Table S1: Reporting of per class metrics or confusion matrix in plankton image classification studies.

Reference	Classif. task	Instrument	Method	CM / per class metrics
Ten most cited papers according to Irisson et al. (2022)				
Gorsky et al. (2010)	Yes	Zooscan	Various	**Yes**
Sosik and Olson (2007)	Yes	IFCB	SVM	**Yes**
Benfield et al. (2007)	No	-	-	**-**
Grosjean et al. (2004)	Yes	Zooscan	Various	**No**
Luo et al. (2005)	Yes	SIPPER	SVM	**No**
Blackburn et al. (1998)	Yes	other	ANN	**No**
Malkiel et al. (1999)	No	-	-	**-**
Culverhouse et al. (2006)	Yes	SIPPER	ANN	**No**
Tang et al. (1998)	Yes	VPR	ANN	**Yes**
Hu and Davis (2005)	Yes	VPR	SVM	**Yes**
Other citations in our paper				
Anglès et al. (2015)	Yes	IFCB	SVM	**No**
Blaschko et al. (2005)	Yes	Flowcam	Various	**No**
Cheng et al. (2019)	Yes	ZOOVIS	CNN	**Yes**
Christiansen et al. (2018)	No	-	-	**-**
Cui et al. (2018)	Yes	IFCB	CNN	**No**
Dai et al. (2016)	Yes	Zooscan	CNN	**No**
Dai et al. (2017)	Yes	IFCB	CNN	**No**
Dieleman et al. (2016)	Yes	ISIIS	CNN	**No**
Ellen et al. (2015)	Yes	Zooscan	Various	**Yes**
Ellen et al. (2019)	Yes	Zooglider	CNN + Various	**Yes**
Gonzalez et al. (2019)	No	-	-	**-**
Guo et al. (2021)	Yes	IFCB	RF	**Yes**
Kyathanahally et al. (2021)	Yes	Zooscan, IFCB, ISIIS	CNN + MLP	**Yes**
Kyathanahally et al. (2022)	Yes	Zooscan, IFCB, ISIIS	CNN + VIT	**No**
Lee et al. (2016)	Yes	IFCB	CNN	**Yes**
Lumini and Nanni (2019)	Yes	Zooscan, IFCB, ISIIS	CNN	**Yes**
Luo et al. (2018)	Yes	ISIIS	CNN	**Yes**
Malde and Kim (2019)	Yes	Zooscan	CNN	**Yes**
Maracani et al. (2023)	Yes	Zooscan, IFCB, ISIIS	CNN + VIT	**No**

Orenstein et al. (2015)	Yes	IFCB	RF & CNN	**No**
Orenstein and Beijbom (2017)	Yes	ISIIS, IFCB, SPC	CNN	**No**
Py et al. (2016)	Yes	ISIIS	CNN	**No**
Rodrigues et al. (2018)	Yes	ISIIS	CNN	**Yes**
Schmid et al. (2020)	Yes	ISIIS	CNN	**Yes**
Schröder et al. (2019)	Yes	UVP5	CNN	**Yes**
Uchida et al. (2018)	Yes	ISIIS	CNN	**No**
Zheng et al. (2017)	Yes	Zooscan, IFCB, ISIIS	MKL	**Yes**
			Total yes	**17**
			Total no	**16**

Classif. task = whether the study tackles a plankton image classification task, CM = confusion matrix. Instruments acronyms: IFCB = Imaging FlowCytobot, ISIIS = In Situ Ichthyoplankton Imaging System, SIPPER = Shadowed Image Particle Profiling and Evaluation Recorder, SPC = Scripps Plankton Camera, UVP = Underwater Vision Profiler, ZOOVIS = ZOOplankton Visualization and Imaging System. Methods acronyms: ANN = Artificial Neural Network, CNN = Convolutional Neural Network, MKL = Multi Kernel Learning, MLP = multilayer perceptron, RF = Random Forest, SVM = Support Vector Machine, VIT = Vision Transformer.

