Streamlined freshwater bacterioplankton *Nanopelagicales* (acI) and "*Ca*. Fonsibacter"

(LD12) thrive in functional cohorts

Running title: Cooperation models for freshwater streamlined bacteria

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ABSTRACT

While fastidious microbes can be abundant and ubiquitous in their natural communities,

many fail to grow axenically in laboratories due to auxotrophies or other dependencies. To

overcome auxotrophies these microbes rely on their surrounding cohort. A cohort may

consist of kin (ecotypes) or more distantly related organisms (community) with the

cooperation being reciprocal or non-reciprocal, and expensive (Black Queen hypothesis)

or costless (byproduct). These metabolic partnerships (whether at single species population

or community level) enable dominance by and coexistence of these lineages in nature. Here

we examine the relevance of these cooperation models to explain the abundance and

ubiquity of the dominant fastidious bacterioplankton of a dimictic mesotrophic freshwater

lake. Using both culture dependent (minimalist mixed cultures) and culture independent

(SSU rRNA gene time series and environmental metagenomics) methods we independently

identified the primary cohorts of *Actinobacterial* genera "*Ca*. Planktophila*"* (acI-A) and

"*Ca.* Nanopelagicus" (acI-B), and the *Proteobacterial* genus "*Ca.* Fonsibacter" (LD12).

While "*Ca*. Planktophila*"* and "*Ca.* Fonsibacter" had no correlation in their natural habitat,

they have the potential to be complementary in laboratory settings. We also investigated

the bi-functional catalase-peroxidase enzyme KatG (a common good which "*Ca*.

Planktophila*"* is dependent upon) and its most likely providers in the lake. Further we

found that while ecotype and community cooperation combined may explain "*Ca*.

Planktophila*"* population abundance, the success of "*Ca.* Nanopelagicus" and "*Ca.*

Fonsibacter" is better explained as a community byproduct. Ecotype differentiation of "*Ca.*

Fonsibacter" as a means of escaping predation was supported but not for overcoming

auxotrophies.

IMPORTANCE

This study examines evolutionary and ecological relationships of three of the most ubiquitous and abundant freshwater bacterial genera: "*Ca*. Planktophila*"* (acI-A), "*Ca*. Nanopelagicus" (acI-B), and "*Ca.* Fonsibacter" (LD12). Due to high abundance, these genera might have a significant influence on nutrient cycling in freshwaters worldwide and this study adds a layer of understanding to how seemingly competing clades of bacteria can co-exist by having different cooperation strategies. Our synthesis ties together network and ecological theory with empirical evidence and lays out a framework for how the functioning of populations within complex microbial communities can be studied.

INTRODUCTION

The stable coexistence of species is described by a continuum of inter-specific symbiotic interactions from parasitism through neutralism to mutualism (1). The extended coexistence of microbial strains is described by intra-specific relationship models limited to niche theory (ecotype differentiation) (2) and predator control of dominant strains (3). Combining these ecological theories of co-existence with phylogenetic information can produce a simplified model with a new holistic perspective for understanding aquatic microbial communities. In aquatic microbial communities, especially for non-particle-associated bacterioplankton, physical structures and proximity as seen in soil, host-

associated microbiome, and biofilm communities (4) are absent. As cooperation models

have been developed from the study of such tightly interwoven assemblages their models

may not be the most suitable. Absent also is the habitat isolation which limits dispersal as

seen in e.g. soil ecosystems. In aquatic systems interactions between nutrients and biota

can occur from micro up to macro-scale distances involving stochastic effectors from

Brownian motion up to whole system circulation currents. Direct but distant interactions

are therefore difficult to identify based purely on proximity as common goods and toxins

in the environment can come from multiple sources and be transported long distances. Data

from long-term monitoring of aquatic environments can be used to test the validity of

ecological models.

Lake Erken has been extensively studied for several decades, and ample background

information on nutrient cycling, planktonic communities and biogeochemical processes

combined with well-established infrastructure makes this ecological observatory an

excellent choice for the study of competing microbial assemblage processes (5–7). Several

studies have investigated the microbial component of this lake ecosystem (8–13), revealing

that the most abundant microbes in Lake Erken belonged to the LD12 (now described as

the candidate genus "*Ca.* Fonsibacter" (14)) and acI (ACK-M1, hgcI, but now described as

the candidate order *Nanopelagicales*) clades (11, 12, 15–20). "*Ca.* Fonsibacter" is a non-

marine genus within the ubiquitous and abundant *Pelagibacteraceae* family which includes

the marine *Pelagibacter* genus (SAR11). *Nanopelagicales* is a freshwater order with two

described genera, *"Ca.* Planktophila*"* and *"Ca.* Nanopelagicus". Both *"Ca.* Fonsibacter"

and the *Nanopelagicales* have small cell size, reduced genomes (1.16 to 1.48 Mbp),

multiple auxotrophies, a requirement for reduced sulfur compounds, have rhodopsins, and

have been recalcitrant to maintenance in axenic laboratory culture (14, 21–23). *"Ca.*

Fonsibacter" and *"Ca.* Nanopelagicus" genera both have additional amino-acid

auxotrophies (23, 24). Recently a single strain of *"Ca.* Fonsibacter" and two strains of the

Nanopelagicales genus *"Ca.* Planktophila*"* (acI-A and acI-A4) were successfully

maintained in axenic cultures by customized liquid media in the case of *"Ca.* Fonsibacter"

(14) and the addition of an active enzyme to filtered lake-water media for *"Ca.*

Planktophila*"* (25). While both have been cultured neither have been deposited in culture

collections and so retain *Candidatus* status. The difference in culture methods point

towards a difference in lifestyle strategies and therefore evolution and ecology in these two

abundant and ubiquitous freshwater bacterioplankton clades.

