

Statistical Analysis Report

Fungal profile from metabarcoding for full project (version June 2024)

Biomcare ApS

08/06/2024

Customer	Innovation Centre for Organic Farming, Tove Mariegaard Pedersen
Customer ID	DA00204
Project	The microbial community of the field (2021, 2022 and 2023).
Sample Type	Soil
Number of samples	102 samples
Type of data	shotgun metagenomics

Introduction to the biostatistical analysis

The Project

The current report describes microbiome profiles of 100 samples collected across 3 project years (2021-2023), across a corresponding number of fields in Denmark. For each field, one sample was collected to represent the field, corresponding to the 'main' samples collected for each field from 2021. These samples were taken for each field based on 16 subsamples taken in a w-pattern throughout the field.

In this report we analyse the full project dataset. We split many analysis by JB values into 2 groups based on initial analysis of data from 2021-2022 where we saw a strong association between JB and microbiome profiles. We split the further analysis based on JB as we find the effect of JB overshadows the associations that may be between the microbiome and other variables of interest. Different from the prior years reports we also added geography information and some weather information like rainfall and temperatures. We will relate these informations to the microbiome as well. Where feasible, we will both look at the cross-year effect where we adjust for the effect of year and look for effects that differ between years thus looking for association between the microbiome and metadata that differ (or depend on) other factors that associate with a specific year. The aim is to evaluate how the microbiome of the fields associate with other field parameters of both agricultural practices and soil indicators of nutrients, type and structure.

The JB groups are:

- JB 1 + JB 2
- JB 5 + JB 6 + JB 7

The one sample with JB4 is removed. (one sample was removed for stating JB 2-4)

Analysis

In "Report 3", biostatistical analyses are performed and the results presented, building on the data generated and evaluated in the 2 prior reports (**Report 1: Sequencing and data processing report, Report 2: Microbiome profiling report**).

Through biostatistical analysis we relate the microbiome profiles to the key variables selected for year 2022. The focus here is to evaluate how and to what extent the variables shape and relate to the soil microbiome composition and diversity. We therefore focus on the overall structure of the microbiome also called the microbiome composition and the diversity.

The key variables assessed in this report are summarized with summary statistics across the 48 samples in the below table.

Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
year	93						
... 2021	10	11%					
... 2022	48	52%					
... 2023	35	38%					
JB_groups	93						
... JB1_JB2	48	52%					
... JB5_JB6_JB7	45	48%					
JB_value	93						
... 1	29	31%					
... 2	19	20%					
... 5	4	4%					
... 6	38	41%					
... 7	3	3%					
Geographic_location_letters	93						
... B	4	4%					
... F	4	4%					
... MJ	28	30%					
... NJ	11	12%					
... S	15	16%					
... SJ	17	18%					

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
... V	14	15%					
Rainfall	93	348	47	256	308	388	437
Average_drought_index	93	6.6	1.6	3.8	4.9	7.9	8.7
Average_temp.	93	13	0.44	13	13	14	14
Earthworm_status	93						
... 0	21	23%					
... 1	72	77%					
Cold_soil	93						
... 0	67	72%					
... 1	26	28%					
Compact_soil	93						
... 0	79	85%					
... 1	14	15%					
field_well_drained	93						
... 0	10	11%					
... 1	83	89%					
Mulching_of_straw	93						
... 0	46	49%					
... 1	47	51%					
Clovergrass_within_3_years	93						
... 0	67	72%					
... 1	26	28%					
No_plough	93						
... 0	72	77%					
... 1	21	23%					
ConservationAgriculture	93						
... 0	87	94%					

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
... 1	6	6%					
Years_since_plowing	93	3.9	3.6	1	1	5	14
Rt	93	6.4	0.51	5.5	6	6.8	7.6
Phosphorus	93	3.1	1.4	0.7	2.1	3.9	8.2
Potassium	93	11	7.1	1.5	6.7	14	50
Magnesium	93	6.5	2.6	1.9	4.9	7.5	16
Cobber	93	2.5	1.1	1	1.8	3.1	7.5
Organic_material_perc	93	3.1	1.4	1.2	2.3	3.6	8.7
Clay_perc	93	8.9	4.4	2.4	4.8	12	20
Nitrogen_perc	93	0.15	0.055	0.07	0.12	0.18	0.35
Organic_farm	93						
... 0	41	44%					
... 1	52	56%					
Years_since_turning_organic	52	14	5.8	1	10	19	21
Livestock	93						
... 0	38	41%					
... 1	55	59%					
Livestock_manure	93						
... 0	23	25%					
... 1	70	75%					
Commercial.fertilizer	93						
... 0	51	55%					
... 1	42	45%					
Vinasse	93						
... 0	87	94%					
... 1	6	6%					
Cast	93						

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
... 0	91	98%					
... 1	2	2%					
Degassed.fertilizer	93						
... 0	70	75%					
... 1	23	25%					
Haveparkaffald	93	0.054	0.23	0	0	0	1
Chalked	92						
... 0	71	77%					
... 1	21	23%					

Table 1: Summary statistics of the key variables selected for evaluation in relation to the fields microbiome profiles in year 2022.

Geography and JB values

As a new feature we include information on the geographic location of the fields collected in the project. We use coordinates to show the location of the fields on a map, and color the data points by JB value and year of sampling to get an understanding of the relationship. We then identify single species that differ in abundance between geographic regions, using an anova model adjusting for year.

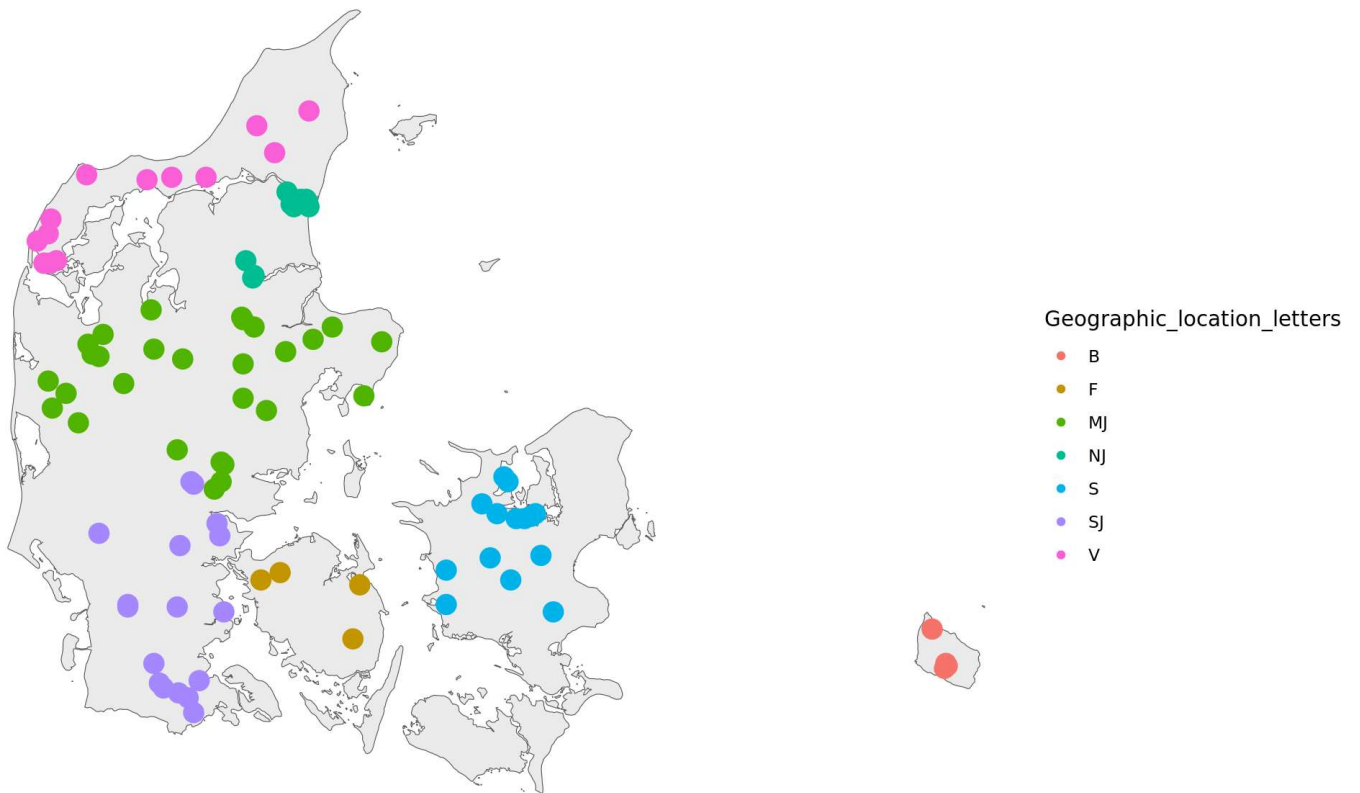


Figure 1: Visualization of the geographic location of the samples. Using the coordinates of each field in the project, we show the locations on a map and color the samples by region to illustrate the regional distribution of samples in the project.

