

A global consistent database of plankton and detritus from in situ imaging by the Underwater Vision Profiler 5

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Abstract. Plankton and detritus are essential components of the Earth's oceans influencing biogeochemical cycles and carbon sequestration. Climate change impacts their composition and fluxes, and marine ecosystems as a whole. To improve our understanding of these changes, standardized observation methods and integrated global datasets are needed to enhance the accuracy of ecological and climate models. Here, we present a global dataset for plankton and detritus obtained by two versions (SD and HD) of the Underwater Vision Profiler 5 (UVP5). This release contains the images classified in 33 homogenized categories, as well as the metadata associated with them, reaching 3,114 profiles and ca. 8 million objects acquired between 2008-2018 at global scale. The geographical distribution of the dataset is unbalanced, with the Equatorial region (30° S - 30° N) being the most represented, followed by the high latitudes in the northern hemisphere and lastly the high latitudes in the Southern Hemisphere. Detritus is the most abundant category in terms of concentration (90%) and biovolume (95%), although its classification in different morphotypes is still not well established. Copepoda was the most abundant planktonic taxon, followed by *Trichodesmium* colonies.

The two versions of UVP5 have different imagers, resulting in a different effective size range to analyze plankton and detritus from the images (HD objects >600 μm , SD objects >1 mm) and morphological properties (grey levels, etc.); however, both systems capture comparable qualitative patterns in object morphology and relative abundance across size classes, even though the absolute ranges differ. Therefore, recommendations are provided for the appropriate use of this data when conducting studies. A large number of images of plankton and detritus will be collected in the future by the UVP5, and the public availability of this dataset will help it being utilized as a training set for machine learning and being improved by the scientific community. This will reduce uncertainty by identifying previously unclassified objects and expand the classification categories, ultimately enhancing biodiversity quantification. The dataset that constitutes this first release is available on SEANOE (<https://doi.org/10.17882/107583>).

Key words: plankton, images, Underwater Vision Profiler, Global Ocean

1 Introduction

Plankton and particulate matter play a crucial role in natural biogeochemical cycles and provide essential ecosystem services, including carbon sequestration, nutrient cycling, and primary food source for various marine organisms (Turner, 2015; Boyd et al., 2019; Stemmann and Boss, 2012; Steinberg and Landry, 2017). These components of the marine environment are significantly influenced by climate change, which alters ocean temperature, acidity, oxygenation, and circulation patterns (Doney et al., 2012; Constable et al., 2014). Such changes may, in turn, impact plankton composition by affecting their growth and survival (Hays et al., 2005; Dam and Baumann, 2017; Yebra et al., 2022), which will impact the production and composition of their solid waste, hereafter referred as detritus, with potential consequences for elemental biogeochemical cycles and deep-sea ecosystems (Du Pontavice et al., 2020).

The size range of plankton and detritus spans from pico- to macro-sizes, influencing the methods required for their observation. Collection methods include, for example, water sampling and microscopy for the smallest size classes, net tows and sediment traps for larger particles, while observation and analysis rely on complementary technologies such as optical imaging systems and remote sensing, depending on the targeted size range (Karsenti et al., 2011; Davis et al., 2005; Stemmann et al., 2008; Möller et al., 2012; Siegel et al., 2024). Consequently, obtaining homogeneous global datasets remains difficult notably if different instruments that measure various properties are used (Moriarty and O'Brien, 2013). Many planktonic organisms and detritus are fragile and their abundances decrease with their size, making their collection and analysis challenging (Stemmann et al., 2008; Soviadan et al., 2024; Atherden et al., 2024). Furthermore, plankton exhibits a patchy distribution in the ocean due to physical, chemical, and biological processes (Suthers et al., 2019). These constraints demand increased sampling efforts and the development of standardized methodologies to enhance comparability of global plankton and detritus observations. Addressing these challenges is critical for improving our understanding of oceanic carbon cycling and ecosystem responses to environmental change.

Predicting the future state of plankton biodiversity and/or biomass with habitat or biogeochemical models is difficult and requires data obtained synoptically and regularly. Deep collection by net tows followed by taxonomic identification with microscopes provides accurate biodiversity data, though this sampling method damages fragile organisms and requires dedicated ship time (Calbet, 2024; Soviadan et al., 2024; Giering et al., 2022). In addition, this classical classification is time-consuming and susceptible to human bias, which can hinder effective quality control (Goswami, 2004). Sensors mounted on conventional in situ platforms may provide better spatial resolution and have less impact on the observed target. In situ acoustics with broadband systems allow for broad taxonomic identification but are not adapted for detritus due to their poor scattering. For plankton, quantitative imaging has been identified as the best means to do so (Lombard et al 2019). In situ imaging methods are better suited to recognize plankton and detritus, but detect them in a smaller volume. Considering the advantages and limitations of each method, we can conclude that in situ imaging is particularly suited for observing plankton and detritus, using their shape to infer taxonomy or morphological attributes (Picheral et al., 2010; Stemmann et al., 2012; Lombard et al., 2019). However, there is a compromise between the observed volume and the resolution of the camera that defines a size range and taxonomic resolution for each type of sensor. Recent publications have suggested (Lombard et al., 2019, Kiko et al., 2023) and showcased (Drago et al. 2022, Clements et al. 2023, Laget et al. 2024) that cooperative observation of plankton with imaging systems can allow an upscaling of regional observations by independent observers to global scale.

The Underwater Vision Profiler camera system (UVP, version 5) is an optical imaging instrument designed to automatically detect, size, and count biotic and abiotic particles in the marine environment as it profiles through the water column (Picheral et al., 2010). To date, the 25 units of the UVP5 have been used at 14,462 sites since 2008 providing 94.8 millions of images and ~1,000 new profiles every year. The number of taxa that can be recognized is over 200, whereas robust data is available for the 30 most abundant taxa (Drago et al., 2022; Panaïotis et al., 2023). Semi-supervised classification (automatic prediction followed by human validation) of plankton images (Irisson et al., 2022) was performed at regional scales, because of the time required to analyze all profiles and the lack of dedicated work flow to deal with millions of images. Recently the development of the collaborative platform Ecopart (<https://ecopart.obs-vlfr.fr/>) for UVP metadata and data curation, and EcoTaxa (<https://ecotaxa.obs-vlfr.fr/>) for supervised image classification facilitated data treatment for the users. The data, initially recorded to address regional questions, can then be aggregated in global datasets to investigate global distributions of counts, size and vertical flux of all detected objects (Kiko et al., 2022; Clements et al., 2022; Clements et al., 2023). Furthermore, these platforms allow global studies on macrozooplankton biomass (Drago et al., 2022), and community composition (Panaïotis et al., 2023), as well as on the community proportions of Rhizaria (Biard et al., 2016), their impact on carbon flux attenuation, and silicification (Laget et al., 2024). To date, these studies provided the following data products: global plankton biomass, counts and group specific carbon demand data. In addition, to facilitate data access for modelers, all UVP5 particle size profiles, which were analyzed without image recognition, were released at a 1 degree spatial resolution (Kiko et al., 2022). A more recent database obtained by combining images from Imaging Flow CytoBot, Zooscan and UVP5 to provide data products on plankton and detritus biomass binned in 1 degree resolution was also released (Dugenne et al., 2024). An attempt was made to classify detritus images based on their morphology

(Trudnowska et al., 2022) but given their high number and the lack of consistent shapes, their classification at global scale is still challenging.

Here, we present the global dataset comprising approximately 8 million validated images of plankton and detritus, rigorously verified by expert taxonomists, associated with relevant metadata and their morphological measurements, that was not released in earlier studies. The dataset is of interest for marine ecologists interested in plankton biogeography and biogeochemical modeling and for computer scientists developing Artificial Intelligence methods to classify images. While the current plankton classification has been homogenized for 33 categories, there remains potential for further improvement to increase the list of taxa consistent at a global scale. Classification of detritus was not performed, as existing methodologies developed at regional scale must be improved for a global approach. By providing the raw images for plankton and detritus, we hope to foster the development of new algorithms to sort and analyze them. The manuscript is organized as follows: the Material and Methods section provides details about the UVP5, the inter-calibration and quality control procedures, as well as the dataset structure. The result section presents maps of the dataset distribution, summarizing statistics regarding taxa composition, size spectrum, description of global detritus and plankton distribution. The Discussion section provides recommendations for dataset use and potential future expansions of it.

2 Material and methods

2.1 Image acquisition with UVP5

2.1.1 UVP5 description

Data from the Underwater Vision Profiler 5 (UVP5), an in-situ imaging system designed to detect, measure, and quantify the distribution of zooplanktonic organisms and marine particles (Picheral et al., 2010), were used. The UVP5 was commercialized in 2010 and produced until 2021. The standard definition (SD) version with a 1.3 Megapixel greyscale camera was produced between 2008 and 2016 (serial numbers 000 to 011) and the high-definition (HD) version with a 4 Megapixel greyscale camera was produced between 2016 and 2021 (serial numbers 200 to 223). The UVP5 (SD and HD) images a volume of about 1 L at a frequency of 5 to 20 Hz and can be deployed down to 6000 m depth. The UVP5 is mostly integrated in the CTD-Rosette and therefore its results (particle and plankton counts) can be related to environmental data obtained with other sensors. All particles larger than appr. 100 μm Equivalent Spherical Diameter (ESD) are sized and counted but their images are not stored because the low number of pixels precludes any recognition of the particles. Recognized objects larger than 30 pixels (UVP5SD) or 80 pixels (UVP5HD) are automatically cropped and the resulting vignettes stored and further analyzed.

