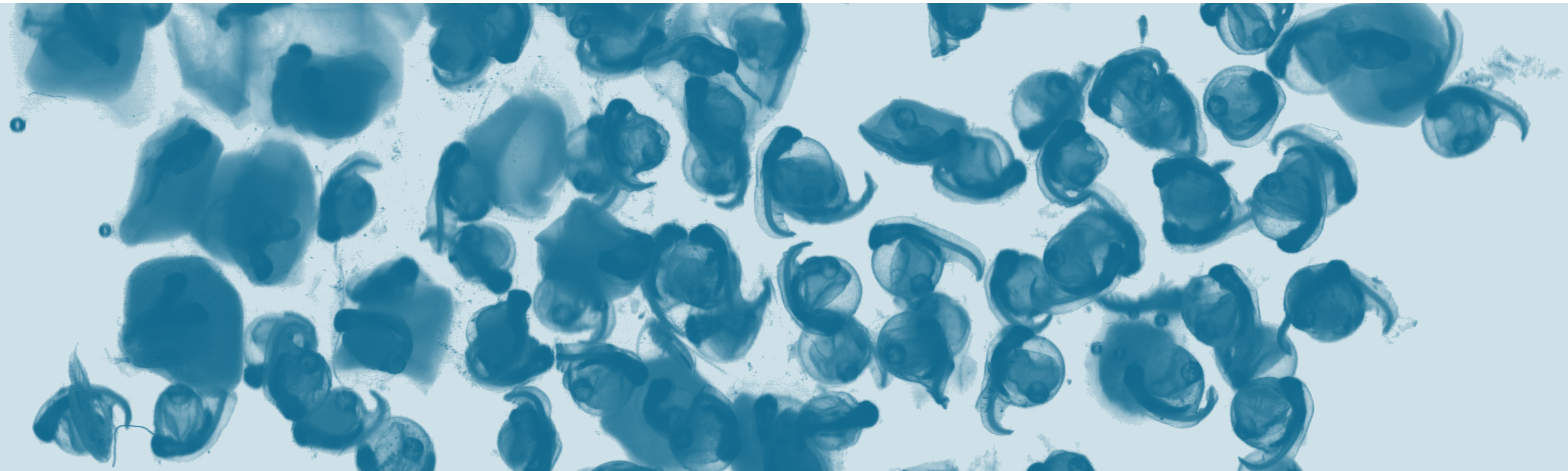


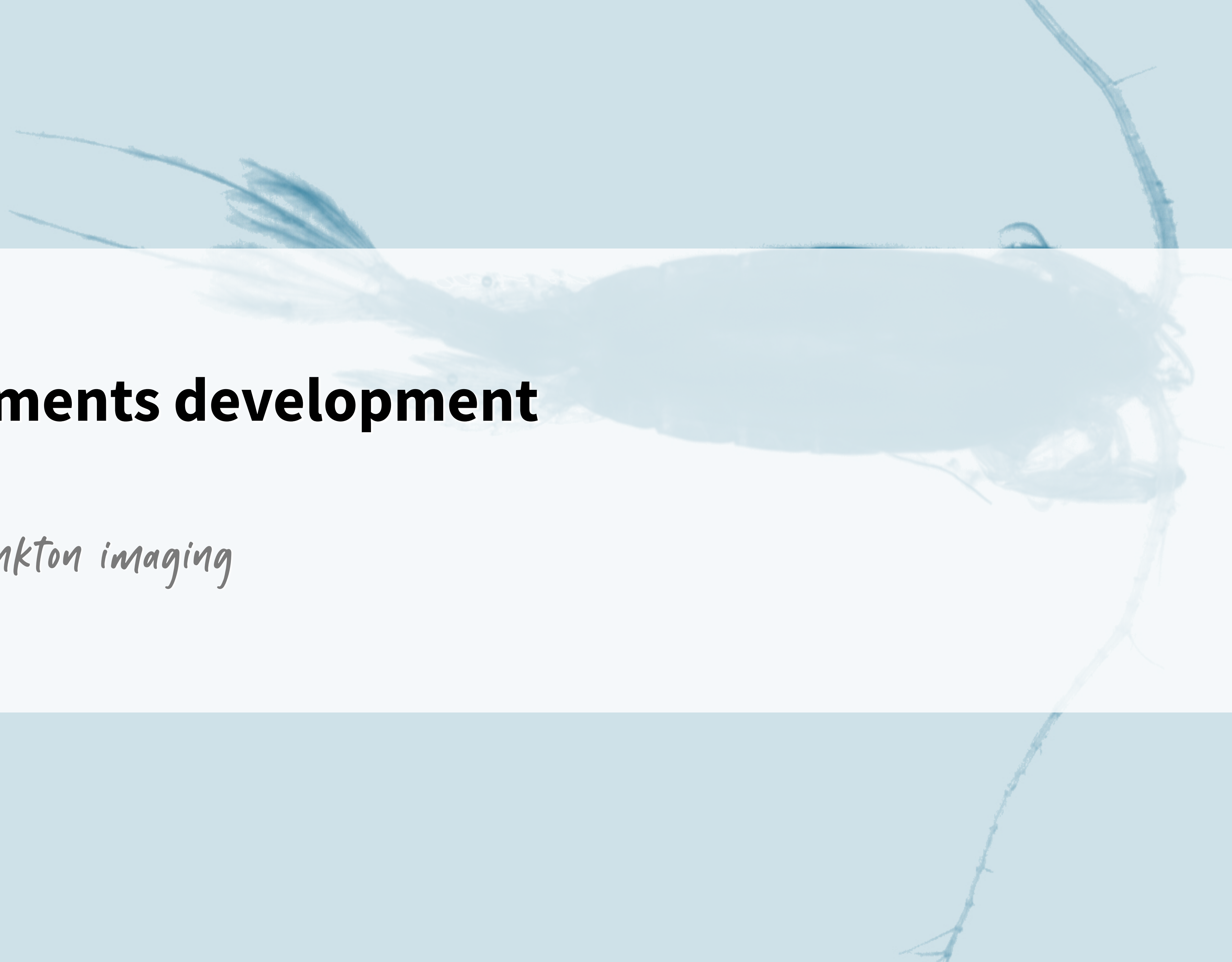
Observing zooplankton: organisation and technological developments

With a bias towards imaging in Villefranche



Outline

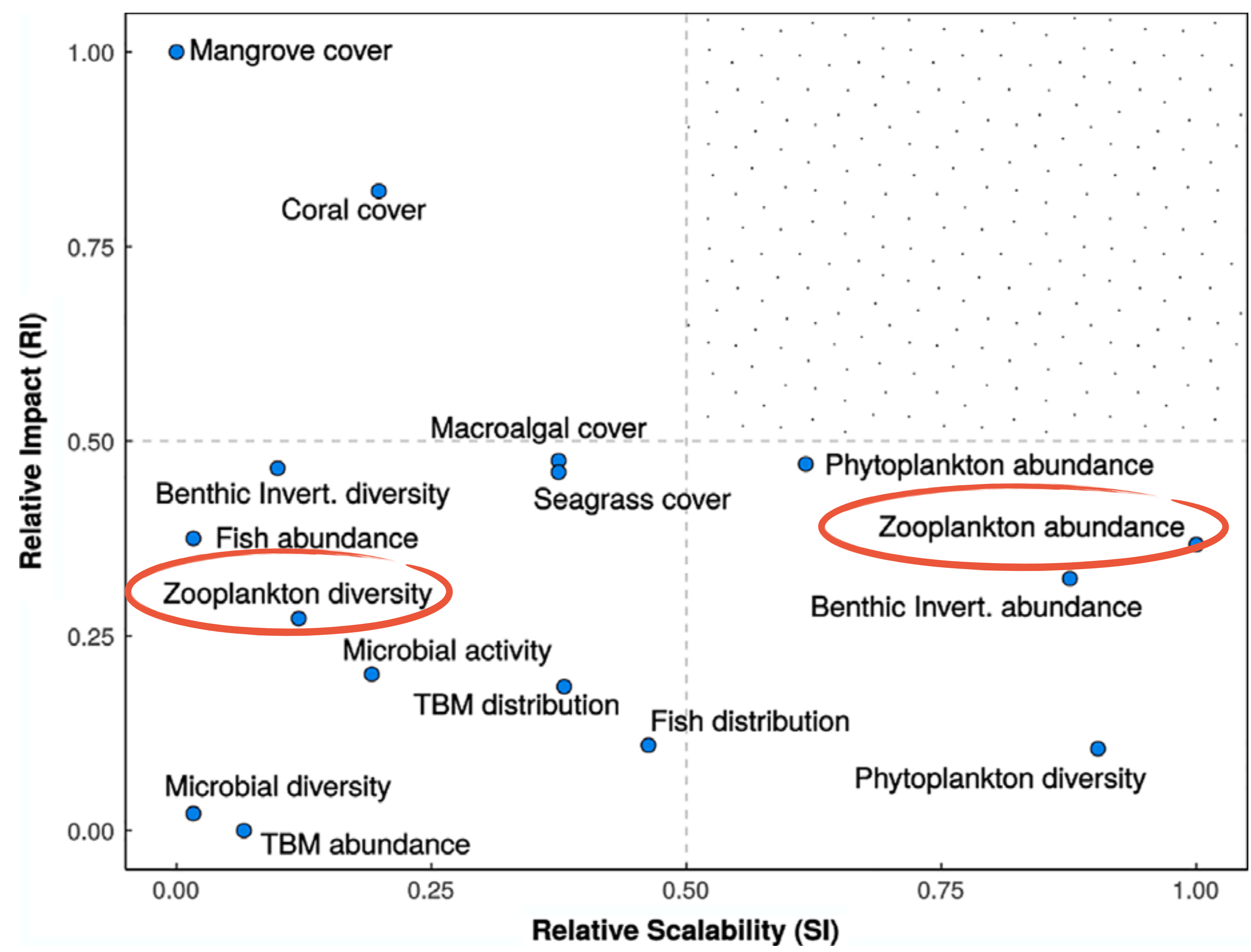
1. Instruments development for zooplankton imaging
2. Software and machine learning developments for zooplankton imaging
3. A few scientific results
4. The landscape of ocean observing (with a bias towards biology) in the EU, France, and Villefranche

A faint, light blue background image of a shrimp-like zooplankton, possibly a mysid, is centered horizontally. The organism is shown in profile, facing right, with its long antennae extending upwards and downwards. The body is segmented, and the tail fan is visible at the rear. The image is semi-transparent, allowing the text to be overlaid clearly.

Instruments development

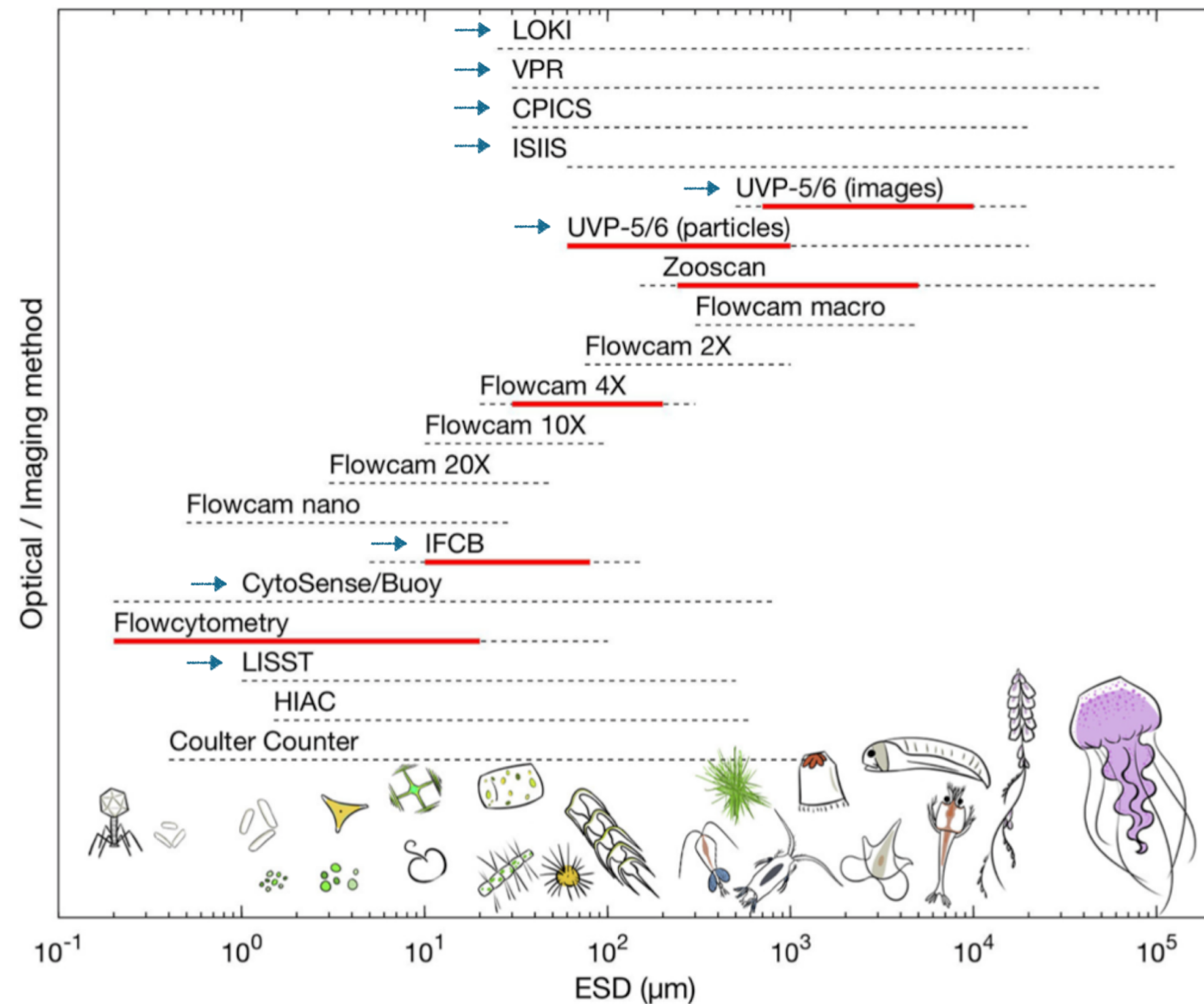
For zooplankton imaging

Among EOVs, plankton monitoring has the potential to scale well





Notably through imaging, but no instrument sees it all



Globally Consistent Quantitative Observations of Planktonic Ecosystems

Fabien Lombard^{1,2*}, Emmanuel Boss^{3*}, Anya M. Waite⁴, Meike Vogt⁵, Julia Uitz¹, Lars Stemmann¹, Heidi M. Sosik⁶, Jan Schulz⁷, Jean-Baptiste Romagnan⁸, Marc Picheral¹, Jay Pearlman⁹, Mark D. Ohman¹⁰, Barbara Niehoff¹¹, Klas O. Möller¹², Patricia Miloslavich^{13,14}, Ana Lara-Lpez¹³, Raphael Kudela¹⁵, Rubens M. Lopes¹⁶, Rainer Kiko¹⁷, Lee Karp-Boss³, Jules S. Jaffe¹⁰, Morten H. Iversen^{11,18}, Jean-Olivier Irisson¹, Katja Fennel¹⁹, Helena Hauss¹⁷, Lionel Guidi¹, Gaby Gorsky¹, Sarah L. C. Giering²⁰, Peter Gaube²¹, Scott Gallagher⁶, George Dubelaar²², Robert K. Cowen²³, François Carlotti²⁴, Christian Briseño-Avena²³, Léo Berline²⁴, Kelly Benoit-Bird²⁵, Nicholas Bax^{13,26}, Sonia Batten²⁷, Sakina Dorothée Ayata^{1,28}, Luis Felipe Artigas²⁹ and Ward Appeltans³⁰

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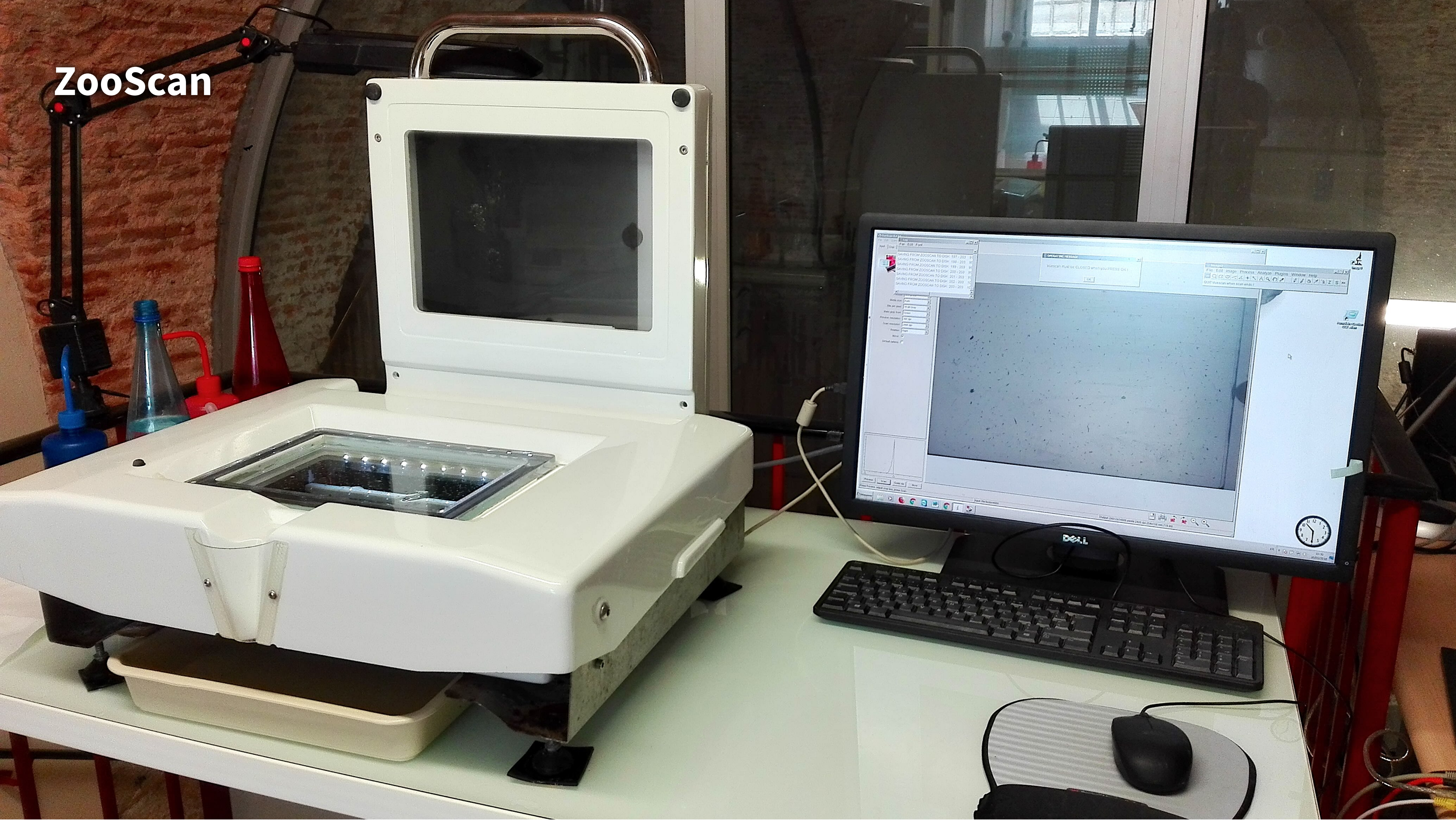
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Lombard F, Boss E, Waite AM, Vogt M, Uitz J, Stemmann L, Sosik HM, Schulz J, Romagnan J-B, Picheral M, Pearlman J, Ohman MD, Niehoff B, Möller KO, Miloslavich P, Lara-Lpez A, Kudela R, Lopes RM, Kiko R, Karp-Boss L, Jaffe JS, Iversen MH, Irisson J-O, Fennel K, Hauss H, Guidi L, Gorsky G, Giering SLC, Gaube P, Gallagher S, Dubelaar G, Cowen RK, Carlotti F, Briseño-Avena C, Berline L, Benoit-Bird K, Bax N, Batten S, Ayata SD, Artigas LF and Appeltans W (2019) Globally Consistent Quantitative Observations of Planktonic Ecosystems. *Front. Mar. Sci.* 6:196. doi: 10.3389/fmars.2019.00196

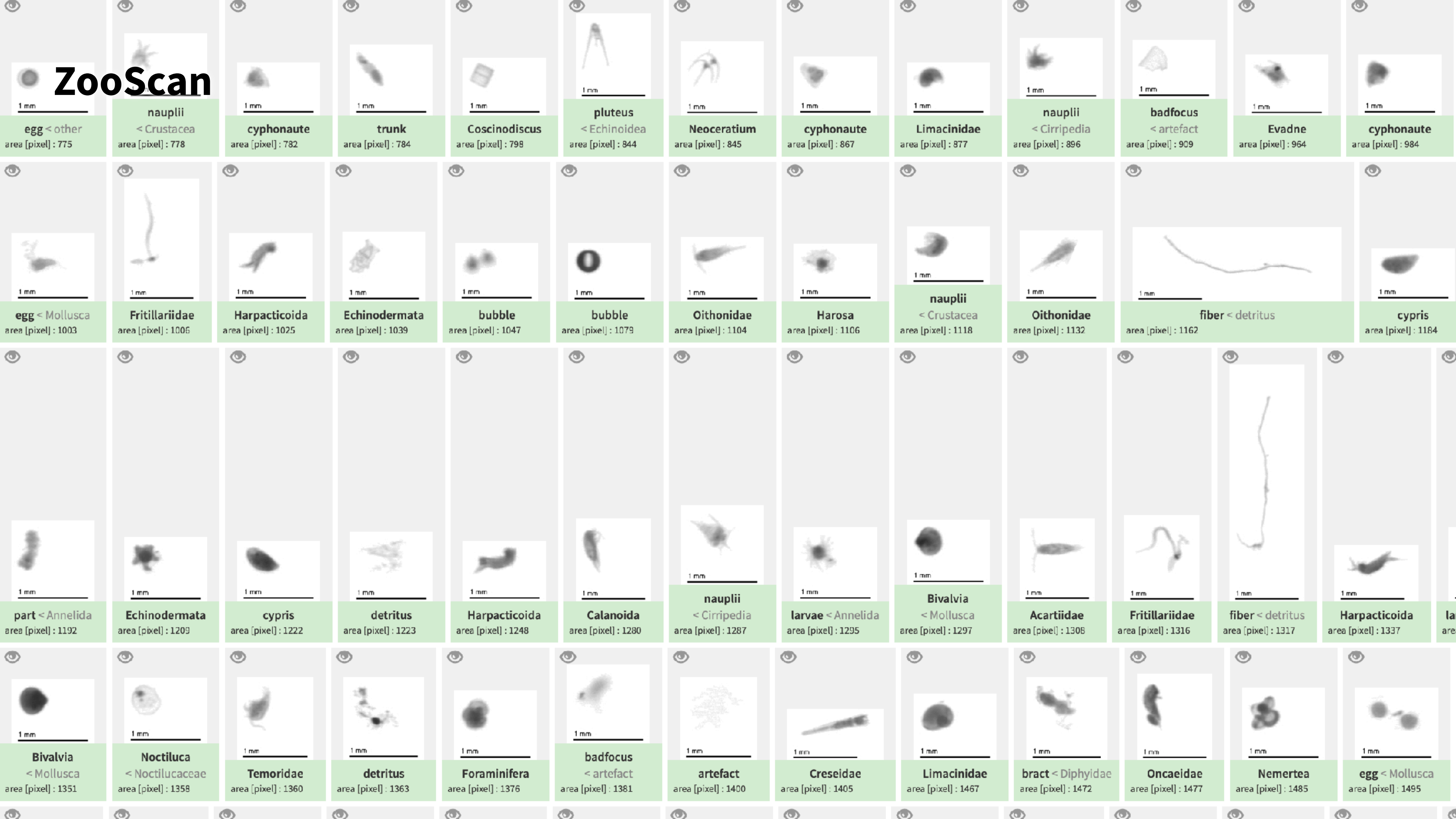
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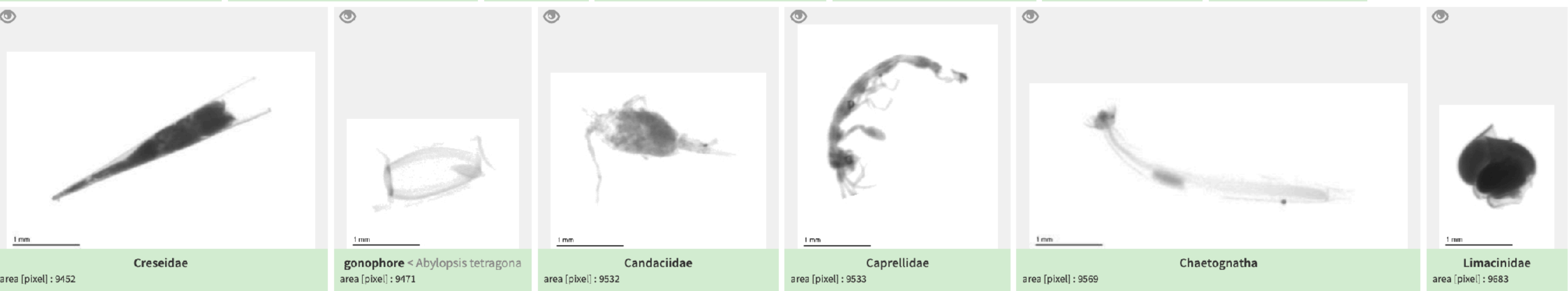
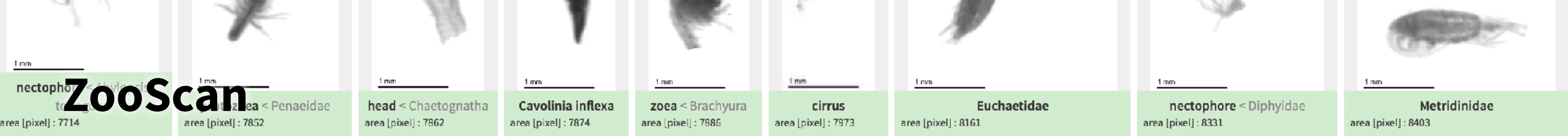
In this paper we review the technologies available to make globally quantitative observations of particles in general—and plankton in particular—in the world oceans, and for sizes varying from sub-microns to centimeters. Some of these technologies have been available for years while others have only recently emerged. Use of these technologies is critical to improve understanding of the processes that control

ZooScan



ZooScan





UVPs



UVP5



UVP6

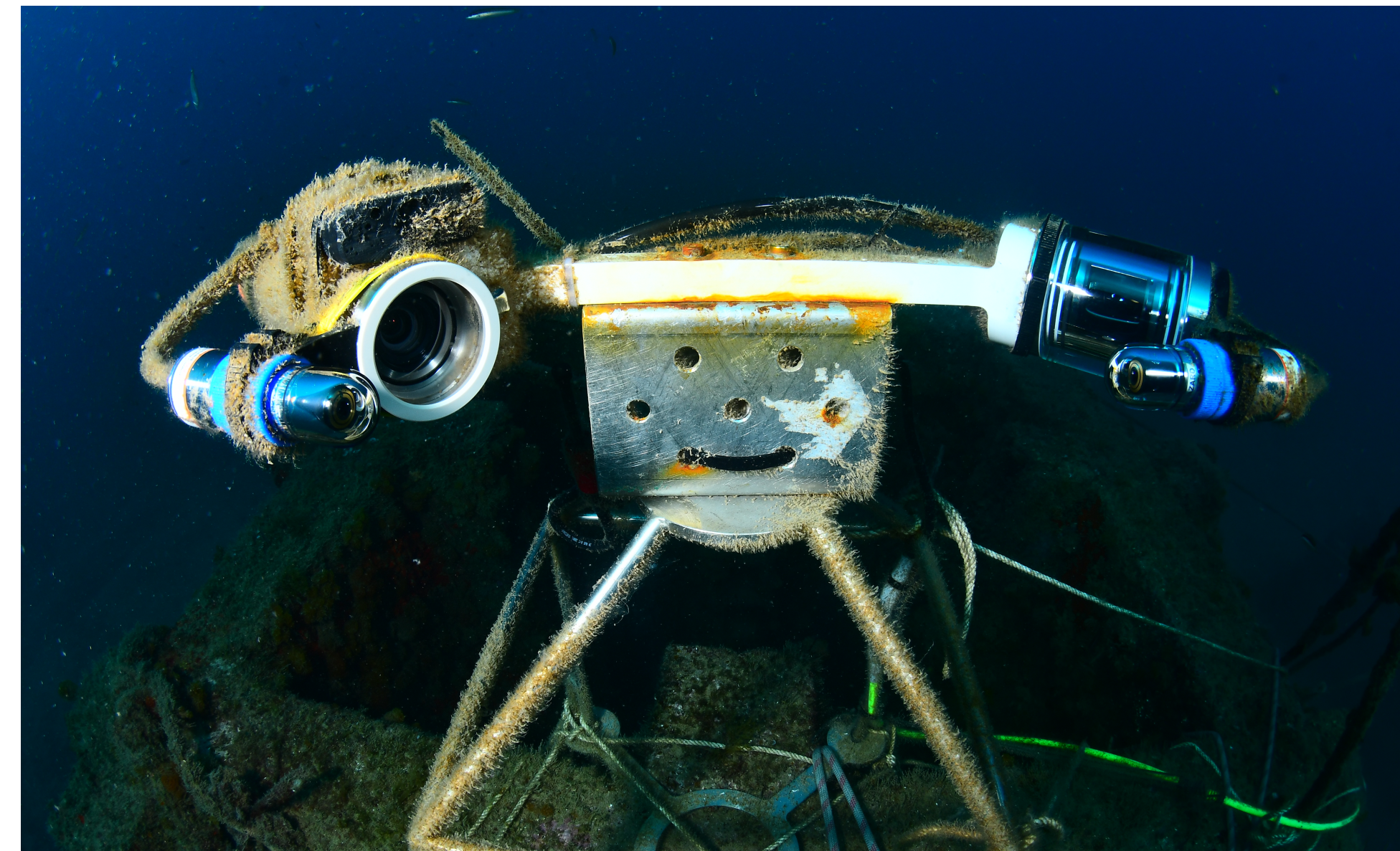
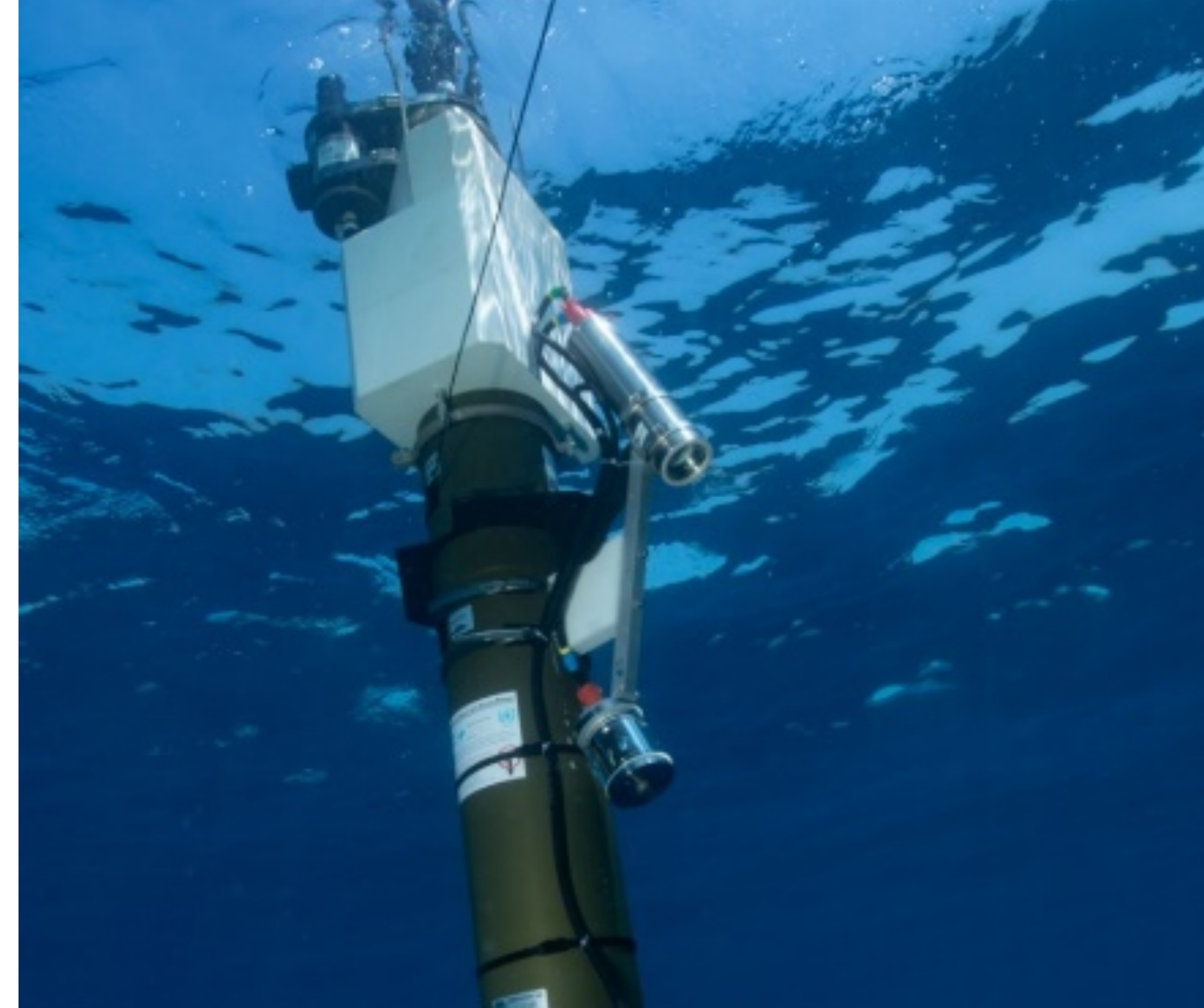
CTDs

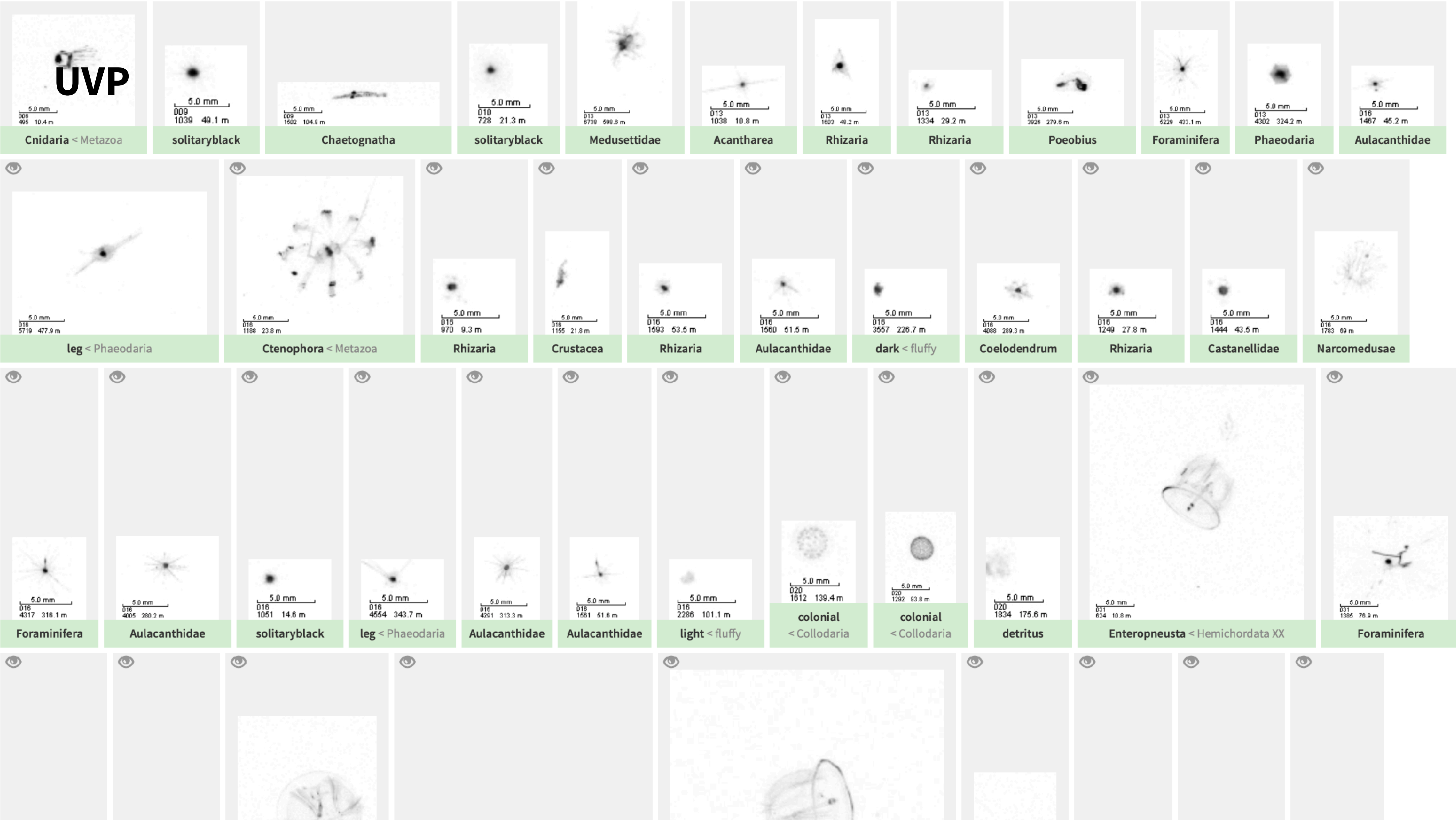
but also

Gliders

Floats

Moorings

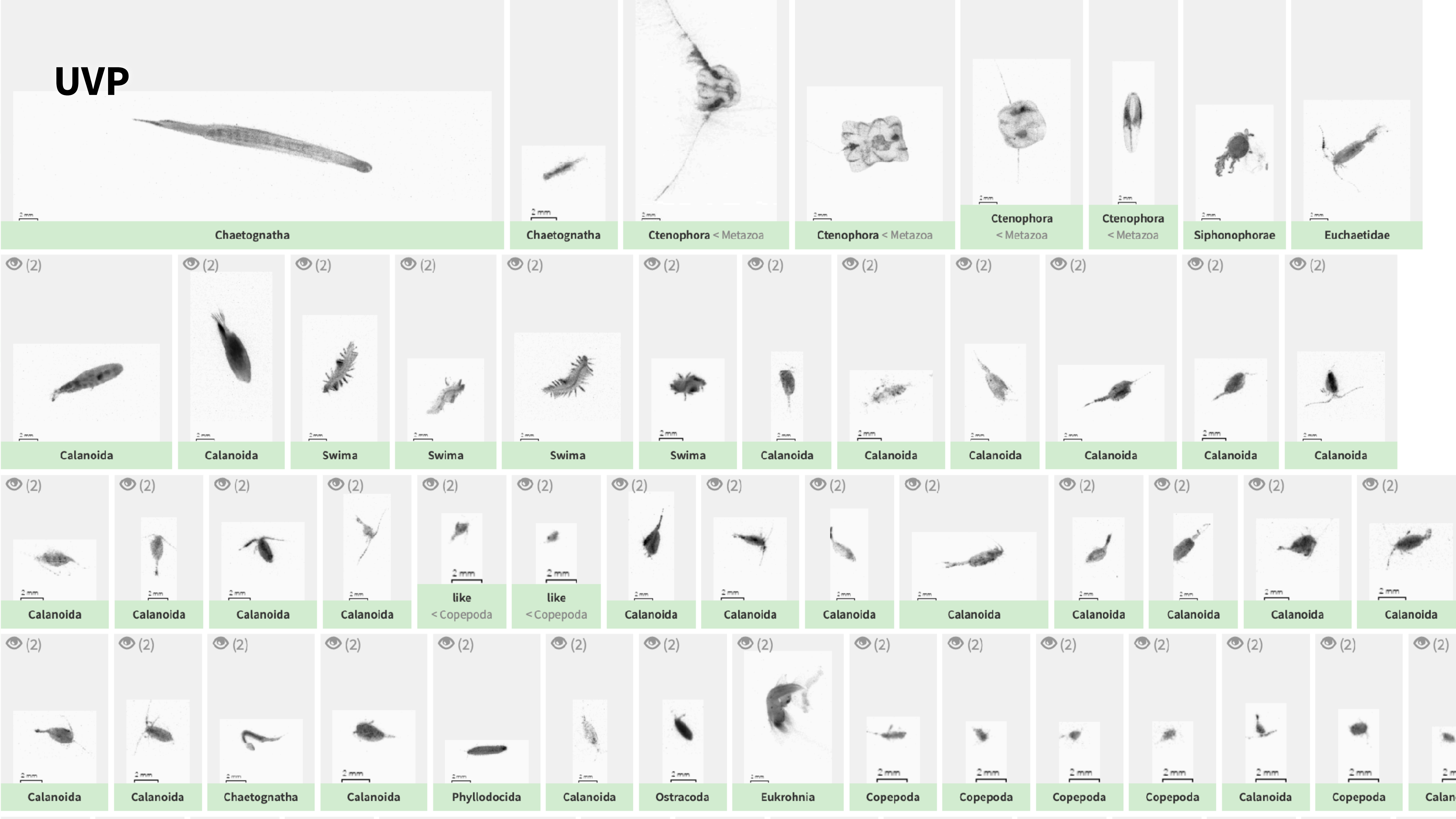




UVP

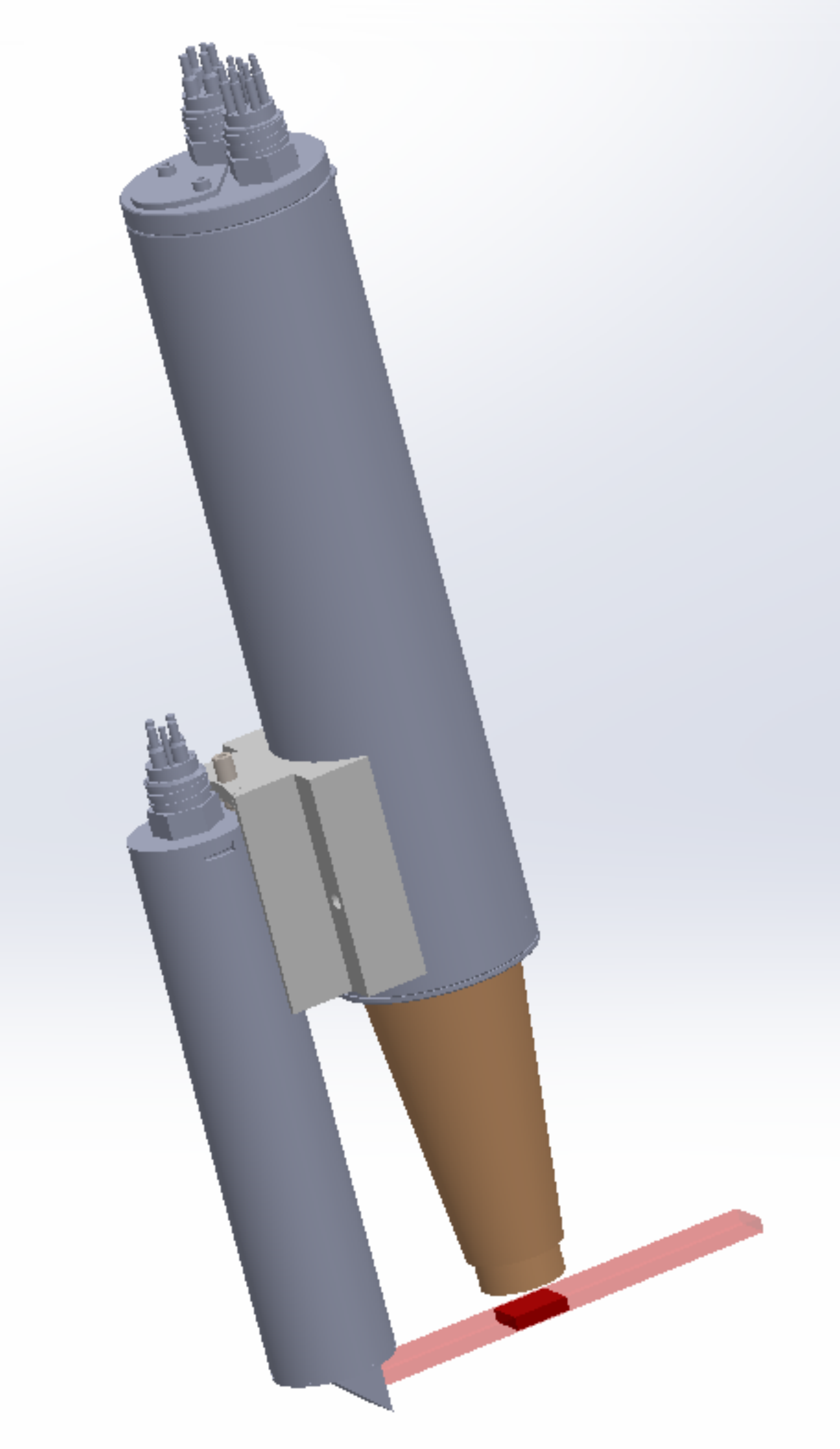


UVP



UVP6m

	UVP6	UVP6m
Particle measurement	100µm → 2cm	10µm → 1mm
Object imaging	800µm → 2cm	100µm → 1mm

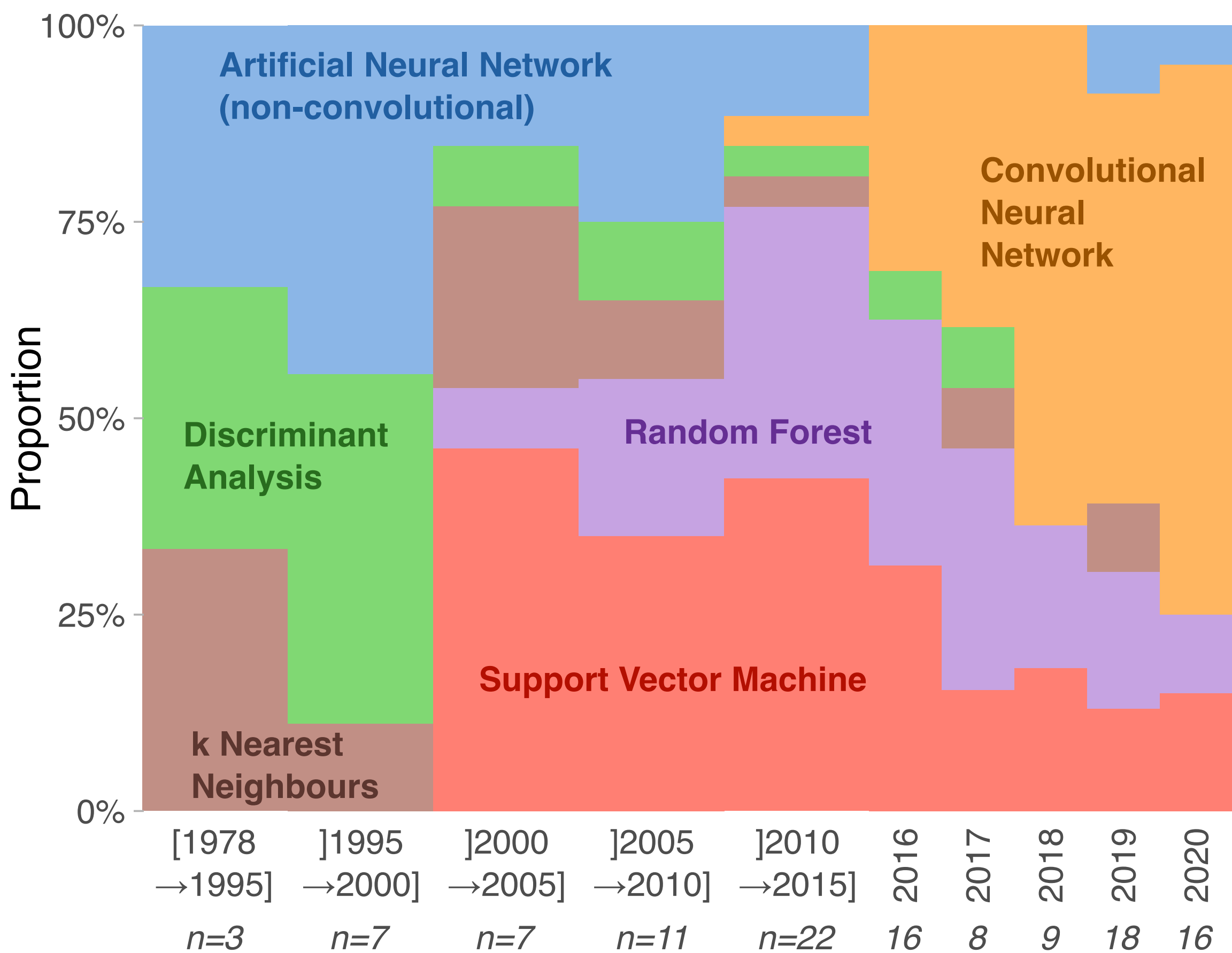




Software and machine learning development

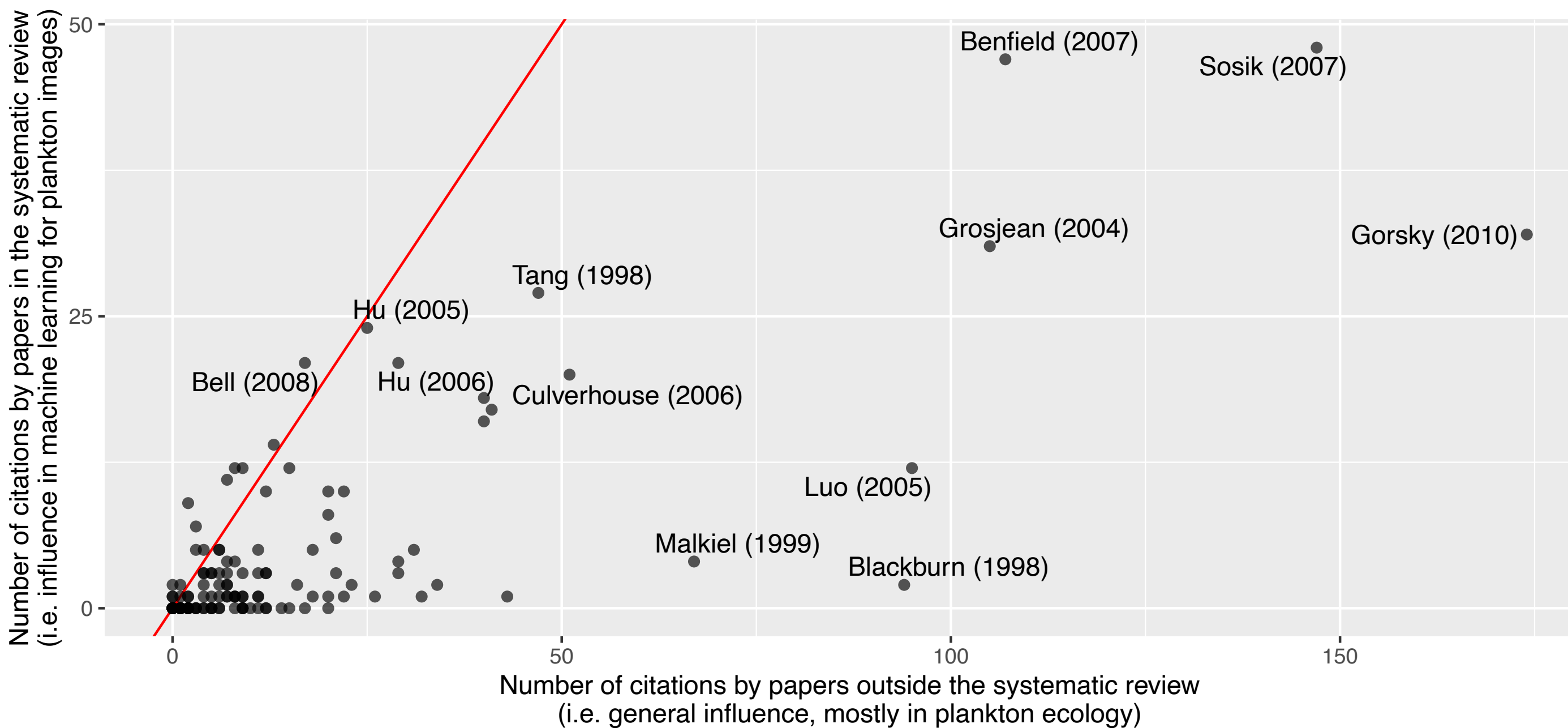
Still for plankton imaging

Historical approaches to (plankton) image classification



RandomForest was popular in technical papers but even more in actually implemented methods

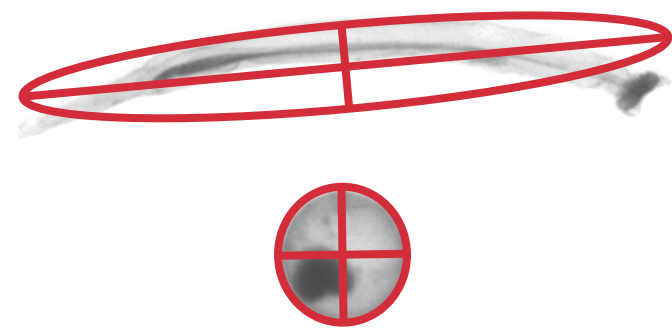
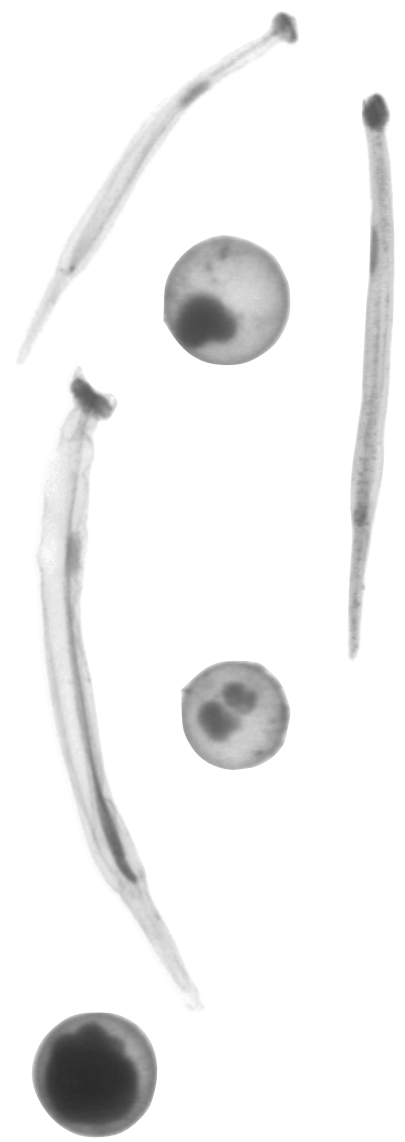
Gradual **transition** from classical feature extraction + classification to CNNs



Computer vision vs machine learning vs deep learning

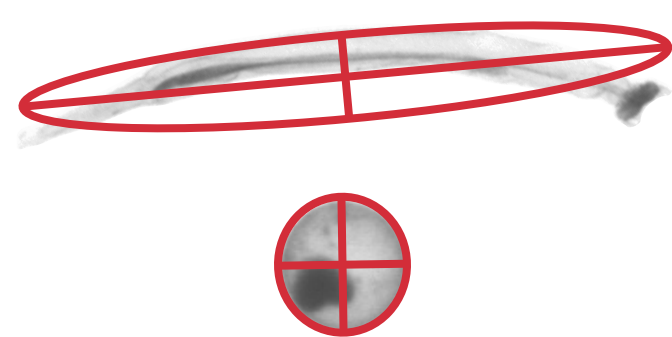


Computer vision vs machine learning vs deep learning

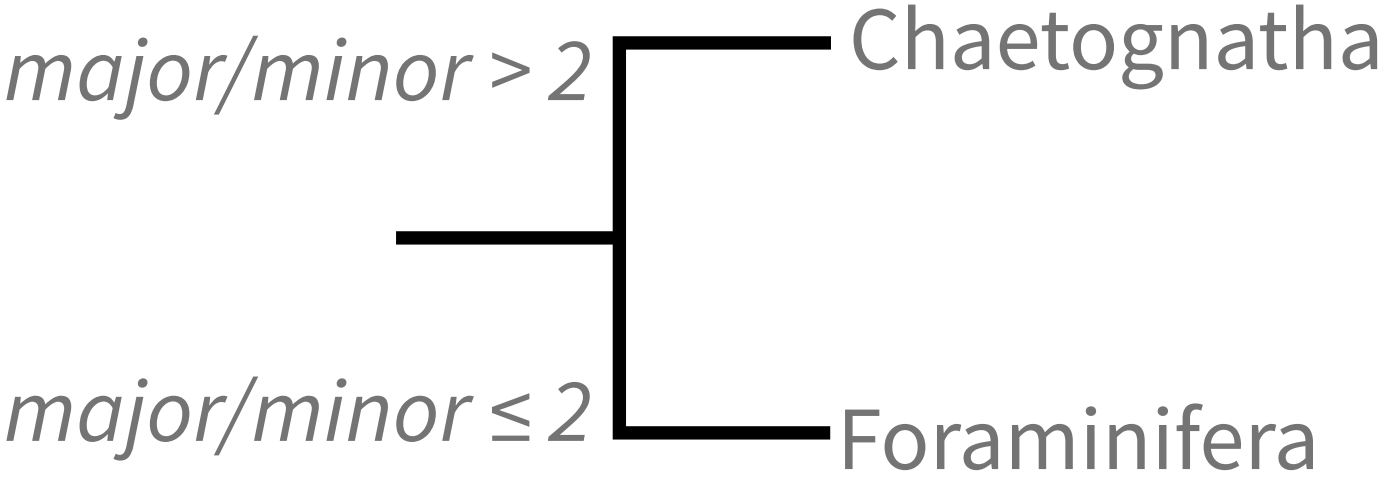


Fit ellipse
↳ Compute major/minor

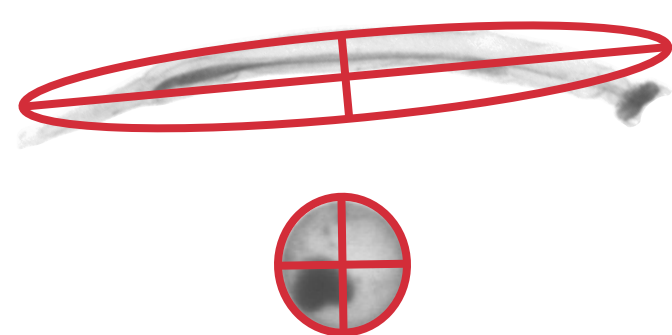
Computer vision vs machine learning vs deep learning



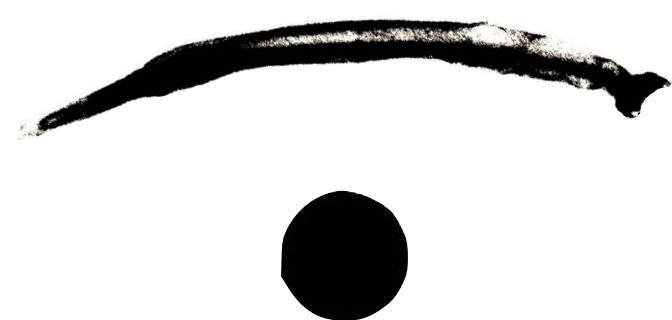
Fit ellipse
↳ Compute major/minor



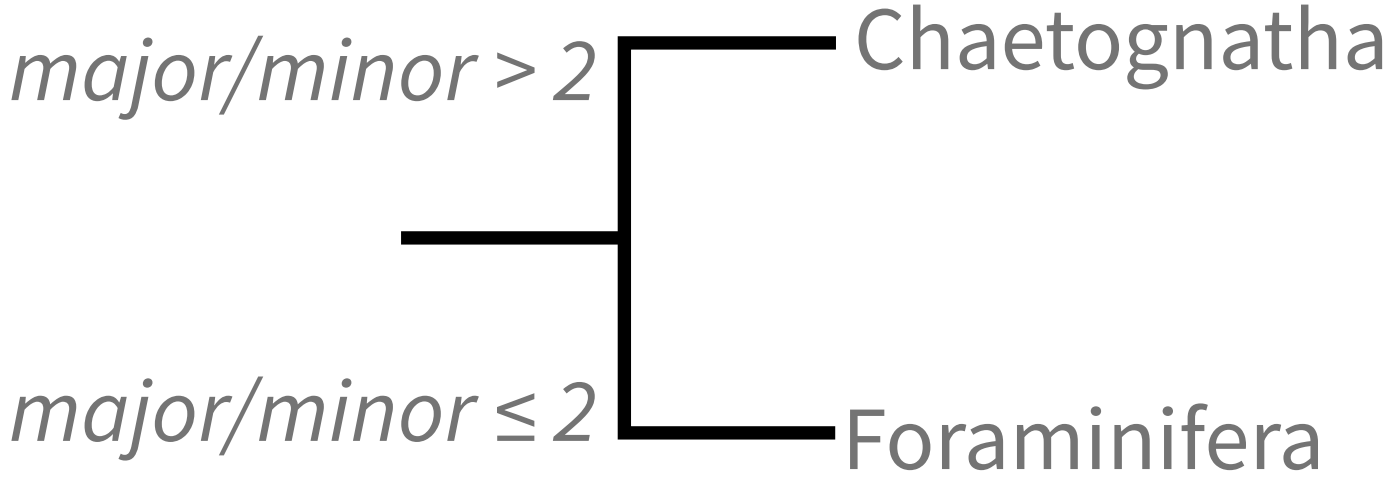
Computer vision vs machine learning vs deep learning



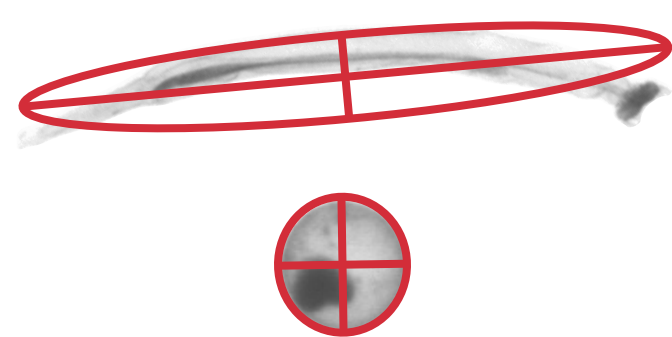
Fit ellipse
↳ Compute major/minor



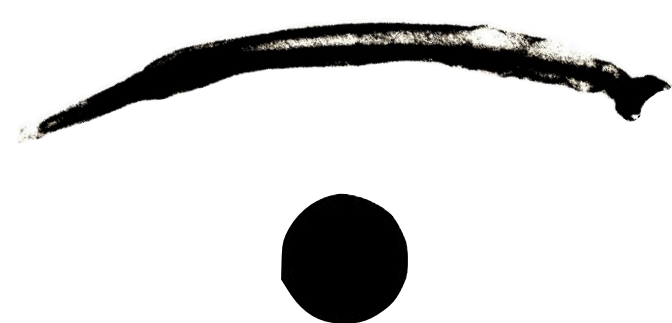
Hu moments
Best fitting ellipse
Grey levels co-occurrence matrix
...



