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Reporting Summary

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Statistics

Software and code

primer' and '–p-f-primer' arguments. The length of the extracted reads was set to min. 250 and max. 450 for the PP1 dataset and min. 200 and max. 400 for the PP2 dataset. A classifier was then created using the fit-classifier-naïve-bayes method with the extracted reads and the reference taxonomy. Finally, this classifier was run on the dataset's sequences using the 'classify-sklearn' method to get the sequences taxonomy4. To keep only high-quality samples, all samples having less than 75% of their ASVs assigned to the phylum level, and 50% assigned to the genus level were removed. This filtering resulted in 2508 samples and 530,254 ASVs for PP1 and 1739 samples and 410,931ASVs for PP2. The ASV tables and metadata tables for these datasets can be found on Zenodo, under the file names: 'Data/PP1_table.tsv', 'Data/ PP2_table.tsv' and 'Metadata/PP1_metadata.tsv' and 'Metadata/PP2_metadata.tsv', respectively.

Metagenomic dataset. To address the functional aspect of identified taxa, accession numbers of studies comprising of the following keywords: metagenomics, whole genome shotgun, and environmental, were queried using NCBi's EDirect (v1.1). The results were manually curated to select studies from a broad Geographic distribution, yielding a total of 382 datasets. The selection of metagenomic samples was further restricted to raw fastq data, thus precluding the use of samples from MG-RAST since only the metagenome assembly files were provided. Additionally, all samples still under embargo in accordance with the Joint Genome Institute (JGI; USA) policy, were excluded. From this collection, samples with fewer than 1 million reads or with a quality of reads less than Q25 were removed for a final collection of 91 samples (Fig. 1A). Paired reads were processed using the Integrated Meta-omic Pipeline (IMP; v2.0). The workflow includes pre-processing such as primer/adapter removal and trimming followed by an iterative assembly. Additionally, functional annotation of genes based on custom databases was performed (described below). The entire workflow is setup in a reproducible Snakemake (v5.16) format. Briefly, after preprocessing the reads, de novo assembly using MEGAHIT (v1.2) assembler was performed. The metagenomic dataset KEGG Orthologs (KO) table, taxonomy table, and metadata are available on Zenodo under the 'Data/MTG_KEGG_counts.tsv', 'Data/MTG_table.tsv', and 'Metadata/ MTG_metadata_tsv'

Metagenomic taxonomic classification and functional analyses. Functional potential analyses from contigs were determined by predicting open-reading frames using a modified version of Prokka (v1.14.5) including Prodigal (v2.6.3) gene predictions for complete and incomplete open reading frames. Genes identified subsequently were annotated with Hidden Markov Models (HMM; v3.153), trained using an in-house database. The annotations were further annotated with KO55 groups using 'hmmsearch' from HMMER 3.153. Upon multiple functional group assignments, the best hits based on bit scores were selected. FeatureCounts56 with the '-p' and '-O' arguments were then used to extract the number of reads per functional category.

Logistic regression classification of cryospheric bacterial communities. The Logistic regression implemented in scikit-learn python module (v0.23.2) was trained on presence-absence ASV tables to classify cryospheric samples. To reduce the amount of ASVs considered, the table was filtered based on relative abundance: presence was defined at a 0.005 relative abundance threshold. A 10-fold cross-validation (CV) was ran and balanced accuracy was averaged across the CVs. The C parameter controlling the L2 penalisation was optimized testing 30 values linearly distributed between 0.01 and 0.5, the one with the best balanced accuracy (averaged values of 5 random iterations of 5-fold cross validation, means of PP1 and PP2 values were averaged) was selected (C=0. 178966). ROC curves were plotted using the 'plot_roc_curve' function of the scikit-learn python module. Balanced accuracy, precision and recall were computed using the 'accuracy_score', 'precision score' and 'recall score' methods, respectively, with sample weights correcting for the sample size of the cryospheric and noncryospheric datasets(Supplementary Table 1). The different accuracy metrics values for the classifiers can be found in table S1. Odds ratios were calculated using the exponent of the logistics models' coefficients. The tables containing the ASVs logistic regressions odds ratios can be found in the Data folder available on Zenodo under the name 'PP1_Logistic_coefs.csv' and 'PP2_Logistic_coefs.csv' for PP1 and PP2, respectively.

