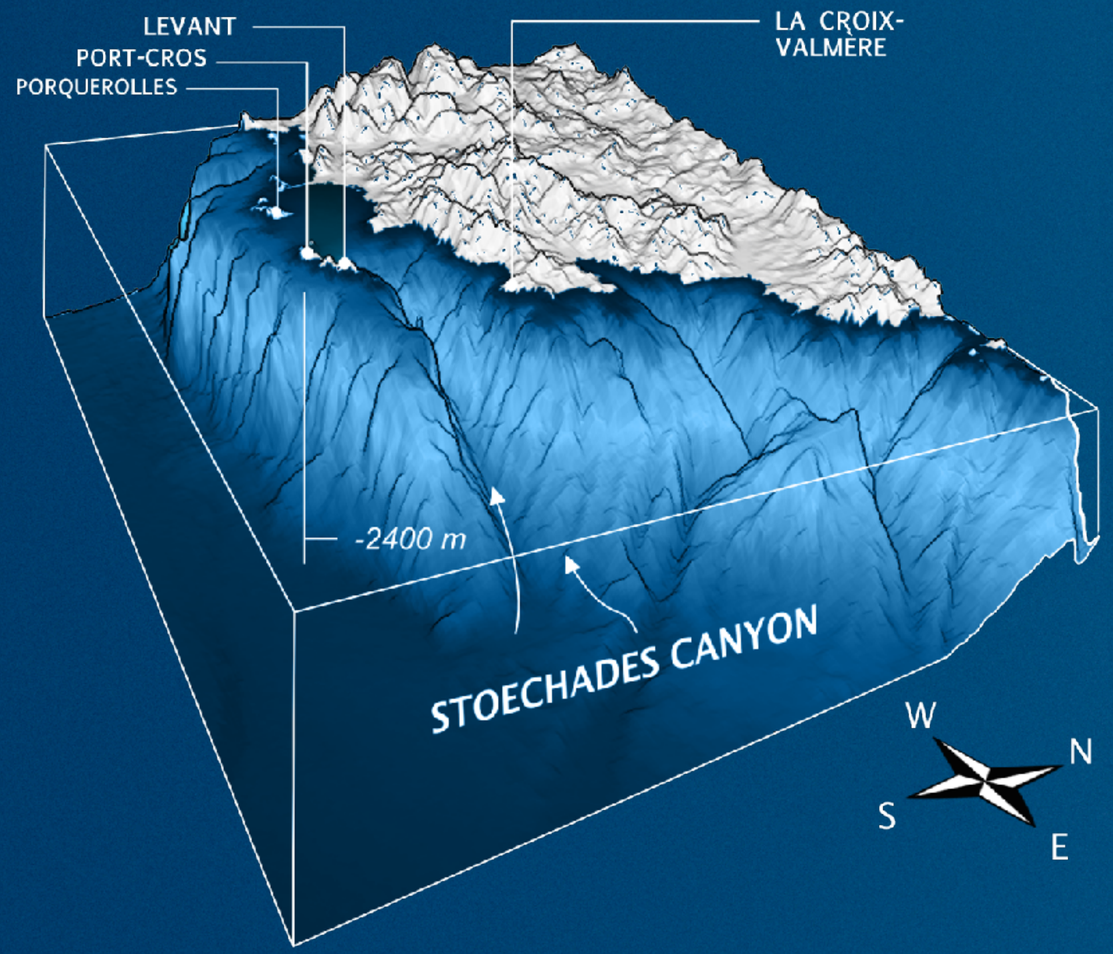
↗ *when delta > 0.5°C*

Predicted map of suitable habitat for sperm whale in the Mediterranean Sea along the impact of each parameters

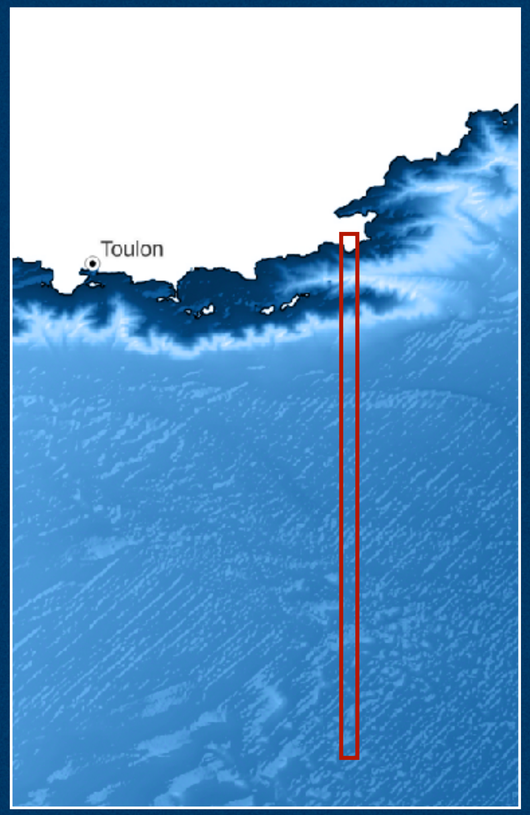
CENTRE int. d'INTELLIGENCE ARTIFICIELLE en ACOUSTIQUE NATURELLE

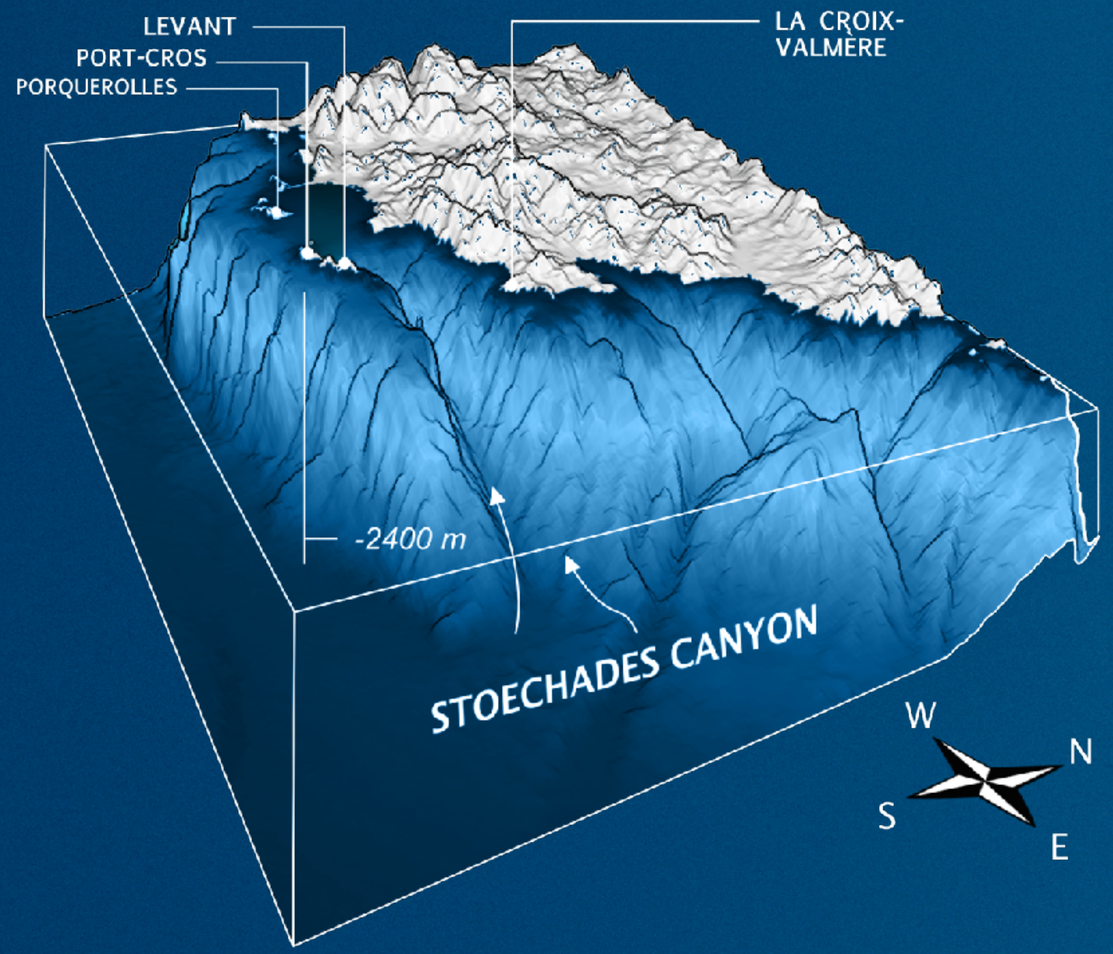
RESULTS : Sperm whale and Stoechades canyon



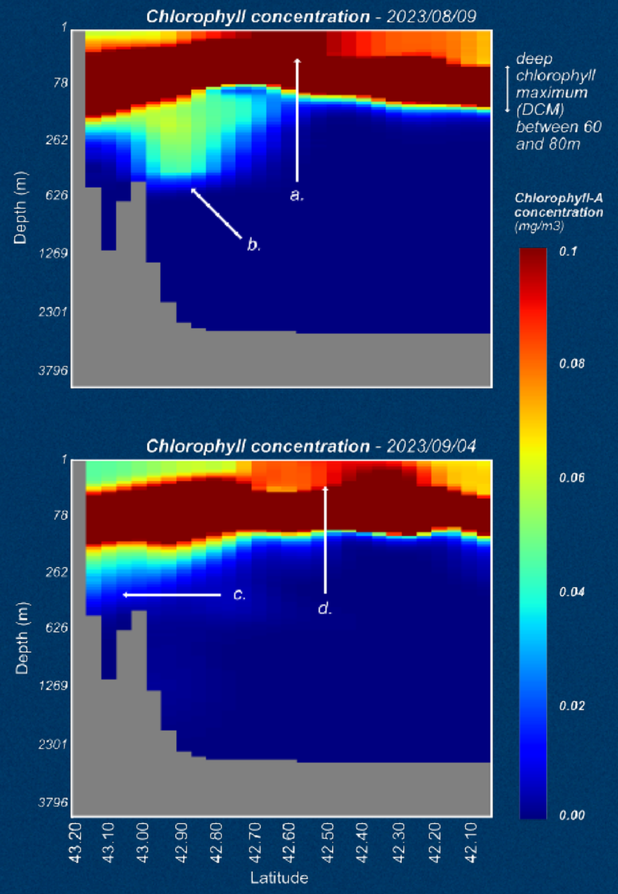


RESULTS : Sperm whale and Stoechades canyon





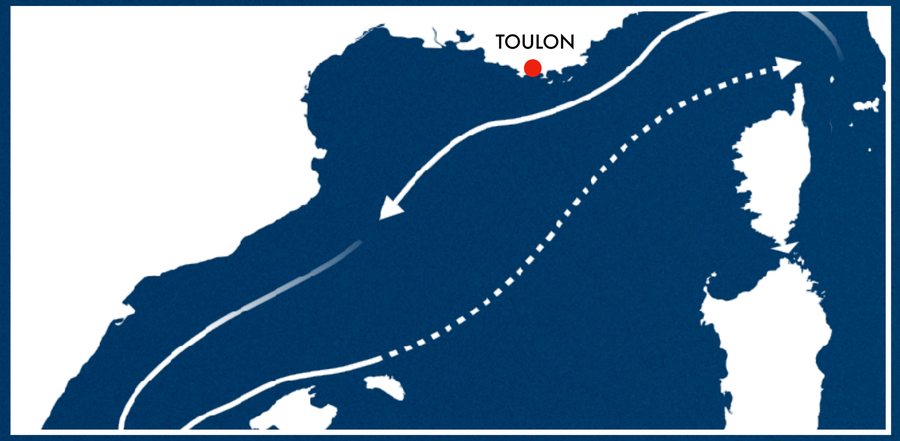
RESULTS : Canyon during August and the beginning of September 2023



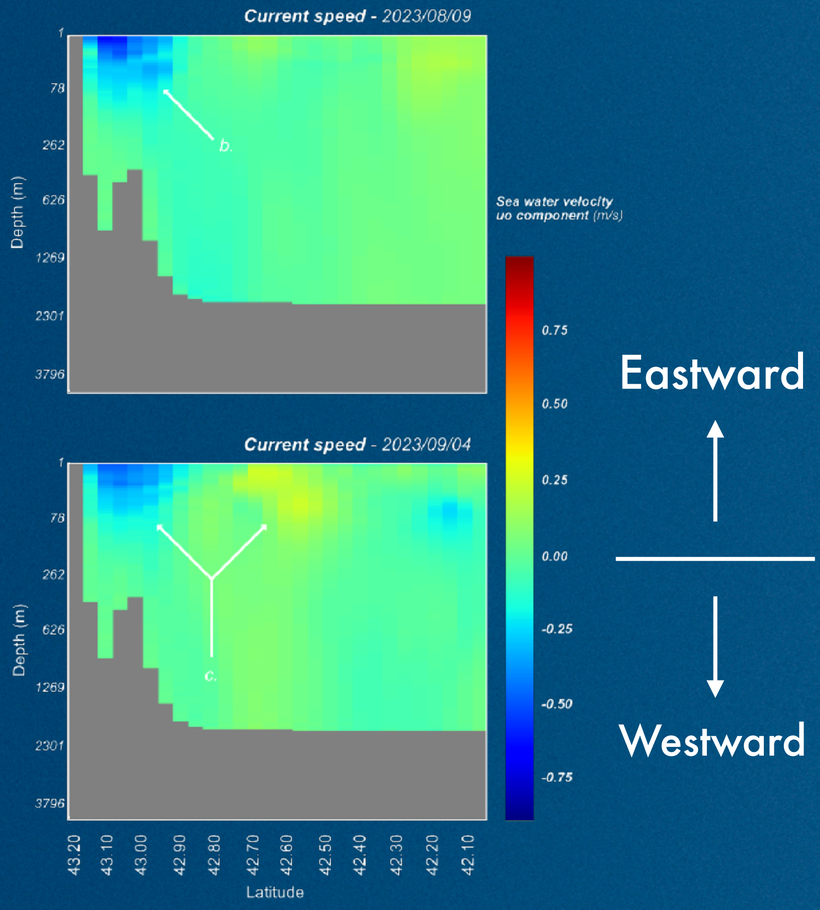
- *Increase in the chlorophyll concentration into the deep waters of the canyon* = Potential downwelling