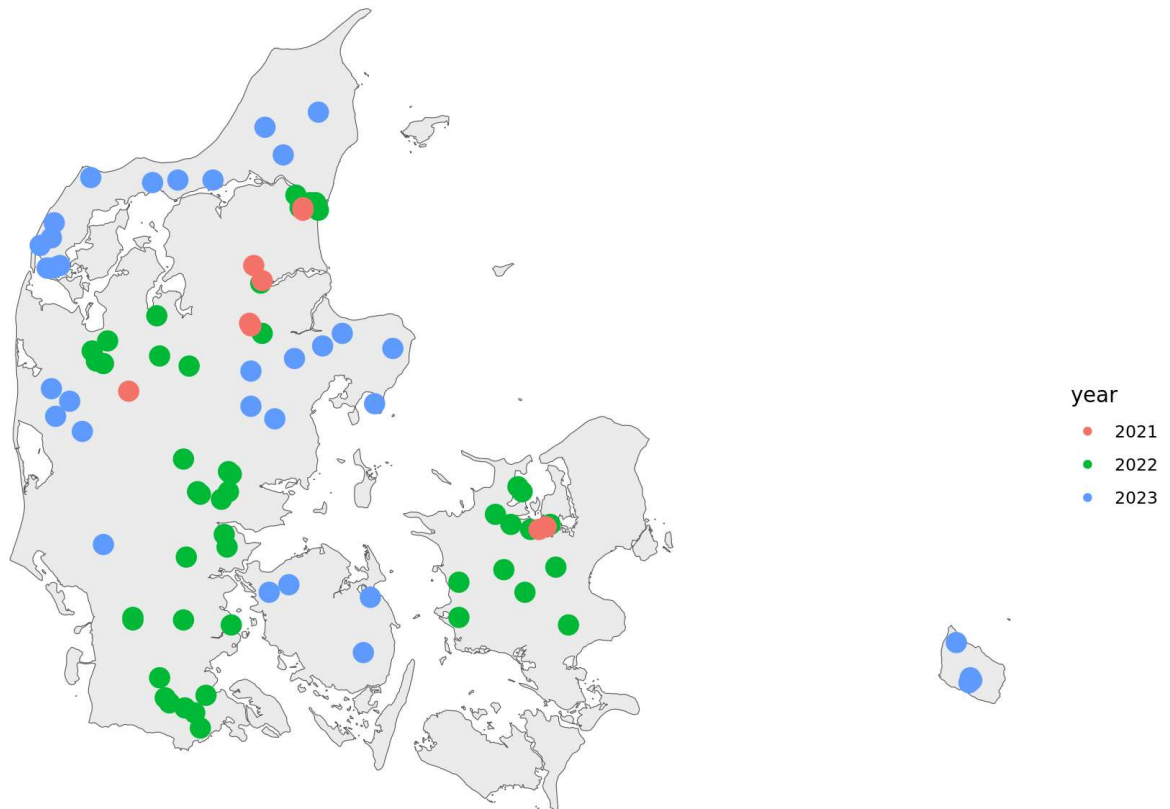


Figure 2: Visualization of the geographic distribution of samples collected each year. Using the coordinates of each field in the project, we show the locations on a map and color the samples by year of sampling.

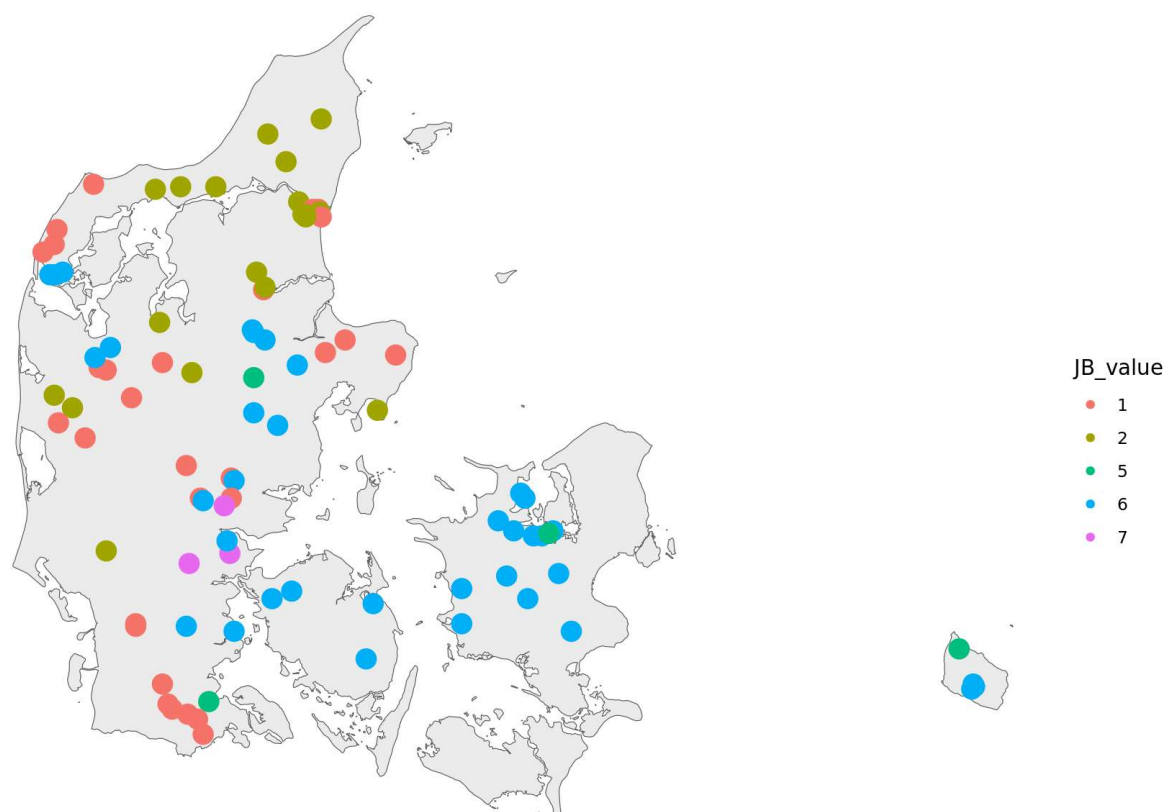


Figure 3: Visualization of the geographic distribution of JB types for the included samples. Using the coordinates of each field in the project, we show the locations on a map and color the samples by year of JB value

The abundance of individual species may also deviate between regions driven by the differences in soil properties, farming practices and climate between the regions. We here identify species that differ in abundance between any two regions and for top deviating species show their abundance on a map.

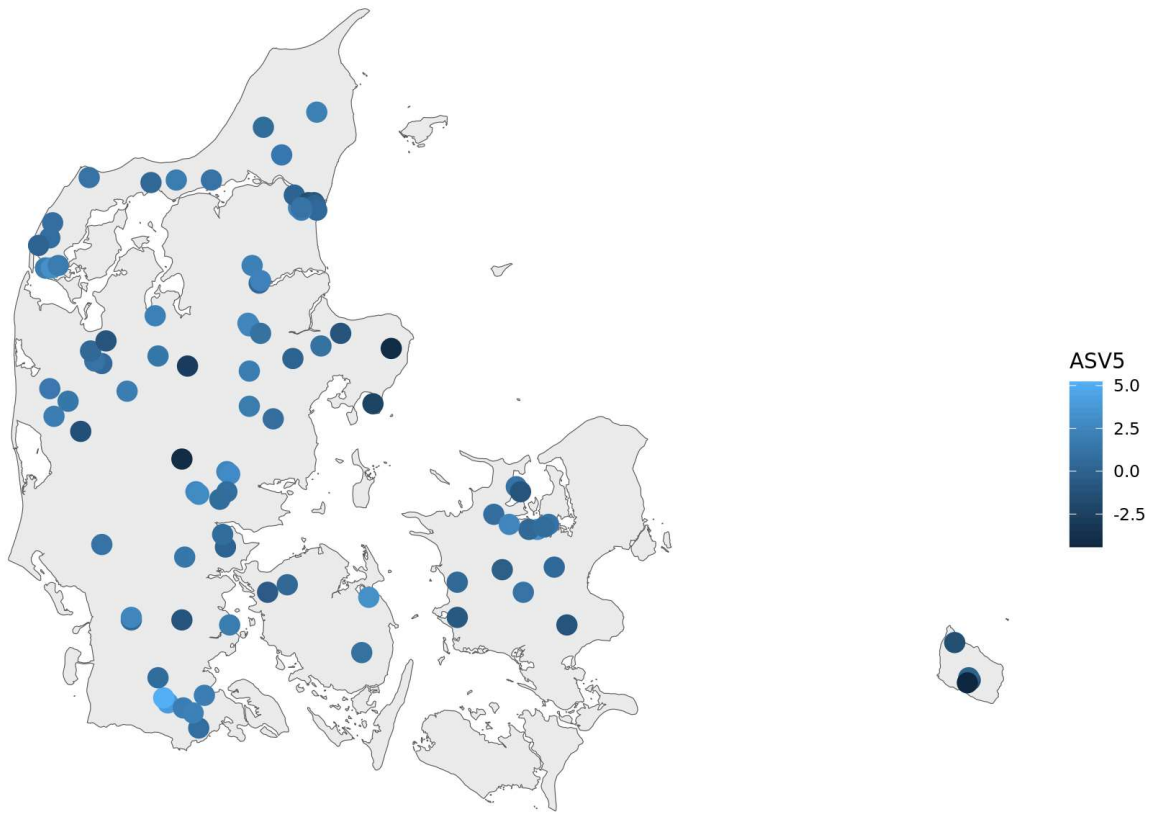
	Sum.Sq	Df	F.value	Pr..F.	p.adj
ASV5	55.191	6	4.287	0.00082	0.0418
ASV44	53.964	6	3.858	0.00192	0.0489
ASV15	14.567	6	3.592	0.00325	0.0553