2.1.2 Image analysis by zooprocess

Vignettes contain plankton organisms, detritus and artefacts larger than approximately 1 mm ESD for UVP5SD and 600 μm for UVP5HD. Pixel size-to-millimeter conversions for UVP5SD and UVP5HD are derived

from objects of 30 and 80 pixels, respectively. For simplicity, we converted the surface area in pixels to its Equivalent Spherical Diameter. In addition, the released dataset contains 42 morphological features characterizing each object (area, major and minor axis, grey level etc.; Picheral and Mérieux, 2026) obtained from the segmentation of raw vignettes. Metadata collection (geographic location, date, etc.) and processing of all 8.46 million images was carried out using the ZooProcess software. For user convenience, the images were inverted to show dark objects on a white background and a scale bar was added to each vignette. Images and metadata were imported into EcoTaxa (Picheral et al., 2017), an application which allows a taxonomic classification of images via supervised learning algorithms, followed by manual validation (Irisson et al., 2022).

The two versions of the UVP5 have been inter-calibrated based on the size spectrum of all particles measured concurrently in natural conditions (Kiko et al., 2022). Therefore, size is a conservative property between the instruments and plankton community composition can be inter-compared. While all parameters, except for shape-based ones, differ between the SD and HD versions due to the distinct resolution of their imagers, other morphological properties, such as opacity, brightness, etc., may not be conservative, requiring caution in their joint analysis. For the HD version, measurements are taken from images with a dark field, which are then converted to a light field comparable to those in the SD version. Additionally, only images from a continuous descent of the instrument were retained. Beyond the SD/HD distinction, individual UVP5 units were operated with different acquisition settings, so their outputs are not directly comparable. In particular, the distribution of morphological features from unit sn000 differs from that of the other serial numbers. Users should therefore consider a correction before pooling data across units; a quantile-to-quantile transformation (code in Appendix B) should be applied to adjust the distribution profile of sn000 to match the other serial-number settings.

2.1.3 Semi-automatic image identification

Using EcoTaxa (<https://ecotaxa.obs-vlfr.fr/>), we applied semi-automated recognition in two steps following the third strategy path defined in Figure 2 by Irisson et al. (2022). First, features obtained using Zooprocess software or features re-calculated by a convolutional neural network (CNN) are considered to automatically predict object identities using a Random Forest algorithm. Therefore, various image learning sets were used independently on a project-by-project basis by different users. In this way, plankton organisms can be successfully classified into a few broad categories from the overdominant category of detritus with reasonable success. In a second step, manual validation and further sorting ensured correct classification of all plankton categories and detritus. In general, the sorting was performed by various users and institutions. To reduce the risk of wrong identification, a shared UVP5 taxonomic guide was used by all annotators to homogenize image sorting (EcoTaxaGuide application). In addition, annotations were rigorously quality checked by the authors. The classification of all images was strictly based on the morphological features of the objects in most cases. However, few annotators have used contextual information provided by other means (e.g., bottle or net collections, depth, GPS position) to classify objects with inadequate morphological attributes into taxa. For example, colonies of *Trichodesmium* (-contextual) can be reliably identified in

images when their presence is confirmed by concurrent bottle samples or net tows, even when their morphological features alone are insufficient for unambiguous classification.

2.2 Dataset

The UVP5 dataset (Figure 2) was compiled from observations across all oceans over a 10-year period (2008–2018) through a collaboration of international partners. It includes 3,114 profiles from 62 EcoTaxa projects conducted during research cruises by different institutions (Table A1), each aimed at addressing specific local or basin-scale research questions. It comprises vertical profiles validated to more than 99% which were retained for subsequent analysis. Currently, the different annotators (in total 71, Table A3) of the 62 EcoTaxa projects chosen have sorted the image datasets in more than 250 categories from species level to phyla or by adding morphological attributes and life stages. Such detailed classification is not possible over the whole dataset with high accuracy because recognition and sorting of organisms can be a source of bias depending on the levels of perception and experience of the people who perform them. Several cognitive biases exist, such as boredom, fatigue or a classification biased towards the most used groups (Culverhouse, 2007; Culverhouse et al., 2014).

In the present dataset, to reduce these errors and ensure classification homogeneity, the images were thereafter grouped into only 33 broader taxonomic groups for living organisms by combining all vignettes within the children categories (Table 1), while in EcoTaxa the original categories are maintained. The broad taxonomy list was established following recent published works using UVP5 data (Drago et al., 2022; Panaïotis et al., 2023; Laget et al., 2024) to ensure a minimum of 50 images per category and ecological patterns at regional or global scales for specific groups or community composition. For example, rhizarians were well studied at local (Biard and Ohman, 2020) and global scales (Biard et al., 2016; Laget et al., 2024) while polychaetes were mostly studied in the tropical Atlantic (Christiansen et al., 2018). Community composition analyzes have been conducted at local scales by Forest et al. (2012) and Barth et al. (2020), and at a global scale by Panaïotis et al. (2022). Global biomass was estimated in Drago et al. (2022). Inter-comparison with plankton net data at global scale (Soviadan et al., 2024) allowed to set confidence in the abundance assessments of many of these groups.

Images of unidentifiable objects exhibiting probable biological characteristics (e.g., symmetry, appendages, or tentacles) were classified into the “plankton-like” category. In this dataset, the term “-like” refers to structured objects that resemble organisms but cannot be taxonomically identified due to limitations such as poor focus, low resolution, incomplete capture, or lack of taxonomic knowledge. For example, copepoda-like contains all vignettes of copepods for which the antenna is not visible while the body shape resembles typical prosome and urosome. When recurring objects that were not yet classified appeared frequently but with uneven spatial distribution, temporary categories were created to accommodate them and labeled as temporary (tmpXXX). When contextual information to identify them was used, “contextual” was added to their names. All images of non-living organisms, including poor-quality images (blurred, low grey level, bubbles, artificial nature, badly segmented images) or particles (aggregates, fibers, pellets) were sorted into several categories without consistency criteria across the consortium. Low-quality

images (mostly objects not completely in focus) were set in a category named “artefact” that includes bad focus particles, plankton and real artefact, while particles were grouped into a single detritus category.

To ensure data consistency across projects, a subset of the dataset was reviewed to verify the accuracy of taxonomic sorting within each group. A total of 200 images were extracted from each category, or all available images if fewer than 200 were present. For detritus, 10 % of the total images were selected and independently reviewed by a different trained operator, working independently of the initial classification, after the final dataset was assembled. The error or uncertainty rate was under 8 % for taxa classification. Among the detritus, less than 0.1 % were plankton organisms. The resulting global dataset consisted of 7.05 million detritus images and 734 thousand plankton images from 3,114 profiles.

Due to the large number of plots required to display the results for all categories, results are shown for a subset of the original categories. From the 33 initial categories derived from taxonomy (Table 1), five broader taxonomic groups were defined for further analysis based on shared feeding strategies and ecological traits (e.g. habitat, life mode, and trophic role). These groups can be highly useful as input for biogeochemical or community ecology models. The groups include Crustacea (Copepoda and Malacostraca), gelatinous filter-feeders (Appendicularia, Salpida), gelatinous carnivores (Chaetognatha, Narcomedusae, Siphonophorae, Ctenophora), Rhizaria (Collodaria, colonial Collodaria, other Rhizaria, Foraminifera, Phaeodaria, Acantharea), and *Trichodesmium*. From these groups, biovolumes were calculated along with concentrations at different depths and for the analysis of the average grey level.

2.2.1 Data output format

We provide four tables with numerical data (in .tsv format), as well as all images (with .jpg extension) while their full description is available in the information documents (UVP5_dataset_organization.txt) during the download. Briefly, ‘objects.tsv’ is the data table which contains each object information. The three first columns refer to the unique object ID given by Ecotaxa, original object classification in Ecotaxa and object classification according to Table 1. The following 42 columns contain all the object features obtained from the image (see Table A2). The ‘samples.tsv’ file is the table with the metadata corresponding to all the coordinates (latitude, longitude, date and time) and acquisition details (pixel size and UVP model). The ‘samples_volume.tsv’ is a table that contains the volume of water in which the object was extracted and that is used to calculate concentrations (middle depth bin and volume imaged). Finally, ‘properties_per_bin.tsv’ is a table with concentrations, biovolume, average size (ESD) of the 33 consistent categories per depth bin and per sample. The native size bin of the dataset is 5 m, but to reduce the size of the file and avoid too many zeros, we provide 25 m depth bins in the surface ocean (down to 200 m depth), 50 m depth bins (down to 500 m depth), 100 m bins (down to 1000 m depth) to 250 m below 1000 m. We provide the code in R to recalculate the table with a depth bin of 5 m. The two files ‘ODV_biovolumes.txt’ and ‘ODV_concentrations.txt’ contains the same information as ‘properties_per_bin.tsv’ but in the ODV format.

Table 1: List of categories that are quantitatively consistent in this work and names of children categories not homogeneous among the projects. Categories also defined by their morphotypes or life stages are in bold. The published dataset contains both the broad and the children categories (when more than 50 vignettes were available for the category). When available publications using the dataset at regional scales are listed. Exponent numbers denote the association with an image example in Figure 1.