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Table S2: Classification report for detailed classes in the FlowCAM dataset. Reported values are F1-scores. The models are described in Figure 1.

Taxon	Grouped	Nat + RF	Mob + MLP600	Eff S + MLP600	Mob + PCA + RF
		Plankton			
Appendicularia	Appendicularia	0	84.8	76.6	88.4
Asterolamprales	Asterolamprales	8.3	50	55	62.5
Bacillariophyceae	Bacillariophyceae	38.1	78.5	75.8	81.7
cyano a	Bacteria	67.7	85.1	84.9	86.9
cyano b	Bacteria	88.8	95.2	94.7	95.4
Katagnymene spiralis	Bacteria	0	72	71.8	77.8
Richelia	Bacteria	22.9	71.5	77	77.8
UCYNA like	Bacteria	0	78	77.6	72.7
Bacteriastrum	Bacteriastrum	27.5	61.7	68.7	74.3
Chaetoceros	Chaetoceros	41.7	79.9	79.9	82.8
Chaetoceros peruvianus	Chaetoceros	0	42.9	66.7	70.6
Ciliophora	Ciliophora	0	42.9	38.9	48.8
Climacodium	Climacodium	22	77.1	72.5	81
Climacodium inter. Crocosphaera	Climacodium inter. Crocosphaera	20	68	68.8	70.8
Calanoida	Copepoda	44.3	72.5	75	84.4
Copepoda	Copepoda	5.6	41.4	29.6	55.9
Oithonidae	Copepoda	36.4	61.7	59.6	74.7
Oncaeidae	Copepoda	53.3	63.8	57.8	70.3
Coscinodiscaceae	Coscinodiscaceae	62.6	79.7	78.8	83.9
Cyttarocylididae	Cyttarocylididae	40.5	89.6	86.9	89.6
chainlarge	diatoma_chainlarge	19.7	85	83.8	85.9
chainthin	diatoma_chainthin	23.7	83	81.9	85.1
Codonaria	Dictyocystidae	0	66.7	72	72
Dictyocysta	Dictyocystidae	32.6	87.5	83.1	91.4
Dinophyceae	Dinophyceae	30.4	68.1	66.4	71.2
Dinophysis	Dinophysiales	0	50	45.8	57.1
Ornithocercus	Dinophysiales	5.4	81.7	83.3	88
Ditylum	Ditylum	31.4	92	92.7	93.9
part<Ditylum	Ditylum	9.3	84	84.5	90
Fragilariopsis	Fragilariopsis	0	76.2	88.9	85.7
Ceratocorys	Gonyaulacales	0	66.7	55.2	64
Cladopyxis	Gonyaulacales	0	72.7	80	96.3
Neoceratium	Gonyaulacales	33.4	88.6	90.7	93.8
Neoceratium furca	Gonyaulacales	18.2	86.4	82.9	93.1
Neoceratium fusus	Gonyaulacales	0	84.7	86.2	91.2
Neoceratium pentagonum	Gonyaulacales	47	92.6	93.4	95.1
Pyrocystaceae	Gonyaulacales	25	0	45.5	47.6
Pyrophacus	Gonyaulacales	38.7	78.9	72.7	87.2
Gymnodiniales	Gymnodiniales	0	5.6	36.4	50
Hemiaulus	Hemiaulus	0	61.8	67.7	70.9
Melosiraceae	Melosiraceae	86.7	96.1	95.8	97.4
Metacylis	Metacylididae	0	66.7	60	64.7
Nitzschia	Nitzschia	13.8	52.6	60.9	67.8
Odontella	Odontella	58.5	95.3	96.2	95.7
part<Odontella	Odontella	32.5	90.1	90.4	93.3
nauplii	other_Crustacea	58.2	94.7	95.3	96.9