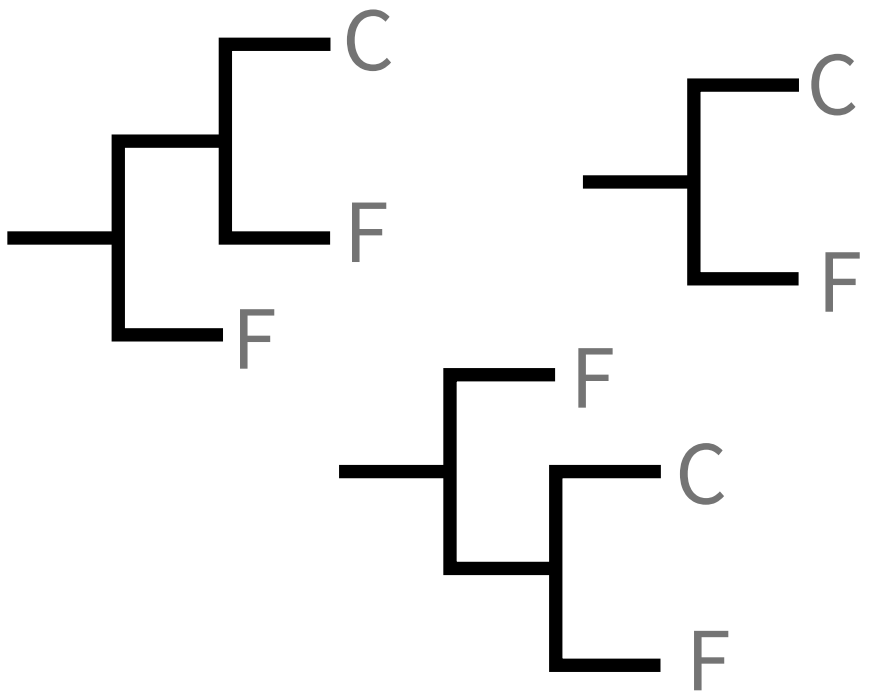
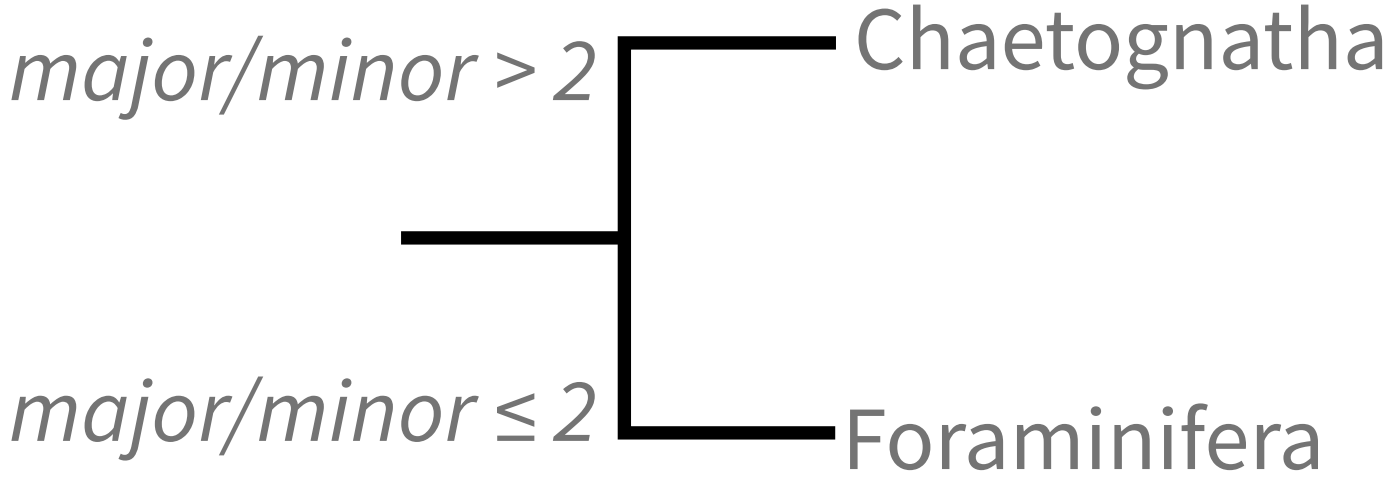
Computer vision vs machine learning vs deep learning



Fit ellipse
↳ Compute major/minor

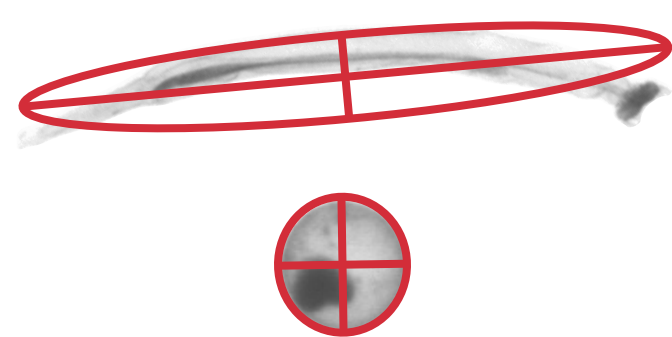


Hu moments
Best fitting ellipse
Grey levels co-occurrence matrix
...

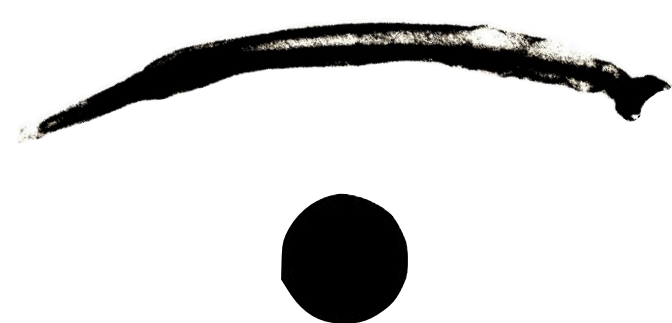


Majority vote → Foraminifera

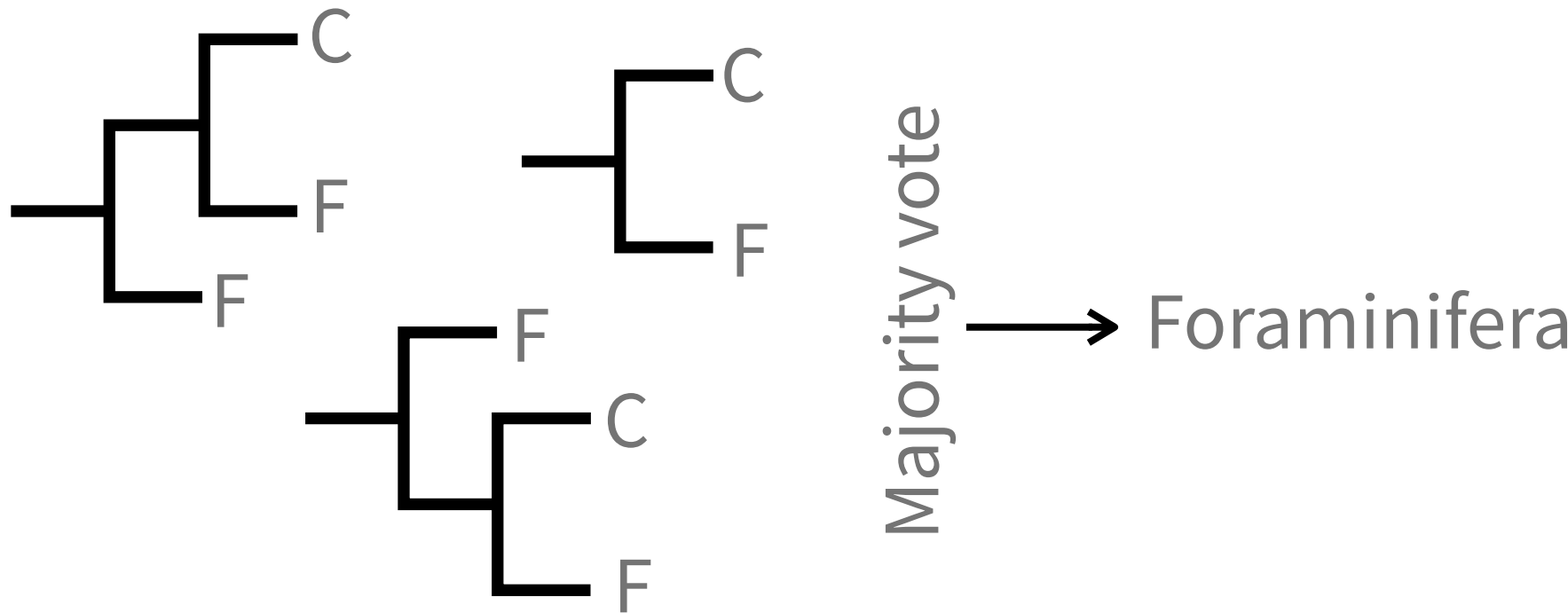
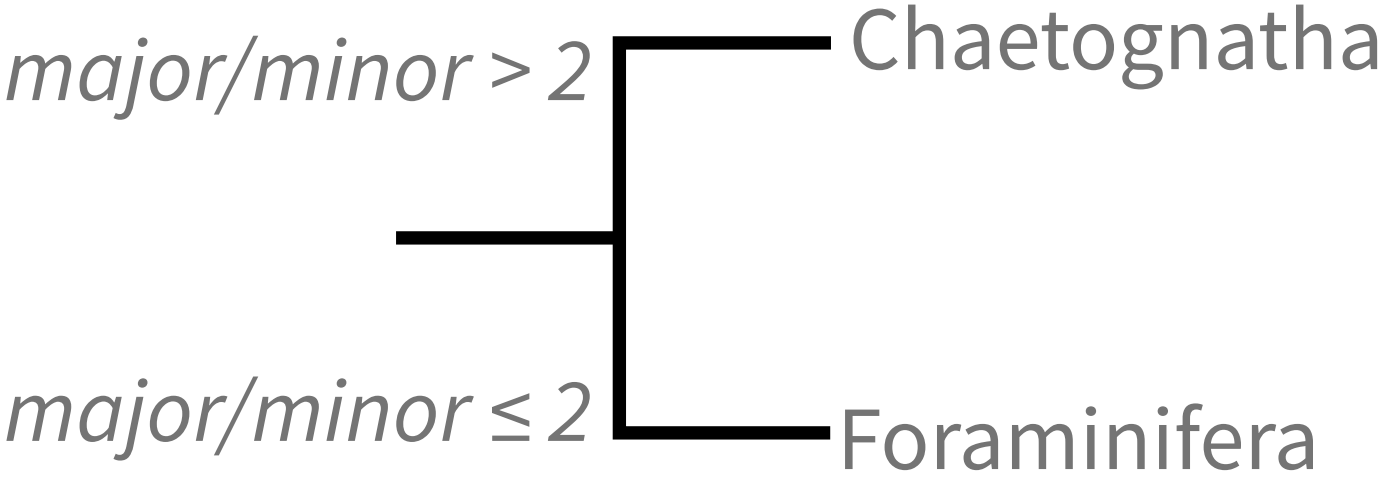
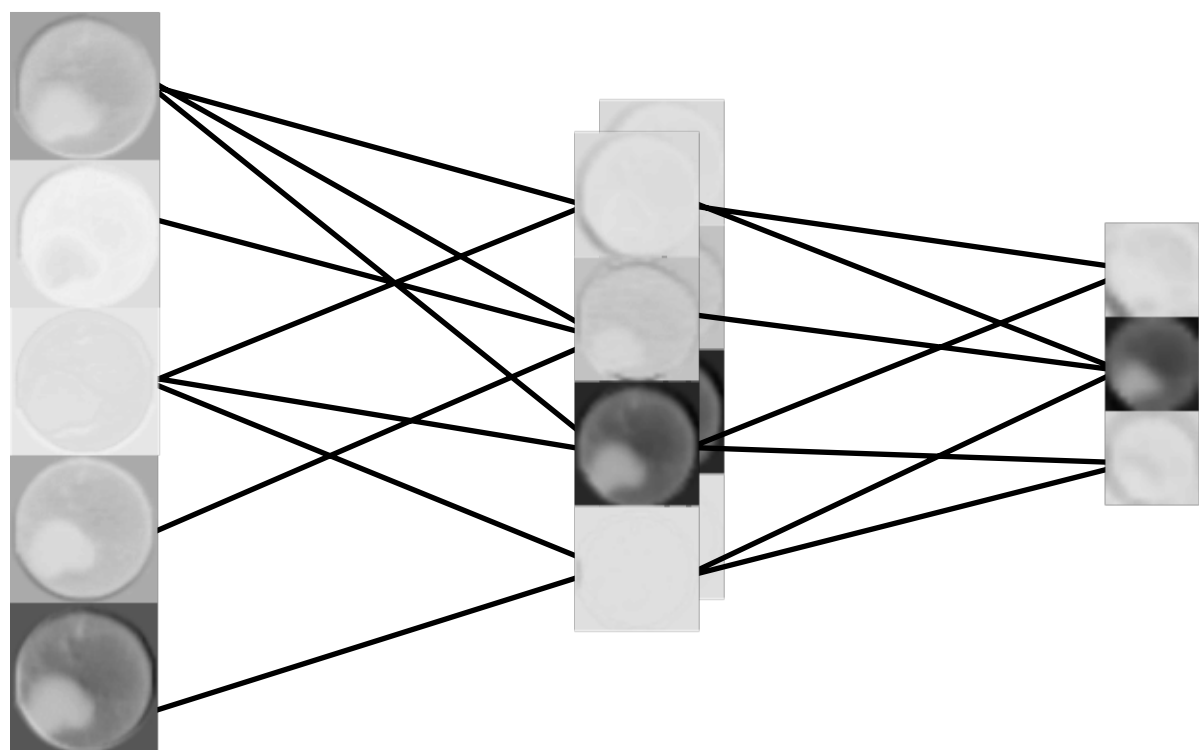
Computer vision vs machine learning vs deep learning



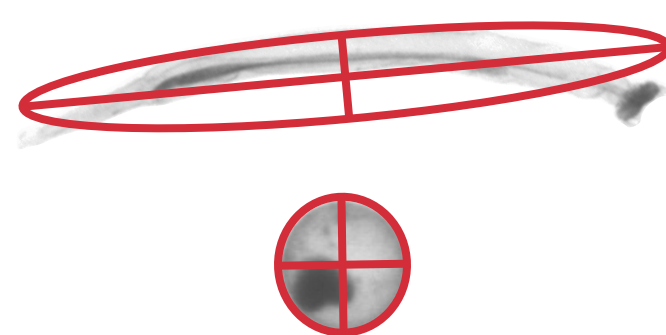
Fit ellipse
↳ Compute major/minor



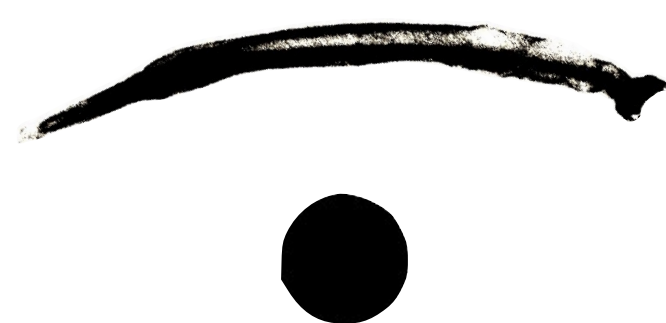
Hu moments
Best fitting ellipse
Grey levels co-occurrence matrix
...



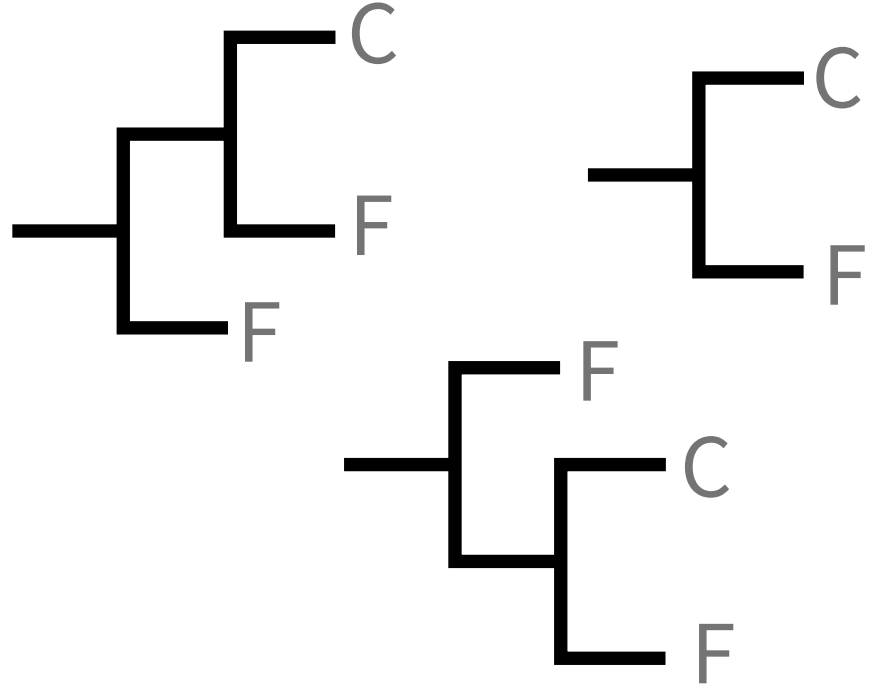
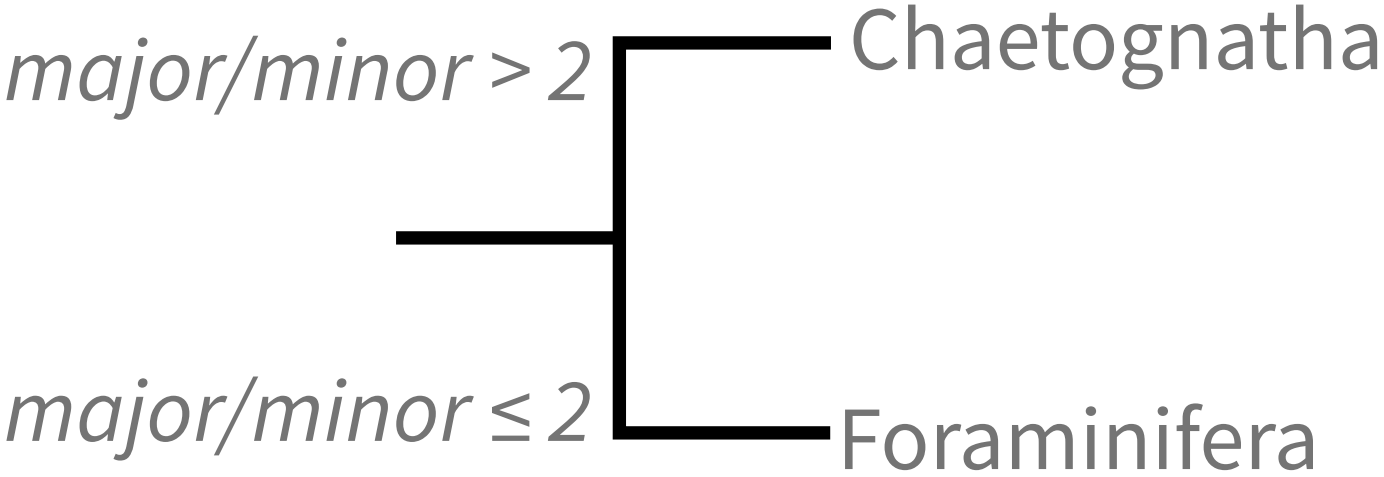
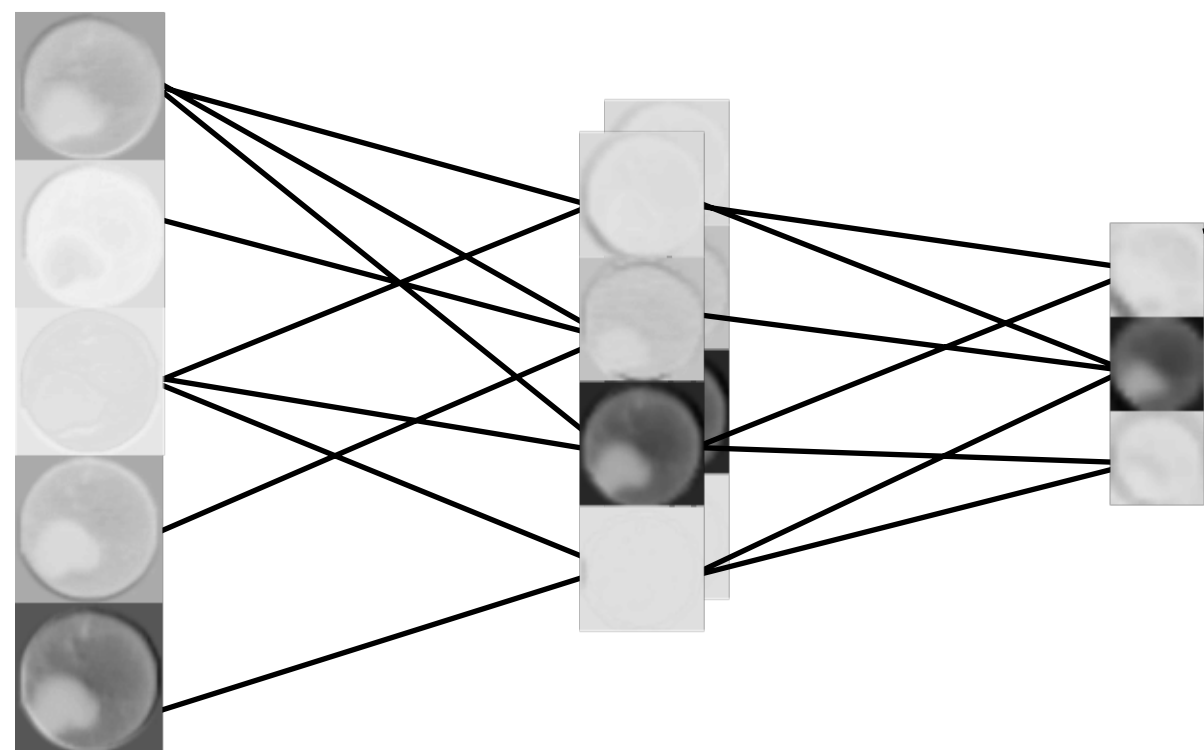
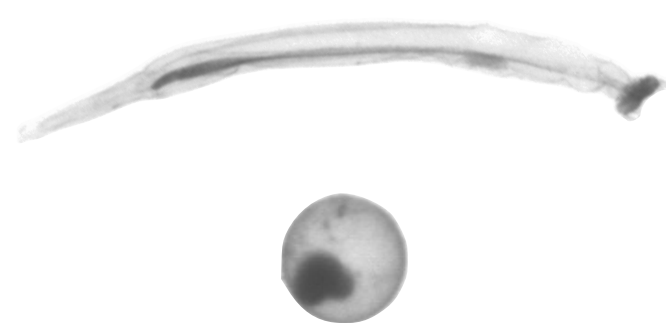
Computer vision vs machine learning vs deep learning



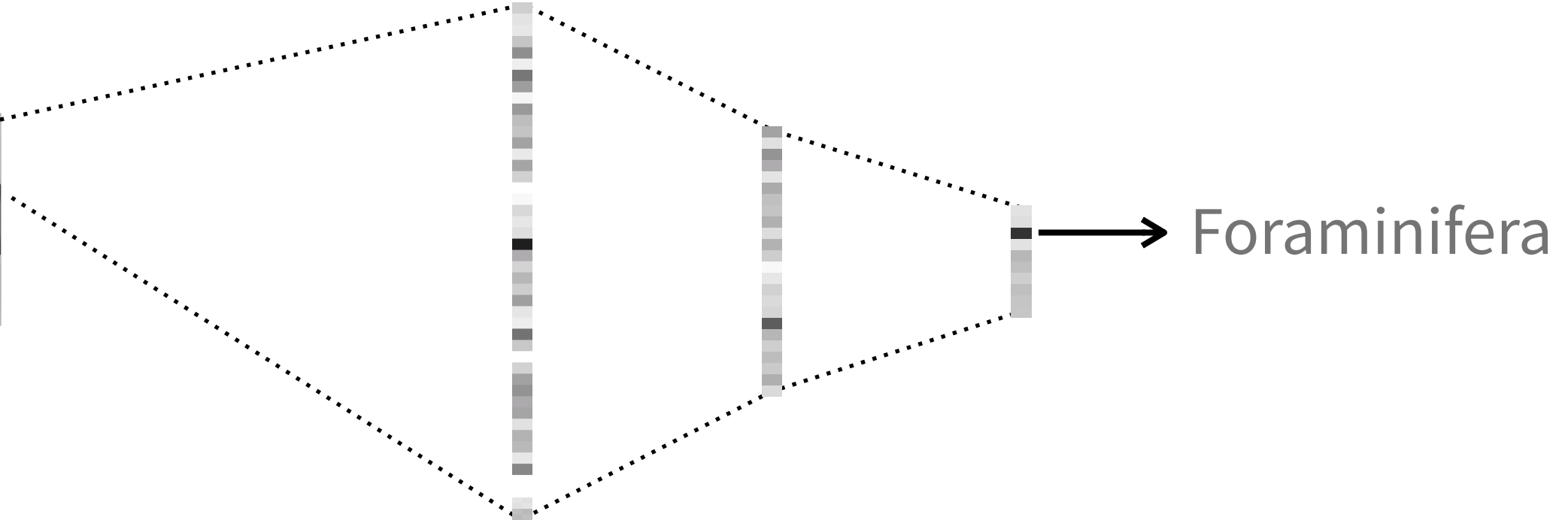
Fit ellipse
↳ Compute major/minor



Hu moments
Best fitting ellipse
Grey levels co-occurrence matrix
...

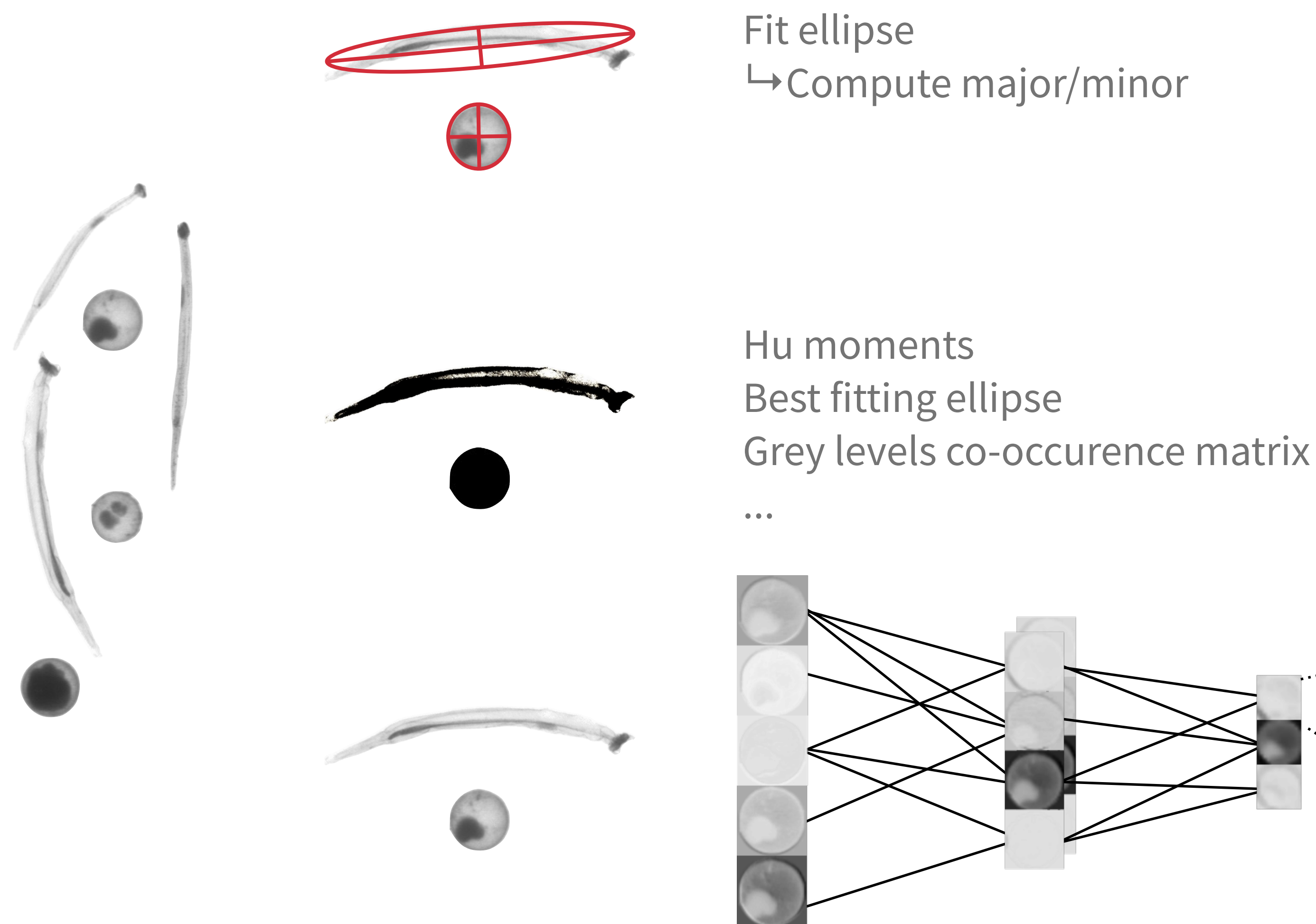


Majority vote
→ Foraminifera

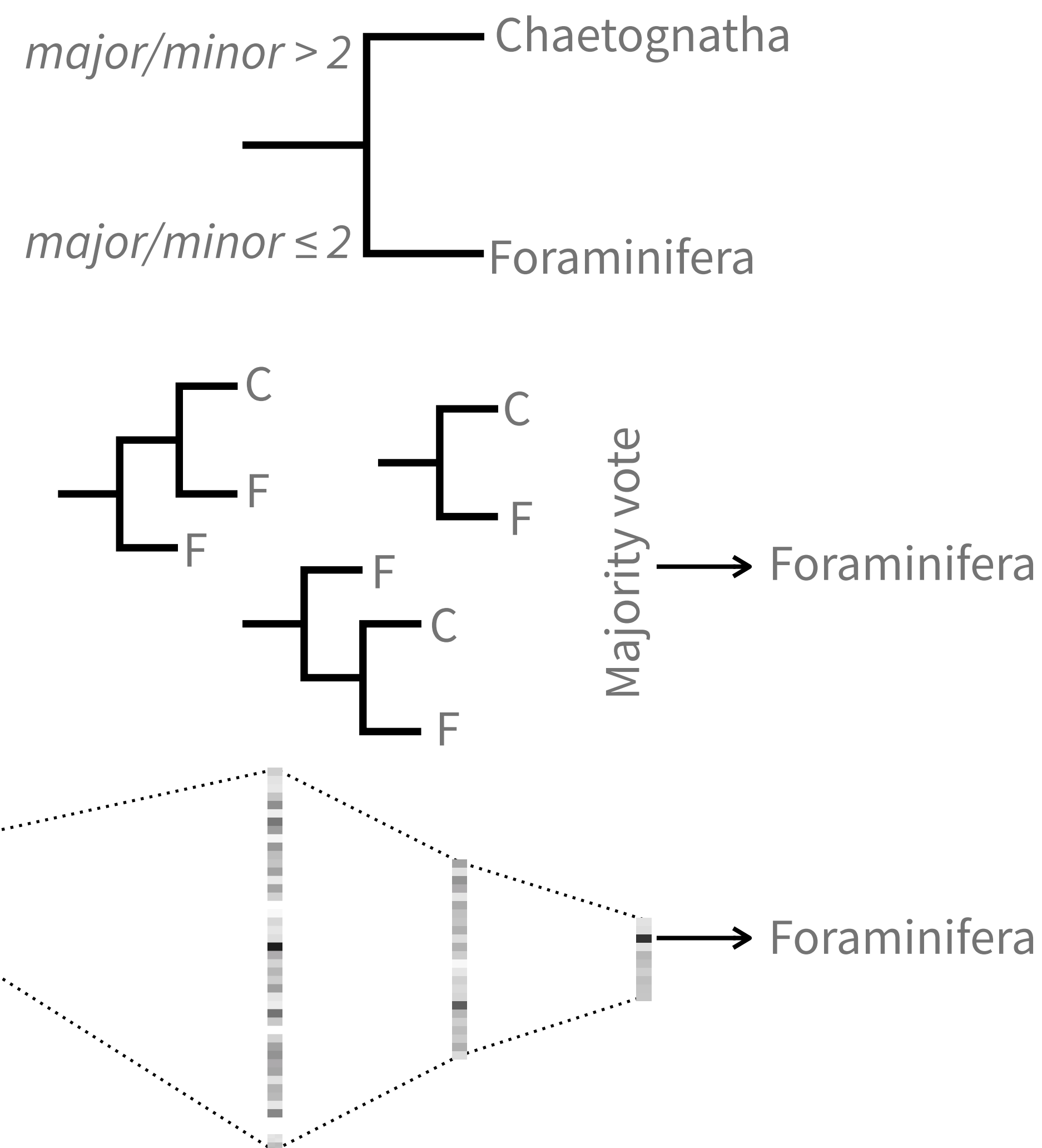


Computer vision vs machine learning vs deep learning

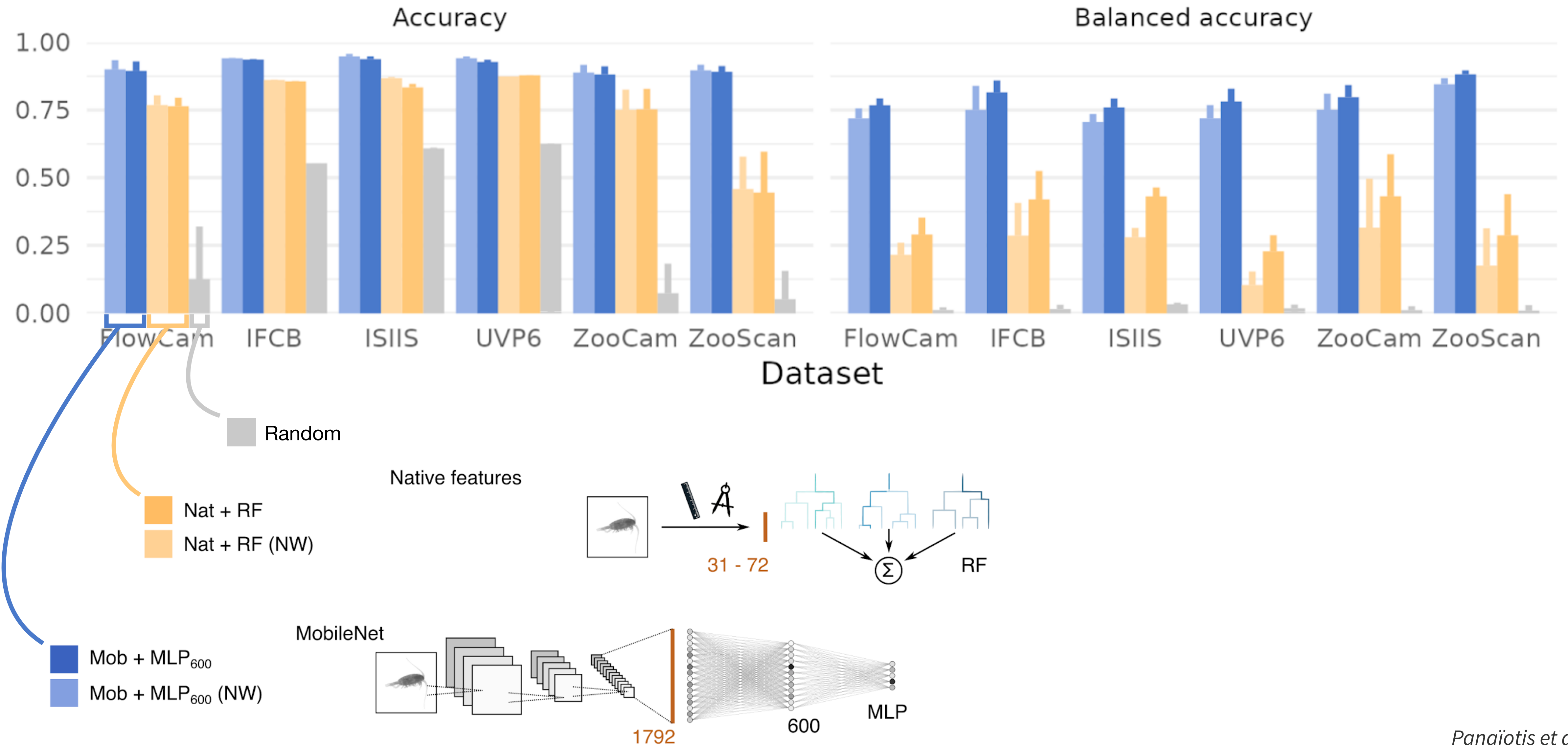
Feature extraction



Classification



Classic vs deep: deep is better, for rare classes



Do we still need human validation?

With CNNs, accuracy **greatly improves**

notably for **rare** classes (see previous slide)



Do we still need human validation?

With CNNs, accuracy **greatly improves**

notably for **rare** classes (see previous slide)

Now



Do we still need human validation?

With CNNs, accuracy **greatly improves**

notably for **rare** classes (see previous slide)

Now

is **80% enough?**



Do we still need human validation?

With CNNs, accuracy **greatly improves**

notably for **rare** classes (see previous slide)

Now

is **80% enough?**

is **60% enough?**



Do we still need human validation?

With CNNs, accuracy **greatly improves**

notably for **rare** classes (see previous slide)

Now

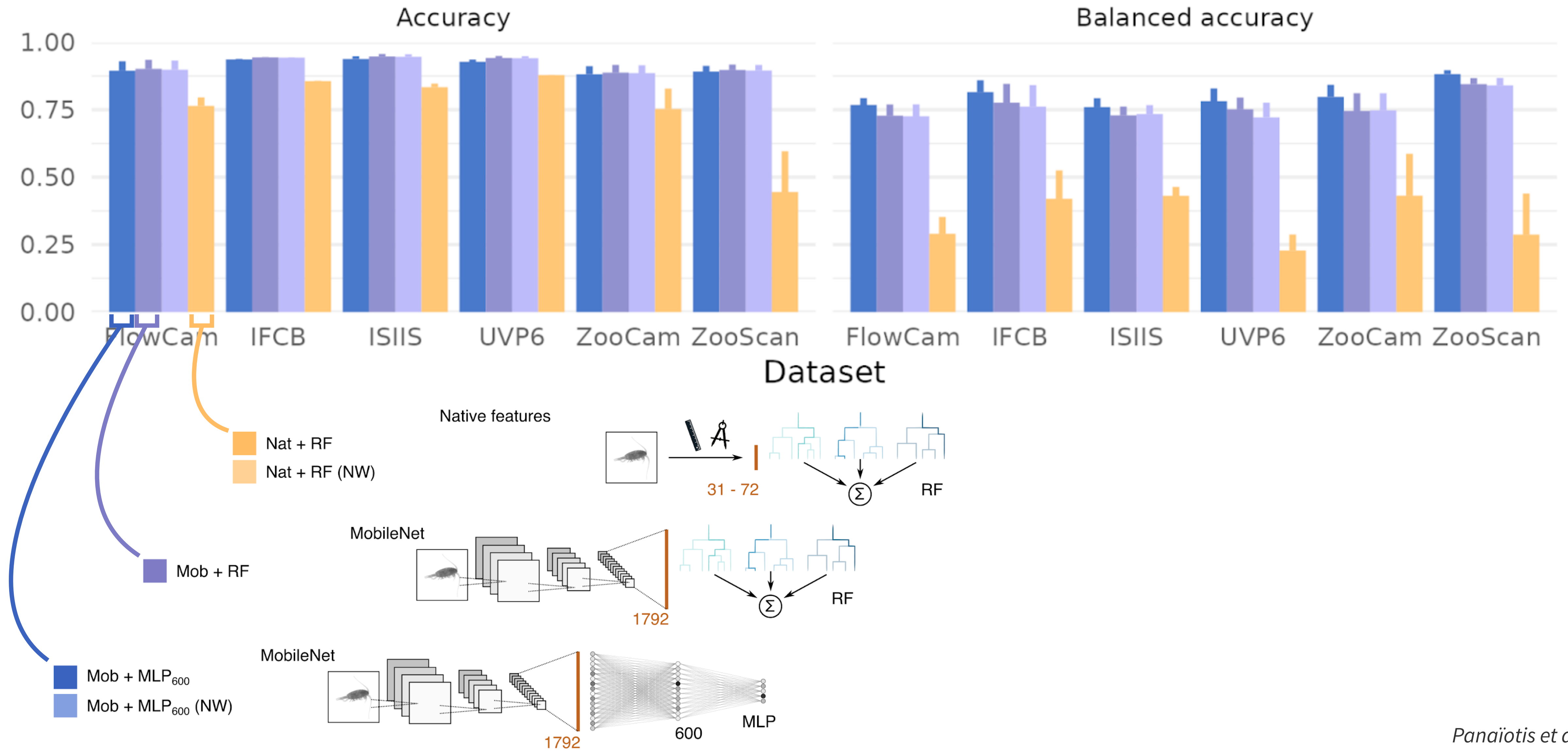
is **80% enough?**

is **60% enough?**

???