Broad categories	Children categories	Reference
Acantharia ¹		
Actinopterygii ²		
Annelida ³	<i>Alciopidae</i> , <i>Phyllodocidae</i> , <i>Tomopteridae</i> , <i>Acrocirridae</i> , <i>Flota</i> , <i>Poebius</i>	Christiansen et al., 2018; Barth and Stone, 2022
Appendicularia ⁴	body, house	Forest et al., 2012
Bacillariophyta-contextual ⁵	All objects classified as such using contextual data	
Chaetognatha ⁶	tail <Chaetognatha, head <Chaetognatha	Forest et al., 2012; Barth and Stone, 2022
other Collodaria ⁷	Solitaryblack, solitaryglobule	Biard and Ohman, 2020
colonial Collodaria ⁸		Biard and Ohman, 2020
Copepoda ⁹	like<Copepoda, Eucalanidae, like<Temoridae, ovigerous, ovigerous_side, ovigerous_top-bottom, Pseudocalanus, Harpacticoida	Forest et al., 2012; Vilgrain et al., 2021; Barth and Stone, 2022
Ctenophora ¹⁰	Beroida, Cestidae, Lobata, tentacle <Ctenophora	Forest et al., 2012
Doliolida ¹¹		
Eumalacostraca ¹²	Amphipoda, Pleuroncodes, Euphausiacea, Munnopsis	Forest et al., 2012; Barth and Stone, 2022
Foraminifera ¹³		
Gasteropoda ¹⁴	Gymnosomata, Limacinidae, Creseidae, other Thecosomata	
Narcomedusae ¹⁵	<i>Solmundella bitentaculata</i> , Solmaris	
Nostocales ¹⁶	Aphanizomenon, Dolichospermum, Nodularia	
Ostracoda ¹⁷		Barth and Stone, 2022
Phaeodaria ¹⁸	Castanellidae, Circoporidae, Tuscaroridae, Aulacanthidae, <i>Aulacantha</i> , <i>Aulographis</i> , <i>Coelodendrum</i> , <i>Coelographis</i> , leg <Coelodendridae, Medusettidae, Aulosphaeridae, <i>Aulatractus</i> , colonial <Aulosphaeridae, like< <i>colonial</i> , Cannosphaeridae, colonial <Cannosphaeridae	Biard and Ohman, 2020
Pyrosoma ¹⁹		
Salpida ²⁰		
Siphonophorae ²¹	part <Siphonophorae, tentacle <Siphonophorae	
Trachymedusae ²²	Halimnecidae, <i>Aglantha digitale</i>	

<i>Trichodesmium</i> ²³	Puff, Tuff	Guidi et al., 2012; Sandel et al., 2015
<i>Trichodesmium</i> -contextual ²⁴	all objects were classified as such by using contextual data, 95% are from the same cruise	Dupouy et al., 2018
other Cnidaria ²⁵	Ceriantharia	
other Crustacea ²⁶	larvae <Crustacea, tail <Crustacea	
other Hydrozoa ²⁷	Leptothecata	
other Mollusca ²⁸	veliger	
other Rhizaria ²⁹	contains plankton resembling to Rhizaria	
tentacle of Cnidaria ³⁰		
plankton-like ³¹	contains all structured objects most probably living organisms, which are in multiple categories to check, possibly plankton, to resort, other living and to rename	
detritus ³²	contains particles such as aggregates, filaments, mucus net which are not yet sorted	Trudnowska et al., 2021
Artefact ³³	bubble, turbid	

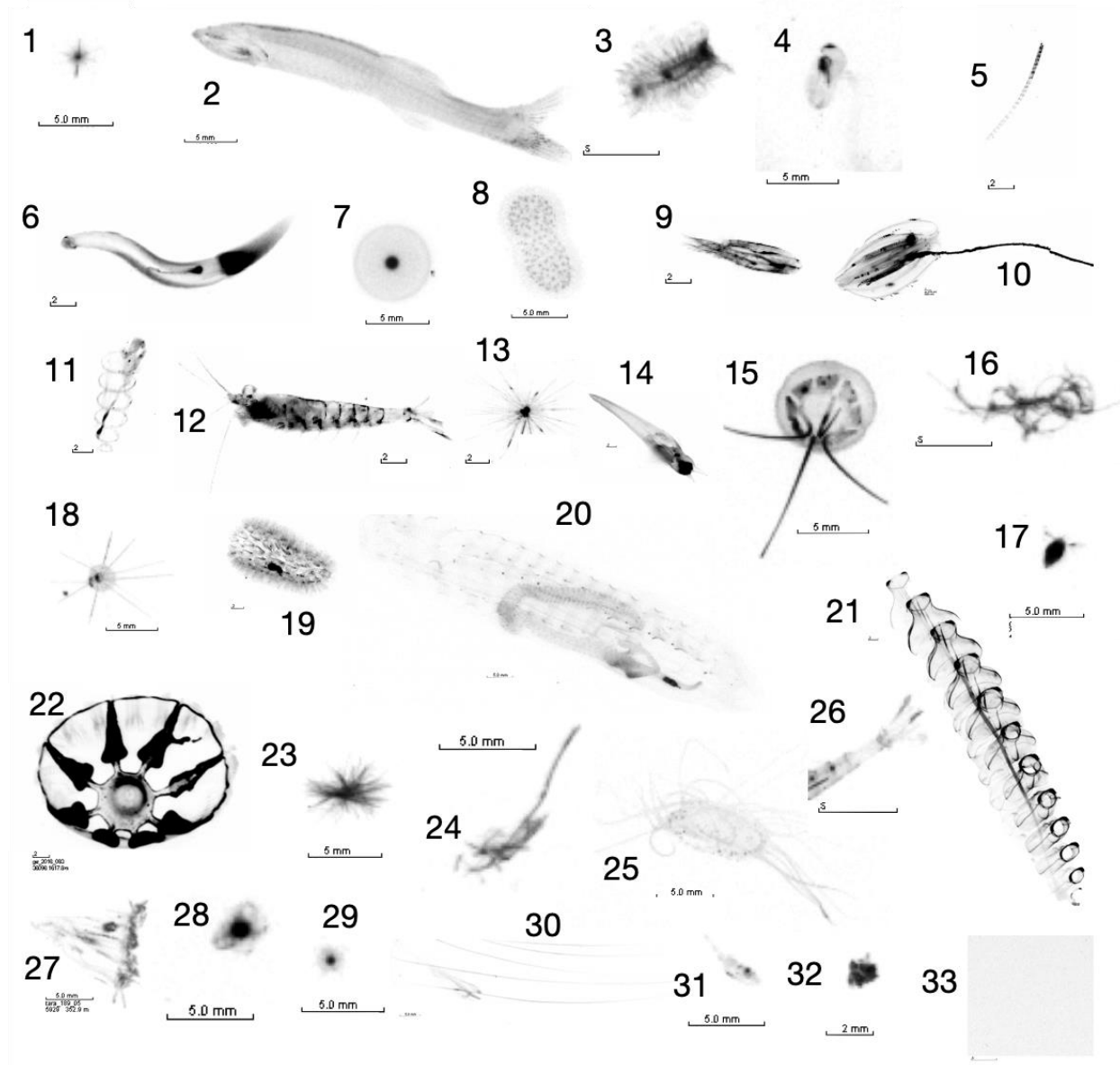


Figure 1: Examples of images for each category (Table 1) present in the dataset. All images contain the same scale bar (5 mm) which appears very small for large objects.

3 Results

3.1 Data coverage in time and space

The dataset presented here revealed a heterogeneous global distribution. The UVP5 deployments predominantly occurred in the northern hemisphere (66.3% of profiles, Figure 2), especially in tropical and temperate latitudes where seasonal variations are well observed. In contrast, the southern hemisphere had fewer observations (33.7% of profiles), resulting in a less comprehensive dataset. The region between 30° S-30° N represented the highest proportion of UVP5 profiles (47.25%). The vertical profiles distribution revealed a predominant concentration of

measurements in the upper 1000 m of the water column, representing 40.6% and 46.8% for the SD and HD models respectively, with a peak occurring within the upper 500 m. Thus, most deployments targeted shallower depths. The SD version of the UVP5 demonstrated the most extensive coverage, with profiles spanning the entire latitudinal range. Meanwhile, the HD profiles were prevalent in the Northern Hemisphere. The profiles also presented a remarkable annual and interannual variation observed primarily in the northern hemisphere and the under-sampling of the southern hemisphere and the deep sea.

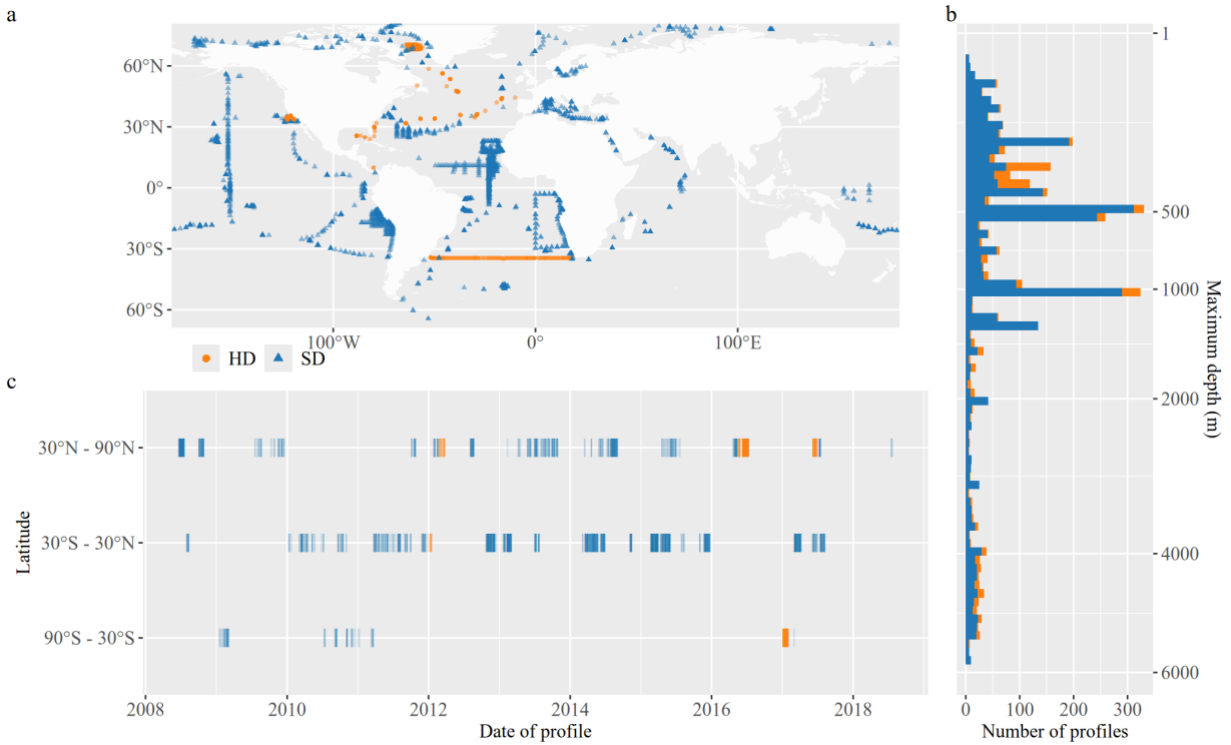


Figure 2: a) Sampling effort for the two versions of UVP5 (SD and HD, blue and orange, respectively) between 2008-2018 in the global ocean. b) Latitudinal distribution of UVP5 profiles and c) Maximum vertical extent of the profiles.