Phylogenetic analyses. Phylogenetic trees were built using the set of ASVs found in the dataset used for the logistic regression classification. Due to the different 16S regions targeted, phylogenies for both PP1 and PP2 datasets were constructed separately. The ASVs sequences were aligned using the FFT-NS-2 algorithm implemented in the Mafft (v7.0) aligner with default parameters. The alignments were subsequently trimmed using TrimAl (v1.3) with the '-gt 0.95' parameter, and the trees built using IQ-TREE (v1.6.12) with the GTR model of nucleotide substitution and the '-fast' option. Phylogenetic tree visualisations were created using the ggtree (v3.15) and ggtreeExtra R (v3.6) packages. Only positive coefficients showing enriched presence in cryospheric environments are shown in the phylogenetic barplots (Fig. 1). The number of ASVs with an odds ratio above 1 was shown for taxonomic summaries.

ß-diversity phylogenetic metrics (Sorensen's Index and ß-MNTD) were computed using the 'phylosor' and 'comdistnt' functions of the Picante (v1.8.2) R package, using custom functions to compute pairwise comparisons. For each metric, 50 iterations were performed where we calculated the pairwise distances between and within 50 cryospheric, and 50 non-cryospheric samples. This random sub-sampling approach was chosen to reduce computing time. Kruskal-Wallis tests were used to determine whether the distribution was different across groups, and Wilcoxon tests were used to calculate pairwise post-hoc comparisons. Wilcoxon tests implemented in the compare_means function of the ggpubr R package were used, effects sizes (r) were calculated with the wilcox_effsize function implemented in the statix R package. Sample specific calculations of ?-PD (and species richness),-MPD and-MNTD were computed using the 'pd', 'mpd' and 'mntd' functions of the Picante R package63. Linear models were used to compare the values of-PD,-MPD and-MNTD across samples, taking the logarithm of the species richness and the dataset (PP1 and PP2) as a fixed effect.

Differential abundance analysis. Using the Silva Taxonomic information, ASV raw counts were aggregated to the genus-level using a custom R script, removing the ASVs not assigned taxonomically to the genus-level. Ancom (v2.1) was used on the count data for the differential abundance analysis, using the default W statistic threshold of 0.764. The 'zero-cut' parameter was set to 0.995 to consider all bacterial genera present in at least 21 samples (n = 4247), and the primer pair (PP1 and PP2) variable was taken as a random effect with the rand_formula parameter ("~ 1 | Dataset"). We considered as significantly enriched genera (i.e. cryospheric genera), the ones with a W statistic above the threshold (0.7) and a positive value of CLR mean difference. GGplot2 (v2.15) was used to modify the Ancom figure showing the results of the differential abundance analysis. The 'heat tree' function of the metacoder R package (v0.3.4) was used to show the number of cryospheric bacterial genera, at various taxonomic level, using taxonomic trees. The results of this analysis can be found in the Data/ folder available on Zenodo under the name 'Ancom_amplicon_res.csv' file.

NCBI Refseq genomes properties. To assess the genome size and GC content of publicly available prokaryote genomes, a non-redundant list encompassing all the genera in our datasets was compiled. Thereafter, the list of prokaryote genomes (prokaryotes.txt) available on NCBI was downloaded on March 15th, 2021 from https://ftp.ncbi.nlm.nih.gov/genomes/GENOME_REPORTS. The prokaryote list was filtered based on the list of genera found in our dataset, simultaneously retrieving the accession IDs. The accession IDs were used to download the complete bacterial genome sequences using the ncbi-genome-download (v1.0) python package (https://github.com/kblin/ncbi-genome-download). The

genome sizes for the downloaded genomes were additionally retrieved from the prokaryotes.txt metadata file. Subsequently, Prodigal was used to annotate the open-reading frames per genome obtaining both the general feature format (gff) files and aminoacid fasta (faa). These were used thereafter as input used to estimate the predicted growth time (in hours) and their codon usage analyses (CUB) using gRodon (v1.0) and coRdon (v1.15) (https://github.com/BioinfoHR/coRdon) R package respectively. The amino acid enrichment analysis was performed on by converting the codon counts to amino acids using the R-package Biostrings using DEseq2 (v2.3) with default parameters (log-median ratio normalization across genera). Wilcoxon tests implemented in the compare_means function of the ggpubr R package were used, effects sizes (r) were calculated with the wilcox_effsize function implemented in the statix R package. The relevant scripts and information for these analyses are openly available and included in the code availability section. The corresponding files used for this analysis can be found in the Data/ folder available on Zenodo under the names 'prokaryotes.txt', 'merged_all_codon_counts.txt' and 'merged_all_growth_prediction.txt'. Structure of the cryospheric microbiome. Non-metric multidimensional scaling was used to visualise the composition of cryospheric bacterial communities according to the ecosystem types and primer pairs. For this, the 'metaMDS' function implemented in the package vegan was used with Bray-Curtis distances. The stress for the chosen value of k=2 was 0.206. The 'adonis2' function was used to perform a PERMANOVA analysis to test the effect of the ecosystem type and the primer pairs on the composition of bacterial communities (Supplementary Table 4). Pairwise comparisons between ecosystem types were tested using the function 'pairwise.adonis2'. P-values were adjusted using the default Bonferroni method, to account for multiple comparisons.