- *Increase of the chlorophyll concentration at the surface offshore* = Potential upwelling

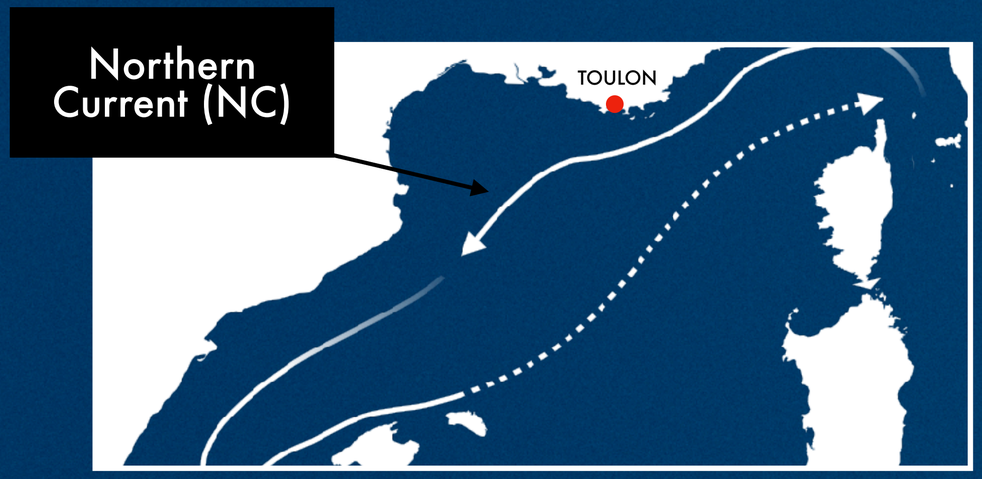
RESULTS : Canyon during August and the beginning of September 2023



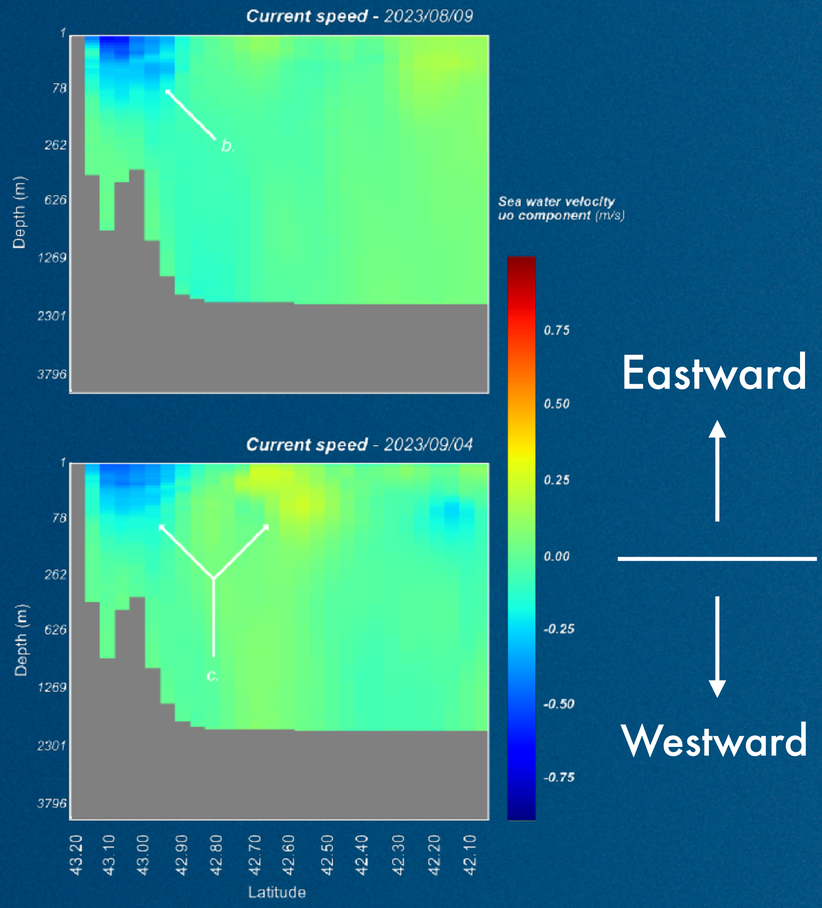
- *Strong current inside the canyon : good orientation to the northern current, can create a downwelling*



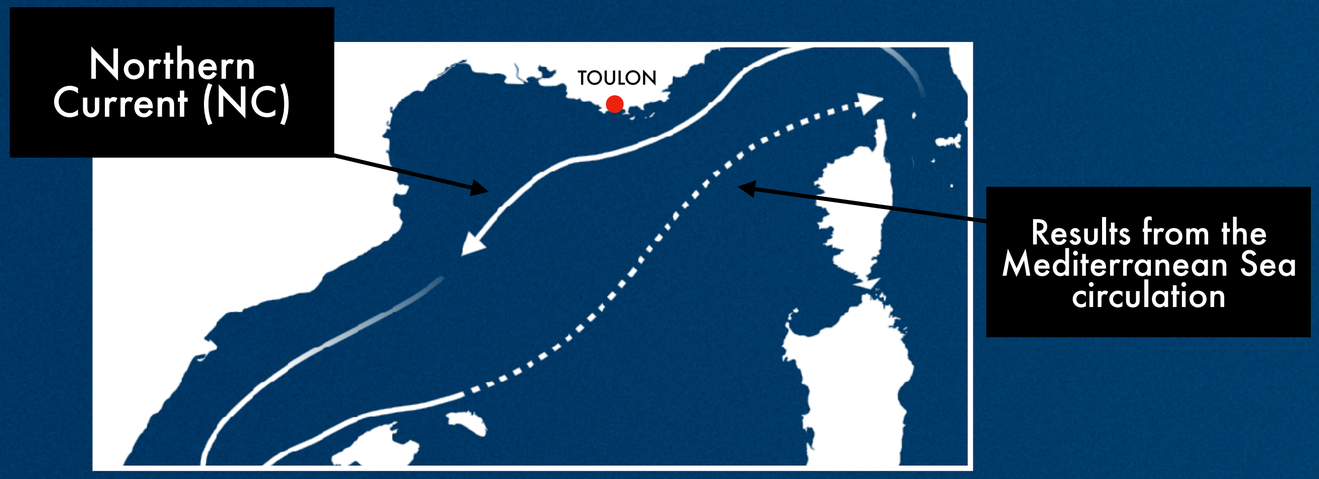
RESULTS : Canyon during August and the beginning of September 2023

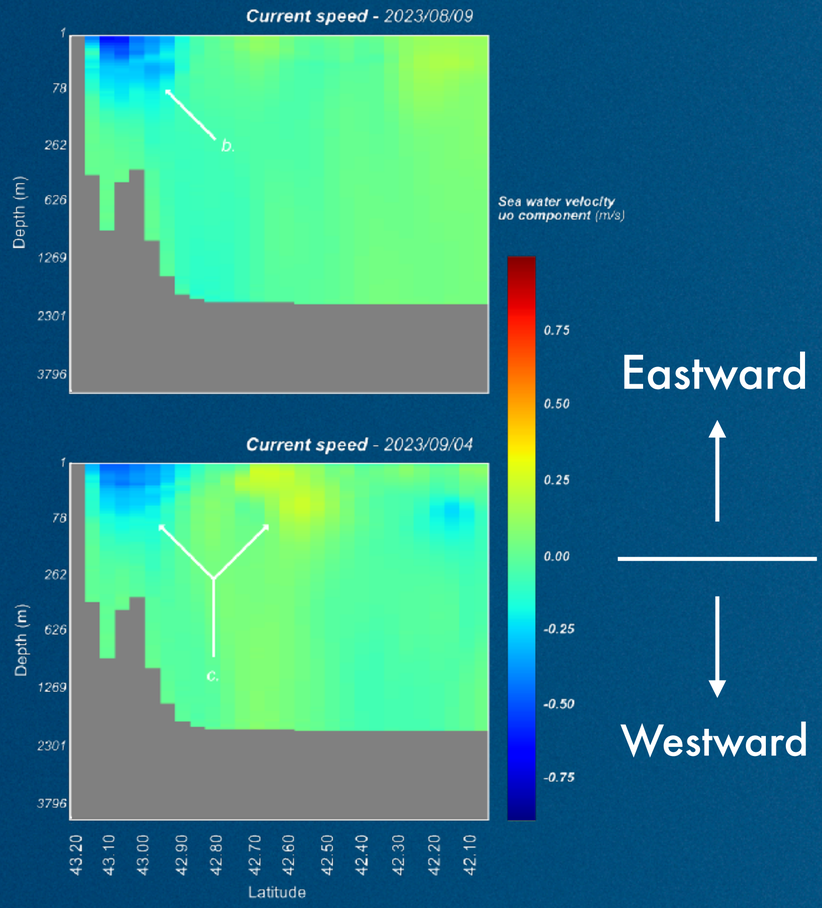


- *Strong current inside the canyon : good orientation to the northern current, can create a downwelling*



RESULTS : Canyon during August and the beginning of September 2023





- *Strong current inside the canyon : good orientation to the northern current, can create a downwelling*
- *Front between 2 currents :*

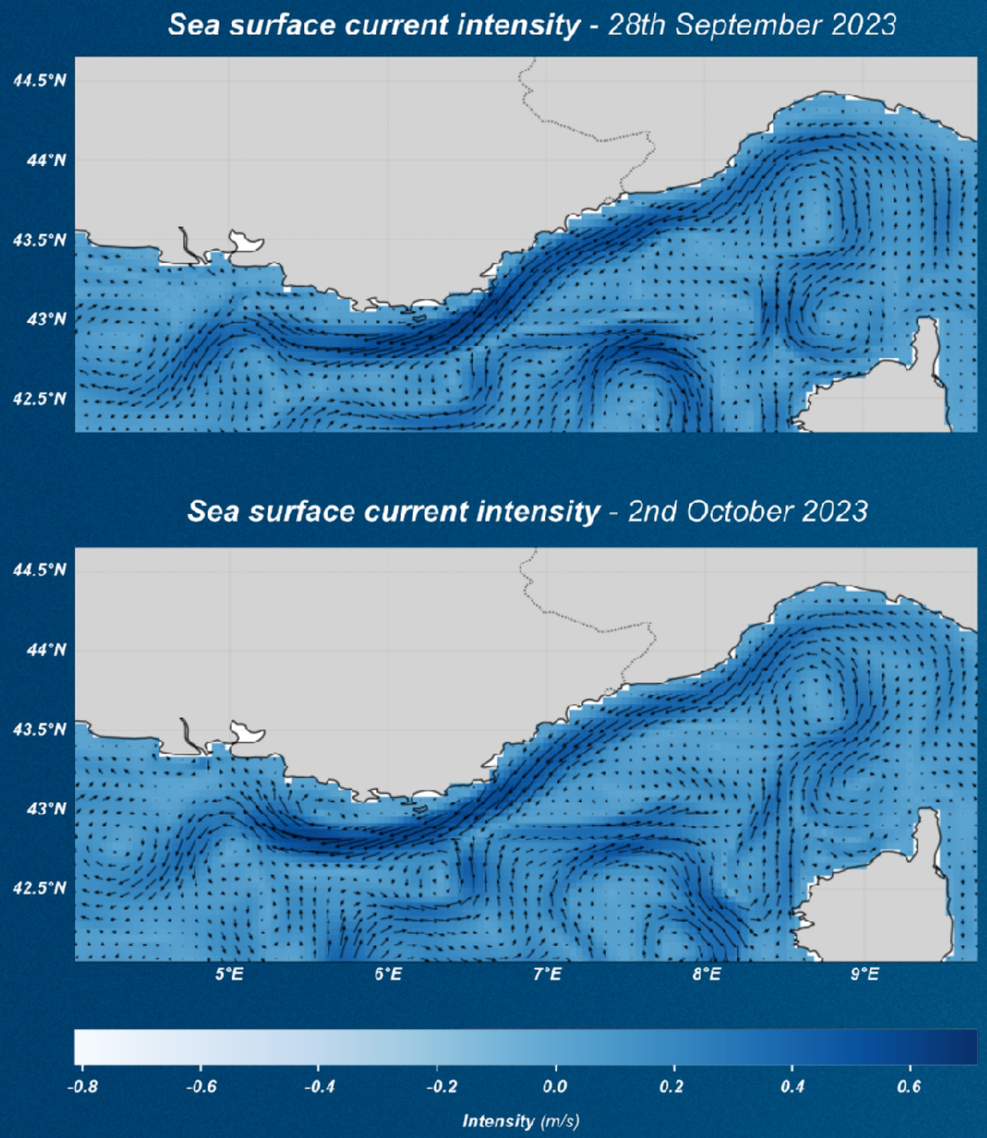
Northern current + an eastward current can create frontal dynamic with divergence = upwelling + lower SSH