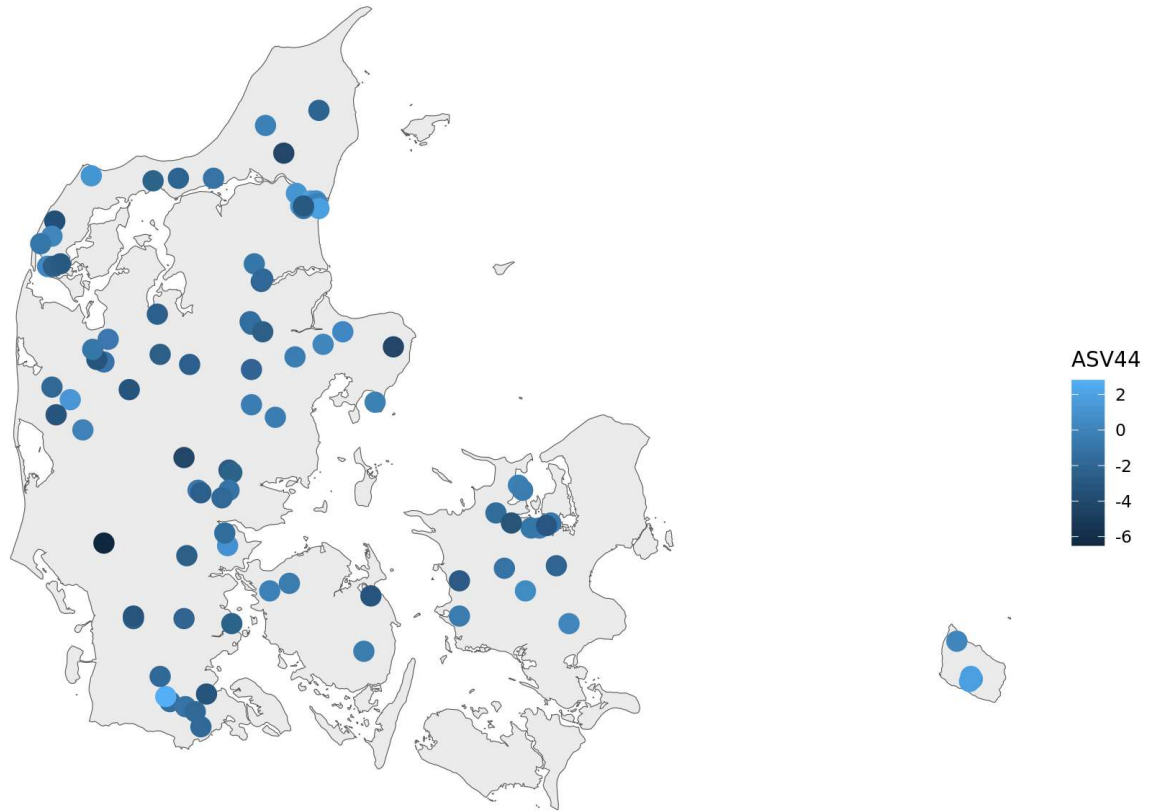
Table 2: Results from ANOVA analysis of single species differential abundance between regions. A anova model was used to identify single species that vary in clr-transformed abundance between any two regions (adjusting for year and JB groups). Species to be analyzed where pre-selected as the top abundant and most varying species in the dataset. The table show species with adjusted $p < 0.15$ and rows are colored red ($p_{adj} < 0.05$) and salmon ($p_{adj} < 0.1$) based on the adjusted p values.

Consider if we do want to adjust the analysis above for JB values. We know there is a strong correspondance between location and JB values, and one could argue that we expect a difference between location largely due to soil type differences. When we adjust for JB, we thus look for any location/region differences not driven by

JB, and leave direct JB differences to the below analyses.

Maps reflecting species abundance of the top 3 species showing strongest region differences The clr-transformed abundance of the top 3 species from the above table is shown on individual maps.





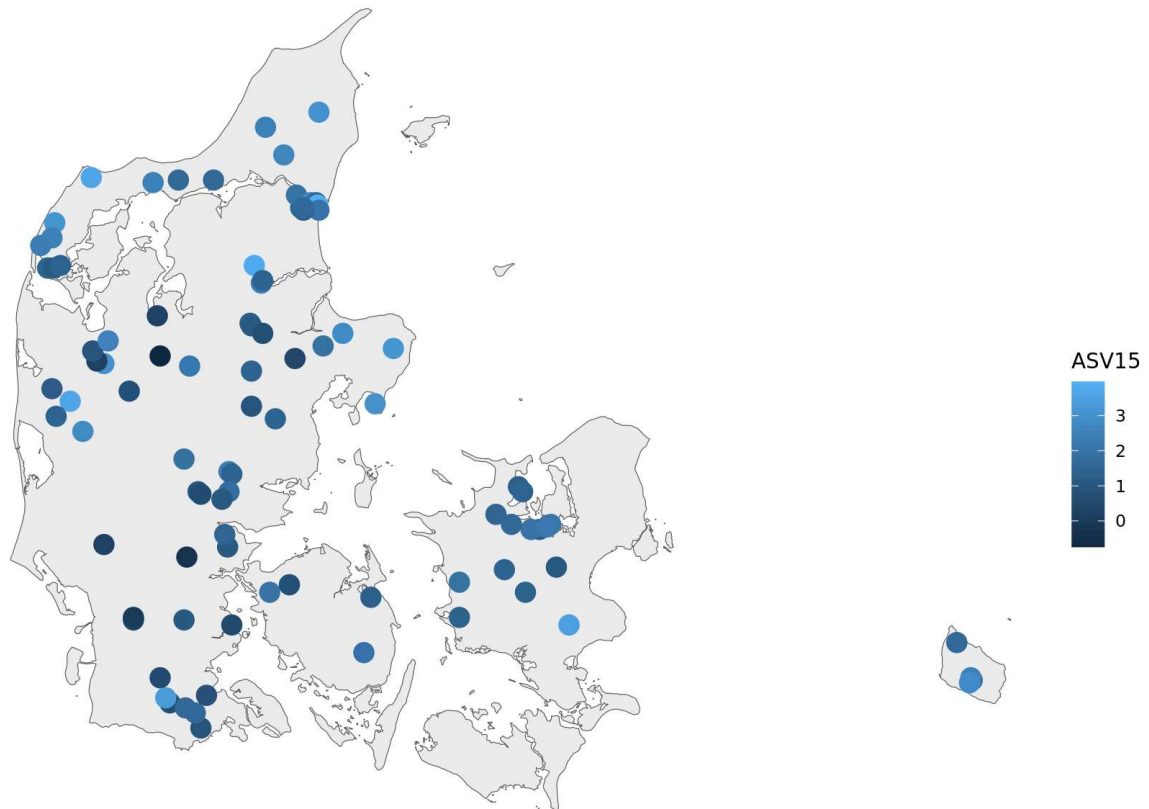


Figure 4: Visualization of the geographic distribution of samples colored by the clr-transformed abundance of one specific species.

The species *Streptomyces sp. RPA4 2* show an interesting pattern on the above plot and we thus zoom in to review the species abundance across the location using a boxplot, and review the association with JB groups and year of sampling.

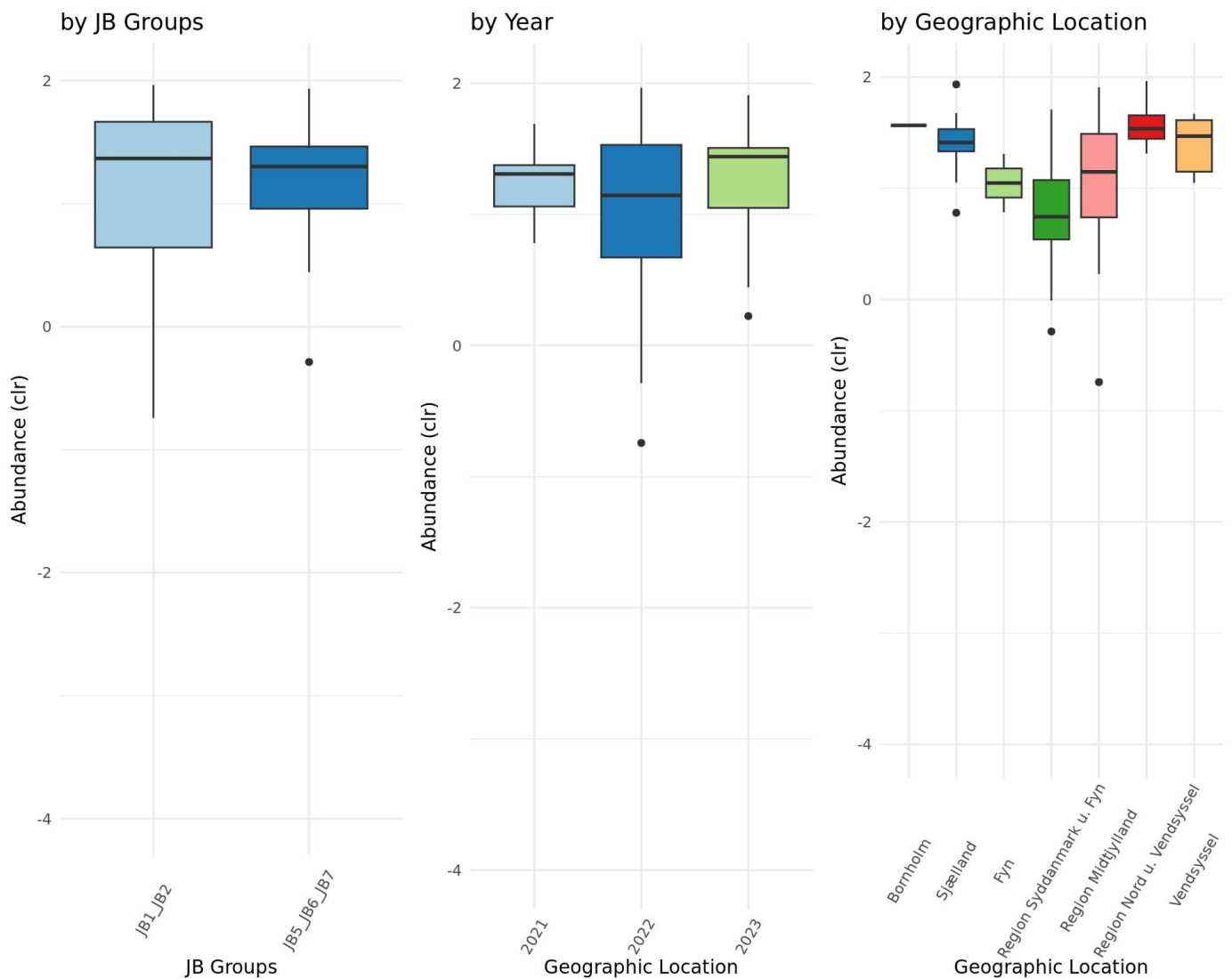


Figure 5: Boxplots showing the clr-transformed species abundance between JB groups, year and region.

