Metabolic differentiation of co-occurring Accumulibacter clades revealed through
genome-resolved metatranscriptomics

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ABSTRACT

Microbial communities in their natural habitats consist of closely related populations that may exhibit phenotypic differences and inhabit distinct niches. However, connecting genetic diversity to ecological properties remains a challenge in microbial ecology due to the lack of pure cultures across the microbial tree of life. *'Candidatus* Accumulibacter phosphatis' is a polyphosphate-accumulating organism that contributes to the Enhanced Biological Phosphorus Removal (EBPR) biotechnological process for removing excess phosphorus from wastewater and preventing eutrophication from downstream receiving waters. Distinct Accumulibacter clades often co-exist in full-scale wastewater treatment plants and lab-scale enrichment bioreactors, and have been hypothesized to inhabit distinct ecological niches. However, since individual strains of the Accumulibacter lineage have not been isolated in pure culture to date, these predictions have been made solely on genome-based comparisons and enrichments with varying strain composition. Here, we used genome-resolved metagenomics and metatranscriptomics to explore the activity of co-existing Accumulibacter clades in an engineered bioreactor environment. We obtained four high-quality genomes of Accumulibacter strains that were present in the bioreactor ecosystem, one of which is a completely contiguous draft genome scaffolded with long reads. We identified core and accessory genes to investigate how gene expression patterns differ among the dominating strains. Using this approach, we were able to identify putative pathways and functions that may differ between Accumulibacter clades and provide key functional insights into this biotechnologically significant microbial lineage.

IMPORTANCE

'*Candidatus* Accumulibacter phosphatis' is a model polyphosphate accumulating

organism that has been studied using genome-resolved metagenomics,

metatranscriptomics, and metaproteomics to understand the EBPR process. Within the

Accumulibacter lineage, several similar but diverging clades are defined by the

polyphosphate kinase (*ppk1)* locus sequence identity. These clades are predicted to have

key functional differences in acetate uptake rates, phage defense mechanisms, and

nitrogen cycling capabilities. However, such hypotheses have largely been made based

on gene-content comparisons of sequenced Accumulibacter genomes, some of which

were obtained from different systems. Here, we performed time-series genome-resolved

metatranscriptomics to explore gene expression patterns of co-existing Accumulibacter

clades in the same bioreactor ecosystem. Our work provides an approach for elucidating

ecologically relevant functions based on gene expression patterns between closely

related microbial populations.

INTRODUCTION

Naturally occurring microbial assemblages are composed of closely related strains or subpopulations and harbor extensive genetic diversity. Coherent lineages are often comprised of distinct clades, ecotypes, or "backbone subpopulations" defined by high within-group sequence similarities that translate to ecologically relevant diversity (1–3). Genetically diverse ecotypes of the marine cyanobacterium *Prochlorococcus* that are 97% identical by their 16S ribosomal RNA gene sequences exhibit markedly different light-dependent physiologies and distinct seasonal and geographical patterns (1, 2, 4, 5). Transcriptional-level differences between closely related microbial lineages have also been demonstrated, such as that of high-light and low-light *Prochlorococcus* ecotypes (6). However, dissecting the emergent ecological properties of genetic diversity observed among coherent microbial lineages is challenging given that these principles are likely not universal among the breadth of microbial diversity, and is further hindered by the lack of pure cultures (7).

Enhanced Biological Phosphorus Removal (EBPR) is an economically and environmentally significant process for removing excess phosphorus from wastewater. This process depends on polyphosphate accumulating organisms (PAOs) that polymerize inorganic phosphate into intracellular polyphosphate. '*Candidatus* Accumulibacter phosphatis' (hereafter referred to as Accumulibacter) is a member of the *Betaproteobacteria* in the *Rhodocyclaceae* family and has long been a model PAO (8, 9). Accumulibacter achieves net phosphorus removal through cyclical anaerobic-aerobic phases of feast and famine. In the initial anaerobic phase, abundantly available volatile fatty acids (VFAs) such as acetate are converted to polyhydroxyalkanoates (PHAs), a

carbon storage polymer. However, PHA formation requires significant ATP input and

reducing power, which are supplied through polyphosphate and glycogen degradation. In

the subsequent aerobic phase in which oxygen is available as a terminal electron

acceptor but soluble carbon sources are depleted, Accumulibacter uses PHA reserves

for growth. Energy is recovered during aerobic PHA utilization by replenishing

polyphosphate and glycogen reserves, which can be later used for future PHA formation

as the anaerobic/aerobic cycle repeats. This feast-famine oscillation through sequential

anaerobic-aerobic cycles operating on minute-to-hourly time scales gives rise to net

phosphorus removal and the overall EBPR process (8, 10). A few 'omics-based studies

have revealed potentially regulatory modules that could coordinate Accumulibacter's

complex physiological behavior during these very dynamic environmental conditions (11–

14).

Accumulibacter can be subdivided into two main types (I and II) and further

subdivided into multiple clades based upon polyphosphate kinase (*ppk1*) sequence

identity, since the 16S rRNA marker is too highly conserved among the breadth of known

Accumulibacter lineages to resolve species-level differentiation (15–18). The two main

types share approximately 85% nucleotide identity across the *ppk1* locus (18) which

mirrors genome-wide average nucleotide identity (ANI) (19). Members of different clades

have been hypothesized to vary in their acetate uptake rates, nitrate reduction capacity,

and phage defense mechanisms (19, 20). For example, clade IA seems to exhibit higher

acetate uptake rates and phosphate release rates, whereas clade IIA can reduce nitrate

and clade IA cannot (21, 22). The persistence of several phylogenetically distinct clades

within the Accumulibacter lineage in both full-scale wastewater treatment plants and lab-

scale enrichment bioreactors suggests that different clades may inhabit distinct ecological

niches (23). This is largely supported by comparative genomics of numerous

Accumulibacter metagenome-assembled genomes (MAGs) recovered from different

bioreactor systems and classified using the *ppk1* locus (12, 19–21, 24). However, the

ecological roles that distinct Accumulibacter clades may play is not yet clear.

Here, we used genome-resolved metagenomics and time-series

metatranscriptomics to investigate gene expression patterns of co-existing

Accumulibacter strains (representing two main clades) during a standard EBPR cycle.

We assembled high-quality genomes of the dominant and low abundant Accumulibacter

strains present in the bioreactor ecosystem. We constructed a contiguous draft genome

of an Accumulibacter clade IIC genome achieved using long Nanopore reads,

representing one of the highest-quality genomes for this clade recovered to date. Using

these assembled genomes, we performed time-series RNA-sequencing over the course

of a typical EBPR feast-famine cycle to explore expression profiles of different

Accumulibacter clades, with an emphasis on core and flexible gene content. More

generally, our work reveals putative ecological functions of co-existing taxa within a

dynamic ecosystem.