Why? It's the features, not the classifier



EcoTaxa today

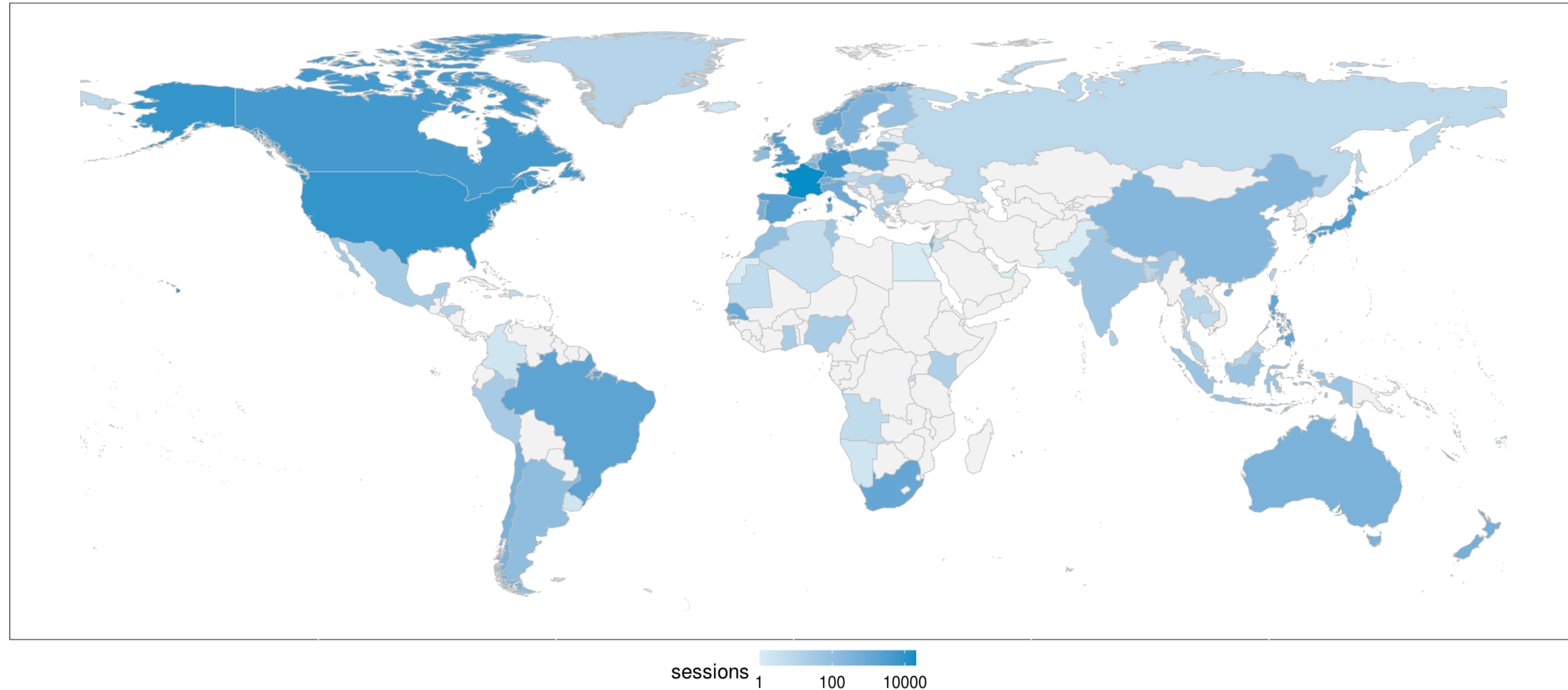
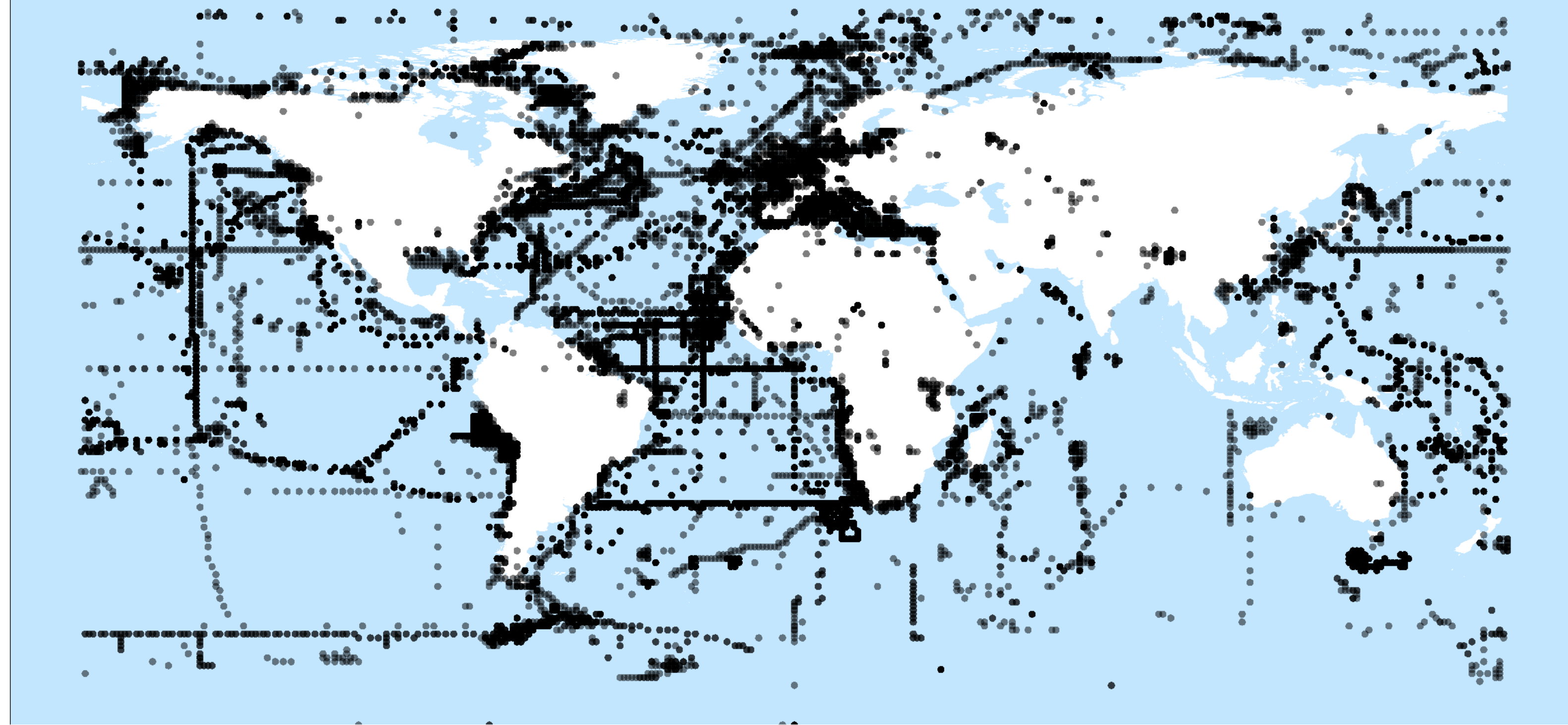
830M images, 280M validated by a human

+18M per month

5000 users from ~900 organisations

~125 concurrent

5,000 to 10,000 validations/operator/d
thanks to AI assistance



EcoTaxa today

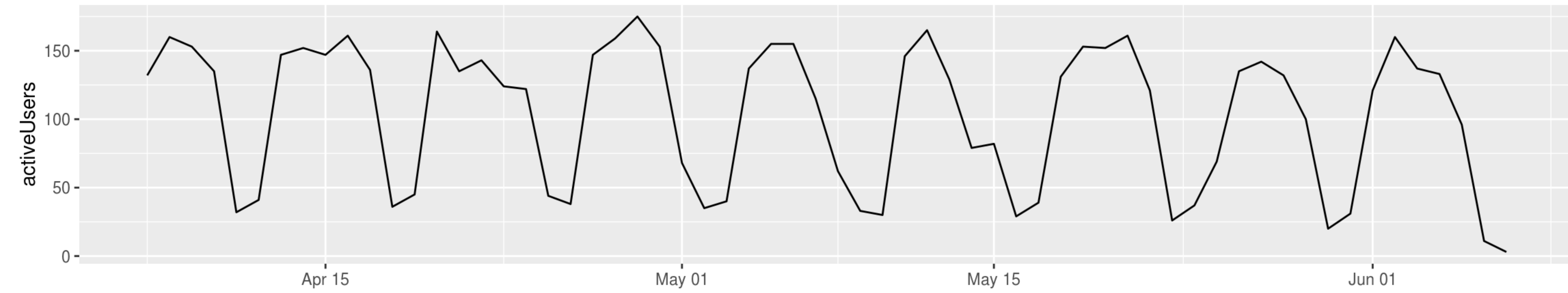
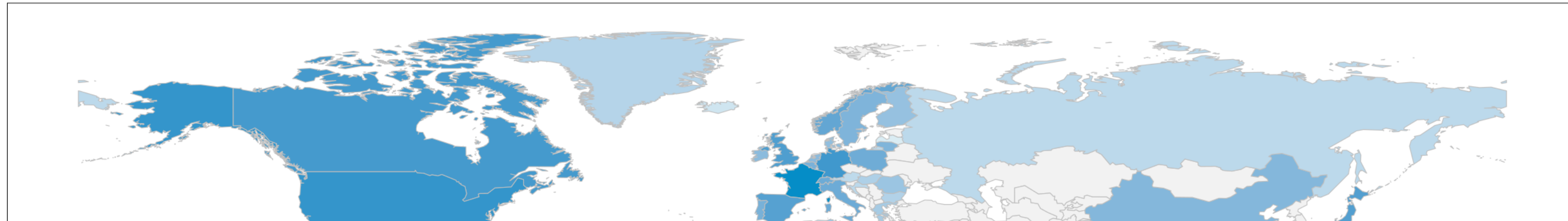
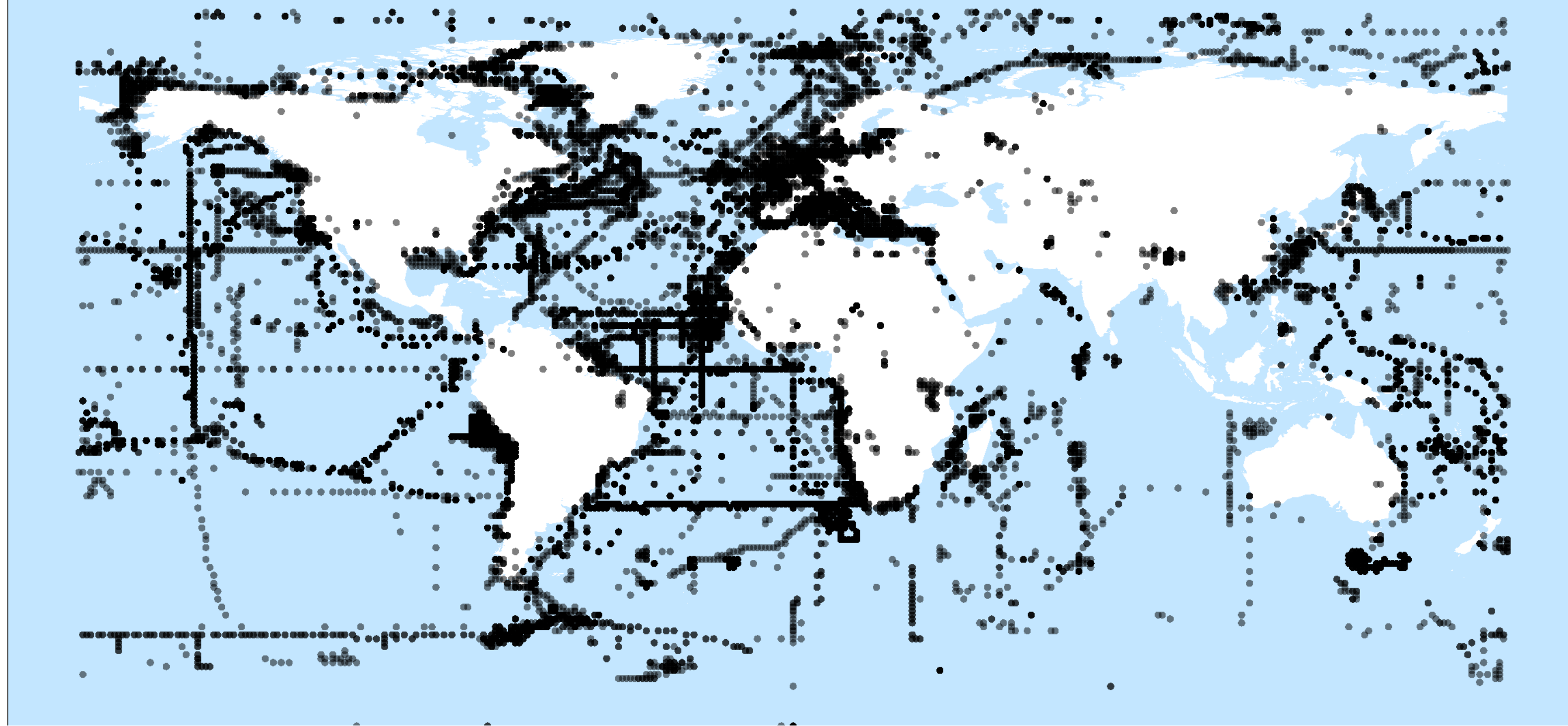
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Update view & apply filter

Select all

Display

Status

All

100

50

Taxonomy filter

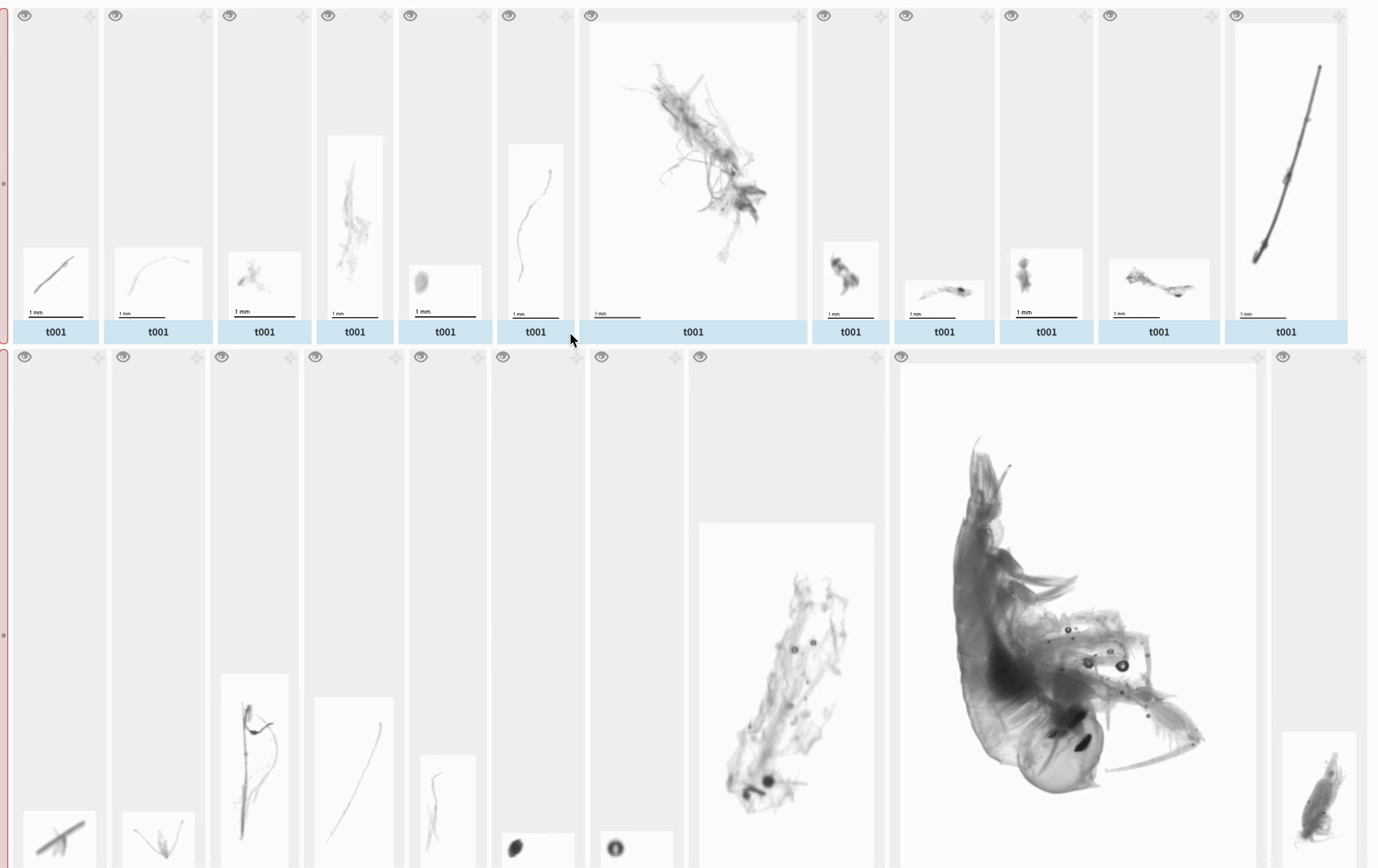
Other filters

t001

0 1397

Recalc. counts

Hide empty categories



Update view & apply filter

Select all

Display

Status

All

100

50

Taxonomy filter

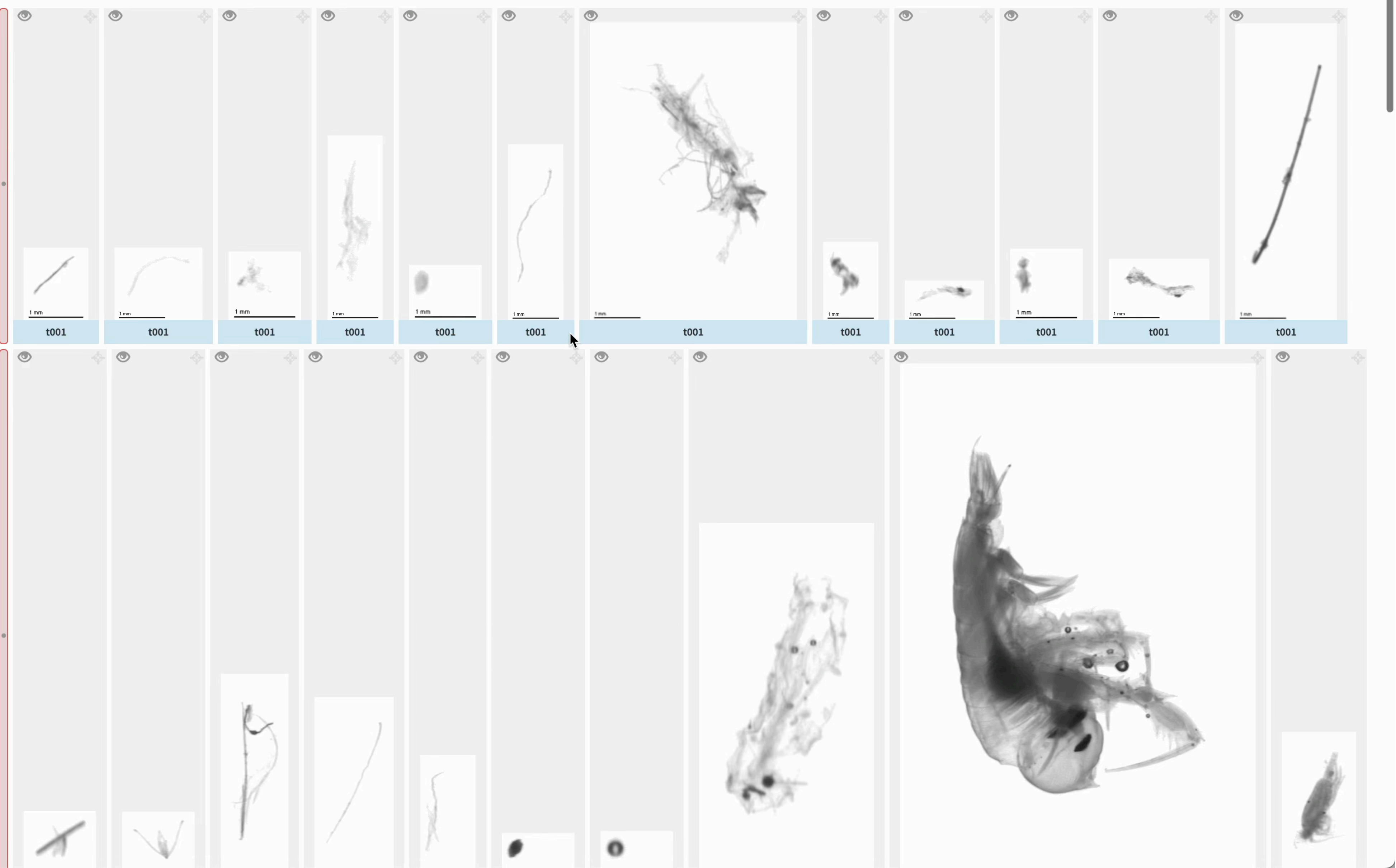
Other filters

t001

0 1397

Recalc. counts

Hide empty categories



Taxonomy filter ⓘ

Other filters

Annelida

Annelida

5

Chaetognatha

2

Copepoda < Maxillopoda

141

732

Siphonophorae

7

11

bubble

3

6

detritus

8

314

fiber < detritus

50

118

Recalc. counts ↻

Hide empty categories

The image displays a grid of 48 microscopic images of copepods, arranged in 4 rows and 12 columns. Each image shows a copepod against a white background with a 1 mm scale bar. Below each image is a blue box containing text: "Copepoda < Maxillopoda", "depth_min : 0.00", and "major [pixel] : [value]". The values for "major [pixel]" range from 60.70 to 98.70. A hand cursor is visible over the 5th image in the 3rd row.

Row	Col	major [pixel]
1	1	64.80
1	2	71.10
1	3	60.70
1	4	61.60
1	5	70.00
1	6	62.00
1	7	82.30
1	8	66.20
1	9	66.30
1	10	61.90
1	11	67.30
2	1	61.60
2	2	64.00
2	3	61.10
2	4	70.50
2	5	62.50
2	6	75.30
2	7	62.50
2	8	58.70
2	9	69.30
2	10	98.70
2	11	84.70
2	12	71.60
3	1	78.60
3	2	71.10
3	3	74.00
3	4	82.50
3	5	62.50
3	6	65.40
3	7	61.80
3	8	70.20
3	9	63.50
3	10	63.90
3	11	69.90
4	1	60.70
4	2	61.60
4	3	62.50
4	4	63.50
4	5	64.00
4	6	65.40
4	7	66.20
4	8	66.30
4	9	67.30
4	10	68.30
4	11	69.30

Taxonomy filter ⓘ

Other filters

Annelida ▼

☰

🔍

Annelida	5	
Chaetognatha	2	
Copepoda < Maxillopoda	141	732
Siphonophorae	7	11
bubble	3	6
▼ detritus	8	314
fiber < detritus	50	118

Recalc. counts ↻

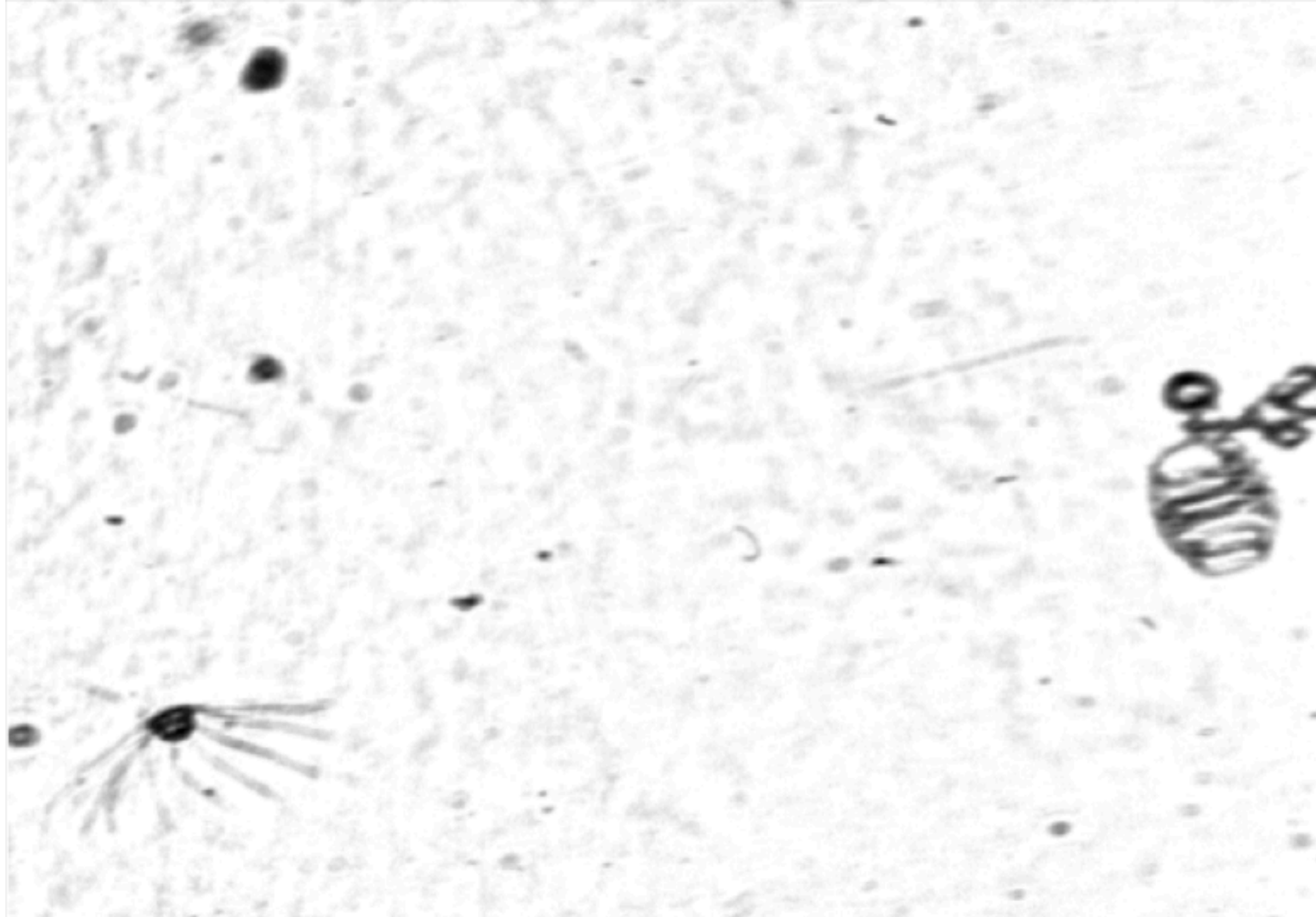
Hide empty categories

The figure displays a collection of 48 copepod specimens, organized into four rows of twelve. Each specimen is shown in a grayscale micrograph with a 1 mm scale bar. The labels below the images provide the following information:

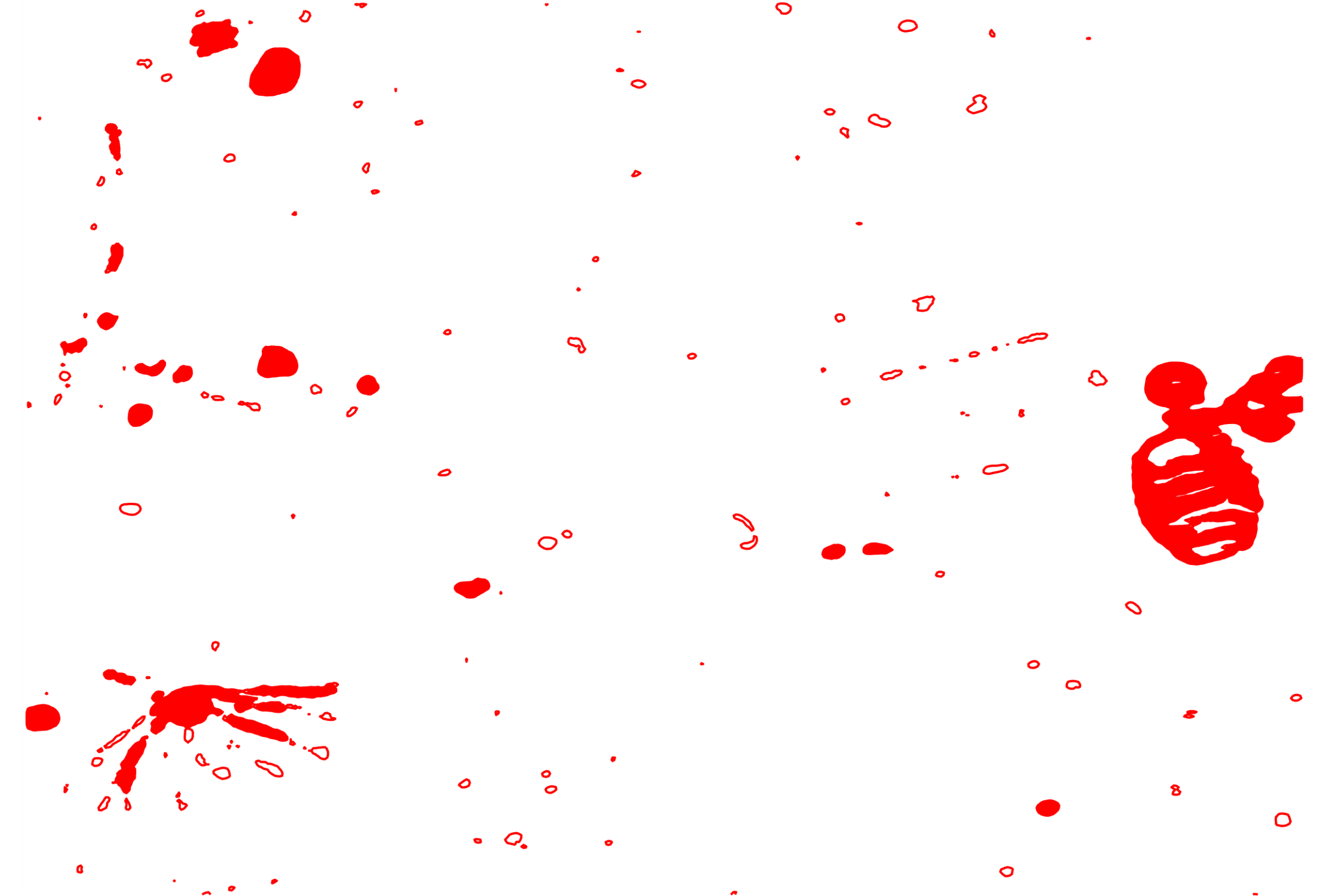
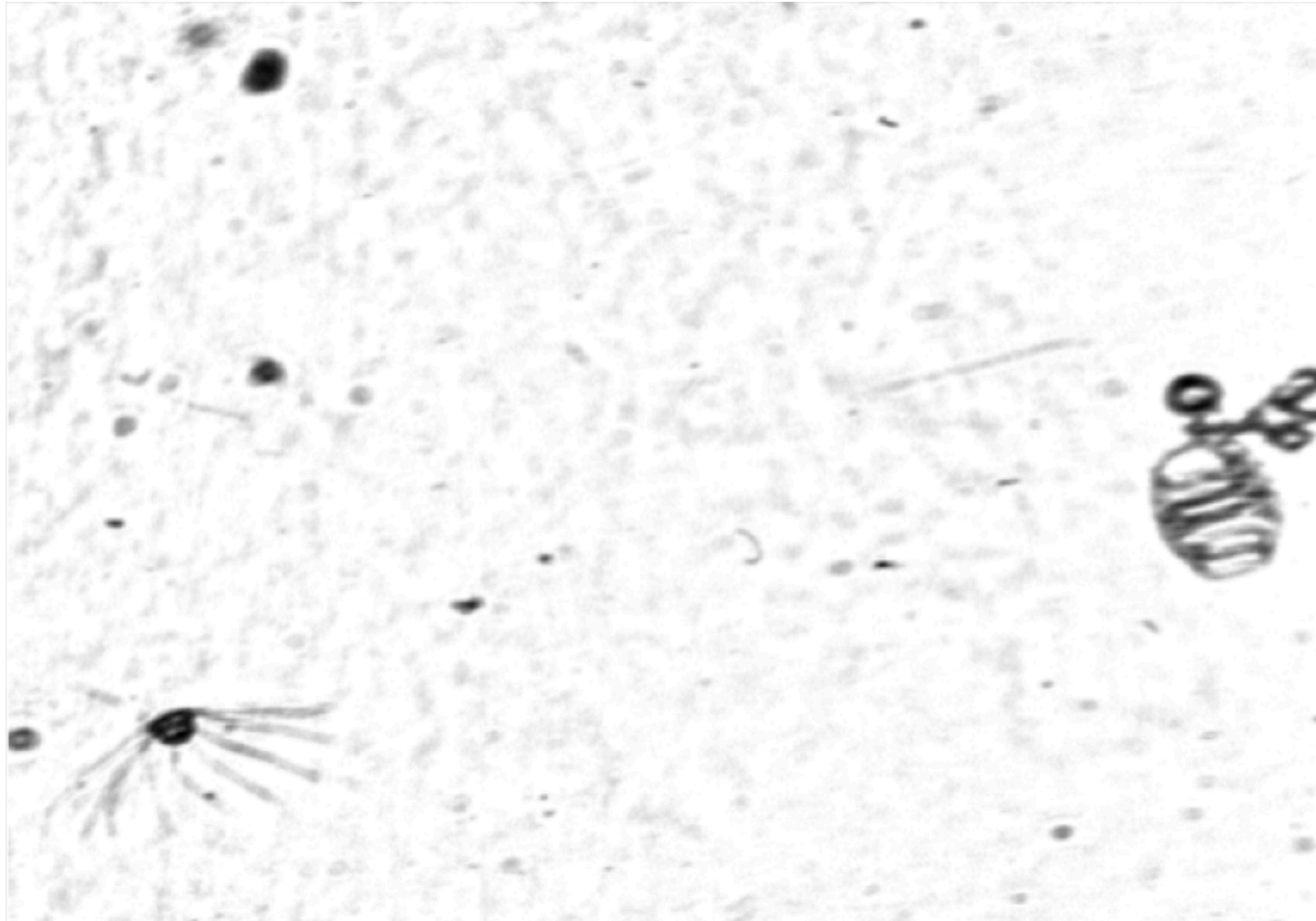
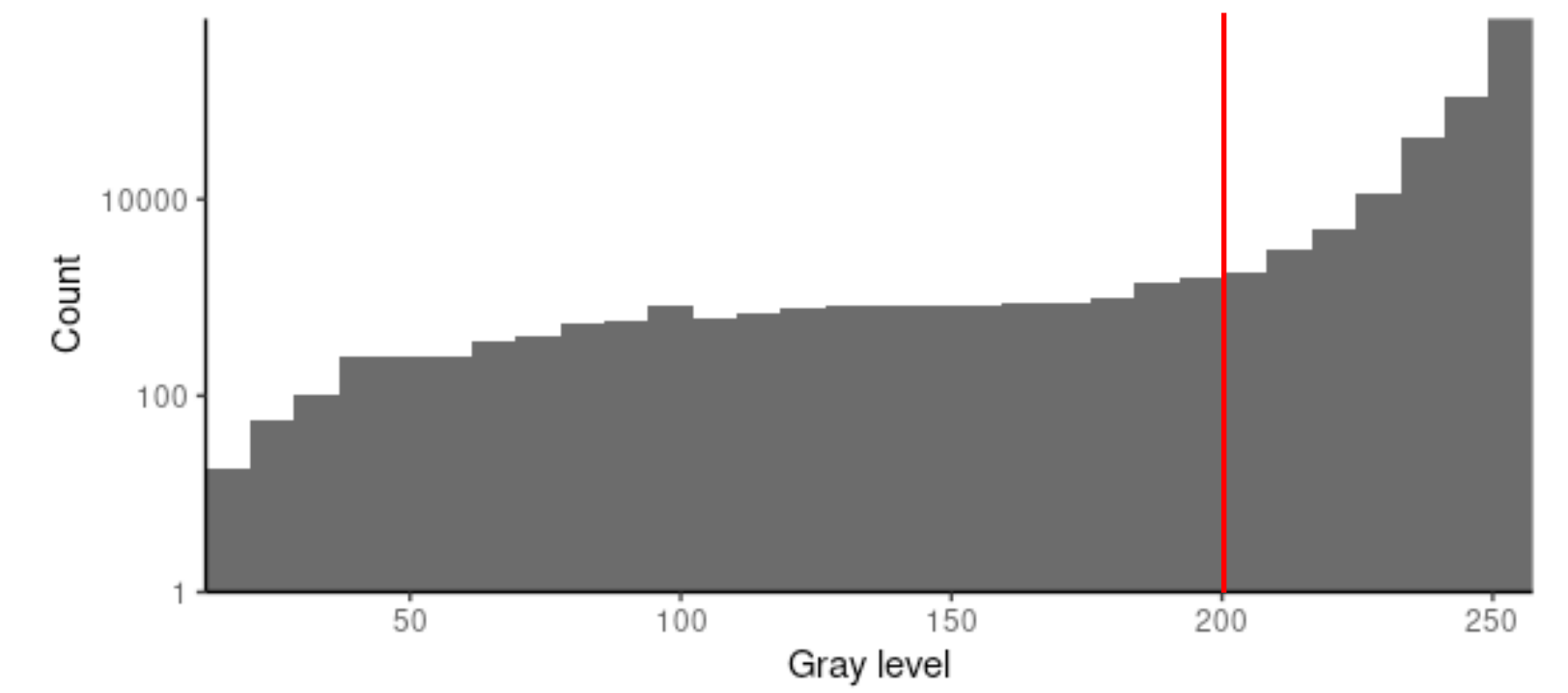
- Taxonomy:** Copepoda < Maxillopoda
- Depth Data:** depth_min : 0.00
- Major Axis Length:** major [pixel] : [value]

Row	Col	major [pixel]
1	1-12	64.80, 71.10, 60.70, 61.60, 70.00, 62.00, 82.30, 66.20, 66.30, 61.90, 67.30
2	1-12	61.60, 64.00, 61.10, 70.50, 62.50, 75.30, 62.50, 58.70, 69.30, 98.70, 84.70, 71.60
3	1-12	78.60, 71.10, 74.00, 82.50, 62.50, 65.40, 61.80, 70.20, 63.50, 63.90, 69.90
4	1-12	[Values partially obscured or missing]

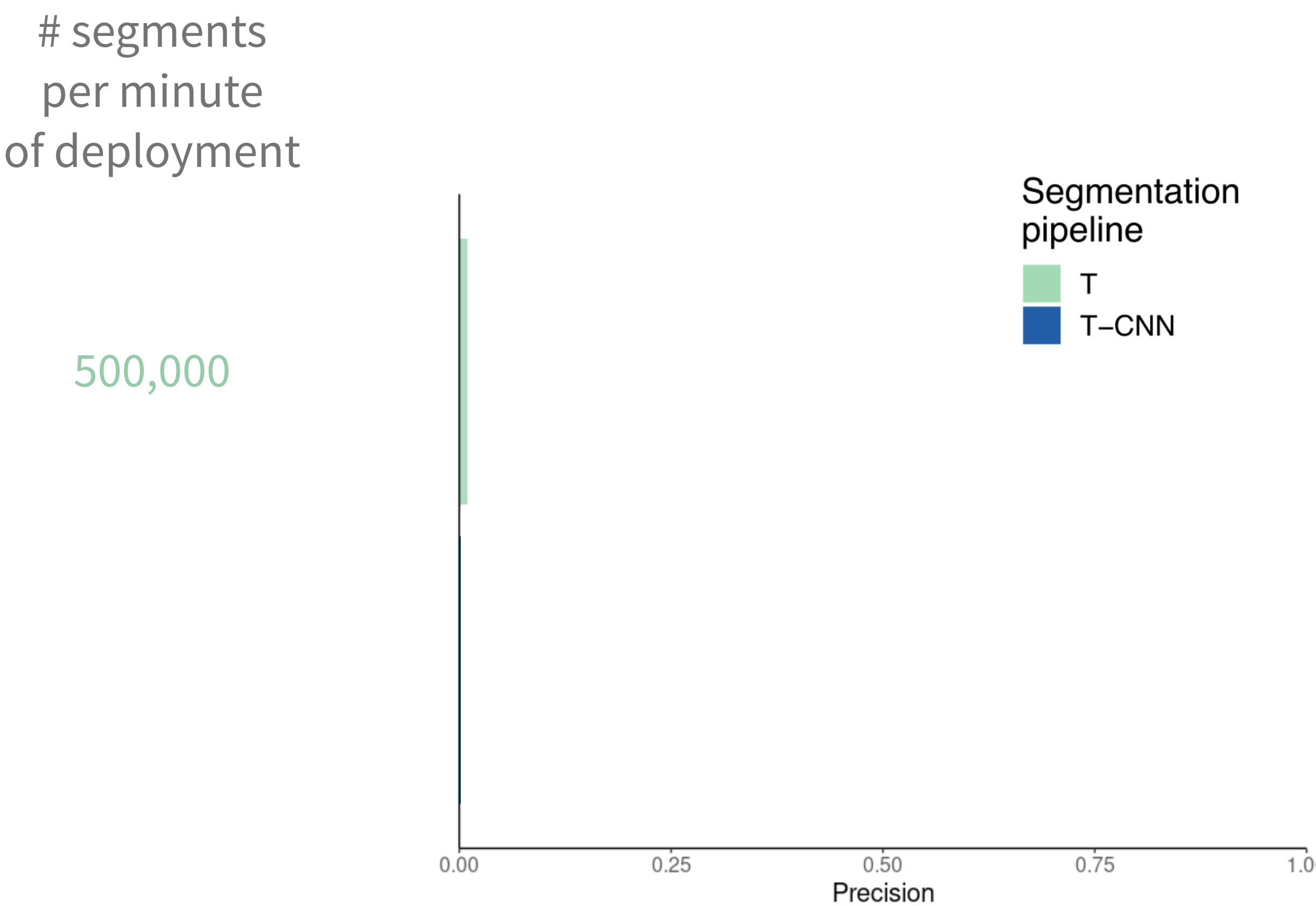
**The segmentation problem:
in situ, many objects are not plankton**



The segmentation problem: in situ, many objects are not plankton



The segmentation problem: in situ, many objects are not plankton



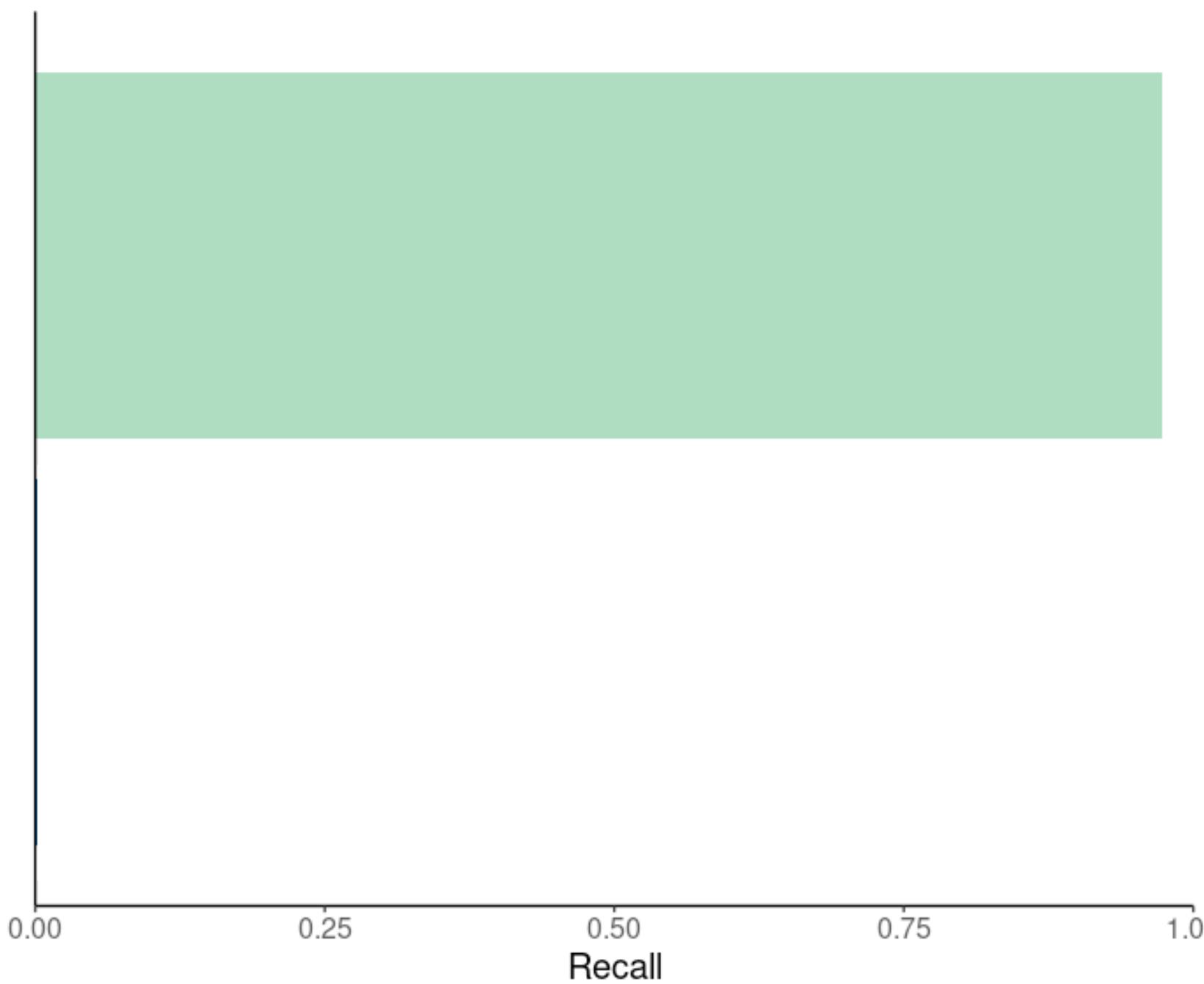
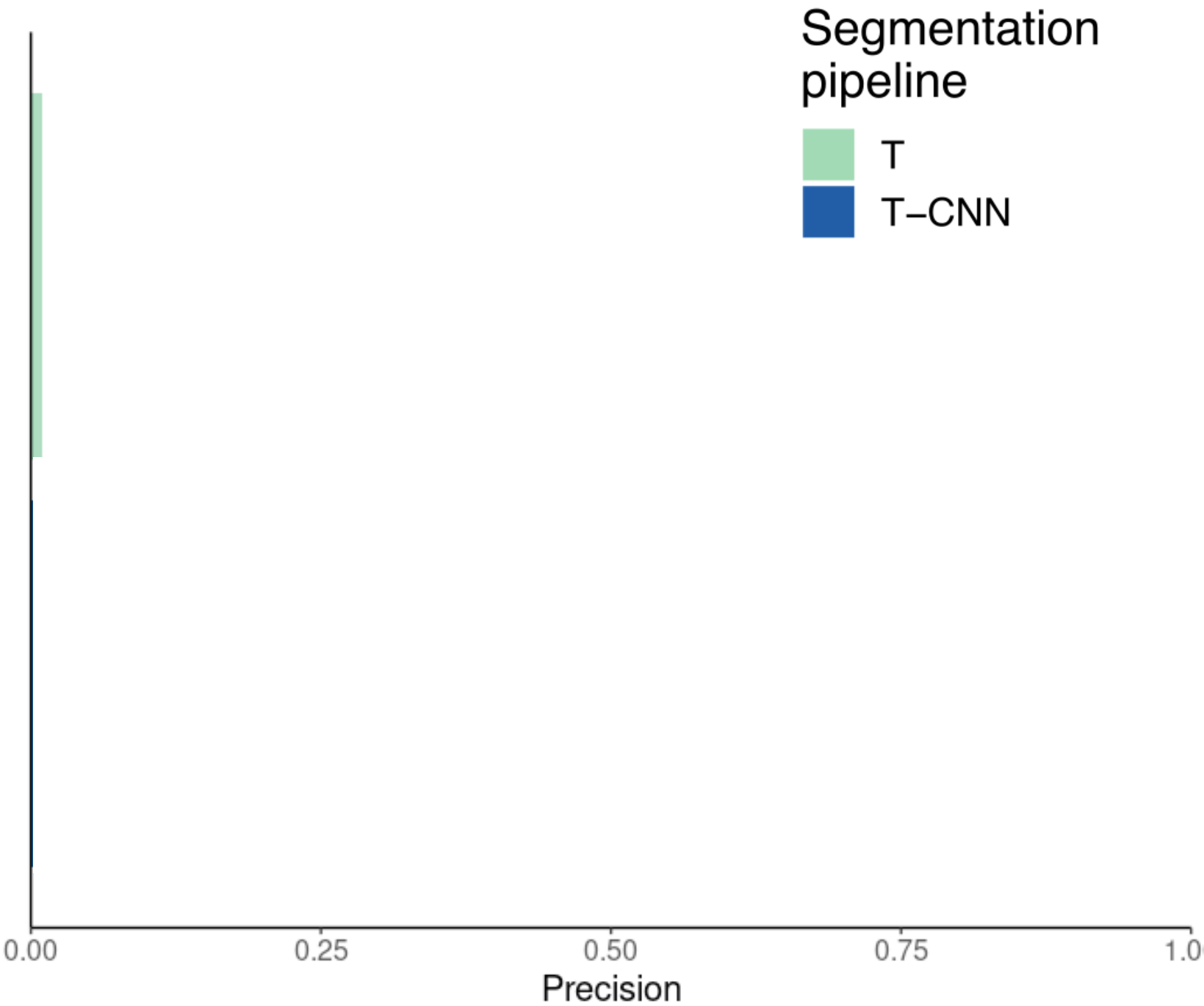
Truth:
5,000

The segmentation problem: in situ, many objects are not plankton

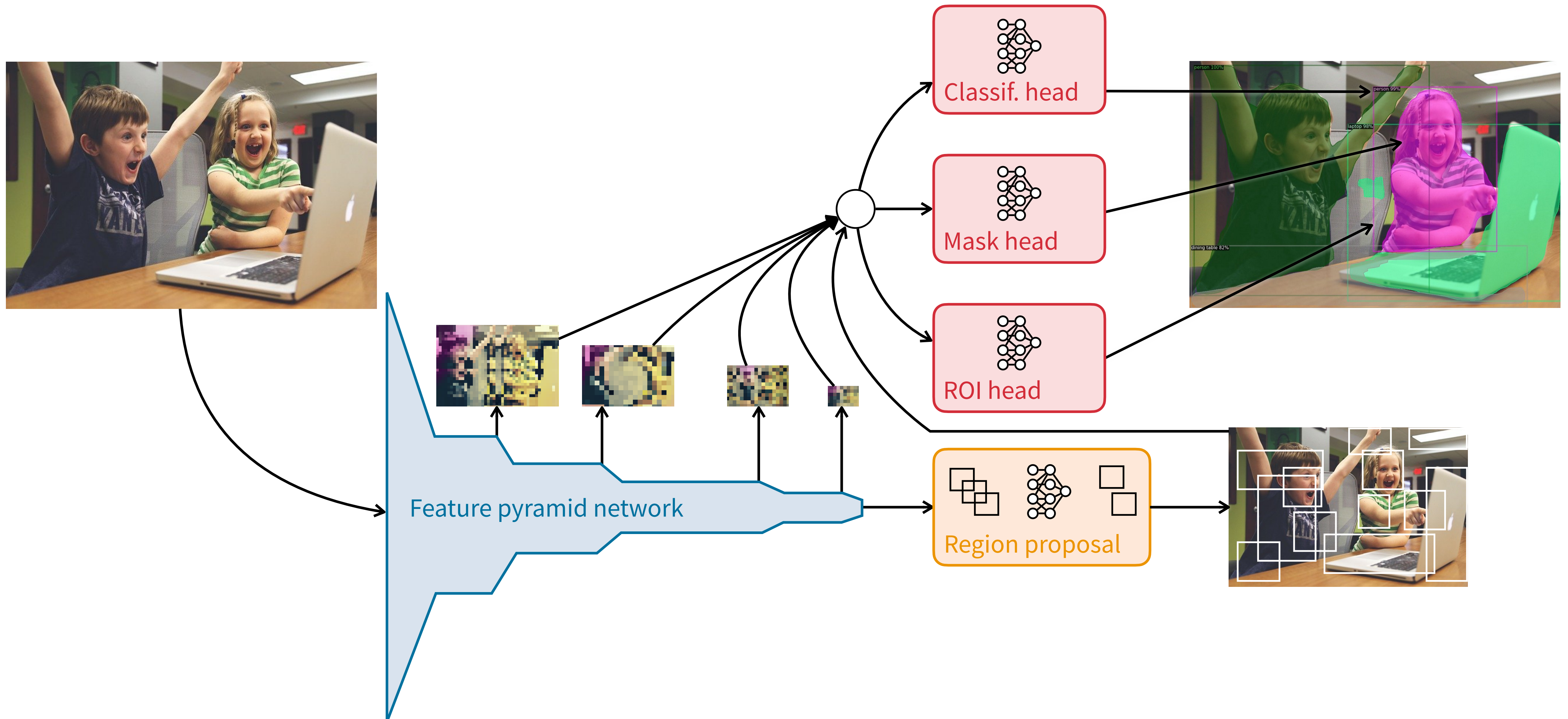
segments
per minute
of deployment

500,000

Truth:
5,000

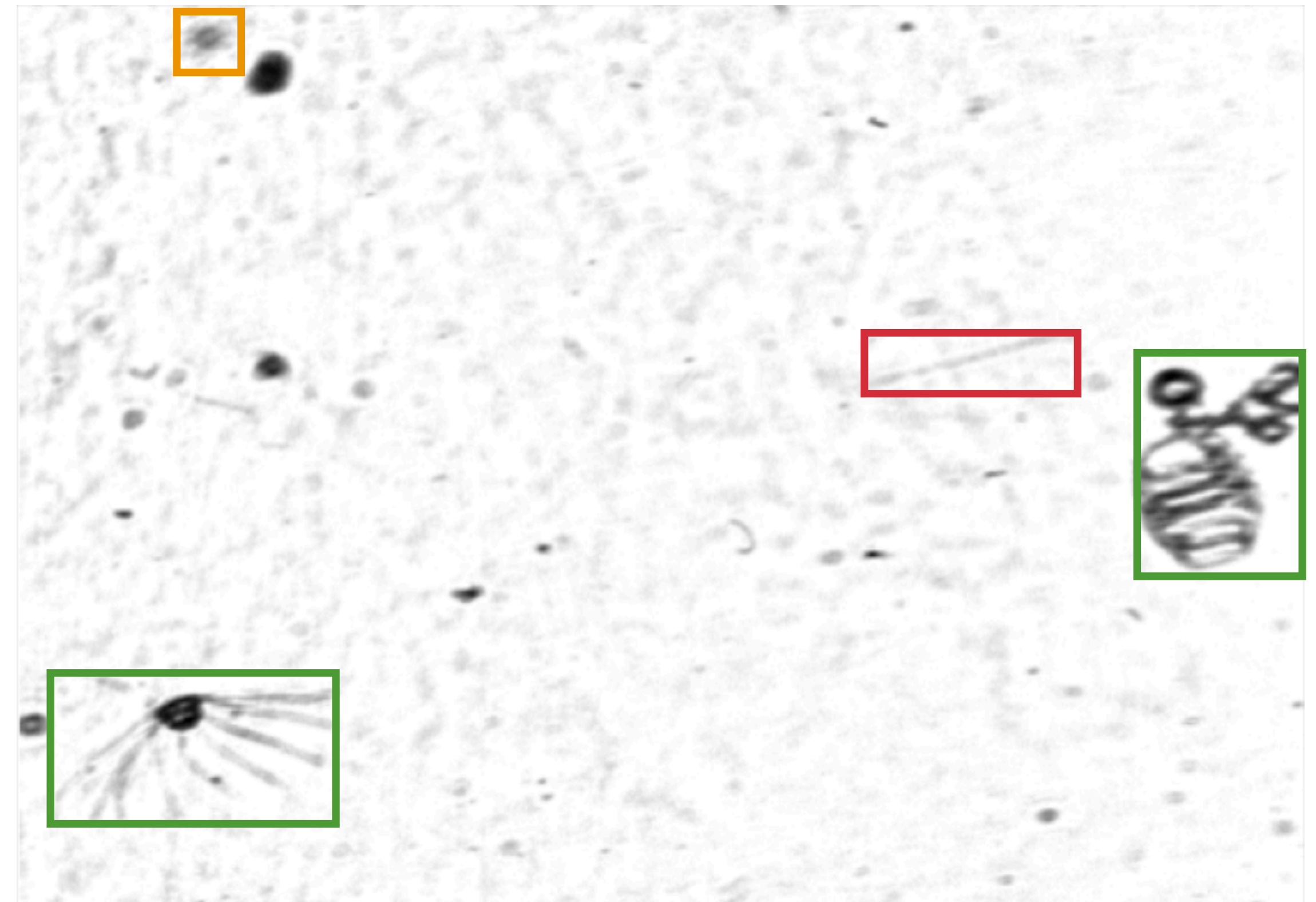
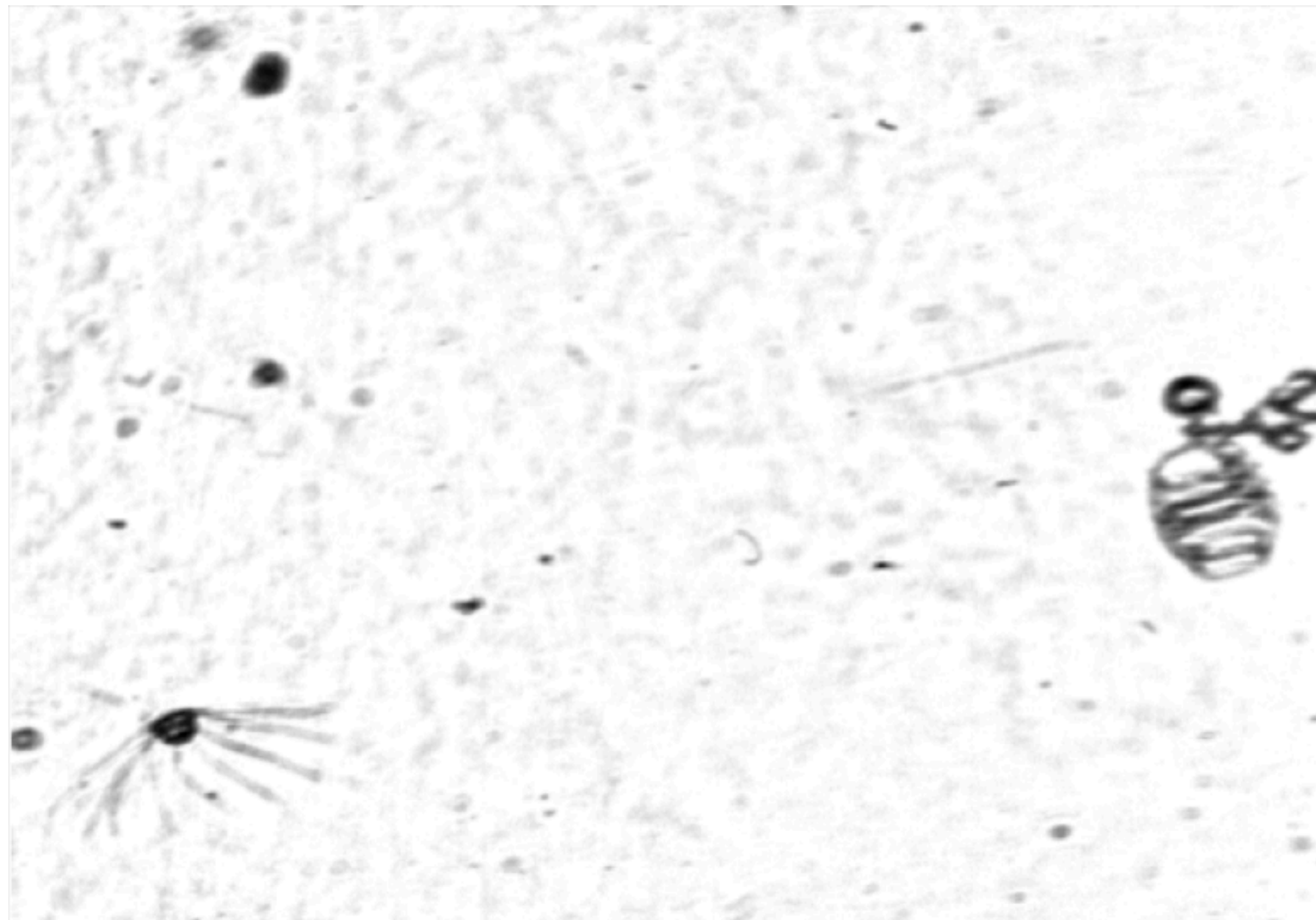


Deep object detection/segmentation:



Deep object detection/segmentation:

