A pipeline for in-situ plankton imaging data: Improving our understanding of ocean particle distribution and carbon fluxes using morphological traits
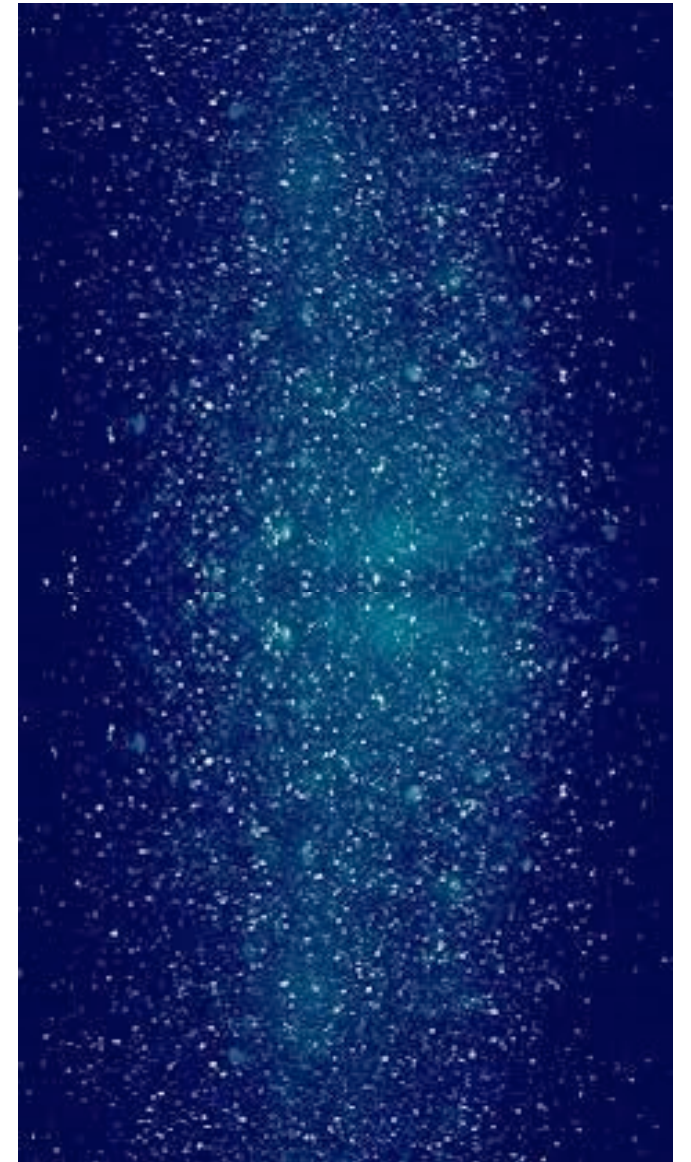
Miriam Beck, Sakina-Dorothée Ayata, Marc Picheral, Fabien Lombard, Rainer Kiko, Lars Stemmann, Lionel Guidi, Jean-Olivier Irisson

Joint Meeting SFE² - GfÖ - EEF
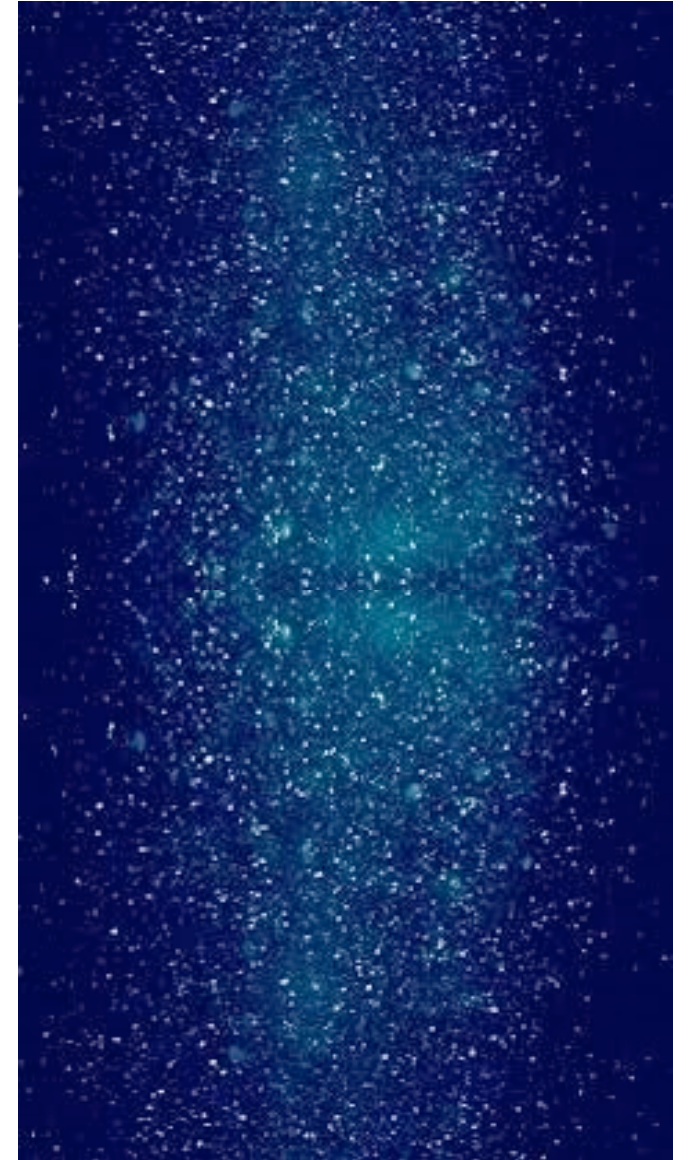
21.-25.11.22 Metz, France

Marine snow

- Up to XX of organic biomass in the ocean// Carbon export up to xx

- High diversity

- Carbon export to deep ocean largely driven by gravity
  —> size

Banerjee *et al.* 2014 (modified)

Marine snow

- Up to XX of organic biomass in the ocean// Carbon export up to xx

- High diversity

- Carbon export to deep ocean largely driven by gravity
  —> size
  —> shape, porosity, composition
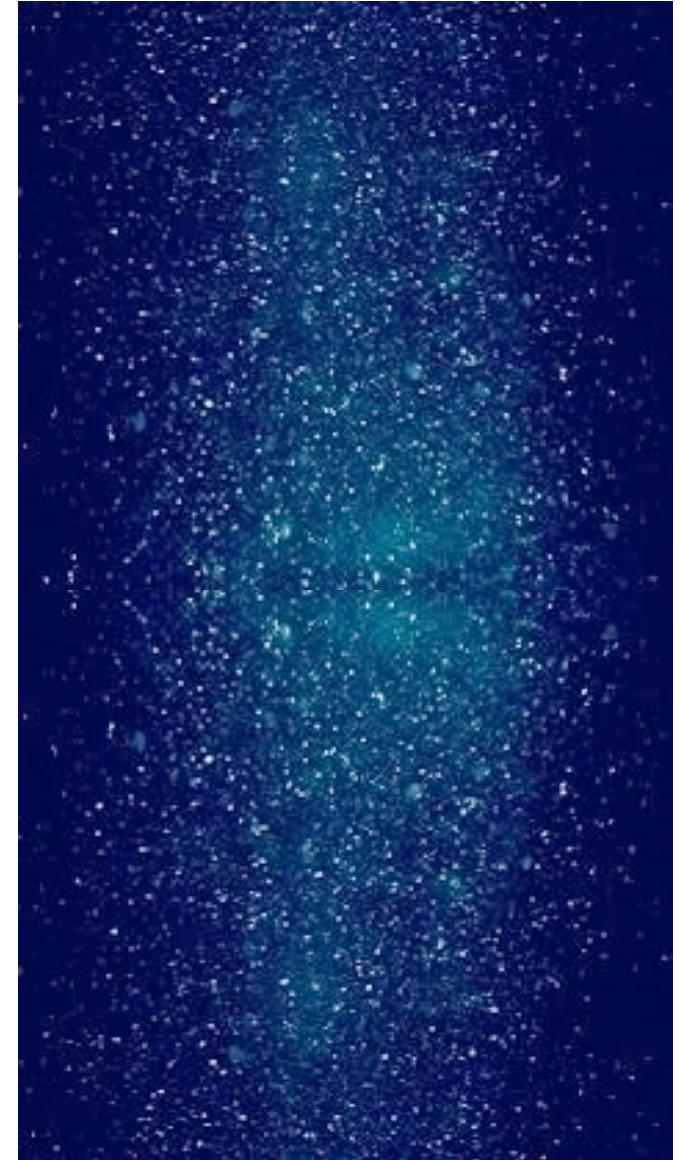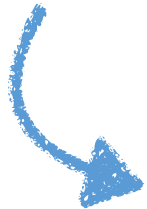
Marine snow