MATERIALS AND METHODS

Bioreactor Operation and Sample Collection

A laboratory-scale sequence batch reactor (SBR) was seeded with activated sludge from the Nine Springs Wastewater Treatment Plant (Madison WI, USA) during August 2015. The bioreactor was operated to simulate EBPR as described previously (24). Briefly, an SBR with a 2-L working volume was operated with the established biphasic feast-famine conditions: a 6-h cycle consisted of the anaerobic phase (sparging with N_2 gas), 110-min; aerobic (sparging with oxygen), 180-min; settle, 30-min; draw and feed with an acetate-containing synthetic wastewater feed solution, 40-min. A reactor hydraulic residence time of 12-h was maintained by withdrawing 50% of the reactor contents after the settling phase, then filling the reactor with fresh nutrient feed; a mean solids retention time of 4-d was maintained by withdrawing 25% of the mixed reactor contents each day immediately prior to a settling phase. Allythiourea was added to the synthetic feed solution to inhibit nitrification/denitrification.

Three biomass samples for metagenomic sequencing were collected in September of 2015 by centrifuging 2-mL of mixed liquor at 8,000 x g for 2 min, and DNA was extracted using a phenol:chloroform extraction protocol. Seven samples for RNA sequencing were collected throughout a single EBPR cycle (3 in the anaerobic phase, 4 in the aerobic phase) in October of 2016 following the sampling strategy conducted by Oyserman et al. (11). Samples were flash-frozen on liquid nitrogen immediately after centrifuging and discarding the supernatant. RNA was extracted using a TRIzol-based extraction method (Thermo Fisher Scientific, Waltham, MA) followed by phenol-chloroform separation and RNA precipitation. RNA was purified following an on-column

DNAse digestion using the RNase-Free DNase Set (Qiagen, Venlo, Netherlands) and

cleaned up with the RNeasy Mini Kit (Qiagen, Venlo, Netherlands). Accumulibacter clade

quantification was performed on biomass samples collected on the same day of the

metatranscriptomics experiment using clade-specific *ppk1* qPCR primers as described by

Camejo et al. (23).

Metagenomic and Metatranscriptomic Library Construction and Sequencing

Metagenomic libraries were prepared by shearing 100 ng of DNA to 550 bp long

products using the Covaris LE220 (Covaris) and size selected with SPRI beads (Beckman

Coulter). The fragments were ligated with end repair, A-tailing, Illumina compatible

adapters (IDT Inc) using the KAPA-Illumina library preparation kit (KAPA Biosystems).

Libraries were quantified using the KAPA Biosystem next-generation sequencing library

qPCR kit and ran on a Roche LightCycler 480 real-time PCR instrument. The quantified

libraries were prepared for sequencing on the Illumina HiSeq platform using the v4

TruSeq paired-end cluster kit and the Illumina cBot instrument to create a clustered flow

cell for sequencing. Shotgun sequencing was performed at the University of Wisconsin –

Madison Biotechnology Center DNA Sequencing facility on the Illumina HiSeq 2500

platform with the TruSeq SBS sequencing kits, followed by 2x150 indexing. Raw

metagenomic data consisted of 219.4 million 300-bp Illumina HiSeq reads with

approximately 3.9 Gpb per sample (Table 1 – supplementary material). Nanopore

sequencing was performed according to the user's manual version SQK-LSK108.

Total RNA submitted to the University of Wisconsin-Madison Biotechnology Center

was verified for purity and integrity using a NanoDrop 2000 Spectrophotometer and an

Agilent 2100 BioAnalyzer, respectively. RNA-Seq paired end libraries were prepared

using the TruSeq RNA Library Prep Kit v2 (Illumina, San Diego, CA). Each sample was

processed for ribosomal depletion, using the Ribo-Zero™ rRNA Removal kit (Bacteria).

mRNA was purified from total RNA using paramagnetic beads (Agencourt RNAClean XP

Beads, Beckman Coulter Inc., Brea, CA) and fragmented by heating in the presence of a

divalent cation. The fragmented RNA was then converted to cDNA with reverse

transcriptase using SuperScript II Reverse Transcriptase (Invitrogen, Carlsbad,

California, USA) with random hexamer priming and the resultant double stranded cDNA

was purified. cDNA ends were repaired, adenylated at the 3' ends, and then ligated to

Illumina adapter sequences. Quality and quantity of the DNA were assessed using an

Agilent DNA 1000 series chip assay and Thermo Fisher Qubit dsDNA HS Assay Kit.

Libraries were diluted to 2nM, pooled in an equimolar ratio, and sequenced on an Illumina

HiSeq 2500, using a single lane of paired-end, 100 bp sequencing, and v2 Rapid SBS

chemistry.

Metagenomic Assembly and Annotation

We applied two different assembly and binning approaches to obtain high-quality

genomes of the dominant Accumulibacter strains present in the reactors. For the first

approach, Illumina unmerged reads were quality filtered and trimmed using the Sickle

software v1.33 (25). Reads were merged with FLASH v1.0.3 22 (26), with a mismatch

value of ≤0.25 and a minimum of ten overlapping bases from paired sequences, resulting

in merged read lengths of 150 to 290 bp. FASTQ files were then converted to FASTA

format using the Seqtk software v1.0 (27). Metagenomic reads from all three samples

were then co-assembled using the Velvet assembler with a k-mer size of 65 bp, a

minimum contig length of 200 bp, and a paired-end insert size of 300 bp (28). Metavelvet

was used to improve the assembly generated by Velvet (29). Metagenomic contigs were

then binned using Maxbin (30). This approach allowed us to assemble high-quality

genomes of clades IIA and IIC, named UW5 and UW6, respectively. Contigs from these

genomes were scaffolded using long Nanopore reads that were generated under the

standard protocol using MeDuSa (31), and manually inspected to remove short contigs

and decontaminated using ProDeGe (32) and Anvi'o (33). Further scaffolding was

performed on both of these genomes using Nanopore long reads using LINKS (34) and

GapCloser (35).

Because this pipeline did not produce high-quality genomes of clades IA and IIF,

we applied a different approach to assemble these genomes. Quality filtered reads from

each metagenome were individually assembled using metaSPAdes and co-assembled

together also using metaSPAdes (36). Reads from each metagenome were mapped

against each of the assemblies using bbmap with a 95% sequence identity cutoff to obtain

differential coverage (37), and contigs were binned using MetaBat (38). Identical clusters

of bins were dereplicated across assemblies using dRep (39) to obtain the best quality

genome of both clades IA and IIF, named UW4 and UW7, respectively. All genomes were

quality checked using CheckM (40) and functional annotations assigned with Prokka and

KofamKOALA (41, 42).