part<Crustacea	other_Crustacea	37	75.6	76.5	82.6
egg<other	other_egg	14.3	69.6	62.5	76.9
part<Ciliophora	part_Ciliophora	0	79.1	66.7	83.3
pennate	pennate	18.5	79.4	83	91
Oxytoxum	Peridiniales	0	41.4	53.3	68.6
Podolampas	Peridiniales	8	71.9	69.4	76.3
Protoperidinium	Peridiniales	18.4	64.3	61.8	66.1
Planktoniella sol	Planktoniella sol	43.5	93	90.8	94
Pseudo-Nitzschia chain	Pseudo-Nitzschia chain	11.3	65.2	60.5	71.4
Acantharia	Retaria	0	44.4	61.5	69
Foraminifera	Retaria	0	72.5	67.5	72.5
Nassellaria	Retaria	0	69	76.5	77.9
Retaria	Retaria	36.6	84.6	85.2	85.8
Spumellaria	Retaria	19.5	56.1	62.3	69.6
Amphorides	Rhabdonellidae	0	78.8	76.9	87.2
Rhabdonellidae	Rhabdonellidae	60.3	89.1	89.5	93.2
Dactyliosolen	Rhizosoleniaceae	0	26.7	53.3	57.1
Guinardia	Rhizosoleniaceae	31.9	69.2	70	81.4
Rhizosolenia inter. Richelia	Rhizosoleniaceae	0	53	51.7	59.1
Rhizosoleniaceae	Rhizosoleniaceae	40.1	78.5	76.7	85.5
Thalassionematales	Thalassionematales	31.3	90.3	89.8	92.3
Codonellopsis	Tintinnidiidae	61.5	95.1	96.1	96.7
Eutintinnus	Tintinnidiidae	30.6	93.7	92.4	95.2
Poroecus	Tintinnidiidae	0	81.6	76	83.6
Salpingella	Tintinnidiidae	0	69.8	79.2	89.4
Steenstrupiella	Tintinnidiidae	0	84.3	87.1	86.8
Tintinnina	Tintinnina	21.4	52.5	50.7	59.1
Undellidae	Undellidae	26.2	86.1	87	92.9
Xystonellidae	Xystonellidae	7.1	64.8	69.5	80
	average	**22.2**	**71.8**	**73.5**	**79.7**
		Non plankton			
artefact	artefact	51.3	94.2	93.4	93.8
badfocus	artefact	11.6	31.8	43.5	36.9
bubble	artefact	53.7	91.4	89.1	89.8
darkrods	darkrods	52.2	68.8	62.3	65
darksphere	darksphere	68.7	84.9	80.8	81.1
dark	detritus	94.9	96.8	96.6	97.1
detritus	detritus	83.5	91.1	90.9	90.6
fiber	detritus	92.5	95.4	94.6	95.7
light	detritus	74.2	85.5	85.4	84.9
lightrods	lightrods	60.1	79.5	80.2	79.3
lightsphere	lightsphere	87	93.8	92.9	93.4
ball_bearing_like	other_living	17.6	58.7	61.5	55.2
contrasted_blob	other_living	62.4	73	69.2	70.3
crumple sphere	other_living	15.4	76.1	70.6	77.3
dinophyceae_shape	other_living	0	67.5	68.4	77.6
other<living	other_living	12.5	49.3	57.7	67.9
polar_view<Dinophyceae	other_living	0	69.1	63.6	73
transparent_u	other_living	0	76.6	77.8	80.7
	average	**46.5**	**76.9**	**76.6**	**78.3**

Table S3: Classification report for detailed classes in the IFCB dataset. Reported values are F1-scores. The models are described in Figure 1.