The ubiquity of the small-genome bacterial lineages, such as *Nanopelagicales* and *"Ca.*

Fonsibacter" in freshwaters, is thought to be a consequence of their streamlined genomes

and small cell size (26). On one hand, small cell size increases surface area to volume

ratio, and improves diffusion, therefore decreasing time for foraging for non-motile

organisms (4). On the other hand, reduced genomes have lost extraneous metabolic

functions while having very low gene redundancy, reduced regulatory components, and

high coding density (27). This combined streamlining and shrinkage reduces the energetic

and material cost of genome, proteome, and cellular maintenance. Because their small

genomes encode fewer metabolic functions than average, it has been proposed they require

a large effective population (large N_e) within which ecotypes diverge to provide the

genomic flexibility usually seen in individual cells of bacteria with larger genomes. A large

N_e is also required for purifying selection to be efficient at reducing and maintaining small

genome size. Such streamlined microbes were first noted in low nutrient aquatic

environments and streamlining has since then been suggested as being of selective

advantage under reduced nitrogen availability (28). *Nanopelagicales* and "*Ca*.

Fonsibacter" clades are dominant and successful in non-marine environments such as Lake

Erken, which far from being nutrient limited is classified as mesotrophic on a

eutrophication trajectory. Further, as Lake Erken is ice and snow covered most winters

(temperature and light limiting) and stratified in summer (thermo and oxy-clines), it is not

a stable environment where organisms with reduced regulatory capacity are expected to

thrive. It is unlikely that dominance in such productive lakes is made possible purely by

streamlining, as the subsequent loss of genomic flexibility required to respond to a dynamic

and variable habitat such as Lake Erken would counteract the benefits. Furthermore, large

populations attract predators though both clades may escape some grazing predation due

to their small size (29, 30). "*Ca*. Fonsibacter" may additionally have similar membrane

properties to its sister marine lineage SAR11(31) to further elude grazing. All three genera

encode cell membrane modification genes in hypervariable regions predicted to assist

escape from viral predation (23, 32). A large N_e where the divergence is focused in

immunogenic or predator-escape mechanisms (defense specialist) will help a species

survive population sweeps caused by predators, though it does not explain the intra nor

inter-specific diversity or the seeming lack of competition between these three genera.

We combined the continuum of symbiotic interactions with phylogenetic information to

produce a simplified model with a new holistic perspective for understanding aquatic

microbial communities. (Fig. 1). Ecotype cooperation model describes how anabolic

variability within a species population i.e. strain level variation, enables all the strains

working together to produce nutrients required for cellular function and replication. It also

allows for recombination and swapping of metabolic modules across strains. The

community cooperation model also has a basis in anabolic complementarity but places the

metabolic variation within a symbiotic group of different species whereby altruistic

members provide expensive (Black Queen Hypothesis) or costless common goods (33, 34).

The community detrital model is similar to community cooperation but focuses on uptake

and catabolism of nutrients released by cellular death mediated by toxicity, starvation, or

predation. Aquatic habitats in particular, due to transport and diffusion, are understood to

have a unique niche for detritivores that may select for streamlined microbes (35).

Here we examine an 8-year time-series along with 26 minimalist mixed-cultures and

selected lake metagenomes, to identify putative supporting microbes (cohort) and whether

that support is best described by ecotype, community, and/or detrital models. We began

with OTU network modelling (to define a candidate cohort that might provide for the target

three genera dependencies), examined the phylogenetic relatedness of each cohort (to

determine if a signal for ecotype or community existed), reviewed the metabolic diversity

of the target group (to establish its dependencies and diversity), and investigated potential

providers of the common-goods catalase-peroxidase (KatG) (a known dependency of some

Nanopelagicales) within the metagenomes. Our proposed framework focusses on neutral

to positive interactions as the laboratory experimental design does not permit detection of

negative interactions even though timeseries can expose potential negative interactions.

Fig. 1. Cooperation models shown in a lake setting. Ecotype Cooperation Model describes

anabolic variability as the main contributor to co-existence while allowing for

recombination and swapping of metabolic modules across strains. Community Cooperation

Model also encompasses anabolic complementarity but between rather than within species

and includes common goods ranging from expensive to costless. The Community Detrital

Model places complementarity both between and within species but describes catabolic

variation.

RESULTS

Taxon abundance and environmental correlates

The most abundant clades detected in the SSU rRNA gene 8-year time-series were the

Actinobacterial order *Nanopelagicales* at 29% average relative abundance (av.ra), the

eukaryote phytoplankton genus *Stramenopiles* 12% av.r.a, the *Actinobacterial* clade 'acIV'

(C111) 11% av.ra, the *β-proteobacterial* family *Comamonadaceae* 5% av.ra, the *α-*

Proteobacterial candidate genus "*Ca.* Fonsibacter" 4% av.ra, and the *Verrucomicrobial*

family *Cerasicoccaceae* 3% av.ra (Fig. S1, Table S1). There were few significant

correlations or differences (Pearsons correlation or Kruskal-Wallis (KW) with post-hoc

testing to identify which pairs were significantly different (KWmc)) between dominant

clade abundance and a broad range of environmental predictors such as lake-cycle/season

or physico-chemical conditions of the water (Fig. S2, Table S2). The three significant linear

correlations detected had only moderate strength (r >= 0.4) with cloud or wedge-shaped

distributions (Fig. S3).