Each genome was assigned to a particular clade both by comparing the *ppk1*

sequence identity and ANI to previously published Accumulibacter genomes. A *ppk1*

database was created using sequences from previously published Accumulibacter

references and clone sequences. We searched for the *ppk1* gene in our draft genomes

using this database and aligned the corresponding hits with MAFFT (43). A phylogenetic

tree of aligned *ppk1* gene sequences from Accumulibacter references, select clone

sequences, and the outgroups *Dechloromonas aromatica RCB* and *Rhodc*yclus *tenuis*

DSM 110 with RAxML v8.1 with 100 rapid bootstraps (44). To use any given

Accumulibacter reference genome in downstream comparisons, a confident *ppk1* hit had

to be identified using the above methods. As a technical note, the IA-UW2 strain

assembled by Flowers et al. (19) was renamed to UW3, as the original assembly

contained an additional contig that was likely from a prophage. The UW3 strain assembly

does not contain this contig, and therefore the UW numerical nomenclature follows in

sequential order after UW3. A phylogenetic tree of *ppk1* nucleotide sequences was

performed and compared to select clone sequences. Pairwise genome-wide ANI was

calculated between the four Accumulibacter draft genomes and all available

Accumulibacter genomes in Genbank with FastANI (45). A species tree of all

Accumulibacter references and outgroup genomes was constructed using single-copy

markers from the GTDBK-tk (46), aligned with MAFFT (43), built with RAxmL with 100

rapid bootstraps (44), and visualized in iTOL (47). To compare genome-wide ANI scores

of Accumulibacter references with pairwise nucleotide identity of the *ppk1* locus of all

references, we performed pairwise BLAST for all coding *ppk1* coding regions and

reported the percent identity (48).

Identification of Core and Accessory Gene Content

We identified core and accessory gene content of Accumulibacter clades through

clustering orthologous groups of genes (COGs) using PyParanoid (49). We used the four

Accumulibacter MAGs generated in this study, high-quality Accumulibacter reference

genomes (above 90% completeness and less than 5% redundancy), and *Dechloromonas*

aromatica RCB and *Rhodocyclus tenuis DSM 110* as outgroups (Accumulibacter

references listed in Supplementary Table 1 available at

https://figshare.com/account/projects/90614/articles/13237148). Briefly, an all-vs-all

comparison of proteins for all genomes was performed using DIAMOND (50), pairwise

homology scores calculated with the InParanoid algorithm (51), gene families constructed

with MCL (52), and HMMs built for each gene family with HMMER (53). A phylogenetic

tree was constructed for genomes used for the COGs analysis by using the coding

regions of the PPK1 locus and overlaid with the presence/absence of core and flexible

gene content using the ete3 python package (54). A similarity score between UW

Accumulibacter genomes was calculated as the pairwise Pearson correlation coefficient

between gene families using the numpy python package (55). The presence and absence

of different gene families was visualized in an upset plot between UW Accumulibacter

genomes using the ComplexUpset package based on the UpSetR package in R (56). All

data wrangling and plotting was performed using the tidyverse suite of packages in R

(57).

Metatranscriptomics Mapping and Processing

Metatranscriptomics reads from each of the seven samples were quality filtered

using fastp (58) and rRNA removed with SortMeRNA (59). The coding regions of all four

Accumulibacter genomes assembled in this study were predicted with Prodigal (60) and

annotated with both Prokka and KofamKOALA (41, 42), and concatenated together to

create a mapping index. Metatranscriptomic reads were competitively pseudoaligned to

the reference index and counts quantified with kallisto (61). Genes with a sum of more

than 10,000 counts across all 7 samples were removed, as these are likely ribosomal

RNAs that were not removed previously. Additionally, genes annotated as rRNAs by

barrnap were manually removed (41). Low-count genes were removed by requiring that

all genes had to have more than 10 counts mapped across 3 or more samples.

To explore genes and metabolic functions that may exhibit hallmark anaerobic-

aerobic feast-famine cycling patterns, we identified sets of genes that were differentially

expressed between anaerobic and aerobic conditions using DESeq2 (62). Differential

expression calculations were performed for each strain separately to account for

differences in the relative abundance of metatranscriptomic reads mapping back to each

of the four MAGs. We analyzed expression patterns of differentially expressed genes

using a threshold cutoff of ± 1.5 log2 fold-change between anaerobic and aerobic

conditions and then identified differentially expressed genes as core or accessory among

clades IA (str. UW4) and IIC (str. UW6). For the core group analysis, the corresponding

ortholog in each genome had to meet the minimum count threshold as described above

to include in the comparison, with genes in one or both of the strains being differentially

expressed. For the accessory analysis for each strain, the gene had to be differentially

expressed and not contained in the other genome, but could be present in other strains

or other genomes belonging to that clade.

Data and Code Availability

Raw sequencing files for the three metagenomes and seven metatranscriptomes

have been submitted to NCBI under the BioProject accession PRJNA668760. Assembled

UW5 and UW6 genomes have been deposited through IMG at accession numbers

2767802316 and 2767802455 respectively. All genomes assemblies used in this study in

their current forms as well as transcriptomic count tables are available on Figshare at:

https://figshare.com/projects/Metabolic_Plasticity_of_Accumulibacter_Clades/90614. All

code is available at https://github.com/elizabethmcd/R3R4.

RESULTS

Enrichment of Co-Existing Accumulibacter Clades

We inoculated a 2-L sequencing-batch reactor with activated sludge from a full-scale wastewater treatment plant in Madison, WI, USA and maintained it for 40 months. The reactor was primarily fed with acetate and operated under cyclic anaerobic-aerobic phases with a 4-day solids retention time to simulate the EBPR process and enrich for Accumulibacter (Figure 1). During a period of stable EBPR (14 months following inoculation) in which acetate was completely diminished by the start of the aerobic phase and soluble phosphate was below 1.0 mg-L^{-1} at the end of the aerobic phase, we collected seven samples across a single cycle (three in the anaerobic phase, four in the aerobic phase) for RNA-sequencing (Figure 1A). We quantified the different Accumulibacter clades by performing qPCR of the polyphosphate kinase (*ppk1*) locus as described previously (23) from samples collected on the same day as the RNA-seq experiment (Figure 1B). At the time of the RNA-seq experiment, the bioreactor was primarily enriched in Accumulibacter clade IA, followed by clade IIC and clade IIA.