 Detectron2



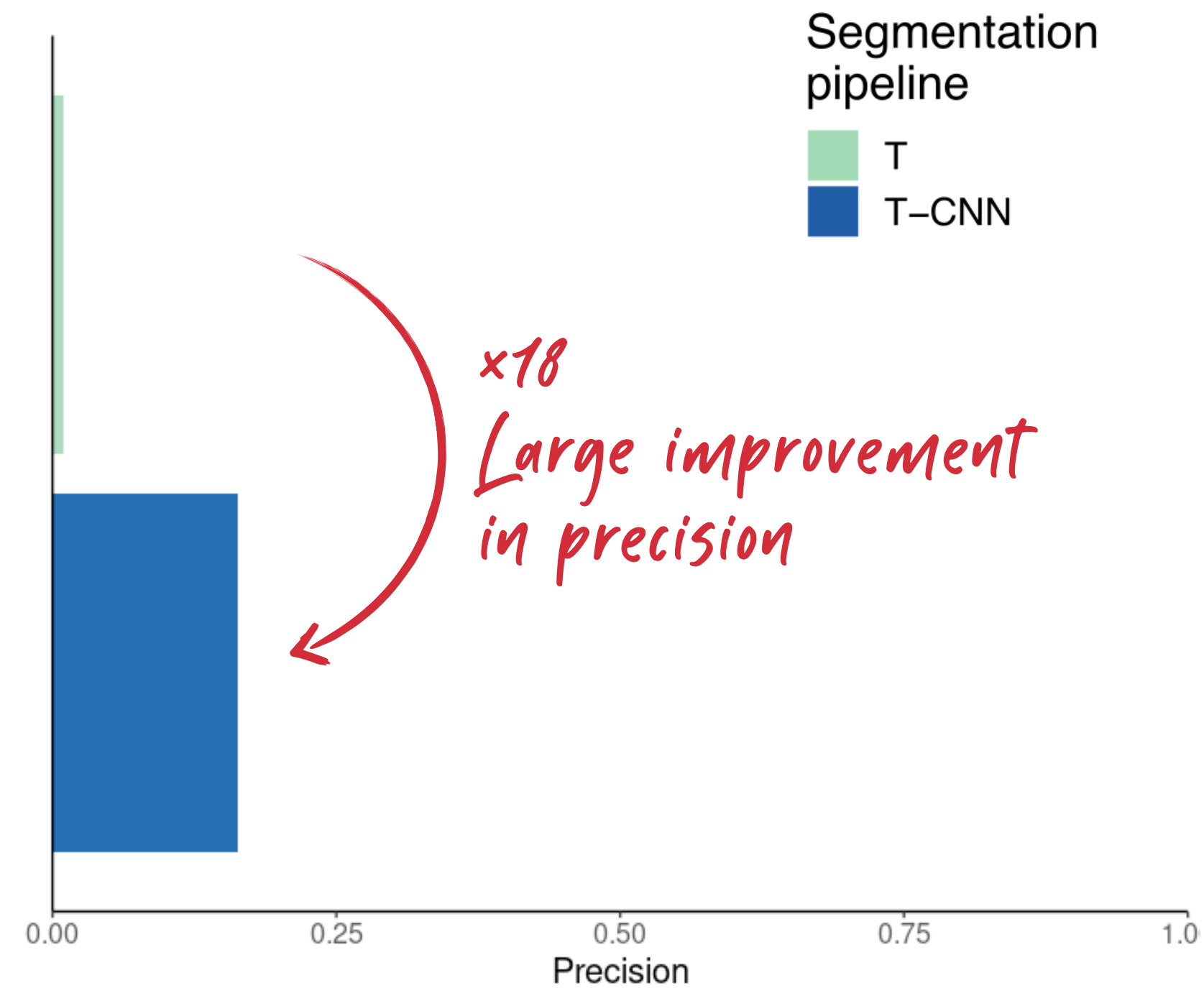
“Intelligent” segmentation uses context to improve precision

segments
per minute
of deployment

500,000

30,000

Truth:
5,000



x0.94
Similar
recall

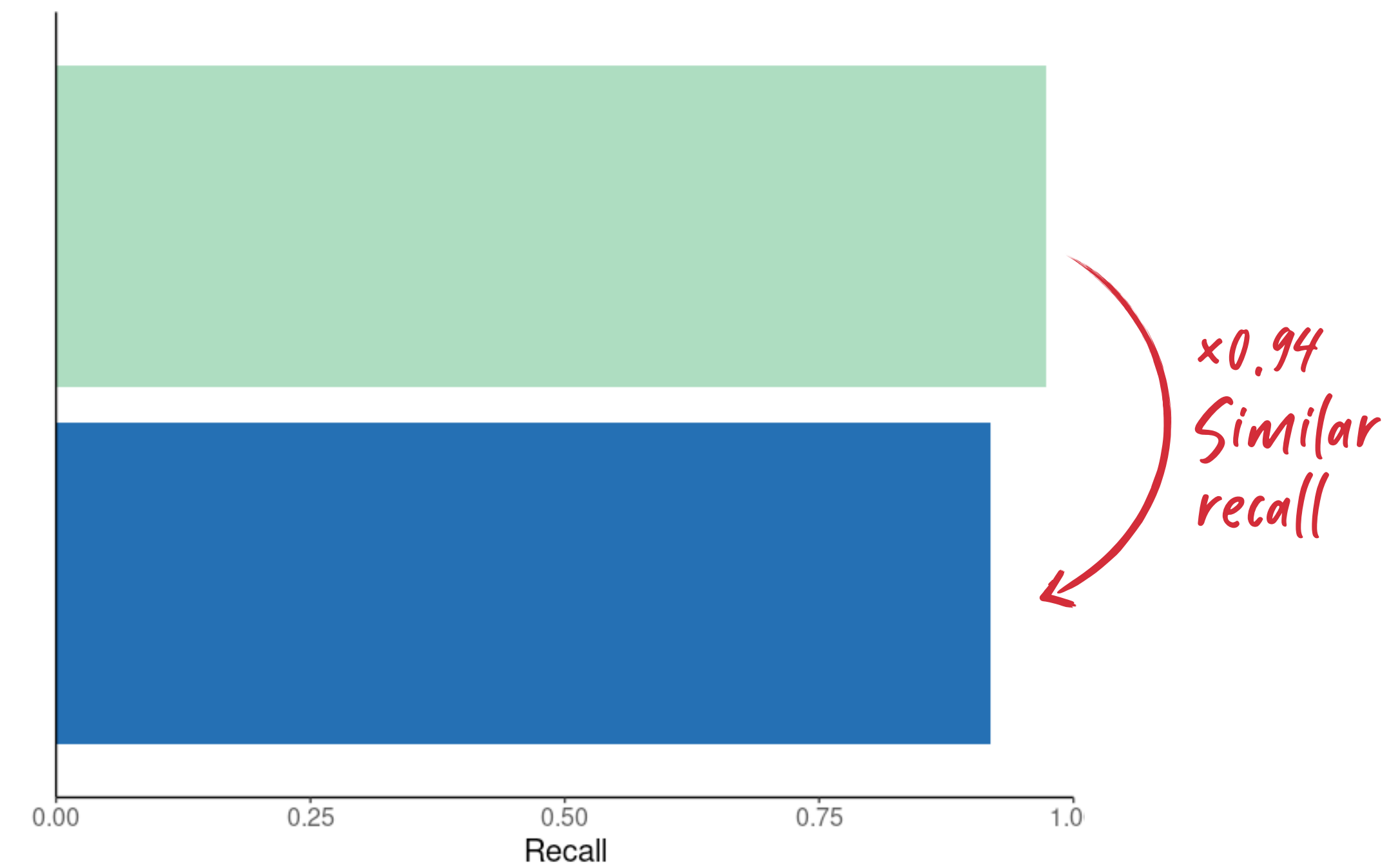
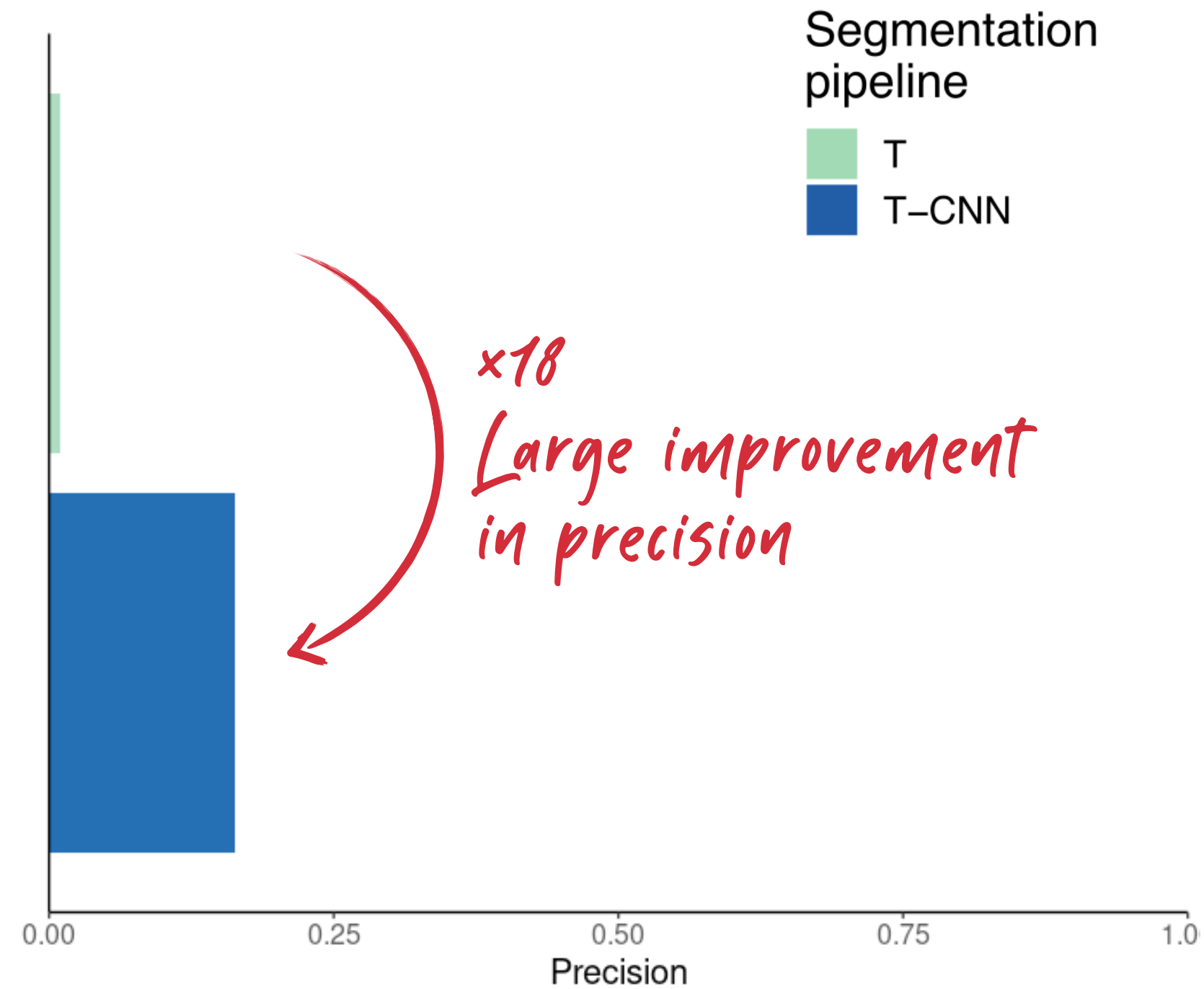
“Intelligent” segmentation uses context to improve precision

segments
per minute
of deployment

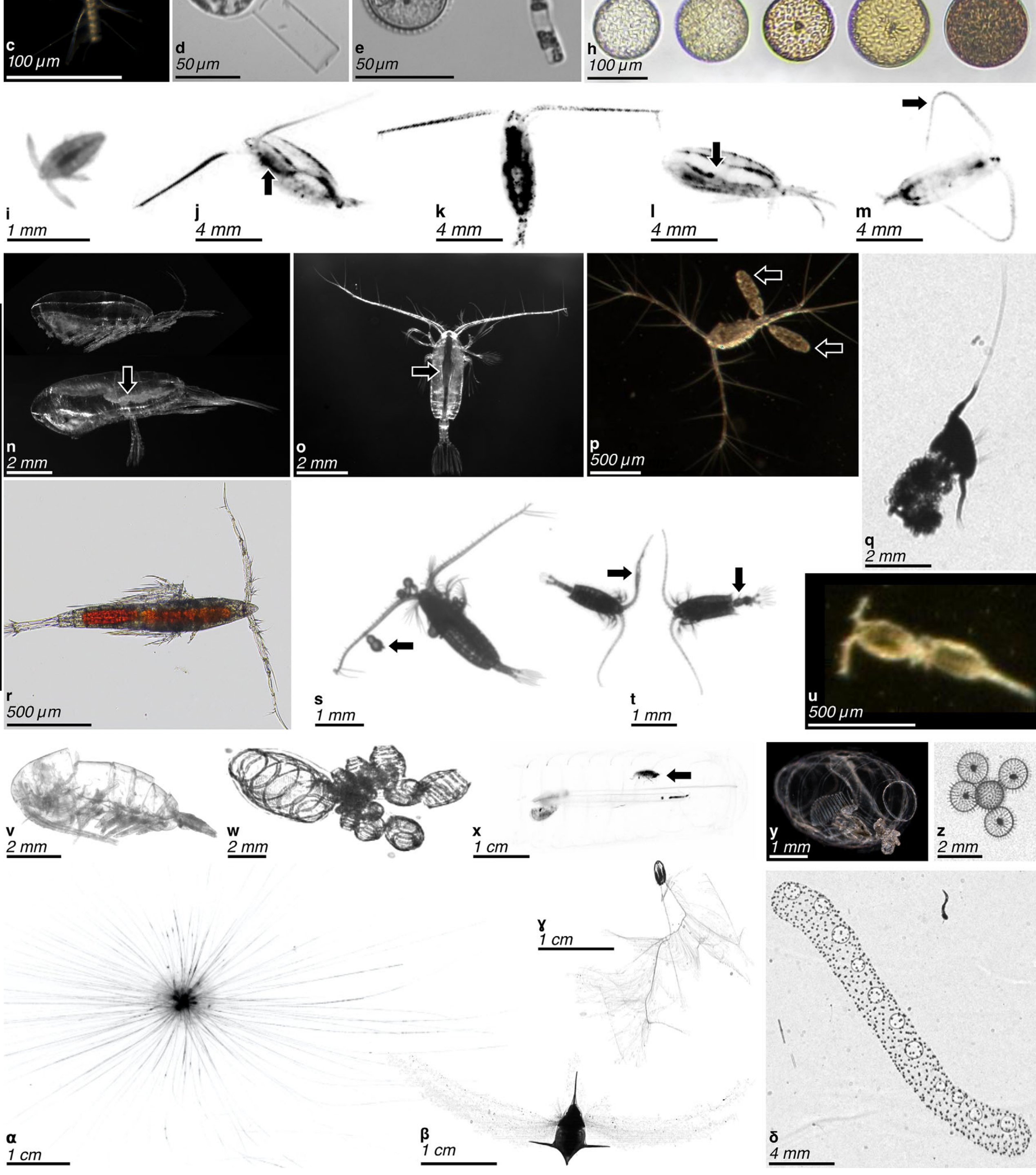
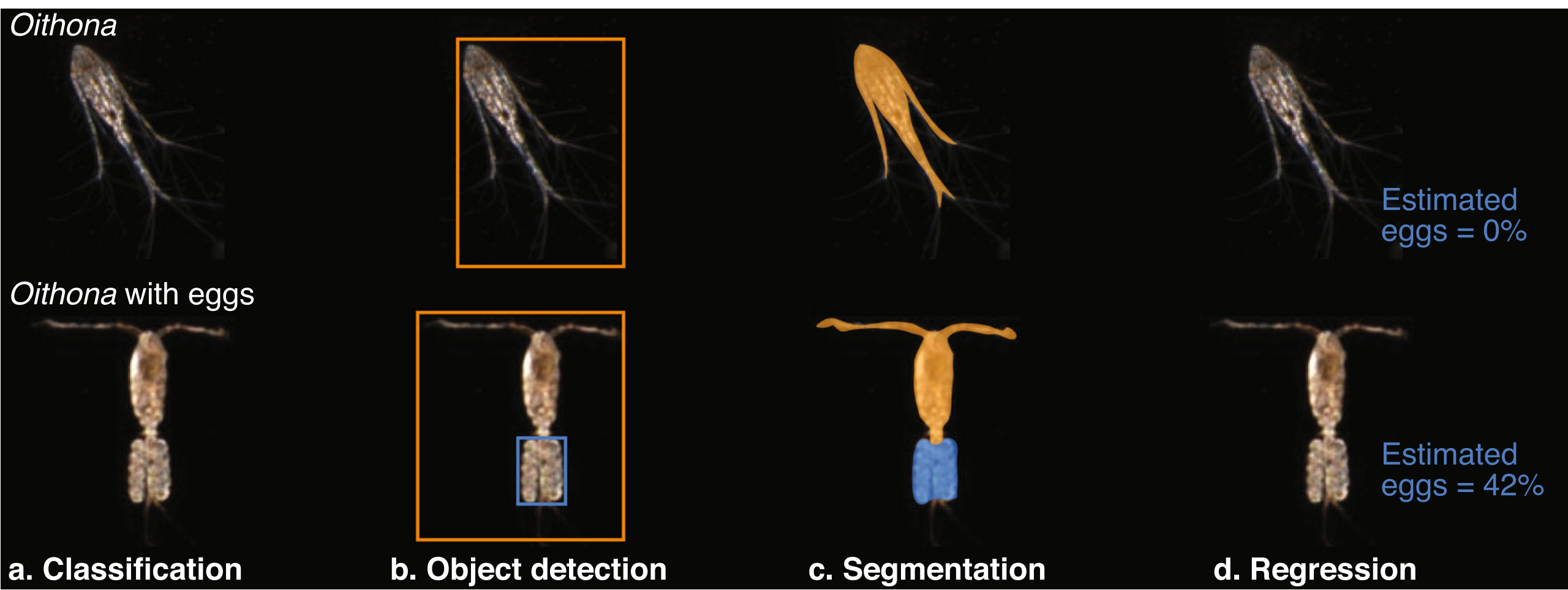
500,000

30,000

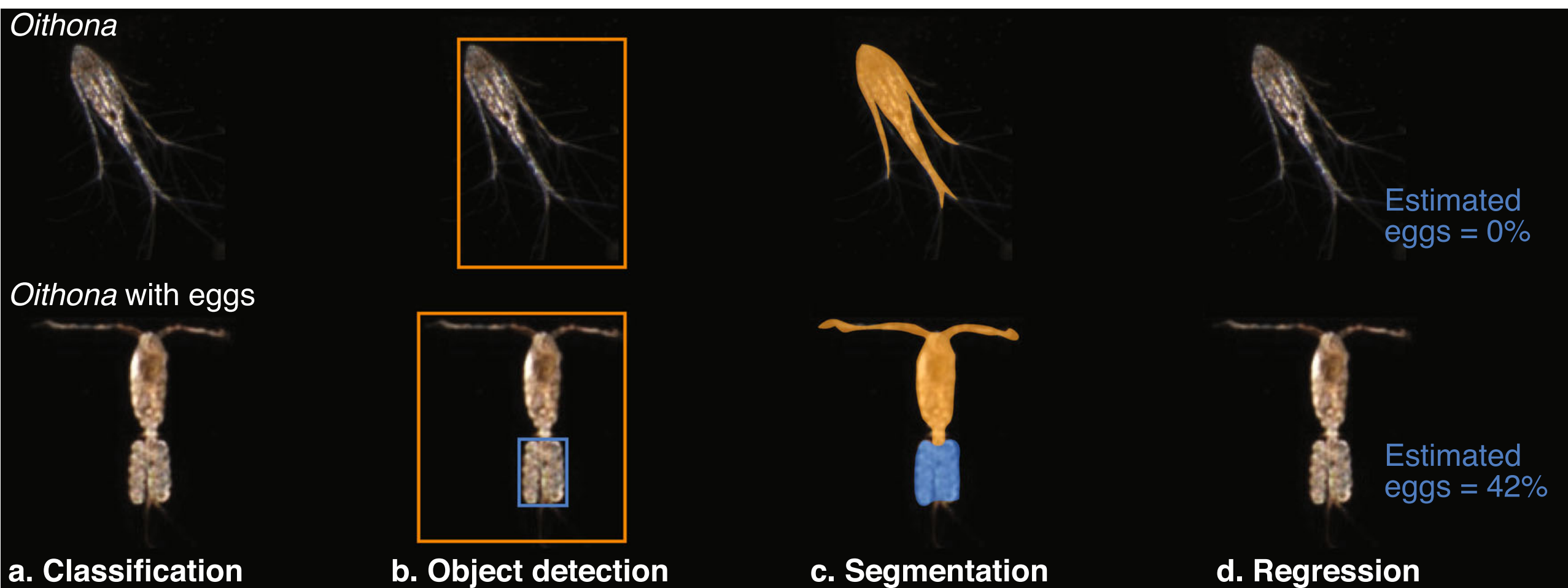
Truth:
5,000



Deep learning for “trait” extraction



Deep learning for “trait” extraction



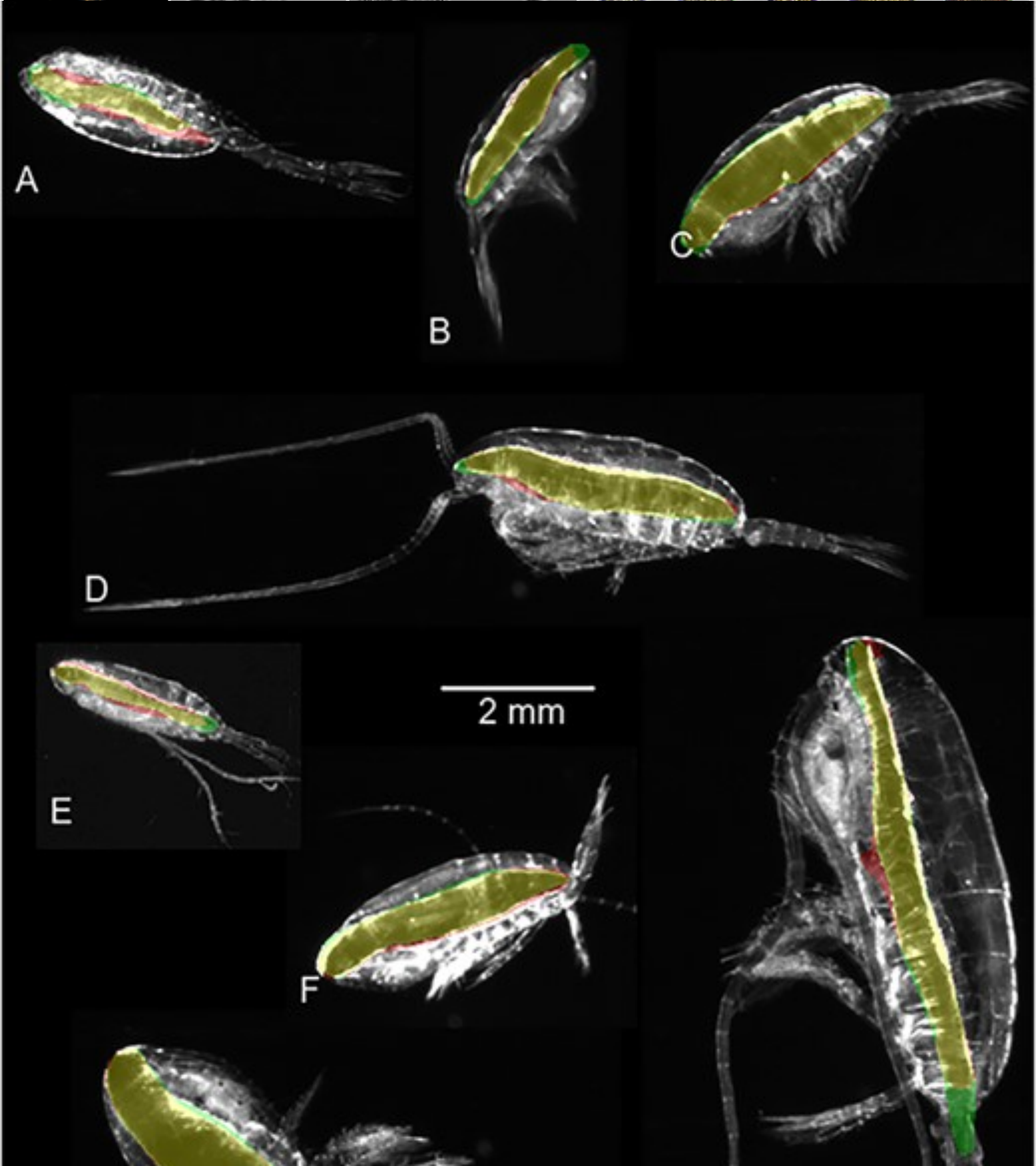
Segmentation of oil sac in Arctic copepods:

Yellow: human and algorithm match

Green: outlined by human only

Red: outlined by algorithm only

$\text{IoU (Yellow / (Yellow + Red))} = \sim 0.8$ for large species

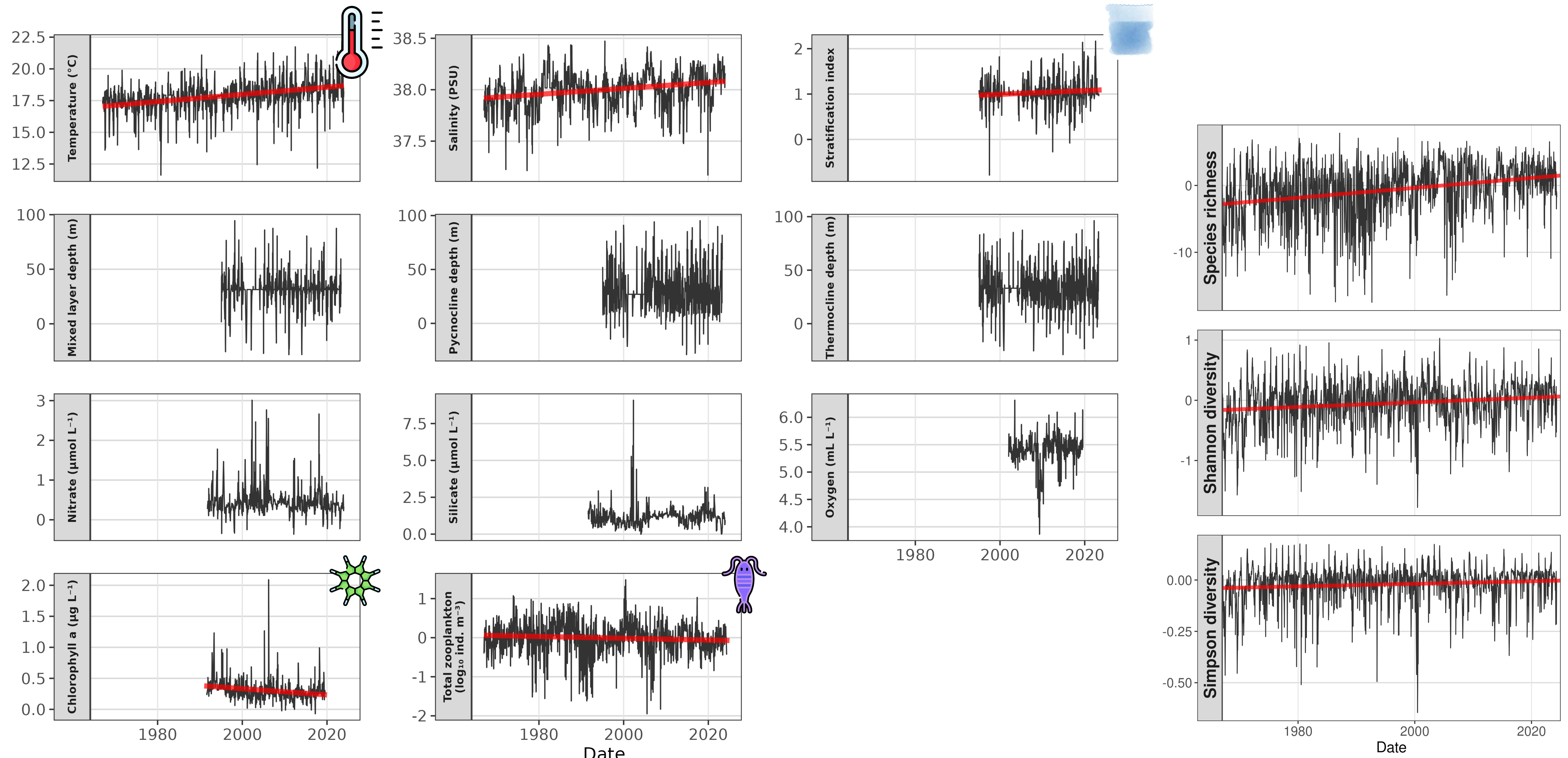


The background of the slide is a light blue, semi-transparent image of a fossilized trilobite. The trilobite's segmented body and prominent spines are visible, creating a textured, scientific backdrop. A white rectangular area is centered over the image, containing the text.

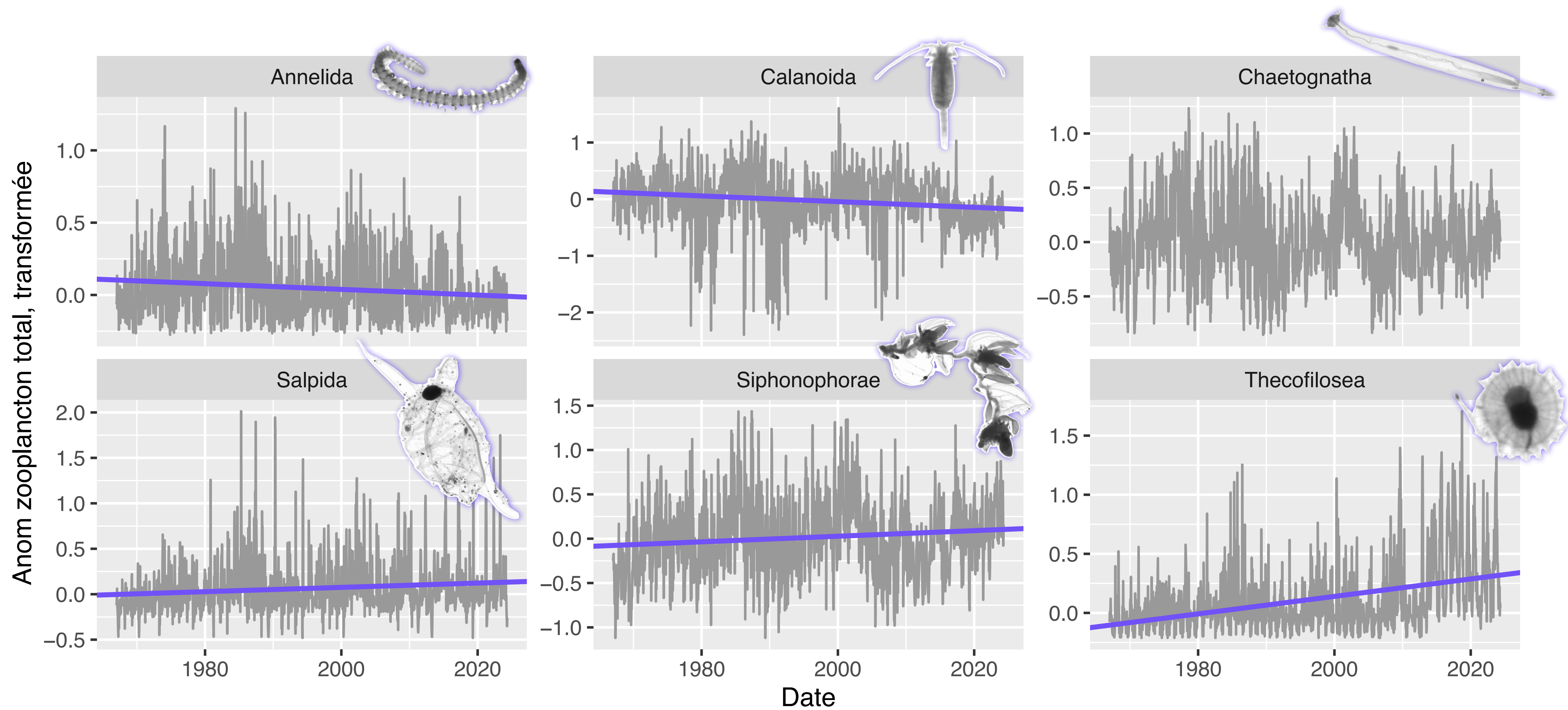
A few scientific results

Because that's what it's all about in the end

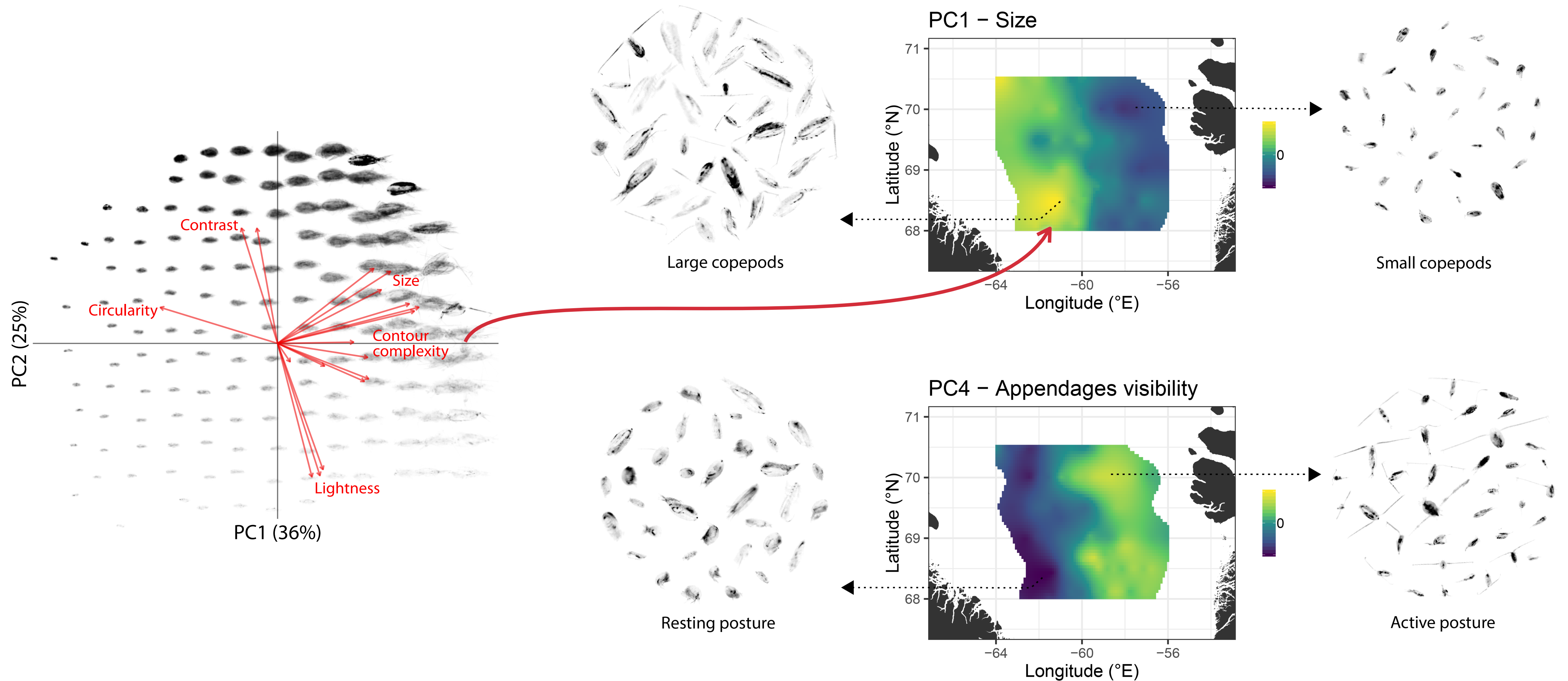
Long term oligotrophication in Villefranche's bay...



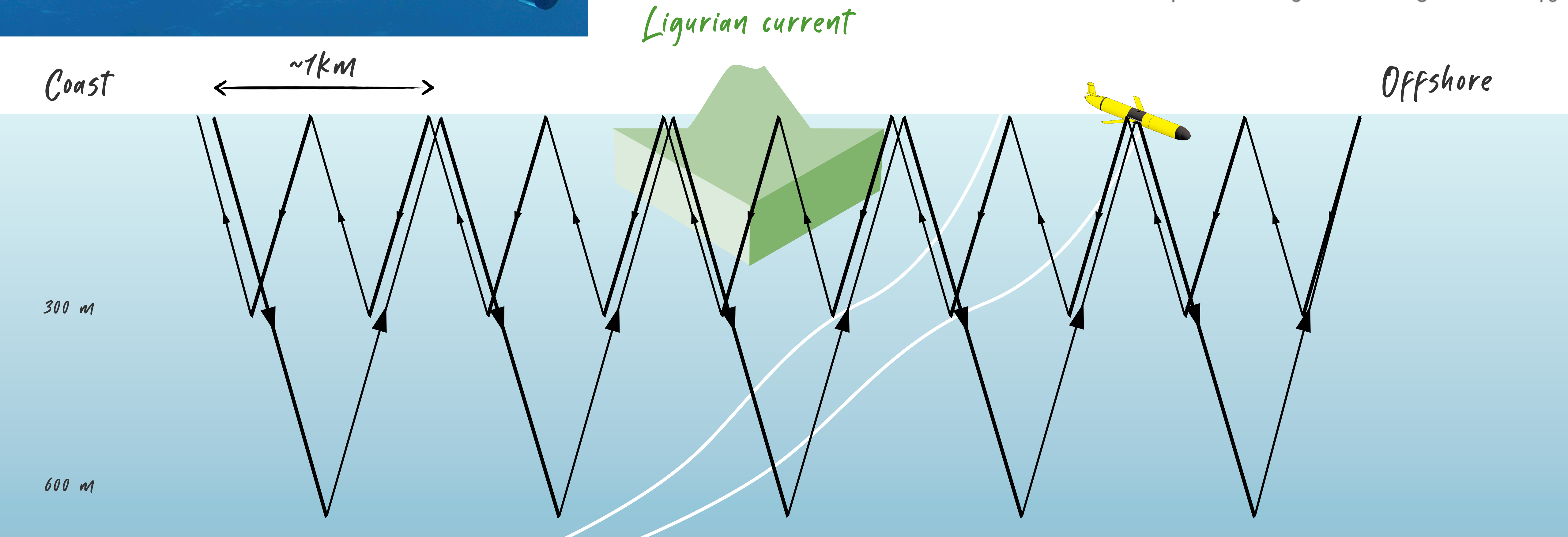
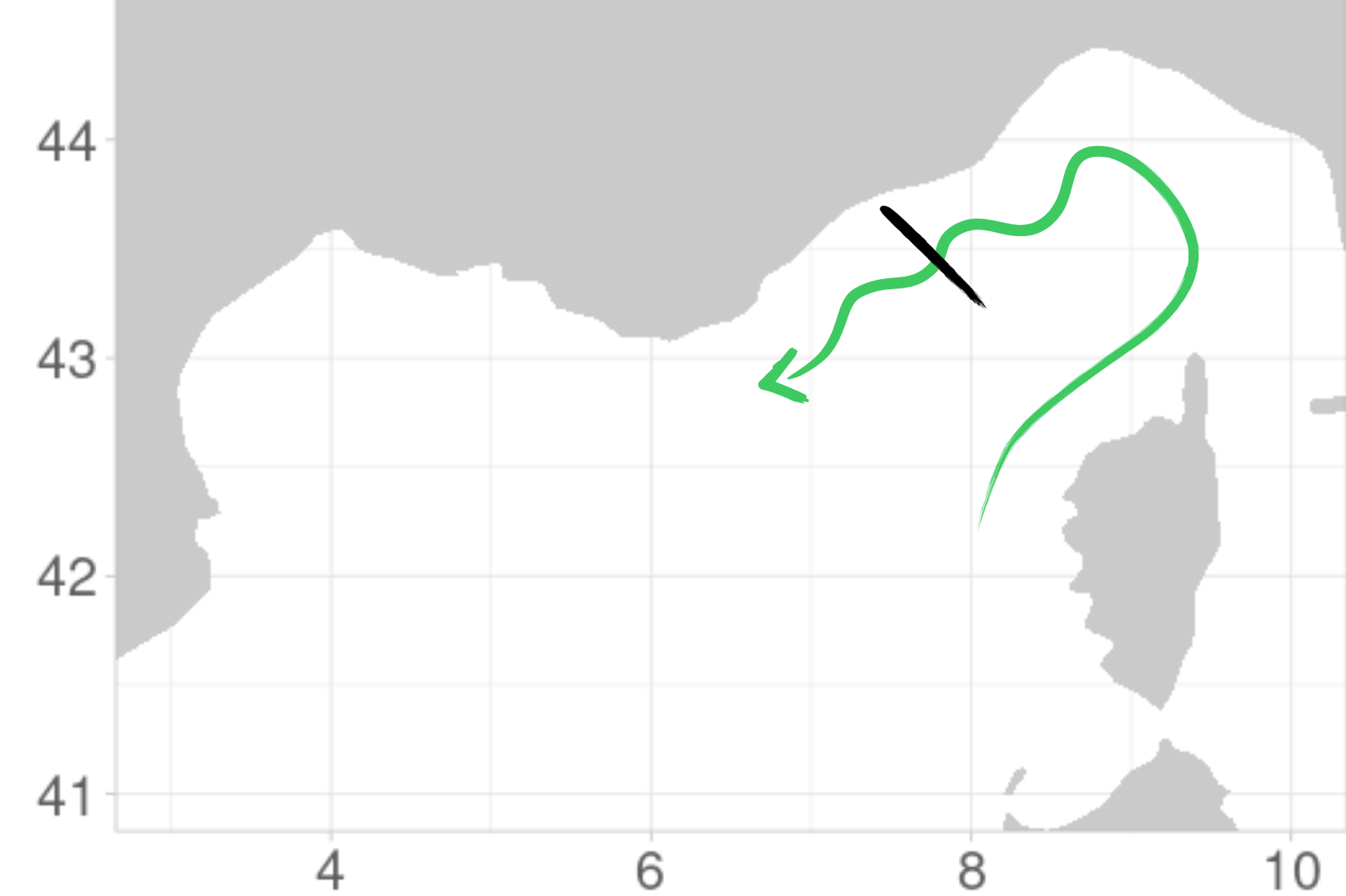
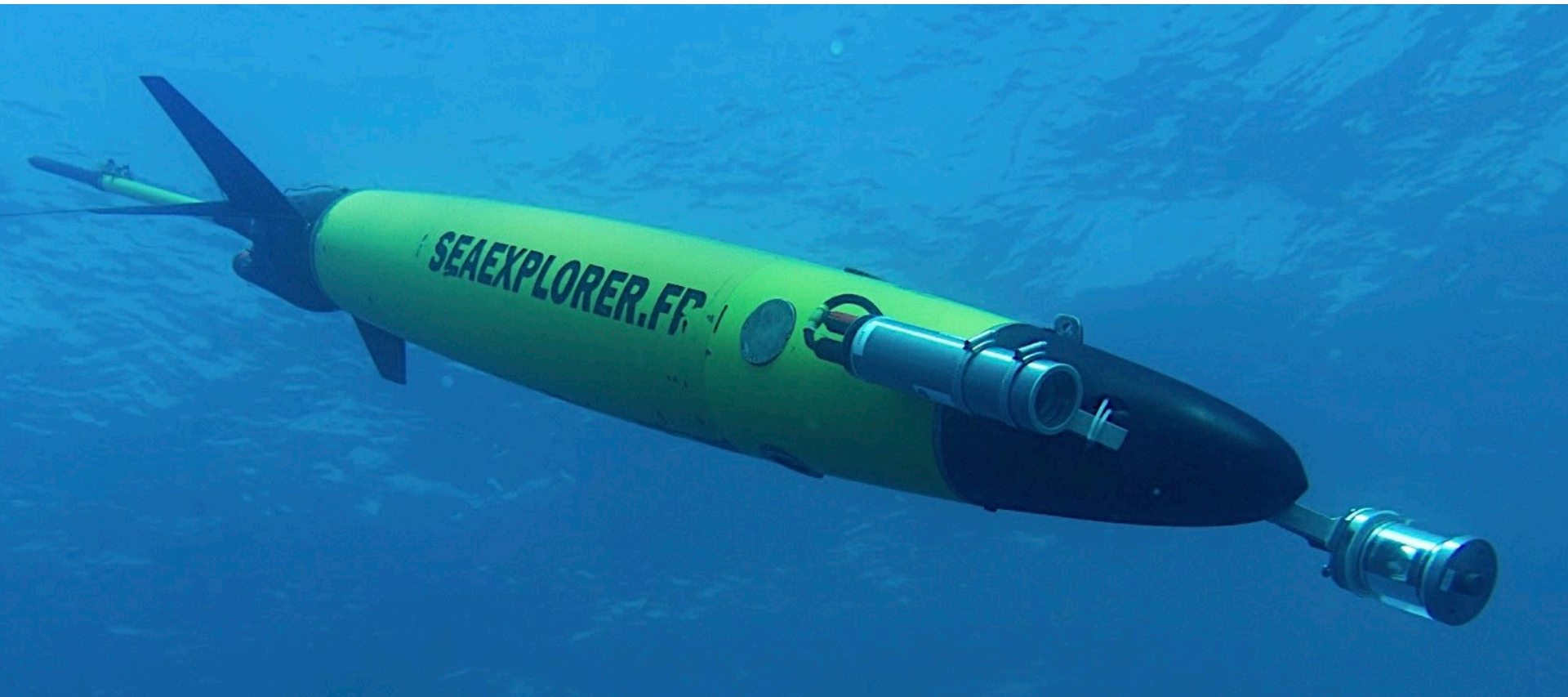
... inducing a community reorganisation



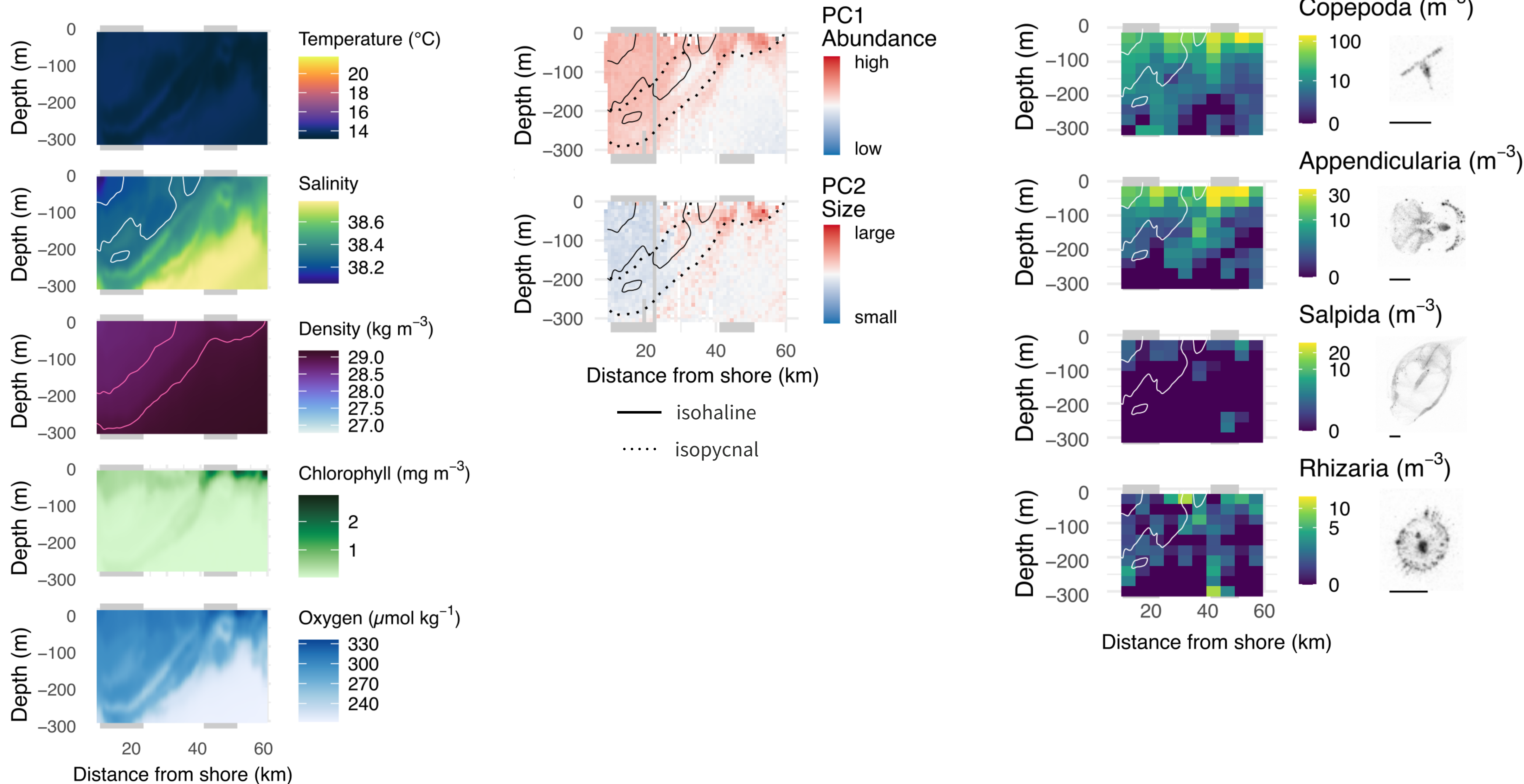
Deep features as objective individual descriptors of morphology