Evaluation of overall microbiome profiles

We initiate the evaluation of the 10 samples (1 per field) with a stacked barplot of the microbiome profiles in each sample. This allows us to make a first evaluation of the extent of difference in the taxonomic profiles between the fields.

Note that in order to show the organisms with a color scheme that is interpretable, it is necessary to filter the profiles and select a subset of the most abundant clades to be included in the plots. The filtering used is specified in the axis labels of each plot (e.g. >2% in the relative abundance plots mean that a clade must have a relative abundance across samples of more than 2% in order to be included in the plot).

Stacked barplots

The stacked barplots allow us to visually access the stability of the taxonomic profile across the fields, and get a feeling of the level to which individual clades are found across field or more sporadic. Compared to the bacterial part of the microbiome, the fungi show a large deviation between fields, with both large variation in some, and others that are dominated by a few clades. And we see how the dominating clade is also different between many fields.

Phylum	Class	Order
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A Overall microbiome communities Relative abundance

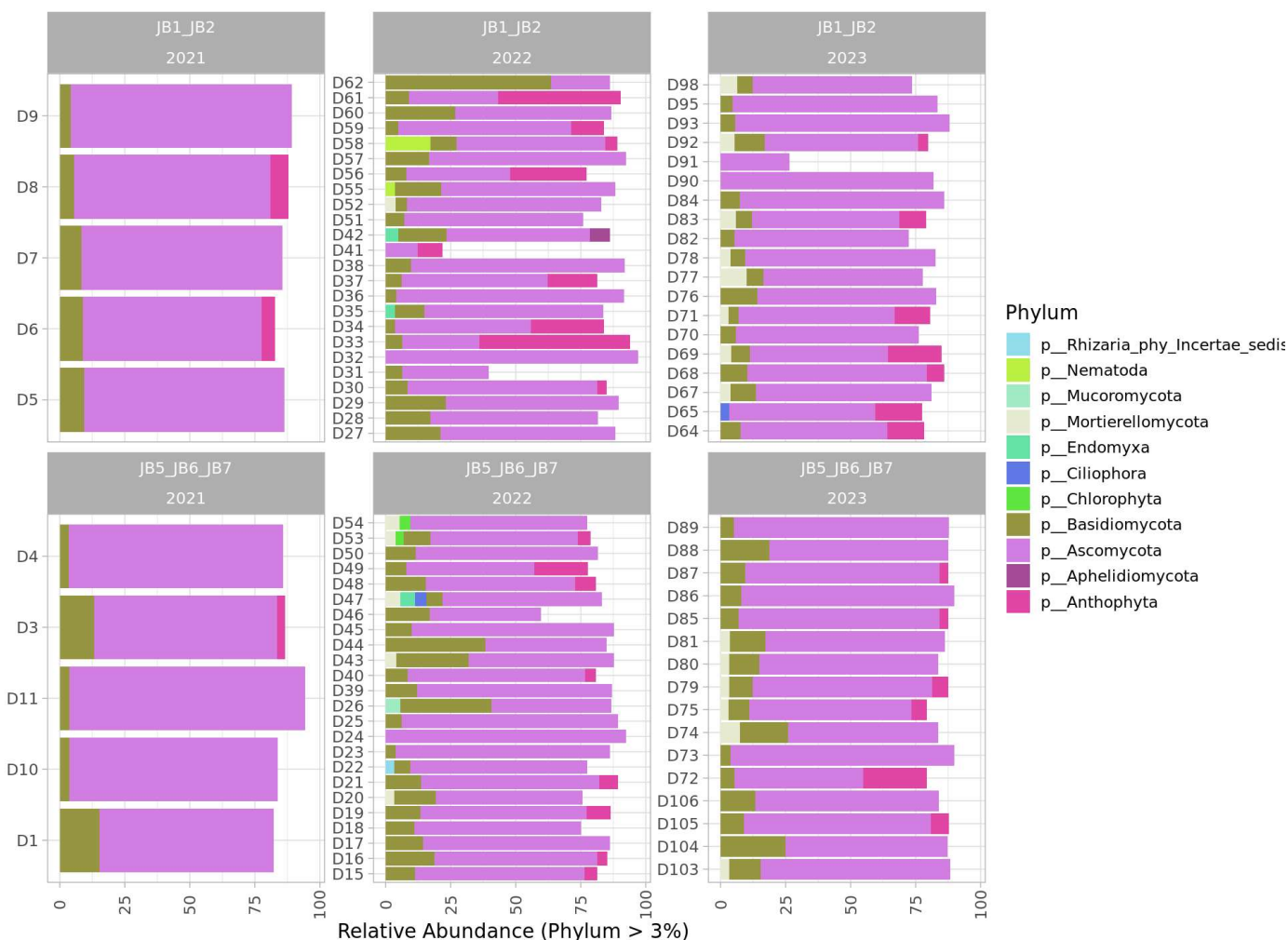


Figure 6: Visualization of the fungal community in the samples. Stacked barplots of taxonomic clades in each of the evaluated samples. Clade abundance was transformed to relative abundance to sum to 100% in each sample. The plot is separated into two parts - one per group of samples based on JB values.

Microbiome communities related to factor variables

We use the overall microbiome profiles presented in the stacked barplots above, to calculate a measure of difference in the microbiome composition between samples (beta-diversity). The calculated beta-diversity measures are used for visual inspection of the relationship between the microbiome profiles in the so called ordination plots (see below), and in a statistical model named ADONIS (or PERMANOVA, see details below) to evaluate if the overall microbiome composition associates with the selected variables. For these evaluations we focus on the variables that can be viewed as binary or generating groups (e.g. JB value, Earthworm status, Crops, Mulching of straw and Years since plowing). These variables are “grouping variables” that allow us to group samples into subgroups. The remaining variables constitute continuous values (concentrations or percentages) and therefore, we use a different set of tools to evaluate how they relate to the overall microbiome composition (see below).

Note that “years since plowing” and “Years since turning organic” are analyzed as integers with increasing values (0,1,2, etc) and could be analyzed both with ADONIS and the model used for continuous variables (ENVFIT, see below). However, we find it interesting to visualize the shift in the composition according to “years” in an ordination plot, and the variable is therefore included here.

Visualization by heatmaps (for single organisms)

We show the relative abundance (0-100) for the most abundant species in samples groups. The samples are grouped first by JB group and then the factor variable. This allow us to inspect JB specific and general effects on the taxa for each factor variable.

Note, we show here plots for one taxonomic level, but plots are made for all levels, and should be reviewed. See these in the project folder under Illustrations (DA00204/data/ITS/4_Statistical_analysis/Illustrations). There heatmaps are found both with samples grouped by factor variables and with abundance shown for each sample separated just by JB value (e.g. Heatmap_Class_byJB.png).

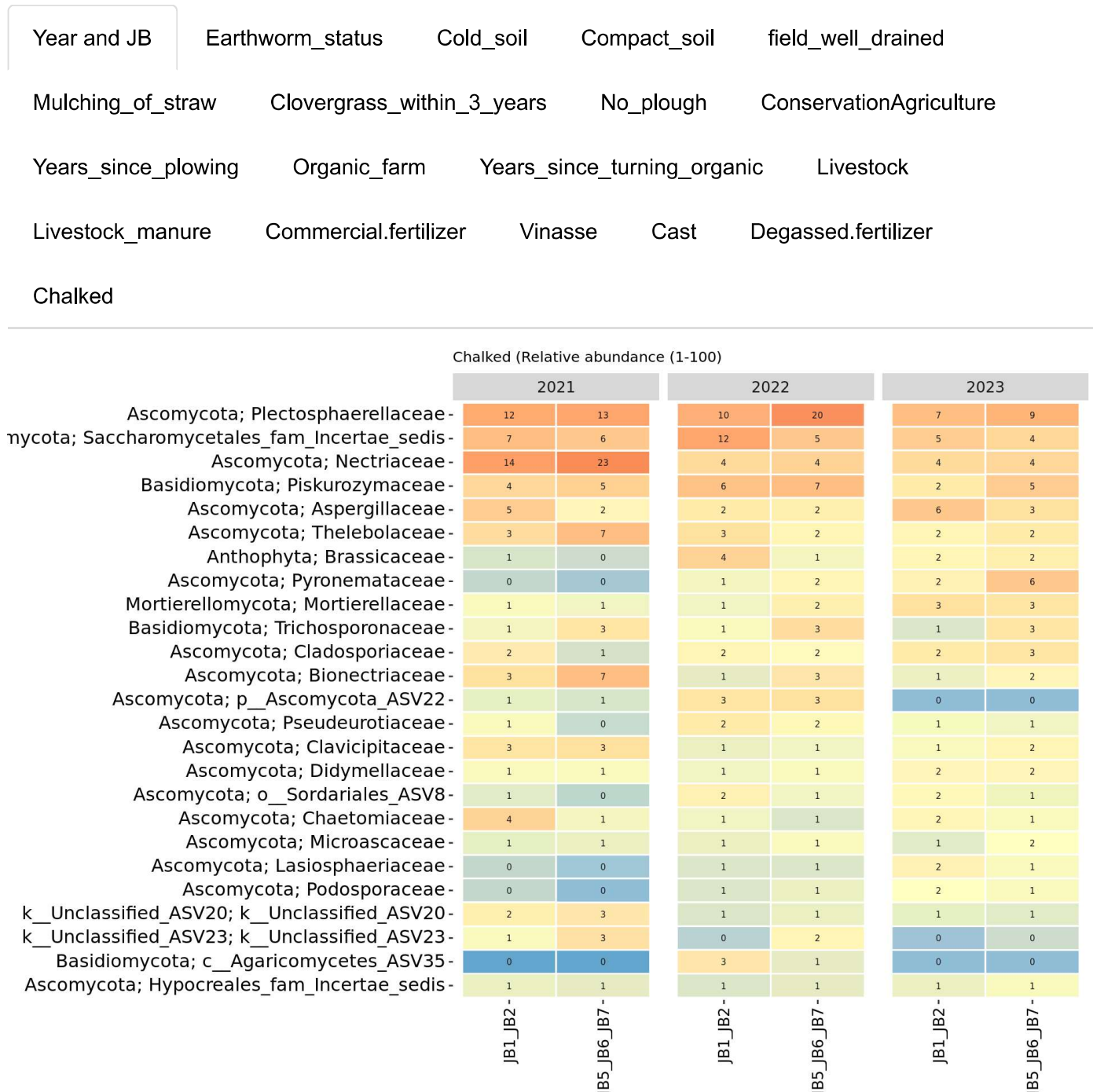


Figure 9: Visualization of abundance of the fungal organism between samples grouped by JB and factor variable.

