


Metagenomic Analysis of Subtidal Sediments from Polar and Subpolar Coastal Environments Highlights the Relevance of Anaerobic Hydrocarbon Degradation Processes

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Received: 6 May 2017 / Accepted: 27 June 2017
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Abstract In this work, we analyzed the community structure and metabolic potential of sediment microbial communities in high-latitude coastal environments subjected to low to moderate levels of chronic pollution. Subtidal sediments from four low-energy inlets located in polar and subpolar regions from both Hemispheres were analyzed using large-scale 16S rRNA gene and metagenomic sequencing. Communities showed high diversity (Shannon's index 6.8 to 10.2), with distinct phylogenetic structures (<40% shared taxa at the Phylum level among regions) but similar metabolic potential in terms of sequences assigned to KOs. Environmental factors (mainly

salinity, temperature, and in less extent organic pollution) were drivers of both phylogenetic and functional traits. Bacterial taxa correlating with hydrocarbon pollution included families of anaerobic or facultative anaerobic lifestyle, such as Desulfuromonadaceae, Geobacteraceae, and Rhodocyclaceae. In accordance, biomarker genes for anaerobic hydrocarbon degradation (*bamA*, *ebdA*, *bcrA*, and *bssA*) were prevalent, only outnumbered by *alkB*, and their sequences were taxonomically binned to the same bacterial groups. BssA-assigned metagenomic sequences showed an extremely wide diversity distributed all along the phylogeny known for this gene, including *bssA* sensu stricto, *nmsA*, *assA*, and other clusters from poorly or not yet described variants. This work increases our understanding of microbial community patterns in cold coastal sediments, and highlights the relevance of anaerobic hydrocarbon degradation processes in subtidal environments.

Electronic supplementary material The online version of this article (doi:10.1007/s00248-017-1028-5) contains supplementary material, which is available to authorized users.

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Keywords Cold environments · Subtidal sediments · Hydrocarbons · Anaerobic biodegradation · Community structure · Metagenomics · Biomarker genes

Introduction

High-latitude regions are increasingly suffering the effects of various environmental stressors derived directly or indirectly from human activities. Climate change, as well as local human activities, are rapidly affecting these environments, with unknown effects at a global scale [1]. Of particular concern is the exploration and exploitation of oil reserves in Arctic and Subantarctic regions, as well as the growth in scientific and tourism activities in Antarctica, which leads to higher risks of oil pollution in these sensitive environments [2]. Despite

similar present environmental conditions, high-latitude regions from both Hemispheres have different geological, oceanographic, and climatic histories, which have influenced their biological history [3]. This is also true for microbial life: besides being tightly coupled to their environment, microorganisms are known to display biogeographic patterns resulting in unique assemblages at each site [3–5]. Therefore, an in-depth study of the microbial communities inhabiting comparable polar or subpolar regions in the Northern and Southern Hemispheres can provide insights into the ways in which microorganisms adapt to these environments and how they cope with anthropogenic impacts.

Coastal sediments provide important ecosystem services, playing significant roles in nutrient cycling, as well as carbon turnover and sequestration [6]. These habitats receive hydrocarbon inputs from various sources (biogenic, diagenetic, petrogenic, pyrogenic) through multiple mechanisms such as oil release, land runoff, urban discharges, and atmospheric deposition. Hydrocarbons are highly hydrophobic molecules with tendency to adsorb to the sediment matrix, reducing their bioavailability and persisting for several years, in particular in fine-grained sediments [7, 8]. In sediments, hydrocarbon biodegradation is a complex process due to the high diversity of microbial populations involved, interacting among themselves and with the environment in a complex fashion [9]. Subtidal habitats are of special concern, as they become anoxic at low depths due to respiration of organic matter [10]. Anaerobic hydrocarbon biodegradation, less understood at the molecular level than its aerobic counterpart, is most likely to occur under these conditions [11–13]. Over the last few years, a series of studies analyzed the response of sediment microbial communities to acute pollution events such as the Deepwater Horizon spill [14–19] and the Prestige oil spill [12, 20]. The integration of these results produced a wealth of knowledge that can be applied to marine environments in general and to coastal sediments in particular [21–23]. Hydrocarbon-degrading populations have been less well studied in environments receiving low or moderate levels of chronic pollution, and existing studies have been mostly limited to the analysis of phylogenetic and functional marker genes [24–29]. Recently, the metagenomic analysis of harbor coastal sediments from the Mediterranean basin revealed that temperature is a major environmental factor controlling hydrocarbon-degrading potential [30].

The aim of this work was to uncover the phylogenetic structure and functional adaptations to both natural environmental factors and anthropogenic stressors of sediment microbial communities from cold coastal environments. To achieve this goal, we carried out deep metagenomic and amplicon sequencing analyses in four distant polar or subpolar regions from both Hemispheres chronically exposed to different levels of anthropogenic activity. The results of this work provide insights into the diversity and composition of the microbial communities inhabiting sediments at remote, high latitude locations, and

uncover relationships between community structure, metabolic potential, and environmental variables. In addition, this work indicates specific taxa potentially associated with hydrocarbon biodegradation in these environments, and reveals the abundance and diversity of biomarker genes for these processes.

Methods

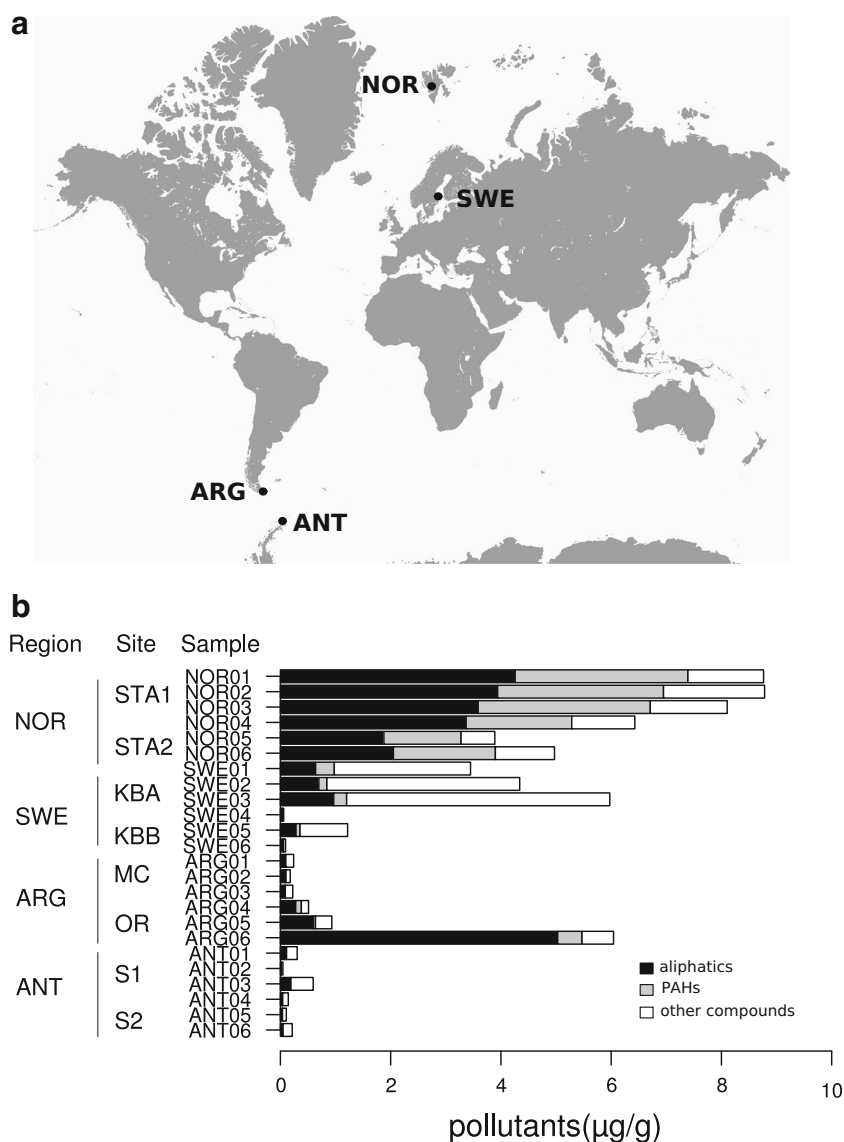
Sampling and Metadata Collection

Four high-latitude coastal environments were analyzed in this study: Adventfjord, Svalbard Archipelago, Norway (NOR); Port Värtahamnen, Stockholm, Sweden (SWE); Ushuaia Bay, Tierra del Fuego Island, Argentina (ARG); and Potter Cove, 25 de Mayo (King George) Island, Antarctic Peninsula (ANT) (Fig. 1a). Two stations per region distanced approximately 500 m were sampled. At each station, three core samples were obtained, separated by 3–5 m (Fig. S0, Table S1). Surficial (top 5 cm) subtidal (10 to 50 m bathymetry) sediments were sampled with cores. Metadata obtained in situ included temperature, depth, conductivity, and salinity using conductivity-temperature-depth (CTD) or multiparameter instruments. Sediment samples were stored at $-80\text{ }^{\circ}\text{C}$ until use in chemical or molecular analyses. Hydrocarbons and other organic compounds were determined by gas chromatography–mass spectrometry (GC/MS), as previously described [16]. When more than one fraction of a core sample was used for hydrocarbon analysis, concentration values were averaged (Table S1). Measured compounds included aliphatic hydrocarbons, polycyclic aromatic hydrocarbons (PAHs), and other organic compounds (Table S2).