Taxon	Grouped	Nat + RF	Mob + MLP600	Eff S + MLP600	Mob + PCA + RF
	Plankton				
Asterionellopsis	Asterionellopsis	32.1	87.8	84.2	84.7
Cerataulina	Cerataulina	54	80.2	78	81.9
Chaetoceros	Chaetoceros	33.3	80.4	78.7	77.6
Chaetoceros_didymus	Chaetoceros	0	67.9	60.6	65.7
Chaetoceros_didymus_flagellate	Chaetoceros	70.7	94.5	91.1	94.9
Chaetoceros_other	Chaetoceros	0	16	14.6	25
Chaetoceros_pennate	Chaetoceros	0	40.8	48.5	48.5
Corethron	Corethron	53.1	97.3	96.8	97.1
Cylindrotheca	Cylindrotheca	63.2	95.9	95.4	95.4
DactFragCerataul	DactFragCerataul	36.5	62.7	58.8	61.7
Dactyliosolen	Dactyliosolen	70.7	95.4	93.6	94.3
Dictyocha	Dictyochophyceae	61.2	92.4	93.1	91.7
Pseudochattonella_farcimen	Dictyochophyceae	40.8	73.8	60.9	60.2
Dinobryon	Dinobryon	61	95.9	95.1	96.8
Ditylum	Ditylum	47.7	90.9	88.7	89.5
Eucampia	Eucampia	46.9	84.2	83.6	87.1
Euglena	Euglena	45.1	77.8	58.1	68.8
amoeba	Flagellates	0	51.2	44.2	47.8
flagellate_sp3	Flagellates	19.4	74.9	73.2	70.4
kiteflagellates	Flagellates	20.5	90.7	84.8	88.9
G_delicatula_detritus	Guinardia	3.3	66.7	54.3	62.5
G_delicatula_external_parasite	Guinardia	0	0	20	21.3
G_delicatula_parasite	Guinardia	30.6	67.2	61.5	61.8
Guinardia_delicatula	Guinardia	74.4	92	89.6	89.5
Guinardia_flaccida	Guinardia	73.3	92.2	85.3	83.7
Guinardia_striata	Guinardia	44.4	85.8	82.1	86.7
Chrysochromulina	Haptophyta	0	58	43.9	53.7
Emiliania_huxleyi	Haptophyta	46.7	88.4	91.7	89.8
Phaeocystis	Haptophyta	64.8	94.5	93.7	90.2
Leptocylindrus	Leptocylindrus	71	86.8	84.9	86.3
Leptocylindrus_mediterraneus	Leptocylindrus	11.8	82.4	66.7	82.4
Ciliate_mix	other_Ciliophora	49	88.8	84.8	87.5
Mesodinium_sp	other_Ciliophora	21.6	82.3	81.7	84.1
Tintinnid	other_Ciliophora	53.4	82	80.9	88.9
Tontonia	other_Ciliophora	66.7	82.4	73.8	64.2
Cerataulina_flagellate	other_diatom	0	47.6	62.5	63.2
Coscinodiscus	other_diatom	73.2	79.5	76.6	81
Delphineis	other_diatom	0	67.4	56.6	61.9
diatom_flagellate	other_diatom	0	35	37.1	40.4
Ephemera	other_diatom	56.5	94.1	88	90.9
other_diatom	other_diatom	0	35.3	51.3	71.4
Paralia	other_diatom	29.6	77.8	85	89.4
pennate	other_diatom	19.2	75.9	72.2	76.2
pennate_morphotype1	other_diatom	82.4	94.3	89.2	94.3