Microbial networks

The OTU network from both the time-series and mixed-cultures (Fig. S4) shows modularity and taxonomic assortativity (grouping of related organisms or under-dispersion) at all taxonomic levels with greater assortativity in the mixed-cultures (Table S3). Assortativity increased with taxonomic level peaking at phylum level in the timeseries, while assortativity was lowest at phylum level in the cultures. First neighbours (the primary cohort) of OTUs in networks provide evidence (but not proof) for preferential association between phylotypes, or when negatively correlated may indicate mutual exclusion. The primary cohorts of "*Ca*. Planktophila, "*Ca*. Nanopelagicus", and "*Ca*. Fonsibacter" (Fig. 2) are overlapping and include phylotypes from each other's cohorts. Primary cohorts from the time-series and mixed-cultures are similar, though the correlation type and strength vary. There was a moderate correlation between relative abundance of OTUs in the timeseries (Fig. 2a) and relative abundance in cultures (Pearsons r = 0.58, p_{adj} = 0, Table S4) but no other correlations between relative abundance or prevalence (percentage of samples an OTU was detected in) were observed.

Actinobacterial order Nanopelagicales (acI)

Nanopelagicales in Erken had higher relative abundances in the hypolimnion, (KW p<0.001, KWmc p<0.001) and were negatively correlated with % O_2 (Pearsons r = -0.4, p<0.001). *Nanopelagicales* were the most abundant clade in Lake Erken and were

a) Lake Erken time-series
1° cohort

b) Mixed-cultures from lake water
1° cohort

Fig. 2. OTU networks of the primary cohorts from amplicons of a) time-series aand b)

mixed-cultures. Nodes sized by average relative abundance in time-series and by

percentage of cultures detected in for mixed-cultures. Pink dotted lines indicate mutual

exclusion of OTUs while grey solid lines are co-occurrence.

represented by 31 OTUs in the lake time-series network with nine *"Ca.*

Nanopelagicus"*,* 21 *"Ca.* Planktophila*",* and one acI-c (Fig. 2a, Fig. S4). A subset of six

*"Ca.*Nanopelagicus" and one *"Ca.* Planktophila*"* phylotype were detected in the mixed-

culture based network (Fig. 2b, Fig. S4).

The time-series primary (1°) cohort (i.e. the cohort immediately surrounding) of *"Ca.*

Planktophila*"* included: other *Actinobacteria*, *Armatimonadetes*, *Chloroflexi*,

Gemmatimonadetes, α- and β-*Proteobacteria*, and *Verrucomicrobia*, while in the

mixed-cultures only *Actinobacteria*, *Bacteroidetes*, and α- and β-*Proteobacteria* co-

existed. A pairwise comparison of the phylogenetic distance and correlation

(averaged edge value from the correlation network) was conducted to see if there was

a relationship between OTU genetic relatedness and co-occurrence; to distinguish

between ecotype and directed reciprocation models. Within the *"Ca.* Planktophila*"* 1°

cohort, there was no support for a correlation between phylogenetic distance and co-

occurrence (Fig. 3) and *"Ca.* Planktophila*"* was the only genera tested that had

negative intra-genus correlations. *"Ca.* Planktophila*"* had more intra-phyla (i.e. non-

Nanopegicales Actinobacteria) correlations than the other genera tested. Unlike the

other genera, *"Ca.* Planktophila*"* had no correlations (positive or negative) with

phytoplankton in its 1° network (Fig. 3). Additionally, *"Ca.* Planktophila*"* were the

dominant Actinobacterial genus in the time-series with "*Ca*. P. vernalis*"* being most

abundant (Fig. 2a). Conversely, in the mixed-cultures, only one *Planktophila* phylotype

was detected, "*Ca*. P. limnetica*"* (Fig. 2b).

"Ca. Planktophila spp." were successfully maintained in axenic culture via the addition

of bovine catalase and therefore the presence, absence, and functionality of the

relevant *Nanopelagicales* catalase-peroxidase (KatG) is debated. We investigated the

presence of the *katG* gene, its gene neighbourhood, and the homology and topology of

its translated product, KatG, to establish if there is evidence to support its activity level or

effect on host abundance. "*Ca*. P. vernalis*"* (acI-A7) KatG had highest homology to the high

functioning *Synechoccocus* version (Fig. S5) and the gene is found near a tRNA (Fig. S6).

"*Ca*. P. limnetica*"*s KatG had highest identity with the assayed low activity KatG from "*Ca*.

P. rubra*"* (IMCC 25003) and was located within a putative DNA repair region (Fig. S5 &

S6). When modelled these KatGs were most similar to *Burkholderia pseudomaleii*s with a

predicted β-sheet around one of the active site residues instead of an α-helix, and are 10 to

20 amino-acid residues longer than known high functioning versions i.e. *Burkholderia* type

A (Fig. S5). All known active site residues involved in heme interaction or enzyme

switching were however present. *"Ca*. Planktophila limnetica*", "Ca*. P. vernalis*", "Ca*. P.

lacus*", and "Ca*. N. limnes*"* all have the repair cassette without *katG*. Metagenomic *katG*

sequences were recovered matching *"Ca*. P. dulcis*", "Ca*. P. limnetica*", "Ca*. P.

versatilis*"*, and *"Ca*. P. vernalis*"*.

Fig. 3. The relationship between OTU phylogenetic distance and correlation of the primary

cohort phylotypes to selected genera: *"Ca. Planktophila"* upper-left, "*Ca*. Nanopelagicus"

upper-right, "*Ca*. Fonsibacter" lower-left, and basal "*Ca*. Fonsibacter "lower-right.