Illumina 16S rRNA Gene Amplicon Sequencing (I-Tags)

Metagenomic DNA was purified using a previously reported methodology [31], performing one to five extractions per core (Table S3). Large-scale sequencing of 16S rRNA gene amplicons was performed as part of the international microbial diversity initiative Earth Microbiome Project (www.earthmicrobiome.org/) [32]. Gene fragments were amplified using primers 515F (5'GTGCCAGCMGCCGCGTA3') and 806R (5'GGACTACHVGGGTWTCTAAT3'), designed to amplify prokaryotes (bacteria and archaea), according to standard EMP Protocols (<http://www.earthmicrobiome.org/emp-standard-protocols/16s/>). Sequence datasets were obtained from all samples, with the exception of two samples from Ushuaia Bay (ARG01 and ARG02) and one from Potter Cove (ANT01) which failed in the amplification/sequencing process (Table S3). Preprocessing was performed according to Caporaso et al. [33]. Briefly, reads were truncated immediately after the first Q3 quality score, and truncated reads which resulted in 75% or less of the original sequence length were

Fig. 1 a Geographic location of the four analyzed sampling regions. *NOR* Adventfjord, Spitsbergen, Svalbard Archipelago, Norway; *SWE* Port Värtahamnen, Stockholm, Baltic Sea, Sweden; *ARG* Ushuaia Bay, Tierra del Fuego Island, Argentina; *ANT* Potter Cove, 25 de Mayo (King George) Island, Antarctic Peninsula. Two sites distanced ~500 m were selected within each coastal environment and sampled in triplicate. For details, see Fig. S0 and Table S1. **b** Organic compounds content of the sediment samples. Values are expressed in micrograms per gram of wet sediment



eliminated. Sequences with ambiguous bases were also eliminated. Closed-reference operational taxonomic unit (OTU) picking was performed at 97% identity threshold in QIIME 1.9.1 against the Greengenes reference database pre-clustered at 97% identity [34]. In addition, an open reference OTU picking strategy was carried out, in which reads that did not have hits with reference sequences using the closed-reference strategy were clustered de novo. Sequences assigned to chloroplasts and mitochondria were eliminated. The resulting OTU table was rarefied to more than 130,000 sequences per sample, and processed in QIIME to build OTU taxonomic assignment tables.

Bioinformatic and Statistical Analyses of I-Tags

Diversity (Shannon) and richness (Chao1) estimators were calculated from the resulting OTU tables in QIIME.

Ordinations based on Bray-Curtis similarity index and weighted UniFrac were performed for OTU tables in R package *vegan* (www.r-project.org/vegan). When more than one community structure dataset was available for a core sediment sample (Table S3), corresponding values were averaged to be included in ordinations and other analyses. Environmental fitting against ordinations was performed with the *envfit* function in *vegan*. For heatmaps construction from the OTU table, data were transformed by square root and standardized using Wisconsin method in R. Canonical correspondence analysis for OTUs assigned at the family level was also performed using *vegan*. Individual correlations of bacterial families were calculated using Pearson's product-moment correlation in R environment. Analyses of the 97% OTUs were performed on the totality of the data, while analyses at the Class and Family level were carried out considering taxa with relative abundances $\geq 1\%$.

Shotgun Sequencing and Functional Annotation of Metagenomes

Shotgun sequencing of sediment metagenomic DNA was performed using Illumina HiSeq™ 2000 platform (2 × 150-bp paired end reads, one lane per sample), at the facilities of the Joint Genome Institute, USA [35]. A total of 23 metagenomes were obtained from the 24 core samples (one of the Baltic Sea samples failed, Table S3). Both the assembled and unassembled fractions of the metagenomes were annotated through the Integrated Microbial Genomes with Microbiome Samples pipeline (IMG/M, <https://img.jgi.doe.gov/m/>) [36].

Bioinformatic and Statistical Analyses of Metagenomes

KEGG Orthology (KO) Terms and Pathways system [37] was used to compare the metagenomes in terms of their potential functions. The number of coding sequences (CDS) assigned to KOs were downloaded from IMG/M for all metagenomes, including assembled and unassembled fractions, with the option “estimated gene copies,” which corrects for read depth in assembled metagenomes. Next, KO abundances were normalized by dividing the total count for each KO term by the total number of reads assigned to KOs in each metagenome dataset, in order to account for differences in sequencing depth. For module- and pathway-level analyses, abundances of KOs were summed for each pathway level (level 2, general categories; level 3, pathways; level 4, modules) to calculate the relative abundances per sample. Abundances were further normalized by dividing by the total sum of abundances for each sample, in order to account for KOs that map to more than one pathway. For comparative analyses with metagenomes from different environments, KO tables were downloaded from IMG/M for a number of publicly available metagenomes (for accession numbers, see Fig. S6). KO abundances were assigned to pathways as described above, analyzed by constructing distance matrices based on these functional categories, and further performing non-metric multidimensional scaling (NMDS) ordination of metagenomes in *vegan*.

Statistical analyses for testing significant differences among pathways from the metagenomes of this work (Kruskal-Wallis test) were performed with STAMP software, using eta-squared as effect size estimator [38]. Multiple test correction was performed by Benjamini-Hochberg false-discovery rate test, and post hoc comparisons were performed by Games-Howell method [38]. Regularized canonical correlation analysis (RCCA) based on KEGG modules or pathways considering environmental and chemical metadata was performed using R package *CCA* (www.r-project.org/CCA). A version of the partial Mantel’s test developed in *vegan*, which finds the correlation between two matrices conditioned on a third matrix and tests its significance by permutation [39], was used to test the hypothesis that the biological (metagenomic) data were

significantly correlated with the measured environmental variables, controlling for the variation attributed to geographic distance, and vice versa.

For biomarker gene analysis, the estimated gene copies of KOs from key enzymes related to aerobic and anaerobic hydrocarbon degradation were obtained from the KO table. These were K00496 (AlkB, alkane-1-monoxygenase, [EC:1.14.15.3]), K14579 (NdoB, alpha subunit of naphthalene 1,2-dioxygenase, [EC:1.14.12.12]), K11943 (NidA, large subunit of PAH dioxygenase, [EC:1.13.11.-]), K14599 (DbfA, alpha subunit of dibenzofuran dioxygenase, first step in aerobic degradation of fluorene, [EC:1.14.12.-]), K00446 (XylE, catechol 2,3-dioxygenase, [EC:1.13.11.2], catechol meta-cleavage), K00450 (GtdA, gentisate 1,2-dioxygenase, [EC:1.13.11.4]), K15760 (TmoA, protein A of toluene monoxygenase system, [EC:1.14.13.-]), K03268 (TodC1, alpha subunit of benzene/toluene/chlorobenzene dioxygenase, [EC:1.14.12.3 1.14.12.11 1.14.12.-]), K15757 (XylM, hydroxylase subunit of xylene monoxygenase, [EC:1.14.13.-]), K14748 (EtbAa; alpha subunit of ethylbenzene dioxygenase, [EC:1.14.12.-]), K07540 (BssA, alpha subunit of benzylsuccinate synthase, [EC:4.1.99.11], participating in anaerobic toluene degradation), K10700 (EbdA, alpha subunit of ethylbenzene dehydrogenase, [EC:1.17.99.2]), K04114 (BcrA, subunit A of benzoyl-CoA reductase, [EC:1.3.7.8], catalyzing the central benzoyl-CoA degradation step shared by toluene, ethylbenzene, and metylnaphthalene degradation pathways), and K07539 (BamA or Oah, 6-oxo-cyclohex-1-ene-carbonyl-CoA hydrolase, [EC:3.7.1.-], catalyzing the ring cleavage step, also central in anaerobic degradation of toluene, ethylbenzene, and metylnaphthalene) [40]. To calculate relative abundances, estimated gene copies (assembled and unassembled fractions of the metagenomes as calculated by IMG) were normalized dividing by the total sequences assigned to KOs in each sample. Individual correlations with chemical compounds and other statistical analyses were performed in R environment. Taxonomic assignments of sequences corresponding to biomarker genes were performed by BLAST search against in-house built reference databases, followed by Least Common Ancestor algorithm (MEGAN, v. 5.11.3) with default parameters, except for `min_score` 35 (recommended for short sequences) and `top_percent` 10 [41]. In addition, the metagenomic sequences assigned to the KOs K00496 (AlkB) and K07540 (BssA) were further phylogenetically placed onto a reference tree containing representative sequences. In the case of AlkB, reference sequences were obtained from a previous analysis performed by Nie et al. [42], while for BssA, deduced amino acid sequences, including homologous genes *bssA* (sensu stricto), *assA*, and *nmsA* from pure cultures and environmental surveys, were selected [43]. The analysis was performed using Evolutionary Placement Algorithm, with RAXML-EPA, which assigns short non-overlapping sequences independently on to a fixed phylogeny by maximum likelihood [44].