We assembled high-quality genomes of four Accumulibacter clades (Table 1), including the dominant IA and IIC (UW4 and UW6, respectively) clades and less abundant IIA and IIF clades (UW5 and UW7, respectively) (Figure 2). Each of the assembled genomes falls within the established Accumulibacter clade nomenclature as defined by *ppk1* sequence identity and phylogenetic placement when compared to other publicly

available Accumulibacter genomes and clone sequences (Figure 2A). Additionally, the

ppk1 hierarchical structure is also reflected by pairwise-average nucleotide identity (ANI)

boundaries between clades, with some exceptions for newly assembled Accumulibacter

genomes that fall outside of the established '*C.* Accumulibacter phosphatis' lineage

(Figure 2B). All assembled genomes are above 90% complete and contain less than 5%

redundancy as calculated by CheckM (40) (Table 1). We were able to scaffold the

assemblies of strains IIA-UW5 and IIC-UW6 using long Nanopore reads, constructing a

completely contiguous draft genome of clade IIC. To our knowledge, the assembled clade

IIC genome (UW6) is the most contiguous, highest-quality reference genome available

for this clade, providing a valuable new Accumulibacter reference genome (Figure 2C).

Distribution of Shared and Flexible Gene Content between Clades

We next characterized the functional diversity of different Accumulibacter clades

through clustering orthologous groups of genes (COGs) (Figure 3A). We performed an

updated COGs analysis from Skennerton et al. (20) and Oyserman et al. (63) to include

high-quality Accumulibacter references, and UW-generated genomes, and the outgroups

Dechloromonas aromatica and *Rhodocyclus tenuis* (Figure 3). The Accumulibacter

lineage exhibits a tremendous amount of functional diversity, with only approximately 25%

of COGs shared amongst all Accumulibacter clades (Figure 3A). Additionally, there is

extensive diversity within the two Accumulibacter types and within individual clades, with

only a few representatives of each clade more than approximately 75% similar to each

other by gene content (Supplementary Figure 1). Specifically, clade IIC broadly harbors

the most diversity of all sampled genomes by gene content, with representatives of this

clade not sharing more than 25% of COGs (Figure 3A). Other clades are more similar by

gene content, but this could be due to fewer genomes sampled from these clades. Most

of the highest-quality, publicly available Accumulibacter genome references belong to

clades IIF and IIC.

We then compared COGs between Accumulibacter clades collected from

bioreactors seeded from the Nine Springs Wastewater Treatment Plant in Madison, as

these genomes represent a shared origin (Figure 3B). In addition to two lab-scale

bioreactors harboring distinct Accumulibacter clades (genomes UW1 and UW3, and

UW4-7, respectively) (19, 24), we recently characterized clade IC (genome UW-LDO-IC)

using genome-resolved metagenomics and metatranscriptomics (12). By calculating the

Pearson correlation similarity of COG presence/absence, genomes in Type I and Type II

cluster respectively, where genomes within Type I are overall more similar to each other,

as expected (Supplementary Figure 1). Clade IIA genomes (strains UW1 and UW5) were

assembled from separate enrichments derived from the same full-scale treatment plant

approximately 12 years apart, but are very similar by gene families (Supplementary

Figure 1). UW genomes within Type II are less similar by gene content and seem to be

more diverse in this regard, though again this could be due to under-sampling of Type I

(8 genomes in Type I and 14 in Type II). Additionally, clade IIF contains more overlap with

Type I genomes in gene families than some Type II genomes do to each other

(Supplementary Figure 1).

COG overlap and uniqueness is shown by the intersection of groups of COGs

between UW Accumulibacter clades and the *Rhodocyclus* and *Decholoromonas*

outgroups (Figure 3B). There are 1075 gene families shared among all UW

Accumulibacter clades and outgroup genomes, with 277 separate gene families only

within the UW Accumulibacter clades (Figure 3B). Among individual clades, there are 887

groups only within clade IIC (UW6), 399 within clade IIA (UW1 and UW5), 399 within IIF

(UW7), 292 within clade IA (UW3 and UW4), and 196 within IC (UW-LDO). Although clade

IIC str. UW6 contains more overlap in gene content with SK-02 (Figure 3A), this

intersection analysis identifies gene families that are available to individual strains within

the same bioreactor ecosystem, highlighting the potential for functional differences. Below

we explore these putative functional differences in shared and flexible gene content

between Accumulibacter clades IA and IIC using time-series transcriptomics.

Transcriptional Profiles of Accumulibacter Clades

Although *ppk1* locus quantification showed that the bioreactor was mostly enriched

in clade IA (Figure 1B), surprisingly, more RNA-seq reads mapped to the clade IIC-UW6

genome than to the clade IA-UW4 (Figure 4A). Approximately 40 million total

transcriptional reads mapped back to the clade IIC-UW6 genome across the RNA-seq

experiment, whereas clades IA-UW4 and IIA-UW5 recruited roughly the same number of

reads, with 14 million and 11 million, respectively (Table 2). Markedly lower reads levels

mapped to the clade IIF-UW7 relative to the other three clades, and therefore we do not

include clade IIF in our subsequent analyses.

The co-existing clades in the bioreactor system differ in both the presence of sets

of nitrogen cycling gene sets and their expression profiles (Figure 4C). In clade IA-UW4,

we detected the *napAGH* genes for nitrate reduction, whereas we did not detect *napB*,

possibly due to these genes being close to the end of a contig in this genome. We also

detected a *nirS*-like nitrite reductase*,* both subunits of the nitric oxide reductase *norQD,*

and the nitrous oxide reductase *nosZ* in clade IA-UW4. Most of these genes in clade IA-

UW4 exhibit the highest expression patterns in the early and late anaerobic stages

(Figure 4C). Conversely, clade IIC-UW6 contains the *narGHIJ* machinery for nitrate

reduction, a different *nirS*-like nitrite reductase than in IA-UW4, and does not contain a

nitrous oxide reductase. However, clade IIC-UW6 does contain the nitrite reductase *nirBD*

for reducing nitrite to ammonium, which is uniformly expressed across the cycle (Figure

4C).

We explored the top differentially expressed genes in clade IIC-UW6, comparing

anaerobic and aerobic conditions (Figure 4B). Genes upregulated in the anaerobic phase

belonged to pathways for central-carbon transformations, fatty acid biosynthesis, and

PHA synthesis. Interestingly, all genes within the high-affinity phosphate transport system

Pst were upregulated in the aerobic phase. This includes the substrate-binding

component *pstS, phoU* regulator, and the ABC-type transporter *pstABC* complex. The

higher overall transcriptional levels of clade IIC-UW6 versus clade IA-UW4 (Figure 4A)

and upregulation of the high-affinity Pst system (Figure 4B) combined with the lower IIC-

UW6 abundance compared to IA-UW4, suggests that clade IIC-UW6 compensates for

lower abundance and competes for substrates through upregulation of transcriptional

programs related to the EBPR process.