"Ca. Nanopelagicus" 1° cohort in the time-series included other *Actinobacteria*,

Bacteroidetes, α- and β-*Proteobacteria*, and the phytoplanktonic *Synechococcus* and

Stramenopiles (identified by chloroplast sequences), while in the mixed-cultures

there was a subset of these phyla with the addition of one γ-*proteobacterial* phylotype

(Fig 2). To calculate whether the presence of an OTU in the mixed-cultures could be

attributed to the probability of it being in the inoculum, the total and average relative

abundances, and the number of samples an OTU was detected in (prevalence) was

compared across the two datasets with Pearsons correlation. There was no

correlation between "*Ca*. Nanopelagicus" OTU relative abundance or prevalence in the

lake time-series as compared to the mixed-cultures (Table S4). "*Ca*. Nanopelagicus"

was overall more prevalent in mixed cultures than in the lake time-series. "*Ca*.

Nanopelagicus" had strong correlation with "Ca. Fonsibacter" in both datasets. There

were between 3 and 19 other phylotypes (non-*Nanopelgicales*, non-Fonsibacter)

detected in cultures with "*Ca*. Nanopelagicus" (Table S5).

The most abundant "*Ca*. Nanopelagicus" phylotypes in both datasets were assigned to the

katG⁻ "*Ca*. Nanopelagicus limnes". Several metagenome-recovered putative "*Ca*.

Nanopelagicus" *katG* genes were identified in IMG databases and while these KatGs had

greatest homology with *Burkholderia* fold type B, they were not located within the repair

cassette and there was no synteny between them. No "*Ca*. Nanopelagicus" katG sequences

were recovered from our metagenomes.

α-Proteobacterial genus "Ca. Fonsibacter" (LD12)

"*Ca*. Fonsibacter spp." had higher relative abundance from winter to spring and moderate

negative correlation with water temperature (r = -0.4, p<0.001, Table S2). "*Ca*.

Fonsibacter" was represented by 10 OTUs in each of the time-series and mixed-culture

networks, with nine OTUs common to both and the alternating OTUs being the least

abundant and least prevalent in both environments. The "*Ca*. Fonsibacter" 1° cohort from

the time-series includes other "*Ca*. Fonsibacter", *Bacteroidetes*, *α-* and *β-Proteobacteria*,

Actinobacteria including "*Ca*. Nanopelagicus" and acI-c, and phytoplankton

Synechococcus and *Stramenopiles*. The "*Ca*. Fonsibacter" 1° cohort from mixed-culture

experiments also included other "*Ca*. Fonsibacter" phylotypes, "*Ca*. Nanopelagicus",

Bacteroidetes, other *α-* and *β-Proteobacteria* and macro-algal eukaryotes of the

Streptophyta order. There was a strong correlation detected between "*Ca*. Fonsibacter"

OTU prevalence in the lake time-series compared to the prevalence of the respective OTU

in the mixed-cultures (corr = 0.82, n=11, p adj = 0, Table S4). Based on OTU identity,

phylogenetic branch placement, and network connections, two "*Ca*. Fonsibacter"

phylotypes were designated as basal and analysed separately for 1° cohort. Unlike the core

"*Ca*. Fonsibacter" phylotypes, these basal phylotypes had no negative correlations with

phytoplankton and no correlations with other "*Ca*. Fonsibacter" phylotypes (Fig. 3).

Other primary cohort members

Both the *Actinobacterial* 'acIV' (C111) and *Comamonadaceae* families were more

abundant in winter when the lake was covered by ice (Fig. S2, KW p<0.001, KWmc

p<0.001). While 'acIV' was abundant and ubiquitous in the time-series (Fig. S1, Table S1),

and also prominent in the *"Ca*. Planktophila" time-series 1° cohort (Fig. 2a), no phylotypes

were detected in the mixed-cultures. *Comamonadaceae* was abundant but patchy in the

time-series and mixed cultures.

DISCUSSION

Taxon relative abundance and environmental correlates

If microbial abundance is directly linked to nutrient availability or other physico-chemical

parameters, then a strong correlation between geo-chemical parameters and relative

abundance is expected. The lack of strong correlation between OTUs or clades and

environmental parameters in Lake Erken indicates that during the 8 years of sample

collection, microbial community composition was not directly and strongly controlled, but

only influenced, by the measured abiotic environmental variables. While short-term studies

have shown significant strong trends and correlations (12), such correlations tend to be

eclipsed in studies spanning multiple years by shifts operating at longer frequencies and

biotic interactions (36–39). Overall, the strength and number (identified via consensus

network) of correlations between taxon relative abundance and the weakness of

environmental predictors for most of the taxa suggest that biological aspects (including

predation, which we did not study) are the greater determinants of microbial population

dynamics, composition and persistence in Lake Erken. It stands therefore that the

dominance of the three streamlined genera in the lake is attributable more to their

interactions with their community than selection by environment.

Microbial networks

Assortativity is a predicted product of ecotype or niche differentiation at species level and

environmental filtering at higher taxonomic levels (40). Ecotype divergence of strains

reduces competition between different members of a population. The detection of highest

assortativity in the time-series networks at phylum level supports environmental selection

as important in the lake habitat but not at taxonomic levels lower than phyla. It is unlikely

that environmental filtering is the main driver behind the success of these three genera in

Lake Erken. High assortativity in the mixed cultures at all levels except phylum, supports

that niche differentiation contributed to co-occurrence in the cultures. Neither result

however fully supports, nor refutes, ecotype theory as the explanation of coexistence or

dominance by "*Ca.* Planktophila", "*Ca.* Nanopelagicus", or "*Ca.* Fonsibacter" genera.