- Up to XX of organic biomass in the ocean// Carbon export up to xx

- High diversity

- Carbon export to deep ocean largely driven by gravity
—> size
—> shape, porosity, composition

Morphological traits

Banerjee *et al*. 2014 (modified)

Marine snow

- Up to XX of organic biomass in the ocea
  Carbon export up to xx

- High diversity

- Carbon export to deep ocean largely driven
  by gravity
  —> size
  —> shape, porosity, composition

Morphological traits

Marine snow

Marine snow morphology illuminates the evolution of phytoplankton blooms and determines their subsequent vertical export

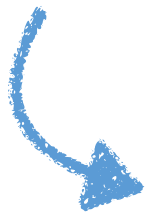Emilia Trudnowska ✉, Léo Lacour, Mathieu Ardyna, Andreas Rogge, Jean Olivier Irisson, Anya M. Waite, Marcel Babin & Lars Stemmann

- Up to XX of organic biomass in the ocea
  Carbon export up to xx

- High diversity

- Carbon export to deep ocean largely drive
  by gravity
  —> size
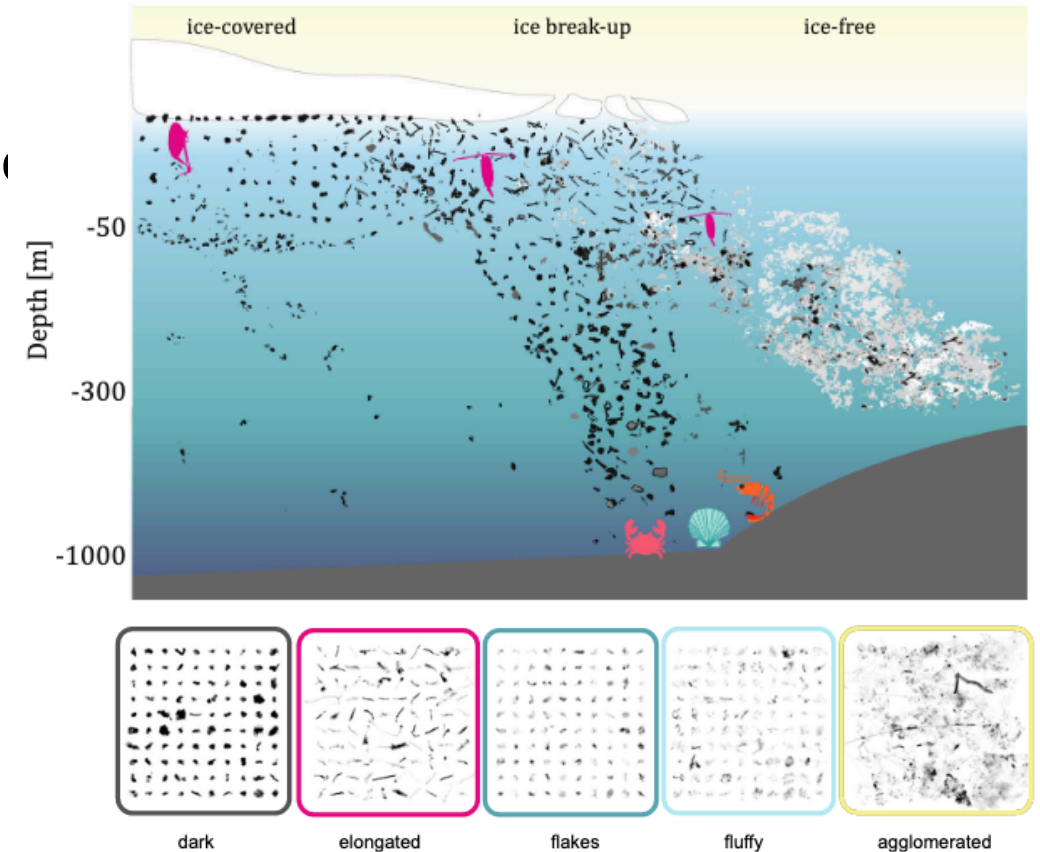 —> shape, porosity, composition

Morphological traits

Marine snow

- Up to XX of organic biomass in the ocean//
Carbon export up to xx

- High diversity

- Carbon export to deep ocean largely driven
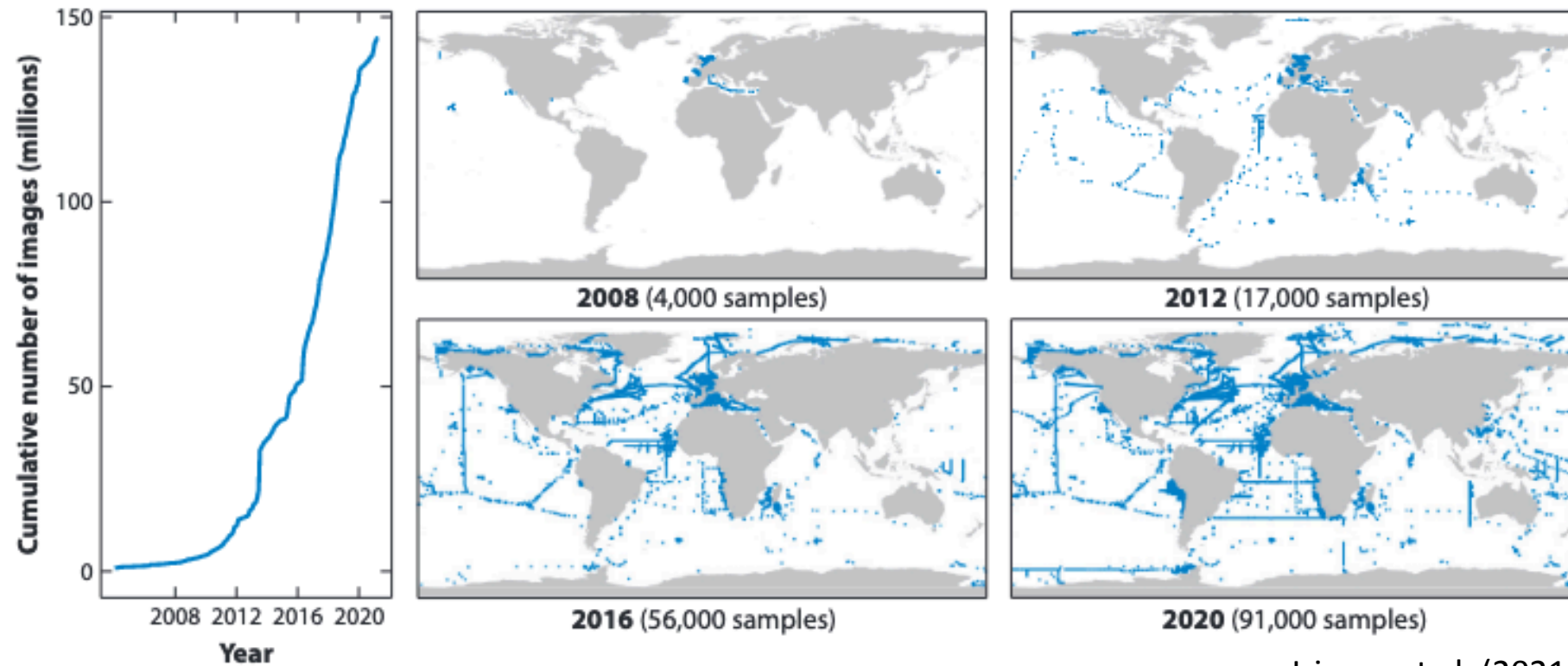by gravity
—> size
—> shape, porosity, composition
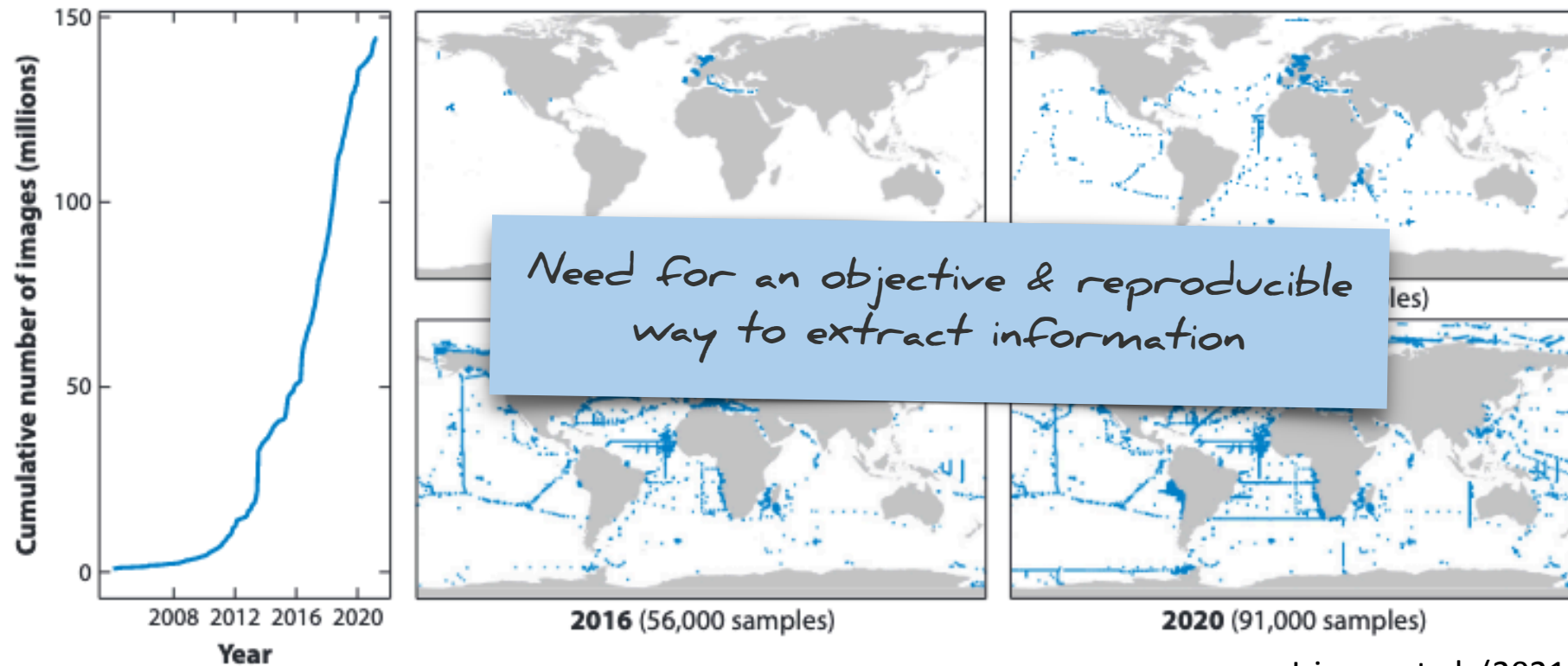
Morphological traits