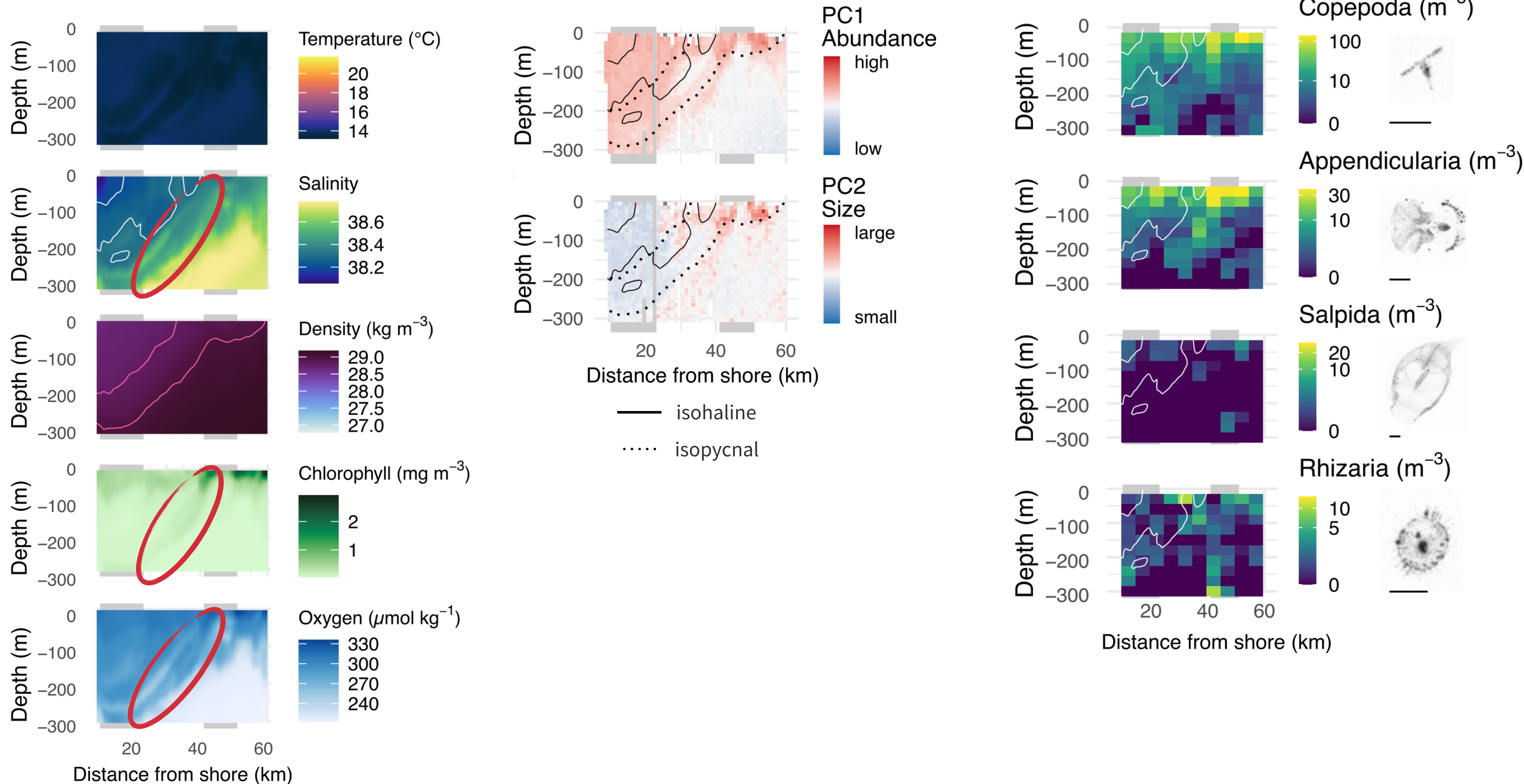
Glider survey through a front



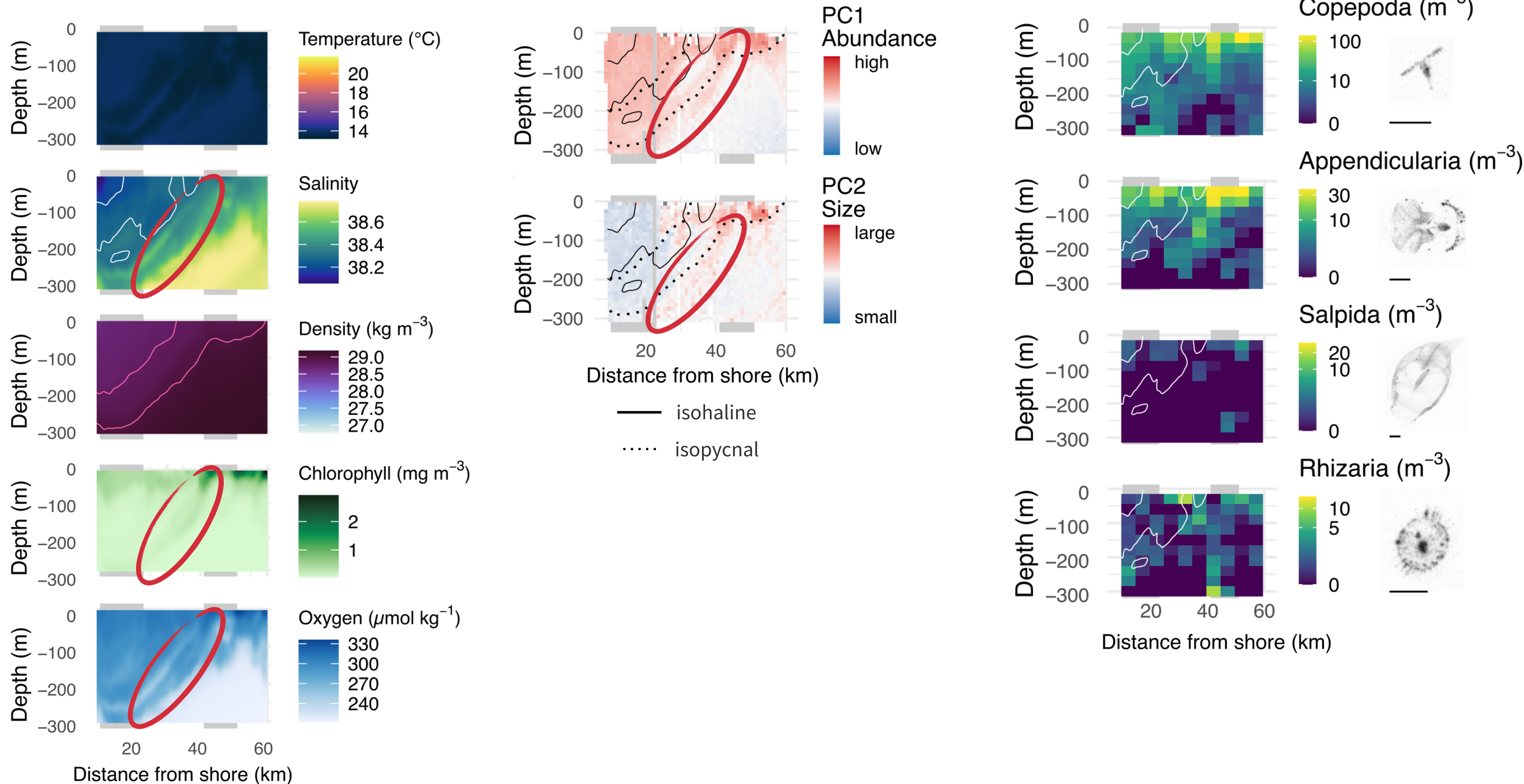
February: Start of the plankton bloom



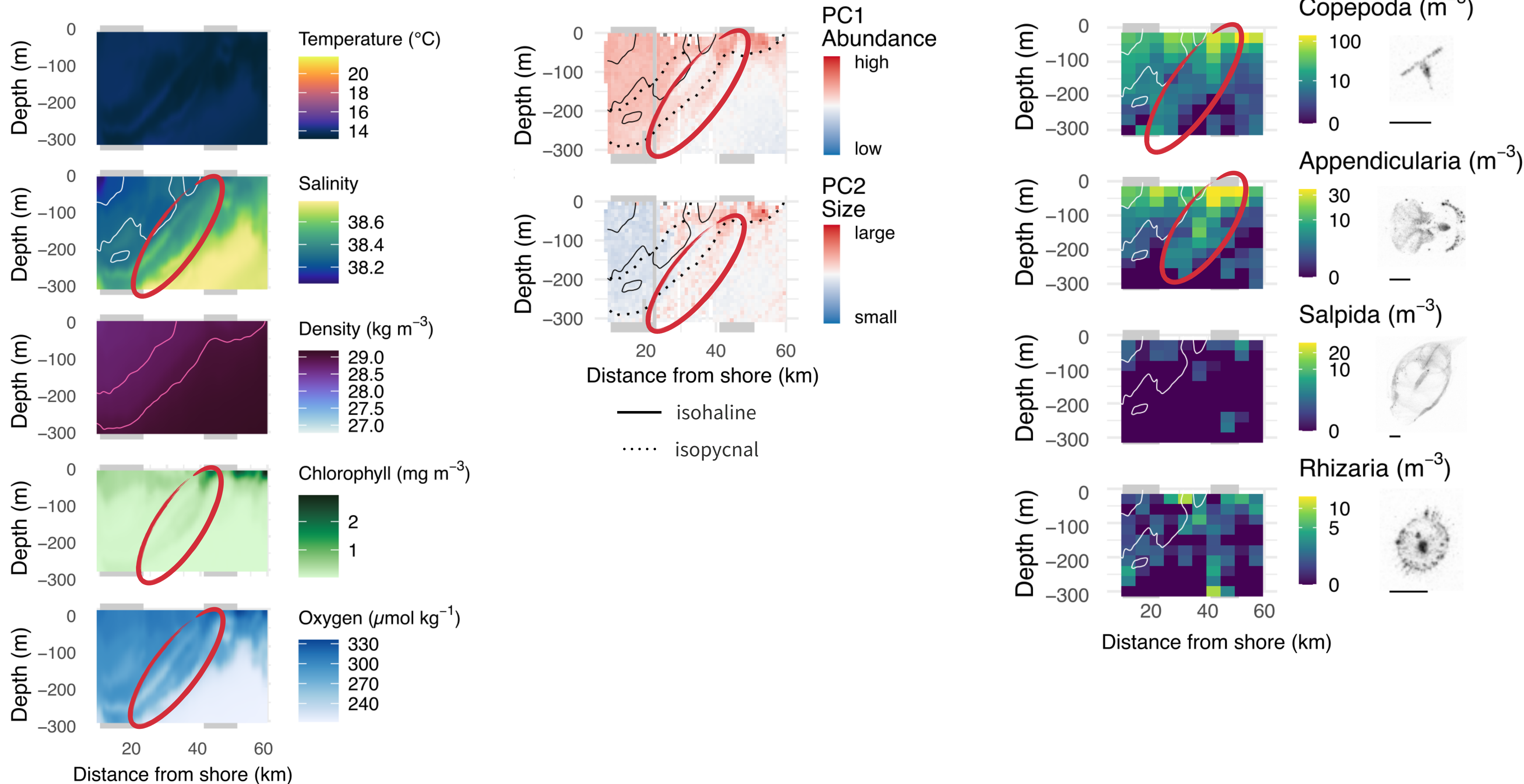
February: Start of the plankton bloom



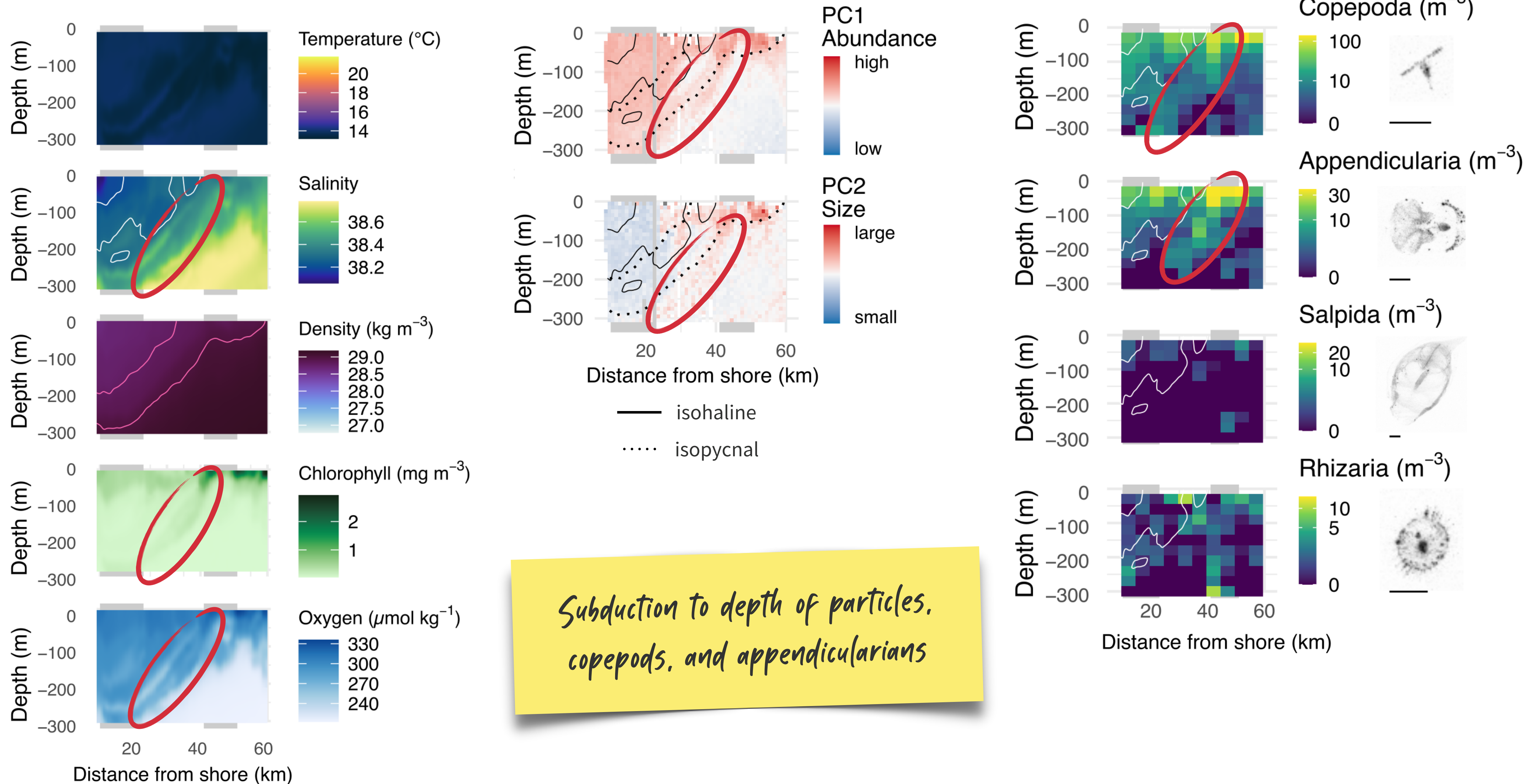
February: Start of the plankton bloom



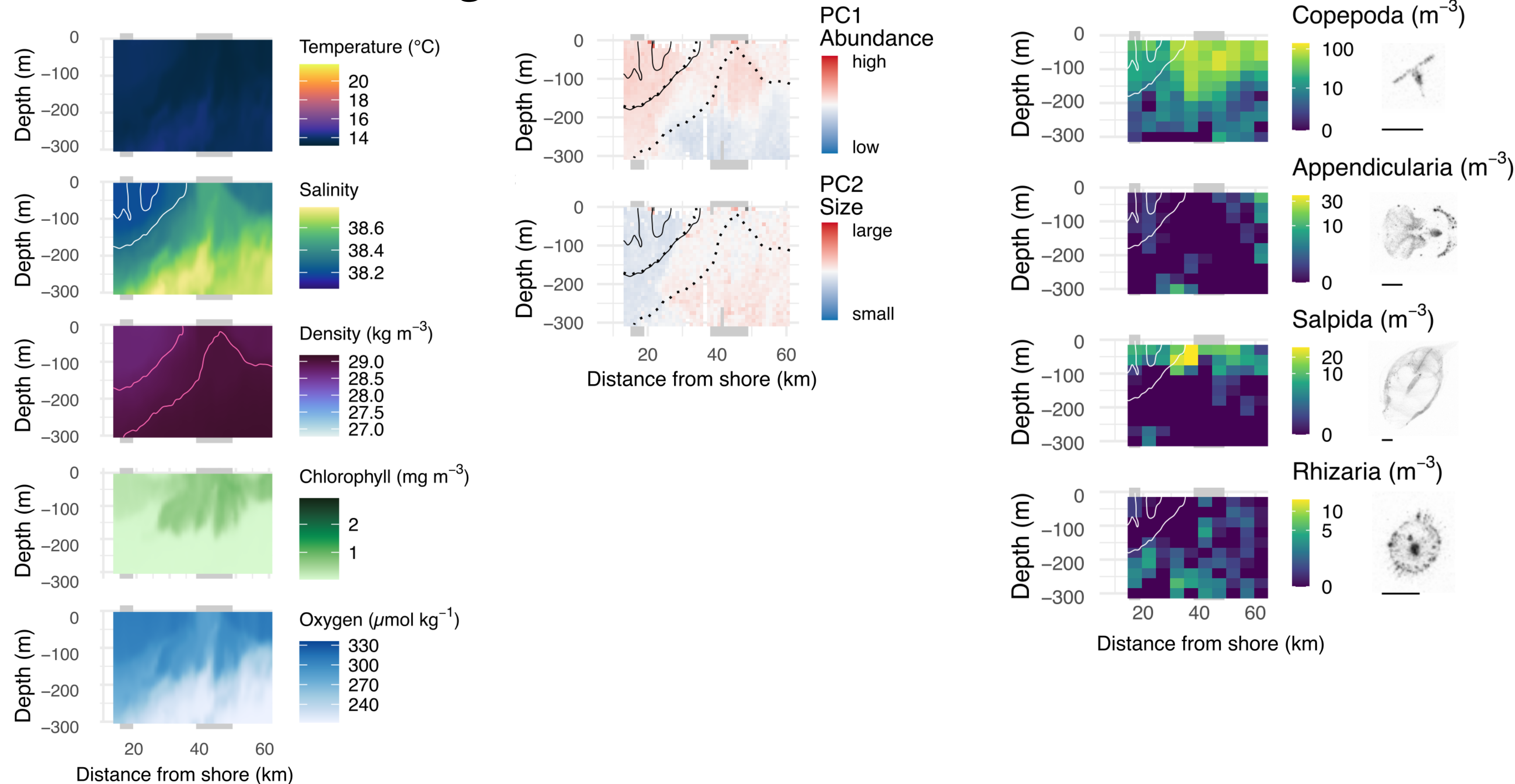
February: Start of the plankton bloom



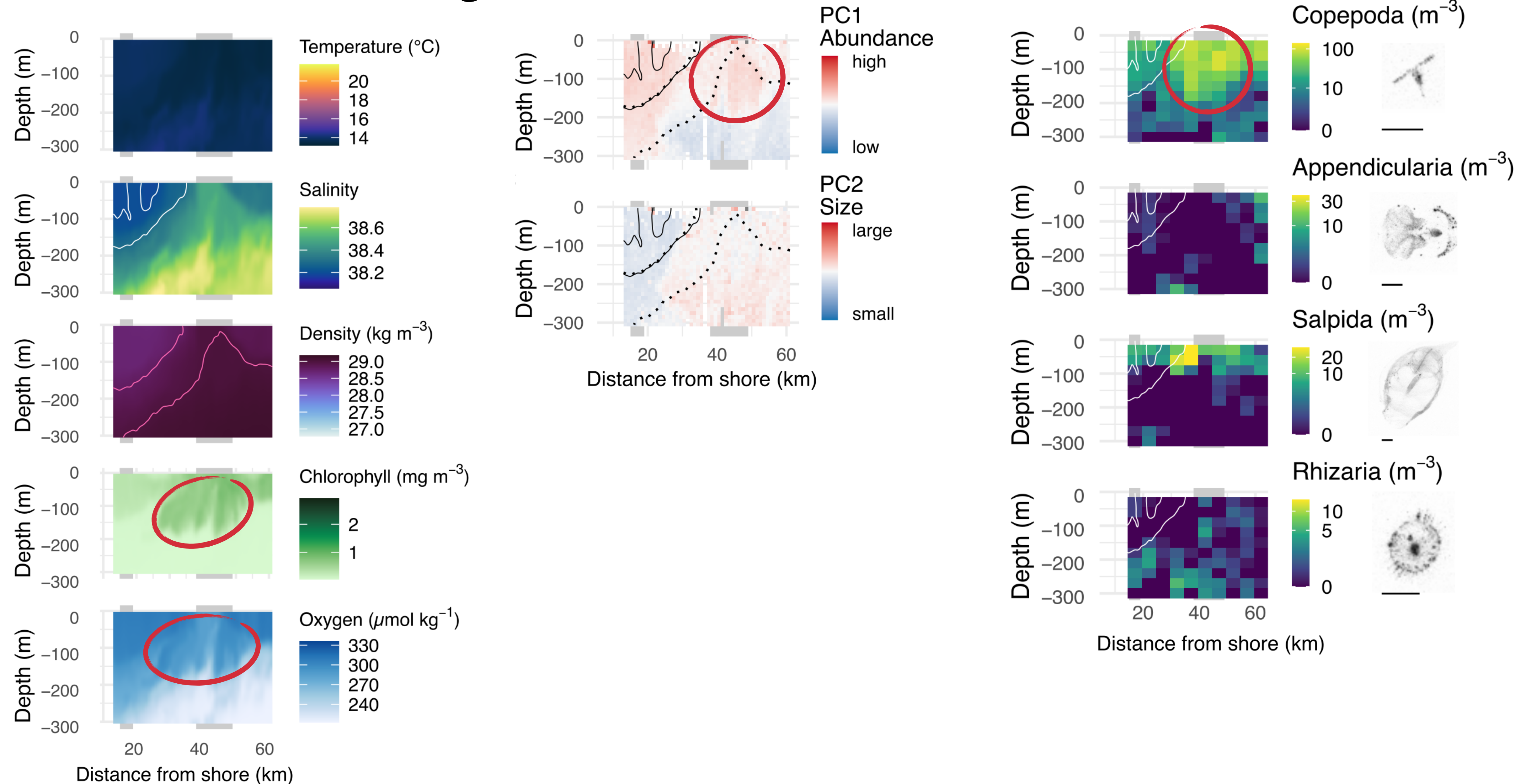
February: Start of the plankton bloom



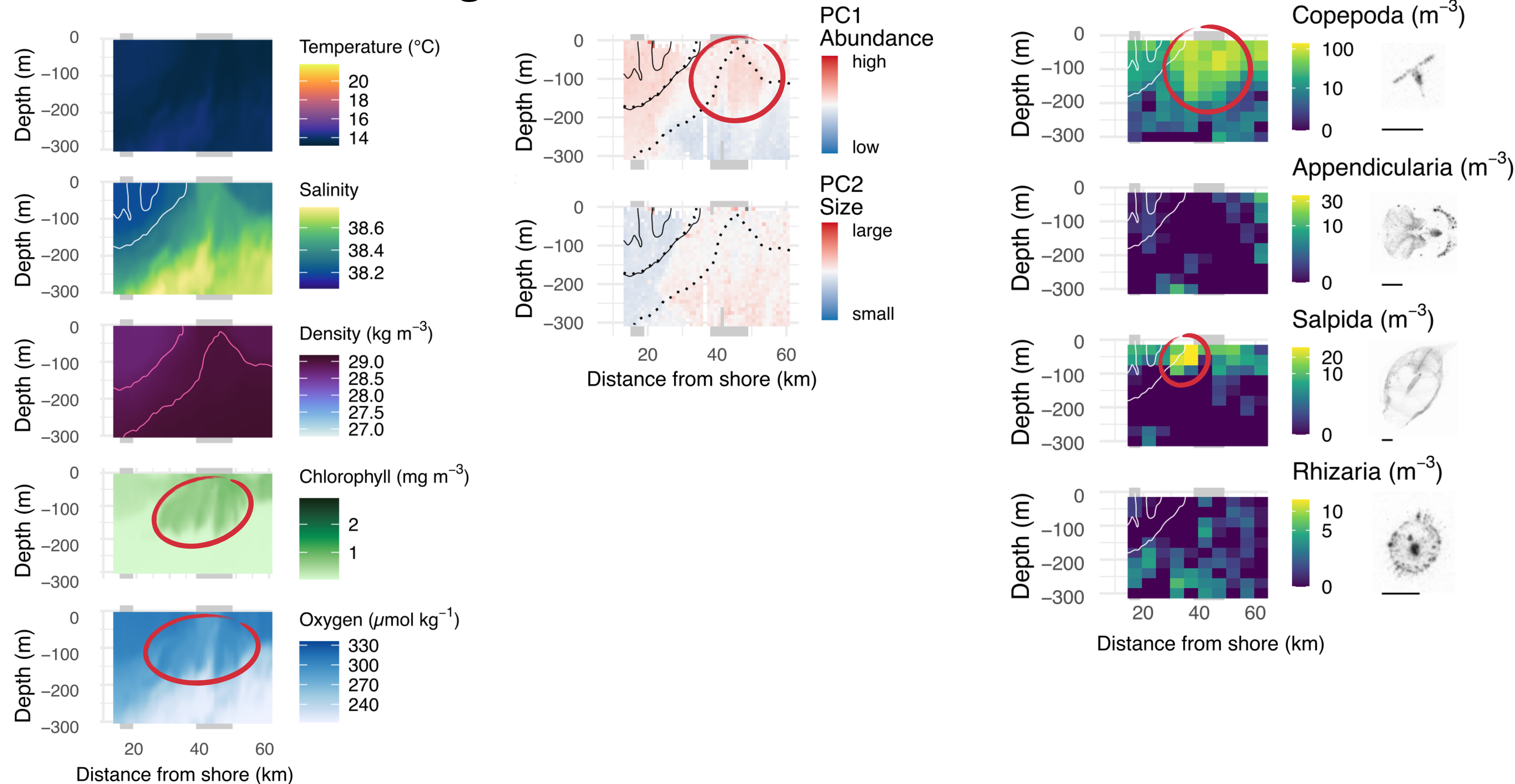
March: A wind mixing event



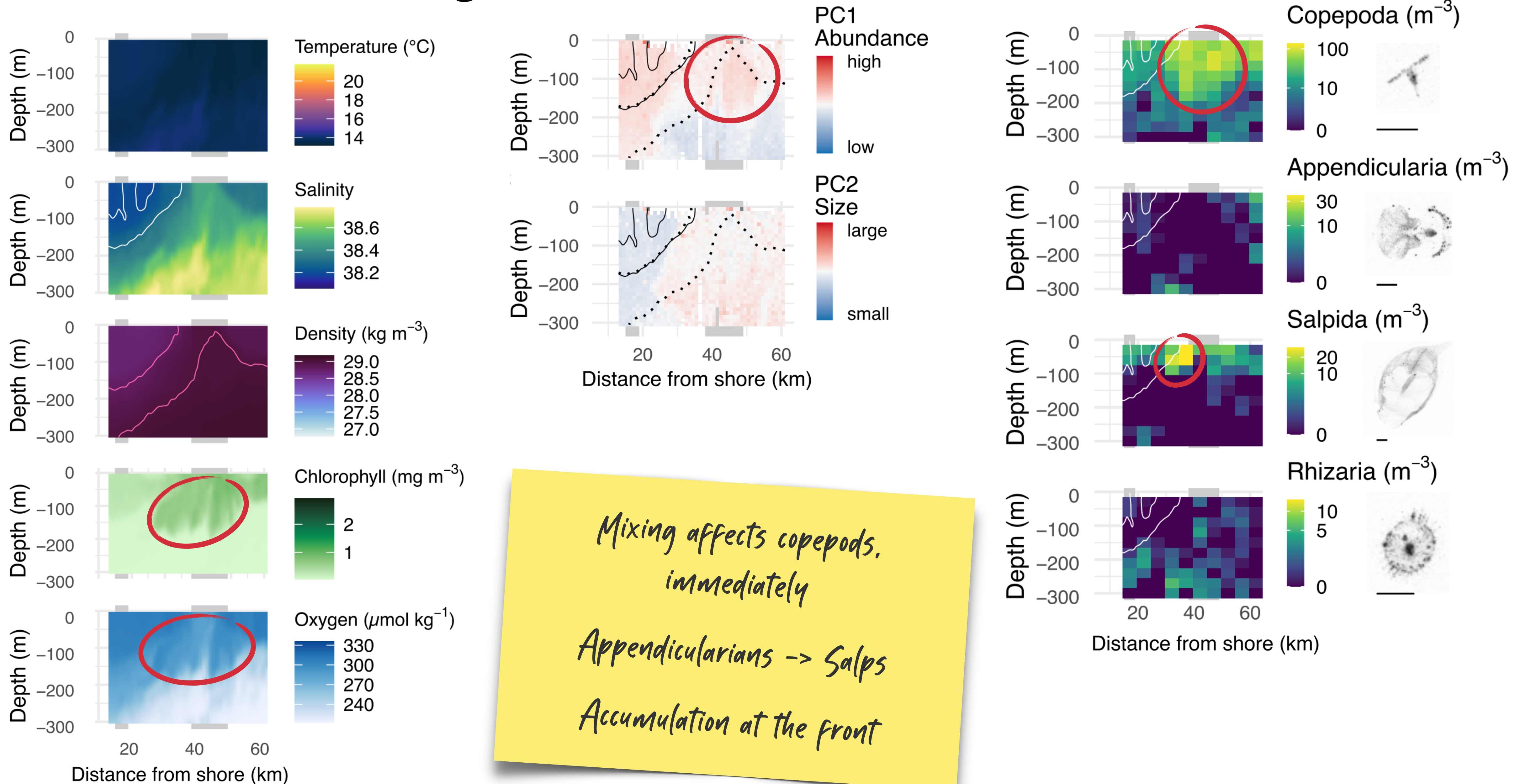
March: A wind mixing event



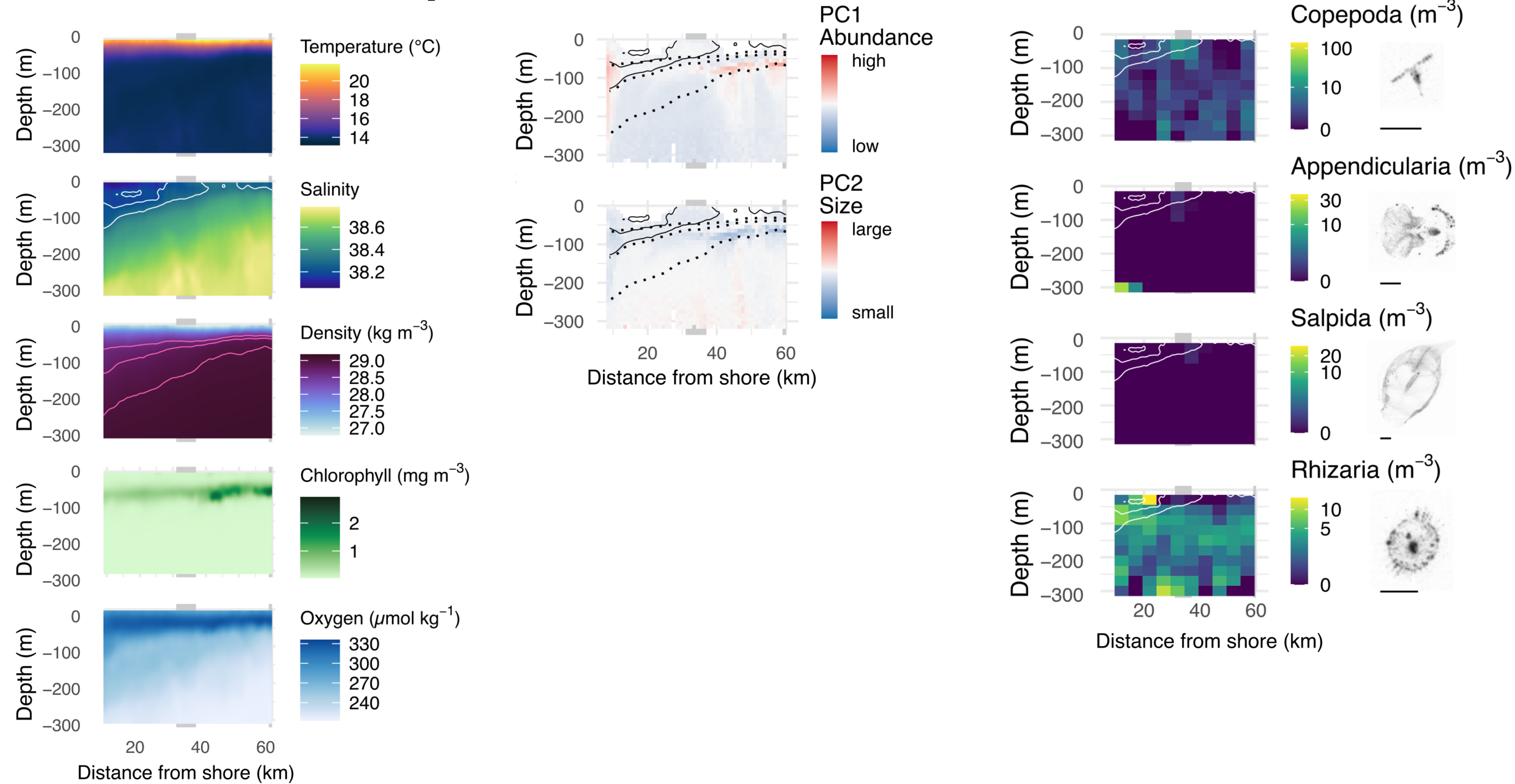
March: A wind mixing event



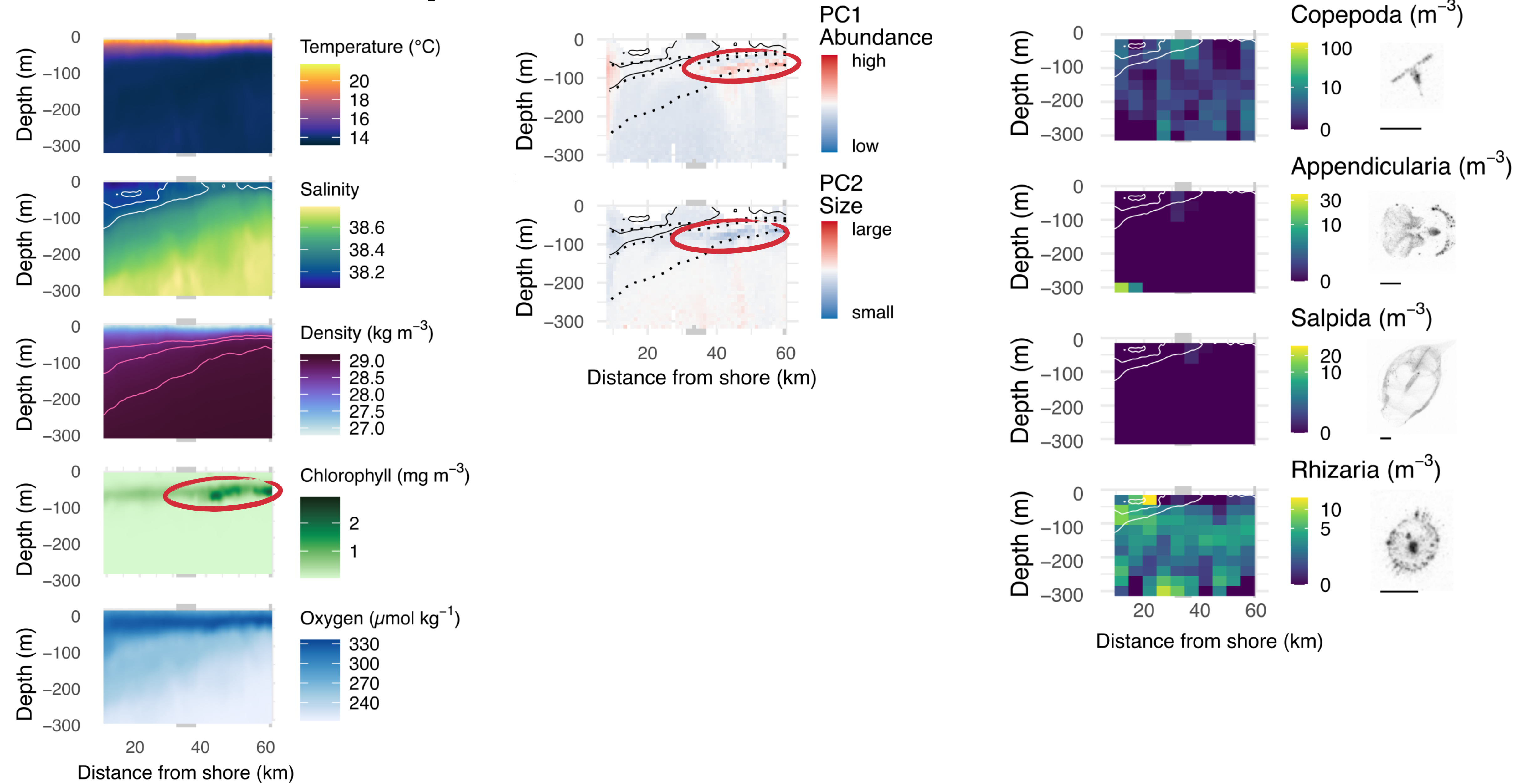
March: A wind mixing event



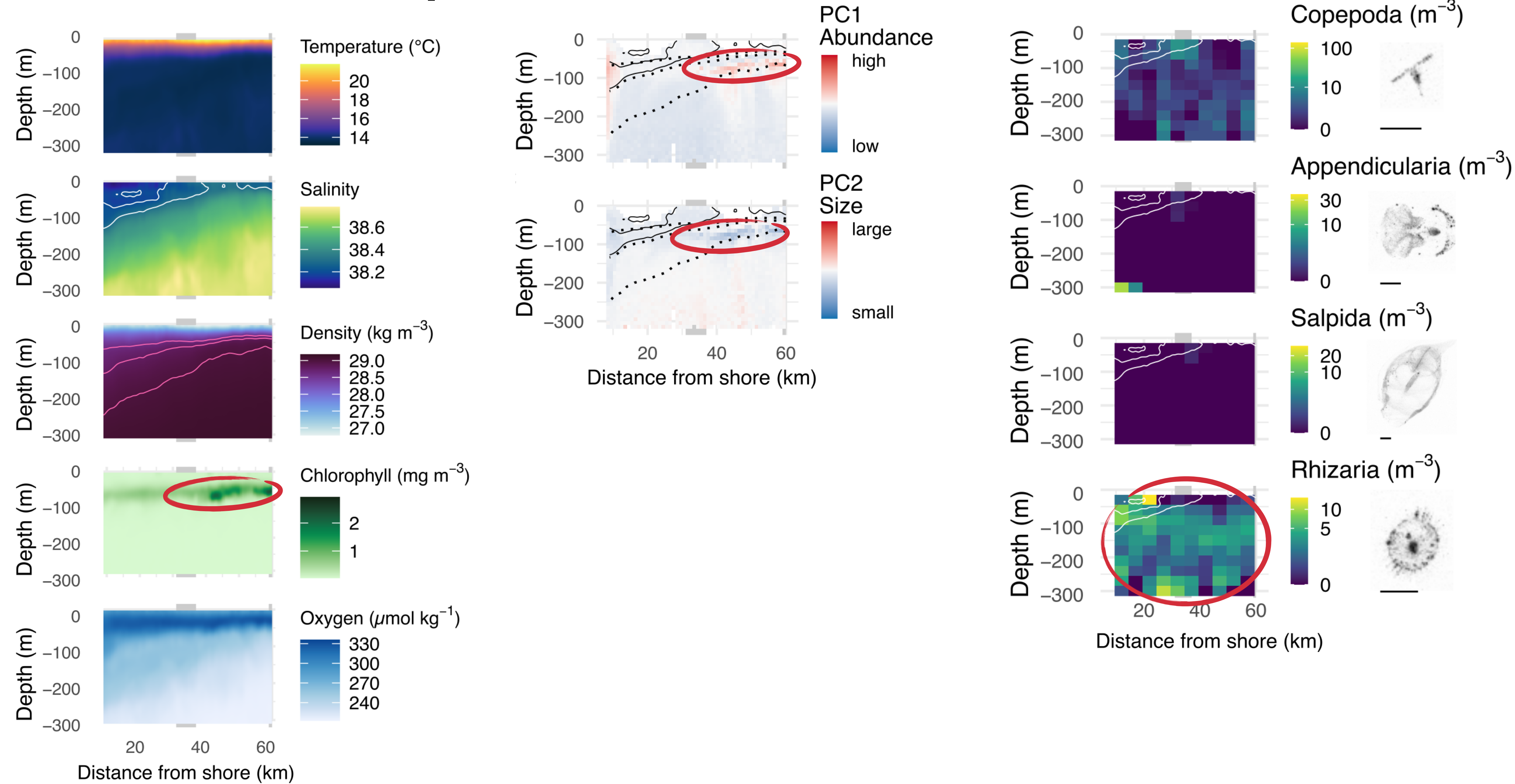
June: A “cleaned up” water mass



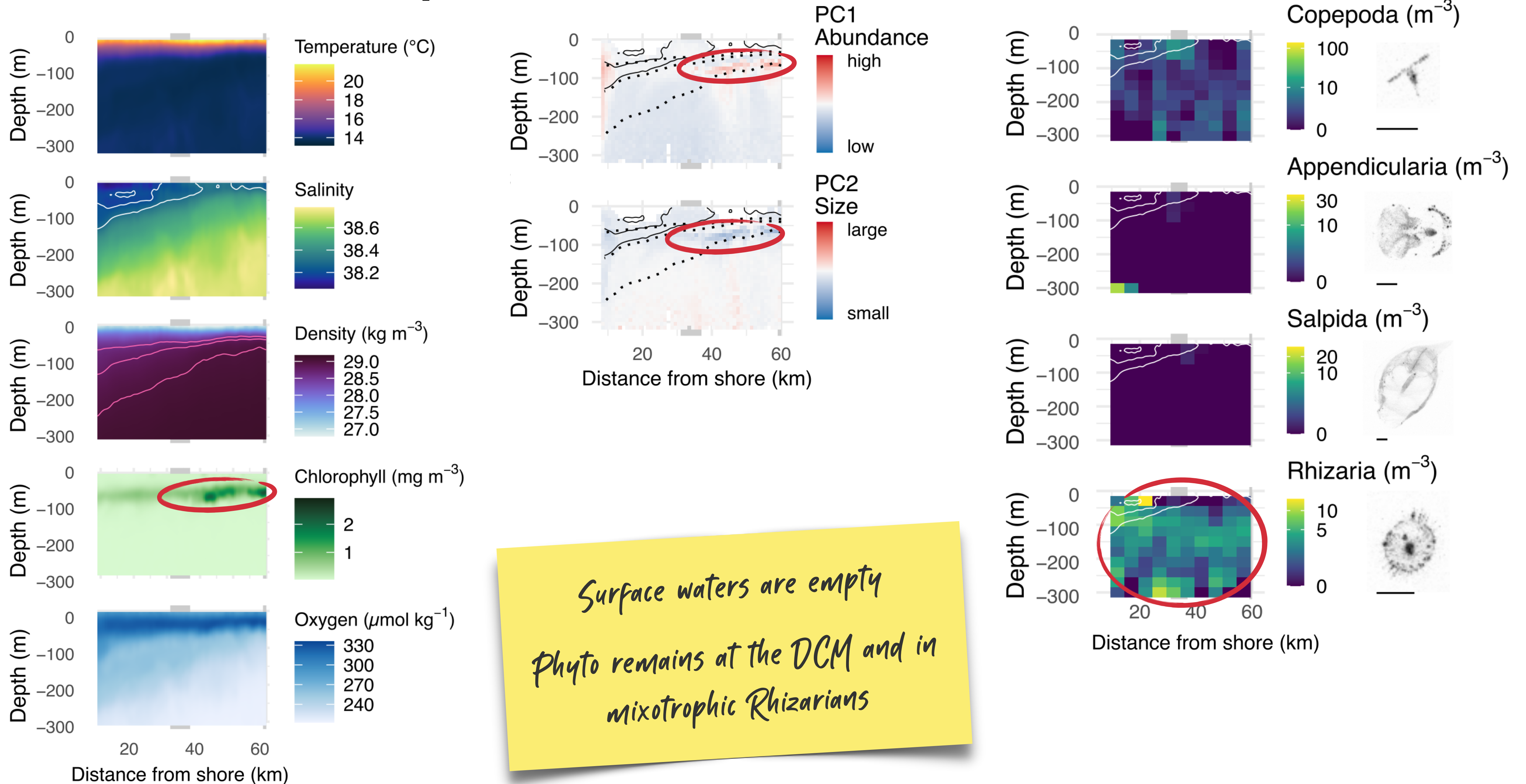
June: A “cleaned up” water mass



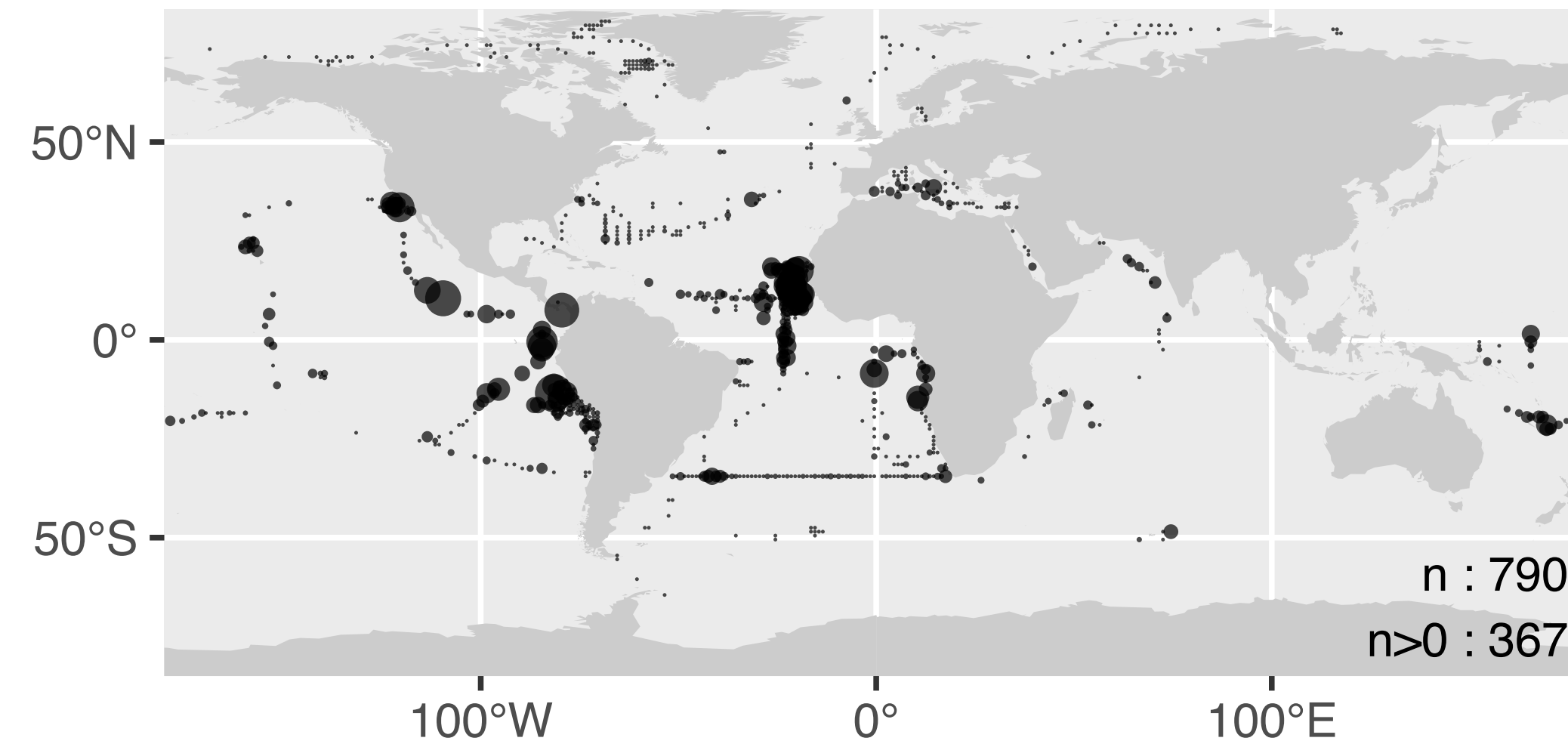
June: A “cleaned up” water mass



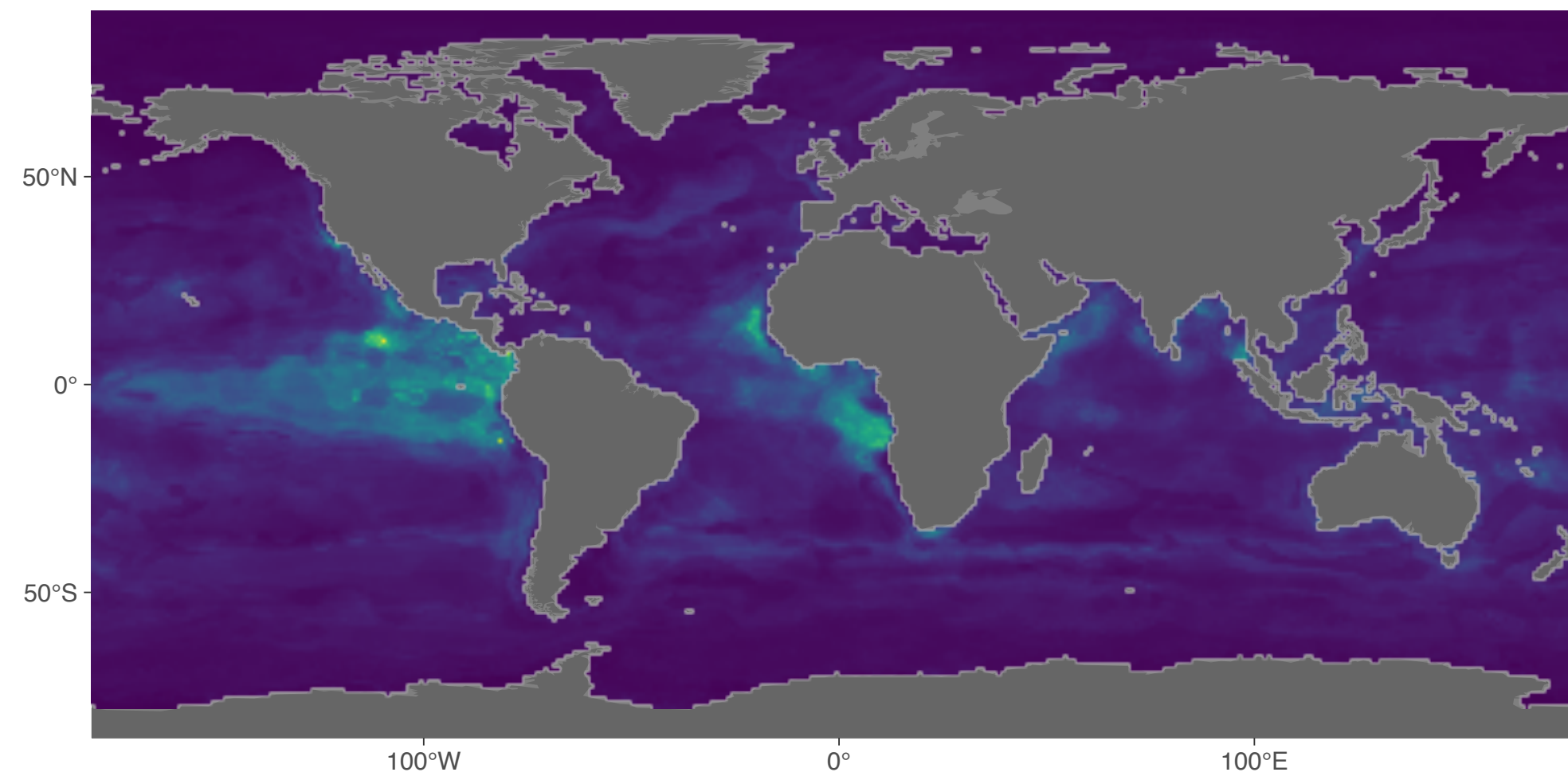
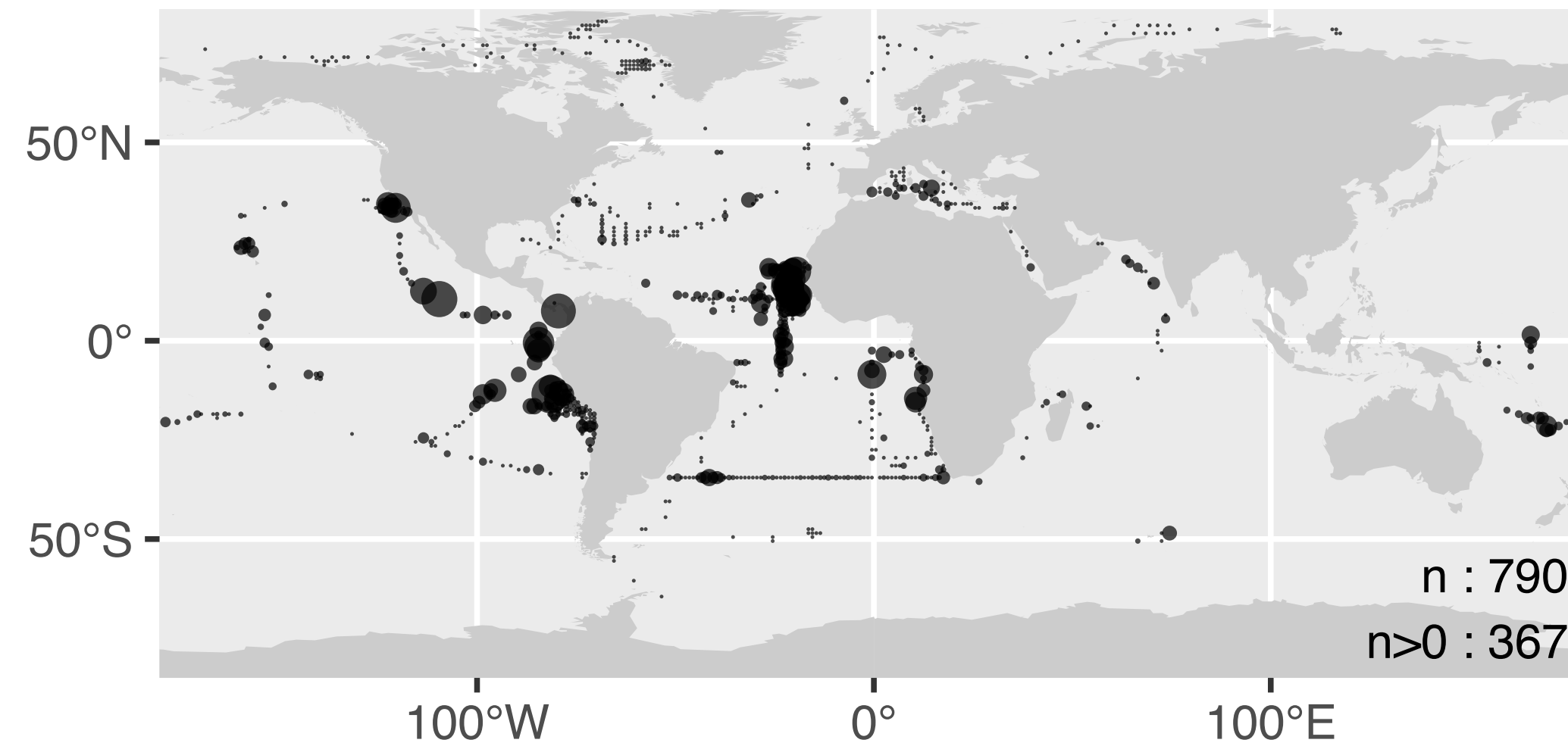
June: A “cleaned up” water mass



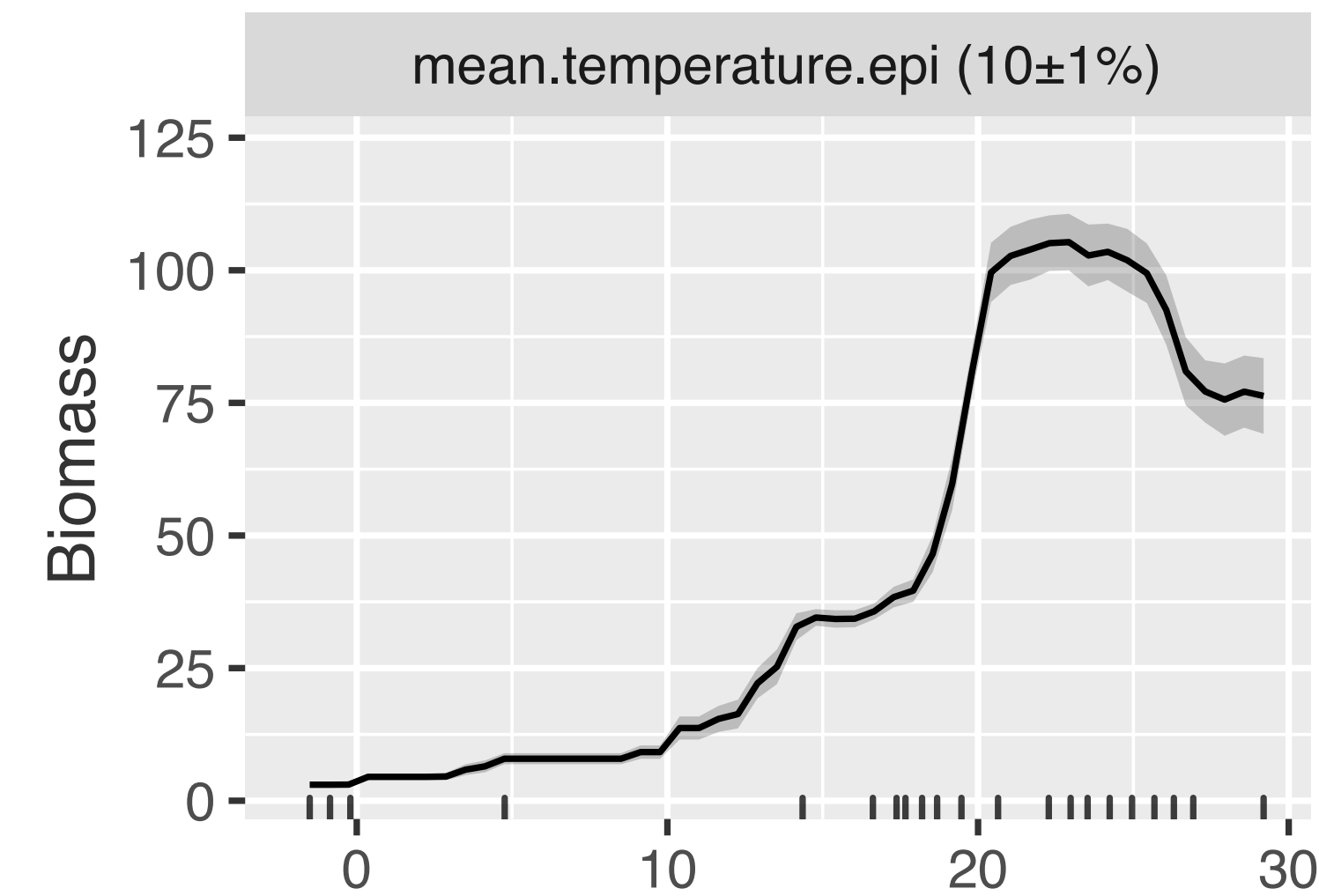
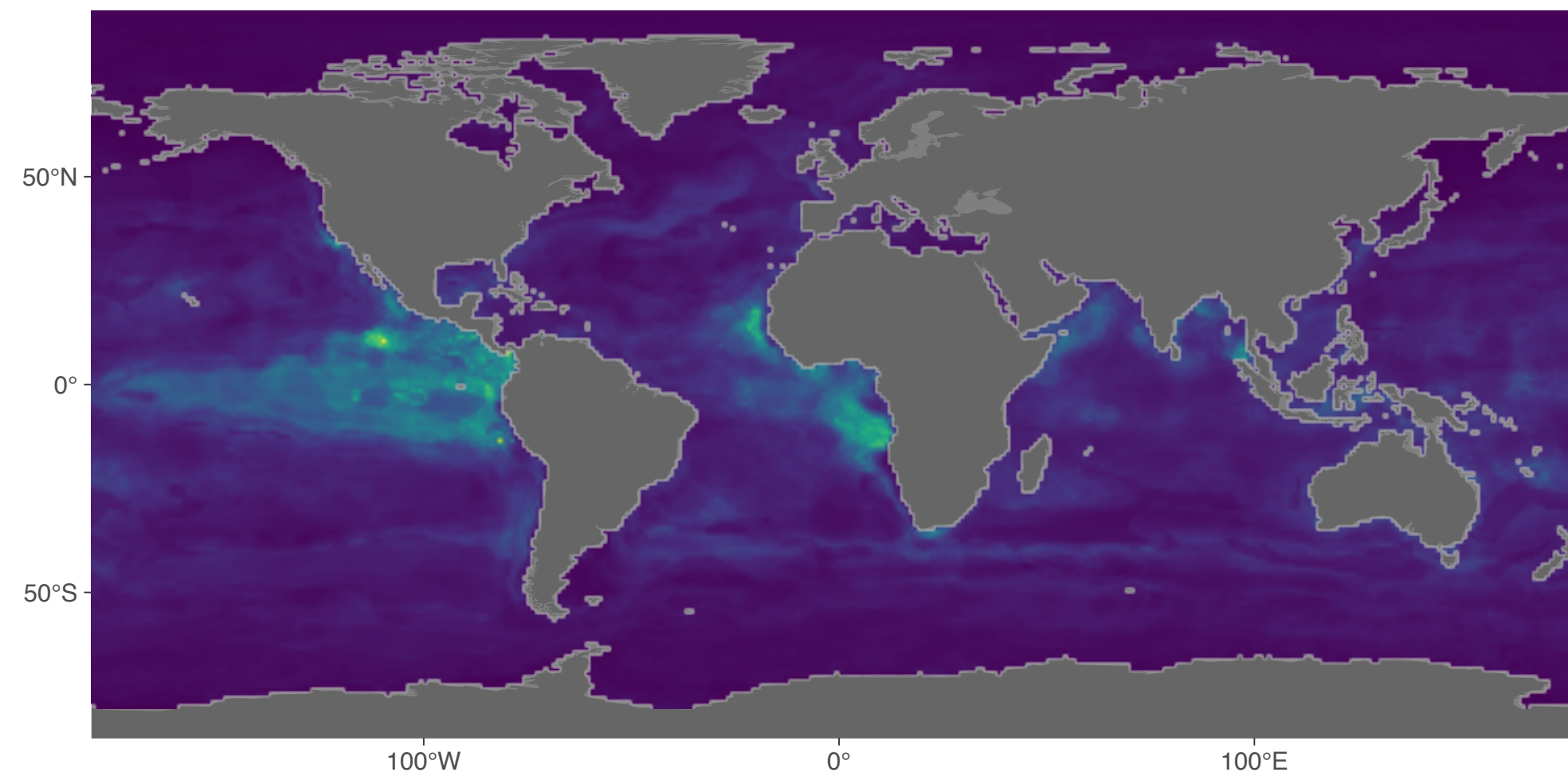
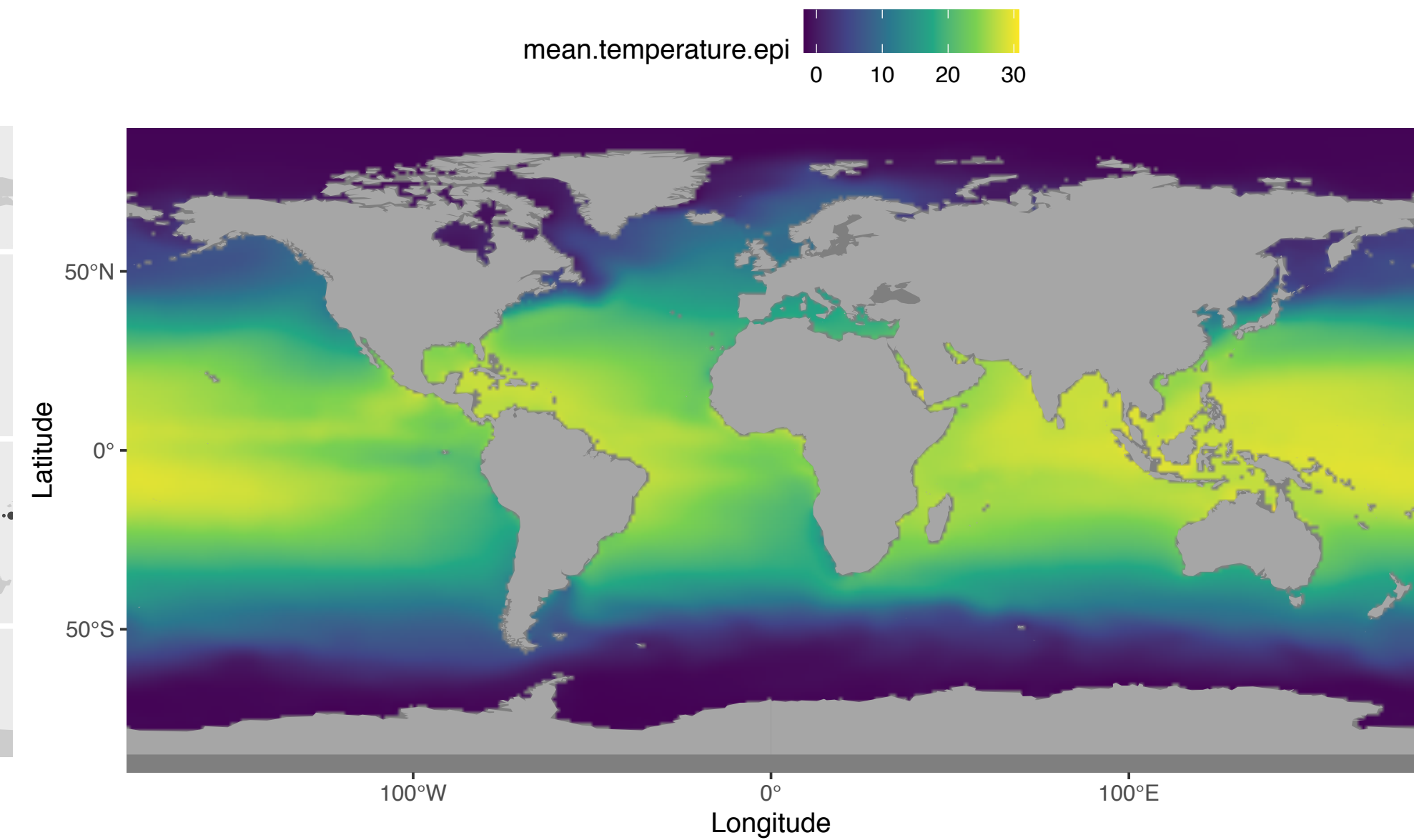
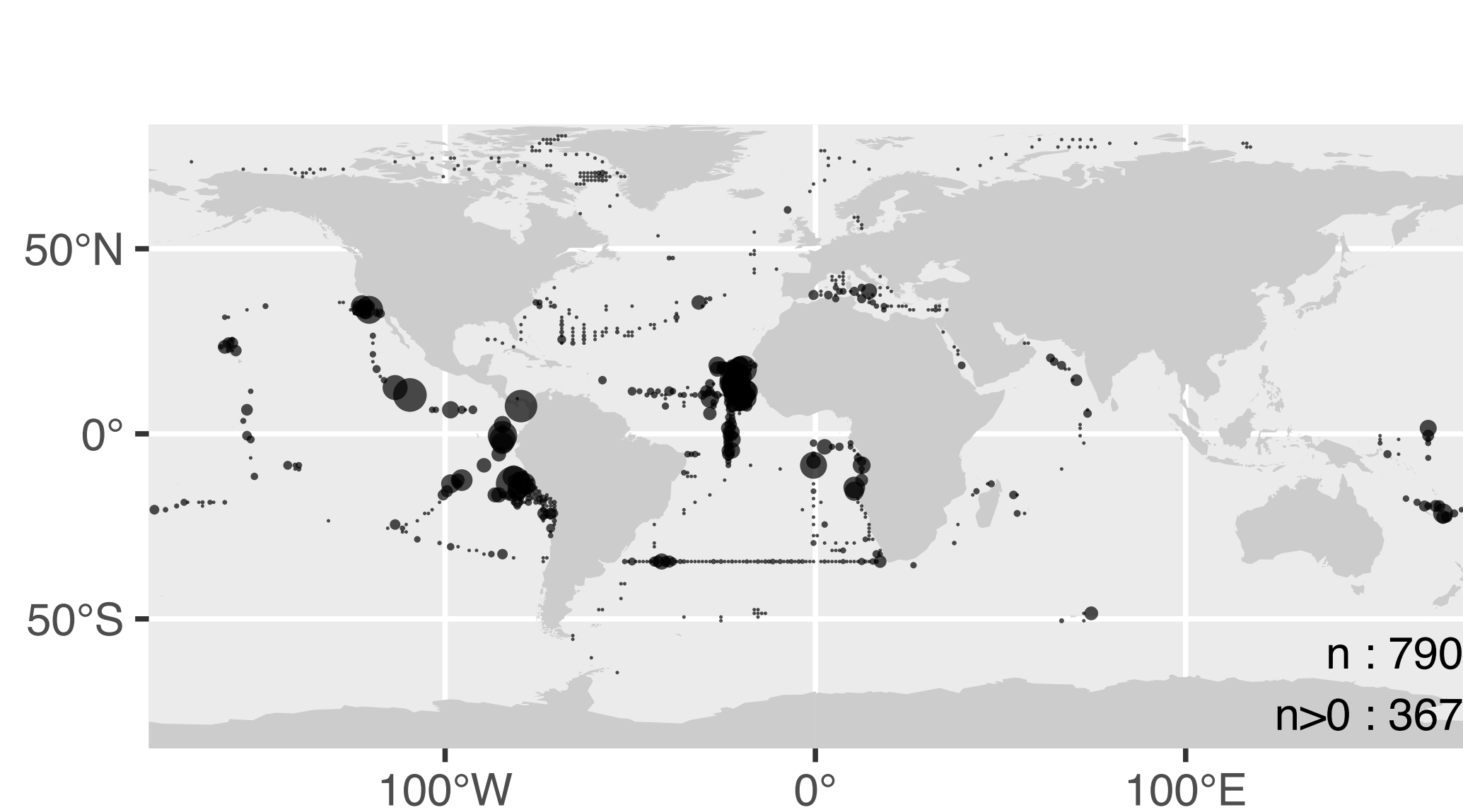
Gradient boosting to predict the basin-scale distribution of organisms