Visualization by ordination (beta-diversity)

As described in **Report 2**, beta-diversity is a measure of how similar or dissimilar the fungal community is between each pair of samples. The measures are useful for statistical analysis and visualization of the overall microbiome community. In ordination plots, each sample is a point and the distance between the points

increases with increasing dissimilarity in the microbiome communities.

Here we evaluate the microbiome communities using the Bray-Curtis, Aitchison and Jaccard beta-diversity measures. If not all plots are shown in this report, you can find them in the project folder. We use a combination of beta-diversity measures as each measure highlights different properties of the microbiome. See more details in **Report 2**.

We use the different measures in combination with different microbiome profiles (taxonomic levels and normalization) as follows:

- Bray Curtis and Jaccard are computed from the relative abundance data, at the the genus level
- Aitchison is computed from the total abundance data transformed with central-log-ratio (CLR), at the genus level

The Aitchison distance is a simple euclidean distance calculated using CLR transformed microbiome profiles. An analysis of CLR transformed data will reveal how the organisms behave relative to the per-sample average microbiome. Values for a microbe can therefore be negative after CLR transformation - meaning that it makes up a smaller amount of the microbiome than the average abundant microbe. This is a very different way to view the microbiome than Bray-curtis and Jaccard that uses the data as relative proportions (i.e. how big a proportion of the sample's microbiome does the individual microbe comprise). This might appear unnecessarily mathematical and unrelated to agrobiolgy but the CLR transformation has proved to be able to pinpoint patterns in microbiomes that are driven by environmental factors such as nutrient content or treatment applied to the samples. We therefore evaluate structures in the dataset using all three measures.

As we move from the per-year analysis to a cross-years analysis, I have changed the ordination method from an NMDS method (metaMDS in package vegan) to MDS/dbRDA (capscale in package vegan), as the capscale approach allows me to condition (or partial out, aka. remove), the effect of year from the data allowing us to better inspect effects of other variables in the ordination plots. In the statistical analysis e.g. the ADONIS model, I do this by including a term for year in the model.

Perhaps when we have data from 2023 as well, we can try to look if any effects are specific to one year, and then discuss what was different between the years to possible cause this. But with the few samples form 2021 we cannot relably extract such information at this point.

Permutational Multivariate Analysis of Variance

To evaluate if the compositional differences evaluated below using ordination plots explain a notable amount of the variation in the microbial composition, and if the amount of explained variation is statistically significant, we perform an analysis named Permutational Multivariate Analysis of Variance (ADONIS). ADONIS uses sums of squares of a multivariate dataset and is analogous to MANOVA (multivariate analysis of variance) using beta-diversity measures. It uses distance matrices among sources of variation and fits linear models to the distance matrices using a permutation test with pseudo-F ratios and can therefore be considered as a "permutational manova".

For the analysis we use Bray-Curtis, Jaccard and Aitchison beta-diversity measures and perform the analysis at the phylum level down to the ASV level. The latter is used in amplicon sequencing in which a group of exact sequences is referred to as an amplicon sequence variant (ASV).

Each table shows results from evaluation of the effect of one variable and there is thus one table per variable.

In each plot, samples are colored by the variable being assessed.

JB value	Earthworm status	Cold_soil	Compact soil	Field well drained
Mulching of straw	Clovergrass within 3 years	No plough	Conservation Agriculture	

Years since plowing Organic farm Years since turning organic Livestock
 Commercial fertilizer Vinasse Cast Degassed fertilizer Chalked

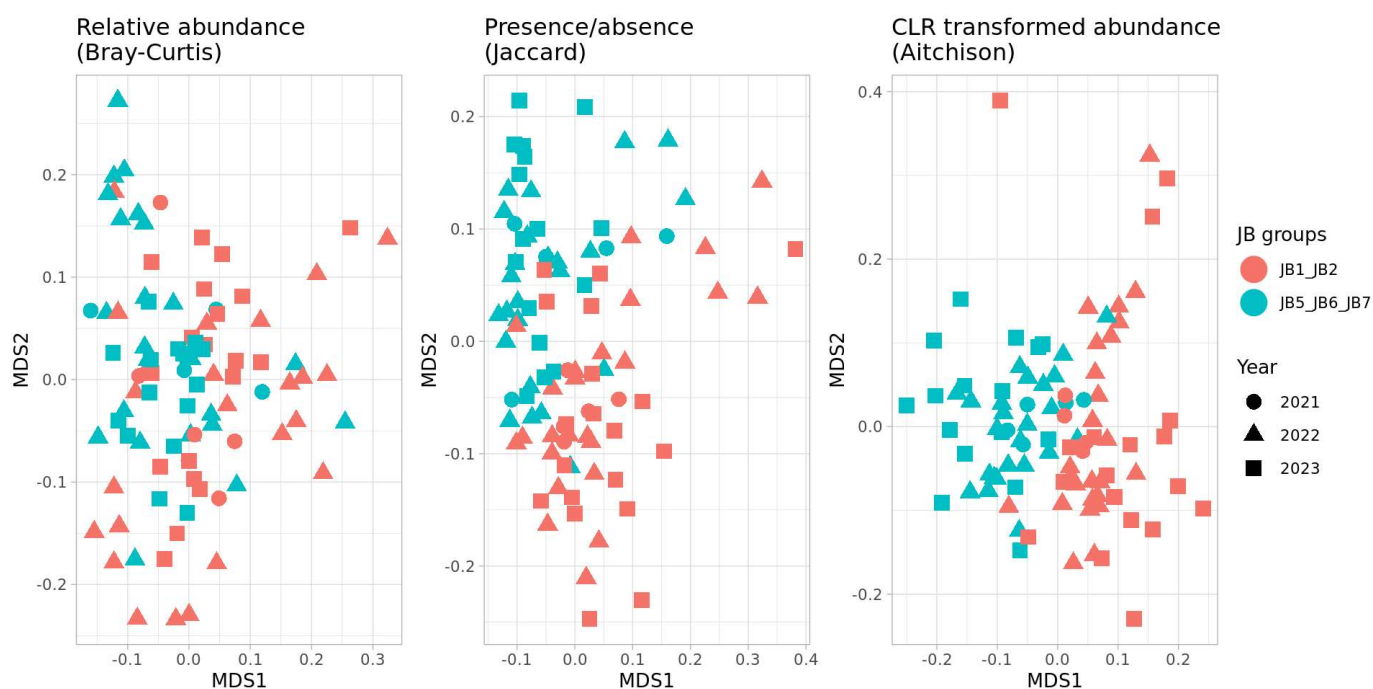


Figure 28: Visualization of structure of the fungal community between the samples. Ordination plots using different beta-diversity measures and data transformations as stated in the plot titles. Dots are colored by the variable of interest as seen to the right of the figure panels.

	Bray-Curtis		Jaccard		Aitchison	
Taxa level	R2	p	R2	p	R2	p
Phylum	0.0297	0.026	0.0149	0.098	0.0314	0.004
Class	0.0417	0.001	0.0219	0.012	0.0332	0.001
Order	0.0351	0.001	0.024	0.004	0.0297	0.001
Family	0.0338	0.001	0.0256	0.001	0.0354	0.001
Genus	0.0359	0.001	0.0304	0.001	0.0414	0.001
ASV	0.0423	0.001	0.0268	0.001	0.033	0.001

Table 3: Results from ADONIS analysis. The table shows results from ADONIS analyses including samples from all fields. The analysis was performed using 999 permutations to robustly calculate significance. The table shows the obtained R-squared values that indicate the percentage of variation that the variable could explain and the corresponding p-values.

With the striking effect of JB groups on microbiome community when viewed in respect to the composition properties (clr data), we look further into the differences. First we apply an ANOVA model to identify single species differing in abundance between the two JB groups.

	Sum.Sq	Df	F.value	Pr..F.	p.adj
ASV27	10.639	1	17.015	8.32e-05	0.00424
ASV2	44.519	1	9.523	2.70e-03	0.04620
ASV45	15.890	1	9.513	2.72e-03	0.04620
ASV9	12.502	1	8.313	4.93e-03	0.05030
ASV16	14.905	1	8.615	4.24e-03	0.05030
ASV12	6.591	1	7.933	5.98e-03	0.05080
ASV1	4.578	1	6.442	1.29e-02	0.08490
ASV15	5.008	1	6.307	1.38e-02	0.08490
ASV50	15.720	1	6.155	1.50e-02	0.08490
ASV20	3.921	1	5.559	2.06e-02	0.10500
ASV30	9.733	1	5.111	2.62e-02	0.10800
ASV33	14.925	1	5.165	2.55e-02	0.10800
ASV195	12.572	1	5.016	2.76e-02	0.10800

Table 4: Results from ANOVA analysis of single species differential abundance between JB groups A anova model was used to identify single species that vary in clr-transformed abundance between any two JB groups (adjusting for year). Species to be analyzed were pre-selected as the top abundant and most varying species in the dataset. The table shows species with adjusted $p < 0.15$ and rows are colored red ($p_{adj} < 0.05$) and salmon ($p_{adj} < 0.1$) based on the adjusted p values.