The prevalence of each genus was modeled as the probability of presence using a logistic binomial regression (with the R stats 'glm' method), using the ecosystem type (snow/Ice, terrestrial, marine and freshwater) and the primer pair as fixed effect. To calculate the probability of occurrence in the cryosphere for each genus, the prediction was calculated for all ecosystem types and primer pair combinations, and averaged. The core microbiome was defined at 0.1% abundance, and 20% prevalence across the cryosphere, for genera present in at least one sample in all four ecosystem types (Supplementary Figure 2B). The core microbiome presence in the different ecosystem types was shown using an upset-plot using the complex-upset (v.1.3.3) R package. The taxonomic tree available in Supplementary Figure 2A was created using the Metacoder R package. The a-diversity was calculated using Shannon's index with a custom R functions. To test the difference across ecosystems and datasets, the Wald-Type statistics implemented in the 'GFD' function of the R GFD package was used (Supplementary Table 5). This test was performed instead of an ANOVA, as the data was not normally distributed. The mean values given by the function were used for the ecosystem comparison.

KEGG enrichment. The standard DESeq2 pipeline with default parameters was used on raw KEGG counts for the enrichment analysis, using the default Wald tests. We considered significantly enriched Kegg Orthologs (KOs) with an FDR adjusted p < 0.01 and a log2 fold-change > 1. To unravel the contribution of these gene families to functional pathways, we ran KEGGdecoder (v1.3) on the KOs enriched in cryospheric samples, to identify environmental-associated pathways in all samples.

To understand and unravel the origins of the gene families specific to the cryospheric metagenomes, contigs were taxonomically classified following which the specific gene families were mapped to the contigs. We used Kraken2 (v2.14) to taxonomically assign all the contigs present in the metagenomes followed by custom python scripts (provided) to link the genes belonging to enriched KEGG orthologs (KO and the corresponding NCBI taxon ID. An R script using the NCBI entrez package was used to retrieve the taxonomy based on the taxon ID, and to get the genus-level taxonomy. To link the Silva genus taxonomies with their NCBI counterparts, the grep function included in R allowing partial matches was used to find Silva genera name matching the NCBI genus name. The DEseq2 results, KEGG-decoder output and taxonomy matches can be found in the Data/ folder of the Zenodo under the names 'KEGG_deseq_results.csv', 'KEGG_decoder_output', and 'KEGG_sign_tax_genera.csv', respectively.

Gene clusters and unassigned protein coding sequences. Predicted gene sequences annotated to the KEGG database and those unassigned were gathered into individual groups based on KEGG ID or Unassigned using a custom python script. 'annotation2gene.py'. The fasta files were subsequently concatenated and clustered to identify functional homologs within the dataset. We used mmseq2 (v13-4511) 'linclust' to cluster the 41,068,842 gene sequences found in the entire metagenomic dataset. Subsequently, fasta sequences associated with each cluster were retrieved into separated clusters (n=12,125) and linked to the coverages to estimate abundances. MAFFT was then used to create a multiple sequence alignment of the sequences per cluster, while the 'cons' method from EMBOSS (v.2.0.0) was used to generate a consensus sequence. The generated consensus sequences from each cluster were subsequently annotated and their identity verified against the UniProt TrEMBL (release 26.0) database. The pairwise identity of sequences within each cluster was measured using CLUSTAL (v2.0) 'distmat' option with the '–percent-id'. Wilcoxon tests implemented in the compare means function of the ggpubr (v0.4.0) R package were used, effects sizes (r) were calculated with the wilcox_effsize function implemented in the statix (v1.3.0) R package. The unassigned clusters summary statistics and Uniprot matches can be retrieved on Zenodo, in the Data/ folder under the names 'Unassigned clusters stats.tsv', and 'unassigned_uniprot_matches.txt'.

Code availability: All scripts used for analyses, along with the conda environments, and additional information is provided in a Github repository archived on Zenodo: https://zenodo.org/badge/latestdoi/371641303.

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Data

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Data availability

The data is fully available on Zenodo at https://doi.org/10.5281/zenodo.6325482

Databases used in the current study include the following:

1. maxikraken database: https://lomanlab.github.io/mockcommunity/mc_databases.html 2. SILVA database: https://www.arb-silva.de/documentation/release-1381/

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Methods

- n/a Involved in the study \sqrt{x} \Box ChIP-seq $\overline{\mathbf{x}}$ \Box Flow cytometry
- $\overline{\mathbf{x}}$ $\overline{\mathbf{x}}$ MRI-based neuroimaging