Expression Dynamics of Genes Shared by Clades IA and IIC

We next characterized expression dynamics of COGs that are shared between

clades IA-UW4 and IIC-UW6 (Figure 5). There are very few orthologs that are

differentially expressed between the anaerobic and aerobic phases in both clades that

met the ±1.5-fold change threshold cutoff. These genes include a coproporphyrinogen III

oxidase, NAD-reducing HoxS subunits, the *phaC* subunit of the PHA synthase, the long-

chain fatty-acid-CoA ligase FadD13, and other hypothetical proteins. The fatty-acid CoA-

ligase incorporates ATP, CoA, and fatty acids of variable length to form acyl-CoA to be

degraded for energy production, incorporated into complex lipids, or used in other

metabolic pathways (64). The acyl-CoA ligase is upregulated in the anaerobic phase of

both clades, suggesting a role in anaerobic carbon metabolism, as acyl-CoA can

ultimately form acetyl-CoA through beta oxidation. The *phaC* subunit of the PHA synthase

is differentially expressed in the anaerobic phase for both clades, as is typical of the

hallmark EBPR metabolism for Accumulibacter (11, 65).

422   Additionally, both clades carry the bidirectional NiFe Hox system, encoding an

anaerobic hydrogenase. The HoxH and HoxY beta and delta subunits form the

hydrogenase moiety, and the FeS-containing HoxF and HoxU alpha and gamma subunits

catalyze NAD(P)H/NAD(P)+ oxidation/reduction coupled to the hydrogenase moiety (66–

68). In both clades, the FeS cluster HoxF and HoxU alpha and gamma subunits are

strongly differentially expressed in the anaerobic phases, as was observed previously in

a genome-resolved metatranscriptomic investigation of clade IIA-UW1 (11). However,

clade IIC-UW6 is missing the HoxY delta subunit of the hydrogenase moiety, and only

clade IA-UW4 exhibits differential expression of the HoxH beta subunit in the anaerobic

phase. Clade IIC-UW6 does exhibit higher expression of HoxH in the late anaerobic and

early aerobic phases, but does not meet the threshold cutoff for differential gene

expression. The prior study focused on clade IIA-UW1 also demonstrated hydrogenase

activity in the anaerobic phase, and also demonstrated hydrogen gas production after

acetate addition (11). The hydrogen gas production was hypothesized to replenish NAD+

after glycogen degradation. In this ecosystem, both clades may exhibit anaerobic

hydrogenase activity and thus produce hydrogen, but due to the missing subunit in clade

IIC-UW6 and lack of differential gene expression, this is uncertain.

Interestingly, several core ortholog subsets important for EBPR-related functions

exhibit differential expression patterns in only one of the clades. For example, subunits of

the high-affinity phosphate transporter Pst system are only differentially expressed in

clade IIC-UW6 and not IA-UW4, as observed for clade IIC-UW6 above (Figure 4C).

Additionally, nitrogen cycling genes that contain orthologs in both clades display different

expression profiles. A nitrite reductase is only differentially expressed in the anaerobic

phase in clade IA-UW4 and the denitrification protein NirQ is differentially expressed in

only clade IIC-UW6. Whereas the nitrogen fixation protein subunit NifU is differentially

expressed in both clades. To activate acetate to acetyl-CoA, the high-affinity acetyl-CoA

synthase (ACS) or low-affinity acetate kinase/phosphotransacetylase (AckA/Pta)

pathways can be employed. Although the clade IA-UW4 assembly is missing an acetate

kinase, a phosphate acetyltransferase is only differentially expressed in this clade. Within

clade IIC, both the acetate kinase and phosphate acetyltransferase genes exhibit

relatively low levels of expression over the time-series. Both clades contain several

acetyl-CoA synthases that are highly expressed in the anaerobic phase, particularly upon

acetate contact, but do not exhibit stark differential expression between the two phases.

Previous work based on community proteomics and enzymatic assays have

suggestedthat although both activation pathways are present and expressed in

Accumulibacter, the high-affinity pathway is preferentially used (69, 70). Although a

phosphate acetyltransferase is differentially expressed in clade IA, this gene has lower

transcripts relative to the acetyl-CoA synthase, providing more evidence that the lineage

(specifically both clades IA and IIC) may employ the high-affinity system.

Differential Expression of Flexible Genes in Clade IA-UW4

We lastly characterized expression dynamics of flexible gene content between

clades IA-UW4 and IIC-UW6, focusing specifically on clade IA-UW4 (Figure 6). A majority

of the differentially expressed flexible genes in clade IIC-UW6 were annotated as

hypothetical proteins, and thus we focused on putative differentiating features of clade

IA-UW4. Flexible gene content for IA-UW4 can be defined as any ortholog that is not

present in the UW6 genome, whether that ortholog is only contained within clade IA

genomes, Type I as a whole, within other Type II or clade IIC genomes, or the

Dechloromonas or *Rhodocyclus* outgroups. Thus, the absence of a particular ortholog in

the clade IIC-UW6 genome but present in the IA-UW4 genome or other genomes was

inferred as a lack of functional capability of IIC in this particular ecosystem. For example,

this analysis identified several groups of genes that are annotated as hypothetical genes

that contain orthologs only within clade IA genomes and that are differentially expressed

between the anaerobic and aerobic cycles.

Particularly striking is the differential expression profiles of nitrogen cycling genes

that do not contain orthologs in the IIC-UW6 genome. As stated above, clade IA-UW4

contains the *nap* system whereas clade IIC-UW6 contains the *nar* system for reducing

nitrate to nitrite (Figure 4C). In clade IA-UW4, the *napDGH* subunits are differentially

expressed between the anaerobic and aerobic phases, and these genes are present in

the outgroups, as well as both Accumulibacter types except the IIC-UW6 genome (Figure

6). Both genomes contain a *nirS* nitrite reductase, but the respective homologs are not

within the same COG, and thus clade IA-UW4 contains a different *nirS* that is upregulated

in the anaerobic phase. Clade IIC-UW6 does not contain both subunits of the nitric-oxide

reductase *norQD,* whereas clade IA-UW4 does. These subunits are not differentially

expressed above the set threshold but do exhibit the highest expression upon acetate

contact in the anaerobic phase (Figure 4B). Additionally, clade IIC does not contain the

nitrous-oxide reductase *nosZ* (Figure 4B)*,* whereas clade IA does and this is differentially

expressed in the anaerobic phase (Figure 6). These results suggest that clade IA-UW4

may have the capability for full denitrification from nitrate to nitrogen gas, or at least use

the reduction of nitrate/nitrite as a source of energy in the anaerobic phase in a denitrifying

bioreactor. Although clade IIC-UW6 does contain the *nirBD* nitrite reductase complex for

reducing nitrite to ammonium, these genes are uniformly expressed throughout the cycle

(Figure 4B).