Can be measured from image-data
—> automated | objective | 'taxa' independent | big data
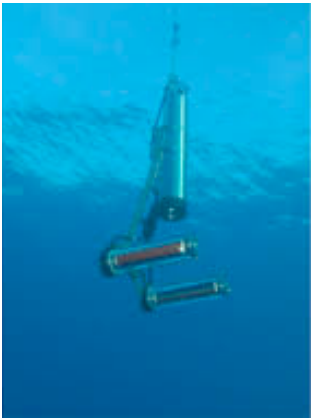
Marine (pelagic) imaging

2008 (4,000 samples)

2012 (17,000 samples)

2016 (56,000 samples)

2020 (91,000 samples)

Irisson et al. (2021)

3

Marine (pelagic) imaging

Need for an objective & reproducible way to extract information

2016 (56,000 samples)

2020 (91,000 samples)

Irisson et al. (2021)

Feature extraction

Imaging

Feature extraction

45 morphological features:
—> size
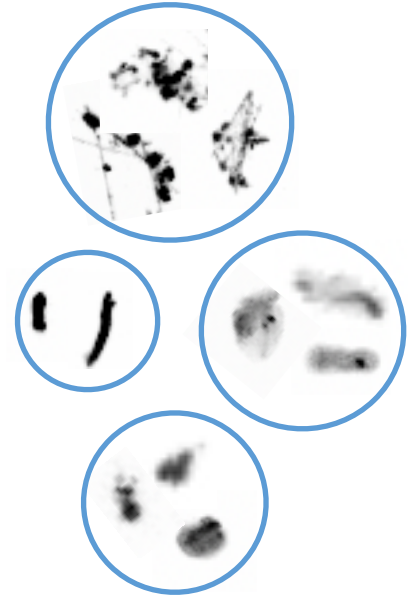—> shape
—> grey level
—> symmetry

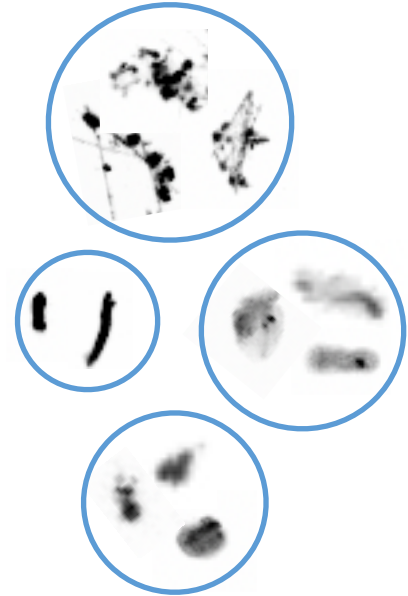# Feature extraction

Groups of morphological similar particles

Imaging

Feature extraction

45 morphological features:
—> size
—> shape
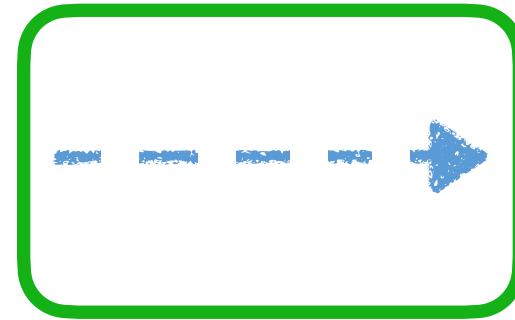—> grey level
—> symmetry

Feature extraction

Groups of morphological similar particles

Imaging

Feature extraction

45 morphological features:
—> size
—> shape
—> grey level
—> symmetry

Feature extraction

Groups of morphological
similar particles

Imaging

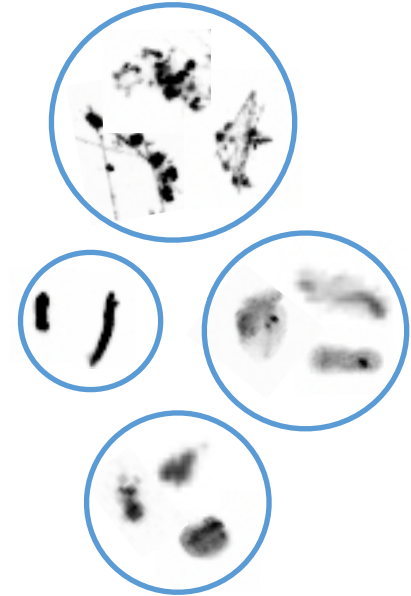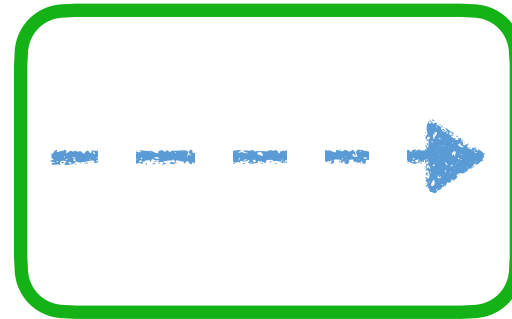Feature extraction

