Temperature and soil moisture control microbial community composition in an arctic-alpine ecosystem along elevational and micro-topographic gradients

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Temperature dependency of alpine microbes

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Detailed information about Illumina sequence analysis

Sequencing resulted in 5.36 million paired end reads. The reads were assembled with PANDAseq [1], and demultiplexed with a Python program (kindly provided by Kurt Stüber, Max Planck-Genome-centre Cologne). Quality check revealed that all sequences had a phred score > 3, as recommended by Bokulich *et al.* [2]. Primer sequences were removed via Cutadapt [3]. After assembly and quality check, 3.06 million reads remained. Sequence alignment was done with PyNAST [4]. Afterwards sequences were clustered into OTUs using UCLUST and the SILVA v.119 SSU reference database (97 % consensus; [5]). Chimeras were removed with USEARCH 6.1 [5] using a Greengenes database (gg 97 otus 4feb2011) as reference. Moreover, singletons, reads assigned to unclassified groups of organisms, chloroplasts and mitochondria were removed from the data set, finally resulting in 2.81 million reads (accounting for roughly 52 % of all generated sequence reads). BIOM files were converted into readable tables for further analyses.

Detailed information about PLSR

PLSR, which is also known as 'projection on latent structures' [6], combines elements from PCA and multiple linear regression (MLR). As a limited information approach, introduced by Wold as a soft modeling technique to handle various modeling problems in situations where it is difficult or impossible to meet the hard assumptions of more traditional statistics, PLSR has the advantage that it works without distributional assumptions and with nominal, ordinal, and interval scaled variables [7–10]. Moreover, PLSR deals efficiently with unreliability and heteroscedasticity issues [11]. The method is well suited for the analysis of datasets in which the number of explanatory variables exceeds the number of observations [12] and/or in case of highly correlated predictors [13, 14]. Instead of using all independent variables simultaneously as predictors, the PLSR extracts just a few components (latent factors) from the independent variables that maximize not only the explained variance in the independent variables (like PCA), but also in the dependent variable. Thus, PLSR uses fewer explanatory variables than were in the original data. Further, PLSR was described as more reliable than PCA-regression and multiple regression when identifying relevant variables, especially in cases of small sample size, and strongly shielded against both type I and type II errors [14]. Thus, PLSR is very useful where emphasis is on theory development instead of testing, in a confirmatory sense, how well a theoretical model fits observed data [15]. Our motivation to apply PLSR was the need to identify – out of all explanatory variables – a subset of relevant variables that is responsible for explaining the variation in the response [16]. In this context of variable

selection, a PLSR model is built and its output is solely used to assess the (relative) importance of each explanatory variable, i.e., the focus is to determine the influential explanatory variables rather than the response [17].

References for methodological details

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Table S2: Sequences of barcoded forward primers targeting the 16S rRNA gene. Primers include a stagger sequence (3 – 5 bp per primer), a barcode (8 bp) and the primer sequence itself. The reverse primer was not modified.

Table S3: Bacterial families showing significant changes in relative abundance in dependence on elevation or micro-topography. Only families with > 1 % read abundance are shown in this table. Responsive families were identified using Kruskal-Wallis tests in the STAMP program.

Figure S1: Ecological response graphs showing exemplarily the ecological response patterns of the verrucomicrobial genus DA101 (left) and unclassified taxa of the order *Methylophilales* (right). Plots display the selectivity ratios (SRs) of PLSR calculated using a rarefied table of taxonomic groups (TG) (A + D), SRs calculated with a centered log-ratio (clr) transformed table $(B + E)$ and significance Multivariate Correlation values (sMC) for a PLSR calculated using the rarefied TG table $(C + F)$. Plots display SR and sMC values of all environmental variables arranged along the x-axis. The first three sections represent soil temperature measures over 1, 2 and 5 years, respectively. Within each temperature section, stepwise increasing threshold values ranging from -16.9 °C to +22.4 °C are shown, followed by single values for amplitude, maximum, minimum and mean. The same pattern is used to present air temperature in a range from -25 °C to +25 °C and soil moisture ranging from 0 to 0.5 m³ H₂O m⁻³ soil. The last section named soil characteristics includes soil texture, C, N, C:N ratio and pH values, according to table S1.

Exemplarily, the plots for DA101 show a TG with consistent results for all PLSR analyses, while the plots for *Methylophilales* are less reproducible based on the different algorithms applied to assess the impact of the environmental factors. In the majority of TGs, the patterns were in general well reproducible, especially the category of the most important driver (i.e. temperature, soil moisture or soil characteristics) remained identical for approx. 70% of all taxa (table S4). However, the specific most relevant driver (e.g., 2-year versus 5-year moisture regime) was not necessarily identical when applying different approaches, due to the fact that SR and sMC values were often in a similar range within a category. Taken together the findings for all analyzed TGs, overall findings about the most important drivers for the whole microbial community were the in good agreement (Figure 4), while the results for individual TGs differ to some extent based on the applied algorithm for environmental parameter identification.

Figure S2: Boxplots displaying soil (A + C) and air temperature (B + D) selectivity value thresholds > 2 for taxa being affected by elevation (A + B), micro-topography (C + D), or being unaffected by elevation or micro-topography, respectively. Displayed are the median and the 25th and 75th percentile as middle line and grey box. Whiskers indicate minimum and maximum.

Figure S3: Plots displaying the maximum selectivity ratio (SR) in dependence on the 5-year soil temperature threshold values of each taxonomic group (TG) evaluated based on a rarefied TG dataset (A + B) or a centered log-ratio transformed dataset (C + D). Different colors indicate TGs that were significantly affected or unaffected by elevation $(A + C)$ or affected by different micro-topographic expositions (B + D) according to STAMP. The dotted line indicates the SR cut-off at the value of 2, below which variables were considered to have no explanatory effect. The comparison of SR values derived from a rarefied dataset are largely in agreement with those derived from a clr-transformed dataset.

Figure S4: Plots displaying the maximum selectivity ratio (SR) in dependence on the 5-year soil moisture threshold values of each taxonomic group (TG) evaluated by using a rarefied TG dataset $(A + B)$ or a centered log-ratio transformed dataset $(C + D)$. Different colors indicate TGs that are affected by different micro-topographic expositions $(A + C)$ or unaffected by micro-topography $(C + D)$ according to STAMP. The dotted line indicates the SR cut-off at the value of 2, below which variables were considered to have no explanatory effect. Plots A and B are identical to those in figure 7 and are included here to allow direct comparison. The comparison of SR values derived from a rarefied dataset are largely in agreement with those derived from a clr-transformed dataset.