The strong correlation between "*Ca*. Fonsibacter" (and also *Comamonadaceae*) prevalence

in the time-series and mixed-cultures supports that its occurrence in the cultures may be

attributed to being present in the inocula and that the filtered lake water media was able to

meet an important proportion of its metabolic needs. Conversely, the lack of correlation in

either relative abundance or prevalence, for the *Nanopelagicales* genera (and also the

'acIV' family) in the time-series compared to mixed-cultures means that there is not support

for their detection being merely due to high-abundance in the inocula. We infer that the co-

presence of other phylotypes were bigger contributors to their growth. It should be noted

that negative correlations are not detectable in the mixed-cultures as the absence of a

phylotype could be stochastic rather than a result of competitive exclusion. Moreover,

competition that prevents growth in a culture cannot be identified.

Actinobacterial order Nanopelagicales 'acI'

Nanopelagicales in Erken were likely more competitive in colder, darker, and oxygen

depleted waters. While *Nanopelagicales* has been associated with oxygen saturated waters

in some locations (41) this lineage has been associated with colder deeper water at others

(30), though the variation in association could be due to the considerable genetic diversity

encompassed in this bacterial order (42). It is also probable that solar-driven formation of

oxygen radicals in surface waters inhibit the growth of $katG^-$ species of *Nanopelagicales*.

Of the seven *Nanopelagicales* phylotypes in the mixed-cultures, six were members of the

candidate genus "*Ca.* Nanopelagicus" suggesting that this genuss dependencies were more

easily met compared to the *"Ca.* Planktophila spp.*"* found in Lake Erken. However,

genomic evidence so far has shown the opposite as "Ca. Nanopelagicus spp." have more

numerous auxotrophies than *"Ca.* Planktophila spp." (23). It is therefore possible that the

difference in culturability seen in this experiment was due to reduced costs via gene loss in

combination with suitable metabolic partners being in the inoculum. In particular the lower

maintenance costs due to the loss of *katG* (25, 33) could increase fitness of the "*Ca.*

Nanopelagicus". The successful maintenance of *"Ca.* Planktophila*"* in culture pinpointed

the low functionality of some *Nanopelagicales* catalase-peroxidases as the culprit for the

difficulties in growing these bacteria. Peroxide is proposed to be an up-regulator of a DNA

repair (43) and in the *"Ca.* Planktophila*"* with the putative low functioning KatG type, the

gene is embedded in a region of DNA hosting other genes for repair of damage done to

DNA under oxidative stress. *P. limnetica* (acI-A3) genomes have this repair cassette but

their *katG* is located elsewhere. The most parsimonious explanation for *Nanopelagicales*

katG presence/absence/homology is that the now low functioning version located in a

repair cassette is in the process of being lost and that the *"Ca.* Planktophila spp.*"* with a

high functioning KatG obtained this version via a HGT event. While *P. vernalis* in Lake

Erken is likely *katG*$^+$, it is likely that *P. limnetica* and *N. limnes* from Lake Erken rely on

"*Ca.* Fonsibacter" in combination with either *Flavobacterium* or *Comamonadaceae* to

detoxify peroxide. This would fit within the community cooperation model. While *"Ca.*

Nanopelagicus"* has more numerous auxotrophies compared to *"Ca.* Planktophila*"* (23)

the higher culturability of *"Ca.* Nanopelagicus"* supports that it may be the cost to

habouring *katG*, whether high or low functioning, and as *katG* is larger than average (44),

and as long as a functional aquaporin exists (45), and cells don't grow too fast, then it

would be an unnecessary cost, as cells can rely on other community members for oxidative

stress reduction. Further the reduction in amino-acid synthesis pathways and therefore

greater reliance on exogenous sources of amino-acids in "*Ca.* Nanopelagicus"* appears to

have paid off if their greater cultivability in these minimalist cultures is any indicator. This

fits within the community detritus model.

α-Proteobacterial genus "Ca. Fonsibacter" (LD12)

Earlier short-term studies found that "*Ca*. Fonsibacter" is highly abundant in Lake Erken

in the late summer-early autumn immediately after an algal bloom i.e. the 'clear water'

phase of the lake's cycle (12). However, we found support for higher long-term relative

abundances in winter and spring and an associated negative correlation with water

temperature. These differences in findings could be due to changes in abundance between

years of different ecotypes (with different temperature and nutrient preferences) that were

not detected via 16S surveys. The ecotype differentiation within "*Ca.* Fonsibacter" is

centered around the HVR1 which is thought to encode genes for defense, i.e. predator

escape via alteration of cellular membranes (3, 46). There appears to be limited intra-

population variability in anabolic or catabolic traits (14, 24, 47) and as such, ecotype

differentiation for overcoming auxotrophies is not supported. While no direct evidence

exists for "*Ca*. Fonsibacter", its similarity to the marine sister clade Pelagibacter suggests

that it has overcome auxotrophic limitations by scavenging metabolites and other

compounds produced by phototrophs (48). In Erken this would primarily be dying and

senescent *Stramenopiles* as reflected in the apparent negative correlation. Evidence points

to "*Ca*. Fonsibacter" relying on detritus to meet its dependencies and ecotype

differentiation for defense.

The combination of network and other correlation analyses with review of published

genomes supports that the most of *Nanopelagicales* have anabolic ecotype cooperation

with reliance on a detoxifying community cohort as main structuring factors. A few *"Ca.*

Planktophila*"* are putatively KatG+ but as they were not detected in Lake Erken it was not

possible to determine the most appropriate cooperation models in this study. "*Ca*.

Fonsibacter" may escape predation via ecotype differentiation, while broadly relying on

community detritus for anabolic deficits.