The species *Luteitalea pratensis* is among the top associated species, and is a species previously found to display a narrower pH, possibly leading to the observed differences. This possibility was supported by a significant association between the species abundance and Rt (correlation test $r = 0.38$, $p = 0.00009$). We thus zoom in to review the species abundance across the location using a boxplot, and review the association with JB groups and year of sampling.

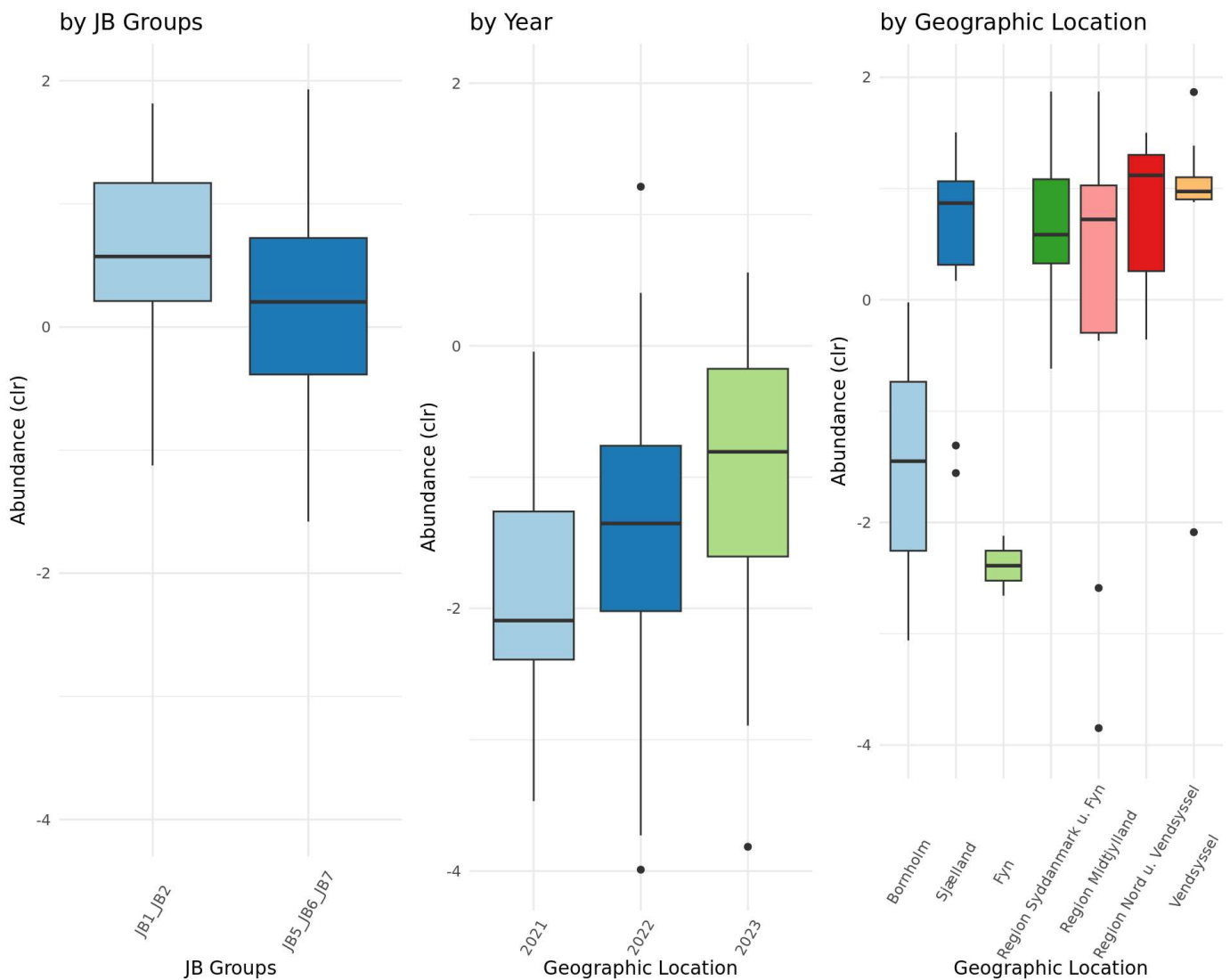


Figure 29: Boxplots showing the clr-transformed species abundance between JB groups, year and region.

Overall microbiome communities related to continuous variables

We now turn to the continuous variables. We continue to use the beta-diversity measure from the microbiome, but use a different analysis model named ENVFIT. We again display the samples in ordination plots but add to these plots arrows representing the association of the variables with the microbiome.

ENVFIT

The function fits environmental variables onto an ordination using multiple regression and thus looks for linear relationships between the axis that drive the main variation in the microbiome and the environmental variables.

The output of the analysis gives the direction of the association in terms of coordinates in the ordination plot (the arrow head). In the plots, the arrows are scaled by their correlation (square root of R^2) so that “weak” variables have shorter arrows than “strong” variables. The arrows point in the direction where they have maximal correlations with the ordination axis. The lengths of arrows for fitted vectors are automatically adjusted for the physical size of the plot, and the arrow lengths can thus not be compared across plots, only the arrows within a plot can be compared.

Note that the ENVFIT analysis uses the ordination axes and therefore is restricted to relate the environmental factors to the part of the microbiome that is represented by these axes (and thus not the full microbiome variation). This fact is also relevant when comparing R^2 (the squared correlation coefficient) from ADONIS and envfit: ADONIS decomposes the entire dissimilarity matrix into “variance” explained by each covariate. In ENVFIT, you have reduced the entire dissimilarity matrix to two dimensions and then look for correlations in

those three dimensions with the covariates. The “discrepancy” is therefore due to the fact that different amounts of variation are assessed by the two models. Therefore, if ADONIS gives higher R² values, this suggests that the effect of the variable is on the parts of the dissimilarity matrix not represented well by the 3-d NMDS solution. We are using capscale, and not the standard NMDS method, for the ENVFIT analysis, as capscale allow us to condition out the effect of year before performing the correlation analyses. * R² - variation explained by the model of multiple regression; the square-root of this value is used to scale lengths of vectors (arrows) in the ordination diagrams (variables with higher squared (R²) are represented by longer arrows). * Pr(>r) - the significance of the multiple regression, calculated by permutation test. Indicates whether the variable is related to ordination axes more than if it is a randomly generated one.