Data Availability

All amplicon sequencing data have been made public through the QIITA portal under Study ID 1198 (www.microbio.me/emp, <https://qiita.ucsd.edu/study/description/1198>) as well as through ENA (Study ERP016557, samples ERS1262253-ERS1262313). The metagenomes are available at IMG (<https://img.jgi.doe.gov/>) under accession numbers 3300000118–3300000136, 3300000241–3300000243, and 3300000792.

Results and Discussion

Characteristics of the Study Sites and Sediment Samples

The four regions analyzed in this work are polar or subpolar coastal environments located in the Northern or Southern Hemispheres (Fig. 1a): (1) Adventfjord, Svalbard Archipelago, Norway (NOR) (polar); (2) Port Värtahamnen, Baltic Sea, Sweden (SWE) (subpolar); (3) Ushuaia Bay, Tierra del Fuego Island, Argentina (ARG) (subpolar); and (4) Potter Cove, 25 de Mayo (King George) Island, Antarctica (ANT) (polar). Svalbard, Ushuaia Bay, and Potter Cove are marine environments, while the Baltic Sea is a brackish environment (Table 1, Table S1). Although most of these regions are located in remote locations with low population densities, they are exposed to variable levels of chronic pollution due to anthropogenic activities. The sediment samples, obtained in triplicate at two sites per region, showed differences in organic pollutant levels (Table 1, Table S1). Up to two orders of magnitude differences were found in hydrocarbon pollution levels among samples, although they were only moderately polluted (<10 µg/g of hydrocarbons, Fig. 1b).

Adventfjord, Svalbard Archipelago, is located near Longyearbyen, a small but active town whose main economic activities are divided between tourism, coal mining, and research infrastructures. High PAH, chlorinated hydrocarbons, and BTEX concentrations have been observed at this site [45, 46]. In accordance, samples obtained in this region were the most polluted (Fig. 1b). In contrast, samples retrieved from

Potter Cove, near an Antarctic scientific base, were the least polluted. This site is only slightly impacted by anthropogenic activities, yet it is exposed to occasional accidental diesel spills [47].

The Baltic Sea is a heavily impacted area as a result of multiple anthropogenic activities. Samples were obtained in Port Värtahamnen, in Stockholm, Sweden, which is among the most polluted areas within this enclosed water body [48]. A distinct pattern in organic compound distribution was observed in these sediment samples in which a variety of organic compounds apart from hydrocarbons were present at higher levels (Fig. 1b, for details of the measured compounds see Table S2). The samples from this region also presented low oxygen levels at the sediment–water interface (Table S1). Samples from the two stations in Ushuaia Bay, Argentina, were very different in their pollution pattern: near the Orion Plant jetty used for loading and offloading refined petroleum products (OR site), the sediments showed higher and more variable hydrocarbon levels than those next to the city commercial pier (MC site). Chronic hydrocarbon pollution has previously been detected in Ushuaia Bay sediments, in particular near the Orion Plant jetty [7, 26]. The sheltered nature of Ushuaia Bay shores results in low-energy conditions that might prevent pollutant dispersion [49]. A more detailed description of the sampling sites is available elsewhere [35].

Diversity

A total of 61 million 16S rRNA gene sequences were obtained from all of the analyzed samples, accounting for more than 130,000 sequences per dataset (Table S3) that were used to calculate diversity estimators and to analyze community composition. At a cutoff of 10^5 sequences, coverage ranged from $98.9 \pm 0.0\%$ (SWE) to $99.6 \pm 0.1\%$ (ANT). Shannon diversity index ranged from 6 to 8.7 using a conservative approach (closed reference OTU picking). When an open reference OTU picking strategy was applied [50], a higher diversity was estimated in all cases (Shannon index from 6.8 to 10.2, with coverage values ranging from $96.9 \pm 0.1\%$ to $99.2 \pm 0.2\%$) (Fig. 2). The estimated diversity is among the highest observed for microbial communities, and comparable

Table 1 General characteristics of the sediments by region

Region	Abbreviated name	Temperature (°C)	Salinity (g/L)	Total organic pollutants (µg/g ws)
Adventfjord, Svalbard, Norway	NOR	6.4 ± 0	34.4 ± 0.05	6.8 ± 2.1
Port Värtahamnen, Baltic Sea, Sweden	SWE	11.3 ± 0.1	$4.74 \pm 2 \times 10^{-5}$	2.5 ± 2.4
Ushuaia Bay, Tierra del Fuego Island, Argentina	ARG	8.6 ± 0.1	29.3 ± 0.1	1.4 ± 2.3
Potter Cove, 25 de Mayo (King George) Island, Antarctica	ANT	0.30 ± 0.2	34.10 ± 0.05	0.24 ± 0.2

ws wet sediment

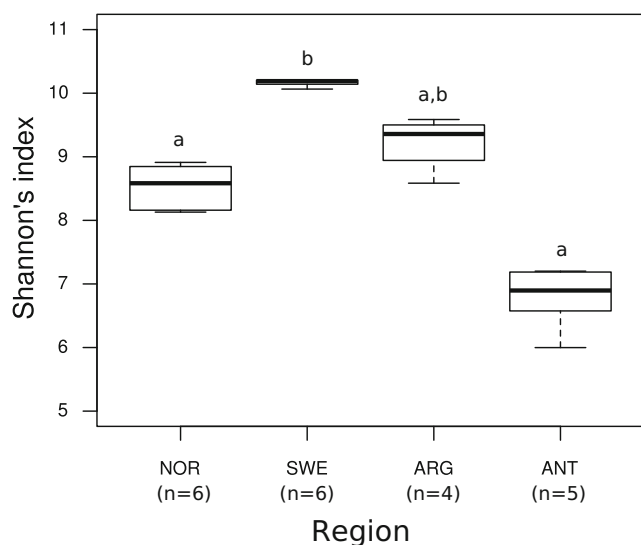


Fig. 2 Alpha diversity estimation of sediment microbial communities per region. *NOR* Adventfjord, Spitsbergen, Svalbard Archipelago, Norway; *SWE* Port Värtahamnen, Stockholm, Baltic Sea, Sweden; *ARG* Ushuaia Bay, Tierra del Fuego Island, Argentina; *ANT* Potter Cove, 25 de Mayo (King George) Island, Antarctic Peninsula. Shannon diversity index was calculated based on OTUs defined at 97% sequence identity (open reference OTU picking method) obtained from the I-tag dataset. In the boxplots, *boxes* represent the standard deviation and *whiskers* 95% confidence intervals, for values obtained from six core samples (three per site), with the exception of ARG (two amplicon sequencing runs failed for station MC) and ANT (one failure for station S1). For further details, see Table S3

to other marine and freshwater sediments [51]. A high richness of Bacteria was estimated for all samples, in particular in sediments of the Baltic Sea brackish environment (Chao1 > 10,000 OTUs, Fig. S1A). For Archaea, however, estimated richness was significantly lower (less than 200 OTUs, Fig. S1B). These results are in agreement with other studies, which found that in coastal and estuarine sediments distributed across salinity and sulfate gradients, only a few groups of Archaea were dominant [52]. In coastal sediments of Antarctica, Archaea were found to contribute only a small proportion of the total carbon flow [53]. However, it must be taken into account that the primer pair used in this study (515F-806R [54]) holds biases against Crenarchaeota/Thaumarchaeota, which could be affecting richness estimates for these groups. In 2015, an updated version of the primers was released, which overcomes this and other biases [55].