DISCUSSION

In this work, we performed time-series transcriptomics to explore gene expression

profiles of two Accumulibacter strains co-existing within the same bioreactor ecosystem.

By applying genome-resolved metagenomic and metatranscriptomic techniques, we were

able to postulate niche-differentiating features of distinct Accumulibacter clades based on

core and accessory gene content and differential expression profiles. We assembled

high-quality genomes from Accumulibacter clades, using long reads to generate a single

contiguous scaffold of the IIC-UW6 genome. By performing an updated clustering of

orthologous groups of genes, we were able to better demonstrate the similarity and

uniqueness among Accumulibacter strains from this system. Unexpectedly, although

clade IA dominates in abundance by *ppk1* locus quantification, clade IIC is

transcriptionally more active. By comparing the expression profiles of COGs shared

between clades IA-UW4 and IIC-UW6, we found that genes involved in EBPR-related

pathways may differ between the clades with respect to transcription-level regulation.

Notably, clade IIC-UW6 shows a strong upregulation of the high-affinity Pit phosphorus

transport system in the aerobic phase and both clades made hydrogenase transcripts in

the anaerobic phase. Clade IA-UW4 contains most of the subunits for the individual key

steps for denitrification, and exhibits strong anaerobic upregulation of these genes,

suggesting a differentiating role for clade IA-UW4 in nitrogen cycling.

The Accumulibacter lineage harbors extensive diversity between and amongst

individual clades which is exhibited not only by *ppk1*-based phylogenies, but also by

pairwise genome-wide ANI and COG comparisons. For example, clade IIA-UW1 and

clade IA-UW3 were present in the same bioreactor ecosystem and are only similar by

85% ANI (19). In the bioreactor enrichment from this study, the dominant clades IA-UW4

and IIC-UW6 are less than 80% similar by genome-wide ANI (Figure 2B). Recently, a

cutoff of >95% ANI has been suggested to delineate distinct bacterial species or cohesive

genetic units (45), originally based on observations of coverage gaps at 90-95%

sequence identity when metagenomic reads were mapped back to assembled MAGs

(71–74). These sequence cutoffs have also been benchmarked against homologous

recombination rates and ratios of nonsynonymous to synonymous (*dN/dS*) nucleotide

differences (75). However, there are some notable exceptions to the 95% ANI threshold

cutoff used for delineating species, as distinct populations of the marine SAR11 clade

have been observed at a 92% boundary and lower (76, 77). Among Accumulibacter

genomes adhering to the established *ppk1*-based phylogeny, genomes within individual

clades fall within the >95% ANI threshold, whereas ANI comparisons within and between

Types I and II are more variable (Figure 2B). Genomes within Type I are similar by

approximately 90% ANI, whereas genomes within Type II are not as coherent.

The apparent coexistence of diverse Accumulibacter clades within an ecosystem

then raises questions of ecological roles, putative interactions, and evolutionary dynamics

of this lineage over time and space. Although the concept of a bacterial species is highly

contested and dependent upon the operational definition of the population in question,

species have been clustered based on phenotypic and metabolic characteristics, and

more recently by DNA-based clustering metrics and recombination signatures (3, 7). The

ecotype model of speciation suggests that cohesive, ecologically distinct ecotypes can

coexist because they occupy separate niche spaces (3, 78). Because Accumulibacter

has not been isolated in pure culture to date, most ecological and evolutionary inferences

have been made from genome-based comparisons (20, 63) or mapping metagenomic

reads back to assembled genomes (79, 80). However, the apparent diversity within the

Accumulibacter lineage may require reevaluation of the phylogeny and taxonomy overall.

Although the *ppk1*-based clade designations coincide with genome-wide ANI based

cutoffs remarkably well (Supplementary Figure 2B), there are some discrepancies. A few

Accumulibacter genomes have been assembled that do not adhere to the *ppk1*-based

population structure, but fall within the Accumulibacter lineage based on a species tree

of single-copy core genes (Supplementary Figure 2A), such as the proposed novel

species '*Candidatus* Accumulibacter aalborgensis' (81). Additionally, a few genomes

preliminarily classified by the GTDB as Accumulibacter branch outside of the established

nomenclature, and are quite divergent based on the species and *ppk1* phylogenies as

well as genome-wide and *ppk1* sequence similarities (Figure 2B, Supplementary Figure

2). Overall, substantial work is needed to reevaluate the phylogenetic structure of the

Accumulibacter lineage as a whole and connect with signatures of homologous

recombination and evolutionary trajectories within coexisting clades to understand the

genetic boundaries and thus ecological interdependencies of individual clades or strains.

Although the boundaries of individual Accumulibacter clades or strains have not

been entirely resolved to infer separate ecotypes, denitrification capabilities of specific

clades has been repeatedly suggested to be a niche-differentiating feature (12, 21, 23).

Previously, two separate bioreactors fed with either acetate or propionate as the sole

carbon source were enriched with different Accumulibacter morphotypes, one with cocci

morphology and the other rod morphology, which were also linked to different

denitrification capabilities (22), A bioreactor highly enriched in clade IC inferred

simultaneous use of oxygen, nitrite, and nitrate as electron acceptors under micro-aerobic

conditions either due to metabolic flexibility or heterogeneity within the IC population (23).

The resident strain IC-UW-LDO also possessed the full suite of genes for denitrification

and expressed them in microaerobic conditions (12); whereas other clades either do not

contain the complete genetic repertoire for denitrification or have not been shown to

express them. As we observed differential expression of denitrification genes in clade IA-

UW4 but not clade IIC-UW6 in this study, these expression differences could explain why

the two clades can coexist and contribute to overall ecosystem functioning (e.g.

phosphorus removal) by using different electron acceptors in the anaerobic/aerobic

conditions. Although the synthetic feed for the bioreactors in this study inhibits

nitrification/denitrification through alythiourea addition, the expression profiles of

denitrification genes in clade IA-UW4 suggests this strain could have a differentiating role

in a denitrifying bioreactor. Recently, a denitrifying EBPR bioreactor enriched in clade IA

encoded genes for complete denitrification, whereas the co-occurring clade IC strain and

other flanking community members did not (82). Additionally, Gao et al. performed an

ancestral genome reconstruction analysis similar to Oyserman et al. 2017 (63) to

specifically understand the flux of denitrification gene families. Interestingly, the *nir* gene

cluster was identified as a core COG that is core to all sampled Accumulibacter genomes,

whereas the periplasmic nitrate reductase *napAGH* and nitrous oxide reductase *nosZDFL*

clusters were core to only Type I Accumulibacter genomes, and inferred to have been

lost for some Type II genomes (82). We observed differential expression of nitrate

reductase and nitrous-oxide reductase genes in clade IA-UW4, where homologs of these

genes were not present in the clade IIC-UW6 genome and other Type II genomes.