MATERIALS AND METHODS

Time series water sampling and environmental parameters

Time series water samples were obtained from dimictic Lake Erken (59.1510N, 18.1360E)

central Sweden at monthly to weekly intervals spanning a total period from February 2007

to November 2015 (Table S6). Samples for genomic and chemical analysis were taken from

the 20 m water column at one meter intervals from the deepest point of the lake (Fig. S7).

Samples for the total water column were pooled during periods of mixing. Samples of the

upper oxygenated water column (epilimnion), middle (metalimnion), and lower oxygen

depleted (hypolimnion) were pooled into separate composite samples during summer

stratification. Annual dates of mixing, stratification, ice-over, and ice-thaw varied, as did

depth of stratigraphic layers (Table S6). Temperature and oxygen concentrations were

analyzed every meter with a portable Oxi 340i oxygen meter equipped with a Cellox 325-

20WTW probe and were used to determine stratification. Chemical analysis of pooled

water samples was carried out by the Lake Erken Field Station ISO certified laboratory and

included pH, conductivity, nitrate, nitrite, alkalinity, turbidity, suspended matter,

phosphate, ammonium, total and particulate phosphorus and nitrogen, chlorophyll-a,

suspended particulate organic matter, silicate, water-colour and absorbance at 420nm

measurements. Water samples for genomic analysis were collected by gentle vacuum

filtration onto 0.2 μm membrane filters (Supor-200 Membrane Disc Filters, 47mm; Pall

Corporation, East Hills, NY, USA). Filters were individually stored in Eppendorfs and

transported back to the University Uppsala laboratory where they were stored at -80 °C

until further processing.

DNA extraction and SSU rRNA gene amplicon preparation

DNA was extracted from filters using MoBio Ultra-clean soil DNA extraction kits (MoBio, Carlsbad) as per manufacturers' instructions. The V3-V4 region of the 16S rRNA gene was amplified using the S-D-Bact-0341-b-S-17 (Bakt_341F: CCTACGGGNGGCWGCAG) forward primer and S-D-Bact-0785-b-A-21 (805RN: GACTACNVGGGTATCTAATCC) reverse primer (49). Template DNA was amplified in duplicate 20 μl reactions containing 1.0 U Q5 high fidelity DNA polymerase (NEB, UK), 0.25 μM primers, 200 μM dNTP mix, and 0.4 μg BSA. The thermocycler program was an initial denaturation step at 95 °C for 30 s, followed by 20 cycles of dissociation at 95 °C for 10 s, annealing at 53 °C for 30 s extension at 72 °C for 30 s, with a final extension of 2 min at 72 °C. Amplicons were pooled and purified with Agencourt AMPure XP purification system (Beckman Coulter, Danvers, MA, USA). Purified amplicons (2 μl) were amplified in second step 20 μl reactions to introduce sample MIDS to each end of the amplicons. Reactions contained 1.0 U Q5 high fidelity DNA polymerase (NEB, UK), 0.25 μM primers, 200 μM dNTP mix, and 0.4 μg BSA. Thermocycler program was an initial denaturation step at 95 °C for 30 s, followed by 15 cycles of dissociation at 95 °C for 10 s, annealing at 66 °C for 30 s, extension at 72 °C for 30 s, with a final extension of 2 min at 72 °C. Amplicons were again purified using Agencourt AMPure XP purification system (Beckman Coulter, Danvers, MA, USA) then quantified using PicoGreen (Invitrogen) before pooling at equi-molar amounts for each

run. Amplicons were sequenced at SciLifeLab SNP/SEQ service on the MiSeq Illumina

platform with 300bp paired-end libraries. MiSeq data was processed, including de-

multiplexing, by the sequencing centre using Illumina pipelines where all reads with more

than 8% mismatch to adapter-MID sequences were discarded.

Water sampling, culture conditions, and DNA amplification for mixed-cultures

Water as both a source of growth-media and culturable-cells was collected from the

epilimnion of Lake Erken on March 8th 2016. Water for growth-media was filter-sterilised

twice through Sterivex filter cartridges 0.22 μm (Millipore). Ten minutes exposure to UV

light further disinfected and disrupted cellular and viral nucleic acids. Ten microliters of

untreated lake water (10^6 cells/ml) were used as a source of cells for inoculation of mixed-

cultures. The untreated lake water was diluted in 1 L of the triple sterilized lake water

(approximately 10 cells/ml). Ninety-eight 1 ml cultures were placed in sterile 50 ml falcon

tubes to allow oxygenation and incubated for two months under 12-hour light-dark cycles

at 11 °C to replicate lake conditions at time of collection. The V3-V4 region of the 16S

rRNA gene was amplified using the S-D-Bact-0341-b-S-17 (Bakt_341F:

CCTACGGGNGGCWGCAG) forward primer and S-D-Bact-0785-b-A-21 (805RN:

GACTACNVGGGTATCTAATCC) reverse primer (49) One microliter of the mixed-

culture after one freeze-thaw cycle was used as template and Q5® High-Fidelity DNA

Polymerase. The PCR conditions consisted of an initial step at 98°C for 10 minutes.

Thereafter, 35 cycles of denaturation at 98°C for 10 s, annealing for 30 s and extension at

72°C for 30 s. Annealing temperature was 48°C which has been tested to get unbiased

products of non-mismatch and 3-mismatch isolates. Final extension was performed at 72°C

for 2 minutes. PCR products were purified with magnetic beads (Angecourt AMPure). A

second PCR was conducted for attaching standard illumina handles and index primers as

described above. Primers and MIDS detailed in Table S7. Prior to sequencing a portion of

amplification product was run on gel to check for amplification and used as proxy for

growth of culture. Only data from the 60 cultures with a visible band after the first PCR

were included in analyses.