pennates_on_diatoms	other_diatom	0	40.4	45.8	50.7
Pleurosigma	other_diatom	66.7	92	91.2	92.6
Amphidinium_sp	other_Dinoflagellates	20	63.4	46.4	35.6
Ceratium	other_Dinoflagellates	63.2	96.8	96.9	95.4
dino30	other_Dinoflagellates	61.4	76.3	72.5	74.9
Gyrodinium	other_Dinoflagellates	55	77.6	65	82.4
Katodinium_or_Torodinium	other_Dinoflagellates	28.6	63.6	62.2	63.9
other_dino	other_Dinoflagellates	30.8	63.4	47.8	56.7
Proterythropsis_sp	other_Dinoflagellates	13.3	66.7	55.3	62.7
Peridiniales	Peridiniales	59.8	81.4	76.6	77.4
Prorocentrum	Prorocentrum	68	89.7	87	91.5
Pseudonitzschia	Pseudonitzschia	16.6	67.4	64.6	70.7
Pyramimonas_longicauda	Pyramimonas_longicauda	24.6	90.9	85.2	96
Rhizosolenia	Rhizosolenia	73	94.4	93.5	92.5
Strombidium	Strombidium	48.7	66.7	58.7	64.7
Thalassionema	Thalassionema	46.3	89.2	88.9	88
Skeletonema	Thalassiosirales	38.6	85	80.9	84.1
Thalassiosira	Thalassiosirales	47	80.8	78.3	80
Thalassiosira_dirty	Thalassiosirales	45.4	69.2	61.5	64.2
average		**38.7**	**75.6**	**72.3**	**75.4**
Non plankton					
bad	bad	96.5	98.4	96.8	97.3
detritus	detritus	59.7	87.8	87.1	87.8
other_interaction	other_interaction	11.7	38.3	37.1	43.2
other_living	other_living	94.8	97.8	97.5	97.6
other_living_elongated	other_living_elongated	44.9	72.1	69.5	70.7
spore	spore	0	76.6	55.4	63.2
average		**51.3**	**78.5**	**73.9**	**76.6**

Table S4: Classification report for detailed classes in the ISIIS dataset. Reported values are F1-scores. The models are described in Figure 1.

Taxon	Grouped	Nat + RF	Mob + MLP600	Eff S + MLP600	Mob + PCA + RF
	Plankton				
Acantharea	Acantharea	40.9	75.9	76.5	79.5
Actinopterygii	Actinopterygii	28.9	59.6	55.7	62.5
Annelida	Annelida	0	64.5	58.8	62.2
Appendicularia	Appendicularia	28.4	62.5	54.7	58.8
body<Appendicularia	Appendicularia	10.4	78.2	76.5	79.8
house	Appendicularia	11.4	14.3	11.1	20.4
like<body<Appendicularia	Appendicularia	0	35.3	39.9	43.8
Aulacanthidae	Aulacanthidae	63.8	84.1	77.7	82.6
Bacillariophyceae	Bacillariophyceae	44.8	80.5	71.4	75.8
Chaetognatha	Chaetognatha	12.2	56	47.6	54.2
Cnidaria	Cnidaria	0	42.9	37.5	51.9
colonial<Collodaria	colonial_colodaria	47.1	76.9	66.7	80.9
Copepoda	Copepoda	34.7	86	85.6	86.1
Harpacticoida	Copepoda	9.4	87.7	80.2	78.8
like<Copepoda	Copepoda	45.6	82.6	82.3	81.5
Crustacea	Crustacea	31.4	65.5	65.8	68.7
Ctenophora	Ctenophora	51.9	81.7	79.7	78.6
Doliolida	Doliolida	72.8	94.9	94.6	95.8
ephyra<Scyphozoa	ephyra	48	83.6	80.3	83.6
Eumalacostraca	Eumalacostraca	16	56	71.4	61.1
like<Acantharea	like_Acantharea	0	66.7	72	74.1
Mollusca	Mollusca	6.7	69.2	58.3	56.4
part<Cnidaria	part_Cnidaria	94.4	95.8	94.4	96.7
Pyrocystis	Pyrocystis	36.1	92.5	92.6	93
Rhizaria	Rhizaria	10.9	64	63.7	65
Rhopalonematidae	Rhopalonematidae	38.1	79.7	80	78.4
Siphonophorae	Siphonophorae	28.3	80.7	80.4	82.3
solitaryblack	solitaryblack	25.5	85.9	82.4	77.4
	average	**29.9**	**71.5**	**69.2**	**71.8**
	Non plankton				
detritus	detritus	94.1	97.7	97.2	97.4
other<living	other_living	0	33	40.4	39.1
streak	streak	92.3	88.6	86.6	87.2
vertical line	vertical line	100	100	95.7	100
	average	**71.6**	**79.8**	**79.9**	**80.9**

Table S5: Classification report for detailed classes in the UVP6 dataset. Reported values are F1-scores. The models are described in Figure 1.