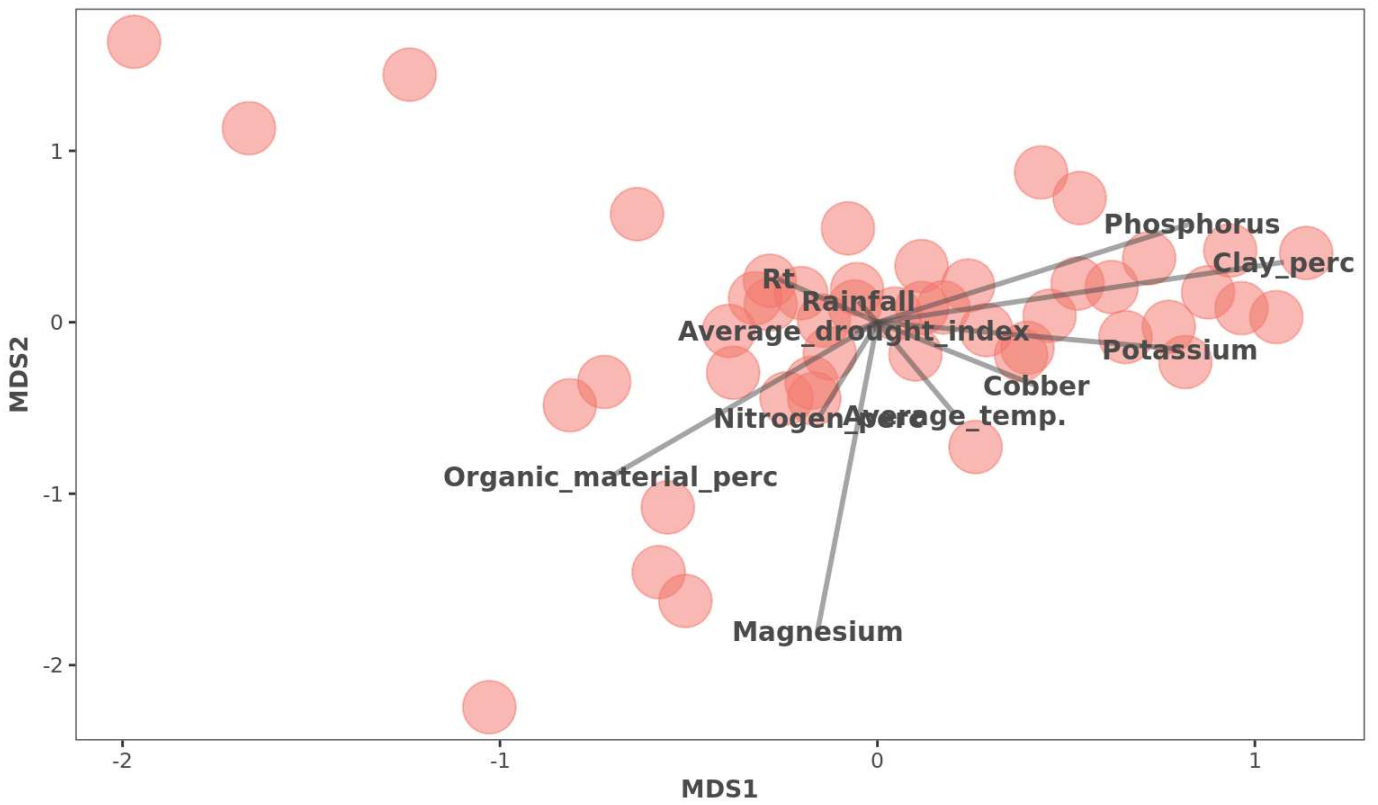
Ordination plots

Bray Curtis

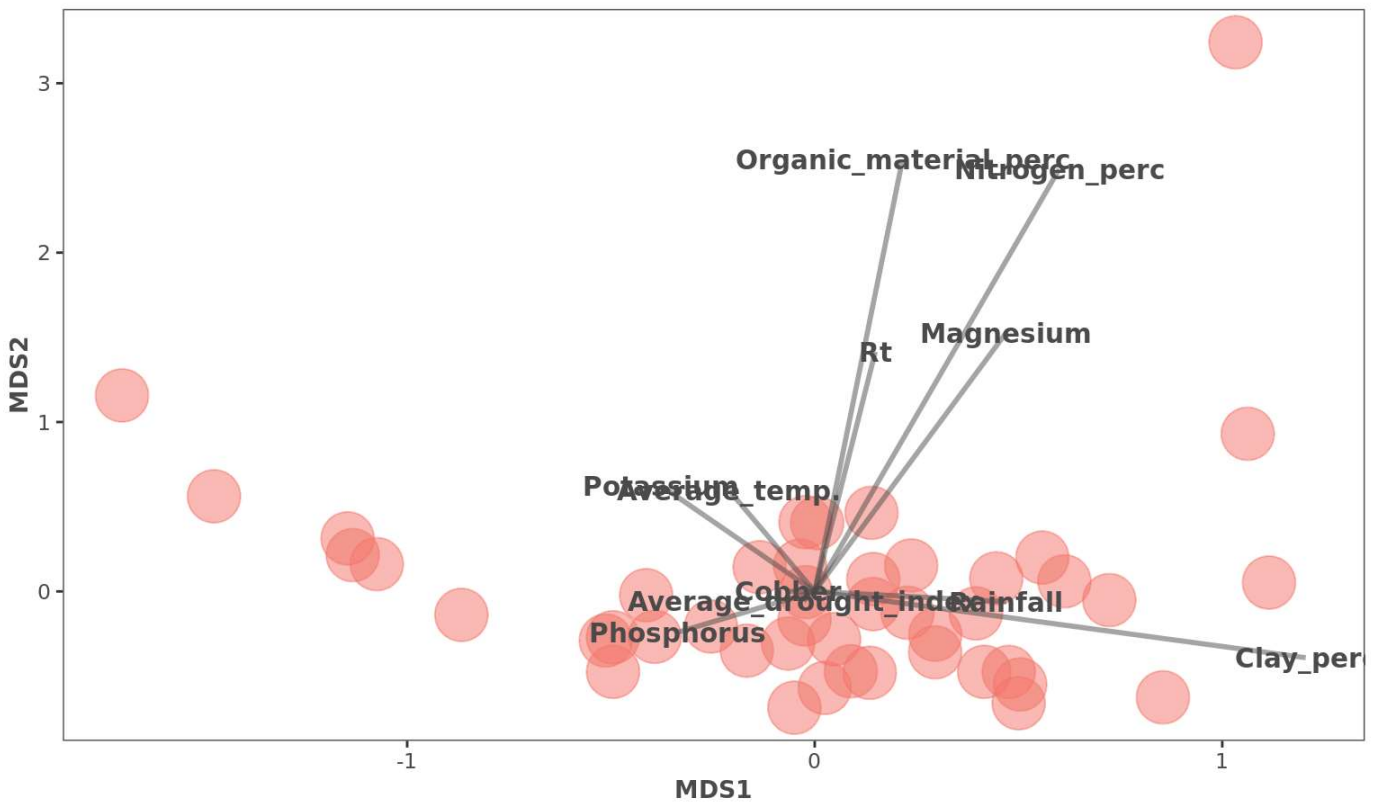
Jaccard

Aitchison

JB 1-2; Bray Curtis



JB 5-7; Bray Curtis



ENVFIT summary statistics tables

ENVFIT for JB 1 & JB2

	Bray		Jaccard		Euclidean	
Variable	R2	p	R2	p	R2	p

Rainfall	0.001	0.976	0.019	0.648	0.001	0.99
Average drought index	0	0.997	0.001	0.977	0	0.992
Average temp.	0.014	0.763	0.05	0.341	0.012	0.765
Rt	0.005	0.864	0.062	0.232	0.055	0.282
Phosphorus	0.042	0.385	0.156	0.028	0.173	0.018
Potassium	0.027	0.534	0.034	0.467	0.011	0.777
Magnesium	0.133	0.053	0.202	0.004	0.133	0.037
Cobber	0.013	0.744	0.01	0.79	0.011	0.793
Organic material (%)	0.053	0.287	0.437	0.001	0.431	0.001
Clay (%)	0.052	0.293	0.037	0.435	0.028	0.558
Nitrogen (%)	0.014	0.737	0.442	0.001	0.387	0.001

Table 32: Results from ENVFIT analysis across JB1 and JB2 fields. The table shows results from ENVFIT analyses including samples from all fields. The table shows the obtained R-squared values and the corresponding p-values from the ENVFIT analysis, for each of the assessed variables in each of the three beta-diversity ordinations.

ENVFIT for JB 1 & JB2

.	Bray		Jaccard		Euclidean	
	R2	p	R2	p	R2	p
Rainfall	0.011	0.814	0.207	0.006	0.016	0.712
Average drought index	0	0.997	0.038	0.436	0.001	0.974
Average temp.	0.019	0.704	0.253	0.002	0.068	0.23
Rt	0.096	0.131	0.149	0.026	0.277	0.002
Phosphorus	0.008	0.826	0.023	0.602	0.055	0.312
Potassium	0.025	0.526	0.004	0.912	0.088	0.13
Magnesium	0.12	0.072	0.06	0.27	0.242	0.004
Cobber	0	0.997	0.041	0.421	0.011	0.789
Organic material (%)	0.309	0.003	0.15	0.034	0.206	0.009

Clay (%)	0.076	0.179	0.045	0.354	0.014	0.751
Nitrogen (%)	0.311	0.001	0.229	0.005	0.321	0.003

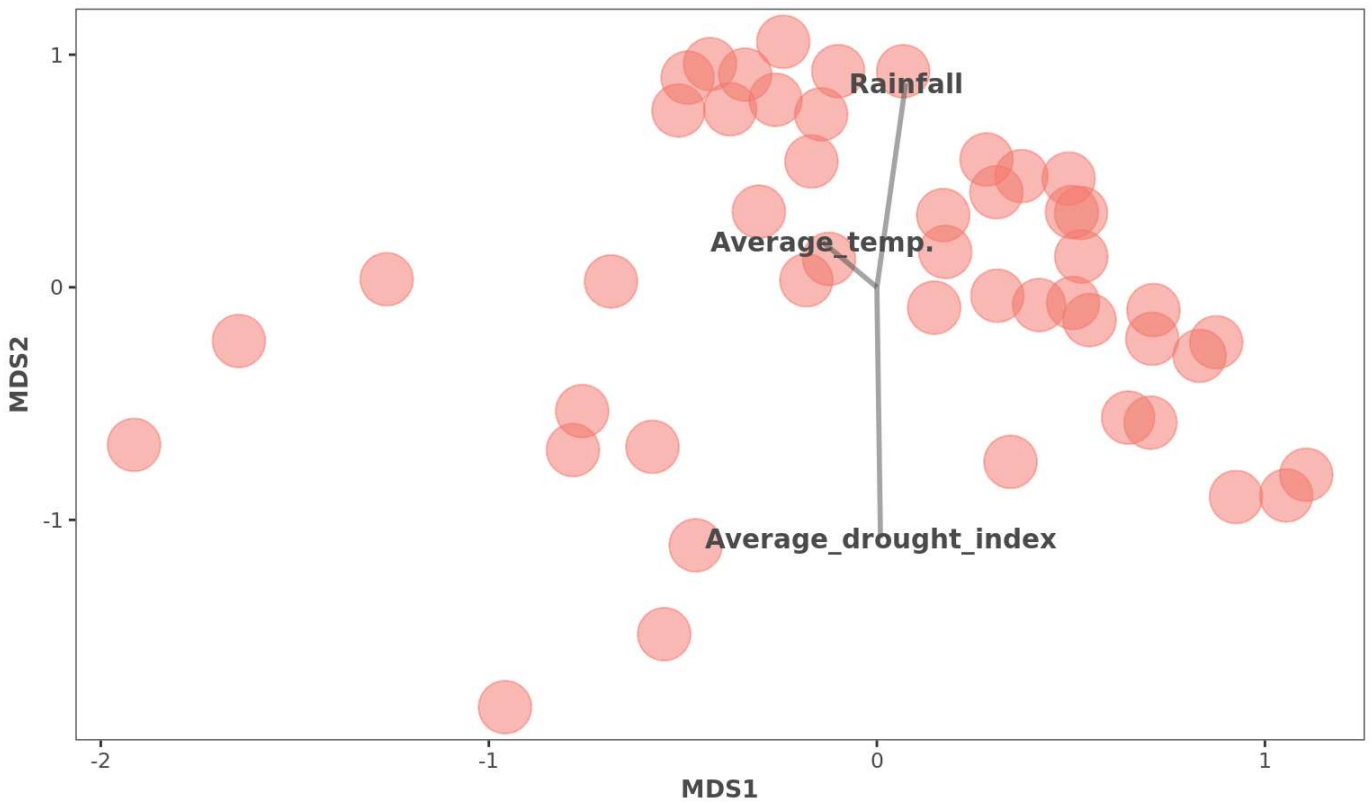
Table 33: Results from ENVFIT analysis across JB1 and JB2 fields. The table shows results from ENVFIT analyses including samples from all fields. The table shows the obtained R-squared values and the corresponding p-values from the ENVFIT analysis, for each of the assessed variables in each of the three beta-diversity ordinations.