Accumulibacter's anaerobic metabolism has also been shown to differ under

varying substrate or stoichiometric conditions and possibly between the two

Accumulibacter types. From recent simulations of 'omics datasets paired with enzymatic

assays, the routes of anaerobic metabolism for Accumulibacter may differ based on

environmental conditions (83). Under high acetate conditions, polyphosphate

accumulation arises through the glyoxylate shunt, whereas under increased glycogen

concentrations, glycolysis is used in conjunction with the reductive branch of the TCA

cycle (83). Furthermore, Welles et al. found that Type II Accumulibacter is able to switch

to partial glycogen degradation more quickly than Type I, enabling Type II to fuel VFA

uptake in polyphosphate-limited conditions (84, 85). Conversely, when concentrations of

polyphosphate are high, VFA uptake rates are higher in Type I. However, these studies

only identified Accumulibacter lineages based on ppk1 types, and therefore extrapolated

metabolic assumptions from presumably more resolved strains to the entire type. These

broad interpretations may obscure apparent functional differences within the two types

and individual clades. Future experiments could integrate multi-'omics approaches to

investigate not only metabolic flexibility under different substrate conditions and

perturbations, but how metabolisms are distributed amongst Accumulibacter clades in

bioreactor ecosystems that are not completely enriched in a single clade or strain.

CONCLUSIONS

In this study, we integrated genome-resolved metagenomics and time-series

metatranscriptomics to understand gene expression patterns of co-existing

Accumulibacter clades within a bioreactor ecosystem. We found evidence for

denitrification gene expression in the dominating clade IA, but higher overall

transcriptional activity for clade IIC along with differential expression of a high-affinity

phosphorus transporter. These results highlight the need for reevaluating the

phylogenetic structure of the Accumulibacter lineage, and defining how potential genetic

boundaries may translate to individual ecological niches allowing for the coexistence of

multiple clades or strains. Additionally, we highlight an approach for exploring functions

of closely related, uncultivated microbial lineages by exploring gene expression patterns

of shared and accessory genes. Overall, this work underscores the need to understand

the basic ecology and evolution of microorganisms underpinning biotechnological

processes to better control treatment process and resource recovery outcomes in the

future (86).

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  FIGURE AND TABLE LEGENDS

Figure 1. Overview of Experimental Design and Enriched Accumulibacter Clades.

1A. Overview of EBPR cycle and sampling scheme. Samples were collected for RNA

sequencing over the course of a normal EBPR cycle, with reported measurements for

soluble phosphorus and acetate normalized by volatile suspended solids (VSS). Samples

were taken at time-points 0, 31, 70, 115, 150, 190, and 250 minutes. **1B.** Abundance of

different Accumulibacter clades by *ppk1* copies per ng of DNA. Quantification of

Accumulibacter clades was performed by qPCR of the *ppk1* gene as described in Camejo

et al. (23).

Figure 2. Assembly of Four High-Quality Accumulibacter Genomes

2A. Phylogenetic tree of *ppk1* nucleotide sequences from existing Accumulibacter

references, clone sequences, and the four assembled Accumulibacter genomes from this

study. Tips in bold represent *ppk1* sequences from metagenome-assembled genomes,

whereas others are sequences from clone fragments available at the referenced

accession numbers. Starred tips represent *ppk1* sequences from the four assembled

Accumulibacter genomes from this study. Tree was constructed using RaXML with 100

rapid bootstraps. **2B.** Pairwise genome-wide ANI comparisons of all publicly available

Accumulibacter references and the four new Accumulibacter genomes, denoted in bold.

Genomes are grouped according to clade designation by *ppk1* sequence identity and in

order of the *ppk1* phylogeny, except for those that do not fall in an established clade. **2C.**

Genome diagram of the UW6 Accumulibacter IIC MAG. Layers represent from top to

bottom: coverage over 1000 bp windows, GC content and skew across the same 1000

bp windows, coding sequences on the positive and negative strands, and positions of

predicted rRNA (red) and tRNA (black) sequences.

Figure 3. Core and Flexible Gene Content among the Accumulibacter lineage and

UW genomes

3A. Phylogenetic tree of the coding regions for the PPK1 locus among high-quality

Accumulibacter references, UW genomes, and outgroup taxa *Dechloromonas aromatica*

RCB and *Rhodocyclus tenuis DSM 110.* Pie chart at each node represents the fraction of

genes that are shared and flexible for genomes belonging to that clade. **3B.** Upset plot

representing the intersections of groups of orthologous gene clusters among UW

genomes and outgroups, analogous to a Venn diagram. Each bar represents the number

of orthologous gene clusters, and the dot plot represents the genomes in which the groups

intersect.

Figure 4. Transcriptomic Profiles of Accumulibacter Clades

4A. Average expression profiles of each reference genome in the anaerobic and aerobic

phases. Reads were competitively mapped to the four assembled Accumulibacter clade

genomes and normalized by transcripts per million (TPM). The sum of the total counts of

the three samples in the anaerobic phase and four samples in the aerobic phase were

averaged, respectively, and plotted on a $\log_{10}$ scale. **4B.** Top 50 differentially-expressed

genes in clade IIC-UW6. All 50 genes pass the threshold of ±1.5 log-10 fold-change

across the cycle. Annotations were predicted from a combination of Prokka (41) and

KofamKOALA (42). **4C.** Denitrification gene expression among clades IIC-UW6, IA-UW4,

and IIA-UW5. We summarized expression for genes involved in denitrification by

highlighting parts of the cycle in which certain genes are expressed the most. This is

characterized by acetate contact (pink), early anaerobic (dark purple), late anaerobic

(purple), early aerobic (dark blue) and late aerobic (light blue), where uniform describes

uniform expression across the entire cycle (grey). If an arrow is missing for a step, that

particular clade did not contain confident annotations within the genome for those genes.

For nitrate reduction, the *nar* system is represented as a black dot and the *nap* system is

represented as a grey dot. Multiple arrows are shown for a single step in which particular

genes were highly expressed in multiple phases.