Taxon	Grouped	Nat + RF	Mob + MLP600	Eff S + MLP600	Mob + PCA + RF
	Plankton				
fuzzy	Acantharia	43.2	90.6	88.5	79.4
spiky<Acantharia	Acantharia	6.1	88.9	95.4	69
star<Acantharia	Acantharia	61.3	98.4	99.2	96.1
Actinopterygii	Actinopterygii	48.3	47.4	48.8	52.4
Amphipoda	Amphipoda	22.7	46.5	56.6	56.2
Hyperiidea	Amphipoda	0	40	38.7	32.7
Annelida	Annelida	13.6	28.1	32.9	36.4
Phyllodocida	Annelida	46.7	78.9	63.3	66.7
Swima	Annelida	18.6	71.9	78.5	68.1
Appendicularia	Appendicularia	66.7	85.7	78.3	73.1
dead<house	Appendicularia	41.3	69	59.7	52.6
Aulacanthidae	Aulacanthidae	59.7	82.6	79.6	78.5
Aulatractus	Aulosphaeridae	11.1	75	59.6	80
Aulosphaeridae	Aulosphaeridae	33.3	86.8	83.5	75.4
Chaetognatha	Chaetognatha	55.1	72.2	65.8	60.4
other<Cnidaria	Cnidaria	11.8	40	45.6	39.7
small<Cnidaria	Cnidaria	55.7	79.7	74	74.5
Coelodendridae	Coelodendridae	27	74.6	71.4	73.5
spiky<Coelodendridae	Coelodendridae	45.5	83.9	84.8	72.2
cloud	Collodaria	10.3	82.2	69.6	68
Collodaria	Collodaria	49.3	87.8	79.8	75.8
solitaryblack	Collodaria	13.3	48.8	48.5	44.7
solitaryglobule	Collodaria	82.7	93.5	92.5	92.7
Calanidae	Copepoda	58.4	80	78.8	78.5
Calanoida	Copepoda	63.6	83.5	81.9	82.5
Copepoda	Copepoda	8.2	44.6	44.8	45.8
copepoda_eggs	Copepoda	0	44.4	44.2	46.5
like<Copepoda	Copepoda	0	14.4	26.3	32.5
Ctenophora	Ctenophora	6.2	41.7	46.6	52.6
Echinodermata	Echinodermata	0	64	63.2	51
Eumalacostraca	Eumalacostraca	44.7	72.5	70.2	63.9
Foraminifera	Foraminifera	52.4	84.2	79.4	83.3
Creseis acicula	Mollusca	69.1	88.4	79.3	54.1
Thecosomata	Mollusca	17.1	65.4	68.9	55.9
Ostracoda	Ostracoda	17.6	73.5	64.7	71.6
like<Rhizaria	Rhizaria	6.5	24.4	36.7	28.3
Rhizaria	Rhizaria	67.2	76.6	75.6	72.4
chain<Salpida	Salpida	37.5	72.7	73.1	59.7
Salpida	Salpida	60.6	72.5	73.2	55.1
Siphonophorae	Siphonophorae	25	38.5	43.8	23.5
Narcomedusae	Trachylina	35.7	64.9	64.9	70
Trachymedusae	Trachylina	11.1	30	34.8	40.9
puff	Trichodesmium	61.6	90.6	89.6	85.5
tuff	Trichodesmium	32.7	84.1	82.5	81.8
	average	**34.1**	**67.3**	**66.3**	**62.6**
	Non plankton				
artefact	artefact	92.1	95.2	93.2	93.2

crystal	crystal	90.6	89.6	87.5	83.4
detritus	detritus	95.2	97.2	96.4	96.4
fiber	fiber	78.6	82.5	80.6	80.5
filament	filament	56.5	68.9	61.4	59.1
darksphere	other<living	20	61.4	36.4	53.8
other<living	other<living	0.8	7.5	18.4	15.2
reflection	reflection	69.1	78.7	71.4	77.8
t004	t004	0	84.6	70.5	70.7
t011	t011	75.9	93.8	82.9	73.9
	average	**57.9**	**75.9**	**69.9**	**70.4**

