

**The potentials &  
limitations when using  
phytoplankton functional  
traits in combination with long-  
term monitoring data**

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# Functional trait table

**Where:**

ResearchGate: “Coastal phytoplankton trait compilation”

or

<https://www.riinaklais.com/phytotraits>

**Statistics:**

2550 taxa (species or higher)

78% of values filled in, accounting for 96% of all records from SCOR datasets.

Trait information based on literature.

**Intraspecific variability not included**

TRAITS:

**N<sub>2</sub> fixation**

**Buoyancy**

**Silica use**

**Motility (flagella)**

**Autotrophy/heterotrophy**

**Pigments (fyco, chl<sub>b</sub>, chl<sub>c</sub>)**

**Chain / colony**

# Reliability of trait information

- i) phylogenetically conserved traits: *silica use, pigments*
- ii) easy to confirm visually, non-facultative: *motility, autotrophy*
- iii) facultative (high degree of uncertainty, difficult to confirm, intraspecific variability): *mixotrophy, N<sub>2</sub>-fixing, chain-forming*
- iv) Flexible: size (intraspecific variability comparable to inter-specific variability)

# Informational value

- i) Non-facultative binary traits: e.g. *motility*, *pigments*, *silica use*.
- ii) Facultative binary traits: *mixotrophy*, *N<sub>2</sub>-fixing*, *chain-forming* – signal the potential of a trait, not the expression of it.
- iii) Many traits become “facultative” when taxonomic resolution is genus or higher.

NB! “expensive” traits : e.g. *mixotrophy*, *N<sub>2</sub>-fixing*. When prevailing in community, they likely gave the needed advantage.

# Size as problematic master trait

- i) Different ways to measure: volume, ESD, maximum linear dimension.
- ii) Most informative if combined with shape factor

In historic data, for chains/colonies: volume reported either for single cell (in colony), counting unit (e.g. 100 um fraction of chain), or full colony/chain.

# Combining traits into measures of functional diversity

How to weigh the ecological importance of traits?

- Based on their ecological importance (e.g. having or not having *chl b*, vs *motility*?)
- Based on their accuracy (e.g. facultative traits, or limited taxonomic information – when only genus is known, and genus includes species with different trait values)

# 2017 papers (“phytoplankton functional traits”)



**42 hits, 15 using phytoplankton observations in combination with functional traits. 6 in SI of JPR (Litchman & CO)**

**-Only 3 used existing long-term data (others were new samplings)**

**-Most (12/15) were descriptive (*what drives the trait composition?*).**

**Exceptions:**

# Functional richness outperforms taxonomic richness in predicting ecosystem functioning in natural phytoplankton communities

András Abonyi<sup>1,2,3</sup>  | Zsófia Horváth<sup>1</sup>  | Robert Ptacnik<sup>1</sup> 

... response group approach, exclusively derived from field observations, outperforms taxonomic richness and trait category richness in predicting ecosystem functioning. This may highlight that our ability to quantify phytoplankton traits is still limited.



## Community assembly and drivers of phytoplankton functional structure

Riina Klais<sup>\*,1</sup>, Veera Norros<sup>2</sup>, Sirpa Lehtinen<sup>2</sup>, Timo Tamminen<sup>2</sup> and Kalle Olli<sup>1</sup>


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**Separating the deterministic and stochastic variation in community assembly: *were co-existing species more or less similar than expected from their individual environmental preferences?***

**Every 4<sup>th</sup> sample showed non-random signal (n=8000)**

# Classification of Reynolds phytoplankton functional groups using individual traits and machine learning techniques

Carla Kruk<sup>1,2</sup>  | Melina Devercelli<sup>3</sup> | Vera L. M. Huszar<sup>4</sup> | Esnedy Hernández<sup>5</sup> |  
Guadalupe Beamud<sup>6</sup> | Mónica Diaz<sup>6</sup> | Lúcia H. S. Silva<sup>4</sup> | Angel M. Segura<sup>7</sup>

Combined expert knowledge, traits and coarse phylogeny, to teach ML to classify the organisms into one of the 28 RFGs.

Morphological traits	Type of trait	Range and categories
Volume (V, lnV in the model)	Continuous	0.33–4.9 e + 6 $\mu\text{m}^3$
Surface area (SA, lnSA in the model)	Continuous	0.036–39.3 $\mu\text{m}^2$
Maximum linear dimension (MLD)	Continuous	0.84–1,785 $\mu\text{m}$
Life-form	Categorical	Unicell, colony or filament
Aerotopes	Categorical	Presence or not
Flagella	Categorical	Presence or not
Mucilage	Categorical	Presence or not
Akinete	Categorical	Presence or not
Heterocyte	Categorical	Presence or not
Siliceous walls	Categorical	Presence or not
Non-siliceous walls	Categorical	Presence or not

# Where next?

- *changing proportion of individual traits (motile species,  $N_2$ -fixers, mean size), pigmentation patterns*
- *shifts in mean pairwise distance, functional redundancy*
- *effect of functional diversity on the ecosystem function (resource use efficiency)*
- *sensitivity analyses (on smaller coherent subsets of data): effect of different metrics, additional/better resolved trait information, differential weighing of traits etc.*

The END