3.2 Detritus and plankton composition in the whole dataset

Detritus was the most abundant category (90.5% of total images), indicating a substantial presence of non-living particulate organic material (Fig. 3). Copepoda dominated zooplankton (2.2%), followed by *Trichodesmium* (1.3%), *Trichodesmium*-contextual (1.1%), the plankton-like category (1%), artefacts (0.9%), Phaeodaria (0.8%), and Bacillariophyta-contextual (0.6%). Each of the remaining groups represent < 0.16% of the total number of objects.

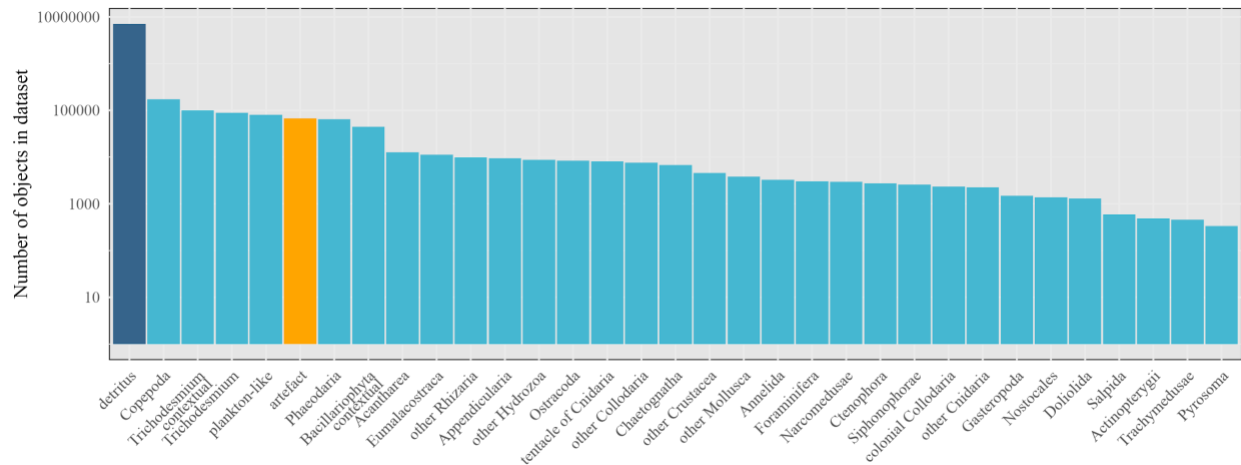


Figure 3: Barplot with total number of objects in logarithmic scale available in the dataset per category (detritus and plankton) for the 33 consistent categories ordered by descending counts with specific categories ("detritus" and "artefact") highlighted in distinct colors.

3.3 Global distribution of plankton and detritus

The spatial patterns of plankton and detritus concentrations in the global ocean vary significantly with depth and location. Across all depth layers, plankton and detritus abundances increased (up to 5 plankton/m³ and 60 detritus/m³ in the 0-100 m depth layer and up 2 plankton/m³ and 20 detritus/m³ in the 500-1000 m depth layer, Figure 4) in eastern boundary current systems (especially in the Californian and Senegal upwelling systems) or in coastal seas. Minimum values (up to 2 plankton/m³ and 20 detritus/m³ in the 0-100 m depth layer and up 1 plankton/m³ and 1 detritus/m³ in the 500-1000 m depth layer) were usually found in the center of large ocean gyres (notably in the South Pacific and the Indian Ocean).

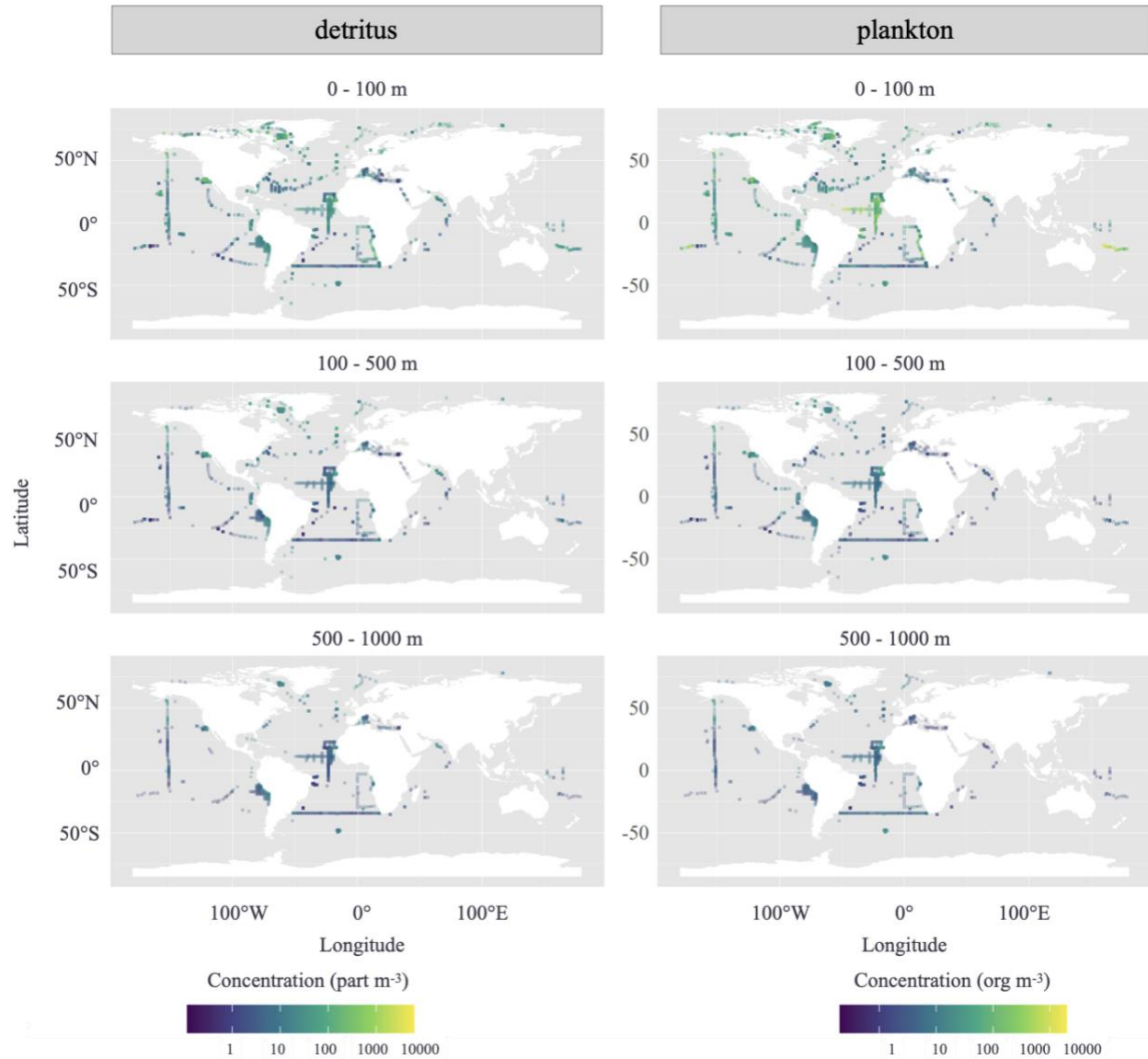


Figure 4: Map of the global distribution of detritus and plankton concentration (log particles/organism m^{-3}) in three layers (0-100, 100-500 and 500-1000 m).

3.4 Average size distribution of SD and HD versions

The distribution of detritus followed a dome-like pattern (criteria from Drago et al., 2022), with UVP5 showing a lower detection threshold for particles below 1 mm for UVP5 SD and 600 μm for UVP5 HD (Figure 5). In contrast, plankton categories exhibited a much flatter normalized biomass/biovolume size spectra (NBSS) distribution. Detritus dominated the smaller size range (<1 mm) while the contribution of plankton increased relative to detritus in the larger size range. Except for Rhizaria, smaller planktonic organisms were more abundant in the upper 100 m in the UVP5HD dataset, emphasizing the detection limits of the two camera versions in the small size range for both plankton and detritus.