45 morphological features:
—> size
—> shape
—> grey level
—> symmetry

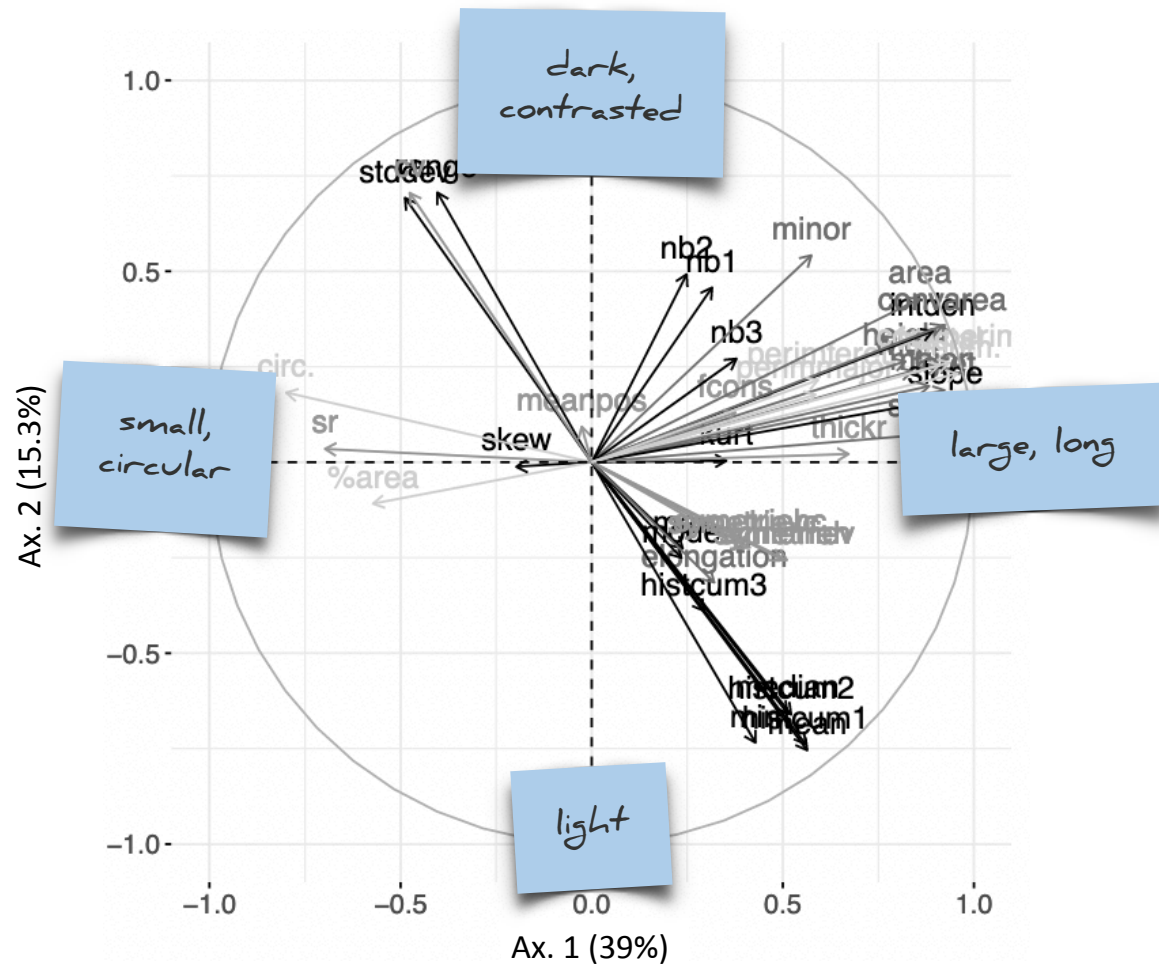Pipeline to define particle morphological groups
using image-derived features

Feature extraction

Groups of morphological similar particles

Imaging

Feature extraction

45 morphological features:
—> size
—> shape
—> grey level
—> symmetry

Pipeline to define particle morphological groups using image-derived features

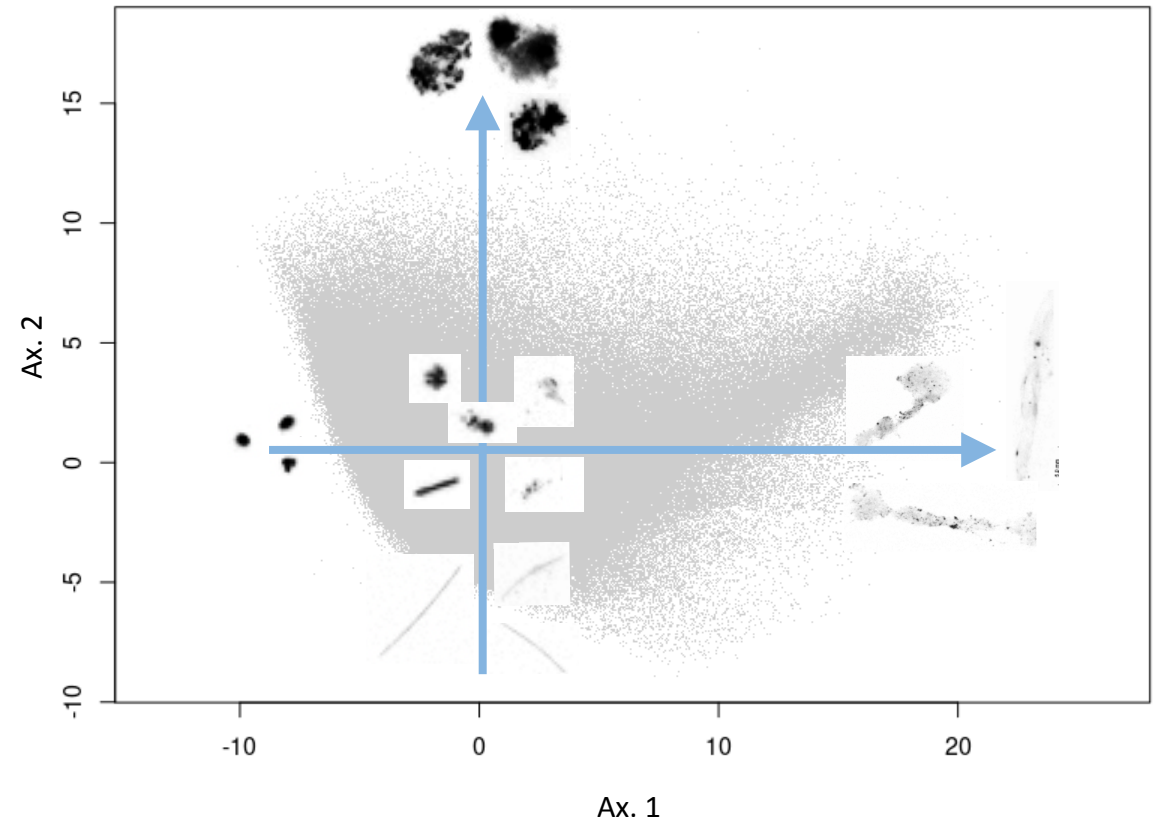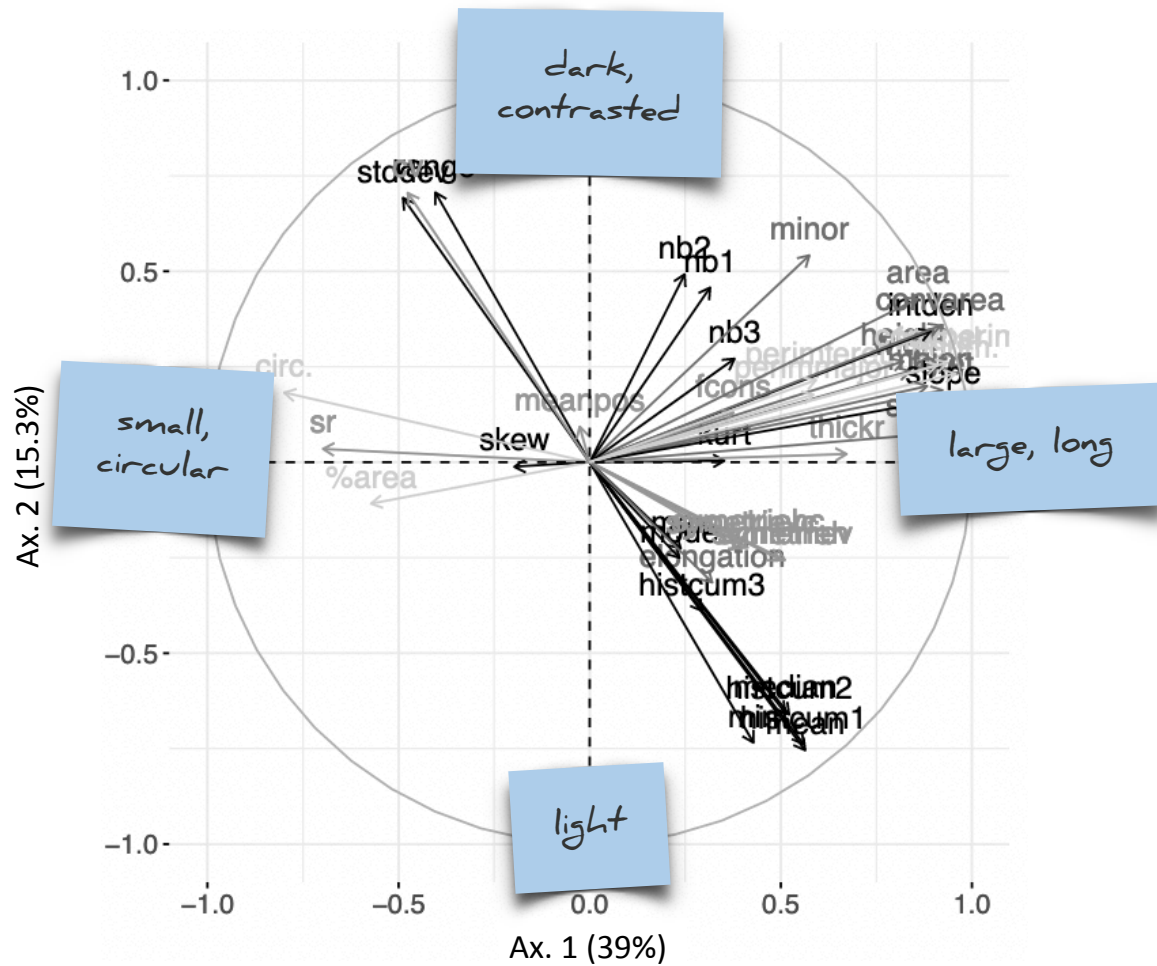Subset of UVP data by LOV and Geomar
—> n=896,095 images
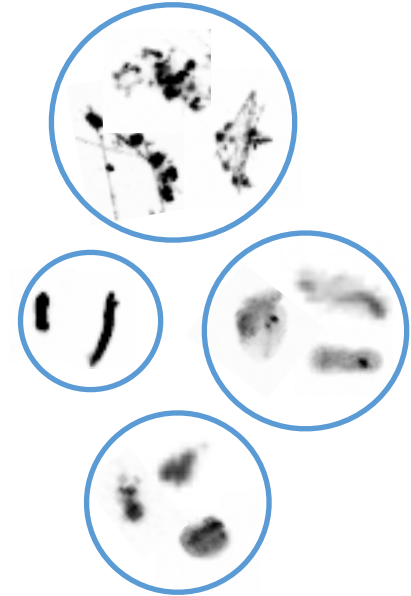
1) Dimension reduction