RESULTS : Surface currents end of September and beginning of October 2023

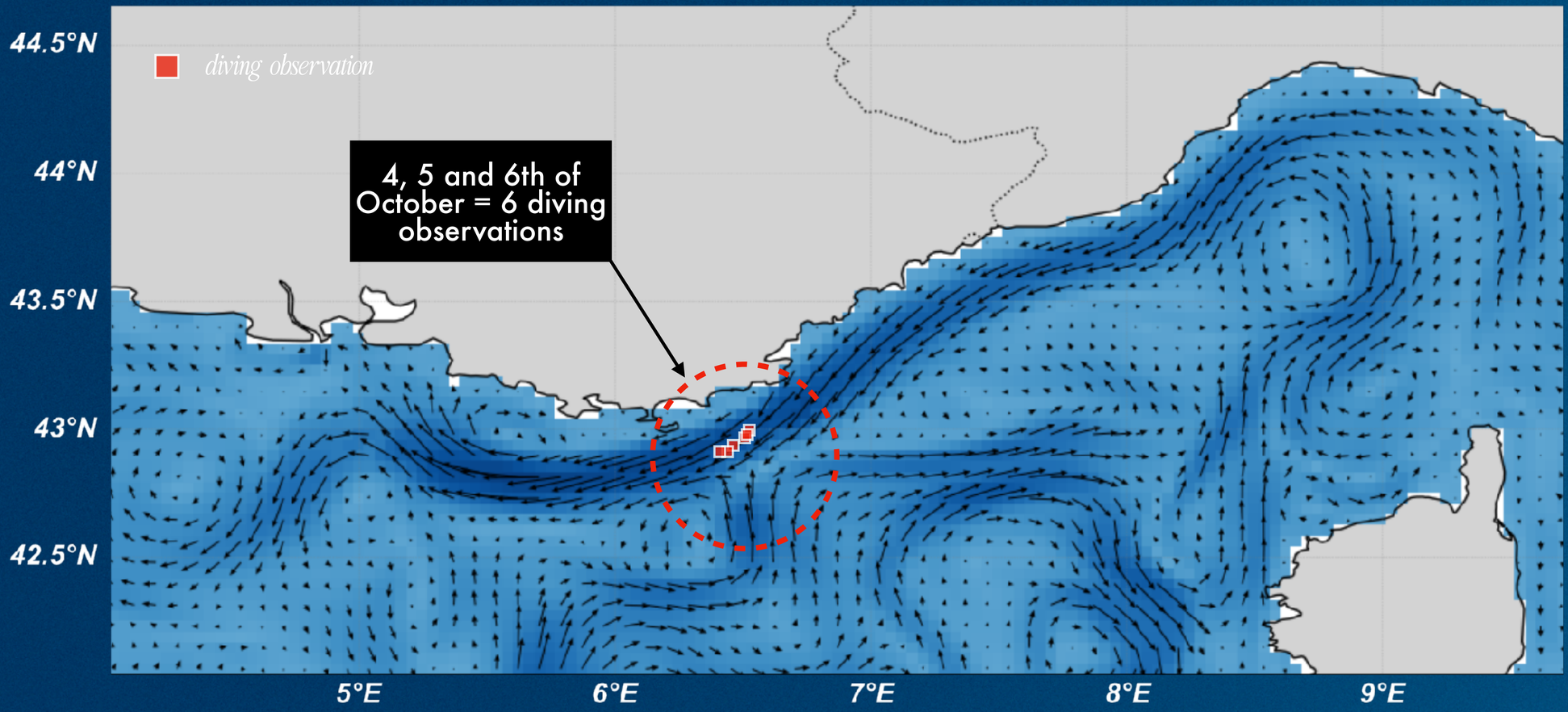
Longitude 181 mission « Whale Way 4 » :

Observations of sperm whale inside and around the canyon

Measure of the frontal dynamic

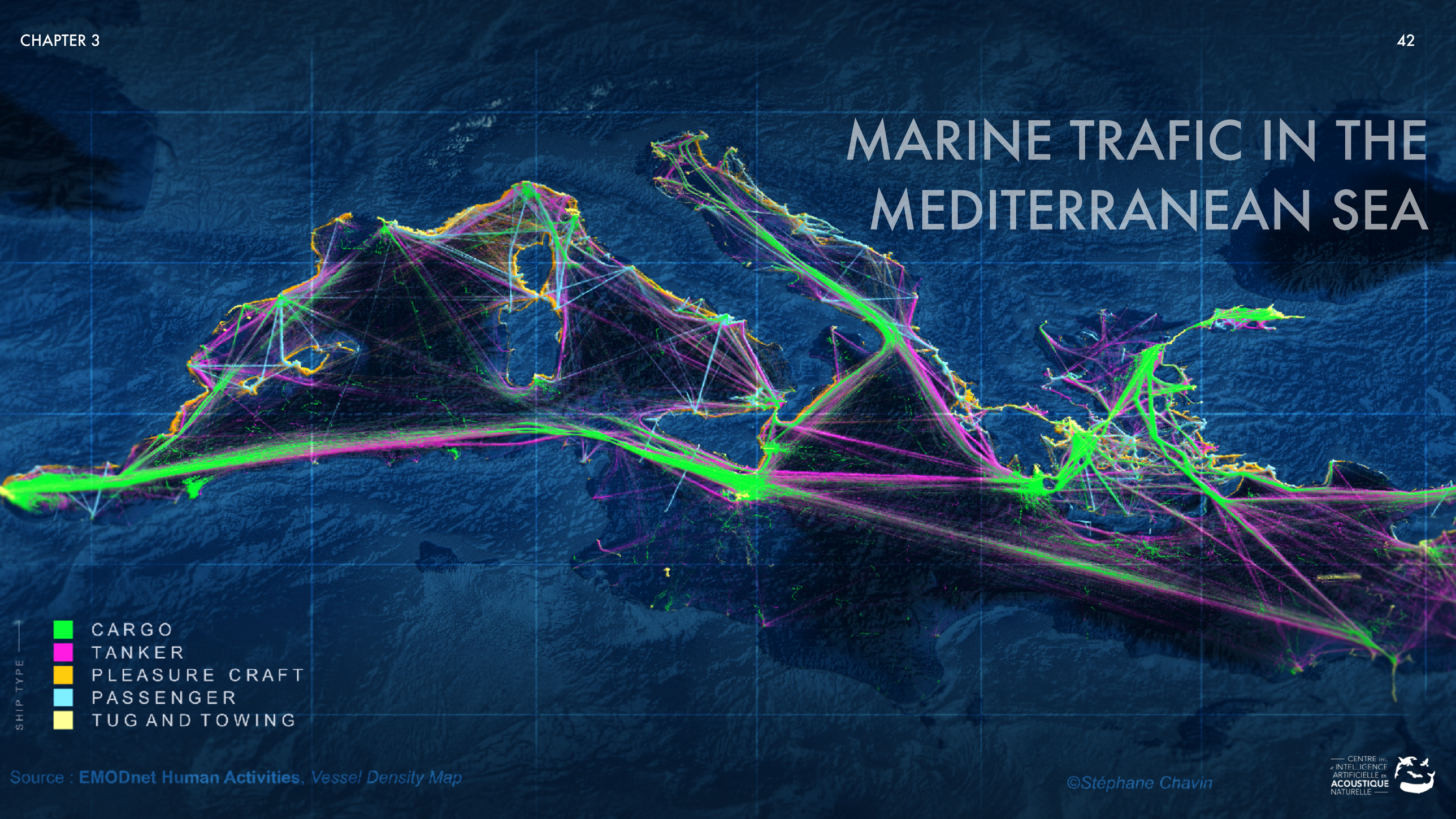


RESULTS : Sperm whale and surface currents



HOW TO APPLY THESES RESULTS TO CONSERVATION ?

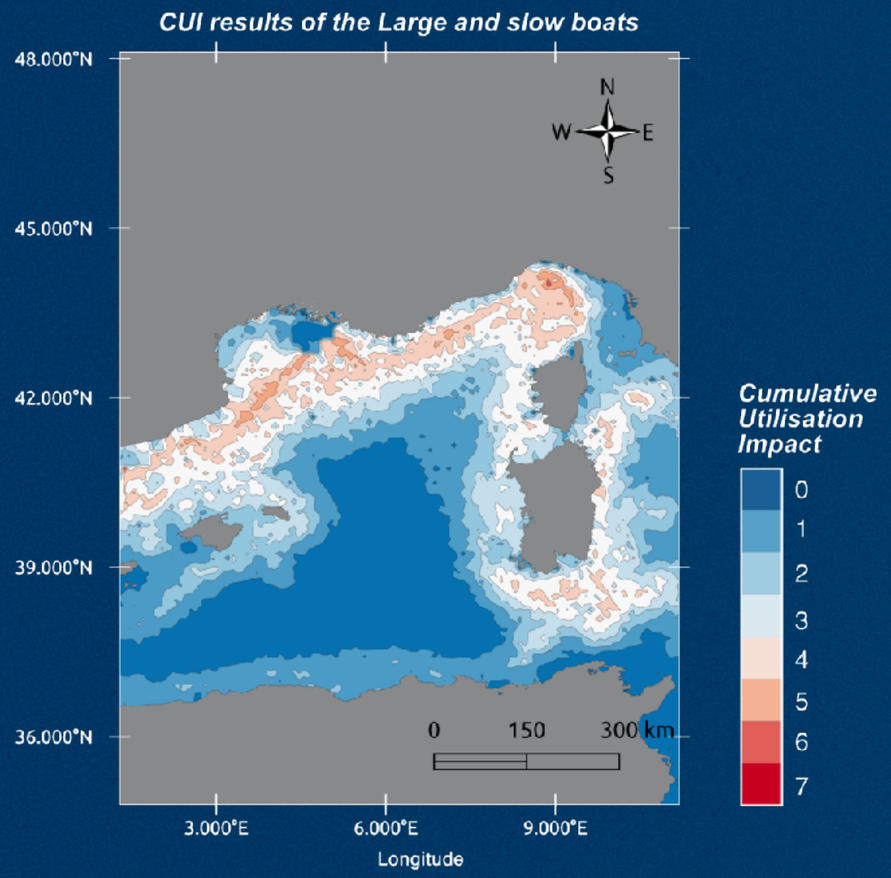
MARINE TRAFIC IN THE MEDITERRANEAN SEA



Source : **EMODnet Human Activities**, *Vessel Density Map*

©Stéphane Chavin

CENTRE IA : INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

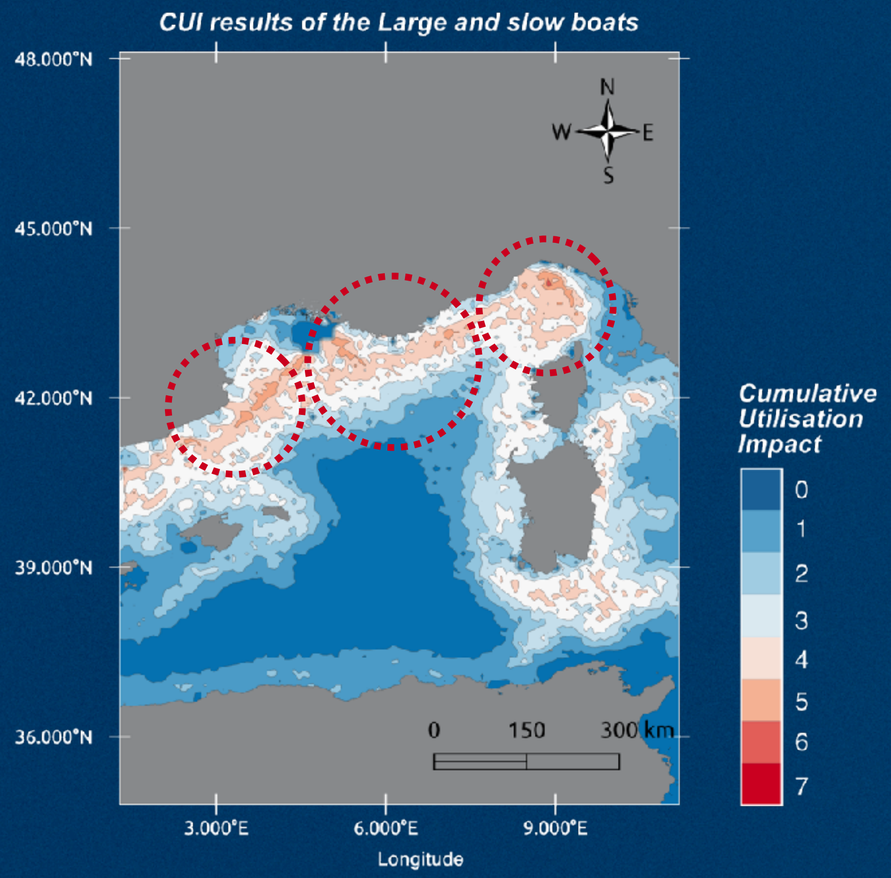


LARGE BOATS (HIGHER RISK 12/20)

- **Cargo, Tanker :** *Can go at high speed (> 15 knots) but have less control on their trajectories = cannot avoid the animal*

$$CUI = \sum_{i=1}^{n} \sum_{j=1}^{m} D_i \times S_j \times u_{ij}$$

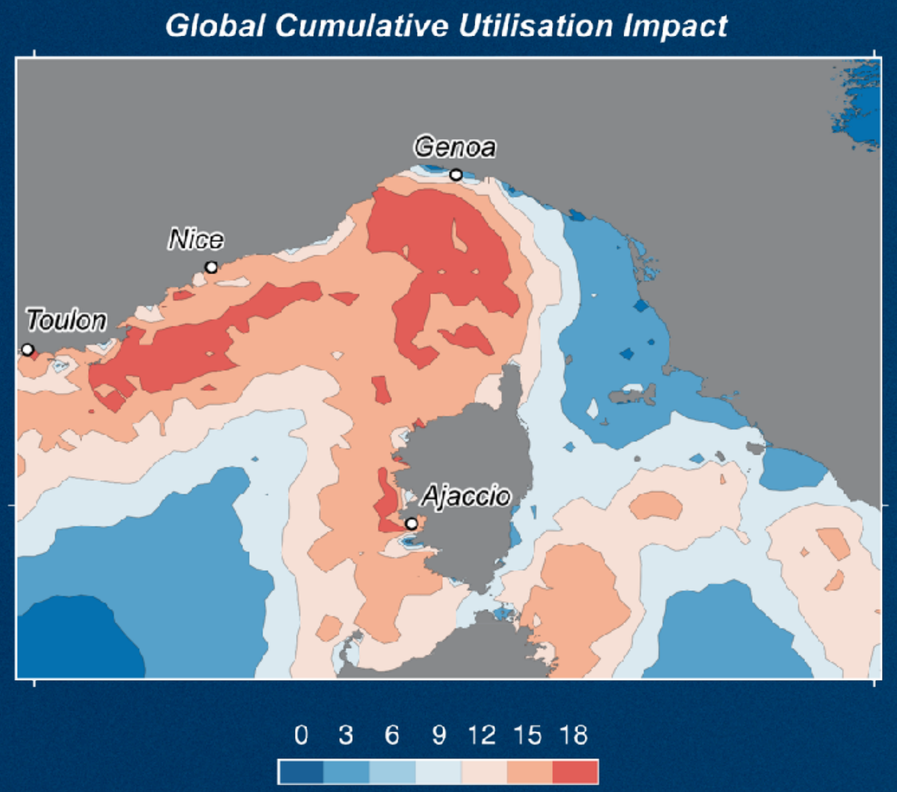
Di : normalised (0-1) log transformed value of the intensity of the anthropogenic impact;
Sj : the probability of the species j;
uij : the weight of the impact of I on the species j