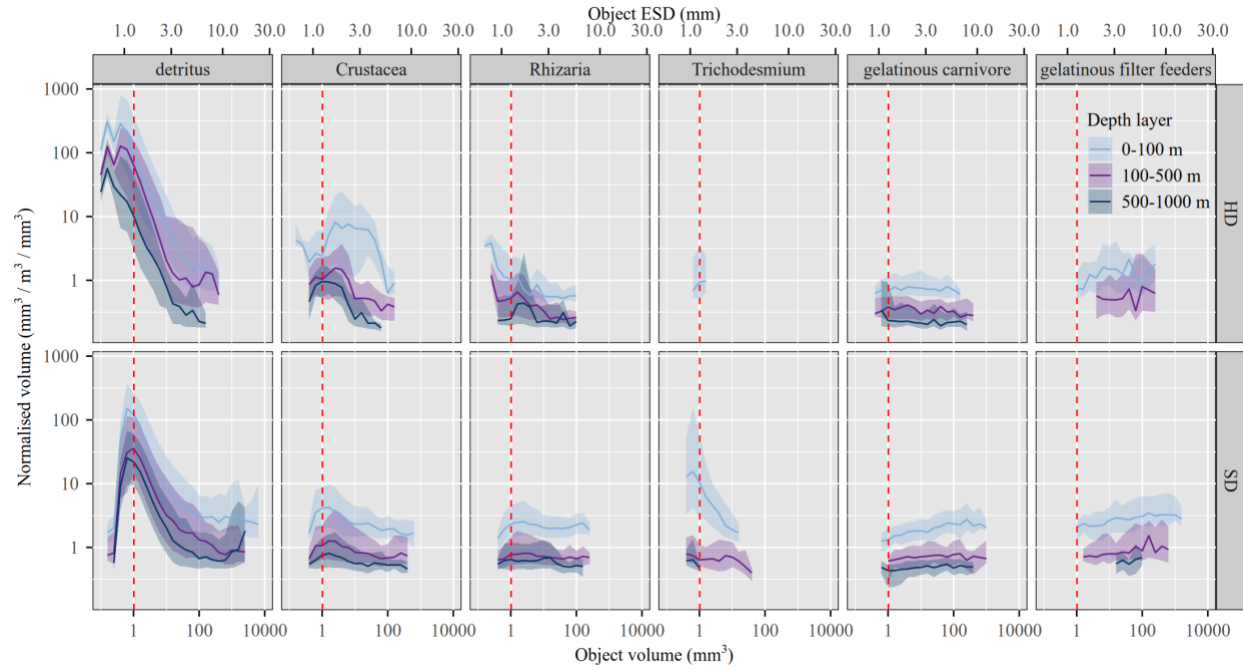


Figure 5: Average size distribution of detritus and plankton categories obtained by the SD and HD version of the UVP5 in three depth layers. Red dashed line indicates the threshold value (1.02 mm) below which UVP5 detection of organisms is difficult to quantify properly. Crustacea (Copepoda and Malacostraca), gelatinous filter-feeders (Appendicularia, Salpida), gelatinous carnivores (Chaetognatha, Narcomedusae, Siphonophorae, Ctenophora), Rhizaria (Collodaria, colonial Collodaria, other Rhizaria, Foraminifera, Phaeodaria, Acantharea), and Trichodesmium.

3.5 Plankton to detritus ratio as a function of size

For both UVP5s, the proportion of plankton images on all images (detritus and plankton) increased with size from 0.01 at 500µm to about 0.8 for objects larger than 3 mm in ESD. The two instruments displayed a similar pattern with a plateau in this ratio starting at about 3 mm. In general, the ratio did not vary with depth and remained at 0.8 for objects larger than 3mm.

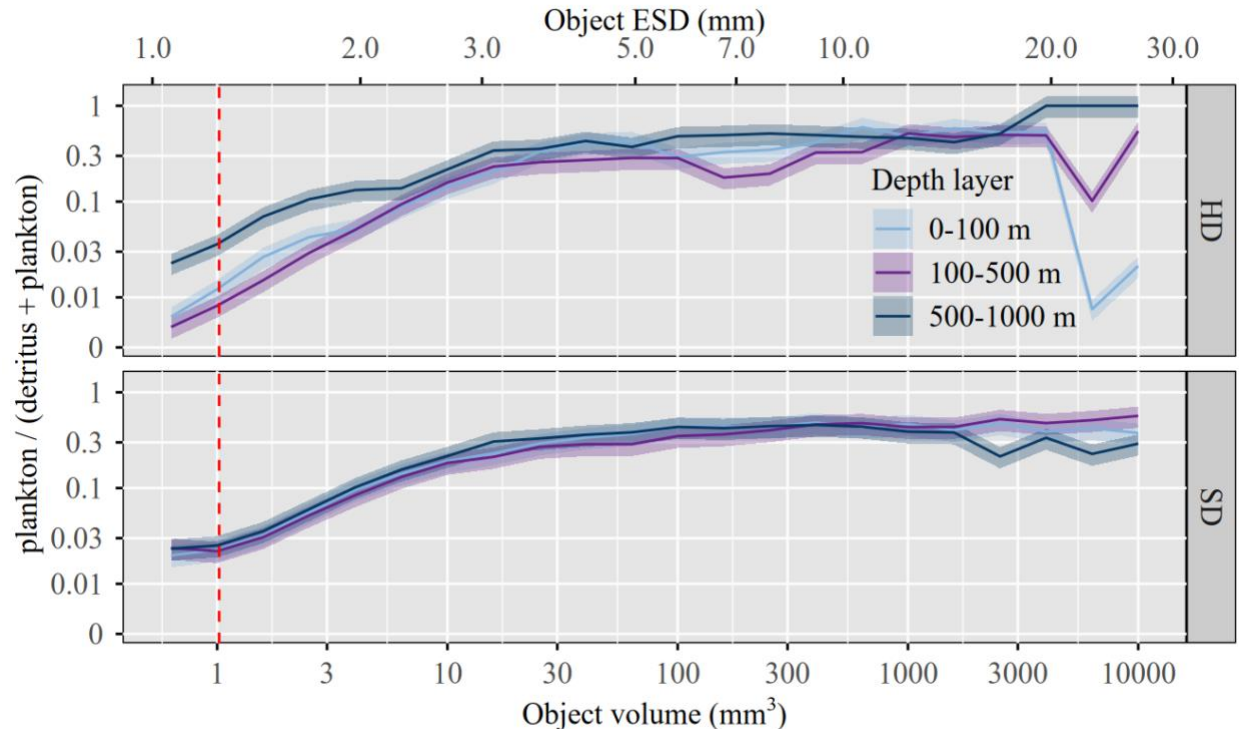


Figure 6: Abundance ratio of plankton (without plankton-like) over all images as a function of size for the two different UVP5 versions. Red dashed line indicates the threshold value (1.02 mm) below which a robust detection of organisms is limited.

3.6 Vertical profiles of detritus and plankton concentrations

When analyzed across vertical layers (Figure 7), detritus showed the highest concentrations in the upper 100 m, with biovolume patterns mirroring concentrations and exceeding those of living plankton by several orders of magnitude. *Trichodesmium* (excluding *Trichodesmium*-contextual) was the most abundant group in surface waters, but contributed relatively little to biovolume due to its small size (Figure 4). Crustacea displayed comparable patterns in concentration and biovolume, with high surface abundance and decreasing values with depth. Gelatinous plankton, including filter feeders (Appendicularia, Salpida) and carnivores (Chaetognatha, Narcomedusae, Siphonophorae, Ctenophora), were characterized by low concentrations but disproportionately high biovolume, particularly in the upper 100 m, with both metrics declining with depth. Rhizaria also peaked in concentration and biovolume in surface waters and decreased gradually down to 1000 m.

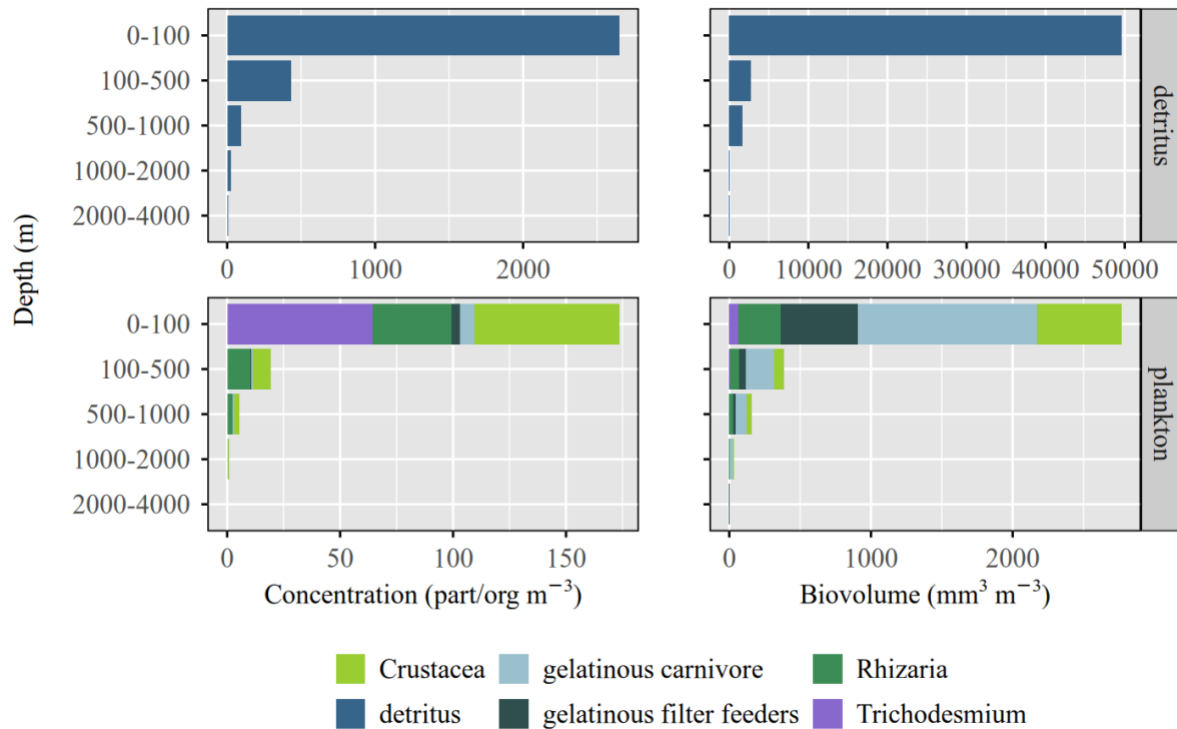


Figure 7: Global vertical profiles of concentration and biovolume for detritus and the five plankton groups. part: particles of detritus; org: organisms from different taxa categories. Crustacea (Copepoda and Malacostraca), gelatinous filter-feeders (Appendicularia, Salpida), gelatinous carnivores (Chaetognatha, Narcomedusae, Siphonophorae, Ctenophora), Rhizaria (Collodaria, colonial Collodaria, other Rhizaria, Foraminifera, Phaeodaria, Acantharea), and *Trichodesmium*.