PCA including all 45 morphological features (1 dot = 1 imaged particle)

1) Dimension reduction

PCA including all 45 morphological features (1 dot = 1 imaged particle)
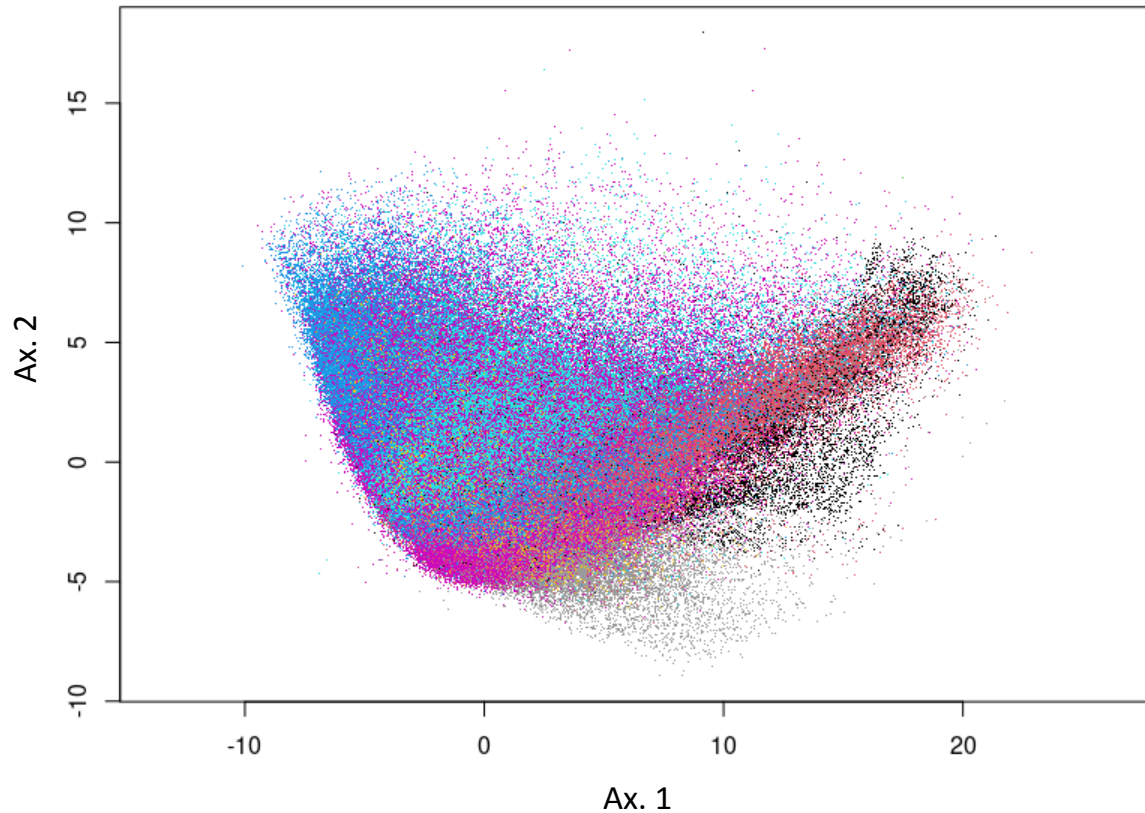
1) Dimension reduction

PCA including all 45 morphological features (1 dot = 1 imaged particle)
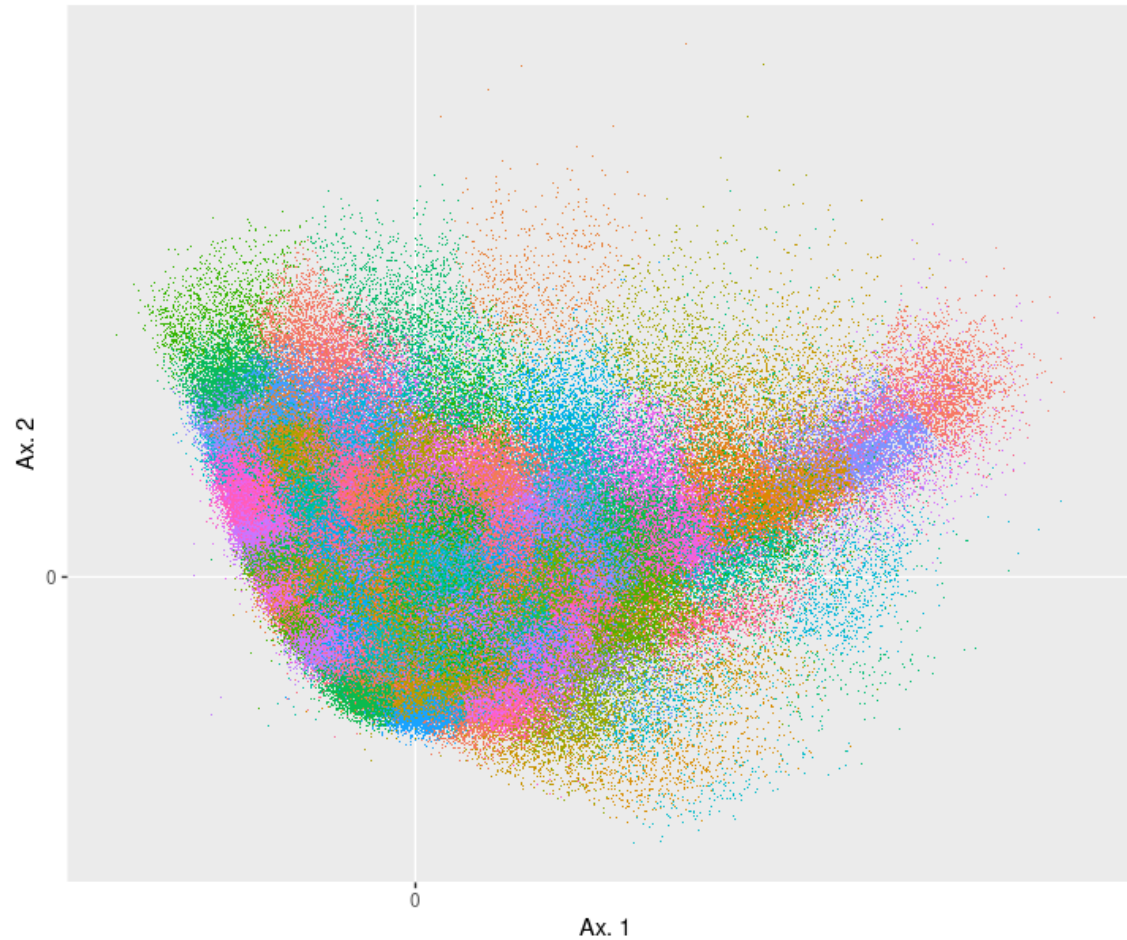
1) Dimension reduction