Table S6: Classification report for detailed classes in the ZooCAM dataset. Reported values are F1-scores. The models are described in Figure 1.

Taxon	Grouped	Nat + RF	Mob + MLP600	Eff S + MLP600	Mob + PCA + RF
		Plankton			
Actinopterygii	Actinopterygii	22.2	61.5	41.9	73.2
Annelida	Annelida	0	47.8	49.6	50.7
larvae<Annelida	Annelida	0	34.7	51.4	51.4
Appendicularia	Appendicularia	61.1	83.1	81.9	84.6
tail<Appendicularia	Appendicularia	11.7	54.5	52.6	54
chainlarge	Bacillariophyceae	89.9	94.8	94.7	94.5
Diatoma	Bacillariophyceae	85	97	96.5	97.2
Diatoma tenuis<Diatoma	Bacillariophyceae	67	88.4	87.3	89.4
Thalassionema	Bacillariophyceae	13.3	80.5	76.6	80
Chaetognatha	Chaetognatha	67.1	85.9	86.2	88.6
Cirripedia	Ciripedia	44.7	88.6	88.3	88
Cladocera	Cladocera	45.1	75.5	75.2	75.5
Evadne	Cladocera	43.3	63.7	67.1	67.5
Penilia	Cladocera	3.2	75.2	79	77.5
Podon	Cladocera	0	64	63.5	67.8
Acartiidae	Copepoda	57.5	92.7	92.8	92.8
Calanidae	Copepoda	71.4	87.2	87.1	88.6
Calanoida	Copepoda	79.5	94.2	94	94.1
Calocalanus	Copepoda	0	65.8	67.4	65.5
Candaciidae	Copepoda	0	51.2	57.1	61
Centropagidae	Copepoda	32.5	81.2	81.8	81.9
Copepoda	Copepoda	39.7	63.2	63.6	63.8
Corycaeidae	Copepoda	16.1	88.3	87.9	88.4
Cyclopoida	Copepoda	83.7	96	96	96.1
empty<Copepoda	Copepoda	5.2	61.5	62.3	65.3
empty<Harpacticoida	Copepoda	0	65.5	54.2	59.3
Euchaeta	Copepoda	56.7	87.2	86.3	86.7
Euterpina	Copepoda	27.2	74.9	74.8	73.6
Harpacticoida	Copepoda	0	62.7	64.4	65.4
Isias	Copepoda	51.7	90.2	82.1	85.7
Metrinidae	Copepoda	38.4	83.5	81.1	83.2
Microstella	Copepoda	22.2	75.9	79.6	85.7
multiple<Copepoda	Copepoda	42.9	71.5	71.9	74.7
Oncaea	Copepoda	37.1	89.8	89.9	89.4
Poecilostomatoida	Copepoda	0	10.9	27.8	21.3
Pontellidae	Copepoda	35.6	95.7	94.4	94.4
Temoridae	Copepoda	31.8	90.9	91	91.7
comb<Ctenophora	Ctenophora	4.8	44.4	51.9	46.2
Ctenophora	Ctenophora	0	19	40	35
cyphonaute	cyphonaute	0	86.9	85.8	84.7
Decapoda	Decapoda	16.7	48.1	48.9	65.2
megalopa	Decapoda	84.4	94.8	94.6	95.9
Porcellanidae	Decapoda	77.5	89.3	91.2	92.7
zoea<Brachyura	Decapoda	85.8	96.9	97.1	97.2
larvae<Echinodermata	Echinodermata	14.8	62.9	60.5	64.2
Luidiidae	Echinodermata	68.8	73.3	68.4	77.3
pluteus<Echinodermata	Echinodermata	13.8	88.1	84.7	88