Amplicon bioinformatics

Demultiplexed MiSeq time-series and mixed-culture data, and 454 Ti time-series data

obtained from Lake Erken 2008 (11), were pre-processed separately and joined once

chimeras had been removed. Pre-processing of MiSeq data started with SeqPrep v1.2

(https://github.com/jstjohn/SeqPrep.git) with default settings to join paired end

reads while discarding reads shorter than 30b and all un-paired reads. 454 and MiSeq

reads with ambiguous bases, low quality average, and low quality sections, were

discarded and trimmed with Qiime v1.9 (50) split_libraries and multiple split libraries

fastq respectively. Singletons and sequences identified as chimeric were removed

with Qiimes' identify_chimeric_seqs, filter_fasta using usearch v6.1 (51), with default

settings and option parameter 'intersection' to select out sequences identified by both

de-novo and reference-based methods. Both GreenGenes (v105 13-8) and SILVA

(v128) reference datasets were used (52, 53). Sequences from the two Miseq runs and

the 454 data from 2008 were then combined. Reads were clustered at 97% identity

into OTUs then assigned taxonomy based on SILVA v128 using QIIMES closed pick

OTU method (uses only template recognition and does not allow for de-novo

sequences) to allow for differences in DNA processing and sequencing across the

three datasets. Sequences from the negative control were removed from the entire

dataset. Samples with potential human-microbiome contamination (Table S8) were

identified and discarded from the dataset due to potential effect on community

metabolism. Sequences identified as eukaryotic (including fungal, mitochondrial and

chloroplast origin) or archaeal were deliberately retained despite the primers not

specifically being selected to amplify such sequences. as they were considered critical

in the mixed-culture analyses from a community metabolism perspective. Samples

were normalized using Qiimes single rarefraction to even depth of 1500 reads per

sample for the time-series and 500 reads for the mixed-culture samples. These

normalised OTU tables were then used for all downstream analyses.

Statistical analyses of time-series environmental correlates and selected taxa

Statistical analyses were done using R v3.3.1 (54) in the RStudio IDE v0.99.903 (55) and graphs processed for publication in Inkscape v0.91. Environmental parameters were removed if more than 40% of the values were missing then remaining twenty-one tested for co-linearity with the usdm v1.1.18 package with vifstep followed by vifcor functions and removed if VIF >10 or correlations were over 0.7 sequentially starting with those with highest number of missing values. The remaining 14 environmental predictors were tested for statistical differences in connection to lake-cycle with Kruskal-Wallis (kruskal.test of the base stats package) and graphed using beanplot v1.2 (56) and scales v0.4.1. Statistical significance of differences between individual paired cycle points were determined post-hoc with the Kruskal-Wallis multiple comparison (KWmc) using thekruskal.mc test of the pgirmess package v1.6.4 (57). Environmental parameter correlates with selected taxa relative abundances were screened using Pearsons correlation with an alpha level of 0.001 and p-values estimated and corrected for multiple comparisons with Benjamini, Hochberg, and Yekutieli (BH) false discovery rate using the psyche package v1.6.12 corr.test function and Pearsons moment r reported. Parameters with weak to moderate correlation ($r > |0.3|$) were plotted in R to observe monotonicity.

Network analyses

The normalized time-series OTU table was further processed for network and correlation

analyses to remove rare OTUs that, while potentially important within the community, are

known to inhibit identification of ecological relationships between OTUs and also between

OTUs and their environment. Recommendations include OTU tables with 50% or less

sparcity and n_{eff} (inverse Simpsons) above an average of 10 and the use of multiple methods

(58). A range of filtering parameters based on frequency of OTU detection, from 2 samples

up to 46 (20% of samples) and total relative abundance ranging from 1 up to 150 (0.1%),

was used on the OTU table to remove type I errors in detection of co-occurrence networks

(58). The best filter combination was found with OTUs at a total relative abundance above

0.1% and occurring in at least 29 samples. All OTU tables were analysed in R (54) using

the vegan v2.4-1 package (59) diversity function to find the n_{eff} and the base stats v3.3.1

package to find min, max and mean of the n_{eff}. The reduced OTU table was analysed with

SparCC (60), Pearsons correlation coefficient, and SPIEC-EASI (61). SparCC analyses

were carried out in Rstudio (55) using both the rsparcc and spiec.easi packages with rsparcc

parameters: max.iter=100, th=0.1, exiter=10 and pseudo p-values generated with

spiec.easis sparccboot (100 bootstraps) and pval.sparccboot scripts (two-sided test).

Pearson correlations were performed using the corr.test of psyche package using the

optional p-values adjustment for multiple testing of Benjamini, Hochberg and Yekutieli

false discovery rate. SPIEC-EASI correlations were analysed using the spiec.easi package

with parameters: method="mb", sel.criterion="stars", lambda.min.ratio=1e-2,

nlambda=20, and 50 repetitions. Singletons were removed from the normalized mixed-

culture OTU table prior to network analysis. The reduced OTU table was analysed with

Pearsons correlation, SpiecEasi (61) and on the binary version of the table, Dice-Sørensen

index (62, 63).

Correlations between OTUs in the time-series and mixed cultures were retained if the

correlation co-efficient was greater than 0.3 absolute for Pearsons, SparCC, or Dice-

Sørensen, or if detected at all by SPIEC-EASI. Time-series and culture networks consisting

of OTU connections detected by at least two correlation methods were visualized in

Cytoscape. All further statistical analyses of the networks were performed in Cytoscape

except for assortativity analyses which were done in R using the igraph v1.1.2 package

nominal assortativity function. Sub-networks of the identified dominant genera ("*Ca.*

Planktophila", "*Ca*. Nanopelagicus", and "*Ca*. Fonsibacter") and their primary cohorts

were extracted from the two initial networks and visualized separately. Layout for the

networks were "edge-weighted spring-embedded" with edge weights calculated from the

average of the correlations. Some nodes (OTUs) were moved to the side of overlapping

nodes for clarity or away from an edge if it appeared to pass through an unconnected node.