PCA including all 45 morphological features (1 dot = 1 imaged particle)
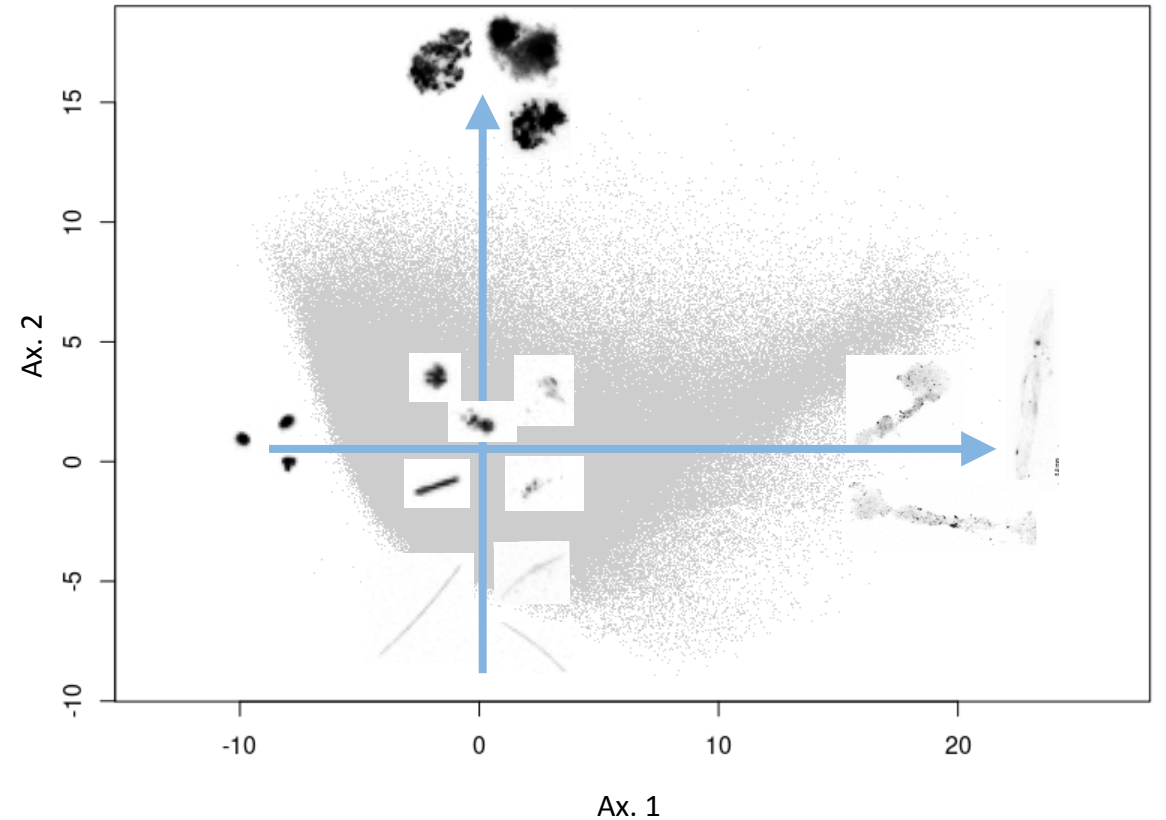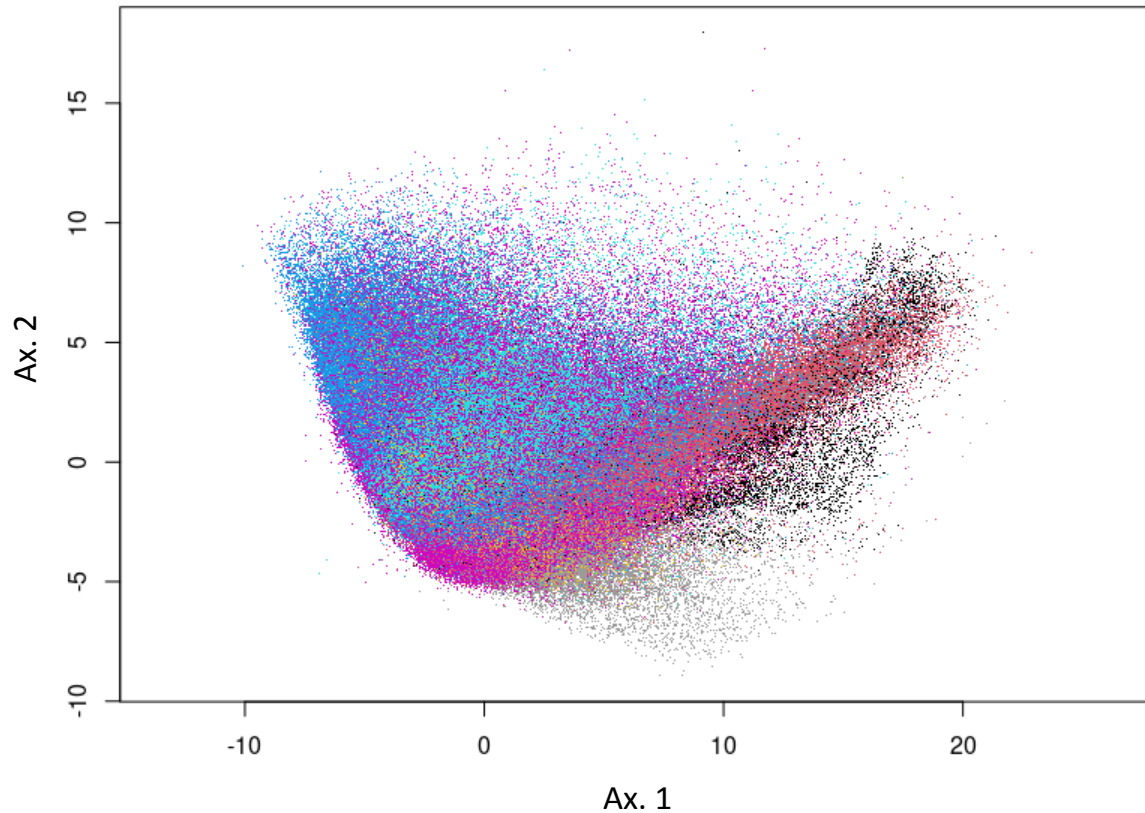
2) Definition of "morphs"

k=200
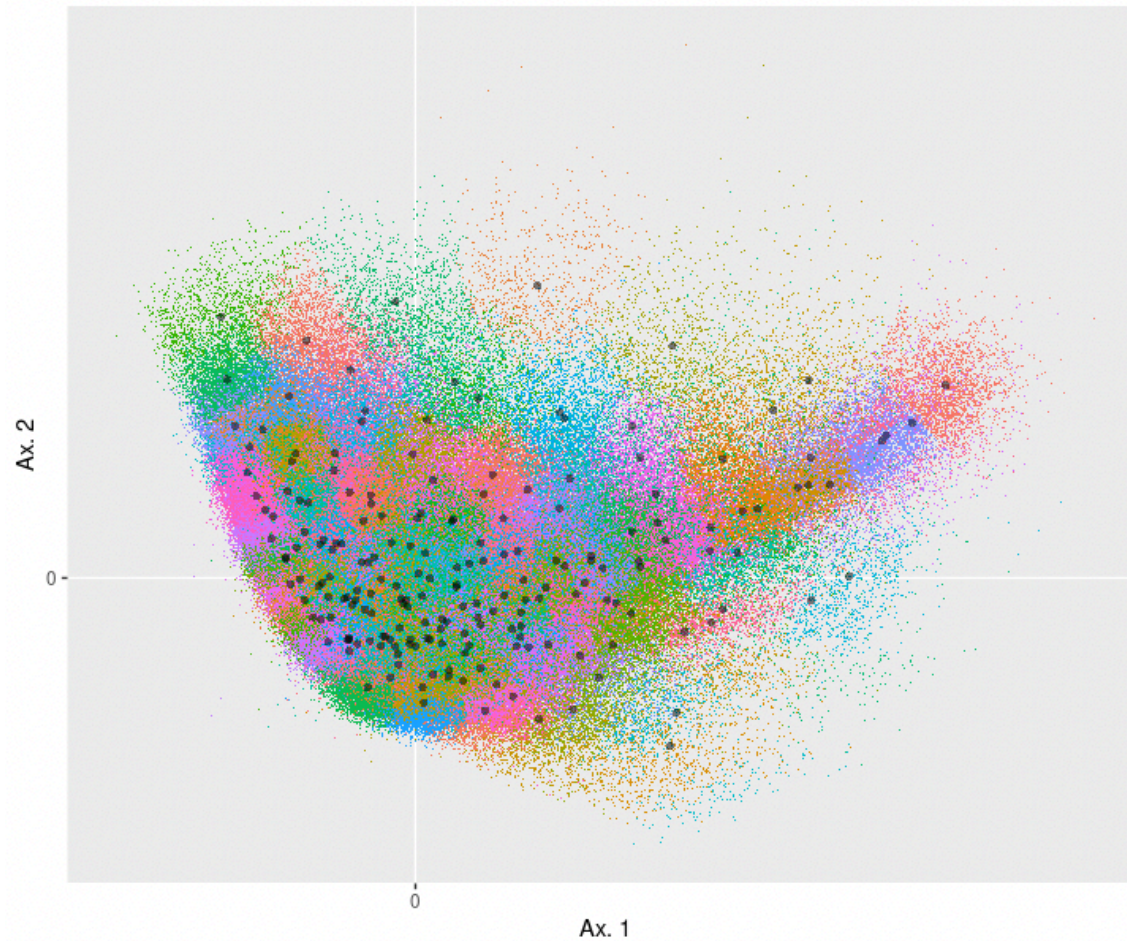
unsupervised clustering (k-means)…