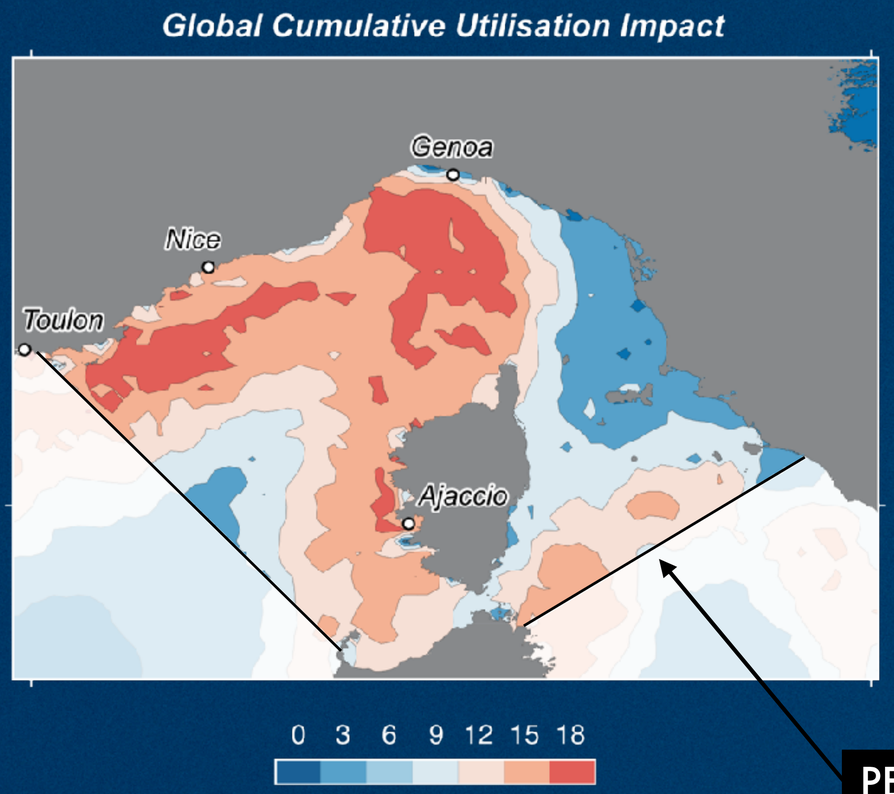
LARGE BOATS (HIGHER RISK 12/20)

- **Cargo, Tanker :** *Can go at high speed (> 15 knots) but have less control on their trajectories = cannot avoid the animal*

- **Risk area:** *North Barcelona (Spain), Marseille-Toulon (France) and Genoa (Italy)*

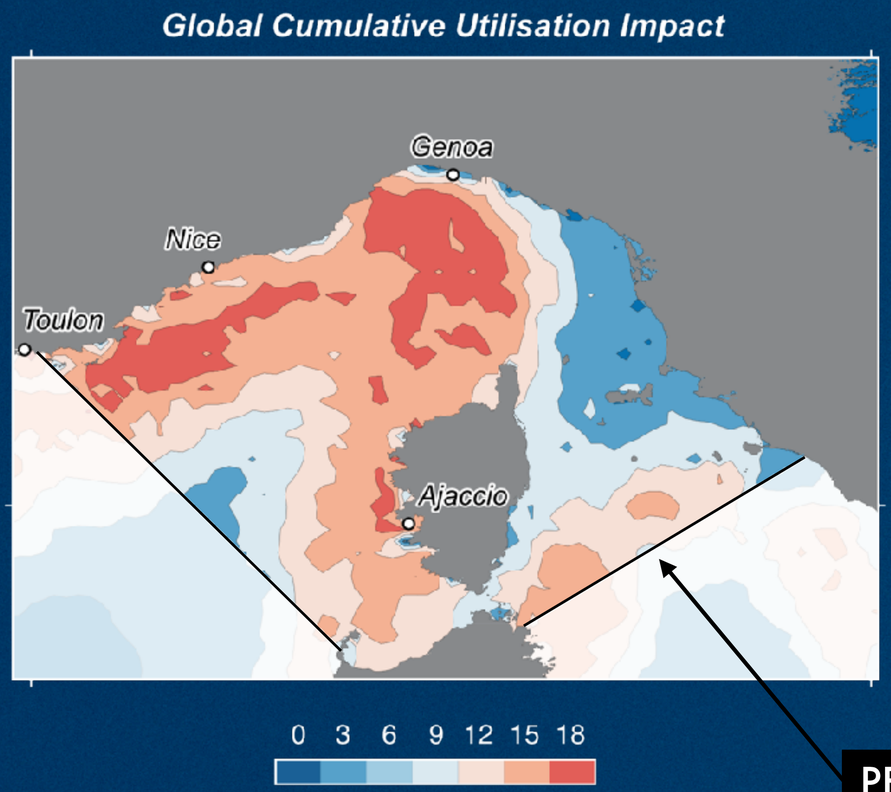


ALL BOATS TOGETHER



ALL BOATS TOGETHER

- *The impact is almost twice higher in the Pelagos Sanctuary rather than in the whole Mediterranean Sea*



ALL BOATS TOGETHER

- *The impact is almost twice higher in the Pelagos Sanctuary rather than in the whole Mediterranean Sea*

Solutions : Decreasing the speed of ship reduce the fatality rate of collision

HUMPBACK WHALE



SPERM WHALE



BIRDS



CREATION OF A VOCAL REPERTOIRE + YOLOV5 MODEL AND ANALYSIS OF MULTI YEAR RECORDINGS FROM BREEDING GROUND

The potential rising of the sea surface temperature may change breeding habits : location or timing ?

CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

HUMPBACK WHALE



SPERM WHALE



BIRDS



ANALYSIS OF > 200 MULTI YEAR VISUAL OBSERVATIONS BETWEEN MARSEILLE AND MONACO, AND HABITAT MAPPING

Sperm whale habitat is linked to the canyons which could be more prone to upwelling or downwelling (noticeable with SSH)

CENTRE int. d'INTELLIGENCE ARTIFICIELLE en ACOUSTIQUE NATURELLE

HUMPBACK WHALE



SPERM WHALE



BIRDS



YOLOV5 MODEL FOR 27 SPECIES, ANALYSIS OF THE RECORDINGS FROM 2016 UNTIL NOW REGARDING THE ENVIRONMENT

Automatically verified from acoustic data that some species have preferences for specific biome

CENTRE INT. D'INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE

	+	-
YOLOv5	Fast, time frequency annotations, highly precise results	Requires precise annotations and computing memory
MaxENT	Visual and easy	Only gives a global idea of the potential areas
GAM	Considers the multiple parameters	Risk of overfitting

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→ *We have to choose between having good recall but lower precision or low recall but higher precision*

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→ *It is not a density or abundance estimation*

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↓

Have more precision on the influence of each parameters

	+	-
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It can be difficult to identify all the variables + some variables are dependent on other

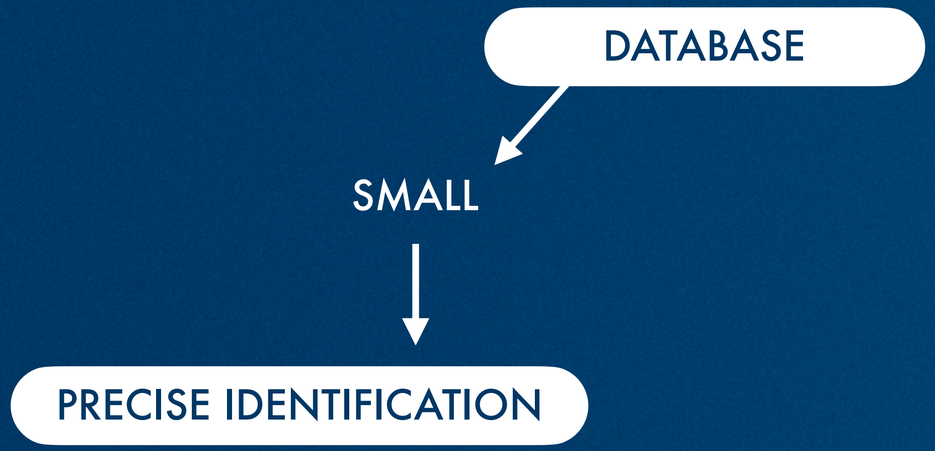
There is a potential sampling biais

HOW TO USE DEEP LEARNING DETECTIONS FROM ACOUSTIC RECORDINGS FOR SPECIES DISTRIBUTION MODELING ?

PERSPECTIVES & RECOMMENDATIONS

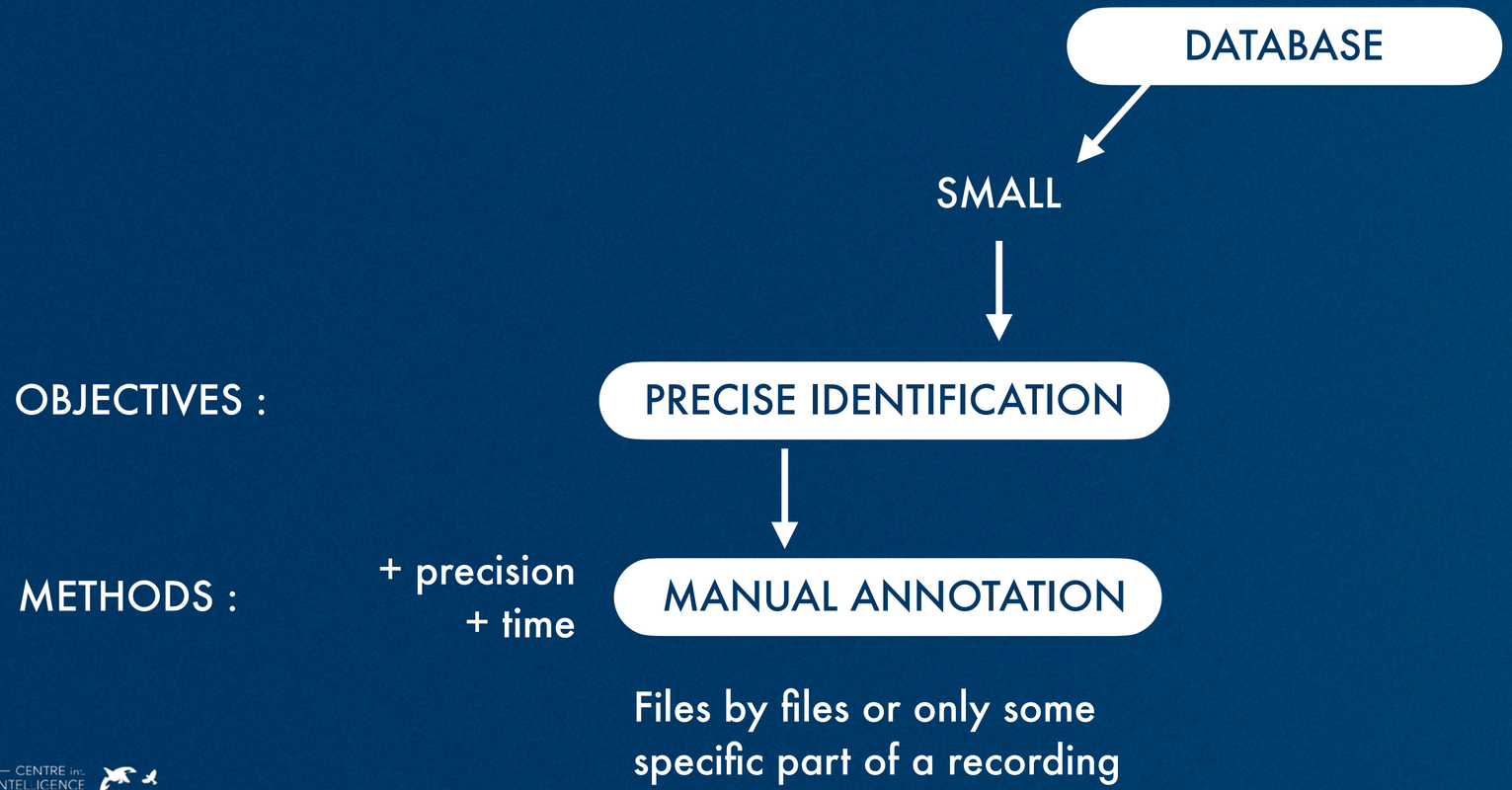
- *Should be considered depending on the objective of the project*

OBJECTIVES :