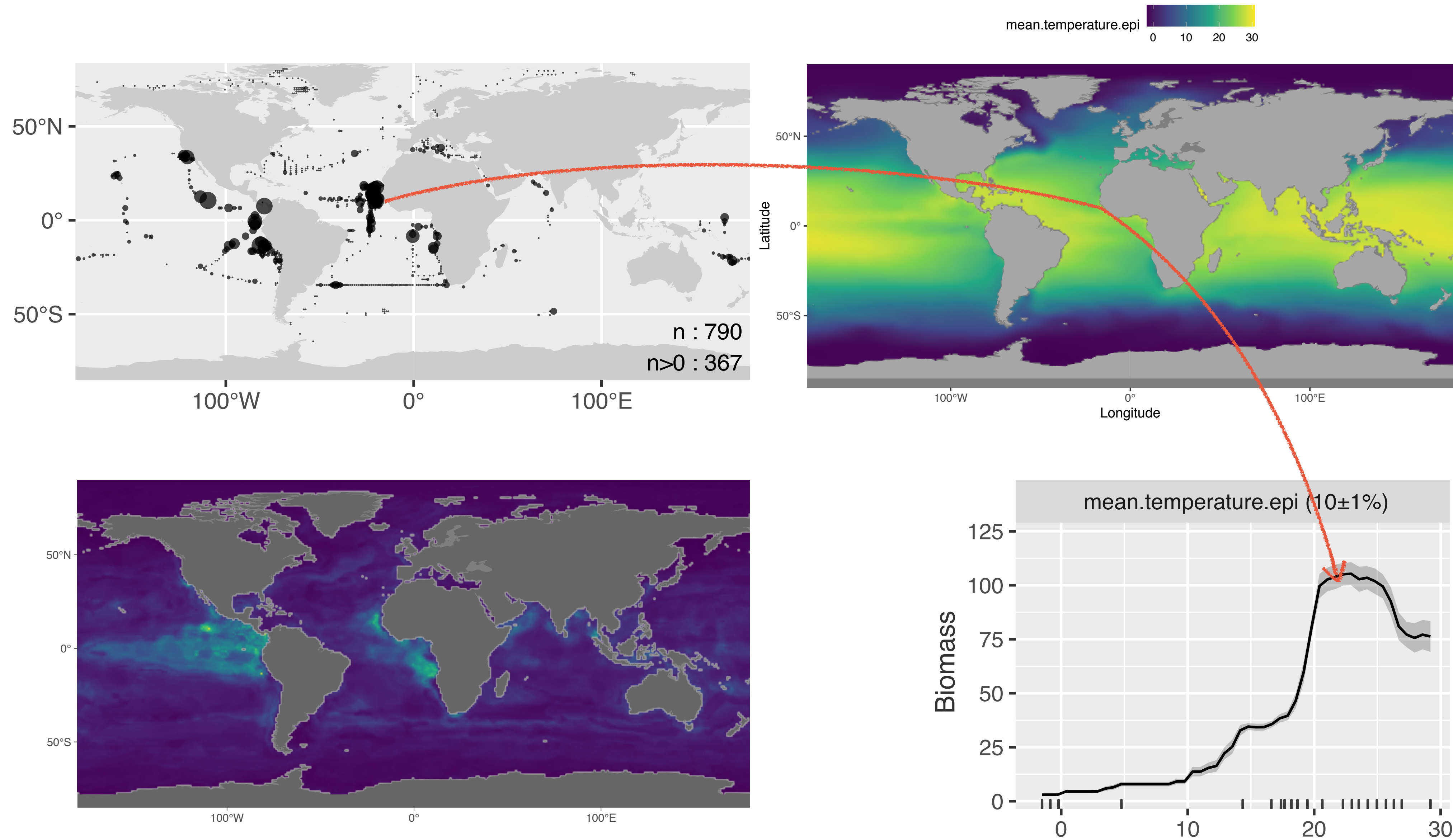
Gradient boosting to predict the basin-scale distribution of organisms



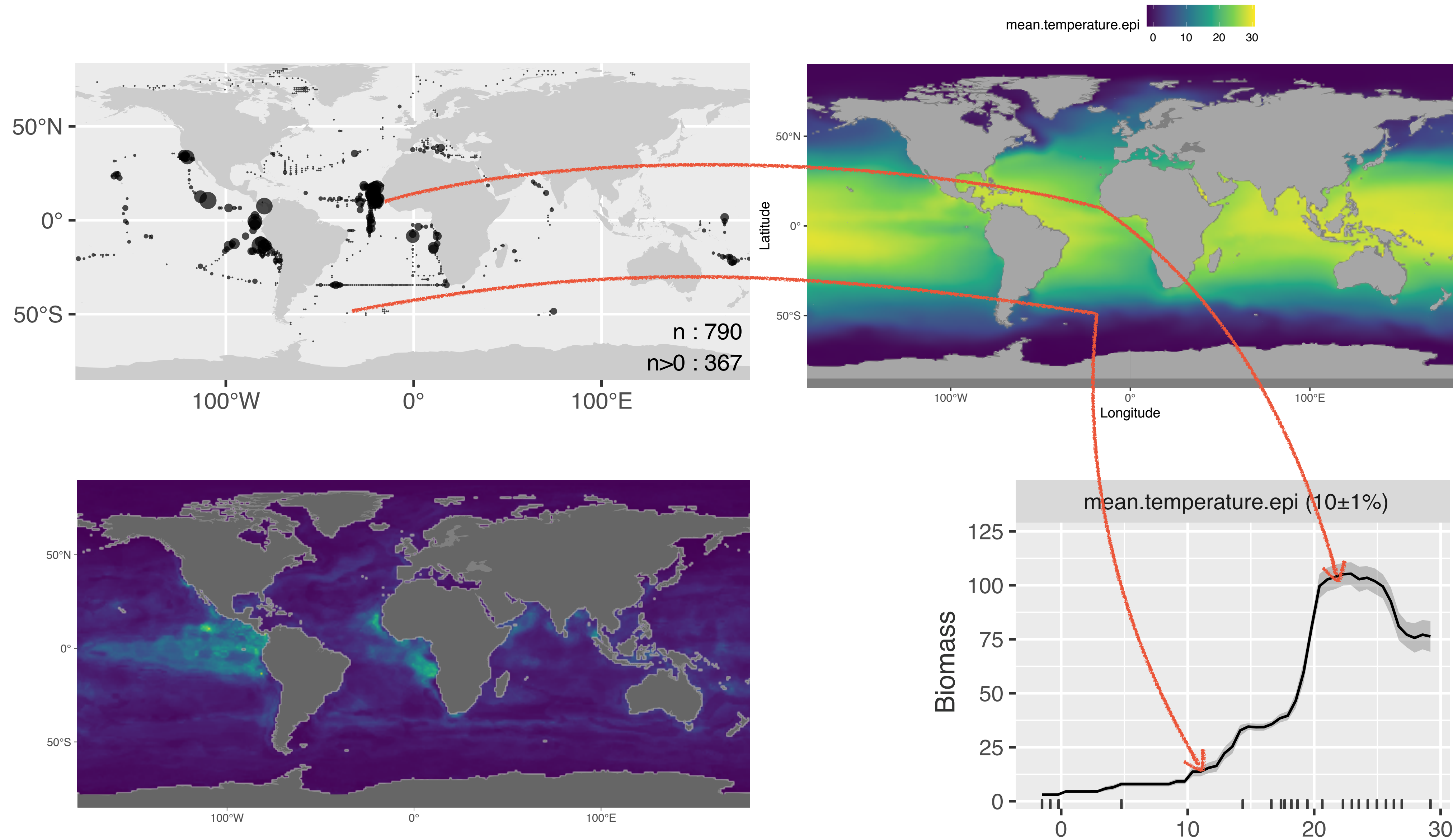
Gradient boosting to predict the basin-scale distribution of organisms



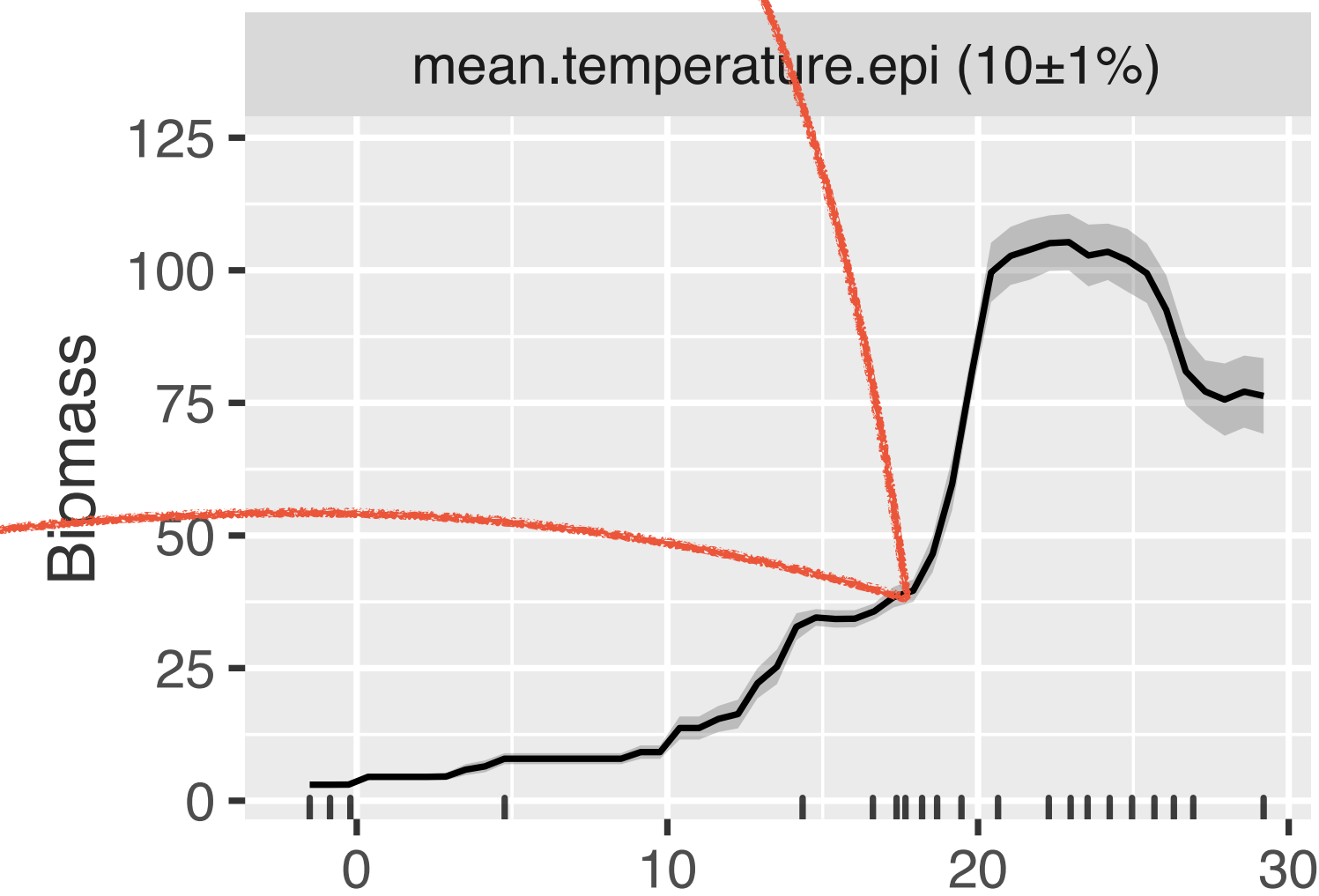
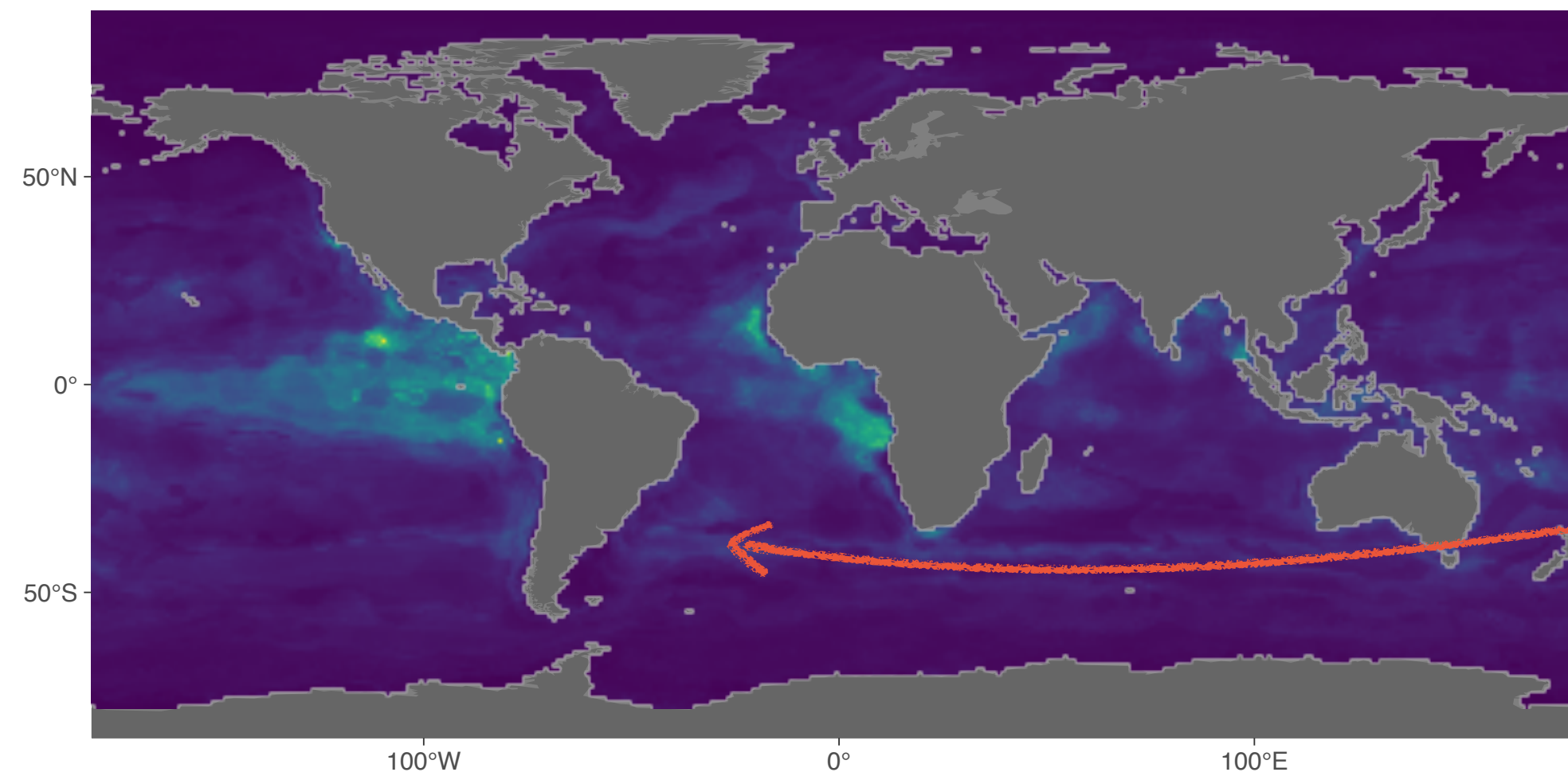
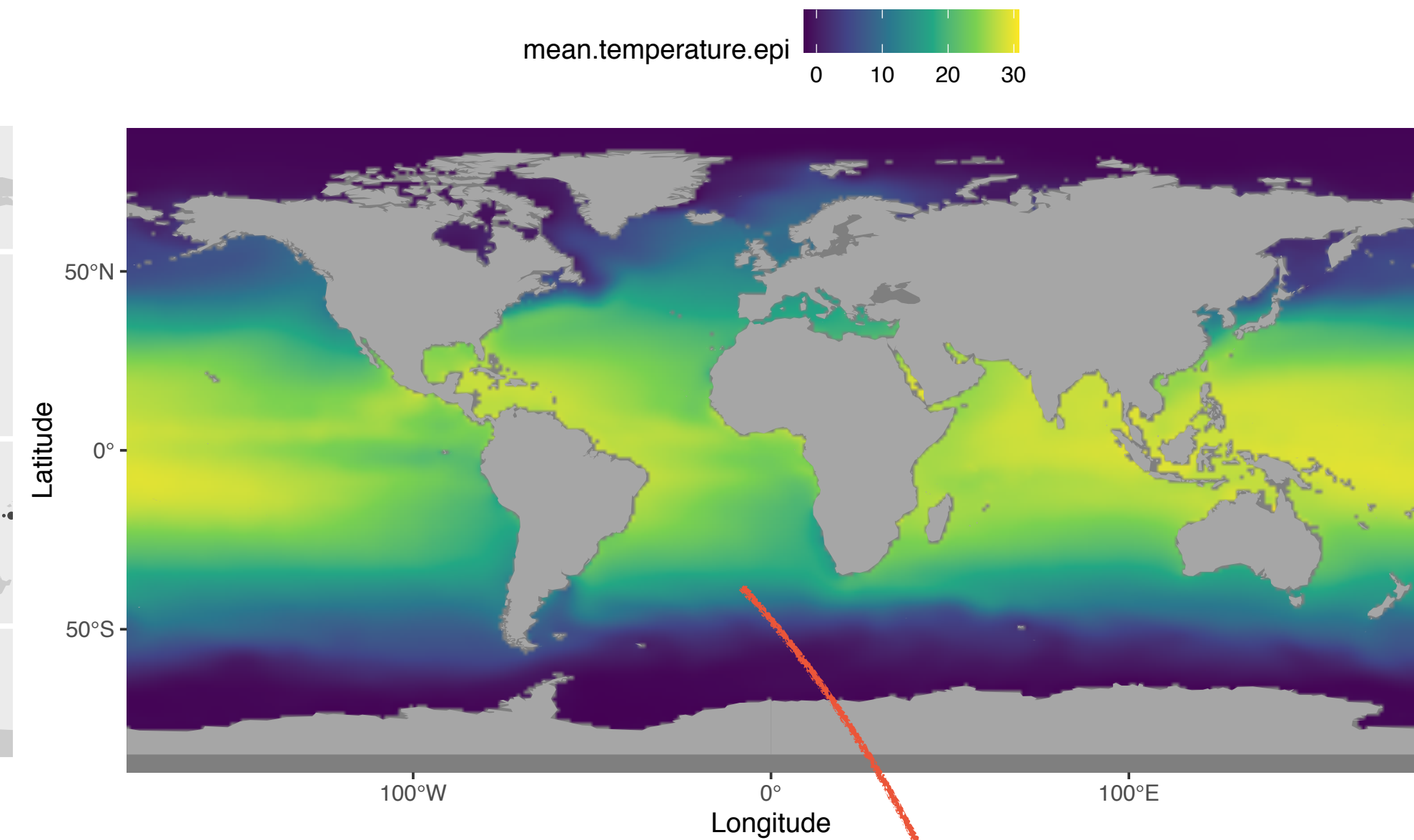
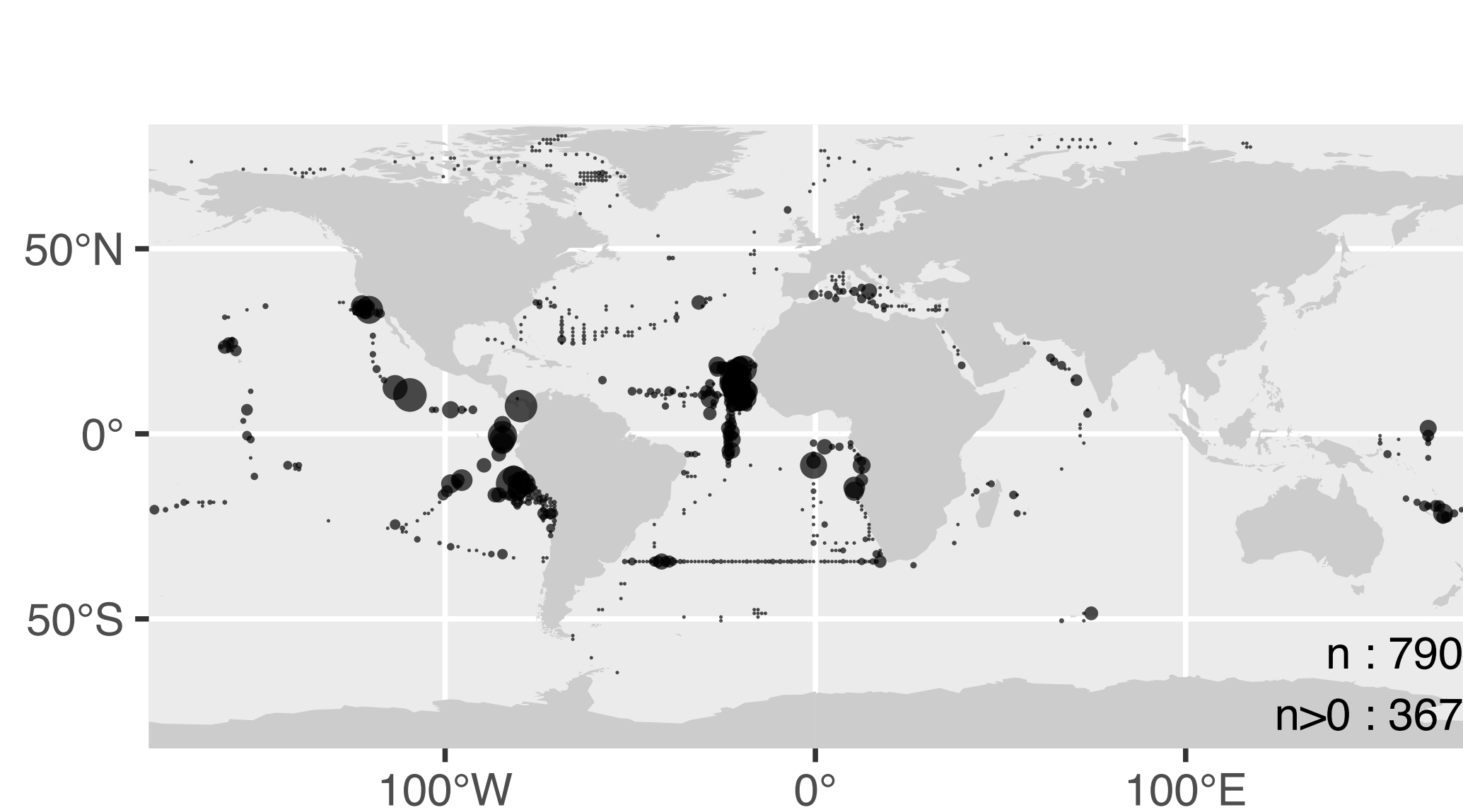
Gradient boosting to predict the basin-scale distribution of organisms



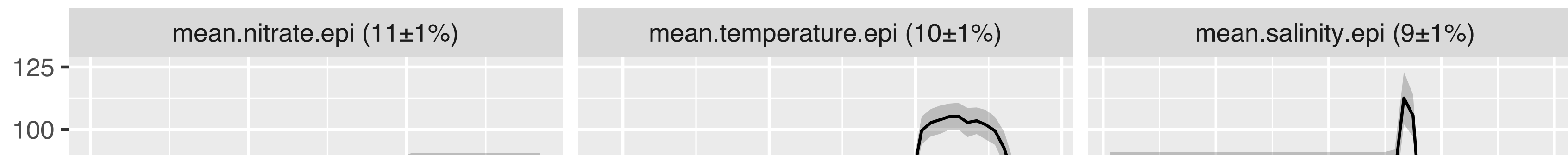
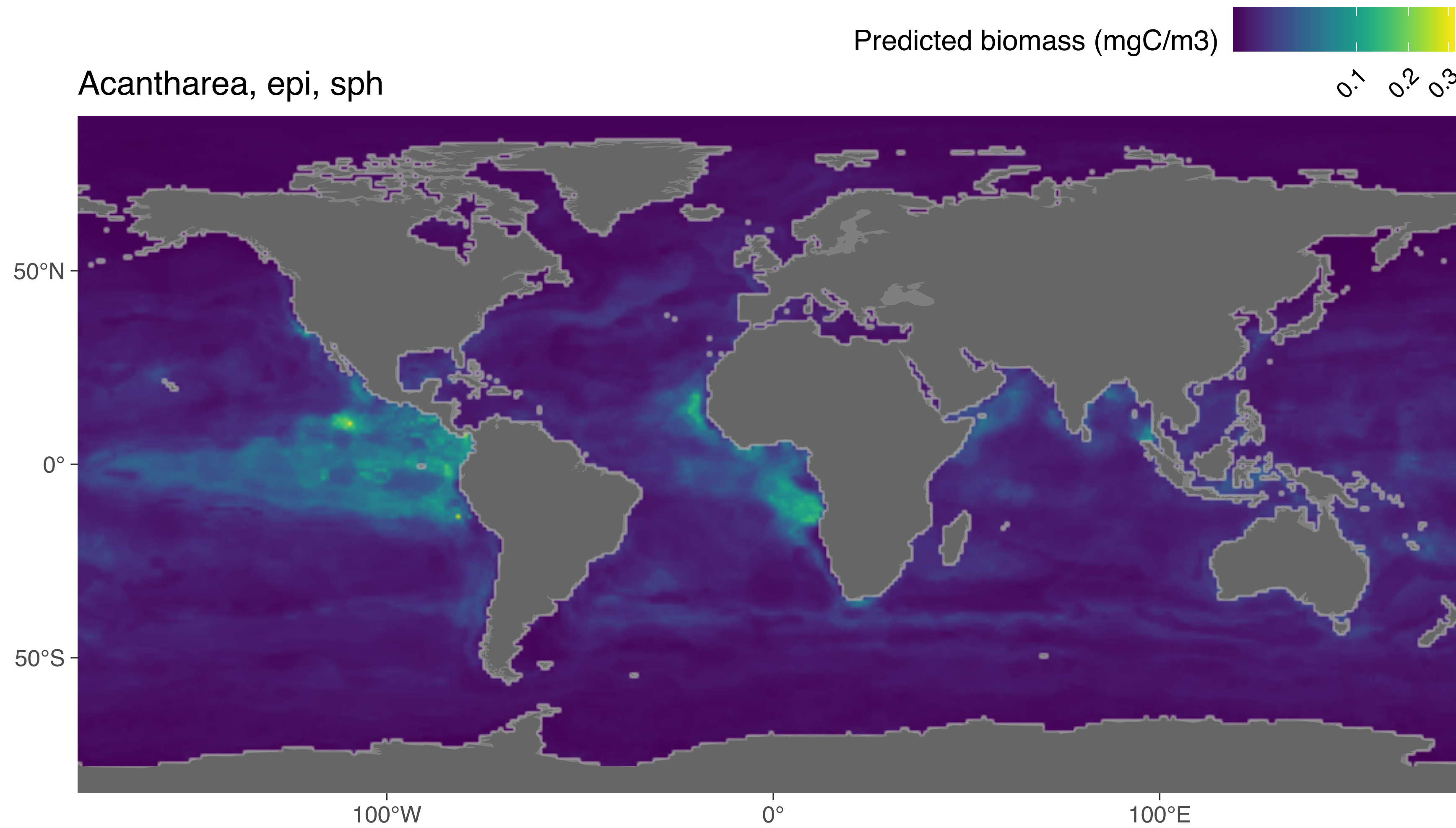
Gradient boosting to predict the basin-scale distribution of organisms



Gradient boosting to predict the basin-scale distribution of organisms



Gradient boosting to predict the basin-scale distribution of organisms



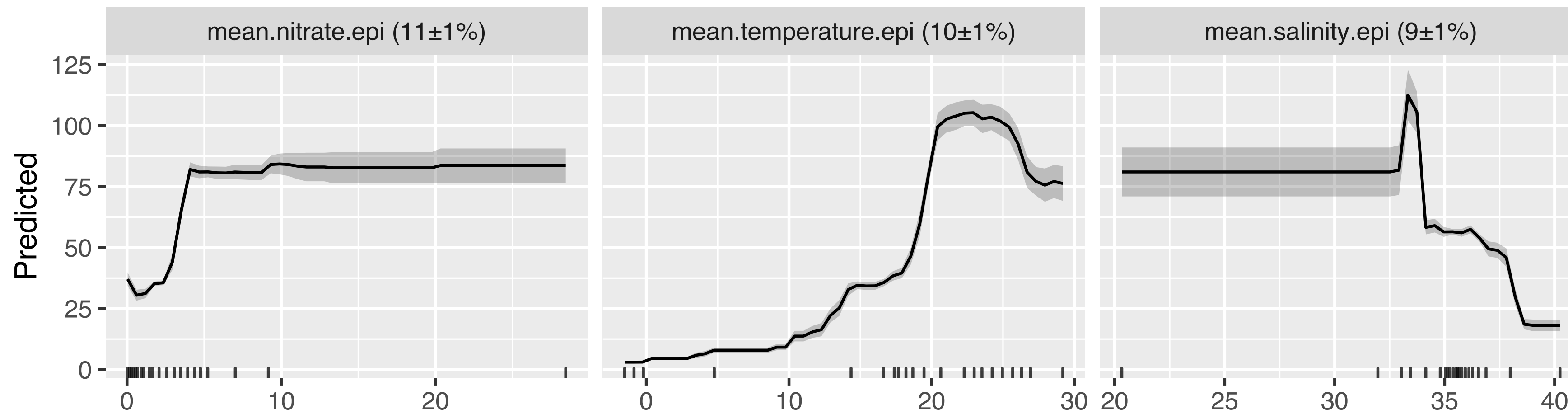
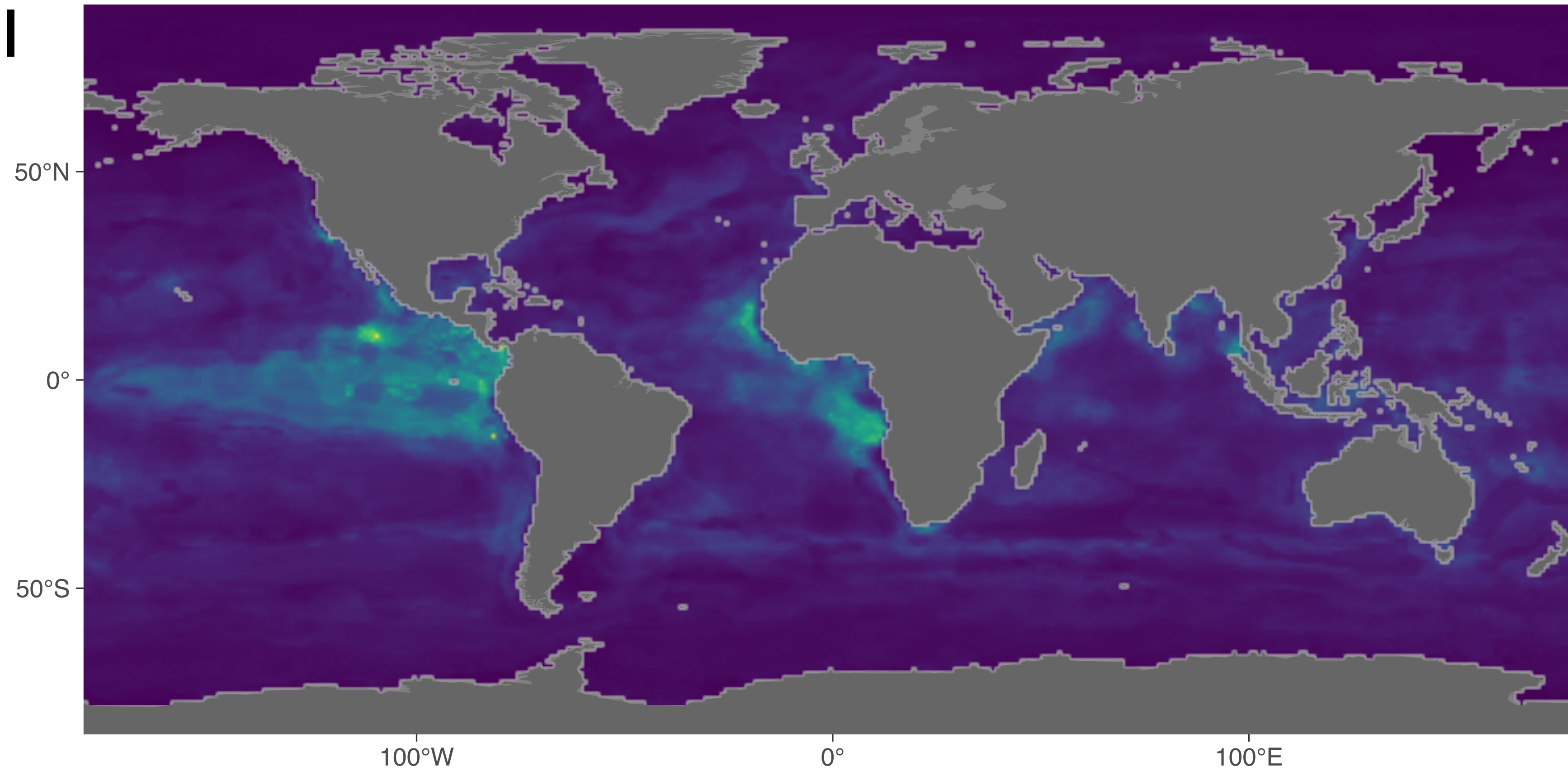
Gradient I

Acantharea, epi, sph

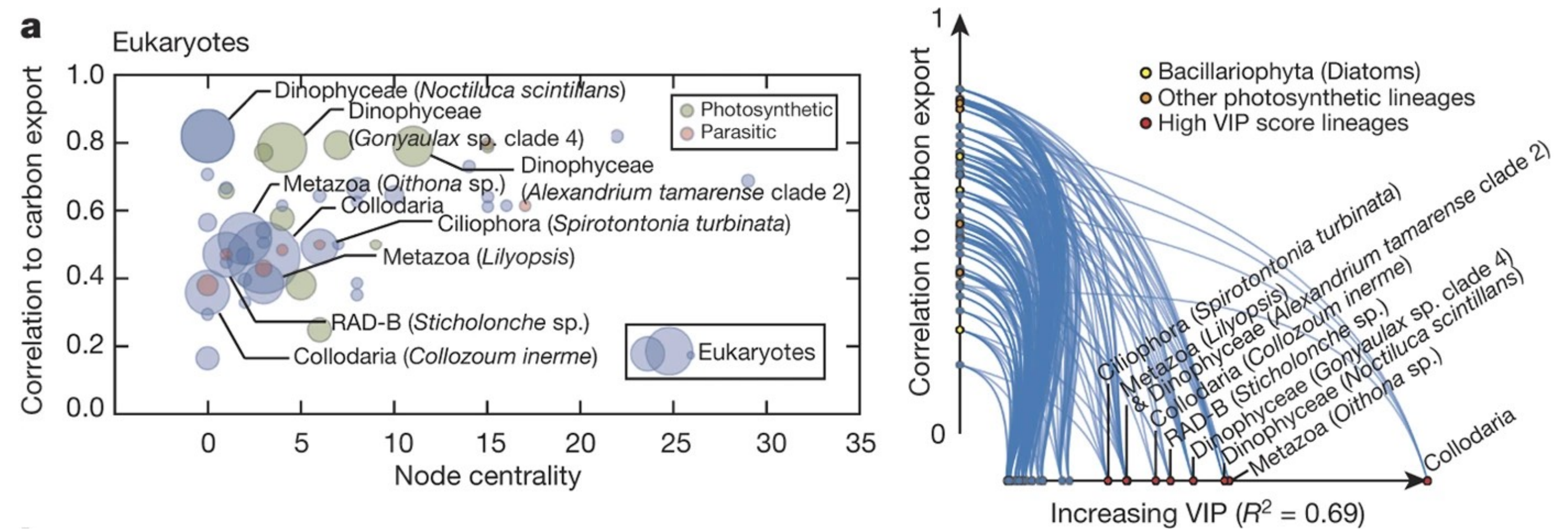
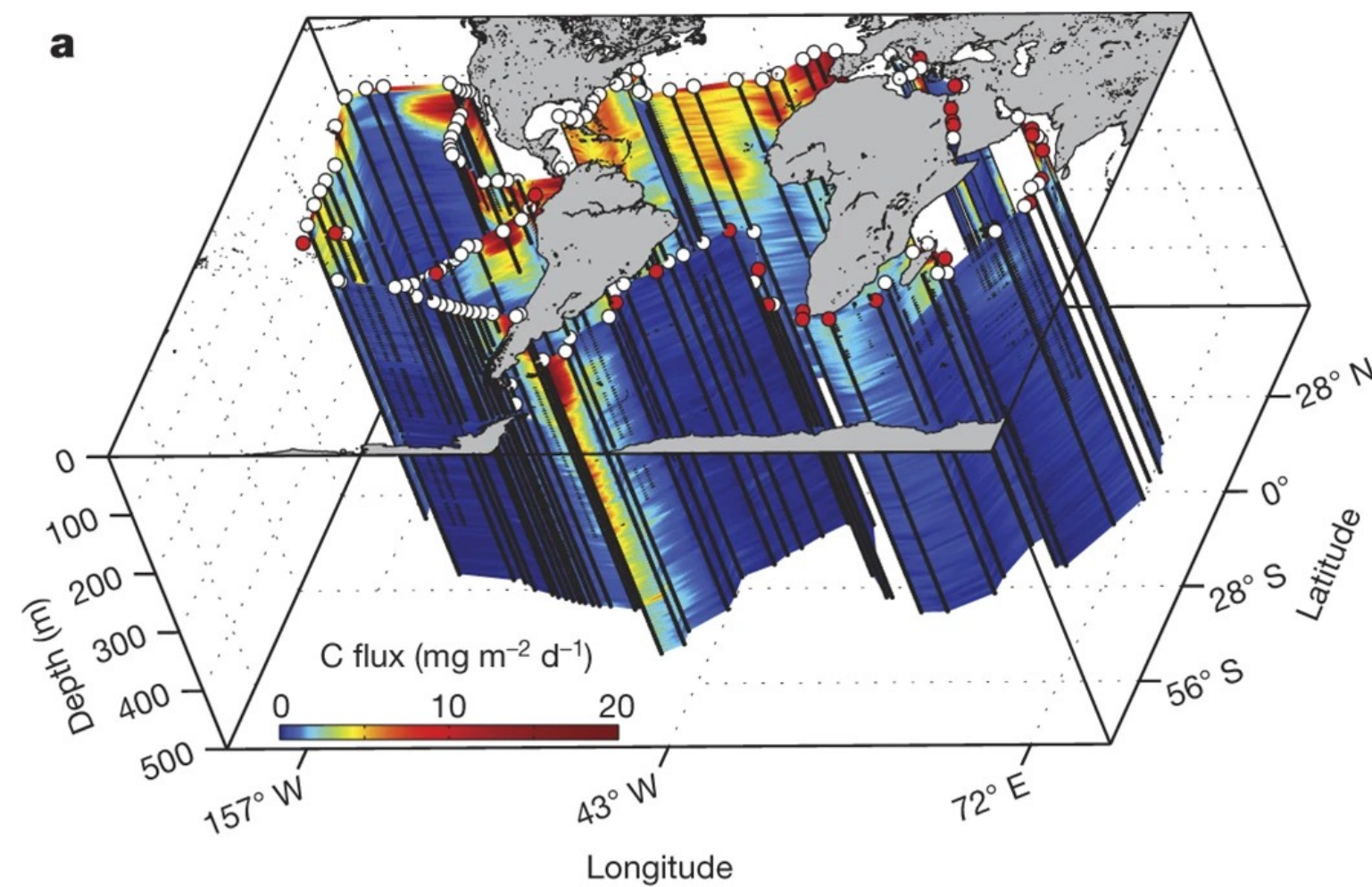
Predicted biomass (mgC/m3)

0.1 0.2 0.3

anisms



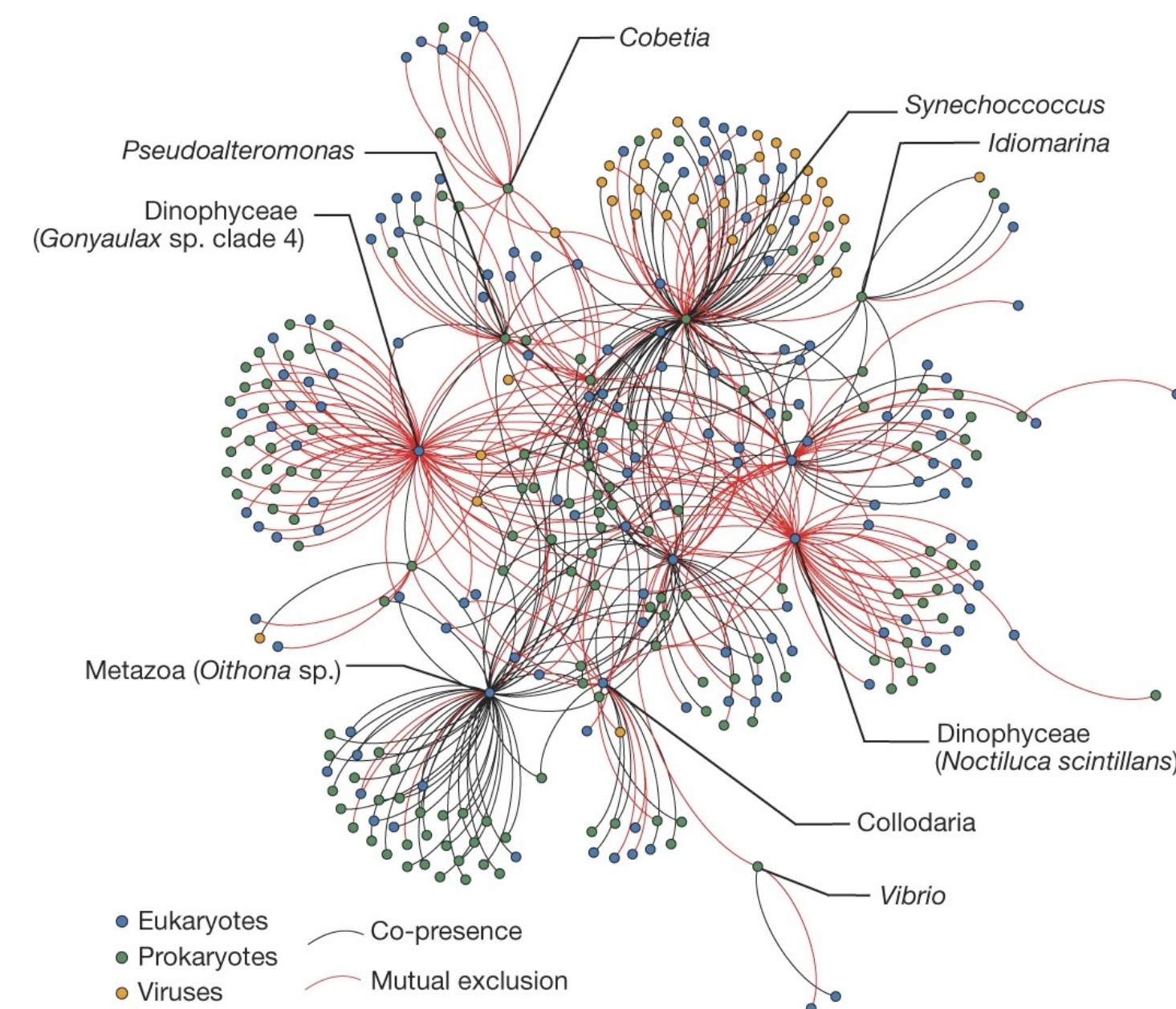
Eucaryotic plankton and carbon flux

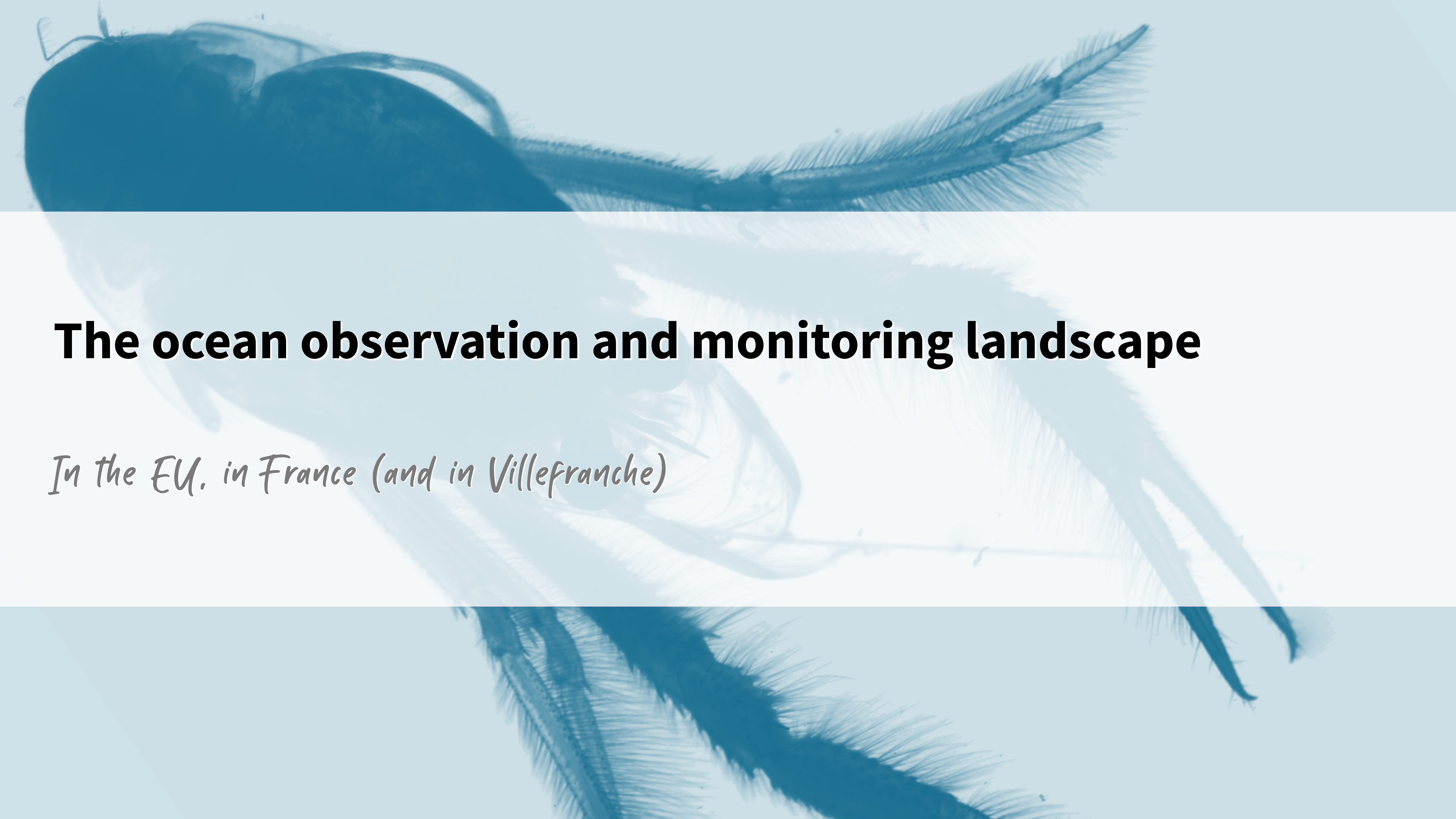


Carbon flux from *imaging*, concurrence from *genomics*

Numerous **little known** taxa **structure** the ecosystem

The **most abundant** ones are **not the most correlated** to carbon export

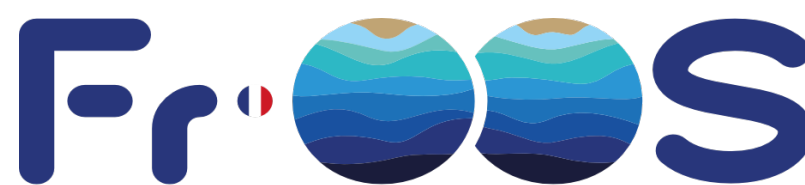
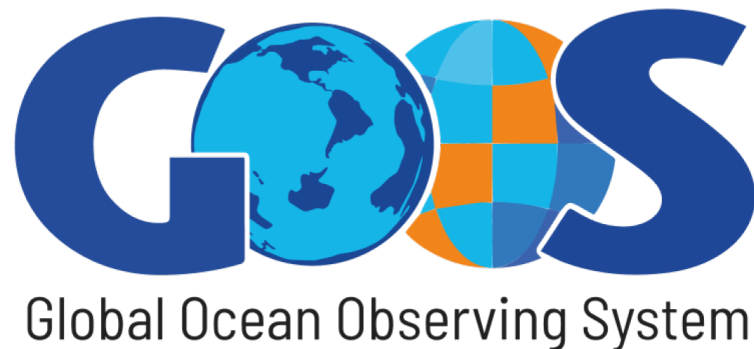
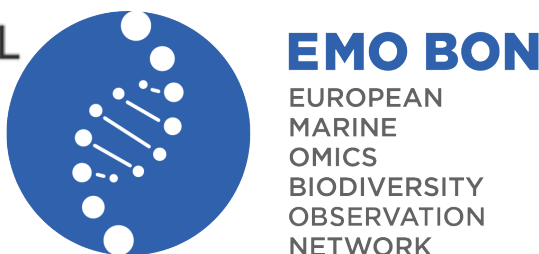


A close-up photograph of a mosquito, likely a blood-sucking species, is shown against a light blue background. The mosquito's head, thorax, and legs are visible, with its long, segmented legs extending downwards. A semi-transparent blue overlay covers the top half of the image, creating a gradient effect. The text is overlaid on this blue area.

The ocean observation and monitoring landscape

In the EU, in France (and in Villefranche)

(Some of the) Observation infrastructures



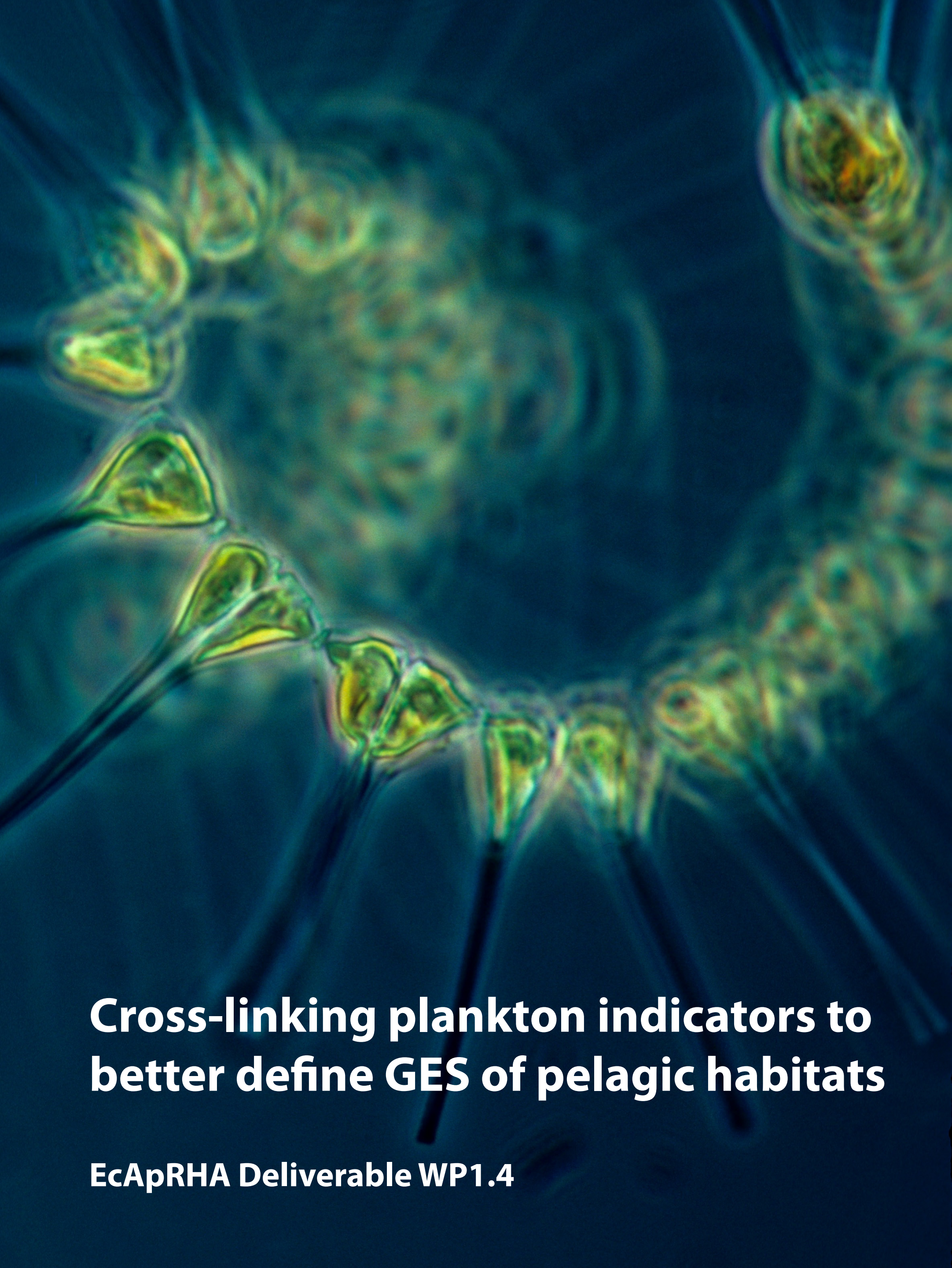
...