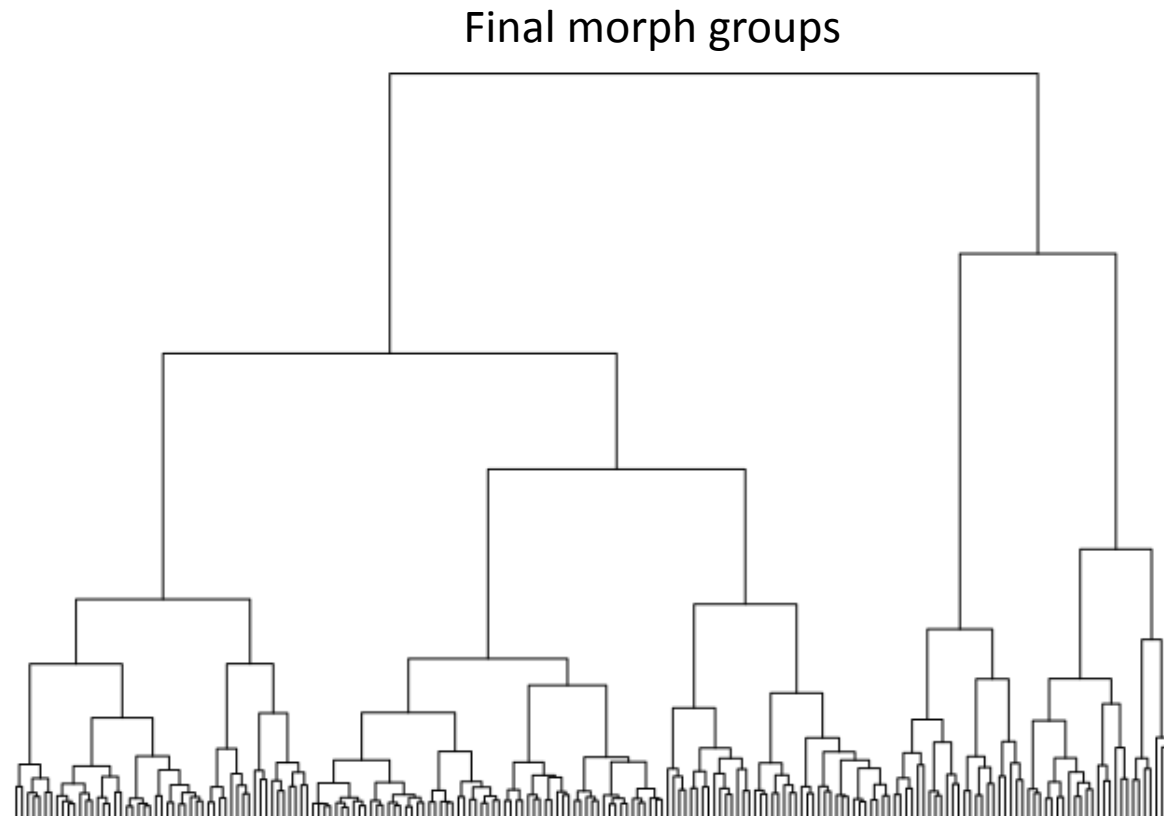# 2) Definition of "morphs"

unsupervised clustering (k-means)…

2) Definition of "morphs"

unsupervised clustering (k-means)…
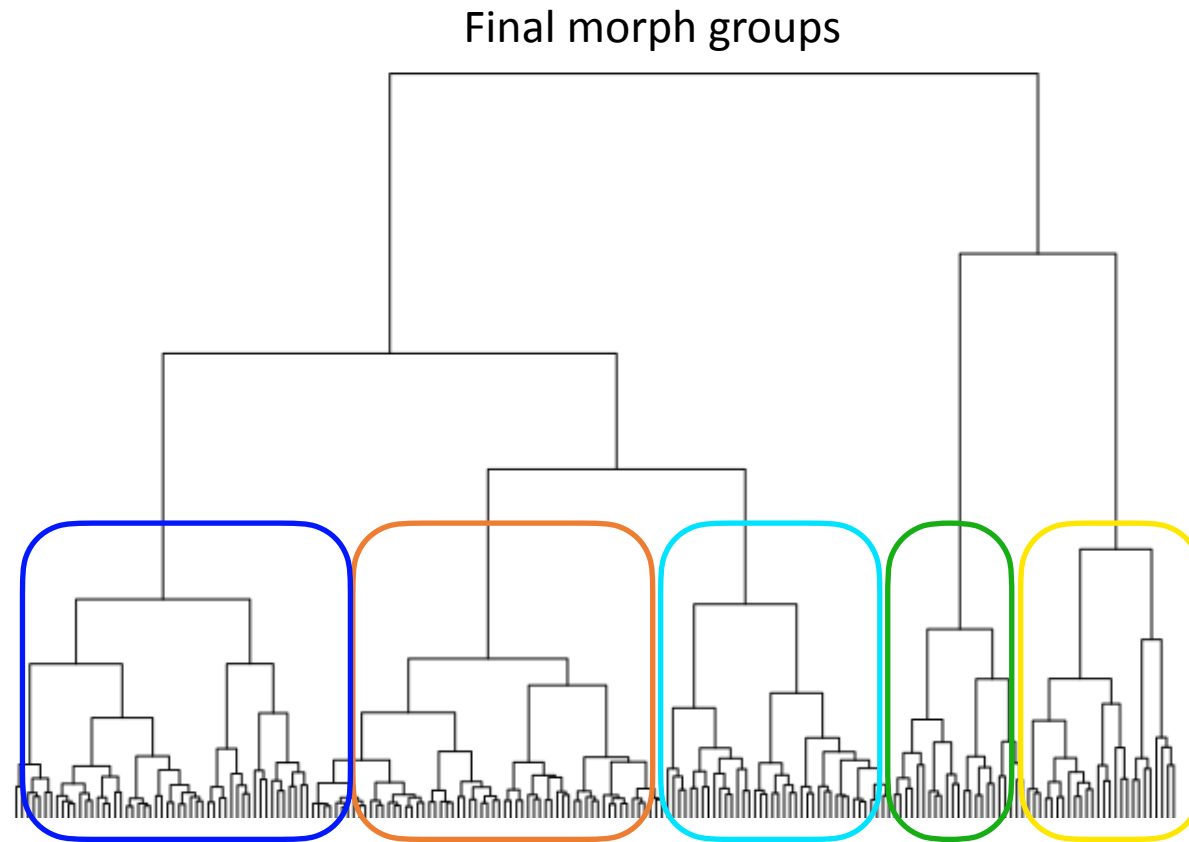…followed by hierarchical clustering on cluster centres

Final morph groups
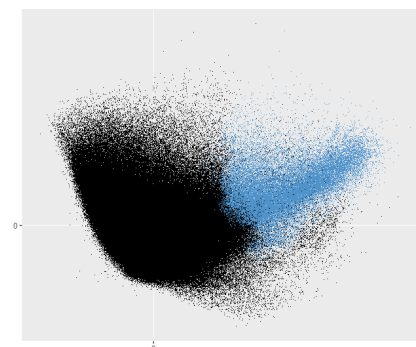
2) Definition of "morphs"

unsupervised clustering (k-means)...
...followed by hierarchical clustering on cluster centres

Final morph groups

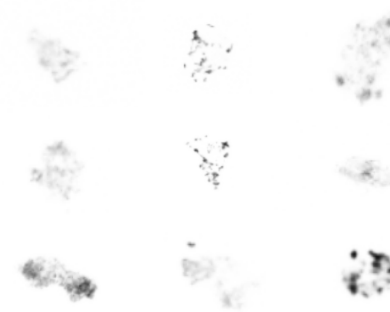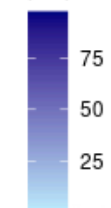# Geographical pattern