ENVFIT for climate

Note above we have adjusted for year in all ENVFIT analyses. But this is not ideal for the climate variables as they often are a direct consequence of yearly differences and thus we remove the effect we are looking the study. Therefore, here we perform ENVFIT analyses again but only for climate variables and this time without adjusting for year.

Ordination plots	ENVFIT summary statistics tables	
Bray Curtis	Jaccard	Aitchison

JB 1-2; Bray Curtis



JB 5-7; Bray Curtis

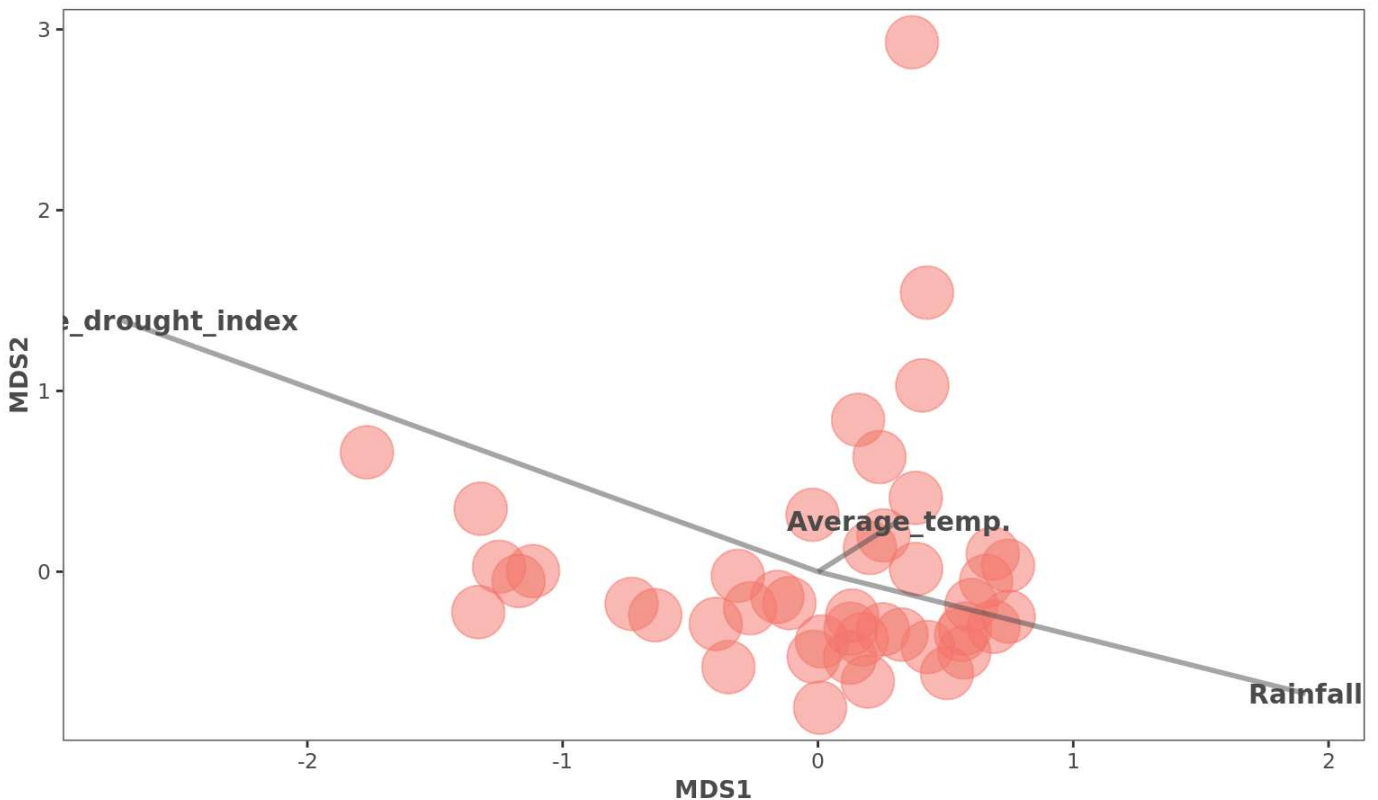


Figure 49: Visualization of the ENVFIT analysis for 3 climate variables. The association of the evaluated environmental variables with the ordination axis is displayed by arrows, with longer arrows indicating a stronger association.

Non-linear relationships for continuous environmental variables

The ENVFIT model looks for linear relationships between the main variation of the microbiome (the separation of the samples along the first ordination axes) and the environmental variables. It can also be relevant to look for non-linear relationships - so called smooth surfaces - where the environmental variable for example is

highest in the centrally located samples on the ordination plot and lower in samples located towards the edges. We use a mode called Ordisurf to look for such non-linear patterns. Ordisurf internally uses generalized additive models with integrated smoothness estimation, so-called GAMs, to fit the variable. Below is a table of the results from the analysis looking for smooth surfaces for the selected variables and further down are the surfaces illustrated on ordination plots.

Euclidean		
	F	P
Rainfall	0.51	1.41e-01
Average_drought_index	1.025	3.67e-02
Average_temp.	0.014	4.00e-01
Rt	0.079	2.75e-01
Phosphorus	0.806	1.54e-02
Potassium	0	8.13e-01
Magnesium	1.198	1.51e-02
Cobber	0	7.77e-01
Organic_material_perc	3.787	2.29e-06
Clay_perc	0.006	4.39e-01
Nitrogen_perc	3.003	1.37e-05

Table 36: Results from non-linear analysis. The table shows results from the non-linear analyses performed using Ordisurf for samples JB1 and JB 2. The table shows the obtained F values and the corresponding p-values, for each of the assessed variables based on the Aitchison beta-diversity.

Euclidean		
	F	P
Rainfall	0.019	4.06e-01
Average_drought_index	1.388	1.55e-02
Average_temp.	0.117	2.29e-01
Rt	1.769	9.96e-04
Phosphorus	0.075	3.04e-01
Potassium	1.17	1.66e-02

Magnesium	1.757	1.36e-03
Cobber	0.847	5.43e-02
Organic_material_perc	1.302	7.08e-03
Clay_perc	0.092	2.95e-01
Nitrogen_perc	3.037	1.33e-04

Table 37: Results from non-linear analysis. The table shows results from the non-linear analyses performed using Ordisurf for samples JB5, JB6 and JB 7. The table shows the obtained F values and the corresponding p-values, for each of the assessed variables based on the Aitchison beta-diversity.

Version information

Table 38: List of used software including the used R-programming environment packages.

Package	Version	Package	Version
OS	Ubuntu 20.04.4 LTS	jpeg	0.1-10
R	4.3.3	utf8	1.2.4
splines	4.3.3	generics	0.1.3
bitops	1.0-7	robustbase	0.99-2
cellranger	1.1.0	class	7.3-22
lifecycle	1.0.4	httr	1.4.7
rstatix	0.7.2	htmlwidgets	1.6.4
sf	1.0-16	S4Arrays	1.2.1
MASS	7.3-60.0.1	pkgconfig	2.0.3
insight	0.19.10	gtable	0.3.5
backports	1.4.1	hwriter	1.3.2.1
magrittr	2.0.3	pcaPP	2.0-4
plotly	4.10.4	htmltools	0.5.8.1
sass	0.4.9	biomformat	1.30.0
rmarkdown	2.26	png	0.1-8
jquerylib	0.1.4	rstudioapi	0.16.0
yaml	2.3.8	tzdb	0.4.0
zip	2.3.1	reshape2	1.4.4
cowplot	1.1.3	coda	0.19-4.1
DBI	1.2.2	nlme	3.1-164

Package	Version	Package	Version
minqa	1.2.6	curl	5.2.1
ade4	1.7-22	nloptr	2.0.3
multcomp	1.4-25	proxy	0.4-27
abind	1.4-5	cachem	1.0.8
zlibbioc	1.48.2	zoo	1.8-12
Rtsne	0.17	rhdf5	2.46.1
RCurl	1.98-1.14	sjlabelled	1.2.0
TH.data	1.1-2	KernSmooth	2.23-22
sandwich	3.1-0	parallel	4.3.3
GenomeInfoDbData	1.2.11	pillar	1.9.0
ggrepel	0.9.5	vctrs	0.6.5
units	0.8-5	ggpubr	0.6.0
svglite	2.1.3	xtable	1.8-4
codetools	0.2-20	cluster	2.1.6
DelayedArray	0.28.0	evaluate	0.23
xml2	1.3.6	mvtnorm	1.2-4
tidyselect	1.2.1	cli	3.6.2
farver	2.1.1	compiler	4.3.3
multtest	2.58.0	rlang	1.1.3
e1071	1.7-14	crayon	1.5.2
survival	3.5-8	ggsignif	0.6.4
iterators	1.0.14	rrcov	1.7-5
systemfonts	1.0.6	labeling	0.4.3
foreach	1.5.2	interp	1.1-6
tools	4.3.3	classInt	0.4-10
glue	1.7.0	plyr	1.8.9
SparseArray	1.2.4	stringi	1.8.4
xfun	0.43	viridisLite	0.4.2
mgcv	1.9-1	deldir	2.0-4
withr	3.0.0	munsell	0.5.1
fastmap	1.1.1	lazyeval	0.2.2
latticeExtra	0.6-30	V8	4.4.2

Package	Version	Package	Version
boot	1.3-30	hms	1.1.3
rhdf5filters	1.14.1	Rhdf5lib	1.24.2
fansi	1.0.6	highr	0.10
digest	0.6.35	broom	1.0.5
timechange	0.3.0	igraph	2.0.3
R6	2.5.1	RcppParallel	5.1.7
estimability	1.5	bslib	0.7.0
colorspace	2.1-0	DEoptimR	1.1-3