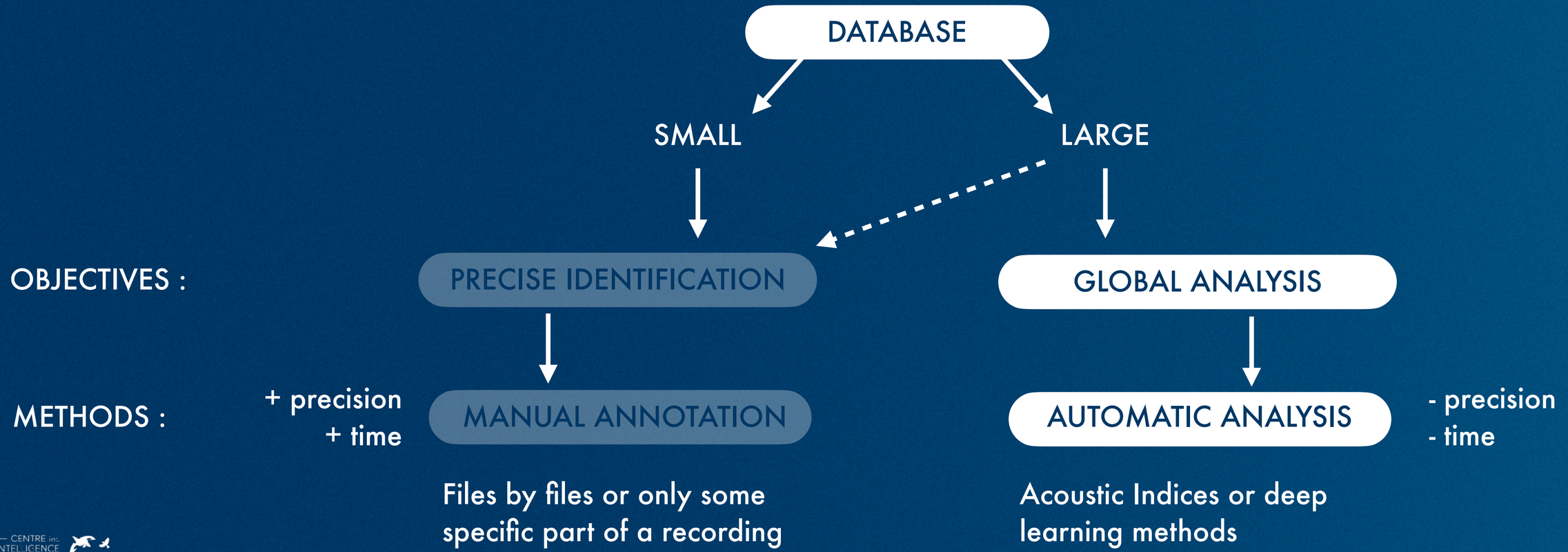
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- *Should be considered depending on the objective of the project*



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PERSPECTIVES & RECOMMENDATIONS

- *Should be considered depending on the objective of the project*
- *Work in collaboration with experts*



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PERSPECTIVES & RECOMMENDATIONS

- *Create a substantial dataset with variabilities in the annotations*

Adapt the model to the reality of the recordings

PERSPECTIVES & RECOMMENDATIONS

- *Create a substantial dataset with variabilities in the annotations*

Adapt the model to the reality of the recordings → GEOPHONY : WIND, RAIN…
CHORUS…
OTHER POTENTIAL SPECIES

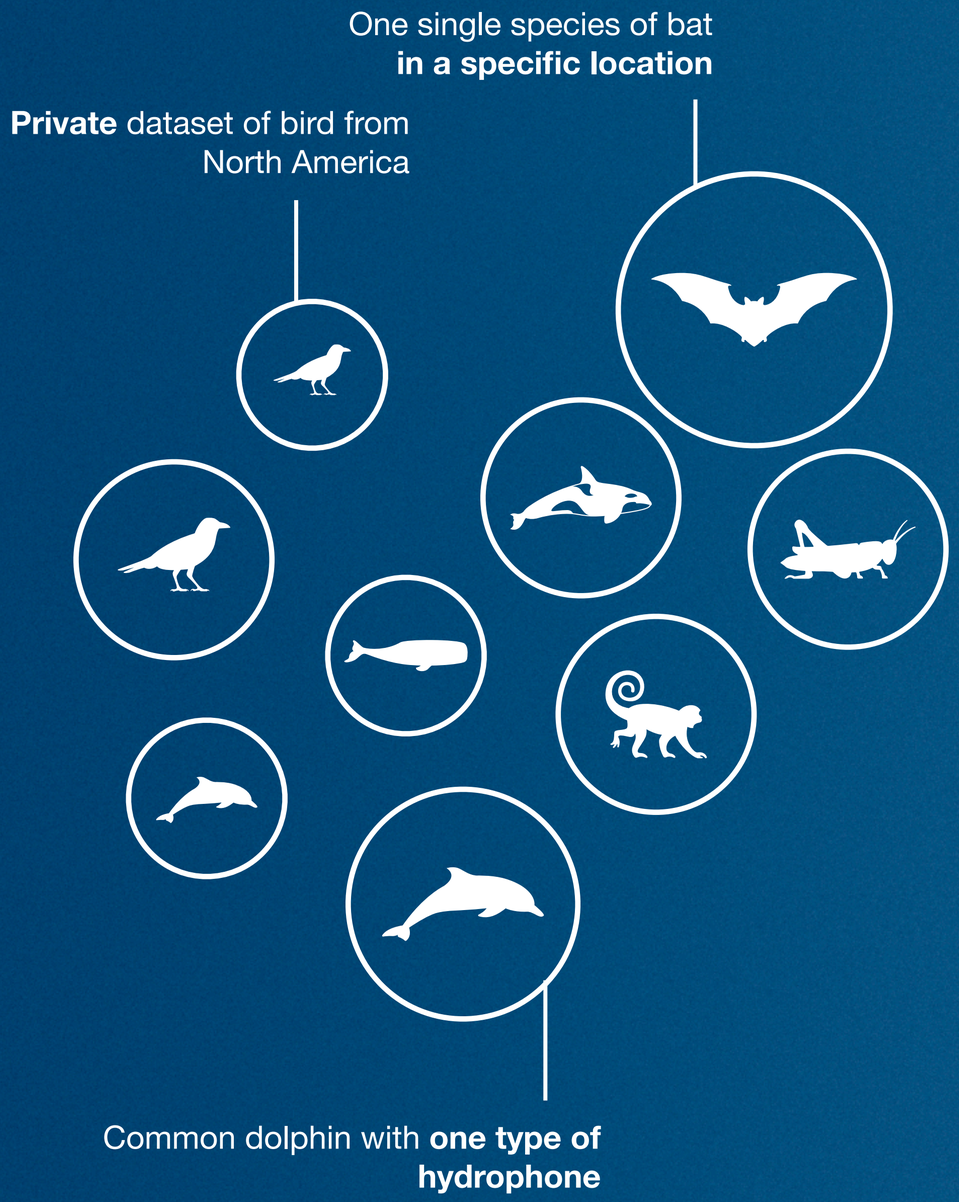
PERSPECTIVES & RECOMMENDATIONS

- *Create a substantial dataset with variabilities in the annotations*

Adapt the model to the reality of the recordings

- *Testing on independent and published datasets*

It is sometimes easier to be good on our personal dataset



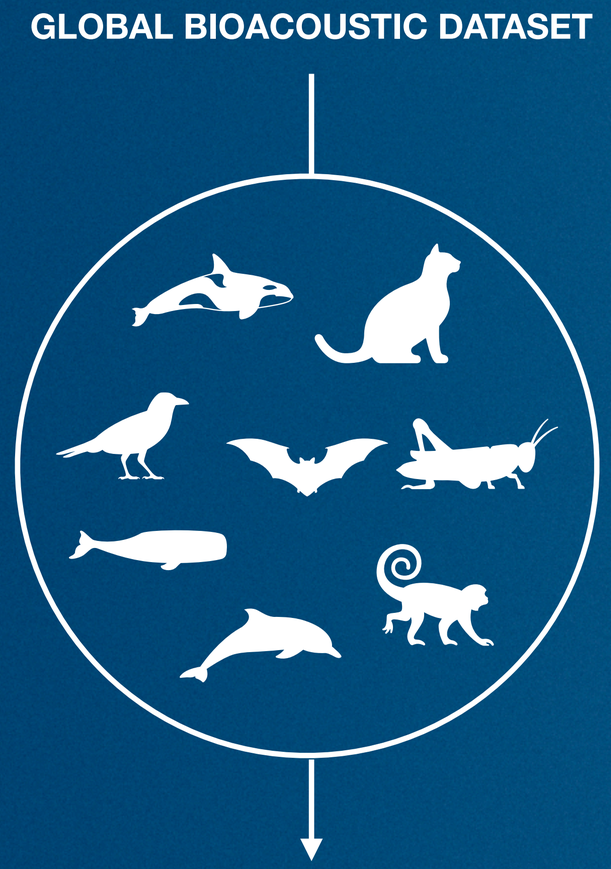
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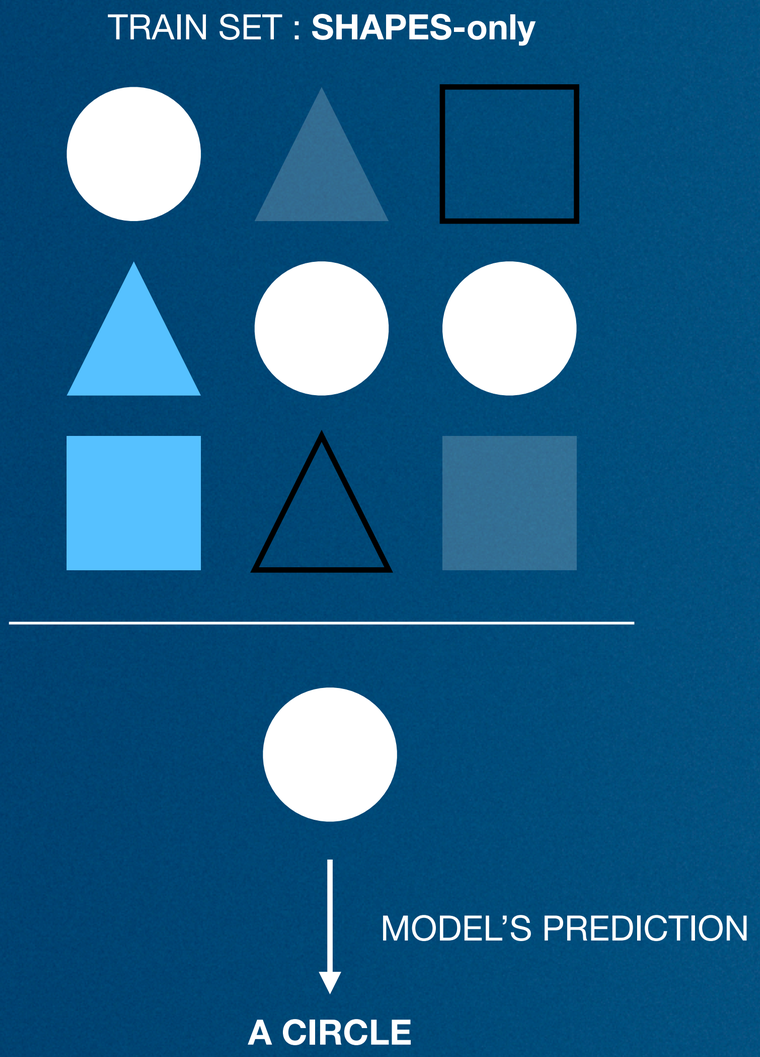
Adapt the model to the reality of the recordings

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- *Keeping in mind the potential of misalignment*

Models can learn the background or other type of features leading to great results but wrong analysis



THANK YOU



©Stéphane Chavin

WHY YOLO V5?

V5

mAP@50 : 82.3% (Precision 81.8% et Recall 77.8%)

9Go GPU

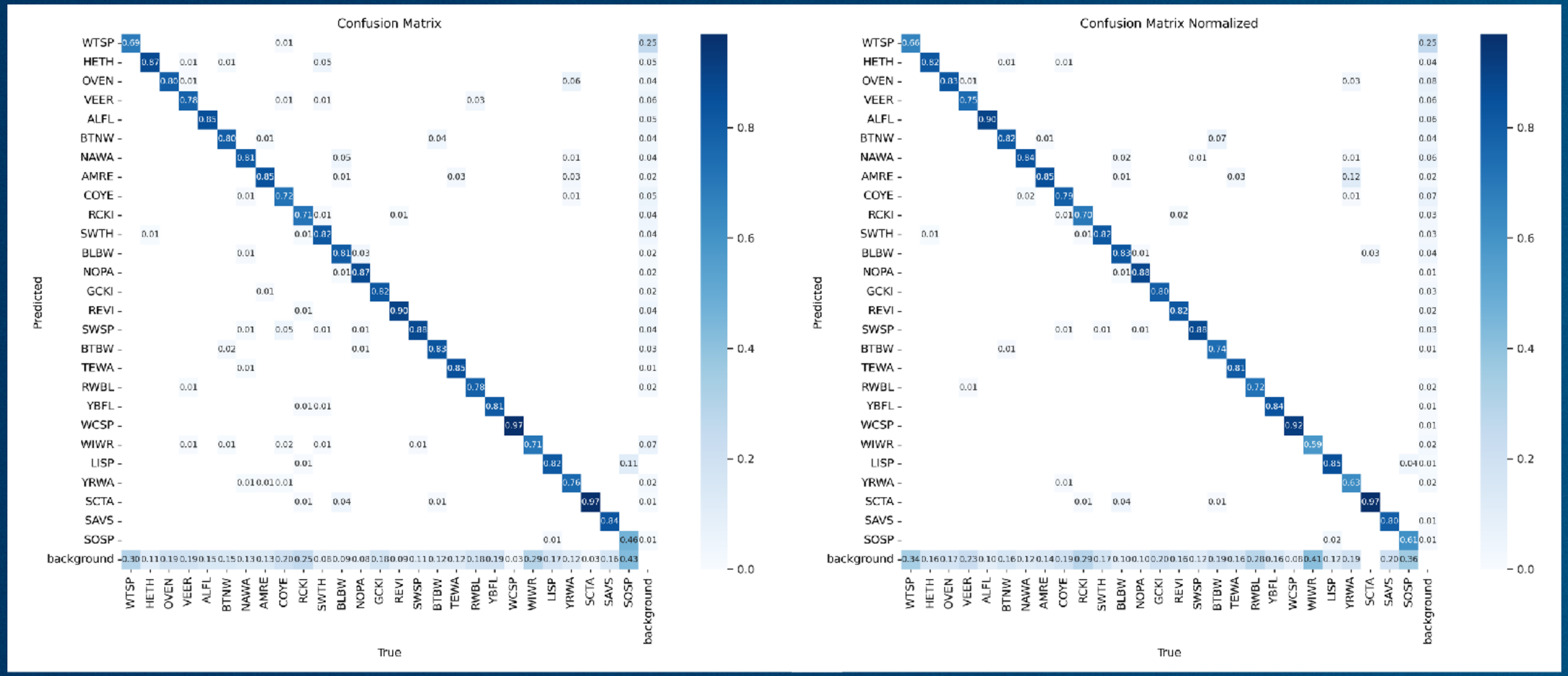
25 epochs in 20 minutes

V12 : transformer-like architecture

mAP@50 : 83.2% (Precision 82.9% et Recall 77%)