Proportion of "long & large" objects in surface layer

5mm

9
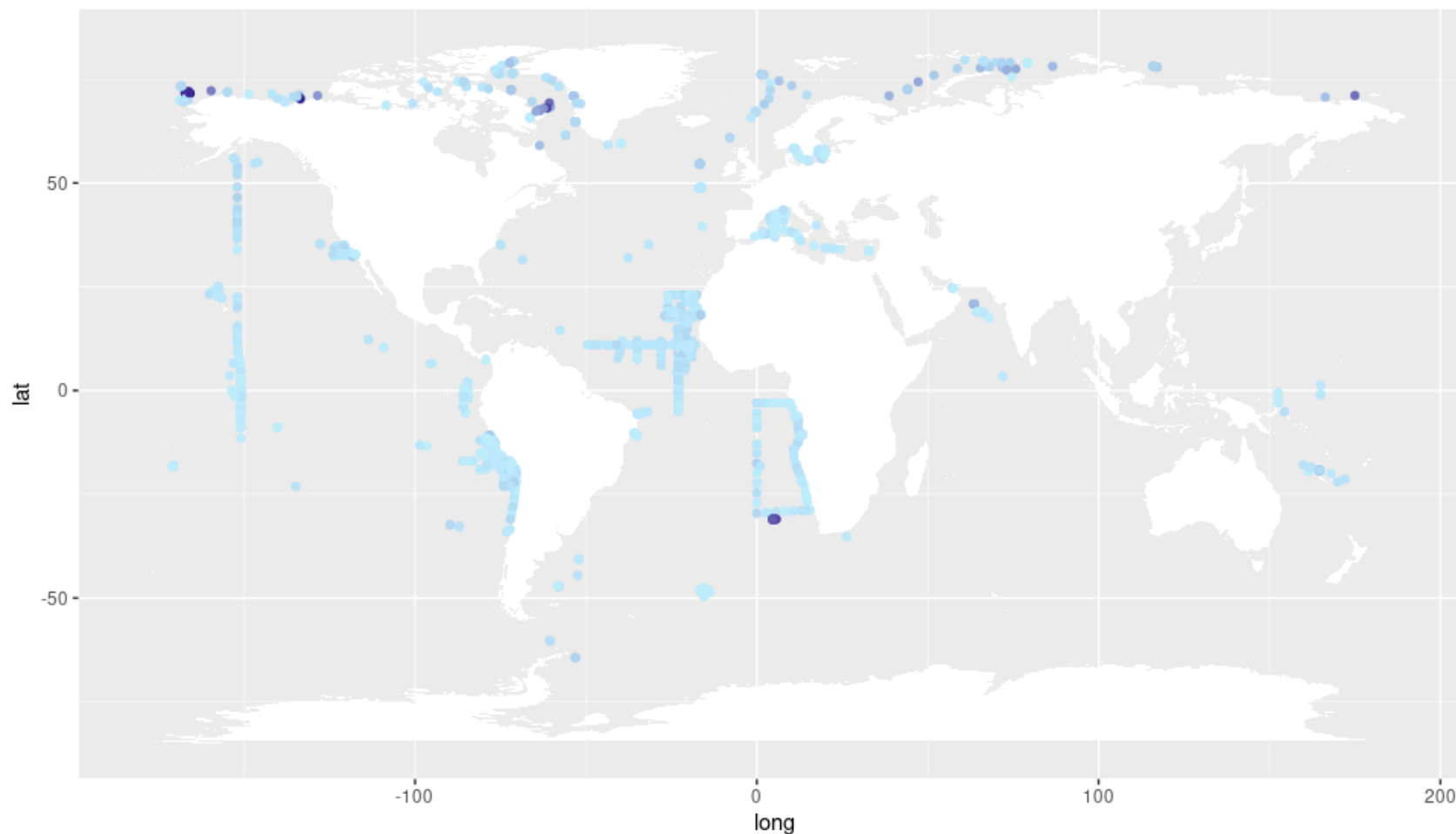
Geographical pattern

Proportion of "small & dark" objects in surface layer
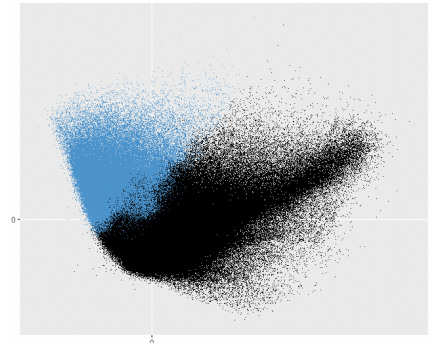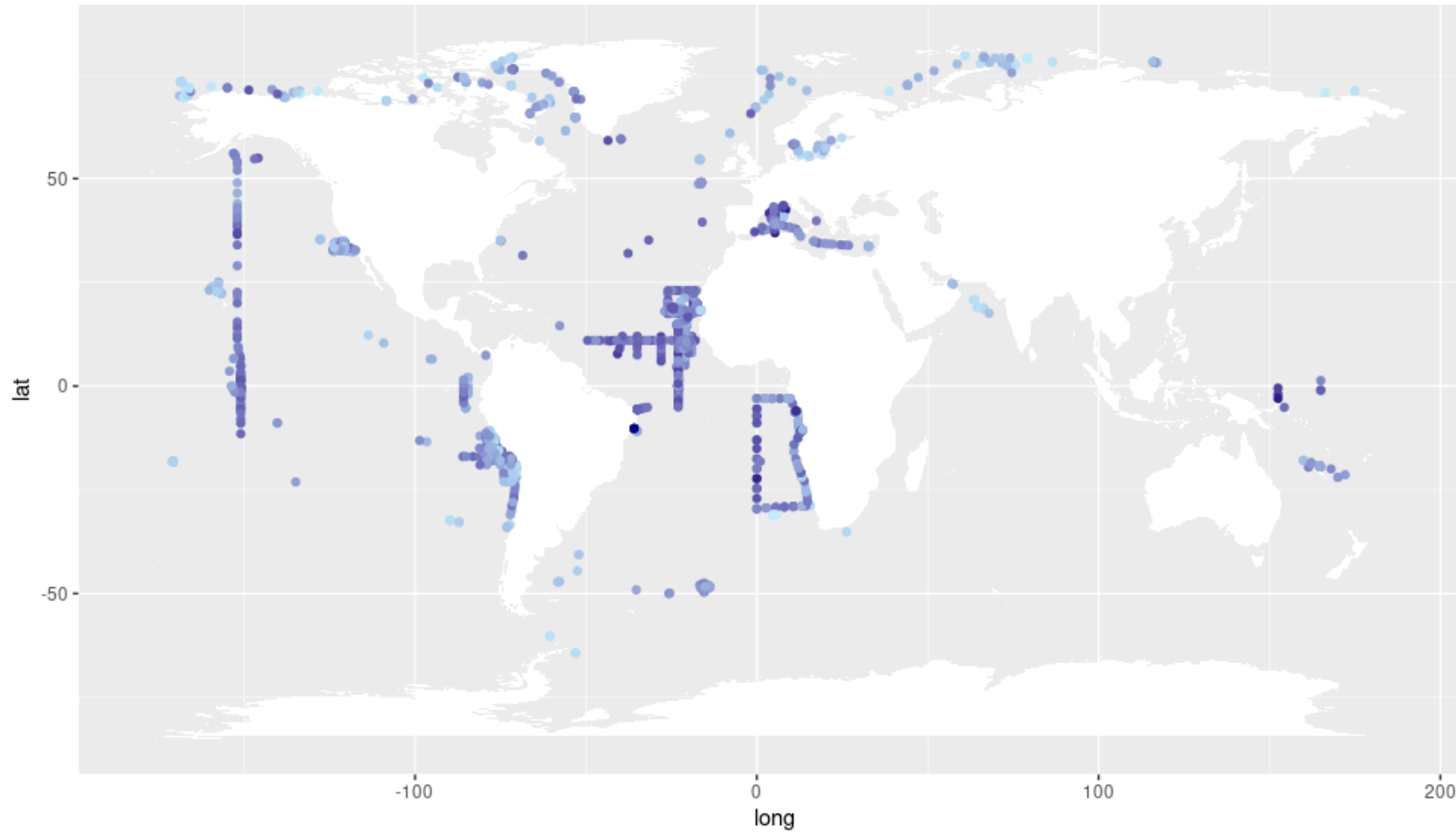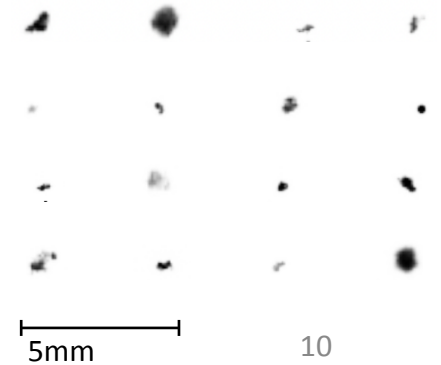
Conclusion

✓ It is possible to define groups of morphological similar particles based on image-derived features
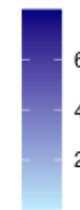—> It's meaningful!

Conclusion

✓ It is possible to define groups of morphological similar particles based on image-derived features
—> It's meaningful!

Next steps

➡ Test & identify best methods for each step

➡ Scale up the dataset

➡ Integration as feature into eco part

Conclusion

✓ It is possible to define groups of morphological similar particles based on image-derived features
—> It's meaningful!

Next steps

➡ Test & identify best methods for each step

➡ Scale up the dataset

➡ Integration as feature into eco part

...and hopefully improve/facilitate our understanding of ecological processes!

Thank you for your attention!

Lionel Guidi

Jean-Olivier Irisson

Sakina-Dorothée Ayata

Marc Picheral

Fabien Lombard

Rainer Kiko

Lars Stemmann

…& all those involved
in the sampling process!