egg<Actinopterygii	egg_Actinopterygii	87.4	96.3	95.6	96.9
egg<Engraulidae	egg_Engraudilae	96.6	99.6	99.5	99.7
egg<other	egg_other	0	84.5	81.9	90
egg<Sardina	egg_Sardina	72.5	97	96.8	97.3
Halosphaera	Halosphaera	72.2	85.5	73.1	77.1
Bivalvia	Mollusca	1.6	67.7	67.8	68.4
Cavoliniidae	Mollusca	3.6	84.5	86.5	85.2
egg<Mollusca	Mollusca	37.5	66.7	68.8	69.5
Gastropoda	Mollusca	46.7	72.7	70.6	70
Limacinidae	Mollusca	73.6	85.8	84.8	86.2
veliger	Mollusca	0	29.4	40	41.4
Neoceratium	Neoceratium	95.6	98.1	98.1	98.1
Noctiluca<Noctilucaceae	Noctiluca	70.2	80.9	79.3	80.2
Hydrozoa	other_Cnidaria	37.4	75.3	75.1	75.1
Obelia	other_Cnidaria	0	85.9	83.1	88.8
other<Cnidaria	other_Cnidaria	36.4	48.8	56	60.4
Amphipoda	other_Crustacea	32.1	67.4	63.5	76.3
larvae<Crustacea	other_Crustacea	27.7	90	89.6	89.7
Nannosquillidae	other_Crustacea	37.5	83.3	82.8	92.3
nauplii<Crustacea	other_Crustacea	18.8	86.6	85.4	87.8
other<Crustacea	other_Crustacea	13.2	68.3	72.5	69.2
part<Crustacea	part_Crustacea	42.3	72.2	74	75.6
Phoronida	Phoronida	0	75.9	52	70.3
Rhizaria	Rhizaria	80.6	92.1	91.1	91.6
Rhizosolenids	Rhizosolenids	85.8	92.8	92.6	93.3
shrimp_like	shrimp_like	66.2	86.5	86.3	88
bract<Diphyidae	Siphonophorae	38.7	74.9	73.8	74.2
eudoxie<Diphyidae	Siphonophorae	16.7	75.6	68.7	74.9
gonophore<Diphyidae	Siphonophorae	53.9	73.2	71.7	72.1
nectophore<Diphyidae	Siphonophorae	57.3	74.9	74.5	77.7
other<Siphonophorae	Siphonophorae	0	11	26.9	26.9
Physonectae	Siphonophorae	31.2	52	63.3	60.3
Doliolida	Thaliacea	0	78.3	58.8	66.7
Thaliacea	Thaliacea	66.7	74.1	74.4	76.8
Trichodesmium	Trichodesmium	79.9	88.3	87.4	87.1
	average	**38.2**	**75.1**	**75**	**77.2**
		Non plankton			
artefact	artefact	93.9	94.7	93.7	93.5
bubble	bubble	90.4	97.3	97.2	97.2
detritus	detritus	69.3	82.1	80.6	81.1
feces	feces	36.6	46.8	43.7	41.5
fiber<detritus	fiber_detritus	89.1	89	88.2	88.9
gelatinous	gelatinous	35.3	40	39.7	43.5
light<detritus	light_detritus	74.8	79.7	79.4	79.8
medium<detritus	medium_detritus	4.8	66.6	66.4	68.5
other<living	other_living	33.8	51.1	49.7	50
fiber<plastic	plastic	0	37	35.6	38.3
other<plastic	plastic	57.5	63.3	63.6	64.7
	average	**53.2**	**68**	**67.1**	**67.9**