18Go GPU

25 epochs in + 60 minutes



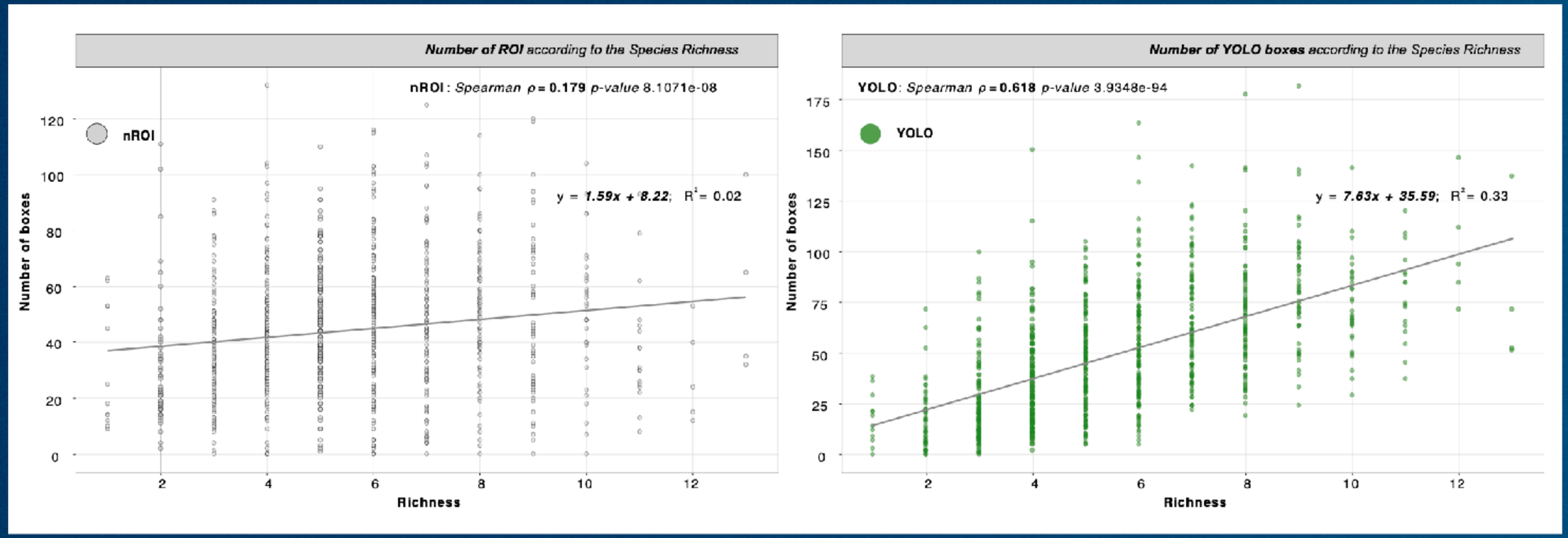
YOLOV5 L vs S

30 epochs, bird dataset

Size	duration (min)	GPU (Go)	optimiser	imgsz (pixels)	batch	pw	Train Precision	Train Recall	Train mAP@50	Train mAP@50-95	Test Precision	Test Recall	Test mAP@50	Test mAP@50-95	inference (ms)
L	23	11.9	SGD	640	32	Y	0.798	0.827	0.842	0.482	0.772	0.820	0.813	0.455	5.2
L	30	6.33	SGD	640	16	Y	0.782	0.843	0.843	0.483	0.775	0.822	0.814	0.458	7.7
S	12	4.82	SGD	640	32	Y	0.777	0.812	0.83	0.470	0.749	0.833	0.802	0.446	2.4
S	18	2.48	SGD	640	16	Y	0.789	0.825	0.845	0.477	0.774	0.816	0.813	0.45	1.7
L	**21**	**11.9**	**Adam**	**640**	**32**	**Y**	**0.798**	**0.82**	**0.846**	**0.476**	**0.79**	**0.799**	**0.820**	**0.452**	**4.9**
L	28	6.51	Adam	640	16	Y	0.795	0.802	0.841	0.479	0.785	0.785	0.815	0.453	5.0
L	14	2.07	SGD	224	32	Y	0.742	0.831	0.799	0.449	0.715	0.805	0.760	0.419	1.7
L	23	1.57	SGD	224	16	Y	0.744	0.833	0.795	0.448	0.719	0.793	0.759	0.421	1.5
L	20	11.9	SGD	640	32	N	0.764	0.838	0.806	0.456	0.700	0.796	0.725	0.409	30.4
L	27	6.33	SGD	640	16	N	0.791	0.838	0.841	0.477	0.787	0.819	0.819	0.451	6.5
S	11	4.82	SGD	640	32	N	0.794	0.833	0.846	0.477	0.785	0.813	0.815	0.451	2.4
S	17	2.48	SGD	640	16	N	0.774	0.813	0.812	0.462	0.775	0.824	0.815	0.453	1.7
L	23	11.9	Adam	640	32	N	0.800	0.839	0.849	0.485	0.773	0.827	0.818	0.46	5.3
L	31	6.83	Adam	640	16	N	0.774	0.830	0.831	0.476	0.765	0.824	0.812	0.454	6.0
L	15	2.07	SGD	224	32	N	0.753	0.850	0.808	0.454	0.718	0.815	0.763	0.415	3.4
L	26	1.57	SGD	224	16	N	0.770	0.834	0.810	0.456	0.726	0.827	0.773	0.424	2.0
S	11	0.719	SGD	224	32	Y	0.728	0.801	0.776	0.419	0.691	0.785	0.740	0.392	0.6
S	20	0.457	SGD	224	16	Y	0.726	0.794	0.784	0.417	0.712	0.779	0.748	0.391	0.7

YOLOV5 for species richness

884 files : nROI (default) vs YOLO number of bounding box, no filtering



Dataset

HUMPBACK WHALE

Unit	N	Train	Val	Test	Precision	Recall	mAP@50
all	3111	2119	481	511	0.836	0.702	0.739
C	513	361	90	77	0.721	0.662	0.706
D	359	260	51	63	0.736	0.754	0.750
V	253	170	49	43	0.921	0.651	0.692
P	227	169	45	30	0.850	0.567	0.652
E	183	127	33	31	0.877	0.839	0.851
B	129	88	30	14	1.000	0.821	0.858
H	131	95	22	23	0.961	0.870	0.868
U	116	87	20	21	0.656	0.546	0.585
A	101	75	16	13	0.848	0.538	0.530
M	113	75	24	21	0.982	0.857	0.858
W	80	57	14	15	0.883	0.667	0.761
G	93	73	15	12	0.399	0.583	**0.481**
O	163	123	21	31	0.858	0.777	0.835
T	65	48	11	12	0.675	0.333	**0.379**
F	61	44	8	12	0.912	0.865	0.909
K	57	39	10	10	0.764	0.650	0.700
L	75	57	12	11	0.946	0.818	0.821
J	49	36	10	9	1.000	0.607	0.667
P′	56	42	9	11	0.656	0.545	0.577
B"	33	22	7	4	0.758	1.000	0.995
X	24	19	3	3	0.907	0.667	0.698
F′	27	17	6	4	1.000	0.889	0.995
I	49	35	5	11	0.914	0.636	0.823

BIRDS

Class	Precision	Recall	mAP50	mAP50_95	Train	Test	Val
all	**0.810** ± 0.007	**0.778** ± 0.011	**0.818** ± 0.012	**0.458** ± 0.007	22360	4881	4823
wtsp	**0.656** ± 0.026	**0.585** ± 0.023	**0.614** ± 0.012	**0.300** ± 0.008	2698	557	614
heth	**0.869** ± 0.024	**0.825** ± 0.028	**0.891** ± 0.007	**0.522** ± 0.006	2026	396	401
oven	**0.847** ± 0.025	**0.794** ± 0.027	**0.872** ± 0.009	**0.474** ± 0.006	1770	345	388
veer	**0.847** ± 0.028	**0.745** ± 0.031	**0.852** ± 0.008	**0.461** ± 0.002	1566	386	322
btnw	**0.848** ± 0.024	**0.803** ± 0.014	**0.871** ± 0.005	**0.560** ± 0.012	1214	274	264
alfl	**0.845** ± 0.048	**0.824** ± 0.026	**0.891** ± 0.037	**0.526** ± 0.020	1136	259	223
nawa	**0.806** ± 0.014	**0.796** ± 0.034	**0.836** ± 0.015	**0.540** ± 0.010	1154	249	236
amre	**0.859** ± 0.024	**0.860** ± 0.032	**0.902** ± 0.029	**0.552** ± 0.015	898	190	197
coye	**0.774** ± 0.031	**0.737** ± 0.047	**0.781** ± 0.028	**0.419** ± 0.019	892	196	192
rcki	**0.749** ± 0.041	**0.711** ± 0.029	**0.774** ± 0.016	**0.380** ± 0.011	947	185	175
blbw	**0.862** ± 0.025	**0.800** ± 0.021	**0.879** ± 0.006	**0.499** ± 0.009	796	187	169
swth	**0.803** ± 0.043	**0.805** ± 0.035	**0.863** ± 0.010	**0.410** ± 0.012	825	143	138
nopa	**0.920** ± 0.031	**0.906** ± 0.011	**0.932** ± 0.004	**0.654** ± 0.008	806	181	178
gcki	**0.859** ± 0.030	**0.768** ± 0.032	**0.845** ± 0.025	**0.438** ± 0.015	685	166	174
revi	**0.728** ± 0.036	**0.837** ± 0.042	**0.813** ± 0.017	**0.353** ± 0.010	568	130	160
swsp	**0.806** ± 0.036	**0.850** ± 0.021	**0.827** ± 0.024	**0.461** ± 0.021	572	161	137
btbw	**0.823** ± 0.042	**0.805** ± 0.037	**0.871** ± 0.012	**0.570** ± 0.008	548	138	124
tewa	**0.926** ± 0.030	**0.843** ± 0.022	**0.917** ± 0.016	**0.590** ± 0.012	428	100	76
wiwr	**0.540** ± 0.080	**0.327** ± 0.134	**0.421** ± 0.076	**0.142** ± 0.026	381	84	68
rwbl	**0.724** ± 0.037	**0.738** ± 0.036	**0.744** ± 0.025	**0.331** ± 0.018	339	93	81
ybfl	**0.895** ± 0.026	**0.817** ± 0.021	**0.846** ± 0.024	**0.326** ± 0.014	353	70	80
wcsp	**0.985** ± 0.014	**0.892** ± 0.085	**0.929** ± 0.09	**0.611** ± 0.062	404	98	101
lisp	**0.908** ± 0.036	**0.843** ± 0.022	**0.901** ± 0.017	**0.608** ± 0.016	438	82	114
yrwa	**0.743** ± 0.049	**0.740** ± 0.049	**0.784** ± 0.020	**0.455** ± 0.012	266	67	55
scta	**0.776** ± 0.018	**0.947** ± 0.031	**0.845** ± 0.022	**0.441** ± 0.019	288	66	64
savs	**0.904** ± 0.054	**0.865** ± 0.017	**0.904** ± 0.007	**0.549** ± 0.044	261	50	73
sosp	**0.557** ± 0.074	**0.541** ± 0.068	**0.482** ± 0.077	**0.197** ± 0.030	101	28	19

DATA AUGMENTATIONS

```
lr0: SGD=1E-2, Adam=1E-3
lrf: 0.1 # final OneCycleLR learning rate (lr0 * lrf)
momentum: 0.937 # SGD momentum/Adam beta1
weight_decay: 0.0005 # optimizer weight decay 5e-4
warmup_epochs: 3.0 # warmup epochs (fractions ok)
warmup_momentum: 0.8 # warmup initial momentum
warmup_bias_lr: 0.1 # warmup initial bias
lr box: 0.05 # box loss
gain cls: 0.3 # cls loss gain
cls_pw: 1.0 # cls BCELoss
positive_weight obj: 0.7 # obj loss gain (scale with pixels)
obj_pw: 1.0 # obj BCELoss positive_weight
iou_t: 0.20 # IoU training
threshold anchor_t: 4.0 # anchor-multiple threshold #
anchors: 3 # anchors per output layer (0 to ignore)
fl_gamma: 0.0 # focal loss gamma (efficientDet default gamma=1.5)
hsv_h: 0.01 # image HSV-Hue augmentation (fraction)
hsv_s: 0.1 # image HSV-Saturation augmentation (fraction)
hsv_v: 0.1 # image HSV-Value augmentation (fraction)
degrees: 0.0 # image rotation (+/- deg)
translate: 0.0 # image translation (+/- fraction)
scale: 0.0 # image scale (+/- gain) shear: 0.0 # image shear (+/- deg)
perspective: 0.0 # image perspective (+/- fraction), range 0-0.001
flipud: 0.0 # image flip up-down (probability)
fliplr: 0.0 # image flip left-right (probability)
mosaic: 0.0 # image mosaic (probability)
mixup: 0.3 # image mixup (probability)
copy_paste: 0.1 # segment copy-paste (probability)
ToGray: 0.0 # image in Grayscale (probability)
GaussNoise: 0.0 # adding Gaussian/white noise (probability)
```