Although only eight sites from four regions were sampled, limiting the power of the analysis, there was a positive correlation between diversity (Shannon's index) and temperature measured in the sediment–water interface (Pearson's product-moment correlation $r = 0.96$, p value ≤ 0.0001). In addition, a weaker but significant negative correlation was found between diversity and salinity ($r = -0.74$, p value ≤ 0.0001). Recently, a negative correlation between richness and temperature was reported in chronically polluted temperate coastal

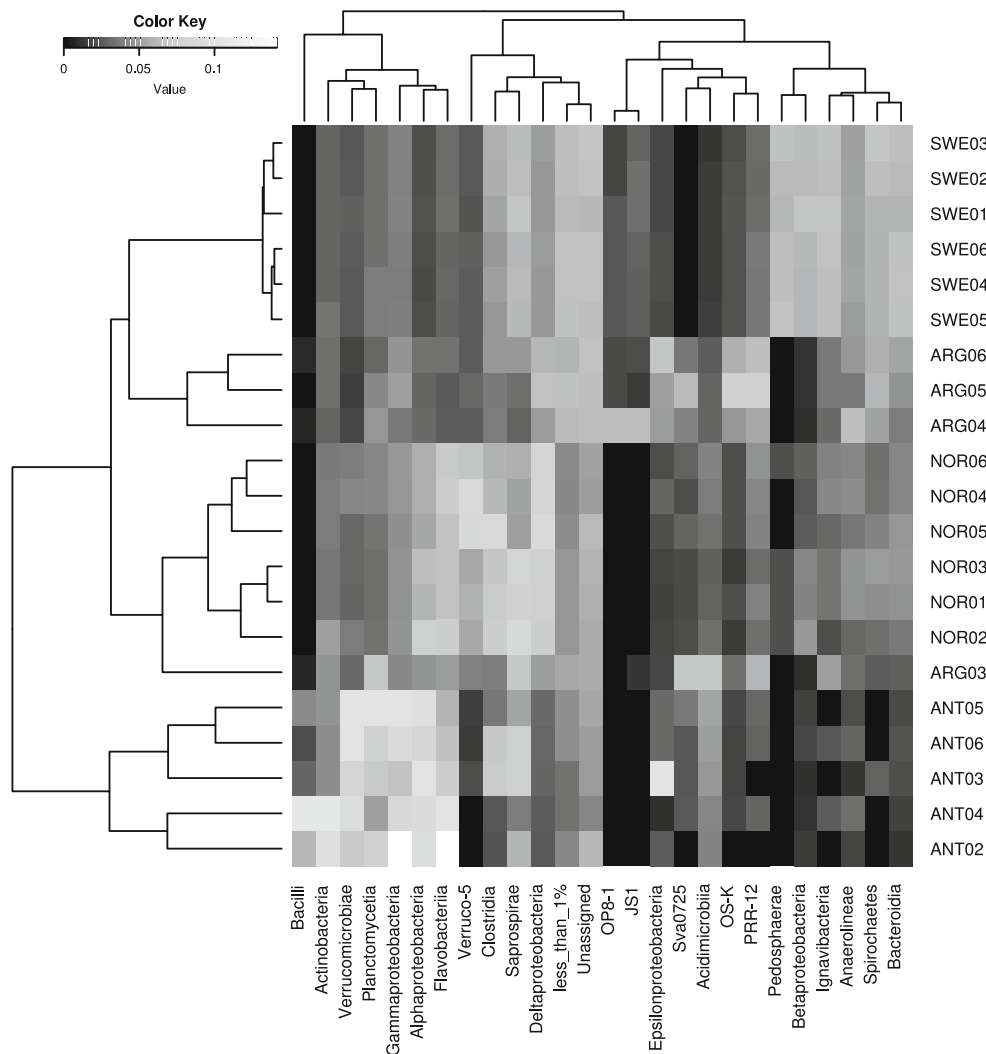
sediments from the Mediterranean basin [30]. In contrast, various studies including a global meta-analysis of marine samples suggested the existence of a diversity latitudinal gradient, with higher richness at lower latitudes and decreasing toward the poles [5]. The sites analyzed by Bargiela and collaborators were placed along a latitudinal gradient ranging from 44° to 30°, which could be affected by local factors, whereas the sampling regions analyzed in this work comprised a latitudinal range of 78° to 54°, and in both Hemispheres. This difference in scale could explain the different results obtained in this study, which are more consistent with global-scale trends.

No correlation was detected between diversity and pollutant levels or other measured environmental variables (data not shown). In coastal sediments affected by the Deepwater Horizon spill, diversity and evenness were negatively correlated with total petroleum hydrocarbons, which is in accordance with the strong selection of certain populations after an acute pollution event [16]. The moderate levels of chronic pollution detected in this work did not seem to affect the diversity of the microbial communities. The presence of microbial communities with extremely high diversity in chronically polluted environments has important implications regarding their role in ecosystem services, as communities with higher diversity are expected to have increased stability, being more capable of responding adequately to disturbances [56, 57].

Community Structure

Distinct patterns of community structure were observed, with the communities generally grouping according to sampling site (Fig. 3, Fig. S2). The most abundant bacterial phylum was Proteobacteria, although different proteobacterial classes were dominant in sediments from different regions. In Svalbard sediments for instance, the Deltaproteobacteria were the most abundant, while in Potter Cove, Gammaproteobacteria were dominant (Fig. S2). Interestingly, the Deltaproteobacteria followed the same trend as the pollution gradient (higher in Svalbard samples, medium in Baltic Sea and Ushuaia Bay samples, and lower in Potter Cove samples; Fig. 1b), while the Gammaproteobacteria followed an opposite trend. We found that members of the Flavobacteria and Alphaproteobacteria were more abundant in sediments from polar regions than those from subpolar regions. In addition, Betaproteobacteria, commonly found at low salinities [58], were abundant in the brackish Baltic Sea samples that have a lower salinity compared to the samples from the marine coasts. We compared these results, which are based on large-scale 16S rRNA gene amplicon sequencing, with those previously reported, based on assignment of metagenomic shotgun sequences to 16S rRNA genes in the same sediment samples [35]. Although similar results were observed by the two methods for dominant bacterial groups (e.g., same trends per region in Deltaproteobacteria and Gammaproteobacteria), a large fraction of the 16S rRNA

Fig. 3 Bacterial community structure (Class level). The heatmap was constructed based on I-tags. Only taxa with relative abundance $\geq 1\%$ are indicated; the others were grouped as " $\leq 1\%$ ". Samples ARG01 and ARG02 from Ushuaia Bay station MC and ANT01 from Potter Cove station S1 were not available due to failure during amplicon sequencing. For further details, see Table S3



sequences obtained from the metagenomes could not be assigned even at the Phylum level [35]. This is probably due to the fact that, unlike amplicon sequencing datasets, which are constrained within hypervariable regions due to primer usage, metagenomic sequences are more variable in length and cover different sections of the 16S rRNA gene, limiting the power of the phylogenetic inference. Furthermore, most of them are short reads, as they were obtained from the unassembled fraction of metagenomes. In addition, the number of sequences obtained per sample was one order of magnitude larger by amplicon sequencing (more than 10^5 sequences, Table S3 vs. 10^4 [35]). The higher coverage allowed the detection of low-abundance groups from candidate bacterial phyla, such as JS1 or PRR-12 (Fig. S2), which are poorly represented in databases and for which limited information is yet available with the exception of metagenomic or single-cell genomics studies [59, 60].

At the OTU level, significant correlations were found between community structure and environmental factors (non-metric multidimensional scaling, NMDS, Fig. 4). Salinity

(highly correlated with axis 1), temperature (dividing polar and subpolar samples along both axes), and organic compounds (associated with samples suffering organic pollution) were the main factors found to correlate with community structure (Fig. 4). Similar results were obtained for ordinations based on weighted UniFrac (Fig. S3). Despite the large geographic distance between the two polar sampling regions, these communities were positioned closely in the ordination space, indicating similar structure (Fig. 4, Fig. S3). Although Arctic and Antarctic regions have been exposed to different geological and evolutionary events, the dynamic of climate drivers can be comparable, and therefore microorganisms subjected to similar environmental stressors could be selected in sites that are geographically distant, resulting in a bipolar distribution [3, 5, 61, 62].

The contribution of different environmental factors toward explaining bacterial community structure was statistically analyzed by canonical correspondence analysis (CCA) after merging OTUs at the Family level (Fig. 5). Among the tested