3.7 Morphological properties

The key morphological properties for detritus and the five plankton categories presented similar patterns between the two UVP5 versions (SD and HD) (Figure 8). In some cases, the range differed between versions for the groups depending on the property examined. Gelatinous groups were the biggest categories in terms of area measured, while they presented the lowest circularity, compared to the remaining groups. Crustacea was the darkest group, whilst gelatinous were the lightest ones.

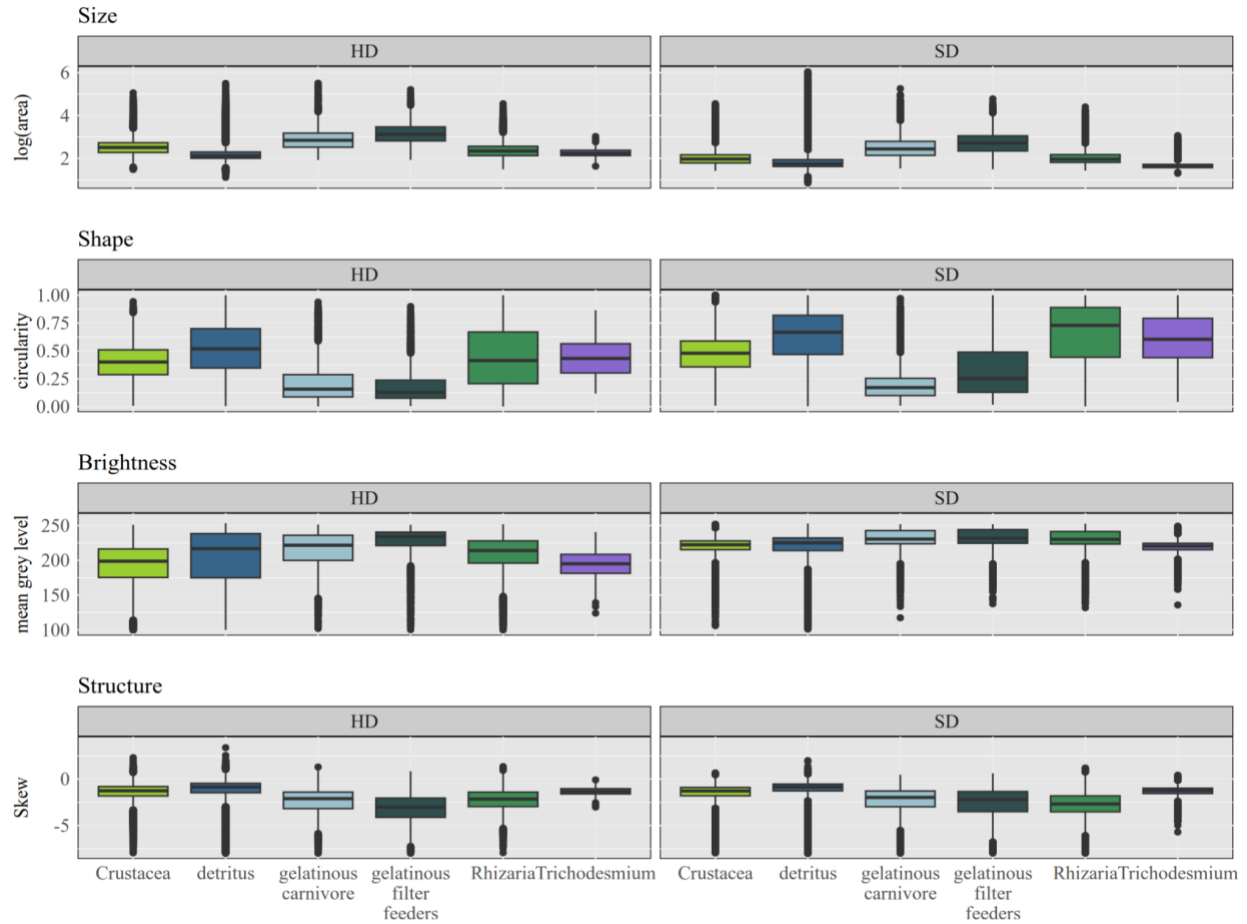


Figure 8: Box plots of key exemplary morphological properties (area, circularity, mean grey level, skew) for detritus and the five taxonomic groups (Crustacea, gelatinous carnivore, gelatinous filter feeders, Rhizaria and *Trichodesmium*) for the two UVP5 versions (HD and SD). Crustacea (Copepoda and Malacostraca), gelatinous filter-feeders (Appendicularia, Salpida), gelatinous carnivores (Chaetognatha, Narcomedusae, Siphonophorae, Ctenophora), Rhizaria (Collodaria, colonial Collodaria, other Rhizaria, Foraminifera, Phaeodaria, Acantharea), and *Trichodesmium*.

4 Discussion

The availability and accessibility of both the UVP5 images and their associated metadata present new challenges, encouraging the scientific community to leverage and refine them for future research. With this objective in mind, the dataset presented here serves as a starting point for further exploration of the current database (10,000 profiles not fully validated) and future data incorporated in EcoTaxa (approximately 500 profiles annually on average over the last three years for UVP5 versions only), covering both plankton and detritus. In this context, we discuss the strengths and limitations of the dataset, as well as its potential applications and future directions for the UVP database.

4.1 Consideration related to spatial coverage and instruments performances

The dataset provides decade-long global coverage with standardized methodologies across UVP5 versions, spanning all major ocean basins. However, the southern hemisphere and deep sea remain undersampled, and profiles are mostly concentrated in mid-high latitude of the northern hemisphere (Figure 2). Well sampled regions correspond to long-term monitoring or time-series programs, such as the California Current, the Western Mediterranean, and the Equatorial region, through initiatives like the CCELTAR program (e.g., Biard and Ohman, 2020), ongoing observational efforts of MOOSE (e.g., Llopis Monferrer et al., 2022), and long-term studies in the Equatorial region (e.g., Kiko et al. 2017, Fernández-Carrera et al., 2023). The even distribution across ocean basins is mostly the result of the Tara Ocean Expeditions (2009-2013). Despite broad coverage, small sampled volumes can limit detection of rare taxa, affect image based identification, and cause "zeros" that may reflect detection limits rather than true absence.

At larger size ranges, rare taxa require aggregation counts across thick vertical ocean layers to achieve statistical robustness (Hauss et al., 2016; Panaïotis et al., 2023). At the surface, abundant taxa may permit 10 m binning intervals (Dupouy et al., 2018; Biard and Ohman., 2020), though 20 m bins are typically more appropriate (Picheral et al., 2010). In this study, data were grouped into five depth layers (0-100, 100-500, 500-1000, 1000-2000 and 2000-4000 m) balancing resolution for abundant surface taxa with sufficient counts for rare deeper organisms. While previous publications have adopted fixed depth ranges of 0-200 m and 200-500 m (Drago et al., 2022), or a dynamic layer, set as the deepest value among the mixed layer depth and the euphotic depth (median 88 m, Panaïotis et al., 2023), the choice of the vertical layering ultimately depends on the scientific question.

The two UVP5 versions are inter-calibrated based on the size spectra from repeated joint profiles (Picheral et al., 2010; Kiko et al., 2022). Users should also account for unit-specific settings: sn000 (used, for example, during Tara Oceans 2009-2012) shows a different distribution of features and may require a quantile-to-quantile transformation, or exclusion, in cross-unit analyses. Detection efficiency varies with object size (Figure 5), where HD version captures detritus <1 mm more effectively than the SD version, while both perform similarly above 1 mm. Size spectra generally show a peak at the detection limit, a steep decline for intermediate sizes, and a flatter distribution for large objects (Stemmann and Boss, 2012).

4.2 Considerations related to classification

Variations in the depth of taxonomic classification among annotators necessitated the merging of certain groups, resulting in a final list of 33 taxa at the lowest common taxonomic denominator (Table 1). To validate classification accuracy, a random subset of images (200 from each taxon and 10,000 for detritus) was independently reviewed by a single operator. Error rates were consistently below 10% across all groups, with most groups exhibiting error rates under 2.5%. A source of error in the case of detritus is that many annotators had moved un-focused particles into the category artefact. This category includes images of objects arising from external or procedural factors. Examples of such artifacts include reflections or shadows from a poorly tied rope, presence of seals near the camera, cables, or other non-biological objects inadvertently captured during image acquisition, as well as badly segmented objects in nepheloid layers that modify the background. On the other hand, it may also consist of effects like bubbles caused by the descent through the air/water interface where bubbles are captured on the hardware, as well as artifacts resulting from image blurriness where no actual object or non-recognizable object is present (real artifact). When analyzing the artefact category which contains some subjectivity, considering for example that bad-focused could be very transparent objects, we found that it consists of 85% of real detritus shaped objects, 5% of plankton and 10% of artefact. Sorting them in the EcoTaxa database system would be too time-consuming, so users must decide whether to include or exclude them during the analysis. Here, we merged them with detritus as they would become a minority (less than few percent). However, it is important to note that objects classified as artefacts (not shown in Figure 7) represent less than 1% of the total dataset when the concentration is calculated, but contribute to more than 200% when volume is considered. Their impact is high mostly on large objects because many artefacts are observed in very turbid water where particles are badly segmented. This highlights the significance of their removal.