Correlations between *Nanopelagicales* OTU and "*Ca*. Fonsibacter" OTU detection in the

time-series versus the mixed cultures were investigated by Pearson correlation of their

relative abundance (log av.ra), prevalence (percent samples or cultures detected in) and

relative abundance versus prevalence to determine if detection in culture was correlated to

occurrence in the lake.

Metagenomic sequencing

Samples for metagenomic sequencing were selected by highest relative abundance of

clades of interest according to amplicon data, greatest available DNA mass, and greatest

variation in environmental parameters. This was done to examine samples with the greatest

potential divergence of environmental conditions under which microbes of interest were

most abundant. These included samples taken during lake circulation and summer

stratification which separately including hypo, meta and epi-limnionic samples. Two

samples per category were selected from different years. Lower biomass during ice cover

meant there was insufficient DNA for metagenomic sequencing. DNA library for

metagenomic sequencing was prepped using the Illumina TruSeq Nano, 550bp NeoPrep

and sequenced with Illumina HiSeq 2500 High Output V4 PE 2x125bp at SciLifeLab

Stockholm.

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Metagenome bioinformatics

HiSeq Illumina paired end reads were pre-processed first using SeqPrep v1.2 (64) to filter

out low quality reads using default settings resulting in removal of all reads less than 30b

in length, un-paired reads and initial clipping of adapter sequences. Next sequences were

cleaned using Trimmomatic v0.36 (65) with removal of any remaining Illumina adapters

allowing for 2 mismatches; followed by 4b sliding window trim with minimum average

quality of 15; then trimming of read ends with 'maxinfo' value less than 1. The eight

metagenomes were individually assembled with megahit (66) using iterative kmers from

21 to 121 at 10b intervals, minimum coverage of 2, and minimum length of 200.

Concatenated assemblies were cleaned of Illumina artifact low complexity (long

homopolymer) contigs with prinseq-lite v0.20.4 (67) removing contigs consisting of

greater than 80% one nucleotide.

Investigation of katG gene and its product: catalase-peroxidase I

Known impediments to axenic growth of freshwater isolates are multiple auxotrophies, and

slow growth and replication rates. The successful axenic cultivation of "*Ca*. Planktophila"

strains by addition of high functioning catalase to reduce oxidative stress, in addition to

catering for predicted auxotrophies, showed that there can be other considerations. To

investigate how both "*Ca*. Planktophila" and "*Ca*. Nanopelagicus" phylotypes grow in

Lake Erken and why "*Ca*. Nanopelagicus" grew more frequently in the minimalist mixed

cultures, the katG gene was investigated. First katG amino-acid sequences for species

identified as belonging to the Nanopelagicales and its primary cohort were retrieved from

IMG and GenBank (68, 69). Second sequences for whom the gene product has been

assayed and/or the 3D crystal structure is known were identified via Phyre2 and then

collected from RCSB PDB (rscb.org (70, 71)). Next these sequences were used as BLAST

(72) queries to retrieve closely related (> 80% aa identity) sequences from Lake Erken

metagenomes. The collected amino-acid sequences were aligned using MAFFT e-insi and

"leavegappy" options (73). Sequences with greater than 99% identity were identified using

CD-Hit and removed (74) while sequences from uniRef useful for constructing a guide tree

were then also added (75, 76). The alignment was evaluated for best amino-acid

substitution model using IQ-tree v.1.6.12 modelfinder (77). This alignment was then

analysed and used to construct a tree in RAXML v.0.9.0 (78) with WAG+IG+R4 model

and 1000 bootstraps and catalase-peroxidase from *Oryza rufipogon* set as outgroup. To

examine functionality secondary structure was predicted and aligned to known models then

tertiary structure predicted in Phyre[2] (71). Further the location of katG genes in

Nanopelagicales genomes and MAGs was examined in IMG using the gene-

neighbourhood function. Images were downloaded with screen shot and processed in

Inkscape.

Data availability

Time-series   MiSeq   sequences   were   deposited   in   ENA

(https://www.ebi.ac.uk/ena/browser/view/PRJEB20109)   under   accession   numbers:

ERS1884053 to ERS1884254, sample details including MIDS are also in Table S6. Mixed-

culture   sequences   are   available   from   ENA   PRJEB35605

(https://www.ebi.ac.uk/ena/browser/view/PRJEB35605) with details also in Table S7. 454

data used in the time-series is available at SRA (https://trace.ncbi.nlm.nih.gov/Traces/sra/)

under accession SRR097418 (11). HiSeq metagenome sequences are available at ENA

project PRJEB37497 under accession numbers: ERS4415328 to ERS4415335 and the

assembled metagenomes are available at IMG (https://img.jgi.doe.gov/cgi-bin/m/main.cgi)

with TOIDs: 3300020141, 3300020151, 3300020159, 3300020160, 3300020161,

3300020162, 3300020172, & 3300020205 details in Table S9. Rscripts used for correlation

and network analyses are available from https://github.com/rmondav/publications.

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AUTHOR CONTRIBUTIONS

SB, SL, and RM contributed to the genomic sampling design, organization, and selection. SLG and MB designed and implemented the mixed-culture experiments. RM designed and performed the bioinformatic analyses. RM and SLG synthesized the conceptual framework which was drafted by RM in consultation with SLG, with editorial contributions from all authors.

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