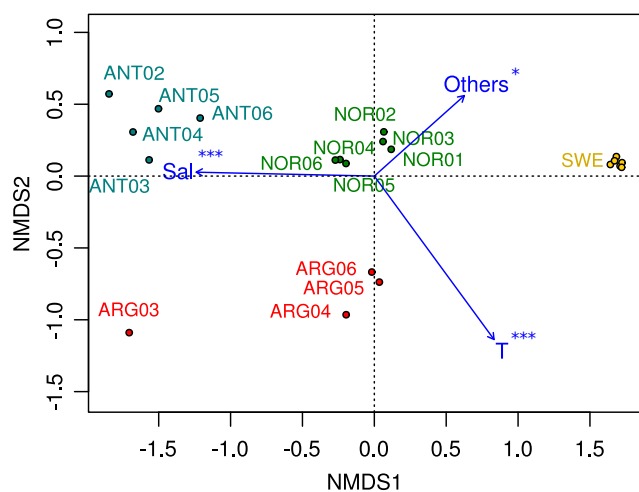


Fig. 4 Ordination of microbial communities based on OTUs defined at 97% sequence identity. Non-metric multidimensional scaling based on I-tag data, standardized by Wisconsin method and transformed by square root before analysis. Stress: 0.02. Environmental variables found to be significantly correlated with ordination patterns are represented as vectors (** $p < 0.001$, * $p < 0.05$). Two samples from Ushuaia Bay station MC and one sample from Potter Cove station S1 were not available due to failure during amplicon sequencing. For further details, see Table S3

environmental variables, the best model using temperature, salinity, depth, and pollution explained more than 75% of the variance ($p = 0.001$). The first canonical axis (CCA 1, associated with temperature and salinity) explained 48.6% of the constrained variation while the second axis (CCA 2, mostly related to depth and hydrocarbon pollution) explained 27.2% (corresponding to 36.1 and 20.2% of the total variation, respectively) (Fig. 5a). According to conventional CCA interpretation, a right-angled projection of a point representing a response variable (species) onto an arrow representing an explanatory variable (environmental variable) indicates the species optimum along that environmental gradient [63]. For instance, various Gammaproteobacterial families are interpreted as likely to reach their maximum at low temperature values (points on negative values of the temperature vector, such as 33, 34, 38, 40, 43, and 45; Fig. 5a). These families (Psychromonadaceae, Colwelliaceae, Alteromonadaceae, and Moraxellaceae, also called *Alteromonas*-like bacteria [64]) are known to have several members with psychrophilic or psychrotolerant characteristics [65, 66]. Accordingly, these were higher in Antarctic sites (Fig. S4). On the other hand, families of the Betaproteobacteria Class, such as the Rhodocyclaceae and Comamonadaceae (14 and 15, respectively; Fig. 5a), were predicted to be more abundant at low salinity values (mainly explained by Baltic Sea samples, SWE; Fig. S4). Members of these families have been previously identified throughout aquatic environments, including the Baltic Sea [51, 67, 68]. Low oxygen concentrations found at the water–sediment interface in the Baltic Sea samples (Table S1), consistent with the high levels of hypoxia and eutrophication encountered in the entire area [48, 68], could also explain the high abundance of

members of these families, which hold many nitrate reducers and denitrifiers. Moreover, from these two families, the most abundant genus identified in the Baltic Sea samples and almost absent in all other sites was *Dechloromonas* (Rhodocyclaceae) (data not shown). These are chemoorganotrophs that can grow on a number of substrates and use multiple electron acceptors for respiration including oxygen, chlorate, perchlorate, and nitrate [69].

Various families of the Deltaproteobacteria class covaried with vectors for anthropogenic pollutants (Fig. 5a, b), and three taxa belonging to the Desulfuromonadales (Deltaproteobacteria) were linearly correlated with the PAHs vector: these included the Desulfuromonadaceae ($r = 0.96$, Bonferroni-corrected p value = 8.5×10^{-10}), Pelobacteraceae ($r = 0.97$, corrected $p = 2.41 \times 10^{-11}$), “unclassified Desulfuromonadales” ($r = 0.96$, corrected $p = 6.11 \times 10^{-10}$), and “unclassified Deltaproteobacteria” ($r = 0.97$, corrected $p = 4.04 \times 10^{-11}$) (Fig. S5). The correlations were slightly lower, but still highly significant, when the total sum (aliphatics, PAHs, and other compounds) was taken into consideration (data not shown). This result was expected due to the presence of various hydrocarbon structures within each pollution source resulting in highly correlated organic compounds among themselves. Together, these taxa accounted for more than 15% of the communities in the most polluted samples, mainly contributed by the “unclassified Desulfuromonadales,” with more than 10% of the I-tag reads in Svalbard (NOR) samples (Fig. S5). Members of the Deltaproteobacteria have been reported to increase in subtidal sediments as a result of acute events of oil inputs [21], and they could be participating in anaerobic hydrocarbon biodegradation in more polluted locations. Still, variables that have not been measured but are related to hydrocarbon content could be responsible for these differences, even in a multicausal way. For example, higher levels of organic matter respiration (including the compounds measured in this work and/or others) could steeply decrease oxygen concentrations along the first centimeters of the sediment at the most polluted sites, contributing to the selection of bacterial groups with anoxic lifestyle. Similarly, a finer sediment granulometry could impair oxygen penetration and contribute in the accumulation of organic compounds through adsorption to the sediment matrix [7].

In samples from marine environments (Svalbard, Ushuaia Bay, and Potter Cove), in addition to the groups previously mentioned, the following taxa were positively correlated with hydrocarbon content: Geobacteraceae (Deltaproteobacteria, Desulfuromonadales); Hydrogenophilaceae (Betaproteobacteria, Hydrogenophilales), Comamonadaceae (Betaproteobacteria, Burkholderiales), and Rhodocyclaceae (Betaproteobacteria, Rhodocyclales); and unclassified Betaproteobacteria (Table S5). Interestingly, all these families were also found by CCA to have their maximum relative abundances near high pollution values but with higher

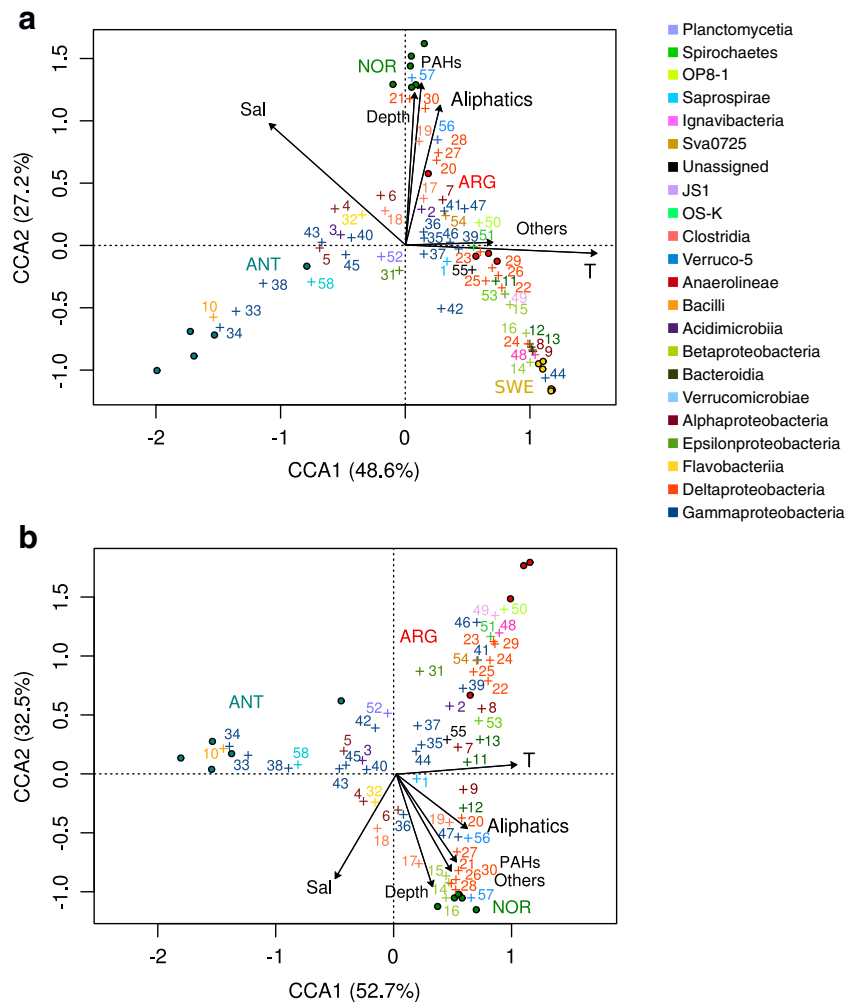


Fig. 5 Canonical correspondence analysis of bacterial families based on taxonomic assignment of I-tags. **a** Analysis based on the complete dataset. **b** Analysis only including samples from marine environments (NOR-ARG-ANT). Only families with abundances $\geq 1\%$ were used for the analysis. Bacterial families are colored based on their assignment at the Class level. 1 Saprospiraceae, 2 kol113, 3 unclassified Acidimicrobiales, 4 Rhodobacteraceae, 5 Phyllobacteriaceae, 6 Sphingomonadaceae, 7 unclassified GCA004, 8 Anaerolineae, 9 unclassified Anaerolineae, 10 unclassified Bacillales, 11 unclassified Bacteroidales, 12 SB-1, 13 VC21_Bac22, 14 Rhodocyclaceae, 15 Comamonadaceae, 16 Hydrogenophilaceae, 17 Lachnospiraceae, 18 Acidaminobacteraceae, 19 Christensenellaceae, 20 Desulfobulbaceae, 21 Desulfuromonadaceae, 22 Desulfobacteraceae, 23 unclassified Myxococcales, 24 Desulfarculaceae, 25 unclassified deltaproteobacteria_1, 26 Geobacteraceae, 27 unclassified deltaproteobacteria_2, 28 unclassified deltaproteobacteria_3, 29

Syntrophobacteriaceae, 30 Pelobacteraceae, 31 Helicobacteriaceae, 32 Flavobacteriaceae, 33 Psychromonadaceae, 34 Moraxellaceae, 35 Piscirickettsiaceae, 36 Marinicellaceae, 37 OM60, 38 Colwelliaceae, 39 unclassified Chromatiales, 40 Thiotrichaceae, 41 unclassified Thiohalorhabdadales, 42 unclassified gammaproteobacteria_1, 43 Altiobomonadaceae, 44 Sinobacteraceae, 45 unclassified gammaproteobacteria_2, 46 Chromatiaceae, 47 unclassified Oceanospirillales, 48 Ignavibacteriaceae, 49 unclassified SB-45, 50 unclassified HMMVPog-54, 51 unclassified OS-K, 52 Pirellulaceae, 53 Spirochaetaceae, 54 unclassified Sva0725, 55 unassigned, 56 unclassified WCHB1-41, 57 WCHB1-25, 58 Verrucomicrobiaceae. Complete names of the families and corresponding class affiliations are detailed in Table S4. Two samples from Ushuaia Bay station MC and one sample from Potter Cove station S1 were not available due to failure during amplicon sequencing. For further details, see Table S3

preference for low salinity, suggesting a synergistic effect (Fig. 5a, b).