Figure 5. Differential Expression of Shared Genes in Clades IA and IIC

Gene expression profiles of core COGs across the EBPR cycle that are differentially

expressed between anaerobic and aerobic conditions in either IA-UW4 or IIC-UW6, or

both strains. To consider a gene differentially expressed in a strain, the COG must exhibit

greater or less than ±1.5 fold-change in expression. Homologs that are directly compared

to each other in IA-UW4 and IIC-UW6 are orthologous genes that belong to the same

cluster.

Figure 6. Differential Expression of Accessory Genes in Clade IA

Gene expression profiles of groups of accessory gene groups in clade IA-UW4 that are

not present in the UW6-IIC genome. A gene was considered differentially expressed

between the anaerobic and aerobic cycles if it exhibited greater or less than ±1.5 fold

change in expression. Colored dots represent whether that gene contains orthologs within

outgroup genomes, other Type II Accumulibacter other than the UW6-IIC genome, within

Type I Accumulibacter, or only within clade IA.

Table 1. Assembled Accumulibacter Genome Statistics

Genome quality calculations for completeness and contaminations were made with

CheckM based on the presence/absence of single copy genes (40).

Table 2. Metatranscriptomic Reads Mapped to Accumullibacter Genomes

Counts of raw metatranscriptomic reads mapped to each Accumulibacter genome with

kallisto (61) in each sample for the three anaerobic samples and four aerobic samples,

and total reads mapped for all samples.

Supplementary Figure 1.

Pairwise Pearson correlation coefficient of shared gene content as a measure of how

similar each of the UW genomes are to each other based on COGs.

1003

Supplementary Figure 2.

S2A) Species tree of all Accumulibacter reference genomes, UW-assembled genomes,

and outgroup genomes using single-copy markers from the GTDB-tk (46). Phylogenetic

tree was constructed using RAxmL with 100 rapid bootstraps and visualized in iTOL. **S2B)**

Pairwise BLAST percent identity scores for *ppk1* coding regions for each reference

genome in Figure 2B, in order of the *ppk1* phylogeny in Figure 2A. Raw pairwise percent

identity scores are available at

https://figshare.com/articles/dataset/Pairwise_Accumulibacter_ppk1_BLAST_Percent_D

_Scores/13237247.

1013

1014   **Supplementary Table 1**

1015   Genome accessions and statistics for all Accumulibacter references used in phylogenies,

1016   ANI comparisons, and COG calculations. A reference genome was used for COG

1017   comparisons if it was a high quality genome (>95% complete and <5% redundant).

1018   Available at https://figshare.com/account/projects/90614/articles/13237148

1019

1020   **Supplementary File 1**

1021   Raw pairwise genome-wide ANI results for each genome calculated with FastANI.

1022   Available at https://figshare.com/account/projects/90614/articles/13237244

1023

1024   **Supplementary File 2**

1025   Raw pairwise BLAST percent identity (PID) results for *ppk1* genes from each reference

1026   genome. Available at https://figshare.com/account/projects/90614/articles/13237247

1027

A.

| | Anaerobic Phase | Aerobic Phase |

IIC-UW6: 41.8 million total reads (61.7% total mapped)

IA-UW4: 14 million total reads (20.7% total mapped)

IIA-UW5: 11.3 million total reads (16.7% total mapped)

IIF-UW7: 11.3 million total reads (0.85% total mapped)

$\log_{10}$ Average Expression - Transcripts per Million (TPM)

B.

log$_2$ Fold-Change

Anaerobic — Aerobic

Hypothetical protein
Long-chain Fatty Acid CoA Ligase
Glycerol-3-Phosphate Dehydrogenase
Hypothetical protein
Type IV pili sensor
Hypothetical protein
Hypothetical protein
Methyltransferase
NAD-reducing Hydrogenase
NAD-reducing Hydrogenase
Hypothetical protein
Putative Ca+-Transporting ATPase
PHA Synthase Subunit PhaC
ATP Synthase subunit a
ATP Synthase subunit delta
Hypothetical protein
Respiratory Nitrate Reductase
NAD-reducing Hydrogenase
Succinate-CoA Ligase
Hypothetical protein
Cytochrome c-551
Hypothetical protein
tRNA-Tyr
Hypothetical protein
Hypothetical protein
Hypothetical protein
Purine Biosynthesis Protein
Hypothetical protein
Sulfate reductase
Hypothetical protein
Hypothetical protein
Biopolymer transport protein ExbB
Periplasmic protein TonB
Biopolymer transport protein ExbD
Ribulose bipsophate carboxylase
Dentrification regulatory protein NirQ
Hypothetical protein
Hypothetical protein
Phosphate-Binding Protein PtsS
Phosphate Transport System Protein PhoU
Phosphate Transport System PstA
Phosphate import ATP-binding PstB
Phosphate import ATP-binding PstC
Phosphate Transport System Permase
Ferredoxin-NADP reductase
Protease HtpX
Carbonic Anhydrase
Phosphoglucosamine mutase
Hypothetical protein
Hypothetical protein

C.

Oxidation State

+5   +3   +2   +1   0   -3

NO_3^- — NarGHIJ / NapAB → NO_2^- — NirS → NO — NorQD → N_2O — NosZ → N_2

NH$_3$

NirBD

Clade IIC ●

Clade IA ●

Clade IIA ●

| | Acetate contact | Early anaerobic | Late anaerobic | Early aerobic | Late aerobic | Uniform |

Genome	Completion	Contamination	Size_Mbp	Contigs	GC
IIA-UW5	98.99	5.24	4.88	68	64.3
IIC-UW6	98.57	2.46	5.18	1	61.1
IIF-UW7	98.97	3.04	4.87	102	66.3
IA-UW4	92.90	3.37	4.29	358	64.0

Clade Genome	Anaerobic-10:45	Anaerobic-11:16	Anaerobic-11:55	Aerobic-12:40	Aerobic-13:15	Aerobic-13:55	Aerobic-14:55	Total Reads Mapped
IIA-UW5	1063676	1357480	1706229	2197556	1763359	1171470	2065179	11324949
IIC-UW6	5226724	5892548	6755519	7902549	5004518	6914956	4132969	41829784
IIF-UW7	51038	78249	84520	121226	86070	90567	63866	575537
IA-UW4	1484341	2216299	2290441	3362431	1950259	1558605	1157345	14019720

A.

Clade IA

Clade IB
Clade IC

Clade IIA

Clade IIC

Clade IIF

Tree scale: 0.01 ⊢─┤

B.

Pairwise
BLAST %
Identity Score
of *ppk1*

Clade IIF

Clade IIC

Clade IIA

Clades IB & IC

Clade IA