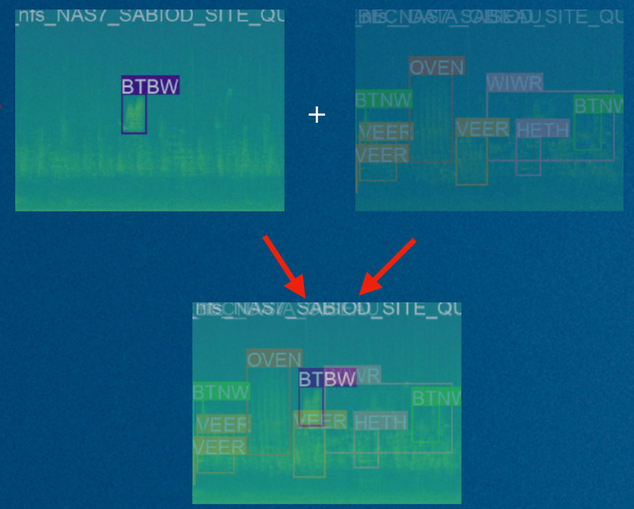
1 value / species based on the ratio in the dataset

Strange parameters for bioacoustics

For birds : 0.1, 0.1 and 0.2

70% opacity

30% opacity



BACKGROUND SIGNALS

HUMPBACK WHALE

1500 8-seconds spectrograms



BIRDS

600 15-seconds spectrograms (2.5 hours)

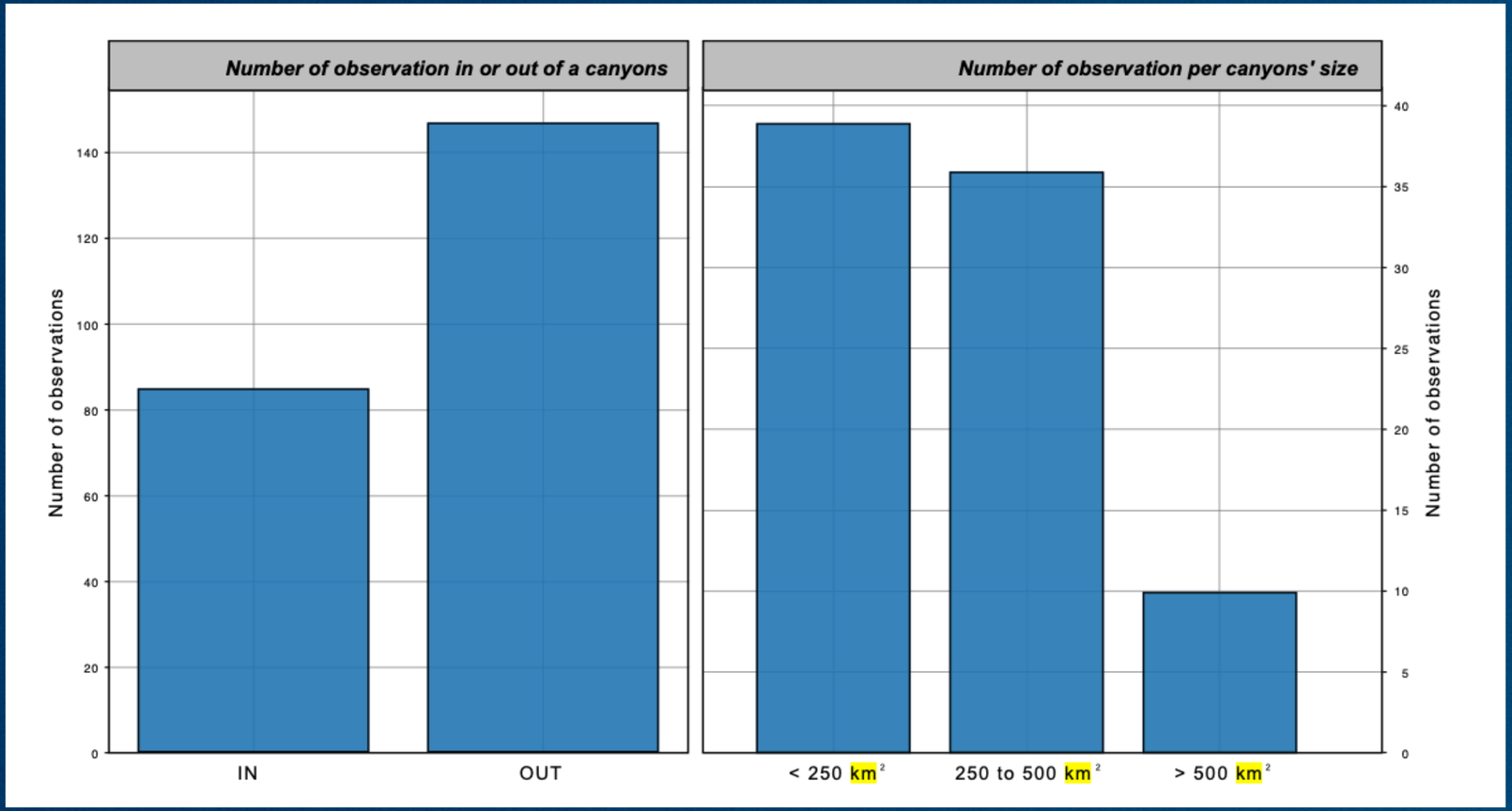


CANYONS

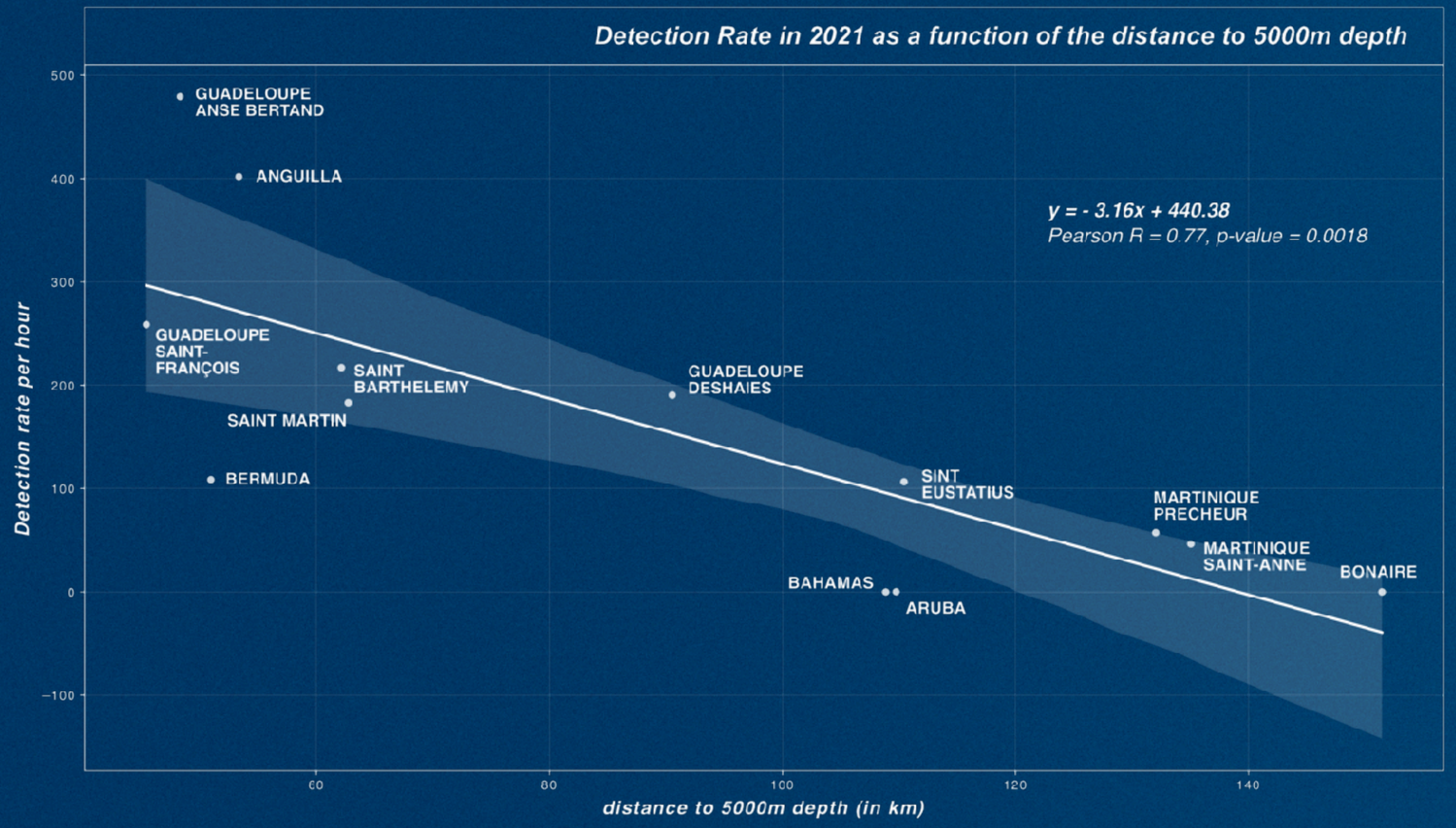
~30% close (1.5 km) to a canyon

14% more than 4km to a canyon

6.5% more than 11km to a canyon (maximum = 13 km)