Metabolic Potential of Cold Sediment Metagenomes

We further aimed to infer how the metabolic potential of the sediment microbial communities varied across the analyzed locations, as well as to gain insight into the relevance of

different environmental factors on these features. We analyzed metagenomic datasets generated from the same core samples described above (Table S3), based on the functional annotation of the protein CDS into KO (KEGG Orthology) terms and pathways. The size of the total metagenomes (assembled and unassembled) ranged from 1.4 to 16 gigabases (Table S3). The estimated gene copies of sequences assigned to the 17,948 KOs available at IMG were mapped into KEGG pathways

and modules, and normalized to avoid biases due to different metagenome sizes (for details see “Methods” section). In contrast to the phylogenetic structure, which exhibited clear distribution patterns among sites and regions even at the Phylum level (Figs. 3, 4, and 5), the metabolic potential of these communities was remarkably similar (Fig. 6). Interestingly, when the metabolic traits of the sediment metagenomes were compared with datasets from other studies annotated in the same pipeline, they were also found to be more similar to the ones from other high-complexity environments (marine sediments, freshwater sediments, and soils) than to those from environments with a lower diversity, such as pelagic or human-associated microbiome (Fig. S6). In this analysis, however, we did not find any evidence of a higher similarity with other communities from cold regions. For instance, cold sediment samples from this work were as similar to permafrost and peat soils from Alaska as to grassland soils from Northern California (data not shown).

The most abundant functional categories in the sediment metagenomes were related to carbohydrate, amino acid, and energy metabolism (Table S6). Of the 148 analyzed pathways (level 3), only 15 showed significant differences among sampling regions (corrected $p < 0.05$ and effect size higher than 0.8, Kruskal-Wallis test, Table S6). Similarly, out of 225 modules (level 4), only 29 showed significant differences (Table S7). Moreover, among samples, there was a higher proportion of shared KOs than shared microbial phyla (data not shown). Overall, these results are in accordance with the hypothesis of environmentally driven adaptations of phylogenetically distinct microbial communities into core metabolic functions, which has been proposed for other habitats [11, 70,

71]. However, it must be noted that the same results could be obtained if the functions in KEGG are not discriminating enough for these environments.

No significant correlation was observed between functional traits (modules) and the geographic distance matrix (Mantel’s test $R = -0.03$, $p = 0.67$), in accordance with the previous results that showed that these metagenomes were all very similar in functional potential despite being far apart. In contrast, a significant correlation between community structure and geographic distance was observed (based on the 16S rRNA gene sequence data described above, Mantel’s $R = 0.38$, $p = 4 \times 10^{-4}$), indicating that there are limits to the dispersion of microorganisms as a consequence of geographic barriers.

The previous analyses indicated that, although similar in their core functions, these metagenomes still presented some differences. For instance, according to the results of the non-parametric analysis of variance and post hoc comparisons, there were significant differences in some KEGG pathways among regions (Table S7), although no relation with environmental factors can be inferred from this test. To better visualize the environmental variables shaping the potential functional attributes of these communities, we conducted a regularized canonical correlation analysis (RCCA, [71, 72]) using the estimated gene copies of KOs mapped into KEGG modules. According to this analysis, salinity and temperature were the main functional drivers of the metabolic potential of these communities, with the majority of modules distributed along this axis (Fig. S7). These variables were themselves inversely correlated, and correlating with canonical variate (CV) 1 with $r = -0.89$ and 0.95 for salinity and temperature, respectively. It has been previously proposed that salinity is a major

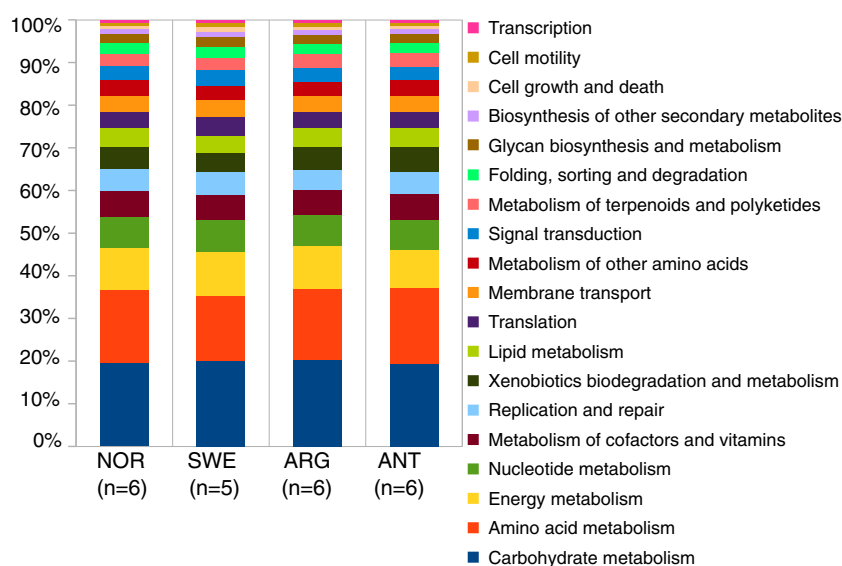


Fig. 6 Distribution of potential functions in cold sediment metagenomes. The relative abundance for each sample was defined as the sum of the total number of CDS assigned to KEGG pathways (level 2), normalizing over total number of assignments to KEGG pathways for that sample, to compensate for coverage differences among samples. Only pathways

with values $\geq 0.1\%$ were considered for the analysis. n = number of metagenomes analyzed per sampling region. In the case of the Baltic Sea region, SWE04 sample from station KBB was not available due to metagenome sequencing failure, and therefore $n = 5$. For further details, see Table S3

determinant of microbial community structure and function [67, 73, 74], and that temperature affects both phylogenetic and functional patterns in marine sediments [30]. In Potter Cove, Hernández et al. [75] also reported that salinity and temperature were the main environmental factors affecting dominance and richness of marine archaeal communities [75]. Interestingly, modules belonging to energy metabolism showed a pronounced variation along CV 1. For instance, nitrate reduction and denitrification (Nit_529, 530, and 531) as well as sulfate reduction (Sul_176 and 595) correlated negatively with CV 1 (Fig. S7 i). This can be explained by a more prevalent nutrient metabolism in colder regions [71]. In contrast, a positive correlation with CV1 was observed for nitrification (Nit_528) and various modules of methanogenesis (Meth_356, 357, 563, 567), suggesting a temperature-dependent enhancement of these functions (Fig. S7 i). Most cofactor and vitamin biosynthesis-related modules were also positively correlated to CV1 (Fig. S7 ii), in accordance with previous observations in the marine environment [72].

Canonical Variate 2 correlated positively with pollutants and other organic compounds vectors ($r = 0.89$, $r = 0.82$, and $r = 0.63$ for aliphatics, PAHs, and “other compounds,” respectively). However, in this case, fewer metabolic modules were positioned along this axis with correlation values higher than 0.5, such as aromatic compound degradation modules AroD_534, 539, and 623, corresponding to naphthalene, *p*-cumate, and phthalate degradation, respectively (Fig. S7 iv).

This indicates a more restricted and specific influence of these factors on the general metabolic potential of these communities. The less evident effect could be due to the relatively low levels of pollutants present in the analyzed samples (Fig. 1).