Observation vs monitoring (observation vs surveillance)

Definition of **indicators** for assessments under the **Marine Strategy Framework Directive** (MSFD)

Plankton is considered under the categories “**pelagic habitat**” (PH), “**food webs**” (FW), and “**non-indigenous species**” (NIS).



**Cross-linking plankton indicators to
better define GES of pelagic habitats**

EcApRHA Deliverable WP1.4

Observation vs monitoring (observation vs surveillance)

Definition of **indicators** for assessments under the **Marine Strategy Framework Directive** (MSFD)

Plankton is considered under the categories “**pelagic habitat**” (PH), “**food webs**” (FW), and “**non-indigenous species**” (NIS).

PH1/FW5: change in plankton **communities** = index based on pairs of taxa

PH2: change in plankton **biomass** = anomalies in time series

PH3: change in plankton **diversity** = richness (Menhinick), dominance (Hulburt), β -diversity

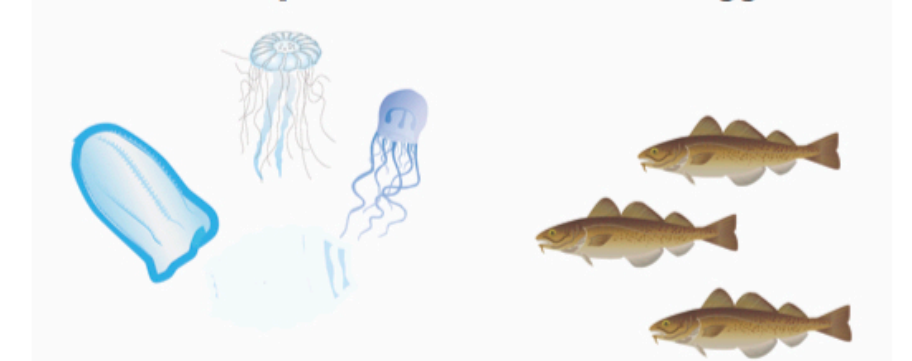
NIS3: trend in the number of recorded **non-indigenous species** = cumulative sum

Diatoms and dinoflagellates



Dominance by dinoflagellates may be an indicator of eutrophication or change in water column stability and result in less desirable food webs

Gelatinous zooplankton and fish larvae/eggs



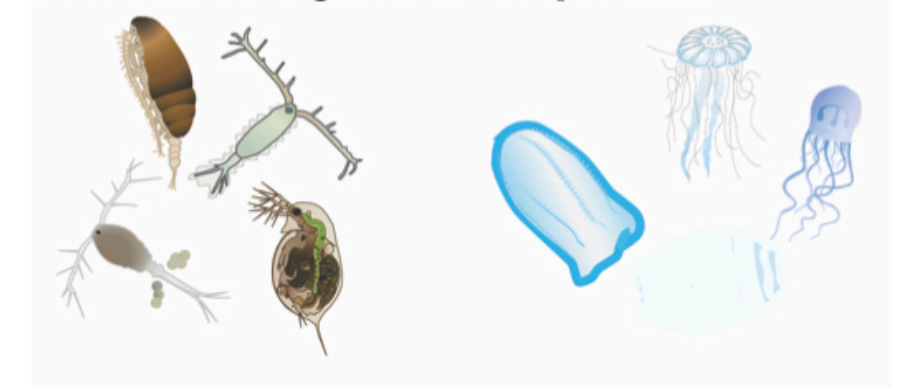
Indicator of energy flow and possible trophic pathways

Small copepods and large copepods



Size-based indicator of food web structure and energy flow

Crustaceans and gelatinous zooplankton



Indicator of energy flow and possible trophic pathways

Large phytoplankton and small phytoplankton



Size-based indicator of the efficiency of energy flow to higher trophic levels

Phytoplankton and non-carnivorous zooplankton



Indicator of energy flow and balance between primary producers and primary consumers

Pelagic diatoms and tychopelagic (benthic) diatoms



Indicator of benthic (sea floor) disturbance and frequency of resuspension events

Holoplankton and Meroplankton



Indicator of strength of benthic-pelagic coupling and reproductive output of benthic versus pelagic fauna

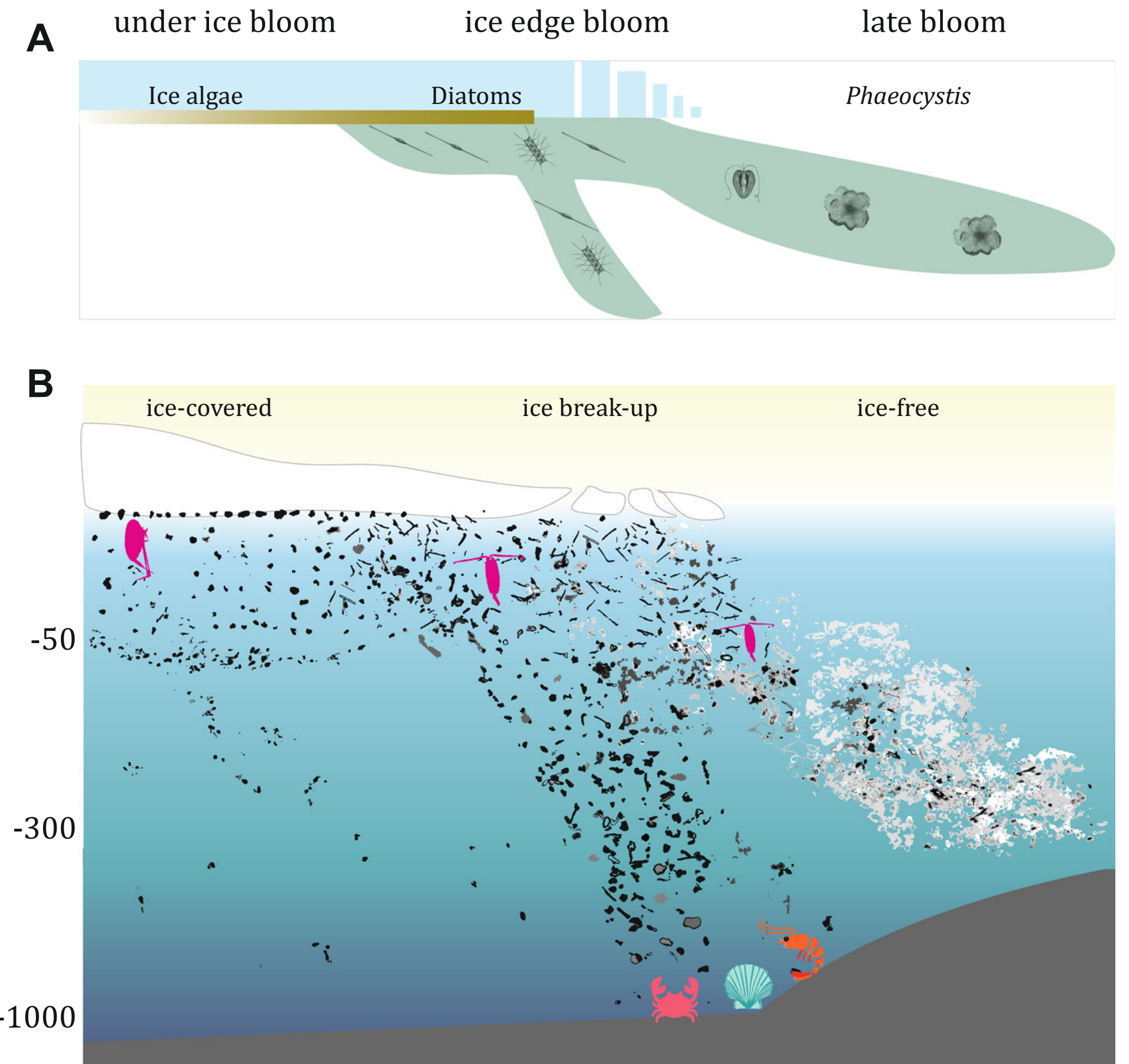
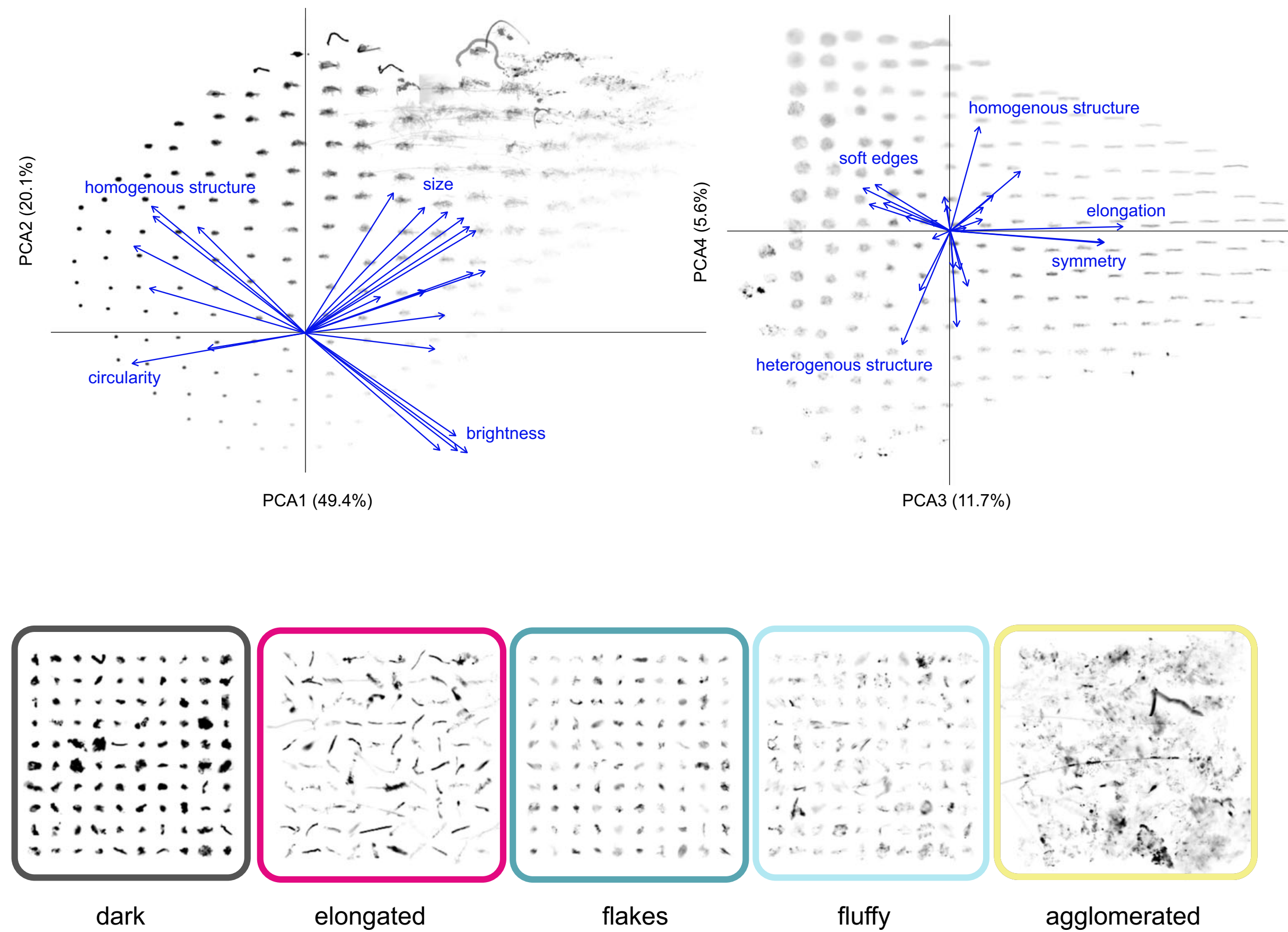
Ongoing zooplankton series in Villefranche

Station	Size	Site(s)	Start	Depth	Frequency	Identification
Vlfr	200µm	SOMLIT Point B	1995	[75, 0]m	weekly	zooscan + identification ~100 taxa
			2017	[75, 0]m	bi-monthly	microscope ~ 200 taxa (and stages)
			2023	[75, 0]m	bi-monthly	metabarcoding
	330µm	DYFAMED	2018	[1/200, 0]m	monthly	zooscan + identification ~100 taxa
		MOOSE-GE	2015	[200, 0]m	yearly	zooscan + identification ~100 taxa
		SOMLIT Point B	1966		bi-monthly	zooscan + identification ~100 taxa
	700µm	SOMLIT Point B	1995		weekly	zooscan + identification ~100 taxa

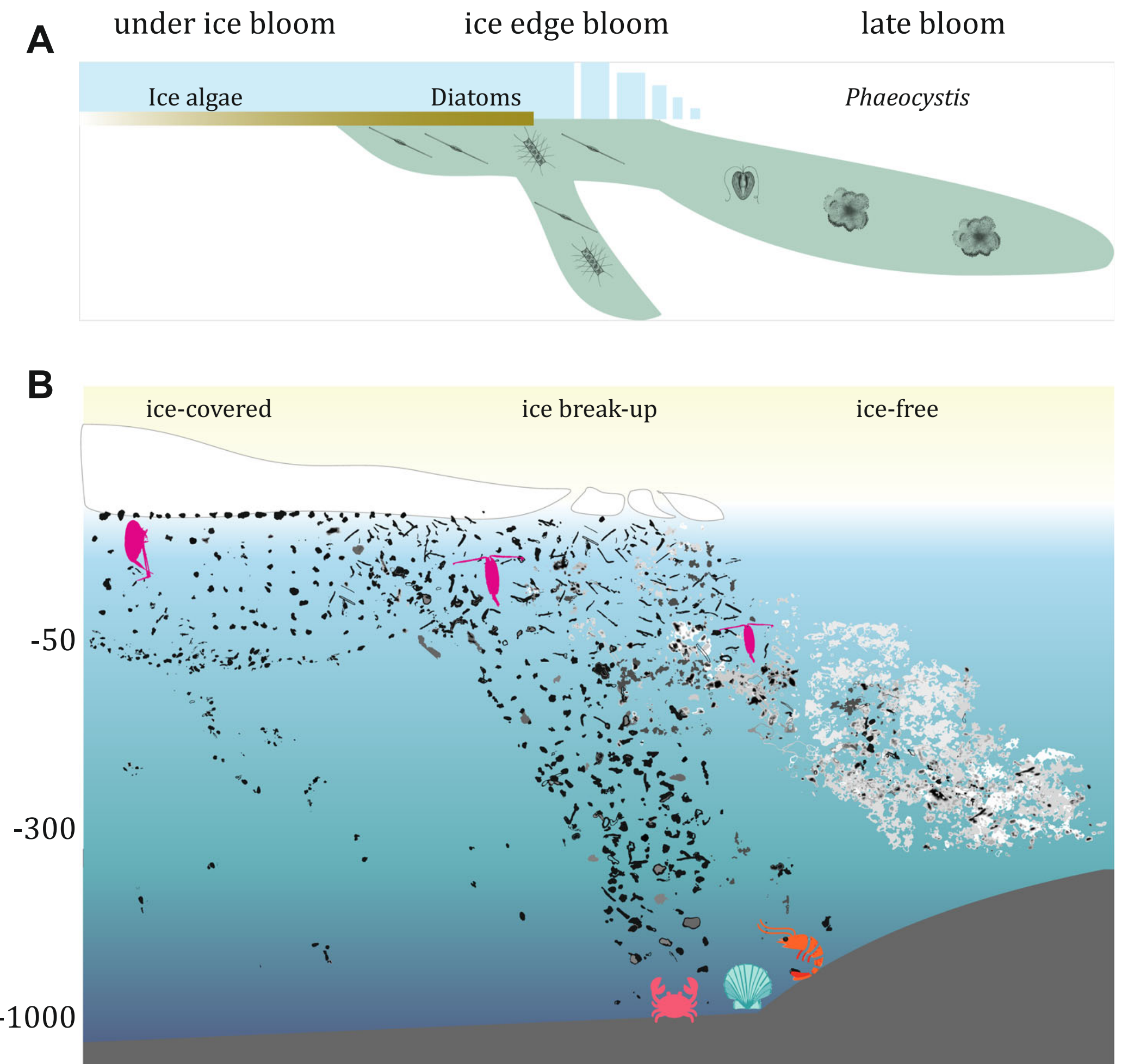
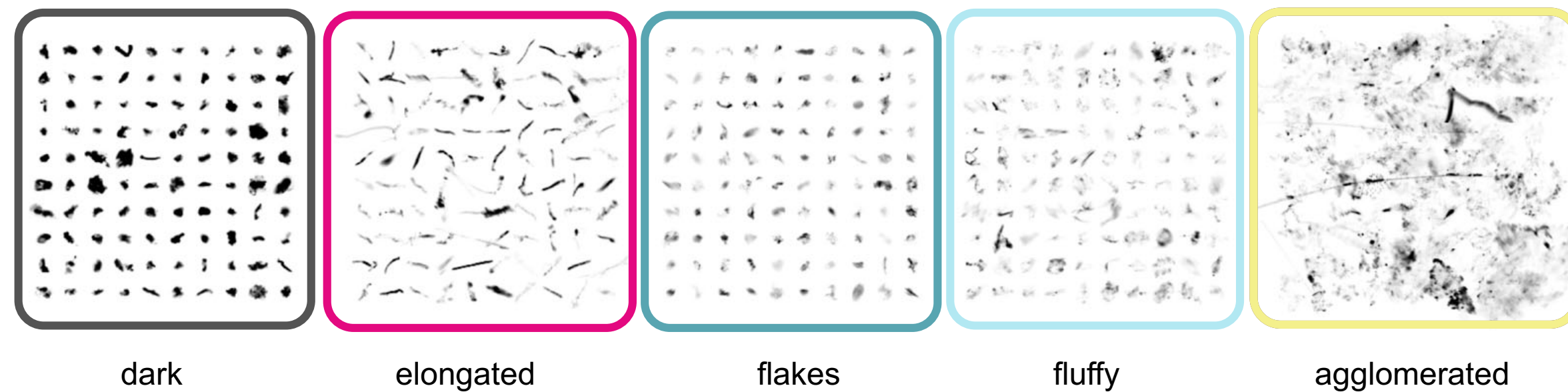
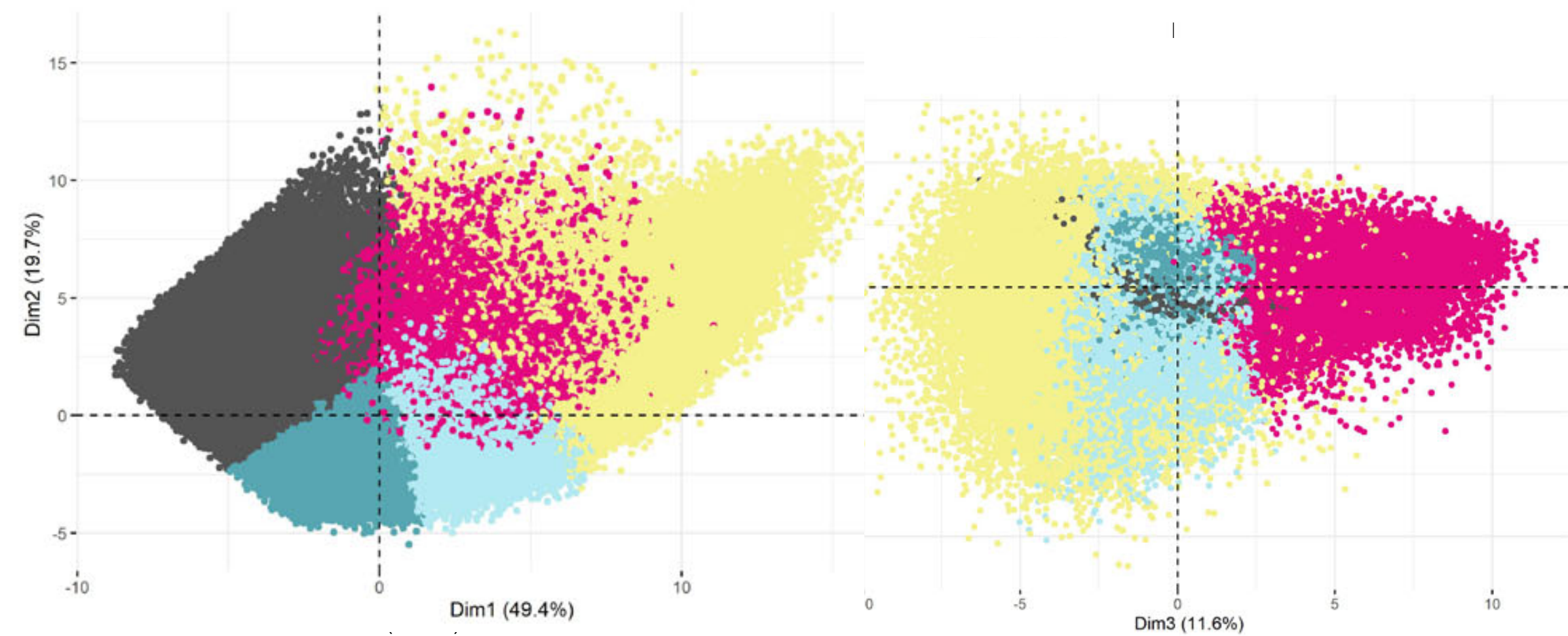


Merci

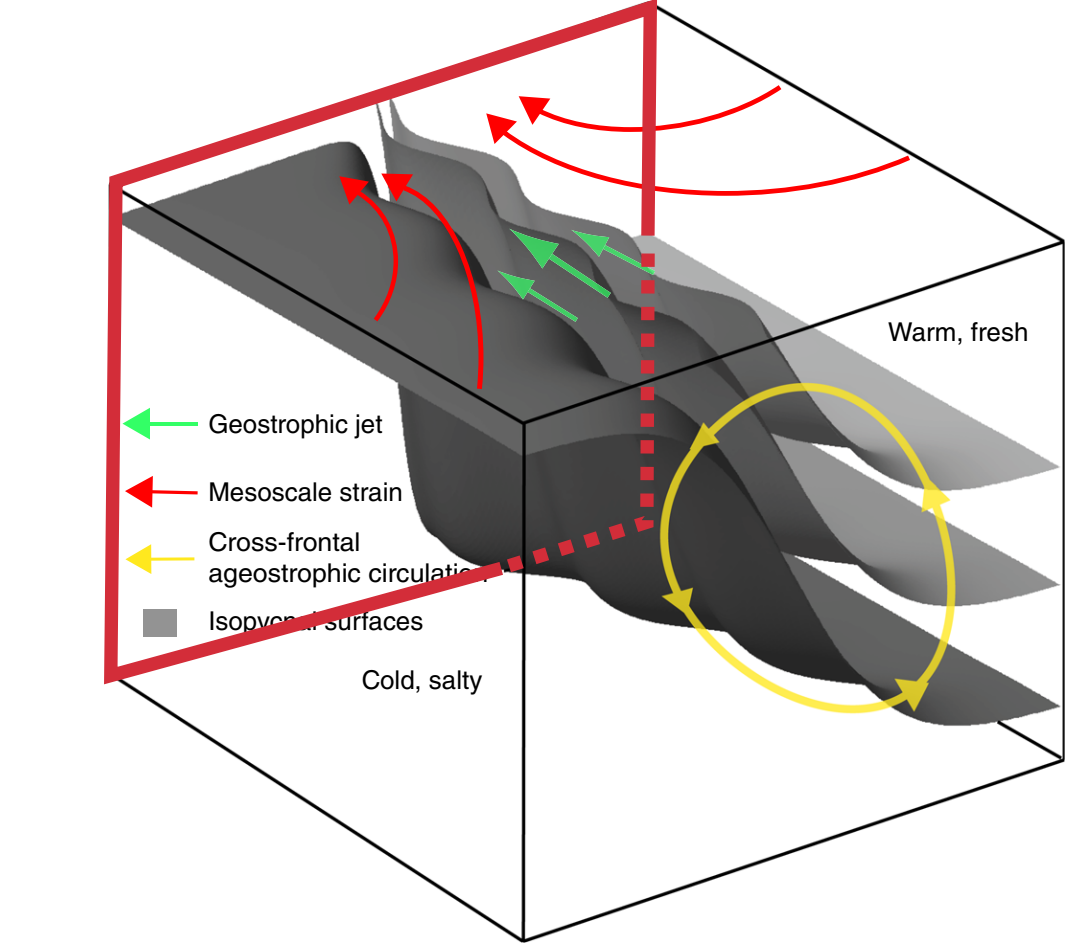
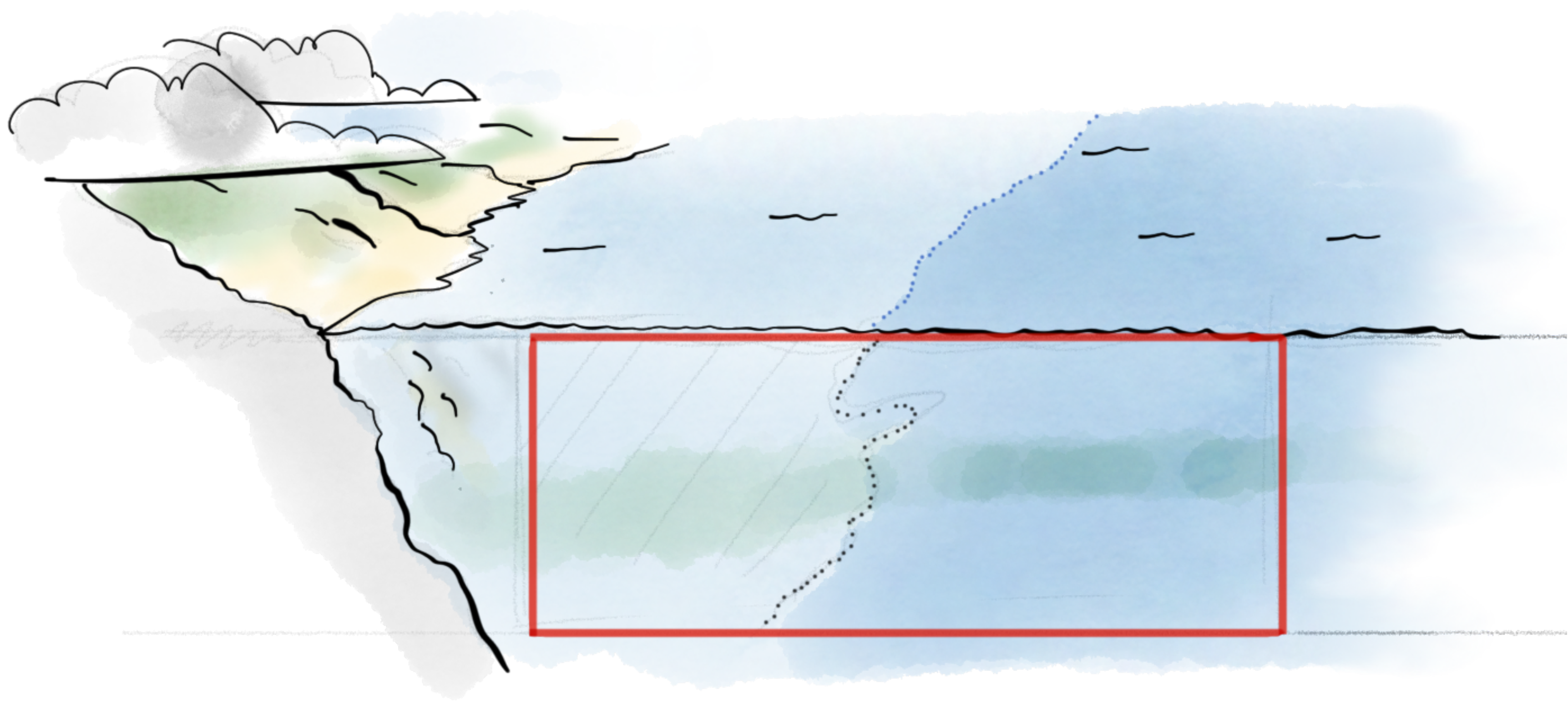
Unsupervised clustering in a morphological space



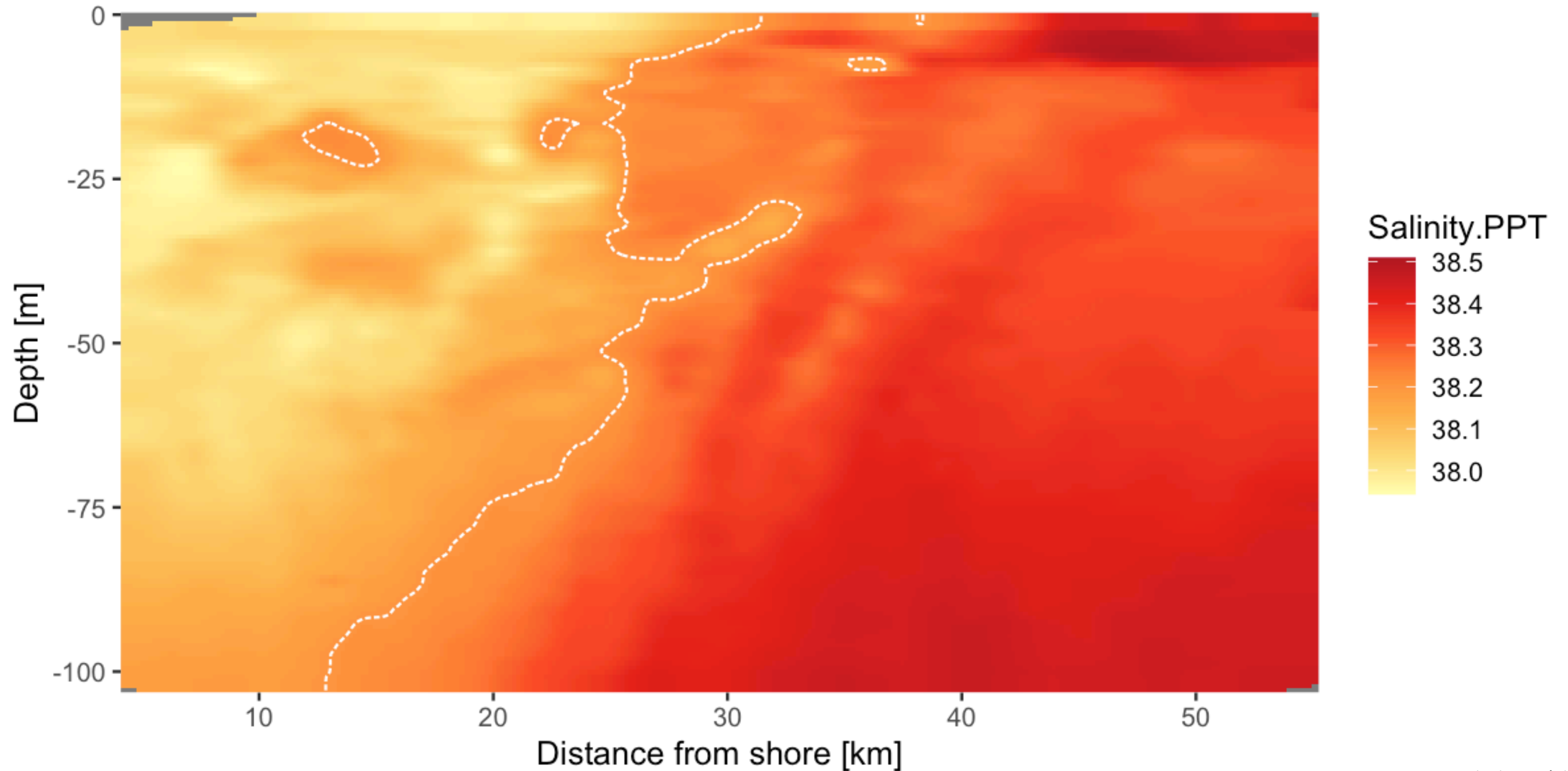
Unsupervised clustering in a morphological space



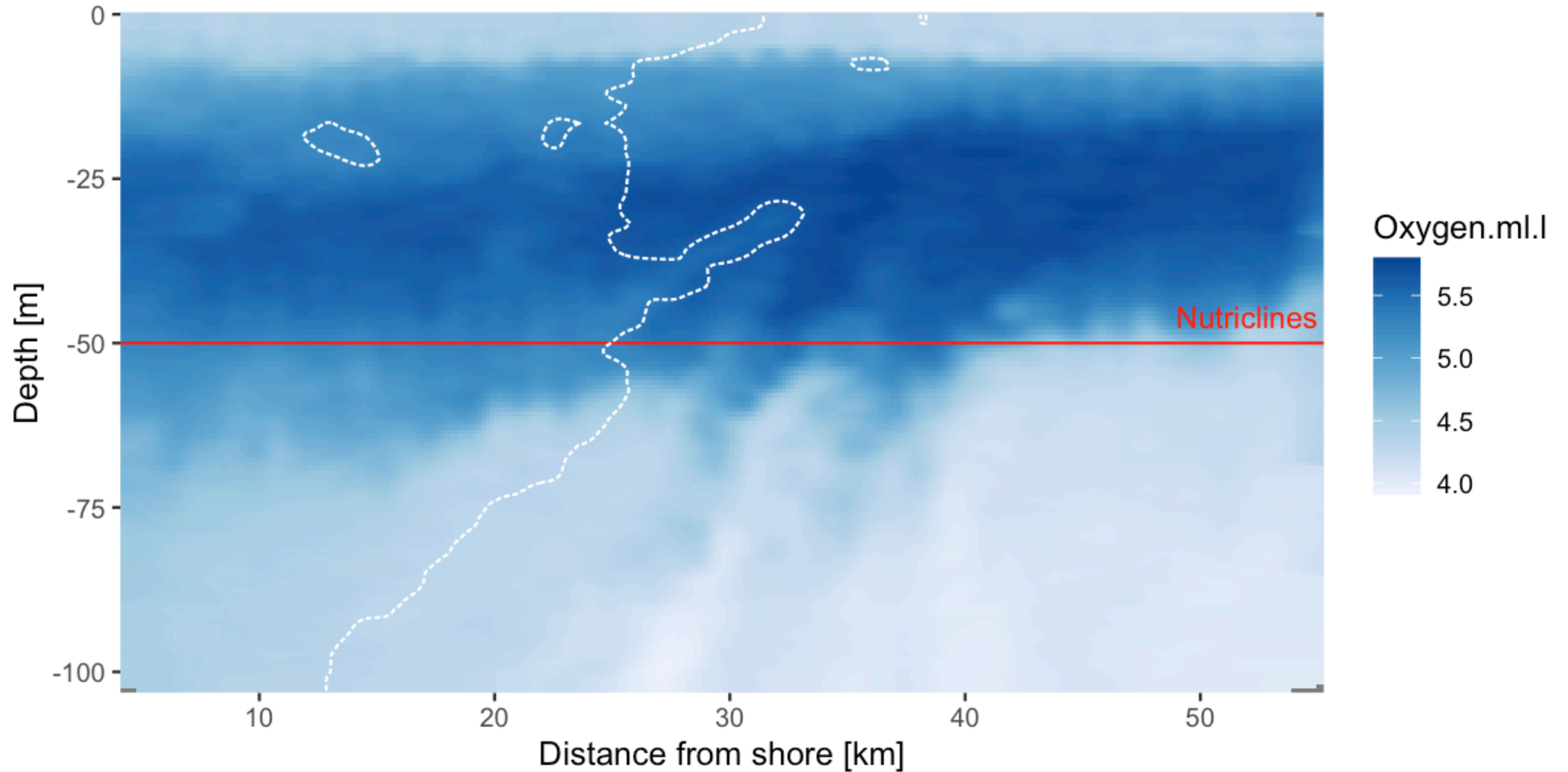
Imaging for high resolution sampling across a front



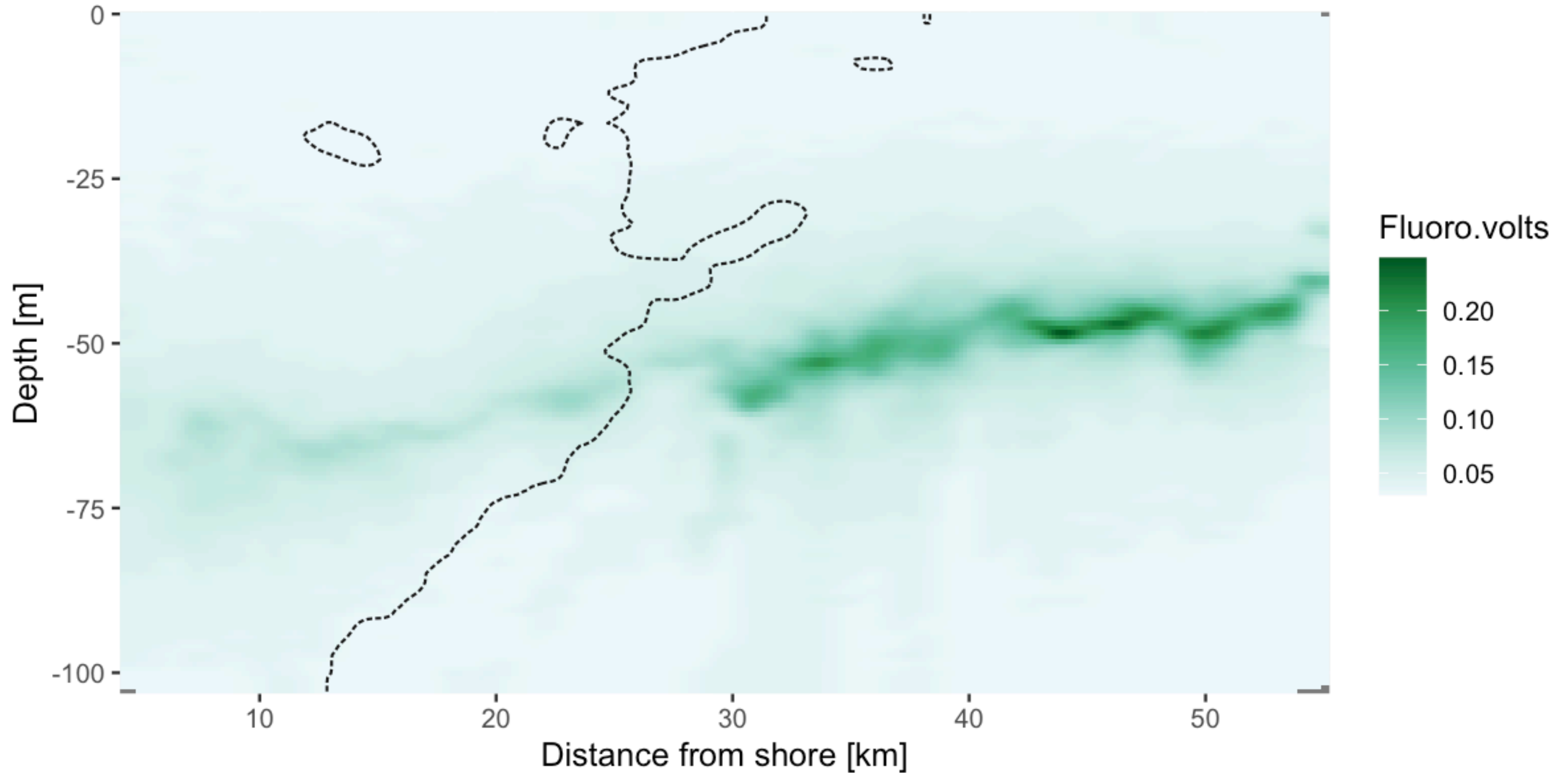
Mesoscale structure and submesoscale subduction



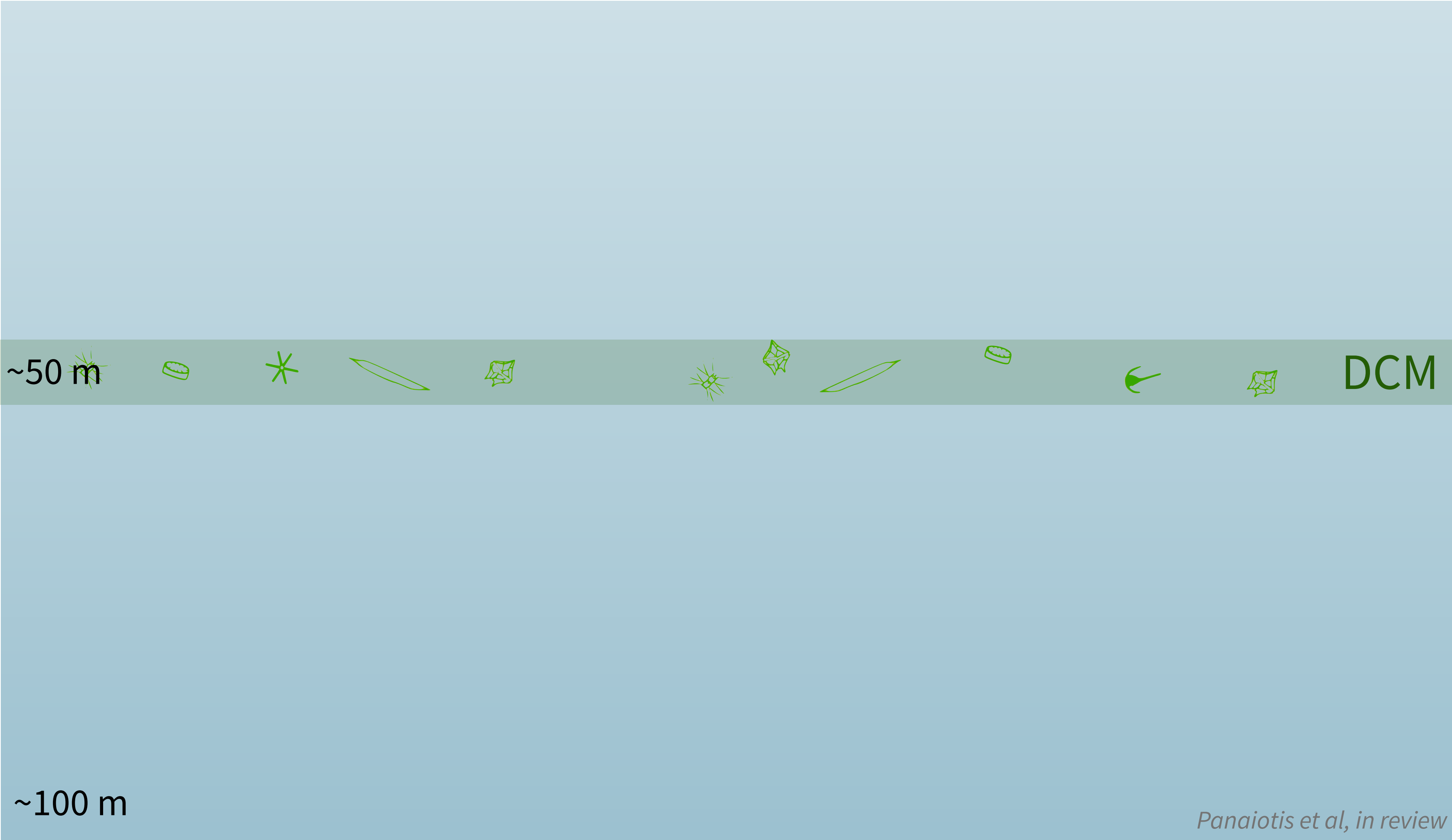
Mesoscale structure and submesoscale subduction



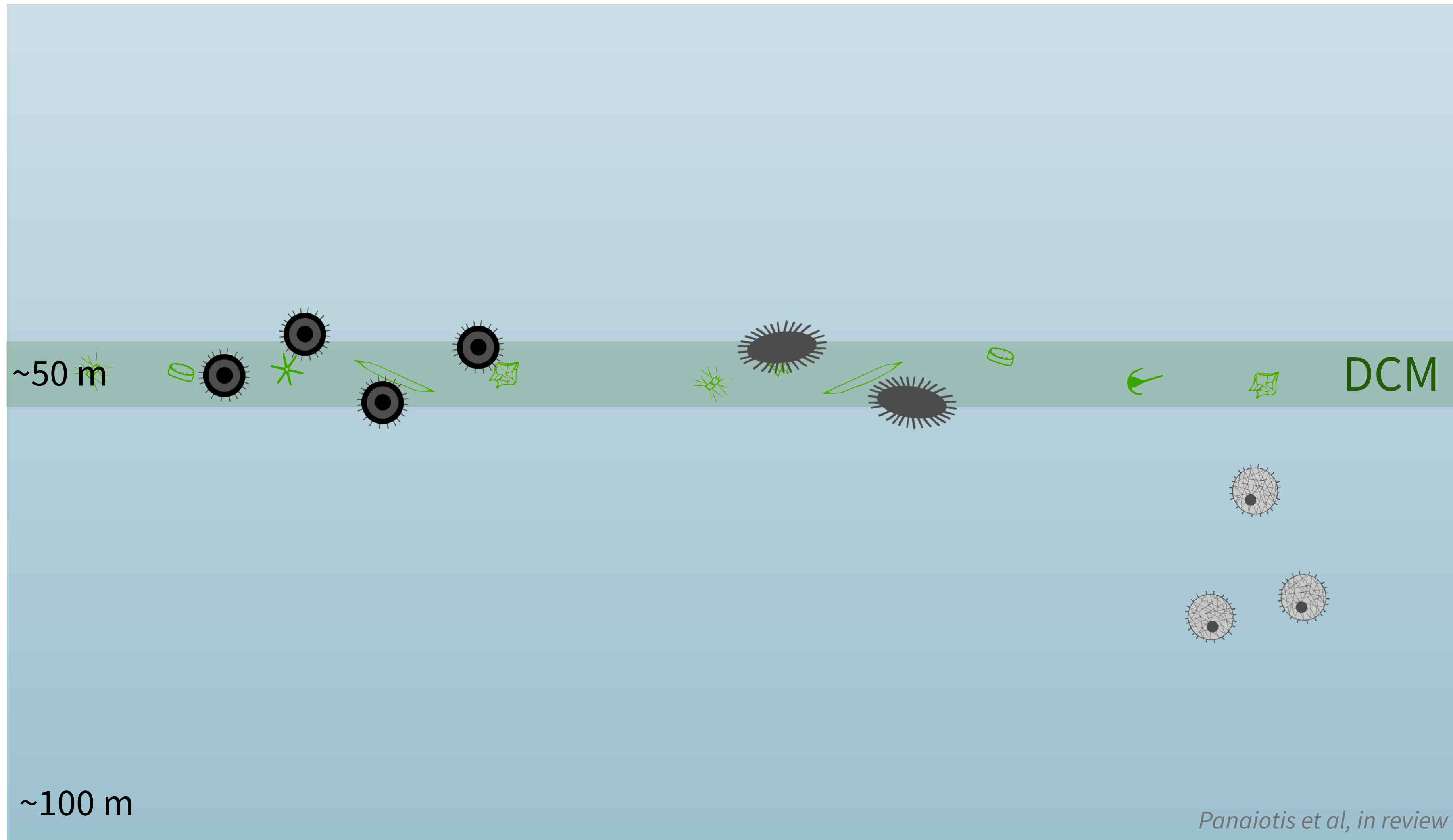
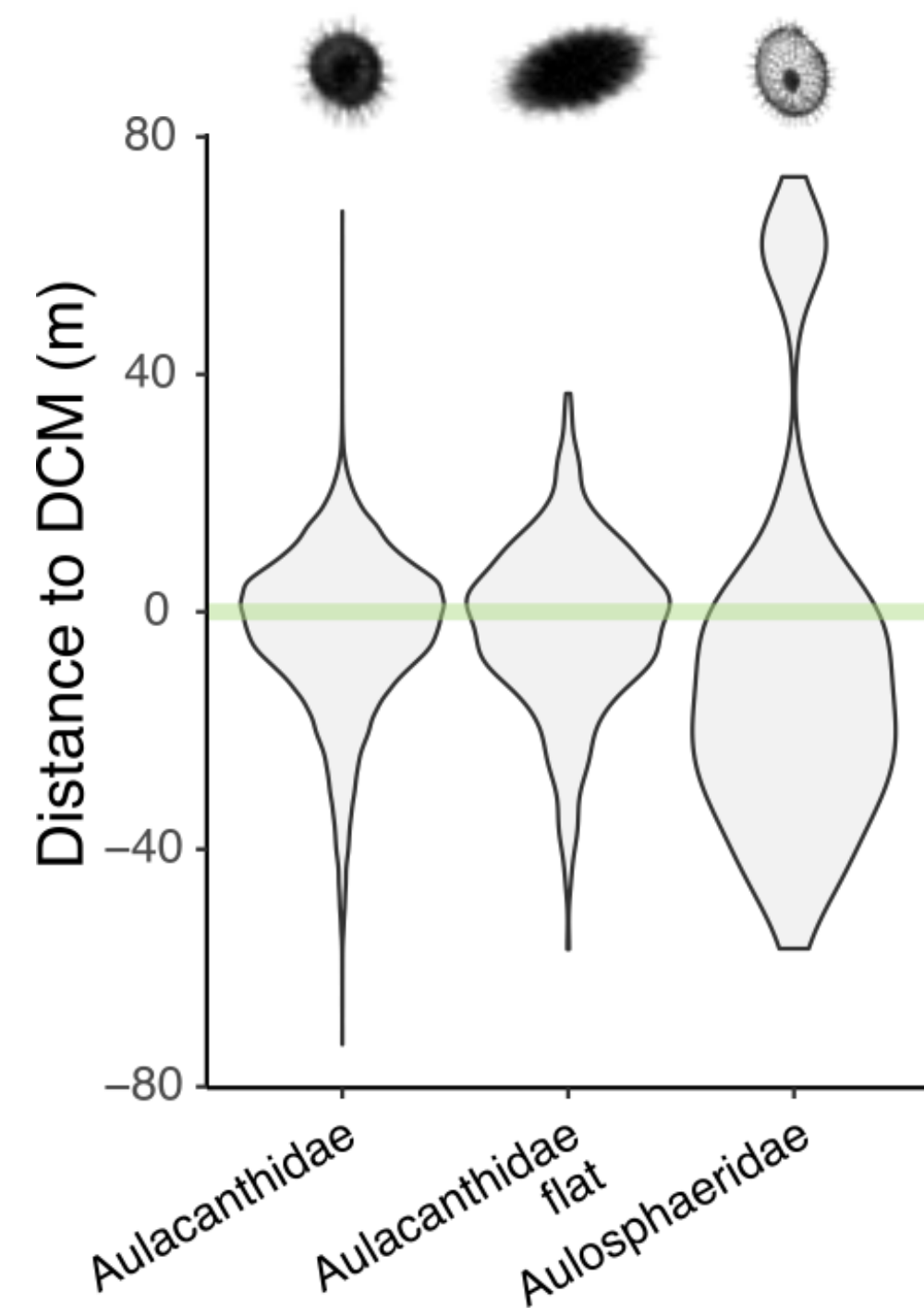
Consequences for phytoplankton



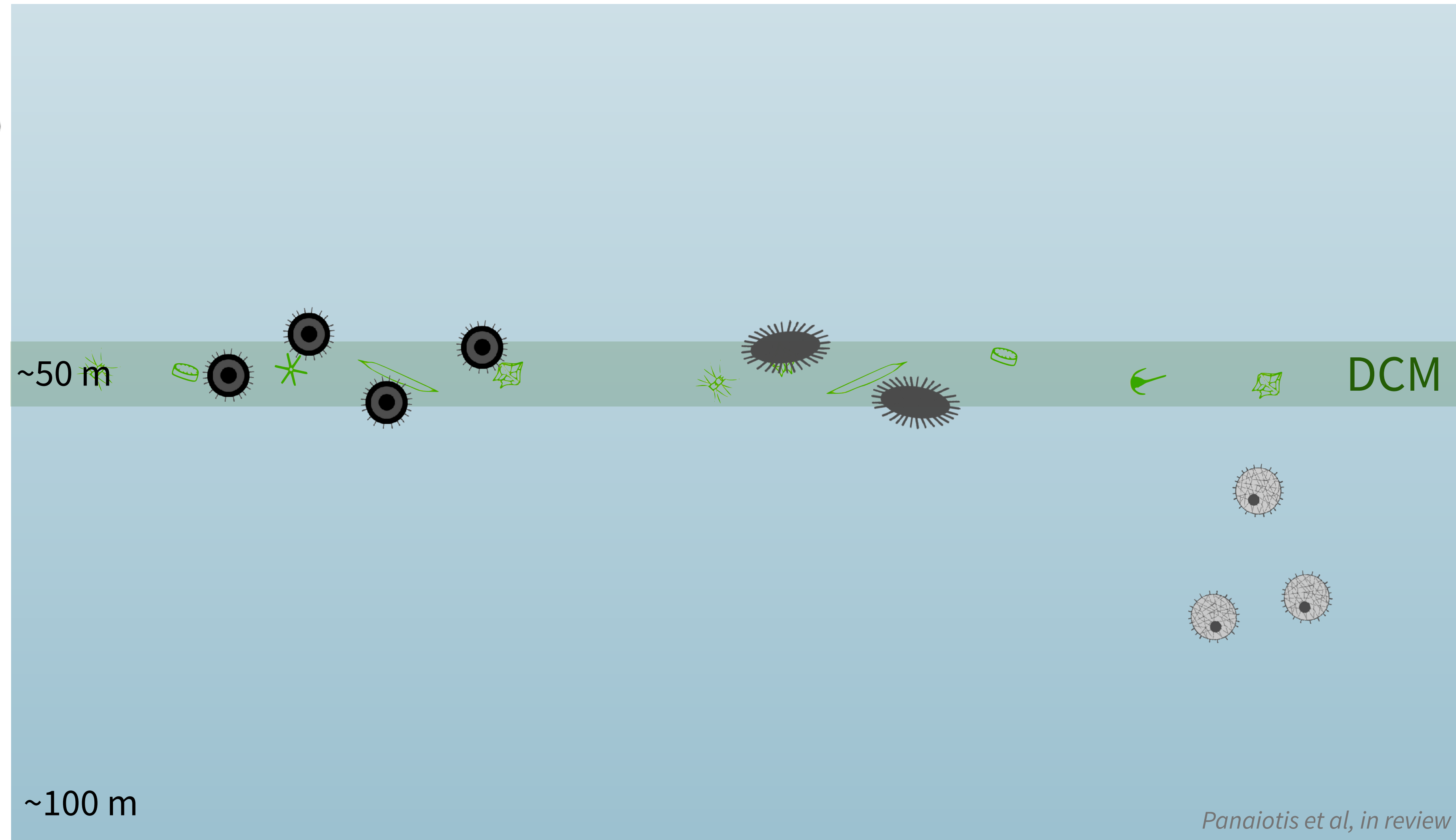
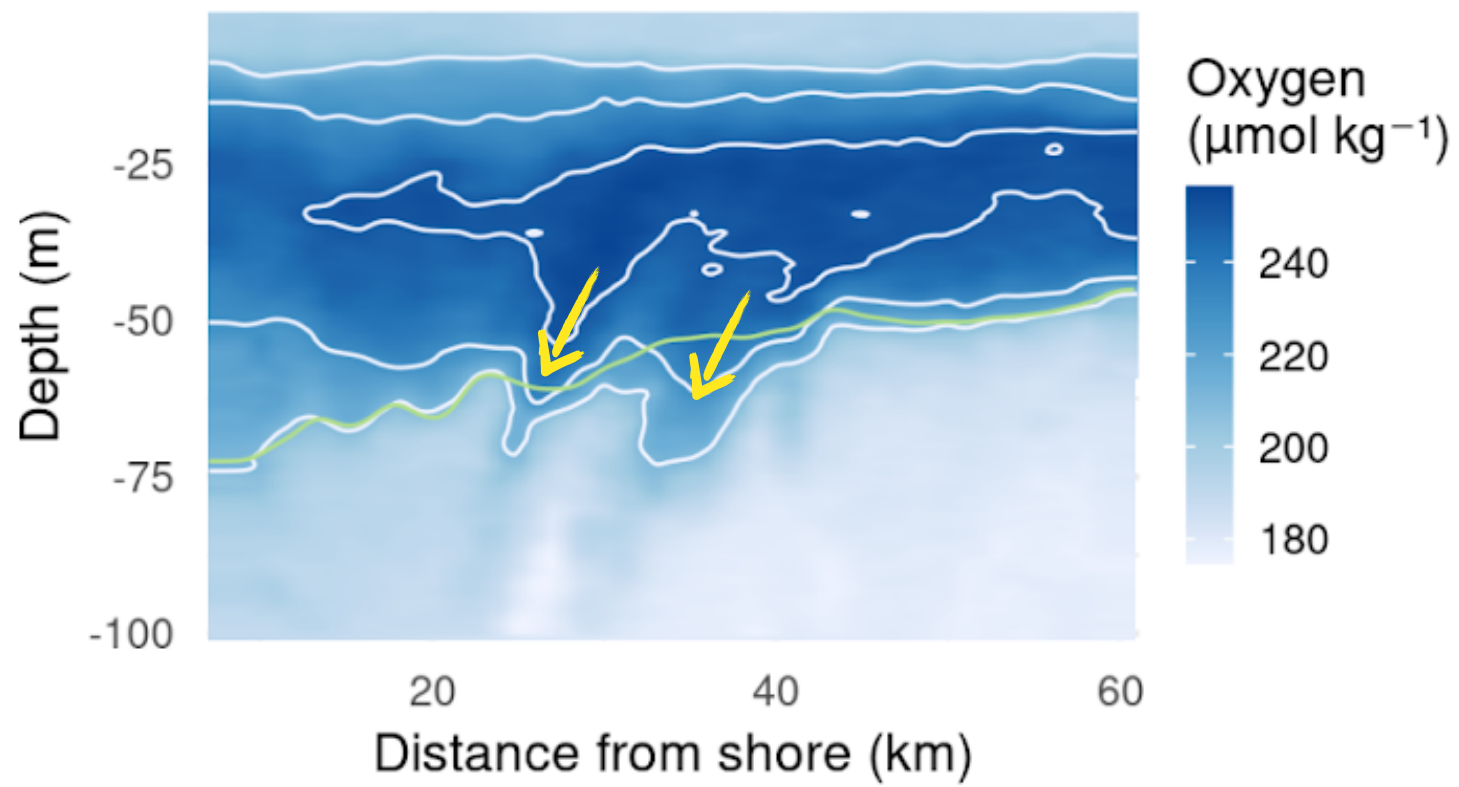
**Non random distribution and orientation,
yet displacement by sub mesoscale vertical flow**