RESULTS : Humpback whale

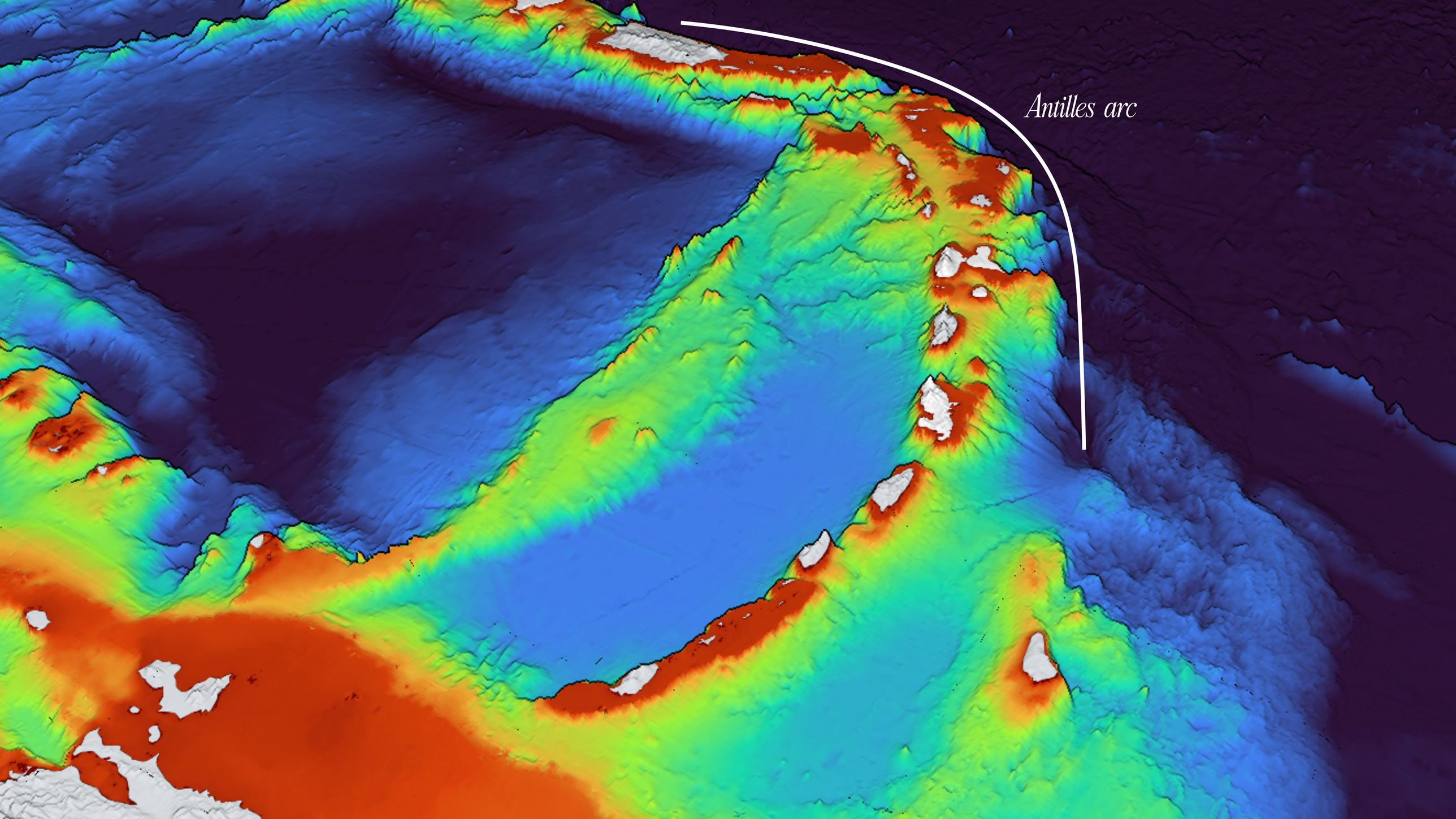


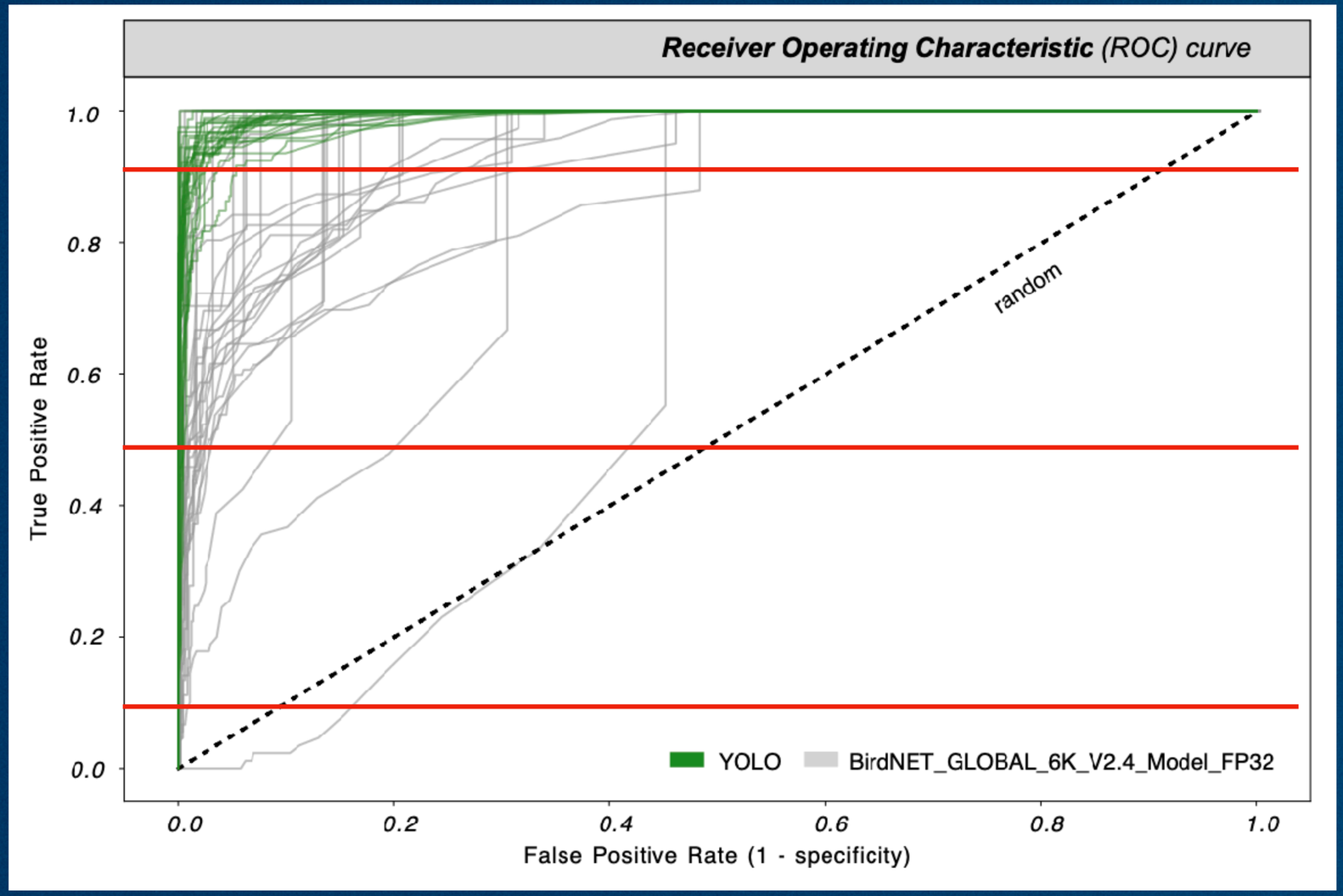
1. FIXED PARAMETER

closer to the Antilles arc
= higher detection rate

Can be an important parameter for sound propagation

CENTRE INTELLIGENCE ARTIFICIELLE EN ACOUSTIQUE NATURELLE


Antilles arc



0.9

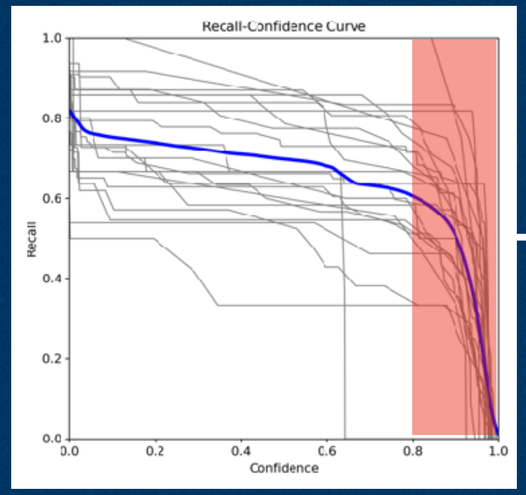
0.5

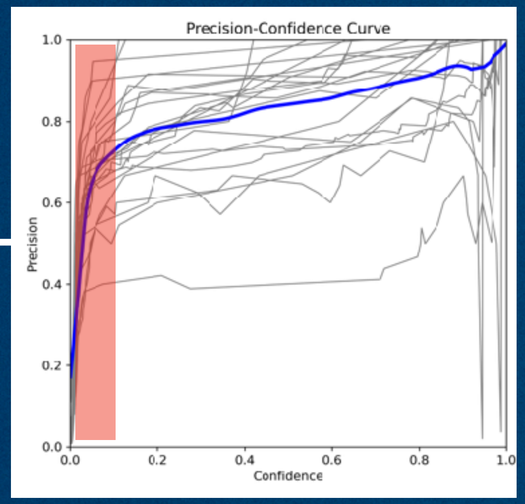
0.1

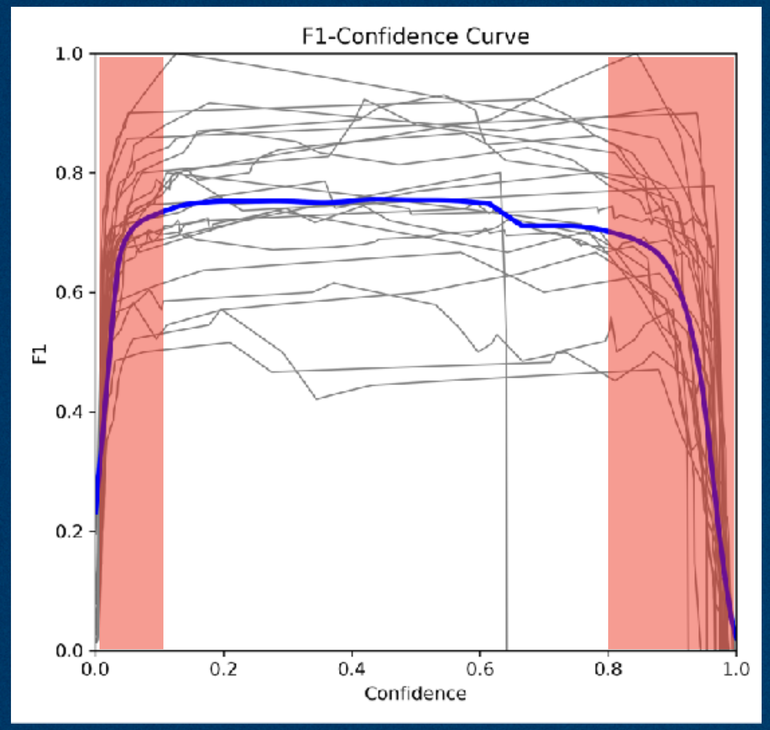
BIRDS

Thresholds are extracted based on the TPR scenario

QUESTIONS





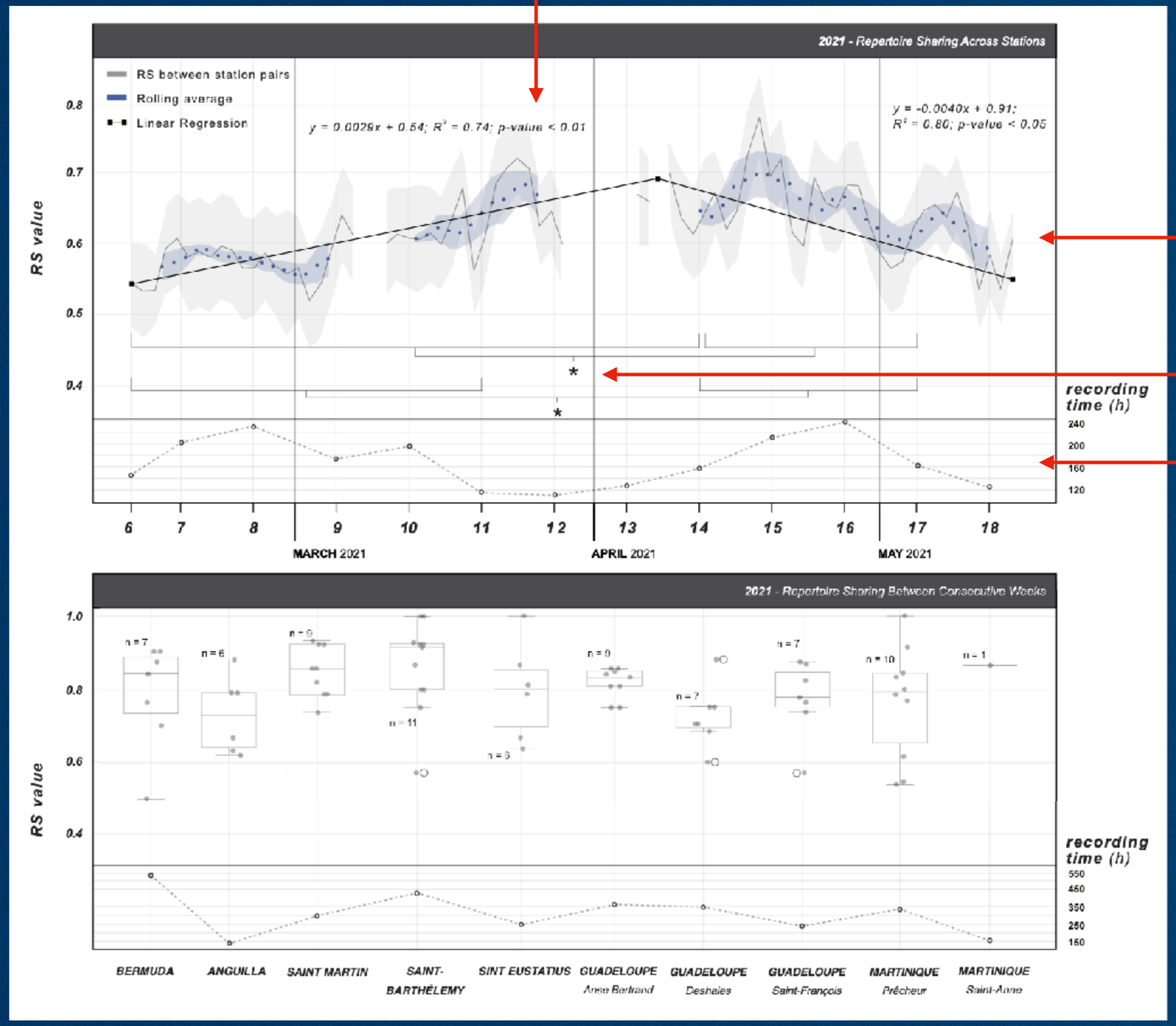


HUMPBACK WHALE

Thresholds are extracted on the F1 curve between 0.1 and 0.8 of confidence

QUESTIONS

Pearson



MannWhitney U

Pearson

Kruskal-Wallis

RS for each weeks every station

Pairwise Wilcoxon

QUESTIONS

Categories	Frequency /4	Direct /Indirect impact /3	Resistance (Likelihood of mortality) /3	Recovery time of individual (years) /4	Reproductive Impacts /3	Population Effects /3	Total /20
small and fast	3	3	1	1	1	1	10
large and "slow"	2	3	2	1	3	1	12
large and fast	2	3	2	1	3	1	12

Vulnerability Measure	Category	Rank	Descriptive Notes	Example
Frequency	Never	0		
What is the frequency of the impact?	Rare	1	Infrequent enough to affect long-term dynamics or **population**	Large oil spill
	Occasional	2	Frequent but irregular in nature	Toxic algal blooms
	Annual or regular	3	Frequent and often seasonal or periodic in nature	Runoff events due to seasonal rains
	Persistent	4	More or less constant year-round lasting through multiple years or decades	Persistent hypoxic zones
Direct/Indirect impact	No impact	0		
What's the mechanism by which it is affecting the **individual**?	Distant indirect impact	1	Effects are more than one degree removed	Trophic cascade, food source; ecosystem degradation; impacts something that impacts prey
	Indirect impact	2	Known to cause impact as a result of an indirect link such as via prey; metabolic or life span effect	Impacts prey, impacts of heavy metals that don't result in direct death
	Direct impact	3	Mortality	Bycatch in fishing gear
Resistance (Likelihood of mortality)	No impact	0		
How likely is that impact to affect the **individual**?	Low	1	Unlikely to result in mortality (0-33%)	Anthropogenic noise
	Medium	2	Moderate likelihood of mortality (33-66%)	Domoic acid
	Low	3	High likelihood of mortality (66-100%)	Large reduction in forage base
Recovery time of individual (years)	no impact	0		
How long does it take the individual to recover from exposure to the impact?	<1	1		
	1-10	2		
	10-100	3		
	>100	4		
Reproductive Impacts	No impact	0		
What is the level of impact on reproduction of an individual?	Low	1	Impacts some aspect (e.g. behavior) but no loss of reproductive capacity	Temporary displacement from feeding ground
	Moderate	2	Decreased reproductive capacity	Changes in SST result in decrease forage species and reduced reproduction
	High	3	Direct mortality	Death of animal resulting in no repro
Population Effects	No impact	0		
How are the impact distributed across the population?	Low	1	Effects one animal at a time	Ship strike
	Moderate	2	Effects specific sectors or large portion of the population	Impacts females only
	High	3	Effects entire population in CCS	Changes in SST reducing forage species

Maxwell, S., Hazen, E., Bograd, S. *et al.* Cumulative human impacts on marine predators. *Nat Commun* **4**, 2688 (2013). https://doi.org/10.1038/ncomms3688