Biomarker Genes for Pollutant Degradation

Due to our previous findings, we hypothesized that there could be only subtle signals regarding microbial adaptation to pollution in these metagenomes. Therefore, we further focused the analyses on specific genes that are considered biomarkers for hydrocarbon degradation, as they are known to participate in key steps of these processes. Fourteen hydrocarbon-degradation biomarker genes were selected based on KO terms, including those that code for enzymes involved in degradation of PAHs, other aromatic compounds including BTEX, and alkanes (for details see the “Methods” section). Sequences coding for alkane-1-monooxygenase (AlkB) were in general the most abundant (Fig. 7). AlkB was previously found to be the most abundant biomarker in the metagenomic analysis of polluted Mediterranean sediments, followed by sequences assigned to catechol- and gentisate-degrading enzymes [30]. This result was attributed to the fact that alkanes are the most readily degradable hydrocarbon compounds. In the Mediterranean samples, however, relative abundances of AlkB-coding sequences were two orders of magnitude higher than those found in this work (0.68

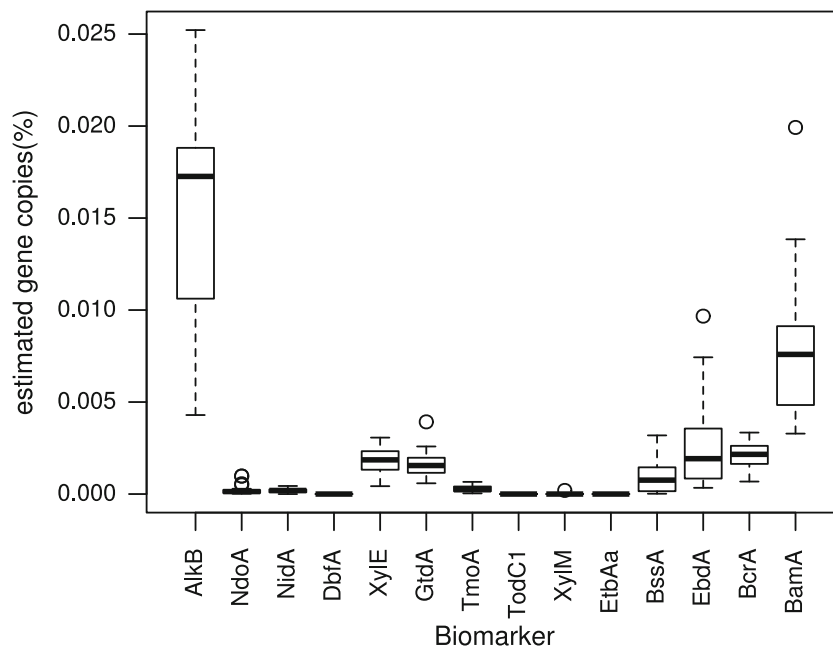
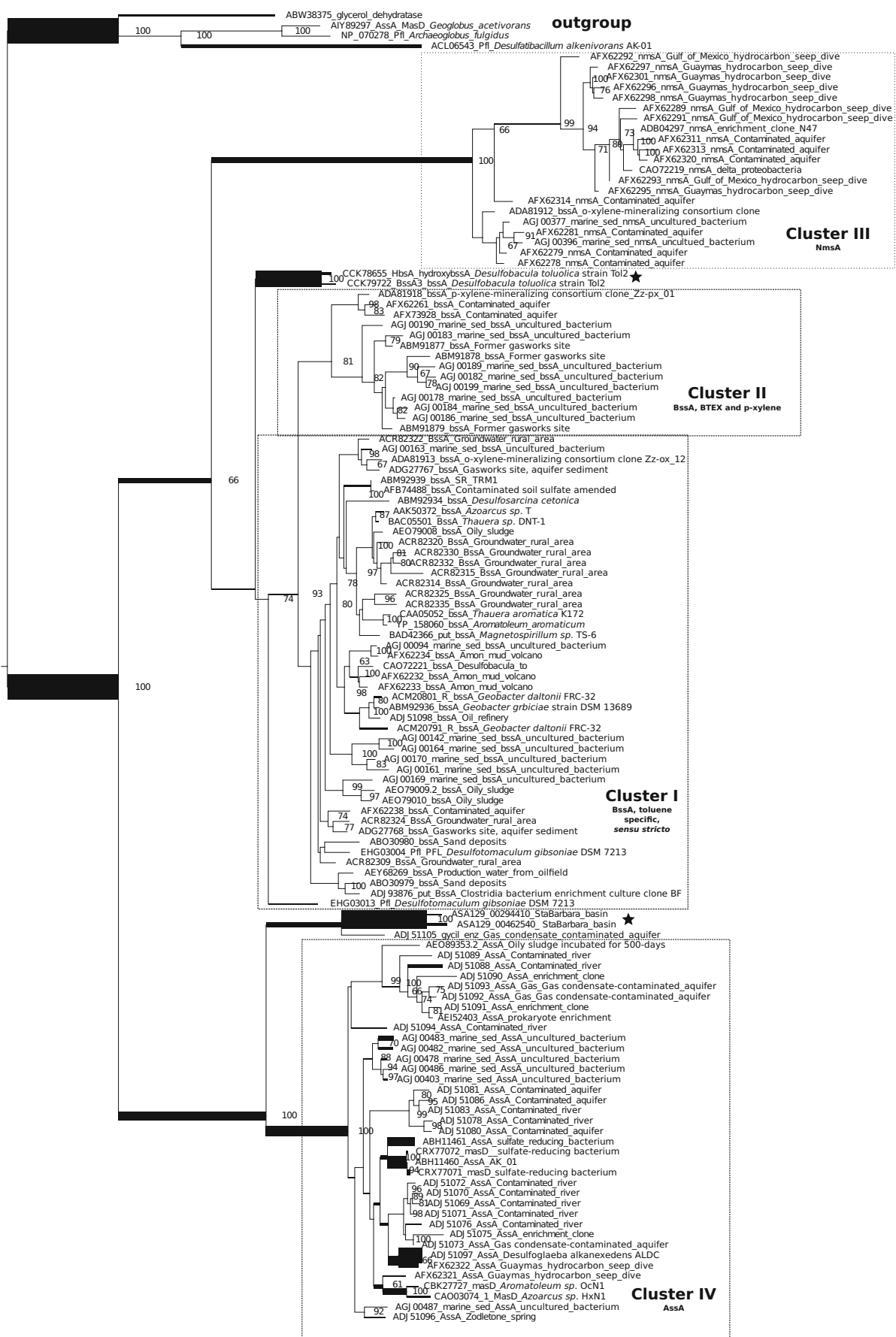


Fig. 7 Relative abundance of biomarker genes for hydrocarbon degradation. Estimated gene copies of sequences assigned to KOs corresponding to enzymes potentially involved in hydrocarbon degradation were divided by the total read count assigned to KOs. *AlkB* alkane-1-monooxygenase, *NdoB* naphthalene 1,2-dioxygenase subunit alpha, *NidA* PAH dioxygenase large subunit, *DbfA* dibenzofuran dioxygenase alpha subunit, *XylE* catechol 2,3-dioxygenase, *GtdA*

gentisate dioxygenase, *TmoA* toluene monooxygenase system protein A, *TodC1* benzene/toluene dioxygenase alpha subunit, *XylM* xylene monooxygenase, *EtbAa* ethylbenzene dioxygenase alpha subunit, *NmsA* naphthyl-2-methylsuccinate synthase alpha subunit, *BssA* benzylsuccinate synthase, *EbdA* ethylbenzene hydroxylase subunit alpha, *BcrA* benzoyl-CoA reductase subunit A, *BamA* 6-oxo-cyclohex-1-ene-carbonyl-CoA hydrolase



◀ **Fig. 8** Evolutionary placement analysis of BssA sequences. Metagenomic sequences were independently assigned on to a fixed phylogenetic tree by maximum likelihood using RaxML [44]. Clusters correspond to the ones previously defined by Acosta-González et al. [43]. Divergent clusters containing metagenomic sequences from this work are indicated with *stars*

to 1.36% for the Mediterranean vs. 0.004 to 0.025% in this work), in accordance with the much higher level of anthropogenic impact of the Mediterranean environment [116–260,000 ppm ($\mu\text{g/g}$) of total petroleum hydrocarbons, one to four orders of magnitude higher than the hydrocarbon concentrations in samples from this work].

In order to gain some insight into the structure of the fraction of the community with alkane-degrading potential, a total of 6908 metagenomic AlkB sequences longer than 70 amino acids from all regions were analyzed by phylogenetic placing onto a reference tree (Fig. S8). Of these, 96% could be unequivocally assigned to one of the clusters defined in a previous study by Nie and collaborators [42]. For all regions, the major fraction of the sequences (47% on average) belonged to Cluster V (Fig. S8). This is a diverse cluster typically composed of putative *alkB* genes identified in genomes from members of the Bacteroidetes, which had not been previously detected in PCR-based studies [42]. Our results are in accordance with metagenomic analyses carried out in Ushuaia Bay [25], and in other metagenomes [42], and suggest that these previously underestimated populations could be important members of the hydrocarbon-degrading community in cold coastal environments. Sequences assigned to Cluster IV (similar to archetypical AlkB1 from *Alcanivorax borkumensis*) were also abundant in all regions (28% on average). Interestingly, sequences assigned to Cluster VII, identified in genomes from members of the Rhodobacterales (Alphaproteobacteria), were more abundant in polar regions (Potter Cove and Svalbard, approximately 20%), while in the Baltic Sea metagenomes, sequences assigned to Cluster I (typically described in Actinobacteria) were instead more abundant (17%).