Plankton-like

We have gathered in plankton-like all objects that are most probably plankton. Inside this category, ~60% of the objects in the possibly plankton group may be Rhizaria, but the image definition impairs their recognition. It is important to keep this category apart from the detritus category because they represent a significant fraction of the total plankton count and probably living biomass. Although a significant portion indicates uncertain classification, it is also in this category that most new findings can be performed.

Plankton contextual

The term -contextual in this dataset refers to objects that were classified as a taxonomic category but do not have the morphology of the taxa. Scientists on oceanographic surveys who had other contextual information have created the category *Trichodesmium*-contextual and Bacillariophyta-contextual for objects that aren't formally identified as *Trichodesmium* puff and tuff or as diatom chains. In this context, the classification is supported by many other optical observations (for example see Dupouy et al., 2018 for *Trichodesmium*). Due to the risk of mis-interpreting ecological results or impairing the quality of the learning set, it is better to distinguish them from objects whose images are typical of plankton organisms. In the case of the two categories, *Trichodesmium* and *Trichodesmium*-contextual, they contain nearly the same number of objects, so including both would double the amount of data for this group. On

the other hand, Bacillariophyta-contextual represents the sole category for this genus within the dataset, where its inclusion or not could lead to its complete exclusion.

4.3 Scientific relevance

Overall, this dataset provides a unique and comprehensive tool for the scientific community, enabling researchers to examine the intricate relationships between plankton, detritus, and ecosystem function. The detailed classification of plankton and detritus provides a valuable resource for understanding the complexity between their abundance distribution and the environmental processes happening at global (Drago et al., 2022; Panaïotis et al., 2023; Laget et al., 2024) and local scales (see references in Table 1) within marine systems. By analyzing the abundance, diversity, and distribution of planktonic organisms, researchers can gain insights into food web structures, energy flow, and the interactions between different trophic levels (e.g., D'Alelio et al., 2016; Perhirin et al., 2025). The data allows ecologists the monitoring of plankton communities, which are essential indicators of environmental health and can reflect changes in water quality, nutrient levels, and ecosystem productivity (Muller-Karger et al., 2018). The dataset is equally valuable in biogeochemical studies, so researchers can better predict how changes in plankton community composition and detritus abundance influence nutrient cycling and the overall functioning of marine ecosystems. Additionally, biogeochemical models that integrate this dataset can help refine predictions of carbon sequestration in the ocean, an essential process for regulating atmospheric CO₂ levels and mitigating global warming. As plankton and detritus play pivotal roles in the ocean's carbon pump, understanding their distribution in different environmental conditions is crucial for assessing the resilience of marine ecosystems and their ability to mitigate or exacerbate climate change effects (e.g., Le Quéré et al., 2016; Rohr et al., 2023). Through these integrated models, the dataset offers a robust framework for exploring the complex feedback mechanisms between marine biological communities and biogeochemical processes, advancing our ability to predict future changes in marine ecosystems under varying environmental scenarios.

4.4 Moving forward: future development

Future classification should focus its efforts on sorting the detritus category, as a recent study highlights that sinking speed estimated for various particle categories varies with particle morphology (Trudnowska et al., 2022; Soviadan et al., 2025) or that mesoscale activities mix them vertically according to their morphology (Accardo et al., 2025). In addition, they represent a very high proportion in abundance and probably of organic biomass compared to the plankton. Additionally, the specific classification of detritus particles, such as fecal pellets and their associated zooplankton communities, will enhance our understanding of their dynamics, improve the accuracy of carbon flux calculations, and refine their representation in biogeochemical models (Perhirin et al., 2025). Therefore, classifying particles based on their traits could provide valuable new insights into their origin and role in the carbon cycle through the gravitational pump (Boyd et al., 2019). When it comes to zooplankton, recent studies revealed that analyzing their traits, such as body size, morphology, and metabolic rates, which significantly influence their ecological roles and interactions within marine ecosystems, provides a framework for linking organismal characteristics to ecosystem

functions, offering deeper insights into zooplankton behavior, community structure, and their contributions to biogeochemical cycles (Titocci et al., 2025).

Transfer learning has shown promising potential in leveraging existing datasets to enhance training for improved recognition tasks. By utilizing the present dataset as a model training for machine learning and artificial intelligence (AI) techniques can be employed to better classify and extract relevant features (Lumini and Nanni, 2019; Irisson et al., 2022). Specifically, AI could play a key role in sorting and categorizing the 7,000,000 detritus images in the dataset, enhancing the processing of the remaining 5,598 UVP5 profiles and their corresponding 70 million images. Furthermore, integrating existent profiles with those acquired in the future, such as the anticipated 500 annually for UVP5 and 5,000 annually for the new version of the UVP (UVP6LP and HD; Picheral et al., 2022), into the observation system will enhance the robustness of the database, ensuring its adaptability and scalability for future data handling and feature extraction. This observation effort is supported by GOOS (Dexter and Summerhayes, 2010) and already in operation in large-scale observing programs, like the Bio-GO-SHIP (Clayton et al., 2022) or possibly by the BGC-Argo (Claustre et al., 2020) program. Having better embedded classifiers is particularly important for BGC Argo for which the floats and the cameras are not recovered. The new UVP6, which can be attached or associated with different platforms, is now widespread distributed and has allowed the acquisition of innumerable profiles and 87 millions of images in the last 4 years since its commercialization in 2020. These advancements will ultimately contribute to more efficient data analysis and support the continuous improvement of environmental monitoring systems.

Data availability

The dataset is available on SEANOE at <https://doi.org/10.17882/107583> (Nocera et al., 2025).

Acknowledgements

We are grateful for the ship time provided by the respective institutions and programmes and we would like to thank all scientists, officers and crew of the various R/V which took part in UVP5 data collection. We acknowledge the MOOSE programme (Mediterranean Ocean Observing System for the Environment) coordinated by CNRS-- INSU and the Research Infrastructure ILICO (CNRS--IFREMER). JOI acknowledges support by the Belmont Forum grant #ANR--18--BELM--0003--01. RK, LS and LD received support from the European Union project TRIATLAS (European Union Horizon 2020 Programme, grant agreement 817578). We also thank the National Science Foundation grants OCE-10-26607, OCE-1637632 and OCE-1614359 which supported the CCE-LTER site.

RK furthermore acknowledges support via a Make Our Planet Great Again grant from the French National Research Agency (ANR) within the Programme d'Investissements d'Avenir #ANR--19--MOPGA--0012 and funding from the Heisenberg Programme of the German Science Foundation #KI 1387/5--1. AR was funded by the PACES II (Polar Regions and Coasts in a Changing Earth System) programme of the Helmholtz Association, the INSPIRES programme of the Alfred Wegener Institute Helmholtz Centre for Polar and Marine Research, and the DFG Priority Program SPP

1158 “Antarctic Research with comparative investigations in Arctic ice areas” (project number 562122740). LS was supported by the CNRS/Sorbonne University Chair VISION to initiate the global observation and the Chair PLACARDO at the Institut de France. This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement #862923. ACN was supported by a postdoctoral fellowship from the National Scientific and Technical Research Council of Argentina. LD received funding from Sorbonne Université through the Ecole doctorale 129 as well as Horizon Europe RIA under Grant Number 101081273 (NECCTON project) for her post-doctoral research funding.

Author contribution method

ACN, JOI and LS formulated the goals for dataset presentation, quality control and the publication of a global UVP5 dataset and their respective images. LS and MP led the community effort supported by all UVP managers and quality control endeavours, supported by all co-authors. ACN and LS conceived and drafted the article. All authors participated in writing the article.

Conflict of interest statement

The authors declare no conflicts of interest.

490 **Appendix A**

491 **Table A1. List of the 62 projects included in the present study, with their corresponding project identification (pprojid),**
492 **project title indicating UVP model and serial number (ptitle), data owner, project number identification in EcoTaxa**
493 **(projid), the project name (title) and license registered on EcoTaxa (<https://ecotaxa.obs-vlfr.fr/>).**