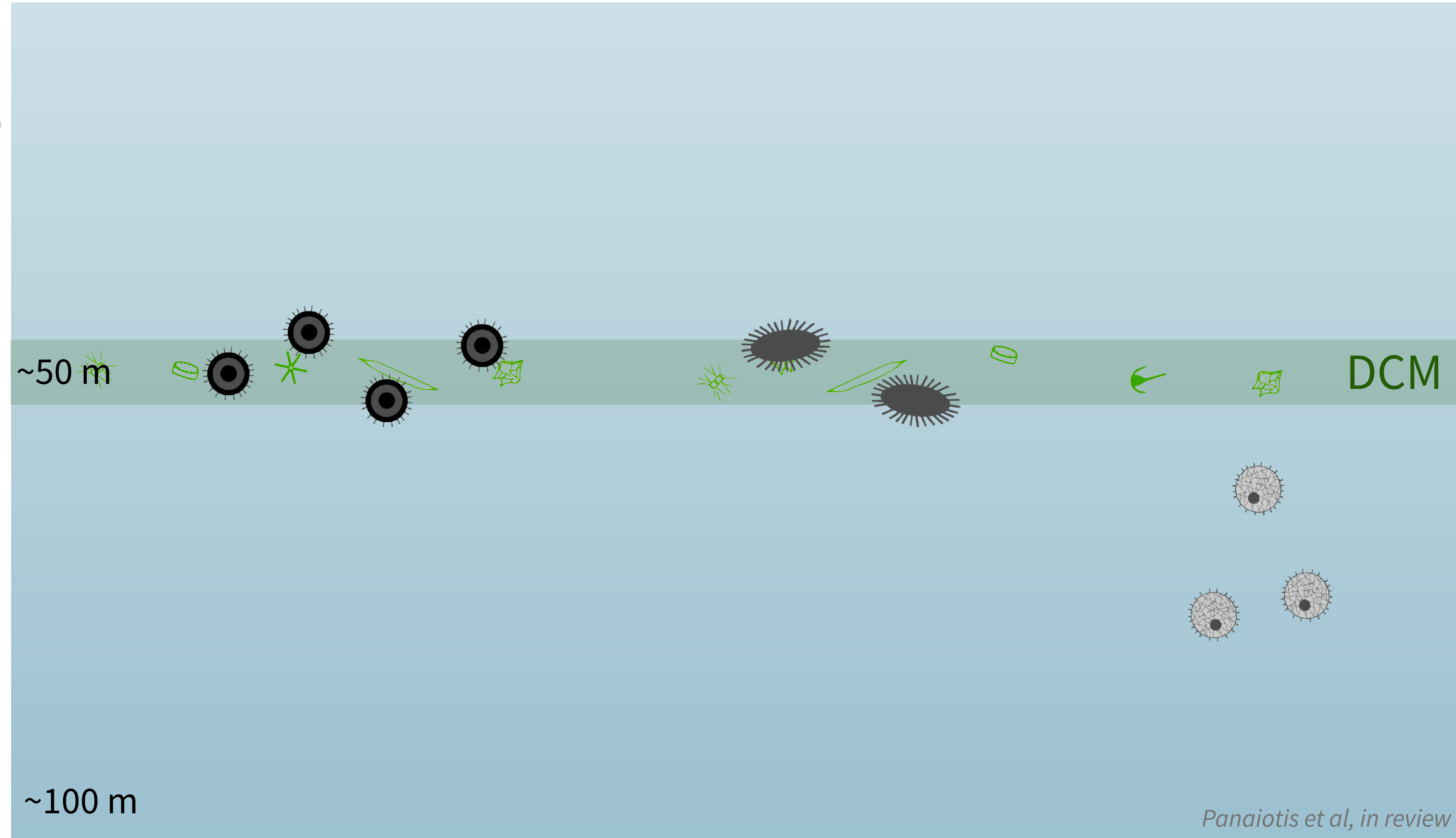
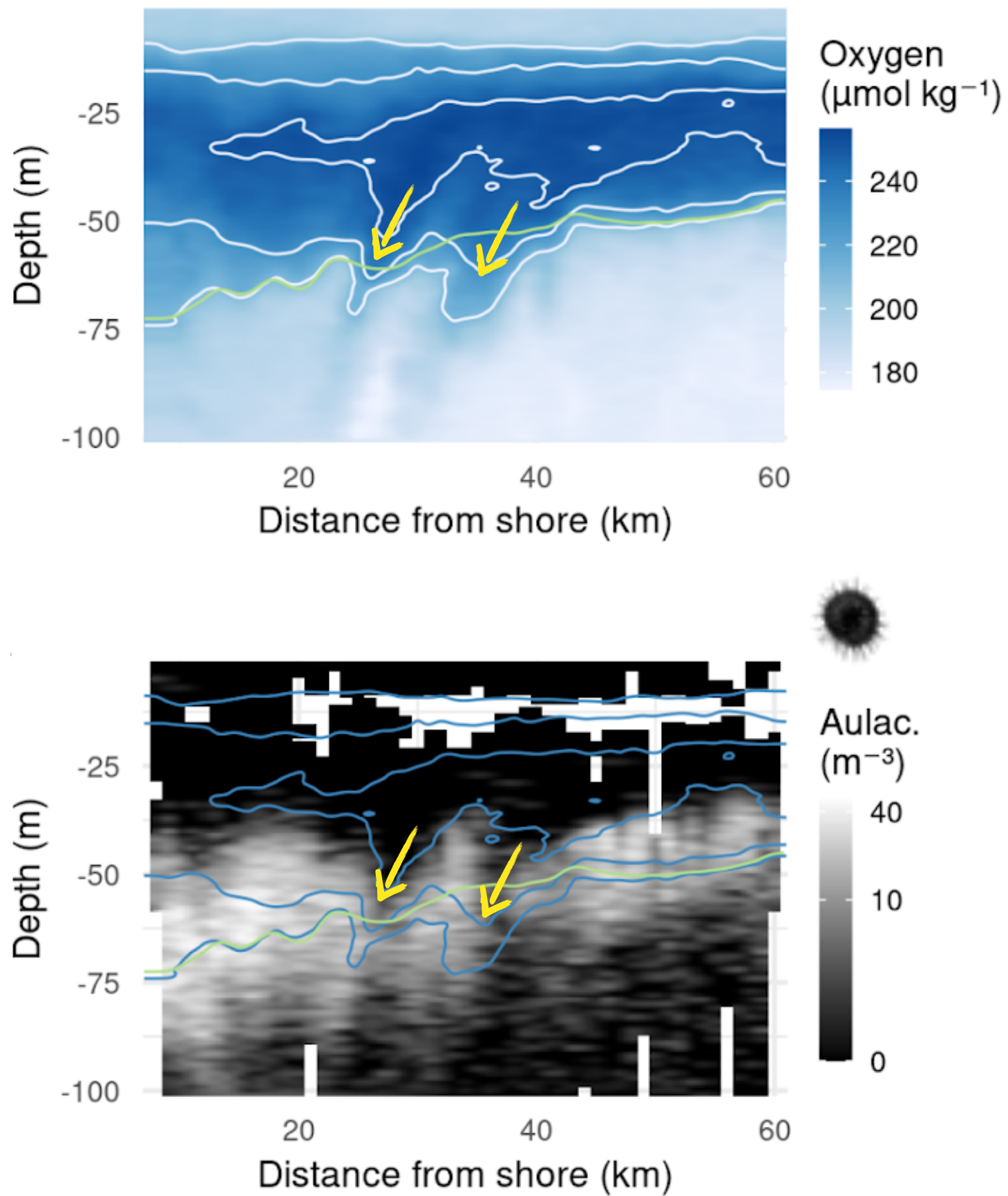
Non random distribution and orientation, yet displacement by sub mesoscale vertical flow



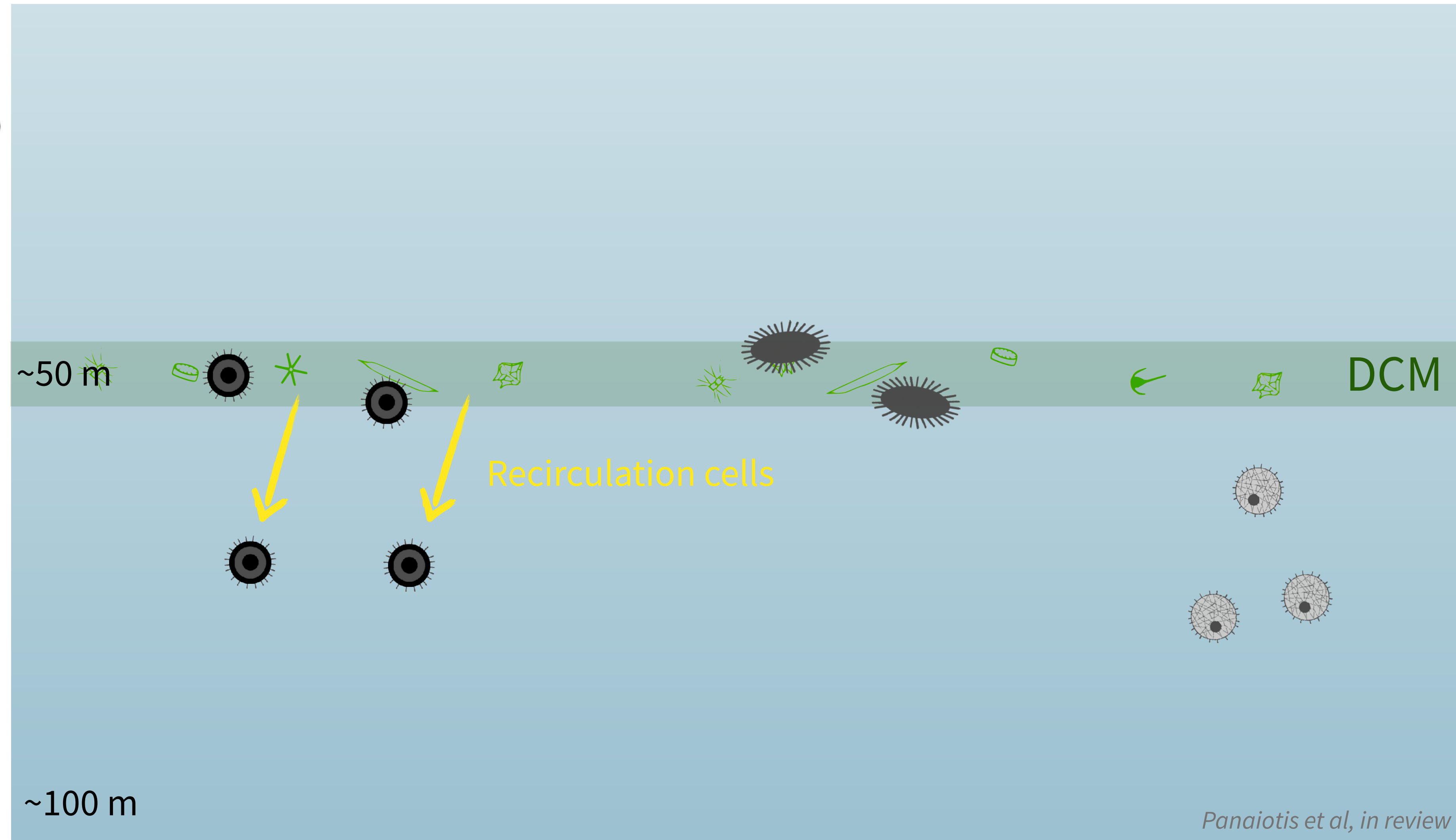
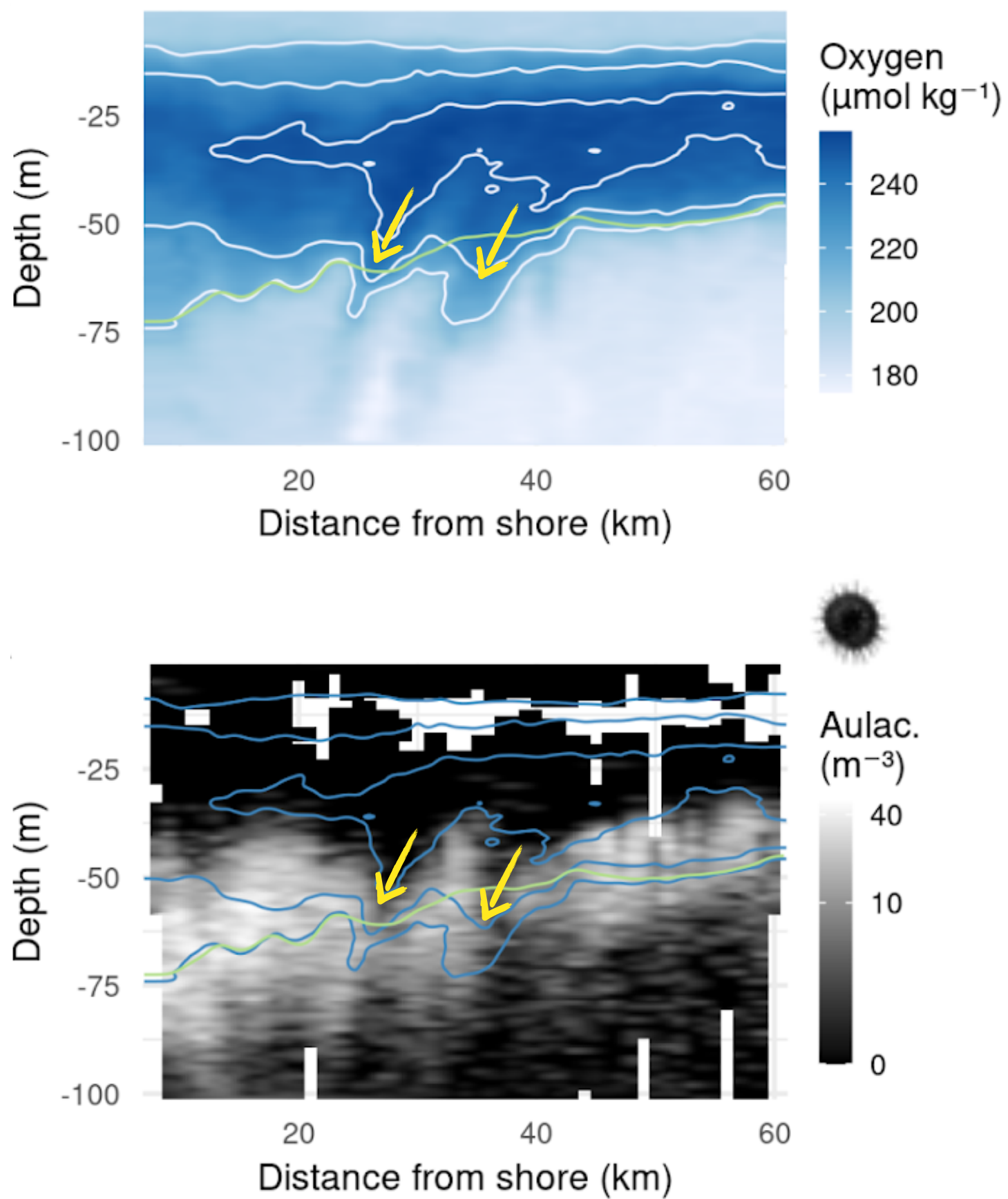
Non random distribution and orientation, yet displacement by sub mesoscale vertical flow



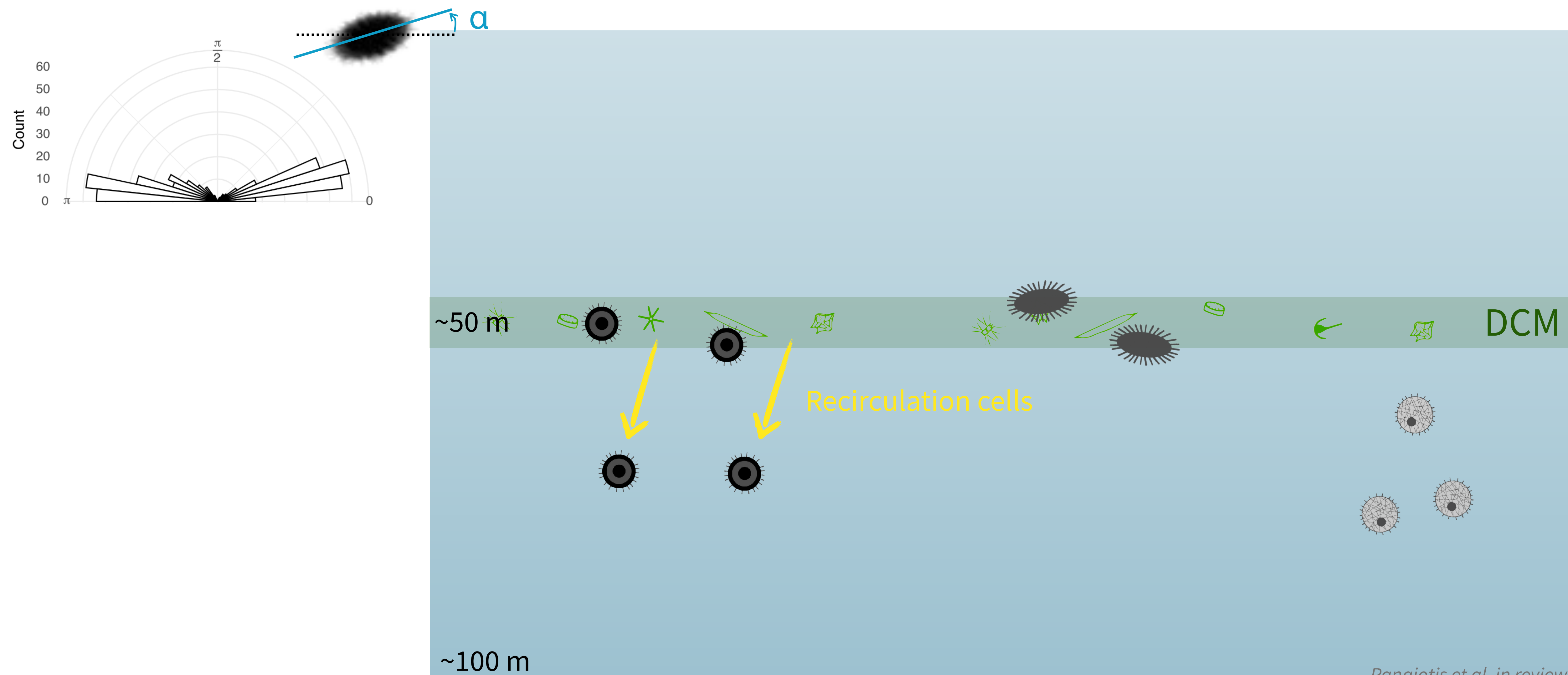
Non random distribution and orientation, yet displacement by sub mesoscale vertical flow



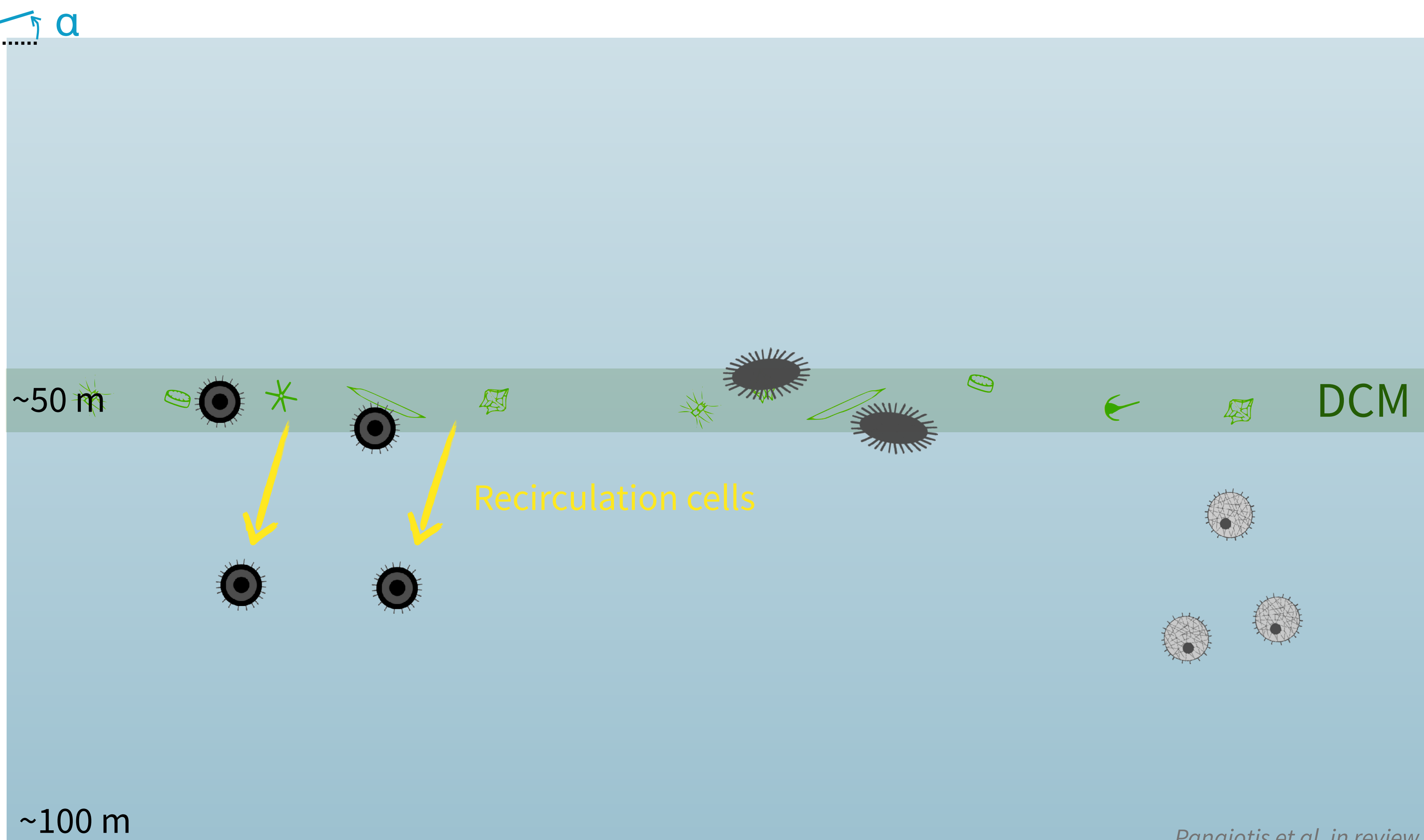
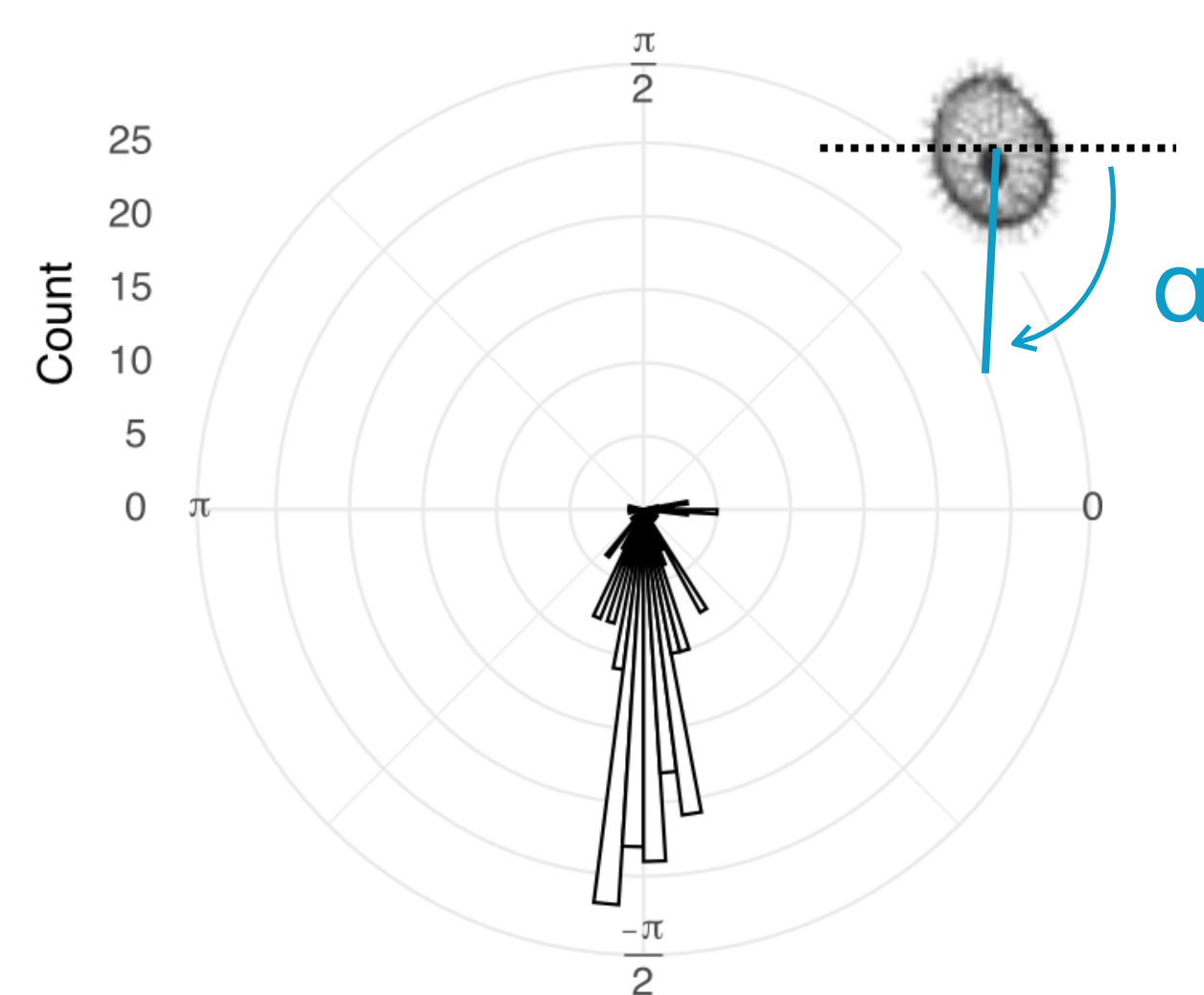
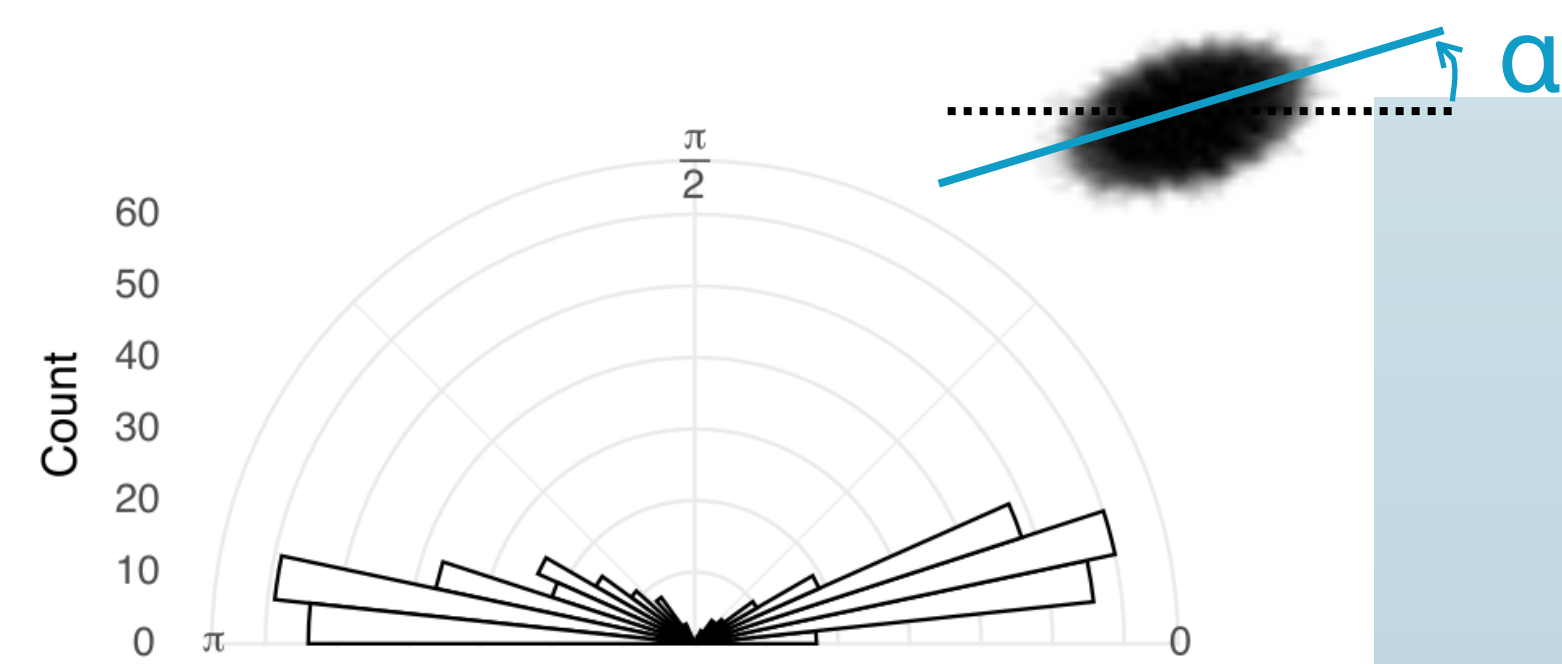
Non random distribution and orientation, yet displacement by sub mesoscale vertical flow



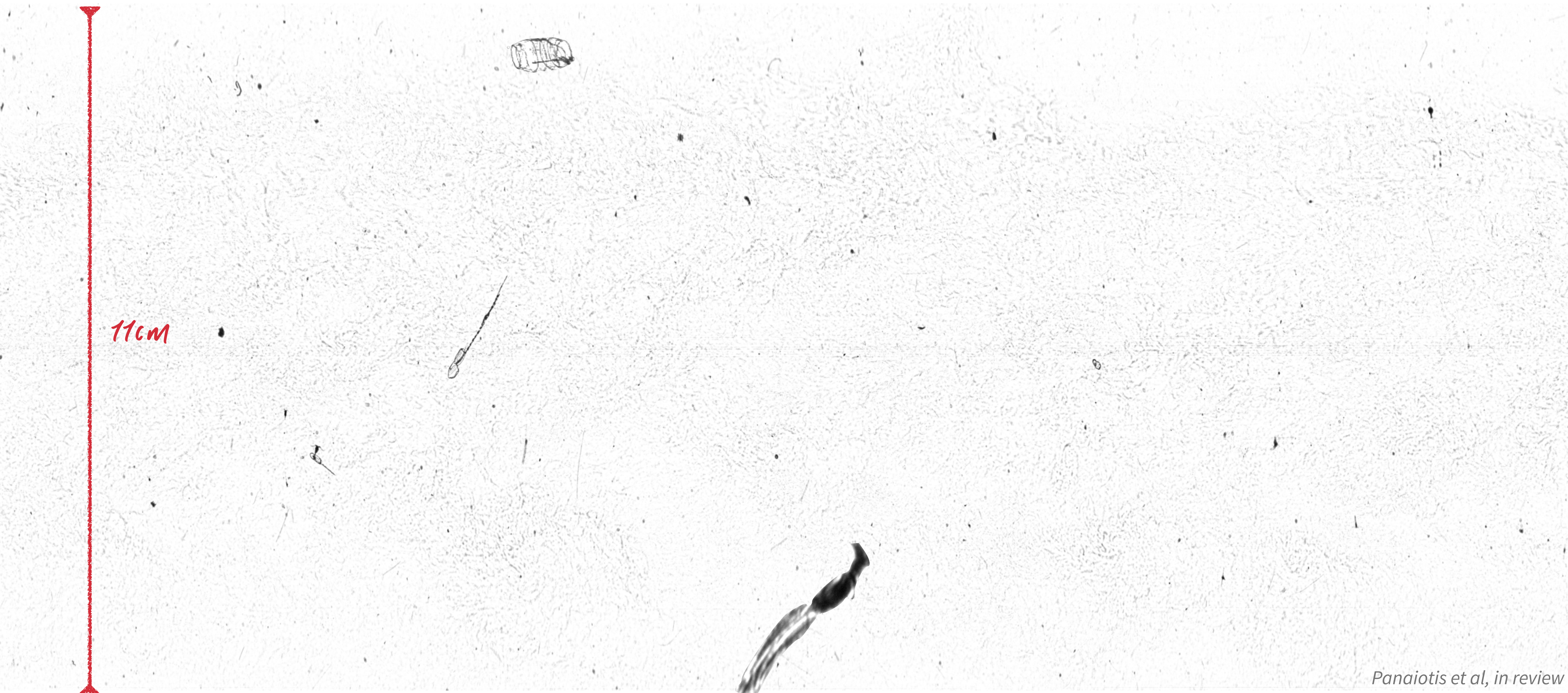
Non random distribution and orientation, yet displacement by sub mesoscale vertical flow



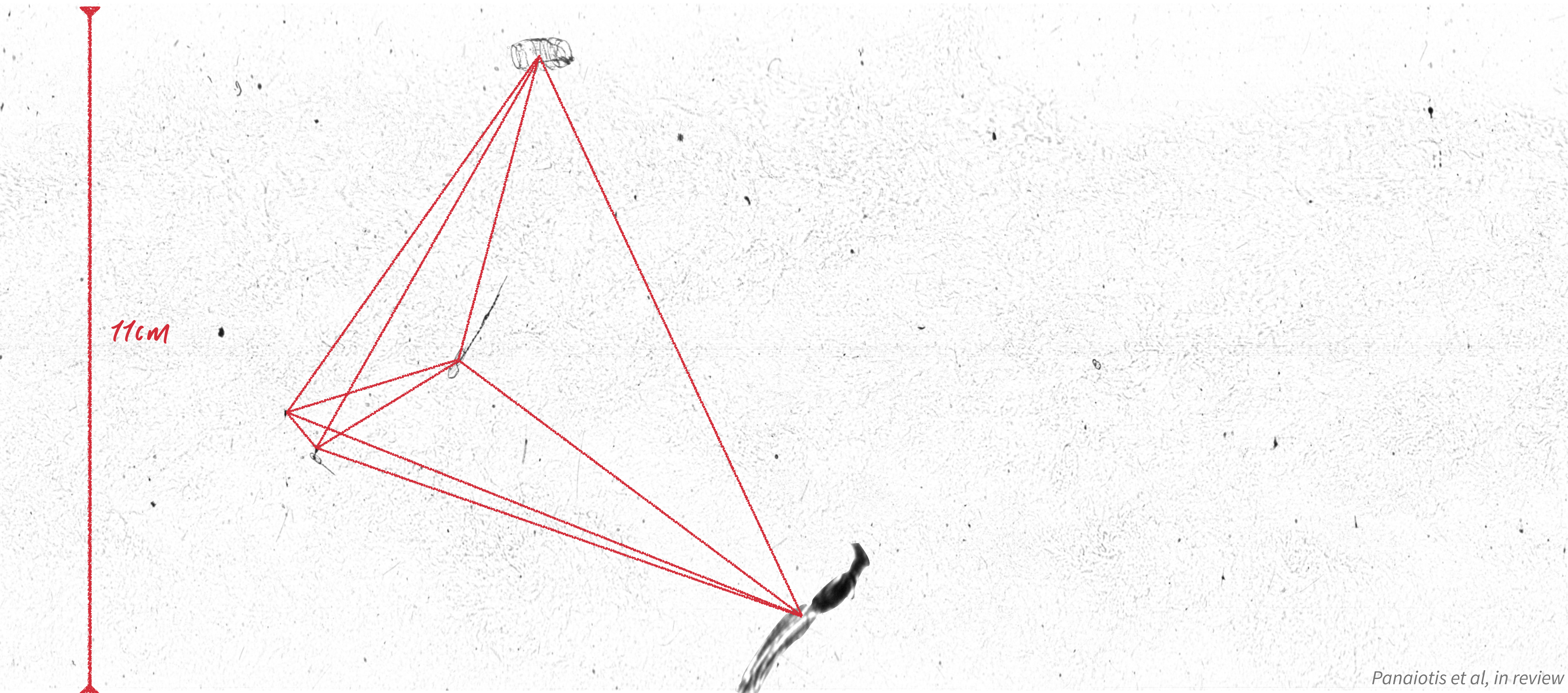
Non random distribution and orientation, yet displacement by sub mesoscale vertical flow



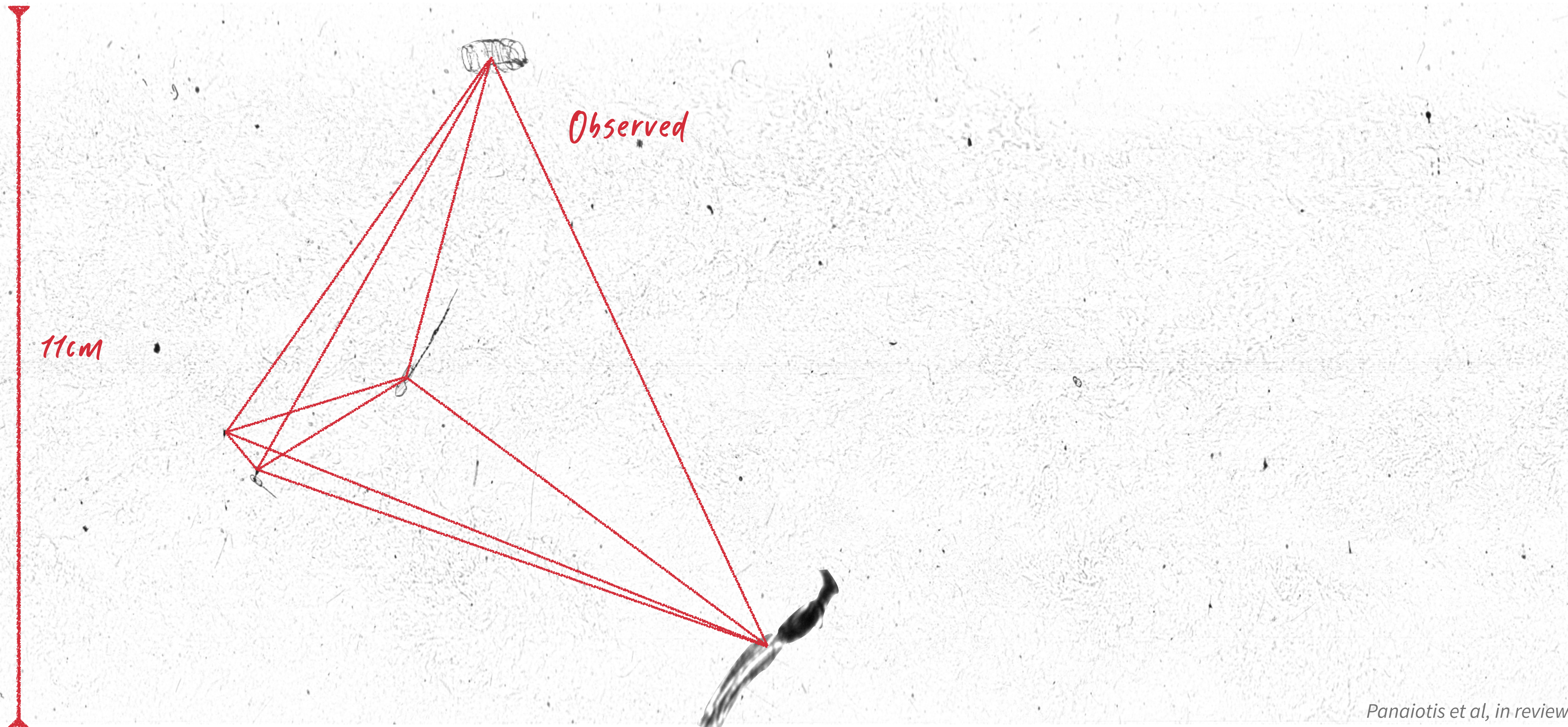
Measurement of inter-individual distances...



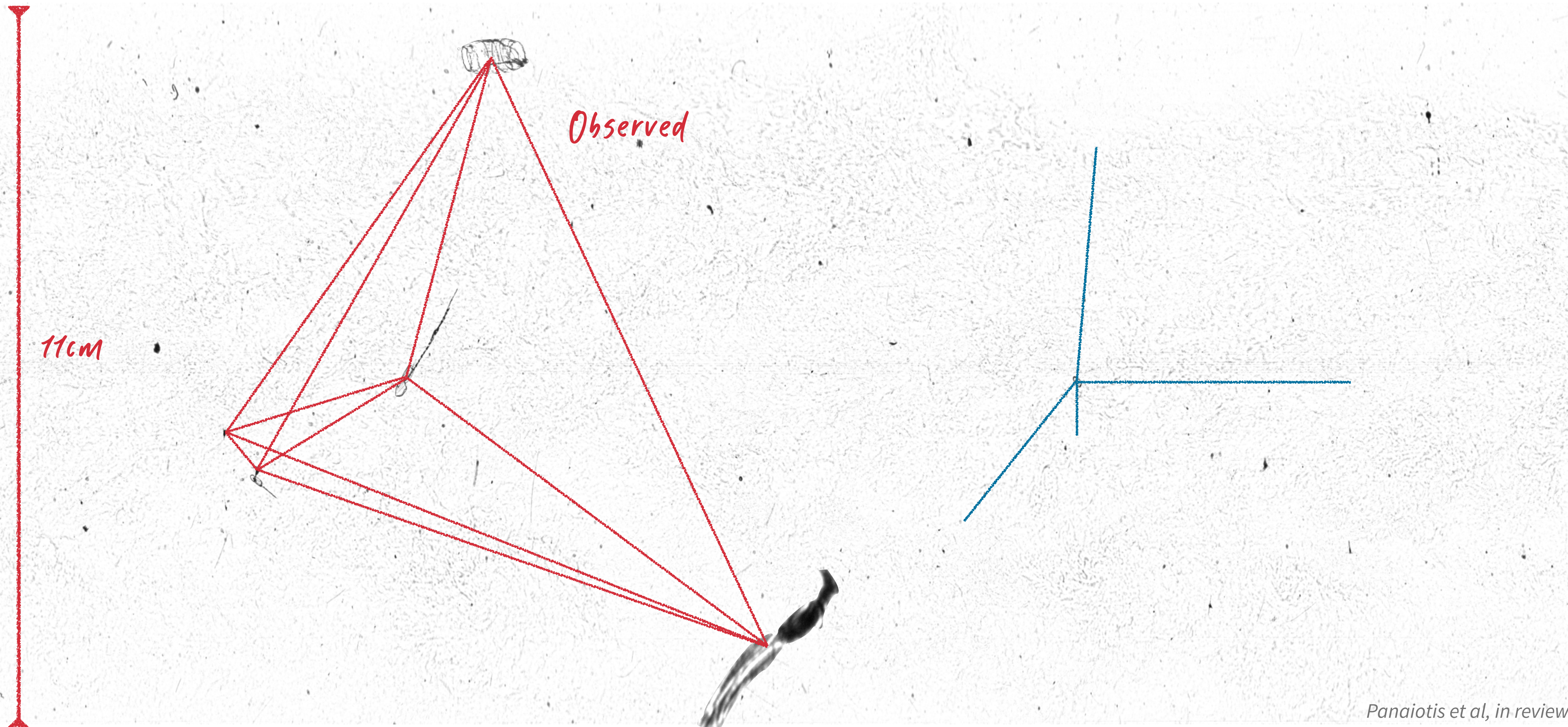
Measurement of inter-individual distances...



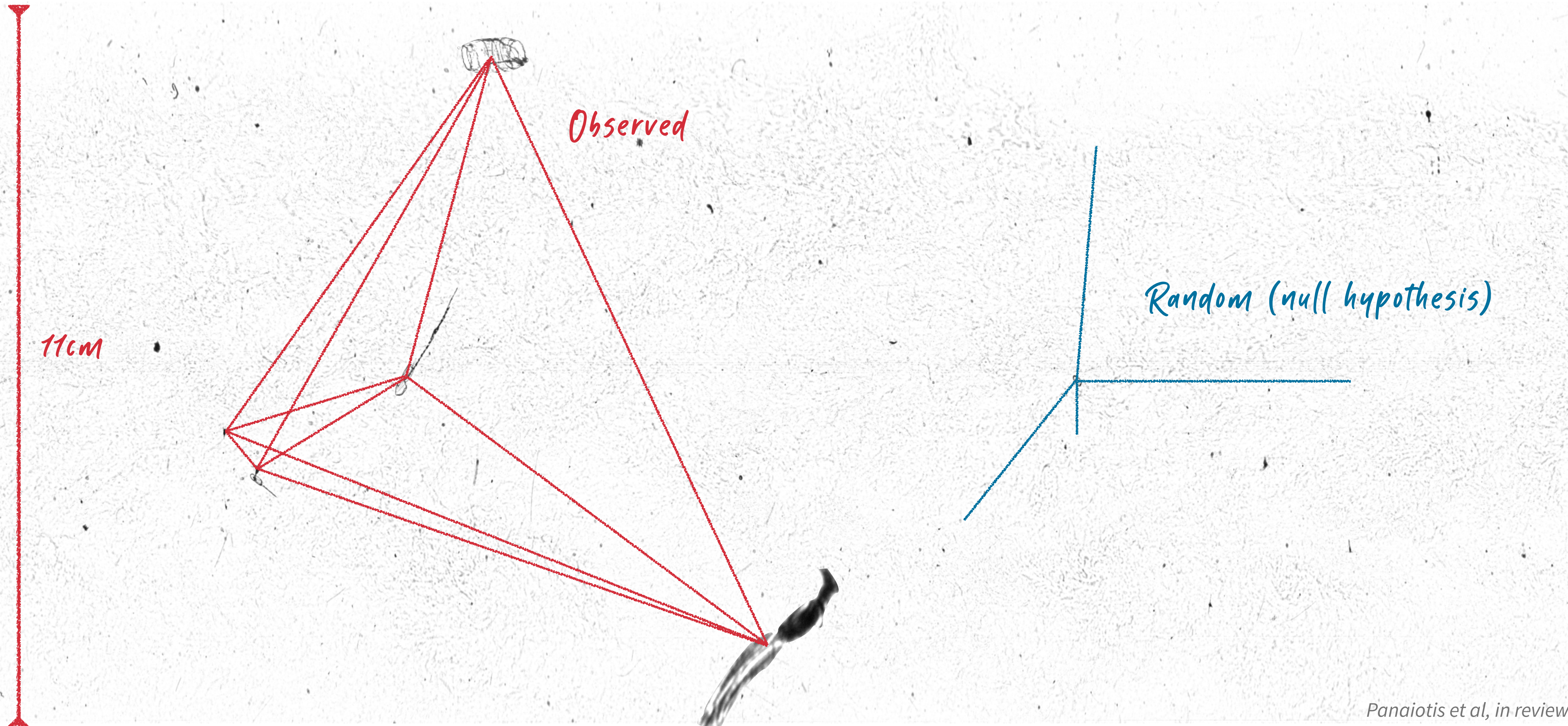
Measurement of inter-individual distances...



Measurement of inter-individual distances...



Measurement of inter-individual distances...



... allows the detection of gregarism in situ

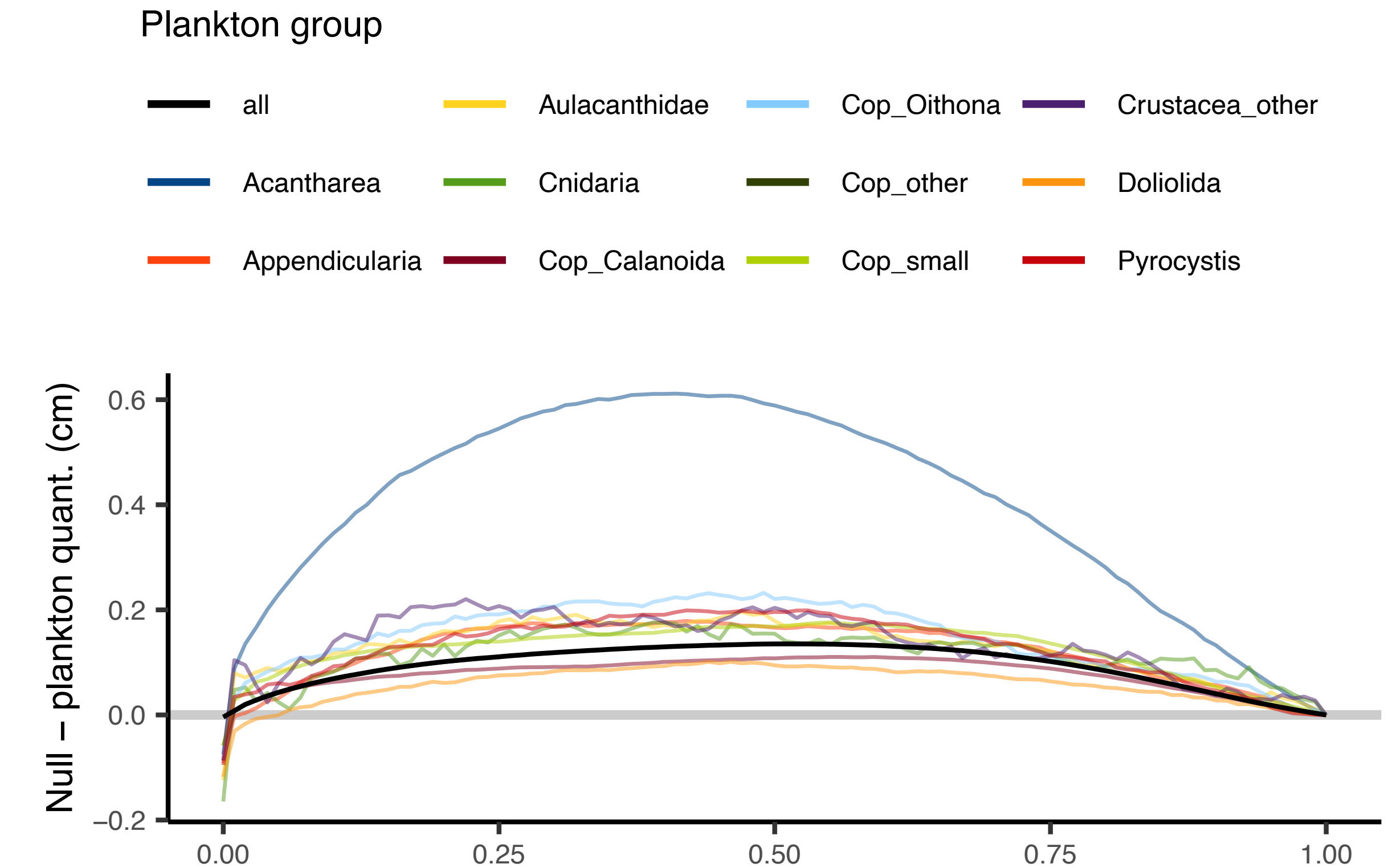
Organisms are **closer** to one another than would be expected by chance, both within each group (a) and between groups (b).

Except for Oithona <> Ctenophora: predator avoidance?

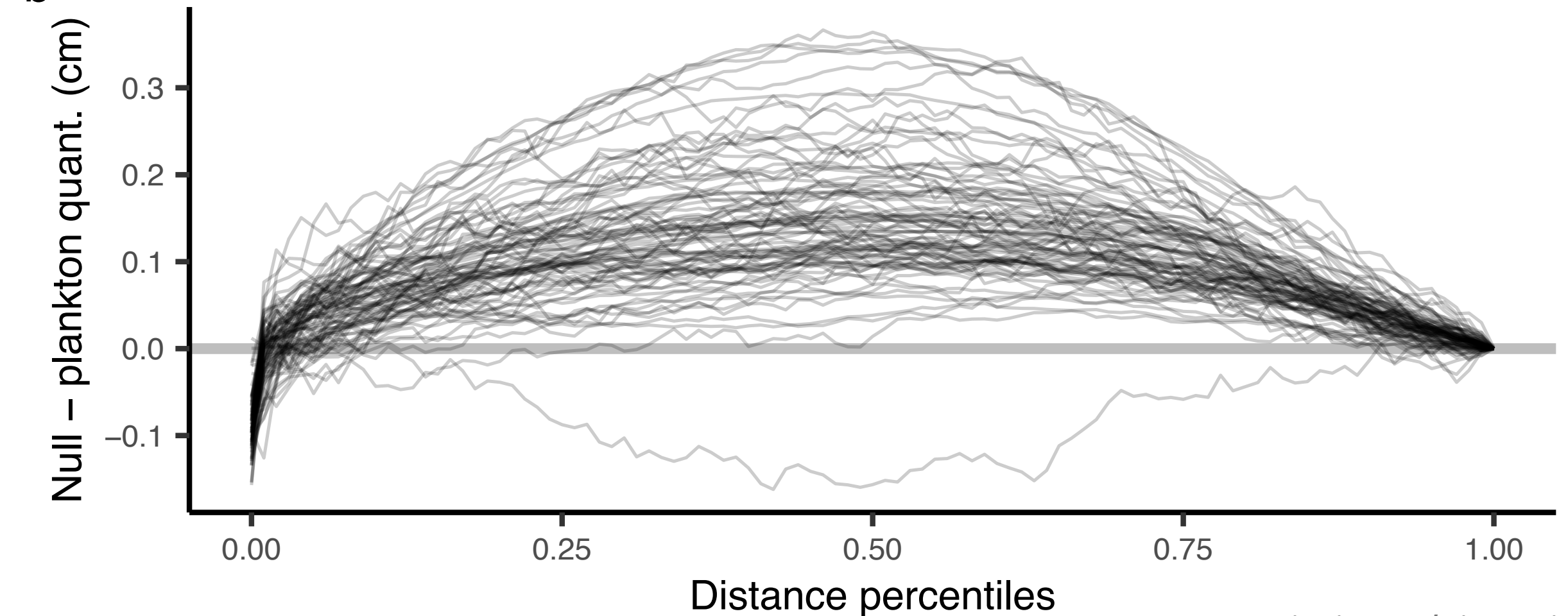
A simple **attraction model** (distance: 10 cm, displacement: 2 mm) reproduces the observations well

The displacement is realistic; the **sensory field** is much **larger** than expected

a



b



... allows the detection of gregarism in situ

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