The second most abundant biomarkers in the sediment samples were those encoding enzymes putatively involved in anaerobic hydrocarbon biodegradation (BssA, BamA, EbdA, BcrA), as well as XylE and GtdA (catechol 2,3-dioxygenase and gentisate 1,2-dioxygenase) (Fig. 7). Notably, in sediments from the Baltic Sea (both sites) and Ushuaia Bay (site OR), sequences assigned to BamA (performing the ring cleavage step funneling the anaerobic degradation of toluene, ethylbenzene, and methylanthalene [40]), were similar in abundance or even higher than AlkB (Fig. S9). Despite the important differences in natural environmental factors such as salinity, these two environments have high levels of nutrient load and suffer eutrophication [76, 77], suggesting a role of organic matter and nutrient availability for microorganisms in the consumption of available oxygen.

The abundances of CDS encoding BssA and NdoB enzymes were found to significantly correlate with pollutant levels (Table S8). Other markers were not correlated or were inversely correlated with pollution, such as the ones targeting the more volatile compounds (TodC1, benzene/toluene dioxygenase alpha subunit, EbdA, ethylbenzene dehydrogenase) (Table S8). On the other hand, 2-naphthoyl-CoA reductase and dihydronaphthoyl-CoA reductase, two enzymes belonging to the Old Yellow Enzyme family that have recently been reported to be involved in the anaerobic degradation of naphthalene [78], have not yet been assigned to KOs and therefore they could not be comparatively analyzed with the other biomarkers. Sequences assigned to the corresponding COG (COG1902, 2,4-dienoyl-CoA reductase or related NADH-dependent reductases) were very abundant in the metagenomes (data not shown), but this COG is not specific as it includes other enzymes as well.

The taxonomic assignment of biomarker gene sequences suggested the dominance of distinct microbial groups according to the potential metabolic condition of the enzymatic reaction (aerobic or anaerobic). In this way, sequences related to aerobic degradation (AlkB, NdoB and NidA, XylE, GtdA) were mainly assigned to Alphaproteobacteria and Gammaproteobacteria, and to a lesser extent to Betaproteobacteria and Actinobacteria (Table S9). These results are in accordance with our previous studies (PCR-based) of functional and phylogenetic biomarker gene diversity in the subantarctic environment of Ushuaia Bay, where these groups were also found to be prevalent [24, 26, 79]. In contrast, biomarkers for anaerobic degradation (BssA, EbdA, BcrA, BamA) showed a different taxonomic distribution. BssA sequences were assigned mainly to members of the Deltaproteobacteria (Desulfuromonadales and Geobacteraceae), and in some cases to Clostridia (Svalbard and Ushuaia Bay, Table S9). Notably, the families that were identified in functional-biomarker gene analyses were the same ones that were detected to be associated with pollution based on a phylogenetic-based approach (e.g., CCA in Fig. 5, individual correlations with pollutants, Fig. S5, Table S5). These results support the hypothesis that these families could have a key role in the degradation processes of both aliphatic and aromatic compounds. Nevertheless, it should be noted that these results will be largely influenced by biases in the databases, leading to the underestimation of the diversity at these sites. Hydrocarbon-degradation genes are extremely diverse and have been poorly characterized so far in these environments, and therefore it is possible that highly divergent sequences (such as many of those found in marine sediments) were missed not only during the taxonomic assignment of biomarker genes but also in the previous step, the functional assignment of metagenomic sequences, especially those with short length.

Metagenomic sequences assigned by KO to the BssA bin (3326 coding sequences for all samples) were further analyzed

by phylogenetic placement against a reference tree that included sequences from all *bssA*-like homologs (*assA*, *bssA* sensu stricto, *nmsA*). These homologous genes code enzymes that catalyze the anaerobic degradation of various hydrocarbon compounds by a general activation mechanism involving fumarate addition [43]. Among the sequences that could be effectively placed on to specific clusters (Fig. 8), the majority (1580) belonged to the AssA cluster (alkylsuccinate synthase, catalyzing alkane degradation). Sequences assigned to NmsA (naphthyl-2-methylsuccinate synthase, participating in methyl-naphthalene degradation) were also found (138 sequences). A total of 414 sequences clustered with archetypical BssA sequences (Fig. 8), which were evenly distributed along the two predefined clusters for this gene (cluster I, toluene-specific, *bssA* sensu stricto, and cluster II, with substrates including BTEX including *p*-xylene) [43]. In addition, 245 sequences were placed within a divergent cluster (Fig. 8, star) formed by hydroxybenzylsuccinate synthase genes (*hbsA*, participating in *p*-cresol degradation) and an additional *bssA* homolog (of unknown function) from *Desulfobacula toluolica* (Desulfobacteraceae). This organism is a sulfate-reducing bacterium isolated from marine sediments, capable of a wide range of biological transformations of aromatic compounds [43, 80].

Interestingly, 337 sequences (mainly from Svalbard samples, data not shown) were placed in a cluster containing hitherto functionally unknown metagenomic sequences from methane-oxidizing archaeal communities in coastal marine sediments of Santa Barbara Basin (California) (Fig. 8, star). Many of these protein sequences were similar to a hypothetical protein from *Desulfosarcina* sp. Bu5 (Deltaproteobacteria, Desulfobacterales), the only pure culture known so far capable of gaseous alkane oxidation under sulfate-reducing conditions [81]. Although culture-based evidence is limited, there is in situ evidence that indicates this process is widespread in the marine environment [82–84]. It has been proposed that not only oxidation of butane and propane but also of methane could be theoretically possible via fumarate addition by glycol-radical enzymes under sulfate-reducing conditions. Chemical evidence of this process has been observed in hydrocarbon-contaminated environments, although it has not fully been proved to date [85, 86]. The presence of non-archetypical gaseous alkane-oxidizing enzymes in polar sediments could have important environmental consequences [87]. More studies are needed in this direction in order to increase our understanding of carbon and sulfur cycles in these environments.

While *bssA* is an already established biomarker and has been widely analyzed in community studies [43, 88], for other genes (*bamA*, *ebdA*) no environmental information was previously available in natural microbial communities [89], and this work is the first to analyze the prevalence of these biomarker genes in the coastal environments. The results from this work highlight the role of microorganisms with an

anaerobic lifestyle in pollutant biodegradation processes and raises questions of whether appropriate deuration rates could be reached, as anaerobic are in general less efficient than aerobic degradation processes [11].

Conclusion

The combination of 16S rRNA gene sequencing and metagenomics, and the broad geographic scale used in this study allowed to increase our understanding of the community structure and metabolic potential of coastal sediments from high-latitude regions. In addition to well-known natural environmental constraints such as salinity and temperature, anthropogenic stressors (namely pollution) were found to be factors shaping the phylogenetic structure of these communities, even at low pollution levels. Our analyses showed that anaerobic biodegradation, a process that has yet to be fully elucidated at the molecular and ecological level, could be driving natural attenuation of hydrocarbon pollution in these environments. The results from this work provide a starting point for integrating ecological insights involving phylogenetic, functional, and environmental data in these vulnerable environments. Further studies will be needed to model the capabilities of key yet-uncultured microbial populations, and to monitor the expression of relevant genes in controlled conditions, in order to integrate this information at different levels, building a more robust and direct link between structure and function.

Acknowledgments M.L. and H.M.D. are staff members from The Argentinean National Research Council (CONICET), and F.E. is a doctoral fellow from CONICET. The amplicon dataset was generated by the Earth Microbiome Project (www.earthmicrobiome.org/). The metagenomic dataset was generated at the Department of Energy-Joint Genome Institute (DOE-JGI) under the Community Sequencing Program (CSP proposal ID 328, project IDs 403959, 404206, 404777–404782, 404786, 404788–404801). Sampling was funded by grants from CONICET (No. 112-200801-01736) and The National Agency for the Promotion of Science and Technology of Argentina (ANPCyT PICT2008 No. 0468), the Argentinean Antarctic Institute, the Universidad de Buenos Aires (UBA 20020100100378), ANPCyT (PICT-O 0124), and the Research Council of Norway (grant no. 228107). This research was also partly funded under the Laboratory Directed Research and Development Program at PNNL, a multi-program national laboratory operated by Battelle for the U.S. Department of Energy under Contract DE-AC05-76RL01830. We would like to thank Ricardo Vera, Horacio Ocariz, and Alejandro Ulrich for their help in sample collection.

Compliance with Ethical Standards

Conflict of Interest The authors declare no conflict of interest.

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