projid	ptitle	projid	title	data_owner	license
1	uvp5_sn003_jerico_2017	578	UVP5 JERICO 2017	lars.stemmann@obs-vlfr.fr	
2	uvp5_sn000_boum2008	122	UVP5 BOUM 2008	lars.stemmann@obs-vlfr.fr	
3	uvp5_sn000_ccelter_2012	45	UVP5 CCELTAR (Iter2008 ccelter_2012 ccelter_2014)	tristan.biard@univ-littoral.fr	CC BY-NC 4.0
4	uvp5_sn000_lohafex2009	109	UVP5 LOHAFEX 2009	lars.stemmann@obs-vlfr.fr	CC0 1.0
5	uvp5_sn000_lter2008	45	UVP5 CCELTAR (Iter2008 ccelter_2012 ccelter_2014)	tristan.biard@univ-littoral.fr	CC BY-NC 4.0
6	uvp5_sn000_tara2009	579	UVP5 Tara Oceans (tara2009, tara2010, tara2011, tara2012, tara2013)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
7	uvp5_sn000_tara2010	579	UVP5 Tara Oceans (tara2009, tara2010, tara2011, tara2012, tara2013)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
9	uvp5_sn000_tara2012	579	UVP5 Tara Oceans (tara2009, tara2010, tara2011, tara2012, tara2013)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
10	uvp5_sn002_moose_dyf_2013	35	UVP5 Dyfamed 2013 2014 2015 2016 2017 2018	lars.stemmann@obs-vlfr.fr	
11	uvp5_sn002_moose_dyf_2014	35	UVP5 Dyfamed 2013 2014 2015 2016 2017 2018	lars.stemmann@obs-vlfr.fr	
12	uvp5_sn002_moose_dyf_2015	35	UVP5 Dyfamed 2013 2014 2015 2016 2017 2018	lars.stemmann@obs-vlfr.fr	
13	uvp5_sn002_moose_dyf_2016	35	UVP5 Dyfamed 2013 2014 2015 2016 2017 2018	lguidi@obs-vlfr.fr	
14	uvp5_sn002_moose_dyf_2017	35	UVP5 Dyfamed 2013 2014 2015 2016 2017 2018	coppola@obs-vlfr.fr	
15	uvp5_sn002_moose_ge_2013	30	UVP5 MooseGE 2012 2013 2014 2015 2016	lars.stemmann@obs-vlfr.fr	CC BY-NC 4.0
16	uvp5_sn000_malina2009	28	UVP5 MALINA 2009	lars.stemmann@obs-vlfr.fr	CC BY 4.0
17	uvp5_sn002_moose_ge_2014	30	UVP5 MooseGE 2012 2013 2014 2015 2016	lars.stemmann@obs-vlfr.fr	CC BY-NC 4.0
20	uvp5_sn000_operex2008	110	UVP5 OPEREX 2008	lars.stemmann@obs-vlfr.fr	CC BY 4.0

21	uvp5_sn001_2012_moose_ge	30	UVP5 MooseGE 2012 2013 2014 2015 2016	stemmann@obs-vlfr.fr	CC BY- NC 4.0
22	uvp5_sn001_2012_msm22	593	UVP5 Geomar 2012 msm22	rkiko@geomar.de	
23	uvp5_sn001_2012_msm23	584	UVP5 Geomar 2012 msm23	rkiko@geomar.de	
31	uvp5_sn002_moose_ge_2015_filtered	30	UVP5 MooseGE 2012 2013 2014 2015 2016	lars.stemmann@obs-vlfr.fr	CC BY- NC 4.0
32	uvp5_sn002_somba_ge_2014	36	UVP5 SOMBA 2014	lars.stemmann@obs-vlfr.fr	CC BY 4.0
41	uvp5_sn003_cassiopee_2015	38	UVP5 CASSIOPEE 2015	lars.stemmann@obs-vlfr.fr	CC BY 4.0
42	uvp5_sn003_ccelter_2014	45	UVP5 CCELTER (Iter2008 ccelter_2012 ccelter_2014)	tristan.biard@univ-littoral.fr	CC BY- NC 4.0
43	uvp5_sn003_ccelter_2016	156	UVP5 CCELTER 2016	tristan.biard@univ-littoral.fr	CC BY- NC 4.0
44	uvp5_sn003_dewex_spring_2013	4	UVP5 DEWEX 2013 (spring)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
46	uvp5_sn003_outpace_2015	37	UVP5 OUTPACE 2015	lguidi@obs-vlfr.fr	CC BY 4.0
47	uvp5_sn003_sargasso_a	22	UVP5 Sargasso 2014 (sargasso_a sargasso_b)	lombard@obs-vlfr.fr	CC BY 4.0
48	uvp5_sn003_sargasso_b	22	UVP5 Sargasso 2014 (sargasso_a sargasso_b)	lombard@obs-vlfr.fr	CC BY 4.0
49	uvp5_sn003_tara2013	579	UVP5 Tara Oceans (tara2009, tara2010, tara2011, tara2012, tara2013)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
51	uvp5_sn003zp_tara2012	579	UVP5 Tara Oceans (tara2009, tara2010, tara2011, tara2012, tara2013)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
53	uvp5_sn005_dewex_2013_winter	3	UVP5 DEWEX 2013 (winter)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
54	uvp5_sn005_dy032_2015_filtered	40	UVP5 DY032 205	francois.carlotti@mio.osupytheas.fr	CC BY 4.0
55	uvp5_sn005_moose_ge_2013	30	UVP5 MooseGE 2012 2013 2014 2015 2016	lars.stemmann@obs-vlfr.fr	CC BY- NC 4.0
56	uvp5_sn008_an1304	41	UVP5 AN Arctique (an1304 an1405 an1407) part A to validate	marcel.babin@takuvik.ulaval.ca	

57	uvp5_sn008_an1405	41	UVP5 AN Arctique (an1304 an1405 an1407) part A to validate	marcel.babin@takuvik.u laval.ca		
58	uvp5_sn008_an1406	618	UVP5 AN 1406	marcel.babin@takuvik.u laval.ca	CC BY- NC 4.0	
59	uvp5_sn008_an1407	41	UVP5 AN Arctique (an1304 an1405 an1407) part A to validate	marcel.babin@takuvik.u laval.ca		
60	uvp5_sn008_green_201 5_icecamp	42	UVP5 GREEN EDGE Ice Camp 2015	marcel.babin@takuvik.u laval.ca	CC BY- NC 4.0	
61	uvp5_sn008_green_201 6_icecamp	315	UVP5 GREEN EDGE Ice Camp 2016	marcel.babin@takuvik.u laval.ca	CC BY- NC 4.0	
62	uvp5_sn008_subice_201 4	107	UVP5 Subice 2014	stemmann@obs-vlfr.fr		
64	uvp5_sn009_2015_p16n	43	uvp5_sn009_2015_p16n	amcdonnell@alaska.edu	CC BY 4.0	
65	uvp5_sn009_2015_p16n _goa	43	uvp5_sn009_2015_p16n	amcdonnell@alaska.edu	CC BY 4.0	
68	uvp5_sn010_2014_m10 5	602	UVP5 Geomar 2014 m105	rkiko@geomar.de		
69	uvp5_sn010_2014_m10 6	595	UVP5 Geomar 2014 m106	rkiko@geomar.de		
70	uvp5_sn010_2014_m10 7	559	UVP5 Geomar 2014 m107	rkiko@geomar.de		
71	uvp5_sn010_2014_m10 8	586	UVP5 Geomar 2014 m108	rkiko@geomar.de		
72	uvp5_sn010_2014_ps88 b	558	UVP5 Geomar 2014 ps88b	rkiko@geomar.de		
73	uvp5_sn010_2015_m11 6	589	UVP5 Geomar 2015 m116	rkiko@geomar.de		
76	uvp5_sn010_2015_m12 1	560	UVP5 Geomar 2015 m121	rkiko@geomar.de		
81	uvp5_sn201_2016_naam es_02	146	UVP5hd NAAMES02	lee.karp- boss@maine.edu	CC BY- NC 4.0	
83	uvp5_sn201_ccelter_201 7	627	UVP5hd CCELTTER 2017	tristan.biard@univ- littoral.fr	CC BY- NC 4.0	
86	uvp5_sn203_greenedge_ 2016	149	UVP5hd GreenEdge 2016	lars.stemmann@obs- vlfr.fr	CC BY- NC 4.0	

87	uvp5_sn203_greenedge_2016_1b	149	UVP5hd GreenEdge 2016	lars.stemmann@obs-vlfr.fr	CC BY-NC 4.0
92	uvp5_sn201_2017_naames_03	637	UVP5hd NAAMES03	lee.karp-boss@maine.edu	CC BY-NC 4.0
95	uvp5_sn010_2017_m135	548	UVP5 Geomar 2017 m135	rkiko@geomar.de	
99	uvp5_sn000_tara2011	579	UVP5 Tara Oceans (tara2009, tara2010, tara2011, tara2012, tara2013)	lars.stemmann@obs-vlfr.fr	CC BY 4.0
105	uvp5_sn008_ips_amundsen_2018	1165	UVP5 IPS Amundsen 2018	marcel.babin@takuvik.ulaval.ca	CC BY 4.0
109	uvp5_sn010_2014_eddy	881	UVP5 Geomar 2014 eddy	rkiko@geomar.de	
166	uvp5_sn002_moose_dyf_2018	35	UVP5 Dyfamed 2013 2014 2015 2016 2017 2018	coppola@obs-vlfr.fr	
231	uvp5_sn202_msm060_filtered	351	UVP5hd msm060 (2017)	andreas.rogge@awi.de, anya.waite@dal.ca	Copyright
236	uvp5_sn201_2018_naames_04_filtered	1252	UVP5hd Naames 04	lee.karp-boss@maine.edu	CC BY-NC 4.0

495 **Appendix B**

496 **Quantile-to-quantile transformation function. The R function below is recommended to be used to adjust the distribution**
497 **of morphological features from UVP5 version with sn000 to match that of the other serial numbers (see Section 2.1.2).**

```
498   #' Transform the distribution of x into that of y
499   #'
500   #' @param x vector of observations to be transformed
501   #' @param y vector of observations to be matched
502   #' @param n number of quantiles to sample (more means more precise transformation)
503
504   quantile_transformer <- function(x, y, n = 1000) {
505     probs <- seq(0, 1, length.out = n)
506     qx <- quantile(x, probs = probs)
507     qy <- quantile(y, probs = probs)
508     approx(x = qx, y = qy, xout = x, rule = 2, ties = "ordered")$y
509   }
```

510 **Table A3. List of annotators involved in the classification of objects within the current UVP5 dataset.**

Annotator name	Annotator name (<i>cont.</i>)	Annotator name (<i>cont.</i>)
Alikacem Yasmine	Gawinski Christine	Panchal Aakash
Andersson Bjoern	Gremion Gwenaelle	Panaïotis Thelma
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Blanc Benjamin	Lafond Augustin	Rogge Andreas
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